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An Adaptive Neuro Fuzzy Inference System for the Diagnosis of Malaria

Osubor, V.I. and Chiemeke, S.C.
Department of Computer Science, Faculty of Physical Sciences
University of Benin, Benin City. NIGERIA

Abstract

Malaria is one of African most silent killer diseases. It is caused by different plasmodium species and the most deadly of them is the plasmodium falciprum. Early detection is one of the keys for diagnosing malaria using the symptoms. In this paper, an Adaptive Neuro Fuzzy Inference System (ANFIS) was developed for the diagnosis of malaria. The system was designed to use the triangular membership function and implements back propagation technique and least square mean as its learning algorithm. It uses the tagaki sugeno fuzzy inference model in providing the rules base of the system. The outcome of the system gave an accuracy of 98% in the classification of malaria patients.

Keyword: Malaria, ANFIS, Fuzzy Inference System

Introduction

Malaria is among the life threatening febrile diseases in developing countries. It is a parasitic disease transmitted by a human-to-human vector called Anopheles mosquito and causes high fever, shaking chills, flu-like symptoms and anaemia. It remains the most complex and overwhelming health problem, facing humanity in vast majority of tropical and sub-tropical regions of the world, with 300 to 500 million cases and 2 to 3 million deaths per year in Saharan Africa[1]. This is because majority of infections are caused by *plasmodium falciparum,* the most dangerous of the four human malaria parasites (*P.falciparum, P.ovale, P.vivax, P.malariae),* accounting for an estimate of 1.4 to 2.6 million deaths per year in this region[2, 3]. In addition, the most effective malaria vector, *Anopheles gambiae* is the most wide spread in the region and the most difficult to control[2].

Malaria is diagnosed conventionally using a combination of clinical observations, case history and diagnostic tests. The classic and most commonly used diagnostic test for malaria is the blood smear on a microscope slide that is stained (Giemsa stain) to show the parasites inside red blood cells[4]. Although this test is easily done, correct results are dependent on the technical skill of the laboratory technician, who prepares and examines the slides with a microscope. Reliance on this method have numerous flaws such as prone to human error, limited access of health professional/expert by the growing population and lack of effective retrieval processes. Therefore, the search for innovative systems using the gains of specialised algorithm for handling decision making is very paramount

The number of amazing and innovative intelligent systems for accurate medical predictions of state of human health have increased tremendously in recent times as a result of the application of Artificial Intelligence Techniques (AITs) such as Fuzzy logic, Neural Network, Expert System, Genetic Algorithms e.t.c in health care practices. Artificial intelligent prediction is based on human-like learning ability in pattern recognition better known as Machine Learning[5-10]. Since medical decisions are very complex and uncertain, the use of AITs has helped in development of intelligent health care system[11]. Therefore, this paper proposed an Adaptive Neuro Fuzzy Inference System in the diagnosis of malaria. The proposed system is a machine learning technique that comprises of neural network and fuzzy logic. It has advantage of combining the computational power of neural network and the explanatory power of fuzzy inference system making it a powerful hybrid system. It is also capable of learning new patterns of malaria symptoms making it more suitable and better than a rule based system.

Review of Related Literatures

Several literatures revealed that the accuracy of conventional diagnosis of malaria depends on the medical expertise of the health care provider performing the tests which are greatly influenced by human error, delay, and poor medical services especially in rural areas. Prompt and accurate diagnosing of malaria can avert millions of death cases. DeMellon and Wootton[12] highlighted the need for timely and accurate diagnosing of malaria. This necessity has led earlier researchers to work on developing automated system to assist in malaria diagnosis. Tohal and Ngah[13] presented integration of soft computing tools which has been successfully designed with capability to improve the image quality, analyze and classify the image as well as the number of malaria parasites to aid diagnosis in Malaysia where the conventional method is time consuming and prone to errors. This is expensive and cannot handle more than one specific disease at a time. In the work of Obot and Uzoka[14], a fuzzy rule based system was used for diagnosing tropical disease which are malaria, typhoid, tuberculosis, STD and chicken pox and the fuzzy logic system was used to determine the degree of cruelty of the diseases. A major shortcoming of their paper was that they did not state with a degree of certainty which

Corresponding Author's Email: viosubor@yahoo.com

disease was diagnosed and there is no assurance level between diagnoses. Lala et al,[15] proposed a Decision Support System (DSS) with a case based reasoning for diagnosis of malaria. However, one of the major short comings was that there was no clear and precise way of distinguishing malaria from typhoid. Donfack et al.[16] proposed Online System for Diagnosis and Treatment of Malaria (OSFDATOM). It is a web-based expert system designed for diagnosis of Malaria. Djam and colleagues.[17] presented Fuzzy Expert System for the Management of Malaria (FESMM) for providing decision support platform to malaria researchers, physicians and other healthcare practitioners in malaria endemic regions. Adetunmbi et al.[18] used machine learning technique, rough set on labelled sets of malaria fever symptoms collected to generate explainable rules for each level of severity and appropriate therapy is provided. Ugwu and others[19] explored the potential of machine learning techniques (decision tree) in the development of algorithm for malaria. Duodu et al.[20] designed an algorithm for malaria diagnosis using Fuzzy logic for treatment. They purported that using fuzzy logic in medical diagnosis yield better result than the presumptive medical doctors' diagnosis. In the work of Oladele and colleagues.[21], a Coactive Neuro Fuzzy Expert System (CANFES) was used in the diagnosing of malaria. It captured all the basic features of neural network and fuzzy logic. CANFES model combines Backward Propagation (BP) and Kohonen Self Organising Feature Map (KSOFM) which is an unsupervised learning algorithm. The major deficiency of the paper is the use of an unsupervised learning algorithm because with an unsupervised learning we have no way of knowing what the "right answer" is.

Model of the Proposed Anfis System for Malaria

The first step of any medical diagnostic process is the examination of patient by a physician. A set of complaints and physiologic symptoms are collected as pre-hospital data. These symptoms are represented using crisp values such as either symbolic or binary digit. These crisp value are captured as input data via the Graphic User Interface (GUI) and are fed into the Knowledge Base (KB) component. The result from KB are further analysed by the Decision Support Engine (DSE) component. Figure 1 shows the proposed Adaptive Neuro-Fuzzy System (ANFIS) for malaria diagnosis and figure 2 depict the structure of ANFIS for malaria diagnosis.

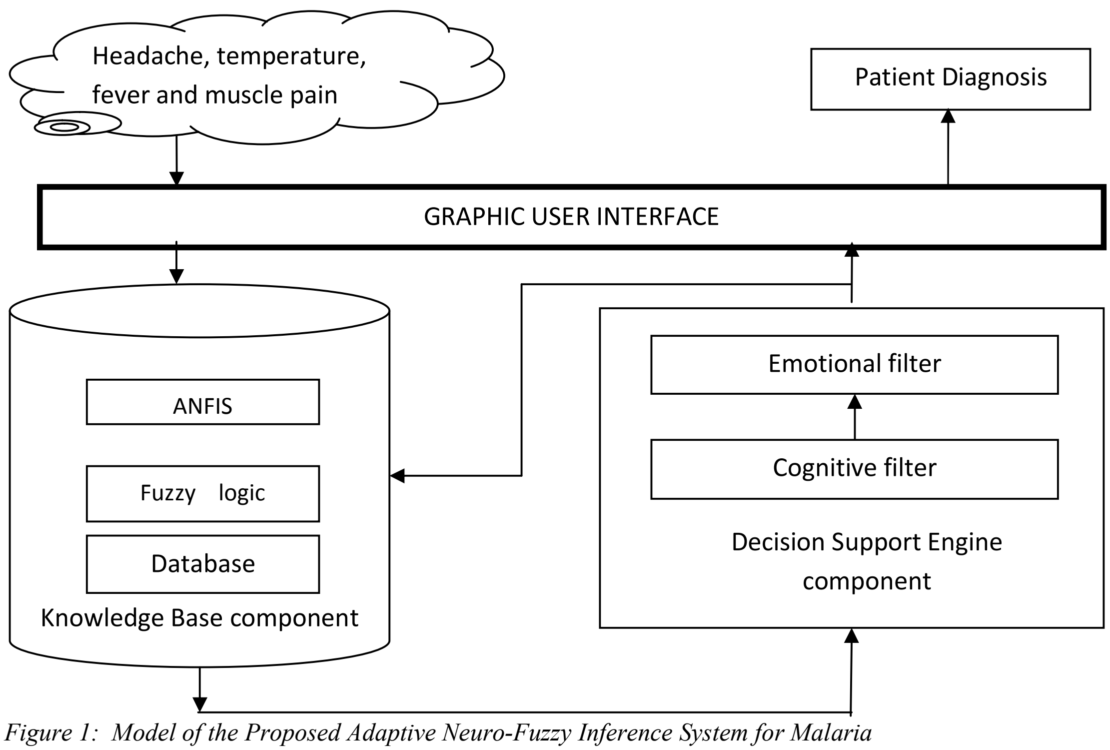

Figure 1: Model of the Proposed Adaptive Neuro-Fuzzy Inference System for Malaria

The KB component consists of ANFIS, Fuzzy Logic and Database. Symptoms of users are passed into the ANFIS section which performs mathematical calculations and passed to the fuzzy logic layer which maps the symptoms as either low, medium or high. The knowledge base contains all the necessary fuzzy rules and information for diagnosing malaria. The information is then passed to the DSE component where the fuzzified results are further processed by emotional and cognitive filter to provide decisions that best suit the diagnosis. The result of diagnosis is then outputted using the user interface to the patient. Symptoms attribute for diagnosis of malaria include: Temperature(T), Headache(H), Fatigue(F), Muscle Pain(MP)

Adaptive Neuro Fuzzy Inference System (ANFIS) Component: The expert system for diagnosing malaria is built using the ANFIS which is a hybrid of the Neural Network (NN) and the Fuzzy Logic (FL). It combines the learning capabilities of NN and the explanatory capabilities of FL. Fuzzy logic handles uncertainty associated with the diagnosis of malaria while NN does the mathematical computation. The ANFIS uses the Tagaki-Sugeno fuzzy inference system and it is a six layer network. In the cause of this experiment, the triangular membership function was used for the fuzzy inference engine. The input fed into the system is the symptoms of malaria which is temperature (T), Headache (H), Fatigue (F), and Muscle pain (MP) representing x_1 to x_4. Figure 2 shows a typical ANFIS Structure.

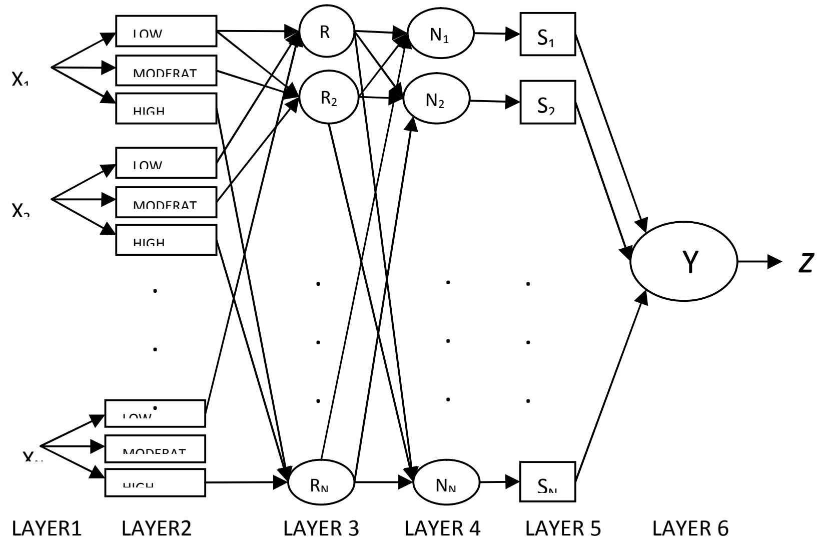

Figure 2: ANFIS Structure for Diagnosis of Malaria

Layer 1: This layer consists of input nodes labelled X_1 to X_4. This node denotes the symptoms of malaria and they hold values fed into the system which are T, H, F and MP.

Layer 2: This layer is called the membership function layer. The membership function used in this layer is the triangular membership function and was adopted because of its ease of use. The function of each node in this layer is to map the input into this layer which is the output of layer 1(input layer) to the linguistic variable (low, medium, high).

$$f(x\colon a,b,c) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \tag{1}$$

Where a,b,c are called premise parameters

Layer 3: This layer is called the rule layer. The nodes in this layer are fixed and labelled R_1 to R_{81} they receive input from the membership function layer and calculates the firing strength of each rule node.

$$f_{3=}\ \mu Ai(x)^*\ \mu Bi(x)^*\ \mu Ci(x)^*\ \mu Di(x) \tag{2}$$

Example of a rule in this layer is;
If (T is low) and (H is low) and (F is low) and (MP is low) then output is *f*

Layer 4: This is the normalization layer and made up of fixed nodes labelled N_1 to $N_{81.}$ Each node in this layer receives input from the rule layer and computes the ratio of the rule's firing strength to the sum of all the rules firing strength.

$$f_4 = \frac{R_1}{R_1+R_2+,\dots,+R_n} \tag{3}$$

Or

$$f_4 = \frac{R_k}{\sum_{j=1}^{n} R_j} \tag{4}$$

Where R_1, R_2, ..., R_{81} are the output of layer 3 while f_4 is the output of layer 4

Layer 5: This layer is made up of fixed node and is labelled S_1 to $S_{81.}$ The node in this layer receives its input from the fourth layer and also the input value from the first layer called the consequent parameters which is denoted $R_{out}(X_i)$

$$f_5 = f_4(X_i) * R_{out}(X_i) \quad (5)$$

Layer 6: This layer is called the output layer. It consists of a single fixed node labelled Y which sums all the incoming signals and produces the output of the ANFIS system.

$$f_6 = \sum_{i=1}^{n} f_4(Xi) = \sum_{i=1}^{n} \left(f_4(Xi) * Rout(Xi)\right) \quad (6)$$

The final output of the ANFIS system represents the diagnosis of a patient and is classified either as low, medium or high.

$$output(Y) = \begin{cases} Low if Y \leq 0.30 \\ Moderate if 0.31 \leq Y \leq 0.70 \\ High if 0.71 \leq Y \leq 1.00 \end{cases} \quad (7)$$

Fuzzy Logic Component: The Fuzzy Logic (FL) component shown in Figure 3 contains the Fuzzification, Defuzzification and Fuzzy Inference Engine components.

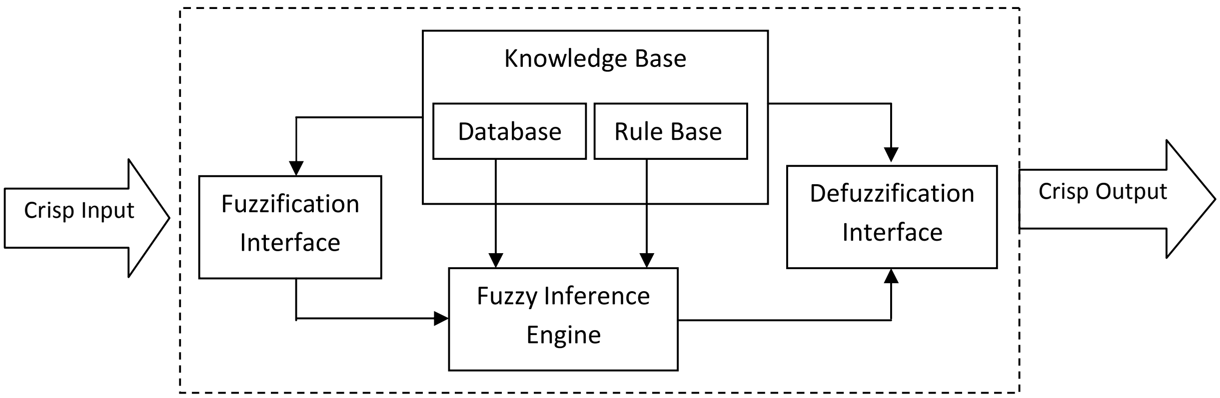

Figure 3: Fuzzy Logic Component

The fuzzification component converts the crisp input into fuzzy value and this value is mapped with the triangular Membership Function (MF) using the formulae represented in equation (1)

Now Suppose f is a fuzzy set of diagnosis variables in *F (*Universe of Discourse) and x_i represents an element in *f*, the fuzzy set *f is expressed as:*

$$f = \left\{\left(x_i \mu_f(x_i)\right) \vee x_i \in F, \mu_f(x_i) \in [0,1]\right\} \quad (8)$$

$$\mu_f : F \to M_f \quad (9)$$

where $\mu_f(x_i)$ is the membership function of x_i in *f* which represents the degree that the value *x* belongs to the fuzzy set *f* which represents contribution of x_i towards the outcome of the diagnosis of malaria M_f is the membership space where each element of *F* is mapped to.
F contains all the symptoms and M_f contains the linguistic variables to which the elements (symptoms) in F is mapped to and each linguistic variable has a value associated with it. The Linguistic Variable (LV)| of an ith diagnostic variable is shown in equation (10)

$$output(Y) = \begin{cases} Low if xi = 0.30 \\ Moderate if xi = 0.70 \\ High if xi = 1.00 \end{cases} \quad (10)$$

Where LVi represents the Linguistic Variable for i[th] diagnosis variable, i=1 to 4.
x_i denotes the value of the i[th] diagnosis variable.
Figure 4 shows the membership function graph for each diagnostic variable with Linguistic Variables (VL) low, medium and high

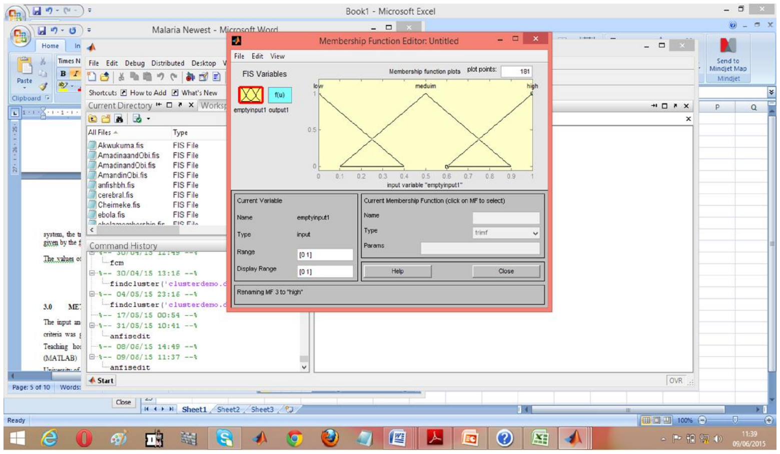

Figure 4: Membership function graph for symptoms

The fuzzy inference engine interacts with the knowledge base. The knowledge base component as depicted in figure 3 above contains a database and a rule base component. In designing the knowledge base component the knowledge of medical experts were employed in the diagnosis of malaria which are represented with a series of 120 rule in the rule base using an "IF THEN" construct similar to Tagaki-Sugeno model. The rule base contains rules assuming this format
If (T is "low") and (H is "low") and (F is "low") and (MP is" low") then diagnosis is *low*
Where T, H, F and MP are diagnostic variables.
The de-fuzzification component converts the fuzzy values into crisp values

Methodology:

The input and output data to the system which are the attributes for diagnosis of malaria and classification criteria were gotten from series of consultations with medical experts (especially those in University of Benin Teaching Hospital, Benin City) and standard literatures in tropical medicine field. Table 1 shows a snapshot of the input data

Table 1: Dataset of 20 patients

PATIENT ID	X1	X2	X3	X4
UBTH 001	0.07593	0.85794	0.88941	0.81502
UBTH 002	0.79897	0.23905	0.84153	0.42721
UBTH 003	0.06502	0.25792	0.008	0.23107
UBTH 004	0.27146	0.75374	0.41677	0.39906
UBTH 005	0.35665	0.74553	0.70096	0.75648
UBTH 006	0.7963	0.64523	0.14458	0.46243
UBTH 007	0.49544	0.9464	0.3447	0.9841
UBTH 008	0.35112	0.2165	0.90136	0.28638
UBTH 009	0.44334	0.52009	0.78715	0.81441
UBTH 010	0.41925	0.32647	0.64732	0.60981
UBTH 011	0.23859	0.09126	0.59844	0.66711
UBTH 012	0.33682	0.47236	0.07769	0.74284
UBTH 013	0.29491	0.70927	0.16605	0.68294
UBTH 014	0.59428	0.19751	0.94468	0.89225
UBTH 015	0.11057	0.06881	0.53296	0.3849
UBTH 016	0.22783	0.54679	0.70027	0.37824
UBTH 017	0.98533	0.9077	0.18924	0.57001
UBTH 018	0.98207	0.47112	0.79139	0.90411

UBTH 019	0.11227	0.93827	0.11979	0.04707
UBTH 020	0.12811	0.58316	0.97056	0.65767

Source: University of Benin Teaching Hospital

Where X1, X2, X3 and X4 represents the symptoms of malaria (Temperature, Headache, Fatigue, Muscle Pain) These crisp inputs are captured via the GUI designed using Matrix Laboratory (MATLAB) version 7.5.0 (R2007b). The diagnostic outcome of the patients is shown in table 2 based on the diagnostic criteria and the various level of intensity while figure 5 shows the plots of the level of intensity against diagnostic level with respect to malaria.

Table 2: Patient Diagnostic Result

PATIENT ID	DIAGNOSIS STATUS	LEVEL OF INTENSITY
UBTH 001	HIGH	88
UBTH 002	MEDIUM	62
UBTH 003	MEDIUM	66
UBTH 004	MEDIUM	49
UBTH 005	MEDIUM	53
UBTH 006	MEDIUM	54
UBTH 007	LOW	25
UBTH 008	MEDIUM	49
UBTH 009	HIGH	76
UBTH 010	MEDUIM	35
UBTH 011	LOW	2
UBTH 012	MEDUIM	32
UBTH 013	MEDUIM	54
UBTH 014	MEDUIM	63
UBTH 015	MEDUIM	35
UBTH 016	MEDUIM	40
UBTH 017	MEDUIM	65
UBTH 018	HIGH	72
UBTH 019	MEDUIM	38
UBTH 020	HIGH	75

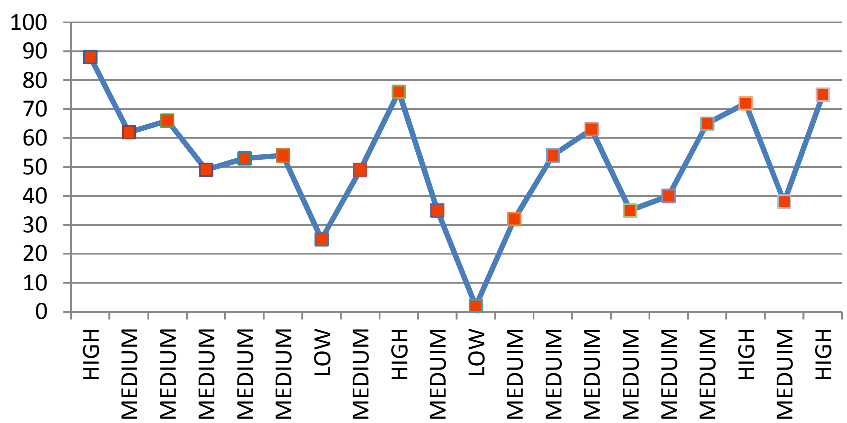

Figure 5: A Graph of Intensity Level of Malaria against Diagnostic Level

Results and Discussion

The dataset used in the ANFIS comprises of 120 cases. 50% (60) of the dataset was used to train the system and 25% (30) each was used in testing and checking. The dataset was scaled using the formulae in equation (11).

This ANFIS was designed with a triangular MF type and an error tolerance of 0.05 with a hybrid learning rule. Figures 6(a), 6(b) and 6(c) show the training, testing and checking of the dataset respectively

$$y' = \frac{y - y(min)}{y(max) - y(min)} \tag{11}$$

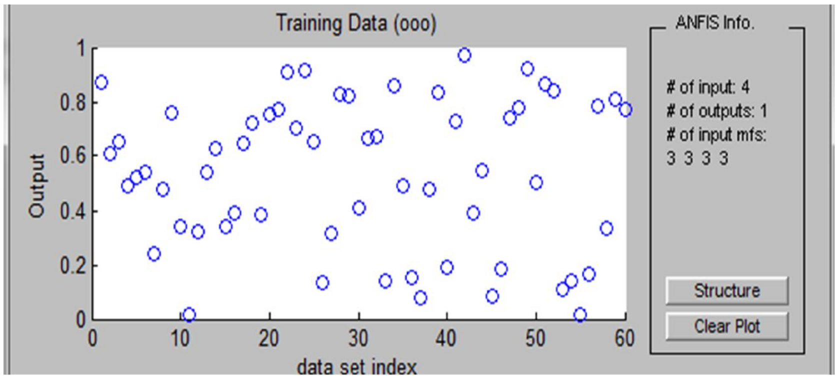

Figure 6(a). Shows the training dataset before training

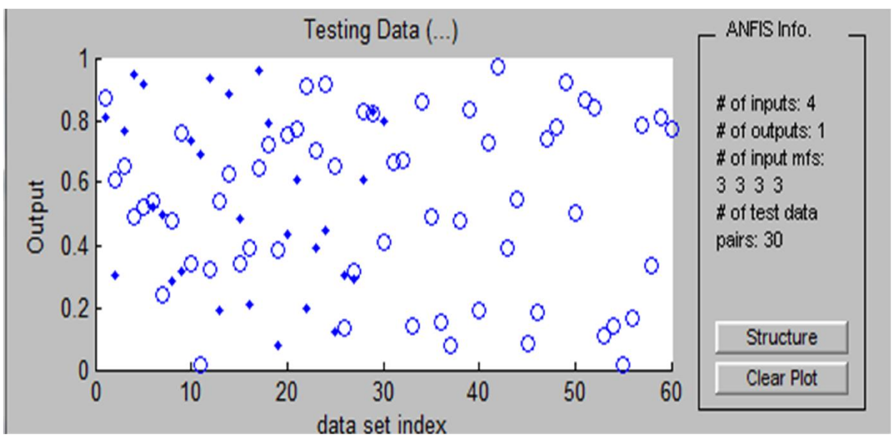

Figure 6(b) shows the testing and training dataset before training

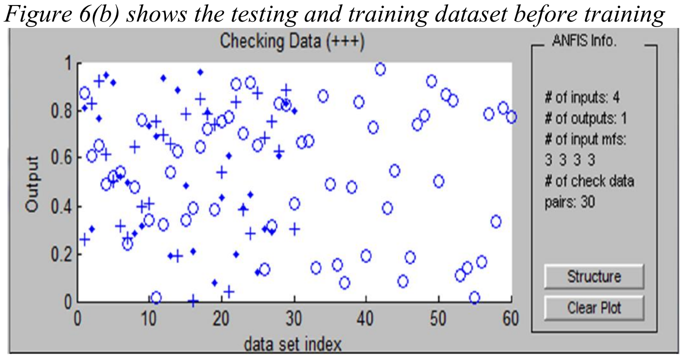

Figure 6(c) shows the checking dataset before training

The ANFIS architecture and the fuzzy inference engine is shown clearly on figures 7 and 8 respectively. Figure 7 shows how each layer in the ANFIS network are connected, Figure 8a shows how the symptoms are connected to the inference engine to give the diagnosis using the adaptive rules shown in figure 8b. At the end of training, the surface view that shows the relationship between the diagnostic variables to the diagnosis of malaria was generated (see Figures 9(a), 9(b), 9(c), 9(d))

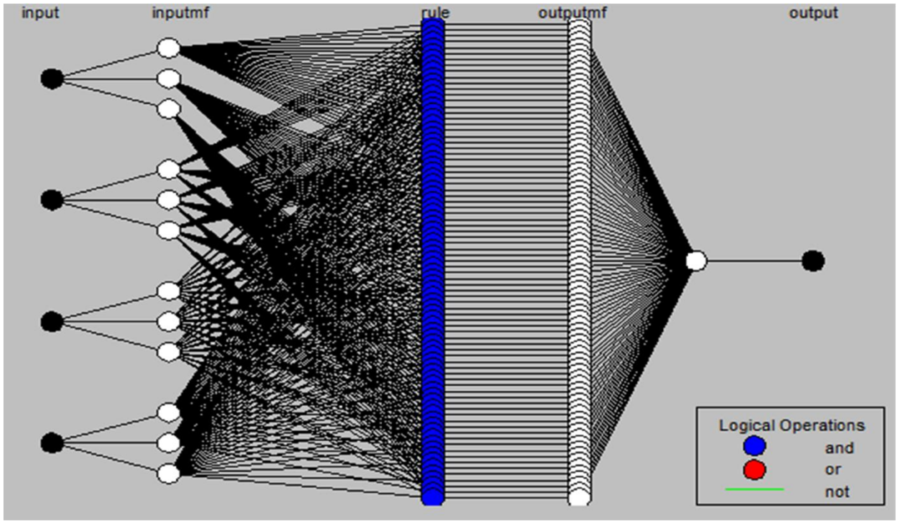

Figure 7: The ANFIS Architecture

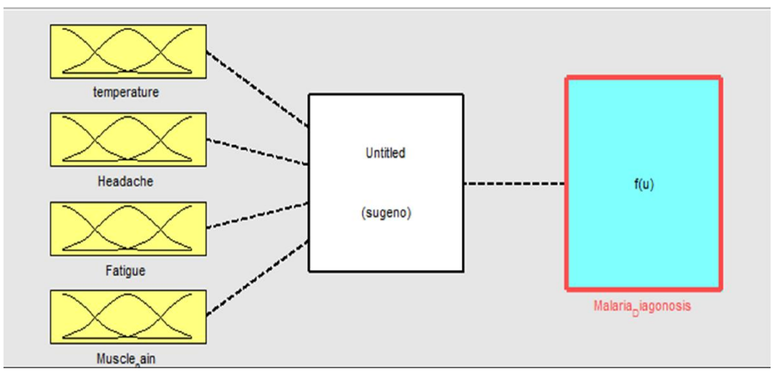

Figure 8a: The Fuzzy Inference Engine

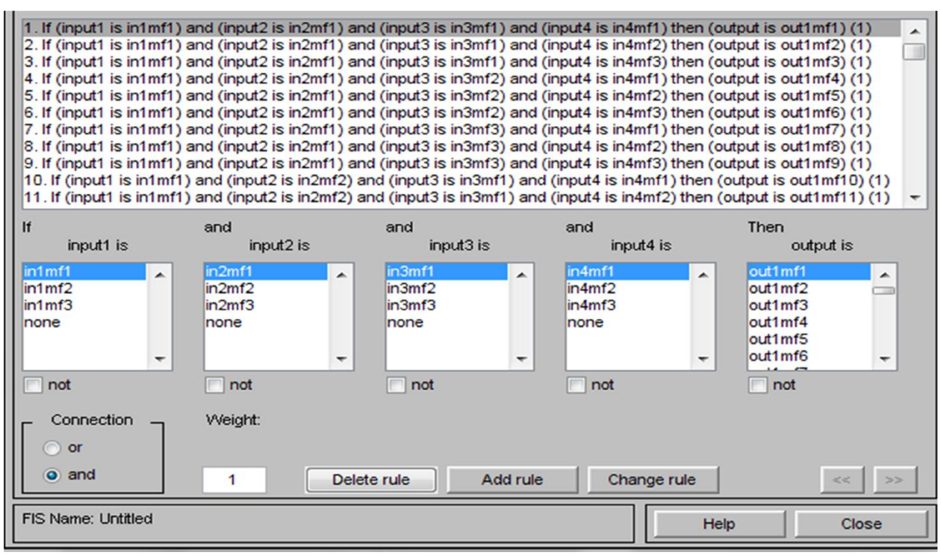

Figure 8b: FIS rules template

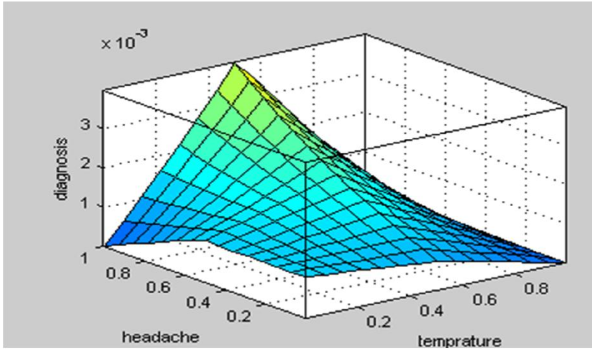

Figure 9(a)

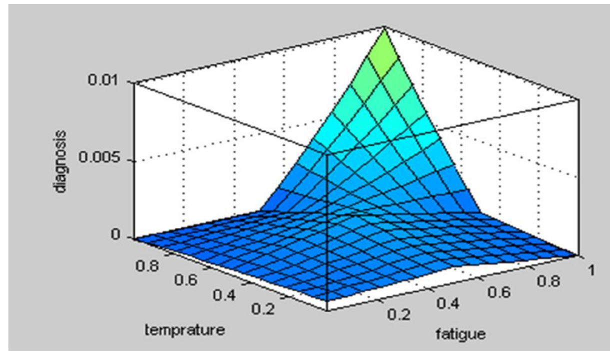

Figure 9(b)

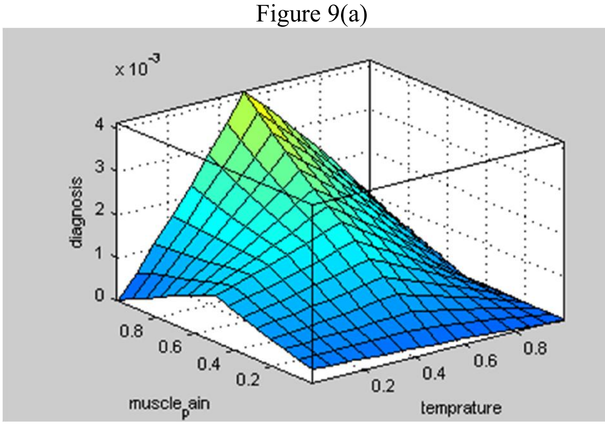

Figure 9(c)

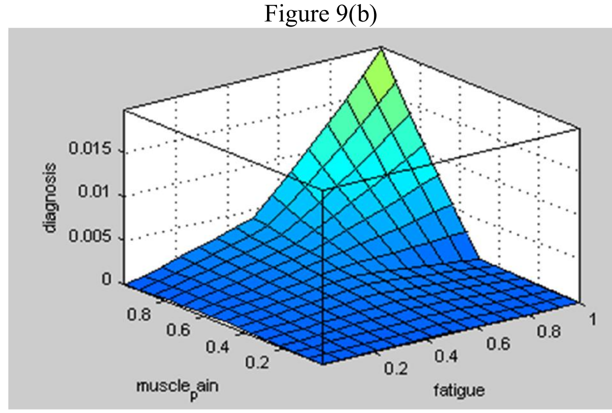

Figure 9(d)

Figure 9(a) shows the relationship between headache and temperature and to what degree the symptoms occur before a patient can be diagnosed with malaria. Figure 9(b) shows the relationship between fatigue and temperature and to what degree the symptoms occur before a patient can be diagnosed with malaria. Figure 9(c) shows the relationship between fatigue and muscle pain and to what degree the symptoms occur before a patient can be diagnosed with malaria Figure 9(d) shows the relationship between muscle pain and temperature and to what degree the symptoms occur before a patient can be diagnosed with malaria.

The result from the proposed ANFIS model indicated high accuracy of the prediction of malaria as shown in the training, testing and checking phase of the ANFIS (See figure 10a, 10b, and 10c respectively)

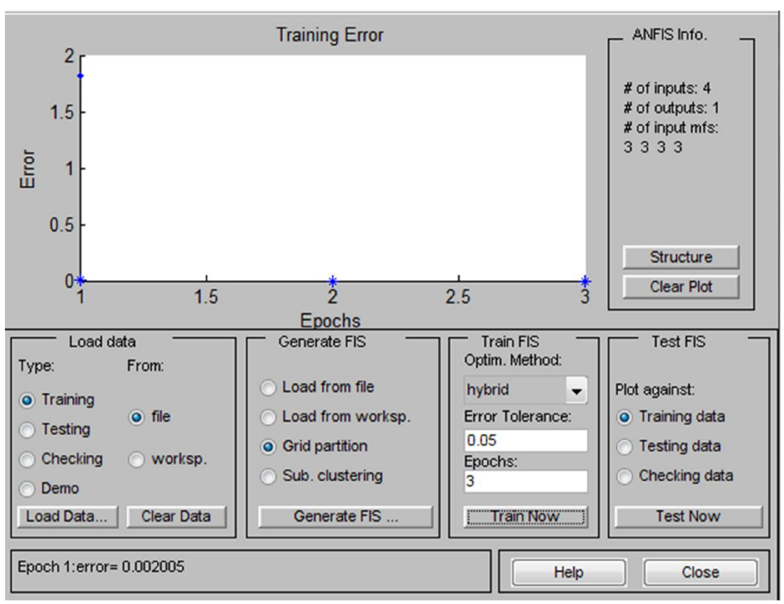

Figure 10a. Training epoch and error

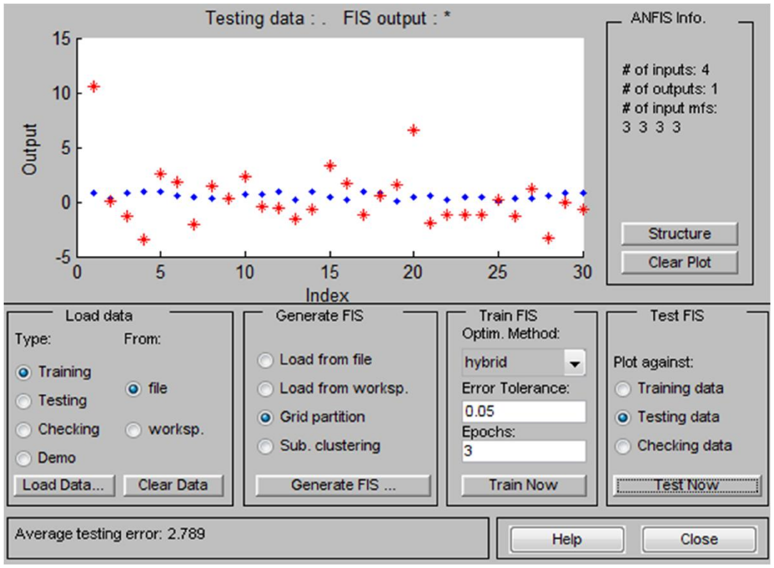

Figure 10b. Testing data vs FIS output

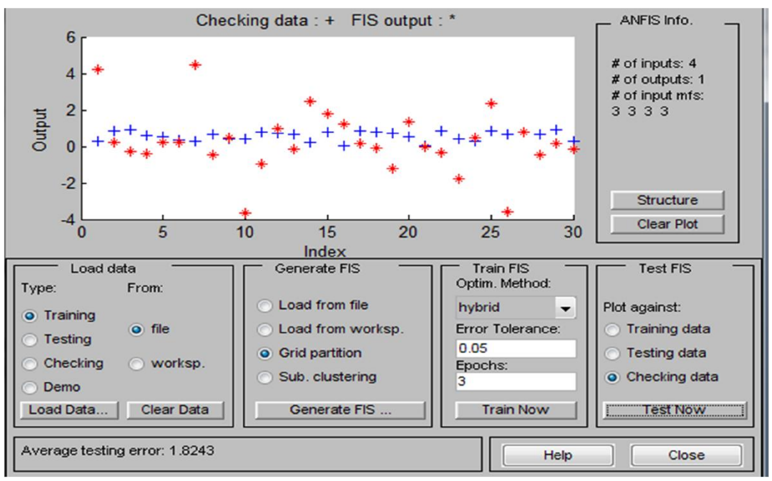

Figure 10c. checking data vs FIS output

The results from the experiment show that an average testing error of 2.78% was detected. This implies that the ANFIS was able to classify 97% of the test data. On check dataset, 98% accuracy was achieved with 1.8243 testing error. It was obvious that the ANFIS model proposed in this paper accurately diagnosed malaria using the set of symptoms.

Conclusion

Expert systems have been found to be very useful in our today's world driven by technology. Having a system with the knowledge of a specialist would be indispensable and such system could be replicated and made use of in times of necessity. The proposed Adaptive Neuro Fuzzy Inference System has shown to be an indispensable tool for diagnosing malaria with the system having an accuracy of 98%.

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