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DIAGNOSIS MODEL OF SOY BEANS DISEASES USING NEURO-FUZZY SYSTEM

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ABSTRACT

Soybean is an important legume crop, extensively cultivated for food on which low-income population highly depend on its proteineous nutrient on daily basis for food. and oil. Soy beans consumption have been the major cheap protein-rich grain useful for treatment of malnutrition among children, for fighting against diabetes, high blood pressure, etc. Despite the nutritional and economic value of soy bean crop, a variety of pest attack such as fungi, nematode, bacteria and viruses are speedily becoming a constraint to quality and bountiful harvest. The effort of farmers to specifically identify the specific pest responsible for damaging of plants' segment such as roots, stem, pod and leaves still remain vague and imprecise to many farmers. In this work, a neuro-fuzzy system was built with MATLAB version 8 with100 rules on six input parameter as linguistic variable or symptoms into the system to determine the disease type either as fungi or bacteria or virus and to also determine intensity rate, that is, level of damage, as the output in form of a crisp. The proposed Neuro-Fuzzy system was developed through MATLAB software using Adaptive Neuro-Fuzzy Inference System (ANFIS) box. ANFIS hybridizes the learning capacity of neural network with if-then rules of fuzzy logic to learn and design the most fitted membership function for a given set of data and thereby map the input with output. The proposed Neuro-Fuzzy System consisted of five stage: input stage, fuzzification, rule base, inference engine and defuzzification. The output of the system was to produce results for the decision maker to provide solution regarding the treatment of the infected plant for bountiful and quality harvest.

Keywords: neuro-fuzzy system; crisp; matlab; fuzzification; de-fuzzification;

1. INTRODUCTION

The technological evolution in computing has been the principal tool in increasing agricultural products. Nevertheless, there are numerous problems and constraints working against the bountiful and quality harvest of soybean commercial production [3]. ICTs play vital role in facilitating agricultural growth. The scientific and technological developments, which include e-agriculture, decision support system for farmers and mobile applications, have tremendously delivered relevant services for farmers in tackling all forms of crop diseases. ICTs have promoted new farming techniques and distributed new knowledge using computing technology for facilitating diagnosis and treatment of crop diseases [10].

Since the discovery of artificial intelligence (AI) theories and techniques over a decade, there have been tremendous growths in the development of expert systems in providing solution to some uncertain and imprecise tasks. The capacity and efficiency of expert system in imitating human reasoning process and providing relevant advice similar to human expertise has singled it out as one of the artificial intelligence branches widely embraced in many fields today [11]. Neuro-Fuzzy as one of the artificial intelligence methods found to be more effective in developing medical system that provide optimal solution to problems that are vague and imprecise in nature.

Neuro-fuzzy is an efficient technique that combines the strength of two different techniques, namely; artificial neural network (ANN) and fuzzy logic (FL) in which back-propagation algorithm of ANN performs the computation of the fuzzy system parameters. The choice of neuro-fuzzy technique for this work is justified as a result of need to accept six major symptoms of soybean disease as input parameters for disease classification and computation of intensity proportion of a particular disease.

In spite of the economical value of soybeans to the farmers, nutritional advantages to the body system of consumers, and the use of organic and inorganic fertilizers to increase total income and bountiful harvest, the main constraints and threats challenging large production of soybean are pests attack and diseases infections.

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Table 1 shows a decline in the production of soybean from 2004 to 2005 virtually in all states except Benue. Production dropped in Ekiti as far back as 2000 and there was no production in Borno and Ogun between 1999 and 2005. Source: Project Co-ordinating Unit, Abuja. Data for Year 2003 not available.

Table 1 Soybean production in some States (2000 – 2005) ('000 Tonnes)

STATES	1999	2000	2001	2002	2004	2005
Adamawa	0.0	0.16	0.0	0.0	0.22	0.22
Bauchi	1.07	1.13	14.41	1.27	1.4	1.31
Borno	0.0	0.0	0.0	0.0	0.0	0.0
Ekiti	0.4	0.44	0.0	0.0	0.0	0.0
Benue	160	180	164.0	164.89	164.89	167.15
Kogi	0.67	0.67	0.7	0.7	0.72	0.32
Enugu	0.0	0.0	0.0	0.0	1.03	0.0
Lagos	0.22	0.25	0.25	0.25	0.50	0.49
Ogun	0.0	0.0	0.0	0.0	0.0	0.0
Plateau	15.92	17.0	19.0	20.5	30.16	27.15

Findings in literatures had established a good number of fuzzy based expert system developed for diagnosis of crop diseases. The limitation and constraints found in the use of fuzzy logic technique in developing expert system is its incapacity to automatically tune or construct appropriate membership functions for the specific dataset in order to provide optimal diagnosis. The non-availability of improved and modern technologies has always been the main constraint to large production of agricultural products [10].

Most existing fuzzy-based expert system for diagnosis of crop diseases only focused on disease classification that is to assign a particular crop to the specific small set of classes of disease. But, the intensity level of those diseases is fairly ignored.

In order to tackle this problem and develop a more robust model, the learning algorithm (Back propagation) of neural network is adopted to compute and construct parameters needed to tune the membership function appropriately for fuzzy system in determining the intensity level of disease infected soybeans plant.

The aim of this study is to develop an interactive neuro-fuzzy based system for identifying specific disease and determining the degree of damage (intensity level) perpetrated on a soybean plant. The specific objectives are:

1. The study of the existing system
2. To design a neuro-fuzzy based system with parameter field.
3. To model the dataset extracted from a database for training through the aid of Adaptive Neuro-Fuzzy Inference System (ANFIS).
4. To implement and evaluate the proposed system for soybean disease diagnosis.

In order to achieve the first objective, a neuro-fuzzy system was built with MATLAB version 8 with 100 rules on six input parameters as linguistic variable or symptoms into the system to determine the disease type and to also determine intensity rate, that is, level of damage as the output in form of a crisp. The dataset that was used for implementation was extracted from Soybean Large Dataset (SLD), of Institute of Agricultural Research and Training, Obafemi Awolowo University, Moore Plantation Ibadan.

To achieve the second objectives, a neuro-fuzzy model was developed, in which the back-propagation algorithm of the neural network was integrated with fuzzy logic to form hybridized model called Hybridized Adaptive Neuro-Fuzzy Inference System (HANFIS). It will provide optimal structure for tuning the membership functions needed for training and learning soybeans disease dataset for diagnosis.

This study is strictly restricted within the scope of using a particular type of ANFIS as one of the types of neural-fuzzy to develop a system that capture specific input parameters as symptom on leaves, leaf halo, leaf spot size, root, area-damaged pod and stem of soybean plant and identify disease-type the plant infected with, along with the extent of degree of the infection as output. Obviously, indigenous methods used by farmers in diagnosis of crop diseases are measured in forms of linguistic values and vagueness. The relevance of this work provides the benefits of:

1. Efficient frameworks for software developers and domain knowledge experts in agriculture in developing robust expert systems that consume the strength of neural network and fuzzy logic together to diagnose soybeans diseases.
2. A promising decision support system for soybeans farmers for diagnosis of soybeans bacteria diseases and computation of its intensity level.

2. LITERATURE REVIEW

The adoption of expert system in diagnosis of crop diseases in agriculture could be dated back to 1980. It is not a new concept because a large number of agricultural institutes and researchers across the globe have been developing different types of expert system for local farmers within their regions and catchment areas. Every expert system requires human expertise to provide knowledge base that could be encoded in solving related problems in a specified domain [8].

A tremendous advancement of technology in software and hardware industries has provided opportunities for researchers to explore every aspect of artificial intelligence technique in building relevant systems and devices for indigenous farmers. It should be noted that the development of expert system could be in various ways and in accordance with the nature of the problem intending to solve. In Computer Science, many researchers have adopted the use of neuro-fuzzy method in enhancing the effectiveness and efficiency of expert systems for agricultural use. Farming all over the world has embraced all forms of technological advancement in classifying livestock disorders, tactical solutions for crop cross-breeding and diagnosing crop diseases [5].

According to [2] most existing expert system for diagnosis was confined to medical field; and robust agricultural expert systems for practitioners are still few in number. [4] and numerous researchers equally acknowledged the scarcity of works on expert systems optimal solution of diagnosis of certain crops diseases [7] and [11] In addition to this, most researches still focus on adoption of only one artificial technique toward designing artificial intelligence based system that could be of help for farmers in the diagnosis of nutritional disorders in cereals and leguminous crops like tomato, soybean, cassava and rice.

A comparison study conducted on various expert systems that were not artificial intelligence-based on agriculture. [1] established that most classical expert systems had the capacities for fertilization scheduling, assessment of a farm and pest control, diagnosis and classification of crop diseases. Artificial intelligence is one of the most widely used concepts in computer science by researchers for modeling and simulating unambiguous tasks. Previous works have adopted various methodologies and techniques in building expert system. Diversity of methodologies mostly used in previous works include neural network, fuzzy logic, case-based reasoning, intelligent agent system, object-oriented methodology, database methodology, knowledge-based system and ontology [7] [9].

In [12] researchers developed a fuzzy logic system for diagnosing various types of chilli plant disease. The architecture of fuzzy logic system was also illustrated. The knowledge base system holds the symptoms for chilli disease. Matlab was used for the rules viewer, rule editor, membership function editor, fuzzy inference system editor and fuzzy modeling.

In [13] researchers focused their work on diagnosis of cassava plant diseases. They proposed the development of fuzzy expert system for predicting cassava plant diseases. Matlab version 9 was used as a fuzzy tool to develop the system. They employed 18 rules for cassava mossaic, 27 rules for the cassava brown streak and 27 rules for cassava bacteria blight. These rules were used for the classification and prediction of cassava plant diseases.

3. RESEARCH METHODOLOGY

3.1 Dataset description

The dataset used for the implementation of the study was extracted from Soybean Large Dataset (SLD), of Institute of Agricultural Research and Training, Obafemi Awolowo University, Moore Plantation Ibadan. In this study, more than one thousand (1000) records of diseased soybean plants were collected and the assistance of agriculture experts was employed in the domain of crop planting for proper interpretation of the dataset

The dataset consists of six categorical nominal attributes with-order and two classes of disease. There are 1,300 datasets with 270 incomplete records. The six attributes which includes; area-damaged, leaves, leaf-halo, leaf-spot-size, root and stem are arranged in first six columns while rows consist of thousands of soybean plants. The last column is the corresponding two classes of disease, one disease for a row. The two classes of disease are 2-4-d-injury and Herbicide injury. The soybean Large Dataset is presented in Appendix A.

3.2 Cloud services

In any dataset, the input variables are the most important parameters, which are subjected to investigation by farmers into the system in order to form basis for disease diagnosis. The description of each attribute (input variable) is presented in Table 2.

Table. 2. Description of attributes of dataset for soybean

Number	Attributes	Description
1	The root	A part that collects nutrients from the soil to the other parts
2	Leaf-halo	Light colour on a leaf
3	The leaves	The greenish parts of the plant where photosynthesis take place.
4	Stem	Above-ground stalk that serves as a channel through which nutrients pass to leaves and other organs
5	Leaf-Spot-Size	Indicated spot on the leaf
6	Area – damaged pod	The area being infected on a seed case of soybean plant

Six (6) attributes as stated in Table 2 are used as input parameters for the symptoms. In the context of this work, the input parameters are referred to as linguistic variables. The linguistic values (fuzzy set) adopted for the design are stated in Table 3.

Table. 3 Description of Fuzzy-set adopted for the attributes in the original dataset

Attributes	Linguistic Values
Area-Damaged-pod	Scattered, low area, upper area, whole filed
Leaves	Normal, abnormal
Leaf-halo	Absent, yellow, No yellow
Leaf-spot-size	$< 1/8$, $> 1/8 \leq 1/4$, $> 1/4$
Root	Normal, Rotten, Gall – Cysts
Stem	Normal, Abnormal

For example, a damage on the soybean pod could either scattered all over the pod or low area of the pod, or upper area or the whole field. The leaves of a soybean plant could either be normal or abnormal. The dataset in Appendix A is in form of nominal-with-order dataset as shown in Table 4.

Table. 4 Interpretation of Linguistic values in form of digits

Ordered nominal values	**0**	**1**	**2**	**3**
Area-damaged-pod	Scattered (0)	Low area (1)	Upper area (2)	Whole field (3)
Leaves	Normal (0)	Abnormal (1)		
Leaf-Halo	Absent (0)	Yellow (1)	No Yellow (2)	
Leafspot-size	$< 1/8$ (0)	$> 1/8 \leq 1/4$ (1)	$> 1/4$ (2)	
Root	Normal (0)	Rotten (1)	Gall – Cyst (2)	
Stem	Normal (0)	Abnormal (1)		

For example, the first record in the dataset in Appendix A as presented below is interpreted as follows:

area.dam	**leaves**	**leaf.halo**	**leafspot.size**	**roots**	**Stem**	**Class**
0	0	0	2	0	1	1

The area_damaged_pod is scattered with indication of “0”, the leaves are normal with indication of “0”, the leaf _halo is absent with indication of “0”, the leafspot size has the value of “2”, the roots are normal with indication of “0”, the stem is abnormal with indication of “1” and the class of disease is 2-4-d-injury with indication of “1” but with the indication of “2” the class of disease will be herbicide injury.

IF area_damaged_pod = 0 AND leaves = 0 AND the leaf _halo = 0 AND leafspot size = 2 AND roots = 0 AND stem = 1 THEN class of disease = 1

This implies that the soybean plant has 2-4-d-injury disease.

3.3 Description of the modeling tool

The proposed Neuro-Fuzzy system was developed using Adaptive Neuro Fuzzy Interference System box of technical programming language known as MATLAB as presented in Fig. 3.1. The use of MATLAB guarantees result accuracy and still remain the best tool for system training and testing within short time (Maryam & Laya, 2016).in this work, the following steps are involved in modeling with ANFIS editor in MATLAB with respect to soybean disease classification.

Step 1: The collection of symptoms from various soybean plants as input and target output in pairs as indicated in Appendix B are allocated for training and testing.

Step 2: The dataset was saved in MS-Excel file format and imported into the workspace of MATLAB by using unimport command.

Step 3: To display ANFIS editor dialogue box, anfisedit command was typed in the MATLAB command area.

Step 4: In the ANFIS editor environment, by clicking "Load Data" command button, the data is loaded from the specified dataset for training and testing, and also to be plotted on the plot region.

Step 5: To view the structure and model of the proposed system based on the input and output, the "Generate FIS" command and structure button are clicked respectively.

Step 6: Under "Train FIS" section group, one can select effective in-built algorithm that integrates back-propagation and least square method known as hybrid method. In addition, the training epoch's number and error tolerance will be chosen.

Step 7: By clicking "Train now" button, FIS model will be trained while the membership function parameters will also be adjusted and the training data error will be plotted in the region.

Step 8: Under the "Test FIS" section group, Test button will be clicked to validate the trained FIS.

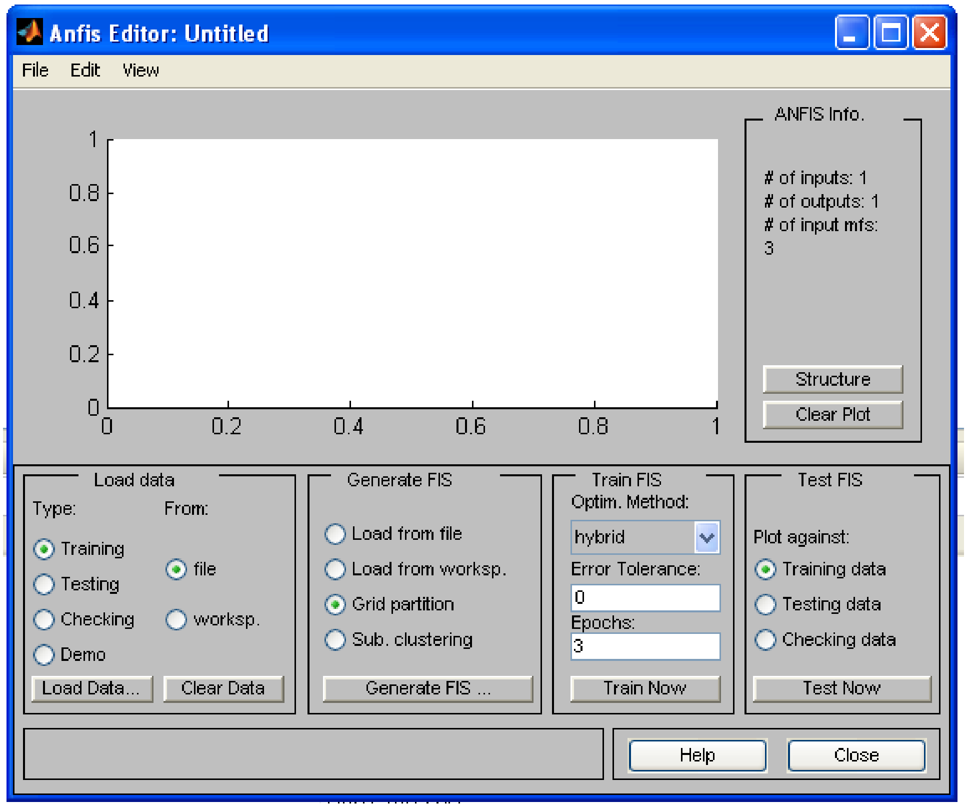

Figure. 1 ANFIS editor environment source: Matlab, (2015)

3.4 ANFIS parameter-settings for the proposed system

ANFIS hybridizes the learning capacity of neural network with if-then-rules of fuzzy logic to learn and design the most fitted membership function for a given set of data and thereby map the inputs with appropriate output. The functionality of if-then-rules is based on fuzzy inference system called Takagi-Sugeno and normally consists of five layers.

In this work, Layer-one consists of seventeen (17) nodes and accepts the linguistic variable symptoms (area-dam, leaves, leaf-halo, leafspotsize, root and stem) as input parameters. All the nodes in this layer are adaptive nodes that produce membership grade of the inputs to layer two, expressed as follow;

$$Zj1 = \mu Kj\ (c),\ j = 1, 2 \text{ -------------------------------} \qquad (1)$$

Zj1 = µLj-2(d), j = 3, 4 ------------------------------- (2)

Where c and d are the linguistic variables as input into node j, where K and L represent linguistic labels or values as presented in Table 3.3.µKjµLj-2are the membership functions that measure the degree of the intensity of linguistic variables c and d. Layer-one is the fuzzification layer.

Layer-two has fixed nodes in which the incoming signals from Layer-one are multiplied and the product generated. The output of every node indicates the strength and firing level of the rule. The operation of this layer is mathematically given below

Zj2 = wj = µKj (c) µLj(d) j = 1, 2 -------------------------- (3)

Layer-three: In the third layer, its output is a normalized capacity, based on the computation of ratio of each jth rule to the computation of sum of all other rules' strengths.

Zj3 = wj = pj/(pj + p2)j = 1, 2 -------------------------------- (4)

The fourth-layer performs its operation by multiplying the output of layer three (firing strength) with the polynomial of first order. The mathematical expression is presented in equation (5) below.

Zj4 = pjfj = pj(pjc + qjd +rj) j = 1, 2 ----------------------- (5)

Layer-five is the last fixed node, which produces the output by summing all incoming signals as presented below.

Zj5 = ∑jpjfj = (∑jpjfj)/(∑jpj)   i = 1, 2 --------------------- (6)

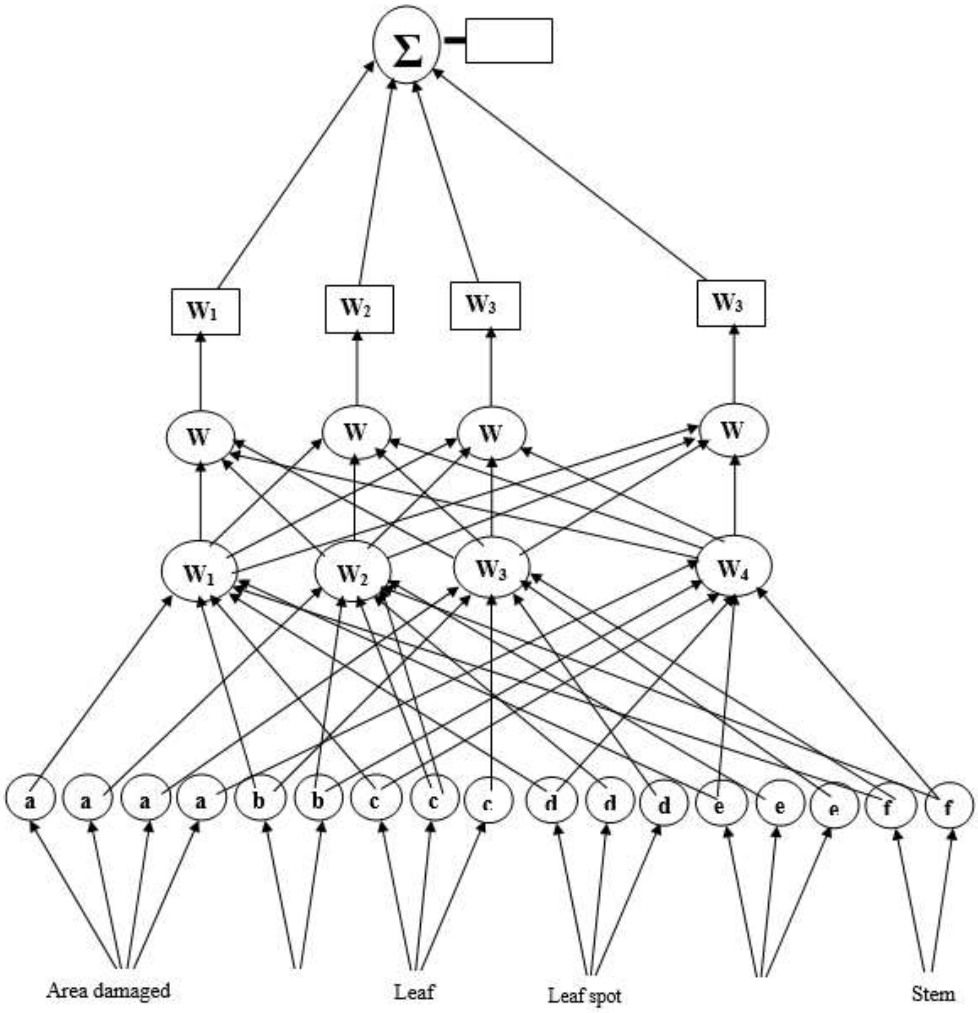

Figure. 2 Block diagram of the proposed system using ANFIS architecture

3.4.1 Parameters' setting for the proposed model

In this work, the following parameters are carefully selected with assigned values.

i) Proportions of dataset used for the simulation

A total of 1000 soybean dataset was obtained for simulation in this study. The dataset contains the first six (6) columns for input variables and last column for target output. The dataset was divided into three workspaces: training, testing and checking.

Five hundred (500) data were assigned for training, two hundred and fifty (250) records were selected from the dataset for testing and Two hundred and fifty (250) records were allocated for checking.

ii) Partitioning of Data Space

Grid partition was used as one of the parameters to divide the data space into regular sub spaces. The justification for this option is simply because of the few membership functions contained in the dataset and in order to have less simulation time during training and testing of the dataset.

iii) Optimization Method

The hybrid optimization method which combines back propagation and least square algorithm together in order to estimate both the premise and consequent parameters formed in layer 1 and 4 sequentially was adopted.

In the forward pass, the consequent parameter P in equation (6) could be expressed as

A = XP, where

A = a column vector that has output of numerical values as presented in appendix C
X = a row of training vector as indicated in Appendix C
P = is the consequent parameter to be computed by using equation (7)

$$P_{k+1} = P_k + \sum k + 1\,\ell_{k+1}\left(A^T{}_{k+1} - \ell^T{}_{k+1} P_k\right)$$

Where

$\ell^T{}_k =$ the K^{th} row vector of X

$A^T{}_k$ = the K^{th} element of V

P* = least square estimate.

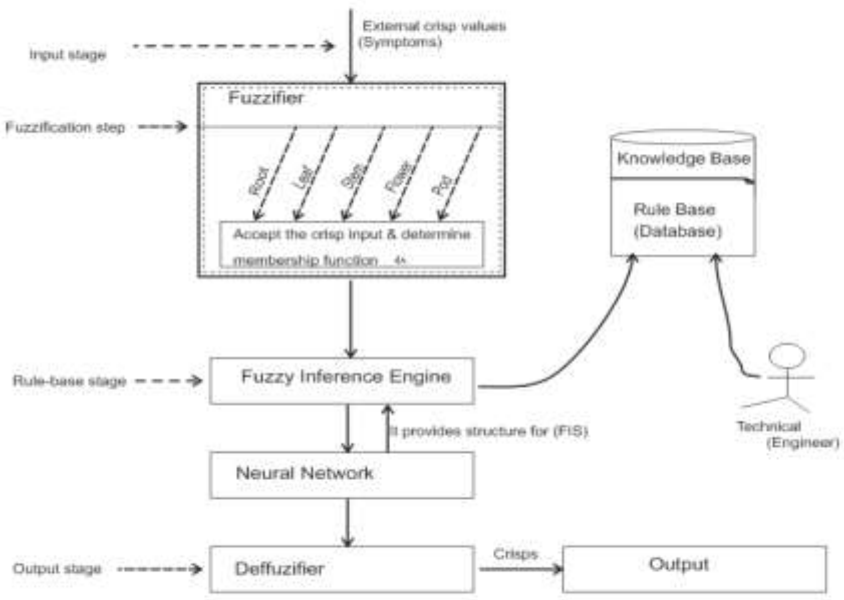

Figure. 3 Conceptual diagram of neuro-fuzzy model for soybean disease diagnosis (proposed model)

3.5 Proposed neuro-fuzzy model

Figure 4 consists of five stages: input stage, fuzzification, rule base, inference engine, and defuzzification. The first stage allows the crisp inputs such as manifested symptoms on soybean plants which include area damagedspot, leaves, leaf halo, leaf spot size, root, and stem to be passed into the fuzzification stage of second step for the membership function type (Gaussian) to compute the degree of fuzzification.

The adoption of back-propagation technique is to subject the inference engine for training and tune it to select most appropriate rule from the rule-base. Back propagation algorithm was used to effectively train the inference engine for the appropriate selection of rule base. The defuzzifier then converts the linguistic output generated by neural network to crisp output for classification.

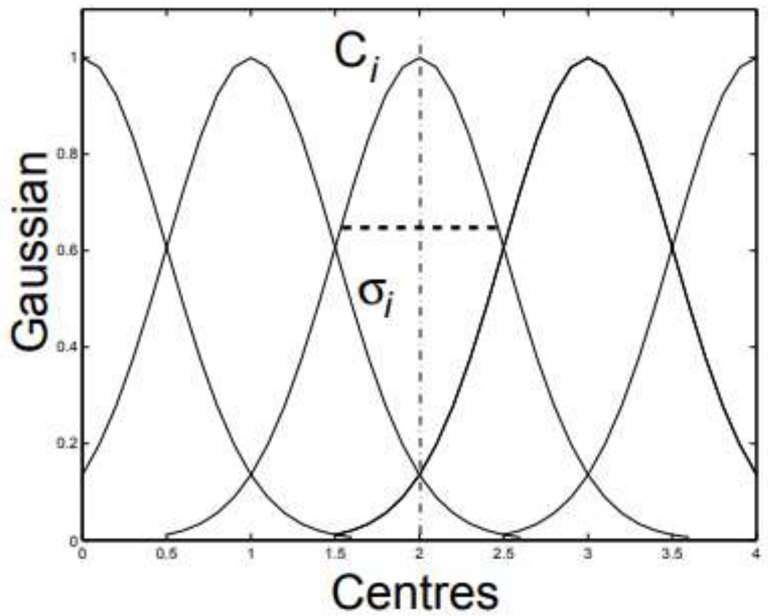

Figure. 4 Conceptual diagram of neuro-fuzzy model for soybean disease diagnosis (proposed model).

3.5.1 System validation

The proposed neuro fuzzy system would be validated through the testing-data that will be supplied to it, after which the performance metric will be used to evaluates the accuracy operation of the proposed model by using Mean Square Error (MSE) formula given below

$$\text{MSE} = (\frac{1}{n}\sum_{i=1}^{n}(a_{(i)} - b_{(i)})^2 \qquad (7)$$

3.5.2 Defuzzification

This technique involves computation of sampled membership functions in order to establish their membership grade to be used in fuzzy logic expression and thereby determine outcome region or produce a single scalar quantity. Center of Area or Centroid (COA) was used as the method for defuzzification

$$\frac{\int_w \mu K(w).wdw}{\int_w \mu K(w).wdw} \qquad (8)$$

From equation (8), w indicates the real output while μK(w)defines the degree or extent by which the aggregated set belongs in respect to w.

3.5.3 Fuzzy rule base

Fuzzy implication rules was adopted to mimic expert's reasoning with statements that are imprecise by nature. With the assistance of Agriculture experts, rules automatically generated by the model were interpreted regarding the diverse symptoms affecting root, stem, leaves,leaf halo,leaf spot size and area-damaged pod of a soybean's plant in accordance with the knowledge on the disease domain. The fuzzy rules are strictly linguistic rules of IF ---- THEN format.

IF uTHEN v

Where

u is the input parameter or linguistic variable known as premise and v stands for the result called consequence.

3.5.4 Membership function plots for input variables

Gaussian membership function was used to plot the degree of membership in the [0,1] interval. The fuzzy sets of the model was graphically represented using equation 9.

$\mu_{A}^{i}(x) = \exp(-(c_i - x)^2 / (2\delta^2_i)$
where
c_i=centre of the ith fuzzy set A^i
δ_i= width of the ith fuzzy set A^i

4. CONCLUSION

The proposed system will provide optimal benefits over the shortcomings found in works that were reviewed, because, once the system has been set-up, neuro-fuzzy technique embedded within the system, has the capacity to identify which of the rules have been developed by the system in order to be examined by experts to ensure that the problems are appropriately addressed. This system will be more effective and efficient to use in the diagnosis of soya bean diseases and determining the intensity level of the disease by using ANFIS. The output will show the intensity level. The design of the system can be divided into 3 stages: ANFIS model development, network training and system validation and testing. When this system is implemented, it will be found that neuro-fuzzy based system will be more suitable and feasible to be used as a supportive tool for soya beans disease diagnosis.

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