A joint neuro-fuzzy malaria diagnosis system

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Abstract. Diagnosis takes a definitive role in the course of determining about clarifying patients as either having or not having the disorder. This method is relatively sluggish and tedious. Various fact-finding and data-mining methods are part of the approach of this article. In the development of the Collaborative Neuro-Fuzzy Expert System diagnosis platform, Neural Networks and Fuzzy Logic, which are artificial intelligence methods, have been merged together. Oral interviews were conducted with medical professionals whose experience was caught in the Expertise Developed Fuzzy Proficient Scheme. With Microsoft Visual C # (C Sharp) Programming Language and Microsoft SQL (Structured Query Language) Server 2012 to handle the database, the Neuro-Fuzzy Expert Framework diagnostic software was introduced. To capture the predominant signs, questionnaires were administered to the patients and filled out by the doctors on behalf of the patients.

1. Introduction
Malaria has been endemic in our society since the dawn of history [1, 2, 3]. Around 40% of the world's populace resides in prevalent areas of malaria. Therefore, in tropical Africa, 90 percent of cases and most deaths occur. Nearly 500M cases and 3M deaths occur each year [4]. Special training and considerable expertise are needed for diagnosis using a microscope [5]. Several studies have
demonstrated that, unlike automatic diagnosis, manual microscopy is not a useful testing tool [6, 7, 8]. A computerized diagnostic scheme can be developed by recognizing the investigative ability to recognize malaria when symptoms prevail [9, 10]. This study is intended to demonstrate the prowess of the medical review approach to ICT. By making the diagnostic method affordable and open to everyone, including at the grassroots level, it would facilitate early malaria diagnosis. The basis for the Neuro-fuzzy method is the fusion of two clever strategies such as neural network and fuzzy logic. Fuzzy’s method of deduction is a well-known computational model focused on Fuzzy set definition concepts, Fuzzy if-then laws, and Fuzzy cognitive [36, 37, 39] principles. It has been used in a variety of fields, including automated monitoring, data collection, decision analysis, expert systems, time series forecasting, robotics, and pattern recognition [10, 11, 12, 13]. Many other titles are known for their multidisciplinary nature, such as the Rule-based Fuzzy Method, Fuzzy Expert System [14], Fuzzy Paradigm [15, 16], Fuzzy Associative Memory [17], Fuzzy Logic Controller [18, 19, 20], and Fuzzy Structures. The description of adaptive networks is known as ANFIS, which serves as a foundational basis for adaptive fuzzy inference systems. ANFIS refers to the Fuzzy Inference System or Adaptive Neuro-Fuzzy Inference System based on the Adaptive Network. [21, 22, 23].

The Neu-Fuzzy Expert System diagnostic technique called the Collaborative Neuro-Fuzzy Malaria Diagnosis Method has been designed and applied in this current research. The diagnosis provided by the Joint Neuro-Fuzzy Malaria Diagnosis Method is based on the patients’ predominant symptoms. In order to determine whether the instrument is correct or not, comparative analysis of the data collected from the conducted questionnaires was also analyzed. The article is formulated as follows: In the next section 2, the literature review is given. Materials and procedures are given in section 3, including data processing and implementation. Section 4 offers implementation, findings and debate, and ultimately, the inference reached in Section 5.

2. Related works
The Fuzzy Infusion Scheme is an overall computing system built on fuzzy theory and flushing if-then rules and faulty reasoning and employed in many different fields, including automatic mechanism, data classification, decision-making analytics, professional systems, prediction of time series, robotics, and design identification. Because it is multidisciplinary, the fuzzy lower scheme is recognized by a large sum of other titles, such as the fuzzy rule-based scheme, fuzzy logic controller [24, 25, 19], and the fuzzy logic controller [20, 26], fuzzy associative memory [27]. ANFIS has made its mark as an adaptive scheme with a great deal of focus on its ability to be a linguistically explainable Fuzzy Inference System (FIS) that consents for the incorporation of prior knowledge into its construction and allows for the interpretation of learning outcomes. The Coactive Neuro-Fuzzy Expert System (CANFES) scheme has been implemented as a generalized version of the ANFIS model [28]. The CANFES model uses a hybrid learning principle using both the backpropagation (BP) and the Kohonen Self Organizing Features Map (KSOFM). While BP is a supervised learning scheme, KSOFM is an unattended learning set of rules.

As in fuzzy inference models, the CANFES framework also retains the concept of human thinking and reasoning. So, it is easy to incorporate the expertise of experts into the design. In the conventional fuzzy inference framework, the CANFES design likewise protects the rule matching the period of the inference engine. The Coactive neuro-fuzzy expert system aims at capturing both the linguistic and numeric parameters to be able to adequately represent the human expert’s reasoning and decision-making capability in the process of diagnosis of malaria.

A model of the CANFIS, generalized as ANFIS [28], has been developed in the Coactive Neuro-Fuzzy Expert System (CANSFES). For a CANFES method, the amalgam learning regulation, which combines both the backpropagation (BP) and the KSOFM. Whereas BP is an algorithm for the supervision of education, KSOFM is an unattended algorithm.
The learning speed for the innovative context propagation learning procedure is restricted by the fact that the minimization of an error signal defined solitary as a result of the output defines all weigh layers of the network, which spends a substantial portion of the time on discovering internal representation.

Online malaria analysis and medical care systems were documented in [29], in which a professional rule-centred method was developed to communicate with the scheme in real-time and employing portable gadgets established on the global mobile communication system (GSM) technology.

Adekoya et al. [30] suggested a homoeopathic expert scheme for the treatment of humid sicknesses. The insinuation device exploits a forward chaining method in the projected Homoeopathic Proficient Scheme (HPS) to scan the knowledge-based device for signs of an ailment and its related treatment that fits the patient's request.

Obot and Uzoka [31] have developed a fuzzy rule-centred system for tropical disease administration. Fuzzy logic was used to assess the degree of seriousness of the tropical disease. A fuzzy expert scheme was utilized to treat hypertension in the fuzzy hypertension management system [32].

There are several other works available in the literature where fuzzy, neural network and neuro fuzzy systems are used for diagnosis of various deceases [33-40].

2.1 The Coactive Neuro-Fuzzy Expert System (CANSFES) model
The CANSFIS model, which is a simplified version of the ANFIS model, has been introduced by the Coactive Neuro-Fuzzy Expert System (CANSFES) model [28]. For the CANSFIS model, a hybrid learning rule incorporating both the back propagation (BP) and Kohonen Self Arranging Features Map (KSOFM) is being used. While BP is an algorithm for supervised learning, KSOFM is an algorithm for unsupervised learning. The CANSFES paradigm still retains, as in fuzzy inference schemes, the principle of human thought and reasoning. So, the expertise of professionals will quickly be integrated into the system. In the conventional fuzzy inference framework, the CANSFES layout also saves the rule-matching time of the inference engine. The model CANSFES is shown in figure 1.

![Figure 1. CANSFES model](image)
3. Material and methods

To be able to regulate the presence or non-appearance of malaria to recognise the dominant symptoms of patients, a questionnaire was created for them. The questionnaire intended for malaria diagnosis is split into three parts.

1. Section A: For example, the demographic and socio-economic physiognomies of the participants were captured; age, sex, place of residence, etc.
2. Section B: Malaria signs such as: fever, fatigue, pain in the body, catarrh, cough, nausea, chills, sweating, bitter taste, vomiting, jaundice, diarrhoea, faintness of the body, sore throat have been reported.
3. Section C: malaria care. This segment is intended to capture the respondent's chosen measure of treatment, such as self-medication, medicinal use, or orthodox medical treatment, etc.

3.1 Data Gathering

Workers and students at the University of Ilorin Health Centre and patients at the Civil Service Clinic in Ilorin, Kwara State, Nigeria, are the focus population for this research. A total of 100 respondents from this population, including staff and teachers, were brought to the Ilorin Health Centre University. In addition, this reflects the sample size of the report, with a total of 80 respondents taken from the Civil Service Clinic. This resulted in 180 respondents in total. At the University of Ilorin Health Center, a total of 100 questionnaire copies were administered, while at the Civil Service Clinic in Ilorin, 80 duplicates were distributed. Of the 100 copies of the questionnaire submitted to the Ilorin Health Centre University, 85 documents were returned. Just 23 copies of the 80 copies administered at the Civil Service Clinic were returned, giving a total of 108 copies of the questionnaire returned.

The phases required for the diagnosis based on ICT are outlined below as follows:

Phase 1: Apprehend individual information in the server of patients
Phase 2: Enter signs and indications of patient complaint into the process
Phase 3: Allocate vague values to variables known as contributory symptoms of malaria
Phase 4: Check the knowledge base for the identified signs and indications
Phase 5: Get the corresponding concentration level; that is, mild, medium, extreme, and very severe.
Phase 6: Apply fuzzy rules
Phase 7: Map fuzzy inputs to determine their degree of membership in their respective weighting variables.
Phase 8: Employ of the neural network to describe the membership functions
Phase 9: Train the neural network
Phase 10: Decide the rule base assessment
Phase 11: Decide the firing strength of the rules
Phase 12: Compute the degree of truth of each rule by measuring the non-zero minimum value
Phase 13: Compute disease frequency
Phase 14: Analysis of the performance of neuro-fuzzy.

These Neuro-Fuzzy measures were adopted in the CANFES model, which was employed in the implementation of Joint Neuro-Fuzzy Malaria Diagnosis System, the diagnostic tool for malaria.

3.1.1 Questionnaire data analysis and interpretation

Table 1 shows the ethnic and social profiles of the respondents. Table 2 indicates that the respondents' average age was 27.08 years. Also, it was evident from the same table that the respondents' expected monthly income was 58,300 Naira. At the time of the investigation, 37.30 Celsius was determined to be the average body temperature of the respondents. With respect to the issue of the incidence of malaria each year, the majority of respondents reported that they had malaria three times a year. A respondent said that he / she had not previously had malaria, although another said he / she had malaria 10 times a year.
Table 1. Demographic and socio-economic characteristics of the respondents.

| Characteristics            | Number | Percentage |
|----------------------------|--------|------------|
| **Age**                    |        |            |
| 15-24                      | 66     | 61.1       |
| 25-34                      | 23     | 21.3       |
| 35-44                      | 4      | 3.7        |
| 45-54                      | 8      | 7.4        |
| 55 and above               | 5      | 4.6        |
| No response                | 2      | 1.9        |
| **Total**                  | 108    | 100.0      |
| **Sex**                    |        |            |
| Male                       | 60     | 55.6       |
| Female                     | 47     | 43.5       |
| No response                | 1      | 0.9        |
| **Total**                  | 108    | 100.0      |
| **Marital Status**         |        |            |
| Single                     | 83     | 76.9       |
| Ever Married               | 25     | 23.1       |
| **Total**                  | 108    | 100.0      |
| **Education**              |        |            |
| Primary                    | 3      | 2.8        |
| Secondary                  | 13     | 12.0       |
| First Degree               | 72     | 66.7       |
| Higher Degree              | 7      | 6.5        |
| Undergraduate              | 8      | 7.4        |
| No response                | 5      | 4.6        |
| **Total**                  | 108    | 100.0      |
| **Place of Residence**     |        |            |
| Urban                      | 96     | 88.9       |
| Rural                      | 12     | 11.1       |
| **Total**                  | 108    | 100.0      |
| **Occupation**             |        |            |
| Civil/Public Servant       | 12     | 11.1       |
| Private Salary Employee    | 3      | 2.8        |
| Self-employed              | 13     | 12.0       |
| Artisan                    | 2      | 1.9        |
| Student                    | 66     | 61.1       |
| No response                | 12     | 11.1       |
| **Total**                  | 108    | 100.0      |
| **Hospitals Used**         |        |            |
| Unilorin Health Services   | 85     | 78.7       |
| Civil Service Clinic       | 23     | 21.3       |
| **Total**                  | 108    | 100.0      |

Source: Survey, 2019
Table 2. Summary of quantitative data

| Characteristics     | Minimum | Maximum | Mean   |
|---------------------|---------|---------|--------|
| Age                 | 16      | 89      | 27.08  |
| Income              | 1000    | 699000  | 58300  |
| Body Temp           | 23˚C    | 42˚C    | 37.3˚C |
| Malaria per year    | N/A     | 10      | 3.0    |

Source: Survey, 2019.

4. Implementation, results and discussion

The full investigation and clarification of the consequences and summary of the observations and effects is covered in this chapter. The developed Coactive Neuro-Fuzzy Expert System method for the diagnosis of malaria in this article is called the JOINT NEURO-FUZZY MALARIA DIAGNOSIS SYSTEM. This section shows snapshots capturing all the interfaces representing the modules in the expert system. Also captured were the processes involved in joining the signs, indications, and historical records, and the diagnosis being made. The interface for deployment is addressed as follows:

4.1 Expert system initial test

This module captures the historical and demographic details of the patient to a certain degree. Based on the selected and entered results, the expert system then assesses the patient as being exposed to malaria. Figure 1 indicates the initial evaluation of the expert system. This module is divided into two columns, which are symptoms and selective symptoms that are variable. Between a selection of mild to high, the varying symptoms are picked while the basic symptoms are tapped as they refer to the patient. Figure 2 shows the universal review tab.

4.2 Expert system general test

This module is divided into two columns, which are symptoms and selective symptoms that are variable. Between a selection of mild to high, the varying symptoms are picked while the basic symptoms are tapped as they refer to the patient. A universal research page is shown in figure 3.
4.3 Expert system secondary and final test
This module often includes complex conditions where the spectrum between moderate to strong is captured by muscle ache, extended cramps, and dizziness. Between regular and irregular, respiratory rate is charged, and lip texture is caught between normal and dry. In figure 4, the secondary test module is seen. This module also incorporates variable symptoms that are meant to capture all the potential signs and symptoms that the patient displays. The final evaluation module is shown in figure 5.
4.4 Inference setting

This module helps the administrator to set rules on which decisions are to be taken for the system. Figure 6 indicates the environment and outcome of the inference. This module acts as a correlation between the performance of the expert system and the biodata of the patient. The patient’s extent or severity of malaria is shown on this page.

Figure 7 shows that the distribution of respondents according to malaria symptoms shows that two out of five respondents (39.8%) said that the most serious symptom of malaria was headaches. This is accompanied by those who said the essential signs of malaria (18.5 percent and 17.5 percent respectively) were body pain and fever. There were the least representations of vomiting and jaundice (0.9 percent). This suggests that the predominant signs of malaria were not both vomiting and
jaundice. Just 4.6% of respondents did not answer the question about the most serious malaria symptoms at all.

![Symptoms of Malaria]  

**Figure 7. Symptoms of malaria**

More than three out of five respondents (72.2 percent) were diagnosed with malaria fever at the time of the inquiry, according to the doctor's records.

5. **Conclusion**

The need to build a device that can support doctors in malaria diagnosis should not be overemphasized. This paper showed the practical use of information and communication technologies in the healthcare field. A coactive neuro-fuzzy specialist system has been used that may help in the diagnosis of malaria. The machine is an interactive interface that forecasts the severity of malaria in a person. Device efficiency is increased by the hybrid learning rule. The research reveals that, based on these findings, the ICT-based Neuro-Fuzzy Expert Method for malaria diagnosis provides correct results. As a result, the Joint Neuro-Fuzzy Malaria Detection Method is proposed for study in the field of academia and industry and to support medical practitioners as an investigation mechanism for malaria.

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