World Journal of Engineering Research and Technology
WJERT
www.wjert.org
SJIF Impact Factor: 5.218

DEVELOPMENT OF FUZZY LOGIC MODEL FOR PREDICTING THE LIKELIHOOD OCCURRENCE AND PREVENTION OF MONKEYPOX IN SOUTH EAST NIGERIA

A. A. Aroyehun*[1], S. O. Olabiyisi[2], O. O. Alo[3], T. O Bello[5] and Y. E. Ogunwale[6]

[1,3,4]Department of Computer Science, Adeyemi College of Education, Ondo, Nigeria.
[2]Department of ComputerScience and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[6]Department of Computer Science, Osun State College of Education, Ilesha, Nigeria.
[5]Department of Mechanical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.

Article Received on 27/06/2018 Article Revised on 17/07/2018 Article Accepted on 07/08/2018

***Corresponding Author**
A. A. Aroyehun
Department of Computer Science, Adeyemi College of Education, Ondo, Nigeria.

ABSTRACT

Monkeypox disease is contacted from a virus transmitted to humans from animals) with symptoms in humans similar to those seen in the past in smallpox patients, although less severe. From literature, a number of predictive models have been in existence that dealt with different related problems. However, these models did not take into consideration some factors that cause Monkeypox disease after eating bush meat. Hence, this research developed a Fuzzy Logic (FL) model which is characterized by eating monkey meat, contact with infected person and eating other bush meat not properly cocked to forecast the likelihood of monkeypox diseases.

KEYWORDS: Fuzzy Logic, Model, Predicting and Monkeypox.

INTRODUCTION

According to the World Health Organization (2017), Monkeypox is a rare disease that occurs mainly in remote areas of central and West Africa near tropical rainforests. Symptoms are similar to those found in human smallpox patients but much less severe, and the disease has a

low fatality rate. Monkeypox is a rare viral zoonosis (a virus transmitted to humans from animals) with symptoms in humans similar to those seen in the past in smallpox patients, although less severe. Smallpox was eradicated in 1980. However, monkeypox still occurs sporadically in some parts of Africa. Monkeypox is a member of the *Orthopoxvirus* genus in the family *Poxviridae*. The virus was first identified in the State Serum Institute in Copenhagen, Denmark, in 1958 during an investigation into a pox-like disease among monkeys. The symptoms include aches, body pain and fever as well as a bumpy localised rash on the skin. Figure1 (a-c).

Monkeypox outbreak of enteric diseases was first identified in humans in 1970 in the Democratic Republic of Congo (then known as Zaire) in a 9 year old boy in a region where smallpox had been eliminated in 1968. Since then, the majority of cases have been reported in rural, rainforest regions of the Congo Basin and western Africa, particularly in the Democratic Republic of Congo, where it is considered to be endemic. In 1996-97, a major outbreak occurred in the Democratic Republic of Congo. In the spring of 2003, monkeypox cases were confirmed in the Midwest of the United States of America, marking the first reported occurrence of the disease outside of the African continent. Most of the patients had had close contact with pet prairie dogs (WHO, 2017).

In 2005, a monkeypox outbreak occurred in Unity, Sudan and sporadic cases have been reported from other parts of Africa. In 2009, an outreach campaign among refugees from the Democratic Republic of Congo into the Republic of Congo identified and confirmed two cases of monkeypox. Between August and October 2016, a monkeypox outbreak in the Central African Republic was contained with 26 cases and two deaths.

Idowu *et al*. (2012), worked on development of a web based geo-spatial environmental health tracking system for Southwestern Nigeria. The work studied and assessed the problem of environmental health, developed a spatial environmental health data and predictive models to forecast the likelihood of environmental health related diseases. This was with a view to prototyping the models for environmental health tracking. Data were collected from purposively twenty four local government areas within Southwestern Nigeria comprising of four local government areas from each of the six states. Observations and personal interviews (both structured and unstructured) were also used to identify and assess environmental health problems within Southwestern Nigeria. The design of a spatial environmental health data model was done using the unified modelling language (UML). The model to predict the

likelihood of environmental related diseases based on environmental health problems was formulated using the MATLAB Fuzzy Logic Toolbox. Data collected from the local government areas were used to validate the performance of the model. The result showed that, when general sanitation, water, toilet facility and refuse disposal facility had probability of 0.000, the probability that environmental related diseases could occur was 0.870. If general sanitation, water, toilet facility and refuse disposal facility had probability of 0.500, then the probability that environmental related diseases could occur was 0.581. Also, if general sanitation, water, toilet facility and refuse disposal facility had probability of 1.00 , then the probability that environmental related diseases could occur was 0.130. In addition, the performance assessment of the environmental health tracking system was done on three occasions and the average value for the three occasions was recorded. The system was accessed for four different mobile broadband networks at the radius of 100m away from their base stations. It was observed that on the average for the four mobile broadband networks, the response time were 2.60, 2.60, 3.00 and 3.00 seconds respectively. On the average, the response time to access the system in any mobile broadband network in Nigeria is 2.80 seconds. In conclusion, the environmental.

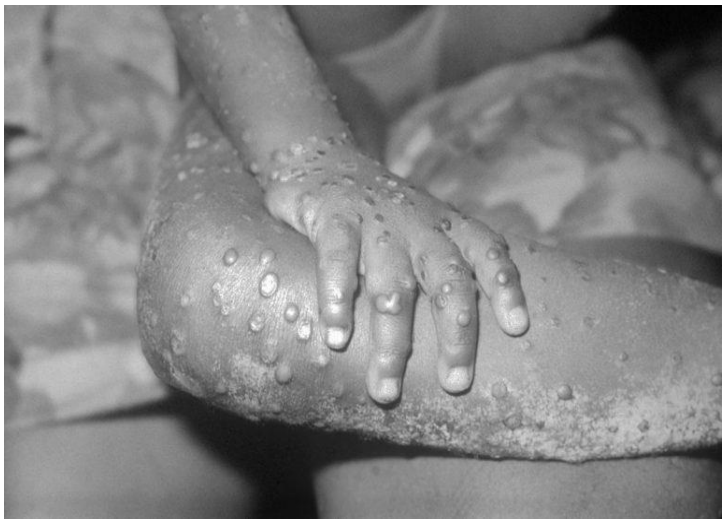

Figure 1(a).

Figure 1(b).

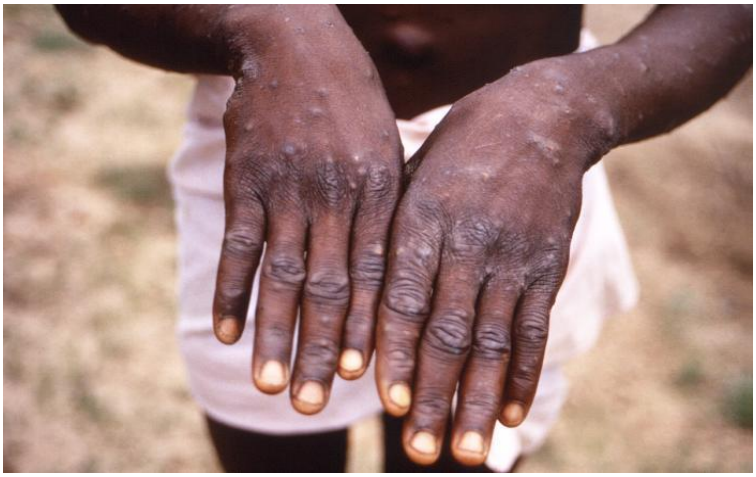

Figure 1(c).

Health tracking system allows real time tracking of environmental health problem with the ability to forecast the possibility of environmental health related diseases within the study area.

Buczak *et al.* (2015), worked on Fuzzy association rule mining and classification for the prediction of malaria in South Korea.. The work studied and assessed the accurate prediction of malaria outbreaks the may lead to public health interventions that mitigate disease morbidity and mortality. The study describe an application of a method for creating prediction models utilizing Fuzzy Association Rule Mining to extract relationships between epidemiological, meteorological, climatic, and socio-economic data from Korea. These relationships are in the form of rules, from which the best set of rules is automatically chosen and forms a classifier. Two classifiers have been built and their results fused to become a malaria prediction model. Future malaria cases are predicted as low, medium or high, where

these classes are defined as a total of 0–2, 3–16, and above 17 cases, respectively, for a region in South Korea during a two-week period. Based on user recommendations, high is considered an outbreak. Model accuracy was described by Positive Predictive Value (PPV), Sensitivity, and F-score for each class, computed on test data not previously used to develop the model. For predictions made 7–8 weeks in advance, model PPV and Sensitivity are 0.842 and 0.681, respectively, for the high classes. The F0.5 and F3 scores (which combine PPV and Sensitivity) are 0.804 and 0.694, respectively, for the high classes. The overall farm results (as measured by F-scores) are significantly better than those obtained by Decision Tree, Random Forest, Support Vector Machine, and Holt-Winters methods for the high class. For the medium class, Random Forest and farm obtain comparable results, with farm being better at F0.5, and Random Forest obtaining a higher F3. A previously described method for creating disease prediction models has been modified and extended to build models for predicting malaria. In addition, some new input variables were used, including indicators of intervention measures. The South Korea malaria prediction models predict low, medium or high cases 7–8 weeks in the future. This paper demonstrates that our data driven approach can be used for the prediction of different diseases.

In the review, models ware developed by Montosi *et al.* (2012); Idowu *et al.* (2012); Corner *et al.* (2013); ChunXiang *et al.* (2013); Fakai *et al.* (2013); Ibrahimma *et al.* (2013); Koepke *et al.* (2014) and Buczak *et al.* (2015) to deal with different bush meat related problems. However, these models did not take into consideration some factors that cause monkeypox after eatingbush meat. Hence, this research developed a model for predicting the likeklihood of monkeypox disease which is characterized eating monkey meat, contact with infected person and eating other bush meat not properly cocked using fuzzy logic.

Statement of the Problem

Owing to the fact that there is no national data base on edible bush meat in some underdeveloped and developing countries which often give rise to some devastating illnesses, a number of predictive models were developed in literature to forecast the likelihood of environmental related diseases with less emphasis on monkeypox diseases. Examples of such existing models which conceptualized environmental related diseases include Idowu *et al.* (2012), Corner *et al.* (2013), ChunXiang *et al.* (2013), Fakai *et al.* (2013), Ibrahimma *et al.* (2013)Koepke *et al.* (2014)and Buczak *et al.* (2015). Thus, most existing models could not be

used to study and predict the lilkelihood of monkeypox. Hence, this research developed predictive models for monkeypox diseases using Fuzzy Logic.

Purpose of the Study

The Study specifically ascertains the efficiency of Fuzzy Logic model in predicting the likelihood of monkypox outbreak in South Eastern Nigeria.

Research design

In this paper, a fuzzy logic-based prediction model is proposed with the aim of predicting the likelihood of edible bush meat related disease in South East Nigeria. The study started with the identification of the problem of predicting monkeypox disease likelihood given a number of symptoms/factors considered as input variables (3 in all). A review of related literature was performed to identify understand monkeypox disease and its symptoms in addition to related works done in the past. Following this, knowledge was elicited from an expert (medical practitioner) located at the primary health Centre, Enugu, Enugu State in understanding and verifying the information concerning monkeypox related disease symptoms. The elicited knowledge was used to build the inference engine of the proposed system – this is part of the model formulation technique which also includes the fuzzification of the input and output variables. the model formulation is made complete by the identification of the aggregation method chosen for the inference engine alongside the defuzzification method required for producing the output variable which is the likelihood of monkeypox disease (No and Yes).

Data identification and collection

A number of symptoms are known to be connected to monkeypox disease, among all these symptoms only three were identified as being the most important and relevant symptoms to the level of monkeypox disease. This information was collected via structured interview with the medical practitioner who identified the factors and emphasized 3 main factors which are most easily used in identifying the likelihood of monkeypox disease based on his experience in medical practice. The monkeypox disease likelihood is defined as either: 0%, between 50% and 100%, and greater than 50%; the monkeypox was classified as either No, probable and high while the degree of likelihood of monkeypox is classified as either less than 50% and greater than or equal to 50%.

In addition to the identification of the data variables, an understanding of the pattern of

distribution was important in identifying the best membership function that could be used in plotting the labels of each variables. The number of rules required by the fuzzy logic inference system was calculated by multiplying the labels of each variable with each other; therefore we have 3*3*3 = 27 different rules. This information was necessary in the development of the fuzzy logic inference system.

Fuzzy logic model formulation

Fuzzy logic systems have the ability to decide and control a system using the knowledge of an expert. Fuzzy logic systems are mostly profitable in systems with sophisticated environments where a clear and obvious model of the system is not achievable. In order to develop the fuzzy logic system required for the prediction of the likelihood of monkeypox disease, a number of activities are needed to be accomplished. The Fuzzy Logic System available in the Fuzzy Logic Toolbox of the Matrix Laboratory 8.1(R20013a) software has three parts:

i. A set of Inputs represented by their respective membership functions;
ii. An Inference Engine which contains the IF-THEN rules (domain knowledge); and
iii. An Output represented by its membership functions.

The membership functions will be used to map the values of each input and output variables into a [0,1] interval with the use of triangular and trapezoidal membership functions (where appropriate); this process is referred to as a Fuzzification process. After Fuzzification; the fuzzified inputs must be mapped to the fuzzified output via the use of operators (AND, OR and NOT) to develop IF-THEN rules that describe the relationship between every input (Eating monkey meat; Contact with infected people; and Eating other bush meat, likelihood factors) and output (likelihood of the monkeypox disease) variable. The different rules are used to generate different results which are then aggregated to just one fuzzified output. This fuzzified output will then be defuzzified using the centroid method which selects the centre of the polygon to determine the label of the output variable as high, probable or No. The most prominent reasons that justify the use of fuzzy logic systems today are (Aramideh et al, 2014):

(a) The sophistication of the natural world which leads to an approximate description or a fuzzy system for modeling; and
(b) The necessity of providing a pattern to formulate mankind knowledge and applying it to actual systems.

The process of development of the fuzzy inference system needed for the prediction of bush meat eating related problem may be summarized as follows:

(i) Fuzzification of inputs and outputs;
(ii) Construction of the inference engine;
(iii) Rule aggregation; and
(iv) Defuzzification of output variables.

Defining membership functions

Before the process of Fuzzification, it is very important to properly describe the crisp values that was used in mapping the values of the membership function which was needed by the fuzzy logic system. For the discrete variables with nominal values or Boolean (yes/no) – the values: 0, 1, 2….. n-1 was assigned to each value for n labels; this is the case for Monkeypox as NO=0, propable=0.2-0.4 and Yes=1. For the continuous variables which are measured; a value of the percentage expressed as a proportion of 0, 0.5and 1 was used, i.e. 0%, 50% and 100% respectively into the appropriate membership functions.

Fuzzification of the variables

For the purpose of this study, the triangular and trapezoidal membership functions were used to map the degree of membership of the labels of each variable used both input and output variable. Following is a description of each variable and the type of membership function used for the labels alongside the ordered pair that was used in mapping the degree of membership for each variable's label.

For the development of the Likelihood of Monkeypox disease Outbreak model; the input variables are:

(i) Eating monkey meat;
(ii) Contact with infected people; and
(iii)Eating other bush meat

Likelihood of monkeypox Disease: No(0), Probably(0.5) and High (1.0) indicated.
Likelihood of monkeypox Disease = (No [-0.25 0 0.25], Probably [0.25 0.5 0.75], Yes [0.75 1 1.25]).

Following are the classification of the degree of membership of each output variable:

Likelihood of monkeypox Disease: No (0), Probably (0.5) and High (1.0) indicated in Figure

2; a For the likelihood of monkeypox disease, they are:

(i) If (Eating monkey meat= Good) and (Contact with infected people= No) and (Eating other bush meat= Good) then (Likelihood of monkeypox disease = No); and

(ii) If (Eating monkey meat= Poor) and (Contact with infected people= Yes) and (Eating other bush meat= Poor) then (Likelihood of monkeypox disease = Yes).

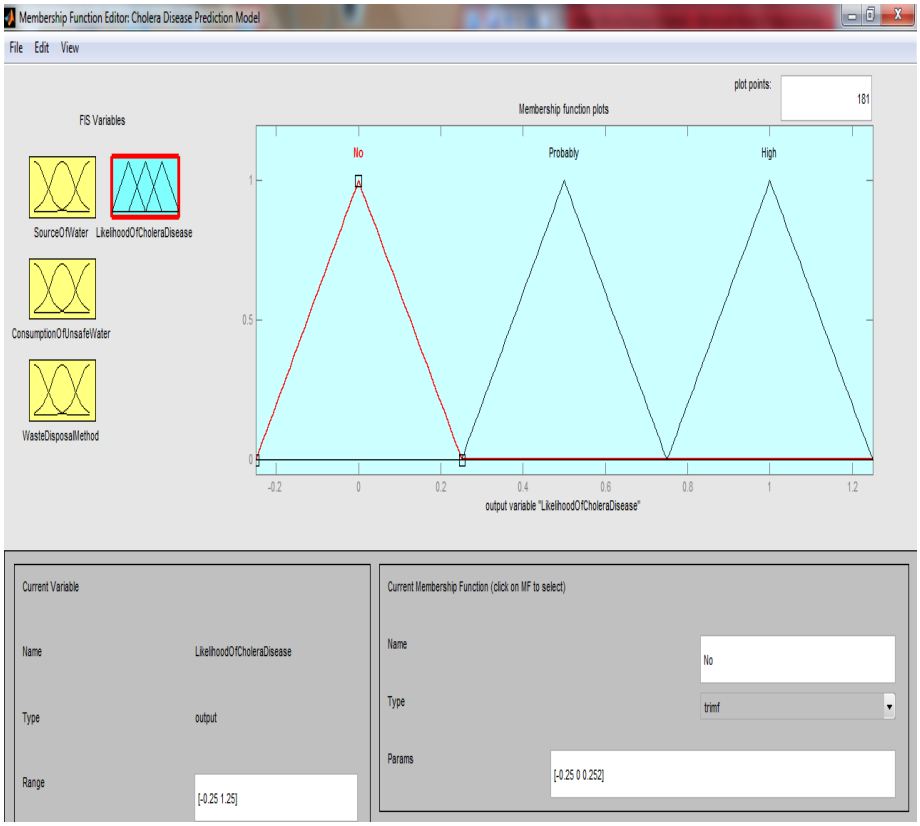

Figure 2: Membership Function for Monkeypox Disease Likelihood.

Simulation of the Formulated Fuzzy Logic Model

The simulation and analysis of FIS model was done in the MATLAB environment using historical bush meat eating disease data. After the development of the Fuzzy Inference System for the prediction of the likelihood of bush meat heating related diseases in eastern part of Nigeria, the developed models were simulated for their functionality and effectiveness. In the simulation of the model, information from 27 patients who were diagnosed by doctors in a hospital in South-Eastern part of Nigeria was taken. The variable that was used by the doctors in diagnosing disease was used as inputs for the model developed using the fuzzy logic inference engine Table 1.

Validation of the developed Fuzzy Logic Model

The simulation results for the model and historical data was used to validate the performance of the model to judge the performance of the results of the model developed. This was done with the use of a confusion matrix. The confusion matrix gave the results of the actual result along the horizontal/row while the predicted results are on the vertical/columns. Correct classifications were plotted along the diagonal from the North-west position for the no cases predicted as no, followed by probably predicted as probably and high predicted as high on the south-east corner (also called true positives and negatives). The incorrect classifications were plotted in the remaining cells of the confusion matrix (also called false positives).

The developed model was validated for the functionality and effectiveness. In the validation of developed model, information from 27 patients who were diagnosed by doctors in a hospital in south-western Nigeria was taken. The variable that was used by the doctors in diagnosing monkeypox disease was used as inputs for the model developed. Out of the total 27 cases there were 23 correct classifications and 4 incorrect classifications which showed the following distributions. Out of the 7 No cases, 6 was correct while 1 was probably. Out of the 16 probably cases, there was 14 correct classifications and 2 misclassification as yes. Out of the 4 High cases there was 1 misclassification and 3 correct classification. The number of correct classifications shows that the monkeypox disease prediction model has an accuracy of 85.19% as shown in Table 2.

Let the null hypothesis be and the alternative hpothesis be

H_0: There is no significant difference between the simulated and real data

H_1: There is significant difference between simulated and real data.

$$\overline{X}_1 = \frac{\sum X_1}{n_1} \quad (1)$$

$$\overline{X}_2 = \frac{\sum X_2}{n_2} = \frac{45}{9} = 5 \quad (2)$$

$$S_1^2 = \frac{\sum X_1^2}{n_2} - \overline{X}_1^2 = \frac{261}{9} - 5^2 \quad (3)$$

$$S_1^2 = 29 - 25 = 4 \quad (4)$$

$$S_2^2 = \frac{\sum X_2^2}{n_2} - \overline{X}_2^2 = \frac{253}{9} - 5^2 = 3.1111 \quad (5)$$

Let t_{cal} represent t-calculated.

$\therefore$

$$t_{cal} = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}} \quad (6)$$

$$= \frac{5-5}{\sqrt{\frac{(9-1)\times 4+(9-1)\times 3.1111}{9+9-2}\left(\frac{1}{9}+\frac{1}{9}\right)}} \quad (7)$$

$$t_{cal} = \frac{0}{\sqrt{\frac{8\times 4+8\times 3.1111}{16}\left(\frac{2}{9}\right)}} \quad (8)$$

$t_{cal} = 0$

t_{table} -at the level of significant t 0.05 is given by 1.75.

Since t_{cal} is less than $t_{cal}(<)t_{table}$, then, the null hypothesis H_0 is accepted while the alternative hypothesis H_1 is rejected. Therefore, it can be concluded that there is no significant difference between the simulated and real data.

Table 1: Rule Base for monkeypox disease prediction model.

Rule#	Eating monkey meat	Contact with infected people	Eating other bush meat	Likelihood of monkeypox Disease
1	Good	Never	Good	No
2	Good	Never	Fair	No
3	Good	Never	Poor	No
4	Good	Sometimes	Good	No
5	Good	Sometimes	Fair	No
6	Good	Sometimes	Poor	Probably
7	Good	Yes	Good	Probably
8	Good	Yes	Fair	Probably
9	Good	Yes	Poor	Probably
10	Fair	Never	Good	Probably
11	Fair	Never	Fair	Probably
12	Fair	Never	Poor	High
13	Fair	Sometimes	Good	No
14	Fair	Sometimes	Fair	No
15	Fair	Sometimes	Poor	Probably
16	Fair	Yes	Good	Probably
17	Fair	Yes	Fair	Probably
18	Fair	Yes	Poor	High
19	Poor	Never	Good	No
20	Poor	Never	Fair	Probably

21	Poor	Never	Poor	High
22	Poor	Sometimes	Good	Probably
23	Poor	Sometimes	Fair	High
24	Poor	Sometimes	Poor	Probably
25	Poor	Yes	Good	Probably
26	Poor	Yes	Fair	High
27	Poor	Yes	Poor	High

Table 2: Performance evaluation results of the monkeypox, diseases likelihood prediction model.

Performance Metrics	**Monkeypox Disease Likelihood**		
Accuracy (%)	85.19		
Likelihood	**No**	**Probably**	**Yes**
TP rate (recall) or Sensitivity	0.857	0.857	0.750
FP rate (false alarm)	0.000	0.182	0.087
Precision	1.000	0.875	0.600
Specificity	1.000	0.818	0.913

Table 2: Data Analysis Table

Actual likelihood (X_1)	**Predicted likelihood (X_2)**	X_2^1	X_2^2
4	5	16	25
9	7	81	49
2	3	4	9
5	4	25	16
7	8	49	64
3	3	9	9
4	3	16	9
6	6	36	36
5	6	25	36
$\sum X_2 = 45$			$\sum X_2^2 = 253$

Fuzzy Logic Model Formulation Result

The formulation results (Figure 3) for membership functions that were developed for the model are as follows:

Monkeypox disease likelihood prediction model Each membership function for Monkeypox disease model is described as follows:

Eating Monkey meat = (Good [-0.25 0 0.25], Fair [0.25 0.5 0.75], Poor [0.75 1 1.25])

$$\text{Eating Monkey meat}\,(Good; -0.25\ 0\ 0.25) = \begin{cases} 0, & x > -0.25 \\ \dfrac{x + 0.25}{0.25}, & -0.25 < x \leq 0 \\ \dfrac{0.25 - x}{0.25}, & 0 < x \leq 0.25 \\ 0, & 0.25 > x > 0.25 \end{cases}$$

$$\text{Eating Monkey meat } (Fair; 0.25\ 0.5\ 0.75) = \begin{cases} 0, & x \leq 0.25 \\ \dfrac{x - 0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \dfrac{0.75 - x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{cases}$$

$$\text{Eating Monkey meat}(Poor; 0.75\ 1\ 1.25) = \begin{cases} 0, & x \leq 0.75 \\ \dfrac{x - 0.75}{0.25}, & 0.75 < x \leq 1 \\ \dfrac{1.25 - x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{cases}$$

Contact with infected people = (Never [-0.25 0 0.25], Sometimes [0.25 0.5 0.75], Yes[0.75 1 1.25])

$$\text{Contact with infected people}(Never; -0.25\ 0\ 0.25) = \begin{cases} 0, & x \leq -0.25 \\ \dfrac{x + 0.25}{0.25}, & -0.25 < x \leq 0 \\ \dfrac{0.25 - x}{0.25}, & 0 < x \leq 0.25 \\ 0, & 0.25 < x > 0.25 \end{cases}$$

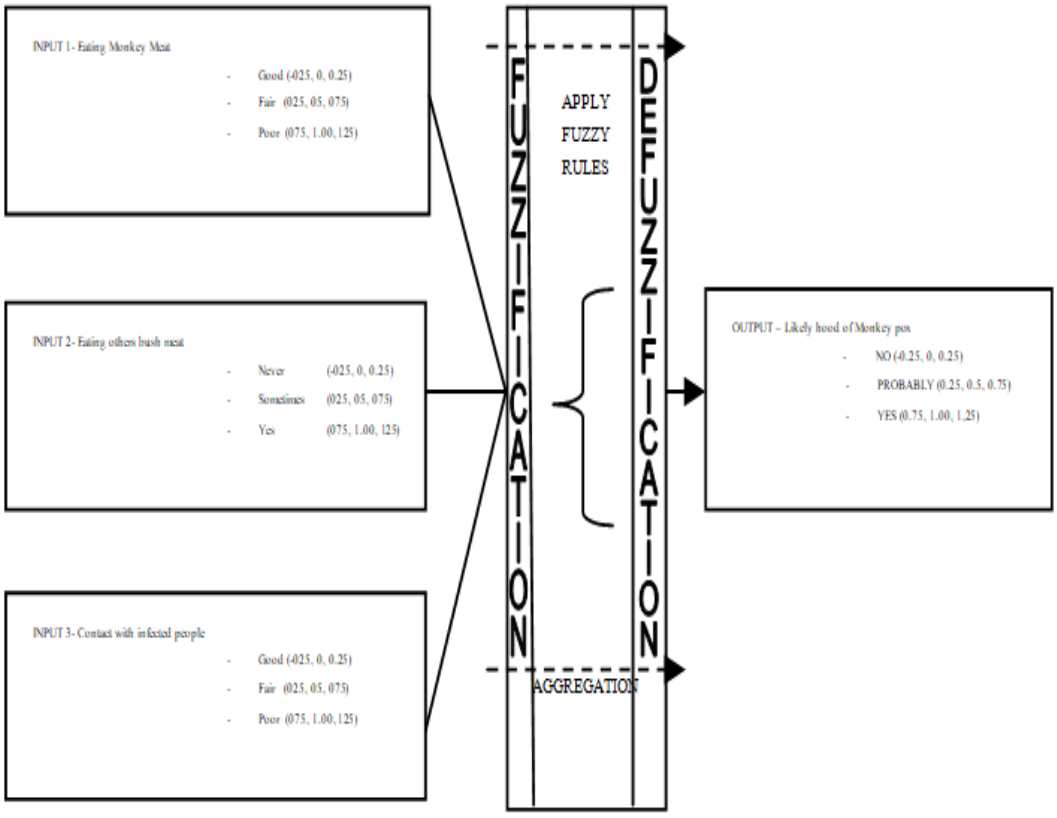

Figure 3: Schematic Diagram of Model for Monkeypox Disease Likelihood Prediction.

Table 3: Results of testing monkeypox Prediction model on patients.

S/N	Source of Water	Consumption of unsafe water	Waste disposal method	Likelihood of Cholera Disease	
				Actual	Predicted
1	Good	Poor	Good	No	No
2	Good	Poor	Fair	No	No
3	Good	Poor	Poor	No	No
4	Good	Fair	Good	No	Probably
5	Good	Fair	Fair	Probably	Probably
6	Good	Fair	Poor	Probably	Probably
7	Good	Good	Good	No	No
8	Good	Good	Fair	Probably	Probably
9	Good	Good	Poor	Probably	Probably
10	Fair	Poor	Good	No	No
11	Fair	Poor	Fair	Probably	Probably
12	Fair	Poor	Poor	No	No
13	Fair	Fair	Good	Probably	Yes
14	Fair	Fair	Fair	Probably	Yes
15	Fair	Fair	Poor	Probably	Probably
16	Fair	Good	Good	Yes	Yes
17	Fair	Good	Fair	Probably	Probably
18	Fair	Good	Poor	Probably	Probably
19	Poor	Poor	Good	Yes	Yes
20	Poor	Poor	Fair	Probably	Probably
21	Poor	Poor	Poor	Probably	Probably
22	Poor	Fair	Good	Probably	Probably
23	Poor	Fair	Fair	Probably	Probably
24	Poor	Fair	Poor	Probably	Probably
25	Poor	Good	Good	Yes	Yes
26	Poor	Good	Fair	Probably	Probably
27	Poor	Good	Poor	Yes	Probably

$$\text{Contact with infected people}(Sometimes; 0.25\ 0.5\ 0.75) = \begin{cases} 0, & x \leq 0.25 \\ \dfrac{x - 0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \dfrac{0.75 - x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{cases}$$

Eating other bush meat = (Good [-0.25 0 0.25], Fair [0.25 0.5 0.75], Poor[0.75 1 1.25])

$$\text{Likelihood Of Monkeypox Disease}(Probably; 0.25\ 0.5\ 0.75) = \begin{cases} 0, & x \leq 0.25 \\ \dfrac{x - 0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \dfrac{0.75 - x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{cases}$$

$$\text{Likelihood Of Monkeypox Disease}(Yes; 0.75\ 1\ 1.25) = \begin{cases} 0, & x \leq 0.75 \\ \frac{x-0.75}{0.25}, & 0.75 < x \leq 1 \\ \frac{1.25-x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{cases}$$

$$\text{Eating other bush meat}(Good; -0.25\ 0\ 0.25) = \begin{cases} 0, & x \leq -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \leq 0 \\ \frac{0.25-x}{0.25}, & 0 < x \leq 0.25 \\ 0, & 0.25 < x > 0.25 \end{cases}$$

$$\text{Eating other bush meat}(Fair; 0.25\ 0.5\ 0.75) = \begin{cases} 0, & x \leq 0.25 \\ \frac{x-0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \frac{0.75-x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{cases}$$

$$\text{Eating other bush meat}(Poor; 0.75\ 1\ 1.25) = \begin{cases} 0, & x \leq 0.75 \\ \frac{x-0.75}{0.25}, & 0.75 < x \leq 1 \\ \frac{1.25-x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{cases}$$

Likelihood of Monkeypox Disease = (No [-0.25 0 0.25], Probably [0.25 0.5 0.75], Yes[0.75 1 1.25]).

$$\text{Likelihood Of Monkeypox Disease}(No; -0.25\ 0\ 0.25) = \begin{cases} 0, & x \leq -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \leq 0 \\ \frac{0.25-x}{0.25}, & 0 < x \leq 0.25 \\ 0, & 0.25 < x > 0.25 \end{cases}$$

$$\text{Contact with infected people}(Yes; 0.75\ 1\ 1.25) = \begin{cases} 0, & x \leq 0.75 \\ \frac{x-0.75}{0.25}, & 0.75 < x \leq 1 \\ \frac{1.25-x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{cases}$$

Simulation Result of the Formulated Fuzzy Logic Model

The simulation result of the model recorded using the data collected from Twenty-seven (27) patients as shown in Tables 3, as depicted in Figure 4 and discussed as follows; The model provided a view also called the surface view which shows the relationship between each variable with respect to the likelihood of bush meat eating related diseases which in the case of this research is Monkeypox.

The result of Monkeypox FIS model reflected in Figure (4-6) showing the relationship between two variables with respect to the likelihood of Monkeypox that is, the relationship between contact with infected people and the Eating Monkey meat which indicates the following observations: the likelihood of Monkeypox disease is No and Probably (0 – 0.5) if the contact with infected people is Never and Sometimes (0.0 – 0.6) and the Eating Monkey meat is also good (0 – 0.2) also, the likelihood of Monkeypox disease is Probably and High (0.5 – 1.0) if the contact with infected people is Yes (0.6 – 1.0) and the Eating Monkey meat is fair and high (0.2 – 1.0). Figure 5 surface diagram shows the relationship betFween Eating other bush meat and contact with infected people which indicates the following observations: the likelihood of Monkeypox disease is No and Probably (0 – 0.5) if the Eating other bush meat is Good and fair (0 – 0.7) and the contact with infected people is Never and Sometimes (0 – 0.7) also, the likelihood of Monkeypox disease is Probably and High (0.5 – 1.0) if the Eating other bush meat is Poor (0.7 – 1.0) and the contact with infected people is Yes (0.7 – 1.0).

Validation Result of Monkeypox Disease Prediction Model

The validation result of developed model for the Monkeypox disease likelihood prediction model was shown in Figure 7 and depicted in table 4 and, out of the total 27 cases there were 13 correct classifications and 2 incorrect classifications which showed the following distributions. Out of the 4 No cases there was no misclassifications. Out of the 9 probably cases, there was 2 misclassifications; 1 was misclassified as No while 1 was also misclassified as High. Out of the 2 High cases there were no misclassifications. The number of correct classifications shows that the Monkeypox disease prediction model has an accuracy of 86.67%.

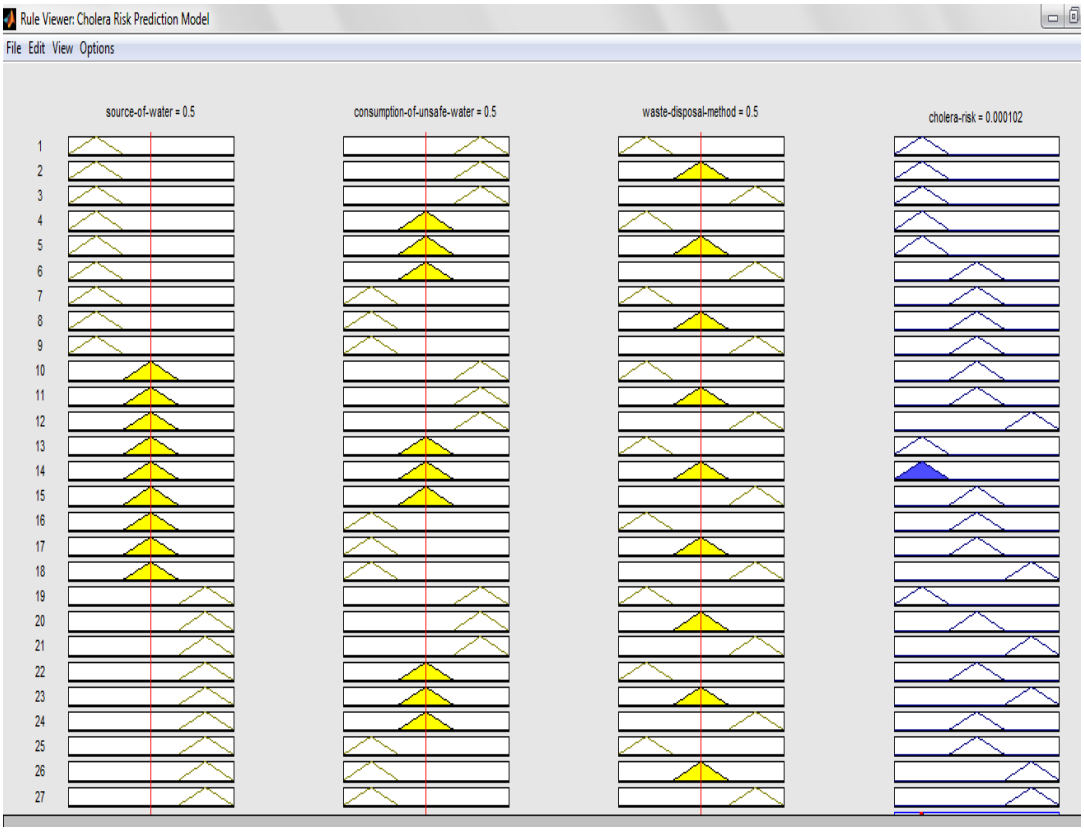

Figure 4: Simulation result of monkeypox prediction.

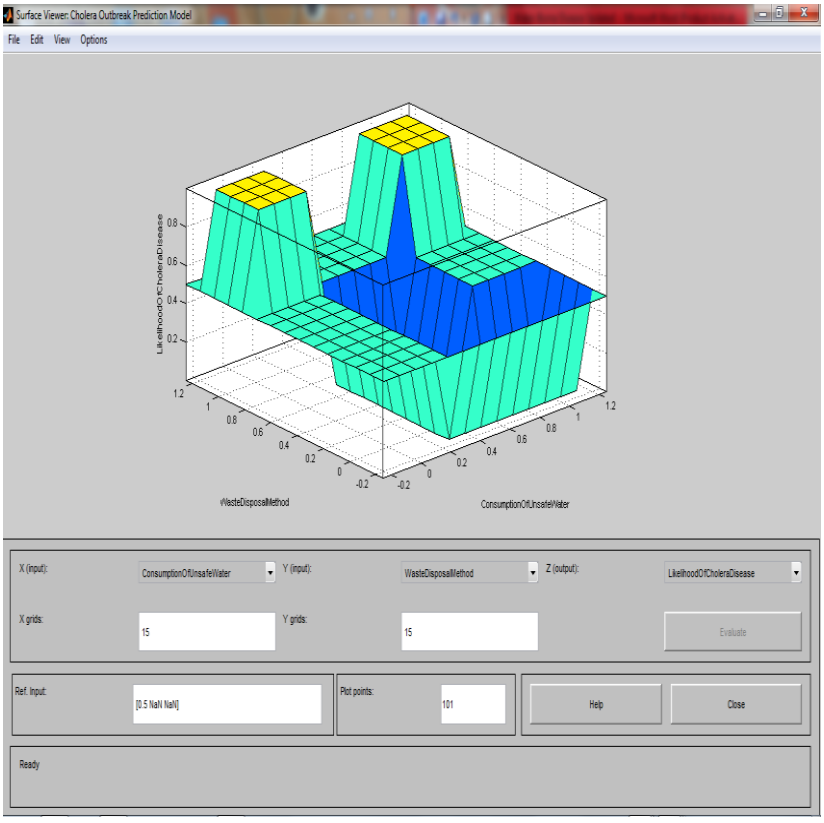

Figure 5: Surface diagram showing the relationship between Eating other bush meat and contact with infected people.

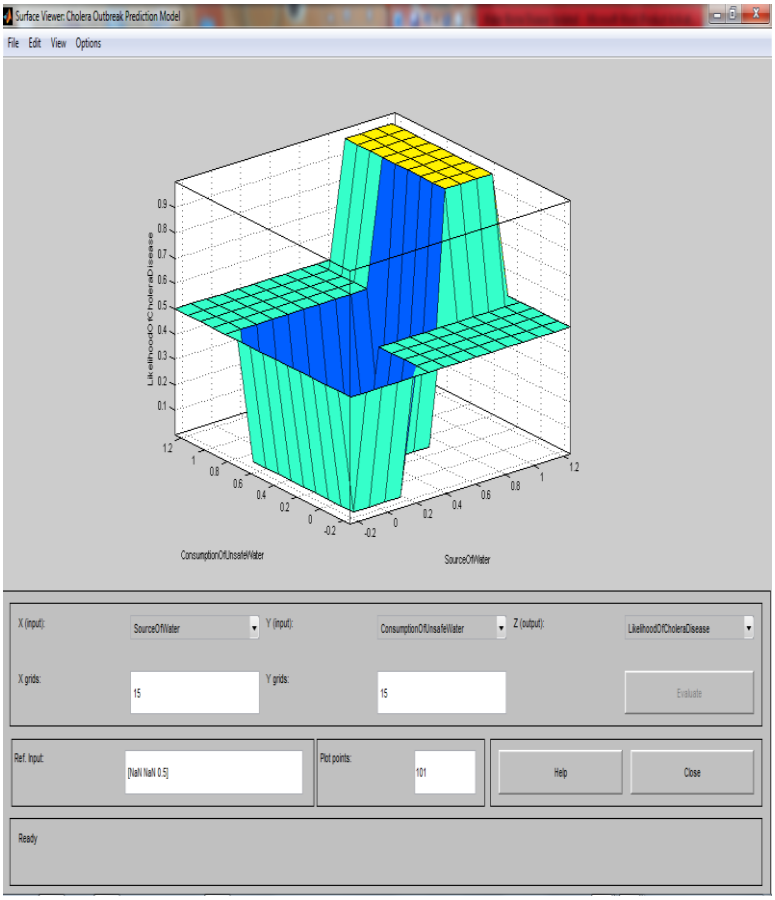

Figure 6: Surface diagram showing relationship between contact with infected peopleAnd Eating Monkey meat.

Table 4: Validation Result of Monkeypox Disease Prediction Model.

	Monkeypox Disease Likelihood		
	No	**Probably**	**High**
Predicted Likelihood	6	16	5
Actual Likelihood	7	16	4

No	Probably	Yes	
6	1	0	No
0	14	2	Probably
0	1	3	Yes

Figure 7: Confusion matrix for the result of the monkeypox disease prediction.

By identifying the no cases as the positive cases while the probable and high cases were negatives and vice versa; the following results were evaluated as shown in Figure 6. The Monkeypox disease likelihood prediction model has the highest likelihood of correctly classifying Probable cases (100%) followed by equal chances of No and High cases (66.7%).

CONCLUSION

The study developed predictive model for Monkeypox diseases using a Fuzzy Logic-Based Model. The model identified the risk factors of bush meat relate diseases, namely: Monkeypox, dysentery and diarrhoea from public health officers in South-Estern Nigeria. Data was collected from 27 patients for Monkeypox based on the identified risk factors. The study used triangular membership functions with three (3) values to fuzzify the input variables of the identified Monkeypox diseases. Rules were formulated by the environmental health officers for the construction of the inference engine of the fuzzy inference system of the prediction model for Monkeypox diseases.

Simulation of the developed fuzzy logic model was carried out using the MATLAB software for the Monkeypox diseases sampled in this study. Three fuzzy logic models were formulated for Monkeypox disease. The study identified Eating Monkey meat, contact with infected people and Eating other bush meats as factors of Monkeypox. The study validated the fuzzy logic model for the Monkeypox diseases based on the data collected. The study concluded that based on the validation of the model, it was observed that the fuzzy logic models had performances of at least 70% with the model for Monkeypox having 85% accuracy. It was concluded form the results of this study that the fuzzy logic model could clearly distinguish cases of those that did not have Monkeypox diseases but difficulty in distinguishing *Probably* and *Yes* cases. The study concluded that the fuzzy logic model would provide an effective means for the detection and management of Monkeypox diseases thereby improving decision-making process.

REFERENCE

1. Abraham, B. & Nath, S. (2003). “Hybrid Intelligent Systems Design”, A Review of a Decade Research, Journal of the School of Computing and Information Technology, Monash, Australia, 1: 1-37.
2. Adebayo Peter Idowu (2015). A Spatial Data Model for Environmental Health Surveillance System in Nigeria. Journal of Research in Science, Technology, Engineering and Management, 1(1): 7-15.
3. Adekunle, L. V.; Sridhar, M. K. C.; Ajayi, A.A.; Oluwande, P.A. & Olawuyi, J.F. (2004). An assessment of the health and socio economic implications of sachet water in Ibadan: A public health challenge. Afr. J. Biomed. Res., 7: 5-8.

4. Adeniyi, I.F. (2004). The concept of water quality. Ife Environmentalist, Official Bulletin of Nigerian Society for Environmental Management (NISEM) O.A.U., 1(1): 2.
5. Akinyokun, O.C., &Adeniji, O.A. (1991). "Experimental Study of Intelligent Computer Aided Medical Diagnosis and Therapy", Association for the Advancement of Modeling and Simulation Techniques in Enterprises (AMSE); Journal of Modeling, Simulation and Control; France, 27(3): 1-20.
6. Akinyokun, O.C. & Shogbon, J.A (2006). "A Framework for Neuro-Fuzzy Expert System for Capital Investment Appraisal", Journal of the Institute of Chartered Accountants of Nigeria, Published by the ICAN, 56-65.
7. Alayon, S., Robersyon, R., Warfield, S. K., and Ruiz-Alzoa J. (2007). A Fuzzy System Forhelping Medical Diagnosis Malformations of Cortical Development. Journalof Biomedical Information, 40: 221-235.
8. Aleix, M.M. and Manli, Z. (2005) "Where Are Linear Feature Extraction Methods Applicable IEEER Transaction on Pattern Analysis and Machine Intelligence, 27(12): 1934-1944.
9. Ambler, W. (2003): The object primer: Agile model driven development with UML 2.0. 1st ed. Canada: Wiley Publishing, 23-77.
10. Anderson, J.A. (1983). "Cognitive and Psychological Computation with Neural Models", IEEE Trans Sys Man Cyb SCM, 13: 799-815.
11. Anderson LJ, MS Brumbaugh, RB Jackson. (2001). Water and tree-understory interactions: a natural experiment with oak wilt in a savanna ecosystem. Ecology, 82: 33-49.
12. Arikpo, A., Etor, R., &Usang, E. (2007). Development imperatives for the twenty-first century In Nigeria. Convergence, 40(1/2): 55-66. Retrieved from: http://www.uk.sagepub.com/journals/Journal201774.
13. Aramideh, J., Jelodar, H. (2014) Application of Fuzzy logic for presentation of an expert system to diagnose anemia. Indian Journal of Science and Technology, July 2014; 7(7): 933-938, ISSN: 0974-6846.
14. Ayoade, J.O. (1975) water resources and their development in nigeria Hydrological Sciences-~Bulletin~des Sciences Hydrologiques, 1975; 4(12): Weather 25, 414-418. Copyright © 2017 Guardian Newspapers.
15. Bagis (2008), "Fuzzy rule base design using tabular search algorithm for nonlinear System modelling", ISA Transactions, 47: 32–44.

16. Balanica, V., Dumitrache, I., Caramihai, M., Rae, W., and Herbst C. (2011). Evaluation of Breast Cancer Risk using Fuzzy Logic. *UPB, Science Bulletin Series C,* 73(1): 53-64.
17. Bai T.; Shui L.; Sun L. and Wang J. (2007). Application of GIS in response to public health emergency. *Strait Journal of Preventive Medicine*, 13(2): 75-76.
18. Berger, M., Rita Shiau, R. and Weintraub, J.M. (2006) Evidence based policy and practice: review of syndromic surveillance: implications for waterborne disease detection Journal of Epidemiology and Community Health *J Epidemiol Community Health,* 2006; 60: 543-550doi:10.1136/jech.2005.038539.
19. Berman, M.G., Jonides, J., Kaplan, S.,(2009). *The cognitive benefits of interacting with nature*. Psychological Science, 19(12): 1207-1212.
20. Bezdek, J.C (1989). "*The Coming Age of Fuzzy Logic*", Proceedings of the 1989 International.
21. Bezdek, J. and Pal, S.K. (1992). "*Fuzzy Models for Pattern Recognition*", IEEE Press, New York (Selected Reprints).
22. Bullinaria, J. A. (2012) Biological Neurons and Neural Networks,Artificial Neurons. Neural Computation: Lecture 2.
23. Buczak, A. L., Baugher, B., Guven, E., Ramac-Thomas, L.C., Elbert,Y., Babin, S.M. and Lewis, S.H.(2015) *Fuzzy association rule mining and classification for the prediction of malaria in South Korea*. *BMC* Medical Informatics and Decision Making, 15: 47. DOI:10,1186/s12911-015-0170-6.
24. Biacino, L.; Gerla, G. (2002). "*Fuzzy logic, continuity and effectiveness*". Archive for Mathematical Logic, 41(7): 643–667. doi:10.1007/s001530100128. ISSN 0933-5846.
25. Carpenter, G.A, Grossberg, S. and Rosen, D.B. (1991): Fuzzy ART: "*Fast Stable Learning and Categorisation of Analog Patterns by an Adaptive Resonance System*". Neural Networks, 4: 759-771.
26. Centres for Disease Control and Prevention. Public health conceptual data model, *US department of health and human services public health service,* 2000. Available from: www.cdc.gov/nedss/DataModels/phcdm.pdf [Accessed 3 Dec, 2015].
27. Craun, M. F., Craun,G. F., Calderon, R. L. and Beach M, J. (2006) Waterborne outbreaks reported in the United States Journal of Water and Health, 04(suppl 2).
28. Craun, G.F., *Gunther F.* Craun and Associates, Staunton, *Virginia* (2012) *The importance of waterborne disease outbreak surveillance in the United States* Ann Ist Super Sanità, 2012; 48(4): 447-459 447.

29. ChunXiang C., DuoChun W., Biao K., Biao J., Biao 1, YunFei X. And XiaoWen L.(2013) *District Prediction of Cholera Risk in China based on environmental factors Preventive Medicine Hygienics*, 58(23): 2798-2804.
30. Corner R.J., Dewan1 A. M. and Hashizume M. (2013) *International Journal of Health Geographics*, http://www.ij-ealthgeographics.com/content/12/1/13 doi:10.1186/1476-072X-12-13.
31. Dom, R.M., Kareem, S.A.,Aabidin, a., Kamaruzaman, a. and Kajindran, a. (2009); the prediction of aidssurvival: a data Mining Approach Analysis with Fuzzy Model., *IEEE Transactions on Systems, Manand Cybernetic*, 1982; 12(6): 903–907.
32. Edwards, D.D. (1993). Trouble waters in Milwaukee. WHO Regional Epidemiology: Man and Disease, 93-109.
33. Enscore RE, Biggerstaff BJ, Brown TL, Fulgham RE, Reynolds PJ and Engelthaler D.M.(2002) *Modeling relationships between climate and the frequency of human plague cases in the southwestern United States*, 1960–1997. Am J Trop Med Hyg, 2002; 66: 186–96.
34. Ekiye, E. and Luo Zejiao (2010) Water quality monitoring in Nigeria; Case Study of Nigeria's industrial cities. [Journal of American Science, 2010; 6(4): 22-28]. (ISSN: 1545-1003).luozejiao@hotmail.com.
35. Fenwick, A. (2006). *Waterborne infectious diseases- Could they be consigned to history*? Science, 313: 1077-1081.
36. Ganiyu, R.A.(2011) *Modelling And Simulation of Multi-Phase Traffic Light Controlled Intersections UsingTine Coloured Petrinets* an Unpublished PhD.
37. Ginsberg J., Mohebbi M., Patel R., Brammer, M. L., Smolinski, and L. Brilliant.(2009) *Detecting inuenza epidemics using search engine query data*. Nature, 457: 1012-1014.
38. Gleick P. H., (2002) Dirty Water*: Estimated Deaths from Water-Related Disease 2000-2020*, Pacific Institute Research Report.
39. Hamed M. M., Khalafallah M. G., Hassanien E. A.(2004): *Prediction of wastewater Treatment plantperformance using artificial neural networks.* Environ. Model. Soft, 2004; 19: 919-928.
40. Hill, G., Horstkotte, E. & Teichrow, J. (1990). *Fuzzy-C development system – users' manual*, Togai Infralogic, 30 Corporate Park, Irvine, CA 92714, USA.
41. Hoberman, S., (2009). *Data Modeling Made Simple 2nd Edition*, Technics Publications, LLC.

42. Hopkins, R. S., Gaspard, G. B., Williams, F. P., Karlin, R. J, Cukor, G., and Bladlow N. R (1984) *A community waterborne gastroenteritis outbreak: evidence for rotavirus as the agent*. Am J Public Health, 74: 263-265.
43. Idowu, P. A. (2012): Development of a Web Based Geo-spatial Environmental Health Tracking System for Southwestern Nigeria. *I.J. Information Technology and Computer Science*, 2012; 7: 61-71 (http://www.mecs-press.org/) DOI: 10.5815/ijitcs.2012.07.08.
44. Ifabiyi, I.E. (2011). Spatial distribution and performance of water pumps in the rural areas of Kaduna State, Nigeria before the Second Republic. *European Journal of Social Sciences*, 25(3): 15-25.
45. Innocent, P.R. (1997). Application of the Fuzzy ART / MAP and MinMax / Map Neural Network Nodels to Radiographic Image Classification: *Journal of Artificial Intelligence in Medicine*, 11: 241- 263.
46. Innocent, P.R. (2000). "*Fuzzy Symptoms and a Decision Support-Index for the Early Diagnosis of Confusable Diseases*", Proceedings of the RASC Conference, Centre for Computation.