Journal of Scientific Research and Development (2020) Vol. 19 (2) 332-340

A bi-annual journal published by the Faculty of Science, University of Lagos, Nigeria
http://jsrd.unilag.edu.ng/index.php/jsrd

Development of a classification model for the assessment of maize plant yield in Nigeria

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(Received 21 October 2020/Revised 27 December 2020/Accepted 31 December 2020)

Abstract
The identification of diseases in plants is usually achieved through the interpretations made of the visual symptoms by an agricultural expert. However, in situations where such experts are unavailable or the farmer's knowledge is insufficient, other methods for field-based assessments are a critical need. The need for a classification model to carry out field-based assessment of the yield of maize plant based on severity of symptoms informed this research. The study proposes a fuzzy-based model with triangular membership functions for the fuzzification of risk factors which were identified by experts of maize plant yield. Thirty-two rules were inferred using IF-THEN statements which adopted the values of the associated risk factors as antecedent and the yield of maize plant as the consequent part. The fuzzy logic model was simulated using five risk factors as input variables and the plant's yield as the output variable. The results showed that associated risk factors include the presence of black mould growth; blights on leaves, rots on cobs, infected husks and black kernels, and seed decay have noticeable influence on the yield of maize plant. The study concluded that the lesser the presence of such risk factors, the higher the yield of the maize plant.

Keywords: maize yield, classification, fuzzy logic modeling, triangular membership function

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Introduction
Plant suffers from various diseases during their life span at any stage of growth. For farmers, disease management is a critical matter which needs an immediate attention. In literature, automation approaches had been engaged to assist farmers. Ramcharan *et al.* (2017) applied deep learning for the processing of images of expert system to detect and diagnose the leaf diseases of cereals in Punjabi Language. The features of leaf diseases were extracted and were used to formulate the diagnosis model by adopting IF-THEN rules from the features. The model was integrated to a web based system using PHP and SQL. Awoyelu and Adebisi cassava plant for the detection of plant diseases. The study collected a dataset of cassava diseases images taken at a field in Tanzania. The images were analyzed using a transfer learning to train a deep convolutional neural network to identify three diseases and two types of pest damages. Kaur and Din (2016) developed a web-based (2015) developed an expert system for the diagnosis of cassava plant diseases. The study identified a number of symptoms that were taken from the leaves, stems and roots of cassava plant required for the diagnosis of 3 different cassava plant disease.

Suharto *et al.* (2013) developed an expert system for detecting coffee plant diseases. The method used was fuzzy logic-based expert system and decision tree using a hierarchical classification. Knowledge about coffee, its symptoms, and its disease was extracted from human expert and then converted into a decision tree. It resulted in the fuzzy logic-based expert systems. Based on the accuracy, it was concluded that the application can assist researchers or observers of the coffee plants in diagnosing coffee plants diseases earlier. Olanloye and Yerokun (2018) developed an expert system for diagnosing poultry diseases. The study identified the factors that were required for assessing the presence of diseases among poultry animals from experts via interviews. The knowledge about the relationship between the factors was created using IF-THEN rules to create antecedent and consequent rules for carrying out field-based diagnoses are a critical need (Vidita *et al*, 2013). Fuzzy logic based expert system is a concept that embeds structured human knowledge into workable algorithms that constitutes fuzzy models that can be used to solve the problem of imprecision and uncertainty or to improve tractability, robustness and low-cost solutions for real world problems (Pasqual and Thorat, 2019). Sequel to the nutritional and economic significance of the maize crop, it is noteworthy to mention the fact that diseases incidence on maize plantations is fast becoming a constraint in farmers' quest for a bountiful harvest. Hence, there is a need for an expert system for the classification of the yield of maize plant to enable efficiency and effectiveness in maize diseases management.

Therefore, this research adopted a fuzzy logic for the formulation of a classification model which was used to detect maize plant disease based on a number of factors associated with the yield of maize.

Materials and Methods

Following the review of related works, a number of risk factors that are associated with the severity of maize plant diseases which affects the yield of the maize plant were identified. The various risk factors were later validated by a crop expert at the department of crop production and needed for the diagnosis of diseases among poultry and was simulated using the Visual Prolog software.

Maize (*Zea mays L.*) is a major cereal crop in the world and ranks third in production after wheat and rice (Vinaya and Dhumale, 2018; Abdurrahim *et al*., 2016). It is a grain crop rich in vitamin A, C and E, carbohydrates, essential minerals including high level of fibre and 9% (Sachin and Kharade, 2015). Maize is important as a staple food in sub-Saharan Africa (SSA) provides food and income to over 300 million resource-poor smallholder farmers (Pramod and Maridal, 2013). Identification of diseases in maize like other plants is through observation of visual symptoms which an agricultural expert could decode to relate to particular diseases in the plant. For places where maize farmer experts are not available or insufficient, other methods protection, Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria. Following validation by the expert, five factors were identified to be associated with the severity of diseases affecting the yield of maize plant, namely: presence of black mould growth on the kernels and ears of maize plant, presence of blight on the leaves of the maize plant, presence of rots on the cobs of the maize plant, presence of infected husks and black kernels of the maize plant, and presence of decay on the seeds of the maize plant.

For each identified risk factors, descriptive variables were used to describe the labels of each risk factor such that a crisp value was used to assigned a weighted value for each linguistic variable. The higher the association of the label of a risk factor with the severity of diseases affecting maize plant yield, the higher the value of the weighted crisp value assigned to that linguistic variable. Therefore, binary labels *yes* and *no* were assigned as the linguistic variables of each risk factor, such that *no* was used to describe the absence of the risk factor while *yes* was used to describe the presence of the risk factor. As a result of this, a crisp value of 0 was assigned to the linguistic variable *no* while a crisp value of 1 was assigned to the linguistic variable *yes*. Table 1 shows the description of the risk factors alongside their respective linguistic variable (label) and crisp value.

Table 1: Identification of risk factors

Variable Name	Linguistic Variable	Crisp Value
Black Mould Growth	No Yes	0 1
Blight on Leaves	No Yes	0 1
Rots on the Cobs	No Yes	0 1
Infected Husks and Black Kernels	No Yes	0 1
Decay of Seeds	No Yes	0 1

Following the identification of the risk factors association with the severity of diseases affecting maize plant yield alongside their respective linguistic variables and crisp values, the classification of the yield of maize plant was determined. Similarly, four linguistic variables were used to describe the severity of diseases affecting maize plant, namely: high yield, moderate yield, low yield and no yield to which were assigned a weighted crisp value respectively. Thus, the higher the severity, then the lower the yield and the higher the crisp value such that high yield was assigned a crisp value of 0, moderate yield was assigned a crisp value of 1, low yield was assigned a crisp value of 2 and no yield was assigned a crisp value of 3. Table 2 shows the classification of the yield of maize plant as function of disease severity.

Table 2: Classification of the yield of maize plant as a function of disease severity

	Linguistic Variable		Crisp Value
	Disease Severity	Plant Yield	
Classification of Maize Plant Yield	None	High Yield	0
	Low	Moderate Yield	1
	Moderate	Low Yield	2
	High	No Yield	3

Formulation of fuzzy logic model for maize plant yield

For the purpose of the development of the fuzzy logic-based model which was required for classification of the yield of maize plant, two triangular membership functions were adopted for the fuzzification of the risk factors and the output class labels while four triangular membership function was adopted for the fuzzification of the four classes of the output variable used to classify the yield of maize plant.

The triangular-shaped membership function required the identification of three parameters namely: *a* which was used to identify the left base of the triangle, *b* was used to identify the central apex of the triangle which assigned the crisp value of the linguistic variable and *c* was used to define the right base of the triangle. Equation 1 shows the expression that was used to derive the triangular-shaped membership function *trimf*. According to the expression, variable x identifies the crisp value while (a, b, c) identifies the crisp interval required for fuzzification of linguistic variable into the fuzzy value.

Therefore, two triangular-shaped membership functions were derived for each risk factors and four triangular-shaped membership functions were derived for each of the classification of the yield of maize plant. Table 3 shows a description of the crisp interval adopted for the fuzzification of the two linguistic variables for the risk factors while Table 4 shows a description of the crisp interval adopted for the fuzzification of the four linguistic variables for the classification of the yield of maize plant.

$$Variable\_label(x; a, b, c) = \begin{cases} 0; x \leq a \\ \frac{x-a}{b-a}; a < x \leq b \\ \frac{c-x}{c-b}; b < x \leq c \\ 0; x > c \end{cases} \quad (1)$$

Table 3: Fuzzification of the risk factors

Linguistic Variable	Crisp Value	Crisp Interval		
		A	b	c
No	0	-0.5	0	0.5
Yes	1	0.5	1	1.5

Table 4: Fuzzification of the classification of maize plant yield

Linguistic Variable	Crisp Value	Crisp Interval		
		A	b	c
High Yield	0	-0.5	0	0.5
Moderate Yield	1	0.5	1	1.5
Low Yield	2	1.5	2	2.5
No Yield	3	2.5	3	3.5

Generation of inference rules of fuzzy logic model

Following the fuzzification of the risk factors and the classification of the yield of maize plant using the triangular membership functions, there was a need to generate the inference rules that were required for manipulating the fuzzified inputs of the risk factors. This was achieved by generating the possible combination of the linguistic variables of the risk factors of by performing a permutation of the binary values, Yes and No. Since there were five risk factors bearing the binary values, the total number of rules were determined as 2^5 which provided a value of thirty-two rules. A typical IF-THEN rule that was inferred using the values of the risk factors as the antecedent and the value of the output class for the yield of maize plant as the consequent is as follows: *IF (Presence of Black Mould Growth = "No") AND (Presence of Blight on Leaves = "No") AND (Presence of Rots on Cobs = "No") AND (Presence of Infected Husks and Kernels = "No") AND (Presence of Decay of Seeds = "No") THEN (Yield of Maize Plant = "High Yield").*

Using the values of 0 for representing *no* and the value of 1 for representing *yes*, the total sum of each rule was determined and an interval was created for the classification of the yield of maize plant. Therefore, if the sum of the values was 0 which meant that none of the risk factors was observed on the maize plant, then there was a high yield. However, if the sum of values was 5 which meant that all risk factors were observed on the maize plant then there was no yield of maize plant. Based on this, four intervals were created for the classification of the yield of maize plant using the 32 rules inferred from combination of the linguistic variables of the 5 risk factors. Based on the knowledge of the expert regarding the relationship between the values of the risk factors and their respective sum, a sum of 0 meant there was high yield, a value between 1 and 2 meant there was moderate yield, a value between 3 and 4 meant there was low yield while a value of 5 meant there was no yield. Table 5 shows the list of the 32 rules that were inferred for the classification of the yield of maize plant.

Table 5: Inference rules for the classification of maize plant yield

Rules#	Black Mould Growth	Blight on Leaves	Rots on the Cobs	Infected Husks and Black Kernels	Decay of Seeds	Yield
1	No	No	No	No	No	High
2	No	No	No	No	Yes	Moderate
3	No	No	No	Yes	No	Moderate
4	No	No	No	Yes	Yes	Moderate
5	No	No	Yes	No	No	Moderate
6	No	No	Yes	No	Yes	Moderate
7	No	No	Yes	Yes	No	Moderate
8	No	No	Yes	Yes	Yes	Low
9	No	Yes	No	No	No	Moderate
10	No	Yes	No	No	Yes	Moderate
11	No	Yes	No	Yes	No	Moderate
12	No	Yes	No	Yes	Yes	Low
13	No	Yes	Yes	No	No	Moderate
14	No	Yes	Yes	No	Yes	Low
15	No	Yes	Yes	Yes	No	Low
16	No	Yes	Yes	Yes	Yes	Low
17	Yes	No	No	No	No	Moderate
18	Yes	No	No	No	Yes	Moderate
19	Yes	No	No	Yes	No	Moderate
20	Yes	No	No	Yes	Yes	Low
21	Yes	No	Yes	No	No	Moderate
22	Yes	No	Yes	No	Yes	Low
23	Yes	No	Yes	Yes	No	Low
24	Yes	No	Yes	Yes	Yes	Low
25	Yes	Yes	No	No	No	Moderate
26	Yes	Yes	No	No	Yes	Low
27	Yes	Yes	No	Yes	No	Low
28	Yes	Yes	No	Yes	Yes	Low
29	Yes	Yes	Yes	No	No	Low
30	Yes	Yes	Yes	No	Yes	Low
31	Yes	Yes	Yes	Yes	No	Low
32	Yes	Yes	Yes	Yes	Yes	No

Simulation of fuzzy logic model

The fuzzy logic model was simulated using MATLAB of version R2015b using four primary GUI tools of the MATLAB Fuzzy Logic System for building, editing, and observing fuzzy inference systems were employed to actualize the simulation. The Fuzzy Inference System (FIS) Editor was used to handle the high-level issues for the system: it was used to define the names and number of input and output variables for the proposed model. For this study, five input variables and one output variable were defined. The membership function editor was used to define the shapes of all the membership functions associated with the linguistic variables of each variable. In this study, the triangular membership function was used to formulate all linguistic variables defined for the inputs and output variable. For this study, two membership functions were used to formulate each risk factor while four membership functions were used to formulate the linguistic variables namely: None, Low, Moderate and High for the output variable. The rule editor was used for editing the various inference rules that defined the behaviour of the system using a set of IF-THEN statements which combined the values of the identified risk factors as antecedents and the classification of the yield of maize plant as consequent. The rule viewer is a MATLAB technical computing environment for fuzzy inference diagram which was used as a diagnostic. It shows which rules are active, or how individual membership function shape influences the results. This interface was needed for testing the validity of the consistency of the fuzzy model based on the inferred rules constructed for the classification of the yield of maize plant.

Results and Discussions

Two triangular membership functions were used to formulate the fuzzy logic model for the labels of each risk factors with centers 0 and 1 for *yes* and *no* respectively. Also, the allocation of the values was done based on the increasing effect of the labels of the identified risk factors used in this study. Therefore, the results of the mathematical representation of the fuzzy logic model formulation using the triangular membership function for each of the labels is presented in equation 2, 3, 4, 5, 6 and 7.

$$Crisp - label\_yes(x; -0.5, 0, 0.5) = \begin{cases} 0; x \leq -0.5 \\ \dfrac{x+0.5}{0.5}; -0.5 < x \leq 0 \\ \dfrac{0.5-x}{0.5}; 0 < x \leq 0.5 \\ 0; x > 0.5 \end{cases} \quad (2)$$

$$Crisp - label\_no(x; 0.5, 1, 1.5) = \begin{cases} 0; x \leq 0.5 \\ \dfrac{x-0.5}{0.5}; 0.5 < x \leq 1 \\ \dfrac{1.5-x}{0.5}; 1 < x \leq 1.5 \\ 0; x > 1.5 \end{cases} \quad (3)$$

Also, the classification of the yield of maize plant was classified into 4 linguistic variables, namely: High Yield, Moderate Yield, Low Yield and No Yield using crisp values with centers of 0, 1, 2 and 3 respectively. Using the 4 triangular membership functions stated in equations (2) to (5), the linguistic variables of the yield of maize plant was formulated.

$$high\_yield(x; -0.5, 0, 0.5) = \begin{cases} 0; x \leq -0.5 \\ \dfrac{x+0.5}{0.5}; -0.5 < x \leq 0 \\ \dfrac{0.5-x}{0.5}; 0 < x \leq 0.5 \\ 0; x > 0.5 \end{cases} \quad (4)$$

$$moderate\_yield(x; 0.5, 1, 1.5) = \begin{cases} 0; x \leq 0.5 \\ \dfrac{x-0.5}{0.5}; 0.5 < x \leq 1 \\ \dfrac{1.5-x}{0.5}; 1 < x \leq 1.5 \\ 0; x > 1.5 \end{cases} \quad (5)$$

$$low\_yield(x; 1.5, 2, 2.5) = \begin{cases} 0; x \leq 1.5 \\ \dfrac{x - 1.5}{0.5}; 1.5 < x \leq 2 \\ \dfrac{2.5 - x}{0.5}; 2 < x \leq 2.5 \\ 0; x > 2.5 \end{cases} \quad (6)$$

$$no\_yield(x; 2.5, 3, 3.5) = \begin{cases} 0; x \leq 2.5 \\ \dfrac{x - 2.5}{0.5}; 2.5 < x \leq 3 \\ \dfrac{3.5 - x}{0.5}; 3 < x \leq 3.5 \\ 0; x > 3.5 \end{cases} \quad (7)$$

The study identified five risk factors required for the classification of the yield of maize plant. Each factor was defined using two linguistic variables for which central crisp values were assigned based on the association with the classification of the yield of maize plant. The higher the association of the linguistic variable then the higher the central crisp values assigned.

The presence of factors (Yes) was an indication of the presence of an infection which reduces the yield of the maize plant while the absence of factors (No) was an indication of the absence of an infection which increases the yield of the maize plant. Each factor was defined using two linguistic variables, namely: Yes and No with crisp intervals of [-0.5, 0.5] and [0.5 1.5] with centers 0 and 1 respectively while four linguistic variables, namely: high yield, moderate yield, low yield and no yield were used to define the yield of maize plant using centers 0, 1, 2 and 3 respectively. Therefore, two triangular membership functions were used to formulate the input factors while four triangular membership functions were used to formulate the target yield of maize plant.

Figure 1 shows the fuzzy logic model that was developed for the classification of the yield of maize plant using the MATLAB fuzzy logic toolbox.

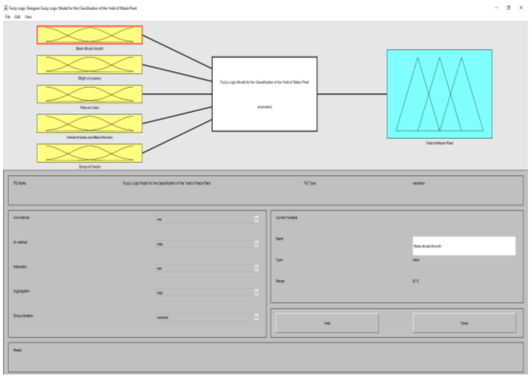

Figure 1: Fuzzification of fuzzy logic model for classification of maize plant yield

Figure 2 (left) shows the fuzzification of the binary linguistic variables of the risk factors using two triangular membership functions while Figure 2 (right) shows the fuzzification of the classification of maize plant yield using four triangular membership functions.

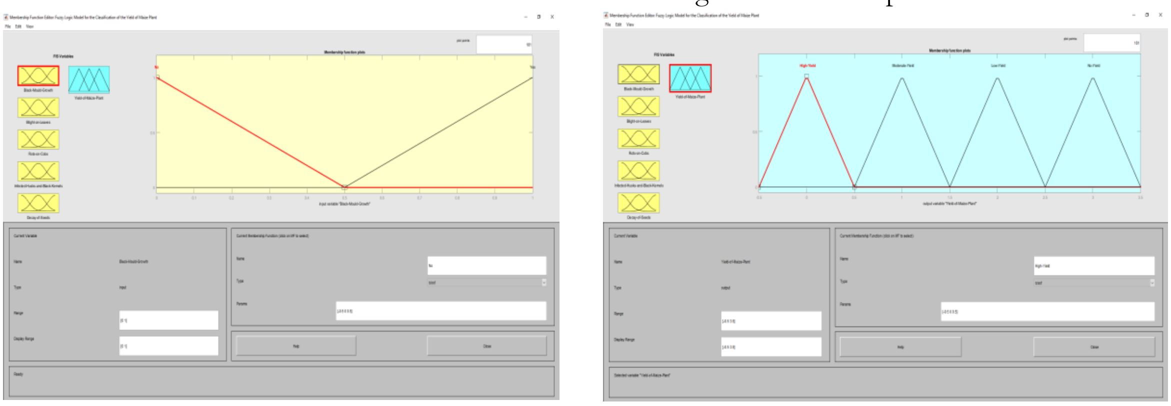

Figure 2: Fuzzification of risk factors (left) and classification of maize plant yield (right)

Figure 3 shows the snapshot of parts of the thirty-two rules that were inferred for the classification of maize plant yield based on the 5 risk factors.

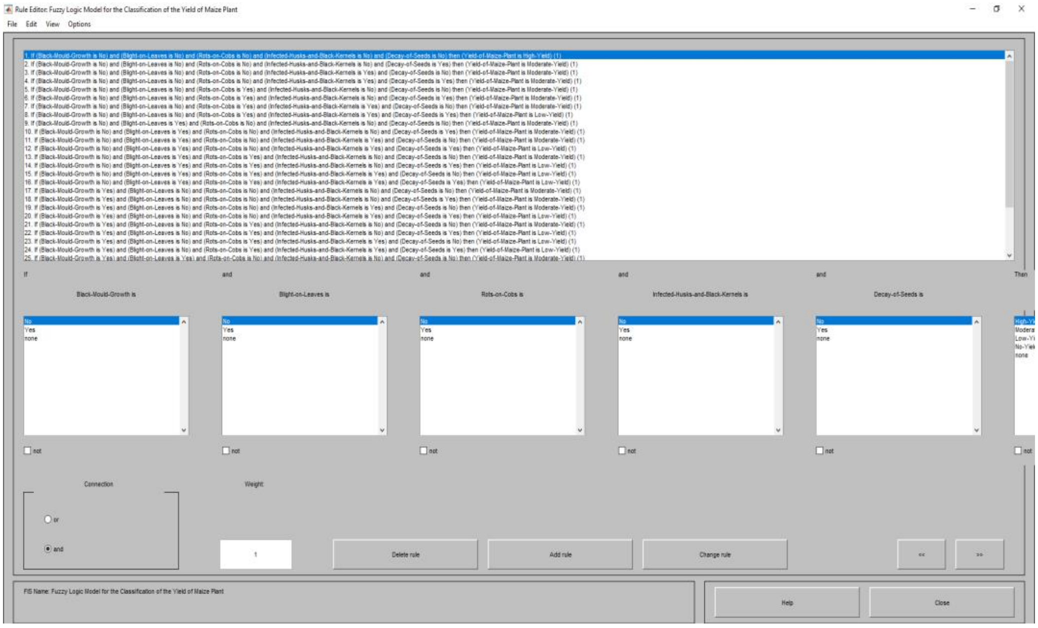

Figure 3: Inference rules created for fuzzy inference engine

Figure 4 shows the validation of the inference rules using the rule editor by testing the output of the fuzzy logic model. As shown in the bottom left part of Figure 4, the values [0, 0, 1, 1, 0] which corresponded to the rule: IF (Presence of Black Mould Growth = "No") AND (Presence of Blight on Leaves = "No") AND (Presence of Rots on Cobs = "Yes") AND (Presence of Infected Husks and Kernels = "Yes") AND (Presence of Decay of Seeds = "No") revealed an output of THEN (Yield of Maize Plant = "Moderate Yield") owing to the output value of 1 shown in the top right corner of the diagram. This output is consistent with the expected value presented in the inference rule number 7 as earlier shown in Table 5.

Figure 4: Validation of inference engine using rule editor

Conclusion

This study developed a fuzzy logic-based model for the classification of the yield of maize plant in order to increase the productivity of the maize plant. Two triangular membership functions were appropriate for the formulation of the linguistic variables of the factors, namely: yes and no while the target yield was formulated using four triangular membership functions for the linguistic variables no yield, low yield, moderate yield and high yield. The thirty-two inferred rules were formulated using IF-THEN statements which adopted the values of the factors as antecedent and the yield as consequent part of each rule. The developed fuzzy logic model was simulated to demonstrate its capabilities in predicting the yield of maize plant. The study concluded that the physical damage made on the plant by pests could be used to estimate the yield of maize such that the lesser the presence of such factors then the higher the yield of the maize plant. This study also, recommends that additional efforts be put in place by agriculturists in the identification of other important factors that are associated with the yield of the maize plant. This would increase the productivity of the crop and in essence contribute to the value of the National economy.

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