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A Machine Learning Approach to Clinical Diagnosis of Typhoid Fever

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Abstract—***Typhoid fever is one of the major life threatning diseases, accounting for the death of millions of people every year apart from contributing to economic backwardness, mostly in Africa. Prompt and accurate diagnosis is a major key in the medical field, the large number of deaths associated with typhoid fever is as a result of many factors which include: poor diagnosis, self medication, shortage of medical experts and insufficient health institutions. These prompted for the development of a typhoid diagnosis system that can be used by anyone of average intelligence as this will assist in quick diagnosis of the disease despite shortage of health institutions and medical experts. A machine learning technique was used on the labelled set of typhoid fever conditional variables to generate explanable rules for the diagnosis of typhoid fever. The labelled database was divided into five different levels of severity of typhoid fever and the classification accuracies on both the training set and testing set are 95% and 96% respectively. Implementation was carried out using Visual Basic as front end and MySQL as backend.***

***Keywords:* Typhoid fever; Symptoms; Diagnosis; Machine Learning; Rough Set.**

I. INTRODUCTION

Health Care Personnel make predictions routinely everyday. They group patients according to disorders, render prognoses of the health status of a given patient at a future point in time, or classify laboratory specimens. With the emergence of integrated hospital information systems, the potential of using computerized predictive models to support tasks like these is significant [14].

Today's world is one with increasing access to intelligent systems. In recent time, Artificial Intelligence (AI) methods have significantly been used in medical applications and research efforts have been concentrated on medical experts systems as complementary solution to conventional technique for finding solution to medical problems. The emergence of Information Technology (IT) has opened unprecedented opportunities in health care delivery system as the demand for intelligent and knowledge-based systems has increased as modern medical practices become more knowledge intensive. The diagnosis of tropical diseases involves several levels of uncertainties. Patients cannot tell exactly how they feel, doctors and nurses cannot tell exactly what they observe, and laboratories' results are dotted with some errors caused either by the carelessness of the technicians or malfunctioning of the instrument. All these complexities in medical practices make traditional quantitative approaches of analysis inappropriate. Computer tools help to organise, store and retrieve appropriate medical knowledge needed by the practitioner in dealing with each difficult case and suggesting appropriate diagnosis, prognosis, therapeutic decisions and decision-making technique [5].

Medical knowledge is today expanding rapidly making computer-aided diagnostic system desirable. Such system can give a clinician a second opinion. Recent advances in Artificial Intelligence(AI) offers methods and techniques with the potential of solving tasks previously difficult to solve with computer-based systems in medical domains. Research worldwide is focusing on the new applications in the medical field and particular in diagnosis [12].One of the basic requirements for any intelligent behaviour is learning. Most of the researchers today agree that there is no intelligent 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 [6].

Machine learning technology is currently well suited for analysing data, and in particular there is a lot of work done in medical diagnosis in small specialised diagnostic problems. In medical domain, diagnostic; classification and treatment are the main tasks for a physician. System development with such purposes is also a popular area in Artificial Intelligence (AI) research [10]. A major focus of machine learning research is to automatically learn to recognise complex patterns and make intelligent decisions based on data; the difficulty lies in the fact that the set of all possible behaviours given all possible inputs is too large to be covered by the set of observed examples (training data). Hence the learner must generate from the given examples, so as to be able to produce a useful output in new cases [8].

Amongst the tasks considered in AI (control, monitoring, scheduling, diagnosis), the diagnosis is considered one of the most complex task and great efforts have been done in AI to solve this problem in different scenarios [7]. 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 [3].

Enteric Fever (Typhoid fever) is an acute illness associated with fever caused by the Salmonella typhil bacteria. It can also be caused by Salmonella paratyphi, a related bacterium that usually causes less several illnesses. The bacteria are deposited in water or food by a human carrier and are then spread to other people in the area [9]. Typhoid fever is a global health problem. Its real impact is difficult to estimate because the clinical picture is confused with those of many other febrile infections. Additionally, the disease is underestimated because there are no bacteriology laboratories in most areas of developing countries. These factors are believed to result in many going undiagnosed [15].

It has been estimated that approximately 17million cases of typhoid fever and 600,000.00 associated deaths occur annually. Typhoid fever also has a very high social and economic impact because of the hospitalization of patients with acute disease and the implications and loss of income attributable to the duration of the clinical illness(s) [15]. Typhoid fever affects more than 13 million people annually, with over 500,000 patients dying of the disease [9]. Typhoid fever constitutes a serious public health problem in many parts of the world [4].

Clinical representation of typhoid fever varies from a mild illness with low-grade fever, malaise, and slight dry cough to a severe clinical picture with abdominal discomfort and multiple complications. Patients who are affected with HIV are at significantly increased risk of clinical infection with S.typhi and S.paratyphi. Acute non-complicated typhoid is characterized by prolonged fever, disturbances of bowel function (constipation in adult, diarrhea in children), headache, malaise and anorexia. Bronchitic cough is common in the early stage of the illness. During the period of fever, up to 25% of patients show exathem(rose spots), on the chest, abdomen and back . Complicated acute typhoid fever may be severe. Depending on the clinical setting and the quality of available medical care, up to 10% of typhoid patients may develop serious complications. Intestinal perforation, abdominal discomfort, peritonitis, altered mental status in typhoid patients has been associated with high case fatality [15].

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 harsh tropical weather or there are no qualified medical personnel in the rural areas to interpret test results. Above all, the lack of regular or no supply of electricity to store available microbiological chemicals, for the prompt diagnosis of the disease, is a great setback [2].

This research work attempts to build a classification model for typhoid fever diagnosis using Rough Set, one of the newest promising machine learning techniques.

II. REVIEW OF RELATED LITERATURE

As it has been identified and intensified earlier in this research work, typhoid fever is a threat to human existence, apart from its contribution to economic drawback, it has claimed the lives of million of people. Due to all these, a lot of researches had been carried to eradicate or reduce the adverse effect of the menace. Some of these earlier works are presented below.

In [1], Knowledge Based Expert System for Symptomatic Automated Healthcare was developed. The system was an online medical system, where the whole process of hospitalization is being implemented through the internet. It was able to diagnose 48 diseases including typhoid fever. It was expected to make life easy and ensure that patients or end-users are not bound to doctors or other sources of medical science. The system is an Artificial Expert or Expert system, having three chief modules – user interface, inference engine and knowledge base. Patients or users remotely interact with the system and find out disease by giving some symptoms to computer, in this way, the system makes feasible diagnosis for patients, and also suggest particular treatment regarding the disease. The system may be inaccurate since there are many diseases under consideration; the accuracy of the system was not measured. A system with main focus on typhoid fever may provide better accuracy.

In [13], A Decision Support System Model for Diagnosing Tropical Disease using Fuzzy Logic was developed. The system was developed to diagnose ten tropical diseases including Typhoid. Fuzzy Logic was employed for the diagnosis. Diagnosis was carried out by weighing each symptom with respect to the disease in question using Generalized Fuzzy Soft Set (GFSS). Many diseases are under consideration here which tends to jeopardize the effectiveness of the system. Typhoid is deadly; a system with keen interest is desirable. It needs a system with a specific attention and not a general one.

Adhor and Burrell in [2] developed the Integrated Management of Health Care Strategies And Differential Diagnosis by Expert System Technology: Single-Dimensional Approach. The system combined the action oriented IMCI (The Integrated Management of Child Illness) and the Disease-Oriented HIS (Health Information System) approaches to diagnose malaria and typhoid fever. The system carried out its diagnosis based on signs and symptoms, but placed great emphasis on the fact that medicine is evidence based. Differential diagnosis was employed, asking questions in two formats, one directed at the user (medical practitioner), while the other is directed at the patient. The knowledge used for the development of the system was gathered using questionnaires and interview techniques. The knowledge were analyzed and represented in the form of Mockler Situation Analysis Methodology. Rapid prototyping, using a simple expert system shell, was used to develop the system due to its simplicity and fast learning curve. Other approaches to diagnosis of typhoid fever as main subject matter are suggested.

Alfred and Akpan in [4] carried out a research on correlation studies on Widal Agglutination Reaction and Diagnosis of Typhoid Fever. In this research, 80 patients suspected of having typhoid fever infections were screened for the presence of salmonella species using blood, urine and stool samples along with widal agglutination tests. The results of statistical analysis revealed significant differences between the widal agglutination reaction and cultural diagnosis of clinical samples and strongly suggested that serological investigation alone may not be a reliable diagnosis for enteric (typhoid) fever infections. This shows the need to look beyond laboratory tests only in the diagnosis of typhoid fever.

In conclusion, due to the significant contribution of typhoid fever to human deaths and economic set back, an effective system prioritising the subject matter with a view to providing better diagnostic tool was developed in this research work.

III. METHODOLOGY

Description of data set

Data on typhoid fever cases were collected from reputable hospitals in Ekiti State, Nigeria. The records of patients diagnosed to have typhoid fever were carefully selected and examined with explanation from medical practitioners on the symptomatic diagnosis of typhoid fever. According to medical experts, the disease share some symptoms in common with other diseases such as malaria and dengue fever, however combination of some symptoms could be used to differentiate the disease as some symptoms in combination are peculiar to certain diseases. The first one hundred (100) data sets, collected in September, 2012 were used as training set while another fifty (50) collected in February, 2013 were used as testing set.

All the data set were assigned classes by the medical practitioners and the medical experts grouped typhoid fever into five different (classes) levels of severity according to the available symptoms of each patient. These classes are- Very Low, Low, Moderate, High and Very High. There are eighteen (18) conditional attributes (symptoms) and one (1) decision attribute (level of severity), shown in the table 1 and table 2 below respectively. All the attributes were discretized.

Table 1: Conditional Attributes of Typhoid Fever

Rough Set Representation	Symbol	Attribute (Symptom)	Attribute Type
A1	FVR	Fever	Discrete
A2	ABP	Abdominal Pain	Discrete
A3	COH	Cough	Discrete
A4	DIA	Diarrhoea	Discrete
A5	CON	Constipation	Discrete
A6	RPT	Rose spot	Discrete
A7	MWK	Muscle Weakness	Discrete
A8	ANR	Anorexia	Discrete
A9	HDH	Headache	Discrete
A10	SKR	Skin rash	Discrete
A11	WTL	Weightless	Discrete
A12	SMD	Stomach Distension	Discrete
A13	MAL	Malaise	Discrete
A14	OBS	Occult blood in the stool	Discrete
A15	HMR	Haemorrhages	Discrete
A16	DEM	Derilium	Discrete
A17	ABR	Abdominal rigidity	Discrete
A18	EPS	Epistaxis (Bloody nose)	Discrete

Table 2: Decision Attribute of Typhoid Fever

Rough Set Representation	Symbol	Attribute	Attribute Type
Dec	Dec	Typhoid Fever diagnosed	Discrete

IV. ROUGH SET

Basic Concept of Rough Set

Rough set theory (RST) is a useful mathematical tool to deal with imprecise and insufficient knowledge, find hidden patterns in data, and reduce dataset size. Also, it is used for evaluation of significance of data and easy interpretation of result. RST contributes immensely to the concept of reducts. Reducts is the minimal subset of attributes with the most predictive outcome. Rough Set is a machine learning method which generates rules based on examples contained within an information table. Rough set theory has become well established as a mechanism for solving the problem of how to understand and manipulate imprecise and insufficient knowledge in a wide variety of applications related to artificial intelligence.

Let K = (U,C) be an appropriate space, where U is a non-empty , finite set called the universe; A subset of attributes $R \subseteq C$ defines an equivalent on U. Let $[X]_R$ $(X \in U)$ denote the equivalence class containing x.

Given $R \subseteq C$ and $X \subseteq U$. X can be approximated using only the information contained within R by constructing the R-lower and R-upper approximations of set X defined as:

$$\underline{R}X = \{x \in X | [x]_R \subseteq X\}$$

$$\overline{R}X = \{x \in X | [x]_R \cap X \neq 0\} \text{ where}$$

$\underline{R}X$ is the set of objects that belong to X with certainty, and $\overline{R}X$ is the set of objects that possibly belong to X. The R-positive region of X is $POS_R(X)$ = $\underline{R}X$, the R-negative region of X is $NEG_R(X)$ = U- $\overline{R}X$, and the boundary or R-borderline region of X is $BN_R(X) = \overline{R}X - \underline{R}X$. X is called R-definable if and only if $\overline{R}X = \underline{R}X$. Otherwise $\overline{R}X \neq \underline{R}X$ and X is rough with respect to R iff $\underline{R}X \neq \overline{R}X$.

The approximation measure $\alpha_R(X)$ is defined as

$$\alpha_R(X) = \frac{|\underline{R}X|}{|\overline{R}X|}$$

where $X \neq \phi$, and $|X|$ denotes the cardinality of set X.

[3]

LEM2 Algorithm below developed by Grzymala-Busse in 1997 [3] was used in building the classification model for typhoid fever diagnosis classes.

LEM2 Algorithm

```
Input: k set of objects
Output: R set of rules
begin
G=K;
R = φ;
 While G ≠ φ do
  begin
  C ≠ φ
  C(G)= {c : [c] ∩ G ≠ φ};
  While (C ≠ φ) or (!([C] ⊆ K)) do
  begin
  select a pair c ∈ C(G) such that |[c] ∩ G| is maximum;
  if ties, select a pair c ∈ C(G) with the smallest
     cardinality |[c]|;
  if further ties occur, select the first pair from the list;
  C = C ∪ {c}; G = [c] ∩ G;
  C(G) = {C : [c] ∩ G ≠ φ};
  C(G)=C(G)-C;
  end;
  for each elementary condition c ∈ C do
  if |C - c| ⊆ K then C = C - {c};
  create rule r basing the conjuction C and add it to R;
  G = K - ⋃_{r∈R} |R|
  end;
  for each r ∈ R do
  if ⋃_{s∈R-r} |S| = K then R = R-r
  end
```

Figure1: LEM2 Algorithm

V. EXPERIMENTAL SET UP AND RESULTS

There are eighteen conditional attributes(symbols) A1 to A18 and one decision attribute(Tyhoid Fever diagnosed) Dec. Each conditional attribute can take a value from High, Low or Default, depending on the patient's feeling. Default exists for symptom not perceived. For the decision atribute, there are five classes- Very Low, Low, Moderate, High and Very High. To make the programming easier and the program more efficient, these values were converted to integer since it is easier to work around with numbers. The conditional variable Low was converted to 1 and the conditional variable High was converted to 2 while default takes value 0. For example, A1 = 2 means Fever is High and A3 = 1 means Cough is Low. For the decision attribute, Very Low, Low, High, Moderate, High and Very High were converted to 1,2,3,4 and 5 respectively. In this case dec =1 means typhoid fever diagnosed is Very Low while Dec = 5, means typhoid fever diagnosed is Very High.

Rough Set used the training set to buld a diagnosis classification model for the five classes of typhoid fever which is inform of explanable rules. These rules are given in the table 3 below.

Table 3: Rules Generated for the five cases of Typhoid Fever

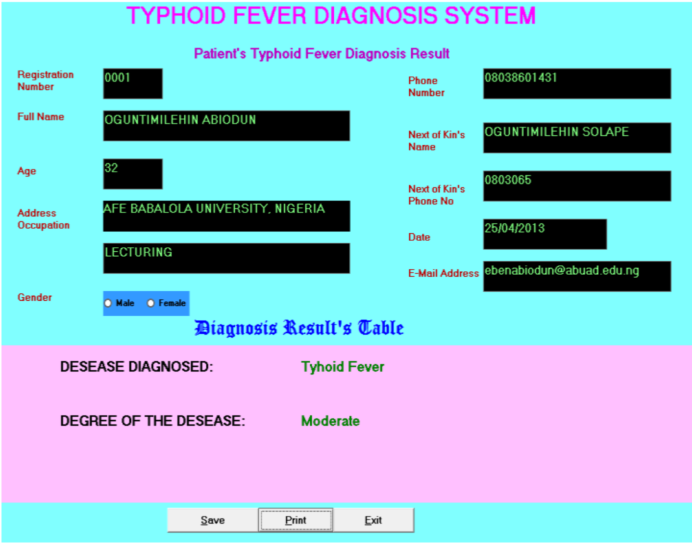
Rule No	Details of the rule
Rule 1	(A7 = 1) & (A8 = 1) & (A9 = 1) & (A10 = 1) & (A11 = 1) & (A12 = 1) & (A15 = 1) & (A16 = 1) => (Dec = 1)
Rule 2	(A8 = 1) & (A10 = 1) & (A11 = 2) & (A15 = 1) => (Dec = 2)
Rule 3	(A4 = 1) & (A5 = 1) & (A7 = 1) & (A9 = 2) & (A13 = 1) => (Dec = 2)
Rule 4	(A4 = 1) & (A7 = 1) & (A8 = 2) & (A9 = 1) & (A11 = 1) & (A18 = 1) => (Dec = 2)
Rule 5	(A7 = 1) & (A8 = 1) & (A9 = 2) & (A10 = 1) & (A13 = 1) & (A14 = 1) => (Dec = 2)
Rule 6	(A7 = 2) & (A14 = 1) & (A15 = 1) & (A18 = 1) => (Dec = 3)
Rule 7	(A4 = 1) & (A9 = 1) & (A12 = 2) => (Dec = 3)
Rule 8	(A10 = 2) & (A14 = 1) & (A15 = 1) & (A18 = 1) => (Dec = 3)
Rule 9	(A13 = 2) & (A14 = 1) & (A15 = 1) & (A18 = 1) => (Dec = 3)
Rule 10	(A4 = 2) & (A8 = 2) & (A15 = 1) => (Dec = 3)
Rule 11	(A7 = 2) & (A15 = 2) & (A16 = 1) => (Dec = 4)
Rule 12	(A9 = 2) & (A15 = 2) & (A16 = 1) => (Dec = 4)
Rule 13	(A5 = 1) & (A14 = 2) & (A16 = 1) => (Dec = 4)
Rule 14	(A7 = 1) & (A8 = 1) & (A15 = 2) => (Dec = 4)
Rule 15	(A16 = 2) => (Dec = 5)
Rule 16	(A4 = 1) & (A7 = 2) & (A10 = 2) & (A11 = 1) & (A15 = 1) => (Dec = 5)
Rule 17	rule 17. (A5 = 2) & (A7 = 1) & (A8 = 2) & (A9 = 2) & (A15 = 1) => (Dec = 2) OR (Dec = 3)
Rule 18	rule 18. (A5 = 1) & (A7 = 1) & (A8 = 2) & (A9 = 1) & (A11 = 1) & (A16 = 1) => (Dec = 4) OR (Dec = 5);

Implementation of the System

The eighteen rules generated by Rough Set served as the engine room for the implementation of the Typhoid Fever Diagnosis System. Visual Basic was used as front end while MySQL was used as the back end. The first interface is a User log in interface which gives the old user opportunity to login and the new users to create a new account by using appropriate username and password. After succesful login or creation of a new account, tyhoid fever diagnosis interface appears in which patient's Registration number and personal information are entered. The symptoms select table on the same interface is then used to carry out the diagnosis. The symptom select table contains eighteen conditional attributes (symptoms) and each attribute has three values(Low, High and Default), in which a patient must select one according to the patient's feelings. Default exists for symptom not perceived by the patients. After the selection of all the symptoms, submission is made to the designed system by clicking submit button and this takes the user to the view result interface. At the view result interface, a user uses the registration number of the patient to check the result of the diagnosis. If typhoid fever is diagnosed, the degree of severity is displayed along the disease name, otherwise the patient is advised to see medical doctor for the possibility of other disease. Each of the interface has cancel button which allows the user to cancel mistakes in the entries, while the exit button is available on all phases to quit the system at any phase of the diagnosis. Print button is available on the the diagnosis interface and result interface. This affords the users the very opportunity to print patient's diagnosis interface as well as the result of the patient's diagnosis.

Figure 2. Patient's Typhoid Fever Diagnosis Interface

Figure 3. Patient's Typhoid Fever Diagnosis Result Interface



Discussion of Results

The performance of the developed system were measured on both the training set and the testing set. On the training set, all the one hundred(100) data sets were tested against the eighteen(18) rules generated by Rough Set and the confusion matrix of the result is given in the table 4 below.

Table 4: Confussion Matrix for the Training Set

Predicted as Actual	Very Low	Low	Moderate	High	Very High
Very Low(11)	11(100%)	0(0.00%)	0(0.00%)	0(0.00%)	0(0.00%)
Low(15)	0(0.00%)	13(86.67 %)	2(13.33%)	0(0.00%)	0(0.00%)
Moderate(24)	0(0.00%)	1(4.16%)	23(95.83 %)	0(0.00%)	0(0.00%)
High(31)	0(0.00%)	0(0.00%)	0(0.00%)	31(100.00 %)	0(0.00%)
Very High	0(0.00%)	0(0.00%)	0(0.00%)	2(0.00%)	17(89.47 %)

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

$$\text{Detection rate} = \frac{TP}{TP+TN} = \frac{95}{100} = 95\%$$

From table 4 above, all the eleven labels classified as Very Low were correctly predicted by the system, thus attaining 100%. Out of the fifteen labels classified as Low,thirteen were correctly predicted, two were predicted as moderate which gives 86.67%. There are twenty four labels classified as moderate, twenty three were correctly predicted while one was predicted as Low, given 95.83%. All the thirty one labels classified as High were correctly predicted, attaining 100% in this case. Finally, of the nineteen labels classified as Very High,seventeen were correctly predicted, two were predicted as High. The confussion matrix for the testing test thus gives 95% accuracy.

For the testing set,fifty labels were also tested against the eighteen rules generated by Rough Set. The five labels classified as Very Low were all correctly predicted, this gives 100%. Out of the eleven labels classified as Low, ten were correctly predicted, while one was predicted as moderate, attaining 90%. Of the eleven labels classified as moderate, nine were correctly predicted, two were predicted as Low, thus gives 81.82%. The fourteen labels classified as High were all correctly predicted, this gives 100%. Out of the nine labels classified as Very High, only eight were correctly predicted, one was predicted as High and this gives 88.89%. Table 5 below gives the confussion matrix for the testing set with detection rate of 96%.

Table 5: Confusion Matrix for the Testing Set

Predicted as Actual	Very Low	Low	Moderate	High	Very High
Very Low(5)	5(100%)	0(0.00%)	0(0.00%)	0(0.00%)	0(0.00%)
Low(11)	0(0.00%)	10(90.91%)	1(9.09%)	0(0.00%)	0(0.00%)
Moderate(11)	0(0.00%)	2(18.18%)	9(81.82%)	0(0.00%)	0(0.00%)
High(14)	0(0.00%)	0(0.00%)	0(0.00%)	14(100.00%)	0(0.00%)
Very High(9)	0(0.00%)	0(0.00%)	0(0.00%)	1(11.11%)	8(88.89%)

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

$$\text{Detection rate} = \frac{TP}{TP+TN} = \frac{96}{100} = 96\%$$

VI. CONCLUSION

A new approach to the diagnosis of typhoid fever using a machine learning technique was developed in this research work and the performance of the system was measured on both the training set and testing set.

With detection rate of 95% for the training set and 96% for the testing set, the success rate of the system is considered excellent and it is hopeful that it will go a long way to assist the medical practitionals in ensuring quick diagnosis of the dreaded disease, thereby reducing the number of patients waiting to consult medical experts on typhoid fever disease and thus reduce the number of deaths associated with the disease. The system will be of assistance in rural areas where there are no enough hospitals and there is shortage of medical practitionals.

In the future, there is need of typhoid fever therapy system that can provide a matching effective therapy for the different levels of severity of typhoid fever diagnosed. A hybrid system that could possibly provide a better performance in the diagnosis of the subject matter is also suggested.

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