

ARTICLE

# Development of an Extended Medical Diagnostic System for Typhoid and Malaria Fever

Temitope Apanisile\*, Joshua Ayobami Ayeni<sup>ORCID</sup>

Department of Computer Science, Ajayi Crowther University, Oyo, Oyo State, 211271, Nigeria

## ABSTRACT

In developing countries like Nigeria, malaria and typhoid fever are major health challenges in society today. The symptoms vary and can lead to other illnesses in the body which include prolonged fever, fatigue, nausea, headaches, and the risk of contracting infection occurring concurrently if not properly diagnosed and treated. There is a strong need for cost-effective technologies to manage disease processes and reduce morbidity and mortality in developing countries. Some of the challenging issues confronting healthcare are lack of proper processing of data and delay in the dissemination of health information, which often causes delays in the provision of results and poor quality of service delivery. This paper addressed the weaknesses of the existing system through the development of an Artificial Intelligence (AI) driven extended diagnostic system (EDS). The dataset was obtained from patients' historical records from the Lagos University Teaching Hospital (LUTH) and contained two-hundred and fifty (250) records with five (5) attributes such as risk level, gender, symptom 1, symptom 2, and ailment type. The malaria and typhoid dataset was pre-processed and cleansed to remove unwanted data and information. The EDS was developed using the Naive Bayes technique and implemented using software development tools. The performance of the system was evaluated using the following known metrics: accuracies of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The performance of the EDS was substantially significant for both malaria and typhoid fevers.

**Keywords:** Malaria; Typhoid; Diagnostic; Fatigue; Symptom; Knowledge-based; Diagnostic

## 1. Introduction

An infectious disease caused by the bite of an anopheles mosquito which causes fever and shivering is malaria. Similarly, a serious infectious disease

### \*CORRESPONDING AUTHOR:

Temitope Apanisile, Department of Computer Science, Ajayi Crowther University, Oyo, Oyo State, 211271, Nigeria; Email: themythurpke09@gmail.com

### ARTICLE INFO

Received: 1 March 2023 | Revised: 5 September 2023 | Accepted: 8 September 2023 | Published Online: 26 September 2023

DOI: <https://doi.org/10.30564/aia.v5i1.5505>

### CITATION

Apanisile, T., Ayeni, J.A., 2023. Development of an Extended Medical Diagnostic System for Typhoid and Malaria Fever. Artificial Intelligence Advances. 5(1): 28-40. DOI: <https://doi.org/10.30564/aia.v5i1.5505>

### COPYRIGHT

Copyright © 2023 by the author(s). Published by Bilingual Publishing Group. This is an open access article under the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License. (<https://creativecommons.org/licenses/by-nc/4.0/>).

of the digestive system, caused by ingesting food or water contaminated with the bacillus salmonella is known as typhoid <sup>[1]</sup>. Malaria is a mosquito-borne infectious disease caused by a eukaryotic protist of the genus Plasmodium. It is widely spread in tropical and subtropical regions, including parts of America, Asia, and Africa. Five species of the plasmodium parasite can infect humans: The most serious form of the disease is caused by plasmodium falciparum. Malaria caused by plasmodium vivax, plasmodium ovale, and plasmodium malaria causes milder disease in humans that is not generally fatal. A fifth species, plasmodium Knowles, is a zoonosis that causes malaria in macaques but can also affect humans <sup>[2]</sup>.

A knowledge-based diagnostic system is a software system, or a software and hardware combination, that is capable of exerting a specific clinical duty that is typically carried out by human medical specialists <sup>[3]</sup>. Computational techniques can be applied to real-time biological situations to solve problems through technological changes <sup>[4]</sup>. Artificial intelligence is majorly connected to synthetic intelligence, which is bound to be exhibited by artificial entities for real-life problem solving; through machine learning or robotic design and the development of computers that act or behave like real humans. Expert systems for intelligent diagnosis or prognosis are becoming increasingly essential in the application of artificial intelligence technology to real-world problems <sup>[5]</sup>. Computer-assisted analysis and decision modeling tools in the domain of knowledge or specific walks of life and human endeavor have continued to evolve <sup>[5]</sup>. The emergence of prognostic systems that possess those properties associated with domain experts like reasoning process, understanding, and critical thinking is now imperative for health services.

These are extremely specialized computer systems that can simulate that aspect of a human specialist's knowledge and reasoning that can be organized into knowledge chunks defined by a collection of facts and heuristic rules <sup>[5]</sup>. They are generalizations that human professionals have gathered over years of intensive problem-solving in the field of a

given task <sup>[5]</sup>. The medical expert system is a class of expert systems that deal with the domain of medicine. They carry out various tasks such as interpretation, diagnosis, monitoring, treatment, instruction, and control. It models the following features of the human expert:

- i. Knowledge
- ii. Reasoning
- iii. Conclusion
- iv. Explanation

The main characteristics of such systems are a graphical user interface, data representation, inference engine, and knowledge base. Its cognitive module is concerned with how information is stored and manipulated thereafter because the storage area keeps the expertise of human specialists that are needed to solve problems, while the inference engine is the algorithm or core operational code of the system which derives conclusions from a knowledge base through reasoning <sup>[6]</sup>. This storage location forms the knowledge base that highlights the purpose of the identified problem domain and a set of rules for problem domain diagnostics. An intelligent agent can process or type a match and achieve a quality that is likely to be real and similar to human natural intelligence or latent physical skills. True data representation aims to facilitate reasoning. A quality factual representation must be a declarative and procedural pattern <sup>[7]</sup>.

#### *Challenges of the existing system*

Most of the identified shortcomings of the models, techniques, methods, and implementation algorithms such as functional mechanisms in the existing systems are highlighted below:

- i. Lack of proper processing of data.
- ii. Delay in the dissemination of health information.
- iii. Lack of enhancing service delivery in health sectors.
- iv. Inadequate delivery of quality-of-service.

In light of the aforementioned, it would be imperative to develop an extended medical diagnostic system for typhoid and malaria fever which will provide a computerized system to complement medical

service diagnosis in places where accessibility is a problem and healthcare facilities where qualified experts are not enough, knowledge-based systems for medical diagnosis of malaria and typhoid fever with the multi-parameters that will capture both the structured and the unstructured patient data to achieve a better diagnosis.

## 2. Review of related literature

Malaria has been a leading cause of sickness and mortality among children and adults in many developing nations during the last three to four decades. Each year, there are between 300 million and 500 million cases worldwide, resulting in over a million deaths<sup>[8]</sup>. Sub-Saharan Africa accounts for about 80% of all cases and 90% of these fatalities<sup>[9]</sup>. Typhoid fever is highly widespread in malaria-affected areas, greatly increasing the public health burden even though malaria is already having severe effects on tropical developing nations. Each year, typhoid causes about 21 million infections and more than 500,000 fatalities worldwide, with most of these deaths occurring in Africa<sup>[10]</sup> due to the consumption of foods and beverages contaminated by diseased waste, known as Salmonella Typhi. Malaria and typhoid have intriguing connections that affect public health despite having different causes and modes of transmission. These connections can be categorized into two main categories: true co-infection and erroneous diagnosis. It is well-recognized that anemia in people with malaria leads to an excessive iron buildup in the liver, which encourages the growth of the salmonella bacteria that cause typhoid fever<sup>[11]</sup>. Malaria infection increases a person's susceptibility to typhoid. During malaria infection, complements are devoured, weakening the host's defences and delaying the expected disease recovery<sup>[12]</sup>.

Additionally, co-infected people have an increased risk of passing away from infections caused by both diseases. Even though the above-mentioned true malaria-typhoid co-infections pose serious issues, incorrect diagnoses that frequently lead to improper care of these illnesses continue to be one of the major public health burdens. Similar symptoms

and indicators of both malaria and typhoid include fever, headache, vomiting, diarrhea, and soreness in the muscles and abdomen<sup>[13]</sup>. This sometimes tempts doctors to link these symptoms and signs to the wrong disease, resulting in a mistaken diagnosis. Additionally, several currently utilized testing techniques frequently give false positive results as the widely used test. For instance, only 15% of zopotyphoid-positive cases were present in one study<sup>[14]</sup> where the wide test indicated roughly 57% of cases. Due to cross-reactivity between typhoid antigens and malaria parasites, there is a considerable probability that widal test results for malaria patients will be falsely positive for typhoid<sup>[15]</sup>. Such incorrect diagnosis could result in the mishandling of these diseases, which would be extremely difficult to control. For instance, prescribing antibiotics to people who appear to have typhoid but have malaria wastes medication and increases the risk of developing drug resistance in the event of a subsequent typhoid infection. Understanding the effects of both true co-infection and incorrect diagnosis on the dynamics of the disease is therefore crucial. Dynamic mathematical modeling of malaria is highly sophisticated<sup>[16]</sup>.

Typhoid fever modeling, however, is relatively limited<sup>[17]</sup>. Although these current models have contributed significantly to our understanding of the dynamics of each disease, they must be taken into account concurrently to develop effective ways to lessen the burdens of both diseases. A recent study<sup>[18]</sup> presented a malaria-typhoid co-infection model that solely takes into account the direct person-to-person transmission of typhoid and makes no assumptions about the recovery of co-infected patients from separate illnesses. In this study, a co-infection model that captures the dynamics of malaria and typhoid models and the already standard malaria model was constructed. A formula for the basic reproduction number of co-infections using the model and comparing it to the basic reproduction number of individual diseases was created. The theory was examined for equilibrium stability and the disease persistence was also observed. Additionally, the actual co-infection dynamics to access the potential for incorrect diag-

noses using parameters pertinent to the Eastern Province of Kenya presents a significant barrier to controlling these diseases. Today's rapidly developing body of medical knowledge makes computer-aided diagnostic tools desirable. A clinician may receive a second opinion from such a system. Recent developments in artificial intelligence (AI) give strategies and tactics that may be used to complete tasks that were previously challenging for computer-based systems to complete in the medical field. The novel uses in the medical profession, notably in diagnostics, are the subject of research on a global scale <sup>[19]</sup>.

In the world of today, intelligent systems are becoming more widely available. Recent years have seen a substantial increase in the use of artificial intelligence techniques in medical applications, and research has focused on the development of medical expert systems as a supplement to more traditional methods of diagnosing and treating medical issues <sup>[20]</sup>. Every day, healthcare professionals routinely make predictions. They can categorize test specimens and make predictions about a patient's health status in the future, or group patients according to their illnesses. With the development of integrated hospital information systems, there is tremendous potential for applying computerized predictive models to such jobs <sup>[21]</sup>. As medical procedures get more sophisticated <sup>[19]</sup>, finding solutions becomes more complex. The eukaryotic parasite *Plasmodium* is the source of the infectious disease malaria, which is spread by mosquitoes. Tropical and subtropical locations, including sections of America, Asia, and Africa, are heavily populated with it. Humans can be infected by five different plasmodium parasite species, with plasmodium falciparum causing the most severe form of the illness. In humans, malaria brought on by *Plasmodium vivax*, *Plasmodium ovale*, and *Plasmodium malariae* causes a milder illness that is usually not lethal. A fifth species, plasmodium Knowlesi, is a zoonosis that may also infect humans and cause malaria in macaques <sup>[3]</sup>. Diagnosis is one of the most complex jobs considered by artificial intelligence (AI) (control, monitoring, scheduling, etc.), and significant attempts have been made in AI to resolve it.

Researchers have conducted some studies to create computer-based systems that could diagnose or diagnose as well as deliver therapy for malaria patients due to the negative impact that malaria has on people and the economy, some of these earlier works are presented below.

### 3. Review of related works

Rajamani and Rathika <sup>[22]</sup> enumerated the essential parameters for regulating fuzzy inference systems from a graphical user interface; editors for handling input/output elements, and membership functions; and the rule and monitoring behavior of specific rules for improving system performance. The fuzzy inference mechanism is specifically applicable to knowledge-based and control systems, with components formation of fuzzification, knowledge base, inference rules, defuzzification, and integration of fuzzy logic in intelligent reasoning on factual data. Its self-control for internal regulation is suitable for solving decision-making problems with ambiguity. Clustering and classification go together and are consequently used interchangeably because clustering is needed for pre-processing, to group datasets into distinct classes (see **Table 1**).

Cheng et al. <sup>[1]</sup> developed a Multi-layer inference system incorporated in an adaptive neuro-fuzzy mechanism for classifying data for liver diseases; though its prediction reliability for illness of the liver was not evaluated. A metric that predicts the presence of cancer-related liver disease which allows early implementation of treatment, it compares the demographic and clinical characteristics of patients with no evidence of liver disease, with cancer-associated liver disease, and with a liver disease not associated with cancer. Methods: Retrospective, hospital-based, cross-sectional study that reviewed the medical records of patients who underwent health examinations. Its strength was knowledge-based reasoning while its weakness was one-dimensional feature severity.

Hepatitis B is one of the liver diseases that are difficult to discover at an early stage of its attack and highly prominent public health problem. As of 2017,

medical statistics recorded that over 23 million Nigerians were living with Hepatitis B. Several decision support systems used in diagnosing liver diseases derived their efficiencies from artificial intelligence techniques in tackling the challenges facing physicians concerning the complexity of the numerous variables involved in liver disease diagnosis. Rahmon et al. [23] carried out their study on the application of a machine learning algorithm for disease classification in a comparison manner. Machine learning algorithms have been widely used in the past for dis-

ease classification in a comparison manner; it does not distinguish between malaria and typhoid bacteria for operational efficacy of the detection system, but its projection of hybridized method is expected to produce perfect prediction with effectiveness.

Chakraborty [5] studied the application of artificial intelligence (AI) for intelligent diagnosis or prognosis and asserted that AI has become increasingly essential in the application of AI technology to real-world problems such as clinical decision support.

Table 1. Table of related works.

S/N	Author/year	Title	Methodology	Limitations
1	Cheng et al. [1]	Association of different types of fever diseases with demographic and clinical factors	Multilayer inference system and adaptive Neuro-fuzzy	One-dimensional feature severity
2	Rahmon et al. (2018) [23]	Diagnosis of hepatitis using adaptive neuro-fuzzy inference system (ANFIS)	Used machine learning algorithm for disease classification in a comparison manner	Irrational label probability
3	Ayushi et al. (2017) [3]	Disease prognosis based on clinical parameters using machine learning approach	Predictive diagnostic technique	Inexplicit projection
4	Chakraborty [5]	Introduction to artificial intelligence	Used artificial intelligence technology to real world problems with clinical support	No performance evaluation to ascertain the system's correctness

## 4. Materials and methods

The research approach signifies the plan and procedures involved in the steps used to complement the clinical support for malaria and typhoid diagnosis in health centers. To achieve the set objectives for this study, here are the multiple steps employed.

Identify and acquire the parameters necessary for the development of the diagnostics system.

Design an improved diagnostic system for the detection of typhoid and malaria fever depicted in **Figure 1**.

Implementation of the designed and developed diagnostics system.

Model Evaluation procedure of the developed system and the performance metrics for the detection system using related metrics.

### 4.1 Procedure phases of development

The implementation of the work was divided

into the following phases: requirement and analysis phase, design phase, implementation and testing phase (as depicted in **Figure 1**).

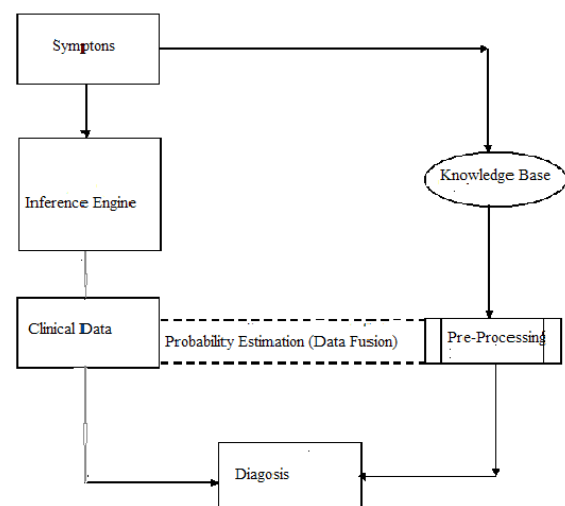


Figure 1. Revised architecture of the existing system.

Requirement phase: Here, a complete description

of the behavior of the system was done. The interaction the users had with the software was mapped for clear development.

Analysis phase: Formal inquiry was carried out to identify a better course of action to develop the system, thoughts were shared, and online resources were perused for clear information and better outcomes.

Design phase: A graphical user interface for the system was developed using Visual studio.net and ActiveX.

Implementation phase: At this stage, the process model was implemented. **Figure 1** depicts the revised architecture of the existing system.

#### 4.2 Analysis of the expert’s detection system

The extended medical diagnosis developed system is a detection system using an improved model. Expert systems are complex software that is designed with great ability to think critically and reason like a human expert in a particular domain area using rules. An expert system is a mind-machine partnership that belongs to a branch of artificial intelligence that engages the usage of human knowledge to solve complex issues that require the human expert to naturally probe and diagnose using clinical aids. To compute the function of uncertainty in probability distribution and type matching towards detection inference with decision support. A production mechanism of the detection system will initialize the Naive Bayes classifier to compute the posterior possibility of a given symptom about a patient by approximating the possibility distribution of the prior selector in observation parameters, and the highest likelihood or tendency is the output class.

#### 4.3 Naive Bayes classification

Naive Bayes model was easily and specifically useful for huge amounts of data. Besides its simplicity, Naive Bayes is generally considered one of the best classification algorithms even beyond some sophisticated and popular classification techniques. It helps in creating context, the input data for the

intelligent reasoning and inference phase contains the nominal value which is converted according to the labeled range and likelihood scale. The Naive Bayesian approach requires training before performing a classification task. Hence, the training set and/or validation data include an amount of factual data, such as domain knowledge for the subjective hypothesis and the predictor class. It uses a target variable as a dependent element on observable selectors or parameter values to classify environmental traits for disease trait or otherwise, just as the training set conveyed in **Table 2** depicts the values of two parameters (T, H, L) and risk level with target output being determined by a sequence of observation data. **Table 2** shows the observable symptoms and parameter values for the training set.

**Table 2.** Observations and parameter values for the training set.

Symptom 1	Symptom 2	Risk	Diagnosis
High	Low	High	True
High	Mild	Low	True
High	Low	Mild	True
High	Mild	High	True
Mild	Mild	Mild	True
Mild	High	Mild	False
Mild	Low	High	False
Low	Mild	Low	False

Bayesian approach is adopted to classify the sequence of symptoms which is observed by analyzing parameter values into a diagnosis class which is likely a predictor in a training set. The classifier is trained to classify a sequence of nominal values into an appropriate ailment by a likely predictor and yield a corresponding output. Accordingly, the observed incidence for the predictor with the highest nominal value and likelihood range must be selected or chosen for a probable outcome. The classification algorithm usually refers to the training instances, to compute probabilities of every class based on the possibility distribution in the training dataset. In the first instance, when computing the possibility of the diagnosis class TRUE, the classifier will count the

number of data cells in which the SYMPTOM 1 scale equals HIGH when the observation sequence in data cells is classified as TRUE. Only four (4) data cells exist with this yardstick, meanwhile, there are five (5) data cells in which the SYMPTOM 1 equals to or greater than MILD and the data cell is classified as TRUE. Therefore, the relative possibility of SYMPTOM 1 equals HIGH given TRUE equals  $4/5$ ; while the relative possibility of SYMPTOM 1 equals MILD given TRUE equals  $1/5$ .

The probability algorithm for classification computes all the relational probabilities for visual analysis by conversion. Raw data being acquired about observations and given symptoms from clinical records cannot be used directly by the Naive Bayes classifier. Defining the labeled ranges by data distribution for observation parameters, and within short intervals will improve the accuracy of the classification process and intelligent reasoning as depicted in **Figure 2**. A system prototype was created to experiment with the classification model and to measure its experimental performance, by approximating the numeric data of chosen parameters and converting them on a nominal scale for a likely predictor. **Figure 3** depicts the architecture of the proposed diagnostic system.

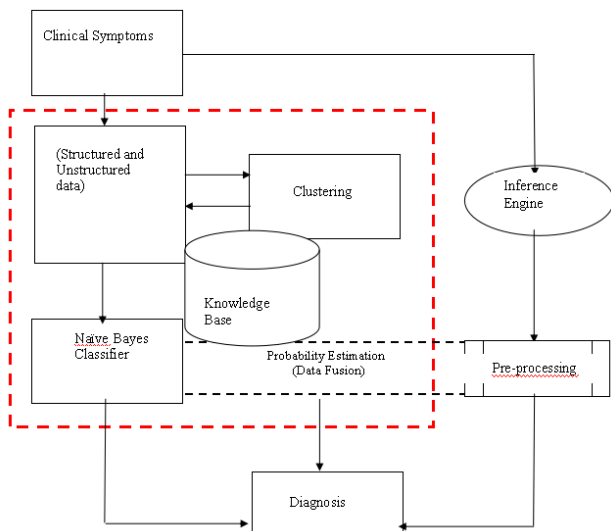


Figure 2. Block diagram of the architecture of the developed system.

#### 4.4 Malaria and typhoid dataset

To achieve one of the building block objectives of

this study, there is a need to acquire a standard dataset to test the developed system. The dataset contains two hundred and fifty (250) records with five (5) attributes such as risk level, gender, symptom 1, and symptoms 2, and ailment type. There is no numerical value; each attribute data type contains only text. The malaria and HMtyphoid dataset was preprocessed, cleansed to remove unwanted data, and then selected in a fashion that leaves it available for further use. The dataset was sourced from experts in the field of medicine and they helped in the recording of fresh data from patients that were diagnosed. It was extracted and developed for the system that contains major symptoms, diagnoses, and prescriptions. The input and output specifications of the symptoms of malaria and typhoid are shown in **Tables 3 and 4**.

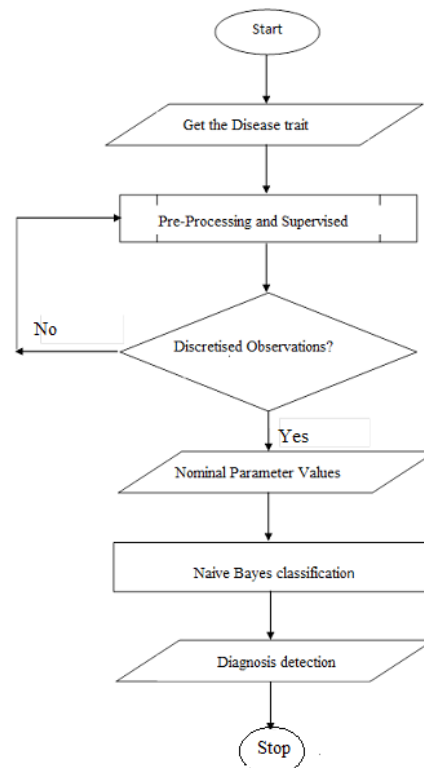


Figure 3. Flow chart of the developed system.

#### 4.5 Experimental evaluation

The objectives include the acquisition of the parameters necessary, implementing the developed frameworks in VB.net and ActiveX environment, and evaluating the accuracy and the overall system

performance under standard metrics: recognition rate and average recognition time. A localized clinical database for observed symptoms was derived from medical records of patients at the Lagos University teaching hospitals in Lagos State, Nigeria. Hence, experimental analysis in this study extracted local clinical datasets with two hundred and fifty (250) data samples and five (5) attributes thereby generating  $250 \times 5$  data samples. In all the two hundred and fifty (250) experimental cases, the data samples are multivariate for the classification task; no instance with a missing value. **Table 6** shows the pre-processed dataset as test samples for experimental diagnosis that contain the essential features that are very germane to the presence of fever in the classification mechanism by selection are the symptoms, and risk level. They were also optimized thereafter to ensure the maximum efficiency of the classifier; having excluded instances with null values.

**Table 3.** Input specification of the symptoms of malaria and typhoid.

Field name	Field type	Null	Field width	Default
Times tamp	Time	No	24	None
Date stamp	Date	No	24	None
Symptom 1	Text	No	16	None
Symptom 2	Text	No	16	None
Malaria	Text	No	16	None
Typhoid	Text	No	16	None

**Table 4.** Output specification of the symptoms of malaria and typhoid.

Field name	Field type	Null	Field width	Default
Times tamp	Time	No	24	None
Date stamp	Date	No	24	None
Symptom 1	Text	No	16	None
Symptom 2	Text	No	16	None
Malaria	Text	No	16	None
Typhoid	Text	No	16	None
Risk level	Integer	No	12	None
Prevention	Text	No	42	None
Treatment	Text	No	42	None

### 4.6 Experimental tests

The extended medical diagnostic system was

tested against some proven cases of malaria and typhoid. The system obtained accurate results when the symptoms of the user were given as input. User inputs from patients suffering from the diseases were taken as clinical data for diagnosis input. **Table 6** shows the classified output in relevance to the presence of fever/malaria and the visual report depicted in this study.

### 4.7 Performance evaluation and metrics

The rate at which classification is done correctly by the developed detection system was determined by ACCURACY when performance metrics for system evaluation were given. Hence, evaluation parameters are being recalled as performance metrics in **Table 4**, in line with accuracy as mathematically expressed in Equation (1). The values were obtained while testing the existing system with retrieved clinical data. The performance of the developed system was measured using parameters like true positive (TP), which stands for the number of datasets that the system correctly classified positively for disease detection, and corresponds to the target output according to the medical history of concerned patients. True negative (TN), which stands for the number of datasets that the system correctly classified negatively for disease detection, and corresponds to the target output according to the medical history of concerned patients. False positive (FP) stands for the number of datasets that the system incorrectly classified positively for disease detection, and corresponds to the target output according to the medical history of concerned patients. False negative (FN) stands for the number of datasets that the system incorrectly classified negatively for disease detection, and corresponds to the target output according to the medical history of concerned patients. All of these are part of the metrics necessary to determine the accuracy by the given formula (see **Table 5**).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{1}$$

An evaluation test was carried out on the developed system with the use of local datasets which were provided as required input and experimental

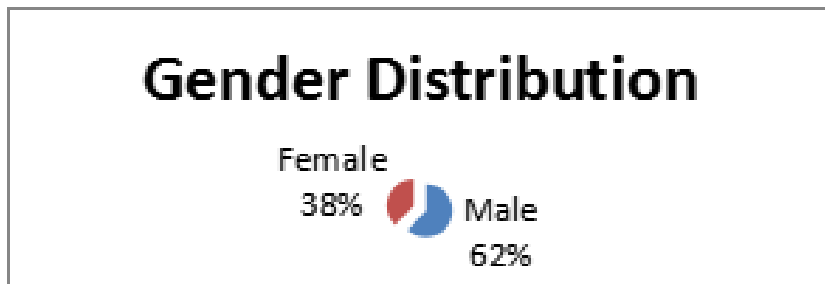


data. Having acquired clinical datasets from local sources as explained in the preceding previously. Seventy-five percent (75%) of the acquired dataset was pre-processed as a training set to train the classifier by a supervised learning algorithm, while the rest twenty-five percent (25%) were pre-processed as a testing set to evaluate the experimental performance of the developed system. This study used two hundred and fifty (250) datasets from different age groups and genders but from the same medical

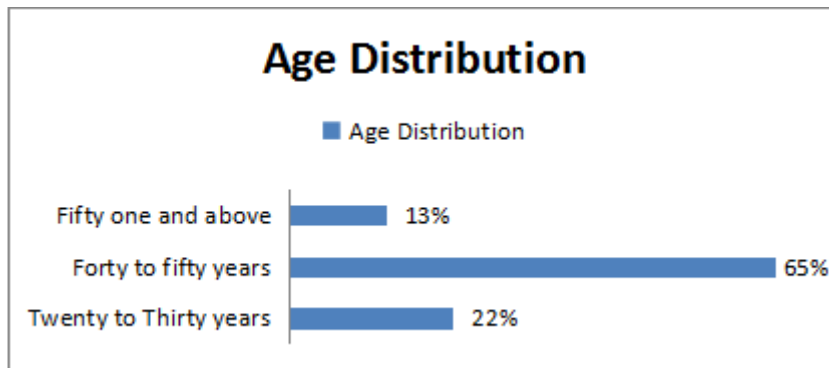
facility. Thus, the findings of this study as shown in **Figure 4(a)** indicate the gender distribution of the patients, where 62% are male and 38% are female. This implies that the majority of the data acquired for this study are male. Also, the findings of this study concerning **Figure 4(b)** indicate the age distribution, where 22% are between the ages of twenty to thirty years of age, 65% are between the ages of forty to fifty years of age, and the remaining 13% are fifty years of age and above.

**Table 5.** Results of performance evaluation.

Performance metrics	Existing system (malaria/typhoid)	Developed system (malaria/typhoid)
True positive (TP)	105	115
True negative (TN)	53	65
False positive (FP)	56	45
False negative (FN)	36	25
Accuracy	63.2%	72%



(a) Gender distribution of the risk level of the disease.



(b) Age distribution of the risk level of the disease.

**Figure 4.** A diagrammatical representation of gender and age distribution of the risk level of the disease.

## 5. Results

### 5.1 Results of findings for malaria

As depicted in **Table 6** shows some of the symptoms of malaria such as vomiting, convulsions, jaundice, shivering, etc., and hemoglobinuria, and retinal damage was selected as symptoms 1 and 2 from the drop-down menu, and was diagnosed by clicking the diagnosis button. The system ran through the dataset and the malaria detection system result was displayed on the screen as 90% and stated that the risk level was highly critical, and applied medication to

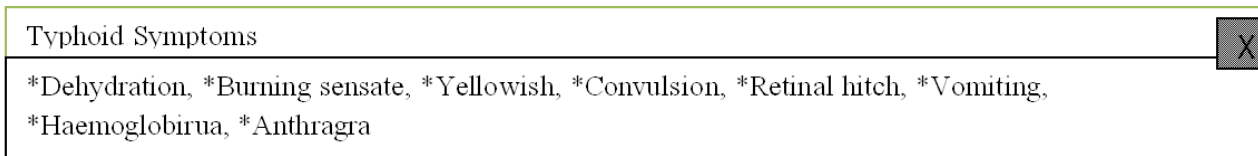
forestall major illness.

### 5.2 Results of findings for typhoid

**Figure 5** shows some of the symptoms of typhoid such as burning sensate, dehydration, retinal hitch, convulsion, yellowish, etc. Sweating and gastroenteritis were selected as symptom 1 and dehydration as symptom 2 from the drop-down menu and were diagnosed by clicking the diagnosis button. The system ran through the dataset and the typhoid detection system result was displayed on the screen as 70% and stated that the risk condition is building up, go for immediate treatment.

**Table 6.** Pre-processed datasets as test samples for experimental diagnosis.

Risk (%)	Gender	Symptom 1	Symptom 2	Ailment type
65	Female	Headache	Burning sensation	Typhoid
62	Male	Shivering	Sweating	Malaria
62	Male	Vomiting	Dehydration	Typhoid
58	Male	Athragra	Yellowish	Typhoid
72	Male	Convulsion	Retinal hitch	Typhoid
90	Male	Haemoglobirua	Pretyohid	Malaria
26	Female	Jaundice	Anemia	Malaria
29	Female	Anemia	Jaundice	Malaria
17	Male	Hemolytic	Haemoglobirua	Malaria
55	Male	Retinal hitch	Convulsion	Typhoid
57	Male	Yellowish	Athragra	Typhoid
72	Male	Dehydration	Vomiting	Typhoid
64	Male	Sweating	Shivering	Malaria
74	Female	Burning sensation	Headache	Malaria
81	Male	Pre-typhoid	Haemoglobirua	Typhoid



**Figure 5.** Some of the symptoms of typhoid fever.

## 6. Discussion of findings

The preceding sections demonstrate the possibility of a tendency to classify parameter values, especially on experimental data from local medical data repositories, which were considered input elements for dependent variables in this study. Experimental analysis of the classification mechanism revealed linear dimensions of real clinical data in the pre-processing phase. Thereafter, the posterior probability is computed by a classification algorithm which also resides on the middleware module, and the possibility of estimation of malaria fever or otherwise is returned to the output terminal of the existing system which does not distinguish between malaria and typhoid bacteria for operational efficacy of the detection system. Consequently, dynamic scenarios were established to ensure confidence in the detection framework of the proposed system to discover the likelihood between rare symptoms of Pretyohid and Haemoglobinuria with the highest risk level.

## 7. Benefits of the developed system

Given the problems inherent in the existing system as just an analytical-deductive reasoning system that captures only structured data, devoid of situational context and the capturing of unstructured data. It is, therefore, necessary to seek improvement. This improvement is surrounded by the multi-parameters and dynamism of the diagnostic system that integrates the power of intuitive and contextual reasoning of the human mind with the dexterity of the analytical and deductive power of a computer machine to achieve better diagnostic results.

## 8. Conclusions

The application of intelligent systems in medicine and healthcare delivery is very interesting and has created considerable importance for diagnostic systems. The developed system can help medical practitioners and patients to provide a decision support system, interactive training tool, and expert advice. The system constitutes part of the knowledge-based

system of diagnostics for malaria and typhoid fever. The study and dissertation thereof presented a diagnostic system for medical cases. An initial evaluation of the detection system was carried out by stakeholders. Some doctors and patients tested the system and responded with positive feedback and asked for future expansion and enhancement of maintenance to accommodate more diseases. Meanwhile, the selection of algorithms is subject to hardware accessibility and the dynamism of factual knowledge. Nevertheless, real-time collection of observable data for probability estimation is possible as well, by segmentation of input features for every attribute of the data instance. In any case, large training sets of clinical data will converge to a stable solution state.

## Author Contributions

The First Author is the Student Researcher (MSc. Thesis) and is currently in her Ph.D. program at Ajayi Crowther University, Oyo, Nigeria, while the second author (An Associate Professor of Computer Science) is the Academic Supervisor of the first author who guided, directed and contributed to the realisation of the paper and the research proper. The paper title is a subtopic of her MSc. Thesis under the supervision of the second author.

## Conflict of Interest

There is no conflict of interest.

## Funding

This research received no external funding.

## References

- [1] Cheng, K.C., Lin, W.Y., Liu, C.S., et al., 2016. Association of different types of liver disease with demographic and clinical factors. *Biomedicine*. 6, 1-7.
- [2] Adetunmbi, A.O., Oguntimilehin, A., Falaki, S.O., 2012. Web-based medical assistant system for malaria diagnosis and therapy. *Computer Science & Telecommunications*. 33(1).

- [3] Ayushi, S., Sharma, V., Gupta, R., 2017. Liver disease prognosis based on clinical parameters using machine learning approach. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*. 5(6).
- [4] Kukucka, M. (editor), 2010. Bayesian methods in artificial intelligence. *Proceedings of 10th World Conference on Computing and System Development*; 2010 Jun 1-4; Prague.
- [5] Chakraborty, R.C, 2010. Introduction to Artificial Intelligence—Computer Science Engineering(CSE) [Internet]. Available from: <https://edurev.in/p/81093/01-Introduction-to-Artificial-Intelligence>
- [6] Lamesgin, A., Sirajudeen, M., 2016. Implementation of an Expert System for Lung Disease Diagnosis [Internet]. Available from: [https://www.researchgate.net/profile/Lamesgin-Almaw/publication/303699292\\_Implementation\\_of\\_an\\_Expert\\_System\\_for\\_Lung\\_Disease\\_Diagnosis/links/574e8dea08ae8bc5d15c0294/Implementation-of-an-Expert-System-for-Lung-Disease-Diagnosis.pdf](https://www.researchgate.net/profile/Lamesgin-Almaw/publication/303699292_Implementation_of_an_Expert_System_for_Lung_Disease_Diagnosis/links/574e8dea08ae8bc5d15c0294/Implementation-of-an-Expert-System-for-Lung-Disease-Diagnosis.pdf)
- [7] Imhanlahimi R.E., John-Otumu, A., 2018. Application of expert system for diagnosing medical conditions: A methodological review. *European Journal of Computer Science and Information*. 7(2), 12-25. Available from: <https://www.eajournals.org/wp-content/uploads/Application-of-Expert-System-for-Diagnosing-Medical-Conditions.pdf>
- [8] Mutua, J.M., Wang, F.B., Vaidya, N.K., 2015. Modeling malaria and typhoid fever co-infection dynamics. *Mathematical Biosciences*. 264, 128-144.
- [9] Iheukwumere, I., Nwachukwu, C.N., Kanu, M.A., 2013. Manifestations, mismanagement and diagnostic challenges of malaria and typhoid fever. *Malar Chemoth Cont Elimination*. 2(109), 38-41.
- [10] Afoakwah, R., Acheampong, D.O., Boampong, J.N., et al., 2011. Pelagia research library. *European Journal of Experimental Biology*. 1(3), 1-6.
- [11] Bashyam, H., 2007. Surviving malaria, dying of typhoid. *The Journal of Experimental Medicine*. 204(12), 2774.
- [12] Nyakoe, N.K., Taylor, R.P., Makumi, J.N., et al., 2009. Complement consumption in children with Plasmodium falciparum malaria. *Malaria Journal*. 8(1), 1-8.
- [13] Isibor, J.O., Samuel, S.O., Ehigiator, E.O., et al., 2011. Plasmid-Mediated methicillin-resistant staphylococcus aureus in patients attending a tertiary health institution in Nigeria. *Pakistan Journal of Medical Sciences*. 27(2).
- [14] Ekesiobi, A.O., Igbodika, M., Njoku, O.O., 2008. Co-infection of malaria and typhoid fever in a tropical community. *Animal Research International*. 5(3).
- [15] Oh, H.J., Pradhan, B., 2011. Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area. *Computers & Geosciences*. 37(9), 1264-1276.
- [16] Chitnis, N., Smith, T., Steketee, R., 2008. A mathematical model for the dynamics of malaria in mosquitoes feeding on a heterogeneous host population. *Journal of Biological Dynamics*. 2(3), 259-285.
- [17] Adeosun, O.O., Adeosun, T.H., Adetunde, I.A., et al. (editors), 2008. Strategic application of information and communication technology for effective service delivery in banking industry. *2008 International Conference on Computer and Electrical Engineering*; 2008 Dec 20-22; Dhaka, Bangladesh. New York: IEEE. p. 135-140.
- [18] Mushayabasa, S., Bhunu, C.P., Mhlanga, N.A., 2014. Modeling the transmission dynamics of typhoid in malaria endemic settings. *Applications and Applied Mathematics: An International Journal (AAM)*. 9(1), 9.
- [19] Shahina, W., Nassara, A., Kalkattawia, M., et al., 2009. Dengue Fever in a Tertiary Hospital in Makkah, Saudi Arabia [Internet]. Available from: <http://apps.who.int/iris/bitstream/handle/10665/170727/db2009v33p34.pdf?sequence>
- [20] Djam, X.Y., Wajiga, G.M., Kimbi, Y.H., et al., 2011. A fuzzy expert system for the manage-

- ment of malaria. *International Journal of Pure and Applied Sciences and Technology*. 5(2), 84-108.
- [21] Vinterbo, S., Ohno-Machado, L., 1999. A genetic algorithm to select variables in logistic regression: Example in the domain of myocardial infarction. *Proceedings of the AMIA Symposium*. 984-988.
- [22] Rajamani, R., Rathika, M., 2015. Analysis of liver cancer using adaptive neuro fuzzy inference system (ANFIS). *International Journal of Innovative Research in Computer and Communication Engineering*. 3(7), 6757-6763.
- [23] Rahmon, I., Omotosho, O., Kasali, F.A., 2018. Diagnosis of Hepatitis Using Adaptive Neuro-Fuzzy Inference System [Internet]. Available from: <http://localhost:8080/xmlui/handle/123456789/774>