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Fuzzy Expert Systems and Applications in Agricultural Diagnosis

A.V. Senthil Kumar and M. Kalpana

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Detailed Table of Contents

Agriculture is an important source of livelihood and economy of a country. Decision making plays an important role in various fields. Farmers are the backbone of agriculture. They need expert systems to make decisions during land preparation, sowing, fertilizer management, irrigation management, etc. for farming. Expert systems may suggest precisely suitable solutions to farmers for all the activities. Uncertainty deals with various situations during sowing, weed management, diagnosis of disease, insect, storage, marketing of product, etc. Uncertainty is compounded by many facts that many decision-making activities in agriculture are often vague or based on perception. Imprecision, vagueness, and insufficient knowledge are handled using the concept of fuzzy logic. Fuzzy logic with expert systems helps find uncertain data. Fuzzy expert systems are oriented with numerical processing.

Agriculture plays a major role in the Indian economy. India is rich in production of crops like rice, cotton, wheat, soybean, sugar; fruits and vegetables like onion, tomatoes, potatoes; dairy; and meat products. India is ranked first worldwide for the production of banana, jute, mango, cardamom, and ranked second worldwide for the production of rice, tomato, potato, and milk. India's agriculture contributed 4759.48 INR billion to the GDP during the first three months of 2018, and it has been reduced drastically during the second three months of 2018 (i.e., it has been reduced to 4197.47 INR billion). The average GDP is 4057.73 INR billion from 2011 until 2018; the agricultural contribution to GDP reached its highest level, that is 5666.82 INR billion, in the last three months of 2017. This chapter explores the application of fuzzy expert systems for analyzing agricultural data.

The authors consider an approach to automatic knowledge acquisition through machine learning on the basis of integrating the two basic reasoning methods – case-based reasoning and rule-based reasoning. Case-based reasoning allows using high-performance database technology for storing and accumulating cases, while rule-based reasoning is the most developed technology for creating declarative knowledge base on the basis of strong logical approach. This allows realizing the transformation of the spiral of knowledge, leading to continuous improvement of the knowledge quality in the management system. In the chapter, they propose one method of obtaining rules from cases based on fuzzy logic. Here the method is considered for solving classification problem, but it also can be applied for solving regression problem. The research shows acceptable accuracy of cases classification even for small training samples. At the same time, smoother (quadratic) membership functions show on average classification accuracy.

Agriculture, cattle breeding, and poultry farming constitute the backbone of the Indian economy. Today, India is ranked first worldwide in terms of milk production, second in terms of farm output, and third in terms of poultry output (eggs production). Over the year, agriculture, poultry farming, and cattle breeding have contributed towards India's GDP but is narrowly declining with the country's economic growth due to lack of initiatives. Fuzzy expert systems are used for various activities with an objective to get better results and good yield. Expert systems combine the experimental and experiential knowledge with the intuitive reasoning skills of a multitude of specialists to aid farmers in making the best decisions to improve the quality and increase the production. Weather and climatic changes play important roles. Thus, any changes in them affect the quantity and quality of production. Therefore, weather prediction plays an important role and helps the farmers to take right decisions and precautions to safeguard the production.

Agriculture is the main domain and need of India. The country is second place in the world in agriculture. Cropping is the main part of agriculture. Various crops like millets, fruits, vegetables, oil seeds are produced and exported to other countries every year. So, various innovative technologies are used to improve the productivity of crops in agriculture. Rainfall is most important for growing crops. The water level for the crops based on rainfall has some uncertainty. Fuzzy regression analysis is one of the methods based on regression analysis that is used to handle fuzzy parameters and crisp data and vice versa. Linear fuzzy regression is one of the methods of fuzzy regression analysis to handle fuzzy parameters. This chapter explores fuzzy classification, which is based on fuzzy regression analysis, and it is compared with other classification algorithms on the agriculture data.

In olden days, the plants used to tolerate and minimize the effect of air pollution caused by the then established industries and some automobiles. But in today's scenario, the rate at which plants and industries are rising doesn't match the count of trees. The plant survival and metabolism are based upon the nitrogen and chlorophyll available. There are several expensive methods to determine the chlorophyll and nitrogen content of the leaf like SPAD meter; the researchers have proposed a simple, inexpensive method that precisely determines the chlorophyll and nitrogen vales with a simple input RGB image. This chapter investigates the variation of content of plants in polluted environments and pollution-free environments.

Agriculture is an important sector in many developing countries, but the traditional methods are not sufficient to produce a good amount of crop. Moreover, the natural calamities are also destroying a large portion of the crop. Hence, this chapter proposes a prototype model, AgriHelp, to address an agricultural issue using fuzzy logic. The model takes two parameters as input: when and where the farmer wants to sow the crop. Using this information along with available dataset, AgriHelp extracts the expected min-max temperature, rainfall and soil type in the region in the specified season and suggests the best-suited crop to the farmer. The model can further be extended by incorporating more features.

This chapter emphasizes the use of adaptive fuzzy inference system (ANFIS) in agriculture. An overview of the basic concepts of ANFIS is provided at the beginning, where the underlying architecture of ANFIS is also discussed. The introduction is followed by the second section which highlights the diverse applications of ANFIS in agriculture during recent times. The third section describes how Matlab software can be utilized to build the ANFIS model. The fourth section describes the case study of the application of ANFIS for crop yield prediction. The conclusion follows this case study.

Section 3
Applications and Cases

Preface

Agriculture is the backbone of India economy in the digital world. Farmers need advice to take decision during their farming activities such as land preparation, sowing, irrigation management, fertilizer management, pest management and storage for higher production of crop. The application of Computers in the field of in agriculture has highly increased. Expert system and its utility play a very important role in all the fields. Decision making application was developed for crop growth and pest population. To improve the decision making capabilities expert system has been used in all the parts of field experiments. In agriculture, the problems are often given by imprecise, uncertain and unknown information Expert system helps to improve the decision result that can be colorfully expressed. Expert system in agriculture helps to make intelligent decision in crop production and crop protection. In agriculture, expert system gets the knowledge from individual disciplines, e.g., agronomy, crop physiology, plant pathology, entomology, agricultural meteorology, horticulture into a framework for farmers.

Fuzzy logic is one of the soft computing methods. Fuzzy logic (FL) is a powerful reasoning method to handle uncertainties and vagueness (Zadeh, 1965). Fuzzy logic application was started by Japanese in electronic field (Grosan & Abraham, 2011) and in latter stages people throughout the world used fuzzy logic to their application. Now fuzzy logic has been used by engineers, sociologists, psychologists, philosophers, medicine PR actioners and agricultural scientist. Fuzzy Expert System is design and development to make innovative decision in agriculture. Combination of Fuzzy Expert System and Agriculture is a relatively new way and used in many areas of agriculture. This combination is used in the area of crop production and crop management. Many fuzzy expert systems have been developed and used for diagnosis.

Computer based information system which helps to make decision on farming activities for scientist and farmers in the form of Fuzzy Expert System (FES). FES enables the farmers as the users to the system and can make decision regarding the farming activities. FES provides solution to complaints given by the farmers; FES is capable of providing solution to problems for uncertain data. FES is the area which provides robust realistic solution to make decision towards the problem. Other diagnostic quantitative approaches, either stochastic or certain, do not have the ability to include qualitative or subjective input variables.

In short term load forecasting, error may occur because of uncertainties in weather variable and statistical model. To have a better accuracy Fuzzy expert system is designed (Hsu & Ho, 1992). Harvinder S. Saini (2002) developed a web based intelligent disease diagnosis system using fuzzy logic concept. The developed system is used to diagnostic disease for oilseeds like soybean, rapeseeds, groundnut etc. It helps farmers and extension workers to increase the ability of cultivation and make decision by themselves. Nureize Arbaiy et al. (2007) developed a fuzzy expert system to forecast the activity of pest in rice fields. The system helps to educate and inform the farmers and smallholders about pest and its activities in the rice field. Virparia et al. (2007) develop a web based fuzzy expert system for controlling the groundnut insect pests, which can perform the identification of various externally observable symptoms, identify the actual insect pest and recommends the appropriate control measures. Robert F. Chevalier et al. (2012) developed a fuzzy expert system named Georgia's Extreme-weather Neural-network Informed Expert (GENIE) to forecast frost and freeze in horticultural crops. Fuzzy expert system for rice by applying the algorithm Fuzzy Assessment Methodology to predict the yield of rice (Kalpana & Senthil Kumar, 2013; Kalpana & Karthiba, 2016).

This book chapter incorporates various techniques using fuzzy expert system. In this context, implementation of these techniques in the field of agriculture will be useful for farmers, extension workers and scientist. With the collection of manuscripts which surrounds applications of fuzzy expert system in various areas of agriculture. This book promotes the understanding of the concepts and the uses of fuzzy expert system in agricultural domain. This book seeks to provide the latest research and developments to the professionals in area of agriculture.

Broader audience of this book will widely vary from individuals, farmers, extension workers, researchers, scientist, academics, students, libraries, and journalist. This book will generate tremendous impetus in terms of solution for diagnosis various application using fuzzy expert system in agriculture.

ORGANIZATION OF CHAPTERS

This book has been divided into three sections: “Concepts and Approaches”, “Innovations and Technologies” and “Applications and Cases”. Together, there are 13 chapters covering a wide range of concepts, technologies and applications.

Chapter 1 provides the Fuzzy Expert System in Agriculture domain which is used in decision making. The need of expert system is to make decisions during land preparation, sowing, fertilizer management, irrigation management etc., for farming. Expert system may suggest precisely suitable solution to farmers for all the activities. Fuzzy logic with expert system helps for uncertain data. Fuzzy expert systems are oriented with numerical processing.

Chapter 2 presents the application of Fuzzy Expert System for Analysing Agriculture Data. Over the year Agriculture has contributed toward the India's Gross Domestic Product (GDP). India's Agriculture contributes towards the GDP is 4759.48 INR Billion during the first three months of 2018 and it has been reduced drastically during the second three months of 2018 i.e it has been reduced to 4197.47 INR Billion. Due to lack of initiatives the contribution of Agriculture towards GDP is reducing gradually as results of that very less GDP 2690.74 INR Billion has been recorded during the third three months of 2011

Chapter 3 explains automatic Knowledge Acquisition in the Form of Fuzzy Rules from Cases for Solving Classification Problem. An approach to automatic knowledge acquisition through machine learning on the basis of integrating the two basic reasoning methods – case-based reasoning and rule-based reasoning.. The research show acceptable accuracy of cases classification even for small training samples. This allows for dynamic human participation in the interaction with case-based system to adapt the system's behavior to specific requirements.

Chapter 4 deals with Applications of Fuzzy Expert Systems in Farming. Fuzzy expert systems is used for various activities with an objective to get better results and good yield. Weather and climatic changes plays important roles. Thus, any changes in them affect the quantity and quality of production. Therefore, weather prediction plays an important role and helps the farmers to take right decisions and precautions to safeguard the production.

Chapter 5 proposes diagnostic Analytics on Agriculture with Fuzzy Classification. Innovative technologies are used to improve the productivity of crops in agriculture. Rainfall is most important for growing crops. The water level for the crops based on rainfall is has some uncertainty. Fuzzy regression analysis is one of the methods based on regression analysis which is used to handle fuzzy parameters and crisp data and vice versa. Linear fuzzy regression is one of the methods of fuzzy regression analysis to handle fuzzy parameters. This Chapter explores fuzzy classification which is based on fuzzy regression analysis and it is compared with other classification algorithms on the agriculture data.

Chapter 6 presents subjective and objective assessment for Variation of Plant Nitrogen Content to Air Pollutants Using Machine Intelligence. This chapter investigates the variation of content of plants in polluted prone environment and pollution free environment. The new algorithm developed produced superior correlations with the true or actual value of foliar Chlorophyll content measured and verified in the laboratory compared with existing non-destructive methods when applied to several plant species. A complete statistical analysis with graphical representation is proposed to compare the variation of Nitrogen levels that are useful for advancements in Machine Intelligence in Agricultural fields. This chapter completely investigates the application of machine intelligence in plants for commercial agriculture and research purpose.

Chapter 7 proposes fuzzy based Sustainable Solution for Smart Farming. This chapter proposes a prototype model, AgriHelp,to address an agricultural issue using fuzzy logic. The objective is to advice the farmers about sowing the crop that can survive with future weather conditions. The model takes two parameters as input: when and where the farmer wants to sow the crop. Using this information along with available dataset, AgriHelp extracts the expected min-max temperature, rainfall and soil type in the region in the specified season and suggests the best-suited crop to the farmer. The model can further be extended by incorporating more features such as soil composition, humidity, etc.

Chapter 8 emphasizes the use of Adaptive fuzzy inference system (ANFIS) in agriculture. An overview of the basic concepts of ANFIS is provided at the beginning, where the underlying architecture of ANFIS is also discussed. The introduction is followed by the second section which highlights the diverse applications of ANFIS in agriculture during recent times. The third section describes how Matlab software can be utilized to build the ANFIS model. The fourth section describes the case study of the application of ANFIS for crop yield prediction. The conclusion follows this case study.

Chapter 9 describes the application of the Enhanced Fuzzy Assessment Methodology, the yield parameters of rice can be diagnosis with Number of tillers per Hill, Number of grains per panicle and 1000 grain weight, pest and disease incidence, which becomes simple for scientist. Enhanced Fuzzy Assessment Methodology uses triangular membership function with mamdani's inference and K Ratio. The proposed algorithm was implemented using MATLAB Fuzzy Logic tool box to construct fuzzy expert system for rice.

Chapter 10 deals with Predictive Fuzzy Expert System for Crop Disease Diagnostic and Decision Support. This chapter presents a case study on the development of a decision support system for prediction of soyabean crop disease severity. The outcome of this system will aid farmers to decide the extent of disease treatment to be employed. Such predictions make use of human involvement, and thus are a source of ambiguities. To deal with such ambiguities in decision making, this decision support system uses fuzzy inference method based on triangular fuzzy sets.

Chapter 11 presents the application of Fuzzy Expert System for Prediction of Farmers Muscle Strength: "A Collective Database & Analysis in Agricultural Sectors of Odisha in India". In this chapter, 168 anthropometric dimensions and the back-leg-chest (BLC) strength as the muscle strength of 113 male farmers and 31 female farmers of Odisha are statistically analyzed. Further an attempt is made by using ANFIS tool to predict the BLC strength of both male and female farmers. It is found that ANFIS could better predict the muscle strength of farmers.

Chapter 12 explains Agricultural health and safety measures by fuzzy ahp. and prediction by fuzzy expert system: Agricultural Risk factor. Agricultural workers need sufficient precaution and safety measures at the time of field and machine work, to minimize risk factor. Still risk factor is major discussion topic in Agricultural business. So, an effort is taken to prioritize safety majors by fuzzy ahp and prediction are done by fuzzy logic modeling.

Chapter 13 describes the application of fuzzy logic in plant disease management. The severity estimation is performed on the basis of the infected area and the number of lesions in the leaf image. Depending on the amount of infection, severity has been classified into early, middle, later, and advanced stage. The proposed technique will help the farmers to identify the disease class at an early stage.

CONCLUSION

Decision making problem is a frequent problem in today' busy world. Fuzzy expert system is very important to make decision in the field of agriculture. Fuzzy expert system belongs to the field of artificial intelligence systems to solve decision making problems with the existence of uncertainty. The last few decades have witnessed that fuzzy expert system have mostly been focused on prediction and diagnosis. Many fuzzy expert systems have been designed and improved to do so efficiently and effectively n agricultural domain. Researchers have suggested numerous approaches and methodologies to deal with diversified issues pertaining to agriculture field. Fuzzy Expert system for various crop has been constructed which helps the scientist for analysis. Fuzzy Expert system developed helps to diagnosis the yield of various crop such as rice, wheat, soybean etc., Fuzzy Expert system helps in decision making for farming communities and becomes major driving force for research in the field of agriculture.

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Section 1

Concepts and Approaches

Chapter 1
Fuzzy Expert System in Agriculture Domain

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ABSTRACT

Agriculture is an important source of livelihood and economy of a country. Decision making plays an important role in various fields. Farmers are the backbone of agriculture. They need expert systems to make decisions during land preparation, sowing, fertilizer management, irrigation management, etc. for farming. Expert systems may suggest precisely suitable solutions to farmers for all the activities. Uncertainty deals with various situations during sowing, weed management, diagnosis of disease, insect, storage, marketing of product, etc. Uncertainty is compounded by many facts that many decision-making activities in agriculture are often vague or based on perception. Imprecision, vagueness, and insufficient knowledge are handled using the concept of fuzzy logic. Fuzzy logic with expert systems helps find uncertain data. Fuzzy expert systems are oriented with numerical processing.

INTRODUCTION

Agriculture sector plays an important role for mankind and three fourth of the entire population in India depends on agriculture. Agriculture is very crucial for the society which we live, the food item we eat, clothes we wear and job we do. 18% of Indian gross domestic products and 50% of employment depends on agriculture. India is the world largest producer of rice, wheat, pulses, spices and its products. Computers and Information technology has made its way to all the crops and update information for decision making. In this competitive world, to succeed in farming the use of computer and its technology helps in decision making. Farmers need advice in all the farming activities such as land preparation, sowing, irrigation management, fertilizer management, pest management and storage for production of crops. The decision making technology provides the farmers with right information at right time, which helps to enhance the yield of agriculture.

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Artificial intelligence is branch of computer science, the machine behaves in a way as human thinks and considered as an intelligent system. Expert system is an application-oriented branch in Artificial Intelligence. Expert system helps to model the knowledge of experts in needful areas such as diagnosis, planning, forecasting etc. Expert system is not only constructed with knowledge but also the experience of domain experts is used. The system can be operated by less educated person or layman. Many decision making application has been developed in the crop growth and pest population areas. PESTDEC (G.G Wilkersan and J.W.Mishoc,1990) model was developed for soybean growth and velvet been caterpillar to improve the decision making capabilities. In agriculture, the problems are always imprecise, uncertain and unknown information. The results from the expert system are colorfully expressed to improve the decision making. In the field of agriculture, the expert system gets knowledge from individual areas such as Agronomy, Plant pathology, Crop Physiology, Entomology, Agricultural Meteorology, Horticulture, Processing into a framework for farmers.

Fuzzy logic is one of the soft computing methods. Soft computing is used in the area if the information is impreciseness, vagueness and thus gives simple, quick and adequate solution for the problems. Fuzzy logic (FL) is a powerful reasoning method to handle uncertainties and vagueness. Mathematical principles are used in FL to represent knowledge with membership rather than crisp membership function used in classical binary logic (Lotfi A Zadeh, 1965). Fuzzy logic in expert system handles imprecise information in the field of agriculture which gives good outputs. Fuzzy expert system uses Fuzzy logic, membership function and rules for reasoning about data. In Fuzzy expert system expertise knowledge are applied to solve problems, classification and modeling in diverse area of Agriculture.

FUZZY LOGIC

Fuzzy logic acts in the way as that of human. It helps to model our sense of word and from that, the decision are made. As it thinks like a human, it is termed as intelligent system. Fuzzy logic follows many value logic in which truth values of each variable shape is real numbers between 0 and 1. In computer science, fuzzy logic handles imprecise and vague, ideas may be represented as “low”, “medium” or “high”. Fuzzy logic used in the field of agriculture for decision making.

Characteristics of Fuzzy Logic

The Characteristic of fuzzy logic are (Chennakesava R. Alavala, 2008)

1. Fuzzy logic deals with matter of degree.
2. Fuzzy logic deals with exact reasoning; it does not deal with approximate reasoning.
3. In fuzzy logic, knowledge is the collection of fuzzy constraints as variables.
4. Elastic constraints are propagated during the process of Inference.

Fuzzy logic is a powerful reasoning method to handle uncertainties and vagueness. FL uses mathematical approach to represent knowledge with membership functions rather crisp membership function are used in classical binary logic (Lotfi A Zadeh, 1965) which was coined by Lotfi A Zadeh. Normally traditional logic uses true and false values, while fuzzy logic values between Zero and One to define the degree of truth. FL helps to frame words, with the help of words; rules are derived (Lotfi A Zadeh, 1996). FL uses fuzzy set theory which is used in the areas such as expert system, fuzzy control, forecasting and decision making (Yongchang Ren et al., 2010). Fuzzy expert system is designed using fuzzy set and fuzzy rule.

Architecture of Fuzzy Logic System

The architecture of fuzzy logic system is as follows.

1. Fuzzification module: In this module the crisp numbers are transformed into fuzzy set.
2. Knowledge base: In knowledge base if then rules are stored which are provided by experts.
3. Inference engine: Inference engine helps to simulate human reasoning process with if-then rule and inputs.
4. Defuzzification module: Defuzzification module transforms fuzzy sets into crisp modules.
5. Membership function: Membership function is a curve defined for each point in the input which is mapped towards membership values between 0 and 1.

EXPERT SYSTEM

Expert System(ES) was coined by by Edward Feigenbaum, “father of expert systems”. In Stanford Heuristic Programming Project the researchers identified domains such as diagnosing infectious diseases (Mycin) and to identify unknown organic molecules (Dendral). Expert system was developed in LISP programming environment and Prolog. An expert system is good example of knowledge based system.

Definitions of an Expert System

A model and associated procedure that exhibits, within a specific domain, a degree of expertise in problem solving that is comparable to that of a human expert.- Ignizio

An expert system is a computer system which emulates the decision-making ability of a human expert.- Giarratono

The traditional definition of a computer program is given by

Program = (algorithm + data structures)

In an expert system, the definition is given by

Expert system =(inference engine + knowledge)

Expert System is the division of Artificial Intelligence fraternity. The idea of expert system is to develop a system with the help of human knowledge. Knowledge is used in the system whenever it is required. The knowledge can be used according to the need of the system. ES also solve the problems in the real world situation. The interdisciplinary research can be developed with the systems.

Expert systems helps to transfer the promotion in agriculture, traditional method problems are identified and helps to overcome the problem. In the field of agriculture expert system are used to make correct decision for farmers. Knowledge from various fields such as pathology, Nematology, weed, entomology and nutrition disorder is used in crop and integrated pest management (Sonal Dubey et al.2013). In last decades the rapid growth of information has increased. So the transformation of information or knowledge in agriculture, many problems is identified. They are

Fixed Information

Information in agricultural domain is static and they do not respond to the growers need. All the result for the documentation is generally given. Many factors are not taken in documentation part.

Integration of Knowledge

The knowledge is constructed to handle problems related to specific field such as agronomy, entomology and nutrition. In practical circumstance the problem may occur due to one or more cause, in such situation, integration knowledge is very much essential.

Combining one or more Information Sources

Many factors are considered to have the accurate result for diagnosis. To give the perfect diagnosis results,all the factors are taken from various information sources.

Updating

Regular updating of information is very much essential to give a perfect result. In traditional method the document updating takes longtime. In expert systems updating is easy with minimum time.

Information Unavailability

Information can be gathered from human experts, experience growers and extension workers. It is very important to transfer the development in agriculture to farmers. But the information from specialist and scientist is very tedious to transfer. So knowledge and information is transferred to the farmers by the development of new technology known as expert system.

Characteristic of Expert System

Stimulation is done with human reasoning about the problem domain, rather than simulating by the domain itself.

- With the human knowledge the reasoning is represented.
- Problems are solved by approximate methods (Prasad & Babu 2006).

Components of Expert System

1. User interface
2. Database
3. Knowledge base and
4. Interface mechanism

The user interface represent query and information to user and the response is directed to interface engine. User interface validates all the response and ensure the correct data, user enters illegal response, informs the user that input was invalid and prompt a message to correct it.

Knowledge base is the collection of rules and other information derived from the human expert. The interface engine interacts with knowledge base through the reasoning capability. Knowledge base solves the problem within each and every domain. Interface engine compares the specific problem domain in general with what is known about specific problems and tries to provide logically a better solution towards the problem. Inference rules are followed by Inference engine to give a solution for diagnosis and prescription problems. The rules can be added, deleted without affecting other rules (Salunkhe and Rai, 2014). The expert system does

1. Problem selection
2. Knowledge acquisition
3. Knowledge representation

Pros of Expert System

- Expert system is available on computer specifically
- The cost of expert advice is reduced.
- The output of expert system provides reliable knowledge base.
- Expert system is faster and responsive than that of human expert system.

Cons of Expert System

- Expert system cannot be adapted to new data, as it is unexpected or unknown to knowledge base.
- It is difficult to use and non expert makes mistake while constructing the system.
- Expert system has no sense like human; it cannot identify or notice the error.

Expert System in Agriculture

Expert system is developed to diagnosis the disease in soybean (Michalski et al., 1983) which is the earliest expert system developed in the field of agriculture. Expert system has two types of rules. They are 1) Experts knowledge to represent rules and 2) Rules are framed from the disease observed. Experimental result indicates that 98% diagnosis results were correct. For apple orchid management expert system developed is called POOME (Roach et al., 1985). The developed system advises the apple grower to spray, to avoid overwhelmed. The system also provides an advice for multiple insect problem, winter injuries and treatment of drought. Expert system for crop management is developed for cotton to predict the growth, yield, soil fertility, soil parameters and pest management called COMAX (Lemmon, 1986). Computer model called Gossym is developed to simulate the growth of cotton plant. This is the first developed simulated expert system used in farm management system. Expert system was developed to speed the agriculture desert development in Egypt in 1987(Rafea and El-Beltagy, 1987). Expert system is used in desert area to develop agriculture. R&D unit was framed to develop and maintain the system. CALEX system was developed for agriculture management (Plant, 1989). CALEX has three components. They are 1) executive 2) scheduler and 3) expert shell. Executive serves as the primary part of interface to the user to model. Sequence of management action is done by the second component scheduler. Decision management is the main activity of the expert system. At initial stage the system was focused for California peaches and cotton. Expert system SOYBUG is developed to control the soybean insect pest (Howard W. Beck et al., 1989). SOYBUG combines varieties of rules based on crop phenology and gives the recommendation regarding the pesticides. The developed system helps to acquire knowledge acquisition and gives advice for four insects (velvetbean caterpillar, stink bug, corn earworm and soybean looper). Expert system with rule based is developed called PEST – Pest Expert SysTem. The system provides advice regarding the insect identification and gives advice to the farmers. The system also gives advice to agricultural entomologist (G.M Pasqual and J.Mansfiled, 1988).

Expert system was developed to diagnosis the disease (Shikhar Kr. Sarma et al., 2010) for rice using ESTA (Expert System for Text Animation). The rice expert system is the collection of knowledge base, inference engine and user-interface. The system was developed with MATLAB programming using morphological features of Rice kernel are classified with Neural network (S.J. MousaviRad et al., 2012).

FUZZY EXPERT SYSTEM

Computer based information system which helps to make decision on farming activities for scientist and farmers in the form of Fuzzy Expert System(FES). FES enables the farmers as the users to the system and can make decision regarding the farming activities. FES provides solution to complaints given by the farmers; FES is capable of providing solution to problems for uncertain data.

FES is recognized for its capability to handle vague, inexact and subjective inputs. FES is the area which provides robust realistic solution to make decision towards the problem. Other diagnostic quantitative approaches, either stochastic or certain, do not have the ability to include qualitative or subjective input variables. The inclusion of qualitative or subjective input variables is necessary to provide a realistic solution. FES provides a natural way to include human expertise in the form of "If-Then" decision rules, based on and very close to the linguistic description of the human expert.

Fuzzy Expert System should cope with inexact information having possible origin in the following sources. They are

- Inbuilt human fuzzy concept
- Reliabilities of facts
- Matching of related experiences
- Imperfect information
- Various opinions from different experts.

FES belongs to the area of artificial intelligence system to solve decision making problem with uncertainty. The system should be designed explicitly and systematically to the trace the output (P. Baraldi et al., 2009). FES uses fuzzy logic in lieu of Boolean logic. It is a collection of fuzzy sets, fuzzy rules that are used to make an inference about data. FES includes many "if-then" rules and this setup is called knowledge acquisition (Hamid Eslami Nosratabadi et al., 2011).

FES is a user friendly approach for reasoning and control of uncertainty for various problem domains. FL should fulfill the needs of human and machine with the associate of fuzzy membership function. Fuzzy Expert System is designed and developed to make innovative decision in agriculture. Combination of Fuzzy Expert System and Agriculture is a relatively new way and used in many areas of agriculture. This combination is used in the area of crop production and crop management. Many fuzzy expert systems has been developed and used for diagnosis.

Construction of Fuzzy Expert System

Fuzzy Expert System is

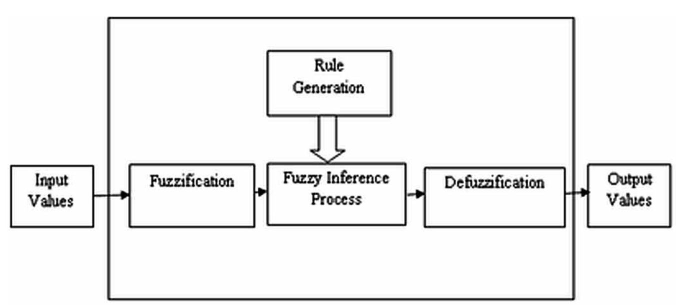
1. Simple to build and debug.
2. Easy to understand
3. Easy and cheap to maintain

Construction of Fuzzy expert system undergoes the following steps (Satya Shah et al., 2004). The overall design of Fuzzy Expert System is shown in Figure 1. Human knowledge is unclear and inexact. Fuzzy set is given with list of number with Fuzzy numbers; Fuzzy uncertainty is modeled with some concepts. Fuzzy number is like ordinary numbers which uses arithmetic operators. The result of the fuzzy number is another Fuzzy number. In expert system Fuzzy number is used to handle fuzziness.

1. Critical Factors, Membership Function and Fuzzy Sets Are Identified

To build a fuzzy expert system the initial step is to classify the significant factors which act as input variables. The next step is to spot the membership function such as triangular trapezoidal or Gaussian function with the membership function fuzzy sets are formed; Fuzzy operator T norm (MIN) and T-

Figure 1. General framework of fuzzy expert system



Conorm (MAX) are used. Fuzzy inference process is selected based on the output variable as mamdani (or) Takagi- sugeno fuzzy model. This step is very essential part in the construction of fuzzy expert system. From the numerical data it is very difficult to identify the fuzzy set and its membership function.

2. Determination of Fuzzification Method

Fuzzification method is determined with the input values. The study of all the variables are made (input and output variable). If the data is vagueness, the fuzzification is necessary. Choose the fuzzification method and membership functions of fuzzy sets. If there is no uncertainty, singleton state variables are used.

3. Determination of the Shapes of Fuzzy Sets

It is essential to find out the shapes of fuzzy sets and their membership functions for the partitioned input spaces and output spaces.

4. Construction of Fuzzy Rule

Knowledge is collected from database, books, human observation and flow chart to construct rules. The rules are constructed with IF (Condition) THEN (action) form.

5. Method to Perform Fuzzy Inference in Expert System

Encode the fuzzy set and fuzzy membership function, where the actual development of fuzzy expert system starts. The system can be build, using programming language C or Pascal or by MATLAB fuzzy logic Toolbar. MATLAB fuzzy logic toolbox is the best choice used for fuzzy expert system which is based on graphical editor.

6. Tune and Evaluate the System to Improve Performance

To evaluate the system; it should satisfy the requirement of the end user. In fuzzy logic tool box surface is generated to analysis the performance of system tuning, a very important part and takes more time than construction of fuzzy sets and rules. Many factors are involved to tune the system. By tuning the system the performance of the system is improved and easy to evaluate the system.

Tuning of the system has to be done in the following order.

1. Input and output variables are reviewed. Units of the variable should be same in Universe of discourse.
2. Fuzzy sets are reviewed, if there is a need additional fuzzy sets are added to universe of discourse. If more fuzzy sets are added performance of the system becomes low.
3. There should be sufficient overlap between sets. Overlapping between them should be 25% to 50% of their bases.

4. Rules are reviewed, if there is need new rules are added.
5. Rules are given with certain weights.
6. Review the shapes of fuzzy sets.

7. Defuzzification

Defuzzification is the final step in the construction of Fuzzy Expert System. Many methods are available, mostly centroid method is used for defuzzification. The defuzzification helps to transform the fuzzy values from the fuzzy inference to crisp values. The crisp values are given to the user to diagnosis the results. There are many methods in the defuzzification stage.

They are

- Centroid Method
- Mean of Maxima Method
- Smallest of maxima method
- Largest of maxima method
- Bisector Method

Application of Fuzzy Expert System

Fuzzy inference system was developed for soil (S. Maria Wenisch et al., 2010). The inference is framed for soil with If-Then rules. Mamdani fuzzy inference system is build by using MATLAB FIS tool box. Fuzzy Expert system is designed to control and measures disease in finger Millet known as Ragi (Philomine Roseline Clarence J et al., 2012). The first section gives the contributions of expert systems in agriculture. The second part explains the Integrated Disease Management. The third part deals about knowledge acquisition and knowledge representation. The fourth part gives the application of fuzzy logic in Integrated Disease Management. Many researches have been made regarding the fuzzy expert system and its application in agriculture. This part of research helps to diagnosis the yield of rice with the input parameters.

Expert system name FuzzyXPest was proposed (Fadzilah Siraj & Nureize Arbaiy, 2006), related to rice crop since rice is a staple food of Malaysia. FuzzyXPest provides the information to farmers and researchers through the internet. It deals with uncertain information derived from the symptoms given by the farmer to forecast the pest activity level that will determine the damages caused by pests in rice crop.

Nureize Arbaiy, et al., 2007 has developed a fuzzy expert system to forecast the activity of pest in rice fields. The system helps to educate and inform the farmers and smallholders about pest and its activities in the rice field. The developed system involves fuzzy logic to deal with natural and uncertainty data. The information about the pests, treatment control measures and prevention steps are stored in knowledge base created in the system.

Robert F. Chevalier et al., 2012 developed a fuzzy expert system named Georgia's Extreme-weather Neural-network Informed Expert (GENIE) to forecast frost and freeze in horticultural crops. The system is incorporates with agro meteorology with additional information such as air temperature, dew point temperature etc., Fuzzy rules and membership functions were developed using the classification of frost and freeze in different level by agricultural experts.

Virparia P.V et al., 2007 has develop an web based fuzzy expert system for controlling the groundnut insect pests, which can perform the identification of various externally observable symptoms, identify the actual insect pest and recommends the appropriate control measures. The system is divided into mainly two parts, the first part is used to identify the externally observable symptoms on crop as well as on insect and the second part is used to identify the actual problem(s) and recommend appropriate control measure.

Harvinder S. Saini, 2002 developed a web based intelligent disease diagnosis system using fuzzy logic concept. The developed system is used to diagnostic disease for oilseeds like soybean, rapeseeds, groundnut etc. It helps farmers and extension workers to increase the ability of cultivation and make decision by themselves.

Kalpana M and Senthil Kumar A.V, 2013 constructed fuzzy expert system for rice by applying the algorithm Fuzzy Assessment Methodology. The elements of Fuzzy expert system are fuzzification interface, Fuzzy Assessment Methodology and defuzzification. Input parameter Pollen Fertility, Productive Tiller Number per Plant at flowering, Panicle Length, Grains per Panicle and Dry Matter Production. The output parameter is Grain Yield per Plant. The components of Fuzzy Assessment Methodology are K Ratio, T fuzzy similarity measure and S value. The overlapping between the membership function is achieved through K ratio. The measure of similarity between fuzzy set, fuzzy number and fuzzy rule are derived through T Fuzzy similarity. Fuzzy sets which are similar are merged to form a common set, a new method was framed to identify the similarity between fuzzy rules with fuzzy numbers. Computation of S value involves T value and F value to manage uncertainty in rules. The proposed algorithm was implemented using MATLAB Fuzzy Logic tool box to construct fuzzy expert system for rice.

Kalpana M. and Karthiba L, 2016 developed fuzzy expert system for rice by applying the algorithm Fuzzy Verdict Mechanism. The components of Fuzzy expert system are fuzzification interface, Fuzzy Verdict Mechanism and defuzzification. Fuzzy Verdict Mechanism, diagnosis the yield parameters of rice with the input parameters number of tillers per Hill, number of grains per panicle and 1000 grain weight, pest and disease incidence, becomes simple for scientist. Fuzzy verdict mechanism uses triangular membership function with mamdani's inference and implemented using MATLAB Fuzzy Logic tool box.

CONCLUSION

Fuzzy logic and Fuzzy expert system is very useful for farmers and researchers in field of agriculture. In agriculture the most challenging issue is to transfer the updated information to the farmers. Expert system is one of the best choices to transfer information to the farmers. The system may be more comfort to the farmers if it is developed in the mother tongue. Including fuzzy logic in the expert system helps to handle imprecise information in the field of agriculture to get good results. The literature shows that Fuzzy Expert System is used in various fields of agriculture. FES is designed to incorporate uncertain measure which performs well in agricultural domain. Fuzzy Inference System presents knowledge in the form of IF-THEN rules and implements fuzzy reasoning. Many organizations are employing FES to capture the problem solving methods from human experts and help to assist the expert or use them where the experts are not available.

Fuzzy Expert System for diagnosis is constructed with input variables, membership function, rule base and output variables. Designed system has to be tested with the experts to fine tune the system. The results are also compared with expert knowledge. Fuzzy Expert System dealing with diagnosis may be implemented with software's. Fuzzy expert system design is very appropriate compared to the Bayesian Statistics, Statistical and other methods. This system simulates as that of human experts. The Fuzzy Expert System is more beneficial for the farmers, extension workers and scientist if it is made available on the World Wide Web.

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KEY TERMS AND DEFINITIONS

Aggregation: Aggregation is the third step in fuzzy inference. It is the process of combining clipped or scaled consequent membership functions of all fuzzy rules into a single fuzzy set for each output variable.

Antecedent: Antecedent is a part of IF rule. It is a conditional statement.

Artificial Intelligence (AI): Artificial intelligence is branch of computer science; the machine behaves in the way as a human thinks and is considered an intelligent system.

Certainty Factor: A number assigned to a fact or a rule to indicate the certainty or confidence, with this value fact or rules are validated.

Defuzzification: Defuzzification is the last step in fuzzy inference mechanism. The process of converting fuzzy values from the combined output of fuzzy rules in crisp values (numerical values). The input to the defuzzification process is an aggregate set and the output from this process is a single number.

Degree of Membership: A numerical value between 0 and 1 that represents the degree to which an element belongs to a particular set.

Expert System: Expert system is a computer-based program which performs like a human expert in a narrow domain. The components of the expert system are the knowledge base, the database, the inference engine, the explanation facilities and the user interface.

Fact: Fact is a statement has the property of being either true or false.

Factual Knowledge: Information widely accepted by the knowledge engineers and scholars in the task domain.

Forward Chaining: Forward chaining is the strategy of working forward for conclusion/solution of a problem.

Fuzzification: Fuzzification is the first step in the fuzzy inference mechanism. The process of mapping the crisp (numerical) value into its degrees to which the inputs belong to the respective fuzzy sets.

Fuzzy Expert System: A fuzzy expert system is the combination of expert system and fuzzy logic. In expert system fuzzy logic is used instead of Boolean logic. A fuzzy expert system is a collection of fuzzy rules and membership functions that are used to reason data. In conventional expert system uses symbolic reasoning, fuzzy expert system is toward numerical processing.

Fuzzy Inference: Fuzzy inference process is based on fuzzy logic. The steps in fuzzy inference are fuzzification of the input variables, rule evaluation, aggregation of the rule outputs and defuzzification.

Fuzzy Logic: Fuzzy logic is multi-valued and handles the concept of partial truth. A system of logic developed for representing conditions that cannot be easily described by the binary terms "true" and "false." The concept was introduced by Lotfi Zadeh in 1965.

Fuzzy Rule: Fuzzy rule is a conditional statement. The form of fuzzy rules is given by IF THEN statements. If y is B THEN x is A, where x and y are linguistic variables, and A and B are linguistic values determined by fuzzy sets.

Fuzzy Set: Fuzzy set is expressed as a function and the elements of the set are mapped into their degree of membership. A set with the fuzzy boundaries are "hot," "medium," or "cold" for temperature.

Fuzzy Variable: A quantity that can take on linguistic values. For example, the fuzzy variable "disease" might have values such as "low," "medium," or "high."

Heuristic Knowledge: Knowledge regarding practice, accurate judgment, one's ability of evaluation, and guessing.

Inference Engine: Inference engine is one of the basic components of an expert system that carries out reasoning whereby the expert system reaches a solution. It matches the rules provided in the rule base with the facts contained in the database.

Information: Available resources like survey on experimental data, literature maps, digital form of photographs.

Intersection: In set theory, an intersection between two sets contains elements shared by all sets. For example, the intersection of short men and tall men contains all men who are short and tall. In fuzzy set theory, an element may partly belong to both sets, and the intersection is the lowest membership value of the element in both sets.

Knowledge: Knowledge is to understand the subject theoretically or practically. Knowledge helps us to make a correct decision.

Knowledge Acquisition: Knowledge acquisition depends on the quality, completeness, and accuracy of the information stored in the knowledge base.

Knowledge Base: Knowledge base is a basic component of an expert system that contains knowledge about a particular domain.

Knowledge Engineers: The knowledge engineer is a person with the qualities of empathy, quick learning, and case analyzing skills.

Knowledge Representation: Method used to organize and formalize the knowledge in the knowledge base. It is in the form of IF-THEN-ELSE rules.

Linguistic Variable: A Linguistic variable has values that are language elements, such as words and phrases. In fuzzy logic, terms linguistic variable and fuzzy variable are synonyms.

Membership Function: Membership function is a mathematical function that defines a fuzzy set on the universe of discourse. Membership functions used in fuzzy expert systems are triangles, trapezoid and Gaussian function.

Production Rule: A statement expressed in the IF (antecedent) THEN (consequent) form. If the antecedent is true, then the consequent is also true.

Chapter 2
Application of Fuzzy Expert System for Analyzing Agriculture Data

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ABSTRACT

Agriculture plays a major role in the Indian economy. India is rich in production of crops like rice, cotton, wheat, soybean, sugar; fruits and vegetables like onion, tomatoes, potatoes; dairy; and meat products. India is ranked first worldwide for the production of banana, jute, mango, cardamom, and ranked second worldwide for the production of rice, tomato, potato, and milk. India's agriculture contributed 4759.48 INR billion to the GDP during the first three months of 2018, and it has been reduced drastically during the second three months of 2018 (i.e., it has been reduced to 4197.47 INR billion). The average GDP is 4057.73 INR billion from 2011 until 2018; the agricultural contribution to GDP reached its highest level, that is 5666.82 INR billion, in the last three months of 2017. This chapter explores the application of fuzzy expert systems for analyzing agricultural data.

INTRODUCTION

Agriculture productions have changed into a multifarious commercial necessitating the gathering and incorporation of data and information from several various sources. In order to take necessary decision making actions usually farms depends on advisors and agriculture specialists whereas assistance of agriculture specialist is rarely available to the farmers when they need it.

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In order to alleviate this problem, expert systems were identified as a powerful tool with extensive potential in agriculture. There are various expert are already developed to assist farmers and for agriculture products management. Some of them are, POMME (G.N.R. Prasad, et al.,2006), is an expert system for apple orchid management. UNU-AES is an expert system which has been designed for the users of agro- forestry management techniques. The objective of this expert system is to increase the benefits obtained by agro- forestry management techniques.

In order to increase the food production and to improve the usage of resources, the Central Laboratory for Agricultural Expert Systems (CLAES)) has designed number of expert system to help farmers all over the Egypt. Few of them are as follows:

The MANAGE has developed an expert system for managing rice crop by detecting the diseases and suggest preventive measure to cure the disease. In current trend, fuzzy reasoning has been adopted in most of the expert system (Tang.H et al.,2009). The development of fuzzy expert system over the years is briefed in the table 2

The fuzzy expert system is extensively used as expert system in other fields also like an assistant for specifying the acceptance by NOET measures, at PH.D level in which fuzzy-expert system taken advantage of the particle swarm optimization (PSO) evolutionary algorithm to specifying the score of each variable, and eventually the final condition of the candidate(S.M.H.Mousavi, et al.,2017).

Authors like Desai, D.K. Sreekantha & Deepthi, M. (2017) have done extensive review on different expert system for Agricultural Crop Disease Diagnoses. The review includes some of the work like designed and developed an architectural framework of rule based expert system for the management of

Table 1. Expert systems designed by CLAES

Name of the Expert System	Objective of the Expert System
Cuptex	To Increase Cucumber Crop Production
Limex	To support Lime growers and Lime Crop Management
Tomatex	To assist formers for disease diagnosis and necessary treatment for tomato plants
Nepher Wheat	Wheat Expert System. Objective is to reduction of risks to formers during the wheat growing season (A.Edrees., et al.,2003)
Citex	An Expert System for Orange Production

Table 2. Various fuzzy expert system

Year	Proposed by	Purpose of Expert system
2002	Harvinder Singh. Et..al	SOYPEST - Integrated Pest Management
2008	Fahad Khan Et.al	Dr. Wheat - diagnosis of diseases and pest in Pakistani wheat
2009	S.Helen Et.al	‘Diagnos-4’- It considered nine different crops of Kerala to deal with the difficulties involved in plant protection
2012	Alavi	Developed a date grading system using rule-based fuzzy inference systems
2010	Kustiyo et. Al	fuzzy expert system was developed to assist in determining the effectiveness of Arbuschular Mychorrizal fungi for biofertilizer
2012	Sangatash et. al	a fuzzy system for classification of raw milk

rice and wheat crop pest (Kaliuday Balleda, D Satyanvesh, NVSSP Sampath, KTN Varma, P K Baruah, 2014), Expert system for Diagnosing Oyster Mushroom Diseases (Munirah M. Y., Rozlini M and Siti Mariam Y, 2013) and etc.

The objective of this paper is to analyse the agriculture data to maximise the crop production. The agriculture data includes the parameters like rainfall, temperature, soli type, PH Value, Humidity etc. Analysis is extended by analysing the rainfall and temperature in the country and analysing the states/ districts having similar soil type and Ph value. Fuzzy expert system is used to predict the different types of crop can be cultivated in the given geographical location by considering the factor like average rainfall, temperature, soil content and ph value etc. The input dataset consist of Rice, Cotton, and Wheat productivity in different districts of Karnataka during 2001-2009 along with the climatic condition.

MATERIALS AND METHODS

The proposed work involves the 2 phases those are, one is knowledge extraction which is also called as data collection and other is model development.

Knowledge Extraction

Knowledge extraction is most important and time consuming task. In this work the data has been collected from Indian Government website and other agriculture websites of Karnataka state. The Cotton productivity of the different states in the Karnataka is analysed by considering the area under cultivation, production, minimum and maximum temperature, rainfall, soil types and PH value

Model Development

Fuzzy Clustering

Fuzzy Expert System is an expert system that uses the fuzzy logic instead of Boolean logic. Conventional rule based expert system can be used to solve real-world problems which uses the human expert knowledge and would require human intelligence (Ajith.A et al.,2005). Fuzzy Rule based expert system is extended version of the Boolean logic that uses the degree of membership with crisp membership. Boolean logic has only two states those are 0 and 1 where as in Fuzzy set every element has a degree of membership which is ranging from 0 to 1(Safdari R, et al.,2018) .

Fuzzy expert system mainly works on the membership function. Fuzzy with membership function can be used to group the similar data together. Fuzzy clustering is soft clustering where the data can be belongs to more than one cluster. Output of the Fuzzy Clustering is that number of clusters along with its cluster members, clusters are formed such that distance between the cluster member within the cluster should be minimum which represents the high similarity between the data points and distance between the cluster members of different clusters should be high which represents that data points belong to the different classes/ groups are distinct to each other. Each cluster content can be analysed to form the set rules for decision making.

In this paper agriculture data is analysed by using the Fuzzy Clustering and Fuzzy clustering based rules. Fuzzy Clustering is used for the formation of rice and cotton crops clusters depending on the productivity criteria.. The data for the clustering is represented as

$$X = \begin{bmatrix} x_{11} & x_{12} \cdots & x_{1N} \\ x_{21} & x_{22} \cdots & x_{2N} \\ \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} \cdots & x_{nN} \end{bmatrix}.$$

Each instance consists of n number of features and formed an n-dimensional column vector $x_k = \left[x_{1k,} x_{2k} \ldots\ldots, x_{nk}\right]^T$., $x_k \in \mathbb{R}^n$. Objects are represented by columns of this matrix and attributes of the objects are represented by rows and X is called as data matrix. In this paper attributes are considered for analysing the rice and cotton productivity are District of Karnataka State, Area, Production, Minimum and Maximum Temperature, Rge of Rainfall, Soil type and PH value for the duration 1998-2009 is considered.

Fuzzy Clustering method is applied to the dataset to form the 5 clusters to represent the High Productivity, Medium Productivity, Medium to Low Productivity, Low Productivity and Very Low Productivity Clusters. Furthermost analytical fuzzy clustering algorithms are based on optimization of the basic c-means objective function. The objective of the fuzzy clustering is to minimization of fuzzy c means functional which can be represented as,

$$J(X;U,V) = \Sigma_{i=1}^{c}\Sigma_{k=1}^{N}(\mu_{ik})^m \parallel x_k - v_i \parallel_A^2 \tag{1}$$

where

$$U = \left[\mu_{ik}\right] \in M_{fc} \tag{2}$$

is a fuzzy partition matrix of X,

$$V = \left[v_1, v_2, \ldots.., v_c\right], v_i \in \mathbb{R}^n \tag{3}$$

is a vector of cluster centriods, which can be determined by,

$$D_{ikA}^2 = \left\|x_k - v_i\right\|_A^2 = \left(z_k - v_i\right)^T A\left(x_k - v_i\right) \tag{4}$$

is a square of inner-product distance norm, and

$$m \in \left[1, \infty\right] \tag{5}$$

is a parameter which determines the fuzziness of the resulting clusters. The value of the cost function (1) can be perceived as a measure of the total variance of x_k from v_i.

Fuzzy C Means Algorithm:

Figure 1 depicts the steps involved in the Fuzzy C Means Clustering. The notation used in the Figure 1 are as summarised in Table 3.

- *Fuzzy C*-means clustering aims to partition *n* observations into *C* clusters in which each observation belongs to the cluster which has the highest membership value, higher the membership value stronger the association between pattern and cluster.
- Recalculate the fuzzy cluster centroids and repeat the same procedure until difference between the degree of membership of last iteration and current iteration falls below b (User defined value between 0 and 1).

Figure 2 illustrates the Fuzzy C Means Clustering wirth simple dataset which consist of 5 objects named as A,B,C,D and E. Objects are represented by the attributes x1, x2. The all five objects can be represeted as A(1,1), B(1,0), C(,2), D(2,4) and E(3,5). Let us consider the number of cluster as 2 and cluster centroids are represented by v_1 and v_2 . In this illustration initial cluster centroids are assigned

Table 3. Notations used in fuzzy clustering algorithm

Symbol	Meaning
‘U’	Fuzzy Partition Matrix
‘X’	Dataset with n number of Features
‘n’	the number of data points
‘v_j’	j^{th} cluster center
‘c’	Number of cluster center
‘μ_{ij}’	Membership of i^{th} data to j^{th} cluster center
‘d_{ij}’	Distance between i^{th} data and j^{th} cluster center
β	Threshold Value

Figure 1. Steps of fuzzy c means clustering

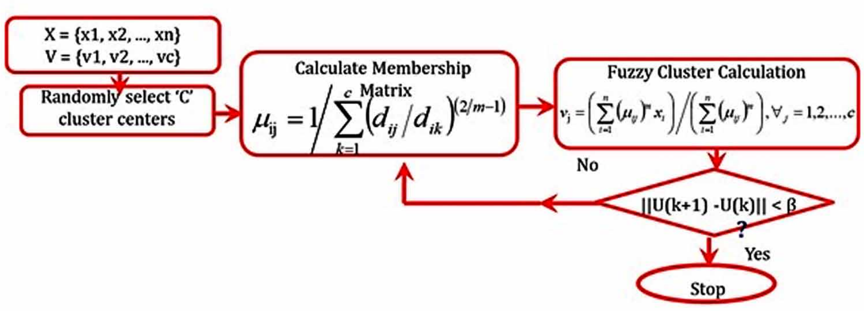
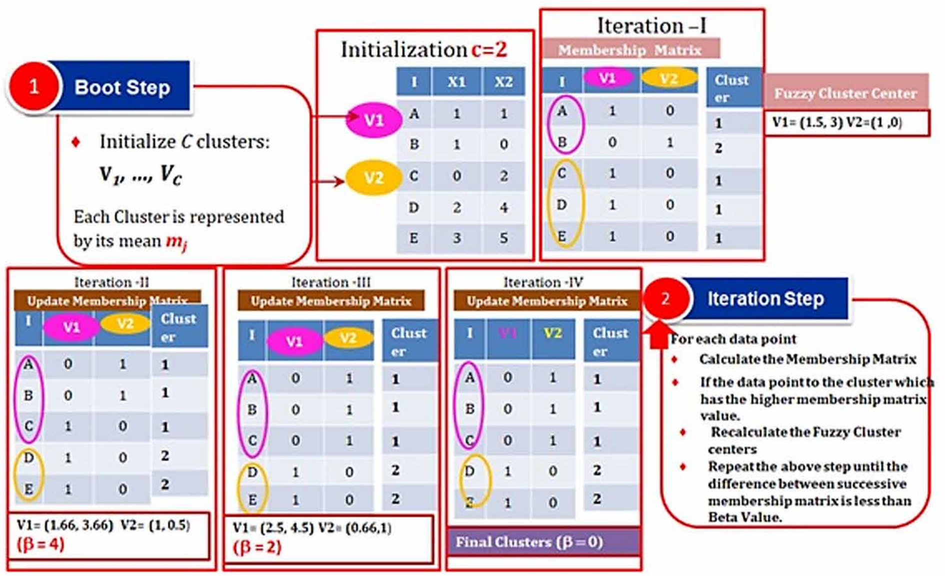


Figure 2. Illustration of fuzzy clustering with simple dataset



as the datapoints of A and C respectively that is $v_1= (1,1)$ and $v_2= (1,0)$. For given dataset and cluster centroids the Fuzzy algorithm has to iterate 4 iterations in order to achive the β value as 0. The membership matrix and fuzzy centroids at e ach iterations are depicted clearly in the Figure2.

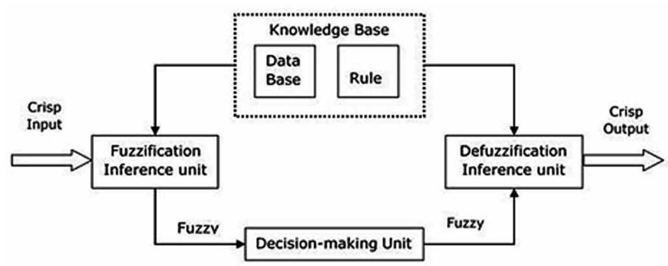
Fuzzification of Input Variables

This phase represents the defining the fuzzy sets along with its respective membership functions. At this stage crisp inputs are changed to fuzzy values through the use of linguistic variables. For example, “Productivity of the cotton in the Karnataka state” is the linguistic variable and “high” is one of its fuzzy sets. The way of forming the fuzzy set depends on the membership value of the object which is in the interval of [0,1]. Membership values represent the degree to which an object belongs to a fuzzy set which can be represented by the equation (6)

$$\mu_A\left(x\right): X \rightarrow \left[0.1\right] \tag{6}$$

In this paper, membership for the each element is calculated by using the Fuzzy Clustering Concept. For Example, consider the fuzzy set formation for the temperature analysis of different districts of Karnataka. The dataset consist of temperature of different districts of Karnataka for the year 2001-2009. Fuzzy clustering method is applied on the dataset and number of clusters to be formed as 3 that is low, medium and high. The output of the clustering is clusters with low temperature, medium and high temperature along with its membership matrix. Suppose the temperature range 28.4 to 28.9 (^{o}C) with membership matrix value 0.8 then fuzzy set for that temperature is “low”.

Figure 3. Blocks of fuzzy inference system



Fuzzy Inference System

The Fuzzy Inference System is very important block and plays a major role in the decision making process. It uses the If .. Then rules along with the connectors like 'AND', 'OR' for taking essential decisions. The basic blocks of the Fuzzy Inference System are depicted in the figure 3.

The flow of the Fuzzy Inference System is as follows:

- **A fuzzification block**: It take the input variables and depending on its membership value assign it to Fuzzy set. The main function of this block is to convert the crisp input into fuzzy input.
- **A knowledge base**: It is assortment of rule base and database which is used to convert the crisp input into fuzzy input.
- **Defuzzification:** The defuzzification module takes the input as fuzzy input and produces crisp output.

The proposed work uses the Mamdani Fuzzy Inference System. The step of this fuzzy Inference Systems are as follows:

Step 1: Determine the set of fuzzy rules
Step 2: Convert the Input variable to fuzzy set by using the membership function.
Step 3: Combine the fuzzified inputs as per the fuzzy rules to the rule strength.
Step 4: Determine the consequent of rule by combining the rule strength and the output membership function.
Step 5: Combine all the consequents to obtain output distribution.
Step 6: Defuzzified output distribution is obtained.

The proposed work uses the mean of maxima defuzzification methods to determine one crisp number which is represented in the equation (7)

$$z = \sum_{j=1}^{l} \frac{z_j}{l} \tag{7}$$

where z is the mean of maximum, zj is the point at which the membership function is maximum, and l is the number of times the output distribution reaches the maximum level.

RESULTS AND ANALYSIS

The Temperature, Rainfall, PH value of the different districts of Karnataka during the 1998-2009 are collected and analysed. The Fuzzy C Means Clustering is applied to the dataset to get the regions having similar temperature, Rainfall and Ph value. The range within the cluster is analysed and fuzzy sets are formed by using range of each cluster. The clustering of the Fuzzy C Means with respect to temperature result in 3 clusters those are High, Medium and Low temperature values. Figure 4 shows the average temperature, rainfall, and Ph value, water requirement for rice crop and nitrogen content in soil for the year 1998-2009. Table 4 depicts results of fuzzy sets values for temperature, rainfall and PH

Fuzzy clusters are formed to cluster the Rice Productivity in different Districts of Karnataka during the year 1998-2009. Based on the clustering results fuzzy sets are formed for the Rice Productivity as shown in the Table 6.

Figure 4. Average temperature, rainfall, PH value, water requirement and nitrogen content of the soil for the year 1998-2009

Districts of Karnataka State	Average Temperature(°C)	Average Rainfall(mm)	PH value	Water required(mm)	Nitrogen (Kg/Ha)
BELLARY	24.1	636	7.6	2000	459
BIDAR	26.65	847	6	1780	481
BIJAPUR	24.28	578	7	1780	380
CHAMARAJNAGAR	29.5	751	8	1150	281
CHITRADURGA	29.9	573	7.8	1500	373
DAKSHINA KANNADA	30.85	3789	7.8	1780	575
DAVANAGERE	30.8	607	7	1150	600
DHARWAD	27	998	6	2300	562
GADAG	27.75	612	8.2	2000	562
GULBARGA	29.8	832	6	1150	372
HASSAN	28.2	977	7	1150	562
KODAGU	26.95	2598	8	1780	267
KOLAR	29.5	743	6.5	1150	199
KOPPAL	31.5	572	7	2300	527
MANDYA	31.2	646	6.2	2300	281
MYSORE	30.2	782	7.5	1780	199
BAGALKOT	26.7	830	4.5	2300	370
BANGALORE(RURAL)	26.7	817	4.5	2000	357
BANGALORE(URBAN)	26.7	867	4.5	2000	388
BELGAUM	26.99	808	6.2	2300	470
SHIMOGA	27.2	1813	5.5	2300	491
CHIKMAGLUR	30.04	1925	7	2000	363
RAICHUR	30.2	688	7.5	2300	627

Table 4. Fuzzy sets for input attributes

Input Variable	Range /Membership Matrix
Temperature	Low (24.1^{0}C – 24.28 ^{0}C) Medium (26.65^{0}C -28.2 ^{0}C) High (29 ^{0}C -33 ^{0}C)
Rainfall	Low (572 mm – 688mm) Medium (743 mm- 998mm) High (1823 mm – 2598 mm) Very high(> 2598 mm)
PH value	Low (3.5- 4.5) High (4.5-8)

Table 5. Productivity of rice under different productivity groups in Karnataka

SL	Productivity Groups	Number of Districts	Productivity (Kg/Ha)	Temperature Range
1	High Productivity (> 2,500 Kg/Ha)	16	3,227	29-33
2	Medium Productivity (2,000-2,500 Kg/Ha)	5	2,482	29-33
3	Medium Low Productivity (1,500-2,000 Kg/Ha)	4	1,793	26-28
4	Low Productivity (1,000- 1,500 Kg/Ha)	1	1489	26-28
5	Very- Low Productivity (<1,000 Kg/ Ha)	1	637	26-28

Table 6. Fuzzy sets for input attributes for cotton dataset

Input Variable	Range /Membership Matrix
Temperature	Low (24.1^{0}C – 26.8 ^{0}C) Medium (27^{0}C -29^{0}C) High (29.5 ^{0}C -32.2 ^{0}C)
Rainfall	Low (557 mm – 1117mm) Medium (1250mm- 1677mm) High (1823 mm – 2200 mm) Very high(> 2230 mm)
PH value	Low (4- 6) Medium(6.1-7.2) High (7.4-8.3)
Nitrogen (kg/Ha)	Low (199- 499) High (499-649)

Table 7. Productivity of cotton under different productivity groups in Karnataka

SL	Productivity Groups	Number of Districts	Productivity (Kg/Ha)
1	High Productivity (> 2,400 Kg/Ha)	1	2946
2	Medium Productivity (2,000-2,400 Kg/Ha)	1	2095
3	Medium Low Productivity (1,600-2,000 Kg/Ha)	3	1762
4	Low Productivity (1,200- 1,600 Kg/Ha)	11	1382
5	Very- Low Productivity (<1,200 Kg/ Ha)	5	966

Initial Fuzzy Rules for Rice Productivity

```
1.        Rules for Temperature
Temperature_High(29, 33)
Temperature_Medium(26.65 -28.2)
Temperature_Low(24.1 – 24.28)
2.        Rules for Rainfall
Rainfall_Low (572, 688)
Rainfall_Medium (743, 998)
Rainfall_High (1823,2598)
Rainfall_Very High(> 2598)
3.        Rules for Ph Value
High_PH (4.5, 8)
Low_PH(3.5,4.5)
4.        Rice Productivity Rules
      High Productivity (> 2500)
      Medium Productivity (2000, 2500)
 Medium Low Productivity (1500, 2000)
 Low Productivity (1000, 1500)
 Very- Low Productivity (0, 1000)
```

Initial Rules for Rice Crop Production

```
Rule 1:
If ((Temperature_High)^(Rainfall_Medium)^(High_Humidity)^(High_PH))
Then High_Rice_Productivity
Rule 2:
If ((Temperature_Low)^(Rainfall_Low)^(Low_Humidity)^(High_PH))
Then Low_Rice_Productivity
Rule 3:
```

```
If ((Temperature_High)^(Rain Fall_Low)^(High_Humidity)^(High_PH))
Then Medium_Rice_Productivity
Rule 4:
If ((Temperature_Medium) ^ (Rainfall_Medium)^(High_Humidity)^(High_PH))
Then High_Rice_Productivity
Rule 5:
If((Temperature_Low)^(Rainfall_VeryHigh)^(High_Humdity)^(Low_PH))
Then Low_Rice_Productivity
```

Initial Fuzzy Rules for Cotton Productivity

```
1.        Rules for Temperature
Temperature_High(29.5, 32.2)
Temperature_Medium(27-29)
Temperature_Low(24.1 – 26.8)
2.        Rules for Rainfall
Rainfall_Low (572, 1117)
Rainfall_Medium (1250, 1677)
Rainfall_High (1823,2200)
Rainfall_Very High(> 2230)
3.        Rules for Ph Value
High_PH (7.4, 8.3)
Medium_PH(6.1,7.2)
Low_PH(4,6)
4.        Rules for Nitrogen Value
High_Nitro (499,649)
Low_Nitro(199,499)
5.        Cotton Productivity Rules
      High Productivity (> 2400)
      Medium Productivity (2000, 2400)
 Medium Low Productivity (1600, 2000)
 Low Productivity (1200, 1600)
 Very- Low Productivity (0, 1200)
Initial Rules for Cotton Crop Production
Rule 1:
If ((Temperature_High)^(Rainfall_Low)^(Low_Nitro)^(Low_PH))
Then High_Cotton_Productivity
Rule 2:
If ((Temperature_Medium)^(Rainfall_Low)^(Low_Nitro)^(Medium_PH))
Then Low_ Cotton _Productivity
Rule 3:
If ((Temperature_Medium)^(Rain Fall_Low)^(Low_Nitro)^(High_PH))
Then Medium_Low_Cotton_Productivity
Rule 4:
```

```
If ((Temperature_High) ^ (Rainfall_Low)^(Low_Nitro)^(Medium_PH))
Then Low_Cotton_Productivity
Rule 5:
If((Temperature_Medium)^(Rainfall_Low)^(High_Nitro)^(High_PH))
Then Very_Low_Cotton_Productivity
```

Figure 5 depicts the how rainfall affects the cotton productivity in different districts of Karnataka. According to the analysis, districts those are having medium to high rainfall are produced better cotton productivity.

Figure 6 depicts the how temperature affects the cotton productivity in different districts of Karnataka. According to the analysis, districts those are having temperature in the range of medium to high are produced better cotton productivity.

Figure 7 depicts analysis of the cotton productivity with respect to temperature. As per the analysis conducted cotton productivity will be high if soil PH value is in the range of 6-8.

Figure 8 depicts analysis of the cotton productivity with respect to nitrogen content in the soil. As per the analysis conducted cotton productivity will be high if nitrogen content is high in the range 499 to 649.

According to the above analysis, the optimal Temperature, Rainfall, Soil type and Soil PH values to produce high cotton productivity is given in the Table 8.

Figure 10 depicts the analysis of rice productivity with respect to average temperature. As per the analysis, districts those are having temperature in the range of medium to high are produced better rice productivity.

Figure 5. Analysis of cotton productivity with respect to rainfall

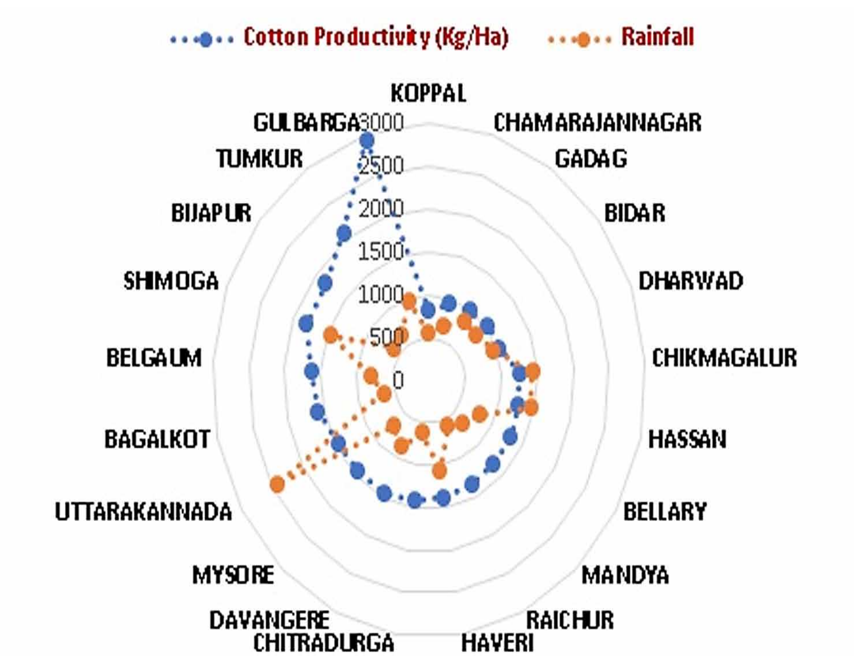


Figure 6. Analysis of cotton productivity with respect to average rainfall

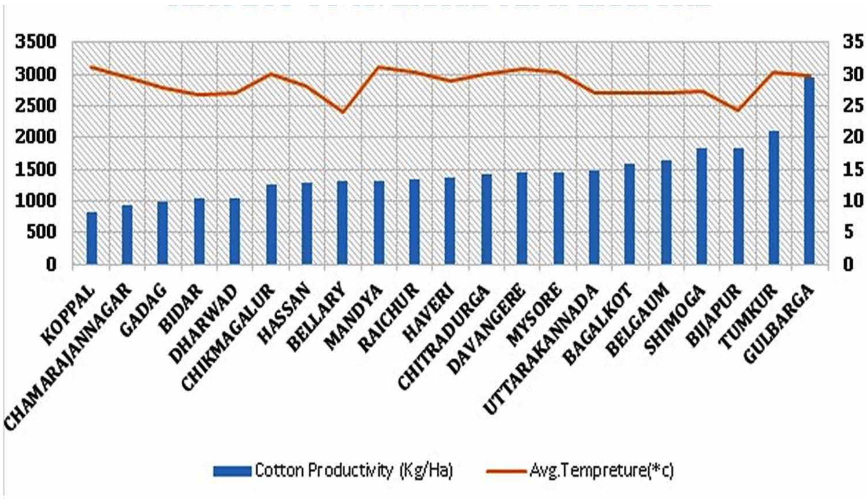


Figure 7. Analysis of cotton productivity with respect to soil PH

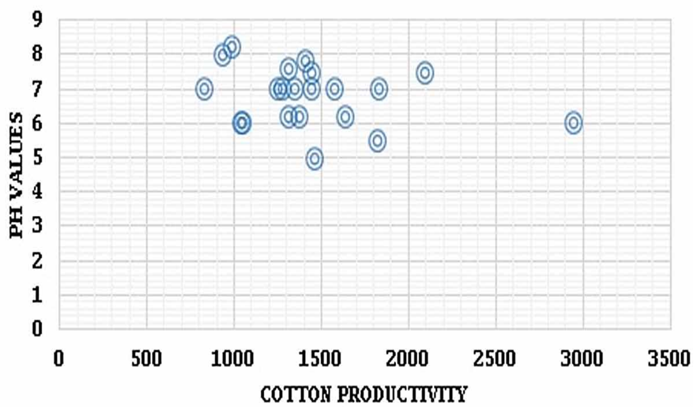


Table 8. Optimal parameters for high cotton productivity

	Temperature	Rainfall	Soil Type	PH Value	Soil Depth
Range	25°C	150 cm – 200 cm	Medium Black to Deep Black	6 to 8	20 to 25 cm

Figure 11 depicts the analysis of rice crop production with respect to rain fall. As per the analysis the rainfall ranges in medium to high can result in high rice productivity. Table 9 the depicts parameters values to achieve better rice production.

Figure 8. Analysis of cotton productivity with respect to nitrogen content in the soil

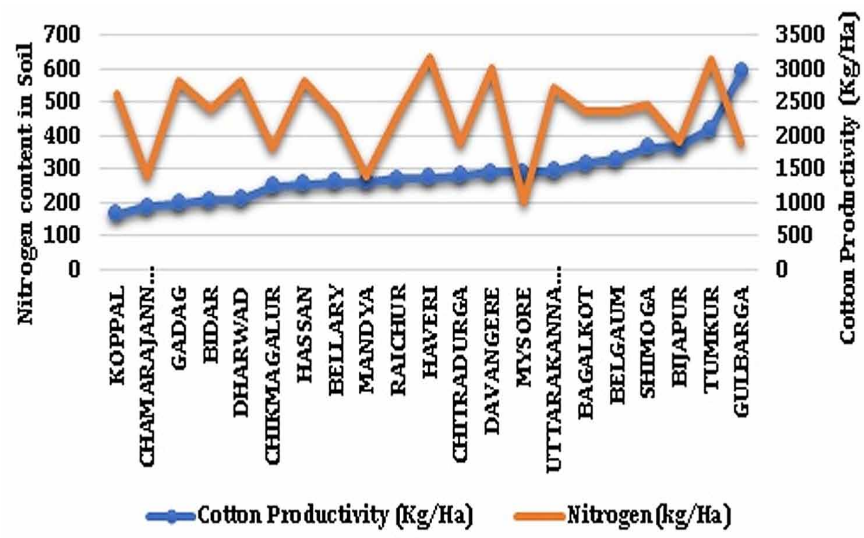


Figure 9. Analysis of cotton productivity with respect to temperature, rainfall, nitrogen content, and PH value

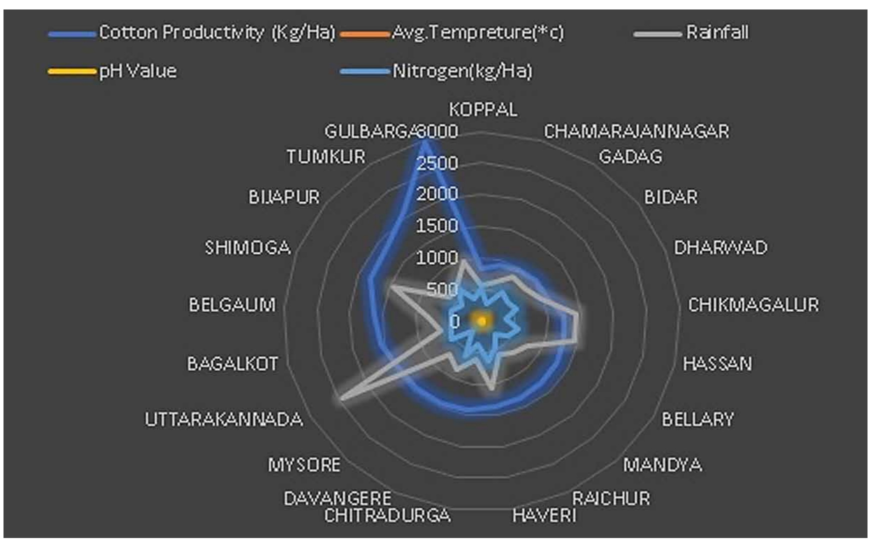


Table 9. Optimal parameters to obtain high rice crop productivity

Parameters	Range
Optimal Temperature	30°C
High Temperature	20° to 40°C
PH Value	5.0-8.0
Rain Fall	Medium to High

Figure 10. Analysis of rice productivity with respect to average temperature

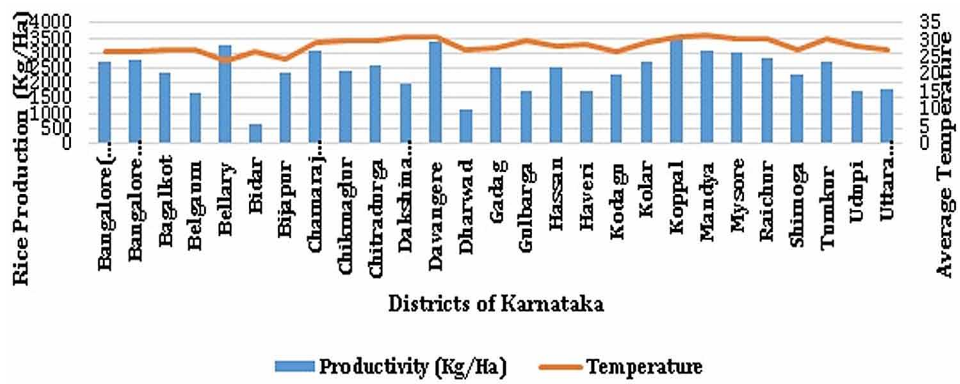
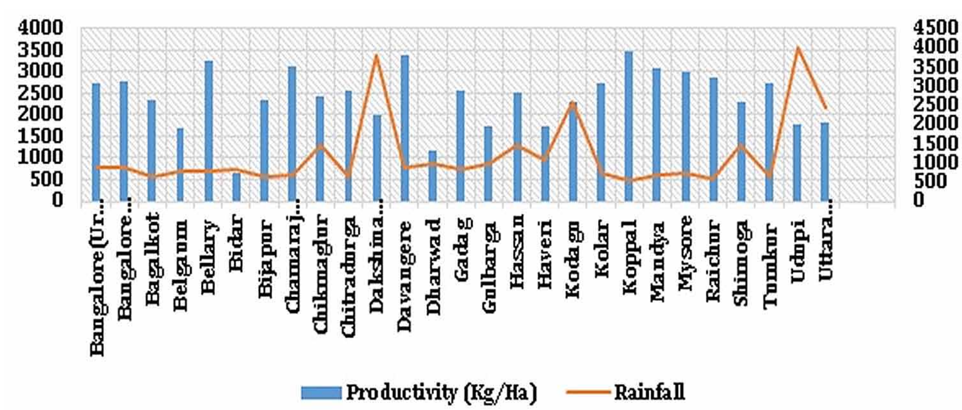


Figure 11. Analysis of rice productivity with respect to rainfall



CONCLUSION

In this paper Fuzzy expert system is used to analysis of rice and cotton productivity in different districts of Karnataka and to derive the set of rules to make intelligent decisions. Fuzzy inference system is used to derive the rules. According to the analysis conducted, the rice production requires high rainfall, temperature and humidity whereas cotton production requires medium to high rain fall, medium to high temperature and PH value should be in the range of 6-8.

A recommendation for future studies is concerned is with different kinds of membership functions for linguistic terms to find the best one.

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Chapter 3
Automatic Knowledge Acquisition in the Form of Fuzzy Rules From Cases for Solving Classification Problem

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ABSTRACT

The authors consider an approach to automatic knowledge acquisition through machine learning on the basis of integrating the two basic reasoning methods – case-based reasoning and rule-based reasoning. Case-based reasoning allows using high-performance database technology for storing and accumulating cases, while rule-based reasoning is the most developed technology for creating declarative knowledge base on the basis of strong logical approach. This allows realizing the transformation of the spiral of knowledge, leading to continuous improvement of the knowledge quality in the management system. In the chapter, they propose one method of obtaining rules from cases based on fuzzy logic. Here the method is considered for solving classification problem, but it also can be applied for solving regression problem. The research shows acceptable accuracy of cases classification even for small training samples. At the same time, smoother (quadratic) membership functions show on average classification accuracy.

INTRODUCTION

The emergence of the so called knowledge based systems (KBS) in the 1970s were definitely associated with "success stories" in the artificial intelligence (AI) development when the AI methods began to be successfully used in the real economy. In the 1980s, the creation of KBS is becoming very popular in different areas of practical use. By 1992 it was implemented about 2,000 expert systems based on knowledge (DTI, 1992). Despite the commercial success of expert systems, from the outset it was clear that the bottleneck in creating KBS was knowledge elicitation, when a transfer of knowledge of an expert in the specific application domain into the knowledge engineer occurs.

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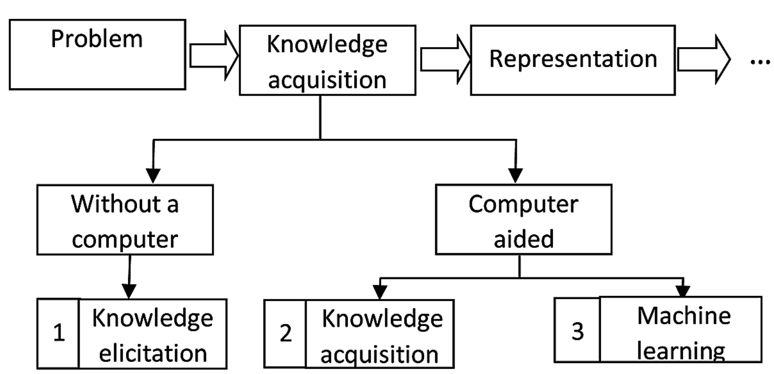
The process of knowledge elicitation is a long and laborious procedure in which a knowledge engineer (or, an analyst) experienced in cognitive science, system analysis, mathematical logic, etc, has to build the model of application domain, which is used to make decisions by experts (Diaper, 1989; Brooke & Jackson, 1991). Inexperienced expert system developers often tried to impose this procedure on the experts themselves. However, this does not lead to successful results, because, first, most of the expert knowledge is of multilayer nature consisting of many levels of experience. Often, knowing that A entails B (A⇒B), the expert does not realize that his chain of reasoning is much longer, for example, A⇒C⇒D⇒E⇒B. Second, thinking is dialogical by nature, so the dialogue of the knowledge engineer with an expert is the most natural way of highlighting shaded places of expert's memory. It is in the process of explaining things to the knowledge engineer the expert puts verbal structures on his fuzzy associative images, i.e. verbalizes the knowledge. Third, it is difficult for the expert to create the formalized application domain model because of the depth of knowledge he owns, and, at the same time, because of his insufficient skills in system analysis methodology.

The term "knowledge elicitation" is used interchangeably with the term *knowledge acquisition* in the literature (Addis, 1987). However, most researchers draw a clear distinction between these two notions emphasizing their relation to knowledge engineering.

Knowledge engineering is the over-arching process of building KBS including problem identification, elicitation, representation, implementation, as shown in Fig.1. Knowledge acquisition is a subset of knowledge engineering which consists of gathering all forms of the domain knowledge using any methods. Finally, knowledge elicitation is a subset of knowledge acquisition and intended to extraction of knowledge from human experts.

By computer aided knowledge acquisition we mean automatic tools of communication with an expert. These tools really acquire ready-made pieces of knowledge in accordance with the structure implemented by the system developers. These tools are not universal, they are focused on specific expert domain with strictly given application domain and specified model of knowledge representation. For example, the system TEIRESIAS (Davis, 1982), the first system for knowledge acquisition, was intended to supplementing the knowledge base for medical diagnosis of the application domain (MYSIN) based on the production model of knowledge representation. Thus, following clear logic of the knowledge base model built in the knowledge acquisition systems while helping to formulate expert knowledge, but hardly helps to reveal hidden (deep, nontrivial, hierarchical) pieces in expert's memory.

Figure 1. Basic strategies of knowledge acquisition in knowledge engineering process



Machine learning is the process of automatic extraction of formal knowledge from data. It is based on data mining and discovery of hidden patterns in the structured and unstructured data. Therefore, as opposed to the knowledge acquisition systems, machine learning systems allow to reveal deep, nontrivial, hidden knowledge completely automatically, without any human involvement, and so is very promising in creating KBS and its filling.

However, Machine learning has not yet become the industrial technology used in the creation of KBS. To achieve this, it is necessary to solve a number of problems related to the creation of a hybrid mechanism of interacting the data and the knowledge in a single intelligent system. The problems are as follows:

- To provide a mechanism for interfacing database and knowledge base with different languages and formal models of knowledge representation;
- To establish correspondence between a set of database tables and attributes, on the one hand, and declarative components of the knowledge base, on the other hand;
- To develop tools for converting the results of machine learning algorithms into the knowledge base according to the model of knowledge representation supported by the KBS.

In accordance with the kind of problem solved, all methods of machine learning can be divided into two large classes - the classification methods and the regression methods. The classification methods solve the problem of determining the class to which the current object belongs, while the regression methods compute the value of the output feature based on the values of the input features. The difference between these two classes of machine learning is formally in the type of output feature. In case of classification, the output feature has a qualitative nature, and can take only discrete values. In case of regression, the output feature is quantitative and can take on any values from specified range.

We propose an approach to solving classification problem on the basis of dynamic integration of the two basic approaches to knowledge representation – case-based and rule-based reasoning (Avdeenko & Makarova, 2017). Case-based reasoning allows to use high-performance database technology for storing and accumulating cases (for example, precedents of previous decision making), and to ensure quick access to them. While rule-based reasoning is the most developed technology for creating declarative knowledge base on the basis of strong logical approach. In addition, rules can be obtained as a result of known data mining techniques such as the decision (regression) trees and association rules. Therefore, the development of methods for converting cases into rules and vice versa allows to approach to solving the problem of automation of the process of obtaining knowledge from data based on machine learning methodology.

The proposed dynamic approach to creating a knowledge base is based on transformation of cases into fuzzy rules with the subsequent applying fuzzy inference to retrieve new knowledge. We consider the expansion of the rule-based approach towards fuzzy logic being a natural direction of its development to create decision-making systems, taking into account such an important aspect of reality, as uncertainty modeling. The fact is that decision making is a complex procedure that uses both numerical information and information in natural language. And natural language, as is well known, has inaccuracies and uncertainties. Methods based on the theory of fuzzy logic are well suited for decision-making, because they allow you to successfully combine both types of information (numeric and symbolic), and thus make decisions close to those made by people. In addition, rigorous mathematical models based on probabilistic approach supposes rather impressive list of a priori assumptions and requirements, that makes them inadequate in the real situation, full of mutual dependencies, nonlinearities and feedbacks. Intellectual technologies, such as fuzzy models, assume significantly less limitations; therefore they often prove to be appropriate to the real situation. At the same time, fuzzy inference is based on classical logic and theory of fuzzy sets that have a rigorous mathematical justification. Therefore, the results obtained using fuzzy models are quite scientific and reasonable.

The further article is organized into a number of sections. After this introduction in section 2 we give an overview of case-based and rule-based reasoning models for KBS and explain the need for their integration. Here we consider how to organize the knowledge transfer between database and knowledge base through the integration of case-based and rule-based reasoning. In Section 3 we describe the machine learning algorithm of transformation of a set of cases into the system of fuzzy classification rules. In this paper we improve classification accuracy of the algorithm in comparison with (Avdeenko & Makarova, 2017) by introducing a new procedure of control sample classification (expanding the scope of the classification rules). In Section 4 we give experimental results confirming the efficiency of the method. In section 5 we give a conclusion.

INTEGRATION OF CASE-BASED AND RULE-BASED REASONING

The first KBS appeared in 1970-s were based on rules. When implementing first rule-based reasoning (RBR) systems, developers faced many challenges. The major one was the problem of knowledge elicitation and formulation in the explicit form:

IF **premise** *THEN* **conclusion**

Most often, the experts intuitively make decisions based on their vast experience, without hesitation, what rules they apply in this or that situation. Partitioning a specific behavior of an expert into a series of implications $A_1 \Rightarrow A_2 \Rightarrow A_3 \Rightarrow A_4 \Rightarrow A_5$ in the rule-based system is very complicated problem requiring highly skilled specialists - knowledge engineers. Therefore elicitation of knowledge from experts in the explicit form is the kea problem of rule-based systems.

However, since 1980s an alternative reasoning paradigm has increasingly attracted more and more attention. Case-based reasoning (CBR) solves new problems by adapting previously successful solutions to similar problems, just as a human does it. First in (Schank & Abelson, 1977) it has been proposed to generalize knowledge about previous situations and store them in the form of scripts that can be used to make conclusions in the similar situations. The model of dynamic memory (Schank, 1982) proposed by Shank became the basis for the creation of a number of other systems: MEDIATOR (Simpson, 1985); CHEF (Hammond, 1986); PERSUADER (Sycara, 1987); CASEY (Koton, 1989) and JULIA (Hinrichs, 1992).

There are different ways of presenting and storing cases – from simple (linear) to complex hierarchical ones. The case can generally include a description of the problem (problem situation), and a solution to the problem (diagnosis of the problem). If cases from the knowledge base has been used to solve practical problems, the additional component may be the result (or forecast) of case application (positive or negative).

CBR allowed to overcome a number of restrictions inherent to rule-based systems (Watson & Marir, 1994). It does not require explicit model of the knowledge domain, so the extraction of knowledge is transformed into a simple task of collecting stories (cases). Implementation of the system is reduced to the identification of essential features, describing the case, which is much easier task than building an explicit knowledge model of the application domain. It is possible to use database technology for storing large volumes of cases. And, finally, CBR-systems can be self-learning from the case base, thus, it is possible to obtain new cases from the past ones.

At the same time there are two essential shortcomings of traditional CBR. The first one is that the cases structure does not usually take into account the deeper knowledge nature of the application domain. The second one reveals itself when the number of cases accumulated in the knowledge base becomes great. The large case base results in reduced system performance. It is difficult to determine good criteria for indexing and comparison of cases. Very often the search dictionaries and algorithms for determining similarity are needed to debug manually. It can neutralize the advantages of case-based approach to knowledge representation.

In order to overcome these disadvantages CBR has been widely integrated with other methods in various application domains (Marling, Sqalli, Rissland, Hector & Aha, 2002; Yang & Wang, 2008). Some systems (ADIOP, CADRE, CADSYN, CHARADE, COMPOSER, IDIOM, JULIA) integrated CBR with constraint satisfaction problem (CSP) algorithm. Some systems (ANAPRON, AUGUSTE, CAMPER, CABARET, GREBE, GYMEL and SAXEX) combined CBR with rule-based reasoning (RBR) approach. It is worth to noting that the first prototype of the system, integrating CBR with RBR was CABARET system (Rissland & Skala, 1989). In (Dutta & Bonisson, 1993) it is proposed possible connection of CBR with RBR and its application to the financial domain implemented in prototype system MARS.

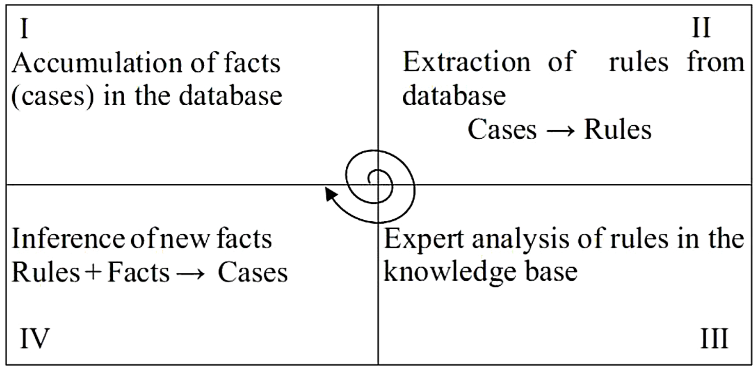
Integration of the theory of fuzzy sets with CBR was considered by some researchers. The work (*Fuzzy set and possibility theory*, 1982) clarified that there is a close relation between fuzzy modeling system and CBR. In (Dubois & Prade, 1980) the fundamental hypothesis for CBR with fuzzy rules was formalized, where the authors created a formal approach on the basis of logical inference, that can be implemented as a special type of fuzzy sets based on approximate reasoning.

Fuzzy sets were used to describe inaccurate characteristics of a case in fuzzy reasoning based on CBR (Marques, Farinha & Brito, 2009). In (Xiong & Funk, 2006) a fuzzy subset “small” was defined for various features in the numerical evaluation of similarity measure between the cases. In addition, fuzzy linguistic rules were adopted in (Xiong, 2011) and (Xiong, 2013) as flexible means for computing similarity criteria.

Here we consider an approach in which it is possible the dynamic interaction of both CBR and RBR models of knowledge representation. Therefore, in practice it would be reasonable to take advantage of both models. The combination of the two methods could be represented as a cyclic knowledge transformation from case-based knowledge representation to rule-based one and vice versa, as shown in Fig. 2.

When we begin to create KBS in a new application domain, we have no insight into the domain. Of course, we could have experts in a given subject area at our disposal, and we could involve them in designing and filling the knowledge base, however, as noted above, this is a rather laborious and costly way that most likely would not lead to the desired result very fast. Therefore at the initial stages of creating the knowledge base it is advisable to use case-based reasoning for presenting knowledge in the form of relevant precedents (cases) of decision making implemented in a particular application domain (stage I, fig. 2). Such cases could be stored in the data base or warehouse containing retrospective data.

Figure 2. Dynamic transformation of knowledge between RBR and CBR



In order to create a case, in the simplest case it is necessary to determine the final set of attributes that uniquely determine the situation and the specific decision made in this situation. However, even in (Wittgenstein, 1953) one can find references that natural domain concepts most often cannot be classified according to a simple set of properties (attributes), but can be described using a more complex structure. This work was later referred to as the philosophical basis of the CBR-approach.

Consider a simple linear representation of a case to be used for integration with fuzzy logic as $(n+1)$ - dimensional tuple

$$CASE = (x_1, x_2, x_3, ..., x_n, s), \tag{1}$$

where $x_1 \in X_1, x_2 \in X_2, x_3 \in X_3, ..., x_n \in X_n$! $= (x_1, x_2, x_3, \ldots, x_{n,} S)$, 345 $x_1, x_2, x_3, \ldots, x_n$ are the values of attributes (features) identifying the situation, $s \in S$ is a solution to the problem defined in the case. Subsequently, with the deepening into the application domain, possible complication of case structure is possible, through, for example, the introduction of hierarchy and other relationships between the features.

Thus, in the form (1) we have knowledge in the implicit (tacit) form, because one cannot use it directly for decision-making as IF-THEN rules which are the explicit form of knowledge representation. However, already at the earliest stages of the development of KBS it is possible to extract, adapt and use cases in order to solve the current problems of decision-making in accordance with the so called 4R-cycle (Aamodt & Plaza, 1994). After applying the case from the knowledge base to the current situation, a new case is recorded to the case base for future use. Note that we do not carry out the formalization of knowledge in the case model (conversion of tacit knowledge into explicit one). Moreover, we do not try to analyze why the decision is made (i.e. we do not try to transform tacit knowledge into formal), but we simply fix the fact of tacit knowledge in a particular case.

As soon as we accumulate sufficient volume of cases in the case base and deepen our knowledge on the basis of the analyzing case sample, it is possible to carry out formalization of knowledge, contributing to the transformation of case-based (implicit, tacit) knowledge into rule-based (explicit) one. The use of methods of data mining to automatically extract new knowledge in the form of rules from cases sample may be of great intellectual support (stage II, fig. 2).

A set of cases of the form (1) can be represented as a table in the database. And we can apply, for example, decision tree method (Quinlan, 1989), to this sample of cases, in which the intermediate nodes of the tree are the attributes of the cases $x_1, x_2, x_3, ..., x_n$, and terminal nodes are solutions to the case $s \in S$, which in this aspect is considered as classifying attribute. The sequence of feature selections in the decision tree is determined, for example, by the amount of information that provides a choice of one or another feature to reduce the entropy – the uncertainty of classification. The approach is now successfully extended to fuzzy decision trees (Janikow, 1998); Begenova & Avdeenko, 2018).

The transition to a rule-based model of knowledge representation means that we obtain the explicit (formalized) form of knowledge, able to explain the cause-conclusion relationships in the application domain. Such rules in the form of implications A⇒B can be presented to experts for analysis and obtaining expert's opinion. This explicit knowledge can be cleaned, refined and interpreted by experts (stage III, fig. 2). Also an important point at this stage is the resolution of conflicts arising in a system of rules (conflicting rules lead to different conclusions for the same set of features).

Note, that the expert can discover that the rules obtained at the stage II from machine learning algorithms, are shallow. In this case perspective technique is integration of knowledge elicitation and machine learning proposed in (Webb, 2002). Another approach based on separating fuzzy inference into two subsequent steps is proposed in the expert system of multi-criteria tax audit planning (Avdeenko & Vasiljev, 2009; Avdeenko, Vasiljev & Mamenko, 2010). At the first step we divide all criteria into two groups, at the second step fuzzy inference is applied to each criterion.

At the stage IV in fig.2 the accumulation of new cases takes place using the received version of KBS. New cases are obtained using the obtained rule base, and as a result of CBR-cycle, adapting from the knowledge base to new problems. Getting new cases on the basis of CBR-cycle means the use of formal (explicit) knowledge and turning them into the implicit form of upper level (in comparison with the previous cases in the case base).

The considered cycle of knowledge transformation is repeated further on the next level. As soon as our knowledge about application domain deepen it is possible to make the structure of cases more complex by transition from the parametric linear form to the hierarchical or more complex logical form, or even presentation of cases in the form of ontology. In addition, when we accumulate a large volume of the knowledge base it would be desirable to execute indexing and clustering cases.

MACHINE LEARNING ALGORITHM FOR EXTRACTION OF FUZZY CLASSIFICATION RULES FROM CASE BASE

Let we have a set of cases in the database that in fact contain implicit knowledge. In this section we develop the machine learning algorithm to convert implicit knowledge into the explicit one, for subsequent discovery of hidden patterns in the database.

In this section, we present a machine learning algorithm for classification of cases, based on generating fuzzy classification rules. In fact the rules are explicit knowledge and can be meaningfully interpreted. They can be shown to the expert for further analysis and then, if they are valid, can be placed into the knowledge base.

The proposed method is simple to implement, but shows a high classification accuracy. In this paper, we investigate an improved version of the algorithm, which allows to improve an accuracy of classification by expanding the scope of the rules, as well as the use of different types of membership functions.

Here we consider the method of obtaining fuzzy rules from cases in application to the problem of cases classification. The idea of the method is as follows. Consider arbitrary case of simple linear form

$$CASE = (x_1, x_2, x_3, ..., x_n, d)\,, \tag{2}$$

with the features $x_1 \in X_1, x_2 \in X_2, x_3 \in X_3, ..., x_n \in X_n$ and classifying attribute value d of the solution. Without loss of generality we assume that the features are numerical and sets $X_1, X_2, X_3, ..., X_n$ are continuous numerical intervals. To solve the classification problem, the attribute d must be categorical. If we were solving a regression problem, this attribute should be numerical.

Let us define linguistic variables V_i corresponding to the features x_i, $i = \overline{1,n}$. Let each linguistic variable V_i has J linguistic values $A_i^{(j)}$ that are fuzzy sets determined by membership functions $\mu_{A_i^{(j)}}$ defined on the universal sets X_i, $j = \overline{1,J}$. Then the rule ***Rule***, corresponding to the case (2), can be formulated as follows:

$$Rule \quad : \quad IF \quad V_1 = F(x_1) \wedge F(x_2) \wedge ... \wedge V_n = F(x_n) \qquad THEN \qquad R = d \tag{3}$$

where R is a variable whose values are the nominal values of the solution classes, $F(x_i)$ is a fuzzy term-value which accepts linguistic variable V_i as a result of fuzzification of the feature value x_i in accordance with the following scheme:

$$F(x_i) = A_i^{(j^*)}\text{, where } j^* = \arg\max_{j=\underline{1,J}} \mu_{A_i^{(j)}}(x_i)\,. \tag{4}$$

Then, knowledge base consisting of a set of rules from the initial case base is formed in accordance with the following algorithm.

Algorithm of Obtaining Fuzzy Classifying Rules from Case Base

Step 1: First, we define the number J and the type (linear, quadratic, etc.) of membership functions $\mu_{A_i^{(j)}}$ and universal sets X_i for each linguistic variable V_i corresponding to the feature x_i, $i = \overline{1,n}$.

Step 2: Define fuzzy rule $Rule$ of the form (3) for each case of the form (2).

Step 3: Assign truth degree $TD(Rule)$ to each rule. The simplest way to do this is to compute minimum of all $\mu_{A_i^{(j^*)}}(x_i)$ for each x_i and fuzzy sets $A_i^{(j^*)}$ defined by the formula (4) as a result of fuzzification for each rule $Rule$ of the form (3). The result is obtained in the following way

$$TD(Rule) = \min_{i=\underline{1,n}} \mu_{A_i^{(j^*)}}(x_i) = \min_{i=\underline{1,n}} \max_{j=\underline{1,J}} \mu_{A_i^{(j)}}(x_i)\,.$$

Step 4: Resolve conflicts between the rules. After the step 2 we have the set of rules uniquely corresponding to the set of cases. But this set can contain subsets of the rules with the same premises. These rules can have the same or different conclusions (solutions $d \in D$). If for all rules in such subset we have the same conclusion we simply remove all duplicate rules from the set except one. For the rules with conflicting conclusions, we propose two different strategies for classification problem. In each case we leave only one rule in the subset with conflicted conclusions in the rule base. Let we have a subset of rules $Rule_1, Rule_2$, ..., $Rule_m$ with the same premise. Divide the set of indexes $I = \left\{1, 2, \ldots, m\right\}$ into K subsets $I_1, I_2, \ldots, I_K$ corresponding to the classes of solutions d_1, d_2, ..., d_K in the conclusions of the rules (3), $\dim I_k = m_k$, $\sum_{k=1}^{K} m_k = m$.

We consider two strategies for resolving conflicts. The first strategy for resolving conflicts between the rules is to obtain the optimal rule in accordance with the following index l^*:

$$l^* = \arg \max_{l \in I} TD(Rule_l),$$

and then to choose a solution corresponding to the conclusion part of the optimal rule.

The second strategy for resolving conflicts between the rules is a bit more complex. The optimal solution d_{k^*} that is assigned to the conflicting set of rules could be obtained as follows

$$k* = \arg \max_{k} \left(\sum_{i \in I_k} TD(Rule_i)\right).$$

In (Avdeenko & Makarova, 2017) it was shown that the second strategy of conflict resolution gave better accuracy of classification. Therefore in present paper we will follow this strategy. Also it was discovered that the decrease in classification accuracy is due to the fact that a small number of rules does not cover all possible cases in the control sample, which in the absence of the corresponding classifying rules led to the incorrectly classified case. So in present paper we modify the strategy of classifying the control sample and expand the scope of each rule by decreasing the number of features in the rule premises.

EXPERIMENT RESULTS

In this section we investigate the proposed approach with the data set Iris (available at http://archive.ics.uci.edu/ml/) with 150 cases, characterized by 4 features ($n = 4$), which are classified into 3 classes ($K = 3$) through classifying attribute.

In the first experimentation, we randomly selected training sample of given size (120 cases) from Iris set, while the rest of the data (30 cases) was used as a control sample. For each feature minimum and maximum values were determined from the training sample. The obtained intervals were used as the universal sets for corresponding linguistic variables. Then we divided each universal set X_i into equal intervals for three variants of choosing the number of term-values $A_i^{(j)}$, $j = \overline{1, J}$: J = 3,5 and 7 (J does not depend on i) for membership functions (3MF, 5MF and 7MF). We also considered two classes of membership functions – linear MF (class T) and quadratic MF (class S).

Then a set of fuzzy classifying rules obtained as a result of machine learning algorithm was applied to randomly selected control sample to compute an accuracy of classification as a ratio of correctly classified cases to the general volume of the control sample. In table 1 we presented the results of classification accuracy for two strategies of control sample classification with linear membership functions (3MF, 5MF and 7MF) . Here we can find that the best results are obtained for 3MF. Reducing in the accuracy for 5MF and 7MF can be explained by the fact that the number of possible combinations of preconditions in the rules increases significantly, so classification on the control sample fails because of the lack of appropriate rule for the classified case. Therefore we compare two types of control cases classification. For the first strategy we apply each rule only to exactly corresponding control cases. If there are no appropriate rules, incorrect classification is registered. For the second strategy, if there is no appropriate rule to classify the control case, we exclude one feature and try to find classifying rule for reduced number of features (Here we assume that the excluded feature is not important for classification). The first appropriate rule is applied for classification of the corresponding case. The second strategy permits to improve the results of cases classification, see table 1. The experiments were performed ten times, each time having arbitrary set of cases for training.

In Table 2 we give classification accuracy for linear and quadratic membership functions (class T and S for 3MF) . Here we can see that for smoother membership functions (class S) the classification accuracy is better.

Table 3 contains comparison between two classes of membership functions (triangular and quadratic) and two strategies of control sample classification for sequentially reducing volume of training sample.

Table 4 contains comparison between the two classes of membership functions (T and S) for 3MF, 5MF and 7MF, for sequentially reducing volume of training sample.

Table 1. Classification accuracy for two strategies of control sample classification with linear membership functions (3MF, 5MF and 7MF)

	Strategy 1 of control sample classification			Strategy 2 of control sample classification		
Number of trial	**3 MF**	**5 MF**	**7 MF**	**3 MF**	**5 MF**	**7 MF**
1	0,90	0,83	0,83	0,97	0,88	0,88
2	0,87	0,80	0,63	0,93	0,92	0,78
3	0,97	0,77	0,73	0,95	0,83	0,83
4	0,80	0,63	0,63	0,97	0,83	0,83
5	0,83	0,73	0,57	0,95	0,88	0,77
6	0,87	0,83	0,60	0,95	0,90	0,82
7	0,80	0,70	0,63	0,97	0,88	0,83
8	0,90	0,77	0,70	0,95	0,85	0,78
9	0,93	0,83	0,73	0,93	0,85	0,83
10	0,87	0,67	0,80	0,97	0,87	0,83
Average	**0,88**	**0,76**	**0,69**	**0,95**	**0,87**	**0,82**

Table 2. Classification accuracy for two strategies of control sample classification with linear and quadratic membership functions (class T and S for 3MF)

	Strategy 1 of control sample classification		Strategy 2 of control sample classification	
Number of trial	**Class Ò**	**Class S**	**Class Ò**	**Class S**
1	0,90	0,97	0,97	0,98
2	0,87	0,97	0,95	0,97
3	0,93	0,93	0,98	0,95
4	0,87	0,97	1,00	0,93
5	0,87	0,83	0,98	0,95
6	0,85	0,92	0,95	1,00
7	0,87	0,88	0,95	0,93
8	0,82	0,90	0,95	0,92
9	0,87	0,87	0,98	0,98
10	0,85	0,90	0,97	0,95
Average	**0,87**	**0,91**	**0,97**	**0,96**

Fig.3 gives visual illustration of the results of Table 4 for linear class of membership function.

From the Tables 3 and 4 and Fig. 2 we can observe that the classification accuracy for sequentially reducing volume of training sample (from 90 cases to 30) remains quite high. The results could be explained by the fact that the number of rules obtained from the initial training sample of 150 cases was not more than 17 in all the experiments. If we randomly choose less amount of cases for training, the information content (or representativeness) of the sample remains still high.

Figure 3. Classification accuracy for sequentially reducing volume of training sample for linear membership function (T) for 3MF, 5MF and 7 MF

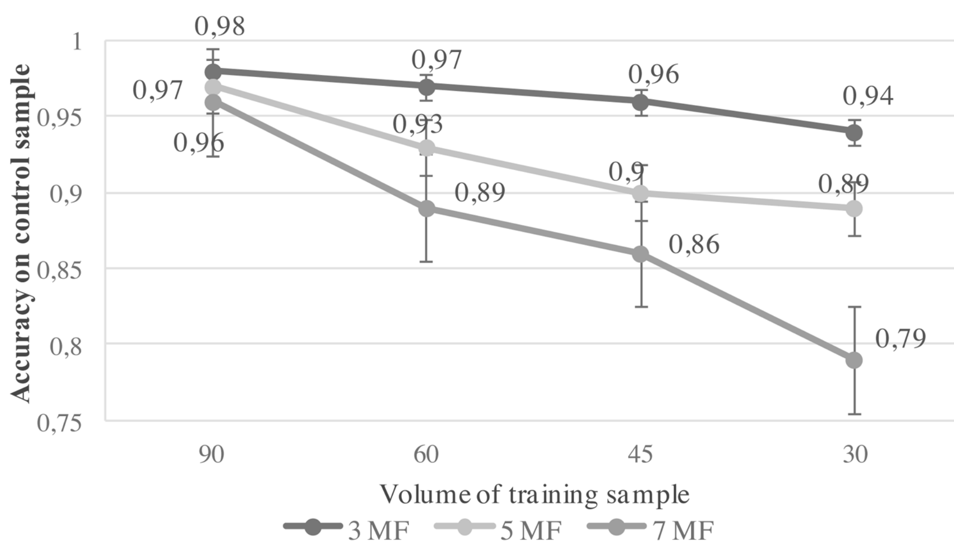


Table 3. Accuracy of cases classification for two classes of membership functions (triangular and quadratic) and two strategies of control sample classification

Number of trial	Volume of training sample	Strategy 1 of control sample classification		Strategy 2 of control sample classification	
		Class Ò	**Class S**	**Class Ò**	**Class S**
1	90	0,90	0,97	0,97	0,98
2	90	0,87	0,97	0,95	0,98
3	90	0,93	0,93	0,98	0,95
4	90	0,87	0,97	1,00	0,95
5	90	0,87	0,83	0,98	0,93
6	90	0,85	0,92	0,95	0,98
7	90	0,87	0,88	0,97	0,93
8	90	0,82	0,90	0,95	0,92
9	90	0,87	0,87	0,98	1,00
10	90	0,85	0,90	0,97	0,95
Average	**90**	**0,87**	**0,91**	**0,97**	**0,96**
11	60	0,84	0,92	0,87	0,92
12	60	0,83	0,90	0,90	0,92
13	60	0,88	0,91	0,97	0,88
14	60	0,88	0,87	0,98	0,90
15	60	0,86	0,90	0,95	0,90
16	60	0,86	0,92	0,98	0,91
17	60	0,86	0,83	0,92	0,88
18	60	0,88	0,89	0,93	0,95
19	60	0,86	0,90	0,93	0,93
20	60	0,87	0,89	0,90	0,90
Average	**60**	**0,86**	**0,89**	**0,93**	**0,91**
21	45	0,94	0,85	0,89	0,85
22	45	0,76	0,86	0,91	0,88
23	45	0,84	0,85	0,91	0,88
24	45	0,91	0,85	0,88	0,90
25	45	0,88	0,90	0,91	0,86
26	45	0,86	0,91	0,87	0,86
27	45	0,86	0,89	0,88	0,95
28	45	0,85	0,84	0,84	0,92
29	45	0,93	0,86	0,92	0,83
30	45	0,87	0,88	0,91	0,89
Average	**45**	**0,87**	**0,87**	**0,89**	**0,88**
31	30	0,83	0,88	0,83	0,91
32	30	0,69	0,67	0,85	0,81

continues on following page

Table 3. Continued

Number of trial	Volume of training sample	Strategy 1 of control sample classification		Strategy 2 of control sample classification	
		Class Ò	Class S	Class Ò	Class S
33	30	0,83	0,81	0,89	0,86
34	30	0,68	0,83	0,88	0,86
35	30	0,79	0,82	0,91	0,88
36	30	0,79	0,84	0,89	0,85
37	30	0,72	0,83	0,90	0,85
38	30	0,87	0,80	0,84	0,86
39	30	0,82	0,86	0,90	0,78
40	30	0,85	0,86	0,89	0,81
Average	**30**	**0,79**	**0,82**	**0,88**	**0,85**

Table 4. Accuracy of cases classification for two classes of membership functions (T and S) for 3MF, 5MF and 7 MF

Number of trial	Volume of training sample	Classification accuracy					
		3 MF		5 MF		7 MF	
		Class Ò	Class S	Class Ò	Class S	Class Ò	Class S
1	90	0,97	0,93	0,97	0,98	0,95	0,97
2	90	0,97	0,95	0,97	0,98	0,98	0,97
3	90	0,98	0,95	0,95	0,97	0,98	0,97
4	90	0,98	0,95	0,97	0,98	0,97	0,97
5	90	1,00	0,98	0,93	0,98	0,97	0,98
6	90	0,97	0,95	0,98	1,00	0,93	0,98
7	90	0,97	0,95	0,97	0,95	0,98	0,95
8	90	0,98	0,97	1,00	0,98	0,95	0,97
9	90	0,98	0,97	0,97	0,98	0,95	0,97
10	90	1,00	0,97	0,95	1,00	0,97	1,00
Average	**90**	**0,98**	**0,96**	**0,97**	**0,98**	**0,96**	**0,97**
11	60	0,93	0,95	0,95	0,97	0,87	0,97
12	60	0,98	0,98	0,90	0,97	0,90	0,98
13	60	0,98	0,97	0,95	0,98	0,88	0,95
14	60	0,95	0,97	0,93	0,97	0,93	0,97
15	60	0,93	0,95	0,92	1,00	0,92	0,98
16	60	0,97	0,95	0,97	0,97	0,88	1,00
17	60	0,98	0,95	0,92	0,98	0,90	0,97
18	60	0,98	0,97	0,95	0,97	0,85	0,98
19	60	0,98	0,97	0,90	1,00	0,88	0,97

continues on following page

Table 4. Continued

Number of trial	Volume of training sample	Classification accuracy					
		3 MF		5 MF		7 MF	
		Class Ò	Class S	Class Ò	Class S	Class Ò	Class S
20	60	1,00	0,92	0,95	0,95	0,87	0,95
Average	**60**	**0,97**	**0,96**	**0,93**	**0,98**	**0,89**	**0,97**
21	45	0,97	0,97	0,90	0,95	0,78	0,95
22	45	0,95	0,93	0,93	0,95	0,90	0,98
23	45	0,90	0,92	0,83	0,97	0,88	1,00
24	45	0,95	0,93	0,88	0,95	0,82	0,98
25	45	0,98	0,92	0,92	0,98	0,82	0,90
26	45	0,97	0,98	0,95	0,97	0,88	0,98
27	45	0,97	0,97	0,93	0,98	0,78	0,97
28	45	0,95	0,90	0,92	0,97	0,95	0,98
29	45	0,95	0,95	0,92	0,98	0,90	0,92
30	45	0,98	0,95	0,85	0,98	0,88	0,97
Average	**45**	**0,96**	**0,94**	**0,90**	**0,97**	**0,86**	**0,96**
31	30	0,93	0,95	0,87	0,98	0,78	0,98
32	30	0,92	0,95	0,88	0,92	0,82	0,87
33	30	0,92	0,97	0,92	0,98	0,77	0,92
34	30	0,85	0,92	0,90	1,00	0,77	0,98
35	30	0,97	0,97	0,83	0,98	0,77	0,97
36	30	0,92	0,95	0,88	0,90	0,77	1,00
37	30	0,98	0,90	0,92	0,92	0,80	0,92
38	30	0,98	0,98	0,90	0,92	0,78	0,97
39	30	0,97	0,92	0,87	0,93	0,77	0,92
40	30	1,00	0,92	0,88	0,97	0,82	0,98
Average	**30**	**0,94**	**0,94**	**0,89**	**0,95**	**0,79**	**0,95**

Thus, we have proposed rather simple method of generating classification rules from case base that can be used in the cycle of knowledge transformation in the KBS. Despite the simplicity we have achieved quite high accuracy of classification even for sequentially reducing volume of training samples.

CONCLUSION

In the article, we considered spiral of knowledge transformation from an implicit form into an explicit one and vice versa on the basis of sequential transitions from case-based model of knowledge representation to rule-based one and, conversely, from rules to new cases. Also we proposed a method for generating fuzzy rules from decision making cases accumulated in the knowledge base to support automatic elicitation of knowledge in the form of rules from case base. The accuracy of the method was studied and confirmed in application to classification problem. It was discovered that the method ensures sufficiently accurate classification even for small training samples.

Thus, throughout the life cycle of a knowledge-based system, the knowledge base contains both explicit rules for decision-making and implicit knowledge in the form of decision-making cases and their various combinations, with a permanent dynamic transformation of knowledge from one form to another. The combination of explicit and implicit knowledge representation in one knowledge base makes it possible to use relevant knowledge in the appropriate form. The explicit form of knowledge representation allows to apply the rule directly for managerial decision-making. The implicit form allows either to confirm the received recommendation with additional similar decision – making cases, or, in the absence of a direct recommendation in the knowledge base in the form of decision-making rule, to obtain relevant (semantically closest) cases for the formulation of new rules.

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Chapter 4
Applications of Fuzzy Expert Systems in Farming

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ABSTRACT

Agriculture, cattle breeding, and poultry farming constitute the backbone of the Indian economy. Today, India is ranked first worldwide in terms of milk production, second in terms of farm output, and third in terms of poultry output (eggs production). Over the year, agriculture, poultry farming, and cattle breeding have contributed towards India's GDP but is narrowly declining with the country's economic growth due to lack of initiatives. Fuzzy expert systems are used for various activities with an objective to get better results and good yield. Expert systems combine the experimental and experiential knowledge with the intuitive reasoning skills of a multitude of specialists to aid farmers in making the best decisions to improve the quality and increase the production. Weather and climatic changes play important roles. Thus, any changes in them affect the quantity and quality of production. Therefore, weather prediction plays an important role and helps the farmers to take right decisions and precautions to safeguard the production.

INTRODUCTION TO FUZZY LOGICS AND FUZZY EXPERT SYSTEM

The fuzzy concept means the vague and lacking the exact and clarity, which means the values or boundaries can vary according to context or conditions, instead of being fixed once and for all. Actually, the fuzzy has different semantics, but these can become clearer only through further specification, including a closer definition of the context in which they are operationalized.

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The reasoning of fuzzy logic looks like human reasoning, instead of the entire data to be relying on crisp line and to have only two values, which may incomplete or ambiguous, Fuzzy logic able to process this situation and to provide approximate solution. A conditional fuzzy proposition or rule has the form:IF w is Z then x is Y, this rule should be interpreted: x is a member of Y to the degree that w is a member of Z, for example; IF experience is high then salary is high. The membership value of salary in the fuzzy set high is specified by the membership value of experience in the set high. Rules are usually expressed in the form: IF variable is ‘property’ then ‘action’.

Practically, the fuzzy inference system can be described in the five steps:

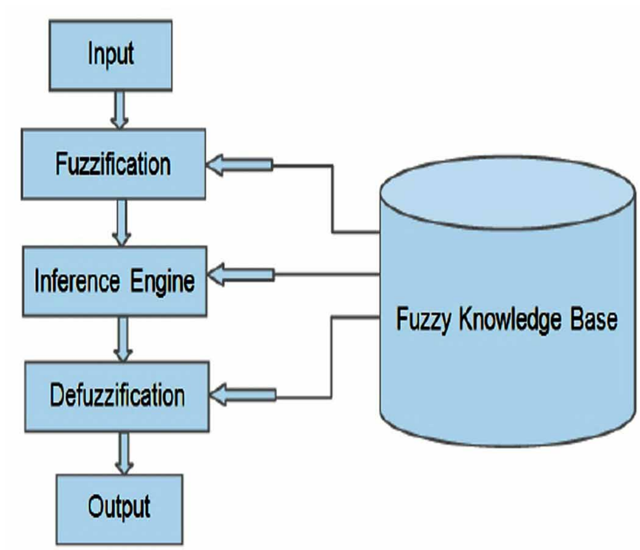
- Fuzzfying Input: Initially, once inputs are available, the degrees of the inputs to which they belong to each of the appropriate fuzzy sets are determined via membership functions.
- Applying Fuzzy Operators: If the rule consists of multiple parts (antecedent), there are need to apply logical operators to evaluate the degree of the strength for the rule.
- Applying the Implication Process: The implication is a process whereby the output membership functions based on the strength of the rule are shaped. The output is a fuzzy set of the consequence, whereas the input for the implication process is a single number given by the antecedent.
- Aggregating All Outputs: Aggregation is unifying the outputs of each rule. The aggregation is performed only once for each output variable. The output of the aggregation process is a single fuzzy set, which is the combination of a list of truncated output fuzzy sets returned by the implication process for each rule.
- Defuzzifying: Finally, the output of the defuzzification process is a crisp value whereas; the input is the aggregated output fuzzy sets. Recently, many of various methods in defuzzification process have been proposed by investigators including, the maximum, the means of maxima, height, and modified height method, and the centroid.

A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing shown in the Figure 1.

FUZZY EXPERT SYSTEM IN AGRICULTURE

Agriculture decision making activates are often vague and based on intuition. This makes agriculture a complex problem and thus requires very complicated optimization and modeling steps when agriculture is attempted through conventional techniques. The agricultural production management problem includes identification of correct sowing period, crop variety selection; land preparation, sowing method, fertilizer and pest selection according to variety. It also includes lack of experts to support the agricultural growers, and the heavy dependence upon the experiences of these experts. Thus, there is need of expert system approach, which is more flexible, and gives the end user wide choices for farming methods. Expert system in agriculture is not a new idea. It is being used in agriculture since the early 1980s. Agriculture Expert systems (AES) are being developed by various Agricultural Research Institutes and researchers

Figure 1.



from different countries to assists the information needs to the farmers for plant-disorder diagnosis, management and other production aspects for agriculture. An expert system is software that manipulates encoded knowledge to solve problems in a specialized domain that normally requires human expertise.

Examples of Fuzzy Expert Systems

POMME is an expert system for apple orchid management. POMME advises growers about when and what to spray on their apples to avoid infestations. The system also provides advice regarding treatment of winter injuries, drought control and multiple insect problems.

CALEX system has been developed for agriculture management. It is domain independent and can be used with any commodity. CALEX consists of three separate modules: an executive, a scheduler, and an expert system shell.

An agro forestry expert system was designed to support land-use officials, research scientists, farmers, and other individuals interested in maximizing benefits gained from applying agro-forestry management techniques in developing countries. United Nations University (UNU) Agro forestry Expert System (AES) is a first attempt to apply expert systems technology to agro-forestry.

Implementation of Fuzzy Expert System in Agriculture

- Irrigation Scheduling
- Weed Management
- Soil Analysis
- Fertilization Techniques

Irrigation Scheduling

Agriculture is the largest user of water worldwide by using about 70 percentage of total consumption. Considering factors such as demographic and climate change, the use of efficient irrigation is necessary to apply the correct amount of water to crops.

Objective of Irrigation Scheduling

The goal of an irrigation subsystem (fuzzy expert system) is to produce a schedule for irrigation of a particular farm based on the moisture content of the soil.

Implementation of Irrigation Scheduling

The subsystem should have sensors, which will help in measuring the moisture content in the soil. The irrigation system will measure and monitor the soil moisture through data acquired from the soil and also from the climatologic factors. These results are tabulated and stored in the database. This data is given as an input to limex machine, it will take it as the input and convert it into fuzzy values (fuzzification), these values will be compared to the values present in fuzzy knowledge base and an optimal value is generated. This value is then defuzzified and is given as an output. This output will help to decide when to water and how much water is required to the plants.

This system will help in controlled distribution of water, which will save water from being wasted and solve the over-irrigation or under-irrigation problem faced by farmers.

Weed Management

A weed is a plant considered undesirable in a particular situation, "a plant in the wrong place". Example: plants unwanted in human-controlled settings, such as farm fields, gardens etc.

Competition from weeds is the most important of all biological factors that reduce agricultural crop yield. This occurs primarily because weeds use resources that would otherwise be available to the crop. The magnitude of yield loss is affected by numerous agronomic and environmental factors, most importantly, weed density and time of emergence relative to the crop.

Objective of Weed Management

Fuzzy expert system has to differentiate between the crop and the weed by image processing and eliminate the weed.

Fuzzy expert system helps in weed management. Fuzzy expert system should combine computer vision and multi-tasking processes to develop a small-scale smart agricultural machine that can automatically detect weed and perform variable rate irrigation within a cultivated field. Image processing methods such as HSV (hue (H), saturation (S), value (V) colour conversion, estimation of thresholds during the image binary segmentation process, morphology operator procedures are used to confirm the position of the plant and weeds, and those results are used to eliminate the weed. Therefore, the deployment of this system in a simulated environment can show a decrease in the use of herbicide by 15% to 64%.

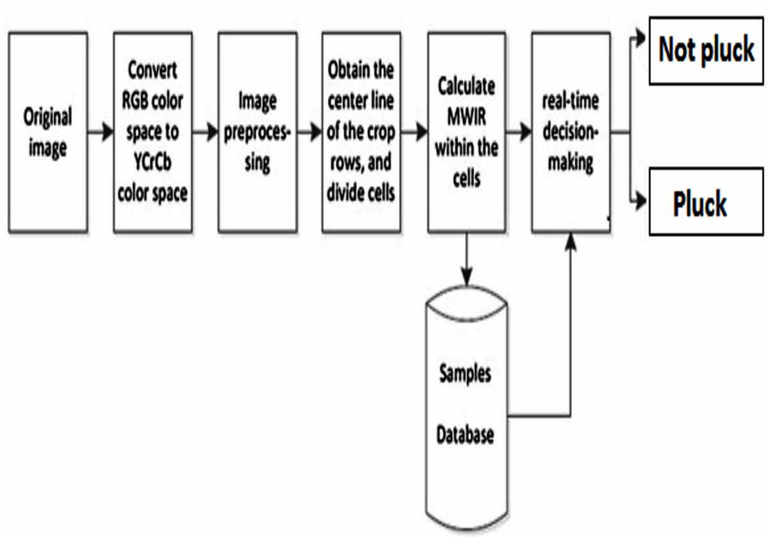
Implementation of Weed Management

Today, the machine vision technology has been sensibly applied to the field to separate crops from weeds, and can be used as a useful tool for precision agriculture in the future. Nevertheless, such technology still needs to be effectively integrated into the machine. Inappropriate integration practices can result in the unstable and inaccurate performance of the robot. Besides, as the machines that were mentioned above only possessed weeding functions, and other tasks required different machinery, they thus lack flexibility. To address this issue, introducing a multi-functional smart machine (Supplementary Materials) will help in removing weeds automatically and helps in variable rate irrigation. The digital camera device of the machine can capture images of growth areas under the machine in real time and use HSV and adaptive threshold methods to distinguish crops from weed areas and estimate the wet distribution area of the surface soil (WDAS), such that the machinery can automatically respond to specific areas with weeding or watering. This scheme allows for the removal of weeds while leaving the crop unharmed. In addition, the modularized mechanism can be used to provide different functions, such as turning soil or sowing. Furthermore, the use of the fuzzy logic control method determines the amount of water that is given to crops depending on the soil moisture content of the root depth and the wet distribution area of the surface soil to ensure that the soil maintains the appropriate moisture rate. Figure 2 shows the block diagram represent the image processing of weed and crop.

Soil Analysis

Important aspects of the soil, like internal heterogeneity, measurement error, complexity, imprecision etc. are ignored by the traditional land evaluation classification. Simple Boolean algebraic operations used in the evaluation process results in considerable loss of information and in such cases fuzzy set theory will be a useful alternative.

Figure 2.



Objective of Soil Analysis

The use of fuzzy logic operations makes it possible to improve analysis and simplification of the soil characteristics that are characterized by vague conceptions and/or subjectivity. Land evaluators and experts can define the ideal requirements of land use. They can distinguish an ideal value for a suitability class clearly, but are often unsure about boundaries between the classes. Besides they are uncertain about the representation of soil characteristics in vague terms such as "Poorly drained", "fine textured", etc.

Implementation of Soil Analysis

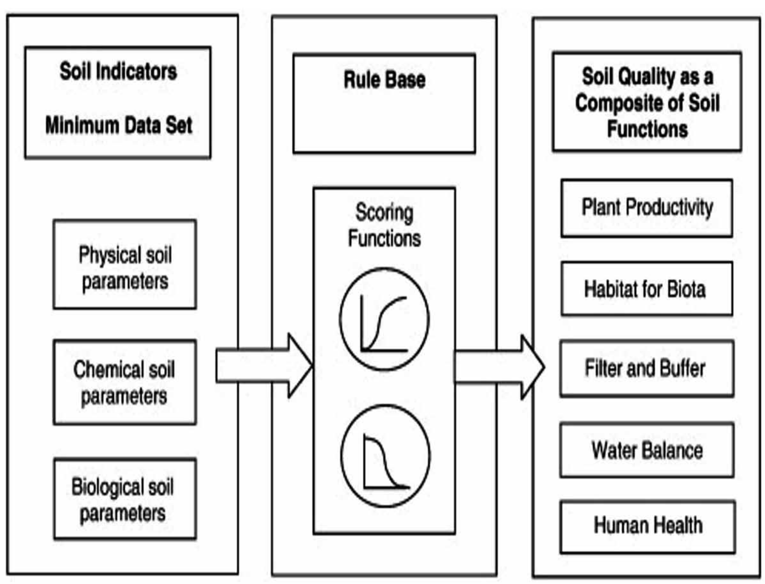
Soil being the primary requirement of any crop to be cultivated, has a major role in the yield of any crop. The three basic constituents of soil are Nitrogen, Phosphorous and Potassium, most commonly known as NPK must be tested beforehand whether it is in the required ratio or not. Apart from these elements, the soil might have been polluted and depleted from its other naturally occurring minerals and microorganisms.

A fuzzy based expert system analyses the soil condition using a fuzzy membership function and tabulates the results. An estimation of the amount of fertilizer to be used can be obtained. The decision made using the results of the findings can be of use not only to reduce the cost of fertilizers applied but also to grow the crops more organically and sustain the natural benefits of the soil. Figure 3 indicates the quality of soil.

Example: Case Study

A small region in the Kocaeli province of Turkey was studied for a soil productivity analysis. Values for pH, salinity, carbonate and organic matter were entered into the system as input variables to obtain soil productivity as the output. After the membership functions related to input and output were determined,

Figure 3.



rules were created. Then, the fuzzy logic system was applied separately to pH, salinity, lime and organic matter values of different soil types present in the Kocaeli region with the aim of obtaining corresponding fuzzy values. Thus, soil productivity profiles of the region were deciphered.

Organic matter levels in the study field remained below 30 g kg (-1) and varied between 22 and 28 g kg (-1). Productivity values were obtained as a percentage and varied between 16.9% and 18.1%. The lime content of the study soils varied in the range of 33-88 g kg (-1). Average totals for salt values of the field changed between 0.58 and 0.77 g kg (-1).

Fertilizing Techniques

A justified decision on fertilizing practices ought to be based on scientific knowledge and experimental results ideally combined with agronomic experience and local environmental conditions. Nitrates in soils consist of a very mobile form of nutrient, making its application a rather demanding and multilevel decision. In order to propose integrated and realistic nitrogen fertilizing recommendations, aspects, like the dose of the proposed fertilizer, its type, meaning the form of the contained nitrogen ions, the number of doses, the time and method of the application and the spatial distribution of the suggested fertilizer quantities, should be considered. The latter is rather imperative as long as there is acceptance of the agricultural environment as a continuous, but ever-changing system influenced by soil, topographic, climatic and agronomic factors.

Objective of Fertilizing Techniques

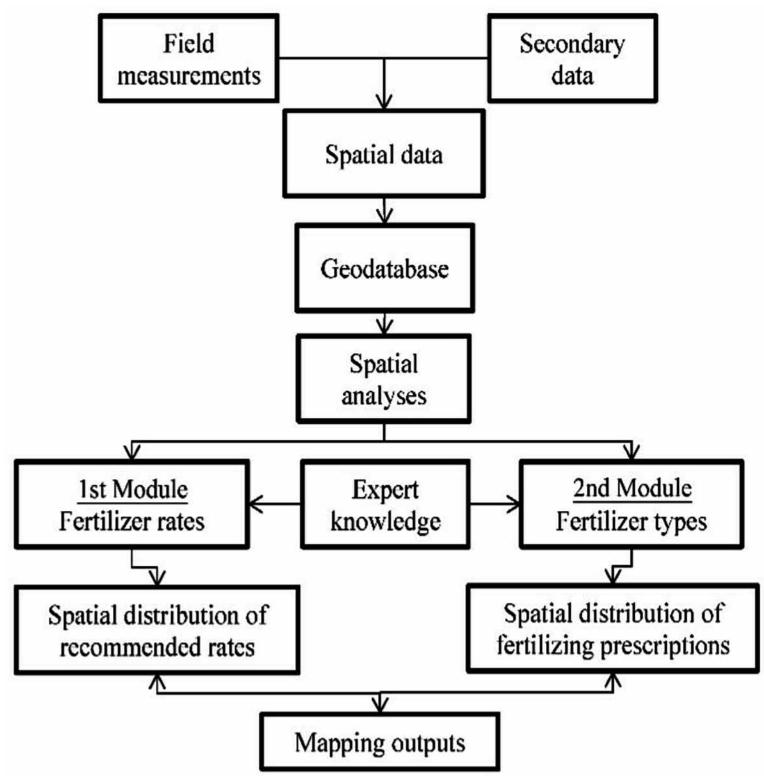
The proposed methodology considers two system spatial modules. The first one undertakes the computation of the fertilizer rates, which are proposed for application during a cultivation period (fertilizing rate), and the second delivers descriptive recommendations regarding the type, time and method of fertilization (fertilizing type). The structure of the rate module is based on the simulation of the nitrogen cycle in agronomic systems, as it is "translated" via the nitrogen balance equation. The type module takes into account two risk criteria: the avoidance of soil degradation due to acidification and the restriction of nitrate leaching losses.

Implementation of Fertilizing Techniques

The "fertilizer rate" module is based on the fuzzy approximation of the nitrogen equilibrium. The module classifies the reference area according to the soils' needs for nitrogen resulting from the fuzzy calculation of nitrogen processes. The processes accounted for in the module are nitrate leaching, de-nitrification, plant uptake and ammonia volatilization, which are considered as outputs from the soil system, and the according soil system inputs, meaning organic nitrogen mineralization, inorganic residual nitrogen and nitrogen added through irrigation water.

The "fertilizer type" module makes use of soil acidity, clay content percentage, and means total rainfall during cultivation period, irrigation system in use and whether the producer makes use of acidifying fertilizers. It also considers two soil degradation risks in order to propose a nitrogen fertilizing prescription. The first one is soil acidification risk and is fuzzy calculated with the contribution of soil pH, mean annual rainfall, the irrigation system in use and the use of acidifying fertilizers. The second risk refers to nitrate leaching potential, which is fuzzy controlled by soil clay content and mean annual rainfall. The module further maps certain fertilizer recommendations in the form of prescription codes to the previously generated fuzzy categories. The concept design of fertilizer techniques represent in Figure 4.

Figure 4.



FUZZY EXPERT SYSTEM IN CATTLE BREEDING

Success of herd management in animal breeding directly affects the continuation of profitable production process. One of the major components of herd management is the rational and the right pick of animals. An efficient picking policy is the vital element needed to reap economic benefits from animals. For example, dairy cow breeders focus on two basic factors when picking animals, i.e., voluntary culling causes (low efficiency level etc.) and involuntary culling causes (breeding problems etc.).

People who work in the field of herd management often seek consultation from experts for their management process, which helps them in raising high amounts of profit. However, considering the high rates charged by consultants and availability issues, such options are not a viable or long-term solution for breeders in terms of make decisions promptly. Therefore, information technology options offer a way out. Today, especially artificial intelligence based software technologies and designed systems can provide information to individuals in many fields, including the one that is being dealt in this section – animal field and herd management. Fuzzy logic-based decision support systems, is one of the methods developed to achieve the optimum solution against the problems of constantly changing living conditions in the case of cattle. These expert systems provide a wide range of solutions to problems that occur recursively in a cattle farm.

Implementation of Fuzzy Expert System in Herd Management

- Fuzzy logic-based decision systems for dairy cattle
- A fuzzy expert system to diagnose diseases in animals
- Fuzzy logic in livestock nutrition management

Fuzzy Logic-Based Decision System in Herd Management

In this study, a Fuzzy Logic based Decision Support System was designed in order to provide solutions for the classification problem involved in picking ideal cattle for rearing. For this purpose, classes of animals were determined using these input variables- 305 daily milk yield (305 DMY), calving interval (CI), service period (SP), the number of animals involved in artificial insemination (AI), and dry period (DP). In addition, the system's output was determined as a classification decision. The purpose of system was to assist the breeders in the identification of animals, i.e., which are elite and which are to be removed from the herd.

Reproduction and milk yield records of 121 Holstein Friesian cows were analysed for this study. Because of factor analysis, three main classes were established- Good (class 1), Normal (class 2), Poor (class 3).

According to the formed fuzzy logic based decision support system, for its input variables' number of artificial insemination (low, medium and high), calving interval (short, normal and long), service period (short, medium and high), dry period (low, medium and high), 305 day

Milk yield (low, medium, high and very high) fuzzy sets were determined to classify the cattle as classes, good, normal and poor after fuzzification. Figure 5 determines the fuzzy system that was created using Mat lab fuzzy logic toolbox, which contains the membership functions of each of the input variables.

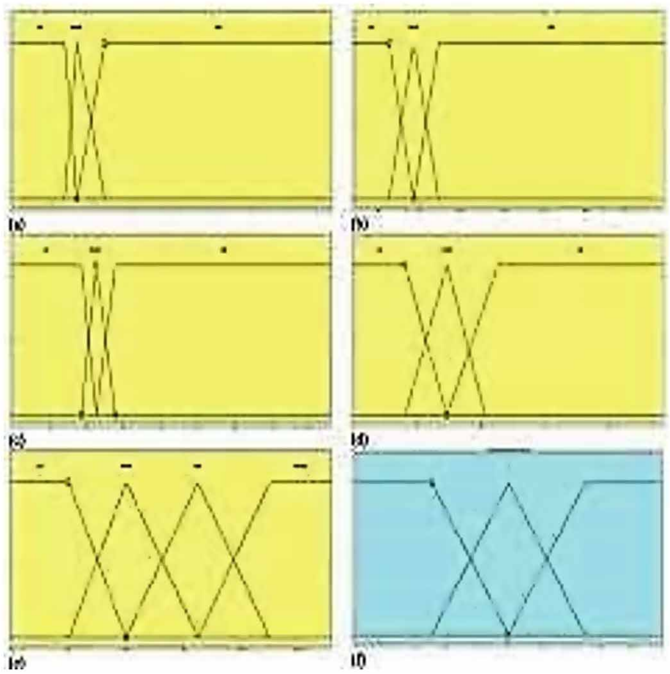
According to the results of analysis in the examined data set, the distribution of cattle is as follows: 35 dairy cows in class 1, 171 dairy cows in class 2 and 15 dairy cows in class 3. Because of the classification, it is observed that animals, which are under class 1, can be chosen for breeding and animals that are under class, 3 can have the possibility of culling.

A Fuzzy Expert System to Diagnose Diseases in Animals

Diagnosis of diseases with neurological signs in cattle solely based on clinical work is not simple. Sometimes there are possibilities that cattle are affected with diseases even though laboratory assessment and parameters are normal or near normal range. In order to diagnose these diseases veterinary experts, need specific tools and instruments which are both time consuming and expensive. These issues played a major role in conducting further research and designing a new way to emphasize and encourage the use of computers as a tool for this purpose.

Many neurological diseases in cattle and characteristic symptoms in each diagnosis have been determined by expert persons. The common symptoms associated with neural diseases are very close to each other, and symptoms of other different diseases are almost the same in many situations, which can result in conflict while identifying these diseases.

Figure 5.



In this section, fuzzy logic used to help discover new ways to diagnose some diseases with neurological signs in cattle that can later be produced to build the fuzzy model. The following procedural steps can be used to define the fuzzy expert system:

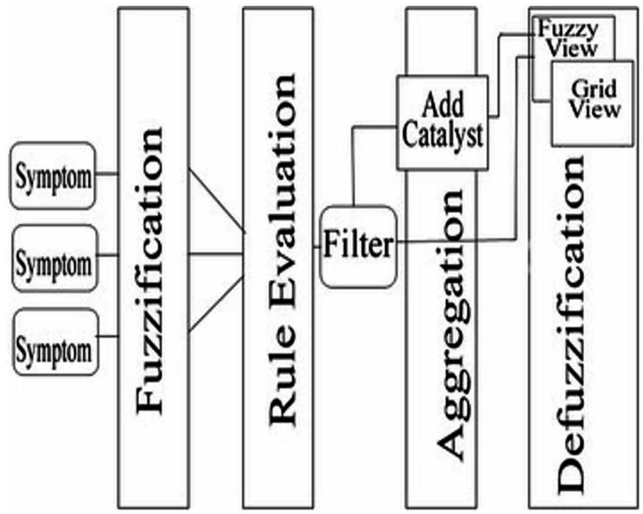
- Defining an input – output set that couples the input - output normalized set to be accepted.
- Production of if - then fuzzy logic based on the input – output pair.
- Create a fuzzy rule base.
- Manufacturing a system based on fuzzy logic rules.

The diseases that occur in animals can be identified by using the following parameters as input to the fuzzy logic system.

1. Animal Body Temperature.
2. Salivary Secretion.
3. Blindness.
4. Hyper Reaction to Environmental Agent.

Based on these four parameters, the fuzzy system can provide outputs stating probabilities of a possible disease. However, diagnosis of these diseases remains an uncertainty. Therefore, the fuzzy system can provide a list of diseases based on the severity of the symptoms in the animals put under observation. Figure 6 shows the identification process. The following are some of the diseases that are considered the output variables from the fuzzy system:

Figure 6.



- Poly-Encephalomalacia (PEM)
- Lactation Tetany (LT)
- Bovine Spongy-Encephalopathy (BSE)
- Rabies (R)
- Lead Poisoning, acute form (LP)

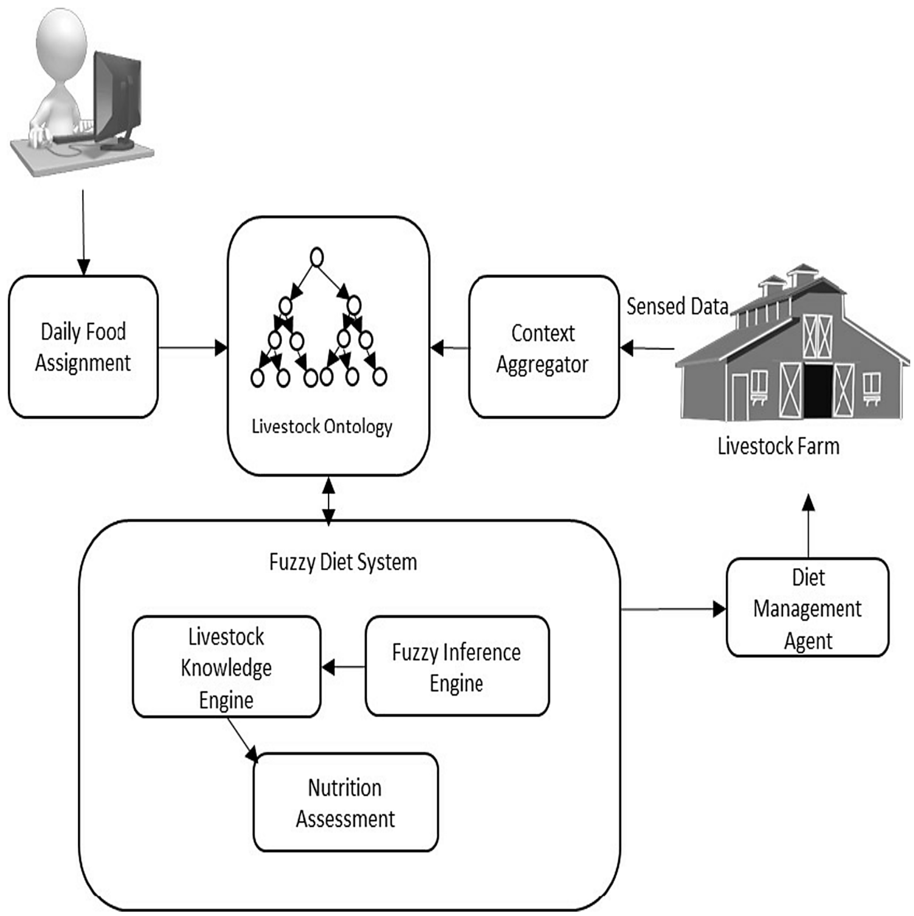
Fuzzy Logic in Livestock Nutrition Management

Given the increase in the population each year, it is evident that the demand for the dairy products will continue increasing. Now, the major concern in livestock farming is the health of cattle such as the cow, which may affect the production. With Ontology, the relationship of the entities and the reasoning are performed, to execute a seamless automation. Even after knowing certain relationships, the decisions to be made over the nutritional needs for each livestock remains a prolonging issue.

To resolve this issue, the fuzzy based-logic can be utilized. The fuzzy logic is similar to human thinking and therefore, is widely used in the decision support system. The number of variables is selected after determining the relationship between the input and the output, also called as linguistic variables. The membership function is used to define the values of these linguistic variables designed in the fuzzy logic rules. Such defined rules offer a valued decision support over the vague and uncertain data. On the whole, fuzzy logic is used to help reduce the uncertainty over the data and to obtain the absolute results. Such researches on the livestock include the Fuzzy BMI, oestrus detection, lameness, herd management and so on. In this section, a fuzzy logic method along with the Ontology is used to make a diet planner by determining the nutritional requirement of each cow in the livestock environment. The proposed system mainly focuses on the livestock's diet, in regard to the age, weight, health and the pregnancy phase of the cow, to model a proper diet plan for the livestock.

Figure shows the system structure of the suggested balanced nutrition system using fuzzy logics, where the nutrition facts received from the domain experts are used to calculate the daily Total Density Nutrition (TDN) required in the livestock through the fuzzy logic technique. In case of a healthy cow,

Figure 7.



the change nutrition requirement may not vary, but according to the health and the pregnancy of the cow, there is a relatively high difference in the nutrition requirement. To resolve such ambiguous data, a fuzzy logic-based technique is applied to find the proper nutritious diet for the respective cow represent in Figure 7.

The Context Aggregator gains various raw-level context information from the sensory devices in the livestock farm through the wireless sensor networks (WSN). The Livestock ontology model receives the context information and the daily food assignment, where the entities are predefined with a clear relationship with the domain set. With the obtained information such as age, weight, health and pregnancy phase of the livestock, the fuzzy logic is applied to obtain the nutrition requirement in the livestock. By acquiring the nutrition percentage, the amount of the food required for the livestock can be determined. The daily food assignment is done with the amount of food available in the food stock, which is further used to determine the amount of food required after calculating the nutrition requirement.

In the selection of livestock for sale, there are two major aspects that need to be considered in the livestock market. One is the health aspect and another is the quality aspect. Periodic health check-ups are supposed to be performed to assure the conditions of the livestock health. In many rural places, the sick and not so healthy livestock is slaughtered for meat consumption. Such kinds of practices must be prohibited as it may result in food poisoning or transmission of many severe diseases. Therefore, the health of the livestock is given utmost care. Even though health check-ups are conducted regularly, there are generic cases where the livestock do not gain weight even after passing their maturity levels.

In the suggested fuzzy logic system, the variables considered for the inputs are “Cow stage”, “Weight”, “Pregnant Phase” and “Health”. The input “Cow stage” is the age of the cow, where it differs from “Calf”, “Cow” and “Mature Cow”. Apart from this, the nutrition of the cow has to differ from the others during the pregnancy and lactation. Therefore, the Pregnant Phase is also used, which has four phases such as “Post-partum”, “Lactating”, “Gestation” and “Pre-Calving”. The input variable Health is divided into “Unhealthy”, “Health” and “Very healthy”. Similarly, the Weight is divided into “Underweight”, “Normal” and “Overweight”.

The output variables in the suggested nutrition system are determined to have a nutrition density that helps in the planning the food schedule for the cows using the ontology model. With the four input variables that have been finalized, the rules are written in the fuzzy rule base. In the fuzzy logic expert system, the input variables are gathered with the logical operators (OR, AND) to form a fuzzy set. To brief it out, the rules are created with an IF – THEN method for the selection of the control system.

For example, a possible combination using the four input variables with each other and the logical operators can be as follows.

IF (Weight == Normal) AND (Cow Stage == Cow) AND (Health == Very Healthy) AND (Pregnancy Phase == Gestation) THEN (Nutrition Requirement == Low)

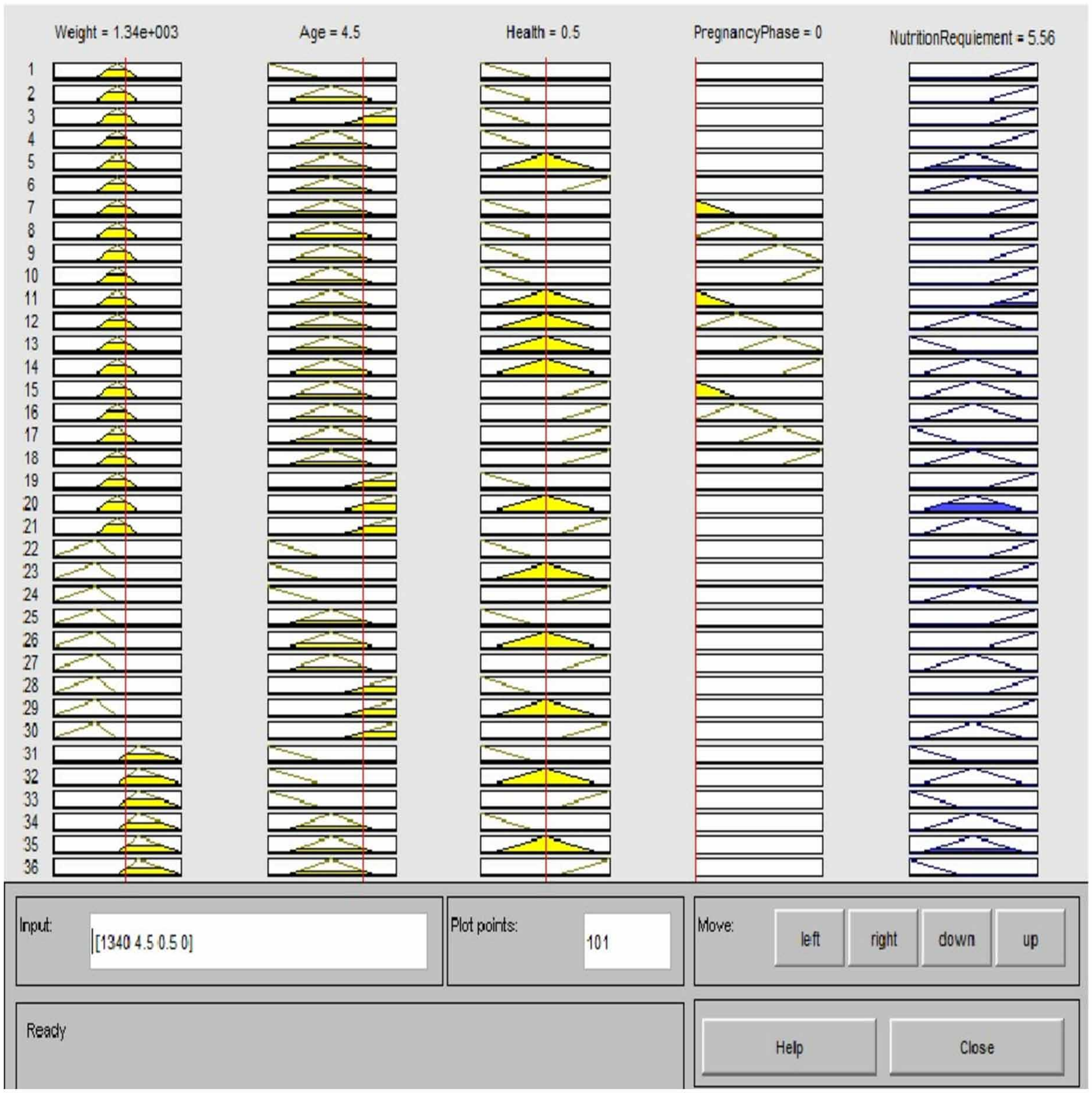
According to the example combination, the cow is very healthy and is in its Gestation phase and during Lactation it needs less nutrition, because the lactation has stopped and it does not require more protein or energy currently. Similarly, the possible rule combination of all the inputs can be obtained. Through the combination of these rules, there can be a proper establishment of a nutrition plan according to the environmental conditions.

Figure 8 shows a part of the possible rule combinations in the MATLAB fuzzy toolbox. The toolbox helped to increase the values of the most important parts of the information that will give the most accurate example to the process. Using Mamdani inference method in the MATLAB fuzzy logic system, the simulated results are obtained. In this simulation, the weight is 1300 lbs with the Cow Stage, that represents the age of the cow, 4 years, the health percentage is 0.4, and the Pregnant Phase is 54, resulting in the output of 4.02 indicating “Normal”.

FUZZY LOGIC IN WEATHER FORECAST

Although there is always, a hope for the future of what will happen for unpredictable situations and events, no anybody knows what will be in the future; for example, the weather forecasts for the next day, the stock market forecasts for tomorrow, or the enrolments forecast for the next year, such of these forecasts are called “time series forecasting”. Humans are always interested in oncoming events; they are important due to its effectiveness in human life. Hence, we can forecast tomorrow’s events by using some prediction techniques.

Figure 8.



Forecasting methods may be classified into three types: judgmental forecasts, univariate methods, and multivariate methods. Judgmental Forecasts based on subjective judgment, intuition, and any other related information. In univariate methods, the forecasts depend only on present and past values of the single series being forecasted. In Multivariate methods, the forecasts of a given variable depend, at least partly, on values of one or more additional time series variables.

There are two types of time series data:

- Continuous time series: an observation is recorded at every instant of time, denoted using observation x at time t, x (t).
- Discrete time series: an observation is recorded at regularly intervals, denoted using observation xt.

A variable is a value or a number that changes in increased or decreased pattern over time. There are two mainly categories of variables, independent variable and dependent variable. The independent variable and dependent variable are differing in an experiment. The independent variable is a variable that is varied or manipulated in the experiments by researchers; it refers to what is the influence during the experiment. The dependent variable is the variable that is simply measured by the researchers; it is the response that is measured.The dependent variable responds to the independent variable. It is called dependent because it depends on the independent variable. We cannot have a dependent variable without an independent variable.

For example, on such types of variables; we are interested in how temperature effects on tourism rate. The independent variable would be the temperature and the dependent variable would be the tourism rate. We can directly manipulate temperature levels and measure how those temperature levels affect tourism rate. It is possible to forecast various kinds of data, anyway time series shows the changing of a value in time. The value can be impacted by also other factors rather only time. Time series represents discrete historical values and from a continuous function, it can be obtained using sampling.

There are four main components of any time series; trend, seasonal, cyclical, and irregular.

They are listed and explained in the followings:

- Trend move up or down in a predictable form, they tell whether a particular related data set have increased or decreased over a period. Trend is a long-term movement in a time series and a rate of change in a time series. It can be shown as an upward or downward tendency. A simple way in trend detection is taking averages over a certain period.
- Seasonal often named to as seasonality, it repeats over a certain period such as a day, week, month, year, season, etc., and they are defined as the repetitive and predictable movement around the trend line.
- Cyclical describes upward or downward movements around a given trend in a time series (any regular fluctuations). Cyclic variations are not regular as seasonal variation. There are different types of cycles of varying in length and size.
- Irregular do not fall under any of the above three components, because it does not predictable. It is caused by unlooked-for circumstances.

Techniques Involved in Weather Forecast

Fuzzy Logic Techniques

A Temperature Prediction model has been proposed Using Fuzzy Time Series. The new fuzzy time series model called the two-factor time-variant fuzzy time series model for temperature forecasting. Two algorithms for temperature prediction then proposed. Both algorithms have the advantage of obtaining good forecasting results. The empirical results show that the results of Algorithm-B are better than the results of Algorithm-A and Algorithm-B. These algorithms have advantages, both they can give good results. The time complexities of the proposed algorithms are O (cwm), respectively, where c is the number of partitioned groups in the historical data, wis the window basis, and m is the number of elements in the universe of discourse.

A novel method was developed to forecast temperature and the Taiwan Futures Exchange (TAIFEX), based on the two-factor high-order fuzzy time series. For each value in a real-valued time series is represented by a fuzzy set, after that, it is represented by fuzzy sets form a fuzzy time series. Therefore, the real-valued time series is transformed into a fuzzy time series. The proposed method is an efficient in term of it has higher forecasting accuracy rate and it has a smaller mean square error than the other methods.

Neural Networks Techniques

There are many studies were done for weather forecasting based on artificial neural networks. Neural networks are appropriate technique for forecasting time series because it can be learned only from examples, without any need to add additional information that can bring more confusion than forecasting effects. Neural networks are able to generalize and are resistant to noise. On the other hand, it is generally not possible to specify exactly what a neural network learned and it is also hard to estimate possible forecasting error.Forecasting of time series using neural network consists of teaching the network with historical data in a selected limited time and applying the taught information to the future.

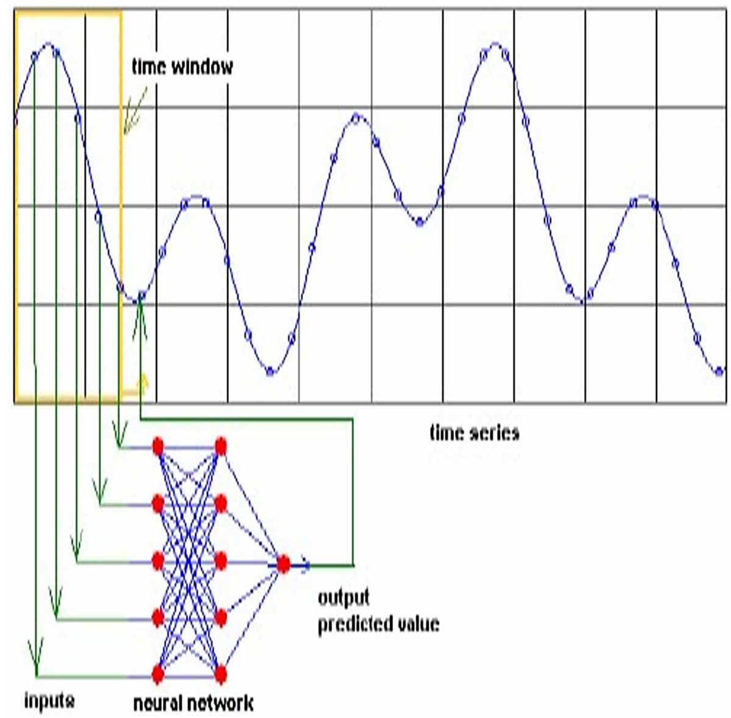
Data from past are provided to the inputs of neural network and as shown in Figure 9. We then expect the future data from the produced data that generated by the network.Several Kinds of neural networks can be used for forecasting, such as Feed-Forward, Back-Propagation, Radial Basis network and others.

Hybrid Techniques

A rough set based fuzzy neural network algorithm has been proposed to solve weather forecasting problems. The experimental data are from World Meteorological Organization. The least square algorithm (LSA) was used in the learning stage of fuzzy neural network to obtain global convergence and the rough sets method was introduced to determine the numbers of rules and original weights. Five attributes or parameters are considered, and these attributes are FRS, dew temperature, wind speed, temperature and visibility. The authors have been selected the data from some city (Date: Jan 1, 2000—Jan 31, 2000) in China. The result of forecasting by the proposed algorithm is that visibility is 10.4202 on Jan 7-2002. Actual visibility is 10.624 on Jan 7-2002. The error rate is (10.624-10.4202)/10.624=1.918%. A Weather Forecasting System was presented using concept of Soft Computing i.e. Aneuro-fuzzy system was used to predict meteorological position based on measurements by a weather system. The authors considered atmospheric pressure a primary key parameter and atmospheric temperature and relative humidity secondary type. They examined temperature as forecasts of weather conditions in some cases to observe the effect of temperature.

A new method was developed for temperature prediction and the TAIFEX forecasting based on mixed techniques, fuzzy logical relationships and genetic algorithms. The method builds two-factors high-order fuzzy logical relationships based on the historical data and uses genetic algorithms to control the length

Figure 9.



of each interval in the universe of discourse. The experiments indicated that this method gets higher forecasting accuracy rates than the methods presented in for temperature forecasting. It also gets a higher forecasting accuracy rate than the methods presented in and for forecasting the TAIFEX.

FUZZY EXPERT SYSTEM IN POULTRY FARMING

Thermal comfort of broiler chickens can be characterized through its physiological responses, such as cloacal temperature (CT), and it is influenced by the climatic conditions, such as air temperature (T), relative humidity (RH), and air velocity (V), among others. Since chickens are homeotherms they can maintain internal temperatures, with minimal metabolic regulation, within a range of ambient temperatures, this range of temperature is called thermoneutral zone. To obtain suitable climatic conditions for animal production, the thermal environment inside of a broiler house should be into the thermoneutral zone (TNZ). In this zone, the animal reaches its maximum potential and body temperature is maintained into acceptable level with minimal use of thermoregulation mechanisms. However, when the thermal environment is out of TNZ, the environment becomes uncomfortable and losses in performance are imminent.

In the TNZ, the CT is maintained between 41.2°C and 42.2°C (TAO & XIN, 2003). According to MEDEIROS and others (2005), for broiler chickens the thermal comfort is characterized by values of temperature (T) between 18°C and 28°C in conventional houses, with RH between 50% and 70% and V around 1.0 to 2.5m s^{-1}. However, MEDEIROS (2001) affirms that the maximum productivity is obtained when the T is in the range from de 21 to 27°C, with 50 to 70% RH and V from 0.5 to1.5ms^{-1}.

As thermal environment influences broiler chicken comfort and, consequently, the performance, thus a decision support system can be drawn to control the thermal environment inside the broiler houses, considering the animal physiological responses, such as CT. Therefore, expert systems based on fuzzy sets theory are an alternative for the management of uncertainties in the rearing environment of broilers.

Fuzzy sets are also called misty sets or diffuse sets, and it is an extension of the classic logic. Fuzzy set theory uses approximate instead of exact information, imitating the human thinking. Nowadays fuzzy set is used in control systems and in decision support systems where the problem description approach cannot be precise.

A fuzzy system is formed of input and output variables. For each variable, fuzzy sets characterize the variables, then they are formulated, and for each fuzzy set, a membership function is built. After that, the rules that relate the output and input variables to their respective fuzzy sets are defined. The computational evaluation of a fuzzy system is formed of fuzzification (input is converted into fuzzy values), inference (reasoning for the fuzzy output) and defuzzification (translation of fuzzy value to numerical value).

Implementation of Fuzzy System for Cloacal Temperature

The development of the fuzzy system was based data from research developed by SEVEGNANI (2000), YAHAV (2004), SOUZA (2005) and MEDEIROS (2005). The following were defined as input variables: air temperature (T, °C), relative humidity (RH, %) and air velocity (V, m s^{-1}). Selection of the variables and their range were based on the availability of the data in the literature to validate the model. Based on these variables, the fuzzy system predicts the cloacal temperature (CT, °C). The fuzzy sets of input and output variables are graphically represented by triangular membership curves (Figure 10). Triangular membership curves are the most common and suitably represent the behavior of input data, according to the literature (AMENDOLA and others, 2005).

Prediction of Cloacal Temperature of Broiler Chicken using Fuzzy Expert System

For the thermal environment defined by T=25°C, RH=55% and V=1.5m s^{-1}, two rules were reached using fuzzysets T1 (used memberships function and degree μ_{T1} (T) = (-T+26)/6 and $\mu_{T1}(25) = 0.17$, respectively), T2 (used memberships function and degree: μ_{T2} (T) = (T-20)/6 and $\mu_{T2}(25)$ =0.83, respectively).

The resultant fuzzy set presented 0.83 as a maximum membership degree. The next step was the defuzzification of this fuzzy set, which consequently had a numerical value of 41.2. Thus, considering a thermal environment with T=25°C, RH=55% and V=1.5m s^{-1}, a resulting CT = 41.20°C was observed. The mean deviation (MD) and mean percentage error (MPE) between the results obtained by the fuzzy system and those measured experimentally by YAHAV and MEDEIROS and others were 0.13°C and 0.31%, respectively, obtaining a coefficient of determination (r^2) equal to 0.9318. The MD, MPE and r^2 obtained show that the fuzzy system satisfactorily simulates the cloacal temperature of broiler chickens. After adjustment of a neural network to predict CT of broiler chickens, LOPES obtained MPE of 0.78% and r^2 of 0.8860 for training, and 1.02% and 0.8205 for validation, respectively.

Figure 11 shows simulations of CT as a function of T and RH, with V held constant at 0.6 and2.4m s^{-1}. Based on the results obtained by the fuzzy system, CT increases with increasing values of T. The V influences the CT when the animal is subjected to hot environments, and thus, in agreement with the results found by YAHAV and others.In addition, the profiles observed in figure 11 are in concordance

Figure 10.

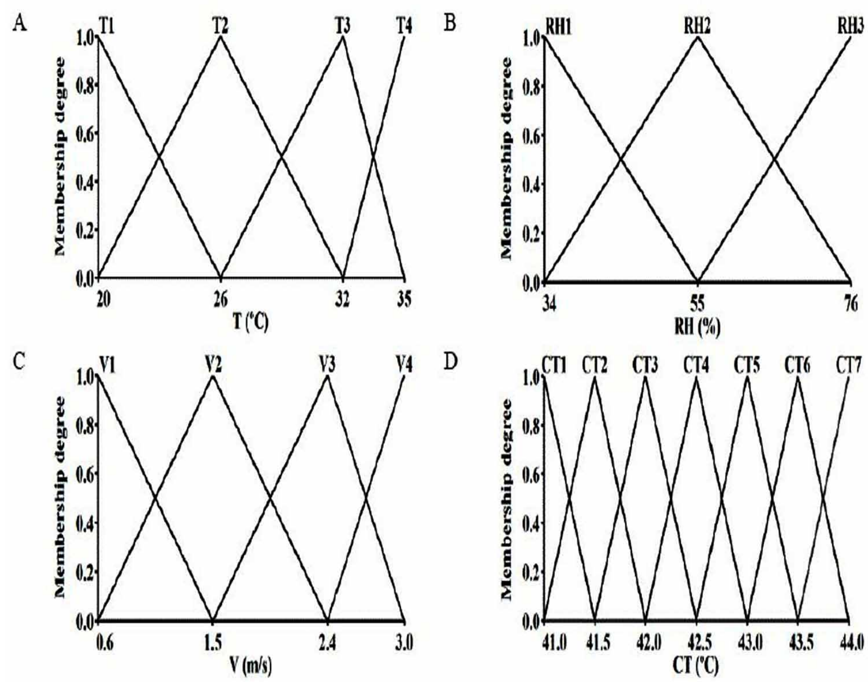
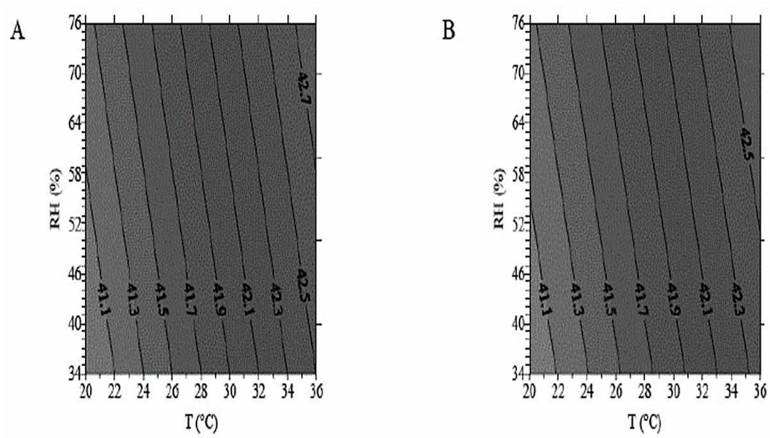


Figure 11.



to the expected physiological responses of broiler chickens, agreeing with the results observed in other studies, such as MEDEIROS and TAO &XIN. The results show that CT increases with an increasing RH, but less so in magnitude than with an increase f of T.

We can conclude that the fuzzy system developed for the prediction cloacal temperature (CT) of broiler chickens, based on the thermal environment, characterized by air temperature (T), relative humidity (RH) and air velocity (V), provided a low standard deviation (±0.13°C), and satisfactorily simulated

CT, helping in the decision-making process. Moreover, the theory of fuzzy sets is a promising tool in predicting the body temperature of broiler chickens, and can be used to help make decisions about the farming system to be used.

CONCLUSION

Fuzzy logic controllers (FLC's) are cheaper to develop, they cover a wider range of operating conditions, and they are more readily customizable in natural language terms. Therefore, using fuzzy expert system in agriculture, cattle breeding and poultry farming will help in increasing the production and quality to meet the demands of the expanding population. It also reduces human errors and the burden on the farmers. Weather prediction/forecast helps the farmers to take required precautionary measures to protect the production. However, the use of fuzzy expert system is limited due to lack of knowledge and resources. Farmers still depend on outdated systems for most of their works. These systems are less efficient when compared to fuzzy logic system and are more prone to errors. So the government has to spread the awareness about the importance of fuzzy logic among the farmers, train them to use the present advanced technology, encourage the engineers of our country to work on this concept and also invest on this project so that the world becomes a better place to live.

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Section 2
Innovation and Technologies

Chapter 5

Diagnostic Analytics on Agriculture with Fuzzy Classification

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ABSTRACT

Agriculture is the main domain and need of India. The country is second place in the world in agriculture. Cropping is the main part of agriculture. Various crops like millets, fruits, vegetables, oil seeds are produced and exported to other countries every year. So, various innovative technologies are used to improve the productivity of crops in agriculture. Rainfall is most important for growing crops. The water level for the crops based on rainfall has some uncertainty. Fuzzy regression analysis is one of the methods based on regression analysis that is used to handle fuzzy parameters and crisp data and vice versa. Linear fuzzy regression is one of the methods of fuzzy regression analysis to handle fuzzy parameters. This chapter explores fuzzy classification, which is based on fuzzy regression analysis, and it is compared with other classification algorithms on the agriculture data.

INTRODUCTION

Fuzzy logic plays a vital role in handling uncertainty of data and data mining. Fuzzy rules providing clear results according to the data in classification. Classification is one of the data mining tasks to classify data based on its characteristics (dmitry, 2004). There are some effective algorithms such as K-nearest neighbor, C4.5, ID3, SVM, naïve bayes and PRISM. Regression analysis is a method of statistics which deals with the investigation of dependence of a variable upon one or more independent variables. Data Analytics is wing of data science, which can analyze data and establish knowledge from the data. There are various types of analytics methods such as descriptive, diagnostic, predictive and prescriptive. The diagnostic analytics provides reasons for happened based on the data (dmitry, 2004). The process of data

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analytics includes data collection, preprocessing, exploration data analysis (EDA), model building and visualizing the data. EDA is the process of analyzing the data with statistical methods or mathematical model (dmitry, 2004).

EXPERT SYSTEM

An expert system is an application which contains some of the rules and it uses AI technology that emulates the decision making criteria of human. The expert system is mainly categorized as inference engine and knowledge base (Baskaran o, 2014). The inference engine applies the various rules to already known reality to get new facts. The knowledge base corresponds to fact and rules. The main aim of knowledge base is to provide more significant information needed for the expert system to work explicitly rather than implicit (Baskaran o, 2014).

The criterion of the expert system is user interface which provides the interaction between the user and the expert system. The Expert system helps the farmers to handle complex problems such as soil erosion, chemical pesticides loss; yield loses, crop selection and resistance of pests. So, expert system plays an intermediate between the highly knowledge scientists and uneducated people to taking the decisions at the right time (philip, 2014).

FUZZY EXPERT SYSTEM

Fuzzy logic is main criteria of soft computing. Lotfi A. Jadedh (Zadeh, 1965) professor of California University at Berkeley proposed the theory of fuzzy logic. Fuzzy set is a modified crispest which contains the membership values between 0 and 1. If a member of the set having the value then, it belongs to the set; else the number does not belong to the set.

Fuzzy Expert system uses the fuzzy logic and set of membership functions instead of normal Boolean logic. It handles the uncertainty of information. In defuzzification, the values are converted into linguistic values with membership functions along with the range between (0, 1) and the result of defuzzification

Figure 1. Components of expert system

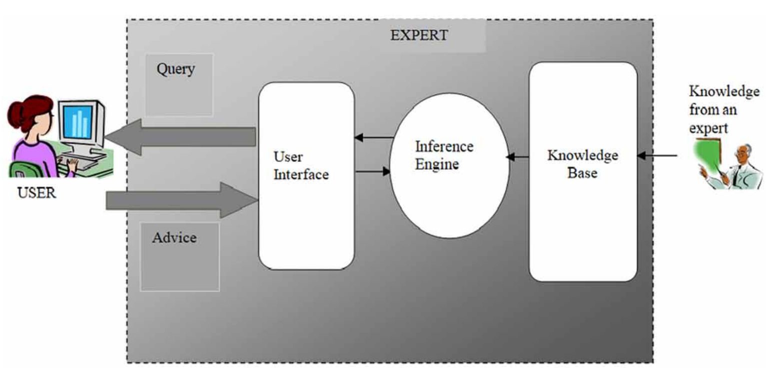
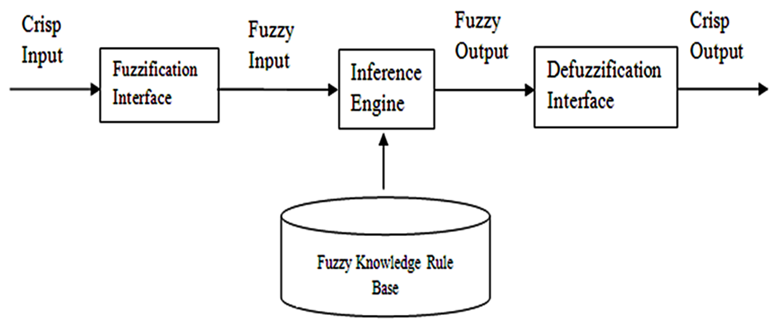


Figure 2. Workflow of fuzzy expert system



will be crisp values. Fuzzy expert system uses the fuzzy logic instead of normal Boolean logic. It is important and model based branch of AI. Fuzzy expert system can operate less educated persons in a specific area of knowledge. The fuzzy expert system is generally expressed as (Miin-shen, 2016),

- If A is low, B is high then C is medium.

AGRICULTURE

Agriculture is the main aspect of our country. Most of the farmers in India are uneducated, they need others knowledge in some unexpected situations like flood and droughts. Rainfall and crops is most important variables in the agricultural field. Most of the crops need water for growing and giving best production .If rainfall is reduced sometimes and some seasons, then the crops will not give good harvesting. There are various fuzzy expert systems designed especially for agriculture. Some of the fuzzy expert systems are listed here (G.M, 2016).

Table 1. List of fuzzy expert systems

S.No	Author	Name of the Expert System	Usage
1.	Javadi Kia Et.al.	Fuzzy Controller(FC)	Drip irrigation duration to reduce water using as variables soil moisture degree and air temperature in greenhouse”
2.	K.N. Singh, N.S. R et.al.	Climate control expert system	Regulate various climatic parameters under greenhouse.
3.	Fadzilah Siraj & Nureize Arbaiy	FuzzyXPest	To forecast the pest activity level by which we will be able determine the damages done by Pests.
4.	Howard W. Beck et.al.	SOYBUG	an expert system was developed to advise Florida farmers on control of four important insect pests of soybeans: velvet bean caterpillar, stink bug, corn earworm, soybean looper.
5.	Peter B Goodell et.al.	CALEX	Developed in Egypt used extensively for Cotton crop.
6.	Savita Kolhe et.al.	WIDDS	Disease diagnostic system was developed particularly for oilseeds like soya bean, groundnut rapeseeds.

REGRESSION ANALYSIS VS. FUZZY REGRESSION ANALYSIS

Regression analysis is familiar method of relationship between the dependent variables and independent variable. The value of one variable is predicted from the other variable. Some fields such as biology, agriculture and engineering cannot give the correct information because of the systems' complexity and vagueness. For handling this vagueness, the usual least squares regression may not applicable. So, fuzzy least square regression analysis is used in various applications .The contrast between the conventional and fuzzy regression is that it deals the fuzziness while normal regression handles randomness data (francis Ndamani, 2015).

BACKGROUND

According to Francis Ndamani and Tsunemi Watanabe, the annual and seasonal rainfall was analyzed and compared with the crop production of the Lawra district of Ghana in Africa. The study used the variables rainfall and important crops of lawra as Maize, Millet, Groundnut, Sorghum, and Cowpea. The relationship between the rainfall and crops was identified and provided the adaptation techniques and measures to moderate the effects of rainfall. The statistical methods such as min, max, correlation coeffeicient, pci were used in this study (Geethaet.al., 2016).

Nureize arbaiy, azizul azhar ramli et al., developed a fuzzy expert system to predict the pest motion in the rice fields. The system helps the farmers to monitoring the activities of pests and their effects on the rice fields. By using the questionnaire method, the solutions for various problems regarding the pests has used in this system (novakowa, 2015). N.sundaravalli and Dr. Geetha has worked on the rainfall and crop production predicted. Clustering and classification done on the data of rainfall with the k-means, fuzzy neuro, neuro-fuzzy with genetic algorithm were used for processing the data (Garibaldi).

Rainfall is most important for the agricultural countries like India.Varsha and maya pai was prognosticated rainfall of Kerala, with the parameters of sea surface temperature, sea level pressure, meridional winds, zonal and humidity. Classification of rainfall done using Fuzzy rule based classification (FRBCS) (pai, 2018).Rainfall forecasting done in the study for the junagadh of Kathiawar region, Gujarat. Artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) was used for modeling the rainfall data.ANN provided much accuracy than the ANFIS model (Kyada PM, 2018).

The need of Decision Support System in agriculture and review of various DSS/expert systems were explained. A Project was developed on DSS on mango for U.P. state according to various Agro-climatic regions of India. Based on the expert system, mango is one of most important horticultural crop and has a wide supply all over the country. Expert system helps to do decision making effectively (Meenakshi malik, 2018).The domain of agriculture is facing many troubles such as inappropriate soil treatment, plant disease and management of pests, inadequate drainage and irrigation. The study covered important contributions on agriculture and listed various expert systems such as COTFLEX for cotton management, POMME for apple plant management and TEAPEST for management of pest on tea plant (indrjith ghosh and uditentu sarkar, 2018).

Expert system of artificial intelligence along with fuzzy logic implementation in agriculture gives satisfied results and it helps in various processes of agriculture. The fuzzy logic controller was developed for water irrigation. During the irrigation cycle, farmers may supply too much of water to the crops. This process is called over watering. Less amount of water supplying causes dryness on crops, which yields low production (Varunkhatri, 2018).

METHODOLOGY

Data Collection

The data of rainfall is collected from the meteorological department (IMD) website of tamilnadu government. The data contains the year wise rainfall for various seasons such as southwest monsoon, northwest monsoon, winter season and hot weather season. The uncertainty is available in the range of rainfall in various districts of Tamilnadu (sing p, 2013).

Fuzzy Least Square Regression

Linear regression model is statistical method which was described as the linear arrangement of values of its input variables,

In some cases, fuzziness may be reflected in either data or model. So, fuzzy linear regression can solve the fuzziness with the various fuzzy membership functions such as triangular, guassian, bell shape, sigmoid, s membership, trapezoidal. In 1982, Tanaka et al has developed fuzzy linear regression model based on linear programming (tauro, 2012). Sakawa and Yano proposed fuzzy parameter estimation for the fuzzy linear regression (FLR) model.

Yj = A0 + A1Xj1 + • • • + AkXjk; j= 1;:::; n;

where input data Xj1;::: ; Xjk and output data Yj. If input and output data are fuzzy, by using the following three indices for the equalities between two fuzzy numbers M and N as

$Pos(M = N) = \sup \min\{\mu_M(x); \mu_N(x)\};$

x

$Nes(M \subset N) = \inf \max\{1 - \mu_M(x); \mu_N(x)\};$

x

$Nes(M \supset N) = \inf \max\{\mu_M(x); 1 - \mu_N(x)\};$

x

Where μM(x) and μN (x) are membership functions of M and N, and Pos and Nes are short for Possibility and Necessity. Fuzzy least square is one of the regression methods, but it is converse of traditional least square method. According to the fitting criteria or measure of compatibility of data, fuzzy regression model is divided into the following methods (sivagnanam, 2012),

- Fuzzy least- squares regression using the maximum compatibility criterion
- Fuzzy least-square regression using the minimum fuzziness criterion
- Interval Regression

RESULTS

The independent variables are the rainfall, various seasons like southwest monsoon, northwest monsoon, winter season and hot weather season. The below figure contains rainfall for the districts of Tamilnadu. The range of rainfall is in the form of interval. Based on the membership functions applied on the fuzzy rules, the fuzzy values will produce better results (wadhwa, 2015).

Based on the input data of the above Table 2, data is measured for every season of rainfall. The below pictures show that the annual rainfall for year 2001-02 to 2015-16.

The above table.3 shows that the coefficients of the linear regression model. P value should be low for a good model. F-statistic value is >100, hence it is concluding that there is high relationship between dependent and independent variable.R^2 value indicates the variation of the variables confined by the model.R^2 value for this model is 77.33 near to 1.So the variance of the model is good fit.

Table 2. Multiple input values generated

Range of rainfall(mm)	Term of rainfall level
0 – 320	Light rain
321-640	Moderate rain
641-960	Slightly heavy
961-1280	Heavy
1281-1600	Very heavy

Figure 3. Range of rainfall data

Range of Rainfall	Distribution of districts by range of rainfall	
	Normal Rainfall expected	Actual Rainfall occurred
Below 800 mm	Namakkal, Coimbatore, Tiruppur, Erode, Karur, Theni and Thoothukkudi	Tiruchirappalli, Namakkal, Karur Virudhunagar, Tiruppur, Coimbatore, Erode, Madurai, and Thoothukkudi.
801 mm to 1000 mm	Vellore, Salem, Dharmapuri, Krishnagiri, Tiruchirappalli, Perambalur, Madurai, Dindigul, Ramanathapuram, Virudhunagar, Sivagangai and Tirunelveli.	Dharmapuri, Krishnagiri, Pudukkottai, Ramanathapuram,Salem, Theni, and Dindigul.
1001 mm to 1200 mm	Thiruvallur, Cuddalore, Villupuram, Thiruvannamalai, Thanjavur, Thiruvarur and Ariyalur, and Kanniyakumari.	and Sivagangai. Thiruvannamalai, Perambalur, Thanjavur, and Ariyalur.
1201 mm to 1400 mm	Chennai, Kancheepuram, Nagapattinam and,Pudukkottai.	Tirunelveli. Villupuram,VELLOR, and The Nilgiris.
1401 mm to 1800 mm	The Nilgiris	Kanniyakumari ,Cuddalore, Thiruvarur, Nagapattinam.
1801 mm and above	–	The Nilgiris, Chennai, Kancheepuram, Thiruvallur

Figure 4. Annual rainfall level

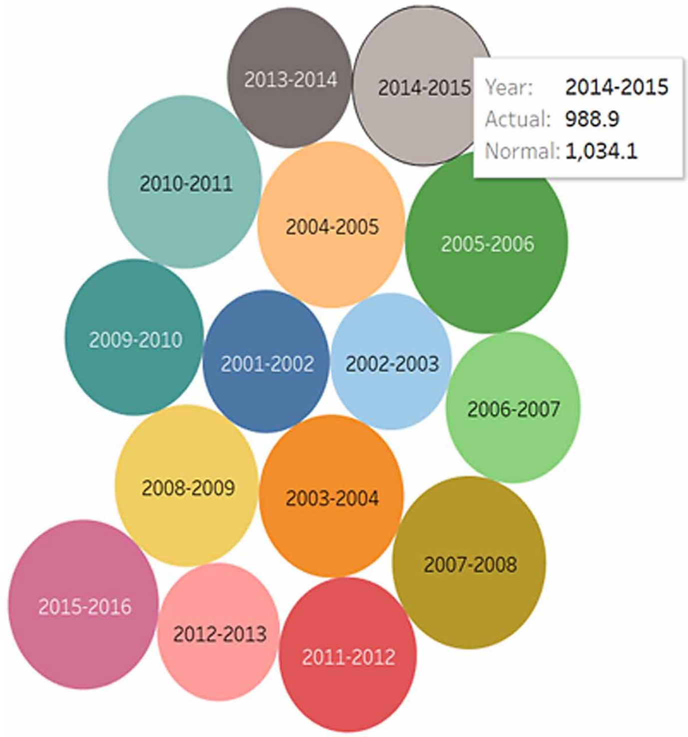


Figure 5. Annual rainfall level

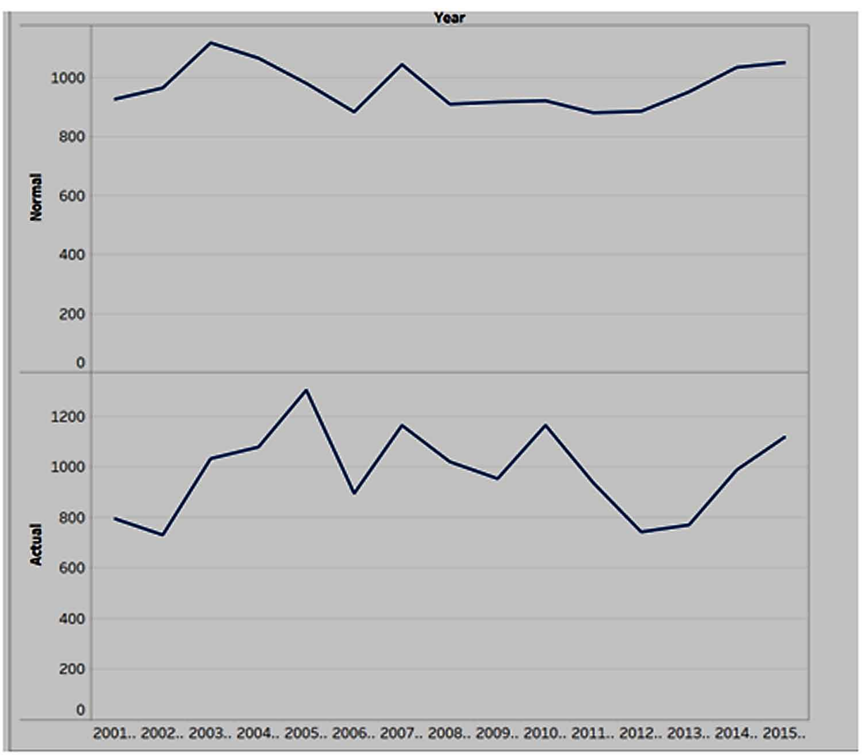
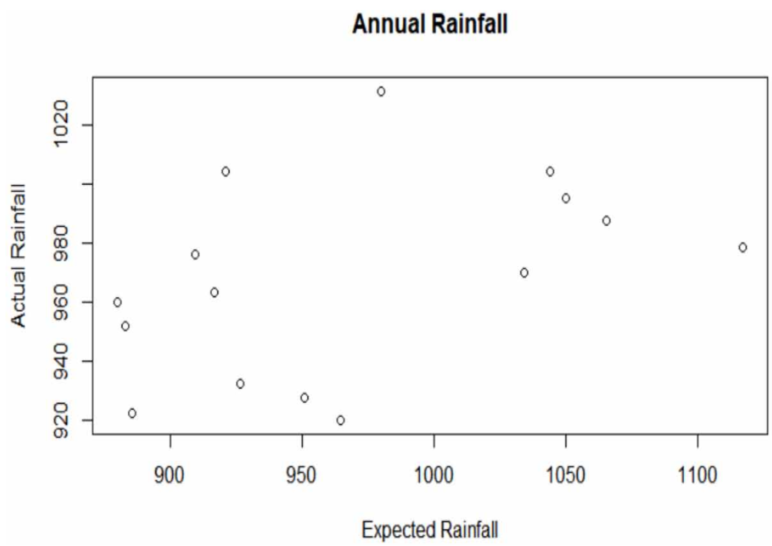


Table 3. Coefficients of linear regression model

Coefficients	Estimate	Standard. Error	t-Value	P value	F-Statistic	R^2 value
Intercept (Actual rainfall)	6.3951	0.2289	18.697	<2e-16	102.3	77.33
Normal rainfall	0.9381	2.1991	0.427	0.677		

Figure 6. Linear regression of rainfall



The linear regression model applied on the variables normal and actual rainfall of the years from 2001 to 2016 is shown in figure.6; it reveals that the correlation among the variables is 67%. So both the explanatory and response variables are closely related to each other. In Linear Regression expected rainfall is slope and rainfall occurred is intercept value.

Fuzzy Least Square Regression

Residual is used to check whether there is best regression model or not on this data. By the rainfall data, the above figure.7 shows that there are some residuals available greater than 50 units.

The comparison is made on the crops production and rainfall. Crops such as rice and ragi were selected and compared with the rainfall. The above figure.8 shows that the production of crop has reduced in the year 2015-16 when compared with the other years.

Figure 7. Fuzzy least square regression on rainfall

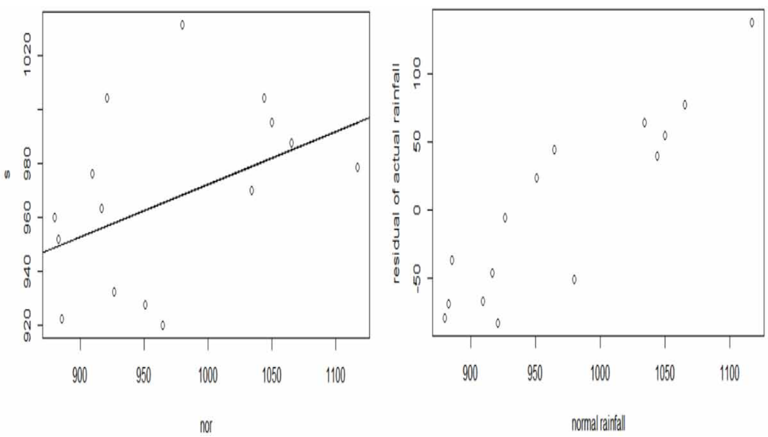
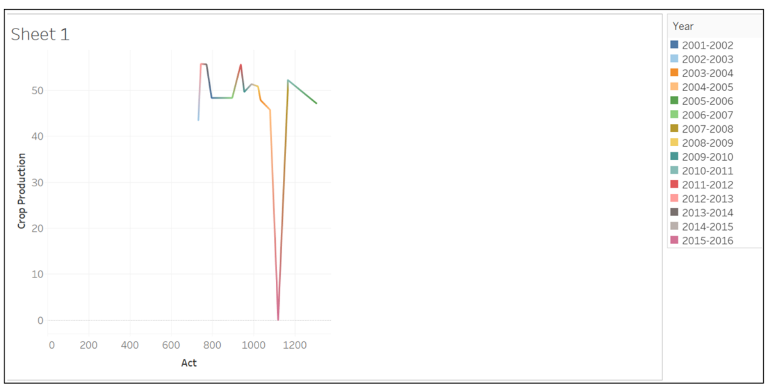


Figure 8. Crop production and rainfall



CONCLUSION AND FUTURE SCOPE

Data Analytics is a new era to analyze data effectively and usefully. Agriculture is the essential thing for human to living. In this chapter the diagnostic analytics has done by using the rainfall data. Fuzzy linear regression is used to handle fuzziness of rainfall and crop production has taken since 2001 to 2016. In certain years the production has reduced even the rainfall was high. So we can take other factors such weather tree and forest density of each year and that may lead to some more accurate results. In future, other analytical methods such as predictive, prescriptive, descriptive may be applied on this rainfall data.

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Chapter 6
Subjective and Objective Assessment for Variation of Plant Nitrogen Content to Air Pollutants Using Machine Intelligence:
Subjective and Objective Assessment

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ABSTRACT

In olden days, the plants used to tolerate and minimize the effect of air pollution caused by the then established industries and some automobiles. But in today's scenario, the rate at which plants and industries are rising doesn't match the count of trees. The plant survival and metabolism are based upon the nitrogen and chlorophyll available. There are several expensive methods to determine the chlorophyll and nitrogen content of the leaf like SPAD meter; the researchers have proposed a simple, inexpensive method that precisely determines the chlorophyll and nitrogen vales with a simple input RGB image. This chapter investigates the variation of content of plants in polluted environments and pollution-free environments.

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INTRODUCTION

Rise in Industrialization, automobiles and so forth have raised a concern in increase of air pollution. Adding to the wound, cutting down of trees for various reasons has given rise to profound deterioration of air quality index. Recently, it is even proven that air pollution can lead to depletion of mathematics skills. Major air pollutants are oxides of Nitrogen, Sulphur and VOCs (Volatile Organic Compounds) that effects health and can even take to death. Plants and trees are the major source of keeping the environment balance but cutting them down is leading to major environmental defects making home earth defenseless. The exposure of these particulate matter or air pollutants in plants have caused a gradual decrease in their Nitrogen pigment levels. Nitrogen is the backbone of a plant. With Nitrogen deficiency, a plant can't survive many days and it is called as plant starvation. Plants are very heavily paying for the pollution caused by road side traffic. Plants can purify the air up to some extent but cannot tolerate excess pollution. There are tolerance levels for every plant where it can balance the environment in its limits. Anything excess can lead to unbalancing the environment which costs humans a lot. The major plant Nitrogen pigments are Chlorophyll and Carotenoids, which are primarily responsible for plant reproductivity, growth, metabolism, germination of seeds. Chlorophyll is the principle photoreceptor in photosynthesis process. Here, carbon dioxide is fixed to produce carbohydrates and oxygen. Carotenoids is a natural fat-soluble pigment that plays a critical role is photosynthesis process. When the plants are exposed to excess pollution, above threshold levels or acceptable range, photosynthesis process will incapacitate leading to plant starvation. The particulate matters have a negative bio effect on plants. They cover the leaf blade reducing the light penetration and blocking the opening of stomata. These impediments influence strongly the process of photosynthesis which rate declines sharply. In India there is an evidence of adverse impacts of air pollution on vegetation around industrial areas and metropolitan cities. It is identified that SO2, the most important air pollutant is contributing to reduction up to 50% of agricultural species growing in the vicinity of industrial and metropolitan cities. The SO2 concentrations of 75 to 135 μm^(-3) were recorded in those areas. It is estimated that an average loss of 20% in paddy is recorded due to cement dust pollution.

Hence, several samples of different plant leaves were carried out for diagnosis in several places including NIT Warangal campus. The research is carried out to analyses and implement statistics by comparing the variation of plant Nitrogen and Chlorophyll pigments according to available density of pollution and pollution free environments.

Finally, the air pollutants lead to acid rains which may lead to a complete dissolution of plant nutrients and completely damage the plant. The acid rains even result in a disastrous damage of the soil.

RELATED WORK

In recent past, air pollutants, responsible for vegetation grievance and crop yield losses, are causing increased concern. Urban air pollution is a serious problem in both developing and developed countries. The increasing number of industries and automobile vehicles are continuously adding toxic gases and other substances to the environment. Environmental stress, such as air pollution, is among the factors most limiting plan productivity and survivorship. Air pollution can straight away affect plants via leaves or indirectly through soil acidification. When exposed to aerial pollutants, most plants experienced physiological changes before exhibiting visible damage to leaves. The atmospheric SO2 adversely affects various morphological and physiological characteristics of plants. High soil moisture and high relative humidity aggravated SO2 injury in plants. Industrialization and the automobiles are responsible for maximum amount of air pollutants and the crop plants are very sensitive to gaseous and particulate pollutions and these can be used as indicators of air pollution. In urban environments, trees play an important role in improving air quality by taking up gases and particles. Vegetation is an effective indicator of the overall impact of air pollution and the effect observed is a time-averaged result that is more reliable than the one obtained from direct determination of the pollutant in air over a short period. Although, many trees and shrubs have been identified and used as dust filters to check the rising urban dust pollution level.

Plants provide an enormous leaf area for impingement, absorption and accumulation of air pollutants to reduce the pollutant level in the air environment, with a various extent for different species. The use of plants as monitors of air pollution has long been established as plants are the initial acceptors of air pollution. They act as the scavengers for many aerial particulates in the atmosphere. The tolerance index values vary for different plant species. It is found that the sensitivity values to the air pollution are in the order: *Herbs* > *Shrubs* > *Trees*. This is because herbs are small plant species and lie close to ground and hence, they are less exposed to air pollutants than the tress, which are exposed to pollution most of the time. Soluble sugar is an important constituent and source of energy for all living organisms. Plants manufacture this organic substance during photosynthesis and breakdown during respiration (Tripathi and Gautam, 2007). Tripathi and Gautam (2007), in their study revealed significant loss of soluble sugar in all tested species at all polluted sites. The concentration of soluble sugars is indicative of the physiological activity of a plant and it determines the sensitivity of plants to air pollution. Reduction in soluble sugar content in polluted stations can be attributed to increased respiration and decreased CO2 fixation because of Chlorophyll deterioration. It has been mentioned that pollutants like SO2, NO2and H2S under hardening conditions can cause more depletion of soluble sugars in the leaves of plants grown in polluted area. The reaction of sulphite with aldehydes and ketones of carbohydrates can also cause reduction in carbohydrate content (Tripathi and Gautam, 2007).

The shading effects due to deposition of suspended particulate matter on the leaf surface might be responsible for this decrease in the concentration of Chlorophyll in polluted area. It might clog the stomata thus interfering with the gaseous exchange, which leads to increase in leaf temperature which may consequently retard Chlorophyll synthesis. Dusted or encrusted leaf surface is responsible for reduced photosynthesis and thereby causing reduction in Chlorophyll content (Joshi and Swami, 2009). A considerable loss in total Chlorophyll, in the leaves of plants exposed to pollution supports the argument that the chloroplast is the primary site of attack by air pollutants such as SO2and NOx. Air pollutants make their entrance into the tissues through the stomata and cause partial denaturation of the chloroplast and decreases pigment contents in the cells of polluted leaves. High amount of gaseous SO2 causes destruction of Chlorophyll (Tripathi and Gautam, 2007). Several researches have recorded reduction in Chlorophyll content under air pollution (Tiwari et al., 2006; Tripathi and Gautam, 2007; Joshi and Swami, 2007, 2009; Joshi et al., 2009).

Typical environmental stress (high and low temperature, drought, air and soil pollution) can cause excess Reactive Oxygen Species (ROS) in plant cells, which are extremely reactive and cytotoxic to all organisms (Pukacka and Pukacki, 2000). High exposure to air pollutants forces chloroplasts into an excessive excitation energy level, which in turn increases the generation of ROS and induces oxidative stress (Woo et al., 2007). The deleterious effects of the pollutants are caused by the production of Reactive Oxygen Species (ROS) in plants, which cause peroxidative destruction of cellular constituents (Tiwari et al., 2006). It has been reported that proline act as a free radical scavenger to protect plants away from damage by oxidative stress. Although, the scavenging reaction of ROS with other amino acids, such as tryptophan, tyrosine, histidine, etc. are more effective compared with proline, proline is of special interest because of its extensive accumulation in plants during environmental stress (Wang et al., 2009).

Traditionally, leaf extraction with organic solvents in solution is required for pigment analysis with chemical methods. Recently, alternative solutions of leaf pigment analysis (i.e., chlorophyll, carotenoids and anthocyanins) with non-destructive optical methods have been developed. The SPAD-502 Chlorophyll meter was used to determine total Chlorophyll meter was used to determine total chlorophyll in leaves are used in the acetone extraction method formation about physiological status of plants. NIR spectroscopy measurement makes it possible to quickly and non-destructively assess the chlorophyll content in leaves. A Simulated annealing algorithm (SAA) is used to select most efficient wavelength for different plant species.

Therefore, this chapter proposes an inexpensive image classification technique with Neural Network model for estimating the Chlorophyll and Nitrogen contents with a simple camera for diagnosis purpose.

BACKGROUND

The present research deals with objective and subjective study under various polluted zones to that of pollution free zones. The heavy traffic present on roadside, NIT Warangal campus, polluted lake side and a normal home are chosen for statistical analysis. The technology used is Neural and Fuzzy Networks. A normal image processing, which outdated method is used to be a simple technology to find the Chlorophyll and Nitrogen components, but due to availability of large datasets and for precise accuracy, intelligent systems such as Deep Neural Networks are into picture. The investigation deals with creation of a Convolutional Neural Network layers consisting of several hidden layers with limited epochs. The accurate value corresponding to the Green pigment present on the plant leaf is captured and several mathematical models are deployed to get the levels of Chlorophyll pigments and Nitrogen content. A high definition camera is used for capturing plant leaves for a high-resolution image so that the captured image intensity is constant throughout the investigation for accuracy. The image recognition feature extraction was deployed in Convolution Neural Network layers. The image classifiers capture the plant leaf, extract RGB pixel arrays from it, and then finally segregate green pixel values from the rest two. Not to make much complex algorithm, a simple image processing toolbox is used for extracting the Green pixels from the plant leaf. This itself will calculate the green intensity present in the leaf and gives us the Green intensity values based on resolution used. From this green intensity pixel values, it is then processed in the standard Spadometer readings to get accurate and precise Chlorophyll pigment values. From the final Chlorophyll values, Nitrogen value is extracted after several iterations. Licensed MATLAB platform is used where Image Processing Toolbox and Neural Networks Toolbox is used for processing the data. MATLAB platform is chosen for its speed and supportive back-end functions which makes the algorithm simple.

The algorithm we propose non-linearly maps the normalized value of G, with respect to R and B, using a logarithmic sigmoid transfer functions as follows:

$$Ch_{OL} = \log sig\left(\frac{G - \frac{R}{3} - \frac{B}{3}}{255}\right) \quad (1)$$

where:

CHL_{ol}: Chlorophyll estimation by Optileaf
G: Green Color; Red Color; Blue Color

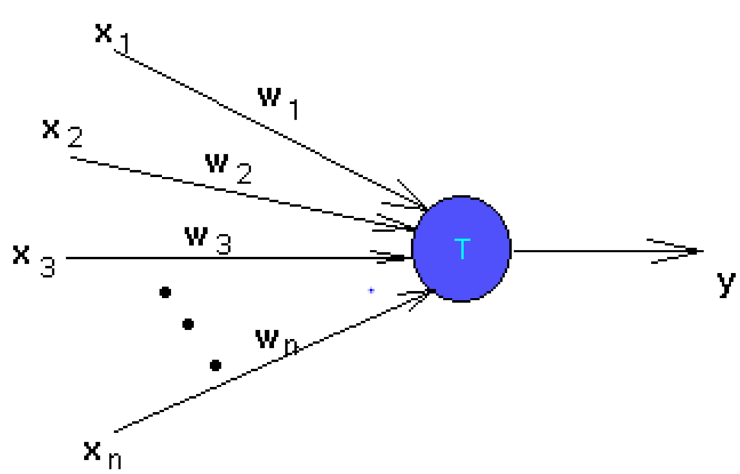
The RGB pixel values are substituted in the above formula to obtain Chlorophyll value. This formula is obtained by comparing and verifying it with the standard Spadometer mechanism. Spadometer is used to estimate the amount of Chlorophyll and Nitrogen values based on light spectrum and light intensity. So, by verifying the obtained values from the above formula are verified with the slope equations attained from Spadometer graph. The resultant values are the final and accurate Chlorophyll and Nitrogen content present in the plants.

Artificial Neural Networks

Neural Networks approaches the mimic of structure and function of our nervous system. Whenever the neural network makes a mistake, some weights and thresholds must be changed to compensate for this error. The Perceptron consists of a single trainable neuron. Trainable means that its threshold and input weights are modifiable. Inputs are presented to the neuron and each input has a desired output (determined by user). If the neuron doesn't give the desired output, then it has made a mistake. To rectify this, its threshold and/or input weights must be changed.

- $x1, x2, ..., x_n$ are inputs. These could be real numbers or Boolean values depending on the problem.
- y is the output and is Boolean.

Figure 1. Perceptron



- w1, w2, ..., w_n are weights of the edges and are real valued.
- T is the threshold and is real valued.

The output y is 1 if the net input which is - w1 x1 + w2 x2 + ... + w_n x_n is greater than the threshold T. Otherwise the output is zero.

The Perceptron is trained to respond to certain inputs with certain desired outputs. After the training period, it should be able to give reasonable outputs for any kind of input. Usually, the inputs are not directly fed to the trainable neuron but are modified by some "pre-processing units".

Computing Neural Networks

The computational progress the decision of accurate threshold levels:

Computing "and": There are n inputs, each either a 0 or 1. To compute the logical "and" of these n inputs, the output should be 1 if and only if all the inputs are 1. This can easily be achieved by setting the threshold of the perceptron to n. The weights of all edges are 1. The net input can be n only if all the inputs are active.

Computing "or": It is also simple to see that if the threshold is set to 1, then the output will be 1 if at least one input is active. The perceptron in this case acts as the logical "or".

Computing "not": The logical "not" is a little tricky but can be done. In this case, there is only one Boolean input. Let the weight of the edge be -1, so that the input which is either 0 or 1 becomes 0 or -1. Set the threshold to 0. If the input is 0, the threshold is reached, and the output is 1. If the input is -1, the threshold is not reached, and the output is 0.

Image Classifications

Image classification is a process of mapping numbers to symbols

```
  f(x): x -> D; x ∈ n times power of R, D = {c1, c2, …, cL }
  Number of bands = n;
  Number of classes = L
  f (.) is a function assigning a pixel vector x to a single class in the set
of classes D.
```

Colours could be represented as RGB values (a combination of red, green and blue ranging from 0 to 255). Computers could then extract the RGB value of each pixel and put the result in an array for interpretation. When the computer interprets a new image, it will convert the image to an array by using the same technique, which then compares the patterns of numbers against the already-known objects. The computer then allots confidence scores for each class. The class with the highest confidence score is usually the predicted one. One of the most popular techniques used in improving the accuracy of image classification is Convolutional Neural Networks. CNN is a special type Neural Networks that works in the same way of a regular Neural Network except that it has a convolution layer at the beginning. Instead of feeding the entire image as an array of numbers, the image is broken up into several tiles, the machine then tries to predict what each tile is. Finally, the computer tries to predict what's in the picture based on the prediction of all the tiles. This allows the computer to parallelize the operations and detect the object regardless of where it is located in the image.

Region of Interest Pooling

Region of interest pooling (also known as RoI pooling) is an operation widely used in object detection tasks using Convolutional Neural Networks. Since, we give a whole set of input image which may include other objects too which are not needed, the input image needs to be pooled to only necessary part and the remaining can be eliminated. The technique object detection which detects the leaf part only and crops the latter is deployed in the algorithm.

The scaling is done by:

1. Dividing the region proposal into equal-sized sections (the number of which is the same as the dimension of the output)
2. Finding the largest value in each section
3. Copying these max values to the output buffer

Figure 2. Region of pooling process

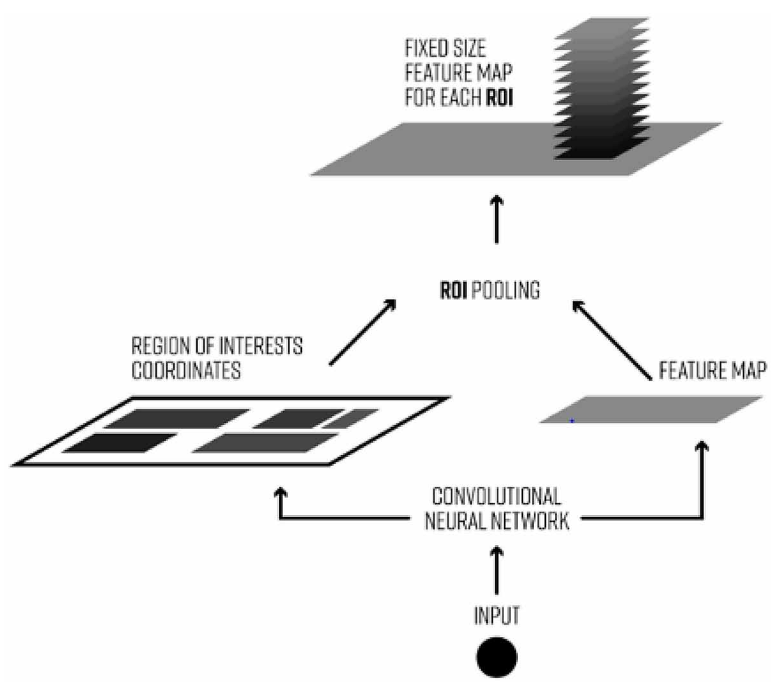


IMAGE PROCESSING ALGORITHM

Image algorithm is used for detecting the "Chlorophyll & Nitrogen" levels in the plant using the "RGB" values of the leaf. The main reason we are focusing on Nitrogen & Chlorophyll content is that Nitrogen is the backbone of the plant hence needs to be monitor consistently for getting an appropriate value of fertilizer to be sprayed. Since, Nitrogen value changes due to several factors such as weather and water, it needs to be monitored in order to save the crop from any disaster to occur. The RGB values of the plant leaf are taken into a matrix form and green content is calculated which is called "Normalized Green Content". This value is equated in the standard Chlorophyll content formula. Then this value is the result of the green content that we have got from the picture snap. This value contains some error with respective to the original Chlorophyll value. Hence this value is evaluated with respect to the standard Spadometer Values, and we get an equation from it. This value is compared with the slope of the Spadometer graph and an equation is derived which is nothing but our desired Nitrogen content. Based on the Nitrogen value, the farmer gets suggestion on the amount of fertilizer and type of fertilizer to be used since the crops are getting affected by pollution and hence a greater damage of crop loss is being noticed every year.

DEEP LEARNING ALGORITHM

Sufficient samples of plants infected with diseases due to variation in Nitrogen content caused by air pollution and excess moisture are taken as training data and the model is trained with N-Class classification because we are opting for classifying each and every possible disease attack specifically for each zone. Our device hence can be deployed in all agricultural farms all over India where we'll be collecting the zone-specific dataset of possible disease attacks and train the model. This reduces the memory constraints and requires less memory. Convolutional Neural Networks is being used. CNN image classifications take an input image, process it and classify it under certain categories (Eg., Disease-1, Disease-2, Moisture Content-High). Technically, deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC) and apply activation function to classify an object. Softmax activation function is then used which classifies the object with probabilistic values between 0 and 1. The Deep Learning architecture can easily classify the object with a minimal amount of time possible.

The first step is the Convolution operation which extracts the features from the image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It's a mathematical operation that takes two inputs such as image matrix and a filter, this is called "Feature Map". Convolution Operation is shown in Fig. 3.

Padding operation is followed after Convolution. It uses a CONV layer without necessarily shrinking the height and width of the volumes. This is important for building deeper networks because the height/width would shrink as we go to deeper layers. 2. It helps to keep more of the information at the border of an image. Without padding, very few values at the next layer would be affected by pixels as the edges of an image. A 2-Stride operation is used in order to avoid the overlapping and reduce the computation. Padding Operation is shown in Fig. 4.

Figure 3. Convolution operation

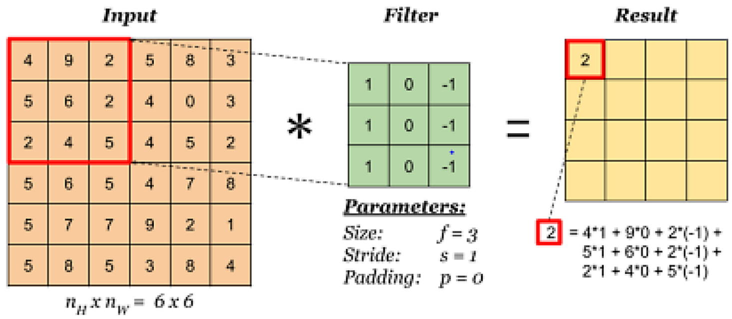
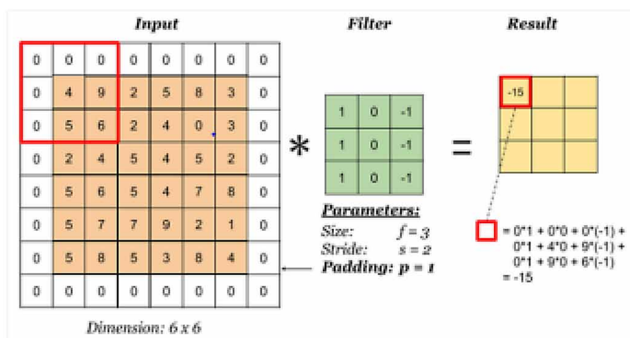


Figure 4. Padding operation



Pooling Layers section would reduce the number of parameters when the images are too large. Pooling simplifies the output by performing nonlinear down-sampling, reducing the number of parameters that the network needs to learn. Spatial pooling also called subsampling or down-sampling which reduces the dimensionality of each map but retains the important information. Max Pooling operation is performed which takes largest element from the rectified feature map. This avoids the data corruption and hence, guarantees all features are rightly chosen and taken into account. After pooling layer, flattened as Fully Connected layer is shown in Fig. 5.

Fully Connected Layer, where matrix is flattened into vector and fed it into a fully connected layer like neural network. Almost 10 billion+ parameters are extracted from the whole training set which gives highest accuracy possible in classifying the disease infected leaves caused due to variation in Nitrogen content and moisture levels as well from a test image. Flowchart of Identifying Disease, Nitrogen and Moisture Content is shown in Fig. 6.

TRANSFER LEARNING

We have proposed Transfer Learning approach to get the highest accuracy possible with a very minimal average loss since the results that we are getting through this algorithm is very crucial for the farmer. The basic intuition of Transfer Learning is shown in Fig. 7. So, we are deploying Transfer Learning where the output layer is taken off and we concatenate with the custom dataset where we train the custom

Figure 5. After pooling layer, flattened as fully connected layer

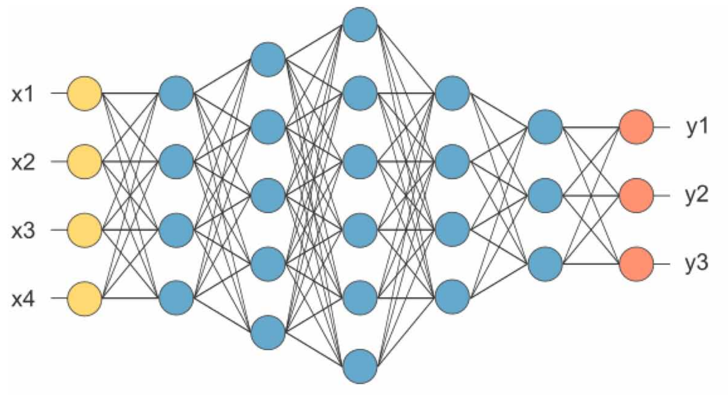


Figure 6. Flowchart of identifying disease, nitrogen, and moisture content

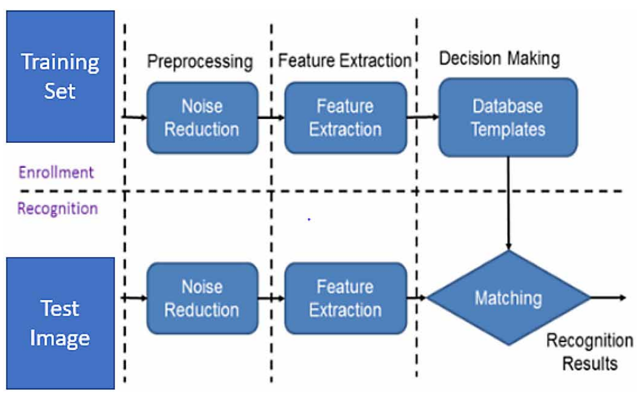
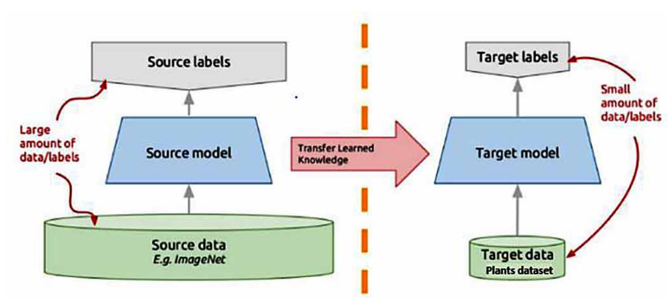


Figure 7. A basic illustration of transfer learning



dataset. We are specifically using Inception model which resulted in a high accuracy test result when we tested. With Transfer Learning, we use an existing trained model and adapt it to our own problem. We are essentially building upon the features and concepts that were learned during the training of the base model. With a Convolutional DNN (ResNet and Inception V3 in this case), we are using the features learned from ImageNet data and cutting off the final classification layer, replacing it with a new dense layer that will predict the class labels of our new domain.

The input to the old and the new prediction layer is the same, we simply reuse the trained features. Then we train this modified network, either only the new weights of the new prediction layer or all weights of the entire network. This can be used, for instance, when we have a small set of images that are in a similar domain to an existing trained model. Training a Deep Neural Network from scratch requires tens of thousands of images but training one that has already learned features in the domain you are adapting it to require far fewer. Transfer learning allows us to train deep networks using significantly less data then we would need if we had to train from scratch. With transfer learning, we are in effect transferring the "knowledge" that a model has learned from a previous task, to our current one. The idea is that the two tasks are not totally disjoint, and as such we can leverage whatever network parameters that model has learned through its extensive training, without having to do that training ourselves. Transfer learning has been consistently proven to boost model accuracy and reduce require training time. Less data, less time, more accuracy.

Initially we tested out with YOLO V3 architecture, ResNet architecture, SqueezeNet architecture, DenseNet architecture and Inception V3 architecture. But, as the latest advancements in Deep Learning taking place, we are even doing a research on pixel-to-pixel grading and annotation for a very precise accuracy where very less research is done on it due to its complexities. Hence, we would like to do a unique research too on pixel-to-pixel level grading in Agriculture domain and test the results and validate it. The research is being focused on Inception V4, Inception-ResNet, Reinforcement Learning and Pixel-to-Pixel grading (through up sampling and down sampling).

The Inception V3 architecture is shown in Fig. 8. The Inception architecture comprises of:

- RMSProp Optimizer.
- Factorized 7x7 convolutions.
- Batch Norm in the Auxiliary Classifiers.
- Label Smoothing (A type of regularizing component added to the loss formula that prevents the network from becoming too confident about a class. Prevents over fitting).

The "stem" of Inception V4 was modified. The stem here, refers to the initial set of operations performed before introducing the Inception blocks.

Figure 8. Inception V3 architecture

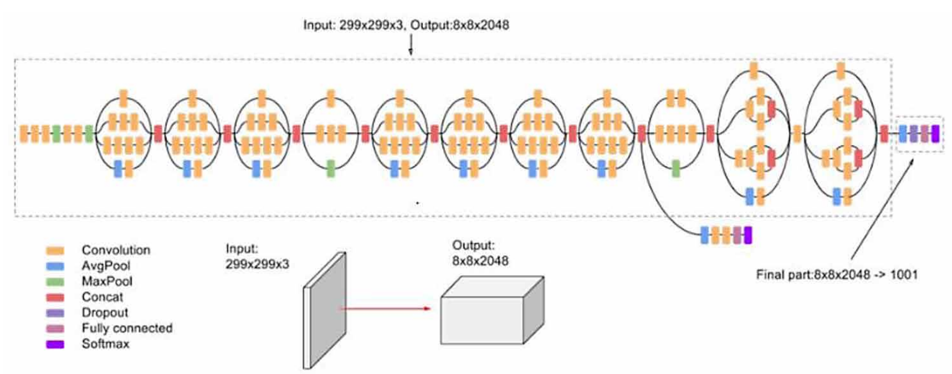
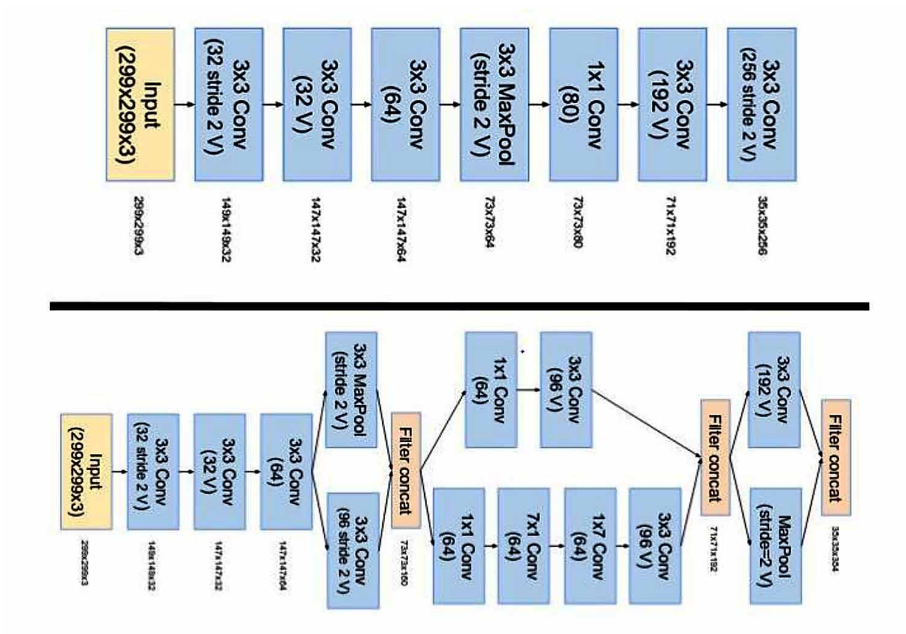


Figure 9. Inception and inception-resnet operation flow



The top image is the stem of Inception-ResNet v1. The bottom image is the stem of Inception v4 and Inception-ResNet v2. (Source: Inception v4)

The basic intuition of Inception and Inception-ResNet is shown in Fig. 9.

- Inception v4 has specialized "Reduction Blocks" which are used to change the width and height of the grid.
- In Inception-ResNet, for residual addition to work, the input and output after convolution must have the same dimensions. Hence, we use 1x1 convolutions after the original convolutions, to match the depth sizes (Depth is increased after convolution).
- The pooling operation inside the main inception modules were replaced in favor of the residual connections. However, you can still find those operations in the reduction blocks. Reduction block A is same as that of Inception v4.

The Fig. 10 and Fig. 11 describes the Inception-ResNet architecture, their internal intuition. Networks with residual units deeper in the architecture caused the network to "die" if the number of filters exceeded 1000. Hence, to increase stability, the authors scaled the residual activations by a value around 0.1 to 0.3.

The Fig. 12 describes the Inception model internal blocks which is responsible for highest accuracy.

Figure 10. (From left) Inception modules A,B,C in an Inception ResNet. Note how the pooling layer was replaced by the residual connection, and also the additional 1x1 convolution before addition

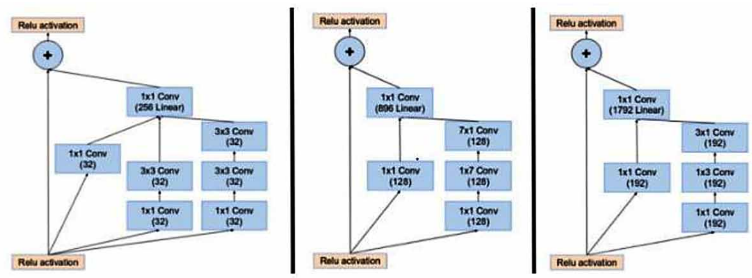


Figure 11. (From Left) reduction block a (35x35 to 17x17 size reduction) and reduction block b (17x17 to 8x8 size reduction)

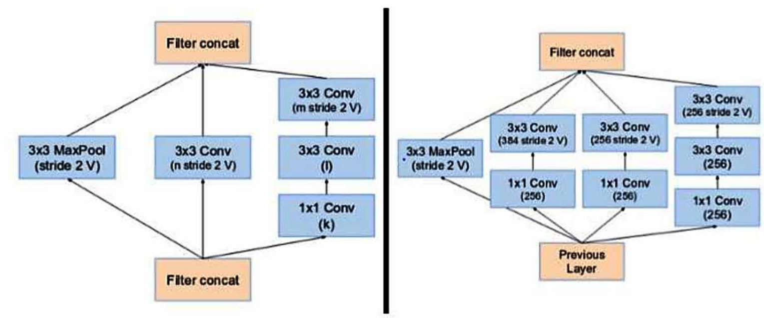
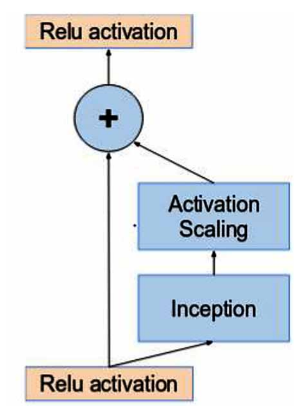


Figure 12. Activations are scaled by a constant to prevent the network from dying



RESULTS AND DISCUSSIONS

Several plant leaf samples from heavily polluted areas were collected and compared with pollution free zone (NIT Warangal Campus). The variations and difference are statistically compared and visualized in bar graphs for easy evaluation. The research is done by collecting a particular plant leaf daily for 1

Table 1. PM vs. Nitrogen comparison

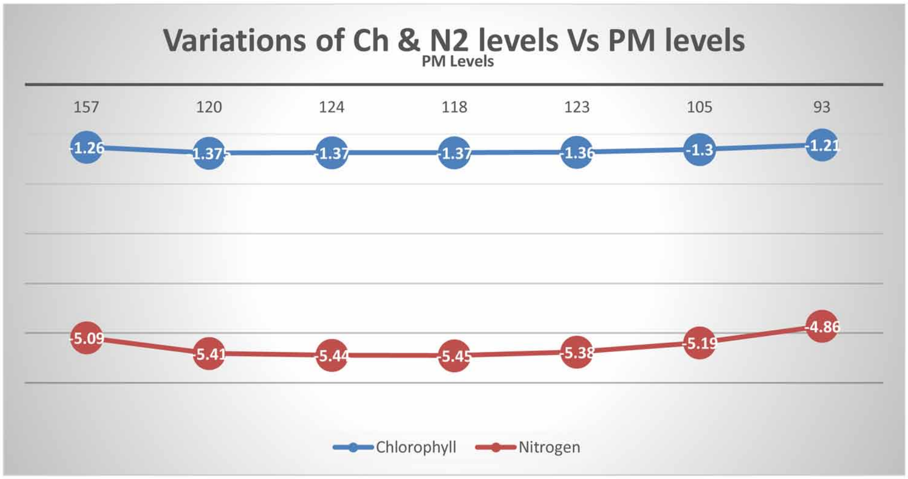
S. No.	PM	Chlorophyll	Nitrogen	SPAD Comparison
Day-1	157	-1.26	-5.09	-37.085
Day-2	120	-1.375	-5.41	-39.32
Day-3	124	-1.37	-5.44	-39.55
Day-4	118	-1.37	-5.45	-39.50
Day-5	123	-1.36	-5.38	-39.08
Day-6	105	-1.30	-5.19	-37.85
Day-7	93	-1.21	-4.86	-35.64

week and compared its Nitrogen value with the air index quality value and graphically visualized for analysis in the variation of Nitrogen values for different particulate matter. This value is calculated with the one obtained from pollution free environment (NIT Warangal campus).

The Table 1 above is the result obtained from the polluted area against its Particulate Matter (PM) air index quality values. It is observed that starting day of weekend and on week days, the air quality is worst and low respectively. Accordingly, the Nitrogen and Chlorophyll values vary with the PM value. When PM value is at its worst case, the Chlorophyll and Nitrogen content are low due to presence of high air pollutants. Surprisingly, it is observed that the Chlorophyll content doesn't vary much when the PM index doesn't jump or have a wide gap between two successive values. It is concluded that Chlorophyll content doesn't vary much for small variations in PM values because small variations result in minor imbalance of present air pollutants that do not eliminate pollutants in the air. Hence, the effect of air pollutants on the plant has almost same effect for Day-2, 3, 4, 5 days in the table above since the PM values didn't very much. The air pollutants have significant effect on the plant that is present over a long time throughout the day. It is found that the pollution effect is present on the plant almost whole day irrespective of the downfall of pollution levels on the same day. So, it may be concluded that it takes some time for getting rid of the pollution effect on plants if and only if the pollution levels get down on a big scale that too the next successive days constantly. Alternate days, i.e., one day high PM levels, next day low and again the next day high, results the same with not much variations as that of the high PM levels effect. Hence, there must be a consistent decrease in PM levels in order to increase the Chlorophyll content. It is even observed that, small plants are not much effected than the big trees to pollution. Lead is a toxic element released in the environment due to automobile activities. The higher traffic exposures decreased the chlorophyll content in leaves due to automobile pollution stress. Graphical Representation of Ch & N2 Vs PM levels is shown in Fig. 13.

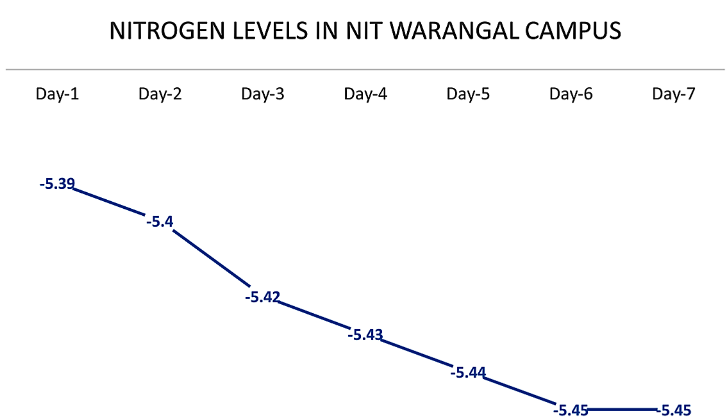
Even a slight presence of air pollutants in the air, gets impeded into the plant's stomata, and interfere with its metabolism resulting in gradual reduction of biochemical parameters in the plants mainly Chlorophyll content. The pollutants toxify the physiological actions of the plants by perturbing its normal activities. It is proven that there is a significant in decline in the stomata size in polluted prone areas which leads to decrease in Chlorophyll content. Almost all the plants which breathe in polluted areas have the same effect. Along with the presence of pollutants, leaf temperature also plays a key role. The temperature must be optimum. Any extreme variations in leaf temperature may lead to crumbling of moisture levels which also have a significant role in Chlorophyll pigments. The pollutants may play a key role in increasing the leaf temperature putrefying its optimum temperature levels. From the above

Figure 13. Graphical representation of Ch & N2 Vs PM levels



graph, it is proven that the plants are adapting themselves to the air pollution, thereby increasing their resistance power. This adaptability in plants is possible only if they are watered well and not exposed consistently to higher temperatures. If the plants are exposed to higher temperature especially during summers and not watered properly, they gradually loose the resistance and tolerance power leading themselves to a drought like condition. This may result in gradual decrease in the Nitrogen levels in leaves, not all at once but one by one. If this continues for a long time, we can find the plant is dried condition ultimately leading to its death. Hence, even if they are exposed to higher temperatures, they must be watered properly and cleanse their leaves too for not getting dried up due to higher temperatures. The air pollutants in air too can cause higher leaf temperature if they are consistently exposed to it. This can optimize by properly watering the plants. Although it is observed that the plants are adapted to air pollution. Nitrogen Variation in Pollution-Free Environment is shown in Fig. 14.

Figure 14. Nitrogen variation in pollution-free environment

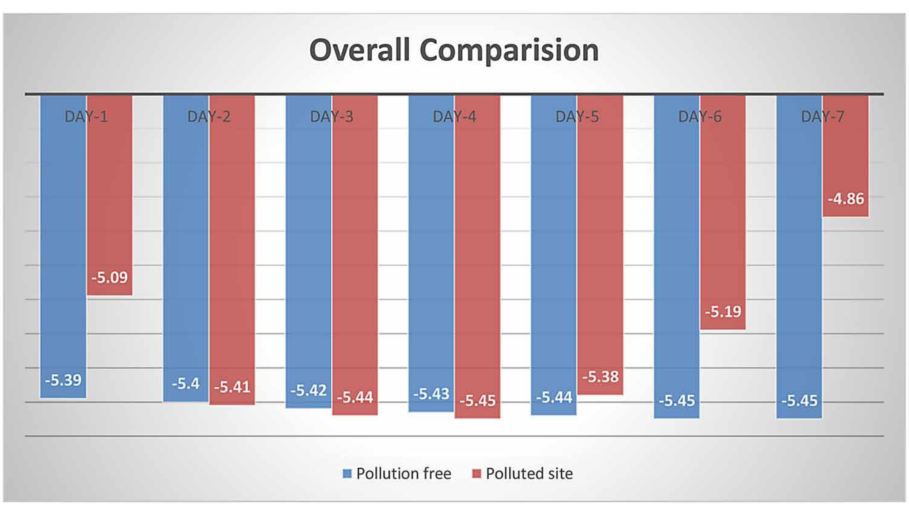


The above graph represents the Nitrogen content variations in pollution-free zone, i.e., NIT Warangal Campus. It is observed that there is a consistent Nitrogen levels with a slight variation. There isn't much effect of plant's chlorophyll content compared with the polluted environment. It can be said that the plants in pollution-free environments are much healthier than the polluted zone plants. But the plant resistance is higher in polluted sites than in polluted free sites, since, the plants in polluted sites have adapted themselves to the pollution. Since, ages and right from the beginning of its birth, it has been grown in pollution unlike the plants in pollution-free zones. Hence, the metabolism of plants in polluted sites is in such a way that it is adaptable to pollution too. But the health condition and age of survival is comparatively less than the plants grown in pollution-free zones. The relative water content in plants will help them to maintain its physiological balance under stress conditions. Since, the air pollutants increase the cell permeability which causes loss of water and dissolution of nutrients, it results in early senescence of leaves. Plants with high water content under polluted environments are considered to be tolerable to air pollution. Therefore, it is necessary to water plants daily which grow in polluted environments in order to sustain the tolerance levels to air pollution, only then can the plants balance the air pollution.

From the overall comparison graph of Nitrogen variations in polluted and pollution-free sites, it is observed that the plants in polluted sites adapted themselves to the air pollution only if they are watered regularly. Nitrogen values are consistent in pollution-free sites and they maintain proper health and metabolism rising to a better health condition than the polluted site plants. If suddenly the plants of pollution-free sites are exposed to severe air pollution, there may be great loss of nutrients in them even if they are watered daily and their health condition gets worse day by day and finally leading to zero Nitrogen levels called as plant starvation. Overall Comparison of Nitrogen Variation in Polluted and Polluted-Free Sites is shown in Fig. 14.

Hence, Particulate matter (PM) levels have greater effect on plant leaves and mostly are tolerated due to adaptability base do their vicinity conditions. Ascorbic acid plays a vital role in cell wall synthesis, defense and cell division. It also plays a crucial role in photosynthetic carbon fixation. Ascorbic acid is a natural de-toxicant which prevent the damaging effect of air pollutants in plant tissues and high amount favors pollution tolerance in plants. Thus, plants maintaining high ascorbic acid level even under pollu-

Figure 15. Overall comparison of nitrogen variation in polluted and polluted-free sites



tion are considered to be tolerant to air pollution. Ascorbic acid levels are normal in polluted-free sites since they are not exposed to air pollution and hence, it doesn't require high quantities to reproduce it. Therefore, not all plants in pollution sites are tolerable, several biochemical factors need to be considered for getting appropriate pollution tolerance index. The plants which maintain an optimum biochemical factor which can adapt themselves to air pollution are tolerant enough to the air pollution. But if the air pollution is very high, it effects the plants present in that area. Tolerance levels are limited up to a certain pollution level. If the level crosses its limits, it has a serious effect on the plant's leaf by increasing their leaf temperature. This gradually reduces the chlorophyll contents and Nitrogen contents since its water levels gets dried up quickly if the temperature is too high.

Another important biochemical factor which needs to be consider is the soluble sugars. Soluble sugars play an important role in maintaining the physiological activities in plants. It determines the sensitivity of the plants. Accumulation of sugars in different parts of plants is enhanced in response to the variety of environmental stresses. The environmental stress is caused due to the air pollution. The air pollutants have significant effect on plant's leaf which disturbs the normal metabolism activities that takes in plants. This overall leads to environmental stress. It is observed that the plants in pollution-free sites are having less stress than the plants grown in polluted sites. Soluble sugars have been reported to play a protective role against stresses. It is observed that the plants in polluted sites are having an increase soluble sugars indicative of stress. The plants in polluted sites have adapted themselves by producing more soluble sugars which acts as a protective layer to the environmental stress. If these plants are not properly watered and sufficient sunlight is not observed, the sugar levels may go down leading to decrease in resistance.

The above figures 16 and 17 describes the air pollutants effect on plants if they are not watered regularly. These snaps are taken from a heavily polluted site where the plants are not watered from a long time. It describes the air pollutants dilutes the nutrients present in the plant leaf thereby causing plant starvation due to lack of Nitrogen. Figure 6 describes the intermediate stage of nutrition dilution and Figure 7 represents the final stage of plant starvation which has a zero-level nitrogen and Chlorophyll in it. Once the plant's nutrition is dissolved due to environmental stress caused by the air pollutants, it finally leads to drought-like condition for the plant which can be seen in Figure 7. We can observe in Figure 7 looks like dried leaves caused due to severe drought. But this is not caused due to drought, but due to lack of sufficient nutrition which are dissolved by air pollutants finally leading to diluting Nitrogen and chlorophyll contents. This can be avoided by watering the plant daily. How much ever the tolerance levels be, if they are provided with sufficient water and sunlight, they are living in a worse

Figure 16. Plant starvation due to lack of nitrogen

Figure 17. Plant starvation due to lack of nitrogen

condition which has significant effect on plants as well the environment. This what leads to massive human effects due to air pollution. If the plants can't balance the pollution levels, the environment is in a serious damage condition. In order to maintain the balance of air pollution, it is highly necessary to properly maintain a greater number of vegetation on ground. This may even affect the farming areas where the crops are affected by all means of pollution. The air, water and land pollution are experienced by the crops in farming areas. Hence, all the means of pollution must be taken care to avoid farming disaster leading to crop loss. Lack of Nitrogen in vegetation in farms can lead to crop loss causing plant starvation. This can be caused even by the massive air pollutants present.

The above figures 18, 19, 20 and 21 are some glimpse of snaps taken from pollution free sites and polluted sites respectively. The snaps of leaves from polluted sites are taken from road side plants which are heavily affected by pollution and are not watered on regular basis. Another set of leaves in pollution site where plants are regularly watered are also taken. Plant leaves from pollution-free site are taken from NIT Warangal campus. It is concluded that auto- vehicular exhaust emission of air pollutants has significantly affected the roadside plants. There is a severe effect on plants which are not watered than which are watered. The plants which are maintained properly by watering well, has resulted in increased tolerance levels to air pollutants even if they are present in polluted sites.

Figure 18. Snap of leaves in polluted-free site

Figure 19. Snap of leaves from polluted-free site

Figure 20. Snap of leaves from polluted site

Figure 21. Snap of leaves from polluted site

ANALYSIS OF DIFFERENT DEEP LEARNING ARCHITECTURAL MODELS FOR IDENTIFYING NITROGEN BASED DISEASES IN MOST POLLUTED SITES

Below are few samples of disease infected leaves caused by variation in Nitrogen levels due to high pollution. The sample real time test images are shown in figures from Fig. 22.1 to Fig. 22.6.

Figure 22. Sample real time test images

Figure 22a. Disease_1

Figure 22b. Disease_2

Figure 22c. Disease_3

Figure 22d. Disease_4

Figure 22e. Healthy_1

Fig. 22f. Healthy_2

Applications of Machine Intelligence and Machine Vision in Agriculture

Sufficient samples of plants infected with pests and diseases and excess moisture are taken as training data and the model is trained with N-Class classification because we are opting for classifying each and every possible disease/pest attack specifically for each zone. Our device hence can be deployed in all agricultural farms all over India where we'll be collecting the zone-specific dataset of possible pest/disease attacks and train the model. This reduces the memory constraints and requires less memory. Convolutional Neural Networks is being used. CNN image classifications take an input image, process it and classify it under certain categories (Eg., Pest-1, Pest-2, Disease-1, Moisture Content-High). Technically, deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernels), Pooling, fully connected layers (FC) and apply activation function to classify an object. We can apply Softmax function to classify the object with probabilistic values between 0 and 1. Deep Learning architecture can easily classify the object with a minimal amount of time possible. The other technological advancements in Machine Vision or Deep Learning is Transfer Learning where with small amount of data available we can get precise accuracy by concatenating the pre-trained model with the custom model. This helps the farmer even in treatment of the plant in much better way with a very-low cost. Several transfer learning architectures like ResNet, Inception V3 can be deployed in agriculture field for much more advanced applications like Moisture content estimation, pest/disease detection, burning sensation prediction. These can be diagnosed and treated then and there by avoiding a crop-loss aftermath.

FUTURE RESEARCH DIRECTION

The present study in this chapter deals with the complete diagnosis of plant's Nitrogen and Chlorophyll variations with the Particulate Matter (PM) present in air. These values are compared with pollution-free values for statistical analysis. This concludes with lot more scope for future research on analysis on estimation of loss of crop due to air pollutants. This chapter can be further be taken to research on combatting the air pollution by planting extreme number of trees. End effect of fruits and flowers due to air pollutants can be analysed. Prediction of diseases and effect of air pollutants on crop can be diagnosed and corrective measures can be given to the crop for minimizing the effect on it. Scope for vertical farming or indoor farming can be compared in order to reduce the indoor pollution. Significant effect on humans due to indoor pollution is more dangerous than outdoor, hence, Nitrogen variation due to indoor pollution can be researched and statistical analysis can be done by comparing it with the outdoor pollution.

CONCLUSION

Generally, the NPK values depends on the intensity levels of the pixel. Hence, on different scales, the values vary. The controlled light intensity which can be set as constant throughout the testing phase helps in retaining the exact value of the NPK and their health levels. So, keeping a constant intensity level of light and getting the NPK values helps the farmers in better diagnosing since Nitrogen is the backbone of the plant. This estimation can help the farmer to analyze how much quantitative amount of Nitrogen fertilizer and pesticides he can spray around the farm. Therefore, Computer Vision plays a crucial role in easing the diagnosis treatment for the plant. All this can be further achieved within a smart phone camera using Edge Computing. Although as proved above that the plants are slowly becoming habituated to deal with the pollution, there is a significant amount of loss in farming crops due to pollution. Due to excess of fertilizers, pesticides, the plants are half away ill-health there itself and above this the pollution PM particles that has severe effect on the plant leaves have proven that the plants too need some amount of clean air in order to survive. It may be awkward that plants need clean air because it is proven fact that plants cleanse the polluted air, but not always if they live in severe pollution condition. Not very early that they are affected due to pollution but in a long term they are definitely effected due to pollution, especially the farms.

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KEY TERMS AND DEFINITIONS

Artificial Neural Networks: Artificial neural networks (ANN) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains. The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs.

Classification: Classification is a process related to categorization, the process in which ideas and objects are recognized, differentiated, and understood.

Computer Vision: As a scientific discipline, computer vision is concerned with the theory and technology for building artificial systems that obtain information from images or multi-dimensional data. This type of processing typically needs input data provided by a computer vision system, acting as a vision sensor and providing high-level information about the environment and the robot.

Convolution: In mathematics (in particular, functional analysis) convolution is a mathematical operation on two functions (f and g) to produce a third function that expresses how the shape of one is modified by the other. The term convolution refers to both the result function and to the process of computing it.

Convolutional Neural Networks: A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data. CNNs are powerful image processing, artificial intelligence (AI) that use deep learning to perform both generative and descriptive tasks, often using machine vision that includes image and video recognition, along with recommender systems and natural language processing (NLP).

Deep Learning: Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on artificial neural networks. Learning can be supervised, semi-supervised, or unsupervised.

Digital Image Processing: Digital image processing is the use of computer algorithms to perform image processing on digital images.

Machine Intelligence (AI): Artificial intelligence is branch of computer science; the machine behaves in a way as human thinks and considered as an intelligent system.

Particulate Pollution: Particulate pollution is pollution of an environment that consists of particles suspended in some medium. There are three primary forms: atmospheric particulate matter, marine debris, and space debris.

Pooling: A pooling layer is another building block of a CNN. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layer operates on each feature map independently. The most common approach used in pooling is max pooling.

RGB Image: A bitmap image holding RGB color values in three image channels.

Chapter 7
A Fuzzy-Based Sustainable Solution for Smart Farming

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ABSTRACT

Agriculture is an important sector in many developing countries, but the traditional methods are not sufficient to produce a good amount of crop. Moreover, the natural calamities are also destroying a large portion of the crop. Hence, this chapter proposes a prototype model, AgriHelp, to address an agricultural issue using fuzzy logic. The model takes two parameters as input: when and where the farmer wants to sow the crop. Using this information along with available dataset, AgriHelp extracts the expected min-max temperature, rainfall and soil type in the region in the specified season and suggests the best-suited crop to the farmer. The model can further be extended by incorporating more features.

INTRODUCTION

Agriculture is one of the life-sustaining aspects of a country's economic system. It is an important sector in many developing countries like India as several acres of land is used to grow various kinds of crops such as staples, vegetables, spices, pulses, etc. India is leading the world in producing a huge variety of staples. By exporting the different products, a nice amount of revenue is generated every year. India is the second largest producer and exporter of spices ("Spice Board", n.d.). Globally, it ranks second in rice and tea production. The agriculture sector counts 16%of total GDP in Indian economy (Datt and Mahajan, 2011).

The agriculture sector has two-fold advantages. It renders employment opportunities to numerous individuals on a large scale and at the same time, it fulfills the need of society to live a healthy life. It is an imperative source of their livelihood. Moreover, life can't be imagined without the hard work of

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farmers. They are the one who works behind the scene as an indirect source in placing the food on our dining table. On the other side of the coin, agriculture is an imperative source of the farmer's livelihood.

Though more than half of the total acquired land is used for agriculture in India, it contributes only 16% to the total GDP in the economy. There are many reasons behind this non-performance in the agriculture sector. One of the most important reasons is poverty and illiterateness among farmers. Although many times, the government comes forward with various policies ("Programmes and Schemes", n.d.) but due to lack of access to the actual data and appropriate analysis, it fails to extend help to the actually needy farmers ("Reducing Poverty", n.d.). Even the government sets various forums to provide consultancy (Agropedia, n.d.) related to various agricultural issues. However, very few farmers are benefitted by such programs due to unawareness about these services and new technologies. Sometimes, even if they are aware, they are not able to utilize the resources to improve the quality and production of the crops as it requires high investment. Their dependence on natural resources and the use of traditional technologies is another cause of hindrance towards achieving the aim of economically viable production.

Nevertheless, the main challenge is thrown by our mother, Nature. Extensive use of natural resources and hazardous chemicals has to lead to serious environmental issues such as climate change, global warming and pollutions. Many times, it results in unexpected rainfall which further causes either flood or drought. It precipitates devastation of a large portion of crops every year. Due to the high cost of seeds, pesticides and other growing equipment, farmers spent a lot of money in growing the crop. Even sometimes they take a loan for bearing the associated investment. As time passes, the farmer is in a handful of debts and it is very difficult for him to survive and fill the needs of his family. Many farmers are unable to bear this loss and sometimes they decide to end their life. As per the latest report of the year 2018, 639 farmers have committed suicide between March and May 2018 in Maharashtra, India (News18, n.d.). Some decide to quit the farming and do something else. According to the report (DowntoEarth, n.d.) the stress, poor income, no future prospects are some of the reasons for stepping out this kind of decisions. Due to these reasons, even farmers don't want their children to choose agriculture as a career option.

As per the survey (DowntoEarth, n.d.) conducted through 18 states, it is revealed that 70% of farmer respondents prefer to do something else other than farming. The main reason for their decision is low crop yield. According to them, the main causes of low production are either pest attack or unpredictable weather conditions like a flood, drought, unnecessary rains, etc. Sometimes, the farmer explores the non-eco-friendly solution like an excessive amount of pesticide to increase the crop yield. As a result, the quality of the crop and land fertility gets affected. Recently farmers of Maharashtra and Odisha conducted a rally and walked 180 KMs for demanding compensation of their crops (India News-Times of India, n.d.).

In some states, governments provide support and compensation to deal with the loss due to these situations. The government also launched few schemes related to agriculture insurance. But these schemes are valid only for farmers having more land area. To get the support of the government, farmers have to complete a number of formalities. They have to show proper evidence. These practices discourage the farmers and force them to sell their land for some other purposes like factories, buildings, etc. If this process continues in a similar fashion, in the coming decades, we will be short of agricultural land and it would be impossible for us to fulfill the food demand of such a highly populated country.

Since independence in 1947, Indian agriculture crossed a long journey but there is very less improvement in the conditions of framers. India achieved a number of landmarks in technology advancements but still, these technologies are not beneficial for the farmers. A large population of farmers is illiterate and they are not aware that how to take benefits from these technological advancements in their agriculture field. Some of the farmers are using the available modern technologies. However, they are not aware of the pros and cons of these technologies such as: Is this a long term or short term solution? Is this solution eco-friendly?

The current challenge for developing countries like India is to meet the food demand. As the population is increasing at a faster rate, thus food demand is also increasing. At the same time, crop production is decreasing. So, it's a high time to stress upon appropriate use of natural resources and move towards smart farming in an environmentally friendly and sustainable manner.

So, this chapter presents a prototype model, AgriHelp, to address an agricultural issue using fuzzy logic. The model takes two parameters as input: when and where the farmer wants to sow the crop. Using this information along with available dataset, AgriHelp extracts the expected min-max temperature, rainfall and soil_type in the region in the specified season and suggests the best-suited crop to the farmer.

The further article is organized into a number of sections. The following section 2 analyses the issues of traditional farming practices and possible solutions. Section 3 discusses the various researcher's solutions, which employed fuzzy logic as a tool and industry-based solutions. Section 4 presents an overview of fuzzy logic, its main components, rules, inference system, etc. The proposed work in detail and its implementation is presented in section 5. It is followed by the conclusion and future research directions in section 6 and 7 respectively.

PROBLEMS WITH TRADITIONAL APPROACH AND POSSIBLE SOLUTIONS

A farmer does not rely on any specific degree or education for farming rather they rely on gained knowledge acquired through their experiences and the knowledge passes through generations to generations. However, in earlier times, this knowledge was sufficient. But nowadays, to handle the crop production requirements of growing world in current scenario's unpredictable environment conditions is quite challenging. Thus, first, we need to analyze the problems of traditional farming and their solutions (Maragelo, 2008). Traditional farming is the natural and the most practiced way of farming which farmers use since its beginning (Dahu, n.d.; Ikasgune, n.d.). The essential steps of farming are listed down as follows:

1. Selection of the crop according to the season and region.
2. Preparation of land through various farming tools.
3. Planting the crop at appropriate time.
4. Time to time care of crop.
5. Crop harvesting.

Farmers want to increase their crop production as much as possible, as the farming is the only source of living. But, they don't want to spend extra money in completing all the activities of farming; like for harvesting, planting etc., they rely on their family members instead of other technological solutions. Similarly, they choose the seed on the basis of the cost rather than the quality. While protecting the crop from pests, they use powerful pesticides, chemical fertilizers without worrying for its effects on soil and plant. The excessive usage of chemical based fertilizer leads to water pollution. A large amount of pesticides remove the harmful insects but it also impacts on the biodiversity of the plant. The produced yield contains a material which has harmful effects on our health which may lead to some incurable diseases.

Moreover, the farmers burn the unwanted plants while preparing the land for farming. It results in a land which is barren and is not able to produce its own organic material. Soil salinization and soil exhaustion is a major cause of land degradation (Wiltshire, 1989). Its effects on the air quality, our environment can be seen in current scenario. The statistics shows that this rise in pollution level, reducing the average age of a person by 10 years (Business Standard, n.d.). Ozone layer also gets depleted due to greenhouse effect ("Aquaponics.com", n.d.).

There are a number of directions where researchers can help the farmers by providing some automated solutions. Researchers can use their insights for providing a number of solutions which can encourage the agriculturists to use the eco-friendly solutions for various agriculture related issues. First, most important issue is to handle the pest infection. Excessive use of pesticides leads to pesticide resistant pests. One possible solution is timely identification of pest infections so that, proper measures can be taken beforehand. Another solution to the same problem is to predict the amount of pesticides and chemical fertilizers to be used in the farms while keeping a harmony between its impacts on harvest quality and soil.

Next issue is to handle the weather conditions which are beyond our control. Solution is to predict the future climate conditions and needs of the crop. It can help the farmers in knowing about the exact time of crop plantation and cultivation. The required measure of water for growing a decent quality of crop can also be predicted as per the upcoming environmental conditions and the prerequisites of the crop. Correct usage of two important resources, water and electricity can be anticipated as per the farm needs.

RELATED WORK

Nevertheless, the problems of traditional farming can be reduced by mechanizing the whole process, improve the crop productivity, and reducing the consumption of input resources along with ensuring the sustainability of the natural resource and hence the sustainable agriculture. Sustainable agriculture is a farming technique of producing food, fiber, plant or animal products to satisfy the human needs while considering the environmental quality, public health and safety. The out product of this type of agriculture is a healthy food without trading off the resources available for our future generation.

Some problems of traditional farming can also be sorted out with the help of smart farming. From the farmer's perspective, Smart Farming provides better decision making or information management systems as a value-added resource using information and computation technologies. In this sense, smart farming is strongly related to three interconnected technologies:

- Management Information Systems (MIS): The MIS collects, stores, and processes the data and produces it in the more friendly and analytical way to the farmers to carry out different farming operations.
- Precision Agriculture: It provides Decision Support Systems (DSS) to the farmers that can help them in utilizing the resources in an optimized way and generate more return. At the same time, it reduces the environmental impacts also.
- Agricultural automation and robotics: The process of applying robotics, automatic control and artificial intelligence techniques and robotics can be applied to enhance the productivity of the farms and reduce the need for the human resource.

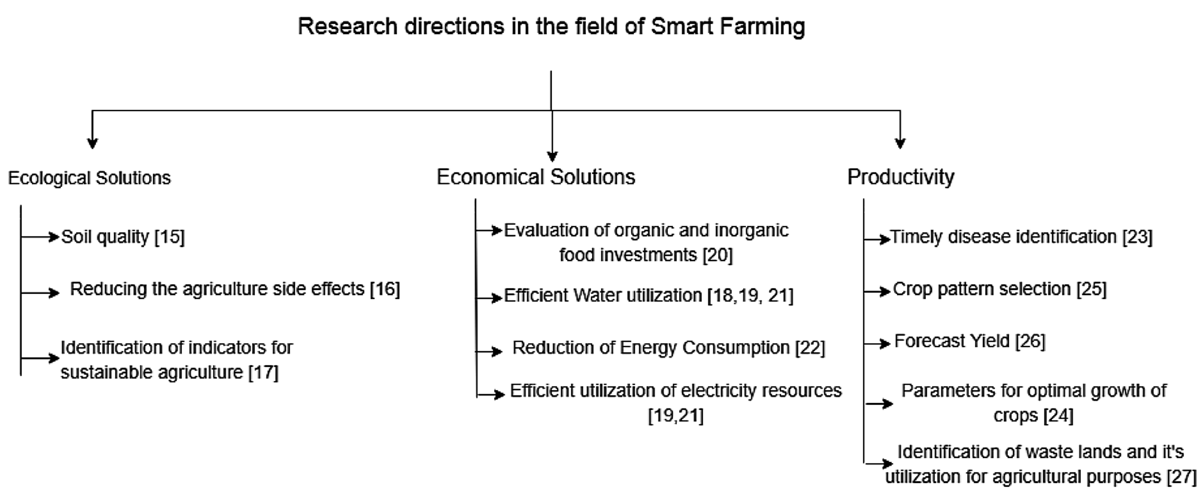
The smart farming can help the farmers in predicting the weather conditions, optimizing the input resources on analyzing the historical data. It can further help them in improving the quality and quantity of the crop while consuming minimal required resources. The benchmarks of agriculture can be achieved by employing various technologies like gathering and processing the data from sensors deployed in the field, applying image processing techniques to judge the quality of plant and crops, applying the computational intelligence techniques to improve the production. The data in the field of agriculture is mostly captured by sensors or taken approximately. This kind of vagueness and imprecision can better be handled using fuzzy logic technique. Recently, a number of researchers have proposed fuzzy logic based solutions to many agriculture related issues. Broadly, these fuzzy logic based solutions can be categorized into three classes as shown in Figure 1. This classification is done to achieve high productivity, reducing the investment cost or maintaining the sustainability goals. Further, each subsection details the researcher's solutions w.r.t achieve a particular goal.

Fuzzy Logic Based Ecological Solutions for Agricultural Related Problems

Rodriguez et al. designed an index to check the dynamic quality of agricultural soils. This index helps the framers to check the sustainability of agricultural soils. To decide the index, various attributes have been explored. To tackle the complex dependency of the soil on various attributes and imprecise value of these attributes, authors used fuzzy logic for designing of dynamic quality index.

The agriculture sector is one of the largest sectors for production of emission of gases. Fellman et al. have taken the European Union as a case study and depicted the impact of measures taken to reduce the gas emissions by agriculture on the production. To meet the needs of climate goals, reduction of agriculture emissions is necessary but on the other hand supply as per the demand cannot be compromised. Fellman et al. suggested that computational intelligence techniques can help us in achieving a balance among the quality and its side effects. On the similar footsteps, Torkashv et al. raised the issue that to handle the high demands of the growing population, the productivity of agriculture needs to be

Figure 1. Classification of literature



enhanced but not at the cost of polluting the environment. Torkashv et al. identified the 21 parameters for assessment of different sustainable agriculture practices. These indicators significance has been evaluated using Yager Fuzzy and the opinion of experts.

Fuzzy Logic Based Economical Exploration of Agriculture Domain

Water is an important resource for all, human being as well as for plants (Haque et. al, 2018). The crop yield gets affected by shortage of water supply but on the other hand, a large amount of water also affects the crop quality. So, a balanced amount of water is very important to reduce the water wastage and for better quality crop. Authors designed a fuzzy logic based automatic irrigation system for providing a balanced amount of water in the field as per the moisture level of soil and needs of the crop. In the similar direction, Cruz et al. showed the importance of smart farming for optimal distribution of water resources in agricultural land and electricity resource for water pump. They designed automated organic farming system using fuzzy logic which ensures the proper distribution of water resources in an agricultural land.

The associated low cost and a good amount of production are the few advantages of inorganic farming (Suder and Kahraman, 2018). However, the raised health issues associated with inorganic farming forces the people to explore organic farming. Suder and Kahraman applied the Fuzzy TOPSIS method to decide about the food investment by exploring the alternatives of organic and inorganic farming using twelve linguistic variables.

Aphale and Rajesh presented an idea of fuzzy logic controller which will help us in deciding the efficient use of water and electricity resources for tomato farming. They discussed the integration of sensor technology and fuzzy logic to improve the tomato crop quality. Ideal conditions for tomato farming have been analyzed by the authors. By seeing an unnatural behavior while processing the data gathered from the sensors, an alarm can be raised but still this idea has not been implemented and tested in real environments. Fuzzy based clustering of agricultural farms has been explored by Khoshnevisan et al. In Iran, energy consumption for wheat cultivation is very high. It produces a large amount of green house gas emissions. A fuzzy based clustering model has been developed for clustering of wheat farms on the basis of three features, gas emissions, energy usage, and benefit cost ratio.

Fuzzy Logic Based Solutions to Increase the Crop Productivity

Existing pieces of literature and experts' opinion emphasis that by maintaining the quantity and quality of food production, the need of the growing population can be handled easily. One of the main hindrances of food production is crop diseases (Rastogi, Arora, and Sharma, 2015). If there is timely identification of diseases in the crops, then solutions can be provided at an early stage and crop yield can be improved. Rastogi et al. proposed an idea of disease identification using artificial neural networks. They also discussed identifying the level of disease using Fuzzy Logic. This automatic work can save the farmer's time and cost. Early detection and grading of the disease can suggest the usage of the correct amount of pesticides which will improve the quality and quantity of crop yields.

A number of parameters affect the growth of crops, but all the parameters are not equally important. Here, authors (CIGR and Majunder, 1999) tried to prioritize the ordering of parameters for protected farming using Fuzzy logic. Protected farming is very helpful in urban areas where space is limited. It is an eco-friendly solution in comparison to open field farming. Authors suggested the ordering of twelve parameters like water quality, availability of moisture and nutrients, temperature, air freshness, air circulation and others for optimal growth of crops in protected farms.

In Quershi, Singh, and Hasan, 2018, the impact of crop pattern selection for sustainable agriculture practices in India has been discussed. Qureshi et al. discussed a variety of criteria's to be considered to achieve social, economic and ecological aspects of sustainable agriculture. Deciding an optimal crop pattern is not easy as it depends on many factors including the place. Authors developed a framework for the selection of Ravi season crop pattern using fuzzy multi-criteria decision-making model. Twelve criteria have been identified for eight Ravi season crops and a preference order for crop pattern has been provided using fuzzy TOPSIS.

A fuzzy-based time series algorithm has been proposed to forecast wheat yield (Garg, Sah, Aggarwal, 2018). The proposed method has been tested on the wheat production dataset. For the training purposes, the neural network has been used. Faridi et al. described the identification of waste lands in Jodhpur district in Rajasthan using GIS and spatial data mining techniques. Authors suggested with the help of fuzzy logic, these wastelands can be utilized as agricultural land on the basis of its soil quality and underneath groundwater.

Industry Based Solutions

Industries have also started working towards improvement in agricultural practices by different means. Ukko Agro is a US-based firm founded in 2017. Its aim is to provide IOT based solution for prescriptive disease/pest management models and input resource optimization. At the same time, it meets sustainability standards for CPGs. Xavier, digital farming solution ("Xarvio", n.d.) is another upcoming company providing digital solutions to an agricultural domain. It allows early disease detection, disease recognition, nitrogen recommendation etc. Moreover, it allows managing all the schedules online.

From the above literature, it can be seen that researchers are trying hard to achieve the benchmarks of the agriculture domain. They have applied the fuzzy logic in a variety of agricultural issues starting from the root level and till production level. Agreeable solutions have been provided for different kinds of problems such as finding the suitability of soil quality, advising the use of natural resources by keeping in mind the goal of sustainability, estimating the crop production, etc. It has been observed that they achieved promising results because fuzzy logic is the best tool to deal with ambiguity and uncertainty. To solve our problem, we employed to use Fuzzy Logic. The following section explains about the Fuzzy Logic.

FUZZY LOGIC AS A TOOL

Most of the data which is used for decision making in the field of agriculture by the farmers is imprecise and ambiguous. Fuzzy logic (Ross, 2016) is the best suited problem solving approach to handle this kind of data. Its decision making techniques resembles with the human decision making capabilities. At the same time, it is easy to understand and use to model any real time problem.

The traditional crisp logic is always either true or false. However, Fuzzy Logic talks about degree of truthfulness. For example, if a criterion to decide the high production (in quintal) is 1000 and if some farmer produces 999, then in case of crisp logic, it will not be considered as high production. However, in case of fuzzy logic, it will be considered as high production with some degree.

Fuzzy logic is a problem solving techniques based on "degree of truthfulness" unlike traditional crisp logic. The degree of truthfulness is indicated by a number in the range from 0 to 1. This value is known as truth value or degree of membership. Here 1.0 represents absolute truth and 0.0 represents absolute falseness.

Let U be the universe of discourse and A˜ be a fuzzy set. Mathematically, the fuzzy set, A˜, can be represented as

$$A^{\sim} = \{ (y, \mu_{A^{\sim}}(y)) \mid y \in U \}$$

Here $\mu_{A^{\sim}}(y)$ is degree of membership of y in the fuzzy set A˜ such that $\mu_{A^{\sim}}(y) \in [0, 1]$.The degree of membership is best represented with the help of membership functions. Different shaped membership functions such as Triangular, Trapezoidal, Gaussian depending upon the problem can be drawn. Figure 2 shows an example of Triangular membership function.

In fuzzy computing, there are broadly three steps: Fuzzification, Inference and Defuzzification as shown in Figure 3. Each one is elaborated as follows.

Fuzzification: It is a process of transforming a crisp set to a fuzzy set. Basically, it defines the crisp values using linguistic term. For example: 1100 quintal crop production will be represented as high production. At this stage, fuzzy sets are decided and membership function is designed for each fuzzy set.

Figure 2. Triangular membership function

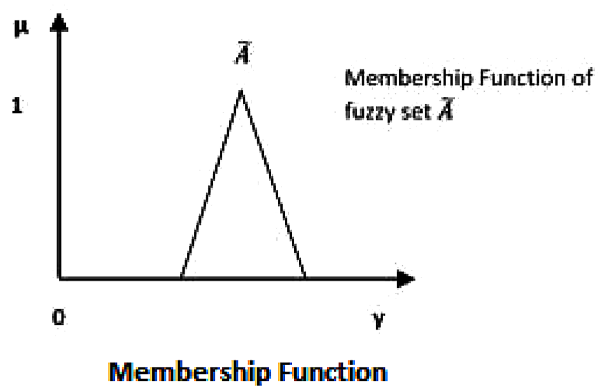
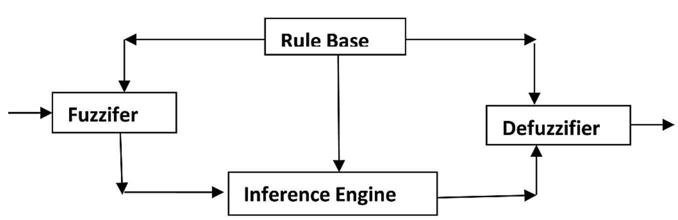


Figure 3. Architecture of fuzzy logic



Defuzzification: It is a process of converting back the fuzzy set into a crisp set. A number of methods exist for defuzzification such as weighted sum, centroid, centre of sum, first of maxima, last of maxima, etc. Centroid defuzzification method is mostly used by the researcher's community, so, we are also going to use centroid defuzzification method here. It is defined as follows

Centroid Method is also known as the centre of area or the centre of gravity method. Mathematically, the defuzzified output x will be represented as −

$$x = \int \mu_{A^{\sim}}(x).x dx \,/ \int \mu_{A^{\sim}}(x).dx$$

Rule Base: Rules are the human known facts that a human being use to make decisions. The syntax of fuzzy logic rule base is similar to the way human makes rule in terms of if-then statement.

IF antecedent THEN consequent

The expression as stated above is referred as the Fuzzy IF-THEN rule base.

Fuzzy Inference System (FIS): Once membership functions and rules have been defined, next step is to make the inference for the given input. This process is known as fuzzy inferencing and the whole system is known as Fuzzy Inference System (FIS).Following are the two important methods of FIS:

- Mamdani Fuzzy Inference System
- Takagi-Sugeno Fuzzy Model (TS Method)

Here, we are going to use *Mamdani Fuzzy Inference System,* so it is explained as follows:

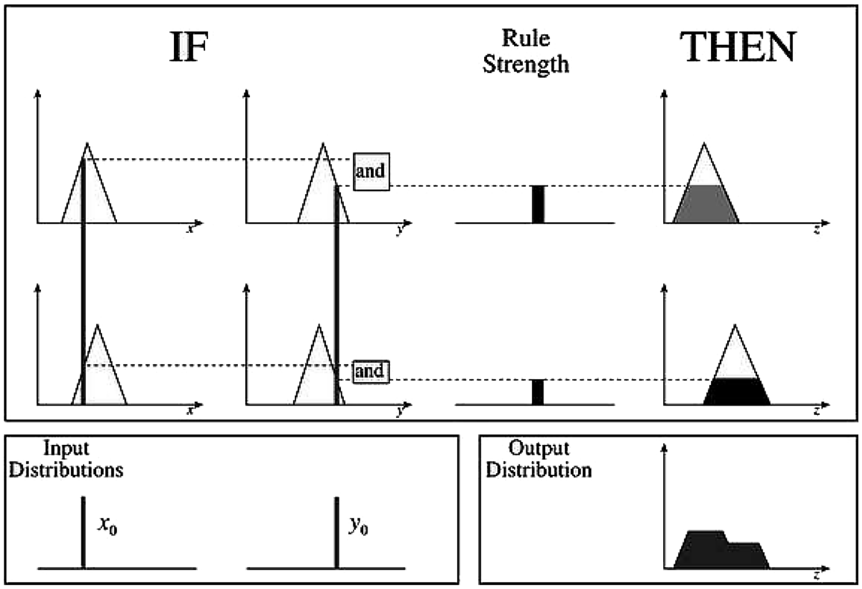
Mamdani Fuzzy Inference System: It was proposed by Ebhasim Mamdani in 1975. This inference system is closer to the way human makes decision. The complete inferencing procedure is shown below in figure 4.

PROPOSED WORK

As discussed in section 3, Fuzzy logic can be used to provide a solution to a number of problems related to agriculture domain such as crop production prediction, disease diagnosis, resource management (Chen and Chen, 1994). Here, we propose a prototype model, AgriHelp, for selection of appropriate crop in a region, in a season. The main intent of the model is to provide help to small farmers which are the most affected section of farmers by any natural unpredictability.

AgriHelp takes input as a text message. It looks for only two inputs: when *(season)* and where *(region)* the farmer wants to sow the crop. The model uses the dataset and determines the type of soil in the given *region* ("MapsofIndia.com", n.d.). Using the value of variable *season,* the average rainfall and min-max temperature of the region in the specified season is determined with the help of ("India Government", n.d.). Now, these attributes namely, *soil_type, temp_min, temp_max* and *rainfall*, are used to suggest the best-suited crop to the farmer. Though, the crop production depends upon a number of factors, these four attributes are the major contributing one and hence, gives a good approximation. Moreover, the objective of the proposed model is to sow the crop that can survive with adverse weather conditions. Fuzzy

Figure 4. Mamdani inference process (adapted from ("TutorialsPoint.com", n.d.))

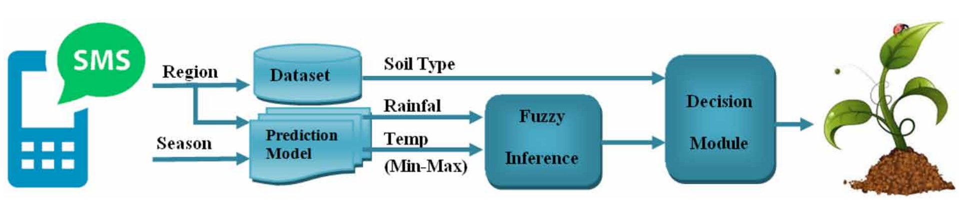


inference system (FIS) uses three variables (*temp_min, temp_max* and *rainfall)* to suggest the possible crops. The final crop is suggested after combining the result of FIS and *soil_type*. The suggestion given by AgriHelp ensures that the crop can survive the predicted weather and hence will reduce the loss to be bear by the farmer due to natural unpredictability.

The production of crop varies from region to region mainly because of variation in the soil type, temperature and rainfall. Moreover, most of the crops are seasonal crops. In India, there are many types of soil available. In the proposed model we have mainly considered four types of soil: Alluvial, Arid and Desert, Black (Regur Soil), and Loamy. Moreover, farmers classify the crops in four broad classes based upon the season: kahrif (July to September), rabi (October to February), summer (March to June) and whole year (January to December). In this article, we consider 6 crops as mentioned in Table 1.

The dataset ("India Government", n.d.) represents the crop production in the different districts of India for different crops in different season. The data includes the details since 1997 till 2014. The dataset provides the area wise Weighted Monthly, Seasonal and Annual Rainfall (in mm) since 1951. Monthly average minimum temperature and maximum temperature from 1901-2000 is given in dataset. The data is arranged district wise.

Figure 5. AgriHelp, the proposed model



AgriHelp: Fuzzy Modelling

The fuzzy modeling basically includes the following three steps:

1. Decide input and output linguistic variables.
2. Design fuzzy membership functions for each variable.
3. Define rules using variables.

This section provides the detailed discussion of these three steps.

Input attributes:

Taking two values (region and season) as input from the user, four attributes are determined using ("India Government Data", n.d.). Out of these four attributes, three attributes (*temp_min, temp_max and rainfall*) are used for FIS and hence fuzzified. The fourth attribute (*soil_type*) is used along with the output of FIS to make the final decision. A detailed explanation of values for these variables is presented next ("India Government", n.d.):

1. *temp_min*: This attribute represents the average minimum temperature of a region in a season in ºC. It is observed that it varies from -12 ºC to 26 ºC. This attribute is represented using three fuzzy sets: low, medium and high. For modelling, it is normalized on the scale of 0 to 38
2. *temp_max*: This attribute represents the average maximum temperature of a region in a season in ºC. It is observed that it ranges from 5 ºC to 40 ºC. This attribute is represented using three fuzzy sets: low, medium and high. For modelling, it is normalized on the scale of 0 to 35.
3. *rainfall*: This attribute represents the average rainfall in a region in a season in millimeter. It is observed that it varies from 2 mm to 1356 mm. This attribute is represented using three fuzzy sets: low, medium and high. For modelling, it is normalized on the scale of 0 to 100.
4. *soil_type:* This attribute represents the type of the soil of a region. It can have values Alluvial, Arid and Desert, Black (Regur Soil), and Loamy. It is used at the end along with FIS output to make the final decision.

Output attributes:

Since we have considered six crops, we have six output variables named as *crop_1, crop_2 …. crop_6*. Each variable represents a crop as shown in Table 1. Given the input parameters (*temp_min, temp_max and rainfall*), each variable represents the expected production of the crop in terms of fuzzy sets: *low, medium* and *high* using FIS.

The summary of input and output attributes is given in Table 2. For instance, input variable *temp_min* has a value range 0-38 and it is represented using three fuzzy sets namely: *low, medium* and *high*. The fuzzy set low and high have trapezoidal shape of membership function with interval points as (0, 0, 9, 19) and (19, 29, 38, 38) respectively. Medium fuzzy set has triangular membership function with interval points as (9, 19, 29).

Table 1. Crop and variable name mapping

Crop	Crop type	Variable Name
Rice	Kharif	crop_1
Bajra	Kharif	crop_2
Wheat	Rabi	crop_3
Barley	Rabi	crop_4
Maize	Kharif	crop_5
Sesamum	Summer	crop_6

Table 2. System variables, associated linguistic terms and Interval points

Variables	Variable type	Linguistic Terms	Interval end points	
			Scale	Ponits
temp_min	Input to FIS	low	(0-38)	(0, 0, 9, 19)
		medium		(9, 19, 29)
		high		(19, 29, 38, 38)
temp_max	Input to FIS	low	(0-35)	(0, 0, 8, 17)
		medium		(8, 17, 26)
		high		(17, 26, 35, 35)
Rainfall	Input to FIS	low	(0-100)	(0, 0, 20, 50)
		medium		(20, 50, 80)
		high		(50, 80, 100, 100)
crop_1 to crop_10	Output of FIS Input to Decision Module	low	(0-100)	(0, 0, 20, 50)
		medium		(20, 50, 80)
		high		(50, 80, 100, 100)
soil_type	Input to Decision Module	-	-	-
crop_list	Output to Decision Module	-	-	-

Fuzzy Rule

A comprehensive set of 36 fuzzy rules are defined to decide the values of ten output variables. These rules (Table 3) consider the entire realm of possible combinations for the input variables.

RESULT ENSEMBLING

Now we have expected productivity of each crop as output of FIS. Also, based upon the region, we know the *soil_type* and hence the possible crops that can be sown in the specified soil type. Next step is to put together the values of both parameters and conclude the best suited crop for the specified region and season.

Table 3. Proposed fuzzy rules

Expected Production	Rainfall	Temp_ max	Temp_ min
Crop_1 (Rice Kharif)			
H	M	L	L
H	L	H	H
M	L	M	M
L	H	-	-
L	M	-	-
Crop_2 (Bajra Kharif)			
H	L	H	H
H	L	M	M
M	L	H	H
L	H	-	-
L	M	-	-
L	L	L	M
L	L	M	H
Crop_3 (Wheat Rabi)			
H	L	M	M
M	L	M	H
M	L	H	M
M	L	H	H
L	M	-	-
L	H	-	-

continues in following column

Table 3. Continued

Expected Production	Rainfall	Temp_ max	Temp_ min
Crop_4 (Barley Rabi)			
H	L	M	M
M	L	M	H
M	L	L	M
L	L	L	L
L	M	-	-
L	H	-	-
Crop_5 (Maize_Kharif)			
H	M	M	H
H	H	M	H
H	M	L	M
M	H	M	M
M	L	H	H
L	L	H	M
L	L	M	M
Crop_6 (Sesamum_Summer)			
H	L	H	H
L	M	-	-
L	H	-	-
L	-	L	-
L	-	-	L

For example,

```
Let soil_type = "XYZ" and hence, the crops that can be sown in this kind of
soil are,
crop_list = {CROP_1, CROP_2, CROP_3}.
Let the output of FIS is
crop_i = {CROP_1 is X1, CROP_2 is X2, CROP_3 is X3, CROP_4 is X4, CROP_5 is
X5, CROP_6 is X6}
Since, with the given soil type only crops CROP_1, CROP_2 and CROP_3 are pos-
sible, so other will be discarded from the FIS output. Now,
crop_i' = {CROP_1 is X1, CROP_2 is X2, CROP_3 is X3}
Now in this subset, let X2 > X1and X2 > X3, then, CROP_2 is the crop with
highest expected productivity. So, the output is crop CROP_2.
```

The model is implemented using fuzzy toolbox of OCTAVE. Mamdani inference engine along with centroid defuzzification method is used to generate the expected production of each crop. Later on, the obtained result is combined with fourth attribute (*soil_type*) to suggest the best crop to the farmer.

DISCUSSION

The behaviour of three attributes namely rainfall, max temperature and min temperature with respect to productivity of six crops is observed with the help of graphs as shown in Figure 6-8. As mentioned in the previous section, first, the value of these attributes is normalised. The y-axis represents the average productivity. In Figure 6, the x-axis represents the range of normalised values with a gap of 10 points. For instance, 1 to 10 represents the average of normalised values of rainfall. In Figure 7 and Figure 8, the x-axis represents the normalized values only.

A Table 4 shows excerpt of the sample cases for which best crop is determined using the location and season as input. For Instance, let the farmer wants to sow some seeds in the area of *Kurnool* district of *Andhra Pradesh* during *kharif* season. As per the prediction, the expected rain during July is 600 mm. the expected max and min temp at the same time is 34 ºC and 25 ºC. Upon normalization, the value comes out to be (44 29 37). The values are passed to designed FIS and the output comes out to be

```
crop_i = {CROP_1 is 33.219, CROP_2 is 33.716, CROP_3 is 26.907, CROP_4 is
19.889, CROP_5 is 50.000, CROP_6 is 33.219}
```

Figure 6. Rain vs productivity

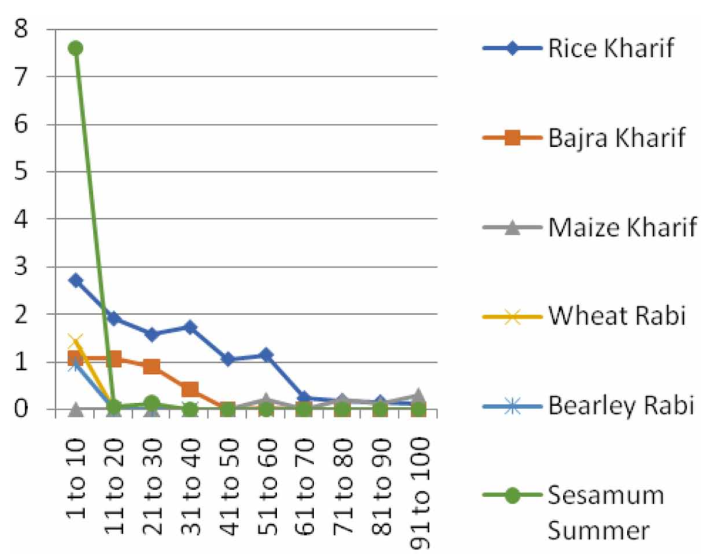


Figure 7. Maximum temperature vs productivity

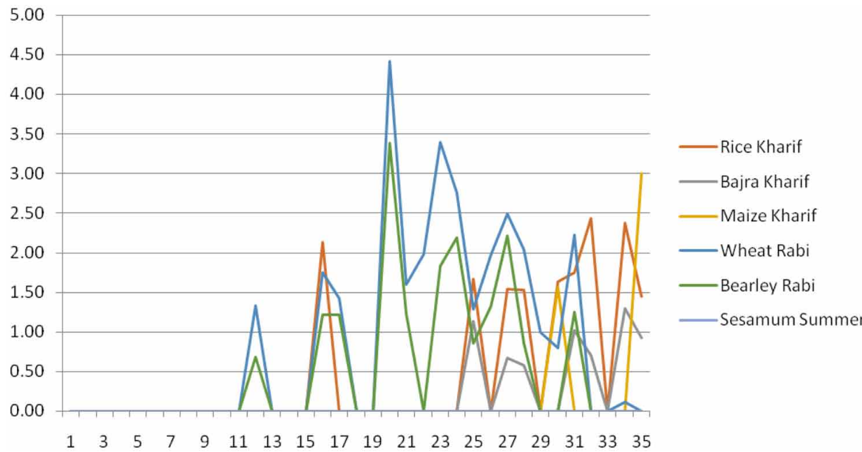
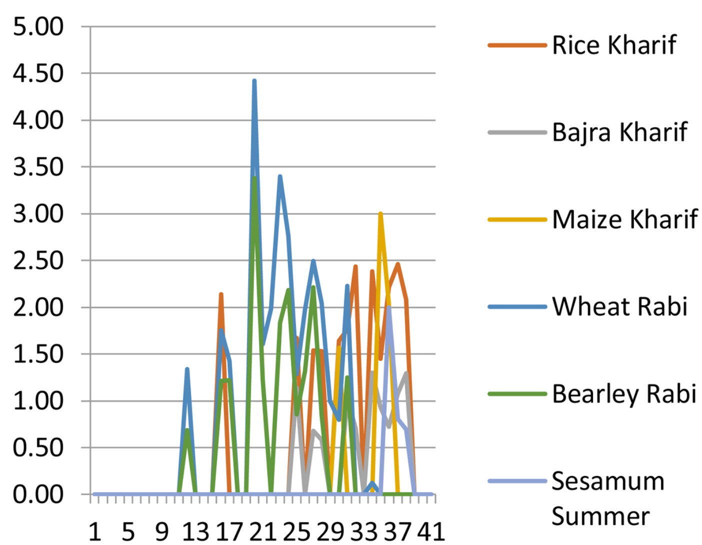


Figure 8. Minimum temperature vs productivity



The soil_type = "loamy" and hence, the crops that can be sown in this kind of soil in *Kurnool* district are,

```
crop_list = {CROP_5, CROP_6}
Applying the result ensembling and principal of maximum belongingness, the
CROP_5 is the best suited crop.
```

Table 4. Excerpts of the sample cases

	Input			Predicted Values				Output	
S No	District	State	Season	Rain	Max Temp	Min Temp	Soil Type	1st Priority	2nd Priority
1	Bhagalpur	Bihar	Kharif	185mm	34 C	27 C	Alluvial	Crop_1	Crop_6
2	Mahesana	Gujarat	Rabi	10mm	30 C	22 C	Arid And Desert	Crop_2	Crop_4
3	Dhule	Maharashtra	Kharif	120mm	30 C	23 C	Black (Regur Soil)	Crop_1	Crop_3
4	Fatehpur	Uttar Pradesh	Kharif	194mm	35 C	25 C	Alluvial	Crop_1	Crop_3
5	Kurnool	Andhra Pradesh	Kharif	600mm	34 C	25 C	Loamy	Crop_5	Crop_6

CONCLUSION

Agriculture is the heart of many developing countries. The traditional methods are not sufficient enough to produce a good amount of crop. Moreover, the natural calamities are also destroying a large portion of the crop. Hence, there is a high need for smart farming so that the farmer becomes aware of the future risk of weather and takes sufficient mitigation measures in advance. Fuzzy Logic is one of the tools that can provide a solution to most of the agriculture related problems. In this chapter, we proposed one prototype model to address an agricultural issue using fuzzy logic. The proposed model AgriHelp is developed with an aim to encapsulate this idea and extend help to small farmers. The model takes two parameters as input from the farmer, that is, when and where the farmer wants to sow the crop. Based upon this information AgriHelp suggests the best-suited crop to the farmer considering the expected min-max temperature, rainfall and soil_type in the region in the specified season.

FUTURE RESEARCH DIRECTIONS

In the proposed model, we have handcrafted the fuzzy rules after analyzing the available dataset. These rules can further be fine-tuned by using genetic algorithms along with fuzzy logic. In the genetic algorithm, each fuzzy rule can be considered as a chromosome. Then, a suitable fitness function can be designed for each crop. By applying appropriate crossover and mutation, the fine-tuned a set of fuzzy rules can be obtained.

Moreover, we have used four parameters to decide the best crop for a season in a region. This model can further be extended using many other parameters such as humidity, soil moisture, temperature at different phases of the life cycle of the crop and so.

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KEY TERMS AND DEFINITIONS

Agriculture: It involves the science and art in food cultivation and rearing animals.

Computational Intelligence: The term computational intelligence refers to applying the distinct techniques, mainly neural networks, fuzzy logic, evolutionary computation, and machine learning to systems so that their learning ability would be improved.

Crop: It is an animal product or plant product that is cultivated on a large scale for a livelihood and profit.

Defuzzification: This process is reverse of fuzzification which changes the fuzzified values back to quantified values in binary logic, after the complete processing is over.

Farming: It is a process of planting seeds, animals rearing, growing crops and plants to satisfy the consumptions of society.

Fuzzification: It is a process to convert inputted binary value into fuzzified value. Any vague or imprecise term which we speak in routine like happy, beautiful, good, etc. can be converted into a mathematical model using fuzzification.

Fuzzy Inference System: It is a framework which depicts the actual process of converting an input into an output using fuzzy logic. Fuzzification, defuzzification, membership function are the building blocks of fuzzy inference system.

Fuzzy Logic: Fuzzy logic is a computing approach based on multi-valued logic where the variable can take any real number between 0 and 1 as a value based on degree of truthness.

Fuzzy Membership Function: It is a way of representing degree of truthness in graphical form.

Fuzzy Rule: These are the rules of inference in fuzzy logic which decides the value of an output variable based on values of input variables.

GDP: The term which depicts the overall development rate and economic activity of a country.

Management Information System: Management information system gathers the data from multiple sources and utilizes this information to make the valuable decisions.

Organic Farming: It is a method of farming where the usage of natural substances as pesticides and fertilizers are emphasized in comparison to synthetic substances with an intend of growing the crops in ecofriendly environment.

Precision Agriculture: It is also known as satellite agriculture. All the pertinent information like water level, soil quality, air quality, temperature, etc. are gathered in real time. The modern technologies analyze this information and encourage the needed substances for better efficiency.

Protected Farming: The kind of farming with greenhouses where traditional farming is preposterous due to poor soil quality or water deficiency on a land.

Smart Farming: The use of present advancements and tools are emphasized to achieve the high quality and supplementary quantity production aim, is known as smart farming.

Sustainable: In simplest terms, sustainable means live the present but not at the expense of compromising the future. A sustainable solution for agriculture implies providing an economical, ecological, high productivity solution to the society.

Sustainable Agriculture: The agricultural practices whose aim is to fulfill the needs of present by keeping the future intact. Productivity should be high but by keeping the nature sound and quality flawless.

Time Series Algorithm: A set of algorithmic procedures that analyze the past information gathered at regular interims (time series data) and predicting the future.

Traditional Farming: The ancient way of agriculture which we practice since thousands of years is known as traditional farming.

Chapter 8
Adaptive Neuro-Fuzzy Inference System in Agriculture

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ABSTRACT

This chapter emphasizes the use of adaptive fuzzy inference system (ANFIS) in agriculture. An overview of the basic concepts of ANFIS is provided at the beginning, where the underlying architecture of ANFIS is also discussed. The introduction is followed by the second section which highlights the diverse applications of ANFIS in agriculture during recent times. The third section describes how Matlab software can be utilized to build the ANFIS model. The fourth section describes the case study of the application of ANFIS for crop yield prediction. The conclusion follows this case study.

INTRODUCTION

ANFIS represents a category of the artificial neural network (ANN) which was founded during the 1990s (Jyh-Shing and R. Jang, 1991). It can capture the strengths of ANN and principles of fuzzy logic into a single framework. The ANFIS possesses an inference system comprising of many fuzzy IF-THEN rules which can learn nonlinear functions (Jyh-Shing and Roger Jang, 1993) due to which ANFIS is called as a universal estimator. The genetic algorithm can be utilized to choose the optimal parameters of the ANFIS (Jyh-Shing et al., 1997).

Both fuzzy logic (FL) and neural networks are universal estimators as they can be utilized for function estimation up to some predefined accuracy, provided an adequate number of fuzzy rules and hidden neurons are available. In ANFIS, the gradient descent (GD) and back-propagation (BP) algorithms are utilized to tune the ANFIS parameters such as the membership functions (MF) and the neural network weights (defuzzification). Fuzzification and defuzzification are the two methods for updating the ANFIS parameters. The efficient integration of significant features of FL and ANN is the primary objective of

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ANFIS. The benefit of FL is that prior knowledge is signified as a set of constraints. Furthermore, the accuracy of ANFIS on test data may be improved if the number of its adjustable parameters is at least equal to the size of the training data (Shodhganga, 2018).

The two soft computing methodologies namely, fuzzy logic (FL) and ANN are combined to form ANFIS. FL can map the qualitative features of human knowledge and perceptions into accurate, quantifiable components. Nevertheless, it does not have a specific technique which could be utilized as a guide for transforming human knowledge into a rule-based fuzzy inference system (FIS). The tuning of membership functions (MFs) takes much time. However, it possesses a better capability to adjust to diverse environments during its learning process than ANN.

Consequently, the ANN could be utilized to automatically fine-tune the MFs and decrease the error rates for creating the fuzzy logic rules. Three critical components of FIS are the rule base that comprises of choosing fuzzy logic rules of the form "If-Then," a database that expresses the MFs to be used in fuzzy rules and reasoning mechanisms to provide the final inference. ANFIS uses hybrid training algorithm which is a grouping of back-propagation and least mean square methods. Its primary purpose is to reduce the error due to approximation. When FIS is trained, many iterations are employed which reduce the error. As the number of iteration increases, the error starts to decrease. In ANFIS, iterations are utilized to tune the weights for decreasing the errors (Suparta & Alhasa, 2016). The chief advantages of ANFIS are highlighted below:

- **To define the behavior of a complex system –** Complex systems such as crop yield prediction in agriculture, soil classification, the circuit design can be modeled adequately by ANFIS.
- **Improvement of fuzzy if-then rules –** The FIS can be improved using the ANFIS model as it adds membership functions to the rules.
- **No need for prior human expertise –** Human knowledge is not required for the initial development of the ANFIS model
- **Greater choice of MFs to use –** Different types of MFs like a trapezoid, triangular are available which offer diverse functions.
- **Fast convergence time-** The converging time of ANFIS to obtain the final solution is observed to be faster than other models.

BACKGROUND

The previous works for predicting the yields of various crops like rice, wheat using different prediction models are surveyed in this section. Table 1 reviews the recent developments done in the agricultural domain using ANFIS.

Most of the related works have not considered critical parameters like crop biomass, rainfall, extractable soil water esw and solar radiation for wheat yield prediction. In this work, we have considered these critical parameters and found that crop yield of wheat can be predicted more accurately by considering them. Further, we have combined the aspects of fuzzy logic and artificial neural networks using ANFIS and shown that it can be successfully applied to predict the yield of wheat.

Table 1. Year wise chronological developments in agricultural domain using ANFIS

Sl No	Research developments in chronological order
1.	Thakare & Baradkar, 2013 proposed a fuzzy system that predicts maximum yield from crops. This system is able to predict the crop name which can provide maximum yield. It is also able to find the particular soil type and climatic condition which is more suitable to the crop. 15 Soil parameters and 22 crops are considered here.
2.	The authors Joshi et al., 2013 proposed a Decision Support System (DSS) for predicting crop suitability. They have summarized fuzzy related aspects which can be incorporated in an online farmer assisting system. Various factors for crop selection have been considered by the authors while proposing the DSS. They observe that such a DSS would minimize losses due to fewer yields.
3.	Soto & Melin, 2013 proposed how Type 2 and 1 Fuzzy Integrators can be optimized using Genetic Algorithms. Their goal was to develop an ensemble approach for ANFIS models which could make the prediction error as minimal as possible.
4.	Rossana et al., 2013 proposed a Prediction Model Framework for Crop Yield Prediction. This study investigates the development of a crop prediction model framework that can pre-process and fuse raw input data from multiple sources, provide an accurate prediction of crop yield, identify significant variables that affect crop yield, and identify useful prediction policies using four climate-related variables, 13 agronomic variables, and variables on weather disturbance. Comparison experiments are performed to determine which data mining technique is used for each framework component.
5.	Buono & Mushthofa, 2012 implemented a Fuzzy Inference System which was able to increase the resilience of Rice Yield. The authors have considered two data sets: SOI data set from 1877 to 2011 and rainy season dataset from Indramaya District. They have observed a correlation value of 0.68 between rainy onset and its predicted value.
6.	Chaudhari & Khot, 2012 proposed ANFIS Based Model for maximizing the profit of rice using Multi-Objective Linear Programming Problem by optimization method. Labor wages, Machinery Cost, Fertilizer_manure_Cost and Seed_Cost were considered as input variables and the profit through produced yield is the output for maximizing the profit.
7.	Qaddom & Hines, 2011 proposed Adaptive Neuro-Fuzzy Modeling for Crop Yield Prediction. The authors have predicted tomato yield using neural networks by considering various environmental variables. The forecasting accuracy is calculated by averaging it over all the years for which prediction is considered.
8.	Srinivasan & Malliga. 2010 proposed a new ANFIS approach which is able to efficiently predict the yield of Crop in the supply chain of Jatropa.
9.	Vizhakat, 2003 proposed an Expert Fuzzy Model which could predict Avalanche. The authors attempted to develop a more straightforward and better technique for Avalanche prediction using an algorithm based on Fuzzy Logic.

ANFIS ARCHITECTURE

The ANFIS architecture is based on the concept of adaptive network and FIS. This section starts with a brief introduction to adaptive networks and FIS before moving onto the actual architecture of ANFIS.

Adaptive networks are one type of feedforward neural networks having multiple layers. They make use of a supervised learning algorithm to learn. It contains adaptive nodes which are directly connected without possessing any weight values between them. The gradient descent or back propagation algorithm are used as learning algorithms in adaptive networks. Figure 1 depicts an adaptive network with 2 inputs (x1 and x2) and 2 outputs (y1 and y2).

A FIS comprises 3 principal components, viz. fuzzification of inputs, decision making and defuzzification as illustrated in Figure.2.

In FIS, the inputs containing the actual values are subject to fuzzification where they are converted into fuzzy values in the range of 0 and 1. The knowledge base holds the database and rule-base. The database comprises of information on the fuzzy sets. The defuzzification procedure involves the transformation of the fuzzy values into actual outputs. The Takagi-Sugeno, Mamdani, and Tsukamoto are some of the FIS models available out of which Takagi-Sugeno model is broadly utilized in ANFIS.

Figure 1. Adaptive network (W. Suparta, & K.M Alhasa, 2016)

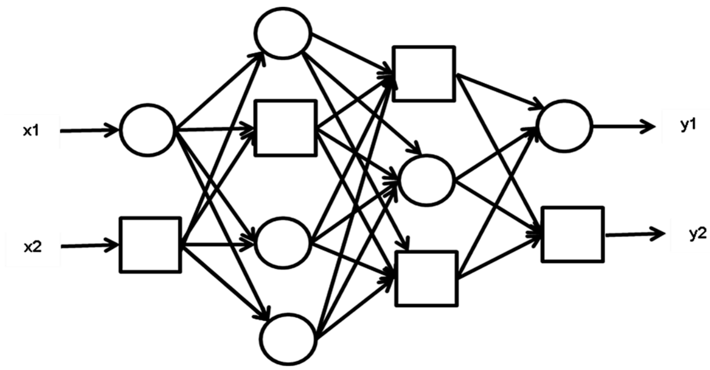
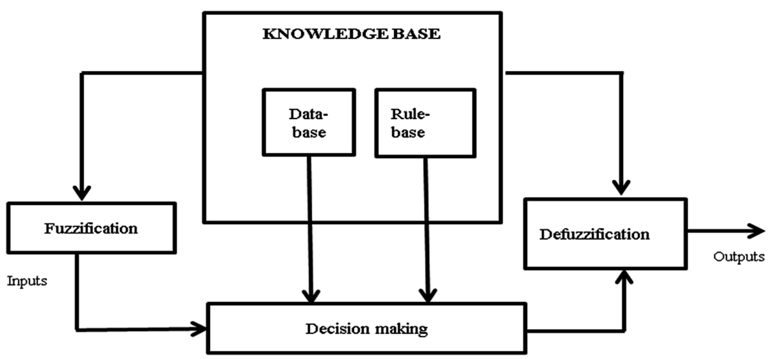


Figure 2. FIS (W. Suparta, & K.M Alhasa, 2016)



As mentioned before, ANFIS architecture is based on the concepts of adaptive network and FIS. Figure 3, describes the ANFIS model based on Takagi-Sugeno FIS. In the Figure, 2 inputs 'x' and 'y' with one output 'o' are present. The two "If-Then" rules used in the model are as follows:

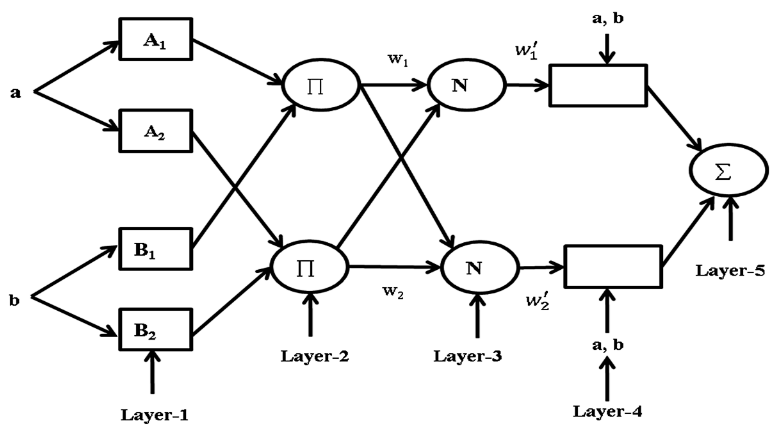
Rule 1 = If x is X1 and y is Y1 Then o1 = l1x+ m1x + n1
Rule 2 = If x is X2 and y is Y2 Then o2 = l2y + m2y + n2

Where:

- X1, X2, and Y1, Y2 denote the membership functions of each input x and y (part of the premises)
- l1, m1, n1 and l2, m2, n2 represent the linear parameters of the consequent part (Then) of Takagi–Sugeno FIS model.

According to Figure 3, ANFIS architecture has five layers. Adaptive node is present in the 1st and 4th layers. The remaining layers consist of fixed nodes.

Figure 3. ANFIS architecture (W. Suparta, and K.M Alhasa, 2016)



The layers of ANFIS are discussed below:

Layer-1: This layer can adjust according to a function parameter. The node output represents a membership degree which is provided by the input given to the MF.

Layer 2: Each node of this layer is fixed or non-adaptive. The output is obtained by multiplying the input of each node which is propagated to the subsequent node. Every node of this layer is responsible for strengthening each rule.

Layer 3: Each node of this layer is fixed and is non-adaptive. The label given to the circled node is 'N'. Every node is the ratio between the firing strength of i-th rules and the sum of firing strengths of all rules. This output (O_{3i}) is called as the normalized firing strength as demonstrated in equation-1.

$$O_{3i=}Nw_i = \frac{w_i}{\sum_i w_i} \tag{1}$$

Layer 4: It comprises of adaptive nodes connected to the final output. The node function is defined as shown in equation (2)

$$O_{4i} = Nw_i f_i = Nw_i \left(p_i a + q_i b + r_i\right) \tag{2}$$

where:

- Nwi represents the normalized firing strength from the 3rd layer
- pix+qiy+ri denotes the node parameter.

Each parameter in this layer is known as consequent parameters.

Layer 5: It is responsible for computing the final output which is the summation of all the incoming inputs from the previous node. This layer contains fixed or nonadaptive nodes. The final output of ANFIS (O5i) is represented in equation (3) below:

$$O_{5i} = \sum_i N w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{3}$$

APPLICATIONS OF ANFIS IN AGRICULTURE

This section describes, in brief, the different applications of ANFIS in agriculture. The main application of ANFIS in agriculture was found to be crop yield prediction. The crop yield forecasting involves the prediction of the yield of crops concerning various parameters of soil and weather.

In (Menaka K, & N Yuvaraj, 2017), ANFIS was utilized to forecast the yield of crops. They considered input parameters such as soil attributes, rainfall, and temperature for predicting the yields of wheat, rice, and maize of India. The soil attributes considered were power of Hydrogen (pH), soil nutrients, soil type, and organic matter. In the case of rainfall, they considered minimum, optimum and maximum rainfall in millimeters (mm). With regards to temperature, they considered the minimum, optimum and maximum temperatures in degree centigrade. With respect to nutrients, they considered Macronutrients such as Nitrogen (N), Potassium (K), Calcium (Ca), Manganese (Mg), Phosphorous (P) and Sulphur. The micronutrients considered were Copper (Cu), Iron (Fe), Boron (B), Manganese (Mn), Zinc (Zn), and Copper (Cu). All nutrient parameters were considered in low, sufficient and high levels.

The model presented the ANFIS system (Benyamin Khoshnevisan et. al., 2014) for the prediction of wheat yield. The energy input values were utilized by the system to generate outputs centered on fuzzy sets. The input parameters considered for prediction were N, Phosphorous Oxide, Potassium Oxide, Labour, Diesel, Electricity, Seeds, Biocides, Water, and Machinery. The creation of fuzzy rules was used with suitable membership function to predict the wheat yield more effectively. The ANFIS demonstrates linearity for certain parameters. The authors observed, improved results were obtained as the input number for every ANFIS model decreased and the number of ANFIS models increased. The best architecture included five networks at the first stage, two networks at the second stage and one network at the final stage.

In (Pankaj Kumar, 2012), the authors have predicted rice yield in Uttarakhand, India. For rice yield prediction, they considered weekly average of temperature (T), weekly average of relative humidity (Rh%), weekly average of sunshine hrs (S), weekly average of total rainfall (P), number of days of rainfall on a weekly average basis (n), and weekly average of pan evaporation (E) as input parameters. They considered 27 years of rice yield data from 1981 to 2008. The root mean square error (RMSE) was used to evaluate the ANFIS model. This work demonstrated that the least value of RMSE was achieved for the ANFIS model with 2 inputs viz. average weekly temperature and pan evaporation data for the rice crop during Kharif season (May 21st to Oct 22nd). The ANFIS model performed better for the trapezoidal MF when compared to other MFs such as bell-shaped, Gaussian, and Triangular MFs. The number of epochs was set to 30.

In (S. P. Srinivasan, & P. Malliga, 2010), authors performed prediction of Jatropha yield using ANFIS model. They considered six input parameters namely irrigation, acidity, temperature, altitude, rainfall, and fertilizer. They developed a graphical user interface (GUI) using Matlab and integrating ANFIS variables. Using single attribute, six ANFIS models were built. For two input attributes, 15 ANFIS models were implemented. For 3 input attributes, 20 ANFIS models were built. All the ANFIS models were analyzed using RMSE. The model possessing the lowest RMSE was got for the input attributes temperature, rainfall, and irrigation. The authors observed that the temperature, rainfall, and irrigation were the primary factors impacting the jatropha yield.

In (D. Stathakis, I. Savin, & T.Negre, 2006), authors predicted the wheat yield using ANFIS model. They considered input parameters such as moisture content of the soil, biomass above ground level, storage organs biomass and normalized difference vegetation index (NDVI). The regions considered were Rostov, Krasnodar, and Stavropol of Russia. Data was considered between the years 1999 and 2004. Authors determined the ANFIS architecture by preliminary testing. They found that better performance was found for ANFIS with triangular membership function.

Khashei et.al. (A. Khashei-Suiki, M. Kouchkzadeh, & B. Ghahraman, 2011), predicted dryland wheat yield in Iran using ANFIS model. The study area was located in Iran. They considered input parameters like Evapotranspiration, temperature (max, min, and dew temperature), precipitation, net radiation, and 22 years average of day-wise relative humidity collected from 9 weather stations. They compared the ANFIS model with multilayer perceptron (MLP) model and found that ANFIS performed consistently with lower RMSE values. The yield was increased by increasing rainfall, which indicated the significance of water in the arid climate. Further, the increase of yield with decreasing temperature was due to avoiding thermal stress under inadequate moisture.

The authors Chaudari et.al (Chaudhari et al., 2012), developed an ANFIS model to enhance the farm cultivation profit. Authors claim that using the ANFIS model, farmers can decide on the expenditure incurred during cultivation of the farm. This facilitates the farmers to obtain maximum yield and in turn, obtain a reasonable profit. Farmers can choose the right quantity of inputs required for cultivation; decide on the purchase quantity and expenses in advance. The authors considered labour_wages, machinery_cost, fertilizer_manure_cost and seed_cost as input parameters. The profit through the produced yield was considered as the output. The data was taken for 13 years.

USING MATLAB TO BUILD ANFIS MODEL

In this section, the discussion of how to develop a simple ANFIS model in Matlab is done. A brief introduction of Matlab is provided and the development of the ANFIS model in Matlab software is described.

Matlab represents a programming language for matrices and is used for linear algebra. Mathworks from USA has developed it. It is used in performing interactive sessions along with the batch job. The full form of Matlab is MATrix LABoratory. It is extensively utilized in applied mathematics, education, research, and industry. Its main components are vectors and matrices. It is a useful tool for solving algebraic differential equations along with numerical integration. Matlab is rich in graphics and can plot sophisticated graphs. Matlab also has specific toolboxes beneficial for the signal as well as image processing, along with optimization techniques (Matlab, 2013).

In Matlab, the ANFIS model can be developed using some simple steps. Table 2 provides the syntax of Matlab commands for ANFIS construction along with their descriptions:

Table 2. Matlab commands for ANFIS construction

Command Syntax	Description
fis = anfis(trainingData)	This command constructs a single output Sugeno FIS. The ANFIS parameters are adjusted based on the training data specified. The FIS object is created utilizing the concept of grid partitioning. The hybrid of BP-GD and least squared algorithms are used to train the ANFIS model.
fis = anfis(trainingData,options)	This command also creates an ANFIS model as above, but additional options can be specified. The following can be specified utilizing this syntax: ● Initial FIS object which needs to be tuned ● To prevent over-fitting, data for validation purpose may be specified. ● Options for training algorithm ● Option on whether or not to display the progress of training.
[fis,trainError] = anfis(___)	This command returns the RMSE value, for each iteration of the training cycle. This value gets stored in the trainError variable.
[fis,trainError,stepSize] = anfis(___)	This command is used to obtain the step size at each training iteration.
[fis,trainError,stepSize,chkFIS,chkError] = anfis(trainingData,options)	This command returns the error on the validation data for each training iteration along with the tuned FIS object.

Following are the steps used to develop an ANFIS model in Matlab Software: (Anfis-Matlab, 2018)

Step-1: As an initial step, the training data needs to be loaded. This data is required to train the ANFIS model. For this purpose, Matlab already has data with single input and output called fuzex1trnData.dat. This data can be loaded into the Matlab workspace using the following command:

```
load fuzex1trnData.data
```

Step-2: The 2nd step is to create and train the FIS. The default FIS structure is constructed utilizing a grid partition with 2 MFs. The command used to create and trains the FIS model in Matlab is shown below.

```
fis = anfis(fuzex1trnData);
        In case, a mismatch occurs between the ANFIS and training data; then
the match may be improved by performing the following steps:
```

- The number of MFs may be increased to four which facilitates the addition of fuzzy rules and adjustable parameters to the ANFIS system.
- The number of training iterations may be increased using the following command:

```
opt = anfisOptions('InitialFIS',4,'EpochNumber',40);
```

Step-3: The final step is to test the trained ANFIS model to evaluate its accuracy. For this purpose, the test data has to be loaded. In this case, Matlab has provided a test data fuzex1chkData.dat corresponding to the training data fuzex1trnData. This test data is loaded into Matlab workspace using the following command:

```
load fuzex1chkData.dat
```

Correspondingly, we can provide additional training options using the commands shown below:

- 5 input MFs with 40 training epochs may be provided using the command:

```
opt=anfisOptions('InitialFIS',5,'EpochNumber',40);
```

- The training progress display may be suppressed using the following commands

```
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

- The validation data can be added to the training options using the following syntax:

```
opt.ValidationData = fuzex1chkData;
```

- The FIS is trained and the validation results are returned using the following command:

```
[fis,trainError,stepSize,chkFIS,chkError] = anfis(fuzex1trnData,opt);
```

Here, variables trainError and chkError are arrays containing one error value for each training epoch.

CASE STUDY 1: APPLYING ANFIS TO PREDICT WHEAT CROP YIELD IN KARNATAKA, INDIA

In this section, the development of ANFIS model for crop yield prediction is discussed. Specifically, the forecast of wheat yield using ANFIS in the Indian scenario is considered. The task was to predict the wheat yield based on soil, fertilizer and weather parameters. A detailed discussion about the experiments carried out is provided below (Shastry et al., 2015). The wheat dataset was collected from 27 districts of Karnataka, India between the years 1950 and 2017. It consisted of 1809 records with 16 input attributes described in Table 3:

The input attributes x1, x2, and x3 denote fertilizer data while x15 and x16 denote crop data which were obtained from India Statistics (IndiaStats, 2015). Attributes x4, x5 and x6 represent weather data collected from Indian meteorological department (IMD) (IndiaWaterPortal, 2013). The attributes from x7 to x14 denoting soil data were collected from National Bureau of Soil Survey and Land Use Planning (NBSS, 2013) and International Crops Research Institute for the Semi-Arid Tropics (Wani et al. 2011). These data from various sources were integrated into a database. The output attribute is the crop yield to be predicted.

Figure 4 depicts the general flowchart for predicting crop yield using ANFIS model.

The ANFIS modeling involved 5 steps which is elaborated below:

Table 3. Dataset features

Features	Description
x1	Amount of Nitrogen applied in fertilizer (N)
x2	Amount of Phosphorous applied in fertilizer (P2O5)
x3	Amount of Potassium applied in fertilizer (K2O)
x4	Average Rainfall
x5	Average temperature
x6	Amount of precipitation
x7	pH value of soil (pH)
x8	Electrical conductivity of soil in dS/m(EC)
x9	Organic carbon content of soil in percentage (OC)
x10	Available phosporous content in soil in ppm (AvP)
x11	Available potassium content in soil in ppm (AvK)
x12	Available sulphur content in soil in ppm (AvS)
x13	Available zinc content in soil in ppm (AvZn)
x14	Available boron content in soil in ppm (AvB)
x15	Area in hectares (A)
x16	Production in tones (P)

Step-1: Fuzzification of inputs: The first step was the fuzzification of inputs using various membership functions like generalized bell function (gbellmf), triangular (trimf), trapezoidal (trapmf), Gaussian (gaussmf), and sigmoid (sigmf) functions. In this work, the triangular membership function gave better results.

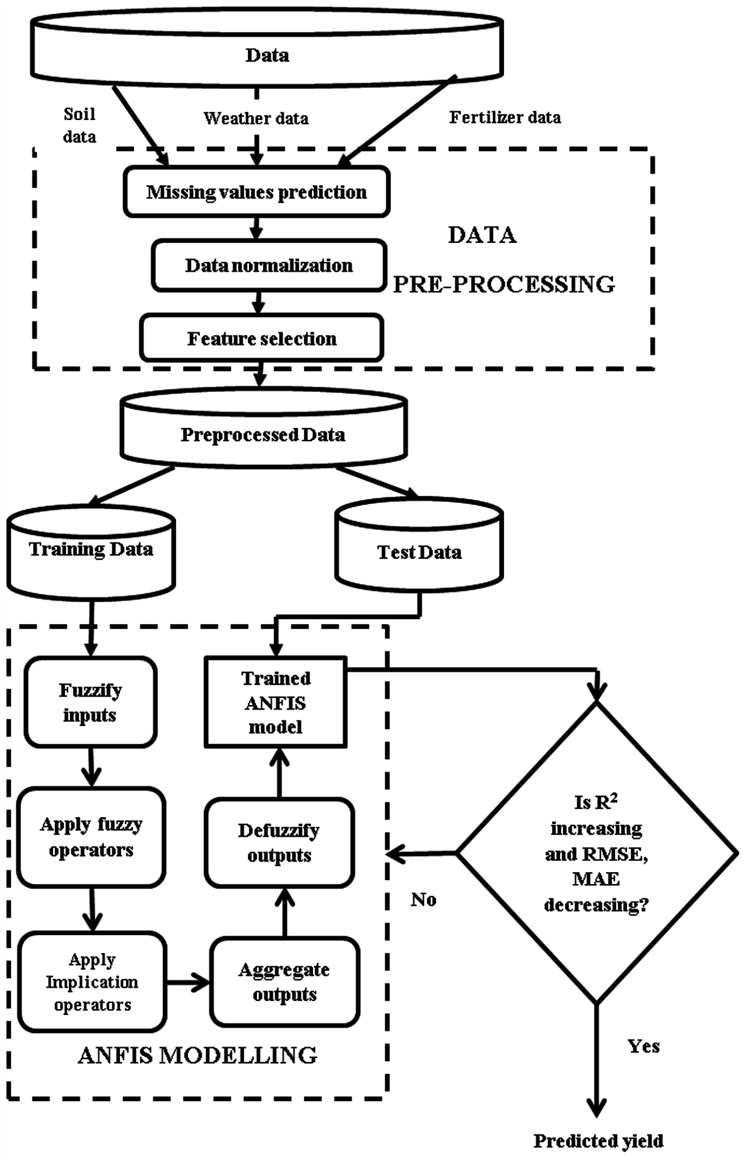
Step-2: Application of Fuzzy operators: Based on the fuzzified inputs, the degree to which every antecedent part of the rule belongs to is identified. We tested with the different AND methods min (minimum) and prod (product) along with the two OR methods namely max (maximum), and probabilistic OR method (probor). The probabilistic OR method (also known as the algebraic sum) is calculated according to the equation (4):

$$probor\left(a,b\right) = a + b - ab$$

In this work, the fuzzy operator probor gave better results.

Step-3: Application of implication operators: After allocation of appropriate weighting to every rule, the implication technique is employed. The membership function characterizes the consequent of the rule, which weights suitably the linguistic features that are credited to it. The consequent is modified using a function related to the antecedent which is a single number. The antecedent provides a single number which will be the input for the implication process, and the output will be

Figure 4. Crop yield prediction using ANFIS (Shastry et al., 2015)



a fuzzy set. The implication is executed for each rule. In this work, AND method: prod (product) and min (minimum) are used. The AND method prunes the output which is a fuzzy set, while the prod method scales the output. A better result was achieved for prod as the implication operator.

Step-4: Aggregate outputs: In this step, the rule outputs which represent different fuzzy sets are integrated to form a single fuzzy set. The outputs from the implication process become the inputs to the aggregation process. We made use of three aggregation operators namely sum (sum of the rule output sets), max (maximum) and probor (probabilistic OR). In this work, the probor as aggregation operator provided better results.

Step-5: Defuzzification of outputs: The output of the aggregation process which is a fuzzy set act as input to this process. The main goal of this process is to obtain a single-valued output from the different ranges obtained during the aggregation step. We made use of 5 defuzzification methods namely: centroid, smallest of maximum (som), middle of maximum (mom), bisector, and largest of maximum (lom) (Matlab-Defuzz). In this case, the centroid method provided better results.

The number of training iterations was set to 40 at the maximum level. After the ANFIS modeling is completed, the trained ANFIS model is tested on test data. The training and testing processes were repeated until the R^2 increases and RMSE, MAE values decrease which resulted in several ANFIS models being generated. We selected the ANFIS model with the maximum R^2 value and least MAE and RMSE values. Sugeno FIS was used as it is more computationally efficient than Mamdani FIS [2016_Sugeno_Mamdani, Matlab-genfis]. Table 4 shows the implementation process of the customized ANFIS model for prediction of crop yield.

After data pre-processing by the Mean-Imputation (), Normalize() and Sel-FS() functions, the Set-MF() function sets the different membership functions trimf, trapmf, gellmf, sigmf and gaussmf. The Set-Fuzzy-Operator function sets the different fuzzy operators minimum (min), product (prod), maximum (max) and probabilistic-or (probor). The Set-Implication-Operator function sets the implication operators minimum (min) and product (prod). The Set-Aggregate-Operator function sets the aggregation operators maximum (max), probabilistic-or (probor) and sum. The Set-Defuzzify-Outputs () function sets the defuzzification methods.

After configuring the ANFIS with these parameters, it was trained using the training data. The training process was repeated with different configuration parameters. The ANFIS model with the highest R^2 value and lowest RMSE, MAE values was chosen as the final model for crop yield prediction. This

Table 4. ANFIS algorithm for crop yield prediction

	Algorithm: ANFIS for crop yield prediction
1.	**procedure** ANFIS(TrngSet,TstSet)
2.	[TrngSet, TstSet] ← Mean-Imputation(TrngInput, TstInput)
3.	[TrngSet, TstSet] ← Normalize(TrngSet,TstSet)
4.	[TrngInput,TrngOutput,TstInput,TstOutput]←Split(TrngSet, TstSet)
5.	FS ← Sel-FS(Feat-Num, TrngInput, TrngOutput)
6.	MF←Set-MF(trimf/trapmf/gbellmf/gaussmf/sigmf);
7.	FO←Set-Fuzzy-Operators(min/prod/max/probor);
8.	IO←Set-Implication-Operators(min/prod);
9.	AO←Set-Aggregate-Outputs(max/probor/sum);
10.	DO←Set-Defuzzify-Outputs(centroid/bisector/mom/lom/som);
11.	ANFIS=Create-ANFIS(MF,FO,IO,AO,DO);
12.	Trained-ANFIS=Train-ANFIS(TrngInput(FS),TrngOutput,ANFIS);
13.	PredOutput=Predict-ANFIS(Trained-ANFIS,TstInput(FS));
14.	[R^2, RMSE, MAE] ← Evaluate(TstOutput,PredOutput)
15.	**end procedure**

trained ANFIS model was then applied to the test set to estimate the performance of the model with respect to R^2, RMSE, and MAE. For all the datasets, the ANFIS model with triangular membership function, probor as the fuzzy operator, prod as the implication operator, probor as the aggregation operator and centroid as the defuzzification operator performed better.

The Figure-5 depicts the ANFIS structure for the prediction of wheat yield obtained from Karnataka, India.

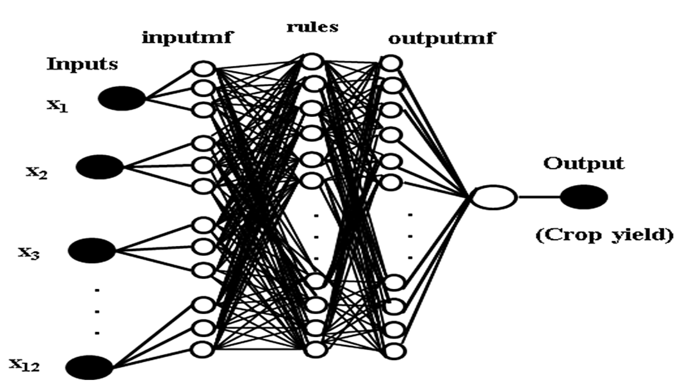
Here, inputmf is the input membership function and outputmf is the output membership function. The inputmf maps the 12 input features to the 16 generated rules. The outputmf maps the rules to the output which is the wheat yield in our case. For the Karnataka, wheat dataset, a better result was achieved for sugeno FIS with triangular membership function; product and probabilistic or as the fuzzification operators; product as the implication operator; sum as the aggregation method and centroid as the defuzzification method on the dataset with 12 GA selected features.

BENEFITS OF ANFIS

This section discusses the various benefits of the ANFIS predictive modeling technique over other predictive techniques such as ANN, Multiple Linear Regression (MLR), etc. Following points highlight the advantages of ANFIS:

1. Since ANFIS combines the powers of ANN and Fuzzy Logic, it has better predictive capability than ANN and MLR.
2. The ANFIS is able to perform better prediction on data which are non-linear in nature while MLR is more suited to linear data.
3. ANN has many parameters such as number of hidden layers, neurons, weights and biases. In ANFIS, tuning of various parameters is reduced.
4. ANFIS is able to converge to a final solution faster than the ANN.

Figure 5. ANFIS structure for wheat yield prediction (Shastry et al., 2015)



CASE STUDY 2: APPLYING ANFIS TO PREDICT WATER QUALITY INDEX OF RIVER SATLUJ (INDIA) (TIWARY ET. AL. 2018)

This case study is taken from the work of Tiwary et al, 2018. The suitable way of understanding the water quality status of water bodies is by using the water quality index (WQI). However, the evaluation of WQI involves human users which can be subjected to human errors leading to uncertainty.

The artificial intelligence (AI) algorithms are suitable for the nonlinear prediction and the handling of uncertainties for forecasting of water quality. This study aims at the development of an ANFIS system for predicting the WQI on real world data obtained from 8 monitoring sites across the Sutlej River in Northern India. The authors have made use of 2 different clustering algorithms strategies using fuzzy C-means and subtractive clustering-based ANFIS and estimating their predictive accuracy. The contribution of this work lies in the prediction of the WQI utilizing these algorithms. Every model was utilized to validate, train and test the WQI which was derived from the 7 water quality parameters namely pH, chlorides, ammonia, and fecal coliforms. The authors concluded that the SC-ANFIS obtained better results in comparison with the FCM-ANFIS model. The sensitive parameters across the 8 monitoring stations were identified by the SC-ANFIS model. These sensitive parameters were able to cause changes in the existing WQI values.

The regulatory agencies are concerned with the evaluation of the surface water quality in order to preserve the quality of water for usage. To ensure water quality, the continuous monitoring is done to estimate the quality of water thereby providing suitable measures for its management. The WQI is used to assimilate the large data produced from the monitoring stations. The WQI represents a single number to denote the water quality by combining the measurements of various water quality parameters. Its output is ranges between the values of 0 to 100. Excellent water condition is represented by 100 while poor quality is signified by 0.

The WQI has seen much advancement in recent times due to the advent of soft computing techniques like data mining, artificial intelligence, and fuzzy modeling system (Horton, 1965). These techniques are capable of handling uncertainties that are not handled by the traditional methods of evaluating WQI (Chau, 2006). Several data mining methods like support vector machines, decision trees, k-nearest neighbor, and naïve Bayes were employed by Babbar & Babbar (Babbar et al., 2017) to classify water quality centered on the overall pollution index. Several AI techniques have been applied by researches around the world to assess the water quality status (Chang et al., 2001, Jin et al.,2003, Sun et al., 2004, Wang et al., 2004, Zhang et al., 2004, Zou et al., 2006, Wang et al.,2008, and Zhou et al., 2009). The quality and quantity of data decides the choice of methods. The quantitative relationships between the input and output variables are established as if-then rules by the fuzzy logic methods (Vernieuwe et al., 2005). Nevertheless, the systematic procedure for defining the membership function parameters is not present in fuzzy models. The expert knowledge is used to determine these parameters. Conversely, the artificial neural network (ANN) is able to learn from input-output pairs with suitable interactions. Due to this, the ANFIS model is getting popular for handling uncertain and not so well defined domains like the predictions of water quality.

As described earlier, the ANFIS embeds the FIS and adaptive networks into a single framework. Hence, it is able to extract the benefits of both ANN and FL models. The fundamental issues of configuring the membership-function (MF) parameters and deriving the fuzzy if-then rules that prevail in fuzzy systems are resolved in ANFIS models. In the ANFIS model, the ANN is responsible for the automatic generation of fuzzy if-then rules and the optimization of MF parameters (Nayak et al., 2004). The concept of

ANFIS was introduced by Jang et al. (Jang et al., 1993) after which it has been widely applied in several problems related to water quality. The ANN was compared with ANFIS model for classification of water quality status by (Yan et al, 2010). The authors have utilized several MFs like Gaussian, triangular, generalized bell, and trapezoidal in the ANFIS model for training and testing the data. The Gaussian MF was observed to perform better when compared to other MFs. The prediction of WQI of groundwater using ANFIS was performed by (Sahu et al., 2011). The ANFIS was applied for the forecasting of oily waste water microfiltration permeates volume by (Rahimzadeh et al., 2016). The ANFIS was found to be superior to ANN for the prediction of fluctuations in lake levels by (Talebizadeh & Moridnejad, 2011) in terms of efficiency. The demand estimation of biochemical oxygen was performed by (Ahmed & Shah, 2017) using ANFIS centered on the water quality parameters. The over-fitting problem still prevails in many applications in spite of improvements in prediction models. It remains a formidable challenge for many researchers even today. Recent research has found that appreciable models performance improves significantly when suitable hybridization of multiple models is utilized rather than using single models for prediction (Temizel & Casey, 2005).

From the above studies, we can infer that ANFIS is gaining popularity in various applications related to WQI prediction. However, the tuning of ANFIS parameters is not been given due consideration. Hence, the authors in this study have performed tuning of MF for WQI prediction using fuzzy C-means (FCM) and subtractive clustering (SC) in the ANFIS model. This has led to the accurate prediction of homogeneous clusters or classes in WQI.

The method of clustering forms one of the significant methods for analyzing data and taking crucial decisions which allows for the retrieval of knowledgeable information by categorizing or grouping multidimensional data into clusters. As the water quality data is multidimensional in nature and clustering methods are suitable for such type of data, two clustering methods were utilized in this work by evaluating and comparing them. Consequently, this study developed ANFIS model using two different clustering methods. Statistical methods were utilized to identify the best methods. Furthermore, the sensitive water quality parameter that causes change in the predicted water quality was also identified by employing the best model.

The River Sutlej was chosen as the study area in this work. It is one among the five rivers of Indus River System which joins the Indus River on its eastern side. The Manasarovar-Rakas Lakes located in Western Tibet is its source. The river is utilized extensively for irrigation and drinking purposes. The Thapar University located at Patiala, India regularly monitors the river in the Punjab area using 8 monitoring stations. It was initiated by the Indian Government during 1996. The water quality deteriorates further downstream due to the toxic materials from industries and sewage.

The water quality parameters considered in this work were chlorides, power of Hydrogen, water conductivity, BOD_5 representing the five day biochemical oxygen demand, TDS denoting the total dissolved solids, SS signifying the suspended solids, ammonical-Nitrogen (ammonical-N), total phosphorous (TP), nitrates, and FC denoting fecal coliform. The data related to these parameters were gathered from eight monitoring sites.

The various water uses namely municipal, ecological, and irrigation, were utilized for computing the water quality index (WQI). The various steps involved are highlighted below:

1. Parameter selection
2. Weight allocation to the parameters which were selected

3. PRC/E representing the parameter rating curves or equations was utilized for converting the monitored parameter values into common environmental scale units.
4. Computation of the final score by averaging or aggregating the different parameter values.

Based on the computed final score, the quality of water was categorized into six classes as follows:

- Very Poor class with final score less than 45
- Poor class with final score between the values 45 to 60
- Fair class with final score between the values 61 to 69
- Good class with final score between the values 70 to 79
- Very Good class with final score between the values 80 to 90
- Excellent class with final score between the values 91 to 100.

The computed WQI was utilized for domestic and municipal water use. The work considered the parameters described above since they were important for characterizing the industrial and municipal waste. They were able to convey sufficient information about the overall quality of the water for designated uses. If more parameters are used, then the logistic concerns associated with the monitoring and analyzing arise for estimating the water quality index.

In the present case study, the ANFIS model with Gaussian MF was loaded with the principal components of the data comprising of the chosen water quality parameters. Equation (5) denotes the association between the input features/parameters/attributes and the water quality index.

$$WQI = f\left(pH, conductivity, TDS, chlorides, nitrates, ammonia - N, fecal\, coilform\right) \tag{5}$$

To model the problem, the 204 records representing the water quality data gathered from eight monitoring stations were split into three sets namely: the training data, the checking or validation data, and the testing data. The ANFIS was trained on the training data, while the validation data was utilized for verifying the identified ANFIS. The models performance was evaluated using the testing data. The training data was composed of 142 records which represented 70% of the total records. Similarly, the validation data was made up of 30 records representing 15% of the total records. The remaining 15% of data which represented 32 records constituted the testing data. The water quality index represented the target values which was computed using equation (6) denoted below:

$$WQI = \sum_{i=1}^{n} W_i Q_i \tag{6}$$

where,

- Q_i represents the sub-index for i^{th} parameter of water quality,
- W_i denotes the weighting factor linked with every parameter of water quality, and
- ‘n’ signifies the number of parameters representing the quality of water.

The WQI computed in this study was utilized to check the quality of water for the domestic and municipal purposes. In this work, the fuzzy logic toolbox with the ANFIS graphical user interface of Matlab was utilized as the modeling tool. The Gaussian membership functions were generated automatically using two distinct clustering algorithms namely subtractive clustering (SC) and fuzzy c-means (FCM). Though, both algorithms generate the fuzzy if-then rules, the method of implementation varies. The membership grade in Fuzzy c-means method specifies the degree of how much every data point belongs to a cluster. It was developed by (Bezdak, 1981). In this work, the FCM was able to generate 12 different clusters when it was run on the water data with multiple dimensions.

Conversely, if ambiguity exists on the number of clusters to be formed for a given set of data then the subtractive clustering is beneficial. The SC algorithm represents a one-pass algorithm which is fast in finding the number of clusters and the centers of the clusters for a set of data (Chiu, 1994). The obtained cluster estimates can be utilized to initialize clustering methods which are iterative and based on optimization. They are also useful for model identification techniques such as ANFIS. For the 204 observations present in the data set a total of fifteen clusters were formed. The number of fuzzy rules that were generated was equal to the number of cluster centers that were formed. Each of the cluster centers signified the characteristic of the cluster.

The various parameter values utilized for the ANFIS by FCM algorithm and the ANFIS by SC algorithms are represented in Table 5.

The two popular optimization algorithms viz. gradient descent back propagation and the mean least squares algorithms are combined to form a hybrid tuning technique in ANFIS. The error measure denoting the squared sum difference among the actual and predicted outputs is reduced at each epoch or iteration. The overall WQI was derived as a linear combination of the input parameters during the learning of the premise parameters.

The three statistical measures viz. root mean squared error (RMSE), mean squared error (MSE), and the R-Squared (R^2) values were utilized to evaluate the performance of the ANFIS model. For the training data, the RMSE, MAE, and R^2 values achieved by SC-ANFIS were 0.8701, 0.7570, and 0.9919 respectively. On test data, the RMSE, MAE, and R^2 values achieved by SC-ANFIS were 1.6092, 2.5896, and 0.9827 respectively. The R^2 for the overall data was observed to be 0.9911 for the SC-ANFIS model.

Similarly, the RMSE, MAE, and R^2 values achieved by FCM-ANFIS on the training data were 1.1590, 1.3434, and 0.9852 respectively. On test data, the RMSE, MAE, and R^2 values achieved by FCM-ANFIS were 2.7743, 7.6966, and 0.9015 respectively. The R^2 for the overall data was observed to be 0.9821 for the FCM-ANFIS model.

Table 5. Values of parameters for the FCM-ANFIS and SC-ANFIS algorithms

Parameters for ANFIS by FCM algorithm	Parameters for ANFIS by SC algorithm
Membership function=Gaussian	Membership function=Gaussian
Number of clusters=15	Number of clusters=12
Number of rules =15	Number of rules = 12
Number of exponent for the partition matrix =3	Cluster radius=0.3
	Squash factor=1.7
	Accepted ratio=0.5
	Rejected ratio=0.15

It can be clearly observed from the RMSE, MSE, and R^2 values, that the SC-ANFIS model performed better than the FCM-ANFIS model. That is, the predictions of the SC-ANFIS model were closer to the actual values in comparison to the FCM-ANFIS model.

Sensitivity analysis is a process that aids in determining how the changes in model input values affect the model output values. In this case study, the sensitivity analysis was performed for determining the parameters that affected the output value (WQI) such that the water quality class shifted from its existing class. The SC-ANFIS predictive model was utilized to note the changes in WQI when the input water quality parameters were perturbed by ± 2 times its standard deviation. This perturbation was employed in order to take into consideration the parameter variability and its related impact on WQI. Lastly, the comparison of the resulting WQI was done with the reference values.

The parameters representing the water quality such as chlorides, TDS, ammonia, and fecal coliforms are strongly associated with domestic or municipal waste. The Sutlej River was found to be sensitive to these parameters across its monitoring stations. This sensitivity specifies that the municipal waste is strongly influencing the river. Hence, the variations in these parameters should be considered when determining the water quality class.

In this case study, the ANFIS model was tuned using two clustering algorithms for predicting the WQI of the River Sutlej located in Northern India. The authors considered seven water quality parameters which were essential for municipal use for computing the WQI. The data set for experiments was gathered across eight monitoring stations for 16 years.

The subtractive clustering and the fuzzy c-means techniques were used to tune two ANFIS models. The WQI was modeled by training, validating, and testing these two ANFIS models. It was observed that, the SC-ANFIS model predicted accurate WQI then the FCM-ANFIS model in terms of the statistical metrics. That is, the predicted values were closer to the actual values in case of the SC-ANFIS model when compared to the FCM-ANFIS model.

The sensitivity analysis was performed using the SC-ANFIS model since it exhibited better predictive ability than the FCM-ANFIS model. The perturbation effect on each parameter of the water quality was analyzed and modeled. Based on this analysis, the authors inferred that the chlorides, fecal coliform, and ammonia were the most sensitive parameters which were able to shift the existing water quality class to poor class. Therefore, the authors suggested that these parameters be given more attention during the computation and analysis of WQI.

This case study has revealed the fact that ANFIS with SC-ANFIS can be a beneficial approach for estimating the WQI. The lengthy computations involved in the traditional estimation of WQI are considerably reduced using this approach. Hence, this approach demonstrates its significance for model development, rapid distribution of information and the identification of important water quality parameters that affect WQI. In future, this work can be enhanced by using the hybrid of SC-FCM and neuro-dynamic fuzzy expert system to assess the quality of water.

CONCLUSION AND FUTURE SCOPE

ANFIS is a significant predictive modeling technique. It is based on the combination of fuzzy technique and neural networks. In this chapter, we have discussed how ANFIS may be used in the field of agriculture. Currently, ANFIS is being used in various agriculture areas such as forecasting the yield of crops, estimating the profit in the farming sector, predicting the energy required for crops to grow, etc. ANFIS is being used primarily in predicting the yield of crops such as wheat, rice, jatropha successfully. It has shown various benefits when compared to traditional farming.

Matlab is a programming language frequently used in developing sophisticated applications. It provides excellent support to develop machine learning applications using machine learning algorithms. In this regard, the Matlab commands for building a simple ANFIS model are discussed. A case study of the design of an ANFIS model using Matlab for predicting the wheat yield of Karnataka, India is described. In this chapter, we have provided the basics of ANFIS, along with its applications in agriculture. Two case studies related to the application of ANFIS models for crop yield prediction and estimation of water quality index is discussed in detail.

Currently, the ANFIS model is being applied for predicting the yield of specific crops such as wheat, and maize. In future, the ANFIS models may be applied for different type of crops such as jowar, corn, barley, etc. Also, only few input parameters such as rainfall are being considered for prediction of yield. In future, the additional significant parameters of soil, weather and crop may be considered for crop yield prediction. The efficiency of ANFIS models may be further improved by considering additional input parameters and proper testing.

Apart from crop yield prediction, ANFIS may be used for other purposes in agriculture such as water quality forecasting, weather forecasting, drought prediction, soil class prediction, soil fertility prediction, etc. to name a few. In future, ANFIS may be applied to provide effective recommendations to agriculture stakeholders regarding production which in turn will aid the decision making process. The integration of ANFIS with sensor data can be done. The ANFIS model may be applied to other sectors other than agriculture as well.

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KEY TERMS AND DEFINITIONS

Antecedent: Antecedent is a part of IF rule. It is a conditional statement.

Artificial Neural Network (ANN): ANN represents a set of algorithms which are designed for pattern recognition. It is modelled after the human brain.

Degree of Membership: It represents a value in the range of 0 and 1. A value closer to 1 indicates that an element belongs to a particular class, while values closer to 0 indicate that the element doesn't belong to the particular class.

Fuzzy Inference System (FIS): The FIS is used for mapping the inputs to outputs by utilizing the fuzzy set theory. The inputs and outputs represent features and classes respectively with regards to fuzzy classification.

Fuzzy Logic (FL): It is a multi-valued logic which deals with the concept of partial truth. It is used in cases where the conditions cannot be described by exact values of 0 (false) and 1 (true). The values can lie between 0 and 1.

Fuzzy Set: Fuzzy set is expressed as a function and the elements of the set are mapped into their degree of membership. A set with the fuzzy boundaries are "hot," "medium," or "cold" for temperature.

Membership Function (MF): MF signifies the degree to which each input feature is mapped to a membership value between 0 and 1. It is basically a curve.

Section 3
Applications and Cases

Chapter 9
Enhanced Fuzzy Assessment Methodology to Find Overlapping in Membership Function Using K Ratio to Find the Yield of Rice

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ABSTRACT

Fuzzy expert systems are designed based on fuzzy logic and deal with fuzzy sets. Many fuzzy expert systems have been developed for diagnosis. Fuzzy expert systems are developed using fuzzification interface, enhanced fuzzy assessment methodology, and defuzzification interface. Fuzzification helps to convert crisp values into fuzzy values. By applying the enhanced fuzzy assessment methodology for rice, the yield parameters of rice can be diagnosed with number of tillers per hill, number of grains per panicle, and 1000 grain weight. Pest and disease incidence becomes simple for scientists. Enhanced fuzzy assessment methodology for rice uses triangular membership function with Mamdani's inference and K Ratio. Defuzzification interface is adopted to convert the fuzzy values into crisp values. Performance of the system can be evaluated using the accuracy level. Accuracy is the proportion of the total number of predictions that are correct. The proposed algorithm was implemented using MATLAB fuzzy logic tool box to construct fuzzy expert system for rice.

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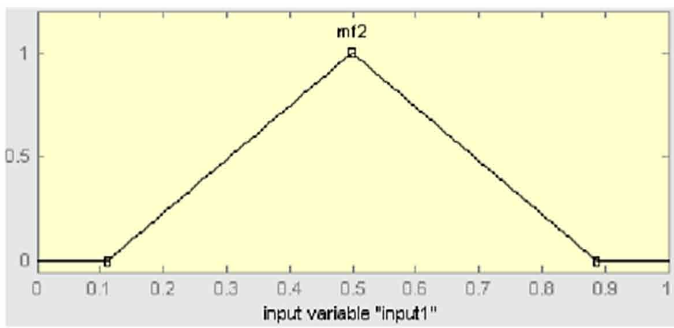
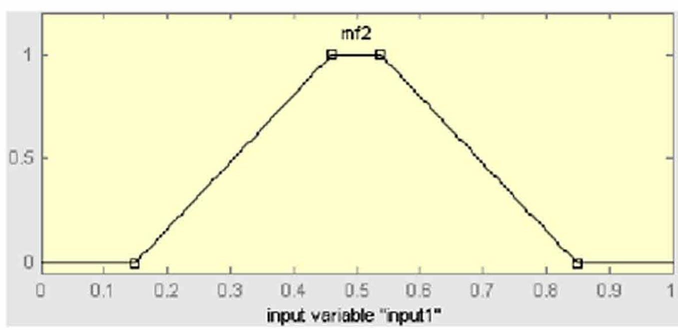
INTRODUCTION

Fuzzy Expert System is developed with the concept of fuzzy logic and fuzzy set. The fuzziness of the fuzzy set is given by the membership function. Membership function is designed for input variable with the labels. Membership function helps to make out the numerical range of the input values with respect to the label. The different shapes of membership function are triangle, trapezoidal and bell as show in Figure 1.

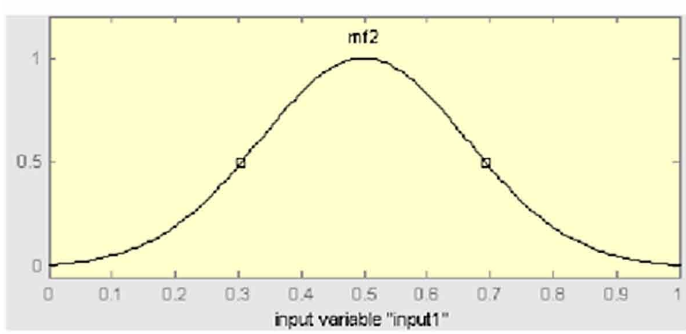
Figure 1. Membership function shapes



(a) Triangle shape



(b) Trapezoidal shape



(c) Bell shape

Membership function always exists in universe of discourse. To design the fuzzy expert system the membership function are to be constructed. In many cases there occurs some problem in membership function. They are

1. In many applications few membership functions will make the response of the developed system very slow. In some cases membership function makes the system fail to provide sufficient output in time, if some changes are made in input. Because of this change there is an oscillation in the system.
2. Membership function also causes rapid firing of many rule consequents for a little modification in input, but the outcome of the system which makes large change in output. This causes the system to be more instable. So while constructing membership function it should be carefully designed.

FUZZY SETS

Fuzzy logic is initiated with the concept of a fuzzy set. Classical sets are with crisp boundaries, usually with ordinary set is called a collection of objects with some properties distinguishing from other objects. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

Membership Function

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is referred as universe of discourse. A fuzzy set membership function is a generalization of the indicator function in classical sets.

In fuzzy logic, it represents the degree of truth as an extension of valuation. Degrees of truth are often confused with probabilities, even though they are conceptually distinct, because fuzzy truth represents membership in vaguely defined sets, not likelihood of some event or condition. Membership functions were introduced by Zadeh, while defining fuzzy sets (1965). Zadeh, in theory of fuzzy sets, proposed a membership function (with a range covering the interval (0,1)) operating on the domain of all possible values. Membership functions for a fuzzy set are represented graphically. The x axis represents the universe of discourse, whereas the y axis represents the degrees of membership in the [0,1] interval.

Definition: a membership function for a fuzzy set A on the universe of discourse X is defined as $\mu A:X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A.

Fuzzy concepts are defined by more complex function which does not add more precision. So simple functions are used to construct membership functions.

In general Fuzzy systems are completely based on numbers. In such situation to convert to numbers into grades of membership, membership function is very essential. Membership functions are defined as function on numbers from real line (William Siler and James Buckley, 2005). Universe of discourse is represented in X axis and Y axis represent the degree of membership with the interval 0 to 1(Arazi et al., 2011).

There are many types of membership functions. Few of them are listed below

1. Triangular function
2. Trapezoidal function
3. Gaussian function

Features of Membership Function

The features of Membership function are as follows.

- The membership function follows normalization. A membership function should monotonically increase in left side and decrease in right side.
- The value of membership function for input and output variable is called degree of membership. Empirically or logically the structure of the membership function is determined.
- Membership function consists of universe of discourse, linguistic terms, shape of membership function, linguistic term numerical range and overlap between membership function.
- Membership function are predefined, they are usually defined by experienced users or human experts. If they are not available the membership function is not very accurate. So a general learning method was derived to build membership (Tzung-Pei and Chai-Ying, 1996).
- A membership function represents all fuzziness for an exact fuzzy set. Every fuzzy set is unique, but the flexibility of set is gained by the membership function (Shendy and Morris, 2000).

Overlapping Between Membership Function

In membership function overlapping occurs. Universe of discourse has input point; these points should belong to one or not more than two membership function. Two membership function overlap, the grades of points within the overlap must be less than or equal to 1.

Correlation Fuzzy Logic

Correlation fuzzy logic helps to find the relationship between the fuzzy numbers and membership function. Overlapping is identified between the fuzzy numbers and membership function, correlation coefficient says whether they are overlapped or not. In correlation fuzzy logic there is no suggestion regarding the overlapping, if it crosses the point of maximal truth of either the membership function.

Membership Function and Overlapping between Membership Function

In membership the values are fixed to form fuzzy set. The values for membership function was fixed by experts, no methods are arrived to fix the values. While fixing values for membership function by experts it varies from one expert to another. So a new procedure was derived to overcome this draw back. The method is MMMSDV (Mean, Minimum, Maximum, Standard Deviation Values).

MMMSDV (Mean, Minimum, Maximum and Standard Deviation Values)

The MMMSDV is calculated with the database, the values are name from 1, 2, 3 …N. Using database values the Mean, Minimum, Maximum and Standard Deviation values are calculated for each input and output variables. D $_{1 \text{ to } N}$ is the fuzzy variable.

Step 1: Calculate mean value

$$Mean_{D_1} = \frac{valueD_{1(1)} + valueD_{1(2)} ...value_{D1(N)}}{N}$$

$$Mean_{D_2} = \frac{value_{D_{2(1)}} + value_{D_2(2)} ...valueD_{2(N)}}{N}$$

$$Mean_{D_3} = \frac{value_{D_{3(1)}} + value_{D_3(2)} ...value_{D_{3(N)}}}{N}$$

$$Mean_{D_4} = \frac{value_{D_{4(1)}} + value_{D_4(2)} ...value_{D_{4(N)}}}{N}$$

$$Mean_{D_5} = \frac{value_{D_{5(1)}} + value_{D_5(2)} ...value_{D_{5(N)}}}{N}$$

Step 2: Calculate standard deviation SD (D_1), SD (D_2), SD (D_3), SD (D_4) and SD (D_5),

$$SD_{D_1} = \sqrt{\frac{\sum_{i=1}^{N} {D_{1i}}^2 - \frac{(\sum_{i=1}^{N} D_{1i})^2}{N}}{N}}$$

$$SD_{D_2} = \sqrt{\frac{\sum_{i=1}^{N} {D_{2i}}^2 - \frac{(\sum_{i=1}^{N} D_{2i})^2}{N}}{N}}$$

$$SD_{D_3} = \sqrt{\frac{\sum_{i=1}^{N} {D_{3i}}^2 - \frac{(\sum_{i=1}^{N} D_{3i})^2}{N}}{N}}$$

$$SD_{D_4} = \sqrt{\frac{\sum_{i=1}^{N} {D_{4i}}^2 - \frac{(\sum_{i=1}^{N} D_{4i})^2}{N}}{N}}$$

$$SDD_5 = \sqrt{\frac{\sum_{i=1}^{N} {D_{5i}}^2 - \frac{(\sum_{i=1}^{N} D_{5i})^2}{N}}{N}}$$

Step 3: Sort all the values in descending order to get Max(D_1), Min (D_1), Max (D_2),Min(D_2), Max(D_3), Min(D_3), Max(D_4), Min(D_4), Max(D_5), and Min(D_5)

Step 4: According to the database the Fuzzy input variables are X1, X2, X3, X4, X5 and the output variable is Y. The fuzzy numbers for D1 is {low, medium, high}. The fuzzy numbers are calculated is shown below

D_1[low] = [Min, Mean-SD, Mean]
D_1[medium] = [Mean-SD, Mean, Mean+SD]
D_1[high] = [Mean, Mean+SD, Max]

For all the fuzzy numbers MMMSDV are calculated, represented in Table I. For the input variables there are three fuzzy numbers and for output variable there are three fuzzy numbers.

OVERLAP RATIO

Overlap should cross the level of maximal truth.

Marsh proposed the overlap ratio (Marsh et. al., 1994) given by the eqn. (1) and (2)

Table 1. Representation of fuzzy variables and numbers

Fuzzy Variables	Representation of Fuzzy Variables	Fuzzy Numbers	Representation of fuzzy numbers
X1	D_1	low	d_{11}
		medium	d_{12}
		high	d_{13}
X2	D_2	low	d_{21}
		medium	d_{22}
		high	d_{23}
X3	D_3	low	d_{31}
		medium	d_{32}
		high	d_{33}
X4	D_4	low	d_{41}
		medium	d_{42}
		high	d_{43}
X5	D_5	low	d_{51}
		medium	d_{52}
		high	d_{53}
Y	O	low	O_1
		medium	O_2
		high	O_3

$$Overlap\ Ratio = \frac{Overlap\ Scope}{Adjacent\ MF\ Scope} \tag{1}$$

$$Overlap\ Robustness = \frac{Area\ of\ summed\ overlap}{Max.Area\ of\ summed\ overlap} \tag{2}$$

$$= \frac{\int_L^U (\mu_1 + \mu_2)dx}{2(U-L)}$$

This method is used for uniform distribution of membership function by using adjustment parameter technique based on overlap ratio(Velez M.A et al., 2002). Neighboring sets should have sufficient overlapping. There is no method to determine the amount of overlap. Triangle-to-triangle and trapezoid to triangle fuzzy set overlap between 25 and 50 percent of their base is adopted (Michael Negnevitsky, 2005). Overlapping ratio and correlation fuzzy logic crosses the point of maximal truth of either the membership function. To overcome this K ratio is derived when the overlap cross the point of maximal truth.

Enhanced Fuzzy Assessment Methodology uses membership function, K ratio is used to find the overlapping between the membership function using Fuzzy Mid Value and Fuzzy Start Value. Membership function, overlapping between the membership function is very important part in the construction of Enhanced Fuzzy Assessment Methodology.

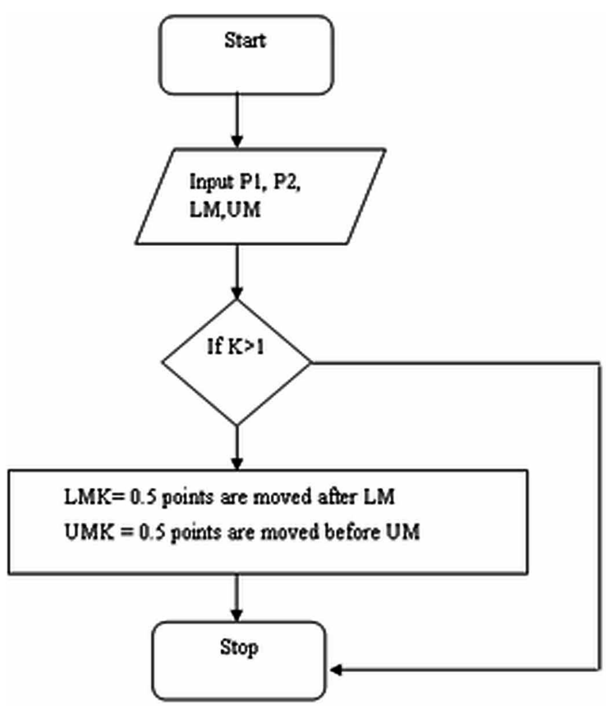
ENHANCED FUZZY ASSESSMENT METHODOLOGY (EFAM)

Enhanced Fuzzy Assessment Methodology input variables are D_1,D_2,D_3,D_4,D_5 and output variable is O. with parameters D_1 to D_5 [Min, Mean-SD, Mean+SD, Max]. In EFAM T-norm operator used is algebraic product and T-conorm operator used is algebraic sum.

K Ratio

To find the overlapping between the membership function K ratio is used. K ratio lies between 0 to 1. It says whether the membership function is correctly overlapped or not. If the K ratio lies above the value 0, method has been defined with Fuzzy Mid Value and Fuzzy Start Value. To compute K ratio the following parameters are used. The input are Lower Member (LM),Upper Member(UM) and line drawn towards the membership function(P1, P2,) for K ratio. The flow chart to compute K ratio is given in Figure 2.

Figure 2. Flowchart to calculate K-Ratio



Computation of K Ratio

For the entire input variable the number membership functions are designed. The membership function overlaps between each other. The intersection of membership function starts with two points. Let A and B be two fuzzy numbers with it membership function. K ratio is computed with the following steps.

Step 1: Compute Lower Member (LM) and Upper Member (UM)

To calculate K ratio, fist determine the Lower Member and Upper Member. The fuzzy numbers A and B interest each other. The first point at the beginning of intersection is Lower Member (LM) and the last point at the end of intersection is Lower Member be Upper Member (UM) as shown in Figure 3.

Step 2: Fuzzy Mid Value (FMV)

The Fuzzy Mid Value (FMV) is the mid point between the UM and LM. A straight line is drawn above the FMV as shown in Figure 4.

Step 3: Fuzzy Start Value (FSV)

Fuzzy Start Value (FSV) is calculated by FSV=FMV-0.5. A straight line is drawn above the FSV as shown in Figure 5. FSV helps to find the P1 and P2 value which is used for the computation of K ratio.

Step 4: P1 and P2 values

A straight line is drawn above FMV. Line is drawn towards the membership function called as P2. P2 is shown in Figure 5. In FSV, a straight line is drawn above; line which touches the first membership function is called P1. P1 is shown in Figure 5.

Figure 3. Lower member and upper member

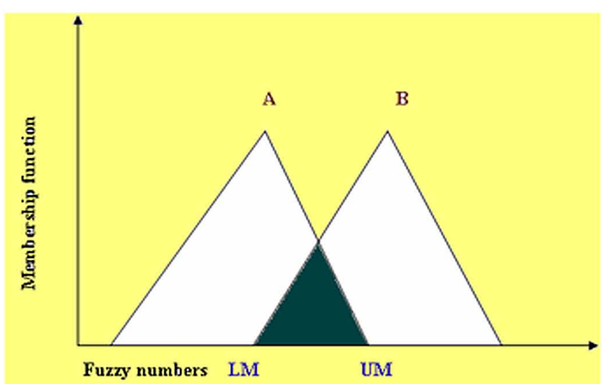


Figure 4. Fuzzy mid value

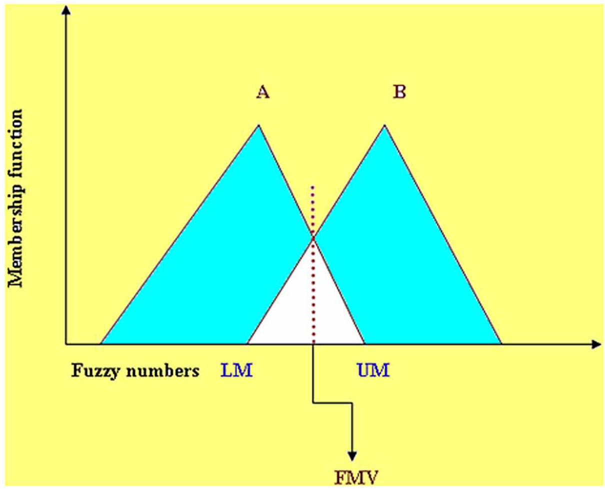
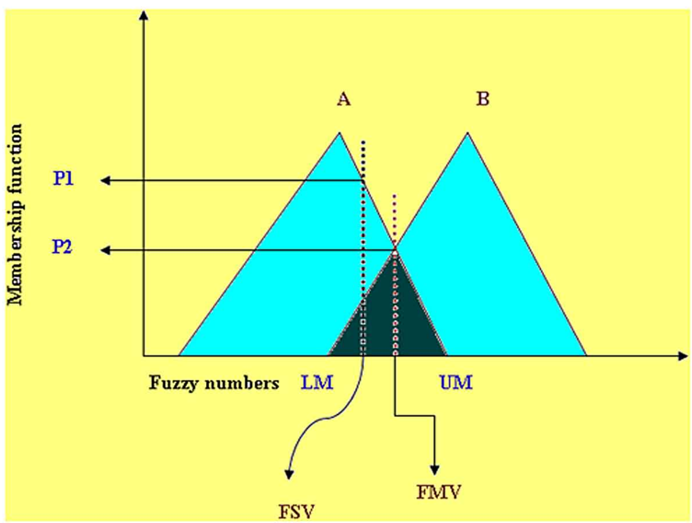


Figure 5. P1 and P2 values



Step 5: K Ratio

Hence K ratio is calculated as

$$K = \frac{P1 + P2}{LM - UM} --> (3)$$

Step 6: Inference

If the K ratio lies between 0 and 1, there is no change in the membership function and there is no change in LM and UM. If the K ratio is greater than 1 or less than 0 then the membership function are fixed to the limit as shown in Figure 6. The A and B are changed as

LMK = FMV- 0.05
UMK= FMV+ 0.05

Thus the fuzzy number is moved to LMK and UMK as shown in Figure 7.

Figure 6. LMK and UMK

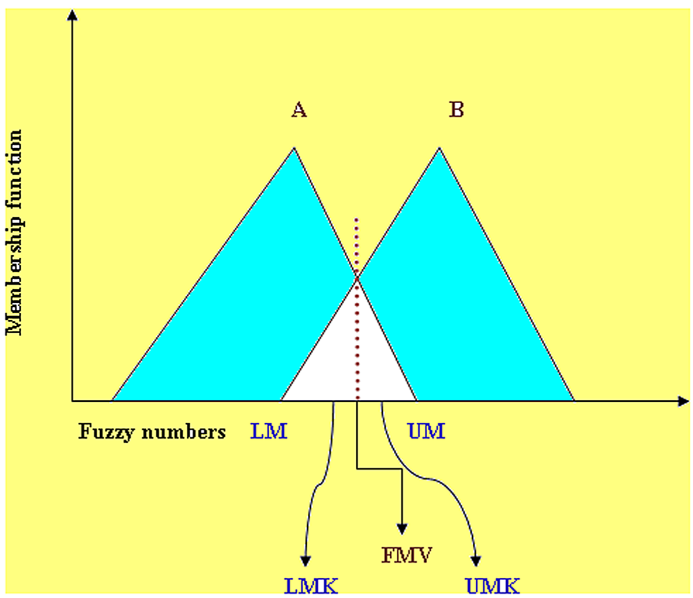
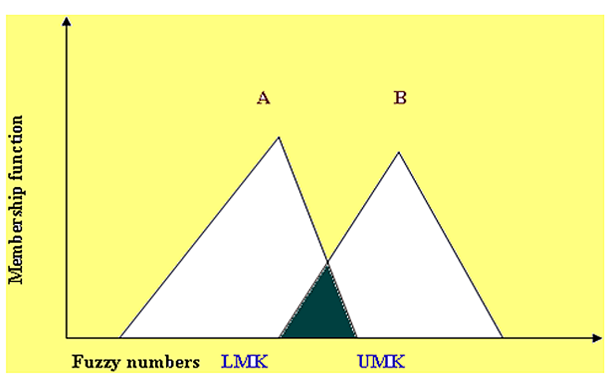


Figure 7. LM and UM computed from K ratio



Agriculture is the main part in India economy. Farmers are in need advice to make decision during their farming activities such as land preparation, sowing, irrigation management, fertilizer management, pest management and storage for higher production of crop. Computers are used in the area of agriculture. Expert system and its role play an important part in the field of agriculture. Decision making is a very important application in crop growth and pest management. Combining fuzzy logic and expert system helps in the area of crop production and crop management. Many Fuzzy Expert Systems has been developed for diagnosis. Rice is the most important crop in the India and worldwide (Brar DS and Khush GS, 2002). The rice production is affected by number of insect pests and disease attacking from nursery to harvesting. This causes enormous yield loss. Of these, the leaffolder insect (Cnaphalocrocis medinalis Guen.) and sheath blight pathogen (Rhizoctonia solani Kuhn) have gained major importance because of their ability to reduce the yield considerably all over the world. The management of rice leaffolder insect pest and sheath blight disease has been almost exclusively based on the application of chemical pesticides(Singh S et al., 1995). Many effective pesticides have been recommended against this pest and disease, but not considered as a long-term solution because of concerns about pesticide residue risks, health and environmental hazards, expense, residue persistence, pest resurgence and elimination of natural enemies. The current study was to develop a biological control plant growth-promoting rhizobacteria (PGPR) strategy for pest and disease that is durable and is an alternative to agrochemicals. Many fuzzy systems were developed. They are

Fuzzy Inference System for an Integrated Knowledge Management System:

Fuzzy Inference System for soil is developed. The inference is framed with If-Then rules. Mamdani Fuzzy Inference System is build by using MATLAB FIS Tool Box(Maria Wenisch S., et al., 2010).

Expert System for diagnosis of diseases in Rice Plant:

An Expert System to diagnosis diseases was developed for rice using the shell ESTA (Expert System for Text Animation). An Expert System for rice is collection of a knowledge base, inference engine and user-interface (Sarma, et al., 2010).

Expert System for Rice Kernel Identification:

An Expert System for rice was developed using the morphological features and implemented with MATLAB programming. Rice kernels were classified using neural network (MousaviRad S.J, et al., 2012).

Fuzzy Expert System for Integrated Disease Management in Finger Millets:

Fuzzy Expert System is developed to control and measure disease in Finger Millet(Ragi). The first part gives the contributions of Expert Systems in agriculture. The second part explains the Integrated Disease Management. The third part deals about knowledge acquisition and knowledge representation. The fourth part gives the application of Fuzzy Logic in Integrated Disease Management (Philomine Roseline et. al.,2012).

Fuzzy Expert System for rice using Fuzzy Verdict Mechanism:

Fuzzy Verdict Mechanism which consists of fuzzy inference, implication and aggregation. Fuzzy Expert System helps to diagnosis the yield of rice which is very much used for agricultural scientists and farmers. Fuzzy Expert System has been developed for rice using Fuzzy Verdict Mechanism (Kalpana M and Karthiba L., 2016).

RICE DATA

Enhanced Fuzzy Assessment Methodology uses rice database with input parameter Leaf Folder pest incidence(LFI), Sheath Blight disease (SB), Number of Tillers Hill(NH), No. of grains per panicle(GP) and 1000 grain weight(GW).The output parameter is Grain Yield per Plant(YD) (Karthiba L et al., 2010).

MODELING FUZZY EXPERT SYSTEMS FOR RICE

Fuzzy expert system for rice can be designed using the following steps.

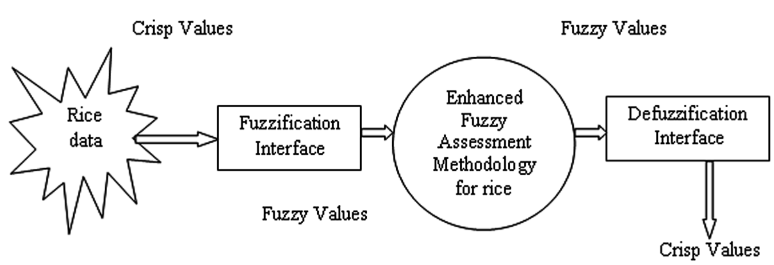
1. Fuzzification interface
2. Enhanced Fuzzy Assessment Methodology for rice
3. Defuzzification interface as shown in Figure 8

Fuzzy set and fuzzy numbers are listed in Table II (Kalpana M and Karthiba L., 2016).

Fuzzification Interface

The values taken from the rice data are crisp values. These crisp values are transformed into fuzzy values by fuzzification interface. The fuzzy values are taken as the input for the Enhanced Fuzzy Assessment Methodology for rice.

Figure 8. Diagram of the fuzzy expert system for rice



Enhanced Fuzzy Assessment Methodology for Rice

Membership function adopted is triangular function with the parameter set[a,b,c]. The parameter is fixed with Minimum, Mean, Standard Deviation, Maximum value for each variables(Senthilkumar A.V and Kalpana M, 2011). Then the membership function μ(x) of the triangular fuzzy numbers (William Siler and James Buckley, 2005). In Enhanced Fuzzy Assessment Methodology (EFAM) three triangular membership functions (MFs) are used for each input variable (D_1,D_2,D_3,D_4,D_5) and three triangular MFs for the output variable (O) listed in Table II (Kalpana M and Karthiba L. 2016).

In the proposed Enhanced Fuzzy Assessment Methodology for rice, the membership degrees for all instances of the fuzzification are calculated using the membership functions. The fuzzy rules uses OR fuzzy disjunction, the operator combines the matching degree of each rule with multiple conditions. Fuzzy interface is invoked by using Mamdani's approach (Arazi Idrus et al., 2011). Inference results of the rules fired by performing MIN fuzzy operations. The fuzzy conclusion is converted into a crisp value by using the centroid method.

Table 2. Representation of fuzzy variables and numbers

Fuzzy Variables	Representation of Fuzzy Variables	Fuzzy Numbers	Representation of fuzzy numbers	Fuzzy triangular numbers
LFI	D_1	low	d_{11}	[2.51,1.72,8.10]
		medium	d_{12}	[1.72,8.10,14.48]
		high	d_{13}	[8.10,14.48,23.29]
SB	D_2	low	d_{21}	[3.05,4.9,15.60]
		medium	d_{22}	[4.9,15.60,26.3]
		high	d_{23}	[15.60,26.3,33.77]
NH	D_3	low	d_{31}	[13.73,15.33,17.74
		medium	d_{32}	[15.33,17.74,20.15]
		high	d_{33}	[17.74,20.15,21.2]
GP	D_4	low	d_{41}	[137.37,165.15,196.70]
		medium	d_{42}	[165.15,196.69,228.23]
		high	d_{43}	[196.70,228.23,228.32]
GW	D_5	low	d_{51}	[18.26,20.15,22.44]
		medium	d_{52}	[20.15,22.44,24.73]
		high	d_{53}	[22.44,24.73,26.36]
YD	O	low	O_1	[6.51,6.71,7.32]
		medium	O_2,	[6.71,7.32,7.93]
		high	O_3	[7.32,7.93,8.18]

K Ratio for Rice Data

To find the overlapping between the membership function K ratio is used. K Ratio are calculated for the all the variables such as LFI, SB, NH, GP and GW in rice data. An illustrative example for LFI is given. To calculate the K ratio for the input variable Leaf Folder pest incidence (D_1) for the membership function(low and medium) d_{11} and d_{12} given as

P1= 0.75
P2= 0.6 and
UM= 6.25
LM= 1.5 and K ratio is calculated using the eqn.(3).
The value for K ratio =-0.29

If the K ratio is greater than 1 or less than 0 then the membership function are fixed to the limit. So the LM can be changed to LMK and UM can be changed to UMK as LMK = FMV - 0.05 and UMK= FMV + 0.05. Figure 9 represents the membership graph for fuzzy variables LFI with the K ratio after fixing UMK and LMK. Figure 10 represents the rule for Fuzzy Expert System.

Enhanced Fuzzy Assessment Methodology for rice analyzes the physical data, converts the inferred results into knowledge, and then presents the decision results through descriptions (Zadeh L. A., 2008) (Margaliot M.,2008). Algorithm for the Enhanced Fuzzy Assessment Methodology for rice is displayed in Algorithm 1.

Figure 9. Membership graph for the fuzzy variable LFI

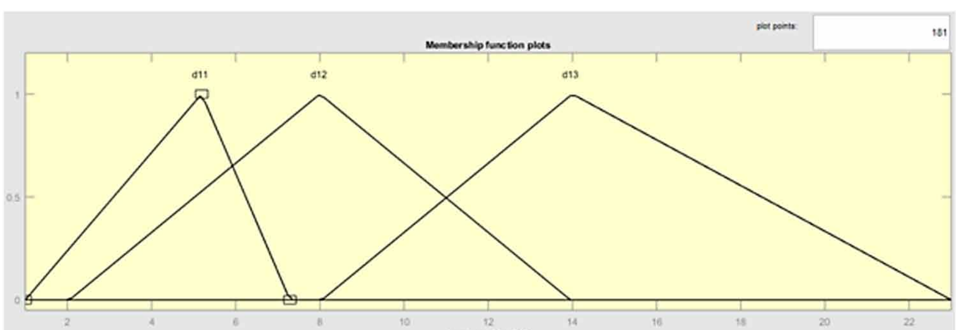


Figure 10. Rule for fuzzy expert system

1. If (D1 is d11) or (D2 is d21) or (D3 is d31) or (D4 is d41) or (D5 is d51) then (O is mf1) (1)
2. If (D1 is d13) or (D2 is d22) or (D3 is d33) or (D4 is d42) or (D5 is d52) then (O is mf2) (1)
3. If (D1 is d13) or (D2 is d22) or (D3 is d32) or (D4 is d43) or (D5 is d52) then (O is mf2) (1)
4. If (D1 is d13) or (D2 is d22) or (D3 is d32) or (D4 is d41) or (D5 is d51) then (O is mf1) (1)
5. If (D1 is d13) or (D2 is d22) or (D3 is d33) or (D4 is d42) or (D5 is d52) then (O is mf2) (1)
6. If (D1 is d13) or (D2 is d23) or (D3 is d33) or (D4 is d42) or (D5 is d52) then (O is mf3) (1)
7. If (D1 is d13) or (D2 is d21) or (D3 is d31) or (D4 is d41) or (D5 is d51) then (O is mf2) (1)

Algorithm 1. Algorithm of enhanced fuzzy assessment methodology for rice

```
BEGIN
1.        Input: Terms (LFI, SB, NH,GP,GW) are selected as  fuzzy input variables
2.        Output: Output term YD as fuzzy output  variables
3.        Input Rice data with N cases
4.        Initialize i←1
 METHOD
Begin
Step1: Input the crisp values for LFI, SB, NH,GP & GW.
Step 2: Built the fuzzy numbers for input and output set
Step 3:Calculate the value of min, max mean and standard deviation
      DO UNTIL(i>N)
           Di [min, max, mean-SD,mean+SD] using triangular membership function.
     END DO UNTIL
Step 4: Calculate K ratio
```

$$K = \frac{P1 + P2}{LM - UM}$$

```
        If (K≥1) then
                      LMK = FMV- 0.05
                      UMK= FMV+ 0.05
              Else
                  LM and UM
Step 5: Fuzzy inference are executed by Mamdani method.
Step 6: Input the rule as {Rule 1,2…..k}
         Step 6.1: Matching degree  of  rule with OR fuzzy disjunction are
calculated for fuzzy input set (LFIlow, LFImedium, LFIhigh, SBlow, SBmedium,
SBhigh, NHlow, NHmedium, NHhigh, GPlow, GPmedium, GPhigh, GWlow, GPmedium,
GPhigh)
         Step 6.2 Calculate the aggregation of the fired rules having same
consequences for fuzzy output set DM (YDlow, YDmedium, YDhigh).
  Step5: Defuzzify into the crisp values by
```

$$DM_i \leftarrow \frac{\sum_{i=1}^{n} Z_i \mu\left(Z_i\right)}{\sum_{i=1}^{i=n} \mu\left(Z_i\right)}$$

Where Z_i means the weight for μ (Z_i) and μ (Z_i) means the number of fuzzy numbers of the output fuzzy variable YD

```
Step6: Present the knowledge in the form of human nature language.
End.
```

EXPERIMENTAL RESULTS

MATLAB Fuzzy Logic toolbox was used to evaluate the performance of algorithm, using rice dataset. The result acquired from the fuzzy logic toolbox is transferred into knowledge and the understandable by human regarding the yield of rice.

EVALUATION OF SYSTEM PERFORMANCE

Performance of the system can be evaluated using the accuracy level. Correct classification is denoted by True Positive (TP) and the True Negative (TN). False Positive (FP) is the outcome when the predicted class is yes and actual class is no. Still, a FalseNegative (FN) is the outcome when the predicted class is no and actual class is yes. Table IV shows the various outcomes of a two-class prediction (Lee C. S. and Wang M. H., 2007). Accuracy is the proportion of the total number of predictions that are correct. The eqn. (4) show the formula for accuracy.

The proposed method achieves the accuracy value 88.88% for rice data with the input parameters Leaf Folder Incidence (LFI), Shealth Blight(SB), Number of Tillers Hill(NH), No. of Grains Panicle(GP) and 1000 Grain Weight(GW) and output parameter is Grain Yield per Plant(YD). This helps the scientist to analysis the yield of rice.

$$Accuracy = \frac{TN + TP}{TN + FP + FN + TP} X100\% \tag{4}$$

CONCLUSION

The proposed algorithm Enhanced Fuzzy Assessment Methodology is very effective to diagnosis the yield of rice. Enhanced Fuzzy Assessment Methodology for rice evaluates the number of membership function and K ratio to identify area overlap between membership function. The proposed EFAM is tested for all rice data with the input parameters using MATLAB Fuzzy Logic Toolbox. Accuracy level achieved through this method is 88.88%. Further investigations have to be carried out to find out the specific interactions that can influence the disease reduction by application of biocontrol strains. Future works also includes S value to manage uncertainty in rules to improve the accuracy level.

Figure 11.

DIFFERENT OUTCOMES OF A TWO-CLASS PREDICTION

Actual class	Predicted class	
	Yes	No
Yes	True positive (*TP*)	False Negative (*FN*)
No	False positive (*FP*)	True Negative (*TN*)

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KEY TERMS AND DEFINITIONS

Artificial Intelligence: The branch of computer science that deals primarily with symbolic, non-algorithmic methods of problem solving.

Certainty Factors (CF): Technique to represent uncertainty in expert systems where the belief in an event (or a fact or hypothesis) is expressed using the expert's unique assessment.

Correlation Fuzzy Logic: Correlation fuzzy logic helps to find the relationship between the fuzzy numbers and membership function.

Expert: Human being who has developed a high proficiency in making judgments in a specific, usually narrow and domain.

Expert System (ES): Computer system that applies to reasoning methodologies to knowledge in a specific domain to render advice or recommendations, much like a human expert.

Fuzzy Logic: A logically consistent way of reasoning that can cope with uncertain or partial information. Fuzzy logic is characteristic of human thinking and expert systems.

Fuzzy Number: Fuzzy number is a generalization of a regular, real number in the sense that it does not refer to one single value but rather to a connected set of possible values, where each possible value has its own weight between 0 and 1.

Fuzzy Set: A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

Fuzzy Variable: In fuzzy logic, a quantity that can take on linguistic rather than precise numerical values. For example, a fuzzy variable, yield might have values such as "high," "medium," and "low."

Inference Engine: The part of an expert system that actually performs the reasoning function.

Inference Rules: In expert systems, a collection of if-then rules that govern the processing of knowledge rules acting as a critical part of the inference mechanism.

K Ratio: K ratio finds whether the membership function is correctly overlapped or not. K ratio lies between 0 to 1.

Knowledge Base: A collection of facts, rules, and procedures organized into schemas. A knowledge base is the assembly of all the information and knowledge about a specific field of interest.

Knowledge Rules: A collection of if-then rules that represents the deep knowledge about a specific problem.

Membership Function: A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

Universe of Discourse: The universe of discourse is the range of all possible values for an input to a fuzzy system.

Chapter 10
A Predictive Fuzzy Expert System for Crop Disease Diagnostic and Decision Support

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ABSTRACT

Soybean accounts for 38% of the total oilseed production in India, and around 50% of the total oilseed production in Kharif season. This crop has shown tremendous growth over the last four decades with an average national yield of 1264 kg/hectare. Currently, soybean is severely attacked by more than 10 major diseases. Yield losses due to different diseases ranges from 20 to 100%. Timely detection of soybean crop disease would help farmers save their money, effort, and crop from being destroyed. This chapter presents a case study on the development of a decision support system for prediction of soybean crop disease severity. The outcome of this system will aid farmers to decide the extent of disease treatment to be employed. Such predictions make use of human involvement, and thus are a source of ambiguities. To deal with such ambiguities in decision making, this decision support system uses fuzzy inference method based on triangular fuzzy sets.

INTRODUCTION

Agricultural production and food security are two interwoven aspects that determine the future of a developing nation. In India agriculture is an important economic sector that looks to improve the methods and other processes in order to obtain good results and to increase the productivity. Drivers like market structures, ecological conditions, and political climate influence the agriculture in India. Thus, appropri-

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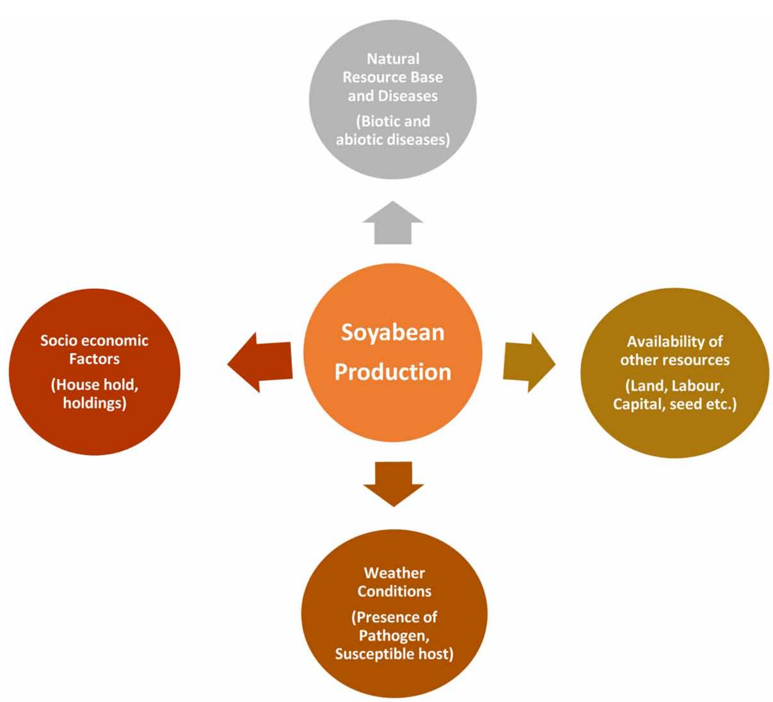
ate solutions are required that considers these dynamic and interwoven drivers and variables (Ahearn et. al., 1998 & Nehru and Dhareshwar, 1994). Viewpoints of various stakeholders are also important while providing solution (Meynard et. al., 2017).

In India, Soybean is mainly grown in the province of Madhya Pradesh, Karnataka, Maharashtra, Rajasthan, Chattisgarh, and Gujrat. This important crop is having a great potential of lessening the protein energy malnutrition and at the same time becoming ideal food of this malnourished country. In the beginning, Soybean was free of diseases and insects in India, whereas ongoing cultivation and continuous increase in area has led to enhancing insects, diseases and other issues. Figure 1 shows different factors, including biotic and abiotic diseases, socio economic factors, weather conditions, land, labour etc., that affect the production of Soybean in India. Since many years, the cultivation of this crop has been implemental in improving the soci-economic structure of a significant number of farmers in the rain-fed agro ecosystems of India (Narolia et. al., 2017). Every kind of agricultural planning has some role to play, and that is reasonable as not all are completely controllable.

Perspectives on agricultural innovation, rural development and hi-tech changes in cultivating frameworks are liable to a noteworthy change in viewpoint. Agricultural development services increasingly work with a participatory methodology. They put forward the farmers as the chief decision makers, extension workers as process catalyst and scientists as knowledge sources. The previous development strategies deserted the variety of developments that developed from the perception of the farmers (Fazey et. al., 2014).

Presently the agricultural diagnostics consider a context-mechanism-outcome trail and also the on-farm research and social surveys are the elements of the change process (Raymond et. al., 2010). These

Figure 1. Factors affecting soybean production



types of approaches assume that changes are not just explicated by context but by the management and decision-making process as well.

A most critical apprehension of agricultural development is environmental, societal and economic sustainability for which mixed cultivation frameworks appear to be suitable (Röling, 2003). The switch over to cost-effectively more sustainable production systems is particularly significant for the "license to produce" in agricultural products. This switch to a great extent relies on decisions of the farmers. A significant challenge is to unravelling the interface amid farmers' perceptions of the modernization and their decisions about effective and sustainable assimilation of a variety of farming components. To design more manageable cultivating frameworks researchers often use simulation modelling, wherein the farmers' perceptions and decision-making process for the most part overlooked. The consideration of farmers' perceptions and intentions appears to be critical for the ongoing pattern to utilize models for the study of policy options, as well as for the tools development to support decision-making at the level of the farm.

Diagnostic decision-making through fuzzy modelling is not a simple task in agriculture. The intention and verification of diagnosis must take into account the farming parameters, the components in the farming system and the farmer's experience and knowledge. The specific case study on soybean crop disease severity detection and forecasting is based on a work reported as "A framework for fuzzy modelling in agricultural diagnostics" (Pandey, Litoriva, Tiwari and Tiwari, 2018). The readers may look into it for further insights.

RELEVANT KNOWLEDGE

The soybean is also called as Glycine max is a species of legume native in East Asia region, It is widely grown for its edible bean, and has several uses (Carter and Shanmugasundaram, 1993). It is a significant, cheap and fat-free meal which is an inexpensive source of protein for the feeds of animal and many other packaged food. For instance the products made by soybean, like textured vegetable protein (TVP), are constituent of many dairy substitutes and meats (Thakur et. al., 2011). Soybean consists of a noteworthy amount of dietary minerals, phytic acid and vitamin B. As a product of soybean crop is soybean oil, which is widely used in food and industrial applications. The convention and unfermented eatable uses of soybeans include soya milk, from which tofu are prepared. Typical examples of fermented soya foods are natto, soya sauce, fermented bean paste etc.

Several diseases, including Rust, Yellow mosaic, Soybean mosaic, Charcoal route, Anthracnose, Myrothecium leaf spot, Frog eye leaf spot, Indian bud blight, etc, are known to affect soybean crop in India (Sharma et. al., 2014 and Ansari and Gupta, 1999). A very little information is available, about the causes, severity, or yield effects of these diseases. Minimising the possibility of diseases are normally determined by the employment of fine practices of agronomic for example rotation of crops and the selection of appropriate and disease resistant varieties.

Figure 2 describes various soybean crop disease detection measures. Soybean crop diseases can be detected through a variety of ways for example plant pathology analysis is an old and convenient way used extensively by the botanists and the agricultural scientists. Early disease detection (EDD) is another popular way used by the farmers and agriculture practitioners early in the soybean crop life cycle. Although there exists some state of the art techno' advanced solutions for crop disease diagnostics, but expert systems are prominent amongst them.

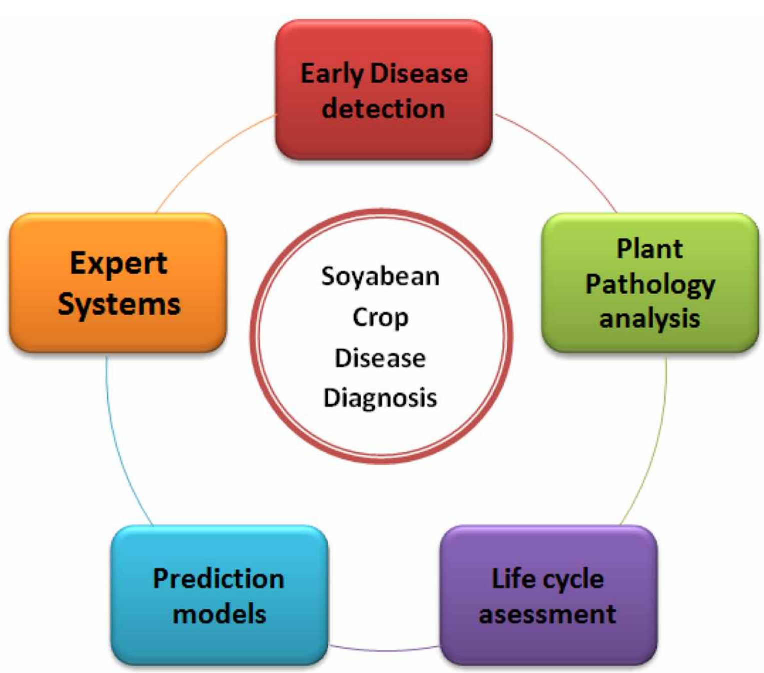
BACKGROUND ABOUT EXPERT SYSTEM

To make a machine solve an intellectual problem the solution must be known. In other words, knowledge of some specific domain is essential. Knowledge can be defined as a practical or theoretical understanding of a domain or a subject. Knowledge is the sum of currently known facts, and in fact, knowledge is power. Persons who possess knowledge are recognized as experts. Experts are the most influential and key people in their organizations. For any successful company or business, at least a few domain experts are always there.

Anybody can be viewed as a domain expert in the event that he or she has profound information (of the two realities facts and rules) and substantial viable involvement in a specific domain. The domain area may be narrow. For instance, specialists in electrical machines may have expertise in transformers, while expert in medical science might have a limited understanding of orthopaedics specialists throughout everyday life. As a rule, a specialist is a skilful individual who can do things other individuals cannot.

In the computational point of view an expert system is characterized as software or program intended to exhibit the problem-solving capability of a human expert (Durkin, 1994). An alternate definition of the expert system may be "a framework that utilizes human learning captured in a computing machine to handle the issues that conventionally require human skill or expertise." A so-called intelligent computer program that utilizes information and inference procedures to answer the problems that was sufficiently troublesome to acquire significant human expertise for their resolution. For this, it mimics the human thinking process by applying particular information and interfaces (Kalpana and Kumar, 2012 & Pandey et al., 2017a,b & Pandey et al., 2013a). Literature, books and other sources consist of enormous information and knowledge yet human needs to peruse and translate the learning for it to be utilized. The thought

Figure 2. Soybean crop disease detection techniques/models

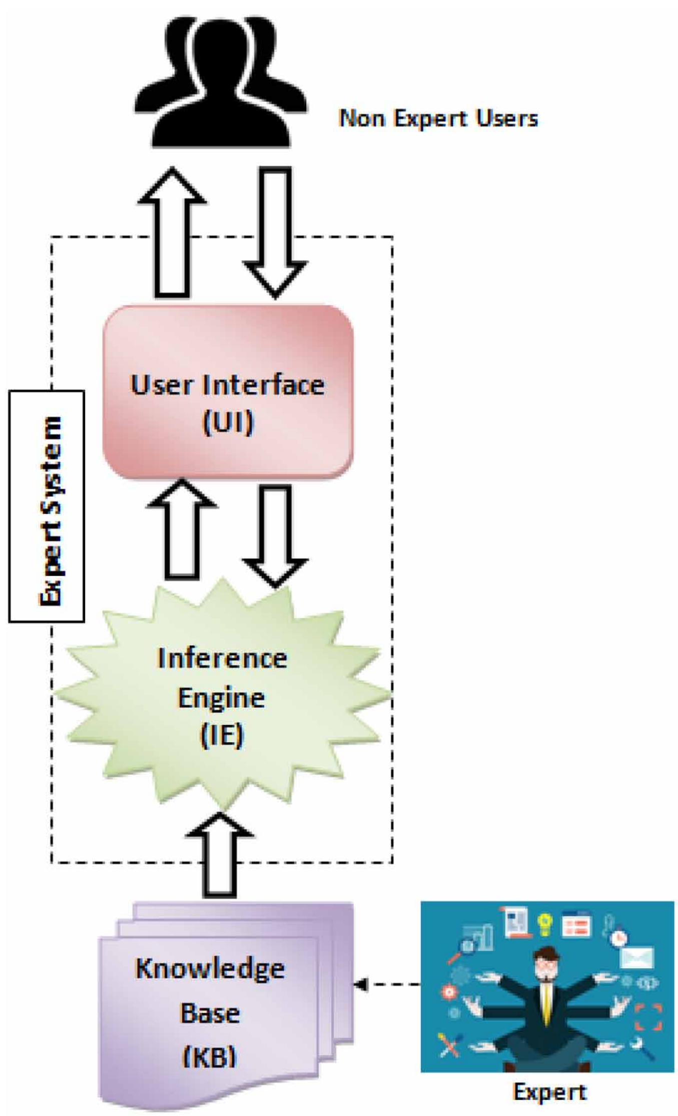


behind making an expert framework for any domain is that it can empower numerous individuals to get benefitted by the learning of one individual - the expert.

The three essential components of an expert system are knowledge base, inference engine, and user interface module (see Figure 3). The knowledge base consists of the knowledge got from the expert of the domain. Typically, the method for representing knowledge is using rules. The core work of the inference engine is to manipulate the knowledge resided in the knowledge base in order to arrive at a solution. The User Interface is the part that enables the end user to query the framework and get the results of those inquiries. Some expert system provides explanations about how the solution has arrived.

Expert systems are being introduced since last three decades as an aide in variety of areas from agriculture to software engineering (Kumar, 2013 & Kalpana and Kumar, 2012 & Pandey et al., 2013b

Figure 3. General architecture of an expert system



& Bhadauriya et al., 2010 & Pandey et al., 2019a & Pandey et al., 2018a & Pandey et al., 2018b, & Pandey et al., 2019b). Interval Fuzzy Logic, for instance, is used as an approach to identify whether the weather conditions are suitable for the growth of fungi or not. The variables used in the approach were leaf wetness, humidity, and pathogens (Rodrigues et. al., 2013). Another expert system that helps farmers taking decisions for enhanced crop production irrespective of the soil conditions in their respective area of cultivation was also proposed by Rafiuzzaman et al.

FUZZY EXPERT SYSTEM FOR SOYBEAN PLANT DISEASE PREDICTION

The domain experts usually depend on the presence of mind when they solve the issues. They additionally make use of dubious and ambiguous terms. For instance, an agriculture expert may state, 'However the Soil condition is good enough, the rainfall will decide the crop production. Other expert has no troubles with comprehension and deciphering this announcement since they have the foundation to hearing issues portrayed this way. Be that as it may, a computer engineer or programmer would experience issues giving a computer with the same level of understanding. The question is, how might we represent the knowledge of agriculture expert that utilizes vague and ambiguous terms in a system?

This section attempts to answer this question by exploring the fuzzy logic. Fuzzy logic can be defined as a set of mathematical principles meant for knowledge representation based on membership degree instead of conventional binary logic (Zadeh, 1965). It is found to be a powerful tool to deal with vagueness and ambiguity. It was primarily introduced to improve, robustness, tractability and low-cost solutions for real-world problems.

Fuzzy logic has been applied in numerous real-life situations in which uncertainty plays a crucial role in which agricultural diagnosis is a remarkable case of ambiguity, uncertainty, and vagueness (Pandey et al., 2015 & Harvinder et al., 2002 & Sumathi and Kumar, 2014 & Pandey et al., 2016 & Pandey et al., 2018a & Pandey et al., 2018b & Pandey et al., 2019c & Pandey and Litoriya, 2019). Fuzzy logic can make decisions in the agriculture domain where information is imprecise, uncertain and incomplete. Since fuzzy logic takes human decision making with its capacity to work from surmised reasoning and eventually locate an exact solution, it tends to be connected in the determination and observing of various disease in agriculture production. Early forecasting of diseases is one of the compelling aspects of precision agriculture. The main aim is to predict the possibility of occurrence of different plant diseases in the early stages so that the stakeholders can perform necessary arrangements in this regard.

Fuzzy framework for soybean crop disease detection and forecasting is proposed in this section. Fuzzy logic is a hopeful practice that can quickly capture the required knowledge of the agriculture domain, and turn up with sound diagnosis decisions. It will calculate and predict the risk of probable diseases in agricultural plants based on the risk factors and the symptoms.

Fuzzy System Architecture for Soybean Crop Disease Severity Detection

The architecture of the fuzzy logic model for soybean crop disease severity diagnosis and forecasting in agriculture is shown in Figure 4. The architecture consists of the knowledge engine, user interface and knowledge base which again encompass the database model, the fuzzy logic model.

Knowledge Base

The knowledge base design of the soybean crop disease severity diagnosis and forecasting framework comprises of a fuzzy logic model and database model. Knowledge base stores both the static and dynamic information about the decision variables. It contains structured as well as unstructured knowledge regarding the soybean agro process domain. This knowledge is conjured of facts, rules and environmental manifestation of soybean plant disease built up by the experts of the field and scientists. However the facts influence diagnostic monitoring decisions, the rules let inferences to be furnished from the information. The structured knowledge is a qualitative knowledge whereas the soybean research scientists obtain unstructured knowledge through lab experiments and experience. The database model comprises of great information regarding soybean farming. The information in the database is both static and dynamic. Database information along with fuzzy logic makes a knowledge base.

Fuzzy Modeling for Soybean Crop Disease Severity Detection

The fuzzy logic model for soybean crop disease severity diagnosis framework is demonstrated by Figure 5. This submodel comprises of three main processes; fuzzification, inference, and defuzzification.

Figure 4. Architecture of a fuzzy expert system for Soybean plant disease severity diagnosis and forecasting in agriculture

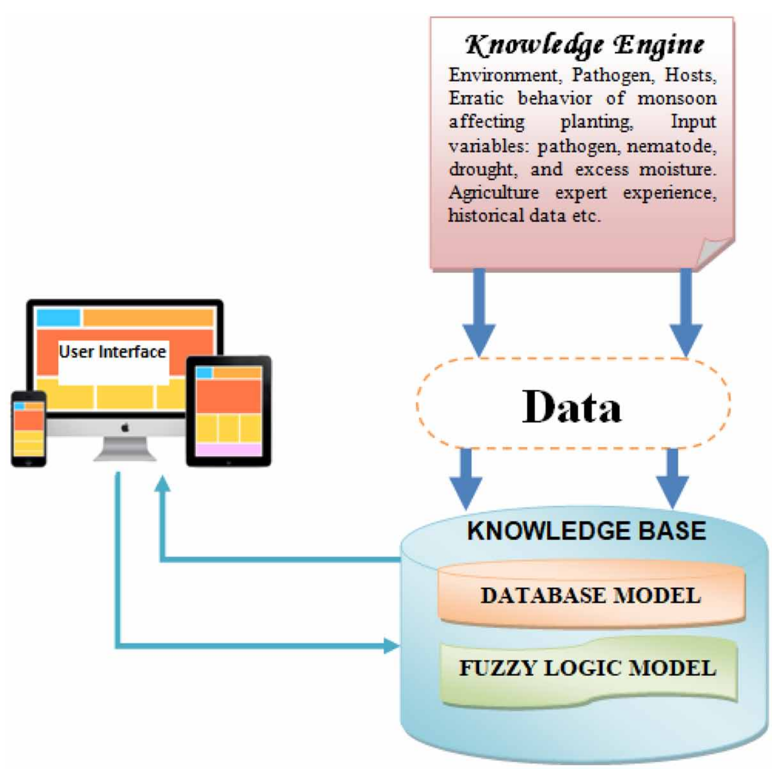
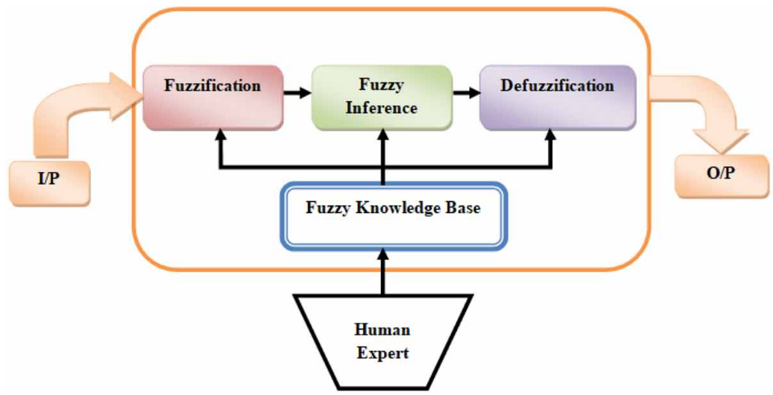


Figure 5. The structure of the fuzzy expert system



Fuzzification

To determine the degree of membership, the fuzzification process of data is performed. It is achieved by adjusting the input parameters of soybean disease severity detection into the horizontal axis and projecting vertically to the upper boundary of the membership function. There exist a lots of parameters, which are responsible for the yield of soybean crop. For the detection and forecasting of extent of disease in soybean plant we have used the biotic and abiotic parameters in the fuzzy logic model. The selected parameters are pathogen (PG), nematode (NT), drought (DR), and excess moisture (EM). These parameters contribute to the fuzzy logic input variables on the way to generate the fuzzy logic model, and the output parameter is Soybean plant disease (SPD).

These different input parameters are used to map the output value specified in the individual rules to an intermediary output evaluating fuzzy sets (mild pathogen, moderate pathogen, severe pathogen, mild nematode, moderate nematode, severe nematode, mild drought, moderated drought, severe drought, etc. 30 rules are developed for this application.

In support of this application, the universes of discourse for Pathogen (PG), nematode (NT), drought (DR), and excess moisture (EM) are selected to be [0, 15], [0, 20], [0, 10] and [0, 15] respectively. The sets of linguistic values for the linguistic variables, PG, NT, DR and, DE are [ML, MR, SV] which represent [mild pathogen, moderate pathogen, severe pathogen] [mild nematode, moderate nematode, severe nematode] [mild Drought, moderate drought, severe drought] and [mild excess moisture, moderate excess moisture, severe excess moisture] respectively. The set of linguistic values for Output is [NO, ML, MR, SV] which represent [no disease, mild disease, moderate disease, severe disease] respectively. The linguistic expressions for PG, NT, DR, DE and output (SPD) variables and their membership functions are calculated through triangular membership function. These functions are presented in (2) to (17). The generation of triangular curve relies on three parameters A_1, A_2, and A_3 where A_1 and A_3 define the triangular endpoints and A_2 defines the triangular peak location. The triangular curve is described by Equation (1). Throughout the process, linguistic labels (values) are assigned to PG, NT, DR and, DE representing the associated degree of influence of membership for every linguistic term that applies to that input variable. The output membership function delineates the rigorousness level of disease present on the diagnosed crop.

Degrees of membership (Ux) is allocated to every linguistic value as presented in (2) to (17) as mild, moderate and severe. The fuzziness is best characterized by its membership function. A membership function for a fuzzy set A on the universe of discourse X is a pictorial representation of the importance of participation of each input. It is defined as μA:X → [0,1], where every element of X is mapped to a value amid 0 and 1. It is linked with a weight to each of the inputs that are processed, expresses functional overlap between inputs, and finally find out an output response.

The membership functions (MF) and rules defined on the selected input parameters are as shown in Box 1.

The linguistic expression for output variables is calculate and given in (18) – (21) (Box 2).

Membership function plots for the pathogen (PG) nematode (NT), drought (DR), and excess moisture (EM) and the outputs (Soybean plant disease) are shown in Figures 6-10.

The degree of membership (DOM) is established by placing the chosen input parameter (PG, NT, DR or EM) into the horizontal axis and vertically projecting to the upper boundary of the membership function. The rule base is obtained from derivation based on the historical data, the experience of experts, and observation of the soybean research laboratory features of symptoms of various diseases in the crop. From this knowledge, various rules can be characterized in the rule base for the decision-making unit and listed in Table 1.

Fuzzy Inference Mechanism

Fuzzy inference mechanism is the main module of a fuzzy logic system which performs decision making. It utilizes the "IF….THEN" rules together with connectors "AND" or "OR" for framing necessary decision rules. The output of this module is always a fuzzy set regardless of its input which may be fuzzy or crisp.

We make use of Mamdani's MAX-MIN fuzzy inference engine (Mamdani and Assilian, 1975) because previous works proved that it provides precise results. Also, it is intuitive and well suited to human input. In this inference method, the rule utilizes the input membership values as the weighting factors to find out their influence on the fuzzy output sets of the final output conclusion.

In the making of the fuzzy rule, we use the notion of "AND", "OR", and occasionally "NOT." This section explains the most common definitions of these "fuzzy combination" operators which are sometimes referred to as "T-norms."

The fuzzy "AND" is written as:

$$\mu A \cap B = T\left(\mu A\left(x\right), \mu B\left(x\right)\right) \tag{22}$$

Where μ_A is understand writing as "the membership in class A" and μ_B is read as "the membership in class B."

The fuzzy "OR" is written as:

$$\mu A \cup B = T\left(\mu A\left(x\right), \mu B\left(x\right)\right) \tag{23}$$

Where μ_A is understood as "the membership in class A" and μ_B as "the membership in class B."

Box 1.

Equation	Equation No.
$$\text{Pathogen}(x) = \begin{cases} 0, & if\ x < 5 \quad \text{"Mild"} \\ \frac{x-5}{5}, & if\ 5 \le x < 10 \quad \text{"Moderate"} \\ \frac{15-x}{5}, & if\ 10 \le x < 15 \quad \text{Severe} \\ 0\ , & if\ x \ge 15 \quad \text{"Very Severe"} \end{cases}$$	(2)
$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1.5}, & if\ 1 \le x < 2.5 \\ \frac{6-x}{2.5}, & if\ 2.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases}$$	(3)
$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \frac{x-5}{3}, & if\ 5 \le x < 8 \\ \frac{10-x}{2}, & if\ 8 \le x < 10 \\ 0, & if\ x > 10 \end{cases}$$	(4)
$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 10 \\ \frac{x-10}{2}, & if\ 10 \le x < 12 \\ \frac{15-x}{3}, & if\ 12 \le x \le 15 \\ 0, & if\ x > 15 \end{cases}$$	(5)
$$\text{Nematode}(x) = \begin{cases} 0, & if\ x < 5 \quad \text{"Mild"} \\ \frac{x-5}{10}, & if\ 5 \le x, \le 15 \quad \text{"Moderate"} \\ \frac{20-x}{5}, & if\ 15 \le x < 20 \quad \text{"Severe"} \\ 0\ , & if\ x \ge 20 \quad \text{"Very Severe"} \end{cases}$$	(6)
$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1.5}, & if\ 1 \le x < 2.5 \\ \frac{6-x}{2.5}, & if\ 2.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases}$$	(7)
$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \frac{x-5}{5}, & if\ 5 \le x < 10 \\ \frac{10-x}{5}, & if\ 10 \le x < 15 \\ 0, & if\ x > 15 \end{cases}$$	(8)
$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 15 \\ \frac{x-15}{2}, & if\ 15 \le x < 17 \\ \frac{20-x}{3}, & if\ 17 \le x \le 20 \\ 0, & if\ x > 20 \end{cases}$$	(9)

continued on following page

Box 1. Continued

$$\text{Drought}(x) = \begin{cases} 0, & if\ x < 3 \quad \text{"Mild"} \\ \dfrac{x-5}{10}, & if\ 3 \le x, \le 7 \quad \text{"Moderate"} \\ \dfrac{20-x}{5}, & if\ 7 \le x < 10 \quad \text{"Severe"} \\ 0\ , & if\ x \ge 10 \quad \text{"Very Severe"} \end{cases} \tag{10}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \dfrac{x-1}{1}, & if\ 1 \le x < 2 \\ \dfrac{3-x}{1}, & if\ 2 \le x < 3 \\ 0, & if\ x > 3 \end{cases} \tag{11}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 3 \\ \dfrac{x-3}{2}, & if\ 3 \le x \le 5 \\ \dfrac{7-x}{2}, & if\ 5 \le x \le 7 \\ 0, & if\ x > 7 \end{cases} \tag{12}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 7 \\ \dfrac{x-9}{2}, & if\ 7 \le x < 9 \\ \dfrac{10-x}{}, & if\ 9 \le x \le 10 \\ 0, & if\ x > 10 \end{cases} \tag{13}$$

$$\text{Excess moisture}(x) = \begin{cases} 0, & if\ x < 5 \quad \text{"Mild"} \\ \dfrac{x-5}{5}, & if\ 5 \le x < 10 \quad \text{"Moderate"} \\ \dfrac{15-x}{5}, & if\ 10 \le x < 15 \quad \text{"Severe"} \\ 0\ , & if\ x \ge 15 \quad \text{"Very Severe"} \end{cases} \tag{14}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \dfrac{x-1}{1.5}, & if\ 1 \le x < 2.5 \\ \dfrac{6-x}{2.5}, & if\ 2.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases} \tag{15}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \dfrac{x-5}{3}, & if\ 5 \le x < 8 \\ \dfrac{10-x}{2}, & if\ 8 \le x < 10 \\ 0, & if\ x > 10 \end{cases} \tag{16}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 10 \\ \dfrac{x-10}{2}, & if\ 10 \le x < 12 \\ \dfrac{15-x}{3}, & if\ 12 \le x \le 15 \\ 0, & if\ x > 15 \end{cases} \tag{17}$$

Box 2.

Equation	Equation No.
$\mu_{No\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 0 \\ \frac{x}{1.5}, & if\ 0 \le x < 1.5 \\ 1.5 - x, & if\ 1.5 \le x < 2.5 \\ 0, & if\ x > 2.5 \end{cases}$	(18)
$\mu_{Mild\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 2.5 \\ x - 2.5, & if\ 2.5 \le x < 3.5 \\ \frac{3.5 - x}{1.5}, & if\ 3.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases}$	(19)
$\mu_{Moderate\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 5 \\ x - 5, & if\ 5 \le x < 6 \\ \frac{7.5 - x}{1.5}, & if\ 6 \le x < 7.5 \\ 0, & if\ x > 7.5 \end{cases}$	(20)
$\mu_{Severe\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 7.5 \\ \frac{x - 7.5}{0.5}, & if\ 7.5 \le x < 8 \\ \frac{10 - x}{2}, & if\ 8 \le x < 10 \\ 0, & if\ x > 10 \end{cases}$	(21)

Figure 6. Membership function plots for pathogen

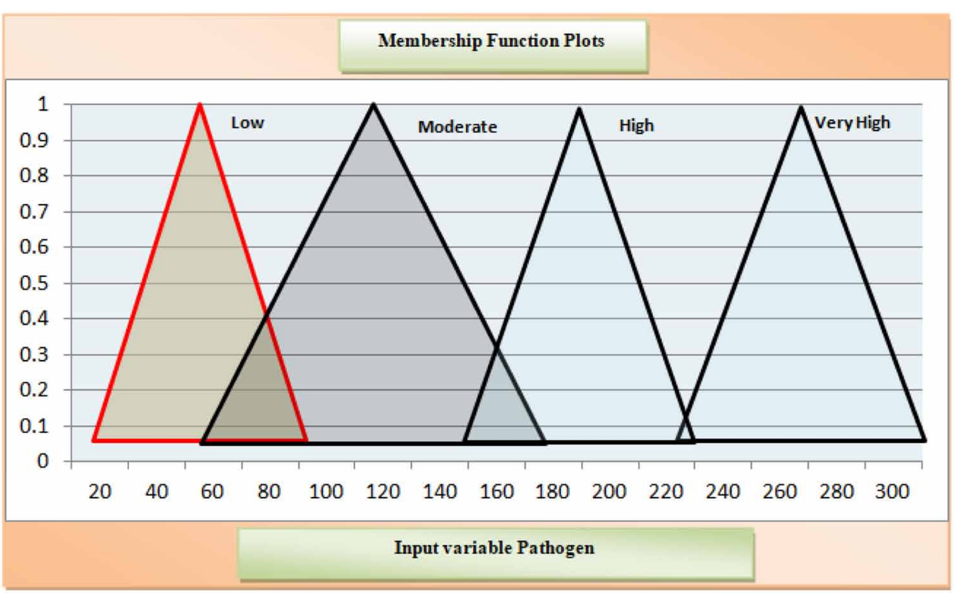


Figure 7. Membership function plots for nematode

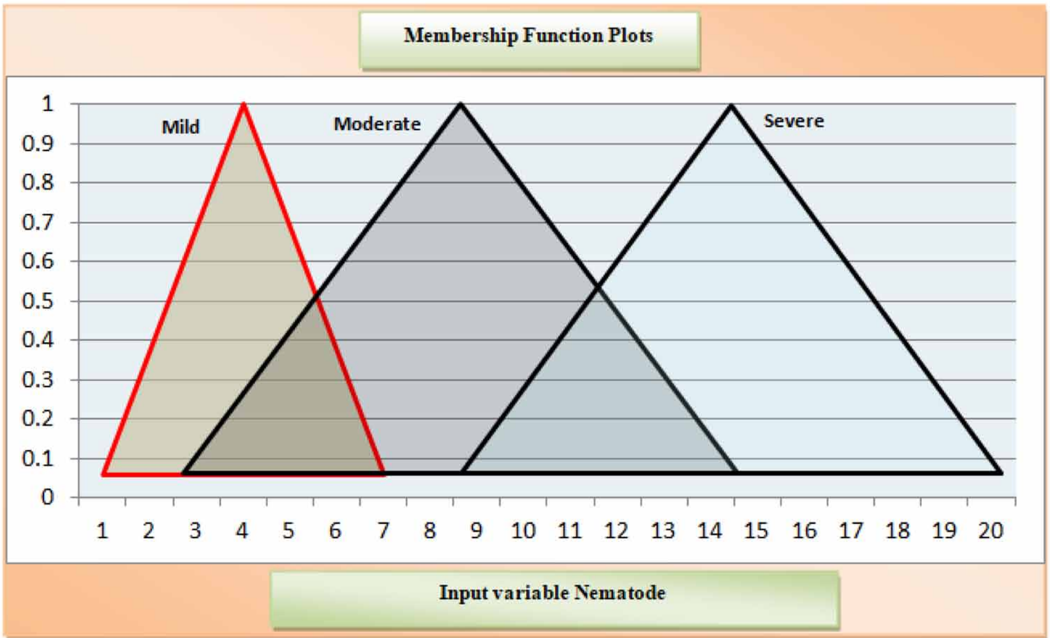


Figure 8. Membership function plots for drought

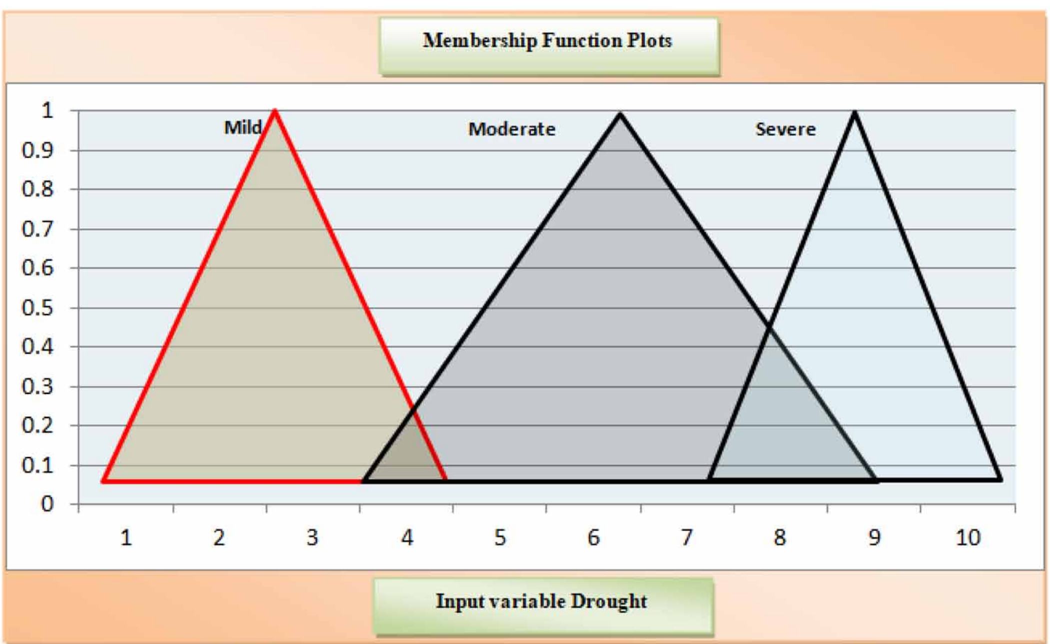


Figure 9. Membership function plots for excess moisture

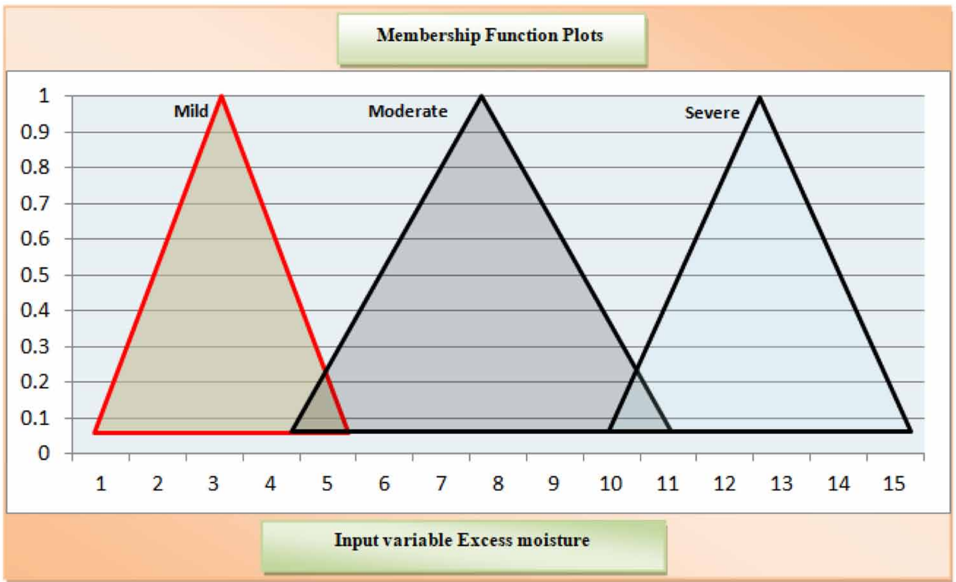
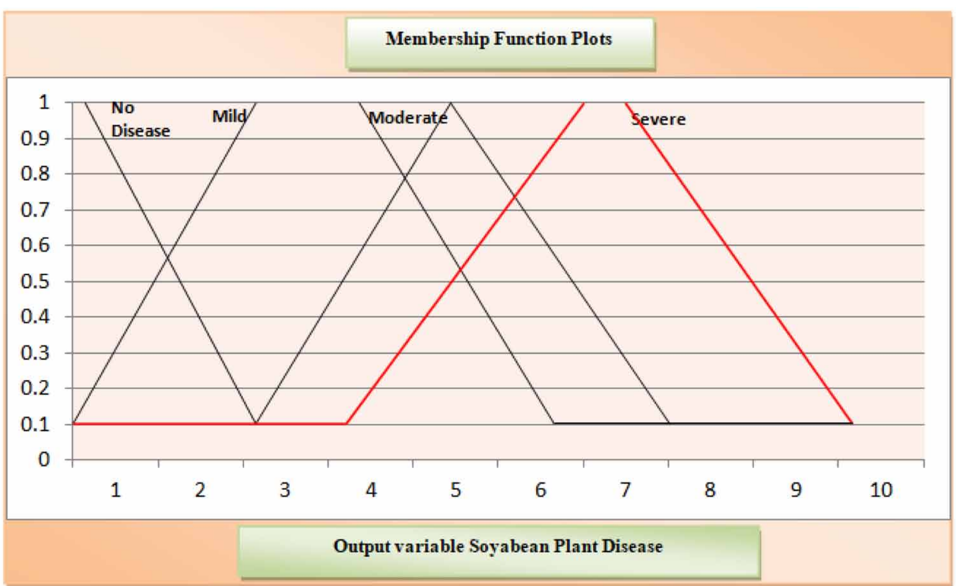


Figure 10. Output membership function plots for soybean plant disease



There are several ways to compute "OR." The most common are max [μ_A (x), μ_B (x)] it simply computes the "OR" by considering the maximum of the two (or more) membership values.

Computing the outcome of a fuzzy rule is a two-step process:

1. Computing the rule strength by joining the fuzzified inputs using the fuzzy combination process.

Table 1. Fuzzy rules for soybean plant disease diagnosis forecasting

#	Rule
1	If PG is MILD AND NT is MILD, AND DR is MILD, AND EM is MILD THEN Soybean plant disease is NO SOYBEAN PLANT DISEASE
2	If PG is MILD AND NT is MILD, AND DR is MODERATE, AND EM is MILD THEN Soybean plant disease is MILD
3	If PG is MILD AND NT is MILD, AND DR is SEVERE, AND EM is MILD THEN Soybean plant disease is MODERATE
4	If PG is MILD AND NT is MODERATE, AND DR is MILD, AND EM is MILD THEN Soybean plant disease is MILD
	....
	....
29	If PG is SEVERE AND NT is SEVERE, AND DR is MODERATE, AND EM is SEVERE THEN Soybean plant disease is SEVERE
30	If PG is SEVERE AND NT is SEVERE, AND DR is SEVERE, AND EM is SEVERE THEN Soybean plant disease is SEVERE
.	
n	....

2. Clipping the membership function of output at the rule strength.

Now the outcomes of all of the fuzzy rules are combined to attain one fuzzy output distribution. This is more often than not, but not always, done by using the fuzzy "OR."

Defuzzification

In several circumstance, it is required to come up with a single crisp output from a Fuzzy inference system. For instance, if one were attempting to classify a letter drawn by hand on a tablet, at last, the Fuzzy inference system would need to concoct a crisp number to tell the PC which letter was drawn. This crisp number is gotten in a procedure acknowledged as defuzzification.

The Defuzzification process replaces the fuzzy output of the inference engine into a crisp value making use of membership functions similar to the ones used by the fuzzification process. The defuzzification process takes fuzzy set as input (the combined output fuzzy set), whereas the outcome of the defuzzification process is a number (crisp value). Although there are more than ten methods exists for defuzzification, but few commonly used defuzzifying methods are Centroid of area (COA), Bisector of area (BOA), Smallest of maximum (SOM), Mean of maximum (MOM), and Largest of maximum (LOM). For obtaining a crisp value for Soybean plant disease diagnosis, we adopt Centroid of area method as shown in 19

$$Crisp\,Output = \mu\left(\boldsymbol{u}\right) = \left[\sum \mu_A\left(u\right) . \frac{u}{\sum \mu_A\left(u\right)}\right] \tag{24}$$

Where $\mu_A(u)$ = Membership value in the membership function and u = Center of the membership function

The centroid of area (gravity) is considered to be the most widely used defuzzification technique because, when it is applied, the defuzzified values tend to move smoothly in the output fuzzy region, therefore giving a more precise representation of a fuzzy set of any shape.

EXPERIMENTAL ANALYSIS AND RESULTS

In this chapter, Fuzzy modelling is applied for soybean disease severity diagnostics and prediction. For a better understanding of this system, some sample data is taken to develop a computer simulation showing the fuzzy inference and user interface and to assist the preliminary decision for the best control action. Results of assessment of fuzzy logic based inference for four ranges of inputs, Pathogen (PG), nematode (NT), Drought (DR), and Excess moisture (EM) are shown in Table 2 and Table 3, respectively.

For instance, if Rules number 3, 4, 15, and 19 fire from the rule base table, when pathogen, nematode, Drought, and Excess moisture values are chosen at 15, 10, 5 and 12 their related degrees of membership are mild = 0.00, moderate = 1.00, severe = 0.00 for pathogen, mild = 0.25, moderate = 0.50, severe = 0.1 for nematode, mild = 0.40, moderate=0.25, severe = 0.70 for drought and mild = 0.00 moderate = 0.50 severe = 0.70 for excess moisture. The relevant output membership function strengths (0-1) from the probable rules are computed using MAX-MIN inference for Soybean plant disease and shown in the respective column of Table 2.

At last, a defuzzification strategy is applied to get a deterministic control action. For inputs [PG, NT, DR, EM] = [15, 10, 5, 12] in Table 2, the crisp output can be computed as;

Crisp Output = ((0.30 x 5) + (0.25 x 5) + (0.80 x 7.5) + (0.45 x 7.5))

/ (0.30 + 0.25 + 0.80+0.45) = 6.7 (67%) Moderate Soybean plant disease

It implies that if these particular input conditions occur in agriculture farm the crop has 6.7 (67% Moderate) degree of Soybean plant disease.

For inputs [PG, NT, DR, EM] = [10, 8, 2, 11] in Table 3, the crisp output can be computed as;

Crisp Output = ((0.40 x 2.5) + (0.50 x 5) + (0.20 x 3) + (0.40 x 5) + (0.60 x 7.5) + (0.50 x 2.5)

+ (0.20 x 2.5) + (0.30 x 5.5) + (0.35 x 7)) / (0.40+0.50+0.20+0.40+0.60+0.50+0.20+0.30+0.35

= 4.60 (47%) Moderate Soybean plant disease

Table 2. Rule base evaluation for input variable at 3, 4, 15, and 29

Rule #	Input Variables				Consequence	Nonzero Minimum
	PG	NT	DR	EM		
3	0.25	0.25	0.40	1	Moderate	0.30
4	1	0.50	0.25	0.25	Mild	0.25
15	0.75	0.75	0.50	0.50	Moderate	0.80
29	1	1	0.70	0.70	Severe	0.45

Table 3. Rule base evaluation for Input variable at 6, 10, 3 and 9

Rule #	Input Variables				Consequence	Nonzero Minimum
	PG	NT	DR	EM		
10	0.50	0.80	0.40	0.40	Mild	0.40
12	0.50	0.80	0.40	0.60	Mild	0.50
14	0.50	0.70	0.40	0.60	Moderate	0.20
18	0.50	0.60	0.70	0.40	Moderate	0.30
21	0.50	0.50	0.70	0.40	Moderate	0.40
05	0.50	0.50	0.30	0.50	Moderate	0.60
21	0.50	0.50	0.30	0.50	Severe	0.50
18	0.50	0.40	0.30	0.50	Severe	0.20
20	0.50	0.40	0.50	0.60	Severe	0.20
27	0.25	0.50	0.8.	0.60	Severe	0.30
28	0.25	0.20	0.60	0.40	Severe	0.35

This indicates that the crop has 47% (Moderate) degree level of disease; therefore, moderate disease is expected with 47% possibility being required system response.

DISCUSSIONS

The crop disease diagnosis is a coveted area of research. This chapter presents a Soybean crop disease diagnostics system based on fuzzy inference systems. The purpose for using fuzzy inference is to handle the issues of ambiguities and impreciseness involved in the decision making due to human intervention. Here the fuzzy inference model explains the extent to which a crop is attacked by a disease. The presented inference model includes four input variables: Nematode, Excess moisture. Pathogen, and Drought. The knowledge base contains ‘n’ number of rules to determine the four different output parameters namely, No Soybean plant disease, Mild Soybean plant disease, Moderate Soybean plant disease, and Severe Soybean plant disease. Triangular fuzzy sets are used to represent the input and output variables. Like other decision systems, in the presented system too historical facts and experts’ knowledge are taken into account to develop set of if-then rules. The type of fuzzy modelling incorporated into use in this presented model is Mamdani type inference. Centroid method is used for Defuzzification method.

For various values of input variables, rule evaluation is performed. Linguistic values are used for for input variables. ‘n’ inference rules are then applied over these four linguistic values. A variety of commercial and non-commercial toolboxes may be used to perform fuzzy inference. The Fuzzy-Toolbox available in MATLAB is a popular commercial toolbox. From model development to performing simulations, this toolbox provides a plethora of built-in functions. This chapter, however, demonstrated the working of fuzzy inference systems in agricultural disease diagnostics using a hypothetical example for Soybean crop. But such kind of diagnostic systems can be developed by exploiting the expertise of agricultural scientists, educated farmers, and other agricultural stakeholders.

CONCLUSION AND FUTURE DIRECTIONS

Agricultural processes are a tedious business to handle. To develop a decision-making system, large number of factors and variable are taken into account. Soybean cultivation processes often involve human interventions; as such processes are generally ambiguous, and incomplete. Yield, demand, market, season, and climate influence agricultural processes, and at the same time, they are also dependent of the perceptions of the involved stakeholders. For these reasons, fuzzy sets and inferences offer a reasonable solution by providing a solution to the inevitable ambiguities involved with the agricultural processes. Fuzzy inference based systems can offer solutions to important agricultural related problems that include, but not limited to, Soybean crop production, plant diseases, soil erosion, optimum use of fertilizers, preventing land degradation and control climate variability. Fuzzy models are being increasingly used in agriculture since last two decades and win the confidence of scientists and researchers, and other stakeholders in making precise decisions about crop cultivation.

The authors of this chapter acknowledge the fact that to develop a decision system of crop disease diagnosis, four variables are insufficient. Therefore, the authors would like to include more variables into the diagnosis for Soybean disease for more accuracy and a reliable forecasting system, as a future work.

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Chapter 11
Application of Fuzzy Expert System for Prediction of Farmer Muscle Strength:
A Collective Database and Analysis in Agricultural Sectors of Odisha in India

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ABSTRACT

In this chapter, 168 anthropometric dimensions and the back-leg-chest (BLC) strength as the muscle strength of 113 male farmers and 31 female farmers of Odisha are statistically analyzed. Factor analysis is done to identify the most significant anthropometric dimensions. Then correlation coefficient and regression analysis are done considering the anthropometric dimensions and BLC strength. Further, an attempt is made by using ANFIS tool to predict the BLC strength of both male and female farmers. It is found that ANFIS could better predict the muscle strength of farmers.

INTRODUCTION

Indian agricultural sector is expected to be the most important driver of its economy within few years because of high investments for agricultural facilities, warehousing and cold storage. The utilization of genetically modified crops and organic farming will improve the fertility of land and the crop production rate of Indian farmers. But still the small and medium agricultural sectors are very poor and neglected, and they are found following the traditional methods of crop production. The conventional methods of

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farming results in physical problems like lungs problem due to exposure to dust, and muskuleskeletal disorders. Moreover, extreme weather conditions, and heavy work loads give them early old age, bone and muscle problems. So to attain better efficiency of performance and to improve productivity of the worldwide farmers in the agricultural sector, it is essential to design the tools and equipments keeping in consideration the farmers capability and limits. The tools and equipments design should be able to provide more human comfort, of good quality, more output focused and able to reduce the musculoskeletal injury. While designing the equipments the operator's biological needs are taken into consideration. The ergonomic guidelines and physical requirement of the equipments are the essential key elements for this purpose (Das and Grady, 1983; Das and Sengupta, 1996). Moreover, anthropometry helps to establish the physical geometry, properties and capabilities of mass as well as strength of the human body. It primarily involves the systematic measurement and dimensional descriptors of body size and shape. As the knowledge of body dimensions is essential for designers of equipment and work places, the anthropometric measurements are essential for the correct design of the work areas (Ray et al., 1995). Thus the anthropometric body dimensions are the most required factors in this regard.

BACKGROUND

Many literatures are found discusing agricultural sectors of India, their problems, but less have focused on anthropometric and muscle strength of farmers. Chakrabarti (1997) has compiled Indian anthropometric dimensions data for males and females. Victor et al. (2002) have collected and compared anthropometric data of 5 males chosen randomly in Chattisgarh and compared with other regions in the world. It was found that except popliteal height in sitting and buttock popliteal length which are higher, other dimensions are lower than western population like American, Sweden and German. Kar et al. (2003) have found a significant difference in hand dimensions of both right and left hand of male and female farmers of West Bengal with other regions in India and the world. Dewangan et al. (2008) have considered only female farmers of Arunachal Pradesh and Mizoram for anthropometric study. Koley and Melton (2010) have collected height, weight and body mass index (BMI) for both males and females of Amritsar in India. Higher mean values for all measurements were found for males. The study concluded with a regular increase of hand grip strength for both males and females. Yadav et al. (2010) have studied 14 strength parameters of both male and female farmers of Saurashtra, Gujarat and found the average push/pull strength of hands and legs, in standing/sitting posture. Sengupta and Sahoo (2012) have considered male tea garden workers of Cooch Behar District in West Bengal and found variations in measurement. Singh et al. (2013) have collected anthropometric data of 150 female farmers of 3 villages of North Gujarat in India and revealed some considerable changes in the body composition characteristics with the increment of age of female farmers. Dixit et al. (2014) have carried out an anthropometric survey of both male and female agricultural farmers of Ladakh region in India and reported a significant variation in the body dimensions when compared with other parts in the country and in other countries i.e. Egyptian, Japanese, British, Thailand, Mexican and Chinese. Premkumari et al. (2016) have studied the anthropometric data of female farmers of Hyderabad Karnataka region in India and recommended to use these data in the design of farm equipments or to improve farm tools ergonomically. Mishra et al. (2018) have considered 10 farm women of Odisha in India and analyzed them while using plain and serrated sickles for cutting crops, and then an improved serrated sickle was recommended based on their anthropometric dimensions which reduced the drudgery level as compared to the plain and serrated sickle.

The muscular strength of farmers is most considerably used in most of the agricultural activities. Therefore to help in the design of agricultural tools and equipments, there is a need to develop a database of static strength capabilities and limitations of farmers. Such that the design & force requirements for different farming activities can be matched with the job demand & capability of farmers enhancing their overall performance. Muscle strength has been revealed as essential for physical performance (Brill et al., 2000) and health (Bohannon, 2008; Ortega et al., 2008). Ten Hoor et al. (2016) have measured the back-leg-chest (BLC) strength of 58 adolescents and 45 adults. It was found that 87% of the variance in BLC strength was explained by the strength variables such as handgrip, knee-flexor, and knee extensor strength. Koley et al. (2010) have evaluated the back strength of male cricketers in India and studied its relationship with leg strength and other selected anthropometric dimensions. It was found that back strength has significant positive correlation with leg strength only. As the anthropometric and muscle strength data collected by various authors and researchers are limited to a few, hence it is a pre-requisite to have a complete and wide data base of these data for designing the tools and machineries based on ergonomic criteria. The objective of the present study is to measure the anthropometric and back-leg-chest (BLC) strength as muscle strength data for the farmers of Odisha in India.

Various studies have already been done in the field of prediction of hand grip strength and other parameters based on the neural network (NN) and regression approach. For instance, Ali et al. (2015) have considered 204 hand held grass cutter workers to study the hand arm vibration exposure during operation which causes loss of hand grip strength. They observed that the performance index of regression were better fit for neural network when compared to multiple regressions for both right and left hands, and also the neural network model was found more better than the linear model. Krueger et al. (2011) have defined ANFIS as a rule based system with 3 components, such as membership functions of input and output variables, fuzzy-rules, and output characteristics & system results. And also ANFIS is able to learn and generalize the training data. ANFIS has been associated with a feed forward neural network structure with each layer as a neural-fuzzy system component (Fahimifard et al., 2009). Seng et al. (2010) have collected handgrip strength of patients and distinguished them from the normal persons using neuro-fuzzy technique. It was observed that the classification accuracy of normal persons was 90% while for pathological patients was 75% respectively. Similarly, Hafiz et al. (2006) have used ANFIS classifier and obtained classifications of normal and pathological as 90% and 75% respectively. Ahmad et al. (2010) have used both linear least squares and neuro-fuzzy (ANFIS) model to relate age, height and weight of adult Malaysia residents with hand grip strength. The ANFIS model was found superior to the linear model as the inputs are non-linearly associated with the output. Apart from the above literature on anthropometry and muscle strength, the adaptive neural-fuzzy inference system (ANFIS) model has been successfully used by different researchers as a prediction tool in agricultural sector also., such as to predict the grain yield of irrigated wheat in Iran (Khoshnevisan et al., 2014; Naderloo et al., 2012), for agricultural information measurement (Liu et al., 2008), for the energetic & economic modeling of lentil and chickpea production in Iran (Elhami et al., 2016), to forecast the agricultural product revenues in exporting (Mohaddes et al., 2015) etc. Hence in the present study an attempt was made to use the ANFIS model for the prediction of BLC strength of farmers' in Odisha.

RESEARCH METHODOLOGY

An anthropometric and muscle strength survey was carried out in Odisha (India). Eight villages were selected from different regions, where maximum population is farmers by their profession. The subjects were selected among self farming category based on their origin and racial strain criteria, to obtain the accurate and valid samples. A total of 113 male agricultural farmers and 31 female farmers were selected from different age groups. Before taking the measurements, respective consents were taken from them and also their personal information was recorded as per the standard practice.

Body Dimensions

One hundred and sixty eight body dimensions including body weight were included in this study. There are 45 measurements including body weight in standing position, 21 measurements for Arm forward reach in standing, 13 hand dimensions, 55 measurements in sitting position and 34 different measurements in squatting position. Different postures are considered for different measurements to have a detailed data base of dimensions, which may be followed to design and improve the farm tools and equipments more conveniently. The anthropometric dimensions, landmarks on body and nomenclature/terminologies were followed as defined by Chakrabarti (1997). For instance few landmarks are illustrated as in Figure 1 for standing, Figure 2 for sitting, Figure 3 for forward arm reach, Figure 4 for hand dimensions, and Figure 5 for squatting postures, respectively.

Equipments

For measuring the body weight a portable weighing scale of 0-150 kg and least count of 100gm was used. It was calibrated against standard weights of 10–100 kg before the actual measurement. For standing, sitting, squatting body dimensions like height, length, breadth and circumference a commercially available anthropometric set, flexible but non stretchable tape of least count 1mm and adjustable stool were used with leveled platform. For hand dimensions wooden cone, vernier caliper was used. The sensitivity of the anthropometer and vernier caliper were 1mm and 0.1mm, respectively. Anthropometers were calibrated periodically before use. The sensitivity of the anthropometer was within the recommended limit of ISO 15535 (2003). Similarly, for the measurement of back-leg-chest (BLC) strengyh, a calibrated

Figure 1. Standing

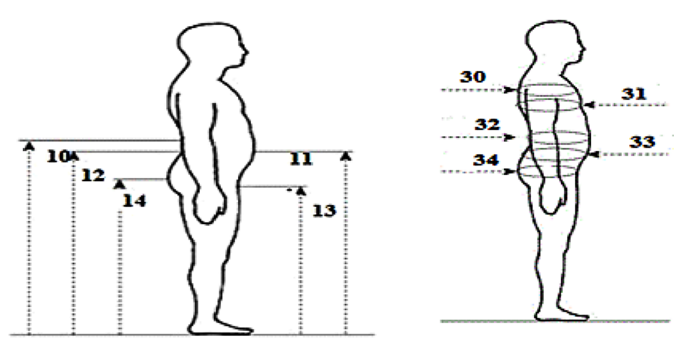


Figure 2. Sitting

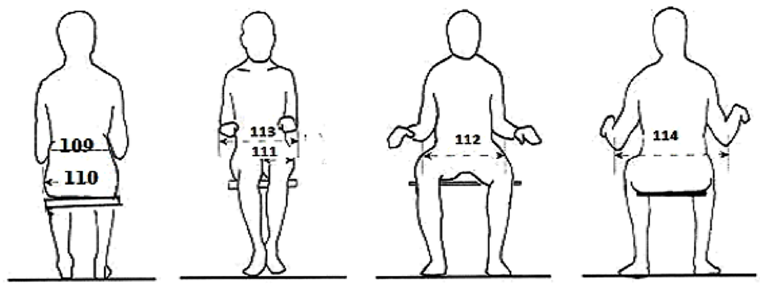


Figure 3. Forward Arm reach

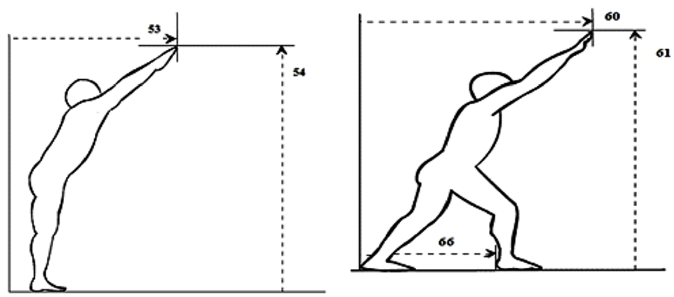
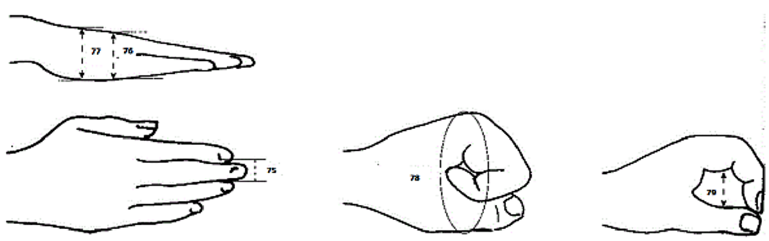


Figure 4. Hand dimensions



BLC dynamometer (Baseline, New York, USA) with dial indicator ranging from 0 to 300 kg in 10 kg increments was used as shown in Figure 6, which recorded the strength in kilograms (kg).

Procedure

Two teams containing two males in one team and two females in other were formulated to take the measurements. Prior training about the landmarks and measurement procedure on body was provided to all team members. One member was assigned to note the readings and the other for taking measurements, in each team. Male farmers' measurements were taken by male team, while female farmers' measurements were taken by the female team. Before starting the actual measurements, the subjects were explained about the purpose and different postures required for the measurements. The farmers with illness or having any injuries were not considered for this study. All the measurements were taken in the morning

Figure 5. Squatting

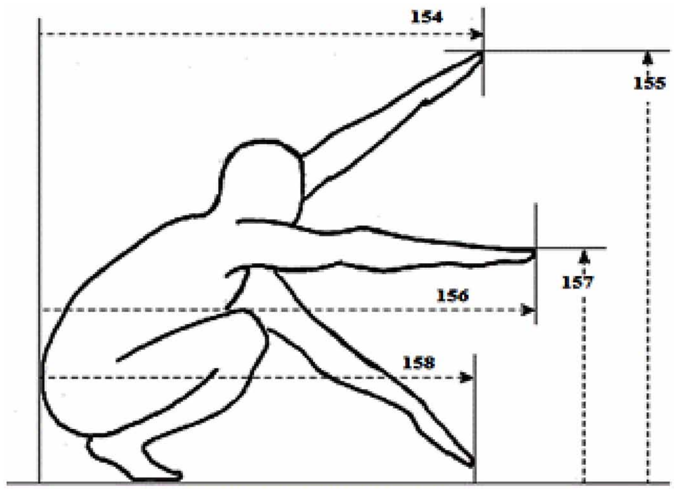


Figure 6. Baseline back-leg-chest (BLC) dynamometer

hour between 6 A.M to 10.30 A.M. In the present study, 168 body dimensions of 113 male farmers and 31 female farmers have been collected. To make the design process more convenient irrespective of any tools or equipment in agricultural sector, this study included some body dimensions in erect, leaning and squatting postures. The different anthropometric dimensions measured are 45 in standing, 55 in sitting, 21 in forward arm reach, 13 hand dimensions and 34 in squatting, respectively.

For the measurement of BLC strength of farmers, the length of the BLC dynamometer chain was adjusted according to their corresponding heights and they were asked to stand on its base by flexing slightly their knees and hips while maintaining an appropriate lordotic curve at the lower back. Then by providing continuous isometric contractions of the extensors of the knees, hips, and lower back while holding the handle, the farmers were asked to lift in a vertical direction by gradually increasing the pull and reach the maximal force in three seconds, while keeping this pull for another two seconds. Subsequently, three trials were performed with rest periods of 30 seconds between trials and maximal strength of the three trials was considered.

Analysis of Data

The measured anthropometric dimensions and BLC strength are statistically analyzed. Using Minitab17 version software, factor analysis to identify the underlying "factors" that might explain the dimensions associated with large data variability was performed. Consequently based on the result of factor analysis, the pearson correlation matrix and regression analysis was performed for both male and female farmers. Then, fuzzy logic toolbox of MATLAB version 2013 was used in order to create the fuzzy inference system (FIS) using ANFIS.

The block diagram below illustrates the entire model of this study,

RESULTS AND DISCUSSION

Descriptive analysis is being carried out for 168 anthropometric parameters of both male and female agricultural farmers (Table 1, Table 2, Table 3, Table 4, & Table 5). The minimum, mean, maximum, standard deviation, coefficient of variance (%), & 5th, 50th and 95th percentile values of each parameter are summarized. It is observed that CV% of some body-dimensions are high such as "Maximum body breadth, relaxed in standing", "Maximum body depth, relaxed in standing", "Hip at gluteal extension in standing", "Forward arm reach, upper position length in erect posture", "Forward arm reach, lower

Figure 7. Step by step procedures followed in the study

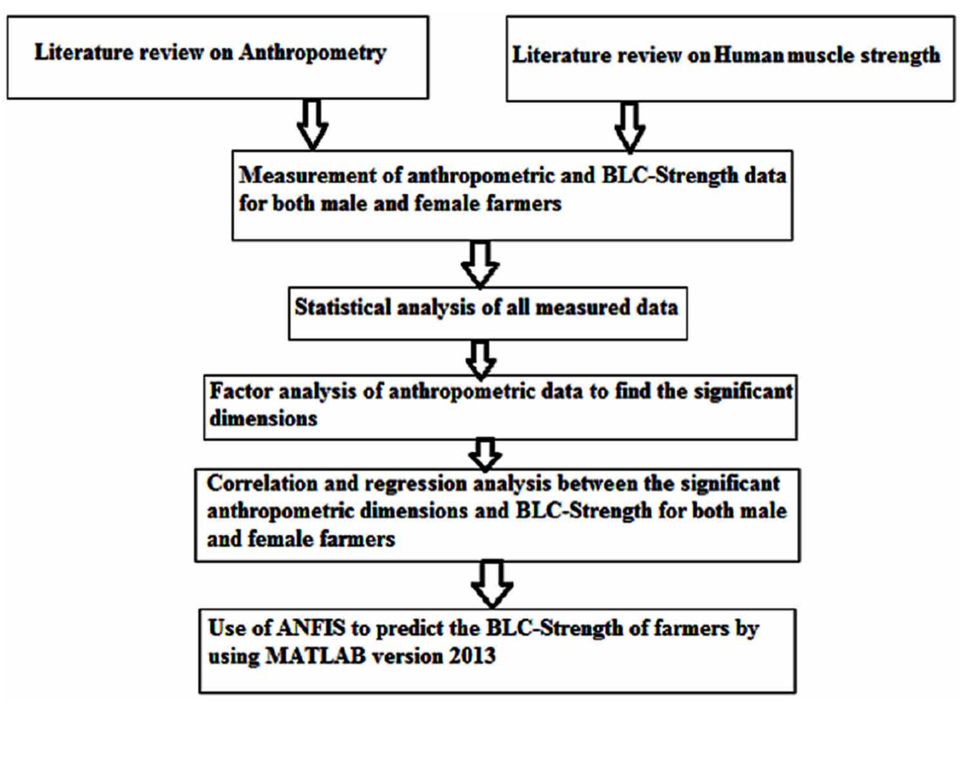


Table 1. Anthropometric data in standing

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
1.	Weight in kg	Male	39	67.5	83	10.8	16.0	42	73	78
		Female	39.2	57.9	73	9.8	16.9	40	60	72
Heights and Lengths										
2.	Normal Standing	Male	139.5	167.8	176.5	7.5	4.4	151.1	169.6	175.2
		Female	132.1	155.9	167	9.5	6.0	140.6	156.7	166.1
3.	Stature	Male	143.9	168.5	178.3	6.9	4.0	153.2	170.3	176.1
		Female	133	160	169.9	9.4	5.8	142.9	164.8	169.9
4.	Eye	Male	129.3	156.9	168.2	7.9	5.0	138	160.1	164.5
		Female	126.6	148.6	158.1	8.6	5.7	131.5	151.4	157.7
5.	Cervical	Male	118.6	139.2	151.2	7.9	5.6	123	139.2	149.5
		Female	118	131.9	141.1	6.5	4.9	118.6	133.4	140.1
6.	Mid shoulder	Male	116.8	136.8	153.5	8.1	5.9	120.1	136.2	148.1
		Female	115.2	128.9	136.4	5.7	4.4	117	130.5	134.5
7.	Acromion	Male	108.8	133.7	149.8	8.3	6.2	118.2	134.9	145.2
		Female	108.8	125.7	139.3	6.4	5.0	109.3	127.3	132.3
8.	Supra sternum	Male	112.1	132.6	161.1	8.2	6.1	116.7	133.4	143.2
		Female	112.1	125	133.9	5.3	4.2	112.8	127	129.1
9.	Sub sternum	Male	97.4	114.3	135.1	10.8	9.4	97.6	115.2	129.1
		Female	97.4	103.9	120.5	5.5	5.2	97.6	104.7	112.1
10.	Elbow	Male	79.1	98.6	121.5	11.9	12.0	80	102.1	118.8
		Female	79.8	87.3	103.9	6.3	7.2	80	86	98.9
11.	Abdominal extension	Male	79.5	96.1	114.5	10.8	11.2	80.2	98.2	112.1
		Female	79.9	85.3	101.9	5.6	6.5	80.2	83.8	94.6
12.	Waist	Male	78.1	92.6	110	9.2	9.9	78.5	93.5	106.1
		Female	76.1	84.1	102.7	6.3	7.4	78.1	81.5	97
13.	Crotch	Male	63.5	73.9	90.2	8.1	10.9	63.7	73.1	88.8
		Female	63.5	67	82.1	4.0	5.9	63.5	66.2	75.7
14.	Buttock extension	Male	57.9	80.2	100.3	11.6	14.4	60	80.5	98.3
		Female	58	70.4	85.6	6.2	8.8	60	70.2	82.6
15.	Gluteal furrow	Male	46.8	69.6	93	12.9	18.5	47.5	69.1	92.2
		Female	46.8	60.3	80.7	8.9	14.7	47.5	62.1	76.4
16.	Tip of radius	Male	61.6	75.9	95.1	10.1	13.3	62	75.3	94.7
		Female	61.7	67.4	81.5	4.4	6.5	62	67.1	76.5
17.	Trochanter	Male	70.1	81.9	103.4	9.5	11.5	70.5	79	100.2
		Female	68.1	74.8	88.8	4.4	5.8	70.1	73.5	85.3

continued on following page

Table 1. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
18.	Knuckle	Male	54.8	67.7	86.2	8.3	12.2	56	67	80.1
		Female	54.8	61.7	85	5.7	9.2	56	60.2	73.4
19.	Dactylion	Male	47	63.3	75.1	7.5	11.8	48.7	63.2	75
		Female	48	56.6	64	4.8	8.4	48.3	57.8	62.8
20.	Mid-patella	Male	34.6	46.2	58.7	5.8	12.5	36.1	45.1	55.4
		Female	33.2	41.4	47.9	3.5	8.4	35.6	42	46
21.	Lateral malleolus	Male	4.2	5.9	7.8	0.8	13.5	4.6	5.7	7.6
		Female	4.1	5.3	6.5	0.5	9.4	4.2	5.5	6.1
22.	Medial malleolus	Male	5.2	6.9	9	1.0	14.4	5.3	6.8	8.5
		Female	4.7	6.2	8.4	0.7	11.2	5.2	6.2	7.3
23.	Span	Male	139.2	168.5	183.1	13.3	7.8	140	170.3	183.1
		Female	139.2	155	167.9	9.5	6.1	139.5	158.1	166.4
24.	Span akimbo	Male	70	86.1	106.5	9.2	10.6	73	85.1	104.9
		Female	65	77.8	88.9	5.0	6.4	69.9	77.5	84.1
25.	Maximum body breadth, relaxed	Male	36.4	52.8	69.5	10.5	19.8	37.5	53.1	69.3
		Female	36.4	43.4	59.9	5.6	12.9	37.1	43.8	51.9
26.	Chest depth	Male	17.3	23	29.5	3.8	16.5	17.9	22.8	29.2
		Female	15.9	19.8	29.3	2.5	12.6	16	19.2	23.7
27.	Maximum body depth, relaxed	Male	19.5	34.5	53.5	10.5	30.4	19.8	33.6	52.8
		Female	19.5	25.5	43.9	5.4	21.1	19.7	24.5	36.9
28.	Acromion to olecranon tip length	Male	23.4	32.2	37.5	3.8	11.8	23.8	32.6	37.1
		Female	20.5	28.5	33.9	2.7	9.4	23.8	28.9	31.6
29.	Olecranon to stylion length	Male	18.6	24.8	33.2	3.9	15.7	18.9	23.7	32.1
		Female	18.5	21.6	26.7	1.7	7.8	18.8	21.8	24.1
Circumferences										
30.	Chest (mid tidal)	Male	67.1	87.3	112.5	14.2	16.2	67.8	84.8	110.3
		Female	67.1	75.3	124.2	10.1	13.4	67.8	74.3	82.9
31.	Chest (mid tidal) below bust	Male	67	81.1	106.2	12.1	14.9	67.2	76.1	103.6
		Female	55.4	70	98.9	6.8	9.7	55.8	70.5	74.9
32.	Abdominal extension Waist	Male	60.2	76.8	116	15.3	19.9	60.3	70.1	108.3
		Female	53.2	66.3	105	9.4	14.1	57.7	64.2	89.4
33.	Waist	Male	60.2	84.5	122.6	16.8	19.8	62.3	80.5	119.6
		Female	56	70.4	93.9	6.8	9.6	60.5	70.1	78.3
34.	Hip at gluteal extension	Male	59	90.6	128.4	19.3	21.3	60.2	88.8	125.3
		Female	59	76.5	126.9	13.1	17.1	60.2	76.8	94.9

continued on following page

Table 1. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
35.	Upper Thigh	Male	34.9	49.9	57.5	6.4	12.8	35.2	52.3	57.1
		Female	30	43.6	57.9	5.5	12.6	33.9	44.6	51.2
36.	Mid Thigh	Male	30.1	55	57.1	7.4	13.4	32.5	45.8	56
		Female	29	38.3	49.9	5.3	13.8	29.9	38.1	46.7
37.	Lower Thigh	Male	28	39.4	52.8	7.5	19.0	28.8	40.2	50.9
		Female	26	31.9	39.9	3.7	11.5	26.3	31.5	39
38.	Knee	Male	28.2	36	43.2	4.7	13.0	28.6	35.6	43
		Female	24.5	31.2	38.9	2.7	8.6	25.9	31.1	34.8
39.	Vertical Trunk	Male	132	164.7	213.5	25.7	15.6	133.1	160.2	211.2
		Female	125.5	141.5	179.9	10.1	7.1	132.9	139.4	158.3
40.	Relaxed elbow	Male	18.8	24.4	30.6	3.5	14.3	19.5	24.4	30.1
		Female	18.8	21.3	24.9	1.4	6.5	19.5	21.5	24.6
41.	Relaxed forearm	Male	18.8	22.9	31	2.8	12.2	18.8	22.2	28
		Female	18.6	21	25.4	1.6	7.6	18.8	20.9	25.1
42.	Wrist	Male	13.2	15.5	19.1	1.3	8.3	13.6	15.3	17.8
		Female	13.6	14.8	16.8	0.7	4.7	13.6	14.9	16
Vertical Arm Reach Heights										
43.	Vertical upward Arm reach, from floor	Male	183	212.5	231	14.4	6.7	184.6	214.1	230.8
		Female	166.5	193.6	210.8	13.5	6.9	174.2	196.8	210.2
44.	Vertical upward Arm reach, body raised on Toe	Male	196	221.8	242.1	14.9	6.7	196.5	223.1	241.8
		Female	183	204.9	219.1	9.2	4.4	184.9	205.2	218.9
45.	Comfortable vertical upward grasp reach from floor	Male	164.3	193.1	217	17.9	9.2	165.2	193.1	216.8
		Female	152	175	200.3	9.5	5.4	164.3	174.6	195.3

position length in erect posture”,” Forward arm reach, upper position length in lean posture”, “Forward arm reach, lower position length in lean posture”, “Forward arm reach, lower position height in lean posture”, “Forward arm reach, upper position length with forward step”, “Forward arm reach, lower position length with forward step”, “Forward arm reach, lower position height with forward step”, “Hand depth at metacarpal”, “Hand depth at metacarpal”, “Elbow rest in sitting”, “Mid thigh in sitting”, “Lower lumbar in sitting”, “Buttock to knee length, normal sitting for males”, “Crotch height in squatting”, “Elbow to elbow distance, relaxed in squatting”, “Knee to knee distance, relaxed in squatting”, “Big toe to big toe distance in squatting”. The CV% value can be minimized by decreasing the standard deviation or, increasing mean values, which may be obtained by increasing the sample population size.

The percentile values can be used to design new agricultural equipment and to modify the existing equipments to suit the farmers, irrespective of their gender and also for work place design. However the

Table 2. Anthropometric data in forward arm reach

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
Standing in Erect Posture, Forward Comfortable Arm Reaches From Back and Heights From Floor										
46.	Upper position length	Male	39.3	63.4	84.1	15.2	23.9	39.5	64.3	83.2
		Female	35	50.8	83.8	11.8	23.2	39.3	48.2	80.9
47.	Upper position height	Male	154.3	185.1	212	16.4	8.8	157.9	188.2	208.1
		Female	129	170.4	205.8	14.9	8.7	151.9	165.9	194.9
48.	Mid position length, forward arm reach	Male	58.9	84.4	109.6	12.6	14.9	59.3	84.2	105.6
		Female	59.1	75	99.9	9.7	12.9	59.3	75.9	91.9
49.	Mid position height	Male	109.5	137.9	175	20	14.5	110	136.2	174.2
		Female	107	122.7	174.1	13.1	10.6	109.5	120.2	143.9
50.	Lower position length	Male	34.5	58.8	83.5	15.1	25.6	36.1	54.1	82.8
		Female	34.5	49.9	81.2	11.7	23.4	36.1	46.8	80.9
51.	Lower position height	Male	51.2	77	96.8	12.9	16.7	56.2	74.8	96
		Female	52	67.5	91.2	9.0	13.3	56	66.8	88.9
52.	Forward mid position grasp reach length	Male	51.9	71.7	84.3	9.8	13.6	52.4	71.8	84.1
		Female	50.5	63.8	83.9	7.6	11.9	51.9	63.2	78.4
Standing in Front Leaning Posture, Forward Comfortable Arm Reaches From Back (Heel)										
53.	Upper position length	Male	42.3	89.2	120.5	22.3	25.0	44.5	88.9	118.2
		Female	43	72.8	118.2	19.3	26.5	44.5	75.2	112.4
54.	Upper position height	Male	123.2	169.8	204	20.3	11.9	130.2	169.9	202.1
		Female	123.6	155.3	200.1	15.9	10.2	130.2	156.1	185.9
55.	Mid position length, forward arm reach (Leaning)	Male	87.5	115.3	145	17.1	14.8	88.9	112.9	143.2
		Female	71	100.1	139.7	11.5	11.4	85.4	101.6	119.9
56.	Mid position height	Male	84.2	122.1	162	19.9	16.2	91.3	119.1	158.2
		Female	73	106.1	148.2	13.9	13.1	83.9	109.8	133.9
57.	Lower position length	Male	59.3	94.1	128.8	19.3	20.5	59.9	96.8	118.2
		Female	29	76.4	115.1	16.5	21.5	59.8	75.6	103.9
58.	Lower position height	Male	00	44.8	94	33.8	75.4	00	43.2	87.1
		Female	00	16.1	86.2	21.9	136.0	00	12.8	72.9

continued on following page

Table 2. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
59.	Forward mid position grasp reach length (Leaning forward)	Male	75.8	102.2	123	15.1	14.7	78.1	100.4	121.1
		Female	68.3	87.7	121.1	10.2	11.6	73.9	86.2	100.1
Standing With Forward Step, Comfortable Arm Reach From Back Heel and Heights From Floor										
60.	Upper position length	Male	67.8	121	164	31.3	25.8	68.2	116.9	162.8
		Female	45	92.1	160.7	21.8	23.6	67.9	93.5	133.9
61.	Upper position height	Male	110	168.8	208	28.5	16.8	111.3	173.8	200.3
		Female	87	144.7	195.9	24.4	16.8	111	142.6	188.9
62.	Mid position length	Male	104.5	144.5	184	26.1	18.0	110.1	138.9	181.1
		Female	100	121.9	175	14.5	11.8	105.3	119.2	150.9
63.	Mid position height	Male	70.8	126.6	190	34	26.8	71.3	125.9	186.2
		Female	70.8	99.7	163.8	21.6	21.6	71.3	95.2	131.9
64.	Lower position length	Male	73	127.1	170	27.8	21.8	78.2	128.6	162.3
		Female	73.1	102.8	155.6	19	18.4	74	102.5	135.9
65.	Lower position height	Male	00	46.3	105.5	34.2	73.8	00	39.6	93.5
		Female	00	92.1	18.3	22.9	125.1	00	14.9	83.9
66.	Forward step length	Male	38.3	62.8	88.3	15.7	25.0	39.9	60.9	84.9
		Female	31	49.2	48.8	9.8	19.9	38.9	49.9	67.9

Table 3. Anthropometric data of hand dimensions

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
67.	Hand length	Male	11.7	18.3	22.9	3.1	16.9	11.9	18.3	22.1
		Female	11.7	15.6	18.7	2.1	13.4	11.8	15.9	18.2
68	Palm length	Male	8.2	11.1	17.6	3.1	27.9	8.4	9.6	17.2
		Female	8.2	9	10.7	0.5	5.5	8.4	9	10.3
69.	Fist length	Male	7.3	9.7	13.8	1.9	19.5	7.4	8.9	13.2
		Female	5.2	8.3	10.6	1.1	13.2	6.1	8.4	10.5
70.	Hand grip, length	Male	3.4	5.1	8.5	1.3	25.4	3.5	4.5	7.5
		Female	3.4	4.3	6.3	0.6	13.9	3.5	4.1	5.5
71.	Hand grip, breadth	Male	6.4	9.3	13.1	1.9	20.4	6.9	8.6	12.9
		Female	5.1	7.9	10.4	1.0	12.6	6.4	8.1	9.6

continued on following page

Table 3. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
72.	Hand breadth with thumb	Male	7.8	9.9	11.8	1.1	11.1	7.8	9.9	11.7
		Female	7.5	8.9	10.4	0.7	7.8	7.7	9	9.9
73.	Hand breadth without thumb at metacarpal	Male	6.0	8.0	10	0.8	10.0	6.1	8.3	8.9
		Female	6	7.4	8.7	0.9	12.1	6.1	7.3	8.7
74.	Finger tip depth	Male	1.0	1.3	1.8	0.2	15.3	1.0	1.3	1.7
		Female	0.8	1.1	1.4	0.1	9.0	0.8	1.1	1.3
75.	Finger tip breadth	Male	1.3	1.4	2	0.1	7.1	1.3	1.4	1.6
		Female	1	1.3	1.6	0.1	7.6	1.1	1.4	1.6
76.	Hand depth at metacarpal	Male	1.5	2.3	3.9	0.7	30.4	1.5	2.2	3.8
		Female	1.5	1.8	2.9	0.4	22.2	1.5	1.7	2.7
77.	Hand depth at thumb base	Male	2.6	4.2	6.5	1.0	23.8	2.8	4.1	6.2
		Female	2.6	3.3	4.4	0.5	15.1	2.8	3.2	4.3
78.	Fist circumference	Male	22.1	27.5	35.3	3.4	12.3	22.9	26.6	34.1
		Female	20	24.3	27.9	1.7	6.9	20.5	24.6	26.5
79.	Grip inside diameter (maximum)	Male	3.9	4.6	6.1	0.6	13.0	3.9	4.5	5.8
		Female	3.9	4.2	5.2	0.3	7.1	3.9	4.1	5.1

selection of the percentile value by the designer depends on his/her requirement. It is desirable to use the 95th percentile values to establish minimum equipment dimensions involving clearances so that the smaller user group will not be adversely affected.

In factor analysis, the principal component analysis method with rotated component matrix was used. The rotation was used to reduce the number of factors on which the variables under study have high loading. For factors selection, Kaiser's Eigen value criteria with Eigen value greater than 1 were selected (Kaiser, 1960). For female farmers, the factor analysis in standing resulted in 4 dominant factors with cumulative variance of 94.14% (Table 6). In factor1, the factor loading is high in "Crotch height, Knuckle (height), Relaxed forearm (circumference), Tip of radius (height), Tro-chanter (height), Buttock extension (height), Waist (height), & Gluteal furrow (height)" i.e. 0.967, 0.957, 0.939, 0.932, 0.931, 0.924, 0.920, & 0.913, respectively. The other variables with factor loading more than 0.6 in factor1 are related to height, breadth, depth and circumference. As all these measures are related to distance, hence the factor1 is named as "Standing distance". Similarly the factor loading in factor2 is high in "Eye height, Mid shoulder height, Stature, Vertical upward arm reach from floor (height), Acromion (height), Cervical (height), and Supra sternum (height)" i.e. 0.965, 0.952, 0.950, 0.932, 0.931, 0.922, and 0.907, respectively. The other variables with factor loading more than 0.6 in factor2 are related to height, length and circumference. As all these measures are related to length, hence the factor2 is named as "Standing length". Only single variables are found in both factor3 and factor4 with factor loading more than 0.6, hence factor3 is named as "Circumference" and factor4 as "Normal height", respectively. While for male farmers, the factor analysis in standing resulted in 2 dominant factors with cumulative variance of 93.25%

Table 4. Anthropometric data in sitting

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
Heights										
80.	Normal sitting	Male	67.8	81.1	92	6.1	7.5	68	81.5	90.1
		Female	65.8	75.6	82.1	4.6	6.0	67.8	77.1	81.5
81.	Erect sitting	Male	69	82.2	98.8	6.2	7.5	69.5	82	90.8
		Female	68.2	76.8	83.7	4.5	5.8	69	79	83.4
82.	Eye	Male	57.3	71.5	84.7	6.0	8.3	58	71	80.3
		Female	52	66.2	73.8	5.6	8.4	57.4	68.8	73.1
83.	Cervical (Trunk)	Male	52.8	61.8	78.7	5.7	9.2	52.8	61.6	73.5
		Female	49.2	57.2	63.5	4.0	6.9	51.2	58.1	62.8
84.	Mid shoulder	Male	46.3	56.3	68.2	5.5	9.7	46.5	56.1	66.8
		Female	41.2	51.9	59.1	4.6	8.8	46.3	52.5	58.8
85.	Acromion	Male	44.8	55.5	65.7	5.8	10.4	45.2	55.8	63.4
		Female	42.6	49.8	55.8	3.5	7.0	44.8	49.8	55.3
86.	Upper lumbar	Male	22.8	28.2	40.7	4.3	15.2	23	28.2	37.6
		Female	19.1	25.4	34.6	2.9	11.4	22.6	24.9	30.3
87.	Lower lumbar	Male	4.8	9.8	20.8	4.8	48.9	5.1	7.9	19.7
		Female	4.9	7.1	18.9	2.8	39.4	5.1	6.3	12.7
88.	Tip of shoulder blade	Male	34	41	58.3	5.9	14.3	34.2	39.2	53.2
		Female	24.3	36.4	42.2	3.4	9.3	30.3	36.4	41.9
89.	Elbow rest	Male	11.8	21.9	32	5.9	26.9	12.3	21.3	31.1
		Female	10.4	16.8	26.5	3.4	20.2	11.9	16.7	21.8
90.	Waist	Male	11.3	21.5	32.8	6.8	31.6	11.5	19.9	32.6
		Female	11.5	16.2	26	3.5	21.6	11.5	16.5	22.1
91.	Mid thigh	Male	6.8	14.2	24.8	5.3	37.3	6.8	14	22
		Female	6.8	9.4	25.4	2.4	25.5	6.8	8.6	13.1
92.	Knee	Male	43.8	51.7	61.2	5.7	11.0	43.8	52	60.1
		Female	42.1	46.1	52	2.4	5.2	43.8	45.8	52
93.	Thigh clearance height with raised knee	Male	46.3	58.8	71.2	7.1	12.0	47.1	58.8	71
		Female	46.3	52.1	59.6	3.2	6.1	46.9	52.5	58.8
94.	Popliteal	Male	33.5	43.4	54.1	6.5	14.9	34.3	42.6	53.8
		Female	30.5	37.4	44.1	2.7	7.2	33.5	37.8	42.6
Vertical Arm reach Heights										
95.	Vertical upward arm from mid-shoulder	Male	49.3	71.7	83.4	9.1	12.6	49.8	73.1	82.3
		Female	47.5	63.5	74	7.5	11.8	49.5	65.3	71.3

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Table 4. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
96.	Vertical upward grasp from mid-shoulder	Male	36.2	61.7	81.1	12	19.4	36.5	61.9	78.2
		Female	36.5	51.5	64.3	7.2	13.9	36.5	54.3	58.9
97.	Vertical upward arm from seat surface	Male	116	129.5	141.9	7.4	5.7	116.6	131.9	140.6
		Female	108.4	121.2	131.7	5.8	4.7	108.5	120.8	130.6
98.	Vertical upward arm from floor	Male	155.7	173.1	186.6	8.7	5.0	156.2	174.8	184.2
		Female	151.8	164.4	173.4	6.3	3.8	152.1	163.6	171.8
Lengths										
99.	Buttock to knee length, normal sitting	Male	40	60.2	86.1	13.4	22.2	41.2	56.9	82.6
		Female	40.8	49.1	58.5	4.7	9.5	41.2	49.9	55.6
100.	Buttock to Popliteal length, normal sitting	Male	35	46.4	59.5	7.4	15.9	35.8	44.2	58.1
		Female	35.2	40.5	49.4	3.7	9.1	35.8	40.8	46.8
101.	Buttock to leg length normal sitting	Male	64	71.4	78.2	4.1	5.7	64.1	72.3	77.9
		Female	53.7	66.9	75.9	5.0	7.4	54	67.3	72.9
102.	Buttock to leg length while raised on toe	Male	52	63.2	77	6.9	10.9	52.8	65.2	73.1
		Female	45	57.9	71.9	6.0	10.3	52.1	55.9	68.9
103.	Buttock to extended (rested on floor) leg comfortable length	Male	68.5	90.4	116.6	10.9	12.0	69.7	93.1	108.6
		Female	66.2	81.5	97.9	8.5	10.4	68.8	82.3	97.6
104.	Buttock to leg full extended length, sitting	Male	87.9	109.6	130.2	12.1	11.0	88.9	110.6	126.8
		Female	86.5	98.1	110.6	6.1	6.2	88.8	98.6	108.8
Breadths										
105.	Bi-acromion, sitting	Male	30.8	37.9	43.8	4.5	11.8	31	38.3	43.3
		Female	23.5	33.1	38	2.8	8.4	29.8	32.8	38
106.	Bi-deltoid	Male	55.2	43.3	57.8	5.6	12.9	35.3	43.1	49.8
		Female	28.1	37.9	44.9	3.3	8.7	31.9	37.3	43
107.	Chest breadth (on bust)	Male	24.6	33.4	59.6	8.4	25.1	24.8	30.1	48.8
		Female	21.5	27	31.3	2.2	8.1	21.7	27.1	30.3
108.	Abdomen[1]	Male	20.5	29.2	42.8	6.2	21.2	20.8	27.3	38.9
		Female	16.7	23.3	27	2.3	9.8	20.1	23.5	26.8
109.	Waist 1*	Male	15.5	28.4	45.3	6.8	23.9	15.8	26.9	37.8
		Female	15.5	22.5	28.9	2.9	12.8	15.5	22.8	26.4

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Table 4. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
110.	Hip breadth	Male	20.9	35.8	55	7.4	20.6	22.3	33.8	45.6
		Female	20.9	30	42.9	4.3	14.3	22.2	30.2	34.3
111.	Thigh (middle) external breadth, single	Male	8.2	13.9	20.5	3.8	27.3	8.2	13.2	19.5
		Female	5.9	10.2	13.6	1.8	17.6	7.5	10.1	13.2
112.	Mid thigh-to thigh breadth (relaxed)	Male	28.5	39.4	49.8	7.2	18.2	28.6	37.3	49.2
		Female	27.3	33.5	52.9	4.9	14.6	27.4	32.8	39.4
113.	Elbow to elbow (closed)	Male	29.6	43.4	74.6	11.2	25.8	29.8	38.9	62.3
		Female	25.7	34.8	43.7	3.6	10.3	28.2	34.8	41.1
114.	Elbow to elbow (relaxed)	Male	33	52	82.1	12.6	24.2	33.6	49.2	74.3
		Female	33.3	42.4	57.2	5.7	13.4	33.3	43.9	51.4
115.	Knee to knee (closed)	Male	16	21.8	36	6.5	29.8	16.2	18.8	34.2
		Female	13.7	17.6	25.3	1.8	10.2	14.3	17.6	19.7
116.	Knee to knee (relaxed)	Male	22	35.4	67.7	10.5	29.6	22.5	34.1	49.5
		Female	19.1	26.4	41	5.0	18.9	22.2	24.5	39.5
117.	Chest, on bust	Male	15.9	25.4	42.5	7.7	30.3	16.2	22.2	38.6
		Female	15.8	19.3	31.5	2.9	15.0	15.9	19.1	23.7
118.	Chest, below bust	Male	15.6	24.7	41.6	7.6	30.7	15.7	21.8	37.8
		Female	14.5	18.1	23.5	2.0	11.0	14.7	18.3	21.2
119.	Abdomen[2]	Male	16.2	26.7	51.8	9.0	33.7	16.5	23.5	39.8
		Female	14.4	19.3	33.2	3.3	17.0	15.5	18.9	22.2
120.	Waist 2**	Male	13.6	23.3	53.8	8.3	35.6	13.7	21.2	36.2
		Female	13.6	16.9	28.9	3.5	20.7	13.6	15.5	24.4
Circumferences										
121.	Chest, on bust	Male	71.5	88	153.9	16.2	18.4	71.7	85.3	106.2
		Female	68.5	76.6	105.4	7.1	9.2	70.9	75.2	88.9
122.	Chest, below bust	Male	68.8	82.3	106.5	10.2	12.3	69.2	80.4	100.3
		Female	66.9	72.1	81.6	3.2	4.4	67	71.8	76.5
123.	Abdomen	Male	62.3	81	183.5	20.8	25.6	62.5	78.4	125.6
		Female	58.8	69.2	88.9	6.7	9.6	59.1	68.5	86.9
124.	Waist	Male	58.9	78.8	121.4	13.3	16.8	58.9	79.1	105.6
		Female	52.8	68	94.6	7.9	11.6	58.5	68.8	81.2
125.	Buttocks	Male	72	93.9	199.2	22.3	23.7	72.5	89.8	138.6
		Female	72.5	83.2	126.9	10.6	12.7	72.5	82.8	97.1

continued on following page

Table 4. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
126.	Scye	Male	23	36.1	60.5	8.1	22.4	23.1	36.1	51.8
		Female	23.1	30.6	43.9	5.2	16.9	23.1	31.8	37.6
127.	Axillary arm	Male	21.5	29.1	41.2	5.2	17.8	21.8	28	38.3
		Female	19.5	24.8	39.9	3.5	14.1	19.9	24.5	28.9
128.	Biceps (relaxed)	Male	19.2	26	36.8	4.8	18.4	19.5	24.8	34.9
		Female	17.3	21.9	29.4	2.3	10.5	17.9	22.3	24.9
129.	Biceps (relaxed)	Male	21	28.4	40.6	5.2	18.3	21	27.5	37.8
		Female	19	23.7	31.9	2.4	10.1	19.1	23.8	26.9
130.	Elbow (flexed)	Male	16.2	27.8	36.7	4.6	16.5	17.3	27.8	34.1
		Female	17.1	24.4	34.3	3.8	15.5	17.3	24.4	31.7
131.	Knee, flexed	Male	29.5	35.7	47.2	4.2	11.7	29.5	35.1	42.5
		Female	20.5	31.3	36.9	3.1	9.9	22.7	32.1	35.9
132.	Calf, sitting	Male	21.2	32.5	45.9	6.5	20.0	21.5	32.1	43.6
		Female	20.1	26.3	32.1	3.5	13.3	20.9	26.1	31.9
133.	Ankle at upper malleolar	Male	16	20.3	28.7	3.8	18.7	16.5	18.6	27.6
		Female	15.6	17.5	21.9	1.3	7.4	15.9	17.1	21.9
134.	Ankle at malleolar ridge	Male	20.5	24.7	34.5	4.6	18.6	20.5	22.8	33.9
		Female	18	21	24.1	1.1	5.2	18.1	20.9	23.4

*waist 1= Maximum horizontal distance across the waist at the upper margin of the lateral iliac crests (where the belt is worn).

**waist 2 = Horizontal distance from the back to the maximum curved point of the abdomen at the upper margin of the lateral iliac rest (where the belt is worn).

[1]Abdomen = Maximum horizontal distance across the abdomen at its maximum extended portion.

[2]Abdomen = Horizontal distance from the back to the front extension of abdomen.

Table 5. Anthropometric data in squatting

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
Heights and Lengths										
135.	Normal squatting height	Male	61.8	81.3	93.1	9.3	11.4	62	82.6	91.6
		Female	61.9	73.7	86	7.1	9.6	62	75.2	85.9
136.	Erect squatting height	Male	78.3	88.6	105.7	7.6	8.5	78.5	88.5	98.9
		Female	71	80.9	92.3	4.8	5.9	71.3	80.2	91.9
137.	Mid shoulder height	Male	46.5	63.9	79.5	11.9	18.6	46.8	65.8	79.1
		Female	45	53.1	68.2	6.3	11.8	46.5	50.8	67.9

continued on following page

Table 5. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
138.	Right knee height	Male	33.2	44.4	54.5	7.5	16.8	33.5	44.5	54.1
		Female	30.1	36.7	45.2	3.3	8.9	30.9	36.7	43.9
139.	Left knee height	Male	32.8	39.1	47.6	4.8	12.2	33.5	37.3	46.9
		Female	30.2	35.2	42.6	2.5	7.1	30.5	34.8	42
140.	Crotch height	Male	2.1	6.4	17	4.2	65.6	2.2	4.8	15.5
		Female	4.9	7.9	16.3	2.5	31.6	5.0	7.3	15.9
141.	Elbow to elbow distance, relaxed	Male	30	44.7	63.5	9.0	20.1	30.5	44.2	62.5
		Female	26	38.5	63.1	7.8	20.2	27.9	37.2	62.4
142.	Knee to knee distance, relaxed	Male	24.4	41.5	61	8.3	20.0	24.6	41.2	55.9
		Female	22	35.4	55.6	7.7	21.7	24.4	36.1	54.9
143.	Heel to heel distance	Male	9	21.1	36.8	9.1	43.1	9.2	19.2	35.7
		Female	6.2	12.9	22.1	3.7	28.6	6.3	12.8	20.9
144.	Big toe to big toe distance	Male	11	30.3	83.7	17.1	56.4	11	22.7	55.8
		Female	9.9	17.1	40	7.6	44.4	10	15.8	39.4
145.	Buttock to knee length	Male	39	50.3	83.5	9.9	19.6	39.5	45.9	68.9
		Female	37	43.8	58.8	4.8	10.9	39.2	42.8	56.9
146.	Buttock to foot distance	Male	29	50.4	81.2	14.8	29.3	29.5	43.1	78.9
		Female	29.5	39.8	57	6.7	16.8	29.5	39.5	55.4
147.	Buttock to heel distance	Male	8.1	14	24.3	3.6	25.7	8.8	13.5	21.2
		Female	8.5	12.5	24.5	4.2	33.6	8.8	11.2	23.9
148.	Vertical Arm reach	Male	108	129.1	158.2	10.7	8.2	109.1	129.9	145.4
		Female	108.5	120.3	141	7.4	6.1	109	120.5	139.9
Squatting in Erect Posture, Forward Comfortable Arm Reaches From Rearmost Point of Back and Heights From floor										
149.	Upper position length	Male	48.2	109.2	71.5	15.6	21.8	48.3	73.1	92.3
		Female	48.2	61.6	101	14.6	23.7	48.3	60.9	97.9
150.	Upper position height	Male	63.5	95.4	138.8	20.6	21.5	65.3	94.5	127.9
		Female	53	81.3	126	17.3	21.2	63.5	80.1	125.9
151.	Mid position length, forward arm reach	Male	66.2	97.7	133.1	18.5	18.9	66.8	96.5	130.2
		Female	56	83.2	114.2	13.1	15.7	66.5	83.3	112.9
152.	Mid position height	Male	36.2	55	99.2	14.9	27.0	36.8	55.6	85.6
		Female	33	44.5	69.1	8.8	19.7	36.2	40.2	67.9

continued on following page

Table 5. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
153.	Lower position length, touching the floor arm from floor	Male	66	87.2	116.2	14.4	16.5	66.2	87.4	114.8
		Female	66.2	76.6	100.2	9.2	12.0	66.2	75.2	97.9
Squatting in Front Leaning Posture, Forward Comfortable Arm Reaches From Rearmost Point of Back and Heights From floor										
154.	Upper position length	Male	51	89.4	126	22.4	25.0	52.3	92.3	118.8
		Female	51.2	72.4	114.5	16.9	23.3	52.3	66	113.9
155.	Upper position height	Male	39	89.8	140	32.2	35.8	39.5	99.9	130.8
		Female	39.2	66.8	122.2	25.5	38.1	39.5	56.3	120.9
156.	Mid position length, forward arm reach leaning maximum	Male	94	116	143.3	13.3	11.4	94.3	118.2	132.1
		Female	86.5	105.4	131	11.7	11.1	89.9	101.8	129.9
157.	Mid position height	Male	33	51.2	71.1	12.1	23.6	33.2	50.3	70.2
		Female	33.2	42.3	63.2	8.3	14.6	33.2	39	61.9
158.	Lower position length, touching the floor	Male	86	107.9	130	12.9	11.9	86.8	108.7	128.7
		Female	77	97.3	125.2	10	10.2	86.3	97.5	123.9
Squatting in Erect Posture, Comfortable Arm Reaches Sideways From Spine Centre and Heights From Floor										
159.	Upper position length	Male	36.3	57.2	108	14.5	25.3	37.1	54.8	80.1
		Female	32	48	76.1	11.4	23.7	36.5	45.8	74.9
160.	Upper position height	Male	76.5	98.2	136	14.7	14.9	76.9	95.9	122.2
		Female	72	88.2	114.5	10.9	12.3	76.8	86.9	112.9
161.	Mid position length	Male	36	82.6	112.9	22.3	26.9	36.3	88.1	110.2
		Female	36.2	65.2	96.1	17.2	26.3	36.3	67.2	94.9
162.	Mid position height	Male	40.8	57.7	74.9	12.2	21.1	41.2	60.7	74.5
		Female	31	46.7	65.3	7.4	15.8	35.8	45.2	63.9
163.	Lower position length, touching the floor, squatting	Male	48.7	69.7	93.5	14.9	21.3	49.2	71.8	90.3
		Female	47	56.7	88	9.3	16.4	48.7	55.1	84.9

continued on following page

Table 5. Continued

Serial Number	Terminology		Min.	Mean	Max.	SD	CV (%)	Percentile		
								5th	50th	95th
Squatting in Side Leaning Posture, Comfortable Arm Reaches Sideways From Original Erect Spine Position and Heights From floor										
164.	Upper position length	Male	37.8	75.6	116.8	20.4	26.9	38.1	48.5	102.2
		Female	27.9	60.9	105.3	17.6	28.8	38.1	58.5	101.9
165.	Upper position height	Male	49.1	94.1	126	23.1	24.5	49.8	98.9	123.1
		Female	49.5	77.1	114.5	19	24.6	49.8	70.9	111.9
166.	Mid position length, squatting	Male	52	94	118	19.9	21.1	42.3	100.2	115.8
		Female	52	78.1	109.4	17.9	22.9	52.3	72.9	107.9
167.	Mid position height	Male	31.8	50.3	78.9	12.6	25.0	32.3	53.2	67.9
		Female	31.9	40.9	67.3	9.7	23.7	32.3	35.4	65.9
168.	Lower position length, touching the floor, squatting	Male	59.6	83.1	116	15.2	18.2	61	81.7	108.2
		Female	59.6	71.5	98.8	9.6	13.4	59.9	70.2	96.9

Measurements are in cm unless mentioned
Min. =Minimum, Max. =Maximum, SD=Standard Deviation, CV=Coefficient of Variance

Table 6. Result of factor analysis for female farmers in standing

Parameters	Factor 1 (Standing Distance)	Factor 2 (Standing Length)	Factor 3 (Circumference)	Factor 4 (Normal Height)
9.Sub sternum(height)	0.812			
10.Elbow(height)	0.888			
11.Abdominal extension(height)	0.819			
12.Waist(height)	0.920			
13.Crotch(height)	**0.967**			
14.Buttock extension(height)	0.924			
15.Gluteal furrow(height)	0.913			
16.Tip of radius(height)	0.932			
17.Trochanter(height)	0.931			
18.Knuckle (height)	**0.957**			
22.Medial malleolus(height)	0.703			
25.Maximum body breadth, relaxed	0.760			
26.Chest depth	0.715			

continued on following page

Table 6. Continued

Parameters	Factor 1 (Standing Distance)	Factor 2 (Standing Length)	Factor 3 (Circumference)	Factor 4 (Normal Height)
27.Maximum body depth, relaxed	0.865			
30.Chest (mid tidal) on bust(circumference)	0.776			
32.Abdominal extension (circumference)	0.833			
34.Hip at gluteal extension(circumference)	0.890			
39.Vertical Trunk(circumference)	0.740			
40.Relaxed elbow(circumference)	0.870			
41.Relaxed forearm(circumference)	0.939			
42.Wrist(circumference)	0.767			
45.Comfortable vertical upward grasp reach from floor	0.713			
3.Stature		**0.950**		
4.Eye(height)		**0.965**		
5.Cervical(height)		0.922		
6.Mid shoulder(height)		**0.952**		
7.Acromion(height)		0.931		
8.Supra sternum(height)		0.907		
19.Dactylion from floor		0.853		
20.Mid-patella(height)		0.780		
21.Lateral malleolus length		0.781		
23.Span on toe		0.894		
24.Span akimbo		0.785		
28.Acromion to olecranon tip length		0.771		
33.Waist(circumference)		0.688		
35.Upper Thigh(circumference)		0.671		
36.Mid Thigh(circumference)		0.766		
37.Lower Thigh(circumference)		0.708		
38.Knee(circumference)		0.772		
43.Vertical upward Arm reach, from floor		0.932		
44.Vertical upward Arm reach, body raised on Toe		0.883		
31.Chest (mid tidal) below bust(circumference)			0.607	
2.Normal Standing				0.705
Eigen value	32.14	7.09	1.84	1.28
Variance in %	71.44	15.76	4.10	2.84
Cumulative variance in %	71.44	87.20	91.30	94.14

Table 7. Result of factor analysis of female farmers for hand dimensions and forward arm reach

Parameters	Factor 1 (Distance)	Factor 2 (Length)	Factor 3 (Hand)
68.Palm length	0.807		
69.Fist length	0.701		
70.Hand grip, length	0.880		
71.Hand grip, breadth	0.677		
76.Hand depth at metacarpal	**0.941**		
77.Hand depth at thumb base	0.715		
79.Grip inside diameter, maximum	0.845		
46.Upper position length, erect	0.881		
48.Mid position length, forward arm reach, erect	0.691		
49.Mid position height, erect	0.732		
50.Lower position length, erect	**0.944**		
51.Lower position height, erect	0.868		
52.Forward mid position grasp reach length, erect	0.786		
53.Upper position length, front leaning	0.786		
54.Upper position height, front leaning	0.733		
57.Lower position length, front leaning	0.644		
58.Lower position height, front leaning	0.874		
60.Upper position length, forward step	0.702		
61.Upper position height, forward step	0.753		
62.Mid position length, forward step	0.693		
63.Mid position height, forward step	0.715		
64.Lower position length, forward step	0.656		
65.Lower position height, forward step	0.820		
66.Forward step length	0.682		
72.Hand breadth, with thumb		0.748	
74.Finger tip depth		0.868	
75.Finger tip breadth		0.901	
78.Fist circumference		0.881	
47.Upper position height, erect		0.612	
55.Mid position length, forward arm reach (Leaning)		0.704	
56.Mid position height, front leaning		0.676	
59.Forward mid position grasp reach length (Leaning forward)		0.657	
67.Hand length			0.765
73.Hand breadth, without thumb at metacarpal			0.777
Eigen value	27.04	3.06	1.06
Variance in %	79.54	9.00	3.14
Cumulative variance in %	79.54	88.54	91.68

Table 8. Result of factor analysis for female farmers sitting

Parameters	Factor 1 (Sitting Span)	Factor 2 (Sitting Length)	Factor 3 (Sitting Distance)	Factor 4 (Sitting Height)	Factor 5 (Bi-Acromion)
87.Lower lumbar(height)	0.771				
89.Elbow rest(height)	0.750				
90.Waist(height)	**0.947**				
91.Mid thigh(height)	0.824				
92.Knee(height)	0.789				
93.Thigh clearance height with raised knee	0.761				
94.Popliteal(height)	0.725				
99.Buttock to knee length, normal sitting	0.754				
100.Buttock to Popliteal length, normal sitting	0.860				
102.Buttock to leg length while raised on toe, sitting	0.841				
103.Buttock to extended (rested on floor) leg comfortable length, sitting	0.639				
109.Waist 1(breadth)[#]	0.679				
110.Hip breadth, sitting	0.738				
112.Mid thigh-to thigh breadth, relaxed	0.799				
114.Elbow to elbow (relaxed) breadth	0.660				
116.Knee to knee (relaxed) bresdth	0.786				
117.Chest, on bust(breadth)	0.822				
118.Chest,below bust(breadth)	0.610				
119.Abdomen(breadth)[2]	0.712				
120.Waist 2(breadth)[##]	0.906				
121.Chest, on bust(circumference)	0.849				
123.Abdomen(circumference)	0.708				
124.Waist(circumference)	0.640				
125.Buttocks(circumference)	0.813				
126.Scye(circumference)	0.738				
127.Axillary arm(circumference)	0.696				
130.Elbow flexed (circumference)	0.733				
133.Ankle, upper malleolar(circumference)	0.715				
80.Normal sitting height		0.647			
82.Eye height		0.734			
83.Cervical(Trunk) height		0.853			
84.Mid shoulder height		0.715			
95.Vertical Upward arm from mid shoulder (height)		0.686			

continued on following page

Table 8. Continued

Parameters	Factor 1 (Sitting Span)	Factor 2 (Sitting Length)	Factor 3 (Sitting Distance)	Factor 4 (Sitting Height)	Factor 5 (Bi-Acromion)
97.Vertical upward arm from seat surface (height)		0.863			
98.Vertical upward arm from floor (height)		0.752			
101.Buttock to leg length, normal sitting		0.750			
108.Abdomen(breadth)[1]		0.701			
111.Thigh (middle) external breadth, single		0.688			
122. Chest, below bust(circumference)		0.868			
131. Knee flexed(circumference)		0.656			
132. Calf(circumference)		0.747			
86. Upper lumbar(height)			0.673		
88. Tip of shoulder blade (height)			0.647		
115. Knee to knee (closed) breadth			0.637		
134. Ankle, at malleolar ridge(circumference)			0.656		
81. Erect sitting(height)				0.610	
85. Acromion(height)				0.765	
104. Buttock to leg full extended length, sitting				0.666	
105. Bi-acromion(breadth)					0.604
Eigen value	41.27	4.48	2.14	1.53	1.01
Variance in %	75.05	8.15	3.90	2.79	1.84
Cumulative variance in %	75.05	83.20	87.10	89.89	91.73

[#]waist1= Maximum horizontal distance across the waist at the upper margin of the lateral iliac crests (where the belt is worn).

[##]waist2= Horizontal distance from the back to the maximum curved point of the abdomen at the upper margin of the lateral iliac rest (where the belt is worn).

[1]Abdomen= Maximum horizontal distance across the abdomen at its maximum extended portion.

[2]Abdomen=Horizontal distance from the back to the front extension of abdomen.

Table 9. Result of factor analysis for female farmers in squatting

Parameters	Factor 1 (Squatting Height)	Factor 2 (Squatting Length)	Factor 3 (Squatting Distance)
136.Erect squatting height	0.731		
138.Right knee height	0.762		
139.Left knee height	0.878		
140.Crotch height	0.826		
141.Elbow to elbow distance, relaxed	0.815		

continued on following page

Table 9. Continued

Parameters	Factor 1 (Squatting Height)	Factor 2 (Squatting Length)	Factor 3 (Squatting Distance)
142.Knee to knee distance, relaxed	0.773		
143.Heel to heel distance	0.755		
144.Big toe to big toe distance	0.715		
145.Buttock to knee length	0.666		
148.Vertical Arm reach(height)	0.710		
158.Lower position length, touching the floor(front leaning)	0.703		
162.Mid position height (erect from spine centre)	0.658		
163.Lower position length, touching the floor(erect from spine centre)	0.658		
135.Normal squatting height		0.857	
151.Mid position length, forward arm reach(erect)		0.656	
153.Lower position length, touching the floor(erect)		0.600	
156.Mid position length, forward arm reach leaning maximum(front leaning)		0.758	
157.Mid position height(front leaning)		0.692	
160.Upper position height(erect from spine centre)		0.621	
161.Mid position length(erect from spine centre)		0.852	
164.Upper position length(side lean),squatting		0.734	
165.Upper position height(side lean),squatting		0.813	
166.Mid position length(side lean),squatting		0.867	
137.Mid shoulder height			0.622
147.Buttock to heel distance			0.715
149.Upper position length(erect)			0.759
150.Upper position height(erect)			0.683
152.Mid position height(erect)			0.627
154.Upper position length(front leaning)			0.641
155.Upper position height(front leaning)			0.768
167.Mid position height (side lean),squatting			0.676
168.Lower position length, touching the floor (side lean),squatting			0.635
Eigen value	29.51	1.66	1.06
Variance in %	86.81	4.89	3.14
Cumulative variance in %	86.81	91.70	94.84

Table 10. Result of factor analysis for male farmers in standing

Parameters	Factor 1 (Standing Distance)	Factor 2 (Standing Length)
6.Mid shoulder(height)	0.697	
8.Supra sternum(height)	0.679	
9.Sub sternum(height)	0.804	
10.Elbow(height)	0.797	
11.Abdominal extension(height)	0.803	
12.Waist(height)	0.819	
13.Crotch(height)	0.878	
14.Buttock extension(height)	0.806	
15.Gluteal furrow(height)	0.808	
16.Tip of radius(height)	0.892	
17.Trochanter(height)	**0.926**	
18.Knuckle(height)	0.866	
20.Mid-patella(height). normal sitting	0.785	
21.Lateral malleolus	0.734	
22.Medial malleolus	0.737	
24.Span akimbo	0.814	
25.Maximum body breadth, relaxed	0.778	
26.Chest depth	0.755	
27.Maximum body depth, relaxed	0.773	
29.Olecranon to stylion length	0.833	
30.Chest (mid tidal), circumference	0.841	
31.Chest (mid tidal) below bust (circumference)	0.897	
32.Abdominal extension Waist(circumference)	**0.900**	
33.Waist(circumference)	0.852	
34.Hip at gluteal extension(circumference)	0.812	
37.Lower Thigh(circumference)	0.704	
38.Knee(circumference)	0.735	
39.Vertical Trunk(circumference)	0.846	
40.Relaxed elbow (circumference)	0.781	
41.Relaxed forearm(circumference)	0.808	
42.Wrist(circumference)	0.606	
45.Comfortable vertical upward grasp reach from floor	0.735	
2.Normal Standing(height)		**0.912**
3.Stature		**0.903**
4.Eye(height)		**0.902**
5.Cervical(height)		0.735

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Table 10. Continued

Parameters	Factor 1 (Standing Distance)	Factor 2 (Standing Length)
7.Acromion(height)		0.743
19.Dactylion from floor		0.749
23.Span		0.775
28.Acromion to olecranon tip length		0.763
35.Upper Thigh(circumference)		0.796
36.Mid Thigh(circumference)		0.709
43.Vertical upward Arm reach, from floor		0.740
44.Vertical upward Arm reach, body raised on Toe		0.701
Eigen value	40.17	1.79
Variance in %	89.26	3.99
Cumulative variance in %	89.26	93.25

Table 11. Result of factor analysis of male farmers for hand dimensions and forward arm reach

Parameters	Factor 1 (Distance)	Factor 2 (Length)
67.Hand length	0.826	
72.Hand breadth with thumb	0.775	
73.Hand breadth without thumb at metacarpal	0.862	
46.Upper position length(erect)	0.786	
47.Upper position height(erect)	0.805	
48.Mid position length(erect)	0.734	
51.Lower position height(erect)	0.720	
52.Forward mid position grasp reach length	0.780	
53.Upper position length(front leaning)	0.817	
54.Upper position height(front leaning)	0.707	
57.Lower position length(front leaning)	0.834	
58.Lower position height(front leaning)	0.759	
59.Forward mid position grasp reach length (Leaning forward)	0.797	
60.Upper position length(forward step)	0.791	
61.Upper position height(forward step)	0.855	
62.Mid position length(forward step)	0.693	
63.Mid position height(forward step)	0.712	
64.Lower position length(forward step)	0.814	
65.Lower position height(forward step)	0.746	

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Table 11. Continued

Parameters	Factor 1 (Distance)	Factor 2 (Length)
66.Forward step length	0.709	
68.Palm length		**0.917**
69.Fist length		0.884
70.Hand grip length		0.880
71.Hand grip breadth		0.855
74.Finger tip depth		0.742
76.Hand depth at metacarpal		0.811
77.Hand depth at thumb base		0.743
78.Fist circumference		0.749
79.Grip inside diameter(maximum)		0.703
49.Mid position height(erect)		0.755
50.Lower position length(erect)		0.740
55.Mid position length, forward arm reach (Leaning)		0.712
56.Mid position height(front leaning)		0.741
Eigen value	30.05	1.23
Variance in %	88.39	3.61
Cumulative variance in %	88.39	92.01

(Table 10). In factor1, the factor loading is high in "Trochanter (height)", and "Abdominal extension waist (circumference)" i.e. 0.926, and 0.900, respectively. The other variables with factor loading more than 0.6 in factor1 are related to height, breadth, depth and circumference. As all these measures are related to distance, hence the factor1 is named as "Standing distance". Similarly the factor loading in factor2 is high in "Normal Standing (height), Stature, and Eye height" i.e. 0.912, 0.903, and 0.902, respectively. The other variables with factor loading more than 0.6 in factor2 are related to height, length and circumference. As all these measures are related to length, hence the factor2 is named as "Standing length".

For female farmers, the factor analysis for "hand dimensions and forward arm reach" resulted in 3 dominant factors with cumulative variance of 91.68% (Table 7). In factor1, the factor loading is high in "Lower position length (erect), Hand depth at metacarpal, Upper position length (erect), and Hand grip length" i.e. 0.944, 0.941, 0.881,and 0.880, respectively. The other variables with factor loading more than 0.6 in factor1 are related to length, height, breadth and depth. As all these measures are related to distance, hence the factor1 is named as "Distance". Similarly the factor loading in factor2 is high in "Finger tip breadth, and Fist circumference" i.e. 0.901, and 0.881, respectively. The other variables with factor loading more than 0.6 in factor2 are related to breadth, depth, height and length. As all these measures are related to length, hence the factor2 is named as "Length". Only 2 variables related to hand dimensions are found in factor3 with factor loading more than 0.6 and it is named as "Hand". While for male farmers, the factor analysis for "hand dimensions and forward arm reach" resulted in 2 dominant factors with cumulative variance of 92.01% (Table 11). In factor1, the factor loading is high in "Hand breadth without thumb at metacarpal, and Upper position height (forward step)" i.e. 0.862, and 0.855, respectively. The other variables with factor loading more than 0.6 in factor1 are related to length, height and breadth. As all these measures are related to distance, hence the factor1 is named as "Distance". Similarly the factor loading in factor2 is high in "Palm length, Fist length Finger tip breadth, and Fist circumference" respectively. The other variables with factor loading more than 0.6 in factor2 are related to breadth, depth, height, length and circumference. As all these measures are related to length, hence the factor2 is named as "Length".

The factor analysis for female farmers in sitting resulted in 5 dominant factors with cumulative variance of 91.73% (Table 8). In factor1, the factor loading is high in "Waist height, Waist 2(breadth), Buttock to popliteal length (normal sitting), and Chest on bust (circumference)" i.e. 0.927, 0.906, 0.860, and 0.849, respectively. The other variables with factor loading more than 0.6 in factor1 are related to height, length, breadth and circumference. As all these measures are related to span, hence the factor1 is named as "Sitting span". Similarly the factor loading in factor2 is high in "Chest below bust (circumference), Vertical upward arm from seat surface height, & Cervical (Trunk) height". The other variables with factor loading more than 0.6 in factor2 are related to height, length, breadth and circumference. As all these measures are related to length, hence the factor2 is named as "Sitting length". The factor loading in factor3 is high in upper lumbar height i.e. 0.673. The other variables with factor loading more than 0.6 in factor3 are related to height, breadth and circumference. As all these measures are related to distance, hence the factor3 is named as "Sitting distance". The factor loading in factor4 is high in acromion height i.e. 0.765. The other variables with factor loading more than 0.6 in factor4 are related to length and breadth. The factor4 is named as "Sitting height". The factor5 containing only one variable i.e. "Bi-acromion (breadth)" with factor loading of 0.604 is named as "Bi-acromion". While the factor analysis for male farmers in sitting resulted in 4 dominant factors with cumulative variance of 93.96% (Table 12). In factor1, the factor loading is high in "Mid thigh (height), Waist (height), & Knee (height)" i.e. 0.854, 0.811, 0.811, respectively. The other variables with factor loading more than 0.6 in factor1 are related to height, length, breadth and circumference. As all these measures are related to span, hence the factor1 is named as "Sitting span". Similarly the factor loading in factor2 is high in "Knee to knee (closed) breadth, Ankle at upper malleolar (circumference), Ankle at malleolar ridge (circumference), and Lower lumbar (height). The other variables with factor loading more than 0.6 in factor2 are related to height, length, breadth and circumference. As all these measures are related to length, hence the factor2 is named as "Sitting length". The factor loading in factor3 is high in eye height i.e. 0.727. The other variables with factor loading more than 0.6 in factor3 are related to height and length. The factor3 is named as "Sitting height". The factor loading in factor4 is high in "Buttock (circumference), & Abdomen (circumference)" i.e. 0.844, and 0.839. The other variables with factor loading more than 0.6 in factor4 are related to circumference. The factor4 is named as "Sitting circumference".

Similarly, the factor analysis for female farmers in squatting posture resulted in 3 dominant factors with cumulative variance of 94.84% (Table 9). In factor1, the factor loading is high in "Left knee height, Crotch-height, elbow to elbow distance (relaxed)" i.e. 0.878, 0.826, and 0.815 respectively. The other variables with factor loading more than 0.6 in factor1 are related to height and length. The factor1 is named as "Squatting height". The factor loading in factor2 is high in "Mid-position length (side leaning), Normal squatting height, Mid-position length (erect, from spine centre), and Upper position height (side leaning)" i.e. 0.867, 0.857, 0.852, and 0.813, respectively. The other variables with factor loading more than 0.6 in factor2 are related to height and length. The factor2 is named as "Squatting length". The

Table 12. Result of factor analysis for male farmers in sitting

Parameters	Factor 1 (Sitting Span)	Factor 2 (Sitting Length)	Factor 3 (Sitting Height)	Factor 4 (Sitting Circumference)
85.Acromion(height)	0.657			
89.Elbow rest(height)	0.625			
90.Waist(height)	0.811			
91.Mid thigh(height)	0.854			
92.Knee (height)	0.811			
93.Thigh clearance height with raised knee	0.777			
94.Popliteal(height)	0.741			
95.Vertical Upward arm from mid shoulder(height)	0.641			
96.Vertical upward grasp from mid-shoulder (height)	0.677			
97.Vertical upward arm from seat surface(height)	0.647			
98.Vertical upward arm from floor(height)	0.758			
104.Buttock to leg full extended length, sitting	0.760			
105.Bi-acromion(breadth)	0.774			
106.Bi-deltoid (breadth)	0.656			
108.Abdomen(breadth)[1]	0.700			
109.Waist 1(breadth)*	0.685			
110.Hip breadth	0.675			
111.Thigh (middle) external breadth, single	0.719			
112.Mid thigh-to thigh breadth, relaxed	0.749			
117.Chest, on bust(breadth)	0.701			
118.Chest,below bust (breadth)	0.702			
119.Abdomen(breadth)[2]	0.644			
130.Elbow flexed(circumference)	0.608			
83.Cervical(Trunk) height		0.648		
84.Mid shoulder height		0.603		
86.Upper lumbar height		0.637		
87.Lower lumbar height		0.813		
88.Tip of shoulder blade(height)		0.784		
99.Buttock to knee length(normal sitting)		0.693		
100.Buttock to Popliteal length(normal sitting)		0.632		
107.Chest breadth (on bust)		0.669		
113.Elbow to elbow (closed), breadth		0.727		
114.Elbow to elbow (relaxed), breadth		0.732		
115.Knee to knee (closed), breadth		0.886		
116.Knee to knee (relaxed), breadth		0.611		

continued on following page

Table 12. Continued

Parameters	Factor 1 (Sitting Span)	Factor 2 (Sitting Length)	Factor 3 (Sitting Height)	Factor 4 (Sitting Circumference)
122.Chest, below bust(circumference)		0.619		
127.Axillary arm (circumference)		0.605		
128.Biceps relaxed (circumference)		0.711		
129.Biceps flexed (circumference)		0.616		
131.Knee flexed (circumference)		0.640		
132.Calf (circumference)		0.604		
133.Ankle, upper malleolar (circumference)		0.839		
134.Ankle, at malleolar ridge (circumference)		0.836		
80.Normal sitting			0.669	
81.Erect sitting			0.648	
82.Eye height			0.727	
101.Buttock to leg length normal sitting			0.623	
103.Buttock to extended (rested on floor) leg comfortable length			0.636	
121.Chest, on bust(circumference)				0.640
123.Abdomen (circumference)				0.839
124.Waist (circumference)				0.629
125.Buttocks (circumference)				0.844
126.Scye (circumference)				0.616
Eigen value	46.704	2.435	1.427	1.115
Variance in %	84.916	4.427	2.595	2.027
Cumulative variance in %	84.916	89.343	91.938	93.964

*waist1= Maximum horizontal distance across the waist at the upper margin of the lateral iliac crests (where the belt is worn).
[1]Abdomen= Maximum horizontal distance across the abdomen at its maximum extended portion.
[2]Abdomen=Horizontal distance from the back to the front extension of abdomen.

factor loading in factor3 is high in “Upper position height (front leaning), Upper position length (erect), and Buttock to heel distance” i.e. 0.768, 0.759, and 0.715, respectively. The other variables with factor loading more than 0.6 in factor3 are related to height and length. The factor3 is named as “Squatting distance”. The factor analysis for male farmers in squatting posture resulted in 2 dominant factors with cumulative variance of 92.08% (Table 13). In factor1, the factor loading is high in “Upper position height (erect, from spine centre), Mid-position length (forward arm reach) leaning maximum, Upper position length (erect), and Vertical arm reach i.e. 0.833, 0.832, 0.827 and 0.825 respectively. The other variables with factor loading more than 0.6 in factor1 are related to height and length. The factor1 is named as “Squatting height”. The factor loading in factor2 is high in “Big toe to big toe distance, and Buttock to foot distance” i.e. 0.880, and 0.849, respectively. The other variables with factor loading more than 0.6 in factor2 are related to height and length. The factor2 is named as “Squatting length”.

Table 13. Result of factor analysis for male farmers in squatting

Parameters	Factor 1 (Squatting Height)	Factor 2 (Squatting Length)
135.Normal squatting height	0.782	
136.Erect squatting height	0.722	
137.Mid shoulder height	0.731	
138.Right knee height	0.693	
147.Buttock to heel distance	0.816	
148.Vertical Arm reach	0.825	
149.Upper position length(erect)	0.827	
150.Upper position height(erect)	0.799	
151.Mid position length(forward arm reach)in erect	0.823	
152.Mid position height(erect)	0.823	
153.Lower position length touching the floor(erect)	0.815	
154.Upper position length(front leaning)	0.792	
155.Upper position height(front leaning)	0.793	
156.Mid position length (forward arm reach) leaning maximum	0.832	
157.Mid position height(front leaning)	0.754	
158.Lower position length touching the floor(front leaning)	0.798	
159.Upper position length(erect, from spine centre)	0.808	
160.Upper position height(erect, from spine centre)	0.833	
161.Mid position length(erect, from spine centre)	0.767	
163.Lower position length touching the floor(erect, from spine centre)	0.698	
164.Upper position length(side lean),squatting	0.797	
165.Upper position height(side lean),squatting	0.805	
166.Mid position length(side lean),squatting	0.810	
167.Mid position height(side lean),squatting	0.792	
168.Lower position length touching the floor(side lean),squatting	0.738	
139.Left knee height		0.806
140.Crotch height		0.785
141.Elbow to elbow distance, relaxed		0.724
142.Knee to knee distance, relaxed		0.656
143.Heel to heel distance		0.803
144.Big toe to big toe distance		**0.910**
145.Buttock to knee length		0.824
146.Buttock to foot distance		0.849
162.Mid position height(erect, from spine centre)		0.727
Eigen value	30.276	1.032
Variance in %	89.048	3.034
Cumulative variance in %	89.048	92.082

The descriptive statistics of the BLC strength for female farmers and male farmers are as summarized in Table 14, and Table 15, respectively. The mean BLC strength with standard deviation for female farmers and male farmers are found to be 53.23 kg ± 2.52, and 62.3 kg ± 4.64, respectively.

As the aim of this study is to analyze the prediction level of ANFIS and the ANFIS also consumes more time when the number of inputs are more. Hence to reduce the number of input variables, the anthropometric variables (dimensions) having more than or equal to 0.940 factor loading values in case of female farmers, and the anthropometric variables having more than or equal to 0.900 factor loading values in case of male farmers, are only considered for further analysis purposes. The eight significant dimensions obtained for female farmers are shown in Table 16, and seven significant dimensions obtained for male farmers are shown in Table 17, respectively.

The strength of linkage between two variables is depicted by their correlation coefficient which is in between -1 to 1. A positive correlation indicates a positive relationship, while a negative correlation indicates a negative relationship between the variables. The pearson correlation coefficients between the BLC strength and the obtained eight significant anthropometric dimensions for female farmers are shown in Table 4 and between the BLC strength and the obtained seven significant anthropometric dimensions for male farmers are shown in Table 5. The correlation coefficients for different parameters along with

Table 14. BLC strength of female farmers (N = 31)

Parameter	Mean	Standard Deviation (SD)	5th Percentile	95th Percentile
BLC strength (kg)	53.23	2.52	48.9	57.2

N = Number of farmers.

Table 15. BLC strength of male farmers (N = 113)

Parameter	Mean	Standard Deviation (SD)	5th Percentile	95th Percentile
BLC strength (kg)	62.3	4.64	54.1	69

N = Number of farmers.

Table 16. Significant variables for female farmers

Serial Number of Measurement	Anthropometric Dimensions
13	Crotch (height)
18	Knuckle (height)
3	Stature
4	Eye (height)
6	Mid shoulder (height)
76	Hand depth at metacarpal
50	Lower position length in erect position
90	Waist (height)

Table 17. Significant variables for male farmers

Serial Number of Measurement	Anthropometric Dimensions
17	Trochanter (height)
32	Abdominal extension waist (circumference)
2	Normal standing (height)
3	Stature
4	Eye (height)
68	Palm length
144	Big toe to big toe distance

the corresponding p-vales are obtained by using pearson product moment correlation using Minitab 2017. It is observed that for female farmers very high correlation coefficient i.e. 0.969 is in between the "BLC strength" and "Mid shoulder (height)". All the correlation coefficients are found significant at $p<0.01$ (Table 18). While for male farmers very high correlation coefficient i.e. 0.917 is in between the "BLC strength" and "Eye (height)". The correlations are found significant at $p<0.01$ (Table 19).

From the residual plot for female farmers (Figure 8), and also for male farmers (Figure 9), it is seen that in both the plots most of the points are clustered around the line in the top left graph which indicates that the error terms/residuals are approximately normal. The residuals plotted against the fitted values in the top right graph indicate that the assumption of residuals having mean zero is valid. The bottom left graph re-emphasizes the normality assumption. The bottom right graph shows a clear cyclic pattern which indicates that the residuals are dependent on number of female or male farmers.

The best fit linear regression equation was obtained as in equation (1) to predict the BLC strength (Y_1) of female farmers considering the BLC strength as dependent variable and the obtained eight significant anthropometric dimensions as independent variables. Also, for the male farmers the predicted BLC strength (Y_2) as in equation (2) was obtained considering the BLC strength as dependent variable and the obtained seven significant anthropometric dimensions as independent variables. The regression model summary for female farmers (R= 98.40%, Adjusted R squared value = 97.82%), and for male

Table 18. Correlation of significant anthropometric dimensions of female farmers with BLC strength

Significant Anthropometric Dimensions	BLC Strength	
	r	p
Crotch (height)	0.761**	0.000
Knuckle (height)	0.769**	0.000
Stature	0.966**	0.000
Eye (height)	0.973**	0.000
Mid shoulder (height)	0.969**	0.000
Hand depth at metacarpal	0.813**	0.000
Lower position length in erect position	0.866**	0.000
Waist (height)	0.908**	0.000

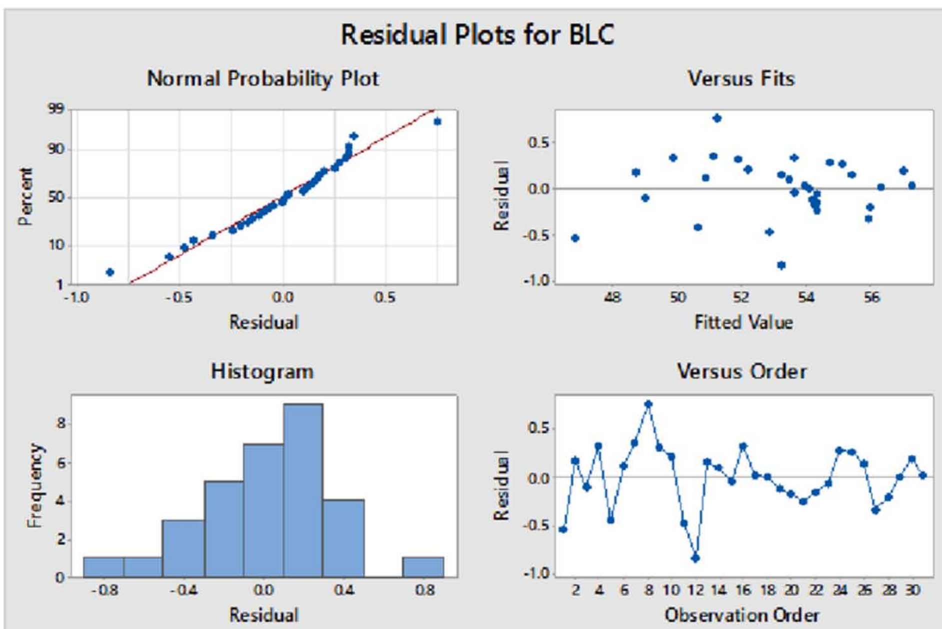
** Correlation is significant at P< 0.01 (2-tailed).

Table 19. Correlation of significant anthropometric dimensions of male farmers with BLC strength

Significant Anthropometric Dimensions	BLC Strength	
	r	p
Trochanter (height)	0.860**	0.000
Abdominal extension waist (circumference)	0.820**	0.000
Normal standing (height)	0.882**	0.000
Stature	0.914**	0.000
Eye (height)	0.917**	0.000
Palm length	0.751**	0.000
Big toe to big toe distance	0.835**	0.000

** Correlation is significant at P< 0.01 (2-tailed).

Figure 8. Residual plot for female farmers

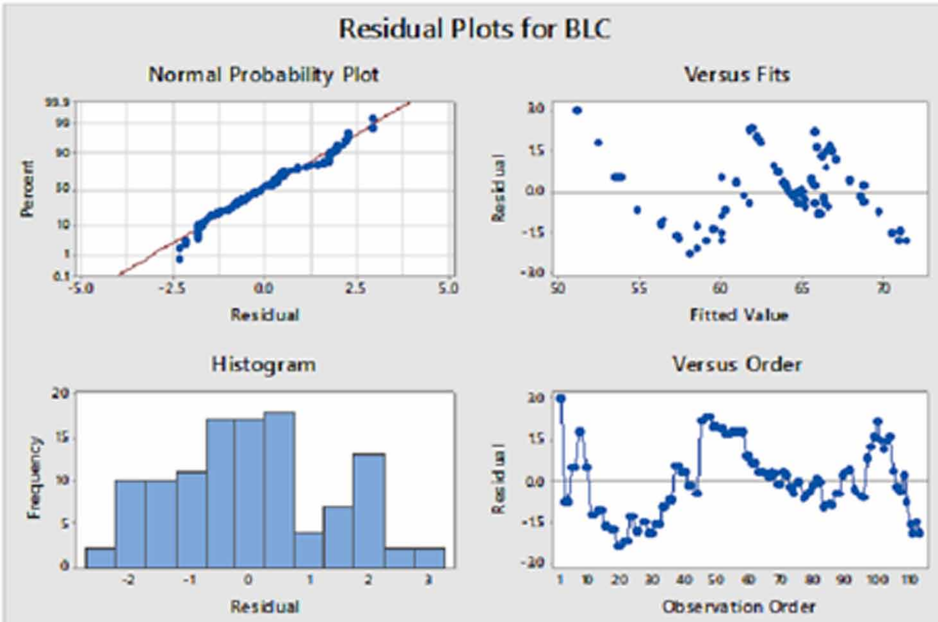


farmers (R= 92.33%, Adjusted R squared value = 91.81%) are illustrated in Table 20, and Table 21, which indicates a good level of prediction.

Predicted BLC Strength (Y_1) of Female Farmers:

$$\mathbf{Y_1} = 13.9 + 0.008\ C_1 + 0.0268\ C_2 + 0.1556\ C_3 + 0.0302\ C_4 + 0.042\ C_5 + 0.485\ C_6 + 0.0501\ C_7 - 0.078\ C_8 \quad (1)$$

Figure 9. Residual plot for male farmers



Predicted BLC Strength (Y_2) of Male Farmers:

$$\mathbf{Y_2} = -32.05 + 0.405\ X_1 - 0.188\ X_2 - 0.806\ X_3 + 0.969\ X_4 + 0.302\ X_5 - 0.031\ X_6 + 0.0347\ X_7 \qquad (2)$$

Where, C_1 = Crotch (height), C_2 = Knuckle (height), C_3 = Stature, C_4 = Eye (height), C_5 = Mid-shoulder (height), C_6 = Hand depth at metacarpal, C_7 =.Lower position length in erect position, and C_8 = Waist (height), for female farmers. Similarly, X_1 = Trochanter (height), X_2 = Abdominal extension waist (circumference), X_3 = Normal standing (height), X_4 = Stature, X_5 = Eye (height), X_6 = Palm length, and X_7 = Big toe to big toe distance, for male farmers.

Table 20. Model summary of regression analysis for female farmers

S	R-sq	R-sq (adj.)	R-sq (pred.)
0.371806	98.40%	97.82%	95.96%

Table 21. Model summary of regression analysis for male farmers

S	R-sq	R-sq (adj.)	R-sq (pred.)
1.32842	92.33%	91.81%	90.72%

Figure 10. ANFIS model 1 for female farmers

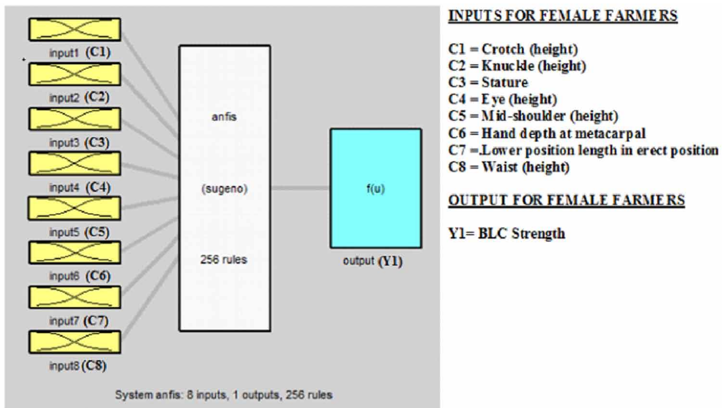


Figure 11. BLC strength prediction of ANFIS model 1 for female farmers

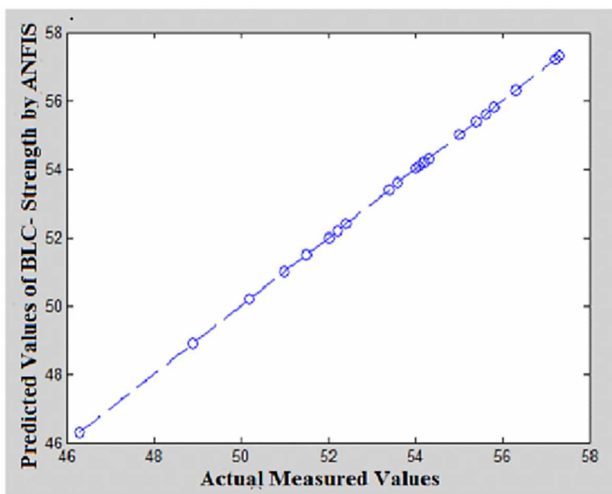


Figure 12. Errors of ANFIS model 1 for female farmers

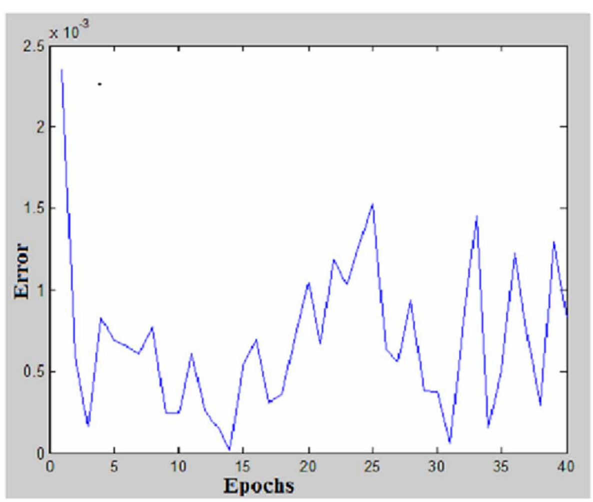


Table 22. Information of ANFIS model 1 for female farmers; Number of nodes: 555

Number of linear parameters: 2304
Number of nonlinear parameters: 48
Total number of parameters: 2352
Number of training data pairs: 31
Number of checking data pairs: 0
Number of fuzzy rules: 256
Start training ANFIS ...
1 0.00234898
2 0.000598618
3 0.000162497
4 0.000827083
5 0.000687981
6 0.000656895
7 0.000613707
8 0.000771185
9 0.000248451
10 0.000242218
11 0.00060675
12 0.000261606
13 0.00015723
14 1.69907e-05
15 0.00053268
16 0.000694875
17 0.000309941

continued on following column

Table 22. Continued

18 0.000358565
19 0.000720078
20 0.00104175
21 0.000671862
22 0.00119051
23 0.00103483
Step size decreases to 0.009000 after epoch 23.
24 0.00128556
25 0.00153431
26 0.000640777
27 0.000562571
28 0.000939144
29 0.000384121
30 0.000376048
31 5.97247e-05
32 0.000808438
33 0.00145234
34 0.000154802
35 0.000507488
36 0.00122399
37 0.000703531
38 0.000292909
39 0.00129509
40 0.000831669
Designated epoch number reached -- ANFIS training completed at epoch 40.

Figure 13. ANFIS model 2 for male farmers

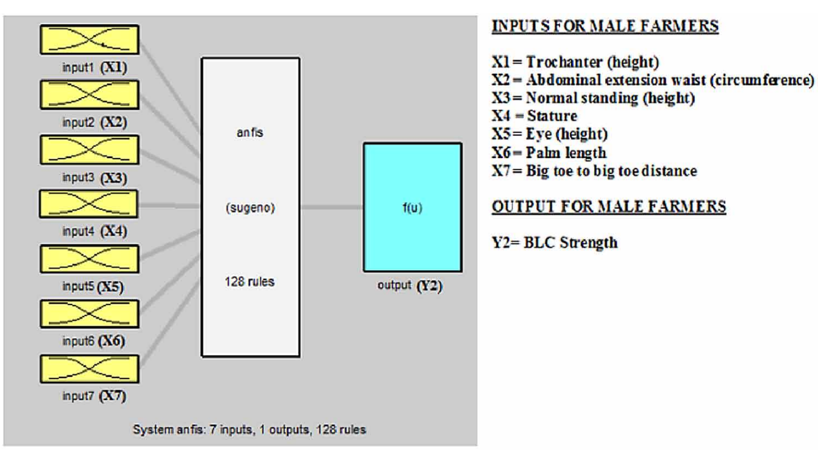


Figure 14. BLC strength prediction of ANFIS model 2 for male farmers

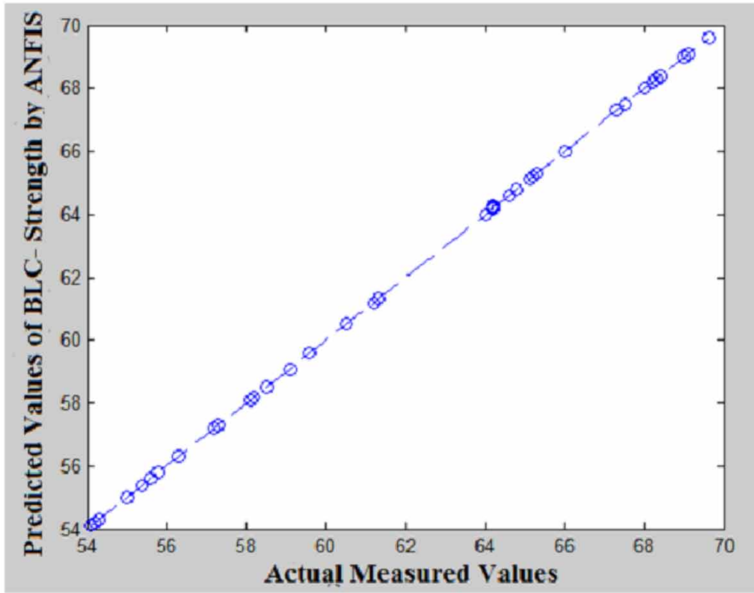
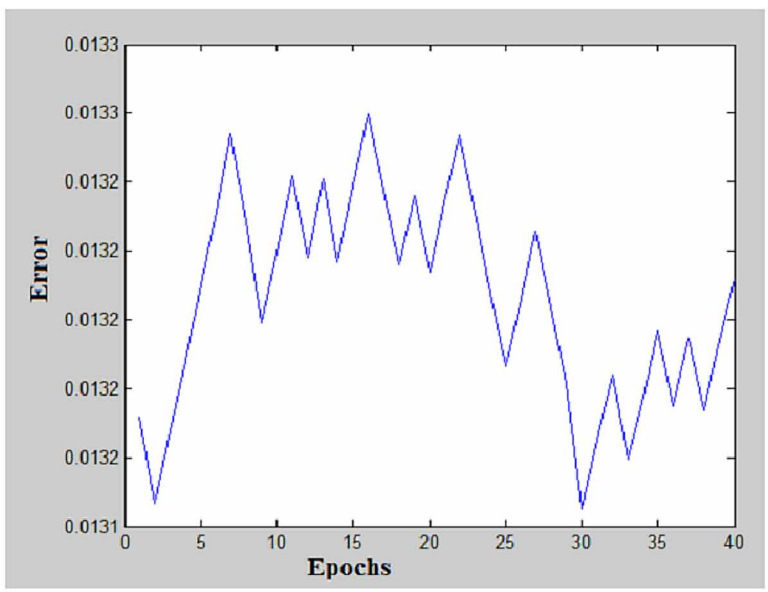


Figure 15. Errors of ANFIS model 2 for male farmers



ANFIS Analysis Output

For the ANFIS model 1, the obtained eight numbers of significant anthropometric dimensions for the female farmers are considered as inputs and BLC strength was considered as output for the prediction (Figure 10). While, the obtained seven numbers of significant anthropometric dimensions for the male farmers are considered as inputs and BLC strength was considered as output to predict in ANFIS model 2 (Figure 13). Subsequently, five significant and important adjustments are done in the structure of ANFIS network, so as to get the most effective ANFIS models. Best adjustments with minimum errors are ensured that included the number of membership functions, different types of membership functions such as triangular, bell-shaped, gaussian, trapezoidal, and sigmoid type, hybrid or back propagation type optimization methods, constant or linear output membership functions, and the number of epochs. For both the ANFIS model 1 and ANFIS model 2, bell-shaped membership function with 40 epochs is selected. BLC strength prediction, errors, and ANFIS information for the ANFIS model 1 for female farmers are illustrated in Figure 11, Figure 12, and Table 22, respectively. While, BLC strength prediction, errors, and ANFIS information for the ANFIS model 2 for male farmers are illustrated in Figure 14,

Table 23. Information of ANFIS model 2 for male farmers

Number of nodes: 294
Number of linear parameters: 1024
Number of nonlinear parameters: 42
Total number of parameters: 1066
Number of training data pairs: 113
Number of checking data pairs: 0
Number of fuzzy rules: 128
Start training ANFIS ...
1 0.0131719
2 0.0131467
3 0.0131675
4 0.0131883
5 0.0132101
6 0.0132316
7 0.0132539
8 0.0132284
9 0.0131992
10 0.0132194
11 0.0132419
12 0.0132179
13 0.0132409
14 0.0132166
Step size decreases to 0.009000 after epoch 14.
15 0.0132389
16 0.0132599

continued on following column

Table 23. Continued

17 0.0132378
18 0.013216
19 0.0132359
20 0.0132139
21 0.0132338
22 0.0132536
23 0.0132309
24 0.0132079
25 0.0131864
26 0.0132059
27 0.0132257
28 0.0132036
29 0.0131817
30 0.0131449
31 0.0131653
32 0.0131842
33 0.0131594
34 0.0131758
35 0.0131968
36 0.0131749
37 0.0131947
38 0.0131739
Step size decreases to 0.008100 after epoch 38.
39 0.0131944
40 0.0132117
Designated epoch number reached -- ANFIS training completed at epoch 40.

Figure 15, and Table 23, respectively. It is observed that a better prediction of BLC strength is achieved by ANFIS with minimum errors.

CONCLUSION

It is generally observed that, there is a non-significant variation in the anthropometric body dimension across the various states of the region, and in other parts in the world. The anthropometric data thus will help the designers and manufacturers to design and develop improved tools, techniques and equipments suitable for both male and female farmers. Moreover, as the agricultural sector needs a great focus on ergonomic design considerations to reduce the farmer's discomfort in their workstations which will enhance the overall productivity. The measurement and prediction of BLC strength of farmers in context with the anthropometric dimensions of the different population groups emphasize the usefulness of this study in the design of agricultural tools and implements. Designs that once suited the British population are followed in India (Chakrabarti, 1997). Thus the tools and equipments designed abroad should be suitably modified before introducing to the Indian farm workers.

ACKNOWLEDGMENT

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KEY TERMS AND DEFINITIONS

Anthropometry: It is the scientific study of the measurements and proportions of the human body.

Back Strength: It refers to the condition of the muscles to better support the spine and withstand stresses that can lead to back and neck pains.

Farmer: A person who is engaged in agriculture, raising living organisms for food or raw materials.

Farming: Farming is a part of agriculture. It is the growing of crops or keeping animals by people for food and raw materials.

Muscular Strength: It is the ability of a muscle or muscle group to exert maximum force against resistance.

Strength: It is the capacity of any object or substance to withstand great forces or pressures.

Chapter 12
Agricultural Health and Safety Measures by Fuzzy ahp and Prediction by Fuzzy Expert System:
Agricultural Risk Factor

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ABSTRACT

Farming is an ancient traditional business, but still it is not a profitable business sector due to risk factor attached to it. It is a high-risk business. Although profit is lucrative, loss rate is also high. Occupational safety is a big issue of discussion for agricultural workers. The methods of working in field in extreme climate (heat, rain) totally depends on environmental factors. Due to rain and droughts, the loss of profit impacts on economic condition and market. Extreme weather condition, heavy workload during their working procedure gives them early old age, bone and muscle problems. So to attain better efficiency of performance and to improve productivity of the worldwide farmers in the agricultural sector it is essential to minimize risk factors. Agricultural workers need sufficient precaution and safety measures at the time of field and machine work to minimize risk factors. Still risk is major discussion topic in agricultural business. So, an effort is taken to prioritize safety majors by fuzzy ahp, and prediction are done by fuzzy logic modelling.

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INTRODUCTION

Agriculture assumes an imperative role in the development of Indian economy, and it additionally contributes around 15% to the nation's GDP, offering work chances to around half of its population. Diverse devices and supplies implied for farming machines are utilized in farming processes which are either manually or mechanically operated. In spite of the fact that there have been advancements in new technologies, still sustainability is the most important issue in farming. Now a days modern farming process and advanced machineries have solved OHS(occupational health and safety) problems of farming .But modern equipment smoke, dust, chemicals and fertilizers both in manual driven farming and modern farming are major environmental issue. Sustainability is a very critical issue in farming, if the farming is traditional manures of animal waste is used instead of chemicals and fertilizers to improve farming prouctivity. But use of wastes of animals also creates pollution. Two of the many possible practices of sustainable agriculture are crop rotation and soil amendment, both designed to ensure that crops being cultivated can obtain the necessary nutrients for healthy growth. Soil amendments would include using locally available compost from community recycling centers. These community recycling centers help produce the compost needed by the local organic farms. *Sustainable agriculture* is a type of *agriculture* that focuses on producing long-term crops and livestock while having minimal effects on the environment. This type of *agriculture* tries to find a good balance between the need for food production and the preservation of the ecological system within the environment.

The utilization of genetically modified crops and Organic farming will improve the fertility of land and improve the crop production rate of Indian farmers. But still the small and medium agricultural sector are very poor and neglected and are following the traditional method of crop production. Risk and uncertainty are inherent to agriculture. The most common sources of risk factor are weather, climate, diseases, natural disasters, and market and environmental factor shocks. Other risks relate to logistics, infrastructure, public policy, the political situation and institutions. Some risks have become more severe in recent years due to climate change and the volatility of food prices. Smallholder farmers' livelihoods are especially vulnerable. They may find difficulty and organization of risks, and fail to get benefit from investment opportunities that could progress their farming businesses and strengthen household resilience. Farmers live with risk and make decisions every day that affect their farming operations due to change in weather conditions, dropping of prices at the time of harvest, availability of hired labor at peak times, machinery and equipment break down when most needed, draught animals death and change in government policy overnight. All of these changes are examples of the risks that farmers face in managing their farm as a business. All of these risks affect their farm profitability. Heavy rains and drought without rain could also damage or even wipe out crops. Another source of production risk is equipment. A farmer's tractor may break down during the production season resulting in an inability to harvest in time, thus affecting yields. Marketing risk and variation in prices are beyond the control of any individual farmer. The price of farm products is affected by the supply of a product, demand for the product, and the cost of production. The technology, assets and labor or human factor is also very important issue. Contacts and exposure with the chemicals & fertilizers, the exposure to soil & dust, the contamination due to bacteria, exposure to animals, injury due to hand tools and muskulateral disorders are the most important injuries faced by all agricultural workers. Indian agricultural business sector is expected to be the most important driver of Indian economy within few years because of high investments for agricultural facilities, warehousing and cold storage. The utilization of genetically modified crops and organic farming will improve the fertility of land and improve the crop production rate of farmers.

But still the small and medium agricultural sector are very poor and neglected, and are following the traditional method of crop production due to high cost of equipment and inability to purchase and due to technology deficiency unable to work with mechanized equipment. For farmers from the low economic sections, the traditional tools and techniques are the only options to carry out the farming activities. Hence respective competent authorities must have a high vision for the farmers to provide them with the latest tools and techniques, providing training regarding the operation and safety measures to consider, providing adequate medical facilities and regular inspection of respective activities. In the present study, a set of twelve design requirements has been suggested. Application of ergonomic approach while designing farm implements and machinery is not very much in practice in developing countries like India due to lack of proper anthropometric database of the user group. Since a non-significant variation was observed in the anthropometric body dimension across the various states of the region, the anthropometric data thus will help the designers and manufacturers to design and develop improved tools and implements suitable for both male and female farmers. The data will also serve as baseline study for design made for user group having similar ethnic origin in neighboring states and countries, also for Software based human posture analysis. The CV% value can be minimized by decreasing the standard deviation or, increasing mean values, which may be obtained by increasing the sample population size.

It is generally observed that, there is great difference in dimensions of tools, machine, workstations and equipment with worker's body dimensions. Discomfort produced due to products or workstation which is not ergonomically designed causes dangerous disorder in various parts of body. In ergonomic evaluation of agricultural equipment, Industrial workstations and office workstations, anthropometric data of particular community is must.

The conventional method of farming gives many physical problems like lungs problem due to exposure to dust and musculoskeletal disorders. Apart from this financial or economic risk plays an important part when money is borrowed to finance the farm business. This risk can be caused by uncertainty about future interest rates, a lender's willingness and ability to provide funds whenever needed, and the ability of the farmer to generate the income necessary for loan repayment. Human risk factor is a major risk to the farm business caused by illness or death and the personal situation of the farm family. Accidents, illness and death can disrupt farm performance. Extreme weather condition, heavy work load during the working procedure gives health and economic problems in farming. So in order to attain better efficiency of performance, and to improve productivity of the worldwide farmers in the agricultural sector, it is essential to design the tools and equipment to make the work easier and risk free. But the design must be done keeping in view the farmer's capability and limits. The tools and equipment design should be of good quality and able to provide more human comfort, more output focused and also reduce the musculoskeletal injury. Risk management has gained relevance in agriculture due to growing risks, for instance the agricultural and input price volatility, climate change, the limited and often decreasing risk-bearing capacity of farms and the intention of the majority of farmers to limit their farm exposure to risks. Therefore, an attempt was made in this study for an effective and systematic risk management process that may be implemented and regularly performed on future-oriented farms.

BACKGROUND

Agricultural workers need sufficient precaution and safety measures at the time of field and machine work, such that no physical damage occurs to them. The fatality rate in agriculture is far higher than any other economic sector. A large proportion of all fatal workplace accidents occur in agriculture, even though a small proportion of the workforce is employed in farming. The level of farm accidents is not decreasing. Many literatures are found discusing agricultural business sectors of India, their problems, but less have focused on agricultural production related risks of farmers. Any occurrence of negative economic outcomes has been defined as risk (Paulson, 2005). Risk also has been defined as negative impact of alterations in business strategy because of external events (Christopher and Lee, 2004), both operational and disruption risks (Tang, 2006). In firm operations, the incidence of damages by events inside firms, the supply chain and the environment affecting the business process has been reported as risks (Kersten et al., 2006). The likelihood of hazards, harms, failures, injuries and other unwanted consequences were reported to be related with supply chain risks (Harland et al., 2003). Barah and Binswanger (1982) have considered the relative importance of production and price risk factor in crop income risk factor. The role of weather factors in crop growth often means that short duration varieties have lower climate and environmental induced variability than long duration varieties. This was demonstrated in the case of wheat cultivars by Kalra and Aggarwal (1996). Factors other than rainfall are important especially for horticultural crops. This was shown in a study of apple yields in Himachal Pradesh over the period 1968-88 (Tewari, 1991). The study showed that yields were better explained by a composite weather index comprising rainfall, temperature and humidity rather than rainfall alone. The Analytic Hierarchy Process (AHP) has been used to improve the preservation practices for agriculture in Delaware (Kent & William, 2010). Nyamah et al. (2014) have proposed the possible supply chain related risks in the agricultural supply chain in Odisha (India), including risks related to market, financial, biological, weather, logistical, operational, political and policy. The demand related risks occurs as a result of variation in demands influencing the domestic or international input and output prices, deviation for quality or quantity attributes in market demands, food-safety requirement variation, market demand variation for product delivery in-time, and supply chain dependability as well as reputation variations (Jaffee et al., 2010). Economic condition has been reported to have considerable effects because of rainfall, shocks and drought (Maccini and Yang, 2009). Thakur et al. (1988) found that in the hill regions of Himachal Pradesh, total net returns of farmers are higher when crop output is half of normal crop output as prices under this situation are doubled. This extreme outcome is because of underdeveloped markets as a result of which the Himachal hill regions are poorly linked to major consuming markets (Thakur et al., 1997). In Turkey, risk assessment has been appeared as an obligated procedure in OHS management with the new law with number 6331 (Guneri et al., 2015). Usually risk assessment process requires the following (Health and Safety Executive, 2014): (a) hazard identification, (b) deciding harmfulness, (c) risk evaluation and control measures, (d) documentation findings, and (e) review and update of the assessment. However, different risk assessment approaches and methods are available to find the causes and characteristics of accidents as well as to evaluate safety condition of workplaces including, natural resources and environment (Ali and Maryam, 2014; Jozi et al., 2012; Wang et al., 2015), energy (Kang et al., 2014; Lavasani et al., 2011; Mahdevari et al., 2014; Saffarian et al., 2015; Verma and Chaudhri, 2014), manufacturing (Djapan et al., 2015; Grassi et al., 2009; Gul and Guneri, 2016; Hu et al., 2009; Kokangül et al., 2017), transport and supply chain (Akyuz, 2015; Akyuz and Celik, 2015; Akyuz, 2017; John et al., 2014; Mentes et al., 2015), building (Ebrahimnejad et al., 2010), chemistry & bio-chemistry (Arslan, 2009; Othman et al. 2016), performance evaluation of emergency department (Gul et al., 2016). It has been reported that three input variables of risk assessment included occurrence probability (OP), detect-ability (DA) and impact severity (IS). And for reducing the risk, one or all of these three variables is required be reduced (Medina et al., 2011). The accuracy of the model as well as the verifiability of the risk data is important for the reliability of risk assessment results (Casal, 2007). Risk assessment methods has been classified as: (a) the qualitative techniques i.e. check-lists, HAZOP and what-if analysis, (b) the hybrid techniques like Fault Tree Analysis (FTA), Risk Based Maintenance (RBM), and Event Tree Analysis (ETA), and (c) the quantitative techniques like Quantitative Assessment of Domino Scenarios (QADS), QRA, and Weighted Risk Analysis (WRA) techniques (Marhavilas et al., 2011; Mohammadfam and Zarei, 2015). As the traditional approaches are not adequate answers to deal with the latest issues and hence, using them may cover other aspects of imprecise & incomplete knowledge and can lead to a wrong impression about the accuracy as well as the precision for the decisions (Ringen et al., 1995). In most of the cases satisfactory information is not available for the frequency distribution estimation and other characteristics in relation to the risk factors (Chongfu, 1996; Pitblado et al., 2001) and the development of a method having novelty of risk assessment which is capable of identifying the critical uncertainty is essential, as the risk assessors are often faced with situations with incomplete & high level of uncertainties in risk data (Guimarães and Lapa, 2007). Fuzzy expert systems with probabilistic risk analysis have been developed to overcome these uncertainties where expert knowledge is the only available source of information and the measured data about the precision and reliability of a system are restricted (Guikema, 2009). Fuzzy logic is capable of exploiting better simulation of complex process with vague or qualitative information. Further, the membership function concept in fuzzy theory helps in illustrating and understanding qualitative, ambiguous or uncertain information (Li et al., 2010). Fuzzy logic is useful to express the linguistic rules used in the structure of risk factors carrying such vague information. Fuzzy expert systems have the capacity of developing the functionality of engineering systems and sets, with linguistic terms in data analysis, processing or decision making (Silva et al, 2012). Other advantages of fuzzy logic includes ability and flexibility to model any arbitrary and complicated function with fuzzy logic capable of manipulating imprecise problems (Haack, 1979; Zadeh, 1984). Azadeh et al. (2014a, 2014b) have assessed the HSE systems of a gas transmission unit by using "Data Envelopment Analysis" and "Fuzzy Data Envelopment Analysis" for reducing the existing uncertainty in qualitative indicators along with human risk failures. A fuzzy rule based safety analysis method by the use of historical accident data, judgment of experts, and the current safety level of a construction site were merged together for assessing the risks of workers exposed in construction sites (Beriha et al., 2012; Gurcanli and Mungen, 2009). Ciarapica and Giacchetta (2009) have studied the benefits and flexibility of the neuro-fuzzy network for occupational study for the injuries. The injury data was analyzed for developing classification schemes based on the injury trend followed by a sensitivity analysis for the injury frequency. A fuzzy expert system has been developed for the performance assessment of "health, safety, & environment (HSE)" and ergonomic system factors in a gas refinery. It was revealed that the use of fuzzy expert systems can reduce human failures, creates expert knowledge and interprets vague data of large amount in an efficient method (Azadeh et al., 2008). The employee's attitude plays a vital role in safety issues. Moreover, the industrial accident not only affects human capital, but also generates financial losses due to interruptions in industrial processes and damages to process of working (Dejoy et al., 2004). Through the Preliminary Hazard Analysis (PHA), seven risk scenarios were evaluated with three of those scenarios classified as high, two as medium, and two as serious, in a risk assessment of twelve standard chemical laboratories for evaluating the OHS of its professionals (Galante et al., 2016). Pluess et al. (2016) have used the "Laboratory Assessment and Risk Analysis (LARA)" method at two European universities, for allowing the untrained personnel for the identification of possible risks and ranking them according to their importance. The results were compared to the classical risk assessment methods such as Failure Mode

Effects and Criticality Analysis (FMECA), Hazard and Operability studies (HAZOP), and PHA. The systematic application of policies, practices, and resources are included in risk management for the assessment and control of risk affecting human health, safety and the environment. Bowles and Pelaez (1995) have demonstrated two methods of based assessments the fuzzy logic of criticality. Xu et al. (2002) have illustrated a fuzzy logic based approach for the failure mode and effect analysis. Moreover, the assessment and characterization of risk is to determine risk acceptability and context, by comparing to similar risk (Risk Management Lexicon, 1998). According to, Operational Risk Management (ORM) Implementation and Execution (1997) and Operational Risk Management (ORM) Guidelines and Tools (1998), there are different qualitative and quantitative techniques for the assessment of risks. And, at extreme cases the risk is determined by multiplication of severity and probability measures. Mostly, banks and insurance companies use these methods. The qualitative one should be applied, if the possible losses are harmful to people or causes death, and ethically the quantitative risk assessment cannot be used (Stein, 1999). Many subjective elements are included in these methods (Leader's Safety Guide, 1998). And, fuzzy-logic is useful in modeling the subjectivity of experts (Pokoradi, 2001). Sulewski et al. (2018) have studied the interdependencies between dimensions for sustainability of farms by using the Polish Farm Accountancy Data Network (FADN) considering the participation of 601 farms. It is clear from the literature that the understanding of agricultural risk factors and the ways of managing it is a most important topic of discussion that deserves serious concentration and investigation. Hence, in the present paper an attempt was made with the application of fuzzy logic for the effective management of risks by the farmers in the agricultural sectors of Odisha in India.

RESEARCH METHODOLOGY

A standard questionnaire was designed and opinions were collected from experts of agriculture, practitioners and researchers and from literature review. As a result six most important risk factors of Indian farming sector were found such as Price or Market Risk, Environmental & Human or Personal Risk, Legal/Policy Risk, Resource Risk, Health Risks, Assets & Technology Risk, respectively. Then Fuzzy AHP was implemented to prioritize the most important risk of agricultural sector in India. Then the risk factors were predicted with respect to output. The selected factors for agricultural risk factor are as shown in Table 1.

RESULTS AND DISCUSSION

Development of Fuzzy-AHP model in multi-criteria decision making (MCDM):

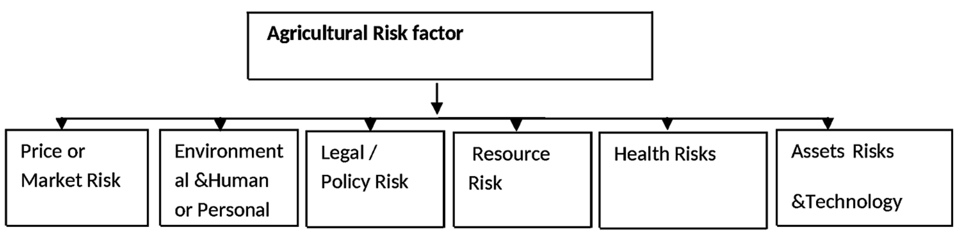
Step 1: Development of a hierarchical structure.

Fuzzy AHP methodology is applied to determine the risk factors in agriculture in India. The hierarchy is structured from the top (the overall goal of the problem) through the intermediate levels (criteria on which subsequent levels depend) and finally at the bottom most level are the sub-criteria. The criteria in the same level are compared using pair wise comparison. Figure 1 describes the hierarchy of a decision making problem.

Table 1. Selected factors for agricultural risk

1	Product recalls, defective products, and rating agencies.
2	Poor market timing and inadequate customer support.
3	Natural hazards, facilities, and disease outbreaks.
4	Health, contract terms, and turnover.
5	No pollution and dust.
6	No injury.
7	War, terrorism, civil unrest, law, and governing agencies.
8	Reporting and compliance, environmental, food safety and traceability.
9	Debt servicing, leverage, liquidity, solvency, and profitability.
10	Cash, interest rates, and foreign exchange.
11	Information asymmetries and adverse selection.
12	Cost, transportation, service availability, and hold-up.
13	Asset specificity, research and development.
14	Complexity, obsolescence, workforce skill-sets, adoption rate, and diffusion rate.

Figure 1. The hierarchy of the criteria and the alternatives



Step 2: Geometric average and weightage statistics of assessment criteria and sub-criteria.

Step 3: Comparison of criteria or alternatives via linguistic terms and transformation of relative importance into triangular fuzzy number

The decision maker compares the criteria via linguistic terms as shown in the Table 3.

According to the corresponding triangular fuzzy numbers of these linguistic terms, for example if the decision maker states "Criterion 1 (A_1) is weakly important than criterion 2 (A_2)", then it takes the fuzzy triangular scale as (2, 3, 4). On the contrary, in the pair wise contribution matrice of the criteria, comparison of A_2 to A_1 will take the fuzzy triangular scale as (1/4, 1/3, 1/2).

Step 4: Building comparison matrices for criteria
Step 5: Calculation of Geometric Mean for fuzzy comparison matrices.
Step 6: Calculation of Relative fuzzy weights (w_i) of each criterion and the relative non-fuzzy weight (w_{di}) for each criterion.
Step 7: Normalization of non-fuzzy relative weights.

Table 2. Geometric average of opinions, overall weightage and ranking statistics for assessment criteria

Assessment Criteria	Assessment sub-Criteria	Geometric Average of Opinions	Overall Weightage	Rank
Price or Market Risk	Question 1	3.310	0.499	13
	Question 2	3.348		11
Environmental &Human or Personal Risk	Question 3	4.505	0.249	01
	Question 4	2.845		14
	Question 5	4.204		03
	Question 6	3.447		09
Legal/Policy Risk	Question 7	3.352	0.499	10
	Question 8	3.696		08
Resource Risk	Question 9	3.320	1.000	12
Health Risks	Question 10	4.240	0.499	02
	Question 11	3.735		06
Assets &Technology Risk	Question 12	3.815	0.333	05
	Question 13	3.940		04
	Question 14	3.729		07

Table 3. Linguistic terms and the corresponding triangular fuzzy numbers

Scale	Definition	Fuzzy Triangular Scale
1	Equally Important	(1, 1, 1)
3	Weakly Important	(2, 3, 4)
5	Fairly Important	(4, 5, 6)
7	Strongly Important	(6, 7, 8)
9	Absolutely Important	(9, 9, 9)
2	The Intermittent Values between Two Adjacent Scales	(1, 2, 3)
4		(3, 4, 5)
6		(5, 6, 7)
8		(7, 8, 9)

Among all risk factors of Agricultural business Assets Risks &Technology Risk ranked first resource risk 2nd and health risk third for Indian farmers. Assets and technology risk are the risk factors canot be solved or resolved by individual farmer or farmer community, agripolicies and government attention towards agribusiness can resolve this risk in terms of new and advanced equipment, proper supply chain distribution, by marketing policies and agricultural policies towards loan and subsidies provided to farmers. Resource risk also include the seeds, pesticides, lands, water provided for irrigation. Health risk can be resolved by providing safety training and security to farmers.

Table 4. Comparison matrices for criteria

Criteria	A_1	A_2	A_3	A_4	A_5	A_6
A_1	(1,1,1)	(0.16,0.20,0.25)	(1,1,1)	(0.25,0.33,0.50)	(1,1,1)	(0.11,0.11,0.11)
A_2	(4,5,6)	(1,1,1)	(0.16,0.20,0.25)	(0.25,0.33,0.50)	(0.16,0.20,0.25)	(0.11,0.11,0.11)
A_3	(1,1,1)	(4,5,6)	(1,1,1)	(0.25,0.33,0.50)	(1,1,1)	(0.11,0.11,0.11)
A_4	(2,3,4)	(2,3,4)	(2,3,4)	(1,1,1)	(0.25,0.33,0.50)	(0.25,0.33,0.50)
A_5	(1,1,1)	(4,5,6)	(1,1,1)	(2,3,4)	(1,1,1)	(0.11,0.11,0.11)
A_6	(9,9,9)	(9,9,9)	(9,9,9)	(2,3,4)	(9,9,9)	(1,1,1)

Table 5. Geometric means of fuzzy comparison values

Criteria	Geometric Mean	
A_1	0.405	0.440
A_2	0.378 0.523	0.440
A_3	0.692 0.831	0.753
A_4	0.890 1.587	1.200
A_5	0.978 1.175	1.087
A_6	4.586 5.451	5.196
SUMMATION	7.929 10.056	9.116
REVERSE(power of -1)	0.13 0.10	0.11
INCREASING	0.10 0.13	0.11

Table 6. Relative fuzzy weights and defuzzified weights of each criterion

Criteria	Relative Fuzzy Weight (w_i)			Defuzzified Weight (w_{di})
A_1	0.405	0.048	0.050	0.050
A_2	0.037	0.030	0.048	0.030
A_3	0.069	0.108	0.082	0.086
A_4	0.089	0.132	0.206	0.142
A_5	0.097	0.119	0.152	0.122
A_6	0.458	0.571	0.708	0.579

Table 7. Normalized relative weights of criteria

Criteria (Risk Factors in Agriculture)	Normalized Weight (w_N)	Ranking of the Barriers
A_1	0.086	5
A_2	0.051	6
A_3	0.148	4
A_4	0.245	2
A_5	0.210	3
A_6	1.00	1

PREDICTION BY FUZZY LOGIC MODELLING

A multi input and output (MIMO) mamdani-type fuzzy model is shown in Figure 2. Each input to the model is nothing but expenses possibly responsible for improving in safety performance is expressed as three fuzzy membership functions (low, medium, high) to account for the risk factors in agricultural sectors. The six types of input parameters are shown in Figures 3, 4, 5, 6, 7, and 8 for "Price or Market risk (monetary risk), Environmental & Human or Personal risk, Legal/Policy risk, Resource risk, Health risks, Assets & Technology risk", respectively.

By taking into account the data on the risk factors affecting the agricultural sustainability in terms of economic growth of country and the environmental conditions, and then combining subjective judgment of experts, linguistic variables are employed to develop fuzzy membership functions for inputs to the model. Fuzzy linguistic variables are extensions of numerical variables in the sense that they are able to represent the condition of an attributes at a given interval by taking fuzzy sets as their values (Wang, 1997). The position of the element is described by the membership function (μ) that has a value of one

Figure 2. MIMO system for evaluating agricultural sustainability

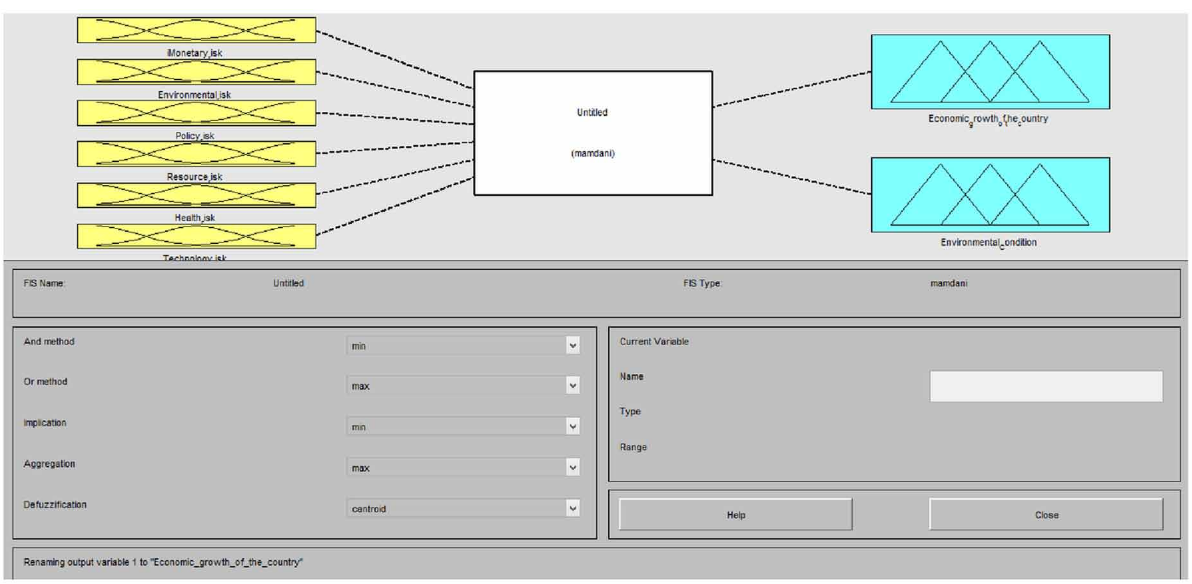


Figure 3. Membership functions for price or market risk (monetary risk)

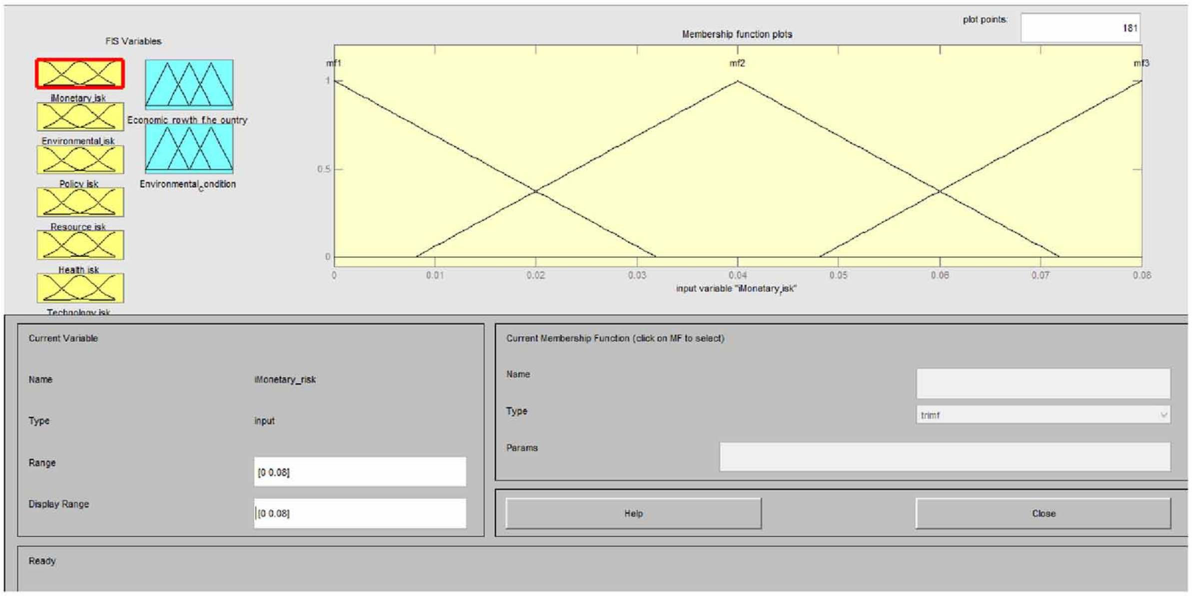
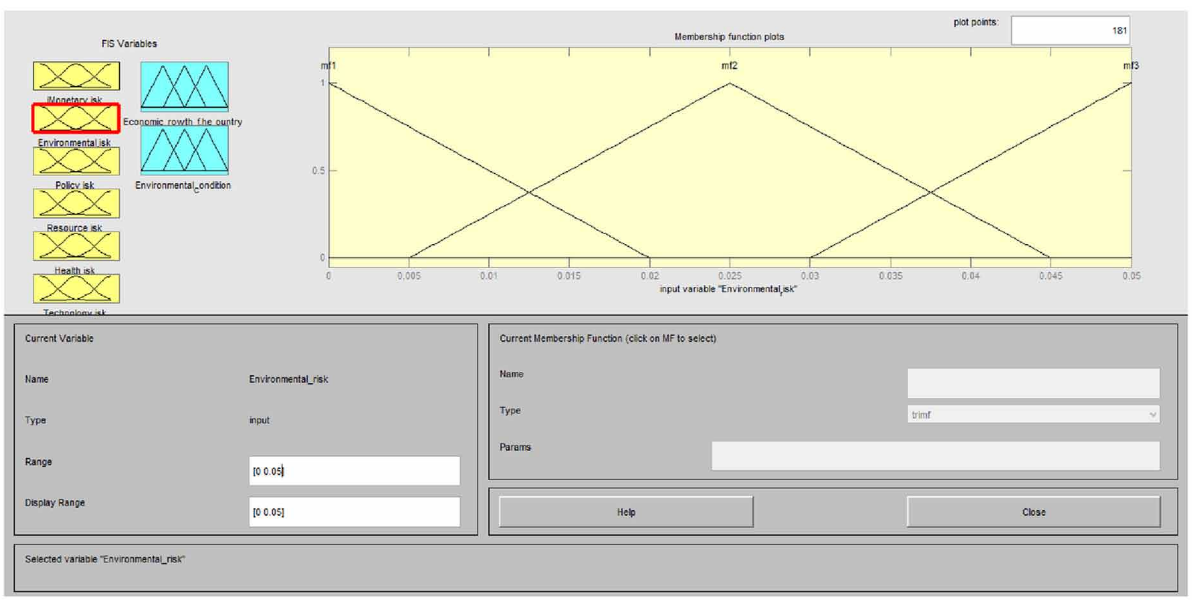


Figure 4. Membership functions for environmental and human or personal risk



(μ=1) if the element belongs completely to the set, a value of zero (μ=0) if the element does not belong to the fuzzy set and value between zero and one (0<μ<1) when the element belongs partially to the fuzzy set. The order to define the fuzzy membership functions of inputs is defined as low, medium and high. Low define as minimum risks, medium describe as average risks and high known as high level of risks. The membership function range in input 1 i.e. Price or Market Risk (monetary risk) is 0 to 0.08, input 2

Figure 5. Membership functions for legal / policy risk

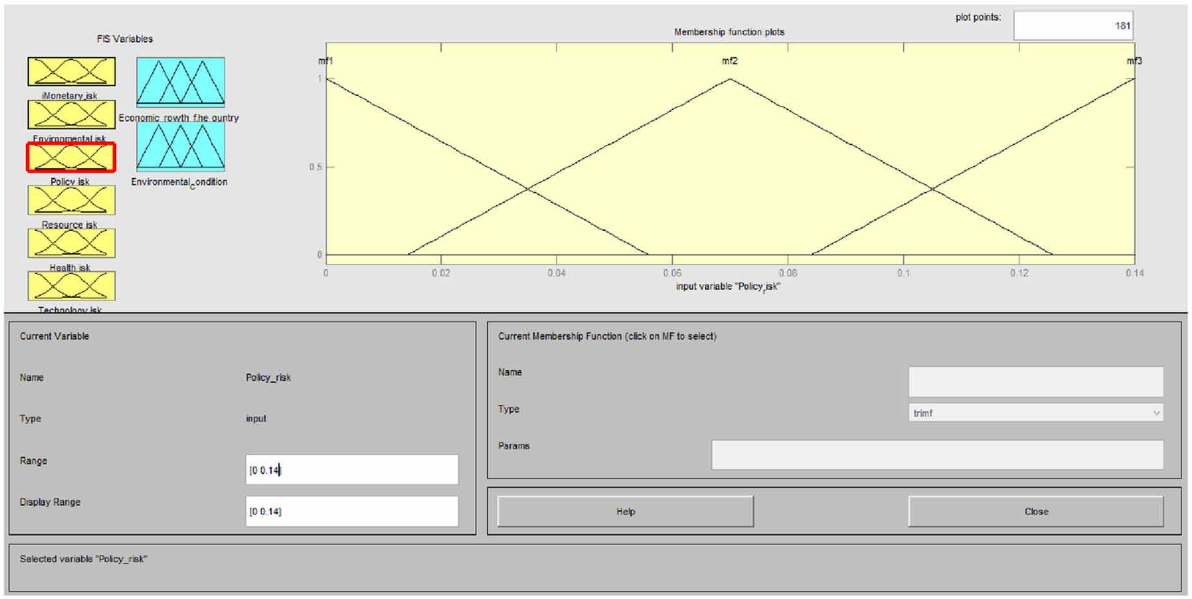
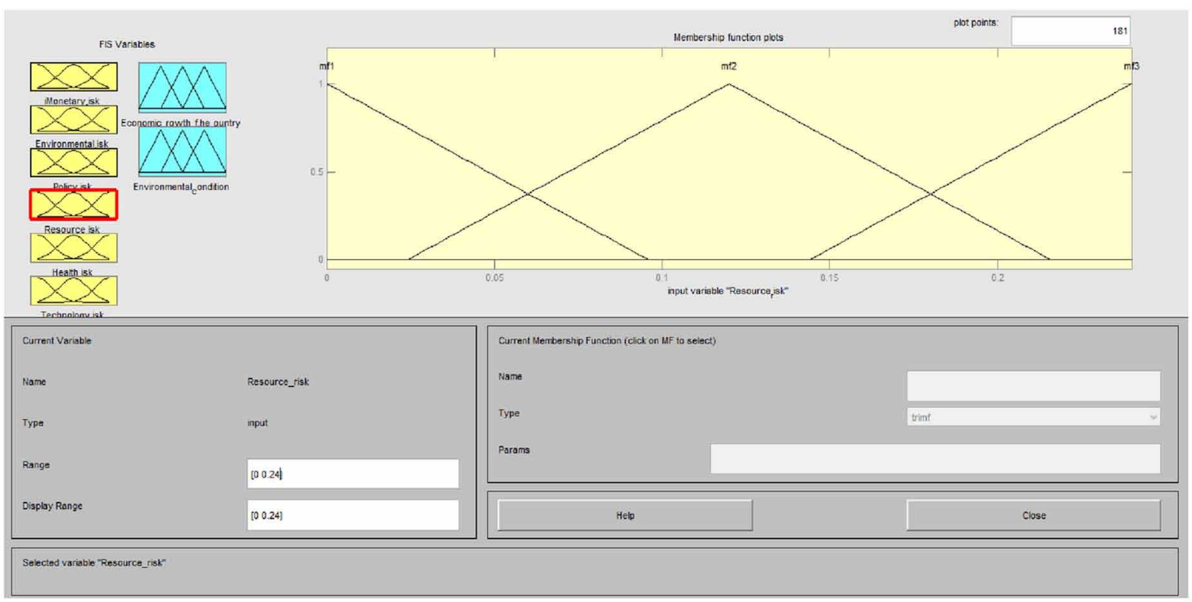


Figure 6. Membership functions for resource risk



(Environmental &Human or Personal Risk) is 0 to 0.05, input 3 (Legal / Policy Risk) is 0 to 0.14, input 4 (Resource Risk) is 0 to 0.24, input 5 (Health Risks) is 0 to 0.21, and input 6 (Assets Risks &Technology Risk) is 0 to 1. Figures 9, 10, 11, 12 depict the output membership function for "Economic Growth of the Country", output membership function for "Environmental Conditions", the rule-base of the model, and the MATLAB rules of the system, respectively.

Figure 7. Membership functions for health risks

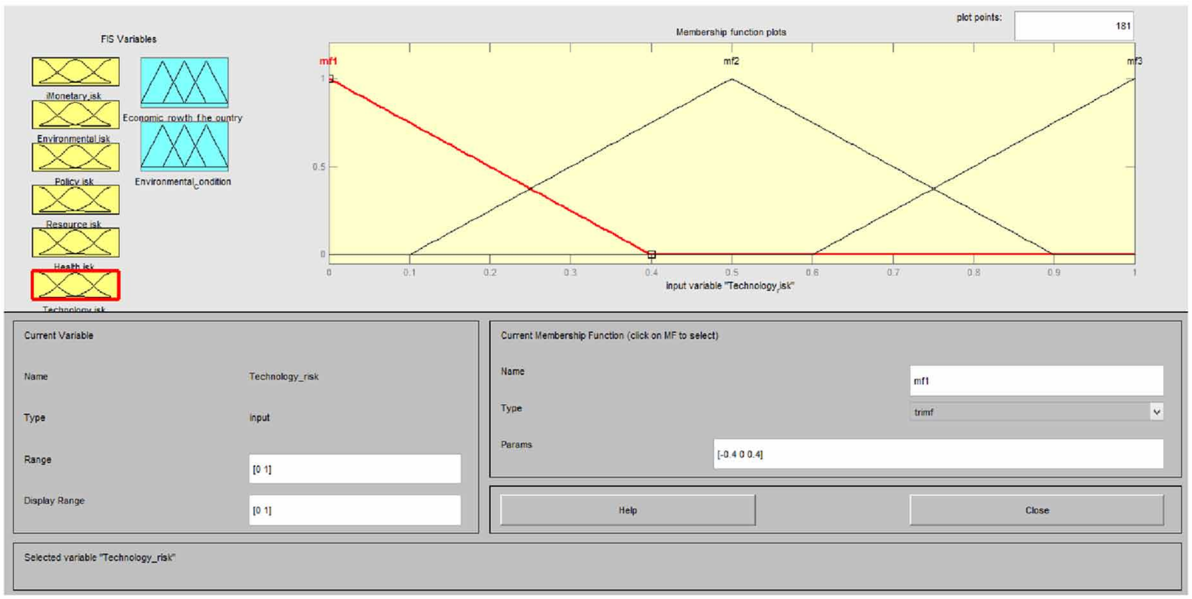
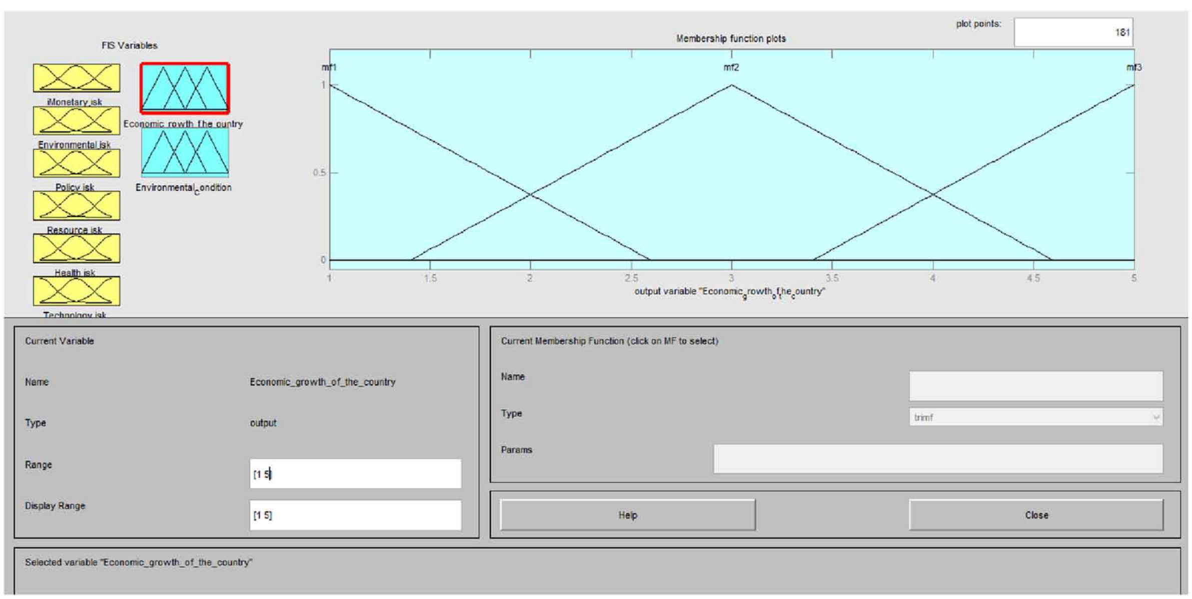


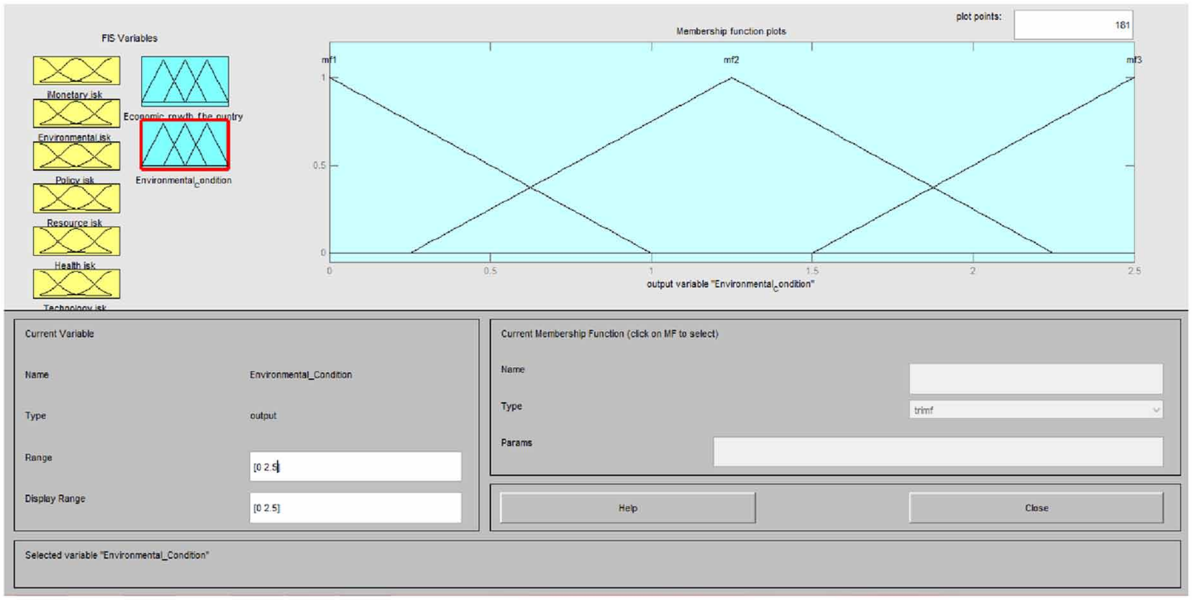
Figure 8. Membership functions for assets and technology risk



CONCLUSION

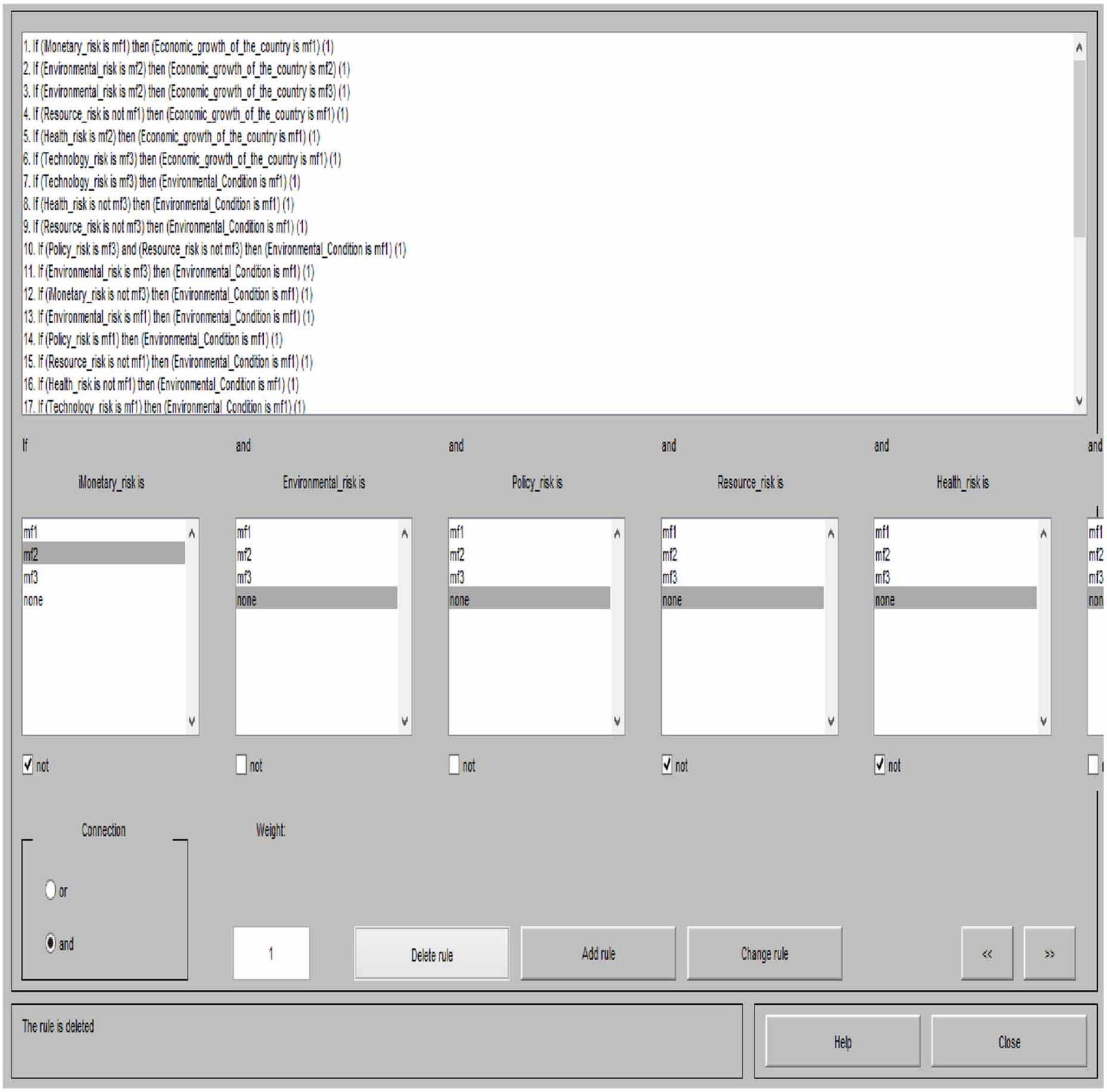
Indian agriculture sector is expected to be the most important driver of Indian economy within few years because of high investments for agricultural facilities, warehousing and cold storage. The utilization of genetically modified crops and organic farming will improve the fertility of land and improve the crop

Figure 9. Output membership function for economic growth of the country



production rate of Indian farmers. But still the small and medium agricultural sector are very poor and neglected, and are following the traditional method of crop production .due to high cost of equipment unable to purchase and the conventional method of farming gives them many physical problems like lungs problem due to exposure to dust, and musculoskeletal disorders .extreme weather condition, heavy work load during their working procedure gives them early old age, bone and muscle problems.so to attain better efficiency of performance and to improve productivity of the worldwide farmers in the agricultural sector it is essential to design the tools and equipment keeping in consideration the farmer's capabilities and limitations. The tools and equipment design should be able to provide more human comfort, of good quality, more output focused and reduce the musculoskeletal injury. Occupational safety is a big issue of discussion for agricultural workers. The methods of working in field in extreme climate(heat, rain), contact with the chemicals (pestisides,f ertilizaers),the exposure to soil, dust, the contamination due to bacteria, exposure to animals, cattles, injury due to hand tools and muskulateral disorders are the most important injuries faced by all agriworkers. Agricultural workers need sufficient precaution and safety measures at the time of field and machine work, such that no physical damage occurs to them .most of the agricultural injuries are resulted from the improper selection and use of hand tools. In agricultural sector the traditional hand tools play a major role in performing the farming activities. The conventional hand tools like spade/hoe, sickle, hammer, shovel, knife etc. Have been used since the ancient though some modifications are found now a day. As most of the farmers in India are from poor economic background, they usually prefer the conventional methods in farming instead of using the developed power operated machineries. The hand tools are mostly used in all farming activities like land preparation, weeding, harvesting of crops etc. but tractors and other machineries are definitely solve injury and safety problems compared to conventional tool. Modern equipment are not sustainable due to high noise, vibration and pollution. Farming equipment modification, system design is essential to provide better life to farmers but without environmental protection, social and economic stability is

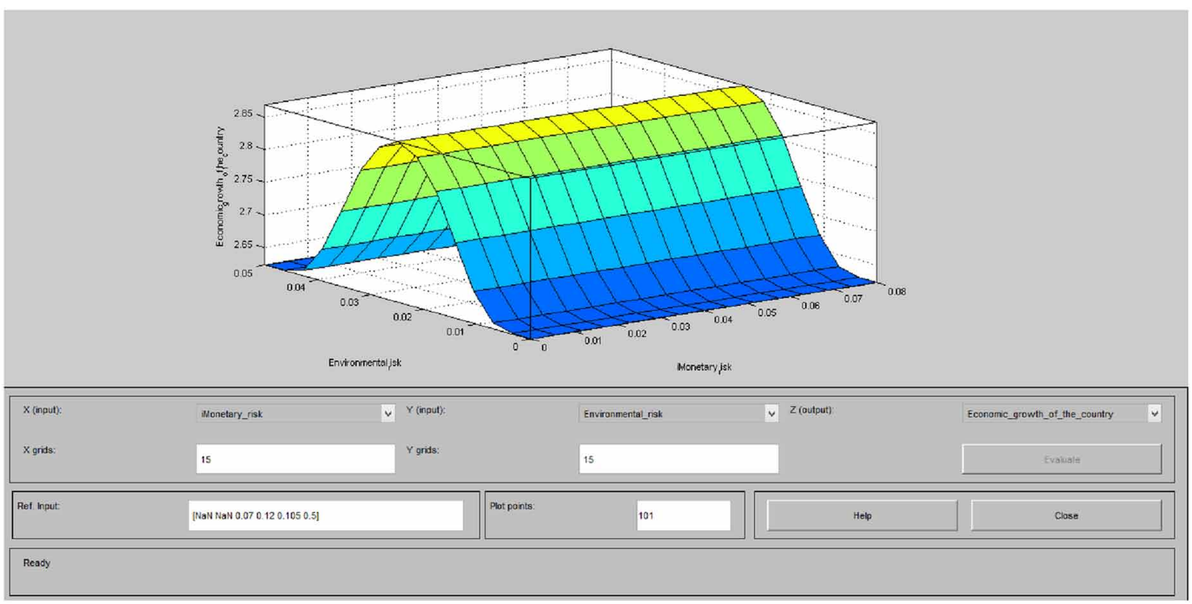
Figure 10. Output membership function for environmental conditions



having no meaning. When all over world is concerned about pollution farming policies must be framed to avoid pollution with improving productivity. Risk management has gained relevance in agriculture due to growing risks (for instance, agricultural and input price volatility, climate change), the limited and often decreasing risk-bearing capacity of farms and the intention of the majority of farmers to limit their farms' exposure to risks. Therefore, a systematic risk management process should be implemented and regularly performed on future-oriented farms. The importance of systematic risk management grows the more non-family workers are hired, the higher the debt to equity ratio, and the higher the share of lease land. The business of agriculture is subject to big and many suspicions and uncertainties. So far maximum people in India make their source of revenue from this agribusiness compared than from all

Figure 11. The rule-base of the model

Figure 12. MATLAB rules of the system



other sectors put together. Understanding agricultural risk factors and the ways of managing it is therefore a most important topic of discussion that deserves serious concentration and investigation. Despite of its noticeable significance, risk factor management in agriculture is an under-researched topic relative to traditional concerns. As safety and sustainability like two sides of a coin, so both parts are important for farming sector. So risk factors must be reduced in agrisector of India.

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KEY TERMS AND DEFINITIONS

ARM Agricultural Risk Management: AARM is an innovative approach for improving the resilience of vulnerable rural households, and leveraging finance and investment. AARM allows farmers and businesses to be pro-active and increases their capacity to assess, prepare for, absorb and adapt to risks.

Fuzzy Logic: Fuzzy logic is multi-valued and handles the concept of partial truth. A system of logic developed for representing conditions that cannot be easily described by the binary terms "true" and "false."

Fuzzy Rule: Fuzzy rule is a conditional statement. The form of fuzzy rules is given by IF THEN statements. If y is B THEN x is A, where x and y are linguistic variables, A and B are linguistic values determined by fuzzy sets.

Fuzzy Set: Fuzzy set is expressed as a function and the elements of the set are mapped into their degree of membership. A set with the fuzzy boundaries are "hot," "medium," or "cold" for temperature.

Fuzzy Variable: A quantity that can take on linguistic values. For example, the fuzzy variable "disease" might have values such as "low" or "high."

Platform for Agricultural Risk Management (PARM): PARM has the global mandate to contribute to sustainable agricultural growth, boost rural investment, reduce food insecurity, and improve resilience to climate change.

Chapter 13
Application of Fuzzy Logic in Plant Disease Management

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ABSTRACT

The timely detection of the infection in plants and its severity is a major concern for the farmers. Although various techniques have been employed to identify and estimate the severity of infection, they generally use a fixed threshold to segment the infected areas from the leaf image. Such methods define the participation of a pixel, as part of the infected area, in the form of a classical or crisp set. Use of fuzzy logic in feature extraction, grading the disease post identification, and estimating the disease severity are seen as rapidly growing techniques. Using fuzzy logic, the infected area is calculated by considering the degree of contribution provided by neighboring pixels to the current pixel. The severity estimation is performed on the basis of the infected area and the number of lesions in the leaf image. Depending on the amount of infection, severity has been classified into early, middle, later, and advanced stage. The proposed technique will help the farmers to identify the disease class at an early stage.

INTRODUCTION TO PLANT DISEASE MANAGEMENT

Agriculture is the backbone of majority nations, especially in the Asian and African continent. Not only it caters to the food requirements, but also builds the economy of these countries. However, the agricultural society around the globe is facing a serious threat in the form of loss of production. The Food and Agriculture Organisation (FAO) estimates that pathogens, insects and weeds together are held responsible for this loss as they reduce 20-40% of the total agricultural productivity around the globe (Dangl, Horvath, & Staskawicz, 2013). All plant diseases result from a three-way interaction between the host, the pathogen and the environment. Losses from diseases affects the economy of the region by causing a reduction in the income of crop producers and price rises for consumers. Various studies

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on variations in environmental conditions have been pursued, in different locations, to estimate the losses occur due to different diseases. Various empirical control practices have been discovered for crop protection even before the causal nature of plant diseases. Parts of the world where the daily survival of a large proportion of the population depends on crops, is at risk, since a crop disease leads them to starvation. In 1980, U.S.A suffered a loss of four billion dollars due to plant diseases while in India it was probably even more than that (Rangaswami G and Mahadevan A, 1998). Crop losses due to pre and post-harvest fungal diseases annually exceed \$200 billion euros and over \$600 million are annually spent on fungicides (González-Fernandez et al. 2010) in the United States alone. In 2007, Georgia faced a loss of about \$539.74 million. So resistance to plant disease and managing it are necessary for the consistent supply of food (Bentley et al. 2009; Martinez A, 2007. Less than 25% of Malawi farmers attained self-sufficiency in maize in years (2000–2001) (Devereux S, 2009). In India, the annual estimated losses due to nematodes have been assessed to be about Rs.242.1 billion. In 19th century (Biffen, 1905) disease resistant plants were grown and the result was the discovery of variety of plants that were resistant to diseases. Disease management was often based on type of the disease, economic value of the crop and quality or demand of the market because the main objective of plant pathology is to control the disease. However, the term control indicates that the measures are taken only one the disease has affected the crop whereas the word "Management" is about continuous processing and managing the damage such that it does not affect o the economic front. Thus, there is a need to identify any disease in the crop and estimate the quantity of infection so as to curb any potential danger to the life of the plant, thereby contributing towards economical, biological, sociological and ecological losses. Plant disease management firmly stands on the shoulders of two major areas, namely, disease identification (or classification) and severity estimation.

Plant disease identification has come a long way from witnessing proximate detection, immunological (Hampton et al. 1990) and DNA-based methods (Lin et al. 2007), remote sensing technologies (Bock et al. 2010; Mahlein et al. 2012; Zhao et al. 2018) to digital imaging based techniques. In imaging based technique, Segmentation is done to separate the infected region from the entire leaf region based on a threshold value (Fan et al. 2001). Generally thresholding is done to distinguish between healthy and infected area. However, in practice, the healthy and infected region of the leaf are uneven and cannot be distinctly distinguished. Pixels of the infected region do contain some green color in them and vice versa. Fuzzy logic is used to overcome the limitations of crisp thresholding. A fuzzy logic model developed by (Kim et al. 2005) estimates apparent infection rate from the environmental temperature. This infection rate is used to predict the severity of soybean rust. Pang et al. (2011) proposed an adaptive segmentation algorithm by integrating local threshold and seeded region growing. Identification of the disease can however be done by using different feature extraction followed by classification techniques (Dhingra et al. 2018; Parikh et al. 2016).

Severity estimation is also the most critical part of disease management system which primarily aims to quantify the severity with which the plant has been affected. The severity estimation methods should be accurate, precise, reproducible, economical and easy to implement. Different parameters like percentage of infected area (Cui et al. 2010), rust color index (Cui et al. 2010), number of lesions etc. are used to estimate the severity of the infection in a leaf image. The occurrence of the number of spots on the infected leaf area needs to be evaluated under a fuzzy logic system

BACKGROUND

Fuzzy Expert System

Introduction to Fuzzy Logic

There has been a rapid growth in the use of Fuzzy Logic (FL) techniques for some years in image-understanding applications such as detection of edges, feature extraction, classification, and clustering. FL mimics the human mind to effectively represent ambiguous data. In classical Boolean logic theory, decisions or actions are based on precision, certainty, and vigor. FL is an extension to Boolean logic in which tolerance and impression are explored in decision making. The exploration of the tolerance for imprecision and uncertainty underlies the remarkable human ability to understand distorted speech, decipher sloppy handwriting, comprehend nuances of natural language, summarize text, and recognize and classify images. With FL, we can specify mapping rules in terms of words rather than numbers. FL works on a set of fuzzy if–then rules. FL rule-based systems have been used in artificial intelligence applications as a translation of a human solution.

Today, techniques such as fuzzy logic, neural networks, probabilistic reasoning, and genetic algorithms or a combination of these techniques are used to design an intelligence system. Neural networks provide algorithms for learning, classification, and optimization, whereas fuzzy logic deals with issues such as forming impressions and reasoning on a linguistic level. Probabilistic reasoning deals with uncertainty. Recently, many intelligent systems called neuro fuzzy systems have been used. There are many ways to combine neural networks and FL techniques. Before doing so, however, it is necessary to understand basic ideas in the design of FL techniques. In this chapter, we will introduce basic FL concepts such as fuzzy sets and their properties, FL operators, hedges, fuzzy proposition and rule-based systems, fuzzy maps and inference engine, de-fuzzification methods, and the design of an FL decision system.

Fuzzy Sets

The term *fuzzy logic* was introduced by L.A. Zadeh in 1965 at the University of California at Berkeley in his seminal work “Fuzzy sets,” which described the mathematics of fuzzy set theory. Zadeh developed fuzzy logic as a way of processing data. Instead of requiring a data element to be either a member or non-member of a set, he introduced the idea of partial set membership. In 1974, Mamdani and Assilian used fuzzy logic to regulate a steam engine. In 1985, researchers at Bell laboratories developed the first fuzzy logic chip. In early 1990’s, Lukasiewicz described a three valued logic in extension to the bi-valued logic of Aristotle. The third value can be best translated as “possible,” and he assigned it a numeric value between True and False. Later he explored four-valued logic and five-valued logic, and then he declared that, in principle, there was nothing to prevent the derivation of infinite-valued logic. FL provides the opportunity for modeling conditions that are inherently imprecisely defined. Fuzzy techniques in the form of approximate reasoning provide decision support and expert systems with powerful reasoning capabilities. The permissiveness of fuzziness in the human thought process suggests that much of the logic behind thought processing is not traditional two valued logic or even multivalued logic, but logic with fuzzy truths, fuzzy connectedness, and fuzzy rules of inference. A fuzzy set is an extension of a crisp set. Crisp sets allow only full membership or no membership at all, whereas fuzzy sets allow partial membership.

Crisp Set

A crisp set A, can be described as a set with only two membership states: true and false. It indicates that every element lying under this set is either completely included or excluded from the set. This inclusion and exclusion of an element x from/to set A can be mathematically expressed in the form of a characteristic or membership function, $\mu_A(x)$ as

$$\mu_A(x) = \begin{cases} 1 & if(x \in A) \\ 0 & if(x \notin A) \end{cases} \tag{1}$$

The output is 1 if the element x belongs to set A and 0 otherwise.

Fuzzy Set

Fuzzy set theory extends the concept of crisp set by defining degrees of membership i.e. the element can be a member of the set with either 100% membership status or a partial membership status (e.g., greater than 0% and less than 100% membership). A membership function is essentially a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Mathematically, an element x can be expressed as a member of the fuzzy set A *as*

$$\mu_A(x) = [0,1] \tag{2}$$

Fuzzy sets represent commonsense linguistic labels like *slow, fast, small, large, heavy, low, medium, high, tall,* etc. A given element can be a member of more than one fuzzy set at a time. Let's absorb the concept of crisp and fuzzy logic in detail with the following example

Example 1: Let x indicates height, then various sets that can be formed are *short, medium,* or *tall*. Let us consider set *tall (where the range of height is 40-90 inches).* With a crisp set, all people with height 72 or more inches are considered tall, and all people with height of less than 72 inches are considered not tall. The corresponding fuzzy set with a smooth membership function defines the transition from not very tall to definitely tall and shows the degree of membership for a given height (as shown in Figure 1).

If we extend the concept to two fuzzy sets say *tall and short,* the crisp and fuzzy membership function would have been as given in figure 2.

Example 2: The membership function for short height is given in the figure 3. Define the given membership function mathematically.

Figure 1. Crisp and fuzzy membership function for the set tall

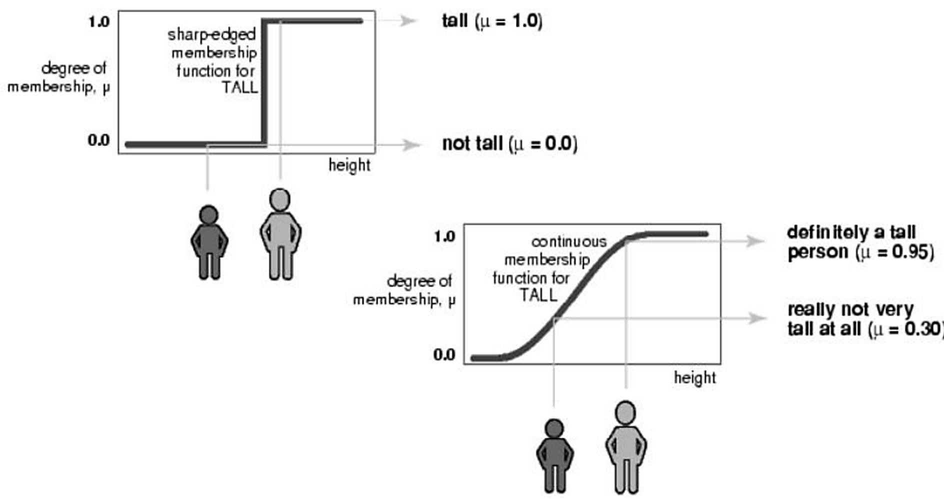
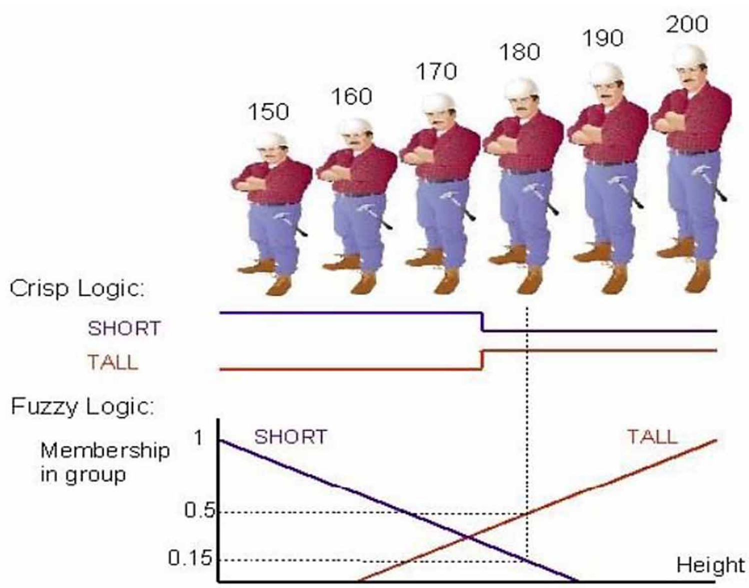


Figure 2. Illustration of crisp and fuzzy logic for short and tall sets simultaneously



Solution

The membership function has a value 1 when the height is less than 1.7m and has a value 0 for height greater than 1.9m. The function however is a straight line gradually decreasing between values 1.7m and 1.9m. The solution to this straight line will provide membership values at different values of heights between these points.

$$\mu_{short}(x)=\begin{cases}1; x\leq 1.7\\ \frac{1.9-x}{0.2}; 1.7\leq x\leq 1.9\\ 0; x\geq 1.9\end{cases}$$

Types of Membership Functions

There are different shapes of membership functions such as triangular, trapezoidal, Gaussian, Bell etc…

- *Triangular*

Let a, b and c represent *x* coordinates of the three vertices of $\mu_A(x)$ in a fuzzy set *A* with a & c as the lower & upper boundary respectively (where membership degree is 0) and b as the centre (where membership degree is 1). Figure 4 shows triangular membership function.

$$\mu_A(x)=\begin{cases}0\ if\ x\leq a\\ \frac{x-a}{b-a}\ if\ a\leq x\leq b\\ \frac{c-x}{c-b}\ if\ b\leq x\leq c\\ 0\ if\ x\geq c\end{cases}$$

- *Trapezoidal*

Let a, b, c and d represents the *x* coordinates of the membership function $\mu_A(x)$ in a fuzzy set *A*, then Trapezoidal membership function is given in figure 5.

Figure 3. Membership function for the set short in measuring height of a person

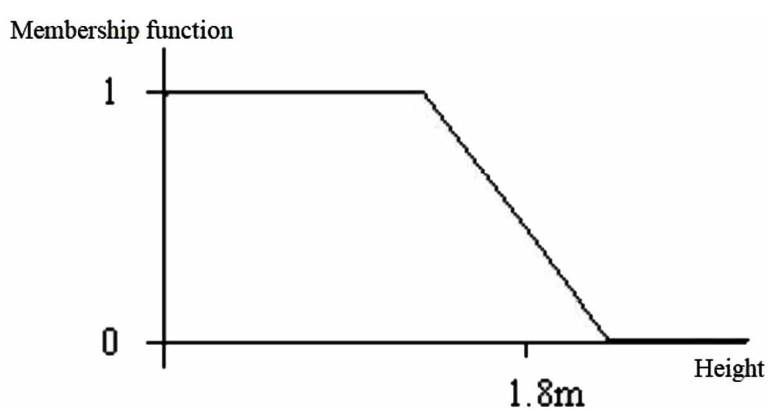


Figure 4. Triangular membership function and its mathematical expression

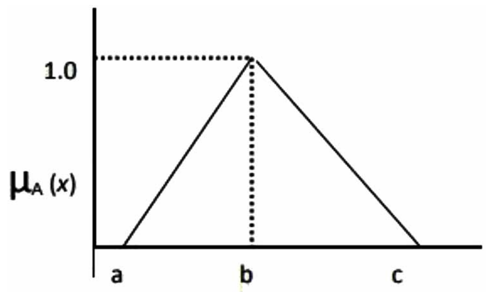
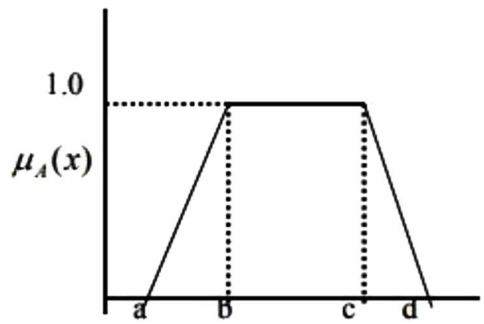


Figure 5. Trapezoidal membership function and its mathematical expression



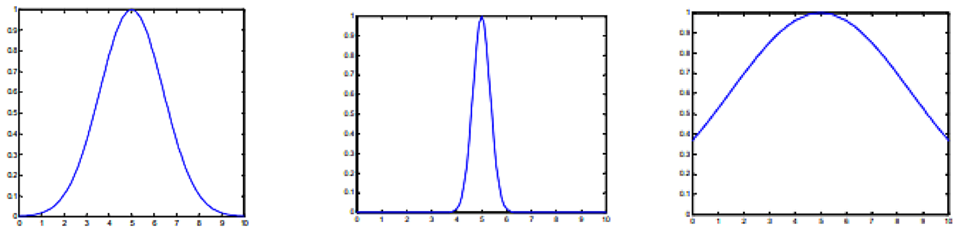
$$\mu_A\left(x\right) = \begin{cases} 0 \, if \, x \le a \\ \dfrac{x-a}{b-a} \, if \, a \le x \le b \\ 1 \, if \, b \le x \le c \\ \dfrac{d-x}{d-c} \, if \, c \le x \le d \\ 0 \;\; if \, x \ge d \end{cases} .$$

- Gaussian

The Gaussian membership function is usually represented as $\mu_A\left(x : c, s\right)$ in a fuzzy set A where c,s represents the mean and standard deviation (shown in figure 6). Considering m as the fuzzification factor,

$$\mu_A\left(x, c, s, m\right) = e^{\left[-\frac{1}{2}\left|\frac{x-c}{s}\right|^{m}\right]}$$

Figure 6. Different shapes of Gaussian MFs with different values of s and m



c = 5, s = 0.5, m = 2   c = 5, s = 2, m = 2   c = 5, s = 5, m = 2

- Generalized Bell

A generalized bell membership function $\mu_A\left(x:a,b,c\right)$ in a fuzzy set *A* has three parameters, a, c and b responsible for its width, center and slopes respectively (as shown in figure 7 and 8).

$$\mu_A\left(x,a,b,c\right)=\frac{1}{1+\left|\frac{x-c}{b}\right|^{2b}}$$

Fuzzy Logical Operations and If-Then Rules

Fuzzy set operations are analogous to crisp set operations. The most elementary crisp set operations are union, intersection, and complement, which essentially correspond to *OR, AND,* and *NOT* operators, respectively. Let *A* and *B* be two subsets of *U*. The union of *A* and *B*, denoted $A\cup B$, contains all elements in either A or B; that is, $\mu_{A\cup B}\left(x\right)=1\, if\ x\in A\, or\ x\in B$. The intersection of *A* and *B*, denoted $A\cup B$, contains all the elements that are simultaneously in *A* and *B*; that is, $\mu_{A\cap B}\left(x\right)=1\, if\ x\in A\, or\ x\in B$. The complement of *A* is denoted by $\overline{A}$ and it contains all elements that are not in *A*; that is $\mu_{\overline{A}}\left(x\right)=1\, if\ x\notin A$, and $\mu_{\overline{A}}\left(x\right)=0\, if\ x\in A$. In FL, the truth of any statement is a matter of degree. In order to define FL operators, we have to find the corresponding operators that preserve the results of

Figure 7. Generalized bell membership function and its mathematical expression

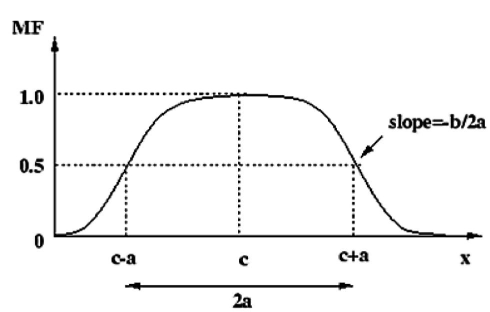
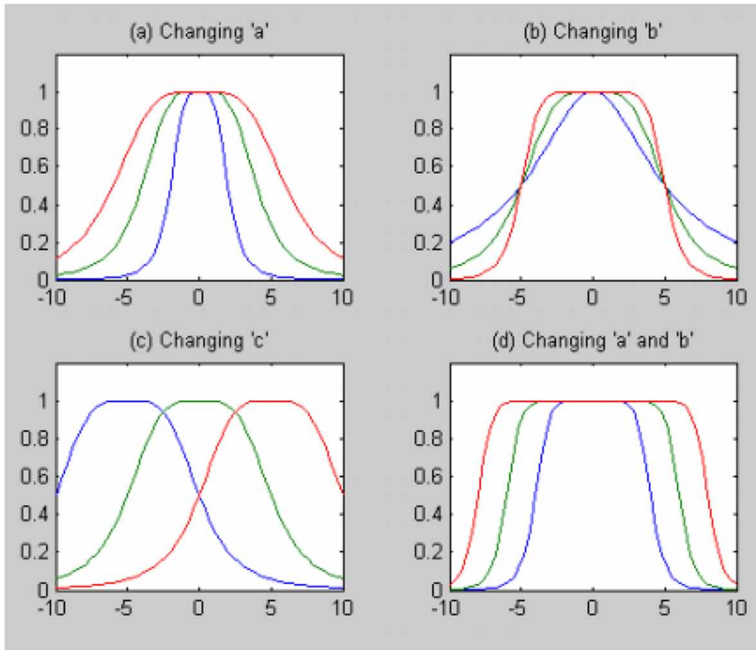


Figure 8. Shapes of generalized bell MF based on different values of a, b and c



using *AND, OR,* and *NOT* operators. The answer is *min, max,* and *complement* operations. These operators are defined, respectively, as

$$\mu_{A\cup B}(x) = \max\left[\mu_A(x), \mu_B(x)\right] \tag{3}$$

$$\mu_{A\cap B}(x) = \min\left[\mu_A(x), \mu_B(x)\right] \tag{4}$$

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \tag{5}$$

Zadeh (1965) defined fuzzy union and fuzzy intersection as

$$\mu_{A\cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x) \tag{6}$$

$$\mu_{A\cap B}(x) = \mu_A(x)\mu_B(x) \tag{7}$$

Most applications use *min* for fuzzy intersection, *max* for fuzzy union, and $1-\mu_A\left(x\right)$ for complementation. We have to remember that operators used in FL, such as union, intersection, and complement, reduce to their crisp logic counterparts when the membership functions are restricted to 0 or 1.

Fuzzy inference systems consist of if–then rules that specify a relationship between the input and output fuzzy sets. Fuzzy relations present a degree of presence or absence of association or interaction between the elements of two or more sets. Let *U* and *V* be two universes of discourse. A fuzzy relation $R\left(U,V\right)$ is a set in the product space $U \times V$ and is characterized by the membership function $\mu_R\left(x,y\right)$, where $x \in U$ and $y \in V$, and $\mu_R\left(x,y\right) \in \left[0,1\right]$. Fuzzy relations play an important role in fuzzy inference systems. FL uses notions from crisp logic. Concepts in crisp logic can be extended to FL by replacing 0 or 1 values with fuzzy membership values. A singleton fuzzy rule assumes the form "if *x* is *A*, then *y* is *B*," where $x \in U$ and $y \in V$, and has a membership function, $\mu_{A\to B}\left(x,y\right)$, where $\mu_{A\to B}\left(x,y\right) \in \left[0,1\right]$. The *if* part of the rule, "*x* is *A*," is called the *antecedent* or *premise*, while the then part of the rule, "*y* is *B*," is called the *consequent* or *conclusion*. Interpreting an if–then rule involves two distinct steps. The first step is to evaluate the antecedent, which involves fuzzifying the input and applying any necessary fuzzy operators. The second step is implication, or applying the result of the antecedent to the consequent, which essentially evaluates the membership function $\mu_{A\to B}\left(x,y\right)$. It can be seen that in crisp logic a rule is fired if the premise is exactly the same as the antecedent of the rule, and the result of such rule firing is the rule's actual consequent. In fuzzy logic, a rule is fired so long as there is a nonzero degree of similarity between the premise and the antecedent of the rule. For most applications, the fuzzy membership function $\mu_{A\to B}\left(x,y\right)$ for a given relation is obtained with the minimum or product implication, given, respectively, as follows:

$$\mu_{A\cap B}\left(x\right) = \mu_A\left(x\right)\mu_B\left(x\right) \tag{8}$$

$$\mu_{A\cap B}\left(x\right) = \min\left[\mu_A\left(x\right), \mu_B\left(x\right)\right]. \tag{9}$$

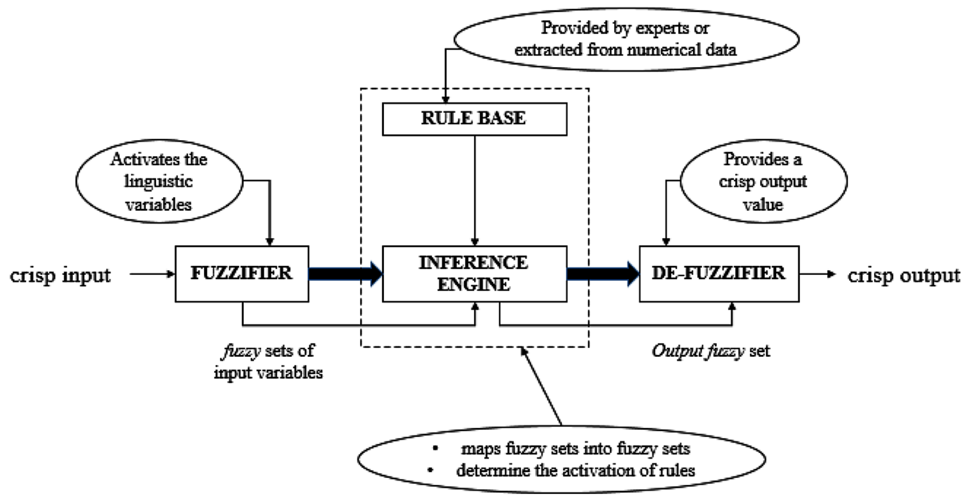
It was Mamdani (1975) who first proposed the minimum implication, and later Larsen proposed the product implication in 1980. The minimum and product inferences have nothing to do with traditional prepositional logic; hence, they are collectively referred to as engineering implications. Details of implication methods can be found in the classic tutorial paper by Mendel (1995).

Fuzzy Inference System

The FIS system nonlinearly maps input data into an output using fuzzy rules.he output from FIS is always a fuzzy set irrespective of its input which can be fuzzy or crisp. The functional block of FIS consists of four blocks: Fuzzifier, De-Fuzzifier, Rule base and Inference engine as shown in Fig. 9.

- *Fuzzifier:* It converts the crisp input into a linguistic variable using the membership functions stored in the fuzzy knowledge database. The process of *fuzzification* is similar to mapping classi-

Figure 9. Generalised block diagram of FIS



cal set to fuzzy set to varying degrees. This is required in order to activate rules that are in terms of linguistic variables. The fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets via membership functions.

For example, let us consider that severity of disease in a plant is evaluated on the basis of the infected area on the leaf image. Depending on the percentage of infection, infected region can be classified into three linguistic variables such as small, medium, and large. Let us assume that the infected area is 62.8% as shown in Fig. 10. The linguistic variable for the infected area would be 0.912 large & 0.088 medium.

- *Rule Base:* The fuzzy rules are given as a sequence of *if-then* statements that decide the necessary action or output to be taken for the respective input information. The *if* statement consists of meaningful conditions, and the *then* part provides the conclusion in the form of a linguistic variable.

For the above example, rule base is given as in Table 1.

- *Inference Engine:* The inference engine uses the fuzzy *if-then* rules to convert the fuzzy input to fuzzy output. It consists of an application of two operations; the first is the application of implication methods such as max, min, and, or etc. on the basis of *the if-then* rule and the second is the aggregation of the outputs from each rule. The inference methods used depend upon the type of fuzzy model being implemented such as Mamdani, Sugeno etc.. Fig. 11 shows the detailed block diagram of an inference engine.

With reference to the above example, the following inference is obtained:

0.088 medium will result in 0.088 middle

Figure 10. Membership function for infected leaf region

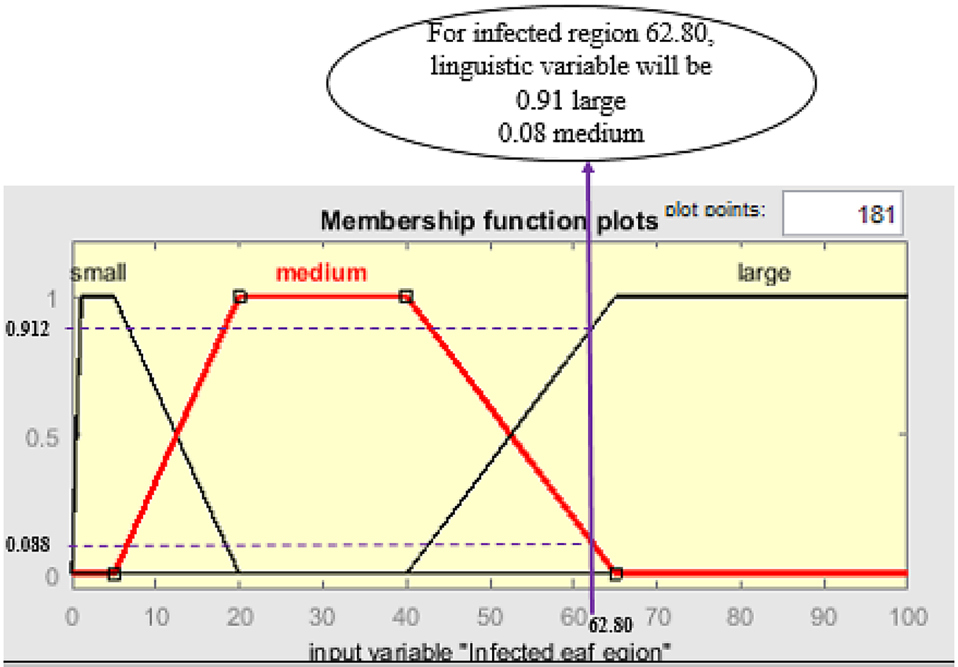
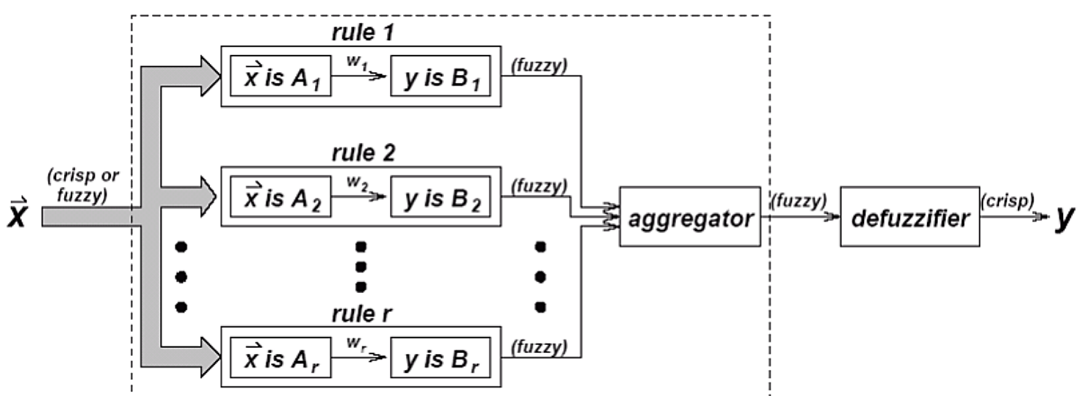


Table 1. Summary of fuzzy rules applied in the form of if-then statements

If Infected area is	Then Severity of the disease is at
small	an *early* stage
medium	*middle* stage
large	*later* stage

Figure 11. Detailed block diagram of an inference engine



0.912 large will result in 0.912 later

- *De-fuzzifier:* It converts the fuzzy output of the inference engine to crisp output using membership functions. The input to the de-fuzzifier is the aggregated output fuzzy set and the output is the crisp value obtained using some de-fuzzification method. Different kind of de-fuzzifying methods are being used such as centroid, maximum, height etc. The method used in the proposed algorithm is the weighted average method where the de-fuzzified value, x* is obtained using the following formula:

$$x^{*} = \frac{\sum x.\mu\left(x\right)}{\sum \mu\left(x\right)} \tag{10}$$

Where, $\sum$ denotes the algebraic summation.
x is the element with maximum membership function.
The fuzzy output obtained from the inference engine for the above example is de-fuzzified using weighted average method as follows:

$$sev = \frac{0.088 \times 50 + 0.912 \times 75}{0.088 + 0.912}$$

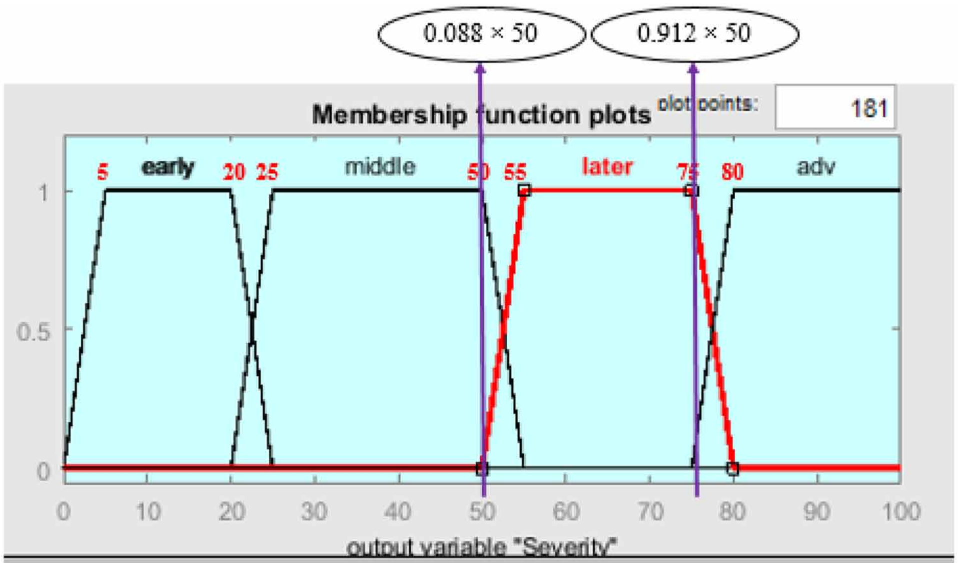
$$sev = 72.8\,\%$$

The assignment of weights to the output (severity) membership function is shown in Fig. 12.

Plant Diseases and Visual Symptoms

Each plant species has special growth habits, colors and growth rates. It is prime job to know the expectations from a healthy plant. Does the plant normally have new foliage that is yellow or red and becomes darker green as the foliage ages? It is required to know what the normal appearance of a plant and that the appearance can vary with different cultivars. Some plant cultivars have naturally yellow to pale green leaves (e. g. herbs like golden oregano) which, at a first glance, appear to have symptoms of under-fertilization, root stress or soil pH problems. Once the "normal" appearance of the specific plant is determined, comparisons can be made between the two on the basis of overall size, shape, and coloration; leaf shape, size, coloration, and distribution; root distribution and coloration; and bark, stem or trunk texture and coloration. Most plant diseases – around 85 percent are caused by the three main pathogenic microbes: fungus, bacteria and virus. A *sign* of plant disease is physical evidence of the pathogen. For example, fungal fruiting bodies are a sign of disease. Appearance of powdery mildew on a lilac leaf, actually shows the parasitic fungal disease organism itself (*Microsphaera alni*). A *symptom* of plant disease is a visible effect of disease on the plant. Symptoms may include a detectable change in color, shape or function of the plant as it responds to the pathogen. Symptoms can be grouped as:

Figure 12. Membership function for disease severity



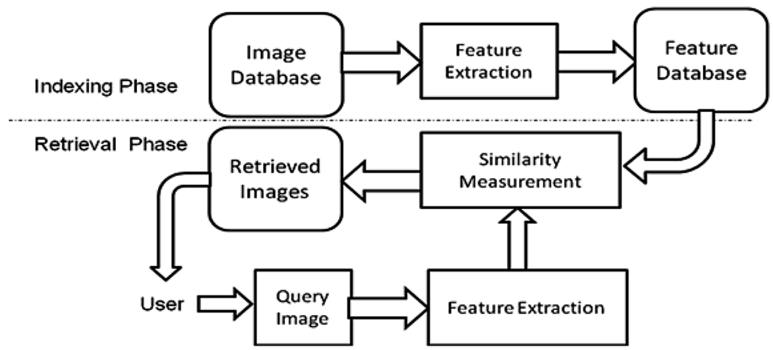
- Underdevelopment of tissues and organs
- Overdevelopment of tissues and organs
- Necrosis or death of parts of plant
- Alteration of normal appearance of plant organs

The affected parts of the plants can be roots, leaves, stems, flowers, or fruit. About 60% to 70% of disease symptom appears on leafs only. The quality of leafs defines the degree of excellence or a state of being free from defects, deficits, and substantial variations. The foundation of quality assessment is basically dependent upon features of leafs such as its appearance, cracks, texture, and surface where human alertness could be easily fooled.

Fuzzy Logic in Feature Extraction

The main objective of image retrieval is to extract the similar images on the basis of their content. The term ‘content’ in this context refers to the significant information that can be derived from the image itself. Content is divided into two types: high level features (human mood, beautiful scenery, nationality etc.) and low level features (color, texture, shape etc.). The use of low level features does not usually give satisfactory results in many cases. This is because the high level concepts in user’s mind are not easily represented in terms of low level features. But still the low level features are widely used because of their simplicity in implementation. A generalized disease identification system in plants is shown in Figure 13. In the indexing phase, features of the images in the database are extracted and stored in the feature database according to the different categories of the leaf images present in the database such as (yellow region, dark spots etc.). To retrieve similar images, user provides the query image to the retrieval system. In retrieval phase, features of the query leaf image are extracted and compared with the features of the

Figure 13. Generalized plant disease identification system



leaf images in the database. The similarity between the features of the query and those of the different images in the database is then calculated.

For an exactly identical pair of images, the similarity value will be equal to one. A similarity value of zero indicates that the two images are not similar at all. Images from the database are retrieved based on the number constraint or threshold constraint according to the descending order of similarity with respect to the query image. When the number constraint is specified by the user, the system will retrieve fixed number of images. In this case, there is no minimum value of similarity. When a threshold constraint is specified, the system will retrieve all the images whose similarities are above the given threshold. In this case, there is no restriction on the number of images to be retrieved.

Feature selection and their combinations are important processes in an identification system. Proper selection and combination of features (Guldogan E and Gabbouj M, 2008; Lin et al. 2003) helps in reducing the retrieval complexity while maintaining high retrieval accuracy. In hierarchical feature selection process (Escarcina and Costa 2007), the low level features are selected in a hierarchy. The hierarchical feature selection process helps in reduction in search space which in turn accelerates the retrieval results in the identification system.

Feature extraction is the process of extraction of significant information present in the image on the basis of which the image can be classified into a specific category. In plant disease identification, color and texture of the leaf is considered for disease detection. The extracted features are stored in a feature database. For classification among different diseases, the extracted features, that are stored in a feature database, are applied to the appropriate classifier such as a neural network. In this way the system identifies whether the input image is healthy or it belongs to a disease class.

Extraction of appropriate features and the decision to apply them as single feature or multiple features in different combinations is an important element of a disease identification system using image processing. Color, texture and shape are called as the low level features. Out of these, color and texture are generally taken into consideration. Shape features are not considered since the database consist of images that comprise of only a part of the leaf and not the entire leaf. These partial images of leaves justify the fact that it is necessary to emphasize only the infected region. Color feature is one of those features which is used most extensively due to its robustness to complicated background and image orientation independence. However, using only color feature does not give encouraging results because of the fact that color histogram does not contain the textual information. In the same manner, texture feature gives the information about the structural arrangement of the surface and does not include the color information. Both crisp features and fuzzy features for color and texture are extracted and their combinations are evaluated for achieving better recognition accuracy.

Color Feature Extraction

One of the most important features that make the recognition of images possible by humans is color. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain. Color is used in day to day life to differentiate among the objects, places, complexions etc. Color is an important cue for image retrieval. Color not only adds beauty to objects but also gives more information, which is used as a powerful tool in identification. The perception of color is greatly influenced by background in the visual scene. The use of color in image processing is motivated by two principal factors.

- Firstly, color is a powerful descriptor that facilitates object identification and its extraction from a scene.
- Secondly, humans can discriminate thousands of color shades and intensities, compared to about only two dozen shades of gray.

In color indexing, given a query image, the goal is to retrieve all the images whose color compositions are similar to those of query image. Color features represent the amount and distribution of colors in the image. Different identification systems adapt different techniques for extraction of color features. Broadly they are divided into two types: Global color feature extraction and Local color feature extraction. Global color features are extracted using color histograms. Local color features are extracted by segmenting the image into regions based on the color features, which are used for feature computation and similarity measurement.

Crisp Color Feature Extraction

Crisp color feature extraction is done by computing the color histogram (Swain and Ballard 1991). Color histogram represents the distribution of colors in an image. Color histogram of an image *X* can be represented as

$$CH(X) = [h_1, h_2, ...h_b], \; i=1,\ 2,\ ....b \tag{11}$$

where $h_i = \dfrac{N_i}{N_T}$ is the probability of a pixel in the image belonging to the i^{th} color bin.

N_i is the total number of pixels in the i^{th} color bin.

N_T is the total number of pixels in the image.

b is the number of bins in the color space.

Color histogram is easy to compute, and is invariant to the rotation and translation of image content. The problem with color histogram is the high dimensionality on representation. Without any quantization, the number of elements of a color histogram is 255×255×255 = 16581375. Even with coarse quantization over a chosen color space, color histogram feature spaces often occupy more than one hundred dimensions (i.e., histogram bins) (Smith and Chang 1996), which significantly increases the complexity of the computation of similarity measurement on the retrieval stage. In this context, dominant colors arise as a powerful tool for describing the representative colors in an image. In dominant color feature approach, the color space is quantized into a small set of color categories. This small set gives a broad description regarding the color of a region. Depending on different databases, different dominant color content look-up tables are prepared by different researchers (Deng et al. 2001; Krishnan et al. 2007).

Using RGB Color Space

The color-content look up table is prepared by considering three primary colors such as Red, Green and Blue, three secondary colors such as Yellow, Cyan and Magenta, and three intensity variations such as Black, Gray and White. The look-up table is presented in Table 2.

By using the look-up table, Color Content Histogram is found out. As the total number of colors in the look-up table is nine, a nine bin color histogram is obtained from each image. The values of the normalized color histogram are considered as the color feature set of the given image. Dimensions of the color feature are significantly reduced in this approach. An example of a color image is given in Figure 12(a). The color histogram of the example image is shown in Figure 12(b).

Using Hue, Saturation, and Intensity (HSI) Color Space

Although RGB color space has been most commonly used for representing color images, it is not well suited for image analysis. Furthermore, the color components of this space do not have an intuitive interpretation according to the human perception of color. The HSI color space mimics human perception and is thus used to analyse the image content. HSI values are calculated from the Red Green Blue (RGB) coordinates (Colombo, Del Bimbo, & Pala, 2001), using the following standard transforms:

Table 2. RGB color-content look-up table

Color-Content	Pixel Value R	Pixel Value G	Pixel Value B
Black	<50	<50	<50
Blue	<50	<50	>150
Red	>150	<50	<50
Yellw	>150	>150	<50
Magenta(Volet)	>150	<50	>150
Cyan(Indio)	<50	>150	>150
Green	<50	>150	<50
Gray	>50 & <10	>50 & <100	>50 & <100
White	>150	>150	>150

Figure 14a. Illustration of an example image

Figure 14a

Figure 14b. Illustration of RGB color content histogram of the example image

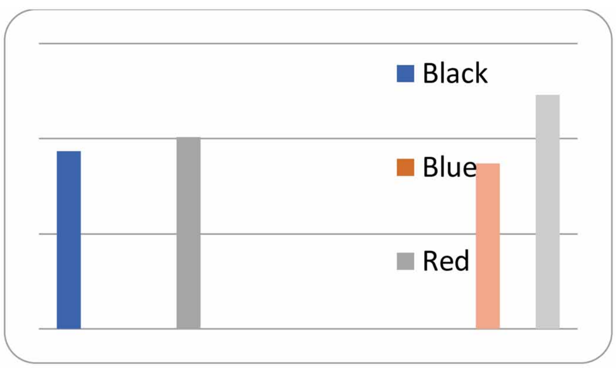
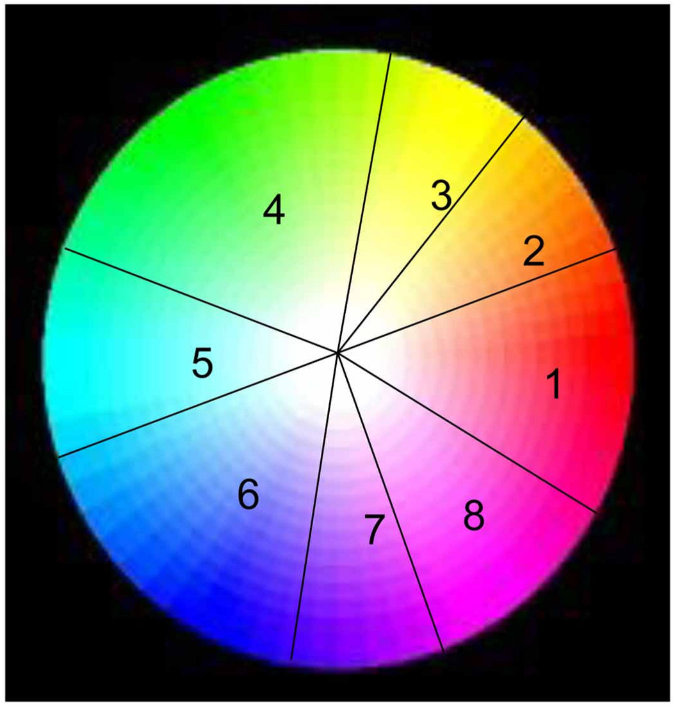


Figure 14b

$$\text{H} = \arctan\left\{\frac{\sqrt{3}\left(G+B\right)}{2R-G-B}\right\} \tag{12}$$

$$\text{S} = 1-\frac{\min\left(R,G,B\right)}{I} \tag{13}$$

Figure 15. Demarcation of different colors on Hue color wheel



$$I = \frac{\left(R+G+B\right)}{3} \tag{14}$$

Extraction of Hue, Saturation and Intensity features are as follows:

Hue Feature

To extract the hue feature, the entire range of hue which is between 0° to 360° is divided into eight different colors. The Hue range generally depends upon the range of wavelength of the particular color. The distribution of different colors on the hue color wheel is shown in Figure 15.

Saturation Feature

To extract the saturation feature from the HSI color space, the entire range of saturation which lies between 0 and 1 is divided into three different saturation levels. The minimum value of saturation is zero, which is obtained when the values of R, G and B components are equal. The maximum value of saturation is one, which occurs when the value of any of the R, G and B components is zero.

Saturation can be expressed as

$$S = \left[1 - \frac{3x}{x+y+z}\right] \tag{15}$$

Where, x is the minimum value of R, G and B.
y and z are the other two components of R, G and B.

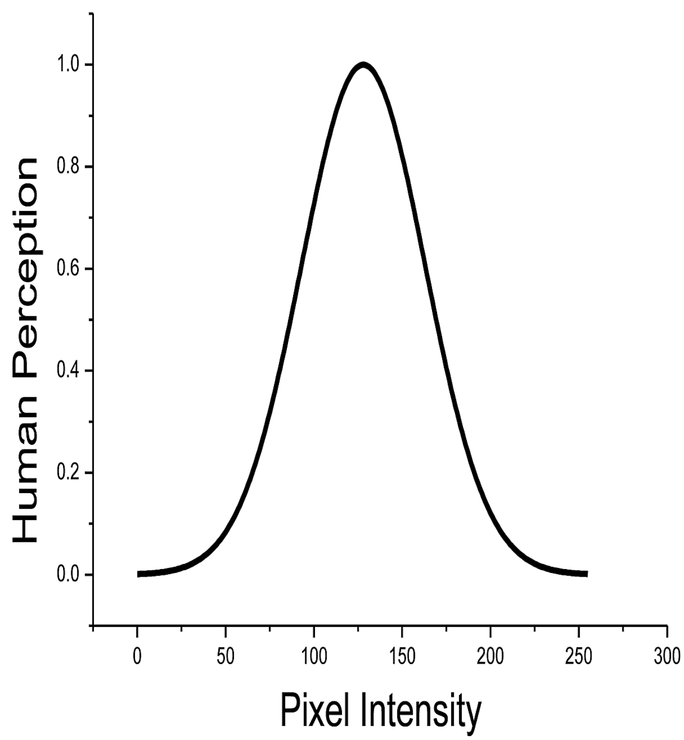
Intensity Feature

To extract the intensity feature from the HSI color space, the entire range of intensity which lies between 0 and 255 is divided into five different intensity levels. As the graph of human perception to intensity is Gaussian in nature (Purves et al. 2004), non-uniform quantization is performed i.e. the step size is more at the edges and it gradually reduces as it approaches towards the centre. Intensity verses human perception is plotted in Figure 16.

Fuzzy Color Feature Extraction

Imprecision is an inherent property in all digital images. The pixel value n in a digital image can be $(n+1)$ or $(n-1)$ without any appreciable change in the visual perception. Fuzzy statistics have proved to be very effective in tackling the imprecision in various image processing applications like image segmentation, object recognition etc. The possibility of existence of a color component in the other color bins is zero in crisp color representation. This is not true when human perception is taken into account. The Fuzzy Color Histogram (FCH) approach helps to define a color as a membership function rather than confining to a fixed color bin. The fuzzy color histogram (Han J and Ma K, 2002), the first-order statistics, of a digital image X can be expressed as

Figure 16. Intensity vs human perception



$$F(X) = [f_1, f_2, ...f_b]\,,\; i = 1, 2, 3.........b. \tag{16}$$

where

$$f_i = \frac{1}{N_T} \sum_{j=1}^{N_T} \mu_{ij} \tag{17}$$

μ_{ij} is the membership value of the j^{th} pixel in the i^{th} color bin.

N_T is the total number of pixels in the image.

b is the total number of color bins in the color space.

In the technique proposed by us, fuzzy membership function and linguistic levels are defined for each color component with the help of Fuzzy HSI color space. Trapezoidal function is used to assign membership values for Hue of different color, different saturation levels and different intensity levels as shown in Figure 17(a), (b) and (c) respectively. Fuzzy color features are obtained by calculating the Fuzzy Color Histogram of Hue, Saturation and Intensity independently.

Texture Feature Extraction

Image retrieval techniques using only color features do not give very encouraging results because the color histograms do not contain the textural information. Texture is one of the most important defining features of an image. Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as grass, leaves, fabric, etc. A mixture of different textures is shown in Figure 16. Texture can be defined as an entity consisting of mutually related group of pixels. This group of pixels is called as texture primitives or texture elements (texels). Texture also describes the relationship of the surface to the surrounding environment. In short, texture is a feature that describes the distinctive physical composition of a surface.

Figure 17a. Illustration of the membership function for hue of different colors

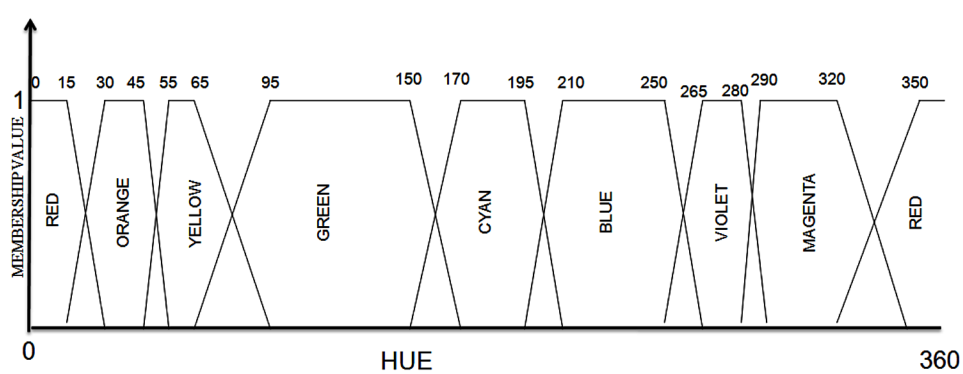


Figure 17b. Illustration of the membership function for different Saturation levels

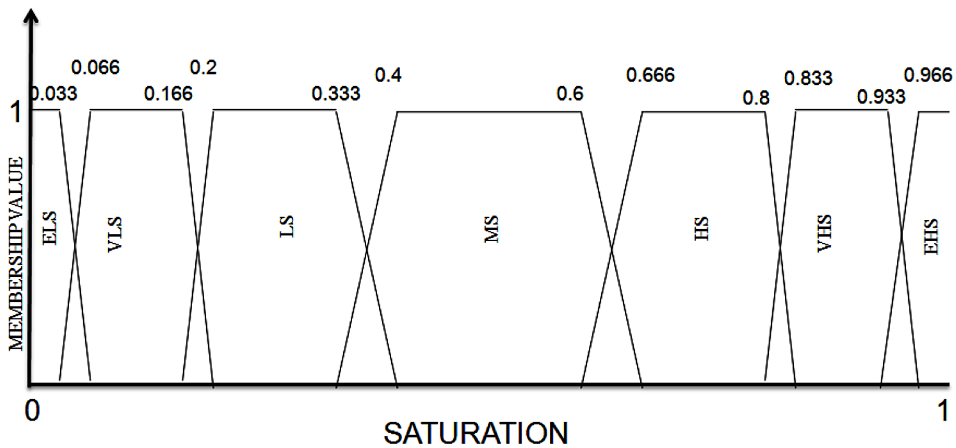
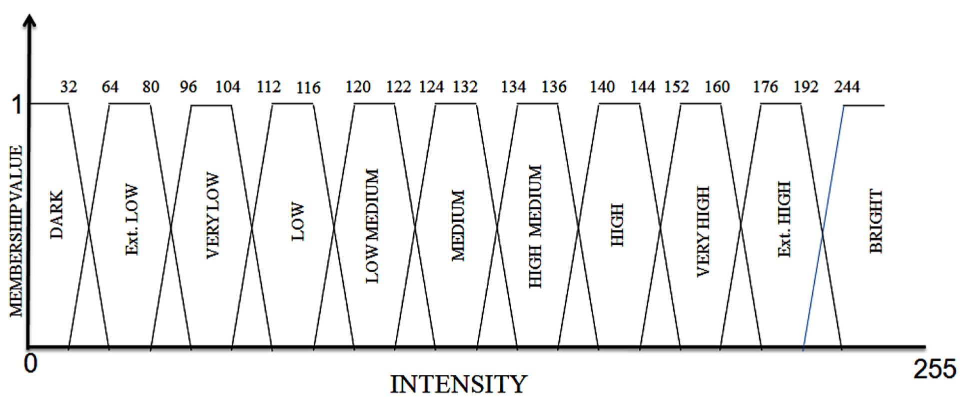


Figure 17c. Illustration of the membership function for different Intensity levels



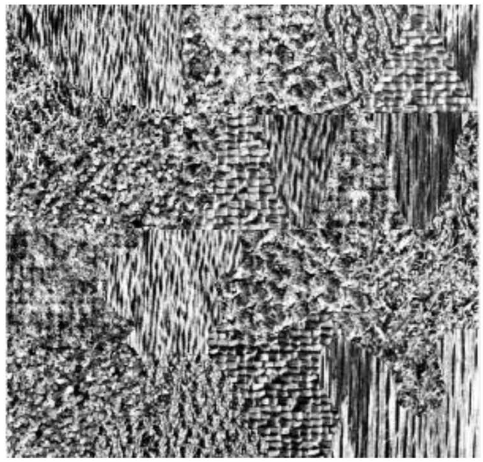
Crisp Texture Feature Extraction

Texture is characterized by the spatial distribution of gray levels in a neighborhood (Rao 1990). Haralick *et al.* derived fourteen statistical features from the co-occurrence matrices to classify images based on textural features (Haralick et al. 1973).Tamura *et al.* proposed six statistical features which correspond to visual perception (Tamura et al. 1978). Haralick features and Tamura features are used separately for texture feature extraction.

Haralick Texture Feature Extraction

Haralick texture features are obtained from the normalized gray-level co-occurrence matrix. The co-occurrence matrix represents the statistics of pairs of geometrically related pixels. Co-occurrences, the second order statistics of an image represents the joint probability or frequency of occurrence of pixels with gray values m and n, separated by a distance δ, at a specified direction θ, and are expressed in the

Figure 18. A mixture of different Texture image [Courtesy:(The USC-SIPI Image Database: V- 5)]



form of a two dimensional matrix $C = [C_{mn}]_{L \times L}$, where *L* is the maximum value of the gray levels. $\left(m, n \in \ell\right)$, ℓ is the integer set of gray values. $\ell = \left\{0, 1, \ldots. L - 1\right\}$.

Example 4: Let the given matrix X contains the pixel values of an image. Compute the co-occurrence matrix for it.

$$X = \begin{pmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{pmatrix}$$

Solution

As the pixel values ranges from 0 to 3, the co-occurrence matrix will be of size 4X4. The co-occurrence matrix *C* is computed by considering the distance $\delta = 1$, and direction $\theta = 0^o$

$$C = \begin{pmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{pmatrix}$$

Once the co-occurrence matrix is computed, the Haralick features are extracted from it using the formulae for each feature. The Haralick features computed from the co-occurrence matrix are listed in the Table 3.

Table 3. List of Haralick texture features, the mathematical formulae for each of their computation and the measure of each feature

S.No	Name of the Texture Feature	Mathematical Formulae	Measure of Each Feature
1.	Angular Second Moment	$f_1 = \sum_{i=1}^{L-1}\sum_{j=1}^{L-1}\left\{p\left(i,j\right)\right\}^2$	Local Homogeneity
2.	Contrast[1]	$f_2 = \sum_{n=0}^{L-1} t^2 \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p\left(i,j\right)$	Amt. of local variation in the image.
3.	Correlation[2]	$f_3 = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\left(i,j\right)p\left(i,j\right) - \mu_x\mu_y}{\sigma_x\sigma_y}$	Linear dependency of gray levels of neighbouring pixels.
4.	Sum of Squares	$f_4 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\left(i-\mu\right)^2 p\left(i,j\right)$	Variation of Image intensity values.
5.	Inverse Difference Moment	$f_5 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{1}{1+\left(i-j\right)^2} p\left(i,j\right)$	Image homogeneity
6.	Sum Average[3]	$f_6 = \sum_{i=0}^{2\left(L-1\right)} i p_{x+y}\left(i\right)$	Average of normalised co-occurrence matrix.
7.	Sum Variance	$f_7 = \sum_{i=0}^{2\left(L-1\right)}\left(i-f_6\right)^2 p_{x+y}\left(i\right)$	Variance of normalised co-occurrence matrix.
8.	Sum Entropy	$f_8 = -\sum_{i=0}^{2\left(L-1\right)} p_{x+y}\left(i\right)\log\left\{p_{x+y}\left(i\right)\right\}$	Randomness
9.	Entropy	$f_9 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p\left(i,j\right)\log\left\{p\left(i,j\right)\right\}$	Complexity
10.	Difference Variance	$f_{10} = variance\, of\, p_{x-y}$	Variation of normalised co-occurrence matrix.
11.	Difference Entropy[4]	$f_{11} = -\sum_{i=0}^{L-1} p_{x-y}\left(i\right)\log\left\{p_{x-y}\left(i\right)\right\}$	Randomness

continued on following page

Table 3. Continued

S.No	Name of the Texture Feature	Mathematical Formulae	Measure of Each Feature
12.	Information Measures of Correlation-1[5]	$f_{12} = \frac{H_{XY} - H_{XY1}}{\max\left\{H_X, H_Y\right\}}$	Information
13.	Information Measures of Correlation-2[6]	$f_{13} = \left\{1 - \exp\left\{-0.2\left(H_{XY2} - H_{XY}\right)\right\}\right\}^{1/2}$	Information
14.	Maximum Correlation Coefficient[7]	$f_{14} = \left(Second\ Largest\ Eigen\ Values\ of\ Q_{corr}\right)^{1/2}$	Correlation

Tamura Texture Feature Extraction

Tamura features characterize low-level statistical properties and also convey visual information of the textures. Tamura texture features are extracted from the image using the following formula proposed by Tamura. Although Tamura features characterize low-level statistical properties of textures, they have been shown visually meaningful and can be easily interpreted through high-level textual concepts. Tamura features are given in Table 4.

Fuzzy Texture Feature Extraction

Fuzzy texture features are extracted by fuzzifying the crisp feature extraction technique.

Fuzzy Haralick Features

Fuzzy Haralick features are extracted from the fuzzy co-occurrence matrix (Jawahar CV and Roy AK, 1996) of the image. The fuzzy co-occurrence matrix, the second order statistics, of a digital image is an array of real numbers $\tilde{C} = [\tilde{c}_{mn}]$, where $\tilde{c}_{mm}$ represents the frequency of occurrence of the gray value "around *m*" separated from another pixel with gray value "around *n*" by a distance δ, at a specified direction θ, that is, $\tilde{C} = f(I, \delta, \theta)$. Here the computation can be performed by fuzzifying the parameter I, δ or θ. In this study, only the intensity parameter is fuzzified by keeping the distance $\delta = 1$, and direction $\theta = 0^o$. The element of the fuzzy co-occurrence matrix (Purves et al. 2004) is represented by

$$\tilde{c}_{mm} = \frac{1}{L^2} \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \min(\mu_{im}, \mu_{jn}) \times c_{mn} \tag{18}$$

where μ_{im} is the membership value of *i* in *m*.

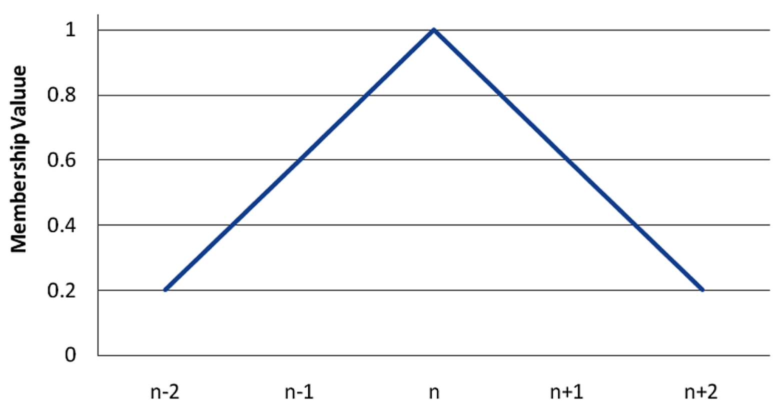
μ_{jn} is the membership values of *j* in *n*.

Table 4. List of Tamura texture features, the mathematical formulae for each of their computation and the measure of each feature

S.No	Name of the Texture Feature	Mathematical Formulae	Measure of Each Feature
1.	Coarseness[8]	$f_{crs} = \frac{2^k}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{best}(i,j)$	Texture granularity
2.	Contrast[9]	$f_{con} = f_2 = \sum_{t=0}^{L-1} t^2 \sum_{i=1}^{L} \sum_{j=1}^{L} p(i,j)$	The difference in intensity among neighboring pixels
3.	Directionality[10]	$H_D(k) = \frac{N_\theta(k)}{\sum_{i=0}^{n-1} N_\theta(i)}$ $f_{dir} = 1 - r \times n_p \times \sum_{p}^{n_p} \sum_{\varphi \in w_p} (\varphi - \varphi_p)^2 \times H_D(\varphi)$	The placement of the texture primitives
4.	Line-likeness[11]	$f_{lin} = \sum_{i}^{L-1} \sum_{j}^{L-1} P_{Dd}(i,j) \cos\left[(i-j)\frac{2\pi}{L}\right] \Big/ \sum_{i}^{L-1} \sum_{j}^{L-1} P_{Dd}(i,j)$	The shape of texture primitives
5.	Regularity[12]	$f_{reg} = 1 - r_n(\sigma_{crs} + \sigma_{con} + \sigma_{dir} + \sigma_{lin})$	Variations of the texture-primitive placement
6.	Roughness	$f_{rgh} = f_{cor} + f_{con}$	Variations of physical surface

The fuzzy membership function of the intensity around *n* is shown in Figure 19. At the pixel intensity *n*, the membership value is one and the membership values decreases with the increase in deviation from pixel intensity *n*. The membership values beyond *n+2* and *n-2* are treated as zero.

Figure 19. Fuzzy membership function of intensity around n



Example 5: Considering the matrix *X* from example 4, compute the fuzzy co-occurrence matrix.

Solution

The co-occurrence of pixel intensity (3,3) in the given matrix X is 6. The membership values of co-occurrence of pixel intensity around 3 and 3 are added together to get the fuzzy co-occurrence of pixel intensity (3,3). The membership values of (3,4) in (3,3) is 0.6. This is obtained by calculating the minimum membership values between 3 in 3 i.e. 1 and 3 in 4 i.e 0.6. Similarly the membership values of co-occurrence of pixel intensity around 3 and 3 are calculated. The fuzzy co-occurrence of pixel intensity (3,3) = 1× co-occurrence of pixel intensity (3,3)+ 0.6× co-occurrence of pixel intensity (3,2)+ 0.2 × co-occurrence of pixel intensity (3,1)+ ……… Similarly the values of the other elements of the Fuzzy co-occurrence matrix are calculated. The fuzzy co-occurrence of pixel intensity (3,3) with $\delta = 1$ and direction $\theta = 0^o$ is

$$\tilde{C}_{33} = sum\left(\left(\begin{array}{cccc} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{array}\right) \times \left(\begin{array}{cccc} .2 & .2 & .2 & .2 \\ .2 & .6 & .6 & .6 \\ .2 & .6 & 1 & .6 \\ .2 & .6 & .6 & .6 \end{array}\right)\right) = 12.8$$

The fuzzy co-occurrence matrix of X with $\delta = 1,$ and direction $\theta = 0^o$ is

$$\tilde{C} = \left(\begin{array}{cccc} 10.4 & 10.2 & 7.4 & 3.2 \\ 10.2 & 14.4 & 10.4 & 6.6 \\ 7.4 & 10.4 & 12.8 & 7.8 \\ 3.2 & 6.6 & 7.8 & 7.6 \end{array}\right)$$

To easily compute the fuzzy co-occurrence matrix form the co-occurrence matrix, the Fuzzy Co-occurrence Operator (FCO) is given in Figure 20(a). Membership function according to FCO is shown in Figure 20(b).

$$FCO = \begin{bmatrix} 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 1.0 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.2 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}$$

Figure 20a. Illustration of fuzzy co-occurrence operator

$$FCO=\begin{bmatrix} 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 1.0 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.8 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 \\ 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.2 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}$$

Figure 20b. Illustration of membership function according to the fuzzy co-occurrence operator

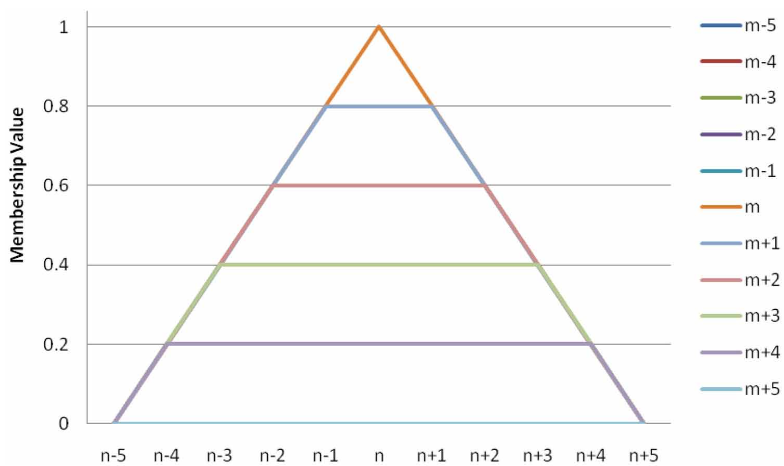
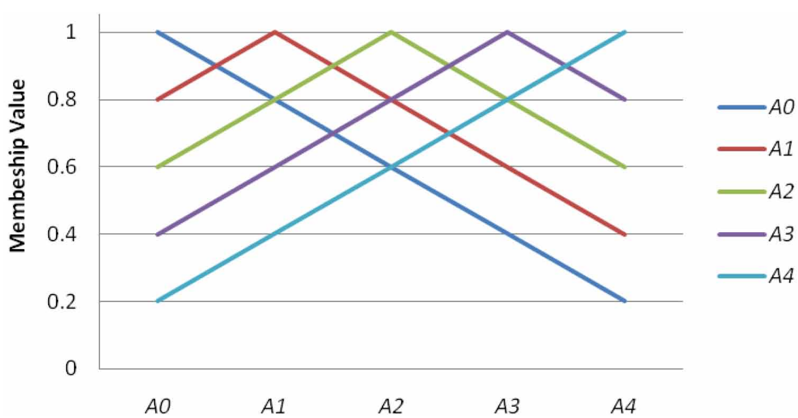


Figure 21. Membership function of difference in moving average (A) for different neighborhoods



The fuzzy co-occurrence matrix is obtained by convolving the mask over the entire co-occurrence matrix. Finally the normalized fuzzy co-occurrence matrix is calculated from the co-occurrence matrix. Once the normalized fuzzy co-occurrence matrix is computed, the features are extracted using the formulae discussed in Section 3.2.1.

Fuzzy Tamura Features

For extraction of fuzzy Tamura features, each feature is fuzzified separately.

Fuzzy Coarseness

As the coarseness value depends on the size of the neighborhood, difference of moving average taken over a $2^k x2^k$ neighborhood is fuzzified to obtain the fuzzy coarseness value of the image. Instead of calculating crisp A_k, fuzzy A_k is calculated.

$$\tilde{A}_k = \frac{1}{N_n} \sum_{j=1}^{N_n} \mu_{jk} A_j \tag{19}$$

where μ_{jk} is the membership values of A_j in calculation of $\tilde{A}_k$

N_n is the total number of different neighborhoods.

$$\tilde{A}_k = \tilde{A}_{\max} = \max(\tilde{A}_{0h}, \tilde{A}_{0v}, \tilde{A}_{1h}, \tilde{A}_{1v}, ...\tilde{A}_{kh}, \tilde{A}_{kv}) \tag{20}$$

Once the value of k is obtained, fuzzy coarseness can be calculated using the formulae for coarseness given in Table 4.

Fuzzy Contrast

Fuzzy contrast is extracted from the fuzzy co-occurrence matrix, instead of crisp co-occurrence matrix using the contrast formula given in Table 4.

Fuzzy Directionality

As the directionality depends on the local direction histogram H_D, H_D is fuzzified to compute the fuzzy directionality.

$$\tilde{H}_D(k) = \frac{1}{b} \sum_{j=1}^{b} \mu_{jk} H_D(j) \tag{21}$$

where μ_{jk} is the membership values of $H_D(j)$ in calculation of $\tilde{H}_D(k)$ b is the total number of bins in the local direction histogram.

Once the local fuzzy direction histogram is obtained the fuzzy directionality can be calculated using the directionality formula given in Table 4.

Fuzzy Line-Likeness

Fuzzy line-likeness is extracted from the fuzzy co-occurrence matrix, instead of crisp co-occurrence matrix using the line-likeness formula given in Table 4.

Fuzzy Regularity

Fuzzy regularity is obtained from the standard deviations of fuzzy coarseness, fuzzy contrast, fuzzy directionality and fuzzy line-likeness parameters.

Fuzzy Roughness

Fuzzy roughness is obtained by adding the fuzzy coarseness and fuzzy contrast.

Fuzzy Logic in Severity Estimation

A plant can be easily classified as diseased if the symptoms are clearly visible but the most critical part is to quantify the disease. Thus, severity estimation is a challenging task which primarily aims to quantify the severity with which the plant has been affected. The severity estimation methods should be accurate, precise, reproducible, economical and easy to implement.

Severity assessment techniques can be broadly classified as visual, semi-automatic and automatic. The visual methods are manual and the severity is calculated with the aid of assessment scales or keys, by one or more expert pathologists from their field. A detailed review of the visual estimation techniques, their disadvantages and improvement methods is provided by Bock et al. (2010). Visual methods introduce subjectivity, are time-consuming and error prone in their estimation (Bock et al., 2008; Bock et al., 2009). With the advent of digital imagery, semi-automatic and automatic methods have come up as a preferred choice for severity estimation. The techniques that require image processing tools (also called third-party tools) are semi-automatic in the sense that they require human intervention in some part of the algorithm and rest of the processing is done by the software tools (Barbedo, Koenigkan, & Santos, 2016). Various commercialised and customised packages are used such as ASSESS (Lamari, 2002), Sigmascan (Biernacki & Bruton, 2001), ImageJ (Peresotti, Duchêne, Merdinoglu, Mestre, 2011), QUANT (Andrade, Alfenas, Mafia, Maffia, Gonçalves, 2005) etc. These packages provide accurate and precise results compared to visual estimation but generally consume more time. The segmentation techniques that they employ struggle to deal with multiple diseases. Also, the person who operates these software packages requires proficient training in order to provide standard measurements otherwise the error of subjectivity remains. Considering the above constraints of manual and semi-automatic techniques, various automatic methods have been employed for symptom quantification in recent years. The leaf images are acquired by imaging devices such as digital cameras and stored in RGB color space format. Most of the methods mentioned in the following discussion employ color space transformations from RGB to HSI, L*a*b*, CMYK etc… as required by the algorithms. Mostly the images are transformed to HSI color space as it separates the brightness component with the hue component and is considered most suitable for visual characteristics of human beings (Weizheng, Yachun, Zhanliang, Hongda, 2008). Segmentation is found to be the most basic technique to separate the infected region from the entire leaf region. To segment the infected region, mostly thresholding is employed. From applying a simple threshold to segmenting the pixels on the basis of their gray level values (Price, Gross, Ho, Osborne, 1993), the technique has witnessed various changes such as identifying symptom edges using Sobel operator (Weizheng et al., 2008), Histogram of intensities (Camargo & Smith, 2009) and triangle thresholding (Patil & Bodhe, 2011). Cui, Zhang, Li, Hartman, and Zhao (2010) extracted two diagnostic parameters, Ratio of Infected area (RIA) and Rust Color index (RCI) and used them as symptom indicators for quantifying rust severity in soybean. Biswas, Jagyasi, Singh, and Lal (2014) used the Back Propagation neural network to estimate the severity of the disease in potato leaves. Wang, Sun, and Wang (2017) proposed disease severity estimation technique using deep learning models. The deep learning approach automatically discovers distinctive features for a precise classification. Parikh, Raval, Parmar, and Chaudhary (2016) employed two cascaded KNN classifiers where the first classifier segments the leaf region from the background and the second one classifies between the infected and leaf region. Infected area can also be segmented out of the leaf region using region growing methods that are centred on a seed or pixel (Fan, Yau, Elmagarmid, Aref, 2001). The automatic techniques are more accurate and precise in their quantification as compared to visual estimation and at the same time being computationally faster than semi-automatic techniques (Barbedo, 2014). All the methods cited above consider that the green colored pixel belongs to the healthy region while the non-green pixel belongs to the infected region of the leaf. This is achieved by using fixed criterions or thresholds to separate infected region (lesions) from the leaf region. However, in practice, the healthy and infected region of the leaf are uneven and cannot be distinctly distinguished. Pixels of the infected region do contain some green color in them. Thus, they are not completely non-green i.e. they have some percentage of non-green content in their pixels depending upon the severity of the infection.

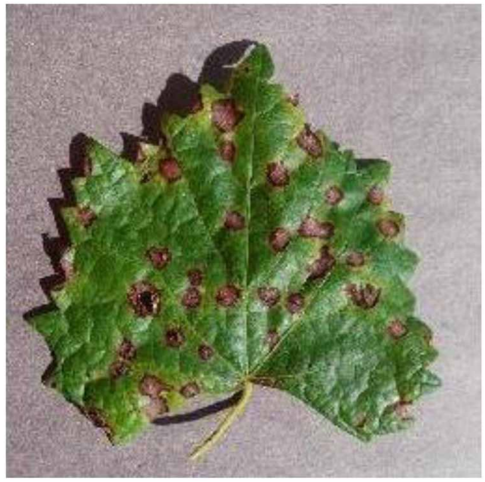
Fuzzy logic is used to overcome the limitations of crisp methods. Its applications can be seen in various disease quantification and classification algorithms. A fuzzy logic model developed by Kim, Wang, and Yang (2005) estimates apparent infection rate from the environmental temperature. This infection rate is used to predict the severity of soybean rust. Zhou et al. (2013) used Fuzzy C-Means clustering (FCM) algorithm for infected area detection and classification of infected rice stems. Pang, Bai, Lai, and Li (2011) proposed an adaptive segmentation algorithm by integrating local threshold and seeded region growing. Sekulska-Nalewajko and Goclawski (2011) performed FCM on cucumber and pumpkin leaves by considering that one image pixel feature can contribute to more than one cluster. Apart from decoloration, infection in the plant causes the appearance of spots on the leaf. While evaluating the severity of the disease, considering either of the two i.e. the infected leaf area or the number of spots, does not provide accurate results. To estimate the severity of the disease closer to actual values, it is required to consider both the parameters together. But, crisp analysis of both the parameters does not improve the quantification performance. This is because it may happen that a leaf with a small infected region has a large number of spots on it while a leaf with a large infected area has lesser number of spots. Hence, the occurrence of the number of spots on the infected leaf area needs to be evaluated under a fuzzy logic system.

Example 6: Given the image of a leaf blight infected grape leaf in Figure 22. Model a Fuzzy Inference System to evaluate the severity of the infection.

Solution

To evaluate the severity of the given leaf image, following steps are taken:

Figure 22. RGB image of a grape leaf infected by leaf blight



Step 1: Process the input image such that the green color of the image is enhanced and the background is removed, as given in the figure 23.

Step 2: Transform the RGB color image to HSI color space. This is done as the HSI color space decouples the color carrying component (hue & saturation) from the intensity value and helps in neglecting the intensity variations.

Step 3: Normalize the hue values in the hue color wheel in the range 0 to 1 (as shown in Table E1). The hue component describes pure color in the form of an angle varying between 0° and 360° where 0 means red, 60° for yellow, 120° for green, 240° for blue, 300° for magenta. Hue value becomes meaningful when saturation component (which varies between 0 & 1) is 1.

Figure 23. Background removed image of a grape leaf infected by leaf blight

Step 4: Extract the infected leaf area by applying fuzziness to the occurrence of hue. The HSI color wheel shows that the hue value for green color varies from 105° to 135°. As the infection develops in a healthy leaf, the green color is no more seen in its pure form. In the infected area, usually the leaf turns yellow in color with hue values varying from 65° to 105°. Lesion regions also tend to appear and depending upon the severity of the infection their color is either red (hue is 0° to 15° or 350° to 360°), orange or brown (hue between 30° to 45°).

A pixel can contribute to healthy as well as infected region simultaneously depending upon the degree of greenness present in the pixel. This degree of greenness is handled by fuzzy logic by assigning membership value for healthy region. As the degree of greenness decreases in a pixel, the pixel is said to be contributing less as a healthy pixel and more as an infected pixel. The trapezoidal membership function is used for segmenting healthy region from the leaf region and is shown in figure 24.

The infected region is segmented out of the entire leaf region (as shown in figure 25),

Step 5: Calculate the number of diseased spots in the following way:

- A segmentation mask is generated such that pixel values are made 1 if the hue value of the respective pixel in the infected image is less than 0.12 or greater than 0.97 and 0 otherwise.
- All the connected components in the leaf area that belong to the above mask are calculated.
- Each connected component is assigned a unique label. The number of pixels that belong to each label is calculated. The number of labels depicts the number of diseased spots on the leaf image.

Table 5. Hue values for different colors

Color	Hue Value [0°,360°]	Normalised Hue Value [0,1]
Green	94° to 148°	0.26 to 0.41
Yellow	65° to 100°	0.18 to 0.28
Red	0° to 15° or 350° to 360°	0 to 0.04 or 0.97 to 1
Orange/Brown	30° to 45°	0.083 to 0.125

Figure 24. Trapezoidal membership function of healthy region of a leaf

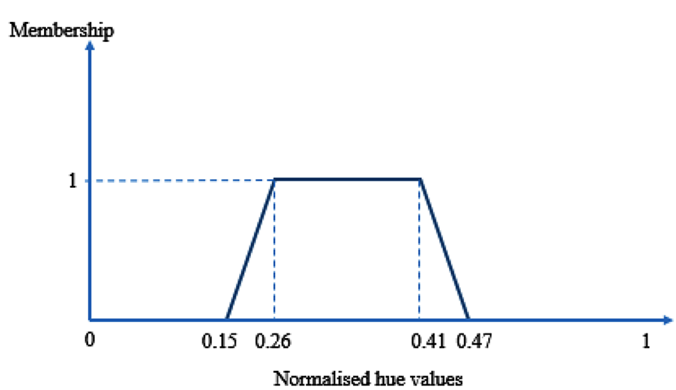


Figure 25. Illustration of segmenting infected region from the original leaf region

Localization of diseased spots are shown in figure 26,

Step 6: Infected leaf area and the number of lesion spots are provided as the inputs to the fuzzifier. Depending on the percentage of infection, infected region can be classified into three linguistic variables such as small, medium, and large (as shown in figure 27). Similarly, the number of spots are classified as little, few, and many. Depending upon the severity percentage, the output variable i.e. severity is also classified into four different linguistic variables i.e. early, middle, later, and advanced.

Step 7: The leaves that are healthy, are independent of infection and contains no spots. Fuzzy rules are given in the form of *if-then* statements that decide the severity for the respective infected region and number of spots. This set of fuzzy rules are summarized in Table 6.

Step 8: The *if* statements are connected via 'and' operation & hence 'min' fuzzy operator is applied to obtain the final value of the rule.

Figure 26. Illustration of localizing the infected areas on the leaf image

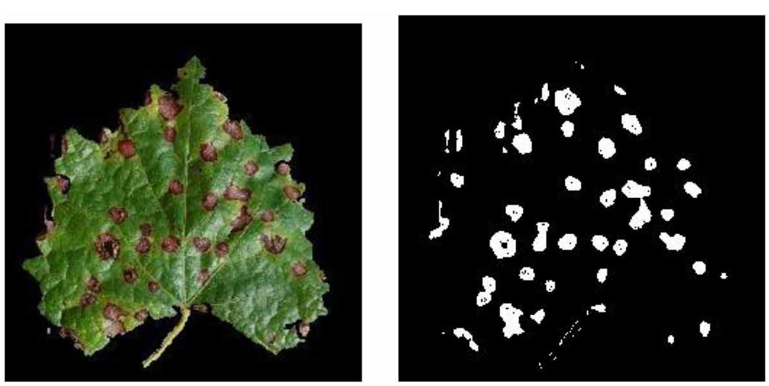


Figure 27a. Membership function for infected area

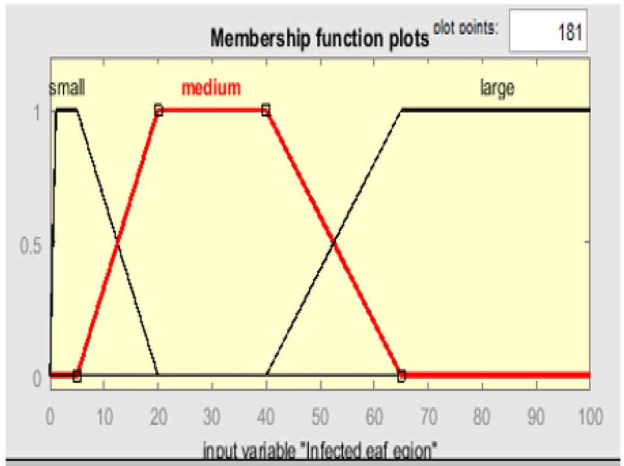


Figure 27b. Membership function for number of spots

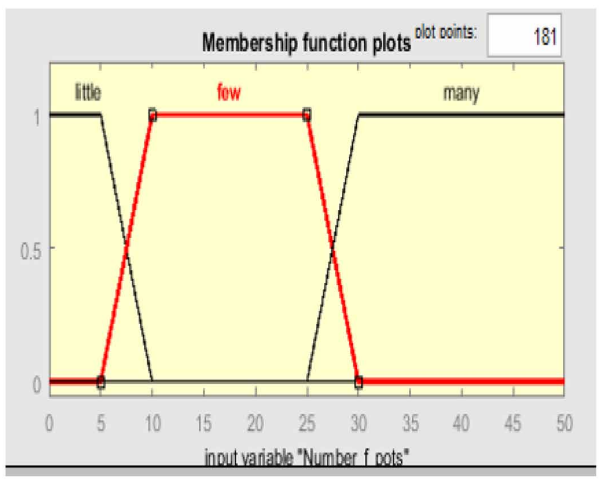
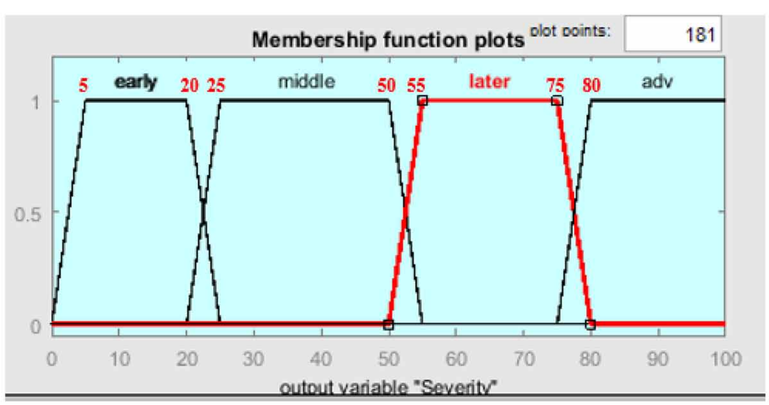


Figure 27c. Membership function for disease severity



Step 9: The fuzzy output obtained from the inference engine is de-fuzzified using the weighted average method. The entire Fuzzy Inference Model is summarized in the figure 28.

The severity of the infected leaf image is found to be 80%.

FUTURE SCOPES

Various kinds of plant disease identification and quantification techniques have been developed such as C-means clustering, thresholding etc. The prime step of identification is feature extraction, where the

Figure 28. Block diagram showing the FIS system for evaluating severity of the disease using a leaf image

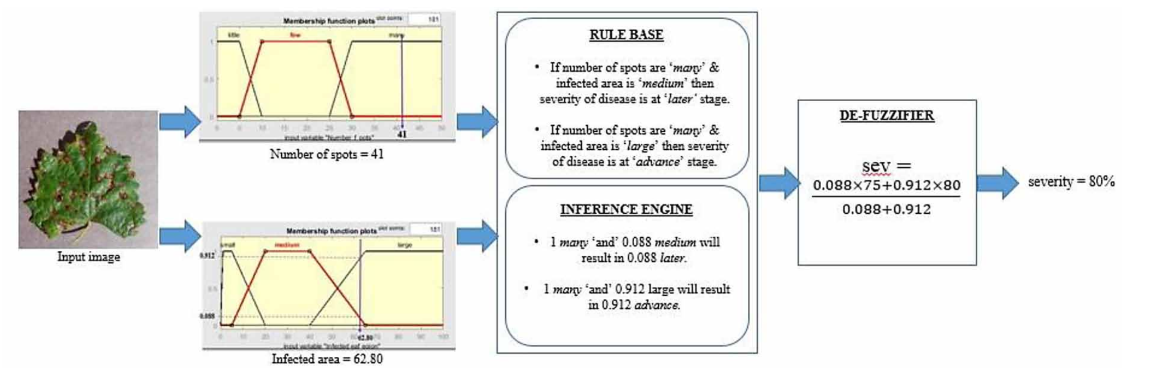


Table 6. Summary of fuzzy rules applied in the form of if-then statements in the proposed algorithm

If		Then
Number of spots are *little*	'and' Infected area is *small*	Severity of the disease is at an *early* stage
Number of spots are *little*	'and' Infected area is *medium*	Severity of the disease is at *middle* stage
Number of spots are *little*	'and' Infected area is *large*	Severity of the disease is at *later* stage
Number of spots are *few*	'and' Infected area is *small*	Severity of the disease is at *middle* stage
Number of spots are *few*	'and' Infected area is *medium*	Severity of the disease is at *middle* stage
Number of spots are *few*	'and' Infected area is *large*	Severity of the disease is at *later* stage
Number of spots are *many*	'and' Infected area is *small*	Severity of the disease is at *middle* stage
Number of spots are *many*	'and' Infected area is *medium*	Severity of the disease is at *later* stage
Number of spots are *many*	'and' Infected area is *large*	Severity of the disease is at an *advance* stage

scope of fuzzy is already being explored. With the advent of neural networks, the identification of images is possible without even extracting the features. Fuzzy logic can be viewed as an option into different layers of the neural network. Disease quantification can also explore fuzzy logic by applying fuzzy *if-then* rules while grading the diseased leaf. The parameters taken into consideration while evaluating the disease severity can also be individually fuzzified for better results. Even the laboratory based methods that use fixed scales, can be improvised in their evaluation by applying fuzziness to the scales.

CONCLUSION

The plant disease management techniques mainly include various identification and quantification algorithms. The diseases are identified through the infected leaf image by extracting color and texture features of the leaf image. The use of fuzzy logic in feature extraction improves the overall accuracy of the identification system. Segmentation of the infected area involves considering every pixel value of the leaf image in such a way that it becomes challenging to decide whether the particular pixel belongs to the healthy region or infected region of the leaf. Thus, fuzzy logic plays a pivotal role in giving an edge to every pixel such that it can partially contribute to the healthy region while contributing to the infected part of the leaf. This helps in identifying the severity of the disease accurately. The use of FIS in overall evaluation of the severity of the infection, helps the user to consider multiple disease symptoms on a single platform and at one time. Overall, the application of fuzzy logic in plant disease management techniques has proved beneficial.

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KEY TERMS AND DEFINITIONS

Antecedent: The part of statements that follow the *if* condition of the fuzzy rule is called an antecedent.

Consequent: The part of statements that follow the *then* condition of the fuzzy rule is called a consequent.

Cultivars: It is a plant variety that has been produced in cultivation by selective breeding.

Fuzzy Logic: Fuzzy logic is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false.

Histogram: A histogram is a chart that shows the frequency distribution of a variable. It is an accurate representation of the distribution of numerical data.

Infected Area: Part of the leaf that changes its color due to the infection is called infected area.

Lesion: A lesion is any damage or abnormal change in the tissue of an organism, usually caused by a disease.

Necrosis: It is the death of most or all of the cells in an organ or tissue due to disease.

Nematodes: Nematodes are roundworms that are found in aquatic habitats, soil, snowy tundra, and hot deserts, inside plants and animals.

Pathogen: It is a bacterium, virus, or other microorganism that causes disease in plants.

Severity Estimation: It is the evaluation of the quantity of the disease with which the crop has been affected.

ENDNOTES

1 $p(i,j)$ is the $(i,j)^{th}$ entry of the normalised gray-tone spatial-dependence matrix; $|i-j| = t$

2 μ_x, μ_y, σ_x, σ_y are the mean and standard deviation of p_x and p_y respectively.

3 $p_x(i) = \sum_{j=0}^{L-1} p(i,j)$; $p_{x+y}(k) = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j)$; $i+j=k,\ k=0,1,2\ldots\ldots2(L-1).$

4 $p_{x-y}(k) = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j)$; $|i-j|=k,\ k=0,1,2\ldots\ldots2(L-1).$

5 $H_{XY} = -\sum_i\sum_j p(i,j)\log(p(i,j))$; $H_{XY1} = -\sum_i\sum_j p(i,j)\log\{p_x(i)\,p_y(j)\}$

6 $H_{XY2} = -\sum_i\sum_j p_x(i)\,p_y(j)\log\{p_x(i)\,p_y(j)\}$

7 $Q_{corr}(i,j) = \sum_k \frac{p(i,k)\,p(j,k)}{p_x(i)\,p_y(k)}$

8 $m \times n$ denotes the size of the image; $S_{best}(i,j) = 2^k$

9 $\left| i - j \right| = t$

10 $N_\theta(k)$ is the number of points at which $\frac{(2k-1)\pi}{2b} \le \theta \le \frac{(2k+1)\pi}{2b}$; θ is the local edge direction; b is the number of bins in the local direction histogram; n_p is the number of peaks; φ_p is the p^{th} peak position of H_D; w_p is the range of p^{th} peak between valleys.

1 $P_{Dd}(i, j)$ is the $L \times L$ local direction co-occurrence matrix of points at a distance d.

2 r_n is a normalizing factor and σ_{xxx} means the standard deviation of f_{xxx}

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