DEVELOPMENT OF A MOBILE APP DIAGNOSTIC SYSTEM FOR TROPICAL FEBRILE DISEASES

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ABSTRACT

Febrile diseases present confusable symptoms that can be highly challenging to inexperienced physicians during diagnosis. This is in addition to the acute shortage of experienced medical experts in rural communities, especially in low-to-middle-income countries (LMICs). To address these challenges, there is a need for the development and adoption of mobile health (mHealth) application - a medical decision support system that is both effective and easy to use by inexperienced physicians and frontline health workers (FHWs) who conduct primary patient diagnosis in rural communities in a number of LMICs. An app developed for the diagnosis and treatment of febrile illnesses, if properly utilized by this category of health workers can serve as a DSS to save many lives lost due to inaccurate diagnosis and self-medication. With data gathered from 3253 patients in four states in Nigeria, several models were developed from the data leading to the use of one of the models (the analytic hierarchy process [AHP] for systems development). This paper presents the methodology of the developed system, based on the AHP model, which showed 90% diagnosis accuracy and 91% precision. A major component of our methodology was the use of elements of design thinking (involving physicians and FHWs) to ensure excellent user experience with functional app features and components usable across a range of devices and platforms.

KEYWORDS

Febrile Disease, Malaria, Multi-criteria Decision Analysis, Analytic Hierarchy Process, Medical Decision Support System

1. INTRODUCTION

Febrile diseases thrive well in the tropical and sub-tropical regions of the world because of high humidity, high temperature, and heavy rainfall, which create a favorable environment for their agents (Nunthavichitra et al, 2020). Poor vector control, poor sanitation, drug resistance, and self-diagnosis have complicated the situation, especially in low-to-middle-income countries (LMICs). These diseases present confusable and sometimes, overlapping symptoms that make it difficult for an inexperienced physician to perform accurate differential diagnosis (Attai et al, 2022). There is a paucity of experienced physicians in LMICs, which has resulted in the reliance on Frontline Health Workers (FHWs) to provide needed health services. According to WHO (2016), the overall global acute shortage of physicians has led to growing interest in the training and use of FHWs to render healthcare services. Most times, patients present multi-diseases and multi-symptom situations, thereby complicating the work of an FHW in the diagnosis process.

Multi-criteria decision analysis (MCDA) requires techniques that include a large number of criteria to guide rational decisions in order to minimize errors. Generally, the procedure presents complexity often due to conflicting criteria that raise the level of uncertainty in the final decision output (Asuquo and Onuodu, 2016). In health care, these procedures are even more complex involving numerous specialists with diverse subjective preferences/opinions, which might hinder the final decision in optimizing health care systems for diverse applications. Though the responsibility for the decision rests on a designated decision maker (DM), the final decision is often a product of an interaction between the DM's preferences and those of other stakeholders to meet economic, social, moral and budgetary expectations (Angelis, Tordrup and Kanavos, 2015). Consequently, this study recognizes the need for the computer analyst who provides methodological support for the decision process, the client who acts as an intermediary between the DM and the analyst, and the medical professionals that know the mechanisms of the behavior of the object of study. The specialists help in identifying the symptoms (criteria) related to each febrile disease (alternative) and provide pair-wise comparison ratings based on their experiential knowledge.

This paper aims at developing a decision support system (DSS) for the diagnosis of febrile diseases by FHWs. The Android app is composed of functional features and components usable across a range of devices and platforms with or without internet access. We focused on domain expertise and end-user involvement, following the principles of design thinking. The specific objectives of the study are to; a) obtain experiential knowledge of medical experts in the diagnosis of febrile diseases; b) apply agile software engineering methodology in the design of an app for differential diagnosis of febrile diseases by FHWs; c) develop and validate an AHP-based MCDA model for the differential diagnosis and d) develop functional graphic user interfaces in collaboration with the FHWs who are the eventual users of the app. The rest of the paper is organized as follows: Section 2 presents related literature while Section 3 describes the methodology of the study. In Section 4, the system implementation results are presented, while the conclusion and recommendations of the study are presented in Section 5.

2. RELATED WORKS

Adehor and Burrell (2008) developed an intelligent DSS for prompt diagnosis of malaria and typhoid fever. Their system diagnosed illness based on users' responses/answers to physical examinations for symptoms which were used to compute the degree of certainty of the disease. Sharma et al. (2013) designed a symptom-based DSS for malaria and dengue diagnosis using fuzzy logic. The system used symptoms of patients, to diagnose dengue fever and malaria. In Patra, Sahu, and Mandal (2010), a diagnostic expert system was developed for diagnosing diseases using data and knowledge from medical experts and secondary sources. Symptoms were categorized into groups and mapped against observed symptoms to indicate the presence of a disease. Similarly, Abiola et al. (2017) developed a rule-based Lassa fever diagnosis system (LFDS) using medical records. Patient symptoms were used to build rules and inputs for intelligent diagnosis. However, these studies did not support predictive learning, thereby limiting the efficacy of their models to predict confusable symptoms.

Oguntimilehin (2020) developed a mobile application for malaria diagnosis using 19 conditional symptoms, with instances of datasets corresponding to selected patients' medical records, using non-nested generalized exemplar (NNGE) was to label and classify the symptoms. Rules were then generated by the NNGE to construct the inference engine for a user-friendly mobile diagnosis application. The datasets in the study lacked verification of symptoms through confirmatory laboratory tests.

Adebayo et al. (2013) developed an expert system for diagnosing and treatment of malaria based on medical expert information collected through structured interviews, and an extensive literature review, the design adopted the waterfall software development method. Fatumo, Adetiba, and Onolapo (2013) proposed an expert System called XpertMalTyph for diagnosing the complications of malaria and typhoid using MySQL, Java, and Java Expert System Shell (JESS). The system was to enable patients with mild cases of malaria and typhoid complications to get treatment without visiting the hospital. However, these systems had no element of intelligent modeling/prediction. Maidabara et al. (2021) developed an expert system using secondary data, for diagnosing malaria and typhoid. They employed three ML algorithms including support vector machine (SVM), artificial neural network (ANN), and Naïve Bayes (NB) but SVM and NB gave the best classification accuracies. However, their work solely relied on patients' medical history and physical examination without confirmatory (laboratory) tests to verify physician suspicion or address confusable symptoms. Furthermore, the authors' datasets were binary transformations (0 and 1) and most unlikely to effectively model the degree or severity of the disease(s). Ozkan, Koklu, and Sert (2018) applied decision tree, SVM, random forest, and ANN in the diagnosis of urinary tract infection (UTI) using examination data and diagnosis results of 59 UTI patients and ANN gave the highest accuracy of 98.3%. Shabut et al. (2018) presented a mobile-enabled plasmonic ELISA-based tuberculosis (TB) detection scheme using smartphones with an ensemble classifier (random forest) and the results showed an accuracy of 98.4%.

From the foregoing literature, our research integrates collaborative crowdsourcing of input symptoms or data–a community-based approach that captures both patient and physician perspectives before a symptom is rendered, hence, eliminating diagnostic biases. Further experiential knowledge in the form of disease-specific thresholds defining the universe of discourse (UoD) or cutoffs to disease burden estimation is also captured, to address disease-specific ecosystems.

3. METHODOLOGY

The development of the application for diagnosing febrile diseases utilized an Agile software methodology that emphasized iterative user involvement. In the Agile model, the processes are interleaved with a significant level of iterative user involvement, based on the principles of empathy in design thinking. Empathy (in design thinking) helped us to: appreciate potential users' (FHWs) needs, gain deep insight into how the FHW interacts with the health system, the Standing Order, and patient in the diagnosis process, realize how patients' lives could be impacted through the diagnosis, and examine the motivations and mental processes employed by physicians and FHWs in the diagnosis process. The functional requirements of the system were iteratively specified at every incremental phase by the FHWs who are the end-users of the system.

3.1 Agile Software Development Approach

The Agile software methodology steps deployed in the app development of our diagnostic system are shown in Figure 1 and are described as follows.

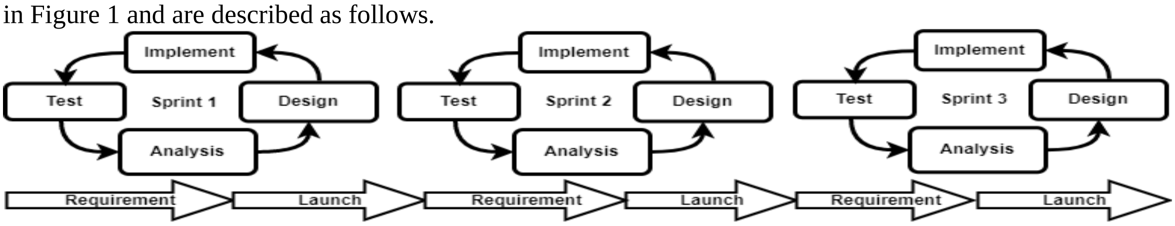

Figure 1. Iterative Process in Agile software development

3.1.1 Requirements Gathering

For a thorough understanding of the proposed system functionalities, relevant stakeholders and users were integrated into the iterative process. From the various meetings held during this stage, the functionalities were elicited from the stakeholders. Three major and overlapping sub-processes were employed for the elicitation, documentation, and understanding of the system functionalities by the stakeholders and users. During requirement elicitation, major and minor use cases were collected from stakeholders and users. Next, requirement documentation was carried out where the elicited requirements were organized and documented in appropriate software engineering format. The use case diagram in Figure 2 depicts the graphical interaction between the febrile disease diagnosing system and the Users, FHW, Facility Head, Record Officer, Patient, and Administrator. The use case model is segmented into Patient Assessment, Appointment and Follow-up, Report Module, Patient Clinical Information, and Personnel information. The four major stakeholders (FHW, Facility Head, Record Officer, and Patient) share various use cases in three of the four modules.

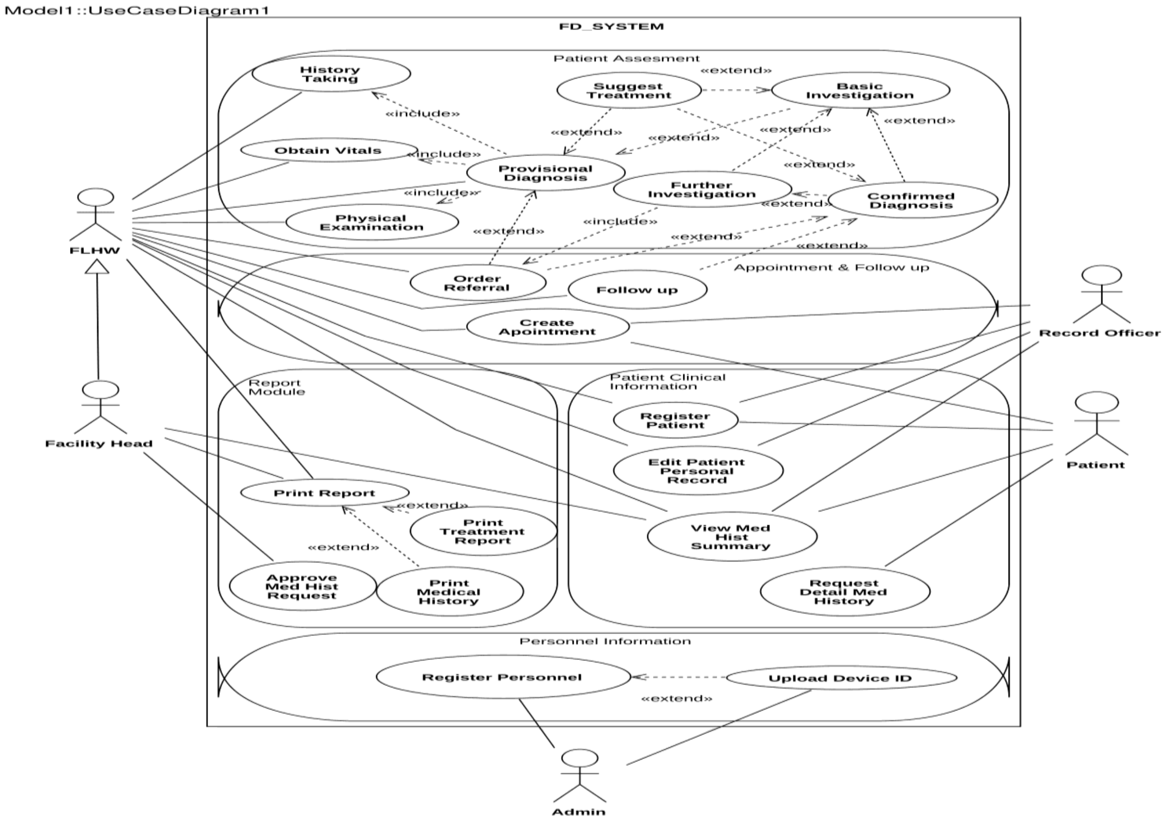

Figure 2. Use Case Diagram of the Febrile Disease Diagnostic System

3.1.2 Requirement Analysis and Validation

To ensure that all the stakeholders and team members share a common understanding of the software to be built, the gathered requirements were analyzed and validated through various convened meetings. The meetings involved additional elicitation and revision of the requirement documentation obtained by considering the strengths and weaknesses of each requirement. The deliverable from these meetings is a unanimous requirement for the proposed system that is documented graphically in a context diagram as shown in Figure 3. The context diagram models the boundary between the system and its environment showing entities that interact with it.

Furthermore, the elements of a Standing Order for the index diseases were integrated to develop the app. A Standing Order is a written protocol that guides the FHWs in the diagnosis and treatment of illnesses at the primary healthcare level. The procedure for using standing order for the treatment of a disease is as follows: Welcome the client and give him /her a seat; introduce yourself and reduce tension by encouraging the patient; collect history; carryout physical examination and record the needful; carryout further investigation to ascertain your findings, if necessary; Treat accordingly.

3.1.3 Design

The user interface, knowledge base, and diagnostic engine are the major aspects designed in this study, and consideration is given to the interactions of the software (comprising the data storage, access logic, application logic, and presentation logic) and the hardware (mobile device and the server). The architecture is presented in Figure 4. The architecture comprises, the medical experts, patients, user interface, knowledge base, a diagnostic system with its sub-components (AHP diagnostic engine, decision support filters), and diagnosis and treatment. The knowledge base contains extracted experiential knowledge from sixty-two (62) physicians in secondary and tertiary health facilities, which have expertise in the domain of diagnosis of febrile diseases including interrelated symptoms.

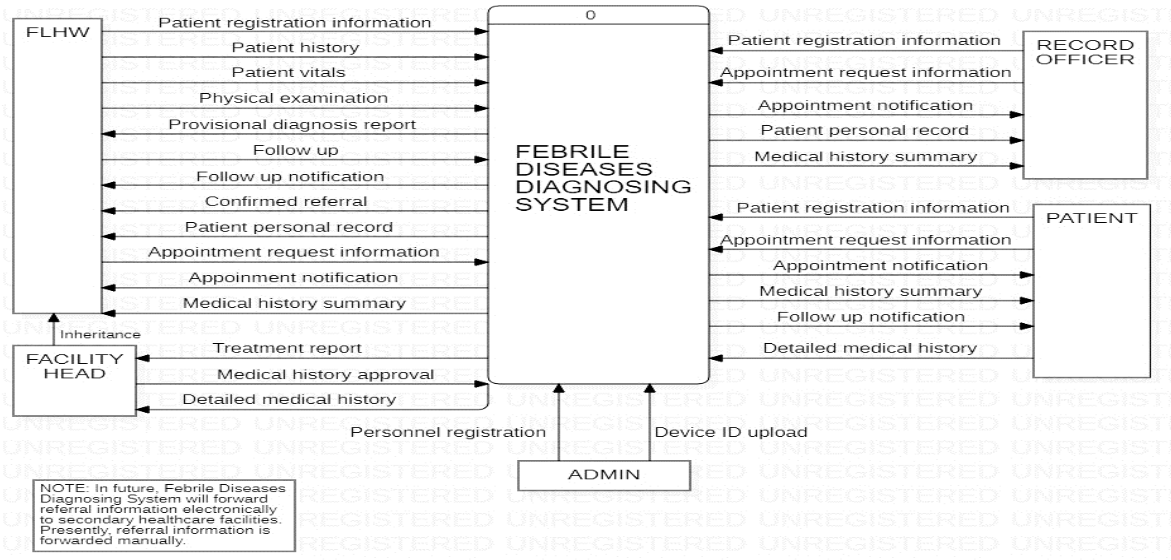

Figure 3. Context Diagram of the Febrile Disease Diagnostic System

It also contains sufficient patient examination and test results including risk factors that predispose a patient to these febrile diseases. This information helps in the formulation of a multi-disease multi-symptom model necessitating their representation in an AHP structure to form the AHP diagnostic engine. The contents of the knowledge base are sent to the diagnostic system, where the decision support filters utilize such information to simulate the behavior of an experienced physician using the AHP diagnostic engine to trigger appropriate individual febrile disease model(s) for further analysis. The AHP engine contains linear consensus models that specify which disease to be triggered by the decision support filters. The AHP diagnostic engines distinguish the symptoms of febrile illnesses and facilitate the identification of the suspected illness based on the patient's symptoms and risk factors to suggest the most suitable form of treatment. The FHW can also visualize the predicted diagnosis on the user interface for timely and accurate healthcare decision-making in terms of medical advice and treatment.

The systematic approach used by the decision support filter of the diagnostic system for malaria (MAL) is presented as follows. The system performs intelligent diagnosis based on the contribution of each symptom to a disease using physicians' consensus preferences and confidence levels. The criteria-by-criteria pair-wise comparison for each disease alternative was evaluated using a typical AHP comparison matrix, with each leading diagonal equal to 1. Later, the AHP method determines the relative weight of each criterion and aggregates the eigenvectors for each comparison matrix until the composite weight (final score) for each alternative is obtained. The values of the final weight vector indicate the relative importance of each alternative with respect to the goal of the decision problem. A DM then uses the eigenvectors to rank the alternatives for appropriate decision-making. The normalized vector matrix is obtained and the relative weight or weighted eigenvector is computed as the row average of the resulting normalized matrix. The consistency ratio (CR) of each performance matrix was estimated to ascertain the level of inconsistency due to the subjective judgment of the DM. If $CR \leq 0.1$, the level of inconsistency is acceptable else, the inconsistency is high and the DM is advised to revise the elements of the matrix to realize a more consistent matrix. The probability of occurrence of each febrile disease was computed from the aggregate diagnostic factor index (ADFI) based on the linguistic score of its symptoms: 1=absent; 2=very low; 3=low; 4=moderate; 5=high; 6=very-high and the weighted Eigenvector (priority score) generated from the AHP process. The ADFI for MAL is expressed in equation (1) while the probability of occurrence (P_i) is expressed in equation (2). Table 1 shows occurrence probability ranges generated from the computed ADFI (Uzoka et al., 2017).

ADFI_MAL=(CHLNRIG_Score*0.115693613)+(FTG_Score*0.108827326)+(FVR_Score*0.132092708)+(GENBDYPN_Score*0.114760331)+(HDACH_Score*0.120826663)+(JONPN_Score*0.107823379)+(BITAIM_Score*0.088720975)+(PRTN_Score * 0.086728546)+(HGDFVR_Score * 0.124526459) (1)

$$P_i = \frac{ADFI}{5} * 100 \qquad (2)$$

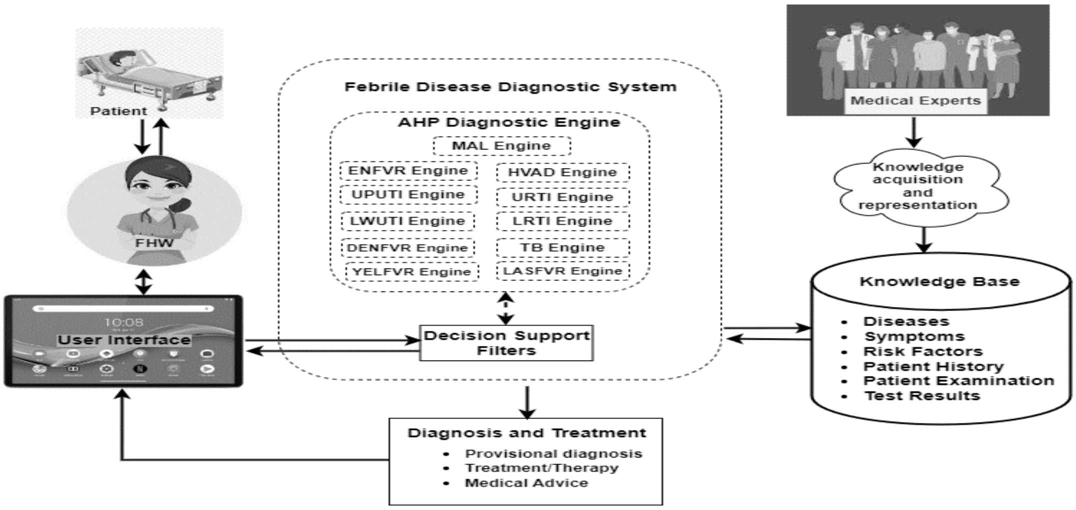

Figure 4. System Architecture

Table 1. Occurrence probability ranges

Uniform Rating	ADFI Range	Probability range (%)
1	0.000 - 1.000	0.01-20.00
2	1.001 – 2.000	20.01 – 40.00
3	2.001 – 3.000	40.01-60.00
4	3.001 – 4.000	60.01 – 80.00
5	4.001 – 5.000	80.01– 100.00

4. SYSTEM IMPLEMENTATION RESULTS

The software tool used for the front-end development was eXtensible Markup Language (XML), to build the mobile layouts – graphical user interface (GUI) while the back-end had SQLite for local database storage, Python and SQL for application programming interface (API) development. Others include; Android Studio Dolphin 2021 v3.3 as the main Integrated Development Environment (IDE) used for building, compiling, and debugging the system app using Java as the programming language. Android Software Development Kit (SDK) Version 28 for the binaries that are used to build, debug, run, and test the App. MPAndroidChart: v 3.0.3 is an Android library used to create graphical representations of computations and data. Git, a source code management tool used to track changes in the code and enable programmers to work together on this nonlinear development, and Adobe Illustrator, a vector-based graphics tool used to create icons and images that are placed in the app layouts to portray more information to users.

Figures 5-8 shows the various screen of the developed app. In the login screen, the FHW is required to input his or her worker identification (ID) and password to control access and prevent unauthorized users into the system. Output from a correct ID entry permits the FHW to view the medical ID screen in Figure 5, and either register a new patient, search for existing patients, or view registered patients in the system. Figure 6 shows the system dashboard which provides the working space for FHW to access different modules (vital signs, diagnosis, follow-ups, and appointments) of the system. Figure 7 shows how patient’s perceived symptom is captured using sliders on a 5-point scale. A slider is a GUI control element that uses a lever moved horizontally to control a variable. It simply allows FHWs to select a range from a fixed set of options by simply sliding the bars corresponding to each sign and symptom. Our approach ensured that the visual design of this element does not hinder its usability. The aesthetic control also ensures that users can make selections correctly without having to struggle to hit a precise value. In addition, the slider labels are displayed below in order to remain visible while the user is selecting a value. These values are combined with the eigenvalues for each symptom in the AHP inference engine for evaluation of ADFI and the probability of each disease diagnosis. Figure 8 shows the diagnosis report depicting the initial diagnosis without risk factors and final diagnosis with considered risk factors for every confirmed febrile illness. Results with risk factors assessment indicate that the AHP model closely mimics domain experts' diagnosis accuracy performance.

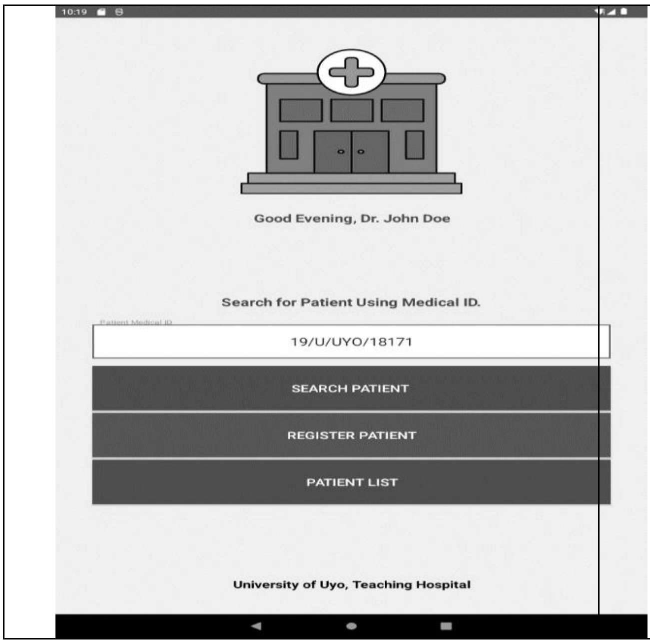

Figure 5. Medical Search ID

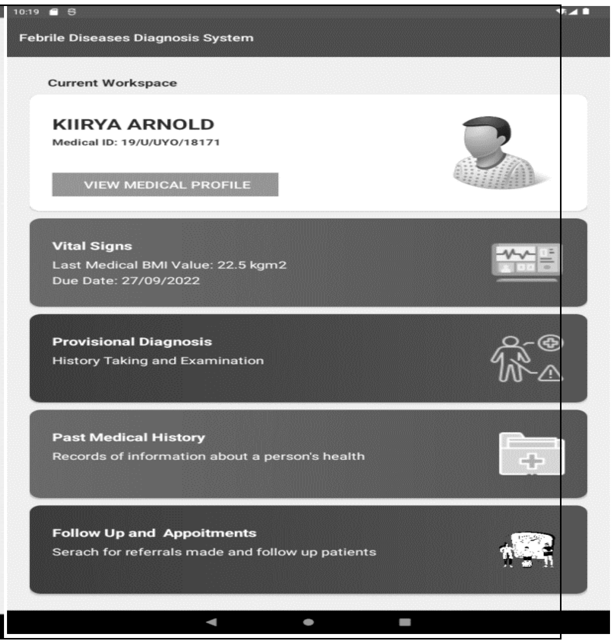

Figure 6. System Dashboard

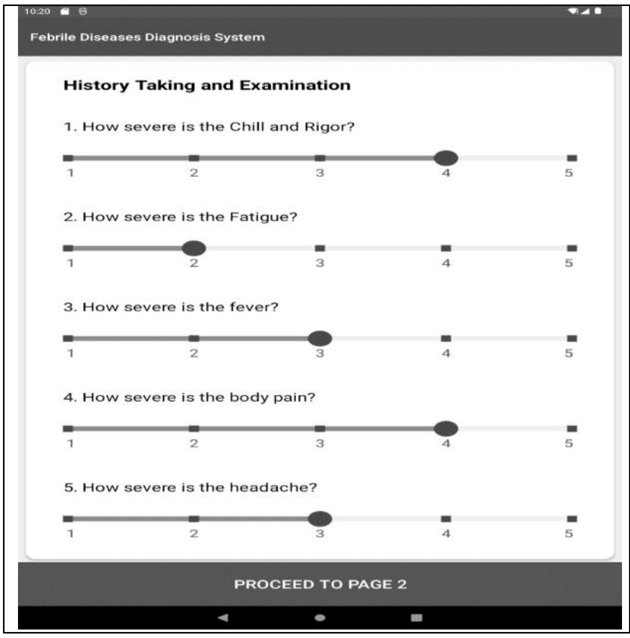

Figure 7. History Taking and Examination

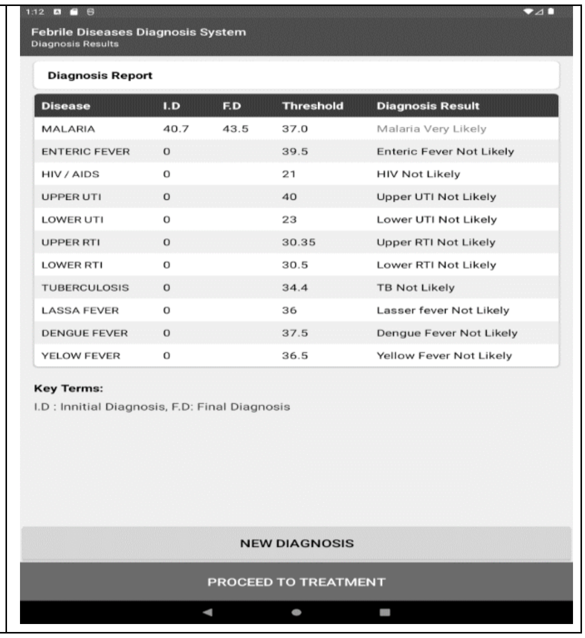

Figure 8. Diagnosis Report

5. CONCLUSION

Medical diagnosis is a complex task and the paucity of experienced physicians in LMICs where febrile diseases seem to be more prevalent presents a huge challenge. Therefore, an app to assist FHWs in diagnosing febrile diseases with overlapping symptoms was developed for this purpose. With a multi-disease multi-symptom analytical model for eleven (11) febrile diseases, AHP, an MCDA methodology was found the most suitable for this task and the results from the AHP-based medical DSS indicate a high accuracy value of 90% when compared to the physician's prediction performance. Thus, this decision tool can be effectively utilized for differential diagnosis of febrile diseases in rural settings and LMICs faced with inadequate medical experts and poor operating conditions. We are presently testing the app in four states where datasets were collected. The app is therefore limited to these four states; so, we are hoping to expand the scope in the future. We have noticed that the results of diagnosis are only accepted as an intermediate result until a rapid test is carried out to give the final results. This will facilitate FHWs in making prompt and accurate decisions regarding the diagnosis and treatment of febrile disease.

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