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Hybrid Intelligent System for the Diagnosis of Typhoid Fever

Samuel Oluwarotimi Williams[1]* and Omisore Mumini Olatunji[1]

Abstract

The diagnosis of Typhoid Fever (TF) is often complicated due to the significant number of vague variables involved. As a result of this complexity, several lives have been lost while others are living with deteriorated health status. This research proposes a Hybrid Intelligent System which provides an efficient means of handling the complexity associated with the diagnosis of TF. The proposed system consists of a Fuzzy Logic (FL) component which handles imprecise and incomplete medical data, a Neural Network (NN) component which automatically generates the parameters that drive the Membership Functions of TF diagnosis variables for the Fuzzy Inference System. The attributes of TF diagnosis serve as the core input parameters to the FL and NN components. The proposed system provides a hybrid platform otherwise known as Adaptive Neuro Fuzzy Inference System (ANFIS) that employs back propagation and least square estimation learning techniques, and uses Sugeno's Inference Mechanism to provide accurate, timely, cost effective, and valid results regarding patient diagnosis. Experimental study of the proposed system was conducted using medical records of TF patients and the results of the study were found to be within the range of predefined limit as examined by medical experts. An evaluation of the proposed system using standard statistical methods proved its efficiency in providing accurate diagnosis.

Keywords

Typhoid fever; Diagnosis; Fuzzy logic; Neural network; Hybrid Intelligent System; ANFIS

Introduction

The prevalence of Typhoid Fever (TF) in developing countries constitutes a major threat to the existence of humans due to inaccurate and untimely diagnosis procedures employed by medical practitioners in the region. In most parts of the tropics, the diagnosis of TF is based on smear microscopy and widal test, while in rare cases it includes bacterial culture [1]. However, in rural settings of Africa, clinical diagnosis (based on symptoms) remains the only option for TF and this makes accurate diagnosis unlikely. Consequently, it is of concern that poor diagnosis continues to hinder effective control of TF in the tropics [1]. Research has shown that a number of factors including non-specific presentation of TF, high prevalence of asymptomatic infections in many rural communities, improper waste management system, lack of good water supply, insufficient access to trained healthcare providers, inadequate healthcare facilities, and widespread practice of self-treatment for clinical suspected TF, contributes to poor diagnosis of TF in the tropics [1,2].

Effective medical diagnosis involves series of steps that must be carefully followed in order to guarantee accurate results. This is highly essential, because it has to do with human life. Accurate diagnosis often aids therapy administration and as well improves the health status of patients [3]. As a result of the flaws associated with the orthodox approach to TF diagnosis in developing countries, many lives have been lost while several others have experienced serious deterioration in their health status. Hence, healthcare organizations in developing countries are expected to provide new and improved patient care capabilities at a reduced cost [4].

This research proposes a Hybrid Intelligent System engineered by Neural Network and Fuzzy Logic techniques for the diagnosis of TF. The hybrid system is aimed at providing an efficient decision support platform to aid medical practitioners in administering accurate, timely, and cost effective diagnosis of TF in developing countries.

The remaining part of this paper is structured as follows: Literature Review presents review of related work; Materials & Methods presents the architecture of the proposed system, methods and materials adopted by the research; Experiment & Results presents an experimental study of the proposed system; System Evaluations presents an evaluation of the proposed system; while Conclusion presents the conclusion which is drawn from the findings of the research.

Literature Review

Expert system

Expert Systems (ESs) are artificial intelligence based computer programs that have received a great deal of attention in recent times and have been used to solve an impressive array of problems in several fields [5-7]. The basic steps in ES development have been reported in [6]. Many intelligent systems have been developed for the purpose of enhancing healthcare delivery, providing better healthcare facilities, and reducing the cost associated with quality healthcare services [3]. Works on some early intelligent computer programs and techniques used in the building of such systems were discussed in [3,8,9]. The core attributes of ESs have been reported in [10]. Early studies in intelligent medical systems such as CASNET, MYCIN, PIP, INTERNIST-I, have been shown to outperform manual practices of medical diagnosis in several domains [11]. The use of ESs in medical analysis have greatly reduced the cost of human support, medical diagnosis, and as well increased diagnosis accuracy [7].

Fuzzy logic

A Fuzzy Logic System (FLS) otherwise known as Fuzzy Inference System (FIS) is defined as a nonlinear mapping of an input data set to a scalar output data set [12]. FISs have attracted growing attention and interest in modern information technology, production technique, decision making, pattern recognition, medical diagnosis and data analysis among others [13-16]. They are also known as fuzzy rule based systems, fuzzy models, fuzzy associative memories, or fuzzy controllers when used as controllers [17]. Fuzzy Logic (FL) has found

***Corresponding author:** Samuel Oluwarotimi Williams, Department of Computer Science, Federal University of Technology, P.M.B. 704, Akure, Nigeria, Tel: +234 8032397138; E-mail: timitex92@ gmail.com

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a variety of applications in industrial process control and securities trading [18-21]. It has equally been employed in the modeling of medical diagnosis systems [22-26]

When a problem has dynamic behavior and involves several variables, FL technique can be applied to solve such problem [27]. One of the main challenges of creating a FIS is the determination of the fuzzy sets and its fuzzy rules which require deep knowledge of human experts in a particular domain [28]. The Membership Functions (MFs) of FISs are arbitrarily chosen, therefore fixed in nature. Generally, the shape of such MFs depends on certain parameters that can be adjusted. Rather than choosing the MF parameters arbitrarily, the neuro - adaptive (Neural Network) learning and tuning techniques provides a method for the fuzzy modeling procedure to learn information about a given dataset in order to automatically compute the MF parameters that allows the associated FIS to track the given input/output data relationship. Hence, FISs can learn from the data they model when Neural Network is incorporated into them.

Neural network

Neural Networks (NNs) have a large number of highly inter-connected processing elements (nodes) that demonstrate the ability to learn and generalize from training patterns or data and are excellent at developing human-made systems that can perform the same type of information processing that human brain performs [25]. NN was traditionally referred to as a network or circuit of biological neurons [29]. The modern usage of the term is often referred to as Artificial Neural Networks (ANNs). ANNs are loosely inspired in biological nervous systems [30], and they simulate the function of human brain to perform tasks that are carried out by human experts [31]. The biological nervous system is highly complex, hence ANN algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view [29].

Each of the above soft computing techniques (NN and FL) has provided efficient solution to a wide range of problems belonging to different domains. However, each of them has advantages and disadvantages. It is therefore appropriate to hybridize these two techniques so as to overcome the weakness of one with the strength of the other [32]. There has been an increasing need to combine NN and FL for a successful development of an ES that would have a human like reasoning capability [25]. NNs derive their strengths from the ability to generalize data relationship and their ability to handle data with non-linear relationship as those found in medical records while FL help in handling uncertainty found in medical data.

Neuro-Fuzzy systems harness the power of NN and FL paradigms [33]. Hybridization of NN and FL provides a solution that is capable of integrating the strength of both techniques and eliminating their weaknesses. The hybrid technique provide a method that allows the NN modeling procedure to learn certain information about a given dataset in order to automatically compute the MF parameters that best drives the associated FIS [7]. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) constructs a FIS whose MF parameters are tuned through NN by using either Back Propagation algorithm alone or in combination with Least Squares Estimation method. This allows the FIS to learn from the dataset that are modeled. The following are some Neuro-Fuzzy systems that have been designed and applied to various fields: GARIC, FALCON, ANFIS, NEFCLASS, FUN, SONFIN, and FINEST [7].

Materials and Methods

The attributes considered for the diagnosis of TF after a series of consultations with medical experts and standard literature in the field of tropical medicine are presented in Table 1. Basically, these diagnosis attributes are classified into three major categories namely, *Patient Laboratory Investigation* (PLI), *Patient Medical History* (PMH), and *Patient Physical Examination* (PPE) as shown in Table 1.

From the content of Table1, fourteen (14) key variables with Codes Q_1 through Q_{14} were considered for the diagnosis of Typhoid Fever.

The architecture of the proposed Hybrid Intelligent System is presented in Figure 1. The architecture consists of a Knowledge Base (KB), a Neuro-Fuzzy Inference Engine (NFIE), a Decision Support Engine (DSE) consisting of Cognitive and Emotional filters that respectively handle the physician's objective and subjective feelings regarding a patient, and a User Interface which serves as a medium for the entry of diagnosis variables and display of diagnosis results. The KB stores both structured and unstructured knowledge about the problem domain and serves as a repository for operational data that are to be processed. The database component of the KB stores patient bio-data, hereditary data, other relevant data, attributes of signs, symptoms, and laboratory investigation of patients.

The proposed Hybrid Intelligent System is conceptualized in the following order: The design of the Fuzzy Inference System for TF diagnosis is discussed in Fuzzy logic component; the design of the Neural Network component that optimizes the performance of the Fuzzy Inference System by automatically computing the MF parameters that best drives the FIS is discussed in Neural network component; the design of the Hybrid Intelligent System (Neuro Fuzzy Inference System) is discussed in Neuro-Fuzzy component; while the design of the Decision Support Engine that enhances the overall performance of the proposed system is discussed in Decision support engine component.

Fuzzy logic component

The FL component of Figure 1 is made up of *a Fuzzifier*, a *Fuzzy Rule Base, Fuzzy Inference Engine*, and *a Defuzzifier*. The function of each of these components is discussed as follows:

Fuzzifier: The fuzzifier converts crisp input values to their

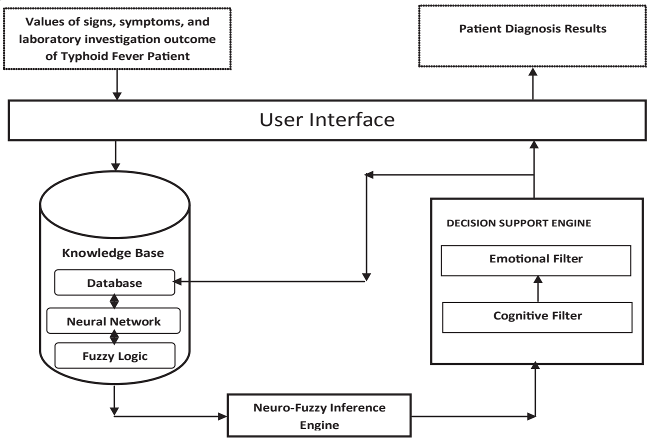

Figure 1: Architecture of the Proposed Neuro-Fuzzy Expert System.

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corresponding fuzzy values. For instance, assuming **v** is a fuzzy set of diagnosis variables in **V** (Universe of Discourse) and x_i represents an element in **v**; therefore, v is described by equation (1).

$$v = \{(x_i, \mu_v(x_i)) \mid x_i \in V, \mu_v(x_i) \in [0,1]\} \quad (1)$$

where $\mu_v(x_i)$ is the MF of x_i in v and it represents the degree of contribution of x_i towards the outcome of a particular diagnosis. The fuzzy set employed by this research to describe the attributes of TF diagnosis is {Very Mild, Mild, Moderate, Severe, Very Severe}. Each diagnosis attribute in Table 1 is represented by a linguistic term that belongs to the defined fuzzy set, while each linguistic term has its associated numeric value. For example, the linguistic term of the i^{th} diagnosis variable as define by medical experts during a consultation is shown by equation (2) as follows:

$$LT_i = \begin{cases} \text{"Very Mild"} & if\ x_i = 1 \\ \text{"Mild"} & if\ x_i = 2 \\ \text{"Moderate"} & if\ x_i = 3 \\ \text{"Severe"} & if\ x_i = 4 \\ \text{"Very Severe"} & if\ x_i = 5 \end{cases} \quad (2)$$

where LTi represents the linguistic term for the i^{th} diagnosis variable, $i = 1, 2, 3, \ldots, 14$; and x_i denotes the value of the i^{th} diagnosis variable. Figure 2 shows the MF graph of input variables. The MF shows the degree of contribution for each input variable towards the diagnosis outcome. *Note that* $x1 = Q_i$.

Rule base: The rule base for TF diagnosis is characterized by a set of IF-THEN rules in which the antecedents (IF parts) and the consequents (THEN parts) involves linguistic variables. The rules that constitute the rule base were carefully formulated with the assistance of medical experts in the field of tropical medicine. A rule fires if any of its precedence parameter such as Very mild, Mild, Moderate, Severe, and Very severe evaluates to true or 1, otherwise it does not fire. An example of the structure of the rules in the rule base is:

If Q_1 is Mild AND Q_2 is Moderate AND Q_3 is Severe . . . THEN TF is Moderate

Fuzzy inference engine: This component represents the decision making engine. It receives its inputs from the rule base and the fuzzification interface, and then it applies a pre-defined procedure to this set of inputs in order to produce the desired output. This research adopts the Root Sum Square (RSS) inferential technique whose formula is presented in Equation (3).

$$RSS = \sum_{k=1}^{n} R_k^2 \quad (3)$$

where R_k represents a fired rule and k = 1,2,3,…,n represents the number of fired rules for a particular diagnosis.

Defuzzifier: The defuzzifier translates the output of the inference engine into crisp values which are mostly required by medical experts for proper analysis and interpretation; this no doubt, aids efficient therapy administration. This research employs the Centroid of Area (CoA) technique for its defuzzification. This interface receives as input the output of the inference engine and applies Equation (4) to arrive at the defuzzified output.

$$CoA = \frac{\sum_{i=1}^{n} \mu Y(xi) xi}{\sum_{i=1}^{n} \mu Y(xi)} \quad (4)$$

where $\mu Y(xi)$ is the membership value of x_i as given by the MF in Figure 2 and x_i is the center of the MF.

Table 1: Categories of Typhoid Fever Diagnosis Attribute.

Patient Laboratory Investigation (PMH)	Code	Patient Medical History (PMH)	Code	Patient Physical Examination (PPE)	Code
Liver Function Test	Q_1	Fever	Q_5	Body Temperature	Q_{13}
		Headache	Q_6		
Blood Test	Q_2	Abdominal Pain	Q_7		
		Stomach Pain	Q_8		
Stool Test	Q_3	Myalgia	Q_9	Pulse Rate	Q_{14}
		Lassitude	Q_{10}		
Urine Test	Q_4	Loss of Appetite	Q_{11}		
		Vomiting	Q_{12}		

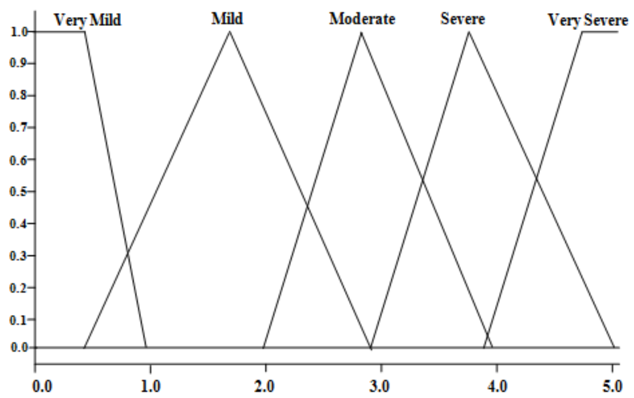

Figure 2: Membership Function Graph of Input Variables.

Neural network component

The NN component of Figure 1 is made up of attributes drawn from the following categories, *Patient Medical History*, *Patient Physical Examination*, and *Patient Laboratory Investigation* as presented in Table 1. The integrated block diagram for the Neural Network component design is presented in Figure 3.

The resulting output at each stage of the NN model in Figure 2 is given by equations (5-8).

$$PLI = \sum_{i=1}^{4} (Qi * Wi) \quad (5)$$

$$PMH = \sum_{i=5}^{12} (Qi * Wi) \quad (6)$$

$$PPE = \sum_{i=13}^{14} (Qi * Wi) \quad (7)$$

$$OUTPUT = (PLI * W_{PLI}) + (PMH * W_{PMH}) + (PPE * W_{PPE}) \quad (8)$$

where Q_i represents the value of the ***ith*** input diagnosis attribute and W_i represents its corresponding weight. PLI, PMH, and PPE are the intermediate results of a particular diagnosis while W_{PLI}, W_{PMH}, and W_{PPE} are their connection weights respectively. The **NN** model in Figure 3 consists of an *Input Layer* that represents diagnosis attributes of TF, one *Hidden Layer* which depicts the intermediate results of the diagnosis, and an *Output Layer* which shows the overall outcome of the diagnosis. The neurons in each layer are connected to the ones in

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the succeeding layer by a link known as connection weight in order to produce the desired outcome at each stage of the diagnosis.

Neuro-Fuzzy component

The block diagram of a Neuro-Fuzzy Inference System (NFIS) that integrates both the NN and FL components and as well drives the proposed system is presented in Figure 4. The NFIS employs Back Propagation and Least Square Estimation learning techniques and is made up of six layers of neurons in which the first, second, and fifth layers consists of adaptive nodes (nodes where several computational procedures take place), while the third and fourth layers consists of fixed nodes.

where X_i represents the category of diagnosis attributes and i = 1, 2, n. $A_1, A_2, \ldots A_n, B_1, B_2, \ldots B_n$, and $C_1, C_2, \ldots C_n$ are the input variables of categories X_1, X_2 and X_n respectively. The rules that drive the NFIS are based on Sugeno's Inference Mechanism and they assume the following structure:

IF (A_1 is VML) AND (B_2 is MLD) AND . . . AND (C_n is SEV) THEN (Y is F)

where VML = Very Mild, MLD = Mild, MOD = Moderate, SEV = Severe, and VSE = Very Sever.

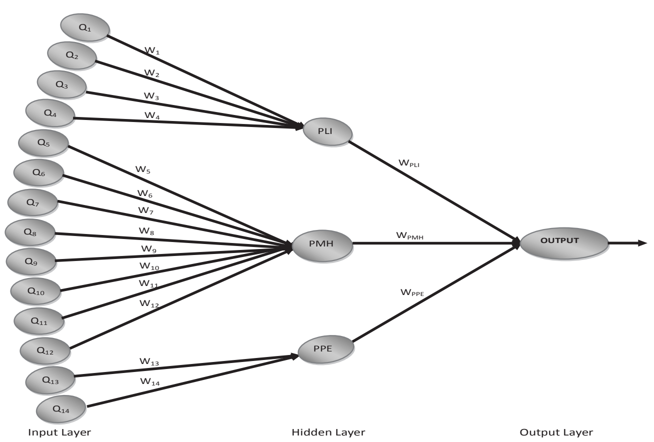

Figure 3: Integrated NN Model for TF Diagnosis.

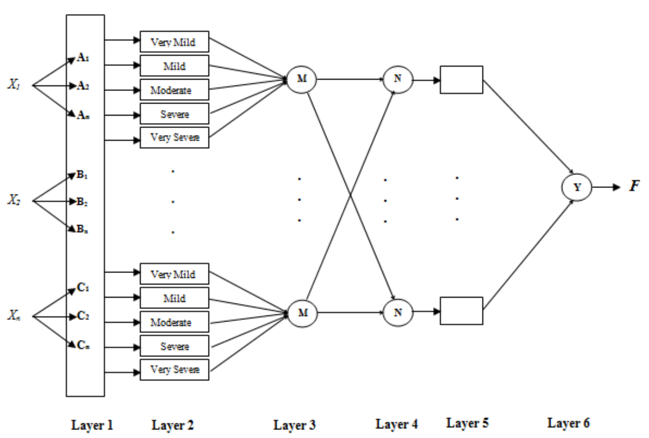

Figure 4: Block Diagram of the Neuro-Fuzzy Inference System for TF Diagnosiss.

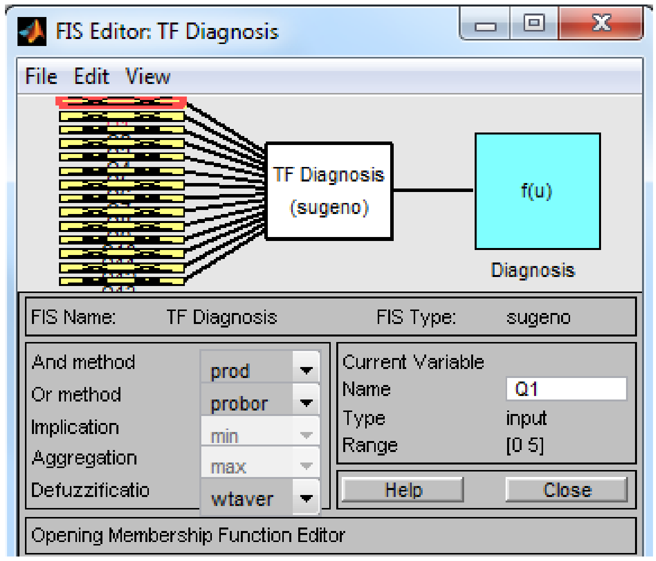

Figure 5: Fuzzy Inference System for TF Diagnosis.

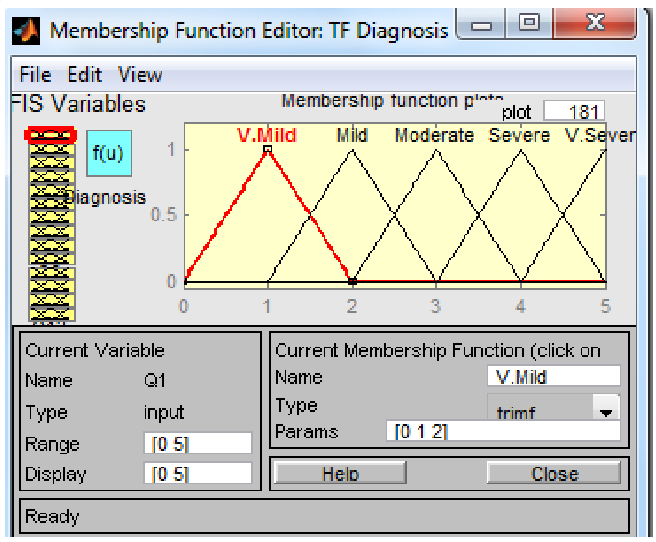

Figure 6: MF attributes for TF Diagnosis Variables.

Layer 1: This layer consists of active nodes which denote inputs to the system. These inputs are numeric values which represents diagnosis variables drawn from the following categories; PLI, PMH, and PPE. The outputs of this layer are linguistic labels corresponding to each input value.

Layer 2: This layer is made up of adaptive nodes and they receive as input the output of the preceding layer and eventually produce their corresponding membership grade as shown in equation (9).

$$f_2(x_i) = \mu_{Ai}(x) \quad (9)$$

There are various types of MFs, but this research work adopted the triangular MF due to its ease of use and its formula is presented in equation (10).

$$\mu_{Ai}(x) = \frac{x-b}{a-b} \quad (10)$$

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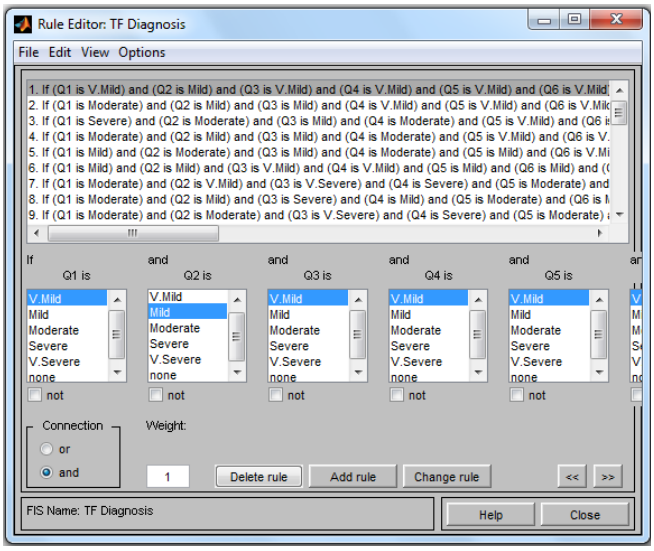

Figure 7: Fuzzy Rule Base for TF Diagnosis.

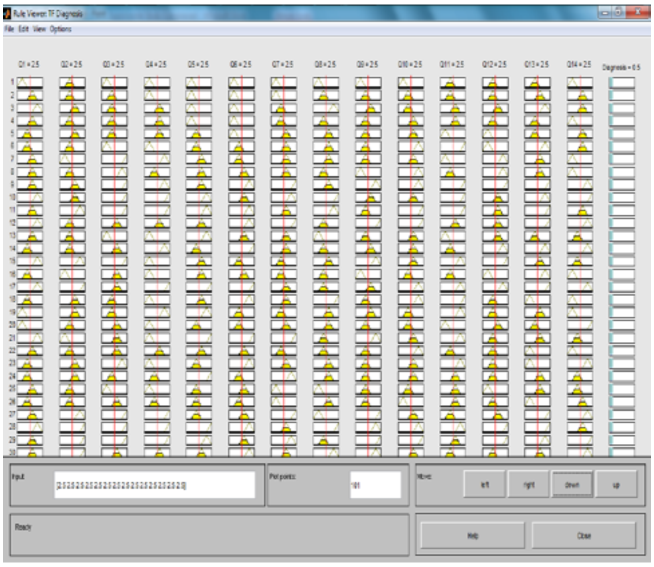

Figure 8: Fuzzy Rule Viewer for TF Diagnosis.

where **a** and **b** are the attributes of the triangular MF that bounds its shape such that $b \leq x \leq a$.

Layer 3: The nodes in this layer are fixed in nature and they are all labeled **M** indicating that they simply act as multipliers. The nodes in this layer compute the firing strengths of their associated rules. This layer's output is represented by equation (11).

$$f_3(x_i) = \mu_{Ai}(x) * \mu_{Bi}(x) * \mu_{Ci}(x) \tag{11}$$

Layer 4: This layer is made up of fixed nodes labeled **N** and they normalize the firing strength of each rule. For example, the normalized firing strength of ***Rule 1*** is shown in equation (12).

$$f_4(x_i) = \frac{w_1}{w_1 + w_2 + w_3} \tag{12}$$

while the normalized firing strength of the ***k****th* Rule is given by equation (13).

$$f_4(x_i) = \frac{w_k}{\sum_{j=1}^{s} w_j} \tag{13}$$

Layer 5: This layer is made up of adaptive nodes and the output of each node is the product of the normalized firing strength of a rule and its corresponding output value. This is shown in equation (14).

$$f_5(x_i) = f_4(x_i) * R_{out}(x_i) \tag{14}$$

Layer 6: This layer consists of a single fixed node labeled **Y** which represents the ANFIS's final output. It is computed by summing all the incoming signals as shown in equation (15).

$$Y = \sum_{i=1}^{n} f_5(x_i) = \sum_{i=1}^{n} (f_4(x_i) * R_{out}(x_i)) \tag{15}$$

The final output of ANFIS is in crisp form and its represents the diagnosis result of a given patient. This crisp output is classified as VMLD or MLD or MOD or SEV or VSEV; depending on its value by

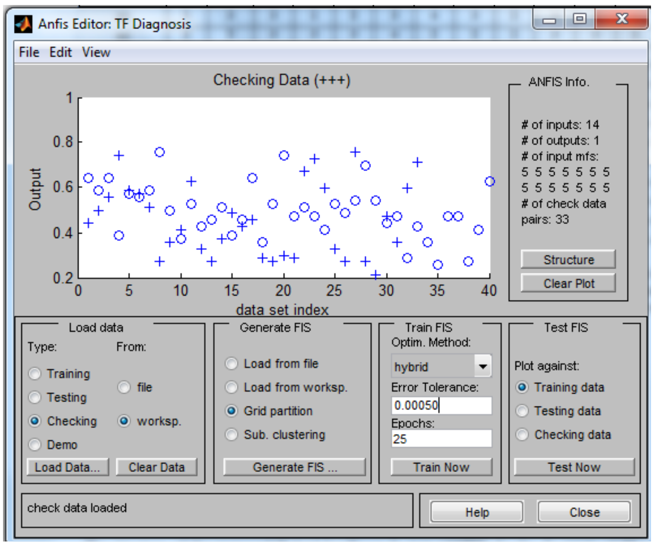

Figure 9: Outcome of the Training & Testing Sessions for FIS.

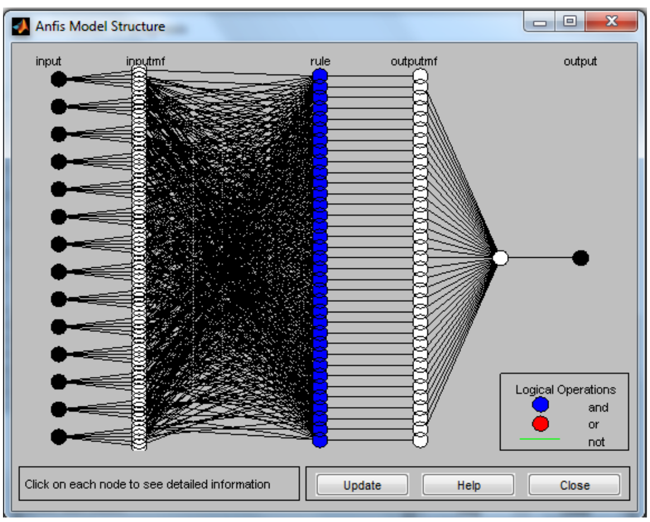

Figure 10: Structure of the ANFIS for TF Diagnosis.

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using equation (16).

$$Output = \begin{cases} \text{"VMLD"} & if\ x_i = 1 \\ \text{"MLD"} & if\ x_i = 2 \\ \text{"MOD"} & if\ x_i = 3 \\ \text{"SEV"} & if\ x_i = 4 \\ \text{"VSEV"} & if\ x_i = 5 \end{cases} \tag{16}$$

Decision support engine component

The output of the NFIS goes into the DSE which is made up the Cognitive and Emotional filters. The Cognitive filter for example enables the physician to know if the patient is pregnant or allergic to certain drugs, while the Emotional filter for example provides the physician with information that enables him to decide whether the patient needs drugs or bed rest or physical exercise. In summary, the DSE further enhances the performance of the entire system and eventually aid efficient therapy administration.

Experiment and Results

Implementation of the proposed hybrid intelligent system was achieved with Matrix Laboratory (MATLAB) Version 7.9.0.529 (R2009b) which served as the core programming tool, Microsoft Access 2007 Version which served as the Database for patient medical records, Microsoft Excel 2007 Version which was used to preprocess the require dataset into a format that could be exported to MATLAB workspace.

The Medical records of 73 TF patients aged 15 to 70 were collected, analyzed, and preprocessed to the required format from the management of the Federal Medical Center, Owo, Ondo-State, Nigeria. The intensity of TF diagnosis variables (Q_1 to Q_{14}) for each of the 73 TF patients were rated as VML (1), MLD (2), MOD (3), SEV (4), and VSE (5) in accordance to equation (2). Weights were also assigned to each diagnosis variable based on their individual contribution towards the overall diagnosis result. Table 2 shows the weight assigned to the diagnosis variables of patients after an extensive interaction with a medical doctor in the field of tropical medicine.

Figure 5 shows the developed FIS module for TF diagnosis and it consists of fourteen (Q_1 to Q_{14}) input variables, an intermediate variable named "TF Diagnosis" which contains all necessary information about the system, and an output variable which signifies the outcome of a diagnosis is represented by "f (u)". Figure 6 shows the MF module of the FIS which defines the MFs associated with all input and output variables. For example, the figure 6 shows the MFs of the input variable Q_1 and its respective numeric value range.

Figure 7 represent the Rule Base module of the FIS and it provides a means of representing all pruned rules that defines the behavior of the FIS. The rule base is made up 50 rules as gotten from medical experts in the field of tropical medicine. Each rule is made up of 14 input variables and 1 output variable.

Figure 8 depicts the Rule Viewer module of the FIS and it shows an interpretation of the entire fuzzy inference process. The Rule Viewer provides Input text field that allows a user (Medical Personnel) to enter specific input values for all the fourteen (Q1 to Q14) TF diagnosis variables of a particular patient, after the entry, the user then hits the Enter key on the keyboard and the diagnosis result for such a patient is displayed.

The diagnosis results produced by the FIS for the 73 TF patients based on the intensities of their individual diagnosis variables is presented in the "Diagnosis" columns of Tables 3 and 4.

Table 2: Assignment of Weight to TF Diagnosis Variables of Patients.

Patient ID	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}	Q_{14}
01	3	3	1	1	5	4	4	3	5	3	4	3	4	2
02	4	4	3	1	4	3	2	3	4	3	1	3	3	3
03	4	2	4	3	2	1	5	4	3	4	3	4	5	1
04	1	3	2	2	3	2	2	1	1	1	1	1	3	4
05	5	2	2	4	3	4	3	2	2	2	3	3	3	2
06	3	1	1	2	4	2	1	3	3	3	3	5	4	4
07	2	3	4	3	3	5	4	2	2	1	1	2	4	5
08	2	5	4	5	5	3	3	5	4	3	4	3	4	3
09	2	3	2	2	5	4	2	2	3	3	3	1	2	1
10	1	2	3	1	3	2	4	3	1	1	2	4	1	1
11	3	3	1	1	4	3	2	2	3	2	5	1	5	2
12	4	2	2	1	4	2	2	3	1	1	3	2	1	2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
70	4	1	2	1	4	3	2	2	2	4	1	1	5	1
71	2	3	1	2	1	2	2	1	2	2	1	2	1	3
72	2	3	5	1	4	2	2	3	5	2	2	5	2	4
73	5	2	1	3	4	3	5	4	4	3	4	3	4	5

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Table 3: Training Dataset exported from MS Excel Worksheet into MATLAB Workspace.

Patient ID	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}	Q_{14}	Diagnosis
01	3	3	1	1	5	4	4	3	5	3	4	3	4	2	0.6428571
02	4	4	3	1	4	3	2	3	4	3	1	3	3	3	0.5857143
03	4	2	4	3	2	1	5	4	3	4	3	4	5	1	0.6428571
04	1	3	2	2	3	2	2	1	1	1	1	1	3	4	0.3857143
05	5	2	2	4	3	4	3	2	2	2	3	3	3	2	0.5714286
06	3	1	1	2	4	2	1	3	3	3	3	5	4	4	0.5571429
07	2	3	4	3	3	5	4	2	2	1	1	2	4	5	0.5857143
08	2	5	4	5	5	3	3	5	4	3	4	3	4	3	0.7571429
09	2	3	2	2	5	4	2	2	3	3	3	1	2	1	0.5000000
10	1	2	3	1	3	2	1	3	1	1	2	4	1	1	0.3714286
11	3	3	1	1	4	3	2	2	3	2	5	1	5	2	0.5285714
12	4	2	2	1	4	2	2	3	1	1	3	2	1	2	0.4285714
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
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.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
38	1	1	1	1	1	2	1	2	1	1	1	2	2	2	0.2714285
39	1	2	2	2	2	2	2	1	1	3	3	5	2	1	0.4142857
40	3	2	4	5	2	3	3	5	2	2	5	2	4	2	0.6285714

Table 4: Testing Dataset exported from MS Excel Worksheet into MATLAB Workspace.

Patient ID	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}	Q_{14}	Diagnosis
41	1	3	3	1	2	3	4	3	2	3	1	2	1	2	0.4428571
42	2	2	3	3	3	4	2	2	2	3	3	2	2	2	0.5000000
43	5	3	3	3	3	4	2	3	4	1	1	1	1	5	0.5571428
44	2	4	3	4	4	5	4	2	5	3	4	3	4	5	0.7428571
45	2	1	3	1	5	4	4	5	1	3	1	4	5	2	0.5857142
46	3	4	5	2	4	2	3	1	3	2	3	2	4	2	0.5714285
47	5	4	2	1	5	3	2	2	2	1	1	2	1	5	0.5142857
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
72	2	3	5	1	4	2	2	3	5	2	2	5	2	4	0.6000000
73	5	2	1	3	4	3	5	4	4	3	4	3	4	5	0.7142857

In this research, 55% of the dataset collected on TF diagnosis was used to train the associated FIS, while the remaining 45% of the dataset was used to Test the trained FIS. The partitioned dataset is shown in Tables 3 and 4.

The outcome of the training and testing sessions of the FIS by the Neural Network module is presented in figure 9 with the training dataset appearing in *circles* and the testing data appearing in the plot as *pluses* superimposed on the training data. An optimal training with *Error Tolerance* of 0.00050 was achieved when the number of *epochs* was 25 as shown by Table 5.

The structure of the proposed Hybrid Intelligent System (ANFIS) for the diagnosis of TF is presented in figure 10 and it is made up of six layers. The first and sixth layers represent the input and output of entire hybrid system. The first layer has fourteen inputs values and the sixth layer has just one output value. The second, third, fourth, and fifth layers represent the hidden layers of the ANFIS where several computations are performed on the input values in order to provide a

Table 5: Neural Network Training Parameters.

S/N	No. of Epochs	Error Tolerance	Training Techniques
1	5	0.79010	Back propagation & Least Square Estimation Methods
2	10	0.31600	
3	15	0.01100	
4	20	0.01400	
5	25	0.00050	

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Table 6: Statistical Analysis of Diagnosis Results obtained from the Orthodox Approach, FIS, and ANFIS.

S/N	DROA	DFIS	DANFIS	ED_FIS |DROA – DFIS|	ED_ANFIS |DROA – DANFIS|	AL_FIS	AL_ANFIS
01	0.690	0.640	0.670	0.050	0.020	0.950	0.980
02	0.640	0.590	0.610	0.050	0.030	0.950	0.970
03	0.390	0.410	0.375	0.020	0.015	0.980	0.985
04	0.330	0.390	0.320	0.060	0.010	0.940	0.990
05	0.500	0.570	0.485	0.070	0.015	0.930	0.985

DROA = Diagnosis Results of the Orthodox Approach; **DFIS** = Diagnosis Results of the FIS; **DANFIS** = Diagnosis Results of the ANFIS (Proposed System); **ED_FIS** = Error in Diagnosis for FIS; **ED_ANFIS** = Error in Diagnosis for AN FIS; **AL_FIS** = Accuracy Level of the FIS; **and AL_ANFIS** = Accuracy Level of the AN FIS.

valid output for diagnosis of a particular TF patient.

System Evaluations

The degree of validity of any system is typically based on its evaluation's outcome. As part of effort to examine the efficiency of the proposed Hybrid Intelligent System, a comparative analysis of the diagnosis results of TF patients obtained from the conventional approach, FIS, and the proposed Hybrid Intelligent System (ANFIS) is obtained. Table 6 shows the analysis of diagnosis results of five TF patients obtained from the orthodox approach, FIS, and the ANFIS respectively.

The mean accuracy and efficiency of the FIS are computed as shown in equations (17) and (18) respectively.

$$\text{Mean Accuracy of FIS (MA\_FIS)} = \frac{\sum_{i=1}^{n}(\text{AL\_FIS}i)}{n} = \frac{4.750}{5} = 0.950 \quad (17)$$

Efficiency of

$$FIS\ (EFF\_FIS) = MA\_FIS * 100 = 0.950 * 100 = 95.0\ \% \quad (18)$$

While that of the proposed ANFIS are computed by equations equations (19) and (20) respectively.

Mean Accuracy of

$$\text{ANFIS (MA\_ANFIS)} = \frac{\sum_{i=1}^{n}(\text{AL\_ANFIS}i)}{n} = \frac{4.875}{5} = 0.975 \quad (19)$$

Efficiency of

$$ANFIS\ (EFF\_ANFIS) = MA\_ANFIS * 100 = 0.975 * 100 = 97.5\ \% \quad (20)$$

A comparative analysis of diagnosis results produced by the Conventional Approach, FIS, and that of the proposed ANFIS was carried out as shown by Table 6 and equations 17-20. From the outcome of the preceding statistical computations, we therefore conclude that the proposed hybrid intelligent system (ANFIS) provides better diagnosis results than that of the FIS.

Conclusion

The need to arrive at accurate and timely diagnosis has prompted several research works in the field of medical diagnosis. This research proposes a Hybrid Intelligent System driven by Neural Network and Fuzzy Logic to provide a decision support platform that will assist medical practitioners in the efficient diagnosis of Typhoid Fever. The system offers a flexible, user friendly, and scalable design that intelligently combines the key attributes of Typhoid Fever diagnosis so as to provide diagnosis results that are accurate, timely and cost effective in developing countries where Typhoid Fever is prevalent. The proposed system will help to address the problem of insufficient medical experts in developing countries and as well lead to significant reduction in the cost of medical services which will in turn promote the social/economic stability of nations of the developing countries. Finally, this research shows that the integration of Neural Network and Fuzzy Logic have the potential to extend the capabilities of a system beyond either of the two techniques applied individually.

However, a major challenge with Neural Networks is lack of specific methods to determine the optimal number and connection weights for hidden layers and their respective nodes necessary for a particular problem. In other words, the connection weights in Neural Networks are generated on trial and errors basis, which in turn increases the cost of computation. In future research, it is recommended that optimization techniques such as Genetic Algorithm or Ant Colony or Particle Swarm Optimization be studied and adopted to evolve optimal connection weights that will provide the best set of parameters for training the Neural Network in order to enhance the overall performance of the proposed system.

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References

1. Malisa A, Nyaki H (2010) Prevalence and constraints of typhoid fever and its control in an endemic area of Singida region in Tanzania: Lessons for effective control of the disease. Journal of Public Health and Epidemiology 2: 93-99.
2. Uneke CJ (2008) Concurrent malaria and typhoid fever in the tropics: the diagnostic challenges and public health implications. J Vector Borne Dis 45: 133-142.
3. Samuel OW, Omisore MO, Ojokoh BA (2013) A web based decision support system driven by fuzzy logic for the diagnosis of typhoid fever. Expert Syst Appl 40: 4164-4171.
4. Samuel OW, Omisore MO, Ojokoh BA, Atajeromavwo EJ (2013) Enhanced Cloud Based Model for Healthcare Delivery Organizations in Developing Countries. Int J Comput Appl 74: 0975-8887.
5. Shaikh AH, Bhagile VD, Manza RR, Ramteke RJ (2010) Development of an Expert System for Diagnosis and appropriate Medical Prescription of Heart Disease Using SVM and RBF. International Journal of Computer Science and Information Security 8: 245-253.
6. Abraham A (2005) Rule Based Expert Systems. Handbook for Measurement Systems Design, John Wiley and Sons Ltd., London, 909-919.
7. Neshat M, Yaghobi M (2009) Designing a Fuzzy Expert System of Diagnosing the Hepatitis B Intensity Rate and Comparing it with Adaptive Neural Network Fuzzy System. Proceedings of the World Congress on Engineering and Computer Science, San Francisco, USA.
8. Mahabala HN, Chandrasekhara MK, Baskar S, Ramesh S, Somasundaram

doi:http://dx.doi.org/10.4172/2324-9307.1000109

MS (1992) An Intelligent Referral System for Primary Child Healthcare. Proceedings SEARCC'92; XI Conference of the South East Asia Regional Computer Confederation, Kuala Lumpur.

9. Salah B, Alshraideh M, Beidas R, Hayajneh F (2011) Skin Cancer Recognition by Using a Neuro-Fuzzy System. Cancer Inform 10: 1–11.
10. Durkin JJ (1994) Expert System Design and Development, New Jersey; Prentice-Hall.
11. Edward H. Shortliffe (1987) Computer Programs to Support Clinical Decision Making. JAMA 258: 103-119.
12. Mendel JM (1995) Fuzzy Logic Systems for Engineering: A Tutorial. Proceedings of the IEEE 83: 345-377.
13. Ojokoh BA, Omisore MO, Samuel OW, Ogunniyi TO (2012) A Fuzzy Logic Based Personalized Recommender System. International Journal of Computer Science and Information Technology & Security (IJCSITS) 2: 1008-1015.
14. Dubois D, Prade H (1998) An introduction to fuzzy systems. Clin Chim Acta 270: 3-29.
15. Kuncheva LI, Steimann F (1999) Fuzzy diagnosis. Artif Intell Med 16: 121-128.
16. Nauck D, Kruse R (1999) Obtaining interpretable fuzzy classification rules from medical data. Artificial Intelligence in Medicine 16: 149-169.
17. Jhy-Shing RJ (1993) Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man, and Cybernetics 23: 665-685.
18. Zadeh LA (1965) Fuzzy sets. Inform Contr 8: 338-353.
19. Sugeno (1985) Ed.: Industrial Applications of Control. Amsterdam, North Holland.
20. Lee CC (1990) Fuzzy Logic in control system: Fuzzy logic controller-Part I & II. IEEE Transaction on Systems. Man, Cybernetics 20: 404-435.
21. Self KL (1990) Fuzzy logic design. IEEE Spectrum 42-44.
22. Zadeh LA (1965) Fuzzy sets. Information and Control, pp. 338-353.
23. Bharti PK, Silawat N, Singh PP, Singh MP, Shukla M, et al. (2008) The usefulness of a new rapid diagnostic test, the First Response® Malaria Combo (pLDH/HRP2) card test, for malaria diagnosis in the forested belt of central India. Malar J 7: 126-132.
24. Obot OU, Uzoka FM (2008) Experimental study of fuzzy-rule based management of tropical diseases: case of malaria diagnosis. International Stud Health Technol Inform 1: 7-17.
25. Chin-Teng L, George C S L (1991) Neural-Network-Based Fuzzy Logic Control and Decision System, IEEE Transactions on Computers.
26. Zadeh LA (1988) Fuzzy Logic IEEE Comput Mag 83-93.
27. Adeli A, Neshat M (2010) A Fuzzy Expert System for Heart Disease Diagnosis. Proceedings of the International Multi Conference of Engineers and Computer Scientists, 134-139,Hong kong.
28. Inyang UG, Inyang MU (2011) A Neuro-Fuzzy Decision Support Framework for Tenants' Satisfaction Assessment in Residential Properties. World Journal of Applied Science and Technology 3: 146-154.
29. Hopfield JJ (1982) Neural Networks and Physical Systems with Emergent Collective Computational Abilities. Proceedings of NatL Acad, USA 2554-2558.
30. Ajith A (2005) Artificial Neural Networks - Handbook for Measurement Systems Design. John Wiley and Sons Ltd London, 901-908.
31. Wan Ishak WH, Siraj F (2000) Artificial Intelligence in Medical Application-An Exploration. School of Information Technology, University of Utara, 06010 Sintok Kedah, Malaysia.
32. Chakraborty RC (2010) Fundamentals Neural Networks: Soft Computing 7-14.
33. Ubeyli ED, Güler I (2005) Automatic detection of erthemato-squamous diseases using adaptive neuro- fuzzy inference systems. Comput Biol Med 35: 421- 433.

Author Affiliation

Top

[1]CDepartment of Computer Science, Federal University of Technology, Akure, Nigeria