ARPN Journal of Engineering and Applied Sciences

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A FUZZY INFERENCE SYSTEM FOR DIAGNOSING OIL PALM NUTRITIONAL DEFICIENCY SYMPTOMS

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ABSTRACT

Automated monitoring of nutrient deficiencies by computers provides more accurate and precise information on current plant health status, which improves the effectiveness of fertilization management on large scale agricultural projects. In comparison to the traditional method which involves judging the deficiencies by personal observation, it is naturally more costly to hire agricultural experts who are more experienced. Besides, judgments by observations are also prone to misinterpretations, which will lead to incorrect applications of fertilizers. In this paper, the automatic detection via Fuzzy Inference System (FIS) is introduced as an automatic classification system for identifying the type of nutrient deficiencies in plant by emulating the judgment made by an agricultural expert when observing the state of the plant leaflets. The main objective of this study is to propose a design of Mamdani-FIS that models the classification of the deficiency type and severity. Oil palm tree (scientific name-ElaeisGuineensisJacq.) were used as the study case for this paper, and leaflet samples are collected which consists of healthy leaflet and nutrient deficient leaflet that have been preprocessed to extract the inference via the fuzzy logic system. This involves the development of the fuzzy rule base, fuzzification and defuzzification process from the extracted features retrieved from leaflet images. The inputs of the membership functions of FIS consist of the number of red pixels, entropy and correlations. Three types of the nutrient deficiencies which are nitrogen, potassium and magnesium, and healthy leaflet condition was selected as the output of membership functions. The implementation of the system demonstrates a promising outcome, with classification accuracy confirmed to 82.67%. The performance of FIS is further evaluated via sensitivity, positive predictive value (ppv) and negative predictive value (npv) calculation which shows desirable rate of above 85%.

Keywords: fuzzy inference system, oil palm, leaf recognition, leaflet, fuzzy logic, nutrient deficiencies, classification.

INTRODUCTION

Researches in these past decades had shown advancements in computing technology, which one of its applications allows for automatic plant or crop diagnosis for detecting plant diseases. One of the most promising researches is the study that relates to automatic classification of the disease or nutritional deficiency based on leaf characteristics [1-4, 8]. In recent years, artificial intelligence techniques such as fuzzy logic and neural network have been explored in developing the disease detection system through recognition of the pattern that appears on crop's leaf. The disease assessment and crop monitoring are normally conducted manually by the agricultural experts to provide the information on crop's nutrient intake and recommend the necessary fertilization routine to combat the nutrient deficiencies. The evaluation on the nutrient deficiencies of the plant is made solely on the knowledge and experience gained by the agriculturalist and are prone to human factors such as sickness or fatigue, psychological and emotional state of the observer which could lead to misinterpretation on the observations. Thus, this contributes to unreliable and inaccurate judgment.

In order to automate the diagnosis made by the agricultural experts, a detection program with Fuzzy Inference System (FIS) as the core of the classification algorithm is proposed. The FIS is intended to be developed for emulating and mimicking the judgments made by agricultural experts when making observation on the plant leaflets. By circumventing the needs of consulting experts, and the human factors that could influence the outcome of the diagnosis, the automatic detection benefits the farm management in which the associated consultation costs can be significantly reduced. The identification process is also significantly faster, more accurate and precise.

This paper will highlight on classifying the disease of the oil palm due to nutrient deficiencies using Mamdani type FIS for identifying the deficiency symptoms that appear on oil palm leaflet surface. The required input to develop the model needs to be retrieved from extraction of features namely number of red pixels, entropy and correlation acquired from pre-processing of the leaflet images. Even though previous studies have been conducted to investigate and examine the automatic technique of recognizing, classifying, grading and detecting the disease for the oil palm, the implementation of the techniques using fuzzy systems is yet to be studied. This framework is established as a means of providing solution to the problem of the system in interpreting the nutrient deficiency symptoms in the same way as an agricultural expert would when dealing with uncertainty during the decision making process. The accuracy of using this method will be evaluated and further validated via statistical measures. The FIS consists of three major process: First process is fuzzification to convert the crisp input variable of number of image pixels into linguistic variable, second process is to apply the fuzzy operator, rule base and implication and lastly the defuzzification of the output variable in the form of nutrient deficiency diagnosis.

Several studies have attempted to combine the image processing approach and different techniques in artificial intelligence to classify the deficiency automatically. Previous literature studies have seen the applications of the automatic disease recognition software based on visual observations on a variety of plants- watermelon, orchid, rubber tree and corn crops. In [1] utilized the application of image processing and fuzzy logic to characterize the Downy Mildew and Anthracnose disease of watermelon based on leaf appearance from RGB color. The image processing technique was used to extract these RGB colors, and then used as input to design the fuzzy system. The authors also initially examined the data using error plot in order to assist the design of fuzzy system that contains 64 generated rules for discerning the watermelon disease. The outcome showed that the designed system could achieve about 60% of classification accuracy.

In [5] evaluated the same method to classify the leaf disease using fuzzy logic using orchids as the case study. They applied disease detection program towards detecting three different orchid leaf diseases using fuzzy logic, whereas the inputs were leaf area and the number of disease spot and the output was leaf condition. The measure on result detection was not well mentioned, but the program was considered as fairly capable to identify the disease. In [6] proposed visual texture classification by using fuzzy system to identify the stage of white root disease. Three stages being healthy, medium and worse was evaluated and classified from leaf vein appearance, quantified as the light reflectance and measurable using spectrometer. Based on two inputs of vein and main vein data collected using light reflectance of the spectrometer, the fuzzy system was tested and has produced satisfactory performance with 78.33% accuracy of disease discrimination. The authors also conducted statistical analysis of normality test, error bar plot and box plot for validating the detection results.

Another interesting study was conducted by [7] who developed a system for forecasting the occurrence of plant disease using climate data such as temperature and humidity. In their papers, authors implemented the fuzzy logic in the disease forecasting system. The authors claimed that the designed system utilizing fuzzy logic reduced the complex mathematical computation to estimate the leaf wetness duration, LWD, a variable used in determining the likelihood of corn plants having rust disease. The output of the program showed the prediction of the probability of the occurrence of rust disease which can be used to assist corn farmers to perform diagnosis on their crops.

RESEARCH FRAMEWORK

The framework of the research is shown in Figure-1; the images were taken from Oil Palm database [2]. The system proposed the processing of image samples of oil palm leaflets that were equally divided from 120 samples which represent the healthy leaflets and deficient leaflets from nitrogen, potassium and magnesium categories. The processing stage involved resizing, filter, shadow removal and segmentation of the image data. This was conducted to enhance the quality of oil palm leaflet image in order to obtain the most suitable feature extraction parameters. Prior to input onto the fuzzy system, the images were preprocessed from the raw captured images and then its essential features were extracted namely the number of red pixels, entropy and correlation. These features were utilized as crisp input variables in FIS model.

In general, FIS derives from the concept of Fuzzy logic theory that relates to several classes of objects with unsharp boundaries and uses linguistic variables instead of numbers to represent the variables [9]. The process of formulating the mapping from a given input (in this case the extracted features from leaflet images) to an output using fuzzy logic or a system that used fuzzy set theory was used to map inputs to output known as healthy, nitrogen deficiency, potassium deficiency and magnesium deficiency. The design process of fuzzy inference involved membership function, fuzzy logic operators and if-then rules. There are two types of fuzzy inference systems in general namely the Mamdani and the Sugeno [13-18]. The model that was selected to categorize the nutrient deficiency is a Mamdani Fuzzy inference system (FIS). Mamdani inference system involves steps of determining a set of fuzzy rules and then fuzzifying the inputs using the input membership functions. After that, the fuzzified inputs will be combined according to the fuzzy rules to establish the rule strength. The consequence of the rule can be found by combining the rule strength and the output of membership function.

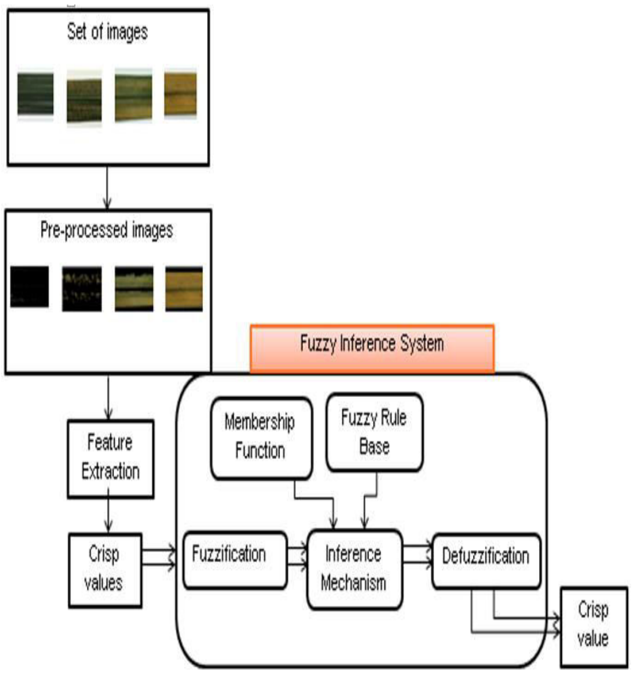


Figure-1. Framework of the research work.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

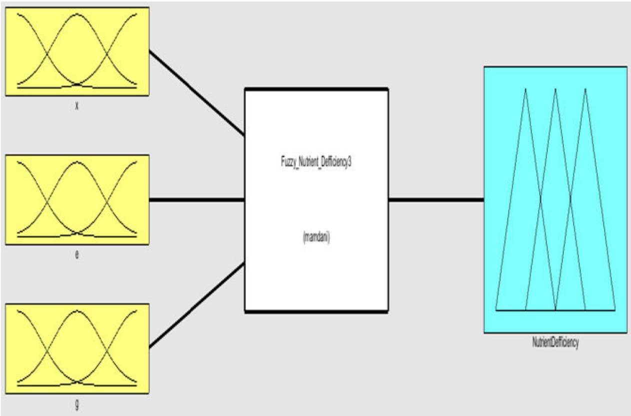
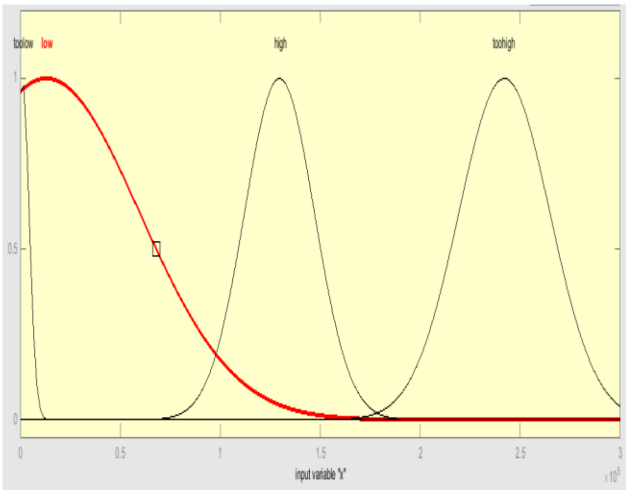
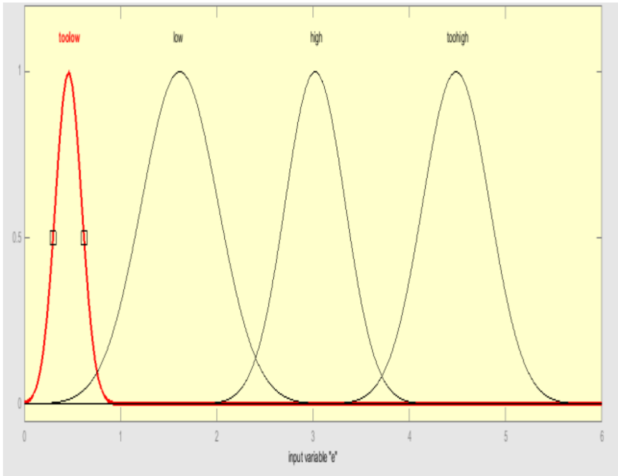


Figure-2. Fuzzy inference system editor.

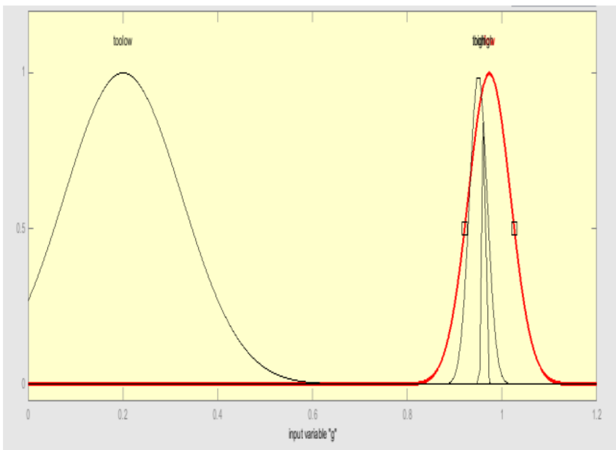
Figure-2 shows the FIS editor. The FIS editor displays general information about Fuzzy logic inference system containing the names of each input variable (x, e, and g) respectively represented as the number of red pixels, entropy, correlation and each output variable (nutrient deficiency). There were five parts of FIS process: fuzzification of the input variables, application of fuzzy operator in antecedent, implication from antecedent to the consequent, aggregation of the consequent across the rules and defuzzification. Figure-3 shows the input and output membership function editor used to display and assign membership function of input and output variables for the entire FIS. Among the available membership function such as piecewise linear functions, the Gaussian distribution function, the sigmoid curve and quadratic and cubic polynomial curve, the Gaussian curve (gaussmf) were chosen as to define each of input membership functions due to the smoothness and non-zero values. Each input variable contains four membership functions (too low, low, high and too high). The parameter range was set based on the median and the standard deviation of the collected oil palm leaflet data. For the output, the triangle curve (trimf) was chosen because the absolute output was needed for this FIS. The output variable also contains four membership functions, namely Potassium (K), Nitrogen (N), Magnesium (Mg) and Fresh. The parameters were set based on the knowledge and experience of an agricultural expert. Refer to Table-1 in which the value range can be varied.



(a)



(b)



(c)

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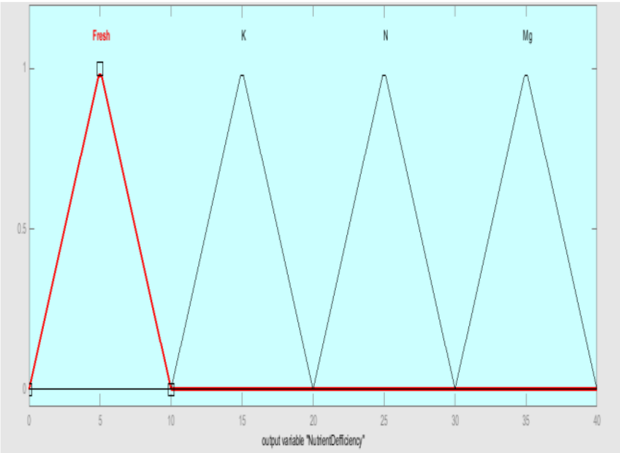

(d)

Figure-3. Membership functions for input and output variables(a) Input x, number of red pixels, (b) Input e, entropy, (c) Input g, correlation and (d) Output, type of nutrient deficiency.

Table-1. Details for all linguistic variables.

Variable types	Linguistic variables	Ranges interval
Input 1	too low	[3396 987.1]
	Low	[4.667x 10^4 1.302e^{+04}]
	High	[1.749 x 10^4 1.296e^{+05}]
	too high	[2.278 x 10^4 2.42e^{+05}]
Input 2	too low	[0.1367 0.4589]
	Low	[0.3966 1.614]
	High	[0.3111 3.021]
	too high	[0.3463 4.485]
Input 3	too low	[0.1236 0.2004]
	Low	[0.04451 0.9735]
	High	[0.01855 0.95]
	too high	[0.00351 0.9621]
Output	Fresh	[0 5 10]
	Potassium	[10 15 20]
	Nitrogen	[20 25 30]
	Magnesium	[30 35 40]

Then, the fuzzy rules were developed to describe how the fuzzy inference system makes a decision to classify the nutrient deficiency using if-then conditions. The if-part of the rule is called antecedent or premise, while the then-part of the rule is called consequent or conclusion. Statement in antecedent parts of the rules may well involve fuzzy logical operators such as 'AND' and 'OR'[10]. Sixteen (16) relevant rules were selected to satisfy the classification of deficiencies as demonstrated in following:

Rule 1	If x is LOW and e is LOW and g is LOW then NutrientDeficiency is K
Rule 2	If x is HIGH and e is HIGH and g is HIGH then NutrientDeficiency is Mg
Rule 3	If x is TOOHIGH and e is TOOHIGH and g is TOOHIGH then NutrientDeficiency is N
Rule 4	If x is TOOLOW and e is TOOLOW and g is TOOLOW then NutrientDeficiency is Fresh
Rule 5	If x is LOW or e is LOW then NutrientDeficiency is K
Rule 6	If x is TOOHIGH or e is TOOHIGH then Nutrient Deficiency is N
Rule 7	If x is HIGH or e is HIGH then NutrientDeficiency is Mg
Rule 8	If x is LOW or g is LOW then NutrientDeficiency is K
Rule 9	If x is HIGH or g is HIGH then NutrientDeficiency is Mg
Rule 10	If x is TOOHIGH or g is TOOHIGH then NutrientDeficiency is N
Rule 11	If e is TOOHIGH or g is TOOHIGH then NutrientDeficiency is N
Rule 12	If e is HIGH or g is HIGH then NutrientDeficiency is Mg
Rule 13	If e is LOW or g is LOW then NutrientDeficiency is K
Rule 14	If x is TOOLOW or e is TOOLOW then NutrientDeficiency is Fresh
Rule 15	If x is TOOLOW or g is TOOLOW then NutrientDeficiency is Fresh
Rule 16	If e is TOOLOW or g is TOOLOW then NutrientDeficiency is Fresh

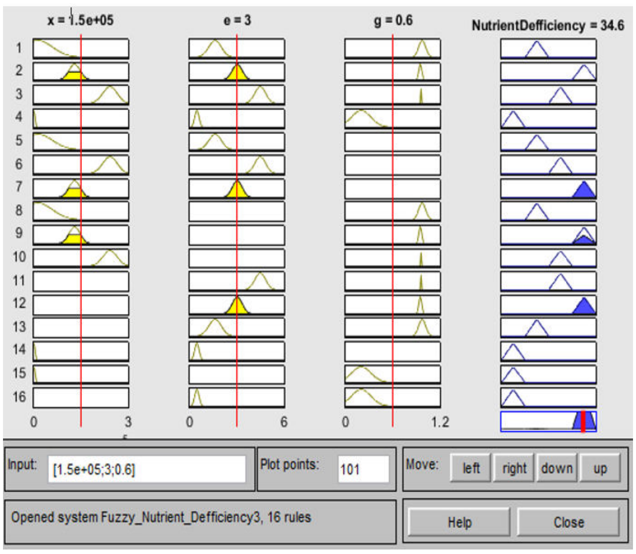

Figure-4. Rule viewer.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Figure-4 shows the rule structure that had been set in this FIS. This rule viewer works to assess individual output values which resulted from if-then conditions that have been previously developed. The surface of the fuzzy set can be seen after the rules have been established. Figure-5 demonstrates the surface view for this fuzzy set. It has three surface view for this fuzzy set, (a) for x and e, (b) for x and g, and (c) for e and g. Finally, the final steps in the design process was to defuzzify the fuzzy set in order to obtain the crisp value to be interpreted as the result of nutrient deficiency symptoms. In general, there are five built-in defuzzification methods supported: centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum and smallest of maximum. However, in this work, centroid defuzzification [11] was selected to calculate the center of gravity for aggregation where z' is a crisp value for z output and$\mu_A(z)$ is an aggregated output membership function.

$$\text{Centroid}, z' = \frac{\int z.\mu_A(z)dz}{\int .\mu_A(z)dz} \text{ x } 100\% \quad (1)$$

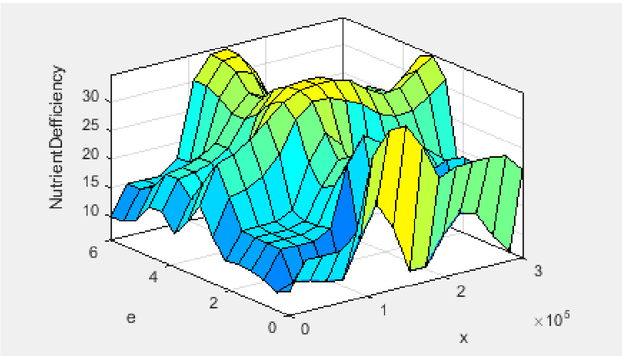

Figure-5a. .input x and e.

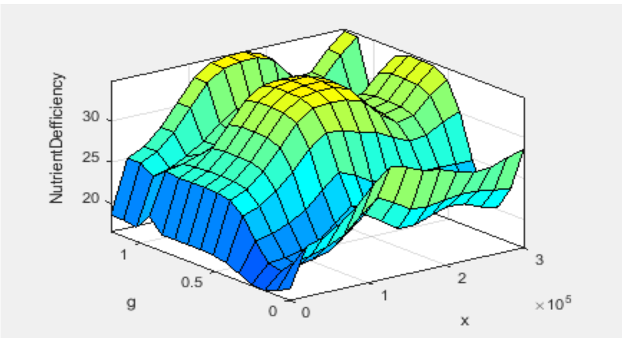

Figure-5b. .input x and g.

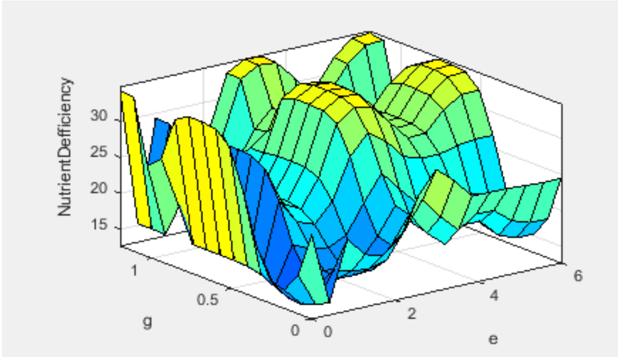

Figure-5c. .input e and g.

RESULTS AND DISCUSSIONS

The output obtained from pre-processed leaflet images will be used as the input for modeling the fuzzy system. The membership function of the input was categorized as too low, low, high and too high. Too low was used to show the membership function for fresh leaves, low was for leaves that lack of potassium, high for leaves that lack of magnesium and too high was for leaves that lack of nitrogen. For each input parameter, the range was set based on the median and the standard deviation of the data collected while the output parameters were designed accordingly to an interval range shown in Table-1.

In order to determine that the diagnosis can be used to represent judgment made by the experts, the evaluation to measure [12] on accuracy (acc) and other statistical measures such as sensitivity (sens), positive predictive value (ppv) and negative predictive value (npv) have been calculated and compared. These evaluations of the performance were utilized to determine the effectiveness of the proposed FIS model. The performance measure includes TP, TN, FP and FN respectively to denote a true nutrient deficiency element as correctly identified, a nutrient deficiency element cannot be identified and correctly classified, a nutrient deficiency element cannot be identified and incorrectly classified and nutrient deficiency element is identified but incorrectly marked as not deficient. The formula of performance measures indicates as follows:

$$\text{Acc} = \frac{TP+TN}{TP+TN+FP+FN} \text{ x } 100\% \quad (2)$$

$$\text{Sens} = \frac{TP}{TP+FN} \text{ x } 100\% \quad (3)$$

$$\text{PPV} = \frac{TP}{TP+FP} \text{ x } 100\% \quad (4)$$

$$\text{NPV} = \frac{TN}{TN+FN} \text{ x } 100\% \quad (5)$$

The calculated measure of accuracy, sensitivity, PPV and NPV are presented in Table-2. Accuracy was used to indicate how accurately the deficiencies being correctly classified. In this research the FIS was able to achieve high accuracy in detecting and classifying the deficiency categories into potassium, magnesium, nitrogen and healthy leaflet respectively as 98.33%, 88.33%,

VOL. 12, NO. 10, MAY 2017 ISSN 1819-6608
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88.33% and 98.33%. Sensitivity is a parameter that was used as a tool to measure how sensitive the deficiencies can be identified correctly based on the specific deficiencies. The FIS developed in this paper indicated a high sensitivity of recognizing potassium deficient, nitrogen deficient and healthy leaves up to 100%. In contrast, the detection program showed insensitivity towards diagnosing leaflets with magnesium deficiencies which was found to be 53.33% due to misinterpretation during processing and discriminating between magnesium deficiency and healthy leaflet. Another measure parameter was PPV which indicates how well the actual deficiencies can be classified correctly. In this case almost all types of leaflet reached a high value of detection, above 90% to be correctly classified except for nitrogen deficiency that suffers from low PPV measurement. Referring to another measure is NPV, which represents how accurately the false deficiencies being identified as a truly false detection. In all disease categories, the FIS demonstrated high NPV result that confirmed the detected deficiencies as correctly being assigned to correct leaflet type. In summary, based on the statistical analysis of the diagnosis results confirmed that the designed FIS model could reliably classify the potassium deficiency and nitrogen deficiency correctly. The most difficult diagnosis was to differentiate between magnesium deficiency and healthy leaflet in which 2% of healthy leaflets were incorrectly diagnosed as magnesium deficiency due to misinterpretation of roughly similar pattern appearance shown by both leaflets. Furthermore, linear regression analysis has been evaluated to measure the relationship between the actual measured and predicted data of correctly classifying the nutrient deficiencies. From Figure-6, the correlation coefficient is 0.90343 or 90.34% of confidence that the measured and predicted classification outcome was correctly conformed to each other. From the linear regression, the predicted classification data can be used to approximate actual classification measurement outcome with high level of accuracy.

Table-2. Statistical performance measure.

Measures	K	Mg	N	Healthy
TP	28	16	30	30
TN	90	90	76	88
FP	2	0	14	2
FN	0	14	0	0
Acc	98.33	88.33	88.33	98.33
Sens	100	53.33	100	100
PPV	93.33	100	68.18	93.75

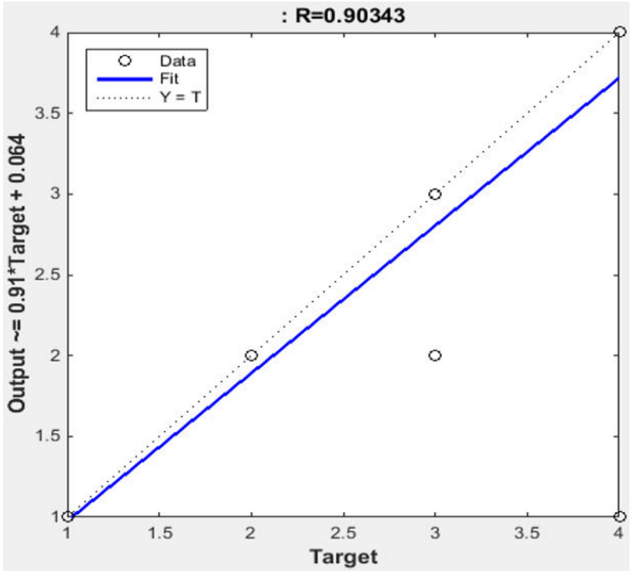

Figure-6. Linear regression analysis.

CONCLUSIONS

The fuzzy inference system has been developed which includes fuzzy variables to be able to detect and classify diseases based on the nutrient deficiencies. The input of the fuzzy system is from the extracted features of oil palm leaflets images, which are the number of red pixels, entropy and correlation. The main objective is to develop a new FIS that could classify the nutrient deficiency of oil palm trees that are also able to produce good accuracy and measured performance. This proposed FIS is the principal work in which fuzzy logic is implemented to diagnose the oil palm nutrient deficiency symptoms. In short, the features extraction information are fuzzified, generate if-then fuzzy rules and finally infers the appropriate deficiencies based on the developed fuzzy rules. Simulated experiment conducted has demonstrated that the proposed FIS successfully recognize the different type of oil palm leaflets that suffered from nutrient deficiencies at 82.67%. With the validation tools calculated using statistical analysis theory; this indicated that the developed FIS has high reliability and accuracy in correctly classifying the nutrient deficiencies of oil palm leaflets.

ACKNOWLEDGEMENT

The authors highly acknowledge the fullest and continuous support through the awarded grant under Ministry of Higher Education (MOHE) and Universiti Teknologi MARA, Pasir Gudang, Johor for the Research Acculturation Grant Scheme (RAGS) no. 600-RMI-RAGS 5/3(188/2014).

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