Volume 4, Issue 6, June 2014 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

A Machine Learning Based Clinical Decision Support System for Diagnosis and Treatment of Typhoid Fever

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Abstract— Health challenges of the world increase daily while medical practitioners and medical facilities ratio to the increasing population is nothing to write home about. As revealed by World Health Organization (WHO), the world is in need of additional over four million medical practitioners. The few available medical facilities and medical personnel are concentrated in the urban centers which tend to make the situation worst in the rural areas. These among other challenges in the health sector make computer based diagnosis systems desirable. Typhoid fever otherwise known as Enteric fever is a trauma to most developing countries of the world with prevalent cases in Africa. It is on the record that more than six hundred thousand deaths occur annually as a result of typhoid fever. This number is very high due to many factors which include insufficient medical facilities, insufficient medical personnel, poor diagnosis and treatment. In this work, a new diagnosis and treatment system was developed to handle typhoid fever cases. A promising machine learning technique-decision tree algorithm was used on labeled set of typhoid fever conditional variables to generate a decision tree and classifiers for the diagnosis of typhoid fever and treatments were provided according to the level of severity of the disease. The accuracy of the system was measured on both the training set and testing set with the detection rates of 100% and 95% respectively. The system was implemented using Visual Basic as front end and MySQL as backend.

Keywords— Machine Learning, Decision Tree, Decision Rules, Typhoid Fever, Diagnosis, Therapy

I. INTRODUCTION

Artificial intelligence is a part of computer science that tries to make computers more intelligent. One of the basic requirements for any intelligent behavior is learning. Most of the researchers today agree that there is no intelligence without learning. Therefore machine learning is one of the major branches of artificial intelligence and indeed it is one of the most rapidly developing subfields of AI research. Machine learning algorithms were from the very beginning designed and used to analyze medical sets. Today machine learning provides several indispensable tools for intelligent data analysis. Machine learning technology is currently well suited for analyzing medical data, and in particular there is a lot of work done in medical diagnosis in small specialized diagnostic problems. Data about correct diagnosis are often available in the form of medical records in specialized hospitals or their departments [8].

Computer-Aided System or Decision Support System (DSS) that can simulate expert human reasoning or serve as an assistant of a physician in the medical domain is increasingly important. In medical domain diagnostic, classification and treatment are the main task for a physician. System development with such purposes is also a popular area in Artificial Intelligence (AI) research. Today, clinical Decision Support System (DSS) are developed to act multi-purposed and are combined with more than one AI method and technique [11]. Data mining is the way of extracting useful information and discovering knowledge patterns that may be used for decision making. Several data mining techniques are association rule, clustering, classification and prediction, neural networks, decision tree, etc. Application of data mining techniques concern to develop the methods that discover knowledge from data and then used to uncover the hidden or unknown information that is not apparent, but potentially useful classification and clustering are the important techniques in data mining. Classification groups data based on a classifier model while clustering groups the data based on the distance or similarity [18].

In most tropical countries, most of which are developing countries, medical personnel and facilities are not adequate for effective tackling of tropical diseases. In rural areas, medical attention is grossly inadequate. Intelligent systems have become vital in the growth and survival of healthcare sector. Recently, much research efforts have been concentrated in designing intelligence systems [7]. Hospitals have some history with mobile technologies as they were first significant institutional adopters of pagers, and many doctors have enthusiastically embraced mobile telephones and personal digital assistants (PDAs) for their use [13]. In most developing countries of the world, insufficiency of medical specialist has increased the mortality of patients who suffer from various diseases. The insufficiency of medical specialist will never be overcome within a short period of time. The instructions of higher learning could however take an immediate step to produce as many doctors as possible. However while waiting for students to become doctors and doctors to become specialists, many patients may die. The waiting time for the treatment normally takes a few days, weeks or even months. By the time the patient sees the specialist, the disease may have already spread out, as most of the high-risk diseases could only be cured at the early stage. Consequently, computer technology could be used to reduce the number of mortality and reduce the waiting time to see the specialist [21].

The use of signs and symptoms for the diagnosis of malaria and typhoid fever does not mean to say that other diagnostic tools are unavailable. The problem here is that these tools are either affected by the harsh tropical weather or there are no qualified medical personnel in the rural areas to interpret test results [2]. Health services depend on having the right people, with the right skills, in the right place. Yet, the world is experiencing a chronic shortage of well trained health workers, a crisis felt most acutely in those countries that are experiencing the greatest public health threats. WHO estimates that over 4 million health workers are needed to fill the gap and the global deficit of doctors, nurses and midwives in particular is no less than 2.4 million [23]. However, there is also a shortage of faculty that can provide high-quality training and mentorship for current training programmes and continuing education opportunities for health workers. The use of new Information and Communication Technologies (ICTs) can help to overcome these challenges [16]. Medical diagnosis is the identification of abnormal condition that afflicts a specific patient based on manifested clinical data or lesions. If final diagnosis agrees with a disease that afflicts a patient, the diagnostic process is correct, otherwise a misdiagnosis occurred [14]. Therapy is the attempted remediation of a health problem, usually following a diagnosis. In the medical field, it is synonymous with the word "treatment" [3].

Earlier estimates of the global burden of typhoid fever indicate there are at least 16 million new cases every year with 600,000 deaths [4]. The prevalence of typhoid fever 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 typhoid fever is based on smear microscopy and widal test, while in rare cases it includes bacterial culture. However, in rural settings of Africa, clinical diagnosis (based on symptoms) remains the only option for typhoid fever [17], and the practice is not being done with care.

It is obvious that the rural areas of the developing countries suffer most and account for the large proportion of the annual deaths associated with the menace. One of the solutions to these challenges is the implementation or use of computer based system that could carry out diagnosis even where there is no medical expert, most especially in the rural areas. This research proposes a classifier model for typhoid fever diagnosis and treatment using a promising machine learning technique (Decision Tree).

II. REVIEW OF RELATED LITERATURE

Computer technology approach to diagnosis of typhoid fever is an ongoing process in the Information Technology domain. A keen study was carried out on some of the existing systems on the diagnosis of typhoid fever with the hope of improving on their weaknesses. Some of these earlier systems are discussed below:

Adebur and Burrrel in [1] designed a Decision Support System for diagnosis of malaria and typhoid fever. The system was designed and developed using rapid prototyping with a simple expert system shell, because of its simplicity and fast learning curve. The degree of severity of each symptom used for the diagnosis was not put into consideration and the system carried out diagnosis without the treatment. A hybrid intelligent system for the diagnosis of Typhoid Fever was developed in [17]. In this work, typhoid fever was diagnosed using fuzzy logic and neural network. The accuracy of this system was measured and found encouraging. However, the system lacks implementation and only carried out diagnosis without therapy. A decision support system model for diagnosing tropical diseases using fuzzy logic was carried out in [12]. The accuracy of the system was not measured so as to enable users have confidence in it. Besides, it carried out diagnosis without therapy.

Machine learning technique -Rough set was used to diagnose Typhoid Fever in [14]. The performance of the system was measured and adjudged excellent. The system lacks therapy. A system that could carry out diagnosis and provide therapy accordingly is desirable. In [2], Adehor and Burrell in [l] developed an Expert System for Differential Diagnosis. The system was developed to diagnose malaria and typhoid fever. The degree of severity of each of the symptoms under consideration was not evaluated. The system only carried out diagnosis without therapy which makes it an incomplete solution to the problem of typhoid fever. In [20], a Rule Based Expert System for diagnosis of fever was developed. Malaria, Typhoid, Dengue among others were diagnosed using this system. The performance of the system was not measured to know its effectiveness. The chance of rule based system in handling cases not in the knowledge base is slim. The severities of the symptoms were not put into consideration.

Putu and Iketut in [15] developed a Fuzzy Knowledge-Based System for the diagnosis of the tropical infectious diseases. The expert system designed in this research work used fuzzy logic and certainty factors for the diagnosis. Malaria, Dengue fever, Typhoid Fever and Chikunguaya were diagnosed with the system. The system carried out diagnosis without therapy. In [19], fuzzy expert system for tropical infectious diseases by certainty factor was developed. The system used fuzzy logic to diagnose tropical diseases including typhoid fever. The system only carried out diagnosis, the therapy that could make it a perfect solution was neglected. Gufran in [16] also developed an Adoptive Medical Diagnosis System using expert system. The developed model could be used to manage Malaria, Typhoid, Plague and Typhus. The system lacks implementation and therapy.

It is to be noted that identification of a problem without a solution does not make much difference. Once a problem has been identified, the best thing to do is to proffer an effective solution. The problems observed in most of these existing systems include: diagnosis without therapy, not putting the weight of the symptoms into consideration (severity), lack of implementation or poor implementation and inability to examine the effectiveness of the system (evaluation). Nevertheless, the most encouraging is that most of these researchers emphasize the need of further research on the subject matter. A system that could carry out diagnosis and provide therapy according to the level of severity of the typhoid fever cases diagnosed is desirable. This will be effective in guiding against drug abuse then the need for this study.

III. METHODOLOGY

Description of Data Set

Two sets of data on typhoid cases were collected from reputable hospitals in Ado-Ekiti, Ekiti State of Nigeria under the supervision of the chief medical directors of the hospitals. The first set of data were two hundred (200) typhoid fever cases collected in January 2014 and were used as the training set while the second one hundred (100) cases collected in April, 2014 were used as testing set. The medical practitioners grouped the typhoid fever cases into five different classes based on the available symptoms of each case. These groups (Classes) are Very High, High, Moderate, Low and Very Low. There are eighteen (18) conditional attributes and one decision attribute. For easy programming, it is easier to work around with numbers, all the attributes were discretized. Table 1 below shows the 18 conditional attributes and the only one decision attribute.

Table 1: Conditional and Decision Attributes of Typhoid Fever

Symbol	Attribute (Symptom)	Attribute Type	Category
FVR	Fever	Discrete	Conditional
ABP	Abdominal Pain	Discrete	Conditional
COH	Cough	Discrete	Conditional
DIA	Diarrhoea	Discrete	Conditional
CON	Constipation	Discrete	Conditional
RPT	Rose spot	Discrete	Conditional
MWK	Muscle Weakness	Discrete	Conditional
ANR	Anorexia	Discrete	Conditional
HDH	Headache	Discrete	Conditional
SKR	Skin rash	Discrete	Conditional
WTL	Weightless	Discrete	Conditional
SMD	Stomach Distension	Discrete	Conditional
MAL	Malaise	Discrete	Conditional
OBS	Occult blood in the stool	Discrete	Conditional
HMR	Haemorrhages	Discrete	Conditional
DEM	Derilium	Discrete	Conditional
ABR	Abdominal rigidity	Discrete	Conditional
EPS	Epistaxis (Bloody nose)	Discrete	Conditional
TDIAG	Typhoid Fever Diagnosed	Discrete	Decision

IV. DECISION TREES AND DECISION RULES

Decision Trees and decision rules are data mining methodologies applied in many real world applications as a powerful solution to classification problems. In general, classification is a process of learning a function that maps a data item into one of several predefined classes. Every classification based on inductive learning algorithms is given as an input, a set of samples that consist of vectors of attribute values (also called feature vectors) and a corresponding class. The goal of learning is to create a classification model, known as a classifier, which will predict, with the values of its available input attributes the class of some entity (a given sample) to an unlabeled record, and a classifier is a model (a result of classification) that predicts one attribute-class of a sample- when the other attributes are given [10]. Classification is one of the key data mining techniques and has been applied to numerous applications. Until now, a number of different classification techniques have been proposed and the induction of decision tree is a well-known approach. A decision tree is a representation of a decision procedure for determining the class of a given instance and it can be constructed by the non-incremental tree-induction algorithm or the incremental tree-induction algorithm [5]. Decision trees are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features [19].

C4.5 Algorithm

In this work C4.5 Algorithm is considered for determining the best decision based on univariate splits. It is ideal for this work because it works with both categorical and numeric feature values. The algorithm was developed by Ross Quillan which is an extension of his earlier ID3 algorithm.

We assumed that we have a set T of training samples.

Let the possible classes be denoted as (C_1, $C_{2,}$. . .,C_K). There are three possibilities depending on the content of the set T.

1. T contains one or more samples, all belonging to a single class C_j. The decision tree for T is a leaf identifying class C_j.
2. T contains no samples. The decision tree is again a leaf but the class to be associated with the leaf must be determined from information other than T, such as the overall majority class in T. The C4.5 algorithm uses as a criterion the most frequent class at the parient of the given node.
3. T contains samples that belong to a mixture of classes. In this situation, the idea is to define T into subsets of samples. Based on single attribute, an appropriate test that has one or more mutually exclusive outcomes $\{O_1, O_2, \ldots, O_n\}$ is chosen. T is partitioned into subsets $T_1, T_2, \ldots, T_n$, where T_i contains all the samples in T that have outcome O_i of the chosen test. The decision tree for T consists of a decision node identifying the test and one branch for each possible outcome.

The same tree-building procedure is applied recursively to each subset of training samples so that the i-th branch leads to the decision tree constructed from the subset T_I of training samples. The successive division of the set of training samples proceeds until all the subsets consists of samples belonging to a single class [10].

V. EXPERIMENTAL SETUP AND RESULTS

These are one decision attribute and eighteen conditional attributes (symptoms). Each conditional attribute could take a value from High/Low/Default depending on the feelings of the patient in relation to the symptom. Default exists for symptom not perceived by the patient but available on the system. In the case of the decision attribute, there are five cases available – Very High, High, Moderate, Low and Very Low. To make programming and interpretation of result easier, these values are decretized as follows:

For the Decision attributes: High = 2, Low = 1 and Default = 0. For the conditional attributes: Very High = 5, High = 4, Moderate = 3, Low = 2 while Very Low is decretized as 1.

The decision tree algorithm used the training set to generate a tree. The decision tree generated by the system is shown in figure 1 and the value count probabilities of some of the nodes are shown in figure 2 below.

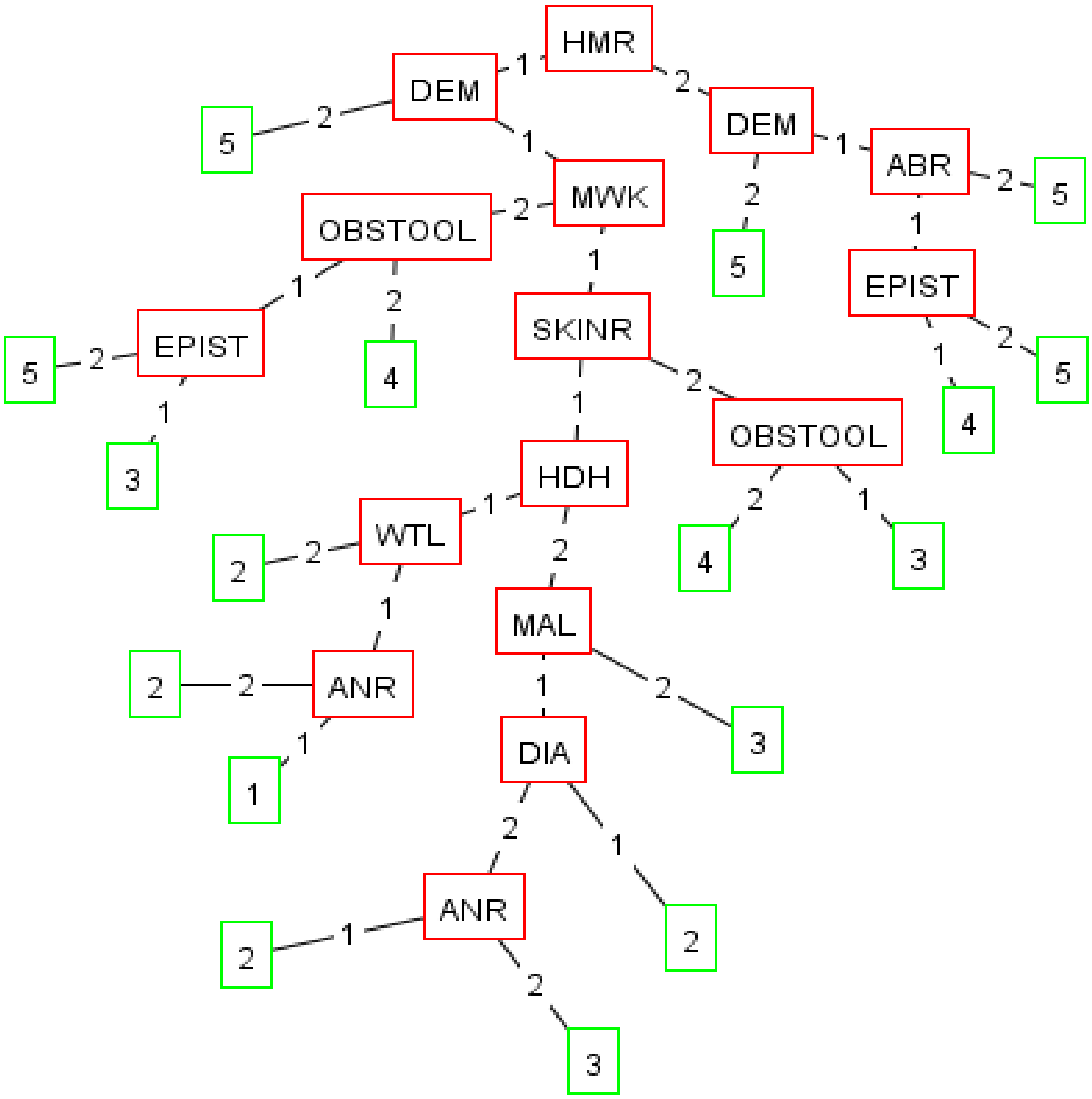

Figure 1: The Decision Tree generated from the training set.

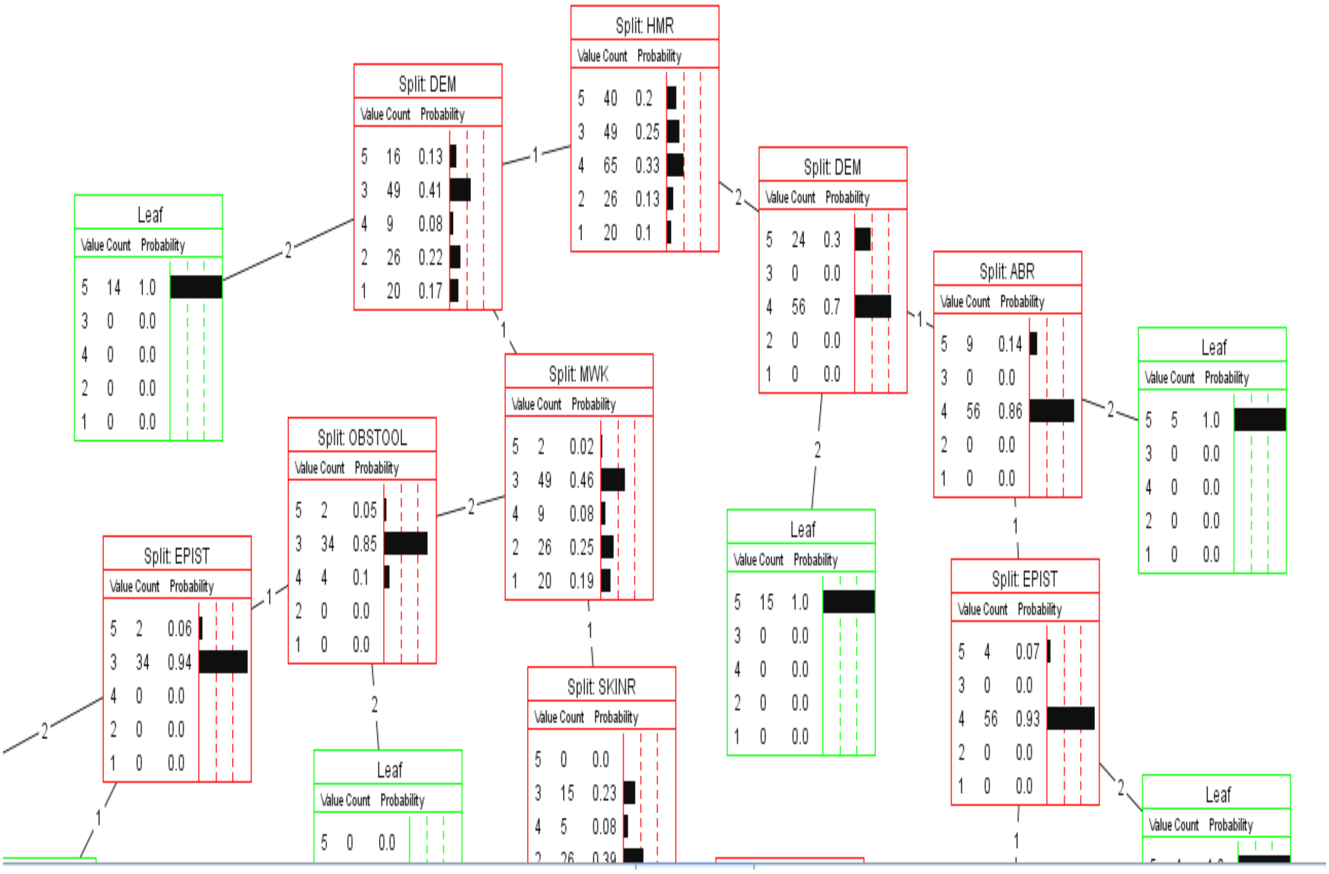

Figure 2: Value Count Probabilities of some of the nodes from the training set

Another peculiar challenge while using decision tree is how to generate decision rules from decision trees. Decision rules generated from the Decision Tree are given in the Table 2 below.

Table 2: Decision rules generated from the decision tree (transforming the decision tree to decision rules)

Rule Number	Rules in details
1	(HMR=1) AND (DEM=2) => TDIAG = 1
2	(HMR=1) AND (DEM=1) AND (MWK=2) AND (OBSTOOL = 2) => TDIAG = 4
3	(HMR=1) AND (DEM=1) AND (MWK=2) AND (OBSTOOL = 1) AND(EPIST=1)=> TDIAG = 3
4	(HMR=1) AND (DEM=1) AND (MWK=2) AND (OBSTOOL = 1) AND(EPIST=2)=> TDIAG = 5
5	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=2) AND (OBSTOOL = 1) => TDIAG = 3
6	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=2) AND (OBSTOOL = 2) => TDIAG = 4
7	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 2) AND (MAL=2) => TDIAG = 3
8	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 2) AND (MAL=1) AND (DIA=1)=> TDIAG = 2
9	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 2) AND (MAL=1) AND (DIA=2) AND (ANR=2)=> TDIAG = 3
10	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 2) AND (MAL=1) AND (DIA=2) AND (ANR=1)=> TDIAG = 2
11	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 1) AND (WTL=1) AND (ANR=1)=> TDIAG = 1
12	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 1) AND (WTL=1) AND (ANR=2)=> TDIAG = 2
13	(HMR=1) AND (DEM=1) AND (MWK=1) AND (SKINR=1) AND (HDH = 1) AND (WTL=2)=> TDIAG = 2
14	(HMR=2) AND (DEM=1) AND (ABR=2) => TDIAG = 5
15	(HMR=2) AND (DEM=1) AND (ABR=2) AND (EPIST=2) => TDIAG = 5
16	(HMR=2) AND (DEM=1) AND (ABR=2) AND (EPIST=1) => TDIAG = 4
17	(HMR=2) AND (DEM=2) => TDIAG = 5

The seventeen (17) decision rules extracted from the decision tree were used as the engine room for the typhoid fever diagnosis and treatment system. A standalone system was developed for this purpose. The choice of standalone is to enable individual have access to the system while avoiding the problem of power supply (electricity) and network which is one of the challenges of the developing countries. Laptops with good battery could be used effectively for the purpose of diagnosis and treatment, thereby saving cost. The system was implemented using Visual Basic as front end and MySQL as the back end. The Graphic User Interface (GUI) of the system allows old user to login with username and password while the new users are allowed to create account with unique username and password. After successful login, a symptom select table appears. There are eighteen (18) symptoms on this interface in which patients select symptoms and degree of severity (High or Low or Default) according to the patient's feeling. A submission is made to the system which will lead to diagnosis and prescription of drugs. If typhoid is diagnosed, the level of severity is displayed and matching treatment based on the level of severity of typhoid is displayed and if typhoid is not suspected, patient is advised to visit hospital for possibility of other diseases. A patient may print both diagnosis and treatment details. The medical practitioners prescribed treatment for each level of severity in accordance with WHO guide line for the treatment of Typhoid Fever. The diagnosis interface is shown in figure 3 while the diagnosis result and treatment interface is shown in figure 4 below.

Figure 3: Typhoid Fever Diagnosis Interface

Figure 4: Typhoid Fever Diagnosis Result and Treatment Interface

Discussion of Results

In order to build confidence for any computer based diagnosis system, it is desirable to evaluate the performance of this system because health care management systems deal with human lives directly, hence caution must be taken. The performance of the system was measured both on the training set and testing set. The two hundred (200) data sets were all tested again the seventeen (17) rules generated from the Decision Tree. The confusion matrix of the training set is given in table 3 below.

Table 3: Confusion matrix for the Training Set

Predicted as actual	Very low	Low	Moderate	High	Very High
Very low(20)	20(100%)	0(0.00%)	0(0.00%)	0(0.00%)	0(0.00%)
Low(26)	0(0.00%)	26(100%)	0(0.00%)	0(0.00%)	0(0.00%)
Moderate(49)	0(0.00%)	0(0.00%)	49(100%)	0(0.00%)	0(0.00%)
High(65)	0(0.00%)	0(0.00%)	0(0.00%)	65(100%)	0(0.00%)
Very High(40)	0(0.00%)	0(0.00%)	0(0.00%)	0(0.00%)	40(100%)

TP= Class group correctly classified
TN= Class group wrongly classified

Detection rate = $\dfrac{TP}{TP+TN} = \dfrac{200}{200+0} = 100\%$

From table 3 above, all the 20 labels classified as Very Low were correctly predicted by the system, likewise all other Classes-26 Low, 49 Moderates, 65 High and 40 Very High, each attaining 100% accuracy. The detection rate for the training set gives overall of 100%.

Table 4: Confusion Matrix for the Testing Set

Predicted as actual	Very low	Low	Moderate	High	Very High
Very low(9)	9(100%)	0(0.00%)	0(0.00%)	0(0.00%)	0(0.00%)
Low(21)	0(0.00%)	18(100%)	3(14.29%)	0(0.00%)	0(0.00%)
Moderate(24)	0(0.00%)	0(0.00%)	24(100%)	0(0.00%)	0(0.00%)
High(27)	0(0.00%)	0(0.00%)	0(0.00%)	27(100%)	0(0.00%)
Very High(19)	0(0.00%)	0(0.00%)	2(10.53%)	0(0.00%)	17(89.47%)

TP= Class Group Correctly Classified
TN= Class Group Wrongly Classified

Detection Rate = $\dfrac{TP}{TP+TN} = \dfrac{95}{95+5} = 95\%$

The One hundred (100) labels used as testing sets were tested against the seventeen (17) decision rules. All the nine labels classified as Very Low were correctly predicted, attaining 100% in this case. The same thing applicable to 24 labels classified as Moderate as well as 27 labels classified as High. However, of the 21 labels classified as Low, 18 were correctly predicted (85.71%) while three (3) were predicted as moderate. In the case of Very High, out of 19 labels classified as Very High,17 were correctly predicted , attaining 89.47% accuracy while 2 were predicted as Moderate. The detection rate for the testing set gives 95% as shown in table 4.

VI. CONCLUSION

In this research work, we have developed a Clinical Decision Support System for the diagnosis and treatment of typhoid fever- one of the most dreaded diseases that constitute challenges to developing countries of the world, Africa in particular. A Machine Learning technique -Decision Tree was used to create a decision tree and the decision rules generated from the Tree served as the engine room of the system. The validation of the system was carried out on both the training set and testing set. The training set gave detection rate of 100% while the testing set gave the detection rate of 95%.

With these laudable results from the system, the performance of the system is adjudged to be excellent and we hope it will be of imminent advantage in reducing the high number of deaths associated with the disease. It will be of great benefit for the health institutions as it will reduce the number of patients waiting to see doctors on typhoid fever cases. However, it is to be noted that the system is not developed to substitute human medical experts but could be of advantage in rural areas, homes and where there is shortage of human medical experts. Treatment was prepared according to the level of severity of the disease; pregnancy status of the patients was not put into consideration, so the treatment provided by the system is not recommended for pregnant patients. The treatment here is mostly recommended for African region. In the future a hybrid diagnosis and treatment system is suggested to further bring the diagnosis and treatment of the menace to the barest minimum.

ACKNOWLEDGMENTS

We appreciate the effort of Dr. Adeife Erinfolami of the State Specialist Hospital, Ikere-Ekiti, Nigeria and his medical team who gave us support during this research work. God bless.

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