Hybrid Intelligent System for the Diagnosis of Typhoid Fever
Samuel Oluwarotimi Williams* and Omisore Mumini Olatunji

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
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 interconnected 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 relationships 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, through Q, 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...
The integrated block diagram for the Neural Network component design is presented in Figure 3. 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).

\[
PLI = \sum_{i=1}^{14} (Q_i \cdot Wi)
\]

\[
PMH = \sum_{i=3}^{14} (Q_i \cdot Wi)
\]

\[
PPE = \sum_{i=12}^{14} (Q_i \cdot Wi)
\]

\[
OUTPUT = (PLI \cdot W_{PLI}) + (PMH \cdot W_{PMH}) + (PPE \cdot W_{PPE})
\]

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

Table 1: Categories of Typhoid Fever Diagnosis Attribute.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Liver Function Test</td>
<td>Qi</td>
<td>Fever</td>
<td>Q1</td>
<td>Body Temperature</td>
<td>Q12</td>
</tr>
<tr>
<td>Blood Test</td>
<td>Q2</td>
<td>Abdominal Pain</td>
<td>Q2</td>
<td>Stomach Pain</td>
<td>Q4</td>
</tr>
<tr>
<td>Stool Test</td>
<td>Q3</td>
<td>Myalgia</td>
<td>Q3</td>
<td>Lassitude</td>
<td>Q8</td>
</tr>
<tr>
<td>Urine Test</td>
<td>Q4</td>
<td>Loss of Appetite</td>
<td>Q4</td>
<td>Vomiting</td>
<td>Q9</td>
</tr>
</tbody>
</table>

\[
LTI = \frac{\sum_{i=1}^{n} \mu_{Y(xi)} x_i}{\sum_{i=1}^{n} \mu_{Y(xi)}}
\]
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 $i = 1, 2, n$. $A_1, A_2, B_1, B_2, C_1, C_2, C_3$ are the input variables of categories $X_1, X_2$ and $X_3$ respectively. The rules that drive the NFIS are based on Sugeno’s Inference Mechanism and they assume the following structure:

$$\text{IF } (A_i \text{ is VML}) \text{ AND } (B_j \text{ is MLD}) \text{ AND } \ldots \text{ AND } (C_n \text{ is SEV}) \text{ THEN } (Y \text{ is } F)$$

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

**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).

$$f_s(x) = \mu_s(x)$$

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).

$$\mu_s(x) = \frac{x - b}{a - b}$$
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).

$$f_i(x) = \mu_A(x) \cdot \mu_B(x) \cdot \mu_C(x) \quad (11)$$

**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).

$$f_i'(x) = \frac{w_i}{w_i + w_j + w_k} \quad (12)$$

while the normalized firing strength of the $k^{th}$ Rule is given by equation (13).

$$f_i'(x) = \frac{w_i}{\sum w_i} \quad (13)$$

**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).

$$f_i''(x) = f_i'(x) \cdot R_{out}(x) \quad (14)$$

**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).

$$Y = \sum f_i''(x) = \sum (f_i'(x) \cdot R_{out}(x)) \quad (15)$$

The final output of ANFIS is in crisp form and it 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
using equation (16).

\[
\text{Output} = \begin{cases} 
\text{"VMLD"} & \text{if } x_i = 1 \\
\text{"MLD"} & \text{if } x_i = 2 \\
\text{"MOD"} & \text{if } x_i = 3 \\
\text{"SEV"} & \text{if } x_i = 4 \\
\text{"VSEV"} & \text{if } x_i = 5 \\
\end{cases}
\] (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 (Q1 to Q14) for each of the 73 TF patients was rated as VML (1), MLD (2), MOD (3), SEV (4), and VSEV (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 variable 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 (Q1 to Q14) 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 Q1 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.

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>Q6</th>
<th>Q7</th>
<th>Q8</th>
<th>Q9</th>
<th>Q10</th>
<th>Q11</th>
<th>Q12</th>
<th>Q13</th>
<th>Q14</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>02</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>03</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>04</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>05</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>06</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>07</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>08</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>09</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>70</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>71</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>72</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>73</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>
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

<p>| Table 3: Training Dataset exported from MS Excel Worksheet into MATLAB Workspace. |
|-----------------------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|---------|</p>
<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Q_1</th>
<th>Q_2</th>
<th>Q_3</th>
<th>Q_4</th>
<th>Q_5</th>
<th>Q_6</th>
<th>Q_7</th>
<th>Q_8</th>
<th>Q_9</th>
<th>Q_{10}</th>
<th>Q_{11}</th>
<th>Q_{12}</th>
<th>Q_{13}</th>
<th>Q_{14}</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>0.6428571</td>
</tr>
<tr>
<td>02</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>03</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>1</td>
<td>0.6428571</td>
</tr>
<tr>
<td>04</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>0.3857143</td>
</tr>
<tr>
<td>05</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>0.5714286</td>
</tr>
<tr>
<td>06</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>0.5571429</td>
</tr>
<tr>
<td>07</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>0.5857143</td>
</tr>
<tr>
<td>08</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>0.7571429</td>
</tr>
<tr>
<td>09</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0.5000000</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0.3714286</td>
</tr>
<tr>
<td>11</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0.4285714</td>
</tr>
<tr>
<td>38</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>0.2714285</td>
</tr>
<tr>
<td>39</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>0.4142857</td>
</tr>
<tr>
<td>40</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>

<p>| Table 4: Testing Dataset exported from MS Excel Worksheet into MATLAB Workspace. |
|-----------------------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|---------|</p>
<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Q_1</th>
<th>Q_2</th>
<th>Q_3</th>
<th>Q_4</th>
<th>Q_5</th>
<th>Q_6</th>
<th>Q_7</th>
<th>Q_8</th>
<th>Q_9</th>
<th>Q_{10}</th>
<th>Q_{11}</th>
<th>Q_{12}</th>
<th>Q_{13}</th>
<th>Q_{14}</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>41</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>0.4428571</td>
</tr>
<tr>
<td>42</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>0.5000000</td>
</tr>
<tr>
<td>43</td>
<td>5</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5571428</td>
</tr>
<tr>
<td>44</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>0.7428571</td>
</tr>
<tr>
<td>45</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>4</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>46</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>0.5714285</td>
</tr>
<tr>
<td>47</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>0.5142857</td>
</tr>
<tr>
<td>72</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>0.6000000</td>
</tr>
<tr>
<td>73</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>0.7142857</td>
</tr>
</tbody>
</table>

<p>| Table 5: Neural Network Training Parameters. |
|------------------|-------|------------------|------------------|---------|</p>
<table>
<thead>
<tr>
<th>S/N</th>
<th>No. of Epochs</th>
<th>Error Tolerance</th>
<th>Training Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>0.79010</td>
<td>Back propagation &amp; Least Square Estimation Methods</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0.31600</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>0.01100</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>0.01400</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>25</td>
<td>0.00050</td>
<td></td>
</tr>
</tbody>
</table>

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

**Mean Accuracy of FIS**

\[
\text{MA}_{\text{FIS}} = \frac{\sum_{i=1}^{n} (\text{FIS})}{n} \times \frac{4.750}{5} = 0.950
\]

**Efficiency of FIS**

\[
\text{EFF}_{\text{FIS}} = \text{MA}_{\text{FIS}} \times 100 = 0.950 \times 100 = 95.0 \%
\]

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

**Mean Accuracy of ANFIS**

\[
\text{MA}_{\text{ANFIS}} = \frac{\sum_{i=1}^{n} (\text{ANFIS})}{n} \times \frac{4.875}{5} = 0.975
\]

**Efficiency of ANFIS**

\[
\text{EFF}_{\text{ANFIS}} = \text{MA}_{\text{ANFIS}} \times 100 = 0.975 \times 100 = 97.5 \%
\]

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.

**Acknowledgements**

We want to use this medium to express our gratitude to the management of the Federal Medical Center, Owo, Ondo State, Nigeria for their outstanding collaboration during the course of this research. Finally, we specially appreciate Dr. Oluwasanmi Olajide Samuel for his remarkable input to the research and his cheerful compliance during the research work.

**References**


8. Mahabala HN, Chandrasekhar MK, Baskar S, Ramesh S, Somasundaram...


Submit your next manuscript and get advantages of SciTechnol submissions

- 50 Journals
- 21 Day rapid review process
- 1000 Editorial team
- 2 Million readers
- More than 5000
- Publication immediately after acceptance
- Quality and quick editorial, review processing

Submit your next manuscript at ● www.scitechnol.com/submission