KWAME NKRUMAH UNIVERISTY OF SCIENCE AND TECHNOLOGY



IMPLEMENTATION OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR

MALARIA DIAGNOSIS.

(A CASE STUDY AT KWESIMINTSIM POLYCLINIC)

By

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College of Science

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CERTIFICATION

I hereby declare that this submission is my own work towards the MPhil and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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DEDICATION

I dedicated this work for Almighty God for helping me come to this far in my academic pursuit as well as granting me strength and wisdom to come out with this piece and my entire family for their support and prayer throughout the progamme.



ABSTRACT

Health issues have become one of the problems bedeviling most developing and underdeveloped countries in our world today. Ghana is of no exception from this menace especially in Africa. One of the prevalent diseases battling with Ghanaians and Africa as a whole is the malaria disease. In 1994, the WHO reported that malaria and measles were the most common causes of premature death. in children under five(5) years. Diagnosis of malaria in many cases has not been accurate by most doctors or physicians due to external human factors such as fatigue and hastiness among others, thereby leading to patients being subjected to treatment again which also come with cost. Hence the need for this research work entitled, "Implementation Of Adaptive Neuro Fuzzy Inference System For Malaria Diagnosis. (A Case Study At Kwesimintsim Polyclinic) This paper employs the use of Adaptive Neuro Fuzzy Inference System (ANFIS) to provide a better option for malaria diagnosis than the traditional diagnosis method which is characterized by erotic guess work and observation of patients by doctors. ANFIS, which is derived from the term Adaptive Network Fuzzy Inference System, was first proposed by Jyh-Shing and Jang and later changed to Adaptive Neural Fuzzy Inference System. This system is designed to allow IFTHEN rules and membership functions (fuzzy logic) to be constructed based on the historical data and also includes the adaptive nature for automatic tuning of the membership functions.

Related works done by various authours in the area of study were reviewed. One hundred(100) datasets of patients from the clinic were used in this research work. Sixty(60) of the datasets were used as training datasets for training the ANFIS and forty(40) datasets were used checking datasets. The results tested after training showed that ANFIS has the ability to diagnose malaria efficiently than the traditional method with very minimal error.

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LIST OF ABBREVIATIONS			

ANFIS	-	Adaptive Neuro Fuzzy Inference System
ANN	-	Adaptive Neural Networks
BP	2	Blood Pressure
CAD	0	Computer Aided Diagnosis
FCM	-7	Fuzzy C-Means
FIS	- 1	Fuzzy Inference System
FL	- 6	Fuzzy Logic
FNA	1	Fine Needle Aspirates
MF	-	Membership Function
мон	5	Ministry Of Health
OPD	AN	Out Patient Department
RMSE	-	Root Mean Square Error
UCI	-	University of California Irvine
WBCD	-	Wisconsin Breast Cancer Diagnosis

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CHAPTER ONE

INTRODUCTION

1.0 Background to the Study

According to WHO(1948), health can be defined as the state of condition of an individual where his social, physical and mental life are sound and not just the lack of infirmity or disease in ones body. Thus health is a good concept that seeks to influence the personal and physical well being of a person. Therefore it is prudent for everyone to engage in a healthy lifestyle in order to contribute meaningfully to the society. One should take enough rest, engage in regular exercise, ensure good personal hygiene and avoid excessive alcohol intake to keep his/her body healthy. Also, the mental capability and social skills of one should be developed to allow one to make a good impact to the society. When an individual is in a state of homeostasis with his environment, then he is healthy.

Health can be said to be the driving force for any nation"s development. A strong and developed nation is directly related to a strong and healthy mind of its citizens. Therefore health issues are of paramount interest in almost all nations of the world. Most developing and underdeveloped nations have a huge section of its people suffering from various kinds of ailment. Ghana is of no exception to this rampant spread of sickness and diseases in

Africa thereby making a negative impact on the nation"s development.

Due to this there have been many attempts by nations including Ghana to curb the problems of health related to its citizens. However the introduction of technology into the health sector of many African countries have been less or negligibly exploited. Due to this less number of people can be attended to by physicians on a daily basis. Technology like health management system which is mostly used in the developed countries has been reported to have an immense positive impact on its citizens thereby leading to the nation''s development. This system used in the health sector helps in achieving more results that would not have been attained without it. It is obvious that those clinics and hospitals that go the manual way record less number of people daily when it comes to treatment of diseases and sicknesses. Diagnosing patients and offering them treatment is very important and crucial to the human being. Any interference in diagnosing a patient such as stress, forgetfulness and fatigue can be very dangerous to the patients. Therefore it is expedient that an easier, less brain work, accurate and flexible system be built to help physicians diagnose patients with less effort. This also can deal with the problem of having to attend to limited number of sick people due to tiredness or stress.

1.1 Fuzzy Logic

Fuzzy logic presented by Zadeh (1965) was used to symbolize and control knowledge and know-how wherein there are quite a lot of forms of vagueness. Fuzzy rule-situated programs use linguistic variables to motive making use of a sequence of logical principles that incorporate IF-THEN rules which join antecedent(s) and consequent(s), respectively. Fuzzy clause with distinctive degree of membership between zero and one can be considered as the antecedent. Fuzzy rules can comprise of a couple of antecedents linked with AND or OR operators, the place all components are calculated concurrently and resolved into a single quantity. Consequents can be constructed from more than one element, that are then aggregated right into a single output of a fuzzy set. A process where mapping from a given input to an output making use of the methods of the fuzzy set is referred to as the fuzzy inference.

1.2 Adaptive Neuro Fuzzy Inference System

Jhy-Shing and Jang(1993) first proposed the ANFIS, which was initially called Adaptive Network Fuzzy Inference System and then subsequently changed to Adaptive Neuro Fuzzy Inference System. The ANFIS system is developed to permit IF-THEN rules and

membership functions(fuzzy logic) to be built with the ultimate support of the historical data and also allows automatic tuning of the membership functions due to its adaptive nature.

(Jang et al 1997)

According to Piero (2000), ANFIS is a type of inference system that combines the fuzzy logic and the best characteristics of neural network. It is an adaptive network comprising of directional links and network of nodes. And attached to the network is a learning rule for modeling. One of the learning rules associated can be termed as the back propagation algorithm. The ANFIS is adaptive in nature because most or all of the nodes have parameters which have effect or influence on the node outputted. This adjustment allows the data used for modeling easy to be learnt by the fuzzy system. This method works like both of the Adaptive Neural Networks(ANN) and FL(fuzzy-logic). That is, in both situations of ANN and FL, the input is sent through the input layer by input membership function and the output could be noticeable in output layer by the output membership functions. Such a sophisticated allows the neural network to make use of a learning algorithm having the parameters modified until optimal solution is reached. The FL uses the neural network"s advantages to adjust its parameters in this advanced fuzzy logic. One of the common methods to evaluate the performance of the ANN establishes the difference real and network output. Thus membership function parameter estimation in ANFIS is achieved by using either back propagation or least squares estimation and back propagation combination.(Jang et al1997).

1.3 Statement of the Problem

It is an established fact that automating procedures of executing tasks have a greater positive impact on any system that is used by any institution, organization or individuals. Automating tasks stand the chance of making tasks easy to accomplish and able to do more than one would naturally do without the automation system.

However many hospitals and clinics including Kwesimintsim Polyclinic in the Shama Ahanta East Metropolitan Assembly have not exploited the use of I.T and technology to automate most of their activities. That are run on day to day basis. Non automation of the system makes it difficult to execute more tasks and achieve more results than they would have loved to attain. It causes a limited number of people to be attended to by the physicians since they have to keenly listen to patients, analyze their situation and diagnose them. It is clear that by this fatigue and stress may set in since the physicians employ the use of their brain in diagnosing the patients. Also patients are delayed in the hospital for a very long time in queues which sometimes deteriorate their condition.

1.4 Objectives of the Study

The main objective of the study is to adopt the use of a quick and better system in the diagnosing of patients.

The study specifically sought to:

i. Employ the use of ANFIS in diagnosing malaria patients. ii.

Come out with a better system for diagnosing malaria.

iii. Reduce the inaccuracy in diagnosing and treating patients.

1.5 Research Questions

Based on the objectives the following questions were set to guide the researcher in the study:

i. To what extent can the ANFIS be suitable for diagnosing people?

ii. How can malaria patients be diagnosed using a better system than the current system? iii. To what extent can the inaccuracies and uneasiness in diagnosing patients be reduced?

1.6 Scope of the Study

The research is carried out within the confines of Kwesimintsim Polyclinic sited in Kwesimintsim which is one of the most accessed clinics in the Shama Ahanta East Metropolitan Assembly. This covers the diagnosis module of Adaptive Neuro Fuzzy System(ANFIS) for diagnosis where the researcher considers training malaria datasets in Matlab 7.10.0(R2010a) to help in diagnosing patients with malaria symptoms.

1.7 Significance of the Study

The research is expedient and useful for the following reasons:

Firstly, the research shall encourage clinics to employ the use of technology in their day to day activities especially in the diagnoses of their patients as this encourages less human efforts.

Also, this august study will help increase the level of easiness and accuracy in diagnosing patients. This is so because human efforts (mental) is reduced when issues like fatigue, stress, forgetfulness, etc set in and these cause inaccuracy and mistakes in diagnosing a patient. Again this study is useful because it shall give quick solution to patients" problem therefore allowing more people to be diagnosed by the physician. Also it is hoped that this research would serve as reference material for policy adoption by the Ministry of Health (M.O.H) and some hospitals who want to remain competitive and efficient. Finally this study will serve as a source of reference for the general public and academia and stimulate interest in further research into this area.

1.8 Summary of Methodology

The study employed a comprehensive methodology that would aid in the attainment of the objectives set at the commencement of the study. The components of the methodology involved the data collection method. The researcher employed the use of literature survey, observation, interview and consultation in collecting the necessary data needed for the study. The data was therefore analyzed and proper deductions made out of them. The tool to be used is also stated in the methodology. Also the existing model which the researcher believes to be problematic in diagnosing a patient was reviewed. Constructive criticism was looked at also in the methodology and lastly a proposed model believed to be an improvement over the old model was given.

1.9 Limitations of the Study

Each research study has some limitations and this study is not an exception. The nature of the researcher required the researcher to collect data from the clinic on the datasets of patients who were diagnosed of malaria. Getting the data was quite uneasy as the data controller so to say was uncomfortable giving it out. However it was given out due to the researcher''s determination but patients'' ID which is confidential was not given so the identity of patients seen in this document were manufactured by the researcher. Also numeric representation of the conditions of malaria such as malaria free, uncomplicated malaria and complicated malaria was not available so it became necessary for coding to be adopted. Thus numbers 1, 2 and 3 were used to represent malaria free, uncomplicated malaria and complicated malaria respectively. It must however, be stated that these constraints do not in any way invalidate the findings of the study.

1.10 Organization of the Study

This research comprises of five chapters. The first chapter comprises of the background to the study, statement of the problem, purpose of the study, research questions, significance of the study, limitations, scope of the study and organization of text. Chapter two contains review of some related works to the researcher"s own in the area of diagnosis and Adaptive Neuro Fuzzy Inference System (ANFIS). Chapter three takes a comprehensive look at the research methodology adopted for the study. The fourth chapter deals with the implementation of the study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Overview

One of the problems that characterized the traditional method of medical diagnostic is inaccuracy and imprecision which has cause many life. The advent of computer has led to the development of several algorithms, models and technologies to ensure accuracy and precision and this has greatly reduced the numbers of patients that die daily in the hospitals and one of such technologies is Adaptive Neuro Fuzzy Inference System which is a branch of artificial intelligence. This section of the thesis reviews some related works done by various authors in the area of study.

2.1 A Neuro-Fuzzy Inference Model For Breast Cancer Recognition

Cardillo et al (2001) argues that one of the key reasons for the high rise of mortality rate in women is breast cancer and it is a factual emergency for healthcare systems in nations that are industrialized. Mehmet (2009) also argues that the second predominant cause of cancer related deaths in the world among women is breast cancer. The affected cells in people battling with breast cancer undergoes through an unusual reproduction or increase in their bodies.

The Neuro-Fuzzy Inference Model proposed by Bekaddour and Chikh(2012) is geared towards the presenting of Adaptive Neuro Fuzzy Inference System(ANFIS), which is well suited to classification of qualitative input and output variables. It looks at a system or technique that seeks to avoid the manual and tedious way physicians distinguish a malignant tumor from a benign one by automating the process thereby making the task an easier one. Researchers at the University of Wisconsin supplied the dataset for the training. This dataset retrieved from the University of Carlifornia (UCI) Machine Learning Repository comprises of 699 data. 34.5% of the data were graded as malignant and 65.5% were graded as benign (Asuncion & Newman, 2007). University of Wisconsin Hospital developed a database on breast cancer termed Wisconsin Breast Cancer Diagnosis(WBCD). The WBCD was used for precisely diagnosing breast masses exclusively on Fine Needle Aspirates(FNA) test (Mangasarian et al 1990). Nine visually assessed characteristics of an FNA sample considered relevant for diagnosis were identified and assigned an integer value between 1 and 10 (Pena-Reyes & Sipper, 1999). The measured variables are described in the table 2.1.

 Table 2.1 Attributes of the diagnosis base

Configuration	Number of rules	Learning Error	Classification rate %
2*2*2*2*2*2	64	0.29843	0.9825
2*3*3*3*2*2	216	0.16176	0.8904
2*2*2*3*2*3	144	0.16982	0.9386

The WBCD database particularly deals with classifying or organizing cases into a malignant or a benign one (Pena-Reyes and Sipper 2000). Researchers have conducted numerous studies based on this database.

Diagnosis systems demonstrating high performance, confidence measure and good interpretability have been made possible through the effort for the WBCD challenge. The databases therefore comprises of 699 cases where 16 absent instances are involved as shown in the table. 2.2

Case	CT	UCS	UCH	MA	SEC	BN	BC	NN	М	Diagnosis
1	5	1	1	1	2	1	3	1	1	Benign
2	5	4	4	5	7	10	3	2	1	Benign
683	4	8	8	5	4	5	10	4	1	Malignant

Table 2.2 The Wisconsin Breast Cancer Data base.

Selection of membership functions is prudent and necessary for the building of neuro fuzzy inference systems. This has an impact on the number of rules generated. Information gain algorithm was used to help minimize the quantity of features of the Wisconsin Breast Cancer database(WBCD). Therefore the features attained for use were six(6) though nine(9) were needed. Part of the results of the experimentation is showed in table 2.3.

Table 2.3 shows some results obtained for the experimentation.

Table 2.2 Error and elegification rate for diffe

Table 2.5 EITOI	and classification rate for	unierent configurations
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Attributes	Signification
CT	Clump Thickness
UCS	Uniformity of Cell Size
UCH	Uniformity of Cell Shape
MA	Marginal Adhesion
SEC	Single Epithelial Cell Size
BN	Bare Nuclei
BC	Bland Chromatin
NN	Normal Nucleoli
М	Mitosis

Error threshold was set to 0.001. The fuzzy model was implemented with TSK as its structure. Two (2) membership functions for every description was adopted to help minimize the volume of rules generated (ie sm:smll. Bg:big) after numerous attempts. Generalized bell functions being a type of membership function secure the readability of results was used. Figure 2.1 represents the initial parameters of membership functions.



Figure 2.1 Initial membership functions(before learning)

Figure 2.2 displays the proposed structure of the neuro fuzzy system.



After the initial configurations, the learning phase was started using the back propagation algorithm and the hybrid method (based on back propagation and least square techniques). At the end of the learning, membership parameters would be modified as shown in the figure 2.3.



Figure 2.3 Final membership functions(after learning)

Rules generated by neuro-fuzzy model were divided into two groups:

- 1st group: Fuzzy rules indicating benign class
 - (1,2,5,7,8,9,11,14,17,20,22,25,31,33,39,45,50,51,53,56)

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- 2nd group: Fuzzy rules indicating malignant class
 - (3,4,6,10,13,15,16,18,19,21,23,24,26,27,28,29,30,32,34,35,36,37,38,40,41,42,43,44,

46,47,48,49,52,54,55,57,58,59,60,61,62,63,64)

The two outputs were coded by two classes: *Benign Class=0 and *Malignant class=1

2.1.1 Results of the Study

Performances of the neuro-fuzzy systems using hybrid and back-propagation algorithms are BADY summarized in table 2.4.

NO

CC %	Error rate %	Se %	Sp %	Nbr Tp	Nbr Tn	Nbr Fp	Nbr Fn	Туре
98.25	1.75	97.5	98.65	78	146	2	2	hybrid
64.91	35.09	0	100	76	148	0	80	Back- propagation

Table 2.4 Different results of ANFIS

From the results, it was clear that the hybrid method exhibiting a combination of back propagation and least square estimation for modeling has a great deal of good outcome than the back propagation method. This is so since the least square method is used in adjusting the rules at the end.

2.1.2 Conclusion

The neuro-fuzzy approach for designing a system which is able to interpret decisions has proved to be accurate for exhibiting knowledge extraction and classification of breast cancer disease. The proposed method can be found to be a very significant tool which can be incorporated into a Computer Aided Diagnosis (CAD) to help physicians in their decision making in the area of diagnosing a patient

2.2 Evaluation of Breast Cancer Risk Using Fuzzy Logic

Victor et al (2011) describe an intelligent procedure based on fuzzy techniques that could be used for the evaluation of breast cancer risk. The procedure used is as follows:

 Fuzzy logic with two input variables and one output variable was used for simplicity.

- ii. The possible input variables together with their relevance concerning the decisional process of the breast cancer risk were presented by clinical experts.
- iii. The relevance factor of the fuzzy input variables decided by the clinical experts is shown in table 2.5

Table 2.5 Possible fuzzy logic input variables

Input variable	Relevance factor
Age	6%
Age of first menstruation	6%
Number of auxiliary nodes	9%
Tumour surface	24%

- iv. The rules that are used considered tumor as the highest significance of the two input variables.
- v. The numerical range for each of the input and output variables used is shown in table

2.6 and table 2.7 respectively.

Table 2.6 Numerical Range for Each Input

Input variable	Min-value	Max-value
Age	30	80

Age of first menstruation	10	15
Number of auxiliary nodes	0	15
Tumour surface(pixels)	0	8000

Table 2.7 Numerical Range for Each Output

Input variable	Min-value	Max-value
Breast cancer risk	0%	100%

vi. The fuzzy systems(rules) used are shown in the table 2.8

	Fuzzy System	Input Variable(1)	Output Variable(O)
	FZ1	I1: Age	O1: Breast cancer risk
		I2: Tumour surface	2
	FZ2	I2: I1: Age of first	O1: Breast cancer risk
-		menstruation	
12		12: Tuomour surface	
1	FZ3	11: Number of auxiliary nodes	O1" Breast cancer risk
	APS	I2: Tumour surface	BADY

 Table 2.8 Fuzzy Systems

vii. The breast cancer risk factor computed by the fuzzy system is presented after defuzzification in terms of the BIRADS score.

- viii. The researched fuzzy system uses the clinicians" logic derived from their medical experiences.
- ix. Centroid defuzzification method was used.
- The researched system was designed and investigated using Matlab and fuzzy TECH software tools.
- xi. The breast cancer risk was evaluated using the design fuzzy system and usedBIRADS scale to the clinical/pathological evaluation.

2.2.1 Results of the Study

- i. For testing processes, information from (60) patient records were used: the age of the patient, the extracted tumor segmentation result from the processed mammograms.
- The age and the segmentation result for each patient were given as inputs in the researched fuzzy system FZ1 and finally the fuzzy output was compared using BIRADS scale to the clinical truth.
- iii. The comparison between clinical and fuzzy system risk evaluation suggests
 agreement between truth values and fuzzy evaluated values.

2.2.2 Conclusion

Computer-based fuzzy logic techniques are becoming powerful enough to emulate an expert"s choice due to their robust behavior in the presence of noise, imprecision and uncertainty. These techniques can obtain better results than classical computer aided diagnostic methods.

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2.3 Anfis Based Classification Model for Heart Disease Prediction

According to Ziasabounchi and Askerzade (2014), heart disease diagnosis procedure is very vital and critical issue for the patient's health. Therefore the role of using machine learning techniques and data mining algorithms in diagnosis of heart disease is very considerable. The aim of this study was to develop a method of classifying for heart disease degree of patient based characteristic data using adaptive neuro fuzzy inference system. The method used are as follows:

i. ANFIS method was applied to Cleveland Clinic Foundation heart disease dataset which has been obtained from the well-known UCI machine learning data

repository.

- ii. The dataset consist of 303 subjects iii. Crisp data collected from Cleveland heart disease dataset was converted in order to be used on the MATLAB environment and was preprocessed by normalization method.
- iv. Gausian membership function was used for fuzzy set description after the seven input variables are introduced.
- w. Gaussian membership function was used for each of the input variables. The number of input member functions were also given.
- vi. Consequent parameters are learnt during forward pass. And this was realized in the training process when least square error estimate approach is employed. And premise parameters are learnt when gradient descent method is applied during backward pass.

Figures 2.4 and 2.5 show the graph of membership functions before and after training respectively.



Figure 2.4 Membership function before training



Figure 2.5 Membership function after training

All the rules in the fuzzy inference system include all the seven variables. These rules are shown in

figure 2.6

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1. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is false) and (ECG is normal) and (Max_hea
2. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is false) and (ECG is normal) and (Max_heat
 If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is false) and (ECG is ST_abnormal) and (Mail)
4. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is false) and (ECG is ST_abnormal) and (Ma
5. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is true) and (ECG is normal) and (Max_hearl
6. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is true) and (ECG is normal) and (Max_heart
7. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is true) and (ECG is ST_abnormal) and (Max
8. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is low) and (Blood_sugar is true) and (ECG is ST_abnormal) and (Max
9. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is high) and (Blood_sugar is false) and (ECG is normal) and (Max_het
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12. If (Age is young) and (chest_pain is angina) and (Blood_pressure is low) and (Cholesterol is high) and (Blood_sugar is false) and (ECG is ST_abnormal) and (I
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19. If (Age is young) and (chest_pain is angina) and (Biood_pressure is high) and (Cholesterol is low) and (Biood_sugar is false) and (ECG is ST_abnormal) and (I
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Figure 2.6 Rule base of the ANFIS

2.3.1 Results of the Study

Proposed system used two or more Gaussian membership functions for each input and

0.01rmse was obtained as smallest error. The convergence curve of ANFIS achieved RMSE

values of 0.01(error goal) as shown in figure 2.7.



Figure 2.7: Plot of RMSE against Epochs

The proposed system was tested with 60 samples and the rate of testing error was 0.15 which was smaller too. The result of validation training and testing data was shown in the table 2.9

Table 2.9 Error values for ANFIS.

ANFIS	
Train Error	0.01
Test Error	0.15

2.3.2 Conclusion

ANFIS technique was used for the classification of heart diseases for helping patients to quickly predict and get reliable diagnosis. Training and average errors which were 0.01 and

0.15 respectively in this model were satisfying.

2.4 Artificial Neural Network Fuzzy Inference System (Anfis) For Brain Tumor

Detection

Sharma and Mukharjee (2012) approach was to detect the presence of brain tumor using the Adaptive Neuro Fuzzy Inference System. The introduction of the neuro-fuzzy system which combines both the features of fuzzy logic and neural networks seeks to deal with the loop holes and thus provide or produce better features.

Information with imprecision present in images is also dealt with the neuro-fuzzy approach.

That is imprecision in geometrical segmentation in the image, uncertain interpretation of a scene, pixel grayness and ambiguity. The methodology that was used for the MR brain tumor was divided into four (4) steps. And the steps are presented diagrammatically in the figure 2.8.



Figure. 2.8: Proposed methodology for the classification of brain tumor

The details of the third step are further represented in the figure 2.9.



Figure 2.9: Proposed methodology for ANFIS based brain tumor detection Giloma type of brain tumour images of GRADE I to IV and astrocytoma were the composition

of the image database used for this study under review. Seven GCLM features(Contrast, Angular Decond Moment(ASM), Homogrnity(HOM), Inverse Difference Moment(IDM),

Energy(E), Entrophy(EN), Variance(VAR)) were used for the study. Each of them were calculated in four directions such as 0,45,95,135 thus giving the total of linguistic variables as seven(7). Number of patterns used was the same as the number of output variables. Table 2.10 shows sample feature value for image 1 and image 2.

	Features	IMAGE1 Range(High-Low)	IMAGE2 Range(High-Low)
1.	Contrast	7.08e+00-6.98e+00	3.60e+00-4.53e-001
2	ASM	8.76e-001-8.72e-001	6.05e-001-6.72e-001
3	HOM	8.87e-001-8.62e-001	8.72e-001-8.62e-001
4	E	2.93e-001-2.85e-001	2.28e-001-2.26e-001
5	EN	2.68e-001-3.44e-001	2.72e-001-3.01e-001
6	VAR	8.96e-001-8.54e-001	9.06e-001-8.81e-001
7	IDM	9.92e-001-9.90e-001	9.94e-001-9.93e-001

Table 2.10 Sample feature value for image 1 and image 2.

Normal and abnormal brains were differentiated based on these values.

Sample of fuzzy if-then rules framed for the MR brain tumor classification is as follows:

Rule 1: If a is contrast1 and b is correlation1 and c is energy1 and d is entropy1 and e is IDM1 and f is variance1, then output = 1

Rule2: If a is contrast2 and b is correlation2 and c is energy2 and d is entropy2 and e is

IDM2 and f is variance2, then output = 2

Rule3: If a is contrast3 and b is correlation3 and c is energy3 and d is entropy3 and e is

IDM3 and f is variance3, then output = 3

The number of membership functions used in this work was 2 (low and high) and hence there were 49 rules framed for this image classification system. The ANFIS structure consisted of seven inputs and a single output.Sixteen(16) fuzzy rules from the fuzzy inference system were formed from each of the training stets. The generalized bell curve membership functions were

assigned to each of the inputs and the linear membership functions represented the output. Two(2) main categories were used for the dataset collected. These are the training dataset and the testing dataset. Images of all four tumor types had their representation in the training dataset that was used. Four dissimilar regions were considered in the grouping of training samples. The regions are namely, grey matter, white matter, the abnormal tumor region and the cerebrospinal fluid. The fuzzy C-means algorithm was used in the abnormal tumor region. All the four classes of the cluster center of the tumor region were observed and stored. Extraction of the features was matched with the appropriate solution in the testing process.



2.4.1 Results of the Study

Fig 2.10: Tumor Segmented from abnormal brain MRI image

Figure 2.10 displays the results obtained after the observation of the cluster center of the tumour region of the four classes, their storage and the extraction of the features.

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2.4.2 Conclusion

The ANFIS was used for the MR brain tumor image classification. Experimentation with ANFIS for classification of image came with very good outcome

2.5 Using Adaptive Neuro Fuzzy Inference System (ANFIS) Algorithm for Automatic Diagnosis of Skin Cancer

Suhail (2011). This paper basically deals with skin cancer diagnosis. It employs the uses ANFIS algorithm applications in the medical field. The G-Flip algorithm was used by the researcher in selecting the features as data inputs. Group of three (3) dissimilar images of skin lesions were gathered and data inputs were extracted or selected from them. Fluorescent technique by the Institute of Biophysics. (University of Rogensburg, Germany) was used in obtaining these images. The lesions were grouped into three (3) categories: Firstly, the skin cancer type, known as Actinic Keratosis or malignant also referred to as the solar keratosis. The Actinic type of cancer is seen as the occurrence of the first step of cancer in affected people. Secondly, the basal cell carcinoma is believed to be the next step of the development of cancer. This type of cancer starts at the deepest basal cell of the epidermis found at the outer layer of the skin. This type is considered as a chronic skin condition termed Psoriasis and also known to be predominant in families.

In order to prevent large feature numbers, the feature selection was used. This was done to allow the feature selection pick out part of the features small enough to forecast the target class well.



(a) Actinic Keratosis



(b) Basal Cell Carcinoma



(c) Psoriasis

Fig 2.11 Samples of fluorescence images of (a) Actinic Keratosis (b) Basal Cell

Carcinoma(c) Psoriasis

Figure 2.11 displays samples of fluorescence images gathered. It shows the images of Actinic Keratosis, Basel Cell Carcinoma and Psoriasis in the order as mentioned. The images above were gathered from different lesion groups and the classes look akin. Several transfer

functioning known as image processing"s methods for transformation were used to transform the images gathered from the lesion groups.

2.5.1 Feature Extraction

Feature extraction was used to extract a total of seventy-five (75) characteristics or parameters. The rationale for the use of the feature extraction was in its ability to simplify the amount of resources required to describe a large set of data accurately. Extraction of correlation coefficient matrix was adopted to prevent redundant features thereby allowing the features with a correlation coefficient beyond 0.98 in relation to other features. Thirty (30) out of the initial seventy-five (75) were selected in this regard. In this paper, different algorithm of image processing was used in this feature extraction. The algorithms were edge detection consisting of two(2) main groups known as laplacian and gradient. Odeh et al (2006), Canny (1986) and Parker (1997) uses the maximum and minimum values that meet the initial derivative of the image for the edge detection. Second is the fourier transform and thirdly is the morphologic operations. The three (3) Parameters were taken from the database holding fifty(50) images of Actinic Kearatosis (pre-cancer), fifty(50) images of basal cell carcinoma(cancer) and sixtyseven(67) images of psoriasis.

2.5.2 Feature Selection

In a given data, there has to be a mechanism for having or choosing a set that best capture the relevant properties of the data. This was necessary to prevent the inclusion of large number weekly relevant and redundant features in the dataset (Narenda. and Fukunaga, 1977).
In this paper, the greedy feature flip (G-flip) algorithm was employed. The selection of these features could be used as inputs for the diagnosis system (Bachrach et al 2004). This type of G-flip algorithm is a search algorithm for utilizing the evaluation function e(F) where F is a set of features. Theg-flip algorithm recursively or iteratively goes through the feature set and updates the set of chosen features. The current feature was added or removed from selected set by evaluating the margin term.

In this application, the modular classification algorithm based on the ANFIS was employed. Gradient descent was used for fine tuning purposes. This was used for premise features that define membership functions. In dealing with consequent features that define the coefficient of each output equations, ANFIS uses the least square method. This approach of combination is called hybrid learning method (Odeh S. 2009). In this paper, six(6) features were used in the diagnosis system. Most suitable six(6) features from the dataset were determined with the help of G-flip algorithm since the features since the features have to be very accurate.

ANFIS was used in this paper to categorize the trial images that belong to probably the most three distinctive varieties of skin lesions. The ANFIS network has two (2) elements similar to fuzzy techniques. The first section is the antecedent and the second is the consequent part linked to each other by using rules in network type. ANFIS is described in this paper as a multilayered neural network demonstrated by means of 5 layers.

The ANFIS model was used to carry out input space partitioning. This splits the input space into local regions from which simple local models are employed. This was accomplished so as

to model non-linear elaborate systems. Fuzzy MFs for splitting each and every input dimension is utilized by the ANFIS. The input space used to be included by means of overlapping MFs which intended that a number of neighborhood regions might be activated at the same time by means of a single input. The ANFIS approximation ability depended on the decision of the input space partitioning determined by way of the quantity of MFs in ANFIS and the number of layer MFs had been used as bell-shaped with highest equal to one(1) and minimal equal to zero(0)(Gbomsheh et al 2007). Member function was used by ANFIS for all the entry. Ten (10) iterations were run for the training. After each and every iteration, the efficiency of the network was calculated on the checking dataset via calculating the root-mean-square errors (RMSE). Also for every iteration, the RMSE was worked on the training dataset.

As soon as the RMSE got to its lowest value, nine(9) epochs were attained as the optimal number of iterations. The error obtained was then converted from RMSE to percentage error. The posed diagnosis difficulty was grouped into two(2) tasks before the usage of the classification methodology.

The difference between pre-cancerous images and psoriasis instances is believed to be the first and easy task. This deals with two courses. The first classification has Actinic Keratosis images amounting to 33 and basal cell carcinoma images amounting to 34. The second classification(psoriasis) is made up of sixty seven(67) images The second undertaking is the "Difficult Task" which is the identification of the cancer(Basal cell carcinoma) in the database. The database comprises of Actinic Keratosis instances amounting to fifty(50) and basal cell carcinoma also equaling to fifty(50). The result of this intended two classes, pre- cancer which is the first class and cancer being the second class. Out of the whole total dataset, 80% was used as the training dataset and 20% was used as testing dataset. In order to validate the outcome three(3) types of those data had been used the place each version was randomly disordered. The minimum RMSE value was reached after the methodology was applied and the classification was run after ten (10) iterations. Table 2.11 represents the classification accuracy of the easy duty and difficult duty for each of the three(3) versions.

Also table 2.12 displays the information of the ANFIS structure.

	Easy Task	Difficult Task					
Version 1	99.77	94.18					
Version 2	99.39	90.83					
Version 3	99.49	92.03					
The Average Accuracy	99 55+0 2	92 35+1 7					

Table 2.11 The classification accuracy of the easy and difficult task.



Table 2.11 displays the classification accuracy in both the easy task and difficult task for all the three(3) versions of the data. The easy task was seen to have a high accuracy of

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99.55 \pm 0.2 as compared to that of difficult task of 92.35 \pm 1.7.

Number of Nodes	1503
Number of linear parameters	5103
Number of non-linear parameters	54
Total number of parameters	5157
Number of training data pairs	80
Number of checking data pairs	20
Number of fuzzy rules	729

Table 2.12 The ANFIS structure Information

Table 2.12 displays the detailed information for the ANFIS structure.

2.5.3 Results of the Study

Results on this learn showed that diagnosis process for biomedical issues have excessive degree of efficiency performance. It was noticeable that ANFIS could safely predict the checking out within the convenient task with the aid of approximately one hundred% and within the elaborate project with the aid of ninety two% which supposed that the ANFIS is strong enough for use as a diagnosis procedure.

2.5.4 Conclusion

Adaptive neuro-fuzzy inference system(ANFIS) used to be presented as a diagnosis method for skin cancer in the biomedical subject. Just right efficiency accuracy was obtained through ANFIS when juxtaposed to other methods that employed the use of same database of fluorescence portraits. The conclusion of the study was that ANFIS centered diagnosis could be applied to different biomedical fields such as breast skin, EEG signals, ECG signals, etc. again the optimization system of the distinctive features was onces validated to a high level of classification accuracy. With this the extraction of the features was done with the help of image processing and G-flip algorithm was used for the selection. The classification result indicated that ANFIS produces better influence than other algorithms.

2.5 Summary of the Study

From the first review entitled "A neuro-fuzzy inference model for breast cancer recognition", Apparently, it can be concluded that the method proposed is an essential tool which can be incorporated into the CAD to help decision making when diagnosing. From the results obtained, the researcher can confidently conclude that the ANFIS is a very good approach in data recognition in the medical field.

From the second paper entitles "Evaluation of breast cancer risk using fuzzy logic", the ANFIS technique could obtain better results than classical computer aided diagnostic methods. But however it was simple as only two input variables are used in its fuzzy rules. This boost the running time of the system and requires less hardware (memory). Also the third paper entitled "ANFIS Based Classification Model for Heart Disease Prediction", the ANFIS system proved to be efficient and also show some high level of accuracy in prediction. Nevertheless the simulation is not so developed to accommodate more input parameters from different databases. It is designed to consider input parameters from only one database. Also, in the fourth paper entitled "Artificial Neural Network Fuzzy Inference System (ANFIS) For Brain Tumor Detection" the researcher noticed that the number of input variables and membership functions must be increased. The ANFIS needs to be enhanced to help achieve high

classification accuracy, measurement of thickness and volume of tumor. Lastly, in the fifth paper entitled "Using Adaptive Neuro Fuzzy Inference System (ANFIS) Algorithm for Automatic Diagnosis of Skin Cancer", the researcher noticed that the number of training and checking data pairs must be increased to achieve a higher classification than that of the difficult task obtained in the study.



CHAPTER THREE

METHODOLOGY

3.0 Overview

The research is conducted to employ the use of Adaptive Neuro Fuzzy Inference System(ANFIS) for better and accurate diagnosing of malaria patients. In this section the methods used to achieve the objectives of the research are carried out. The sub-sections data collection, literature survey, observation, interview, consultation, analysis of data collected, etc are considered.

3.1 Data Gathering

Observation, literature survey, interview and consultation were used to gather information about patients and various diseases. Also the researcher used them to gather data on fuzzy logic concept, ANFIS, and to decide on the input and output variables and the degree of membership functions among others. The simple random sampling technique also known as chance sampling or probability sampling where each and every item in the population has an equal chance of inclusion in the sample and each one of the possible samples, in case of finite universe, has the same probability of being selected.(Kothari, 2004). The simple random sampling technique was to select malaria patients to participate in this study. Data of malaria patients from the records section of the clinic were picked randomly to be trained in the ANFIS editor. One hundred (100) patients were chosen as the sample size for conducting this study.

3.1.1 Literature Survey

The literature survey was used to gather a lot of information regarding health, fuzzy logic, ANFIS, etc. The following were noticed during the literature survey from books, research journals and the World Wide Web (www). The health of a population is a direct index of development of a nation. It affects the productivity, the potential of children and allocation of resources within a family, community and nation. Many researchers have proved that telemedicine services have the potential to improve both the quality of and access to health care regardless of geography (Amrita et al 2005, Ganapathy, 2002). Fuzzy relation can be defined as more or less vague relationships between some fixed numbers of objects, and it can formally be treated like fuzzy sets (Bandemer and Gottward, 1995). Fuzzy control can be defined as the application of fuzzy logic (Lin and Pang, 1994).

Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the hybrid neuro-fuzzy inference expert systems and it works in Takagi-Sugeno-type fuzzy inference system, which was developed by Jyh-Shing and Roger Jang (1993).

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3.1.2 Observation

Many astonishing cases were observed during the period of data collection for this study. The following are some of the observations made by the researcher:

Because the current model for diagnosing patients involves a great use of the human brain it becomes more complex and cumbersome when diagnosing patients. Due to this the physicians are only able to diagnose very minimal number of patients as compared to the number of sick people who attend hospital daily. Also the physicians spend more time on a patient in trying to diagnose them. Again patients had to wait for a very long time before his/her turn may be up. This sometimes deteriorated the conditions of patients where it became almost impossible to bear. Another problem observed was inaccuracies in the doctors" decisions. This occurred frequently in the physicians" diagnosis and thus patients had to be re-diagnosed. Some of the factors that led to the inaccuracies are as follows:

- i. Doctors rush through their diagnosis and consultations because of the heavy schedule and the sight of the long queues.
- ii. Having sat down for a long time, fatigue sets in and makes their cognitive processing of the patients information affected negatively.
- iii. Again pressure from external factors such as financial issues, family cares, social problems among others affected the turn out of the diagnosis of the doctors.

3.1.3 Interview

An interview with some of the doctors revealed that indeed not too many patients are diagnosed in a day due to the current mode of operation in diagnosis. Also it was clear that the physicians spent quite a long time in diagnosing patients due to the complex nature of the cases and diagnosis. Also an interview with the administrator and some selected patients disclosed that sometimes the diagnosis and prescriptions of the physicians are not accurate thus causing them to revisit the hospital for re-diagnosis or even try different hospital. Again fatigue, pressure and stress affected the number of patient treatment per day thereby delaying the process of the health restoration of patients.

3.1.4 Consultation

In consultation with the administrator and some doctors, it was agreed that a good, dynamic and robust system is needed to solve the problem of guessing during diagnosing, delay of patients and inaccuracies in diagnosis of patients. Such system should be able to diagnose patients quickly and effectively with efficiency when the symptoms are known and should be able to detect the status of the illness whether it is low, mild or severe and probably give some medication.

3.2 Analysis of Data Collected

The literature survey informed the researcher that health is the driving force for a person"s success and even the nation"s development. Interview with patients and administrator showed that inaccuracies occurred in diagnosis and patients were delayed respectively in the hospital. Through the researcher's initiatives, it was considered a good thing to have a system that will greatly curb all the problems.

3.3 Tools Used

Matlab 7.10.0(R2010a) which is a powerful mathematical and scientific tool used for various works including ANFIS modeling was used. It was used to simulate the system for diagnosing WJSANE the patients.

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3.4 Existing Model at the Hospital for patient diagnosis Figure 3.1 is the existing model of the structure a patient goes through at the hospital in order to receive treatment. First and foremost the patient goes to the Out Patient Department (OPD) for the necessary data to be taken including the



Figure 3.1 Existing diagnosis model

temperature and weight. Afterwards the patient queues to meet the doctor in the consulting room. On meeting the doctor, symptoms are given decision to be made on what the patient is suffering from. The patient goes to the laboratory if necessary for investigation else goes to the pharmacy for collection of drugs prescribed.

3.5 Criticism of the existing model

The researcher found problems with the existing model. The z-shaped or zig-zag shaped lines around the head of the doctor represents external factors that can affect the doctor"s decision or conclusion. The external factors such as stress, fatigue, ill health, marital issues, monetary issues, complexity of symptoms among others sometimes lead to wrong or inaccurate diagnosis. Under this model, the absolute decision of the doctor is totally dependent on his/her frame of mind. If the soundness of mind was affected in anyway, the decision or diagnosis would be definitely affected.

3.6 Proposed Model

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Figure 3.2 Proposed diagnosed model The model shown in figure 3.2 follows the same order the existing model goes through except where the patient meets the doctor in the consulting room. Under the new model, the diagnosis is not entirely dependent on the frame of mind of the doctor. An ANFIS is designed to intelligently carry out the diagnosis when the symptoms are known.

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CHAPTER FOUR

IMPLEMENTATION AND EXPERIMENTATION

4.0 Introduction

The purpose of the research is to implement adaptive neuro fuzzy inference system(ANFIS) in diagnosing malaria patients. The chapter focuses on the implementation and experimentation of the research. Tools such as flowchart, algorithm design and MATLAB

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7.10.0(R2010a) were used in achieving the result.

4.1 Anfis Architecture

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Figure 4.1: Structure of the ANFIS network.

Figure 4.1 which is the structure of the ANFIS is represented in a block diagram in figure

4.2 and the layers further explained.



Layer 1 (L1): Each node generates the membership grades of a linguistic label.

An example of a membership function is the generalised bell function:

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}$$

where $\{a, b, c\}$ is the parameter set. As the values of the parameters vary, the form of the bellshaped perform varies. Parameters in that layer are referred to as premise parameters. Layer 2 (L2): Every node calculates the firing force of each rule making use of the min or prod operator. Quite often, any other fuzzy AND operation can be used.

Layer 3 (L3): The nodes calculate the ratio of the rule"s firing strength to the sum of all the rules firing strength. The result is a normalized firing strength.

Layer 4 (L4): The nodes compute a parameter function on the layer 3 output. Parameters in this layer are called consequent parameters.

Layer 5 (L5): A single node that aggregates the overall output as the summation of all incoming signals.



The flowchart of the algorithm



Figure 4.3 Flowchart of the Algorithm

4.3 Development of the ANFIS Model

An ANFIS-GUI was created to help user to use artificial intelligence (AI) such as ANFIS (Adaptive Network-based Fuzzy Inference System) to predict output. ANFIS can predict data using Sugeno FIS (Fuzzy Inference System) to relate membership and tune it using either back propagation or hybrid method. In the present research work three input corresponding parameters namely; temperature, BP(blood pressure-systolic) and weight with their respective linguistic values low, medium and high were used for the ANFIS training. ANFIS architecture utilizes sugeno- type fuzzy- inference systems triangular built-in membership function to emulate a given training dataset. It employs 78 number of nodes, 108 linear parameters, 27 nonlinear parameters, 135 total numbers of parameters, 60, training data pairs, 60 checking data pairs, 40 and 27 fizzy rules to predict the diagnosis and treatment of malaria. In modeling the ANFIS, 100 dataset input-output data pairs on malaria patients were collected and divided it into training and checking datasets.

4.4 Modeling with The ANFIS Editor

i. First dataset that contains desired input/output data pairs of the target system to be modeled were collected. The datasets are now divided into training and checking

datasets.

- ii. The training and checking datasets are saved in excel files.
- iii. The training and checking datasets are imported individually into matlab workspace using the command *uiimport* in the Matlab command area.

- iv. The command anfisedit was typed in the Matlab command area to display ANFIS editor dialogue box.
- v. In the load data section of the ANFIS editor, training and checking data were loaded by selecting appropriate radio buttons and then clicking "Load Data". The loaded data is plotted on the plot region.
- vi. FIS model was generated by clicking on grid partition in the "Generate FIS" section of the ANFIS editor.
- vii. FIS model structure was viewed once an initial FIS has been generated or loaded by clicking the **Structure** button.
- viii. The FIS model parameter hybrid optimization method: which is a mixture of back propagation and least squares method was chosen in the "Train FIS" section of the ANFIS editor. The error tolerance and the training epoch number were also chosen

in this section.

- ix. FIS model was trained by clicking the **Train now** button. This training adjusted the membership function parameters and plotted the training data error plots in the plot region.
- x. The test button in the "**Test FIS**" portion of the ANFIS editor was clicked to view generate the testing plot against the training dataset.

Some of the snapshots of the interfaces regarding the procedure for modeling in the ANFIS editor are displayed in fig 4.3.

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a) An empty dialogue box of the ANFIS Editor



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c) Plot for checking dataset

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d) Specifying membership function



e) Training the FIS

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Fig 4.4 Snapshots of the procedures in modeling with ANFIS editor

4.5 Dataset Used

The researcher used several patients" data on temperature, BP and weight in building the ANFIS model for malaria diagnosis. Out of 100 dataset, 60 were used for the training of the system and the remaining 40 were used as the checking dataset. The researcher used values 1,2 and 3 to depict the grade or level of the malaria to be malaria free, uncomplicated malaria and complicated malaria and its treatment to be "Discharge without medicine", "Artesunate Amordaiquine (tab or syrup)" and "IM Quinine or Quinine Tablet or IV" respectively. Also the researcher generated personalized id for patients since they remain confidential from the hospital where they were collected from and could not be given out.

The training and checking datasets are represented in table 4.1 and table 4.2 respectively

No	Temperature	BP	Weight	Level of Malaria
AK001	28.7	72	7.1	1200
AK002	36	80	37	1
AK003	35.6	120	85	17
AK004	36.2	160	9	
AK005	37	120	9	2
AK006	38.5	127	9	3
AK007	37	80	30	2
AK008	36.6	90	45	1
AK009	36.4	120	41	1

	AK010	36.8	100	29	1	
	AK011	38.1	130	30	3	
	AK012	35.5	100	33	1	
	AK013	36	90	18	1	
	AK014	35.5	90	66		
	AK015	36.4	120	64	1	
	AK016	36.1	108	53	1	
	AK017	36.3	125	70	1 4	
	AK018	36	122	65	1	
	AK019	36.6	150	23	1	
	AK020	36	130	83	1	1
	AK021	36.3	160	80	18 25	3
	AK022	36.4	128	89		
	AK023	36.5	110	65	15555	
	AK024	34.7	100	65	1	
	AK025	35.8	120	64	1	
-	AK026	38	138	30	3	5
	AK027	37.9	160	15	2	1
	AK028	37.4	68	15	2	
	AK029	37.2	82	39	2	
	AK030	36.4	95	36	1	
	AK031	36	80	33	1	

AK032	37.3	98	31	2	
AK033	36	164	55	1	
AK034	36.3	150	15	1	
AK035	35.8	138	80	1	
AK036	37.2	100	15	2	
AK037	36.2	230	34	1	
AK038	36.4	200	30	1	
AK039	36	150	12	1	
AK040	35.5	120	56	1	
AK041	35.2	100	11	1	
AK042	37	120	27	2	1
AK043	36.3	125	74	18 75	3
AK044	36.7	130	36.2		
AK045	36.2	100	51	15000	
AK046	35.7	120	76	1	
AK047	38.5	119	46	3	
 AK048	36.2	220	12		5
AK049	36.4	110	14		1
AK050	36.4	136	69	5 BAD	
AK051	36.4	120	92	NO	
AK052	36.5	220	87	1	
AK053	36.1	160	50	1	

AK054	36.3	120	60	1
AK055	36.5	110	68	1
AK056	35.4	119	70	ICT
AK057	36.6	130	99	
AK058	36.4	120	85	
AK059	38	100	64	3
AK060	38.5	127	9	3

 Table 4.2: Checking dataset for checking in ANFIS

	No	Temperature	BP	Weight	Level of Malaria	
	AK061	35.5	110	32	1 SF	3
	AK062	35.5	100	78	135	1
	AK063	36.2	130	75	1	-
	AK064	38.4	140	77	3	1
	AK065	36.2	1004	79	1	0.
17	AK066	37.3	90	10	2	51
13	AK067	36	120	60	1 /0	E/
	AK068	37.5	110	82	2	
	AK069	36.8	108	71	5	
	AK070	35.8	115	46	1	
	AK071	35.8	95	46	1	

	A 17070	26.6	100	107	1	
	AK072	36.6	120	106	1	
	AK073	38	130	7	2	
	AK074	36.6	130	99	1	
	AK075	36.4	120	85		
	AK076	37.4	112	62	2	
	AK077	37.8	108	41	2	
	AK078	36.2	130	61	1	
	AK079	36.2	130	61	1	
	AK080	36	100	78	1	
	AK081	36.8	120	14	1	
	AK082	37.5	135	10	2	1
	AK083	36	100	64	1257	
	AK084	36.4	120	7	1 AL	
	AK085	36	100	64	Tass	
	AK086	38.6	150	10	3	
	AK087	36.6	110	63	1	
z	AK088	36	115	60	1 /5/	
3	AK089	36.4	122	60		
	AK090	36.2	120	61	5 BAD	
	AK091	38.1	130	138	3	
	AK092	36.2	140	9.1	1	
	AK093	36.3	134	55	1	

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AK094	36.4	110	84	1
AK095	36.1	100	73	1
AK096	36	150	90	
AK097	36	90	67	
AK098	36	140	85	
AK099	34.6	120	85	1
AK100	36.2	130	89	1

4.6 Experimentation

The researcher selected some patients from the dataset through random picking to help test the performance of the ANFIS model. Table 4.3 shows the result obtained from the experimentation.

Table 4.3: Experimen	tation of the	ANFIS Model
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Patients ID	Tested Result	Degree of Malaria/Treatment		
AK002	1.01	Malaria Free - Discharge without medicine		
AK005	2.03	Uncomplicated Malaria – Artesunate		
~	PR	Amordaiquine(tab or syrup)		
AK008	0.935	Malaria Free - Discharge without medicine		
AK013	0.987	Malaria Free - Discharge without medicine		
AK015	0.986	Malaria Free - Discharge without medicine		

AK026	2.95	Complicated Malaria – IM Quinine OR Quinine
		Tablet or IV
AK027	2	Uncomplicated Malaria – Artesunate
		Amordaiquine(tab or syrup)
AK028	2.01	Uncomplicated Malaria – Artesunate
		Amordaiquine(tab or syrup)
AK032	1.89	Uncomplicated Malaria – Artesunate
		Amordaiquine(tab or syrup)
AK067	0.964	Malaria Free - Discharge without medicine

4.7 Simulation of the Model

The model was simulated using ANFIS editor in Matlab 7.10.0(2010a). screen shots of the FIS editor, rule view, surface view, input temperature variable, input BP Variable, input weight variable and output diagnosis variable are shown in the appendices.



CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.0 Overview

The research is conducted to employ the use of Adaptive Neuro Fuzzy Inference System(ANFIS) for better and accurate diagnosing of malaria. This chapter deals with comparing results of the experimentation, discussion of the results, conclusion, recommendation and suggestion for future research work.

5.1 Comparing Results of the Experimentation

The purpose of the comparison is to find out how accurate or close the results of ANFIS are close to the expected degree or level of intensity of the malaria condition. Table 5.1 shows the id of some selected patients through random picking, expected degree of malaria condition, ANFIS result and ANFIS Diagnosis.

Patients ID	Expected Result	ANFIS Result	ANFIS Diagnosis
AK002	12R	1.01	Malaria Free
AK005	2	2.03	Uncomplicated Malaria
AK008	1	0.935	Malaria Free

Table 5.1: Comparison of results of ANFIS and expected level of malaria condition

AK013	1	0.987	Malaria Free
AK015	1	0.986	Malaria Free
AK026	3	2.95	Complicated Malaria
AK027	2	2	Uncomplicated Malaria
AK028	2	2.01	Uncomplicated Malaria
AK032	2	1.89	Uncomplicated Malaria
AK067	1	0.964	Malaria Free

5.2 Discussion of Results

Table 5.1 shows the ANFIS results of some selected patients. Also given the values for the linguistic input variables, degree or intensity of the malaria condition were assigned to them as output to be modeled in ANFIS. The intensities malaria free, uncomplicated malaria and complicated malaria were coded into figures 1, 2 and 3 respectively. The results after training in table 5.1 show very good results. Though there are some differences between the expected malaria intensity and the ANFIS, it can be confidently said that the errors are very minimal. For example the result of patient AK002 after the trained ANFIS is 1.01 which is undoubtedly close to 1. Again patient AK067 had result 0.964 after the trained ANFIS which is also very close to the expected result which is 1. Patient AK027 had 100% accuracy in diagnosis since 2 was obtained after ANFIS training equaling the expected result which is 2.

The researcher realized from the experiment conducted on the sampled patients that their results of level or intensity of malaria condition were very close to the expected degree of malaria condition used as output to train the dataset.

5.3 Conclusion

The ANFISS editor in Matlab 7.10.0(R2010a) is a powerful tool in model systems. The software is proven to be able to provide the actual model by using both neural systems and fuzzy logic. The ANFIS has achieved close results to the expectation of the researcher with very minimal errors. The use of ANFIS in the design of the diagnostic system proposed in this paper is believed to serve as a dependable and cheap means of treating malaria. Furthermore, implementation of ANFIS based medical diagnostic system will reduce doctors'' job during consultation and the problem of patients delay in hospitals due to the slowness of the existing model.

5.4 Recommendation

Hospitals and clinics in Ghana should employ the use of technology and artificial intelligence such as ANFIS in diagnosing patients to reduce the many guess work done by some doctors which in many cases lead to wrong diagnosis and inaccuracies. To be able to do this successfully, it is necessary for the hospitals to invest in enough storage media to safely the data of its patients.

5.5 Suggested future work

The ANFIS has proven to be a good tool for modeling systems. Nevertheless, more advanced ASFIS should be designed to be able to diagnose not just a particular sickness in the case of this paper which deals with only malaria but multiple sicknesses. Also future research in this

area should look at some of the safest ways of guarding patients" data as this is necessary for use as medical history.

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Generated Model Structure of the ANFIS



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Input Variable Weight



Output Variable Diagnosis Treatment

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