IOSR Journal of Mobile Computing & Application (IOSR-JMCA)
e- ISSN: 2394-0050, P-ISSN: 2394-0042.Volume 8, Issue 2 (Mar - Apr 2021), PP 07-15
www.iosrjournals.org

An Autonomous Strategy for Casava Plant Infection Identification

Moshood Olatunji Lawal [1], Olajide Blessing Olajide [2], Habibu Lawal Olawale [3,] Lawal Tadese Aderonke [4,] Olatunji A. Funsho[5]
[124] Computer Science Department, Federal Polytechnic, Ede, Nigeria
[3] Retail Operations Department, 9Mobile Telecommunication Company, Ilesa, Nigeria
Corresponding authors: Moshood Olatunji Lawal

Abstract
The motivation for this research is to adopt fuzzy logic for the groupings of a categorization model which will be used to detect cassava plant infection based on a group of dependent factors observed from various parts of cassava plants. Based on review of related works surrounding cassava plant infection detection, some factors that are related with the identification were identified and validated by experienced Botanists. Trilateral membership functions were formulated using the input and output variables via fuzzification. The rule base model was put together using IF-THEN statements to combine the values of the inputs with their respective output values. The MATLAB Fuzzy Logic Toolbox was used to simulate the Fuzzy logic model for the categorization of the likelihood of cassava plant infection. The results revealed that 7 likelihood factors were similar with the likelihood of cassava plant infection. While the target likelihood was formulated using four trilateral membership functions for the linguistic variables no likelihood, low likelihood, moderate likelihood and high likelihood. This study concluded that using fuzzy logic modelling can be adopted for foretelling the likelihood of cassava plant infection based on knowledge about the likelihood factors.

Keywords: *fuzzy logic, cassava plant, plant diseases, fuzzification, fuzzy logic model, categorization, MATLAB, rule base.*

Date of Submission: 15-04-2021 Date of acceptance: 29-04-2021

I. Introduction

Cassava (Manihot esculenta) is a root crop which is mostly grown in every two to five Africa countries. It is mostly grown by small house hold farmers with low income and in food-deficit areas, it usually does not require high fertility condition of the soil for germination and irregular rain fall pattern is not a major factor cassava growth (De Bruijn and Fresco, 1989). Managing the spotting and spread of cassava infection at early stage on the farm is a crucial first step. Normal spotting of infection approaches depends on the use of agricultural extension support groups. And these methods are limited in countries and locations with low human infrastructure capacity and are expensive to scale up. Internet usage in such areas is usually low at best and smartphone usage and other useful technologies like unmanned aerial vehicle (UAV) will offer in-field plant infection detection systems using automated image recognition that help in the early detection of infection at an early stage (Puig et al., 2015).

The method of identifying infection in plants on the plant-field is by use of visual symptoms which an agricultural expert is able to relate to particular diseases in the plant. For places where experts are not available or where farmer knowledge is insufficient, other methods for carrying out plant field-based diagnoses are a decisive need. Research work in the area of infection detection are usually about automation, and involves building machine learning models that will take the images of the plant leaf and check whether the plant is infected with a specific type of disease or not (Owomugisha et al., 2018). This research work is looking at the possibility of creating a model that will help in the process of detecting plant infection earlier before the plants infected become symptomatic. Advances in agriculture technology as led to demand for automation using a non-destructive method of plant infection detection. Therefore, some approaches have recently discovered the use of computer vision and machine learning techniques to build fast methods of plant infection detection at early stages before they become symptomatic.

Unfortunately, adopting such techniques are most difficult a strategy especially in developing nations such as Nigeria. Nigeria does not have large repositories that are available for storing information about image-based cassava plant infection such as roots, leaves or stems.

Researchers in Nigeria have observed certain areas of cassava plant for areas of making diagnosis, and have establish the need for the use fuzzy logic for the extraction of expert knowledge using representative

IF-THEN rules deduced from factors identified by experts on plant-field, hence this study.

II. Literature Review

Plant suffers from various infections during their life span at any stage of growth. For farmers and agricultural experts infection management is a critical matter which needs an immediate attention. It needs urgent diagnosis and preventive action to maintain quality and to minimize the loss. Many researchers have contributed to technologies for detection and categorization of plant infection so as to support quick infection diagnosis. Research papers were reviewed on the subject matter.

Owomugisha et al. (2018) developed a model for the discovery of plant infection using spectral data. The research collected image data of parts of fine plant and an infected plant which were classified respectively using a 3 class system. The image data were pre-processed via feature extraction to identify important regions of the images collected for each plant. The categorization model was developed using 4 machine learning algorithms which were compared based on performance.

Ramcharan et al. (2017) discusses how applying deep learning for image processing can help to detect cassava plant infections. The research gathered dataset of cassava infected plant images taken at a field in Tanzania. The images were analyzed using a transfer leaning to train a deep convolutional neural network to identify 3 diseases and 2 types of pest damages. The best model achieved an overall accuracy of 93% for data not used for the training process.

Kaur and Din (2016) developed a web-based expert system to find infected plant and diagnose the leaf infection of cereals in Punjabi Language. The features of leaf infections were collected and used to formulate the diagnosis model by adopting IF-THEN rules from the features. The system was designed using unified modeling language (UML) tools such as use case diagrams and data flow diagrams. The design was implemented using PHP, SQL and deployed as a web based system.

Malu, S. *et all* (2015) in his research use assignment of parameters with fuzzy logic to develop a system that diagnosis asthma. The research was performed in Iran and it reached a conclusion that precision is 100% and the responsiveness is 94%.

Obahiagbon, K *et all,* (2015) also developed a system using Nuero-Fuzzy fitting tools with SOM, LVQ and BPNN algorithms for adult asthma diagnosis. The back-propagation is chosen to be the best among all at period 9 using 535 samples.

Waijee, A.K. et all (2013) established a model for diagnosing diabetes infection based on PCA and ANFIS methodology with 8 input features implemented in MATLAB. The expert system showed 89.47% accurate with 85% sensitivity, 92% specificity and 0.262 root mean square error.

III. Methodology

The aim was accomplished through the following approach: Identify the factors required for assessing cassava plant infection;

1. Formulate the fuzzy logic model based on (1);
2. And simulate the model.

3.1 Method of Recognition of Associated Risk factors

To develop the categorization model for the likelihood of cassava infection, an amount of associated likelihood factors were identified. After consideration the review of related work over the internet, some associated likelihood factors were also identified. Each risk factor identified had a relative relationship with the likelihood of cassava infection, and since some risk factors increased the associated likelihood, some actually reduced the associated likelihood of cassava disease.

Furthermore, crisp values were proposed for each likelihood factor assessed as a way of quantifying the response to each likelihood factor by a user. Hence, higher values were given to intervals that increased the risk while lower values were given to intervals that reduced the likelihood of cassava infection. Linguistic value were given crisp intervals and they were used as a normal tag with which each fuzzy membership function was needed to formulate the values of the crisp interval. Following the review of related works, few likelihood factors were identified such that some were age-related, lifestyle-related, dietary-related etc.

3.1.1 Description of Likelihood factors

As discussed earlier, an amount of likelihood factors that are associated with the likelihood of cassava infection were identified and described in order to understand their respective associate likelihood of cassava infection based on the selected value. The likelihood of cassava infection was determined as a cumulative of the worth of all likelihood factors assessed for the likelihood of cassava infection. The likelihood factors that were identified to be associated with the likelihood of cassava infection are presented alongside their respective association with the likelihood of cassava infection.

3.1.2 Identification of crisp and linguistic values of associated variables

After pinpointing all the likelihood factors that are related with the likelihood of cassava infection, the illustration of the linguistic values and the linguistic variables were made. Table 3.1 shows a abstract of the crisp values and linguistic variables for each identified variables. The crisp values for each of the identified likelihood factor was done by allocating the values 0, 1 and 2 to some risk factors or the values 0 or 1 to binary risk factors such that the value with highest association with the likelihood of cassava infection was given the value of 2 or 1 while the value with the lowest likelihood of cassava infection was given a value of 0. As shown in table 3.2, each likelihood factor was discretized into 2 or 3 parts such that the values of 0 and 1 or 0, 1 and 2 were allocated to each linguistic variable defined. Due to the outcome of the result, the likelihood factors were classified as follows. The appearance of discolored leaves was divided in increasing order of risk cassava disease as No, Mild and Yes hence was given 3 linguistic variables; the appearance of stunted growth was divided in increasing order of likelihood as No and Yes and hence was given 2 linguistic variables; the appearance of small distorted leaves was divided in increasing order of risk as No and Yes and hence was given 2 linguistic variables; the appearance of blights was divided in increasing order of risk as No and Yes and hence was given 2 linguistic variables.

The appearance of yellow/brown gums was divided in increasing order of risk as No and Yes and was given 2 linguistic variables; the presence of wilted leaves was divided in increasing order of risk as No and Yes hence was given 2 linguistic variables; the seriousness of defoliation was divided in increasing order of risk as None, Low and High and was given 3 linguistic variables; the appearance of dieback stems was divided in increasing order of risk as No and Yes hence was given 2 linguistic variables

Table 3.1: identification of Crisp and Linguistic Values of Likelihood Factors

Likelihood Factor	Linguistic Variable	Crisp Value
Discolored Leaves	**No**	0
	Mild	1
	Yes	2
Stunted Growth	**No**	0
	Yes	1
Presence of Small Distorted Leaves	**No**	0
	Yes	1
Presence of Blights	**No**	0
	Yes	1
Presence of Wilted leaves	**No**	0
	Yes	1
Severity of Defoliation	**None**	0
	Low	1
	High	2
Presence of Dieback Stem	**No**	0
	Yes	1
Likelihood of Cassava Infection	**None**	0
	Low Risk	1
	Moderate Risk	2
	High Risk	3

3.2 Method of Fuzzy Logic Model Formulation for Likelihood of Cassava Infection

In categorization of model for the likelihood of cassava infection using fuzzy logic theory, each variable identified was fuzzified using a trilateral membership function. The trilateral membership function required the provision of 3 parameters which consisted of the left-hand base of triangle (a), the central apex of the triangle (b) and the right-hand base of the triangle (c).

The values (a, b, c) of the trilateral membership function corresponded to an interval of such that the parameters are numeric valued. The span of this parameter was used to interpret the crisp interval within which each crisp value required for calling the linguistic variable was assigned. And since there were 2 or 3 linguistic variables defined for each likelihood factor identified then there were 2 or 3 trilateral membership functions such that one was assigned to each linguistic variable identified for each likelihood strand as appropriate.

Therefore, 2 or 3 trilateral membership functions were formulated for each likelihood strand that was identified in this discuss based on the mathematical expression in equation (3.1). The cast shows how the trilateral membership function was used to put together the label of a variable called variable label by fitting a numerical value x into a crisp range of (a, b, c). Using 2 or 3 triangular membership functions, the tag of the identified likelihood strand were put together using the crisp intervals of (-0.5, 0.5), (0.5, 1.5) and (1.5, 2.5) to model the linguistic variables for 0, 1 and 2 respectively such that the values 0, 1 and 2 became the center b of each interval as shown in Table 3.2.

Table 3.2: Description of Crisp Intervals used during Fuzzy Model Formulation

Crisp Value	Interval	a	b	C
0	(-0.5, 0.5)	-0.5	0	0.5
1	(0.5, 1.5)	0.5	1	1.5
2	(1.5, 2.5)	1.5	2	2.5

3.2.1 Fuzzification of the Likelihood of cassava infections

Following the identification and the fuzzification of the likelihood elements of cassava infection, there was a need to work out the target changes that was used to define the likelihood of cassava infection. The trilateral membership function is used to work out the fuzzy logic model for the target variable by assigning crisp values of 0, 1, 2 and 3 to the target class labels, namely: No risk, low risk, Moderate risk and High risk using the intervals (-0.5, 0.5), (0.5, 1.5), (1.5, 2.5) and (2.5, 3.5) respectively. Therefore, four (4) trilateral membership functions were used to formulate the fuzzy logic model required to outline the 4 labels of the target class that was used to narrate the likelihood of cassava infection using the identified crisp as shown in table 3.3. Using the description provided in Table 3.3, the relationship that exists between the likelihood factors and the likelihood of cassava infection was proposed using the fuzzy inference system.

3.2.2 Fuzzy Inference Engine Design

Following the conceptualization of the fuzzy logic model using trilateral membership functions to model the likelihood strands and the likelihood of cassava infection, the fuzzy inference engine was implemented.

For the motive of creating a connection between the identified non-invasive parameters, rules were inferred from the experts to enable the establishment of relationship linking the parameters identified and the likelihood of cassava infections. In order to build the knowledge base of the categorization model using fuzzy logic, few IF-THEN rules were used by combining the likelihood factors as the precedence while the likelihood of cassava infections was used as the resultant variable.

Using the likelihood factors that were identified for assessing the likelihood of cassava infections, the inference rule generation usually follows the fuzzification process. A typical rule that can be inferred is as follows: IF (Discoloured Leaves = “No”) AND (Stunted Plant Growth = “No”) AND (Presence of Small Distorted Leaves = “No”) AND (Presence of Blights = “No”) AND (Presence of Yellow/Brown Gums = “No”) AND (Presence of Wilted leaves = “No”) AND (Severity of Defoliation = “No”) THEN (Likelihood of Cassava Infection = “No Risk”)

Table 3.3: Formulation of the Likelihood of Cassava infection

Target Class	Interval	a	b	c
No Risk	(-0.5, 0.5)	-0.5	0	0.5
Low Risk	(0.5, 1.5)	0.5	1	1.5
Moderate Risk	(1.5, 2.5)	1.5	2	2.5
High Risk	(2.5, 3.5)	2.5	3	3.5

The rules that were required to be formulated for the fuzzy model were estimated from the product of the number of linguistic variables for each variable. Therefore, since each of the factors considered has two linguistic variables each. Therefore, the total number of rules were 288 () rules.

3.3 Simulation Environment used

MATLAB is a language use for technical computing. Short Matrix Laboratory, It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Fuzzy Logic Toolbox™ provides MATLAB functions, graphical tools, and a Simulink block for analyzing, designing, and simulating systems based on fuzzy logic.

IV. Results of the Formulation of the Fuzzy Model for Categorization of Cassava Plant Infections

This section presents the results of the formulation of the fuzzy logic model using trilateral membership functions based on the crisp intervals defined for each linguistic variable identified in this study. 2 and 3 trilateral membership function were formulated for the labels of each likelihood factor identified where appropriate while 4 trilateral membership functions were formulated for the linguistic variables of the target class which defined the classification of cassava plant infections. Therefore, since the same crisp interval defines the labels of each likelihood factor using 2 trilateral membership function with centers of 0 and 1 alongside 3 triangular membership functions with centers of 0, 1 and 2..

The illustration of the mathematical depiction of the fuzzy logic model used to work out the categorization model was presented in the following paragraphs. As stated earlier, 2 and 3 trilateral membership functions were used to work out the fuzzy logic model for the labels of each likelihood factors which centers 0 and 1 for yes and no respectively alongside the centers 0, 1 and 2 where appropriate.

Also, the assignment of the values was done based on the increasing effect of the labels of the identified likelihood factors used in this study. Therefore, the results of the mathematical presentation of the fuzzy logic model formulation using the trilateral membership function for each of the labels is presented in equation (4.1).

Also, the categorization of the classification of cassava plant infections was classified into 4 linguistic variables, namely: No, Low, Moderate and High using crisp values with centers of 0, 1, 2 and 3 respectively. Using the 4 trilateral membership functions stated in equations (4.2a) to (4.2d), the linguistic variables of the categorization of cassava plant infections were formulated.

4.2 Results of the Simulation of the Fuzzy Model for Categorization of Cassava Plant Infections

Using the trilateral membership functions stated in equations (4.1a), (4.1b) and (4.1c), the labels of the identified likelihood factors were simulated while the membership functions stated in equation (4.2a) and (4.2d) were also used to simulate the categorization of cassava plant infection using the MATLAB software. The results of the simulation of the membership functions and of the inference rules used to generate the final .fis file of the Fuzzy Logic Model for the categorization of cassava plant infection is presented in the following sections.

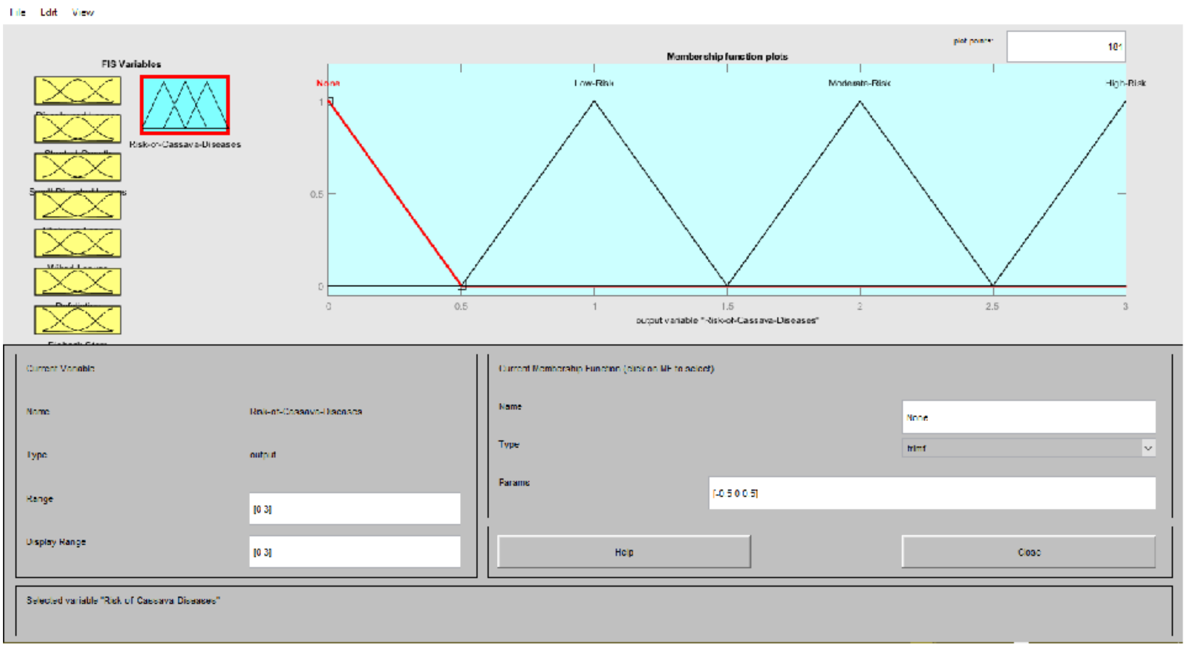


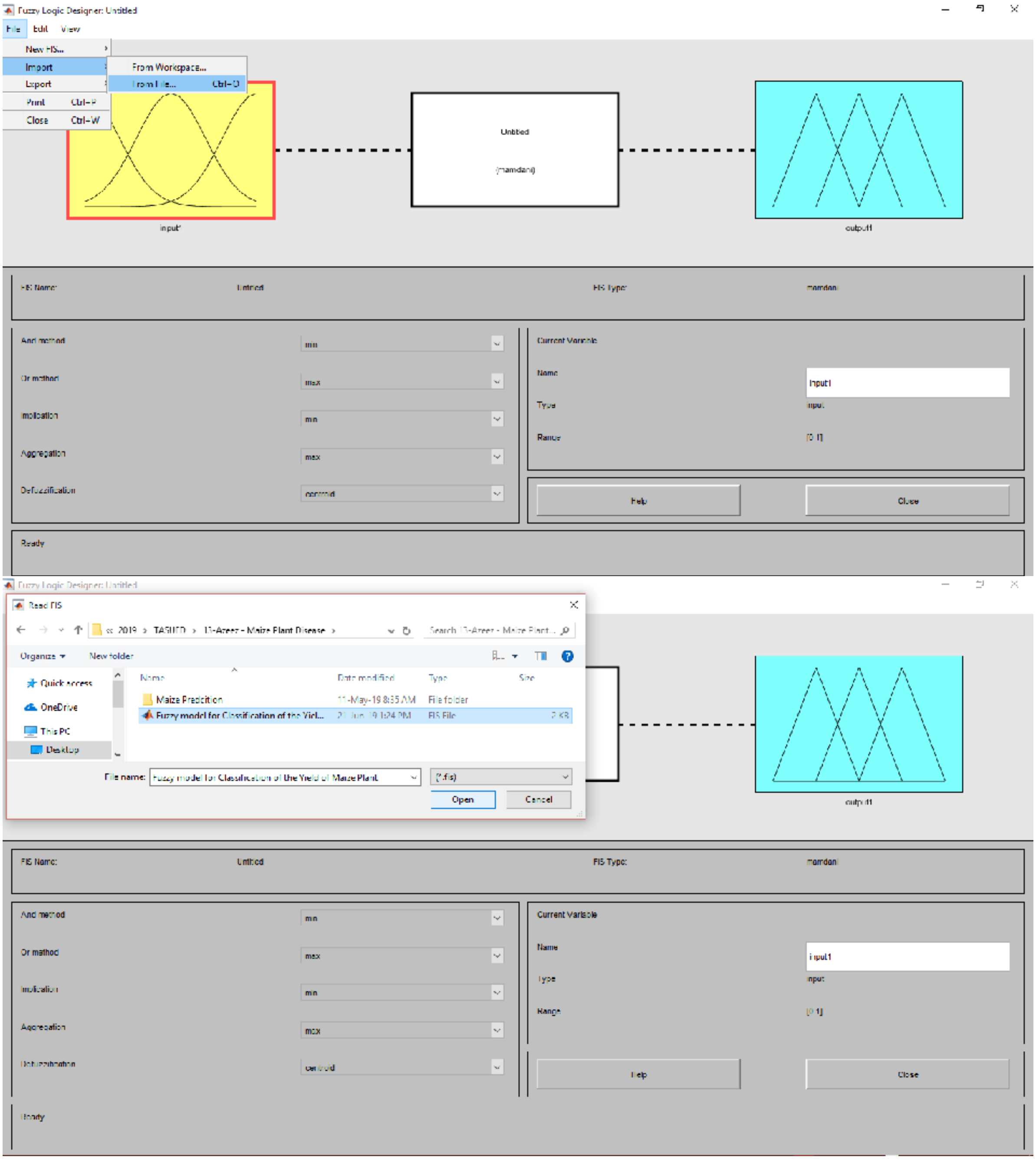
Figure 4.8: Fuzzification of Classification of Cassava Plant Diseases

4.2.2 Results of simulation of Fuzzy Logic Model for Classification of Cassava Plant Diseases

Figure 4.10 show the procedure of importing the completed source file of the fuzzy model for the categorization of cassava plant infection using the MATLAB Fuzzy Logic Toolbox.

Figure 4.10 (above) shows the procedure of selecting the location of the .fis file in the file directory which is the desktop as shown in Figure 4.10 (center). Figure 4.10 (below) shows the final fuzzy logic model displaying the seven input and output variable used to dictate the categorization of cassava plant infection.

The 288 rules that were inferred for regulating the categorization of cassava plant infections were defined using the rule editor interface. Figure 4.11 shows the complete insertion of the 288 rules that were inferred for regulating the categorization of cassava plant infection. It is clear that each rule inferred is unique and does not contain linguistic variables occurring within the pattern in any of the rules defined. Therefore, for any given set of rules r and s among the 288 rules there is no rule r that has the set of linguistic variables as another rule s. This is illustrated by the rule viewer in Figure 4.12. Figure 4.12 displays the graphical region of each variable selected by each rule with respect to the linguistic variables of the categorization of cassava plant infection. As illustrated in the bottom left part of the figure, the crisp values entered were 1, 0, 0, 1, 1, 0 and 1 which were consistent with the linguistic values namely: low for presence of discolored leaves, no for presence of stunted growth, no for presence of small distorted leaves, yes for blight on leaves, yes for presence of wilted leaves, none for defoliation and yes for presence of die-back stem.



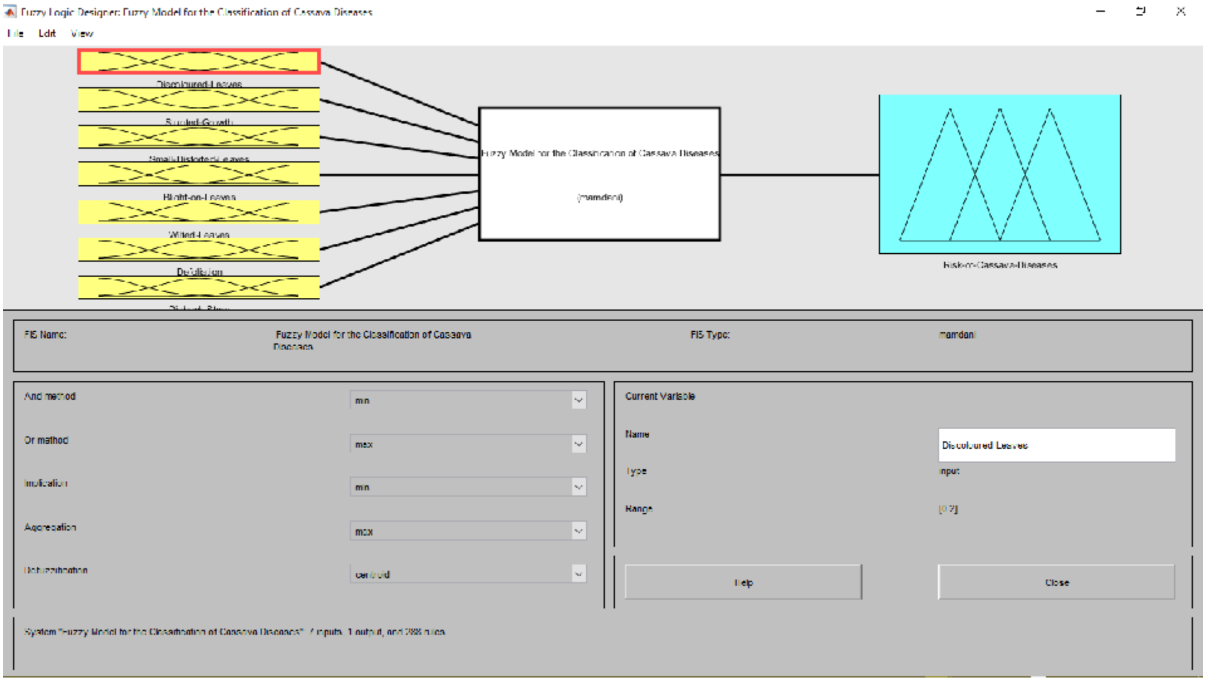


Figure 4.10: Importing .fis File for Classification of the Categorization of cassava plant diseases

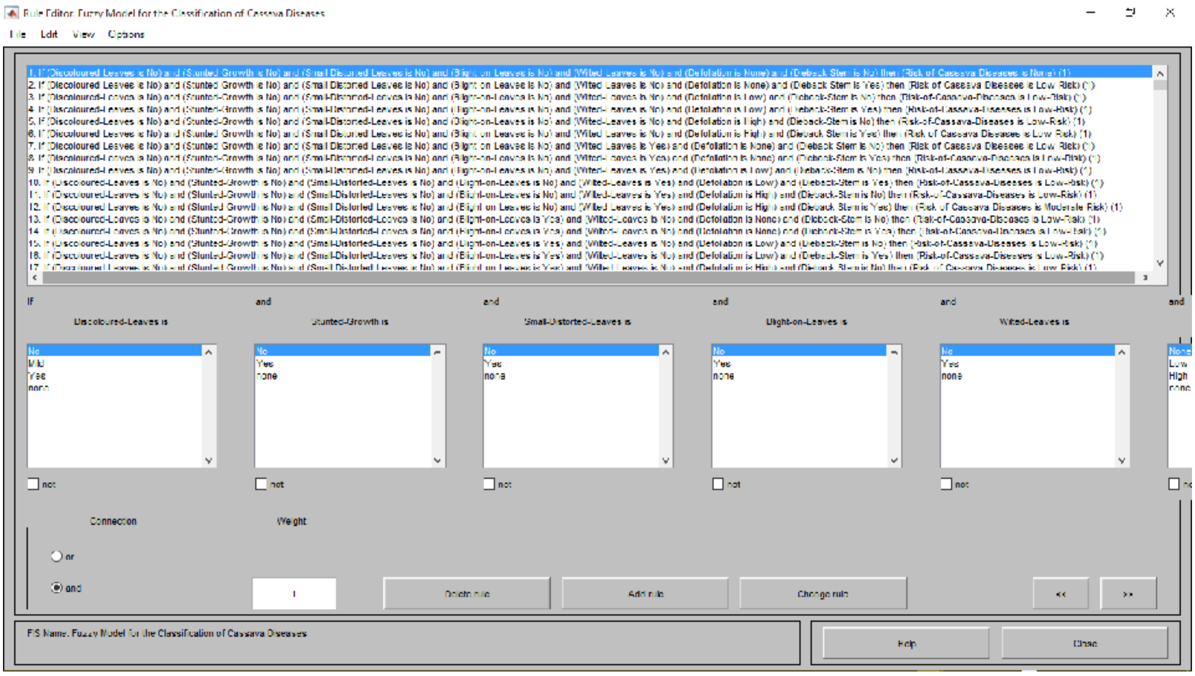


Figure 4.11: The Inferred Rules located in the Fuzzy Inference Engine

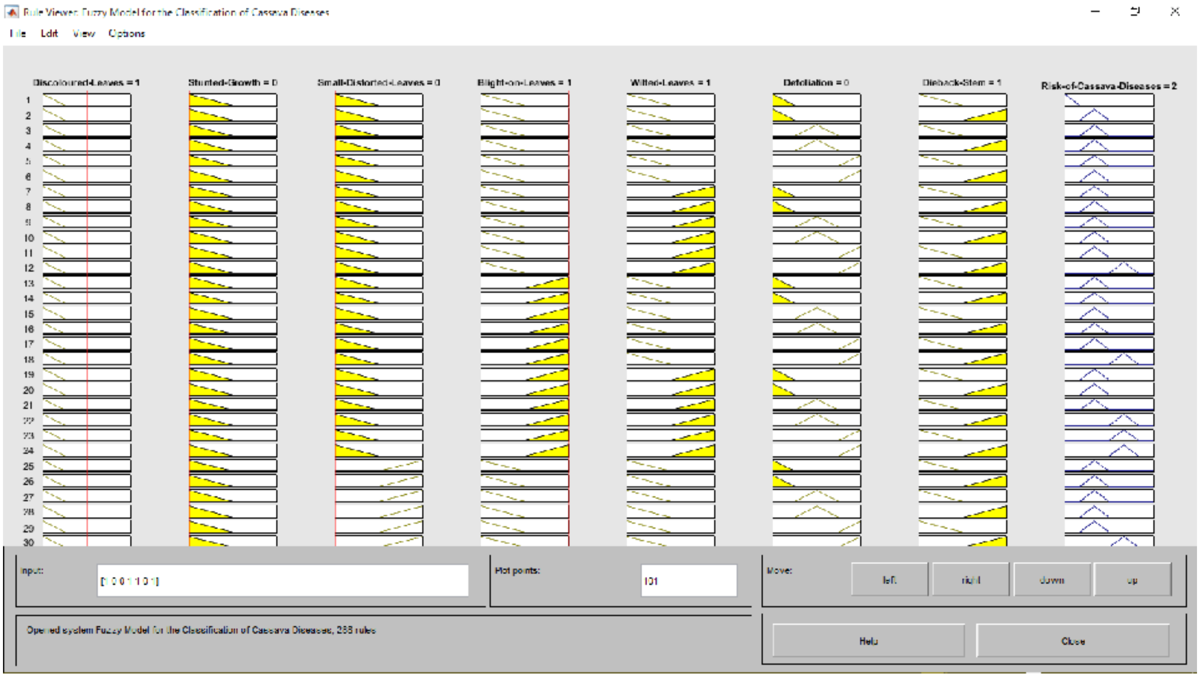


Figure 4.12: Testing the credibility of the Inference Engine

According to rule# 116, the combination of these linguistic variables should have moderate categorization of cassava plant infection which amounted to a crisp value of 2 which is within the interval of moderate categorization of cassava plant infection defined as [1.5 2.5].

4.3 Discussion of Results

This study adopted fuzzy logic for the formulation of a categorization model which is used to detect cassava plant infection based on few dependent factors observed from various parts of cassava plants.

The study identified 7 risk factors required for the categorization of the likelihood of cassava plant infection. Each likelihood factor was defined using linguistic variables for which central crisp values were assigned build on the association with the likelihood of cassava plant infection. The higher the association of the linguistic variable then the higher the central crisp values assigned.

The crisp values for each of the identified likely factor was done by allocating the values 0, 1 and 2 to some likelihood factors with 3 values and the values 0 and 1 to binary likely factors in increasing order of association with the likelihood of cassava plant infection. Each risk factor was discretized into 2 or 3 parts such that the values of 0 and 1 or 0, 1 and 2 were allocated to each linguistic variable defined. Therefore, crisp intervals with centers of 0, 1, and 2 were used to define the labels of the identified likelihood factor using trilateral membership functions to identify labels in intervals [-0.5 0.5], [0.5 1.5] and [1.5 2.5] respectively.

Showing a link between the identified non-invasive likelihood factors identified, 288 rules were inferred from the experts in order to decide the relationship linking the likely factors identified and the likelihood of cassava plant infection. For knowledge base to be build, the categorization model using fuzzy logic must have some IF-THEN rules which will in turn be used to combine the likely factors as the precedence while the likelihood of cassava plant infection will be used as the consequent variable. Using the likelihood factors that were identified for assessing the likelihood of cassava plant diseases, the task of inference rule generation was achieved.

V. Conclusion

The motivation for the study is to provide a means via which cost-effective measures could be put in place to estimation the likelihood of cassava plant infection based on the existence of some factors. This was achieved by simulating a fuzzy based model for the categorization of the likelihood of cassava plant infection using rules inferred from experts. Therefore, the presence/absence of 7 factors was used to determine the likelihood of cassava infection. The study identified 7 factors for determining the categorization of cassava plant infection and was established using trilateral membership functions. The model was simulated using the MATLAB Fuzzy Logic Toolbox.

This study developed a fuzzy logic-based model to categorize of the categorization of cassava plant infection in order to determine the effect of the pests and diseases that productivity of the cassava plant. Thus study concluded that the presence and/or absence of likelihood factors that could be used to predict the likelihood of diseases affecting the cassava plant such that the lesser the existence of such factors then the lower the likelihood of cassava plant infection.

References

[1]. Alexander, G.L., Warren, J.M., Andras, T., Allison, S., Andrea, D., Carlos, A.R., Denice, S.F., Melinda, T. and Joseph, A.C. (2007).Mobile Phone-Based Remote Patient Monitoring System for Management of Hypertension in Diabetic 25: 1 - 12.
[2]. Bhatta, N. and Jyoti, K. (2012). A Novel Approach for Still-birth Diagnosis using Data Mining and Fuzzy Logic. 16 - 21.
[3]. Djam, X.Y. and Kimbi, Y.H. (2011).Fuzzy Expert System for the Management of Hypertension.
[4]. Imianvan, A.A. and Obi, J.C. (2012).Cognitive Neuro-Fuzzy Expert System for Hypotension Control.Computer Engineering and Intelligent Systems 3(6): 21 - 31.
[5]. Khormehr, A. and Maihami, V. (2016). A Novel Fuzzy Expert System Design for Predicting Still-birth. 138(4): 33 - 38.
[6]. Liu, W., Ma, L. and Wei, D. (2010). Data Mining Based on Rough Sets in Risk Decision-making: Foundation and Application. Transactions on computers 9(2): 113-121.
[7]. Lopez, A.D., Andrea, D. and Carlos, A.R. (2006). Global and regional burden of disease and risk factors: Systematic analysis of population health data.
[8]. Lancet 367(9524): 1747 - 1757. Malu, S., Pal, B.L. and Kumar, S. (2015). Detection of Anemia using Fuzzy Logic. 4(10): 762 - 766.
[9]. Obahiagbon, K and Odigie, B.B. (2015).A Framework for Intelligent Remote Blood Pressure Monitoring and Control System for Developing Countries. Journal of Computer Sciences and Applications 3(1): 11 - 17.
[10]. Obanijesu, O. and Emuoyibofarhe, O. J. (2012).Development of a Neuro-Fuzzy System for Early Prediction of Heart Attack. 9: 22 - 28.
[11]. Oladapo, O.O., Salako, L., Sadiq, L., Shoyinka, K., Adedapo, K. and Falase, A.O. (2010). Target-organ damage and cardiovascular complications in hypertensive Nigerian Yoruba adults: a cross-sectional study. 23: 379-384.
[12]. Waijee, A.K., Higgings, P.D.R. and Singal, A.G. (2013). A Primer on Predictive Models.Clinical and Translational Gastroenterology 4(44): 1 - 4.
[13]. World Health Organization (WHO) (2002). The World Health Report: 2002: Reducing the Risks, Promoting Healthy Life. Geneva.

Moshood Olatunji Lawal, et. al. "An Autonomous Strategy for Casava Plant Infection Identification." *IOSR Journal of Mobile Computing & Application (IOSR-JMCA), 8*(2), (2021): pp. 07-15.