A DIAGNOSIS SYSTEM FOR LASSA FEVER AND RELATED AILMENTS USING FUZZY LOGIC

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Abstract
Lassa fever is a pandemic hemorrhagic fever brought about by the Lassa virus, a greatly destructive virus. This deadly disease kills 10% to half of its casualties, yet the individuals who survive it in early stages normally recoup and gain resistance to auxiliary assaults. One of the real difficulties in giving proper treatment is lack of fast and accurate diagnosis of the disease because of variety of symptoms related with the infection, which could be similar to other clinical conditions and makes it difficult for early diagnosis of the disease. Thus, this research work developed a diagnosis system for Lassa fever and related ailments using fuzzy logic. The system was designed and implemented using MATLAB R2013a version. The new diagnosis system allows users to select symptoms from the symptoms interface page that display when the application is launched. Results of this project was tested and found to be efficient in handling Lassa fever diagnosis. It is therefore recommended that it should be adopted in hospitals and health care centres especially in developing nations.

Keywords: Lassa fever, hemorrhagic fever, symptoms, fuzzy logic, diagnostic system

Introduction
Lassa fever is an acute viral hemorrhagic disease of 2 to 21 days that happens most frequently in West Africa. The illness was discovered in 1969 when two missionary nurses died in Nigeria (Lecompte *et. al*., 2006). Presently, the viral hemorrhagic illness is still a threat in Sub Sahara Africa. The virus is transmitted to humans through contacts with food or other domestic items contaminated with rodent urine or faeces. Recently, a national newspaper "Punch" reported on 19th February, 2018 that in Delta State, three persons out of the seven confirmed cases of Lassa fever have passes away since the outbreak of the disease was reported on 26th January, 2018 in the State. Besides, twenty four (24) persons have been placed under surveillance.

The cause of the illness was found to be Lassa virus, named after the town in Nigeria where the first cases originated. The virus, a member of the virus family Arenaviridae, is a single-stranded RNA (ribonucleic acid) virus and is zoonotic, or animal-borne. In some areas of Africa where the disease is endemic (that is, constantly present), it is a significant cause of morbidity and mortality. While Lassa fever is mild or has no observable symptoms in about 80% of people infected with the virus, the remaining 20% have a severe multisystem disease (Amorosa *et. al.,* 2010).

Lassa fever is also associated with occasional epidemics, during which the case-fatality rate can reach 50% (Asogun *et. al*., 2012). The number of Lassa virus infections per year in West Africa is estimated at 100,000 to 300,000, with approximately 5,000 deaths. Unfortunately, such estimates are crude, because surveillance for cases of the disease is not uniformly performed (Amorosa *et. al.,* 2010). In some areas of Sierra Leone and Liberia, it is known that 10%-16% of people admitted to hospitals have Lassa fever, which indicates the serious impact of the disease on the population of this region (Bausch *et. al.,* 2001). The reservoir, or host, of Lassa virus is a rodent known as the "multimammate rat" of the genus Mastomys. It is not certain which species of Mastomys are associated with Lassa; however, at least two species carry the virus in Sierra Leone.

Mastomys rodents breed very frequently, produce large numbers of offspring, and are numerous in the savannas and forests of West, Central, and East Africa (Baize *et. al.,* 2001). In addition, Mastomys generally readily colonize human homes. All these factors together contribute to the relatively efficient spread of Lassa virus from infected rodents to humans. Immunohistochemistry performed on tissue specimens can be used to make a post-mortem diagnosis (Baize *et. al.,* 2001). The virus can also be detected by reverse transcription-polymerase chain reaction (RT-PCR); however, this method is primarily a research tool. Therefore, timely diagnosis could be a life saver using one of the artificial intelligence techniques such as fuzzy expert system (Bazmara & Donighi, 2014).

A fuzzy expert system is a collection of fuzzy rules and membership functions that are used to reason about data. Using fuzzy expert system, it has the capacity to give fairly accurate recommended solution for uncertain and also certain complex systems to ease perception and flexible (Rahmani *et. al.,* 2014). Fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of membership rather than the crisp membership of classical binary logic. Unlike two-valued Boolean logic, fuzzy logic is multi valued. Fuzzy logic is a logic that describes fuzziness. As fuzzy logic attempts to model human's sense of words, decision making and common sense (Hassan *et. al.,* 2010).

The rest of the paper is organized as follows: related works is contained in section II, while section III captures the methodology. Section IV entails the discussions and results of the proposed system implemented. And section V concludes the paper.

Related Works

This research work establishes the fact that other fever related ailments share similar symptoms with that of Lassa fever unlike in the research work of Osaseri *et al.* (2014) who concentrated on symptoms of Lassa. Therefore, in order to have proper diagnosis of the ailment, this paper aimed to diagnose Lassa fever and related ailments. Similarly, the following related literatures were considered and review on the course of this work.

Osaseri and Osaseri (2016) presented an adaptive neuro fuzzy inference system (ANFIS) for the prediction of Lassa fever. The input parameters adopted were Temperature on admission (TA), White Blood Count (WBC), Proteinuria (P) and Abdominal Pain (AP). Sixty-one percent of the datasets were used in training the system while fifty-nine percent were used in testing. Experimental results from this study gave a reliable and accurate prediction of Lassa fever when compared with clinically confirmed cases.

Adeboye and Haruna, (2015) developed a mathematical model for the transmission and control of malaria and typhoid fever. The method used involved development of a model for malaria and Typhoid co-infection. The model is a system of eight (8) Ordinary Differential Equations (ODE). The first five (5) odes are for humans: susceptible S, Malaria infectious humans, Typhoid-infections humans, Malaria and typhoid co-infected humans, and the recovered human's sub-population. The next two (2) are for mosquitoes: Non-carrier mosquitoes M and infections mosquitoes N subpopulations: The last one is for salmonella typhi Bacteria B. All these were used in the mathematical models that led to the diagnosis of co-infection of malaria and typhoid fever.

Putu and Iketut (2012) implemented a fuzzy knowledge-based system for the diagnosis of the tropical infectious diseases. The expert system designed in this research work used fuzzy logic and certainty factors for the diagnosis of tropical diseases including malaria, dengue fever, and typhoid fever. The result obtained showed 91.07% accuracy. However, the system only carried out diagnosis, but the therapy that could make it a perfect solution was neglected.

Oguntimilehin *et. al.,* (2015) used a machine learning technique to carry out clinical diagnosis of typhoid fever. Method used were: Data on typhoid fever cases were collected from reputable hospitals. Medical experts classified typhoid fever cases into five different level of severity based on available symptoms. A hundred data sets were used as training set; while another fifty data sets were used as testing set. A machine learning technique – Rough set was used to train the system and a total of eighteen (18) rules were generated during the training phase. These rules were used as the engine of the developed diagnostic system. An eighteen conditional attributes and one decision attribute were employed in the work. However, the performance of this research work was not evaluated.

Oladipo *et. al.,* (2014) developed a mobile compactable expert system for the treatment of typhoid fever in developing countries. The methodology involved the use of object oriented programming approach. The application framework has three parts – user interface, application logic (written in PHP programming language) and database component using Mysql server. The limitations of this approach were that no evidence of consultation with medical experts, data collection and usage. In addition, the prior knowledge and the basis for the diagnosis were not discussed.

Samuel *et. al.,* (2013) proposed a web-based decision support system (WBDSS) driven by fuzzy logic (FL) for the diagnosis of typhoid fever. The system consists of of a knowledge base (KB) and a fuzzy inference system (FIS).The FIS is composed of a Fuzzifier, fuzzy inference engine (FIE), and a Defuzzifier. The FIE is the core of the FIS and it adopted the root sum square (RSS) technique in drawing valid conclusion. The medical records of typhoid fever patients obtained from the Federal Medical Center, Owo, Ondo State-Nigeria over a period of six months were used to evaluate the proposed system and the results of the study were found promising. The accuracy of the proposed system was compute to be 94%.

Umoh and Ntekop (2013) developed a fuzzy expert system for the diagnosis and monitoring of cholera. The developed system provides decision support platform to cholera researchers, physicians and other healthcare practitioners in cholera endemic regions. Twenty patients with cholera were selected and studied and the observed results computed in the range of predefined limit by the domain experts.

Igodan *et. al.,* (2013) presented a model of a web-based system for knowledge warehousing and mining of diagnosis and therapy of HIV/AIDs using fuzzy logic and data mining approach. The model was developed using the predictive modeling technique, for predicting HIV/AIDs and monitoring of patient health status. The fuzzy inference rule and a decision support system based on cognitive filtering were employed to determine the possible course of action to be taken.

Samuel and Omisore (2013) presented a genetic neuro-fuzzy system for the diagnosis of typhoid fever. The proposed system consists of a fuzzy logic (FL) component, which handles imprecise and incomplete medical data, a neural network (NN) component that automatically generates the parameters that drives the membership functions of the fuzzy inference system, and a genetic algorithm (GA) component that produced optimum weights for training the NN. The attributes of the typhoid fever diagnosis served as the input parameters to the FL and NN components of the proposed system. The system employed back propagation learning technique and used Sugeno's Inference Mechanism to provide accurate, timely, cost effective, and valid results regarding patient diagnosis. The evaluation of the proposed system gave an accuracy of 96%.

Djam *et. al.* (2011) designed a fuzzy expert system for the management of malaria (FESMM) as well as providing decision support platform for healthcare practitioners in malaria endemic regions. The study explored triangular membership function and root sum square (RSS) fuzzy inference methods respectively. The fuzzy expert system was designed based on clinical observations, medical diagnosis and the expert's knowledge. Thirty-five patients with malaria were selected and the results that were in the range of the predefined limit by the domain experts were as well computed.

Materials and Method

Data Collection

The data collection methods utilized to get information for the research work is listed below. The collection of data was carried out at Niger State General Hospital (NSGH). The data were collected using secondary data collection method, which involved direct interview of five medical personnel of the hospital. The data collected include various signs and symptoms of Lassa fever. Example of sample question is given as follows:
Interviewer: What are the typical symptoms of Lassa fever?
Interviewee: signs and symptoms of Lassa fever are of various degrees. That is, level one symptoms, level two symptoms and level three symptoms. The level depends on the severity of symptoms emanated from patients.

Data Variable (Input and Target)

The input variables are those symptoms that a patient observed before coming to hospital, and the symptoms are classified into three level. Level one consists of three symptoms, level two nine symptoms and level three with three symptoms.

Inputs for symptoms level one are: Fever, Headache, and Weakness of the Body.
Input for symptoms level two are: Sore Throat, Vomiting, Diarrhea, Fatigue, Muscle pain, Facial Swelling, Abdominal Pain, Rashes, and Weight Loss.
Input for symptoms level three are bleeding, low blood pressure, deafness.

Table 1: Data Variable Transformation for Symptoms Level One

S/N	Input Set	Domain 1	Domain 2	Domain 3
1	Fever	Yes=1	No=0	
2	Headache	Yes=1	No=0	
3	Weakness	Yes=1	No=0	

Table 1 summarizes the data variable transformation. It shows input set and the range of their possible values called domains. Fever, headache and weakness has two possible domain values which can be either yes or no i.e. 0 or 1. While domain three is the expected output.

Table 2: Data Variable Transformation for Symptoms Level Two

S/N	Input Set	Domain 1	Domain 2	Domain 3
1	Sore throat	Yes=1	No=0	
2	Vomiting	Yes=1	No=0	
3	Diarrhea	Yes=1	No=0	
4	Fatigue	Yes=1	No=0	
5	Muscle pain	Yes=1	No=0	
6	Facial swelling	Yes=1	No=0	
7	Abdominal pain	Yes=1	No=0	
8	Rashes	Yes=1	No=0	
9	Weight loss	Yes=1	No=0	

Table 2 summarizes the data variable transformation. It shows input set and the range of their possible values called domain. Sore throat, vomiting, diarrhea, fatigue, muscle pain, facial swelling, abdominal pain, rashes, and weight loss has two possible domain values which can be either yes or no i.e. 0 or 1. While domain three is the expected output.

Table 3: Data Variable Transformation for symptoms level three

S/N	Input Set	Domain 1	Domain 2	Domain 3
1	Bleeding	Yes=0	No=0	
2	Low blood pressure	Yes=0	No=0	
3	Deafness	Yes=0	No=0	

Table 3 summarizes the data variable transformation. It shows input set and the range of their possible values called domain. Bleeding, low blood pressure and deafness has two possible domain values which can be either yes or no i.e. 0 or 1. While domain three is the expected output.

Modeling Fuzzy Inference System

In this work, a Fuzzy Inference System (FIS) was modeled to make precise decision regarding the uncertainty in medical diagnosis using fuzzy logic. The tool used in the modeling of the classifier proposed in this research is MATLAB R2013a, which is one of most acknowledged tool for data analysis in science and engineering community. MATLAB being a bundle of several packages used in computation, one of the packages was used to train the fuzzy rules.

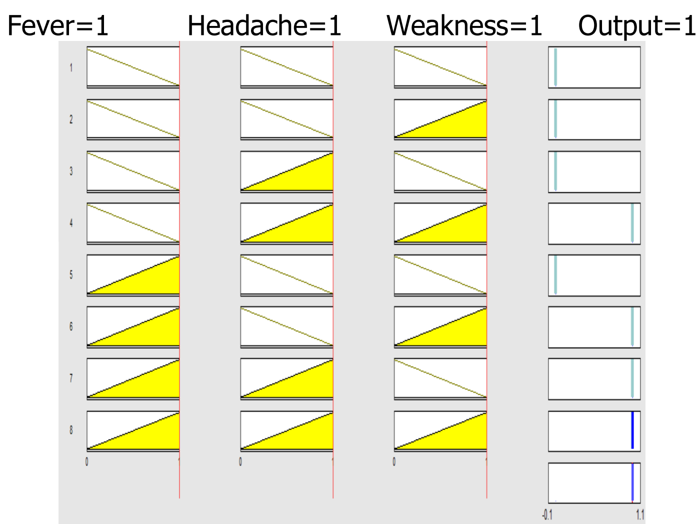

Figure 1: Fuzzy Rules for Symptoms Level One

The Fuzzy rules in Figure 1 shows the input variables for symptoms level one, the derived membership function and the output variable.

The Proposed System in Use Case Diagram

A use case is a methodology used at its simplest in a representation of a user's interaction with the system, understanding and identification of the system's requirement that shows the relationship between the user and the different use cases in which the user is involved. Thus, proposed system is represented using the use case diagram as depicted in Figure 2 and well represented in Table 4.

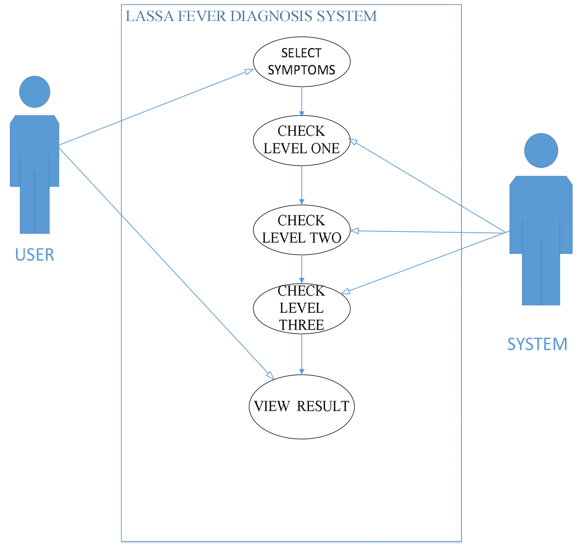

Figure 2: Use Case Diagram for the Developed System

Table 4: Use Case Description

S/N	Use Case Name	Description	Actor Involve
1	Select symptoms	The user enters his or her symptoms by answering the question on the symptoms interface.	Patient
2	View result	A button on the symptoms interface where the user submits the answered question.	Patient
3	View result of related ailments	The user view the displayed result of Lassa fever or related aliments	Patient
4	View result of Lassa fever level	The user view the displayed result of Lassa fever level	Patient

The Proposed System in Flow Chart

The flowchart diagram is an effective graphical representation of the system program depicting the workflow of processes to be carried out on the proposed system and the order in which these operations can be performed. As such, Figure 3 shows the flowchart of the proposed system.

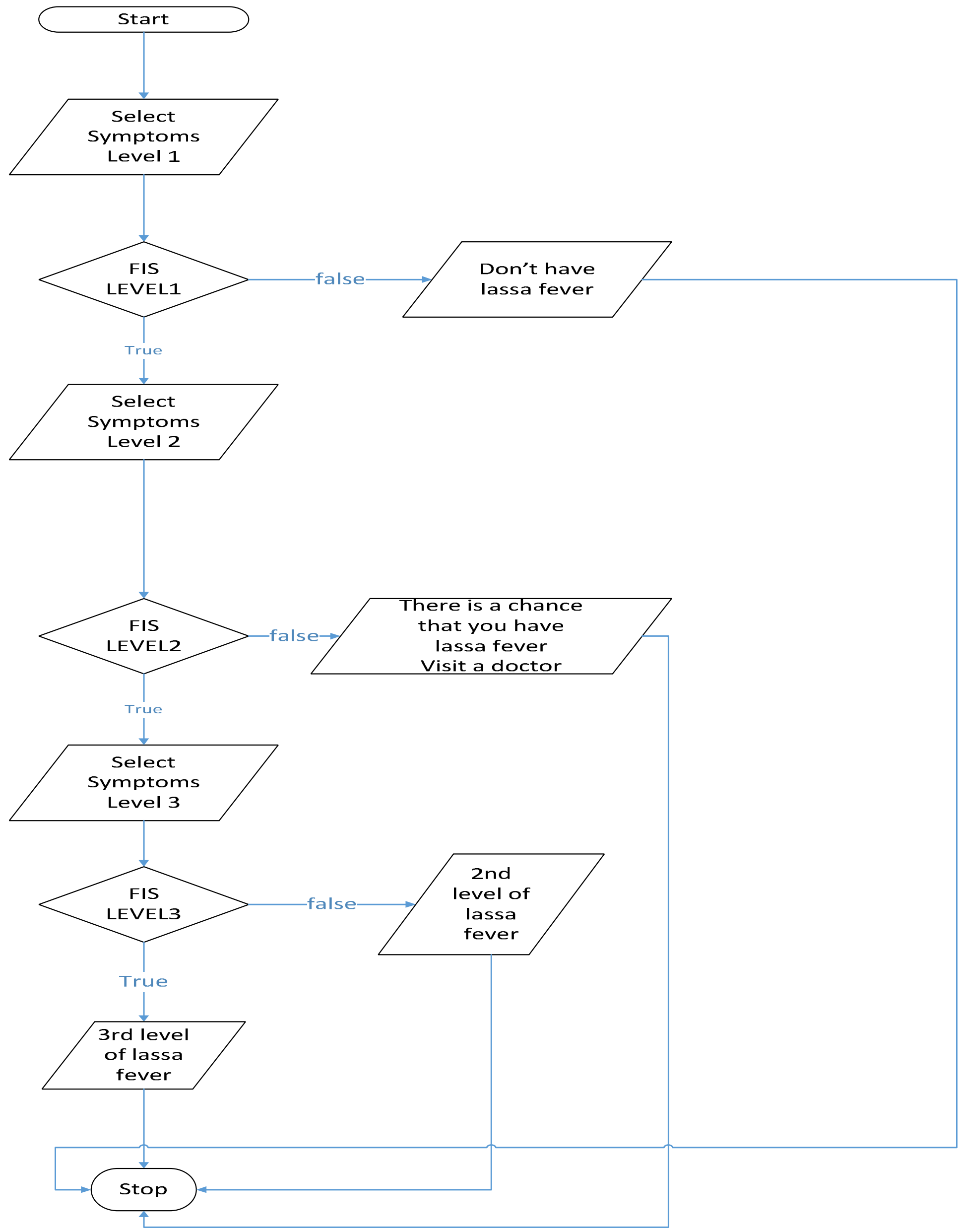

Figure 3: The Flowchart Representation of the Proposed System

The user starts the application and enters symptoms in each level as shown Figure 3. User selects display symptoms for level one and if the symptoms entered does not returns true, it means the ailment is not Lassa fever but advice to diagnose for malaria or typhoid fever. Conversely, if at level one the system returns true, then it further proceeds to test for levels two and three symptoms respectively to further ascertain and authenticate that ailment is Lassa fever.

The System Architecture

The system architecture as shown in Figure 4 depicts the structure and shows the structural view of the system and various actions that users can take in order to utilize the system. First, a user launched the application, the symptoms interface for level one is displayed to the user, the user then selects the symptoms presented on the level one symptoms interface and proceed to the fuzzy inference system where class likelihood measure is computed before displaying the output. Then, the user proceeds to the level two symptoms interface, where user selects the symptoms presented on the symptoms interface and proceed to the fuzzy inference system where class likelihood measure is computed before displaying the output. Furthermore, the user is taken to the level three symptoms interface, where user selects the symptoms presented on the symptoms interface and proceed to the fuzzy inference system where the system then compute class likelihood measure and finally, an output result is displayed to the user.

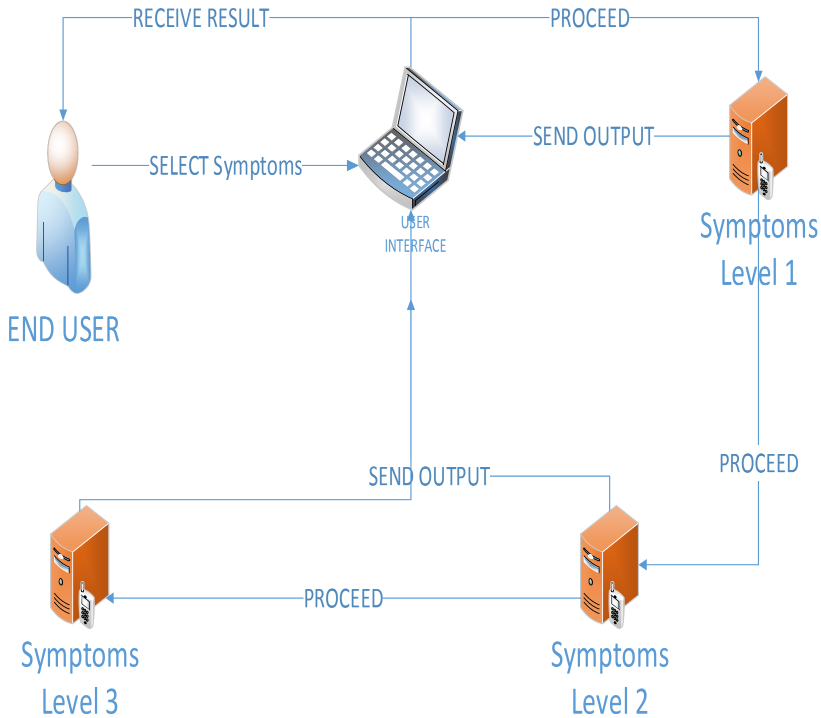

Figure 4: System Architecture of the Proposed System

Results and Discussion

This section presents results obtained from the proposed system. The implementation and designed of the developed system was carried out using MATLAB R2013a for training the classifier of the symptoms. The results and various functionalities of the system were thus, discussed.

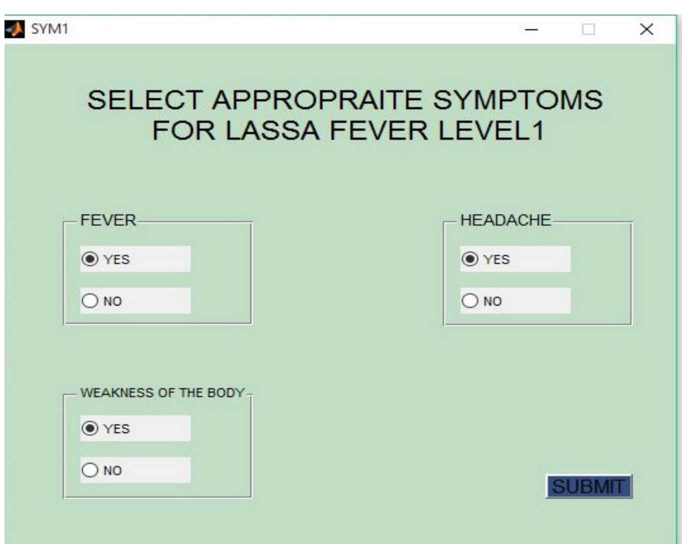

Figure 5: Graphical User Interface of the Proposed System at Design Time

Figure 5 represents the code view and image at the design time. The view of the Graphical User Interface (GUI) during design, the palette at the right side shows different controls that can be used for design of the interface. Also contains different properties that can be applied such as colour.

The Implemented System

The system was implemented using MATLAB R2013a. Figure 6 represent the design environment of the GUI of the system.

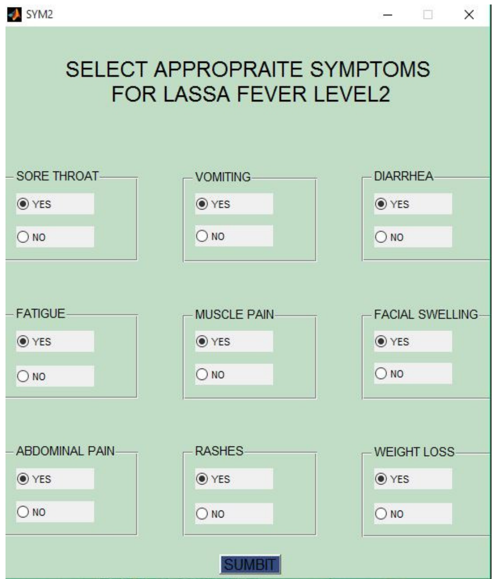

Figure 6: Graphical User Interface of the Implemented System at Run Time

Fig. 6 represents the graphical user interface of the system at run time, which display the symptoms interface page where the user can select symptoms.

The System Testing

In this section an integrated testing was carried out on the GUI implementation of the classifier system. The GUI was developed using MATLAB R2013a.

Figure 7: Start-up Interface or Home Page

Figure 7 show the start up interface or homepage, once the start button is clicked on by the user, the Lassa Fever Diagnosis System takes the user to the "symptoms interface". This interface allow user to select symptoms and user click on submit button to get output.

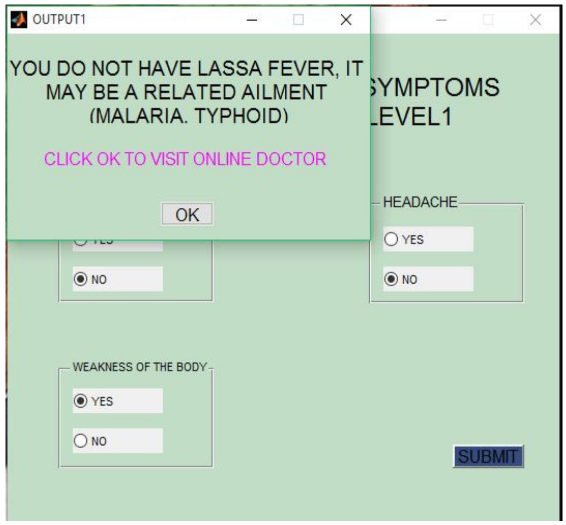

Figure 8: The Implemented System at Testing Phase of Symptoms Level One

Figure 8 shows the output after a user has responded to the question on the symptoms interface page and likelihood measure has been computed before displaying an output for level one. At this testing phase, it is assume that user response to level one symptoms fever, headache and weakness of the body are no, no and yes respectively. Then the system would response as clearly shown by Figure 8.

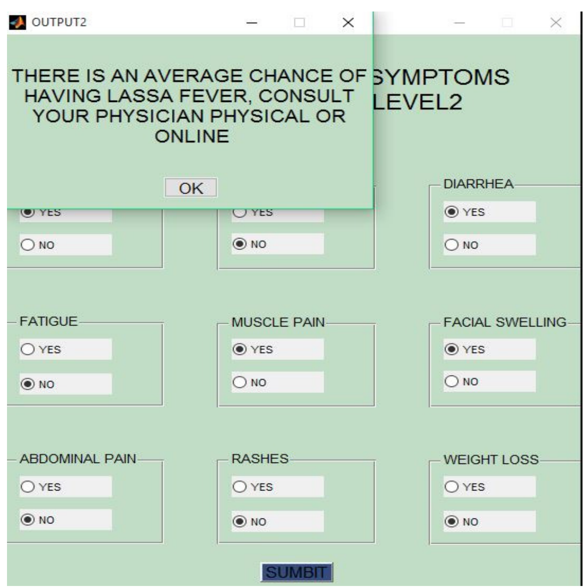

Figure 9: The Implemented System at Testing Phase for Symptoms Level Two.

Figure 9 shows the output after a user has responded to the question on the symptoms interface page and likelihood measure has been computed before displaying an output for level two. At this testing phase, user response to level two symptoms: sore throat is yes, vomiting is no, diarrhea is yes, fatigue is no, muscle pain is is yes, facial swelling is yes, abdominal pain is no, rashes is equally no and weight loss is also no. Then the system would response as clearly shown by Figure 9.

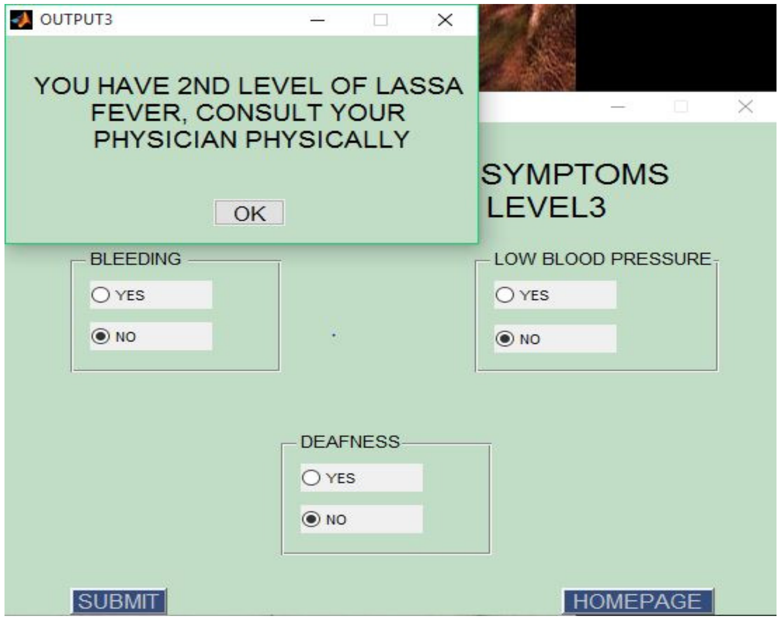

Figure 10: The Implemented System at Testing Phase

Figure 10 shows the output after a user has respond to the question on the symptoms interface page on level three and likelihood measure has be compute before displaying an output. At this testing phase, user response to level three symptoms bleeding, low blood pressure and deafness are assume to be no. Hence, the system would response as shown by Figure 10.

Summary and Conclusion

Lassa fever is acute viral diseases that are so popular in most Africa nations. The complication aspect of the diseases is the exhibition of related symptoms to other ailments. Therefore, this paper aimed to apply fuzzy logic that would be able to handle proper classification of symptoms. In this research, an existing medical records obtained from a government own hospital were analyzed in order to extract both the symptoms and the laboratory results associated to the symptoms. Fuzzy logic was used to train the symptoms and carried out thorough classifications owing to the fact that there are some ailments that have related symptoms with that of Lassa fever. The application of the algorithm was implemented in MATLAB R2013a platform.

The choice of Fuzzy logic was influenced owing to its capacity to offer reasonably precise recommended solution for uncertain and also certain complex systems to ease perception and flexible. Finally, the Lassa fever and related ailment classifier was implemented as a stand alone system, which can be used by both patients and medical specialists to accurately diagnose the ailment especially in developing countries where there are no medical facilities or grossly inadequate. Nonetheless, just like any other research work, further researches in terms of making the proposed system an internet-based and its security aspect are still open to actualize. Besides, modifying the system in more viable platforms for instance, mobile applications is also open to research.

References

Adeboye, K. R., & Haruna, M, (2015). A mathematical model for the transmission and control of malaria and typhoid co-infection using SIRS approach. *Research Journali's Journal of Mathematics,* 2(2), 1-24.

Amorosa, V., MacNeil, A., & McConnell, R. (2010). Imported Lassa Fever. *Emerging Infectious Diseases,* 16(10), 1598-600.

Asogun, D. A., Adomeh, D. I., & Ehimuan, J. (2012). Molecular diagnostics for Lassa fever at Irrua specialist teaching hospital, Nigeria: Lessons learnt from two years of laboratory operation. *PLoS Neglected Tropical Diseases*, 6, 18-39.

Baize, S., Marianneau, P., & Georges-Courbot, M. C. (2001). Recent advances in vaccines against viral haemorrhagic fevers. *Current Opinion in Infectious Diseases*, 15(5), 513-8, 2001.

Bausch, D. G., Demby, A. H., & Coulibaly, M. (2001). Lassa fever in Guinea, West Africa. Epidemiology of human disease and clinical observations, *Vector Borne and Zoonotic Diseases*, 1, 269-82, 2001.

Bazmara, A., & Donighi, S. S. (2014). Bank customer credit scoring by using fuzzy expert system. *International Journal of Intelligent Systems and Applications,* 11, 29-35.

Djam, X. Y., Wajiga, G. M., Kimbi, Y. H., & Blamah, N. V. (2011). A fuzzy expert system for the management of malaria, *International Journal of Pure Applied Science and Technology,* 5, (2), 84-108.

Hassan, M. A., Sher-e-alam, K., & Chowdhury, A. R. (2010). Human disease diagnosis using a fuzzy expert system. *Journal of Computing,* 2(6), 66-70.

Igodan, C., Akinyokun, O., & Olatubosun, O. (2013). Online fuzzy-logic knowledge warehousing and mining model for the diagnosis and therapy of HIV/AIDS. *International Journal of Computational Science and Information Technology (IJCSITY)*, 1(3), 27-41.

Lecompte, E., Fichet-Calvet, E., & Daffis, S. (2006). Mastomys natalensis and Lassa fever, West Africa. *Emerging Infectious Diseases*, 12(12), 1971-1974.

Oguntimilehin, A., Abiola, O. B., & Olatunji, K. A. (2015). Computer aided diagnostic systems for managing typhoid fever: A review of diagnosis techniques. *International Journal of Computer Applications,* 126.

Oladipo, O., Olayinka, C. T., & Popoola, O. L. (2014). Mobile compactable expert system for the treatment of typhoid fever in developing countries. I*nternational Journal of Computer Applications,* 5(2), 16-19.

Osaseri, R. O., & Osaseri, E. I. (2016). Soft computing approach for diagnosis of Lassa fever. *International Journal of Computer and Information Engineering,* 3(11).

Osaseri, R. O., Onibere, E. A., & Usiobiafo, A. R. (2014). Fuzzy expert model for diagnosis of lassa fever. *Journal of the Nigerian Association of Mathematical Physics,* 27. 533-540.

Putu, M. P., & Iketut, G. D. P. (2012). Fuzzy knowledge-based system with uncertainty for tropical infectious disease diagnosis. *IJCSI International Journal of Computer Science Issues*, 9, 157-163.

Rahmani, M., Piltan, F., Matin, F., Cheraghi, H., & Sobhani, N. (2014). Design intelligent system compensator to computed torque control of spherical motor. *International Journal of Intelligent Systems and Applications,* 8, 87-96.

Samuel, O. W., Omisore, M., & Ojokoh, B. A. (2013). A web based decision support system driven by fuzzy logic for the diagnosis of typhoid fever. *Expert Systems with Applications*, 40, 4164-417.

Samuel, O. W., & Omisore, M. O. (2013). Genetic neuro-fuzzy system for the diagnosis of typhoid fever. *Conference on Medical Innovation and Computing Service,* Pp. 1-13.

Umoh, U. A., & Ntekop, M. M. (2013). A proposed fuzzy framework for cholera diagnosis and monitoring. *International Journal of Computer Applications,* 82, 1-10.