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A Predictive Fuzzy Expert System for Diagnosis of Cassava Plant Diseases

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Abstract- Cassava is an important tropical root cropwidely grown in many part of the world in a range of agro-ecological environments. The crop can be used for food and non-foods products. Cassava is capable of providing starch for use in drug industries, it is a stable source of dietary energy for more than 500 million. Nonetheless, despite the nutritional and economic significance of the cassava crop, the diseases incidence on cassava plantations is fast becoming a constraint in farmers' quest for a bountiful harvest. The efforts of agricultural extension agents seem not to be sufficient in tackling this menace since there is always a limit to how far the human capacity can be stretched in the face of highly demanding situations. Hence, this paper proposed the development of fuzzy expert system for predicting cassava plant disease. The system was developed with the help of fuzzy tool in MATLAB vs. 9. It employed 18 rules for the Cassava Mosaic, 27 rules for the cassava brown streak and 27 rules for cassava bacteria blightfor the classification and prediction of cassava plant diseases. This would provide immediate and instant information to the possible disease. It would fast-track information service delivery on the part of the large-scale industrial cassava farmers which make use of it for emergency situations of disease outbreak on the farm, pending the arrival of the agricultural extension agent. The fuzzy expert system predicts accurately once the symptoms and conditions are quantized. The result showed that the system was able to effectively predict and classify cassava diseases considered.

Keywords: cassava diseases, symptoms, prediction, fuzzy expert system, fuzzy inference system.

I. Introduction

Cassava is the third largest source of carbohydrates for human consumption worldwide, providing more food calories per cultivated acre than any other staple crop. It is an extremely robust plant which tolerates drought and low quality soil. The foremost cause of yield loss for this crop is viral disease [1]. The plant grows in a bushy form, up to 2.4 meters high, with greenish-yellow flowers. The roots are up to 8 centimeters thick and 91 centimeters long. Two varieties of the cassava are of economic value: the bitter, or poisonous; and the sweet, or non-poisonous. Both varieties yield a wholesome food because the volatile poison can be destroyed by heat in the process of preparation. Cassava is the chief source of tapioca, and in South America a sauce and an intoxicating beverage are prepared from the juice. The root in powder form is used to prepare *farinha*, a meal used to make thin cakes sometimes called cassava bread. The starch of cassava yields a product called Brazilian arrowroot. In Florida, where sweet cassava is grown, the roots are eaten as food, fed to stock, or used in the manufacture of starch and glucose.

The economies of many developing countries are dominated by an agricultural sector in which small-scale and subsistence farmers are responsible for most production, utilizing relatively low levels of agricultural technology. As a result, disease among staple crops presents a serious risk, with the potential for devastating consequences. It is therefore critical to monitor the spread of crop disease, allowing targeted interventions and foreknowledge of famine risk.

An expert system is a system that could keep knowledge in its knowledge base as the system knowledge resources and manipulate that knowledge, so it could prepare the high level decision tool to the user that is called inference engine as the brain of the system. On the other hand, expert system could help people in many cases in order to get decision in solving a problem.

A number of cassava diseases is responsible for reducing the overall production of cassava to a great extent. A disease is an alteration of one or more ordered series of physiological processes as caused by irritation from some factors or agents resulting into loss of co-ordination in plants. An accurate diagnosis of cassava diseases is essential for the appropriate management of the plant. The diagnosis of cassava plant diseases requires highly trained and experienced experts but there is dearth of experts. Therefore, a system is needed to diagnose cassava diseases, predict their outbreak and prevent their spread. Hence this paper proposes an expert system for diagnosing and predicting cassava diseases which could also be used both by the farmer and the experts to train their students.

The rest of this paper is arranged as follows. Section 1 deals with the introduction, section 2 presents a review of the related works on the developments of expert systems in agricultural field. The methodology used to achieve the set objectives is described in section 3. Section 4 contains implementation of the proposed system and result discussion. Finally, section 5 presents the conclusion.

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II. Existing Works

Expert systems have been developed and applied in many fields like medicine, engineering, agriculture, physical sciences and business. In agriculture, expert systems are developed to diagnose the diseases and pests of various crops[2]. Farmers across the world face problems like soil erosion, increasing cost of chemical pesticides, weather damage recovery, the need to spray, mixing and application, yield losses and pest resistance. On the other hand, researchers in the field of agriculture are constantly working on new management strategies to promote farm success. In many countries today, farming has become technologically advanced and expert systems are widely used in the field of agriculture. In this way, farmers can get expert opinions on their specific problems like selection of most suitable crop variety, diagnosis or identification of livestock disorder, suggestion of tactical decisions throughout production cycle from the expert system [2].

There have been some existing works on the development of expert systems in the agricultural field. A myriad of expert systems for various crops such as wheat, rice, maize, sunflower, lime, tomato, apple, orange, soybean and cucumber have been developed [3].[4] developed AMRAPALIKA - an expert system for the diagnosis of pests, disease and disorders of Indian mango. The objective of this work is to provide computer-based support for agricultural specialists or planters. The expert system makes diagnosis on the basis of response/responses of the user made against queries related to particular disease symptoms. The knowledge base of the system contains knowledge about symptoms and remedies of fourteen (14) diseases of Indian mango tree appearing during fruiting season and non-fruiting season.

Web-based Fuzzy Expert System for Integrated Pest Management (IPM) in Soybean was proposed by [5]. The system was developed with an objective to provide IPM decision support to the planters through the Internet. Besides that, the system applied the application of the fuzzy logic in uncertainty management during pest identification as well for estimating pest activity level using a new adjustable operator introduced by the authors. Pest Control Expert System for Tomato (PCEST) was developed by [6]. The system involves two main subtasks, namely: diagnose and treat. The diagnose subtask finds out the causes of the growers' complaints, while the treat subtask finds out a treatment plan for these causes. [7] developed a web-based expert system for fish disease diagnosis called Fish-Expert. This web-based intelligent system can mimic fish disease expertise and diagnose a number of fish diseases with a user-friendly interface. The system has over 300 rules and 400 images and graphics for different types of diseases and symptoms. It can diagnose 126 types of diseases amongst nine species of primary freshwater fishes. The system is in pilot use by fish planters in the North China region.

Fuzzy logic has been used to solve numerous problems ranging from prediction rate to classification rate. In the modeling of crop disease and control, fuzzy logic was used to model and monitor crop diseases in developing countries of the world. Models of crop disease are used for understanding the spread or severity of an epidemic, predicting the future spread of infection, and choosing disease management strategies [8]. [9] proposed the radial basis feed forward neural network model and generalized regression for surface roughness prediction for face milling of Al 7075-T735. The Pearson correlation coefficients were also calculated to analyze the correlation between the five inputs (cutting speed, feed per tooth, axial depth of cut, chip's width, and chip's thickness) with surface roughness. [10] used radial basis function network to predict surface roughness and compared with measured values and the result from regression analysis. [11] considered three variables, that is, cutting speed, depth of cut and feed rate to predict the surface profile in turning process using radial basis function (RBF). Experiments have been carried out by [12] after end milling of steel C45 in order to obtain the roughness data and model of ANN for surface roughness predictions [13]. [14]developed a neuro-fuzzy system for Animal Feed Formulation (AFF) where percentage of each ingredient in poultry feed was determined by ANN and their different ingredients were combined with the help of Neuro-fuzzy and network.

Moreover, Fuzzy Inference System has been used for surface roughness prediction model for ball end milling operation. For the prediction of surface roughness, a feed forward ANN was used for face milling of aluminum alloy by [15] high chromium steel (AISI H11) by [16] and AISI 420 B stainless steel by [17].[17] proposed the analytical and artificial neural network models. [18] worked for selection of optimal machining parameters (that is, spindle speed, depth of cut and feed rate) for face milling operations in order to minimize the surface roughness and to maximize the material removal rate using response surface methodology (RSM) and perceptron neural network.

III. System Methodology

Data for the cassava diseases were gotten from domain expert. Crisp values are transferred into fuzzy values through fuzzification. The fuzzy inference mechanism uses predicted value to diagnose the cassava diseases as shown in Figure 1. The proposed mechanism was tested with the cassava diseases datasets. The mechanism was developed using MATLAB. Defuzzification converts the fuzzy set into crisp values. The proposed method with predicted value technique can work more efficiently for diagnosis of cassava disease and also compared with earlier method using accuracy as performance metric.

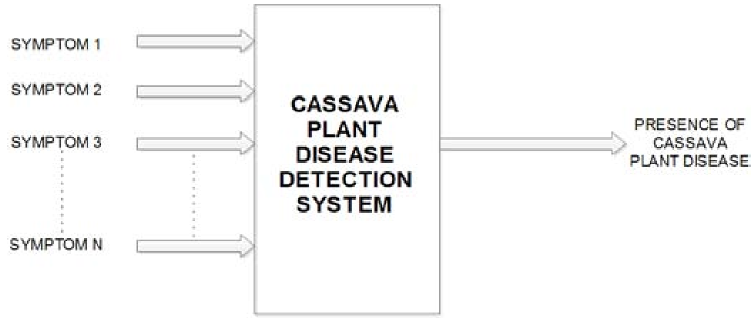

Figure 1 : Architecture for the Proposed Cassava Plant Disease for the Fuzzy Inference System

a) Diseases and their Symptoms

Different types of diseases affects the cassava plant, but in this paper, three of such diseases isput into consideration. These include Cassava Mosaic disease, Cassava Blight disease and Cassava Bacteria blight.

The symptoms for which these cassava diseases occur are: Chlorotic Leaf, Brown Lesions, Root Necrosis, Leaf Blight/spot, Distorted Leaf, Reduced Mishapen, Die-back and Gum Exudation. The value for the fuzzy variables are shown in Table 1.

Table 1 : Fuzzy variables and their Representations

Fuzzy variables	Representation of Fuzzy Variable(Linguistic terms)
Chlorotic leaf	No Chlorosis, Early Stages, Advanced Stages
Brown Lesions	No Presence, Early Stages, Advanced stages
Root necrosis	No symptom, Early Stage, Advanced Stages
Leaf blight/spot	No spots/Blights, Minor Spots/ blights,Major Spots/blights
Distorted Leaf	No Distortion, Lesser leave distortion, More leaf distortion
Reduced-Mishapen	No symptom, Stunted Growth
Die-Back	No symptom, Early Stage, Advanced Stages
Gum Exudation	No symptom, Early Stage, Advanced Stages

The input functions of the variables are represented in the membership function of the corresponding input and output.The data used were not too large, but the prediction was accurate to some extent.The output function is the result generated from the input function.

All the above-mentioned diseases have their own respective symptoms associated with them and were simulated using the Fuzzy logic inference system of Matric Laboratory (MATLAB) and implemented using C-Language Integrated Production System (CLIPS). This is a shell programming variety of PROLOG for developing expert systems. The first part of building an expert system is the knowledge acquisition. For this project, most knowledge was obtained from a human expert, an agriculturist who is specialized in detecting plant diseases. This knowledge was converted into a knowledge base using a set of rules and facts. The rules in this system represent symptoms and the actual results of every response. The proposed system uses the forward chaining inference mechanism, instead of backward chaining. The reason for using this mechanism is because when dealing with cassava plant disease detection, it is more important to collect information about the plant's symptoms first before making a decision. The forward chaining provides this competency.

IV. Result and Discussion

The fuzzy system is an in-built system that takes in multiple inputs into its membership function, these inputs are gotten from the data. The data, which in turn, has numeric values and assigned numbers and variables were used to classify and arrange these data. Sequelto this, some of these data were classified as categorical or numerical, in which there is adequate implementation.

A Fuzzy Inference System modelisrepresented in Figure 2. The systemcan either be loaded from the file. Loading the system from the file means inputting the name of the saved file where it has been kept. The input variables using membership functions are as shown in Figure 3, Figure 4 and Figure 5. The output model is shown in Figure 6. For the prediction, the rules used were 18 rules for the Cassava Mosaic and 27 rules for the cassava brown streak and 27 rules for cassava bacteria blight. These rules were sufficient for the prediction and the analysis shown in Figure 7. Rule Viewer Predicting Disease Severity is shown in Figure 8.

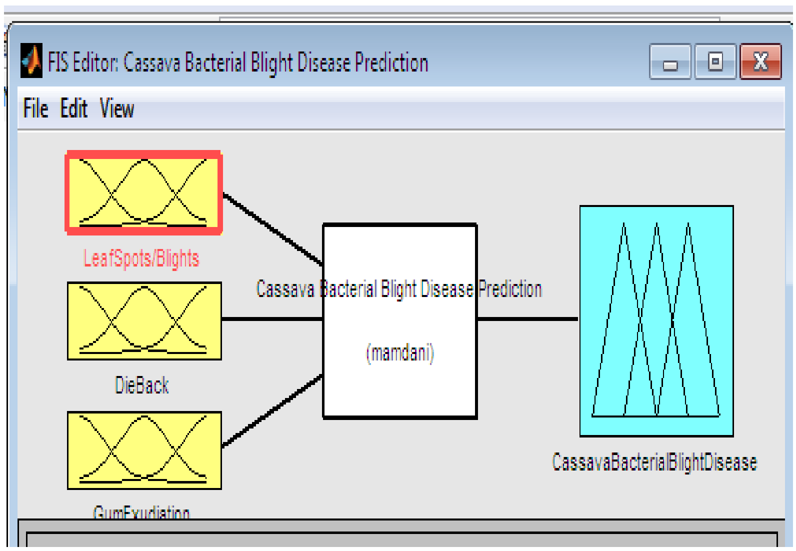

Figure 2 : FIS interface for Cassava Bacteria Blight

Input Variables

These variables are represented by triangular membership functions.

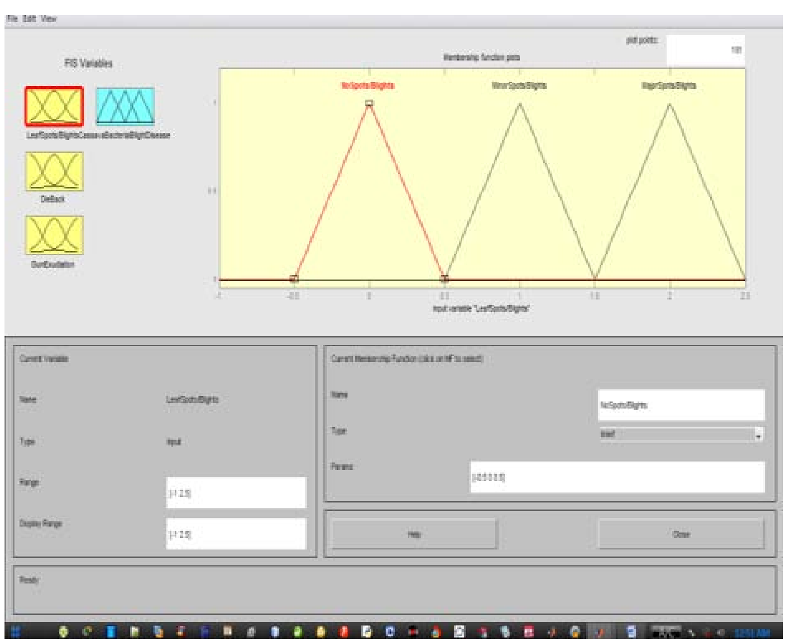

Figure 3 : Membership Function forLeaf Spot

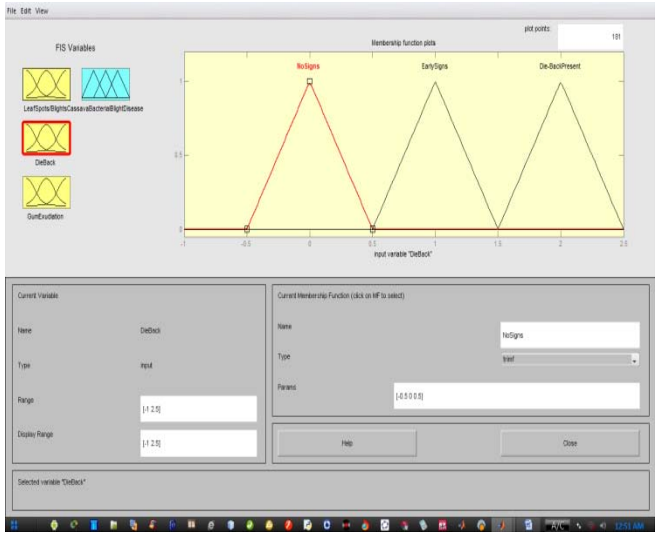

Figure 4 : Membership Function for Die-back

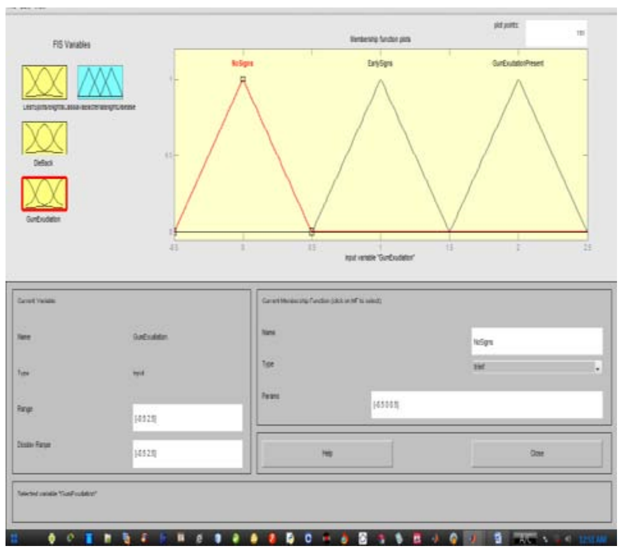

Figure 5 : Membership Function for Gum-exudation

Figure 6 : Membership function for Output Variable

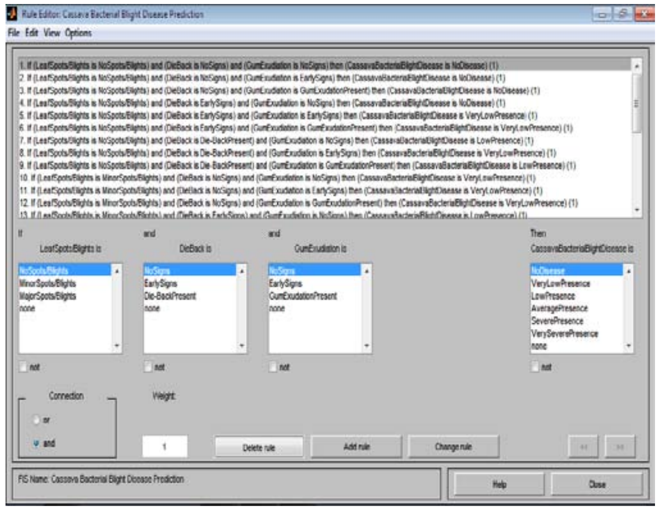

Figure 7 : FIS Output showing Rules Cassava Bacteria Blight

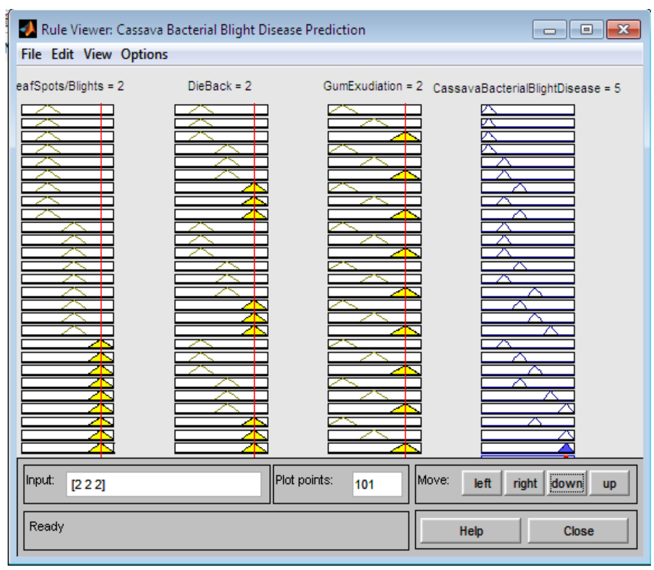

Figure 8 : Rule Viewer Predicting Disease Severity

Table 2 : The Diagnosis and Prediction of Cassava Mosaic Disease

Leaf Chlorosis	Leaf Distortion	ReducedMis-shapen	Output
No chlorosis	No distortion	No symptom	No disease
No chlorosis	No distortion	Stunted growth	No disease
No chlorosis	Lesser leaf distortion	No symptom	No disease
No chlorosis	Lesser leaf distortion	Stunted growth	Very low
No chlorosis	More leaf distortion	No symptom	Very low
No chlorosis	More leaf distortion	Stunted growth	Low
Early stages	No distortion	No symptom	No disease
Early stages	No distortion	Stunted growth	Very low
Early stages	Lesser leaf distortion	No symptom	Very low
Early stages	Lesser leaf distortion	Stunted growth	Low
Early stages	More leaf distortion	No symptom	Average
Early stages	More leaf distortion	Stunted growth	Severe

Advanced stages	No distortion	No symptom	Very low
Advanced stages	No distortion	Stunted growth	Low
Advanced stages	Lesser leaf distortion	No symptom	Low
Advanced stages	Lesser leaf distortion	Stunted growth	Severe
Advanced stages	More leaf distortion	No symptom	Average
Advanced stages	More leaf distortion	Stunted growth	Very severe

a) System Evaluation Using Domain Expert Diagnosis for Cassava Diseases

The system was tested with seven (7) cases for cassava diseases specified by the system and observed by the domain expert in line with his diagnoses. The diagnoses made by the system were classified as:

a. *Correct:* The system's diagnoses was identical with the pathologist's own diagnoses.
b. *Acceptable:* The system's diagnoses was different from that of the pathologist, but considered an acceptable alternative.
c. *Not complete:* The system's diagnoses was distinct enough for conclusion.

The accuracy of the system was calculated using the below formular.

Accuracy = (Number of Correct Diagnoses *100)/Total Number of Test Cases

The accuracy yields 71.4%.

V. Conclusion and Recommendations

The fuzzy inference system has broken the bounds of conventional programming, which is actually a function of its ability to adapt, adopt, adjust, evaluate, learn and recognize the relationship, behaviour and pattern of series of data set administered to it. It is tailored after the human reasoning and learning mechanism. This enables the FIS to handle and represent more complex problems than conventional programming. Fuzzy Inference System (FIS), fuzzy logic and expert system have helped in diagnosing and predicting diseases accurately.

Future work can be carried out with respect to more variables such as humidity and moisture content.

References Références Referencias

1. N. G. W. Otim, T. Alicai and J. M Thresh, "Changes in the Incidence and Severity of Cassava Mosaic Virus Disease, Varietal Diversity and Cassava Production in Uganda, "*Annals of Applied Biology*, 138 (3): 313–327, 2005.
2. S. F. Khan, S.Razzaq, K. Irfan, F. Maqbool, Farid A., I. Illahi and Tauqeerulamin, "A Web-based Expert System for Diagnosis of Diseases and Pests in Pakistani Wheat," *Proceedings of the World Congress on Engineering, London, UK,*(1): 1-6,2008.
3. P. Shrivastava, S. K. Satpathy and K. K. Nagwanshi, "Development of an Expert System as Spiritual Guru," *Machine Learning and Computing (ICMLC), Second International Conference. Pp.166-168, 9-11,* 2010.
4. R. Prasad, K. R. Ranjanand A. K. Sinha, "AMRAPALIKA: An Expert System for the Diagnosis of Pests, Diseases, and Disorders in Indian Mango," *Knowledge – Based Systems 19(1): 9-21,* 2006.
5. S. S. Saini, R. Kamal and A. N. Sharma, "Web Based Fuzzy Expert System for Integrated Pest Management in Soybean,"*International Journal of Information Technology.* 8, 54-74, 2002.
6. E. El-Azhary, H. A. Hassan and A. Rafea, "Pest Control Expert System for Tomato (PCEST),"*Knowledge and Information System,* Springer-Verlag London, 242-257, 2000.
7. D. Li, Z. Fu, and Y. Duan, "Fish-expert: A Web-Based Expert System for Fish Disease Diagnosis," *Expert System with Applications:* 23(3), 311–320, 2002.
8. J. A. Quinn, K. Leyton-Brown, E. Mwebaze. Modeling and Monitoring Crop Disease in Developing Countries. *Conference of the Association for the Advancement of Artificial Intelligence (AAAI)*, 2011.
9. Patricia Munoz-Escalona and Paul G. Maropoulos (2009). Artificial Neural Networks for Surface Roughness Prediction When Face Milling Al 7075-T7351. *Journal of Materials Engineering and Performance*, *19*(2), 185-193.
10. L. Zhanjie, Y. Bing, and T. Meili, "Prediction of Surface Roughness of Diffi cult-to-Cut Material by HSM Based on RBF Neural Network," in *Proceeding of 6th International Conference on Instrumentation, Measurement, Circuits and Systems*, Hangzhou, China, 2007.
11. C. Lu and J. Costes, "Surface Profile Prediction andAnalysis Applied to Turning Process," *International Journal of Machining and Machinability of Materials, 4*(2-3), 158-180,2008.
12. C. Brecher, G. Quintana, T. Rudolf and J. Rudolf, "Use of NC Kernel Data for Surface Roughness Monitoring in Milling Operations,". *International Journal of Advanced Manufacturing Technology, 53*, 953–962, 2011.

13. S. J. Hossain and N. Ahmad, "Adaptive Neuro-fuzzy Inference System (ANFIS) Based Surface Roughness Prediction Model for Ball end Milling Operation," *Journal of Mechanical Engineering Research. 4(3), 112-129,* 2012.
14. G. A. Aderounmu, E. O. Omidiora, B. O. Adegoke and T. A. Taiwo, "Neuro-fuzzy System for Livestock Feed Formulation (Africa Poultry),"*International Journal of Engineering and Science (IJES),* 2(5), 25 – 32, 2013.
15. P. G. Bernardos and G. C. Vosniakos, "Predicting Surface Roughness in Machining: a Review", *Int. J. Machine Tools Manufacture,* 43:833- 844, 2003.
16. R. Rai, A. Kumar, S. Rao, and S. Shriram, "Development of a Surface Roughness Prediction System for Machining of Hot Chromium Steel (Aisi H11) Based on Artificial Neural Network", *ARPN J. Engr. Appl. Sci*., 5(11): 53-59, 2010.
17. C. Bruni, d'Apolito, L., Forcellese, A., Gabrielli, F. and Simoncini, M. (2008). Surface Roughness Modeling in Finish Face Milling Under MQL and Dry Cutting Conditions. *International Journal of Material Formation, 1*, 503–506.
18. M. R. S. Yazdi and A. Khorram, "Modeling and Optimization of Milling Process by Using RSM and ANN Methods," *IACSIT International Journal of Engineering and Technology, 2*(5), 474-480, 2010.