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Development of a Fuzzy Logic Predictive Model for Lassa Fever Risk Detection

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ABSTRACT

Although there is no vaccine to prevent Lassa fever, symptomatic therapy increases the patient's chances of survival. The antiviral medicine Ribavirin demonstrated being effective when administered early enough in the illness. Lassa fever clinical research is difficult. To lower the mortality and morbidity of Lassa fever, urgent research is underway. Through a search of pertinent literature and organized interviews with medical professionals, risk factors for Lassa fever were discovered. Fuzzy Logic Toolbox, MATLAB® R2009a, was used to create and simulate the model for predicting Lassa fever risk. The risk factors and target risk were created using triangle membership functions, which fuzzy inference engine inferred 384 rules from six risk parameters. The target class has No, Low, Moderate, and High risk as the linguistic labels. In the MATLAB environment, the validity of the inferred rules was tested. This work built and developed a model for predicting Lassa fever risk, which patient and non-medical specialists can use for early Lassa fever risk diagnosis. This will help decrease the mortality rate because early treatment aids in recovery.

Keywords: Lassa fever, Rodent, Fuzzy Logic, Predictive Model, Simulation, Risk Factor.

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1. INTRODUCTION

The Health Information System (HIS) framework, developed by the Ministry of Science and Technology, and the Ministry of Health in Nigeria, is explicitly concerned with applying information technology in a health system. In applied terms, a health information system (HIS) ensures that correct health data is delivered in a timely, coordinated, and secure manner via electronic methods. The goal is to increase the efficacy and quality of healthcare delivery and preventive- healthcare programs (NHICTSF, 2015) The use of information and communication technology has revolutionized healthcare services by allowing medical practitioners to rapidly update patient records, make more accurate judgments, and aid in the diagnosis, early detection, and management of patients' health (Egejuru, Ogunlade, and Idowu, 2019a). Health is essential for any country's development, and a good health information system is required to make successful decisions and assist in resource allocation. Globally, the shift from curative to preventative healthcare has necessitated using computer-based information systems to assist in successful decision making. One of the most important requirements for establishing a health information system is to collect data on how each condition is managed in the target population (Egejuru et. al., 2019a).

It is not enough to have effective healthcare services; it is also necessary to have information about where such services can be found and the availability of such services. People would be able to make good health decisions if they had access to appropriate information about their health. This is one requirement that an information system would address and to which people would have access. This study focused on predicting the risk of a disease called Lassa fever, to detect it early and reduce mortality and morbidity rates. The Lassa virus, a member of the arenavirus family of viruses, is the cause of Lassa fever, an acute viral hemorrhagic sickness. Lassa fever is an acute viral disease that is transmitted by the common African rat and is animal-borne, or zoonotic. Rodents can spread the acute viral disease lassa fever to people. The most common way for humans to contract the Lassa virus is through contact with food or household items that have been tainted by the urine or feces of infected Mastomys rats. In some regions of West Africa, the disease is endemic among the rodent population. (CDC, 2022; NCDC, 2022; WHO, 2022).

Lassa fever is endemic in the Sub-Saharan African, like Benin, Liberia, Guinea, Sierra Leone, and Nigeria (ALIMA, 2020; CDC, 2022). In the 1950s, Lassa fever was discovered for the first time in Sierra Leone. It was not until 1969 that the virus that caused the deaths in Nigeria, West Africa, of two missionary nurses, was identified. The virus known as Lassa, named after a town in Nigeria (Lassa in the Yedseram River basin), was connected to the illness, and the initial cases were identified. Several outbreaks of the virus have been reported in Nigeria, including Jos, Zonkwua, Aboh Mbaise, Onitsha, Owerri, and Ekpoma. Ghana reported its first cases in late 2011, while Mali, Liberia, and Guinea reported the first incidence in 2009 from a visitor in Southern Mali and Benin Republic (CDC, 2022).

In Nigeria for the year 2022, as at 9th October 2022, being week 40, Nigeria recorded 937 confirmed cases, 173 deaths, and 18.5% case fatally ratio (CFR) of lassa fever for year 2022. 104 Local Government Areas in 26 States had at least one verified case. 71% of all confirmed cases originate in the states of Ondo (33%), Edo (25%), and Bauchi (13%). The impacted age range is primarily between 21 and 30. (Range: 0 to 90 years, Median Age: 30 years). For confirmed cases, the male-to-female ratio is 1:0.8 (CDC, 2022, WHO, 2022).

Nonspecific symptoms like malaise, headache and generalized weakness, and Fever usually appear first, followed by retrosternal pain, sore throat, stomach pain, diarrhea, and conjunctival infection within days. Shock, hemorrhage, neck and facial edema, and multiorgan system failure can all occur in severe cases. Although there is presently no vaccine to prevent Lassa fever, symptomatic therapy increases the likelihood of survival, and the antiviral drug Ribavirin has been shown to be useful when

administered early in the course of the illness (ALIMA, 2020).
If treatment is started within six days after the symptoms onset, the outcome is better. Although most patients are asymptomatic, the Lassa fever incubation period falls within 2 to 21 days (NCDC, 2022). Lassa fever affects people of all ages and genders. Rural residents, on the other hand, are more vulnerable to the carrier rat, especially if there is poor cleanliness or overcrowding. The health personnel, who are not well covered and do not follow infection control and prevention methods when caring for Lassa fever patients, are another group of persons in danger.

The study found a yearly rise in the number of LASV-infected persons in Nigeria, according to Yaro et al., (2021). Ondo and Edo States continue to be the virus's hub, having more than 60% of all cases yearly. In 32 states and the FCT, the LASV is endemic with an annual CFR (Case Fatality Rate) of 18.5%. Every year, between 100,000 and 300,000 people contract lassa fever, with 5,000 of them dying. These figures are approximations since Lassa fever surveillance is not standardized. Each year, 10–16 % of people hospitalized in different parts of Liberia and Sierra Leone have lassa fever, which highlights the disease's disastrous effects on the area (CDC, 2022).

Clinical trials are urgently needed to investigate novel therapies and assess the safety and effectiveness of the sole available medicine, ribavirin, which has a scant clinical data base, in order to lower Lassa fever mortality and morbidity. Clinical research on Lassa fever is tough, and it belongs to the group of infectious diseases that are difficult to study. Only one randomized controlled trial evaluating the safety and effectiveness of treatment therapies for Lassa fever has been done. In laboratory-confirmed cases, the overall case fatality ratio was 30% (Merson et al., 2021).

Approximately 80% of infections are asymptomatic, while the remaining 20% of patients experience severe multi-system illness, with up to 15% of hospitalized cases experiencing fatal outcomes. 25% of those who survive the illness develop hearing loss. After 1-3 months, hearing returns partially in half of these individuals. In fatal situations, death typically happens within 14 days of start. One out of every five infections progresses to a serious illness in which the virus attacks many organs, including the liver, spleen, and kidneys. Infection can be avoided with proper hygiene practices and early antiviral treatment with ribavirin. Along with rehydration and symptomatic therapy (CDC, 2022; NCDC, 2022; ECDC, 2022; WHO, 2022),

Using observable related factors to determine the risk of Lassa fever can improve the early detection of the Lassa virus in humans. There is a need to create a model that medical practitioners or patients can use to determine the risk of Lassa fever before going to the hospital. Using Fuzzy Logic to develop a system for detecting Lassa fever early has made it easy for patients or individuals to take precautions and medical advice. Williams et al., (2015), stated that fuzzy logic systems can decide and govern a system utilizing expert knowledge.

It's an artificial intelligence technique that handles numeric data and linguistic information at the same time, as well as presenting an inference morphology that allows for the application of relevant human reasoning capabilities to knowledge-based systems. Fuzzy logic techniques are rapidly used in various fields to aid database mining (Lekha et al., 2015). The Fuzzy Logic methodology is based on the Fuzzy Set Theory and is used to express knowledge using an operative powerful method while reasoning with ambiguous and imprecise information (Yalcin, and Kose, (2009)). The fuzzy set theory focuses on a

set's membership degree (Idowu et al., 2015).
By taking into account the characteristics highlighted, this work investigated the development of a predictive fuzzy logic model for the early identification and prediction of Lassa fever. The model was developed and validated using the MATLAB environment and the fuzzy inference engine.

2. RELATED WORKS

Fuzzy logic was used in the research by Enesi et al. (2018) to develop a diagnosis system for Lassa fever and related illnesses. MATLAB R2013a was used to design and implement the system. Users can choose symptoms from the symptoms interface page that appears when the application is launched using the new diagnosis system. The outcomes of this experiment were evaluated and determined to be effective in diagnosing Lassa fever. The information used in the paper includes a variety of Lassa fever signs and symptoms. The risk factors were just not taken into account.

According to the study by Shehu et al., (2018), bleeding diathesis was the most prevalent symptom, with over half of the confirmed cases have stomach pain and headaches. Changes in the clinical presentation and geographic distribution of the disease may have an impact on local and international efforts to control the disease as well as the risk of Lassa Fever transmission. To inform their decisions, public health officials should be aware that epidemic patterns may be shifting in order to guide actions.

The novel study by Nnebe et al. (2019), showed that the diagnosis of Lassa fever can be greatly aided by the integration of various approaches. Three main algorithms were used in the Neuro-fuzzy CBR framework's design for comprehensive diagnosis: the fuzzy clustering algorithm, the nearest neighbor algorithm, and the back propagation technique. Based on the 29 observed symptoms recorded, the Neuro-fuzzy CBR framework is intended as an effective way to diagnose a suspected case of Lassa fever. To properly combat this Lassa fever threat, researchers should think about various hybrid approaches and machine learning techniques.

Using information on non-invasive risk factors, Balogun et al. (2020), developed a classification model for monitoring females' risk of sexually transmitted diseases (STDs). To determine the risk variables linked to STDs risk in Nigeria, structured interviews with doctors were conducted. The fuzzy logic toolbox included in the MATLAB® R2015a was used in simulating the model. The findings indicated that among female patients in Nigeria, 9 non-invasive risk factors were linked to an increased likelihood of STDs. The language variables of the factors should be formulated using two, three, or four triangle membership functions,

Egejuru et al., (2021) worked on identifying hypertension risk factors, classifying risks, and helping patients understand their risks. Based on the variables specified, the model was created using the Adaptive Neuro-Fuzzy Inference System (ANFIS) and simulated using MATLAB Tools. Ojo and Goufo (2022) present a deterministic mathematical model to study the dynamics of Lassa fever in Nigeria. The transmission between two interacting hosts, notably the rodent and human populations, is described by the model. utilizing the overall quantity of instances that the Nigerian Center for Disease Control has reported. The outcome demonstrates that an increase in Lassa fever transmission is linked to an increase in the transmission probabilities ((βh, βr , βhr , βrh) aand an increase in the population of rodents (πr).

Additionally, a decline in the spread of Lassa fever is connected to an increase in rodent mortality. With parameterized data, numerical simulations were run to describe the dynamics of Lassa disease in the population. It will be helpful to look into the effects of utilizing various control measures in order to eradicate the disease in order to lessen the burden of Lassa fever in each area of Africa where it is endemic.

The following significant facts about Lassa fever were highlighted:

- A viral hemorrhagic illness called Lassa fever appears throughout West Africa and it lasts 2-21 days.
- People can contract the Lassa virus by coming into contact with household objects or food contaminated by rodent urine or feces.
- With insufficient infection prevention and control procedures especially in hospitals, infections can spread from patient to patient and from laboratory to laboratory..
- Although it is believed that Lassa fever exists in other West African nations, it is endemic in Nigeria, Guinea, Sierra Leone, Ghana, Mali, Liberia, and Benin.
- There is a 1% overall case mortality rate and hospitalized severe patients have 15% Case Fatality Rate (CFR).
- The likelihood of survival increases with early supportive care, such as symptomatic therapy and rehydration.

Risk variables connected with the risk of Lassa fever and the methods used were discovered in the related papers evaluated. Some of the works used symptoms in diagnosis. Where emergency epidemic preparation measures are in place, timely detection of outbreaks is followed by prompt and adequate response, as measured by morbidity and death annually. Furthermore, because of the nature of Lassa fever's propagation in an outbreak scenario, developing a model for the early detection of new patients became critical.

3. METHODS

A review of pertinent literature was carried out in order to identify the risk factors of Lassa fever. Utilizing triangle membership functions, the risk factors and Lassa risk labels were produced. The inference engine was built using IF-THEN rules, with risk factors as antecedents and Lassa risk as the consequent element of each rule. MATLAB® R2009a was used in simulating the fuzzy logic model.
The study was limited to non-invasive Lassa fever risk variables for predicting Lassa virus risk.

A. Identification of Associated Risk factors

To forecast the risk of a disease, there is a need to identify the risk factors (Egejuru et al., 2019b). The risk of Lassa fever was assessed using non-invasive risk variables such as age, lifestyle, environment, and social factors. From the literature, a number of risk factors for Lassa fever have been found. Six (6) risk factors, Age of patient, Gender, Presence of fever, Immunosuppression, Exposure to infected individuals, and Presence of rodents, were identified for the classification of the risk of the Lassa fever model. They were validated by five medical doctors with knowledge and experience of more than ten years To quantify a user's response to each risk factor, numeric integer values (called crisp value) were utilized to specify the label of each risk factor examined. Labels that raised the risk of Lassa fever were given higher crisp intervals, while labels that lowered the risk were given lower crisp intervals. This required writing each fuzzy membership function and assigning a linguistic value to each crisp interval. Table 1 gives an overview of the linguistic variables, together with the crisp values of each detected variable and the triangle membership functions' matching crisp center value. In order to increase the risk of Lassa fever, the patient's age was labeled using linguistic values: child, teenager, adult, and aged, having crisp central values of 0, 1, 2, and 3 accordingly. As a result, the elderly with crisp value 3 are more likely to contact Lassa fever, while the children with crisp value 0 are less likely to contact the fever. The linguistic values were used to label gender: male and female, using crisp central values, 0 and 1, ensuing how Lassa fever risk increases. As a result, male patients are less likely than female patients to contract Lassa fever.

To increase the danger of Lassa fever, the presence of fever in a patient was labeled using the linguistic values: No fever, Low fever, Moderate fever, and High fever having crisp central values being 0, 1, 2, 3 accordingly. As a result, people with a low fever are less likely to get Lassa fever than those with a high fever. Immunosuppression was classified with the following; No or Yes for linguistic values, and 1 or 0 for crisp central values, as it increases Lassa fever risk.

Table 1: Identified Risk Factors' Linguistic and Crisp Values

Identified Risk Factors	Linguistic Values	Crisp Values
Ages of Patients	Child Teenager Adult Aged	0 1 2 3
Immunosuppression	No Yes	0 1
Presence of Fever	No Fever Low Fever Moderate Fever High Fever	0 1 2 3
Gender	Male Female	0 1
Exposure to infected individuals	No Yes	0 1
Presence of Rodents	None Slight High	0 1 2
Risk of Lassa Fever	No Risk Low Risk Moderate Risk High Risk	0 1 2 3

As a result, patient with no immunosuppression history is less likely to get Lassa fever than those having immunosuppression history. Exposure to infected people was categorized as increasing the risk of Lassa fever, where no and yes are regarded as the linguistic values, having crisp central values as 0 and 1, correspondingly. As a result, patients who have not been exposed to an infected person are less likely to develop Lassa fever than patients who have been exposed to an infected person. The presence of rats was classified as None, Slight, or High, having crisp central values 0, 1, and 2 correspondingly, as such increasing risk of Lassa fever. As a result, people who do not live near rats have a lower risk of contracting Lassa fever than those who do. With crisp values of 0, 1, 2, and 3, the danger of Lassa fever was divided into four linguistic values, namely: No, Low, Moderate, and High Risk. Membership function utilized to build the fuzzy logic model was determined after the variables recommended for this study were identified.

B. Formulation of a Fuzzy Logic Model for Lassa Fever Risk

A classification model was developed with fuzzy logic. A triangle membership function was used to fuzz each detected variable. Three (3) parameters are required in the triangular membership function: triangle a left-hand base, triangle b - center apex, and triangle c - right-hand base. The values of triangle membership function are a, b, c, matched to an abc interval.

The crisp interval within which each crisp value required for invoking the linguistic variable was assigned, was defined by this parameter's interval. As a result, triangular membership functions of 1, 2, and 3 were given to each language variable detected for each risk factor as appropriate. This is expressed in equation 1. The triangle membership function was used to create variable label (a, b, c) which fits inside a crisp interval of 1, a numerical value x.

$$Variable_{label(x;a,b,c)} = \begin{cases} 0; x \leq a;\ 0; x > c \\ \dfrac{x-a}{b-a}; a < x \leq b \\ \dfrac{c-x}{c-b}; b < x \leq c \end{cases} \qquad (1)$$

As shown in Table 2, the linguistic variables were modeled by utilizing a crisp center value of 0 for crisp interval of [-0.5, 0.5], 1 for interval [0.5, 1.5], 2 for [1.5, 2.5] and 3 is for [2.5 3.5].

C. Fuzzification of Risk of Lassa Fever

The target variable developed to characterize the risk of Lassa fever once the risk factors for the disease were identified and fuzzified. The target variable have the target class labels—No, Low, Moderate, and High risk. They have crisp values of 0, 1, 2, and 3, and corresponding intervals (-0.5, 0.5), (0.5, 1.5), (1.5, 2.5), and (2.5, 3.5).

In order to explain the four labels that were used to define the risk of Lassa fever, the fuzzy logic model required the employment of four (4) triangle membership functions. Based on the description given in Table 2, the fuzzy inference technique was employed to suggest a connection concerning the risk of Lassa fever and risk factors.

D. Fuzzy inference system design

The fuzzy inference engine was implemented after the model was developed with triangle membership function to represent the risk of Lassa fever and risk factors. Experts' guidelines were inferred to identify the association between the identified non-invasive parameters and the risk of Lassa fever to create a relationship between the risk and parameters identified of Lassa fever. A number of IF-THEN rules were utilized to develop the knowledge base of the fuzzy logic classification model. This considered the risk of Lassa Fever as the consequent variable and risk factors as the precedence. Following the fuzzification procedure and utilizing the risk factors identified for determining the risk of Lassa fever, the development of inference rules is often the next step. The following is an example of an inferred rule:

IF (Age = "Child") AND (Gender = "Female") AND (Presence of Fever = "No Fever") AND (Immunosuppression = "No") AND (Exposure to infected Individual = "No") AND (Presence of Rodents= "No") THEN (Risk of Lassa Fever = "No Risk")

Table 2: Crisp Interval for the Formulated Model

Crisp Value	Intervals	a	b	c
0	[-0.5, 0.5]	-0.5	0	0.5
1	[0.5, 1.5]	0.5	1	1.5
2	[1.5, 2.5]	1.5	2	2.5
3	[2.5, 3.5]	2.5	3	3.5

The rules developed for the model was calculated as the product of the number of linguistic variables in each variable. Since age had four linguistic variables, gender had two, the fever had two, immunosuppression had two, exposure to infected individuals had two, and the presence of rodents had two, the results were as follows: age had four linguistic variables, Gender had two, Fever had two, Immunosuppression had two, Exposure to infected individuals had two, and the presence of rodents had two. As a result, the inference engine's total number of rules inferred was 384.

E. Simulation Environment Used

MATLAB was used in simulation and the elements of the MATLAB Fuzzy Logic System used include:

- Fuzzy Inference System (FIS) Editor It was used to specify various high-level system issues as well as the names and quantities of input and output variables. For this experiment, six input and one output variable(s) were defined and used.
- Membership Function Editor Using this technique, the four membership functions connected to the linguistic variables were defined and formulated. Four membership functions were used in this study to formulate the linguistic variables, which included No, Low, Moderate, and High risk for the output variable.
- Rule Editor/viewer, The different rules that guided the system's behavior were changed using IF-THEN statement that combined the discovered risk variables with the risk of Lassa fever labels. In this work, 384 rules were developed utilizing IF-THEN approach, centered on

potential combinations of the linguistic elements of input variables required for defining their relative risk of Lassa fever.

4. RESULTS AND DISCUSSIONS

A. Fuzzy Model Formulation for Prediction of Lassa fever Risk

The findings of the model formulation with triangular membership function are reported. For the labels of each identified component, triangular membership functions 1, 2, and 3 were formed, considering the linguistic variables of the target class that determined prediction risk of Lassa fever. Using 1, 2, and 3 triangular membership functions with centers of 0 and 1 or 0, 1 and 2 or 0, 1, and 2 accordingly, the labels of each risk factor were defined using the same crisp interval. The fuzzy logic model that was utilized to create the prediction model is represented mathematically.

The triangular membership functions 1, 2, and 3 were utilized to create the model, with crisp centers of 0 and 1; 0, 1, and 2; and 0, 1, 2, and 3 accordingly. Additionally, the values were determined based on how the labels of the discovered components grew over time. The mathematical representation of the model using each label is shown in Equations 2a, 2b, 2c, and 2d.

$$linguisticLabel_{0(x;-0.5,0,0.5)} = \begin{cases} 0; x \leq -0.5; 0, x > 0.5 \\ \dfrac{x+0.5}{0.5}\ ; -0.5 < x \leq 0 \\ \dfrac{0.5-x}{0.5}; 0 < x \leq 0.5 \end{cases} \quad (2a)$$

$$linguisticLabel_{1(x;0.5,1,1.5)} = \begin{cases} 0; x \leq 0.5; 0, x > 1.5 \\ \dfrac{x-0.5}{0.5}\ ; 0.5 < x \leq 1 \\ \dfrac{1.5-x}{0.5}; 1 < x \leq 1.5 \end{cases} \quad (2b\ )$$

$$linguisticLabel\_2(x; 1.5, 2, 2.5) = \begin{cases} 0; x \leq 1.5; 0, x > 2.5 \\ \frac{x-1.5}{0.5}\ ; 1.5 < x \leq 2 \\ \frac{2.5-x}{0.5}; 2 < x \leq 2.5 \end{cases} \quad (2c)$$

$$linguisticLabel\_3(x; 2.5, 3, 3.5) = \begin{cases} 0; x \leq 2.5; 0, x > 3.5 \\ \dfrac{x-1.5}{0.5}\ ; 1.5 < x \leq 2 \\ \dfrac{2.5-x}{0.5}; 2 < x \leq 2.5 \end{cases} \quad (2d)$$

Additionally, the risk of Lassa fever has four linguistic variables: No, Low, Moderate, and High risk with crisp center values of 0, 1, 2, and 3. The linguistic variables of the risk of Lassa fever equation (3d) were created considering the 4 triangular membership functions shown in equations (3a) to (3d).

$$Crisp - no\_risk(x; -0.5, 0, 0.5) = \begin{cases} 0; x \leq -0.5 ; 0; x > 0.5 \\ \dfrac{x + 0.5}{0.5} ; -0.5 < x \leq 0 \\ \dfrac{0.5 - x}{0.5} ; 0 < x \leq 0.5 \end{cases} \quad (3a)$$

$$Crisp - low\_risk(x; 0.5, 1, 1.5) = \begin{cases} 0; x \leq 0.5; 0; x > 1.5 \\ \dfrac{x - 0.5}{0.5} ; 0.5 < x \leq 1 \\ \dfrac{1.5 - x}{0.5} ; 1 < x \leq 1.5 \end{cases} \quad (3b)$$

$$Crisp - moderate_{risk(x;1.5,2,2.5)} = \begin{cases} 0; x \leq 1.5; 0; x > 2.5 \\ \dfrac{x - 1.5}{0.5} ; 1.5 < x \leq 2 \\ \dfrac{2.5 - x}{0.5} ; 2 < x \leq 2.5 \end{cases} \quad (3c)$$

$$Crisp - high_{risk(x;2.5,3,3.5)} = \begin{cases} 0; x \leq 2.5; 0; x > 3.5 \\ \dfrac{x - 2.5}{0.5} ; 2.5 < x \leq 3 \\ \dfrac{3.5 - x}{0.5} ; 3 < x \leq 3.5 \end{cases} \quad (3d)$$

B. The Result of input variables and output variables fuzzification

The membership function editor was used for fuzzification of input and output variables as shown in Figures 1, 2, 3, 4, 5, 6, and Figure 7. A screenshot of the source code with the .fis extension from the simulation of building the model for Lassa fever risk is shown in Figure 8.

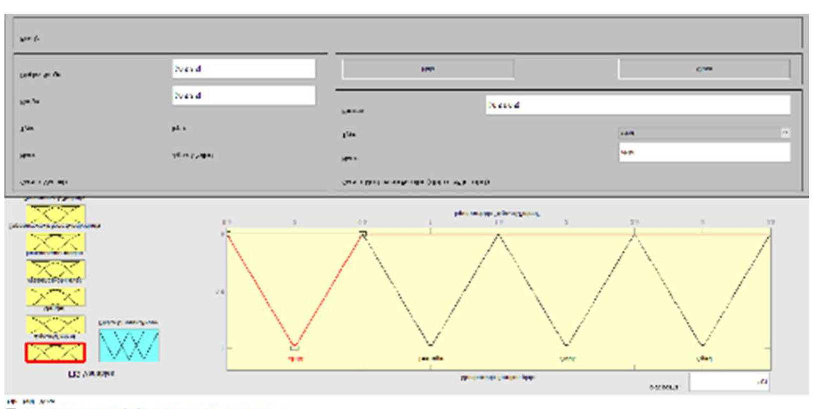

Fig. 1: Fuzzification of Age of Patient

Fig. 2: Fuzzification of Gender

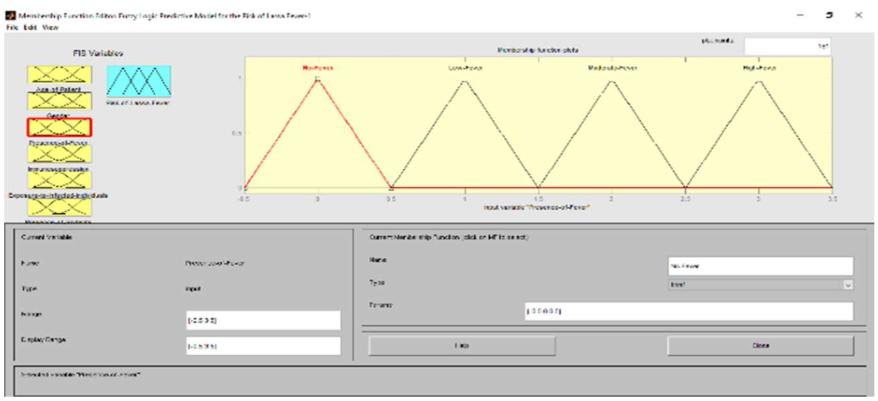

Fig. 3: Fuzzification of Presence of Fever

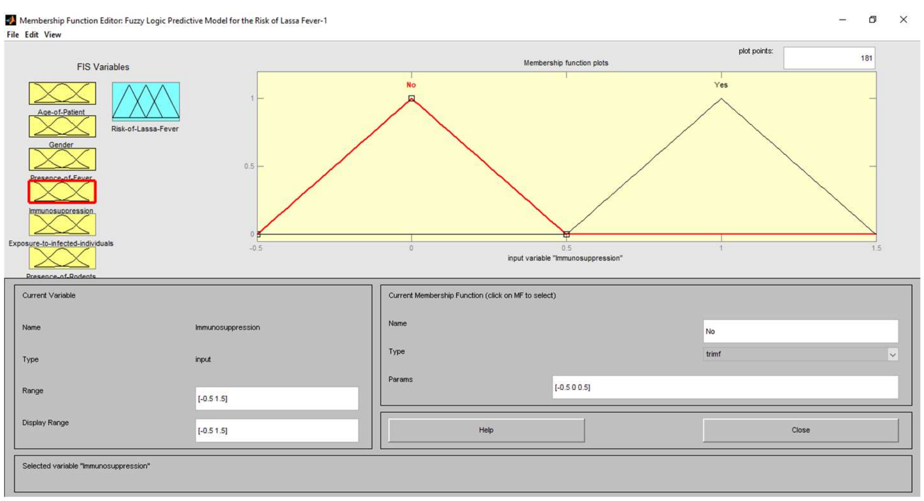

Fig. 4: Fuzzification of Immunosuppression

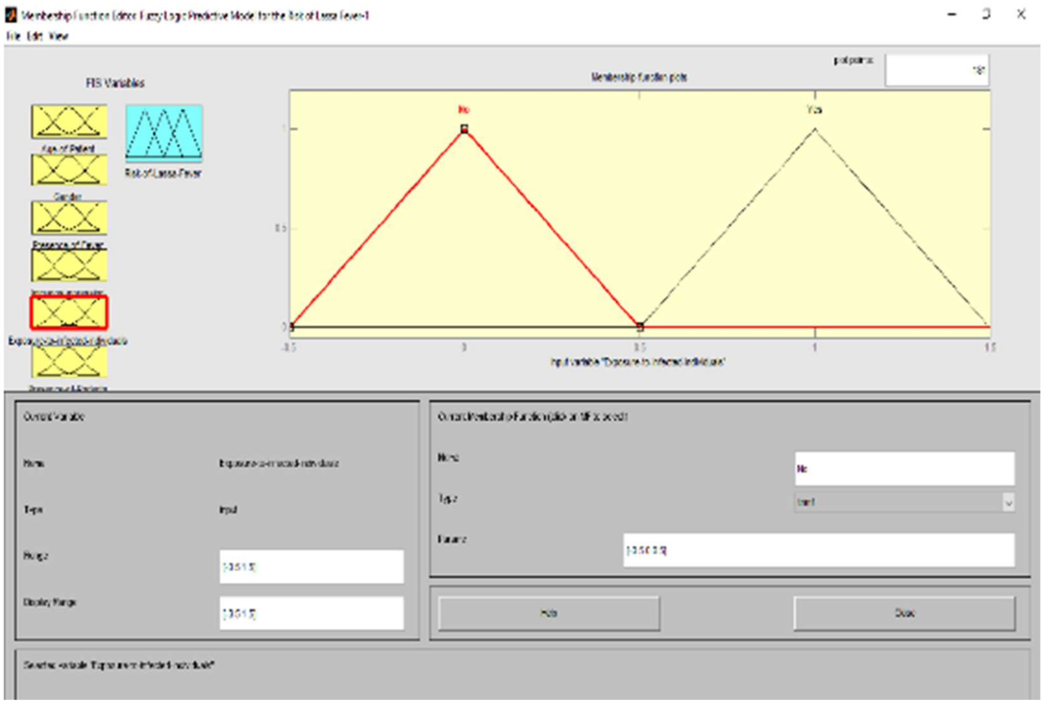

Fig. .5: Fuzzification of Exposure to infected individuals

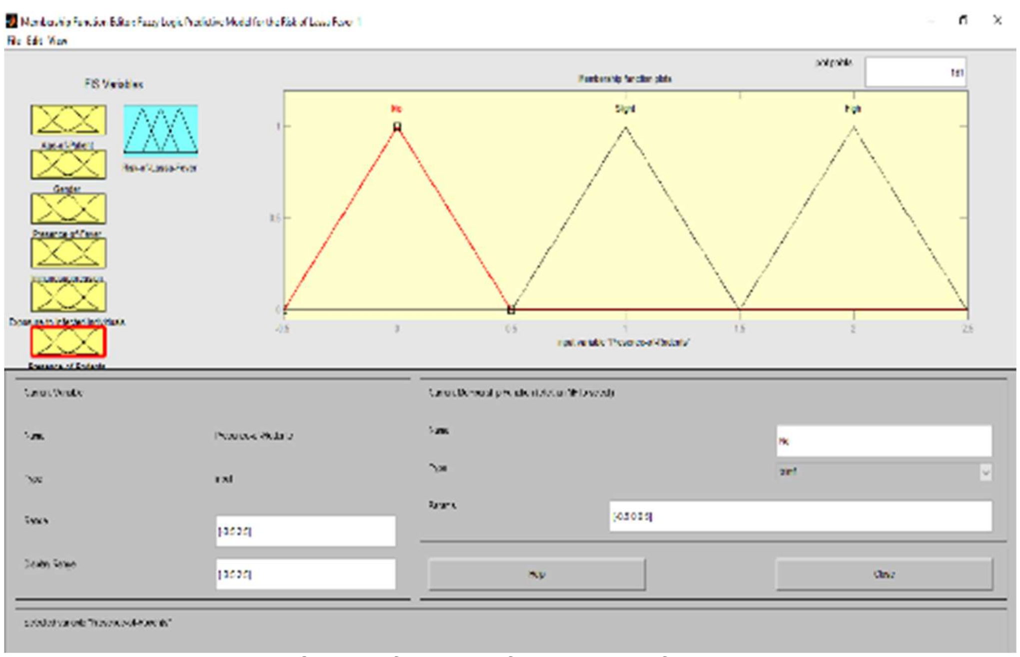

Fig. 6: Fuzzification of Presence of Rodents

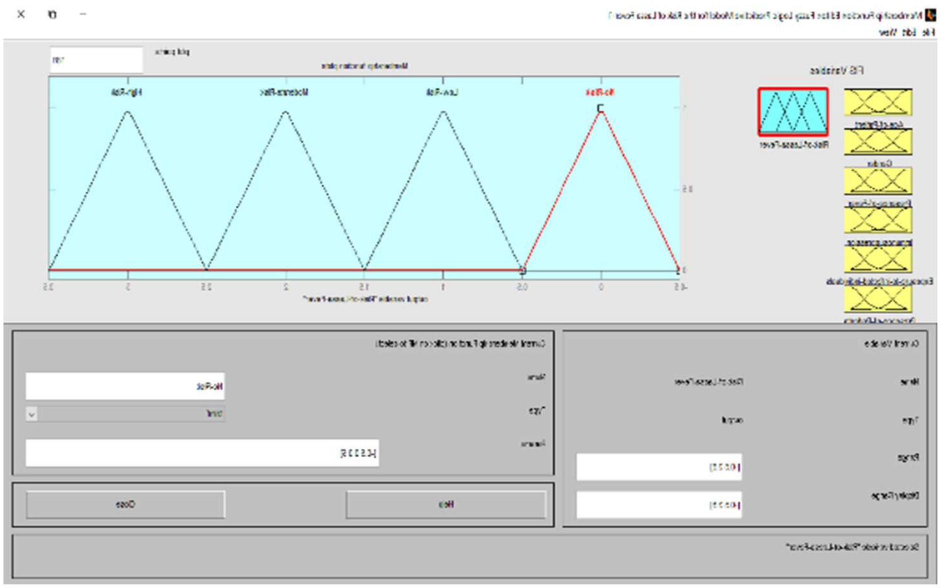

Fig. 7: Fuzzification of Risk of Lassa Fever

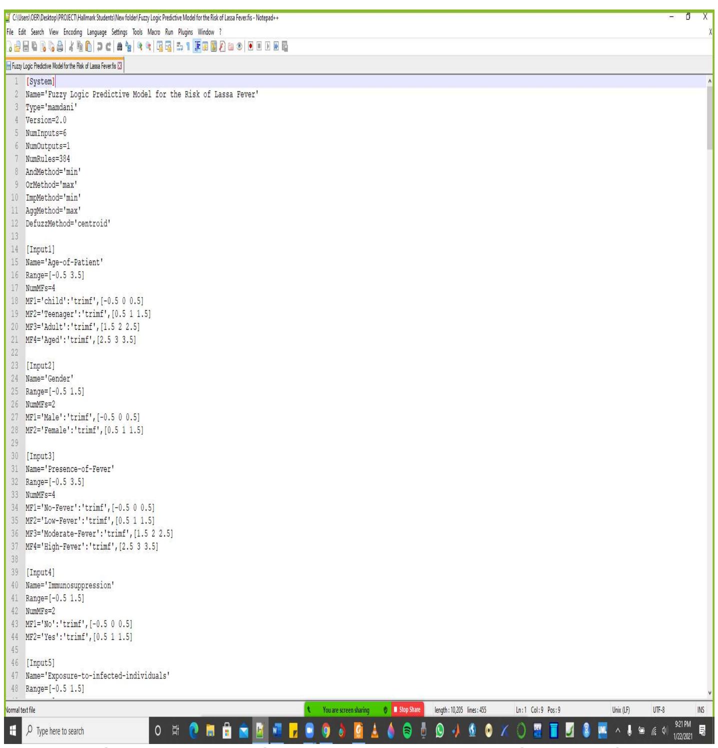

Fig. 8: The Risk of Lassa Fever Model Source Code

C. Simulation Results of the Lassa Fever Risk Predictive Model

Figure 9 displays how to import the finished source file for predicting Lassa fever risk with MATLAB. The method of choosing the .fis file's location in the desktop-based file directory is shown in Figure 10. Figure 8 shows the finished fuzzy logic model with the six input and output variables used to predict the risk factors for Lassa fever.

Figure 10 displays the 384 rules inferred for determining the Lassa fever risk, using the rule editor interface. It is evident that each inferred rule is distinct, with no linguistic variables repeating themselves in any of the rules defined.

In regard to the linguistic variables of the Lassa fever risk prediction, Figure 11 shows the graphical region selected by each rule for each variable. The crisp values were 1, 0, 0, 0, 0, 2, entered were constantly with the linguistic values of Teenager for Patient Age, Male for Gender, No Fever for Presence of Fever, No for Immunosuppression, No for Exposure to Infected Individuals, and High for Presence of Rodents, as shown in the bottom left part of the figure. According to rule number 99, combining these linguistic variables should result in a crisp value of 1 within the Low Risk of Lassa fever interval, indicating a prediction of Lassa fever risk.

The results show that using the information presented about the factors associated with the risk of Lassa fever, one can infer that the patient (or user) has a low risk of Lassa fever. The most important part of this model is the ability to predict and detect the early risk of Lassa fever for professional and unprofessional users. This model will facilitate the early detection of Lassa fever among individuals at risk.

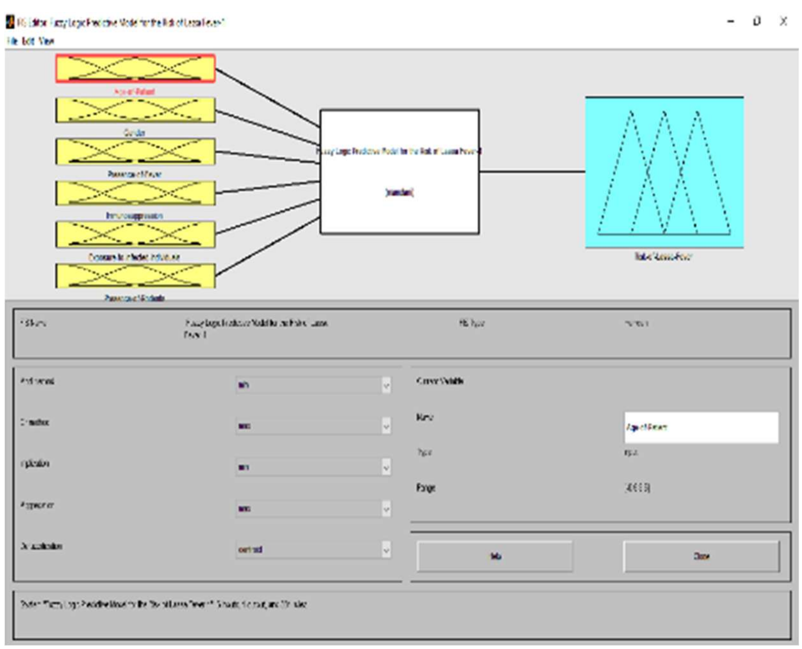

Fig. 9: Import .fis File for Prediction of Lassa fever Risk

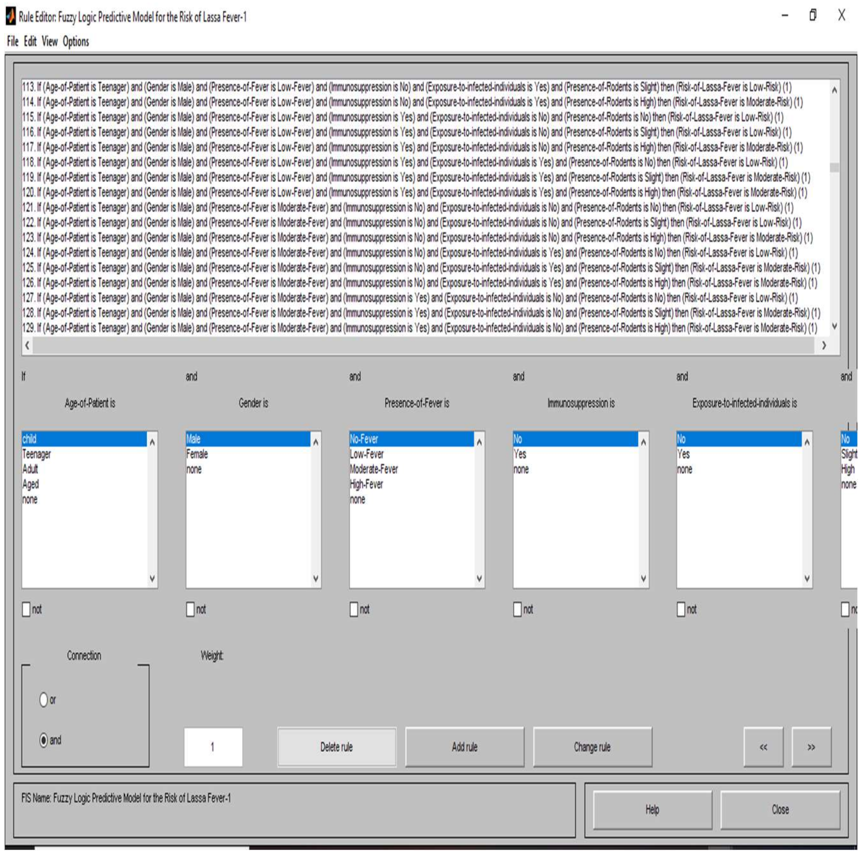

Fig. 10: IF-THEN Statement (Inferred Rules)

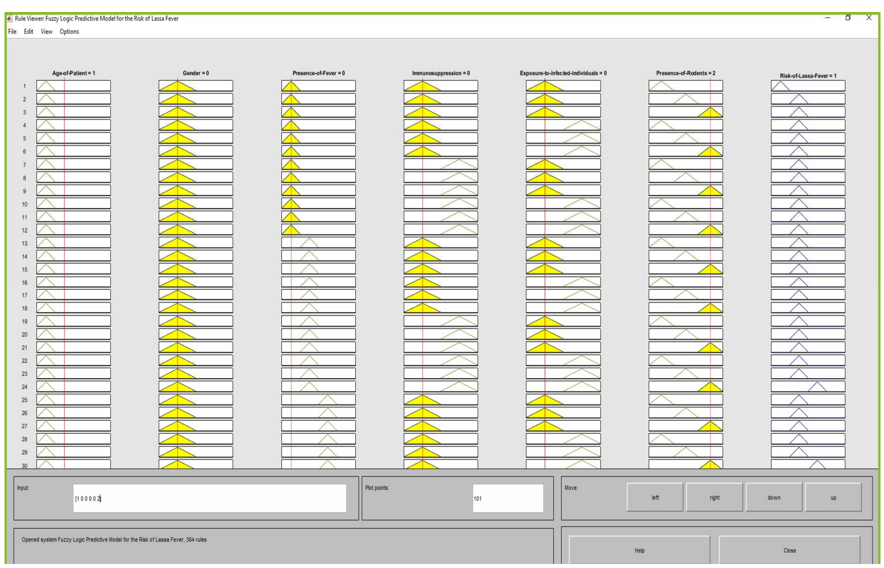

Figure 11: Inference Engine Validity Testing

E. Discussion of the Results

Based on the information supplied regarding the related risk variables, this study built a prediction model that medical experts or even laypeople may utilize to forecast the risk of Lassa fever. The study discovered six non-invasive risk variables that were used in predicting the likelihood of Lassa fever. Each risk factor was created using a set of linguistic variables, with crisp central values assigned based on the association with Lassa fever risk prediction. The given crisp central values increase as the linguistic variables' correlation increases.

Crisp values were assigned to each identified risk factor and were divided into two, three, or four parts, with 0 and 1 or 0, 1 and 2 or 0, 1, 2, and 3 assigned to each linguistic variable. As a result, triangle membership functions were used to identify labels in the intervals [-0.5 0.5], [0.5 1.5], [1.5 2.5], and [2.5 3.5], respectively, utilizing crisp intervals with centers of 0, 1, 2, and 3. Experts deduced the 384 rules to ascertain the connection between the identified risk factors and the likelihood of Lassa fever, which were utilized to develop the knowledge base of the fuzzy logic prediction model. The procedure of inference rule generation was accomplished utilizing risk factors found in estimating the risk of Lassa fever.

5. CONCLUSION

The requirement for developing a model for predicting Lassa fever risk, prompted this study. The risk of Lassa fever was assessed using information gathered on some factors linked to the disease, as identified by experts. Six factors were found to be linked to the risk of Lassa fever in the study. This was accomplished by developing a Fuzzy Logic model for predicting Lassa fever risk based on inferred rules from experts and interpreting them as IF-THEN rules, resulting in 384 inferred rules built using the membership functions. The linguistic variables for risk factors were formulated and language variables, No, Low, Moderate, and High risk were used to define the goal risk of Lassa fever. MATLAB® R2009a was used in simulating the model.

This research designed and developed a model predicting the risk of Lassa fever, which can be used to predict Lassa fever in anyone at risk of contracting the deadly disease. Detecting Lassa fever as preventive approach with the associated risk factors, which controls the hazard of Lassa fever and more cost-effective, is better than implementing a corrective approach for a patient who is already exhibiting symptoms of Lassa fever that may result in too expensive or unavailable medical treatment. These enable medical professionals and patients to take the essential steps before the condition progresses to its acute stage, which can result in sudden death

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