# Intelligent Diagnostic Model for Early Malaria Symptoms

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***Abstract*—One of the most significant worldwide health concerns in low-middle-income nations over the past few decades is Malaria, especially in Kenya. In Kenya, seventy per cent of people reside in areas where malaria is widespread, and most of them face obstacles getting access to medical care because of social culture, distance, and lack of money. Malaria transmission is high, particularly in Kenya's remote areas, despite a plethora of scientific efforts to combat the disease. This study aims to design and develop an intelligent malaria diagnosis model for early symptom detection using an Adaptive Neuro-fuzzy-Inference System with a 2000 dataset extracted from Six Types of Patient Data Inputs to optimize the model performance. The result achieved was 98.3% accuracy, which contrasted with the pertinent cutting-edge finding to illustrate the benefits of the suggested approach. The main contributions of this study are a combined Six Types of Patient Data Inputs, including Demographic, Symptoms, Blood pressure, Heartbeats, Height, and Weight, using fuzzy Systems techniques to detect early malaria symptoms accurately. The combined patient data input used for evaluation is demonstrated in the results, and the technique can identify different forms of malaria and has the best outcome when compared to relevant findings from the existing studies.**

***Keywords*—Malaria diagnosis system; malaria symptoms; classifier; ANFIS; fuzzy rules**

## I. Introduction

In sub-Saharan Africa, the prevalence of malaria is still high despite a number of control measures. Malaria is a potentially fatal illness caused by parasites carried by infected female Anopheles mosquitoes [37]. Among the potential forms of malaria are Malignant (M), Tertian (T), Quartan (Q) malaria describe different malaria fever cycle patterns or refer to types of malaria defined by the periodicity of fever spikes that are caused by various species of Plasmodium. Different parasites are responsible for each type of malaria. *Plasmodium falciparum*, the worst malaria parasite, causes malignant malaria, a deadly type of malaria. It has an irregular or quotidian (daily) fever pattern. Patients with falciparum may develop a typhoidal illness if they do not receive timely treatment because the disease's presentation is so varied and mimics typhoidal symptoms. Oval parasites and *Plasmodium vivax* are the causes of Tertian malaria. Every second day, this parasite creates a fever. *Plasmodium malariae* is the organism that causes quartan malaria. Every third day, this parasite creates a fever [37].

Globally, 247 million cases of malaria were reported in 2021, up 2 million from 245 million in 2020 [1]. This projected increase in 2021 was majorly reported in sub- Saharan Africa [1]. In Kenya, it was estimated approximately 3.3 million malaria cases and remains a major public health problem with 70% of the population at risk of the disease [2].

The government of Kenya launched a 2 day program, training around four fifty private medicine retailers in 3 Kenya endemic districts. The funding total ranged from US$5,000 to US$6,000 per district. The United Nations Children's Fund (UNICEF) and the Global Fund supported implementation costs to Fight AIDS, Tuberculosis, and Malaria [3]. However, high rates of deaths still exist through malaria. According to the World Health Organization (WHO), about 3.4 million malaria cases and 12,000 deaths have been registered in Kenya in 2021 [4]. In sub-Saharan Africa, where 94% of deaths are reported each year, this issue is particularly serious [5]. This condition is predicted to become worse especially in the Coastal and Western regions with the pandemic that has compromised malaria treatment and intervention measures [5]. Malignant/tertian malaria caused by *Plasmodium falciparum* species accounts for over 99% of malaria cases [6].

Although study focus on medication over the counter carried out which revealed that malaria medications over- the-counter (OTC) are often the first point of care for African adults and children. Using the diagnosis system in private drug outlets remains low, leading to overprescribing antimalarials [1].

Research including Machine Learning (ML) techniques with features have been conducted to predict malaria [7], [8], [9]. This procedure involved illumination correction, erythrocyte categorization, feature collecting and classification. However, mortality is still increasing.

Neuro-Fuzzy expert system diagnostic software has also been developed with Microsoft Visual C# (C Sharp) programming language and Microsoft SQL Server 2012 to manage the database [10]. Multiple algorithms were also employed to optimize model performance and classify malaria accuracy [11]. Moreover, some studies focused only in various studies researchers have utilized different numbers of symptoms, for instance, 10 symptoms [12] and 12 symptoms [13].

Despite various malaria diagnosis approaches focusing toward solving the problem, these approaches suffer from a lack of comprehensive data [14]. The literature reveals that previous malaria diagnosis studies have only conducted research employing two inputs, symptoms and non-symptoms.

This proposed study aims to fill this significant gap, by introducing a novel methods combining Six Types of Patient Data Inputs that include Demographic (name, address, date of birth, and contact details), Symptoms, Blood pressure, Heartbeats, Height and Weight, based on ANFIS that can be utilized in healthcare in Kenya to conduct a comprehensive clinical diagnosis of malaria to detect early symptoms accurately and plan appropriate treatment. The definition of Six Types of Patient Data Inputs is presented in Section III(D). To the best of our understanding, previous studies haven't utilized a method combining the Six Types of Patient Data Inputs.

### A. Main Contribution

Our main contribution is a novel method, combining Six Patient Data Inputs, which include Demographic, Symptoms, Blood pressure, Heartbeats, Height, and Weight, based on ANFIS to detect malaria accurately. From these Six Patient Data Inputs, 2000 data were gathered that were utilized to produce fuzzy models, fuzzy rules leading to detecting early malaria symptoms. Using data based on the Six Patient Data Inputs leads to higher accuracy and reliability, while using a few symptoms often results in uncertainty and potential misdiagnosis. This study is the first to utilize the novel method combining Six Patient Data Inputs in the field.

The main goal of this research is to design and build an intelligent malaria diagnosis model for early symptom detection using an Adaptive-Network, such as a Neuro-Fuzzy Inference System (ANFIS) with Six Types of Patient Data Inputs. Thus, the study's main objectives are:

*1)* Identify and extract features based on the Six Types of Patient Data Inputs.

*2)* Develop state-of-the-art models based on advance techniques such as ANFIS.

*3)* Train and test the model to measure the performances.

*4)* Compare findings of the proposed study with the existing findings in the field to clearly show the merit of the proposed method.

Advantages of the new method: significantly help doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment, improved accuracy of early malaria diagnosis and reduced malaria risks. Increase patients' confidence in early malaria symptoms diagnosis. Using six different data types will enable the implementation of the real-world AI App for early malaria symptoms diagnosis in remote settings.

This study's remaining sections are organized as follows: Section II offers literature review which is approached critically. Section III describes methodology and methods including Data collection and Sources, Six Types of Patient Data Input, ANFIS and Fuzzy rules together with Ethical consideration. Section IV presents the description of experimental procedures, including training and testing. While the study's findings are shown in Section V, the discussion of the results, including contribution of the proposed method, comparisons, limitations and strength are presented in Section VI. The study concludes and provides directions for future research in Section VII.

## II. Literature Review

### A. Multiple Algorithms: ANN, CNN, ANFIS

First, when making decisions that could affect a patient, practitioners use the information provided by a malaria diagnosis. To detect malaria and predict risk factors, Artificial intelligence (AI) has been employed as a usable tool [15].

Uzun et al., utilized [16] data from 2207 patients which was reduced from the initial dataset of thirty-two criteria samples to fifteen to carry out research on Machine Learning based malaria detection. The research investigated and validated the effectiveness of several algorithms using 15 criteria samples from malaria patients. Following training, ANN achieves the highest *R* (99%) compared to ANFIS (97%), MLR (92%) and Random Forest (68%) respectively [16]. The outcome demonstrated that healthcare systems allocate resources more effectively and make better decisions. However, some of the algorithms have incurred 8%, 11% and 23% error rates which are a high risk. Moreover, due to 15 sample datasets used, the findings may not be broadly applicable, limiting generalizability.

Yang et al. presented [17] a 5-fold cross-validation for two-step CNN models. The model employs an intensity-based iterative Global Minimum Screening technique in the first stage to categorize malaria parasites, and subsequently, a CNN employs a custom CNN to categorize the existence of malaria parasites. The accuracy achieved for this technique is 93.46%. However, the approach suffered high false positives.

Vijayalakshmi et al. proposed [18] a transfer learning method with a classification with 93.13% accuracy to discriminate between illustrations of malaria-diseased cells and healthy cells utilizing the VGG16 model and a support vector machine. However, distinguishing between images of healthy and malaria-affected cells alone could be risky because most malaria is caused by a mosquito bite and goes through various stages before the changes in cells could be detected.

Another study suggested a better dynamic routing method that employs a fully trained capsule network to distinguish between healthy and malaria-infected cells, and the model accuracy was 98.82%. However, similarly, malaria goes through various stages before the changes in cells could be detected [19].

Loddo et al. [20] used the DenseNet-201 neural network to diagnose *Plasmodium falciparum* life stages into four groups and used two different datasets to assess the robustness of the model. The accuracy rate for binary was 97.68%, and the multi-classification accuracy rate was 99.40%. Although the accuracy is high, a wide range of data could be beneficial in accurate diagnosis.

Equally, another study Utilized ML techniques to examine haematological data taken from 2,207 participants in Ghana, such as ANN to identify methods that can reliably distinguish between severe malaria (SM) and non-malarial infections (nMI) and uncomplicated malaria (UM), employing haematological parameters. To classify UM, nMI, and SM ANN with 3 hidden layers was utilized. The accuracy scores of the multi-classification models ranged from 94% to 98%. Although many machine learning models using traditional features have been developed for malaria classification and decision-making, these models lack generalization ability [21].

To combat malaria, other researchers adapted a different strategy. Santosh and Ramesh [22] conducted research to determine malaria abundances using an ANN with clinical and environmental variables with Big Data on the geographical location of Khammam district, Telangana, India. To increase accuracy in actual practice, their approach made use of a lot of data from various seasons. 81.7% was the highest accuracy attained. To enhance malaria models, more research is necessary to determine their accuracy. Although these variables are required to achieve accurate predictive power, 12% of environmental data and 7% of clinical data were missing. As a result, accurate predictive data is necessary to increase accuracy [22].

The study by Arowolo et al. [23] proposed a combined a novel analysis of variance (ANOVA) with ant colony optimization (ACO) approach as a hybrid feature selection to select relevant genes to minimize the redundancy between genes, using SVM for classification. The results of the experiment based on high-dimensional gene expression data show that ANOVA-ACO can help clinicians make pertinent choices when developing medications and strategies to end human malaria infections. Even so, the strength appears promising. However, to be competent amongst the existing relevant work, the speed of the performance should be provided.

Awotunde et al. [24] also developed a model to diagnose Malaria and Typhoid Fever using a Genetic Algorithm (GA), a Neuro-Fuzzy Inference System (GENFIS). They discovered that the GA module distributes the optimal set of network parameters to the relevant hidden layer nodes. The accuracy of their model was 97.2%. However, there are 2.8% average error rates, which could be because of overfitting.

To improve malaria diagnosis models, Awotunde et al. [25] utilized Support Vector Machine (SVM) algorithms and Adaboost, together with ensemble methods. Chi-square was used to extract redundant or unnecessary features in order to evaluate the model. With data input, the classification accuracy was 97%. The classification accuracy seems high. But the number of features used is too small. Using more features could improve the model.

Based on AI techniques, Datilo et al. [26] reviewed epidemic prediction using Artificial Neural Networks, highlighting the value of precision disease prediction and suitable methods for making malaria predictions using Artificial Neural Networks. They carried out a thorough evaluation of ANNs and found that the training and generalized capacity of ANNs are greatly enhanced when hybrid models are used in conjunction with meta-heuristics in detecting diseases. However, using a small dataset reduces the performance and effectiveness of the model.

Another study by [35] used AI techniques to detect diseases. They made individualized treatment programs, which support medical professionals in making decisions, instead of simply making tasks automatic. Developing technologies that can enhance patient care in various healthcare domains is one of AI's strengths. Data privacy, bias, and the requirement for human expertise are limitations that must be addressed for the ethical and successful application of AI in healthcare.

### *B. Long Short-Term Memory (LSTM)*

A framework for predicting malaria endemicity in specific geographic areas, like Nigeria, was presented in another study. They used satellite and clinical data to train a long short-term memory (LSTM) classifier. The findings show that the LSTM algorithm offers a practical way to identify instances of widespread malaria [27]. The outcome shows improved accuracy. However, there was no indication of the size of data used, and the data is used in the valishowsson strategy [27].

The aforementioned studies examined the application of machine learning techniques and NF rules based on symptoms to create models for diagnosing malaria. However, a combined approach has not been taken into consideration in the current approaches integrating Six Types of Patient Data Inputs that include Demographic, current Symptoms, Blood pressure, Heart beats, Height and Weight, based on ANFIS to more precisely categorize malaria into four potential types. Moreover, the microscopic testing techniques cause a delay at the start of treatment [28]. This is due to a lack of adequate supply for diagnostics. Rapid diagnostic tests (RDTs) and microscopic parasitological testing are required to determine whether prospective patients have malaria parasites.

Despite all these efforts to diagnose malaria, there is still a lack of real-time malaria diagnosis Apps in the remote setting and malaria zones in Kenya [29]. A survey showed that 20% of the health facilities experienced a total absence of diagnostic services. The studies have only focused on symptoms. Ramdzan [8] and Shimizu [9] only focused on detecting risk factors of malaria. Other research only focused on using different numbers of symptoms. Therefore, the previously employed techniques aren't strong enough to tackle the issue robustly.

The previous studies have not employed a combined method integrating six patient data inputs.

To fill this gap, the proposed study addresses this problem by introducing significant methods combining Six Types of Patient Data Inputs that include Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight, based on ANFIS that can be utilized in healthcare to conduct a comprehensive clinical diagnosis of malaria to detect early symptoms accurately and plan appropriate treatment.

## III. Methodology

The new approach employs Intelligent Systems utilizing an Adaptive Network such as a Neuro-Fuzzy Inference System (ANFIS) with integrated Six Types of Patient data Inputs. 2000 data was extracted from a combined Types of Patient data Inputs, which include Demographic, Symptoms, Blood pressure, Heart beats, Height and Weight. The reason for using this method is not only to extract comprehensive data, but also to use effective techniques to detect malaria effectively. The proposed approach has four functional components that are Data Sources, Six Types of Patient Data Inputs, ANFIS and fuzzy rules. This is illustrated in Fig. 1 and described in detail in Section III.

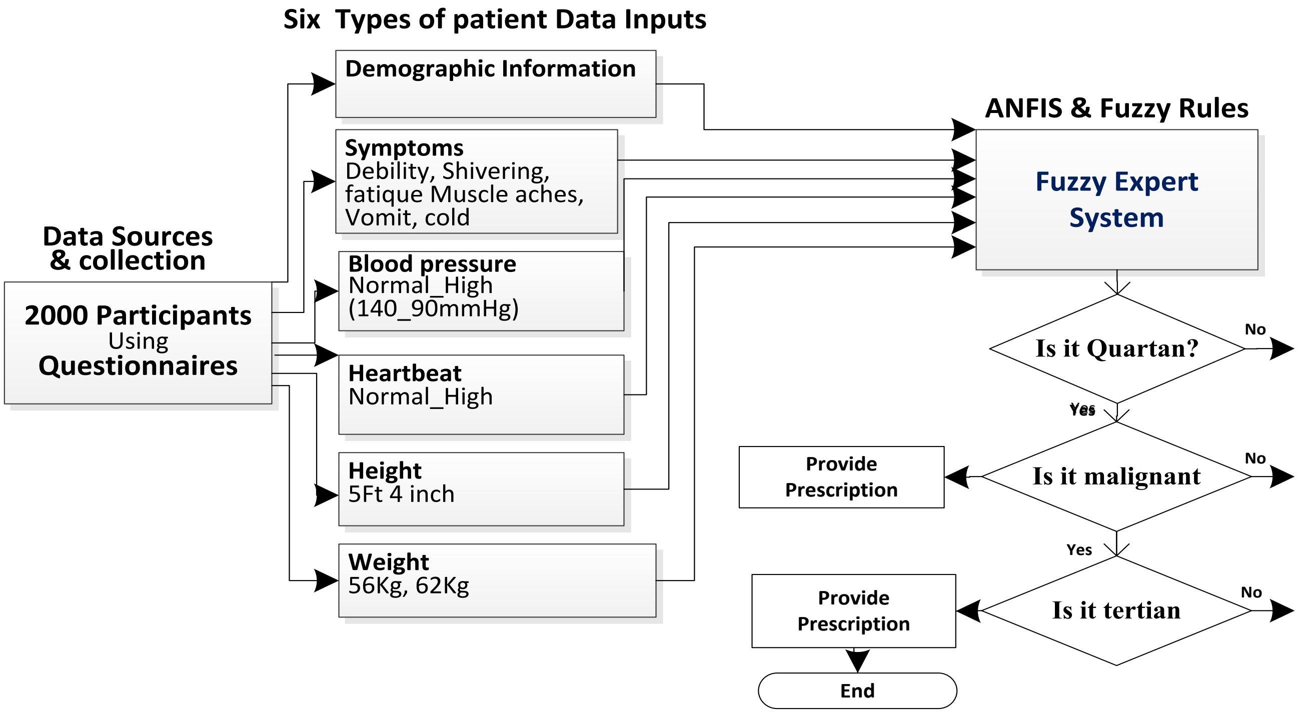


Fig. 1. Intelligent malaria diagnosis architecture.

## A. How does the Proposed Approach Differ from the Existing Ones?

The proposed method integrates Six Types of Patient Data Inputs which are Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight. From these wide-ranging, 2000 data are extracted which are used to generate, fuzzy models, fuzzy rules, to train and test the models. Whereas some studies only used symptoms and non-symptoms. For instance, the work of Bria et al. [12] only used 10-12 malaria symptoms for malaria diagnosis which is too small for generalization, while the study of Uzun et al. [16] had a limited generalization, only used 12 symptoms. Other notable research that explored malaria diagnosis through ML techniques are Santosh and Ramesh deployed clinical and environmental variables. ANNs and big data are used to predict mosquito abundance in the Telangana district of Khammam in India the data sizes are not specified [22]. The average error ranges from 82% to 17% accuracy. The literature reveals that the existing approaches suffer from a lack of comprehensive data [14]. Therefore, the proposed method advances the existing work by offering comprehensive data extracted from 2000 participants based on Symptoms, Blood pressure, Heartbeats, Height and Weight (diverse sources). The model demonstrates significant potential in providing enhanced high accuracy and reliable diagnosis for early malaria symptoms.

## B. Data Sources and Data Collection

To diagnose malaria attacks accurately, careful consideration needs to be taken to identify important sources to extract comprehensive data. The study was conducted using questionnaires, which were randomly handed to 2000 malaria patients in five General Hospitals including Kenyatta National Hospital (KNH); Kisumu General Hospital (KGH); Jaramagi Oginga Odinga Hospital (JOOH); Maseno Mission Hospital (MMH) and Siaya Referral Hospital (SRH), which are malaria endemic areas in Kenya. Questionnaire was utilized because the questionnaire questions were designed to capture information that could contribute to malaria parasite diagnosis such as Demographic, Malaria Symptoms, Blood pressure, Heart beats, Height and Weight from patients who formerly and currently confirmed malaria positive from blood Smear. Permission was obtained from Clinical Officers in charge of each healthcare facility and consent sought from patients before data gathering. Each constituency achieved 400 patients' respondents. The study was administered during the period between March and May 2025. The Data from the 2000 patients were encoded and entered in an Excel Sheet, taking 2000 rows and twelve columns. The most common symptoms include vomiting, limpness, diarrhea, loss of appetite, joint pain, dizziness and the most severe symptoms are shortness of breath seizures, loss of consciousness and jaundice. The anonymous data captured are summarized in Table I.

TABLE I. SUMMARY OF DATA GATHERED FROM PATIENTS WHO TESTED MALARIA POSITIVE FROM BLOOD SMEAR

| General Hospital | Gender | Age | Education Level | Got Malaria in last 12 Months? | Confirmed Malaria via Blood Smear | Malaria Symptom | Blood Pressure | Heartbeat | Height | Weight |
|---|---|---|---|---|---|---|---|---|---|---|
| KNH | Man | 40-49 | Secondary | Yes | Yes | Fever (Q) | High140/90mmHg | 60 bpm | 5 “6” | 54 kg |
| KNH | Woman | 30-39 | Secondary | Yes | Yes | Fatigue (Q) | High138/139mmHg | 91 bpm | 5 “10” | 59 kg |
| KNH | Man | 50-59 | Secondary | Yes | Yes | Muscle pain | Norm142/91mmHg | 71 bpm | 5"9" | 65 kg |
| KNH | Man | 20-29 | Secondary | Yes | Yes | Coma (M) | High140/90mmHg | 100 bpm | 6”0” | 100 kg |
| KNH | Man | 30-39 | Secondary | Yes | Yes | Nausea | Low140/90mmHg | 61 bpm | 5 “6” | 58 kg |
| KGH | Man | 30-39 | Secondary | Yes | Yes | Headache (Q) | High140/90mmHg | 72 bpm | 5 “7” | 68 kg |
| KGH | Man | 40-49 | Secondary | Yes | Yes | Sweating | High141/90mmHg | 100 bpm | 5 “9” | 61 kg |
| KGH | Man | 40-49 | Secondary | Yes | Yes | Debility | Norm91/39mmHg | 72 bpm | 5 “8” | 56 kg |
| KGH | Woman | 30-39 | Primary | Yes | Yes | Anemia (T) | High142/97mmHg | 61 bpm | 5 “7” | 58 kg |
| KGH | Man | 40-49 | Primary | Yes | Yes | Dry lips | High141/90mmHg | 101 bpm | 5 “7” | 59 kg |
| JOOH | Woman | 30-39 | Secondary | Yes | Yes | Chills | Norm90/60mmHg | 85 bpm | 5 “8” | 64 kg |
| JOOH | Woman | 50-59 | Secondary | Yes | Yes | Nausea | Low81/58mmHg | 61 bpm | 5 “6” | 58 kg |
| JOOH | Man | 50-59 | Secondary | Yes | Yes | Convulsions | High141/90mmHg | 101 bpm | 5 “6” | 57 kg |
| JOOH | Woman | 40-49 | Secondary | No | Yes | Seizures (M) | High141/90mmHg | 61 bpm | 5 “7” | 58 kg |
| JOOH | Woman | 50-59 | Secondary | Yes | Yes | Vomit | Low87/59mmHg | 60 bpm | 5 “8” | 56 kg |
| **MMH** | Woman | 40-49 | Secondary | Yes | Yes | Dizziness | High130/139mmHg | 92 bpm | 5 “11” | 68 kg |
| **MMH** | Man | 20-29 | Secondary | Yes | Yes | Chills | High141/90mmHg | 99 bpm | 5 “11” | 65 kg |
| **MMH** | Nan | 30+ | Secondary | Yes | Yes | DifficultBreathing | Low89/59mmHg | 60 bpm | 5 “6” | 55 kg |
| **MMH** | Woman | 30-39 | Graduate | Yes | Yes | Intestinal disorder | Low80/59mmHg | 60 bpm | 5 “7” | 58 kg |
| **MMH** | Woman | 30-39 | Secondary | Yes | Yes | Diarrhea | Norm91/60mmHg | 71 bpm | 5"9" | 64 kg |
| **SRH** | Man | 40-49 | Secondary | Yes | Yes | tiredness | High140/90mmHg | 100 bpm | 6”0” | 100 kg |
| **SRH** | Man | 30-39 | Secondary | Yes | Yes | Coma (M) | High140/90mmHg | 100 bpm | 6”0” | 100 kg |
| **SRH** | Woman | 60+ | Secondary | Yes | Yes | Jaundice (T) | High139/90mmHg | 61 bpm | 5 “7” | 58 kg |
| **SRH** | Woman | 50-59 | Secondary | Yes | Yes | Shiver | Norm>90/>60 | 85 bpm | 5 “8” | 62 kg |

**Key:** KNH =Kenyatta National Hospital; KGH = Kisumu General Hospital; JOOH = Jaramobi Oginga Odinga Hospital
MMH = Maseno Mission Hospital; SRH = Siaya Referral Hospital

### C. Six Types of Patient Data Inputs

A combined Types of patient data inputs from patients refer to clinical details gathered during a patient’s meeting with a health officer, which include Demographic (patient personal details like age, sex, income test results), Symptoms, Blood pressure, Heart beats, Height and Weight. These combined Types of patient data inputs are collected to ensure safety and for patient quality outcomes. The information is kept digitally in a secure record, considered confidential and adhering to legal guidelines. The patient’s demographic significantly relates to sic types of patient data inputs by influencing their type, severity, prevalence of certain conditions, and how healthcare is accessed.

### D. Six Types of Patient Data Inputs and Definitions

*1) Demographic information*: Basic characteristics identifier of a Patient such as their name, address, date of birth, and contact details are made up. Other relevant descriptive information such as ethnicity, gender, marital status, and unique identifiers are also included. Identification of patients, administrative procedures, and the delivery of secure, efficient healthcare services all depend on this information [38].

*2) Heartbeat:* "Patient heartbeat" refers to the heart rate of a patient, which is defined as the frequency of heart beats per minute and serves as a crucial indicator of their general health. For adults, a normal resting heart rate generally ranges from 60 to 100 beats per minute, but this can be affected by factors like fitness level, stress, medication, and illness [39].

*3) Blood pressure*: Refers to the force exerted by circulating blood on the walls of blood vessels. The majority of this pressure is generated by the heart as it pumps blood throughout the circulatory system [39].

*4) Height:* Height measurements are utilized to determine your body mass index (BMI), which serves as an indicator of healthy versus unhealthy weight [40].

*5) Weight:* "Patient weight" refers to the body mass of a person receiving medical care, recorded in units like kilograms or pounds. This measurement is crucial for various clinical reasons, including accurately calculating medication dosages, assessing and managing nutrition and fluid balance, monitoring patient status, and selecting appropriate medical equipment, like specialized scales for immobile patients. Accurate and regular weight recordings are vital for safe and effective patient care [39].

*6) Symptoms:* Symptoms are mental features that a patient experiences that may indicate that the patient has a disease or condition. Malaria symptoms are for example, fever, chills, headaches, sweats, fatigue and more. These constitutes the most important part of our integrated framework, from which 2000 dataset extracted is utilized to develop fuzzy rules, to create fuzzy models, to train and to test the models.

### *E. Dataset Choice*

Choosing data for malaria symptom diagnosis needs careful consideration. The use of 2000 participants enables data extraction based on Six Patient Data inputs. The dataset was chosen because comprehensive (large and diverse) datasets enable high accuracy and reliable diagnosis results, and could also identify complex or severe malaria symptom patterns.

### *F. ANFIS*

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of neural network employed for the purpose of adaptive learning [33]. The algorithm is chosen since it is capable of managing both qualitative and quantitative values and demonstrates resilience against outliers. It has a universal approximation with the ability to use Fuzzy IF...THEN rules while using fuzzy logic to model systems with linguistic terms and neural networks to optimize the fuzzy system's parameters [30]. The system checks individual patient inputs. If malaria symptoms are detected, before a recommendation of blood tests is generated, the system identifies if it is quartan malaria, malignant, or tertian malaria. If no symptoms are identified, the patient is notified, and no further action is undertaken.

ANFIS has the ability to handle and model uncertainty and imprecision inherent in complex, real-world data by combining the symbolic reasoning behind fuzzy logic with the learning abilities of neural networks. This architecture is particularly effective in enabling ANFIS to model complex data and nonlinear relationships while effectively managing six different types of data input uncertainty [31].

### *G. Fuzzy Rules*

An intelligent malaria diagnosis structure has inputs that are represented as x, y, and one output, z. Two fuzzy sets are utilized on behalf of a single input, and a first-order polynomial is used to represent the output. Where x, y and z (symptoms and heartbeat, high blood pressure, weight, height) are linguistic variables, 1A, 2A, 3A (fever, fatigue and muscle-pain) Linguistic values determined by fuzzy sets within the universe of discourse x; 1B, 2B, and 3B represent fuzzy sets within this universe of discourse z(symptoms).

### *H. Advantages of the Proposed Method*

The primary advantages of the suggested approach are, firstly, the results will greatly help doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment. Second, the approach will improve the accuracy of early malaria diagnosis and reduce malaria risks. Users' confidence will increase in early malaria symptom diagnosis. The use of six different data types will enable the implementation of the real-world Artificial Intelligence App for early malaria symptoms diagnosis in remote settings.

### *I. Ethical Consideration*

The current study is part of a large project "Bringing together researcher from Kenya, Tanzania and the UK to Network and explore factors causing challenges in accessing Healthcare services (especially malaria diagnosis) in rural areas in Kenya and Tanzania", whose ethical approval (Ref/17086) was obtained from the ethics committee within the Computer and Information Science department at Northumbria University. Written informed consents were obtained from each participant before participating in the research. Participants understood that they had the right to withdraw from the study at any time if they chose to do so.

## IV. EXPERIMENTAL PROCEDURE

The experiment concerning the intelligent diagnosis of malaria relies on ANFIS, utilizing data for both training and testing sets. The fuzzy system is employed due to its nature as a feature-based fuzzy model that handles uncertain and complex data to represent fuzzy sets and rules. Besides, an ANFIS has the benefit of both a neural network, which has the capability of learning new data, and fuzzy logic, which deals with linguistic values as well as making decisions using fuzzy [If-THEN] rules [31]. 2000 data is used, and the reason for the chosen size is to have a representative sample of the larger population of the community in Siaya County. To create and evaluate the model, a two-fold cross-validation method was deployed because it can handle the conventional data well and helps to avoid overfitting [32]. This method involves splitting data randomly into training sets and testing sets.

### *A. Training*

To enable the training of an intelligent model for malaria diagnosis. Parameters are carefully tuned to find the best set, ensuring high-quality performance using an optimization method. A hybrid learning approach that combines the least-squares method with the gradient descent technique. Initially, the training was carried out by introducing a training set to the input layer of the network once, and the network transmits the input from one layer to another, until it gets to the output layer. There, an error is computed and propagated backward through the network from the output layer to the input layer. The feature model is trained only once using the training set [33].

### *B. Testing*

After training is complete, testing was carried out, presenting a test-set only once to the network's input layer. The neurons transmit the inputs from Layer 1 to each layer until they reach the output layer. The roles of training and testing are reversed so that training is conducted on the test set, while testing is performed on the training set. After training and the test process, the results are achieved, with getting average error. The outputs achieved are discussed in Section VI. [33].

### *C. Membership Functions*

To obtain efficiency, Five Membership Functions (MFs) were assigned as Generalized bell membership (Gbellmf) type, as shown in Fig. 2, using 12 epochs and zero (0) tolerance. The membership functions (MFs) of fuzzy sets are represented as a curve, which delineates how each point within the input space corresponds to a membership value ranging from (0, 100) to (0, 1) [31]. Consequently, the output can fluctuate between (0, 100 and (0, 1). The intelligent malaria diagnosis model membership function map for data contains risk values where 10 = NonSymptom indicates no risk and 100 = Quartan represents the highest possible risk. 30 = Suspect indicates low risk, while 80 = Malignant being high risk. 50 = Tertian being moderate risk.

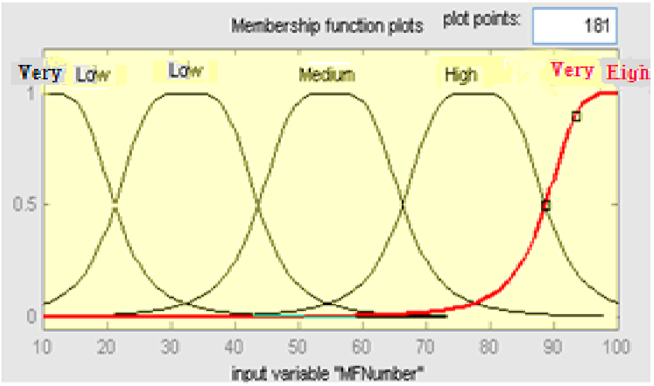


Fig. 2. GBell membership function.

## D. Fuzzy Inference Systems and Rules

The intelligent malaria diagnostic model uses an Adaptive Neuro-Fuzzy Inference System learning structure [33]. The FIS is functionally equivalent to fuzzy inference systems. To decompose the parameter set in order to apply the hybrid learning rules, the process goes through the Neural Network and the inference engine decides which is reached by reasoning in connection with the Fuzzy [IF-THEN] rules shown in Fig. 3 and reaches the output layer [33].

Quartan rules

1. If (input is ache-quartan) and (input is argue-quartan) and (input is bronchitis-quartan) and (input is cold-quartan) and (input is bronchitis-quartan) and (input is eruption of herpes-quartan) and … (input is neck_back_pain-quartan) then output is quartan mf1(1)

Malignant rules

2. If (input is teeth-chatter-malignant) and (input is temperature_rises_to_$104_o$-malignant) and (input is temperature_rises_to_$105_o$-malignant) and (input is vomit-malignant) and (input is developmental-malignant) and (input is intestinal_disorders-malignant) and … (input is herpes_around_mouth-malignant) then output is malignant mf2(1)

Tertian rule

3. If (input is abdominal_Pain-tertain) and (input is anemia-tertain) and (input is back-Pain-tertian) and (input is bloody_Stools-tertian) and (input is body-ache-tertian) and (input is chills-tertian) and … (input is hypothermia-tertian) then output is tertian mf3(1)

Suspected rules

4. If (input is irritability-suspected) and (input is jaundice-suspected) and (input is join_Pain-suspected) and (input is kidney_Failure-suspected) and (input is limpness-supected) and (input is loss_of_consciousness-suspected) and … (input is non_prescribed_medication-suspected) then output is suspected mf4(1)

Non_symptom rules

5. If (input is age-non_symptom) and (input is sex-non_symptom) and (input is education-non_symptom) and (input is income-non_symptom) and (input is malaria_History-non_symptom) and (input is location-non_symptom) and … (input is buy_unprescribed_medication-non_sysmtom) then output is non_symptom

Fig. 3. Fuzzy [IF-THEN] rules.

This FIS is a multilayer feedforward network in which each individual neuron carries out a designated function. The related ANFIS architecture is depicted in Fig. 4.

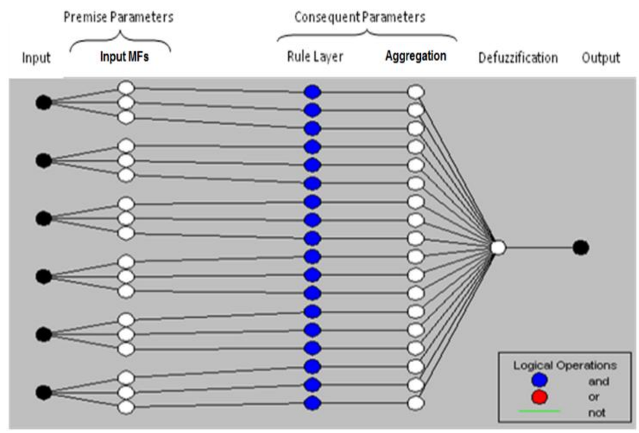


Fig. 4. Fuzzy structure for intelligent malaria diagnosis.

The FIS has six layers which are Layer I - input, Layer II – fuzzification, Layer III – fuzzy rule, Layer IV – normalization, Layer V – defuzzification and Layer VI – crisp output. The learning process takes the form as follows:

*1) Layer 1:* This is the input. Neurons in Layer I transmit external inputs to Layer II. This is specified as:

$$y_i^{(I)}=x_i^{(I)} \tag{1}$$

where, the input is $y_i^{(1)}$ and the output in layer 1 is $X_i^{(1)}$ [36].

*2) Layer II:* This is the fuzzification. Neurons in Layer ll perform fuzzification. The Sugneo model fuzzification have a Gbell shape activation function [36]. This is specified as:

$$y_i^{(2)} = \frac{1}{\left[\frac{x_i^{(2)}-ai}{ci}\right]} 2b_i \tag{2}$$

where, the input is $x_i^{(2)}$and the output is $y_i^{(2)}$of neuron I Layer II, and $a_i$ $b_i$ and $c_i$ are parameters that control the center width and slope of the bell-shape function of neuron [31].

*3) Layer III:* This is a rule layer. Every neuron in Layer III matches a single fuzzy rule. A rule neuron receives input from fuzzification and calculates the execution strength of the rule it represents [36]. Thus the output in Layer III is expressed as:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \tag{3}$$

where, inputs are $x_{ji}^{(3)}$and $y_i^{(3)}$ are output of rule neuron in Layer III.

*4) Layer IV:* This is normalization. Every neuron in this layer receives outputs from the rule layer and the normalized execution strength of any given rule is calculated [36]. Therefore, the output of Layer IV is expressed as:

$$y_i^{(4)} = \frac{x_i^{(4)}}{\sum_{i=0}^{u} x_{ji}^{(4)}} = \frac{\mathrm{ui}}{\sum_{i=0}^{u} uj} = ui \tag{4}$$

where, the input $x_{ji}^{(4)}$ from neuron j is allocated in Layer III to Layer IV.

5) *Layer V:* This is defuzzification. Each neuron in Layer V is connected to the normalization neuron, as well as receives the initial input $x_1$and $x_2$. A neuron defuzzification calculates the value of weight consequent of any given rules [36]. It is specified as:

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1}x1 + k_{i2}x2] = u_i[k_{i0} + k_{i1}x1 + k_{i2}x2] \quad (5)$$

In which the input is $x_i^{(5)}$ and the defuzzification output neuron is $y_i^{(5)}$in Layer V. $k_{i0}, k_{i1}$ and $k_{i2}$is a set of parameter consequent of rule I [36].

6) Layer VI: This is denoted by a singular neuron sum. The neuron calculates the total output of every defuzzification and produces the overall output y which is specified as [36]:

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} u_i\,[k_{i0} + k_{i1}x1 + k_{i2}x2] \quad (6)$$

As demonstrated, the fuzzy structure is in fact functionally equivalent to a first-order Sugeno-fuzzy model [31].

After completion of the training, the model undergoes testing with a separate, unseen 50% test set. The process of training and testing is conducted twice, with roles being reversed; the model is trained on the test set and subsequently tested on the training set. The network processes its input as the weights are modified and transmitted to the subsequent layer, where the output is aggregated, and the sum of squared errors is computed in real-time as end results. The effectiveness of features is evaluated using randomized methods as well as time required to construct models. The level of standard confidence for error is established at 5% across all utilized algorithms, as an average error exceeding 5% is deemed unsuccessful, while an average error below 5% is regarded as successful [33].

## V. Results

### A. Adaptive Neuro-Fuzzy Inference

The primary aim of the research was to create and implement an intelligent model for diagnosing malaria in endemic areas, utilizing the Adaptive Neuro-Fuzzy Inference System (ANFIS) with six different types of patient data inputs. The performance of the proposed intelligent malaria diagnosis method was assessed through ANFIS, employing 2-fold cross-validation. The training was conducted on the training set, while the model was evaluated on a test set. The roles were switched, with training conducted on a test set and evaluation carried out on a training set [33]. The average test error rate results achieved was 1.68%, as shown in Fig. 5. When the results are expressed as a percentage and rounded to two decimal places, the overall average test error rates are 1.68%. Therefore, the overall average accuracy attained during testing was 98.3%, which is considered outstanding performance [30], [33].

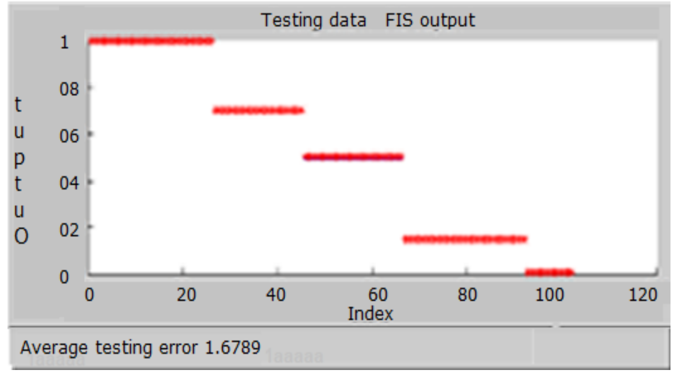


Fig. 5. Average testing error result using ANFIS.

## VI. Discussions

The proposed study presents an experimental procedure to diagnose early malaria symptoms. In this study, we deployed ANFIS and a combined Six Types of Patient Data Inputs. Deploying a sample of 2000 patient's data from a combined Six Types of Patient Data Inputs, the finding of the proposed research provides insight information of how well ANFIS can detect early malaria symptoms. ANFIS showed a remarkable level of performance, demonstrating its ability to handle both the training dataset and the test dataset. Deploying a hybrid approach helps to get the best set of parameters tuned to maximize the system performance. The contribution of the proposed study is demonstrated in Section V(A).

### A. Contribution

The proposed study contributes to the field by introducing a novel method, combining Six Patient Data inputs. The Six Patient Data inputs are: Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight based on ANFIS to optimize the model performance. From these Six Patient Data inputs, 2000 data were collected which were utilized to create fuzzy models, fuzzy rules as well as to detect early malaria symptoms. Using data based on the Six Patient Data inputs leads to higher accuracy and reliability, while using few symptoms often results in uncertainty and potential misdiagnosis. This study is the first to utilize the novel method combining Six Patient Data inputs in the field. The experiments based on ANFIS with data have consistently produced the best results. Using the MATLAB toolbox, ANFIS achieved 98.3% accuracy. The novel method achieved best results so far compared to the related cutting-edge in the domain. Overall, the outcomes indicate that the new method, using Six Types of Patient Data Inputs provide enhanced accuracy and deliver optimal performance. Comparative analysis is carried out in Section V(B).

### B. Comparison of the Proposed Study with the Existing Related Works

To compare the results of the new approach that achieved 98.3% accuracy with the work of Uzun et al. [16] and the work of Bria et al. [12] which are closest to the proposed study.

The proposed study outperformed the study by Uzun et al. [16] with 1.3% difference, while the study of Bria et al. [12] is outperformed with a difference of 2.3%, as shown in Table II. The proposed model's higher accuracy is supported by its use of six different data types, unlike the other models using 10 to 12 symptoms only [12]. As we can see, the work of Bria et al. [12] used 10 to 12 malaria symptoms for malaria diagnosis which is too small for generalization, while the study of Uzun et al. [16] though had 2700, generalization was limited.

TABLE II. COMPARISONS OF THE PROPOSED STUDY WITH RELATED WORK

| Schedule | Algorithms | Data Symptoms | % |
|---|---|---|---|
| Barraclough et al. | ANFIS | 2000 | 98.3 |
| Uzun et al. (2024) | MLR/ANN/ANFIS/R | None | 92%, 99%, 97%, 68% |
| Bria et al. (2021) | LR, SVM, KNN | 10-12 | 84% -86 |
| Santosh & Ramesh (2019) | ANNs | Big data | 82% |
| Morang'a et al. (2020) | ANNs) | 2207 | 94% |
| Uzoka et al. (2016) | NF | 12 | None |

A direct comparison of our results against previous results is not possible because our method integrates Six Types of Patient Data Inputs, which is wide-ranging, while the existing results only used symptoms and non-symptoms.

Morang'a et al. [21] employed haematological data extracted from 2,207 participants in Ghana, using multi-layer classification and Blood count. ANN scored a range of 94% accuracy. However, these models were restricted to base-learners with fewer features from one source, achieving (82% - 94%) less than the standard confidence of 5% errors, whereas our method achieved 98.3% accuracy, demonstrating that the method used is far better than the related existing methods. Our research findings suggest that the method we proposed accurately diagnoses malaria in real-time and have a high level of performance compared to the reported related results. Other notable research that explored malaria diagnosis through ML techniques are as follows: Santosh and Ramesh deployed [22] clinical and environmental variables with big data using ANNs for mosquito abundance prediction in the geographical location of Khammam district, Telangana, in India. The average results range from 82% to 17% accuracy. The big data used is not specifically for malaria symptoms.

### C. Strengths and Limitations

In the process of experimenting with different numbers of hidden neurons, the experiment indicated that the number of neurons in the hidden layers affects the speed of training the network in the method, achieving a time to build the model in the range of 0.01 to 0.006 seconds [34]. Complex patterns cannot be identified by a limited number of hidden neurons. However, numerous such patterns can significantly increase the load on the computational domain. As the quantity of hidden neurons increases, so does the network's capacity to identify existing patterns. However, if the quantity of hidden neurons is excessively high, the network may merely memorize all training examples. This could hinder its ability to generalize or generate accurate outputs when faced with unseen data [33].

Conversely, we utilized the capabilities of algorithms through the application of fuzzy rules. The models developed with ANFIS demonstrate greater reliability and sophistication in classifying instances from both the training and testing sets through two-fold cross-validation.

## VII. CONCLUSION

We have described the proposed method using a combined Six Types of Patient Data Inputs and Adaptive-Network-based Neuro-Fuzzy Inference System. By employing a hybrid approach using parameter tuning with a combined Six Types of Patient Data, ANFIS can refine the given rules to describe the system's input and output. The experimental findings indicated that the proposed approach is proficient in diagnosing malaria symptoms more accurately and reducing malaria burden. Recognizing that elevated scores may result from utilizing limited data, which indicates that the dataset comprises only 1 to 10 samples. A comparatively limited dataset may adversely impact a model's performance because of overfitting, a phenomenon where a model excels with the training data yet struggles with new, independent data. A viable approach to addressing this issue is the implementation of cross-validation. To solve the small sample problem, the proposed method was evaluated based on ANFIS, using 2000 data extracted from Six Types of Patient Data inputs selected with InfoGainAttributeEval and Ranker. Two-fold cross-validation was employed and ANFIS demonstrated the merit of the new method. The results revealed that the data have a strong correlation with classes. The experimental outcome for the new method was 98.3%.

The main contribution: This study presents a novel method, combining Six Patient Data Inputs that include Symptoms, Blood pressure, Heartbeats, Height and Weight, using ANFIS to detect malaria accurately. The results demonstrate that a combined method using Six Types of Patient Data Inputs can accurately classify malaria symptoms in a matter of seconds and demonstrate superior performance when compared to the results reported in the field.

The significant finding is that the new model has a higher accuracy, supported by using six different data types, which is different to other models that used 10 – 12 symptoms/features. Therefore, this study fills the gap by providing diverse six data types that can be used in the field to diagnose malaria.

The finding will potentially enable doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment. It will help the remote community user to reduce malaria risks by detecting early malaria symptoms.

The finding will lead to a fully developed real-world application vigorously tested and validated to diagnose malaria symptoms for remote settings.

### A. Future Work

Next step is to develop a mobile-based application designed for the early detection of malaria, suitable for use in rural areas. Electricity and computers are scarce in the remote settings in Kenya, while mobile devices are accessible by most of the population using designated shopping centers to charge the mobile devices to be usable. Therefore, this method will allow malaria diagnosis to be accessible in the diverse community.

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## CONFLICT OF INTERESTS

There is no conflict of interest to declare.

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## REFERENCES


[1] A. Otieno, L.M. Were, C. K. Sagam, S. Kariuki and E. Ochodo, Evaluating the impact of malaria rapid diagnostic tests on patient-important outcomes in sub-Saharan Africa: a systematic review of study methods to guide effective implementation. *BMJ Open* (2024) 14:e077361. doi:10.1136/ bmjopen-2023-077361

[2] Severe Malaria Observatory, (Malaria facts, 2023) https://www.severemalaria.org/countries/kenya

[3] L. Hester, J. Nityanand, S. Mai, S. Masako, R Ieva, O. Kevin, Combating malaria in Kenya through collaborative population health education: *a systematic review and pilot case study, Infectious Diseases*, 55:10 (2023) 664-683, DOI: 10.1080/23744235.2023.2231082

[4] World Health Organization WHO. (World Malaria Report 2022). https://www.who.int/teams/global-malaria-pro gramme/reports/world-malaria-report-2022

[5] World malaria report 2022. Geneva. (World Health Organisation, 2022). https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2022

[6] Kenya Malaria Indicator Survey (KMIS), (Final Report 2020), https://www.dhsprogram.com/pubs/pdf/MIS36/MIS36.pdf

[7] S. S. Devi, S. N. Herojit, L. R. Hussain, Performance Analysis of Various Feature Sets for Malaria-Infected Erythrocyte Detection. Soft Computing for Problem Solving. *Advances in Intelligent Systems and Computing,* 1057 (2020). Springer, Singapore. https://doi.org/10.1007/978-981-15-0184-5_24

[8] R. Ramdzan, A. Ismail, Z. S. M. Zanib, Prevalence of malaria and its risk factors in Sabah, *Malaysia. Int J Infect Dis*; 91 (2020) 68–72.

[9] S. Shimizu, S. Chotirat, N. Dokkulab, I. Hongchad, K. Khowsroy, K. Kiattibutr, Malaria cross-sectional surveys identified asymptomatic infections of Plasmodium falciparum, Plasmodium vivax and Plasmodium knowlesi in Surat Thani*, a southern province of Thailand. Int J Infect Dis*; 96 (2020) 445–51.

[10] T. O. Oladele, R. O. Ogundokun, J. B. Awotunde, M. Adebiyi, J. K OAdeniyi,. Diagmal: a malaria coactive neuro-fuzzy expert system. In: *Lecture notes in computer science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), LNCS* 12254 (2020) 428–441

[11] K. Hemachandran, A. Alasiry, M. Marzougui, S.M. Ganie, A. A. Pise, M.T.-H. Alouane, C. Chola, Performance Analysis of Deep Learning Algorithms in Diagnosis of Malaria Disease. *Diagnostics* (2023) 13, 534. https://doi.org/10.3390/ diagnostics13030534

[12] Y. P. Bria, C.-H. Yeh, S. Bedingfield, Significant symptoms and nonsymptom-related factors for malaria diagnosis in endemic regions of Indonesia. *International Journal of Infectious Diseases*, 103 (2021) 192-200.

[13] F-ME. Uzoka, B. A. Akinnuwesi, T. Amoo, F. Aladi, S.Fashoto, M. Olaniyan, A framework for early differential diagnosis of tropical confusable diseases using the fuzzy cognitive map engine. *Int J Health Med Eng*;10 2 (2016) 346–53.

[14] T. Santosh, D. Ramesh, Artificial neural networks-based prediction of malaria abundances using big data: *a knowledge capturing approach. Clin Epidemiol Glob Heal*, 7 (2019) 121–6. https://doi.org/10.1016/J.CEGH.2018.03.001.

[15] W. K. Phang, M. H. B. A Hamid, J. Jelip, T.W. Chuang, Y. L. Lau, M. Y. Fong, Predicting Plasmodium knowlesi transmission risk across Peninsular Malaysia using machine learning-based ecological niche modeling approaches. *Front. Microbio*l, 14 (2023) 1126418.

[16] D. O. Uzun, B.B. Duwa, I. Ozsahin, B. Uzun, Quantitative Forecasting of Malaria Parasite Using Machine Learning Model: MLR, ANN, ANFIS and Random Forest. Diagnostics (Basel). 14(4) (2024) 385. doi: 10.3390/diagnostics14040385.

[17] F.Yang, M. Poostchi, H. Yu, Z. Zhou, Silamut, K. Yu, J. R. J. Maude, S. Jaeger, S. Antani, Deep learning for smartphone-based malaria parasite detection in thick blood smears. *IEEE J. Biomed. Health Inform.* 24(5) (2019) 1427–1438

[18] A. Vijayalakshmi B., R. Kanna, Deep Learning Approach to detect malaria from microscopic images. *Multimed Tools Appl* 79 (2020) 15297–15317. https://doi.org/10.1007/s11042-019-7162-y

[19] G. Madhu, A. Govardhan, B. S. Srinivas, K. S. Sahoo, N. Z. Jhanjhi, K. S. Vardhan1, B. Rohit, Imperative dynamic routing between capsules network for malaria classification. *Comput. Mater. Contin.* 68(1) (2021) 903–919.

[20] A. Loddo, C. Fadda, Ruberto, C. Di, An Empirical Evaluation of Convolutional Networks for Malaria Diagnosis. *J Imaging*. 7;8(3):66 (2022). doi: 10.3390/jimaging8030066. PMID: 35324621; PMCID: PMC8951236.

[21] M. Morang'a, L. Amenga–Etego, S.Y. Bah, Machine learning approaches classify clinical malaria outcomes based on haematological parameters. *BMC Med* 18 (2020) 375 https://doi.org/10.1186/s12916-020-01823-3.

[22] T. Santosh, D. Ramesh, Artificial neural networks-based prediction of malaria abundances using big data: a knowledge capturing approach. *Clin Epidemiol Glob Heal*, 7 (2019) 121–6, https://doi.org/10.1016/J.CEGH.2018.03.001.

[23] M. O. Arowolo, J. B. Awotunde, P. Ayegba, S. O. Haroon-Sulyman, Relevant gene selection using ANOVA-ant colony optimisation approach for malaria vector data classification. International Journal of Modelling, *Identification and Control*, 41(1-2), (2022) 12-21.

[24] J. B. Awotunde, A. L. Imoize, D. P. Salako, Y. Farhaoui, An Enhanced Medical Diagnosis System for Malaria and Typhoid Fever Using Genetic Neuro-Fuzzy System. *In The International Conference on Artificial Intelligence and Smart Environment (*2022) 173-183. Cham: Springer International Publishing.

[25] J. B. Awotunde, S. Misra, F. E. Ayo, A. R. A. Agrawal, Hybridized Support Vector Machine and Adaboost Technique for Malaria Diagnosis. In Frontiers of ICT in Healthcare: *Proceedings of EAIT* (2023) 25-38. Singapore: Springer Nature Singapore.

[26] P.M. Datilo, Z. Ismail, J. A Dare, review of epidemic forecasting using artificial neural networks. Epidemiol. Health Syst. J., 6 (2019) 132–143

[27] J. B. Awotunde, R. G. Jimoh, I. D. Oladipo, Abdulraheem, M. Prediction of malaria fever using long-short-term memory and big data. In International Conference on Information and Communication Technology and Applications, *Cham: Springer International Publishing.* (2020) 41-53.

[28] R. Parveen, A.H. Jalbani, M. Shaikh, K.H. Memon, S. Siraj, M. Nabi, Prediction of malaria using artificial neural network. *Int J Comput Sci Netw Secur*. 17 (2017) 79–86.

[29] E. O. Marita, R. Gichuki, E. Watulo, S. Thiam, S. Karanjam, Determinants of quality in home-based management of malaria by community health volunteers in rural Kenya. *J Infect Dev Ctries,* 15 (2021) 897–903. doi: 10.3855/jidc.13565. PubMed

[30] M. Negnevitsky, (2002). Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. Pearson Education, (Chapter 8).

[31] S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system. *IEEE,". Transactions on systems, MAN, and Cybernetics*, 23, 3 (1993).

[32] P. B Sivarao,. N. S El-Tayeb,. M. A. New Approach of Adaptive Network-Based Fuzzy Inference System Modelling in Laser Processing. A Graphical User Interface (GUI) Based, *Journal of Computer Science.* 5 (10), (2009) 704-710.

[33] M. Negnevitsky, Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. *Pearson Education* (2005).

[34] S. Haykin, Neural Networks—A Comprehensive Foundations. Prentice-Hall International, *New Jersey* (1999).

[35] S.A. Alowais., S.S. Alghamdi, N. Alsuhebany, *et al.* Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ* 23, 689 (2023). https://doi.org/10.1186/s12909-023-04698-z

[36] M. Negnevitsky, (2002). Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. Pearson Education, Section 8.2, Chapter 8.

[37] P.A Barraclough, C. M Were, H. Mwangakala, G. Feheringer, D. O. Ohanya, H. Agola, P.Nandi, Artificial Intelligence System for Malaria Diagnosis, (IJACSA) International Journal of Advanced Computer Science and Applications, (2024), Vol. 15, No. 3, 2024

[38] M. J. Barcus, H. Basri, H. Picarima, C. Manyakori, Biomedis Puslitbang, Farmasi; Demographic risk factors for severe and fatal vivax and falciparum malaria among hospital admissions in Northeastern Indonesian Papua. Am Soc Trop Med Hyg 2007;77(5):984–91.

[39] L. Deepak, M.D. Bhatt, What is begeminy in heartbeat (2021)' Accessed at "https://www.health.harvard.edu/heart-health/what-is-bigeminy-in-a-heartbeat"

[40] M. Roser, C. appel, H. Ritchie, The History of Human Height, (2024) Accessed at https://ourworldindata.org/human-height