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CONTENTS

- 1-14 Importance of Participant Characteristics in Software Systems Design in the Informal Sector**
C. Chepken
School of Computing and Informatics, University of Nairobi, Nairobi, Kenya
- 15-26 A Novel Framework for Cloud Energy Metering System (CEMS) in Solar PV Plant**
O.U Oparaku, F.N.Ugwoke, K.C Okafor, C.C Udeze, I.O.Okeke,
Dept of Electronic Engineering, University of Nigeria, Nsukka.
- 27-32 Computationally Efficient Algorithm for computing Cumulative Grade Point Average of a Large Number of Students**
R.O. Akinola
Department of Mathematics, University of Jos, Jos, Plateau State, Nigeria
- 33-44 Comparative Analysis of Base Transceiver Station (BTS) and Power Transmission Lines Effects on the Human Body in Lagos Environs**
L.A Akinyemi, O.O Shoewu, N.T Makanjuola, A.A Ajasa, C.O Folorunso & F.O. Edeko
Department of Electronic and Computer Engineering, Lagos State University
Epe Campus, Epe, Lagos, Nigeria.
- 45-52 A Network-Based Key Exchange Cryptosystem Using Elgamal Algorithm**
Adewole K. S., Babatunde A. O., Abdulraheem M., Oniyide S. A.
Department of Computer Science, University of Ilorin, Ilorin, Nigeria.
- 53-66 Design Specification for Cloud Energy Metering System (CEMS):Models, Algorithms and Design Dimensions for Renewable Energy Grid**
K.C.Okafor, Ugwoke,F.N, C.C Udeze, I.O. Okeke, O.U. Oparaku
Dept of Electrical/Electronic Engineering, Federal University of Technology, Owerri,(FUTO), Nigeria.
- 67-70 Lyapunov-Like Functions: A Condition for Stabilizability of Non-Linear Systems.**
S. Aniaku
Department of mathematics
University of Nigeria Nsukka, Nigeria.
- 71-76 Towards Shared Understanding of Proof Beyond Reasonable Doubt**
A. O. Ameen , J.S. Sadiku & J.A. Gbadeyan
Department of Computer Science
University of Ilorin, Ilorin, Nigeria.
- 77-84 An Intelligent Financial Fraud Indication System Using Fuzzy Logic**
M. Danlami, A. M. Aibinu & O. M.Olaniyi
Computer Engineering Department
Federal University of Technology, Minna, Niger State, Nigeria
- 85-92 Design and Development of a Radio Frequency Identification (RFID) Based Library Books Security System.**
Akinyemi, L.A, Makanjuola, N.T, Shoewu, O. & Edeko, F.O.
Department of Electronic & Computer Engineering, Faculty of Engineering, Lagos State University, Epe Campus.
- 93-98 Power-Delay Product Minimization of Mixed Full Adder Topologies for High-Performance**
Nilesh Firake& Dr. Shyam Akashe
ITM University, Gwalior, India
- 99-106 Medical Diagnosis System Using Fuzzy Logic**
J.B. Awotunde, O.E. Matiluko & O.W. Fatai
Computer Science Department, Faculty of CIS, University of Ilorin, Ilorin, Nigeria.

- 107-110 Causes of Software/Information Technology Project Failures In Nigerian Software Development Organizations**
 F.A. Egbokhare
 Department of Computer Science, University of Benin, Benin City, Nigeria
- 111-128 Modeling the Influence of Information Technology (IT) Adoption Factors on the Electronic Voting (E-Voting) Technology Using Partial Least Squares-Structural Equation Model (PLS-SEM) Methods**
 I.R. Salimonu, W.R. Shiek Osman & A. J.K. Shittu,
 School of Computing, Universiti Utara Malaysia, Malaysia
- 129-134 Necessary Condition For Complete Controllability of Nonlinear Control Systems to be Stable Under Small Perturbations**
 S. Aniaku
 Department of mathematics
 University of Nigeria Nsukka, Nigeria.
- 135-142 An Enhanced Speech Recognition Algorithm Using Levinson-Durbin, DTW and Maximum Likelihood Classification**
 A.A. Adegun, Asani E.O. & M.M. Yusuff
 Computer Science Programme, Landmark University, Omu-Aran, Nigeria
- 143-150 Design and Analysis of Low Standby Leakage Current and Reduce Ground Bounce Noise of Static CMOS 10T Full Adder**
 Raghvendra Singh & Shyam Akashe
 ITM University, Gwalior, India
- 151-156 Design of an Expert System to Calculate Inheritance Shares Based on Islamic Law**
 Jimoh, R. G., Adebayo, I. R., A.O. Ameen & Ahmad, H. O.,
 Department Of Computer Science, Faculty Of Communication And Information Sciences, University Of Ilorin, Nigeria.
- 157-164 Modeling the Effect of Dropped Calls on Cell Traffic in Established 3G-Based Cellular Networks**
 M. Ekpenyong, J. Isabona
 Department of Computer Science University of Uyo, Uyo Nigeria
- 165-172 Design and Development of a Superheterodyne Frequency Modulation Radio Receiver Using TDA7000IC (88MHz – 108MHz)**
 L.A Akinyemi, O.O Shoewu, N.T Makanjuola, A.A Ajasa, C.O Folorunsho & F.O. Edeko
 Department of Electronic and Computer Engineering
 Lagos State University, Epe Campus, Epe, Lagos, Nigeria.
- 173-186 Coactive Neuro-Fuzzy Expert System: A Framework For Diagnosis of Malaria**
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Coactive Neuro-Fuzzy Expert System: A Framework for Diagnosis of Malaria

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ABSTRACT

Diagnosis is a crucial aspect in medical care. It entails both the process of examination and decision related to prognosis and interventions. In the traditional or conventional diagnosis of malaria, information is gathered from physical examinations, history, system reviews and selected tests. The goal of this paper is to demonstrate the practical applicability of Information and Communication Technology (ICT) for the diagnosis of malaria based on a set of symptoms. In this paper, a Coactive Neuro-Fuzzy Expert System model was developed for the diagnosis of malaria based on a set of symptoms. The architectural framework for the model was also presented. A hybrid learning algorithm comprising of both supervised learning (such as Back Propagation Network) and unsupervised learning (such as Kohonen Self Organizing Feature Map) were employed in order to enhance the adaptive capability of the expert system and make it handle fresh cases that have not been predefined in the knowledge base.

Keywords: Information and Communication Technology, Diagnosis, Expert System, Neuro-Fuzzy Modeling, Symptoms.

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1. INTRODUCTION

Expert medical consultation is a scarce, expensive and critical component of any health system [40]. The World Health Organization (W.H.O.) in a 2006 annual report reported that, the global population is growing but the number of health workers is stagnating or even dwindling in many of the places where they are needed most [71, 75]. They further added that an additional four million health workers are needed throughout the world. Due to the deficit in health workers, at least 1.3 billion people around the world have no access to basic health care. Increase in demand for high-quality and timely medical services has led to the application of Information and Communication Technology (ICT) in assisting physicians and other health care providers in discharging their clinical roles in areas such as diagnosis, therapy and treatment. Malaria is a devastating disease and a major cause of morbidity and mortality throughout the world. It is a life threatening disease transmitted from person to person by the female anopheles mosquito. Early diagnosis of the disease is very paramount in order to stop the spread of the disease and to prevent death. Hence, expert medical care is needed in order to put a stop to this menace. Information and Communication Technology has been used in the diagnosis of various diseases including malaria. Malaria is a serious communicable disease caused by a blood parasite called plasmodium. It is currently one of the major tropical communicable diseases adversely affecting the health of people and the economic development of many

developing countries, particularly in the Sub-Saharan Africa (SSA). According to W.H.O. findings, reported in [38], it causes more than 1 million deaths arising from approximately 300-500 million infections every year. Although, there are newer techniques such as manual microscopy for the examination of blood smears which was invented in the late 19th century and is currently "the gold standard" for malaria diagnosis [22, 74]. Arriving at accurate medical diagnosis may sometimes become a very complex and cumbersome task.

A very important aspect in achieving hospital efficiency is to optimize the diagnostic process in terms of the duration and number of patients being examined with corresponding accuracy, sensitivity and specificity, as this is known to reduce morbidity and mortality rates and to reduce cost. The emergence of ICT has opened several opportunities in the health care delivery system as the demand for intelligent and knowledge-based systems has increased as modern medical practices has become more knowledge intensive [17]. In this paper, a Coactive Neuro-fuzzy Expert System (CANFES) model for diagnosis of malaria, where both neural networks (NN), also known as Artificial Neural Networks (ANN) and Fuzzy Expert Systems (FES) play active roles is being developed. The architectural framework for the CANFES model was also developed. The CANFES model for diagnosis of malaria was simulated using MATLAB.

2. LITERATURE REVIEW

ICT based diagnosis of malaria and some other diseases have been reported in the literature. In the paper, a fuzzy expert system for the management of malaria [17], fuzzy logic was used. Online system for diagnosis and treatment of malaria was reported in [18] where a rule based expert system was designed with the possibility of interacting with the system in real time and through mobile devices based on global system for mobile communication (GSM) technology. In the paper, diamaltycin for the diagnosis of malaria and typhoid fever; a decision support system for medical application was reported in [42], a decision support system which is based on case based reasoning was used to make diagnostic decision for malaria and typhoid. Neural network and fuzzy logic were not applied to this study. There was no precise method of distinguishing between malaria and typhoid. The paper, decision support system model for diagnosing tropical diseases using fuzzy logic was reported in [53] where fuzzy logic was used for diagnosing tropical diseases such as malaria, typhoid, tuberculosis, sexually transmitted diseases, yellow fever, hepatitis-B, leprosy and chicken pox.

They did not compute the confidence interval to give the assurance that the diagnosis given was actually for the specified disease. A medical expert system for managing tropical diseases was proposed in [1]. In the proposed Medical Expert System (MES), the inference engine uses a forward chaining mechanism to search the knowledge-base for symptoms of a disease and its associate therapy which matches the query supplied by the patient. Obot and Uzoka [55] designed a fuzzy rule based framework for the

management of tropical diseases. Fuzzy logic was applied to determine the degree of severity of tropical diseases. In fuzzy expert system for the management of hypertension [17], a fuzzy expert system was used to diagnose hypertension. In another study on a decision support system for tuberculosis diagnosis also reported in [2] a decision support system based on fuzzy logic was used in the diagnosis of tuberculosis. Application of neuro-fuzzy expert system for the probe and prognosis of thyroid disorder was reported in [2], where a hybrid neuro-fuzzy expert system was used in the diagnosis of thyroid disorder. This hybrid system is not adaptive in nature. Hence, it can only serve for cases that have been predefined in the knowledge base.

3. NEURO-FUZZY MODELING

The synergy of two intelligent techniques such as neural network and fuzzy logic form the basis of Neuro-fuzzy modeling.

3.1. Fuzzy Inference Systems (FIS)

The fuzzy inference system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. It has been applied in variety of fields such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics and pattern recognition. Because of its multidisciplinary nature, the fuzzy inference system is known by numerous other names, such as fuzzy rule-based system, fuzzy expert system [34], fuzzy model [68, 69], fuzzy associative memory [39], fuzzy logic controller [43, 44, 46] and fuzzy system. Figure 1 shows the block diagram for a Fuzzy Inference System with Rule Aggregator.

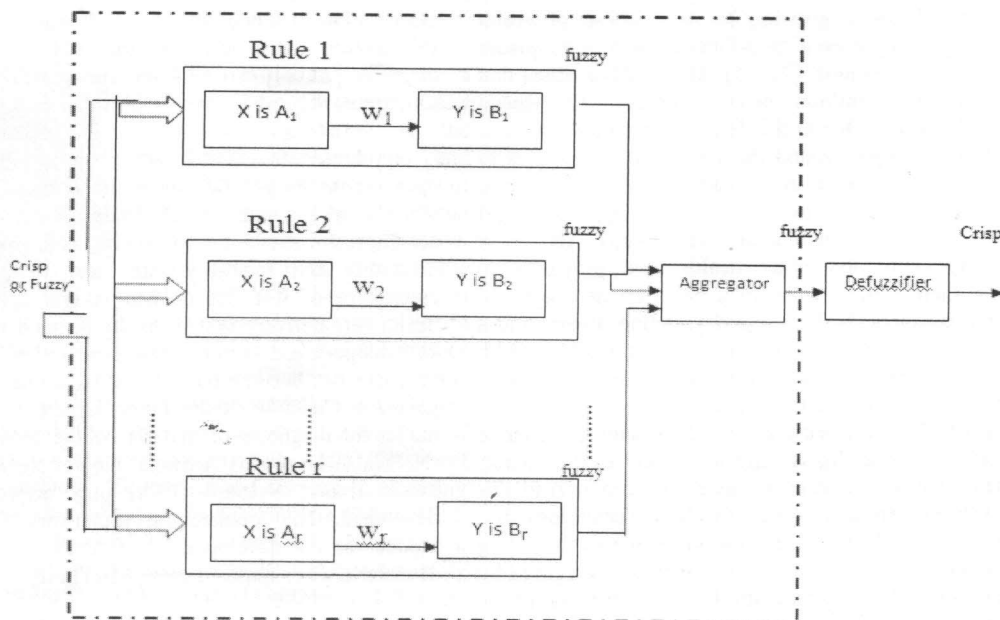


Figure 1: Block diagram for a Fuzzy Inference System with Rule Aggregator.

Layer 5: The single node in this layer is a fixed node labeled Σ , which computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \text{overall output} = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \quad (5)$$

The output is linear in consequent parameter.

3.3 Coactive Neuro-Fuzzy Inference System (CANFIS)

ANFIS has made its mark as an adaptive system with much emphasis on its capability of being a linguistically interpretable fuzzy Inference System (FIS) that allows prior

knowledge to be embedded into its construction and allows the possibility of understanding the results of learning. A generalized ANFIS which emphasize characteristics of a more fused neuro-fuzzy system that enjoys many of the advantages claimed for Neural Networks (NNs) and the linguistic interpretability of a FIS, is known as CANFIS. CANFIS stands for Coactive Neuro-fuzzy Inference System. The application of back propagation algorithms to fuzzy systems in a network layered presentation spurred the development of neuro-fuzzy modeling [26,27,28]. A single output CANFIS can be illustrated in the same schematic diagram of ANFIS as shown in figure 3.

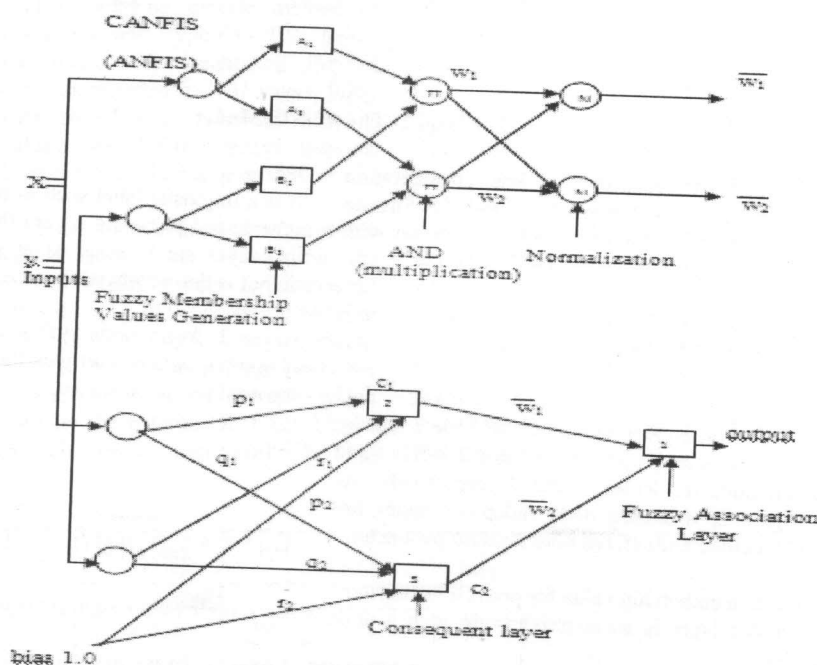


Figure 3: CANFIS Model

where,

$$C_1 = f_2 (p_1 x + q_1 y + r_1)$$

$$C_2 = f_3 (p_2 x + q_2 y + r_2)$$

When all the three neurons (1,2, and 3) have identity functions, the presented CANFIS is equivalent to the Sugeno Fuzzy Inference System (Takagi et al, 1985), which accomplishes fuzzy if then rules (linear rules) such as the following:

Rule 1: if x is A_1 and y is B_1 then $C_1 = p_1 x + q_1 y + r_1$

Rule 2: if x is A_2 and y is B_2 then $C_2 = p_2 x + q_2 y + r_2$

In this study, the CANFES model was adopted from CANFIS. While CANFIS is specific to controllers, CANFES is best suited for domains where human experts have to make decisions in real time.

4. METHODOLOGY

The process of the clinical diagnosis of malaria begins when an individual consults a doctor and presents a set of complaints which are referred to as symptoms. The doctor then requests for further information from the patient or from close associates who knows about the patient's symptoms, in severe cases. The data collected include the patient's previous state of health, living condition and other medical conditions. A physical examination of the patient's condition is also carried out. From the symptoms presented by the patient, the doctor narrows down the possibility of having malaria or not. These symptoms are usually ranked in the order (mild, moderate, severe and very severe). The doctor then studies the medical records, conducts a physical examination and also asks further questions.

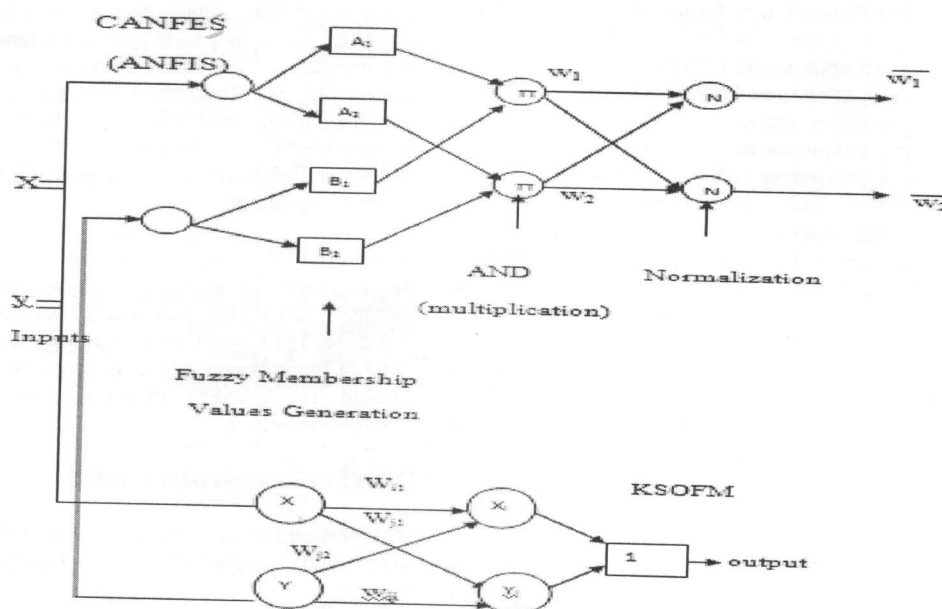


Figure 4 (a): The CANFES Model

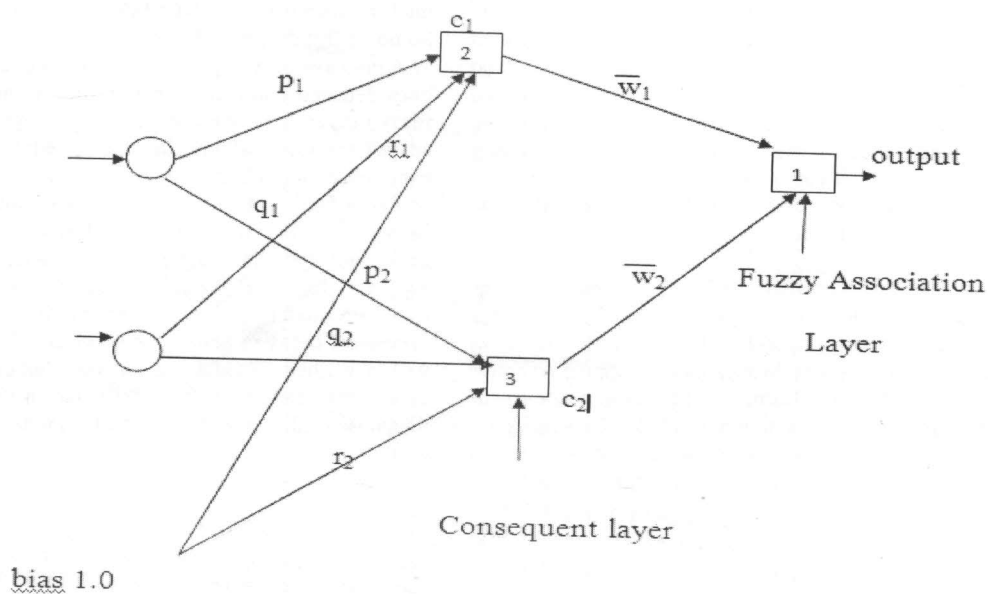


Figure 4 (b): Architecture of the Back Propagation Network.

5.2 Architectural Framework for the CANFES Model

In the course of this study, an architectural framework was developed for the CANFES model. The architectural framework is shown in figure 5. This framework captures all the features and components that are involved in the entire coactive neuro-fuzzy expert system model.

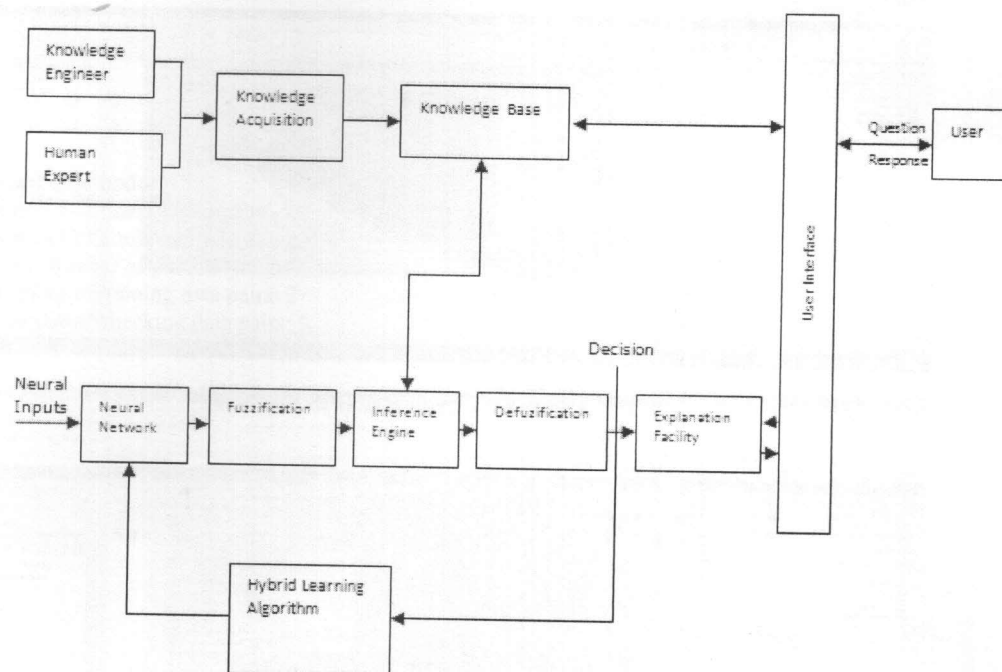


Figure 5: Architectural Framework for the CANFES Model

Most of the architectural frameworks for neuro-fuzzy expert systems which have been proposed and reported in the literature only portray the neural network and fuzzy logic features therefore leaving out the expert system component. The developed framework has been able to capture all the basic features and components of neural networks, fuzzy logic (fuzzy inference system) and expert system in totality. This framework is being developed for the embodiment of knowledge and to enhance and encourage research in the field of coactive neuro-fuzzy modeling. As shown in figure 5, the knowledge engineer and human expert (domain expert) have long sessions of dialogue in order to elicit knowledge for the expert system. The result of the communication and dialogue between the knowledge engineer and domain expert establishes the knowledge acquisition module. The acquired knowledge is then deposited into the knowledge base. Neural inputs which are numerical in nature are entered into the neural network for processing, the neural outputs is then fuzzified into fuzzy values which are linguistic in nature before entering the inference engine where decisions (such as diagnosis) are made.

If the output from the inference engine does not conform to the target output or does 632 diagnosis, then hybrid learning rule is being applied to train the neural network and the input data is reprocessed by adjusting weights (training) before it is being sent back to the inference engine. The inference engine communicates with the knowledge base in order to apply appropriate rules for decision making. The output from the inference engine (decision) is then sent into an explanation facility where the actual result or output will be interpreted to the user. The user interacts with the expert system by asking questions or performing queries, and the expert system gives its response according to the decision made in the inference engine.

5.3 Simulation of the CANFES Model

The CANFES model was simulated by using MATLAB (Matrix Laboratory) which is a mathematical tool for solving scientific problems. A typical ANFIS structure as presented in MATLAB is shown in figure 6 and the ANFIS Training Interface is shown in figure 7.

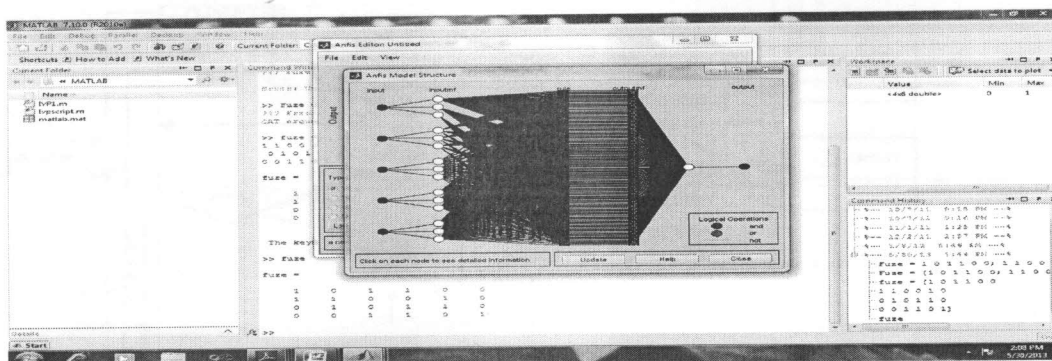


Figure 6: A Typical ANFIS Structure

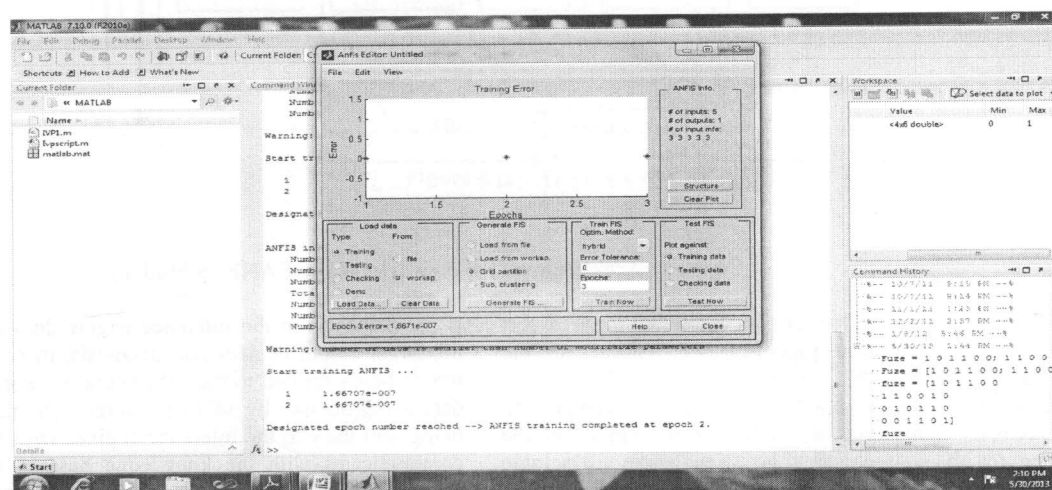


Figure 7: ANFIS Training Interface

5.3 MATLAB Results for ANFIS Training

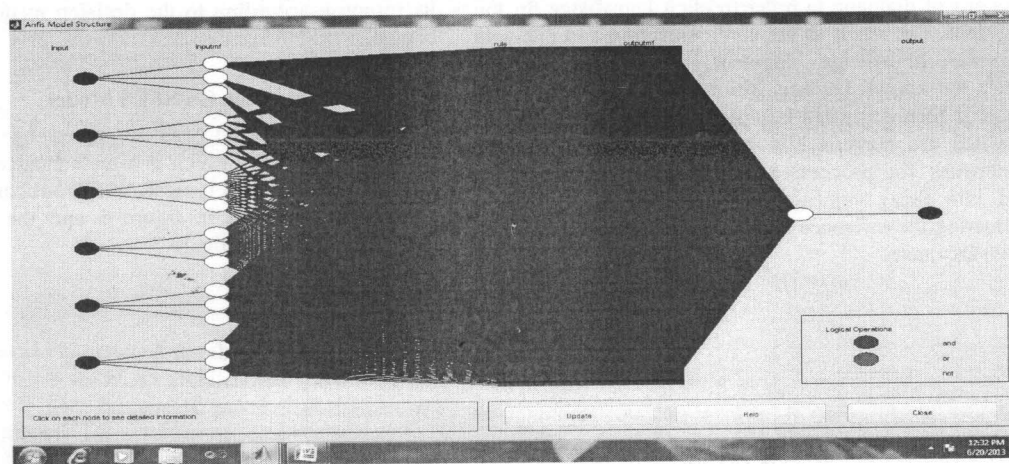


Figure 8: ANFIS Training for Patient Number 1.

```
>> patent1=[1 0 1 1 0 0 0
1 1 0 0 1 0 0]
patent1 =
    1     0     1     1     0     0     0
    1     1     0     0     1     0     0
>> ANFIS info:
Number of nodes: 1503
Number of linear parameters: 5103
Number of nonlinear parameters: 54
Total number of parameters: 5157
Number of training data pairs: 2
Number of checking data pairs: 0
Number of fuzzy rules: 729
```

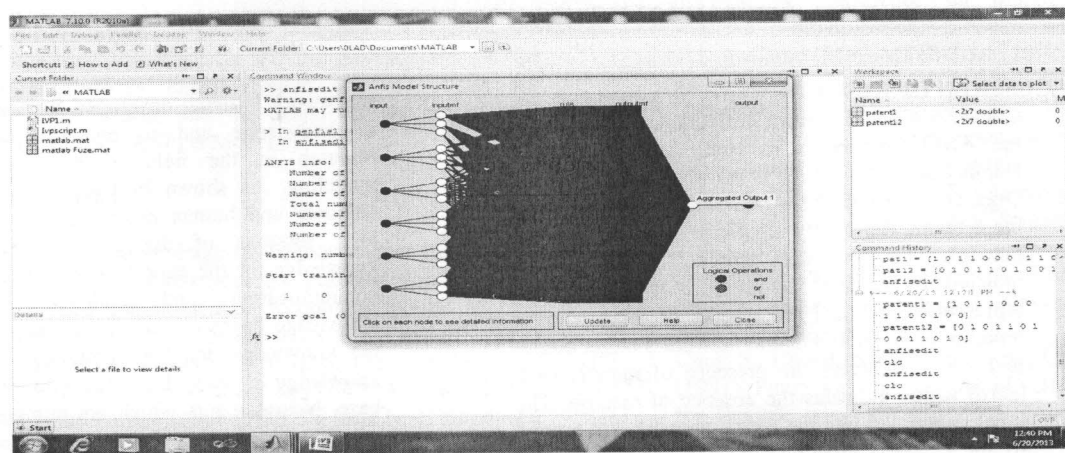


Figure 9: ANFIS Training Output for Patient Number 1.

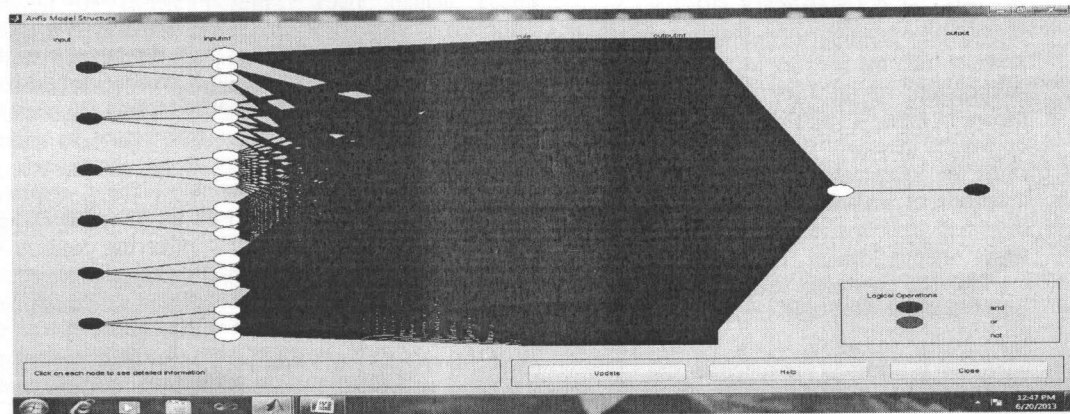


Figure 10: ANFIS Training for Patient Number 12.

```
>> patent12=[0 1 0 1 1 0 1
0 0 1 1 0 1 0]
patent12 =
    0     1     0     1     1     0     1
    0     0     1     1     0     1     0
```

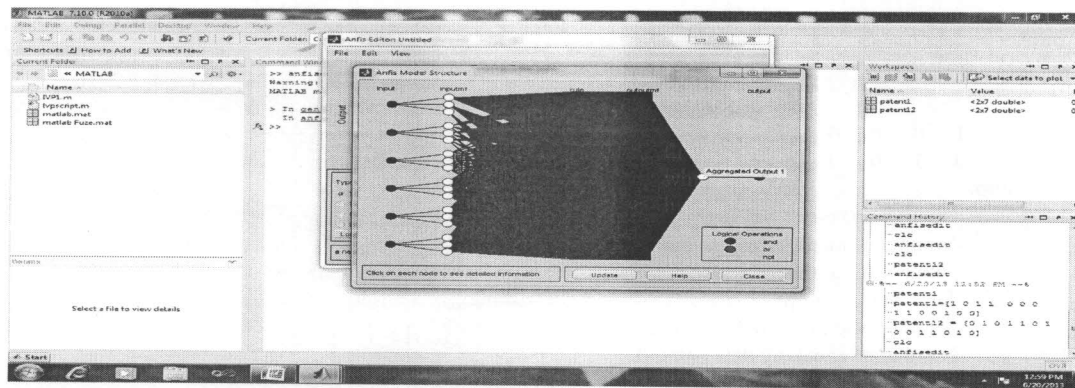


Figure 11: ANFIS Training Output for Patient Number 12.

6. DISCUSSION OF RESULTS

- 1) CANFES Model is shown in figure 4 (a). It also has the ANFIS model as its root. An unsupervised learning algorithm which is known as Kohonen Self Organizing Feature Map (KSOFM) is used to train the network. Since only input data is entered into the network, this input data represent the symptoms indicated by patients. The presence of a symptom is represented by 1 and the absence of a symptom is represented by 0. The neural network's target output is 1 which indicates the presence of malaria or 0 (zero) which indicates the absence of malaria. The input data is fed into the neural network and trained by the KSOFM learning algorithm. In training the network, the KSOFM algorithm maps the input data to the membership functions of their fuzzy values. If the value of the output is not equal to 1, a back propagation learning algorithm is then applied in order to train the network by adjusting the weights. Architecture of the back propagation network is shown in figure 4 (b). Conceptually, the adjustment of weight here will represent the probe for other signs or symptoms that can tend towards the diagnosis of malaria by moving the value of the output to tend towards 1 or to be 1 which is the target output, which indicate the presence of malaria. The input data was captured from the data set of patients who were considered for malaria at the University of Ilorin Health Centre. The table of input data is shown in the appendix.
- 2) The Architectural Framework of CANFES Model is shown in figure 5. Most of the architectural frameworks for neuro-fuzzy expert systems which have been proposed and reported in the literature only portray the neural network and fuzzy logic features therefore leaving out the expert system component. The developed framework has been able to capture all the basic features and components of neural networks, fuzzy logic (fuzzy inference system) and expert system in totality. This
- 3) Simulation of the Coactive Neuro-Fuzzy Expert System (CANFES) Model: Two input data sets were used in the simulation of the CANFES model. The input data for patient number 1 (patient with serial number 1) as shown in Table 1 in the Appendix is given the variable name Patient1. The ANFIS Training for Patient1 is shown in figure 8. The result is indicated by ANFIS information, which states

that, there are 1503 nodes, 5103 linear parameters, 54 nonlinear parameters, 2 training data pairs, no checking data pairs and 729 fuzzy rules. The Output of the ANFIS training for patient number 1 is shown in figure 9. This indicates that the output aggregates to 1, which indicates the presence of malaria in the patient. The input data for patient number 12 (patient with serial number 12) as shown in Table 1 in the Appendix is given the variable name Patent2. The ANFIS Training for patient number 12 is shown in figure 10. The corresponding output for the training process is given in figure 11. The output also aggregates to 1 indicating the presence of malaria in the patient.

6.1. Research Output

The outcome of this research are the development of the coactive neuro-fuzzy expert system (canfes) model for diagnosis of malaria; and the design of an architectural framework for the CANFES Model.

7. CONCLUSION

The need for ICT-based diagnosis cannot be over emphasized. This paper which demonstrates the practical application of information and communication technology in the medical domain has presented a coactive neuro-fuzzy expert system that can help in the diagnosis of malaria. The extended ideas of CANFIS which is a generalized form of ANFIS, which was presented in the framework of CANFES, have been introduced in this paper. Hence, CANFES was adopted from CANFIS which has its basis in ANFIS. While CANFIS is used in the development of controllers, CANFES is used in the development of expert systems, where human expert knowledge is represented and decisions are made in real time. This paper has shown the practical applicability of neuro-fuzzy methodology in the diagnosis of malaria. The hybrid learning rule has enhanced the performance of the system much more than the previous systems where just the back propagation learning rule was used.

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APPENDIX

Table 1: Input Data

S/N	Fever	headache	Body Pain	Catarrh	Chills	Vomiting	Jaundice	Diarrhea	Body weakness	Sore Throat	Cough	Nausea	Sweating	Bitter taste
1	1	0	1	1	0	0	0	1	1	0	0	1	0	0
2	1	1	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	1	0	0	0	0	0	0	1	0	0	0
4	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	0	1	0	0	0	0	0	0	0	0	1	0	0
6	1	0	0	0	1	0	0	0	1	0	0	0	0	0
7	1	1	0	0	1	0	0	0	0	0	0	0	0	0
8	1	0	0	1	0	0	0	0	0	0	1	0	0	0
9	1	1	1	0	0	0	0	0	0	0	0	0	0	0
10	0	1	1	0	0	0	0	0	0	0	0	0	0	0
11	1	1	1	0	0	0	0	0	0	0	0	0	0	0
12	0	1	0	1	1	0	1	0	0	1	1	0	1	0
13	1	1	1	0	0	0	0	0	0	0	1	0	0	0
14	1	1	1	1	0	0	0	0	0	0	0	0	0	0
15	0	0	1	0	0	0	0	0	1	0	0	0	0	0
16	0	1	0	1	0	0	0	0	1	0	0	0	0	0
17	1	1	0	0	0	0	0	0	0	0	0	1	0	0
18	0	1	0	0	0	0	0	0	0	1	1	0	0	0
19	0	1	1	0	0	0	0	0	0	0	0	0	0	0
20	1	0	0	1	0	0	0	0	0	0	0	0	0	0
21	1	0	0	0	0	0	0	0	0	0	0	0	0	0
22	1	1	0	0	0	0	0	0	0	0	0	0	0	0
23	1	0	0	1	0	0	0	0	0	0	1	0	0	0
24	1	1	0	0	1	0	0	0	0	0	0	0	0	0
25	1	0	1	0	0	0	0	0	0	0	0	0	0	0
26	1	0	0	1	0	0	0	0	0	0	1	0	0	0
27	1	1	1	0	0	0	0	0	0	0	0	0	0	0
28	1	1	0	0	0	0	0	0	0	0	0	0	0	0
29	1	0	1	0	0	0	0	0	0	1	0	0	0	0
30	0	1	0	1	0	0	0	0	0	1	0	0	0	0
31	0	1	0	1	0	0	0	0	0	1	0	0	0	0
32	1	1	0	0	0	0	0	0	0	0	1	0	0	0
33	1	1	0	0	0	0	0	0	0	0	0	0	0	0
34	1	0	0	0	0	0	0	0	1	0	0	0	0	0
35	1	0	0	1	0	0	0	0	0	0	0	0	0	0
36	1	1	0	0	0	0	0	0	0	0	1	0	0	0
37	1	0	0	0	0	0	0	0	1	0	0	0	0	0
38	1	1	0	0	0	1	0	0	0	0	0	0	0	0
39	0	1	0	1	0	0	0	0	0	0	0	1	0	0
40	1	0	0	0	0	0	0	0	0	0	0	1	0	0
41	1	1	0	0	0	0	0	0	0	0	0	0	0	0
42	1	1	0	1	0	0	0	0	1	0	0	0	0	0
43	1	1	0	0	0	0	0	0	0	1	0	0	0	0
44	1	1	1	0	0	0	0	0	0	0	0	0	0	0
45	1	0	0	0	0	0	0	0	0	0	0	0	0	0
46	1	0	0	0	0	0	0	0	0	0	0	0	0	0
47	1	1	1	0	0	0	0	0	0	0	0	0	0	1
48	1	1	0	1	0	0	0	0	0	0	0	0	0	0
49	1	1	1	0	0	0	0	0	0	0	0	0	0	0
50	1	1	0	1	0	0	0	0	1	0	0	0	0	0
51	1	1	0	1	0	0	0	0	0	0	0	0	0	0
52	1	1	0	0	0	0	0	0	0	0	1	0	0	0
53	0	1	0	1	0	0	0	0	0	0	0	0	0	0
54	1	0	1	0	0	0	0	0	0	0	0	0	0	0
55	1	0	0	0	0	0	0	0	0	0	0	0	0	0
56	1	1	0	0	0	0	0	0	0	0	0	0	0	0
57	1	1	0	0	0	0	0	0	1	0	0	0	0	0
58	1	1	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	1	0	0	0	0
60	1	1	0	0	0	0	0	0	0	0	0	0	0	0
61	1	1	0	0	1	0	0	0	0	0	1	0	0	0
62	0	0	0	1	0	0	0	0	0	0	0	0	0	0
63	1	1	0	0	0	0	0	0	1	0	0	0	0	0
64	0	1	0	1	0	0	0	0	0	1	1	1	1	1
65	1	1	0	0	0	0	0	0	0	1	1	1	1	1