# A Neuro-Fussy Based Model for Diagnosis of Monkeypox Diseases

**Article** · May 2018



Joshua Tom
Elizade University



Promise Nlerum
Federal University, Otuoke, Bayelsa State

RESEARCH ARTICLE OPEN ACCESS

# A Neuro-Fussy Based Model for Diagnosis of Monkeypox Diseases

Tom, Joshua Joshua [1], Dr. Anebo, Nlerum P [2]
Department of Computer Science, Federal University of Technology, Akure
Department of Computer Science, Federal University, Otuoke
Nigeria

**ABSTRACT**
The largest vertebrate viruses known, infecting humans, and other vertebrates are poxviruses including cowpox, vaccinia, variola (smallpox), and monkeypox viruses. Monkeypox was limited to the rain forests of central and western Africa until 2003. A smallpox-like viral infection caused by a virus of zoonotic origin, monkeypox belongs to the genus *Orthopoxvirus*, family *Poxviridae*, and sub-family *Chordopoxvirinae*. Monkeypox has a clinical presentation like ordinary forms of smallpox, including flulike symptoms, fever, malaise, back pain, headache, and characteristic rash. In view of the eradication of smallpox, such symptoms in a monkepox endemic region should be carefully diagnosed. The problem in diagnosing monkeypox lies in the fact that it is clinically indistinguishable from other pox-like illnesses making virus differentiation difficult. In this paper, we present a neuro-fuzzy based model for early diagnosis of monkeypox virus with a differentiation from other pox families.
***Keywords*** :- Monkeypox, zoonosis, fuzzy logic, diagnosis.

## I. INTRODUCTION

Monkeypox was first discovered in 1958 when two outbreaks of a pox-like disease occurred in colonies of monkeys kept for research, hence the name ‘monkeypox.’ The first human case of monkeypox was recorded in 1970 in the Democratic Republic of Congo during a period of intensified effort to eliminate smallpox. Since then monkeypox has been reported in humans in other central and western African countries.

Monkeypox is a rare disease that is caused by infection with monkeypox virus. Monkeypox virus belongs to the *Orthopoxvirus* genus in the family *Poxviridae*. The *Orthopoxvirus* genus also includes variola virus (the cause of smallpox), vaccinia virus (used in the smallpox vaccine), and cowpox virus. Symptoms include: Fever, Tiredness, Headache, Body Aches, Pustular Rashes, Swollen lymph nodes amongst others.

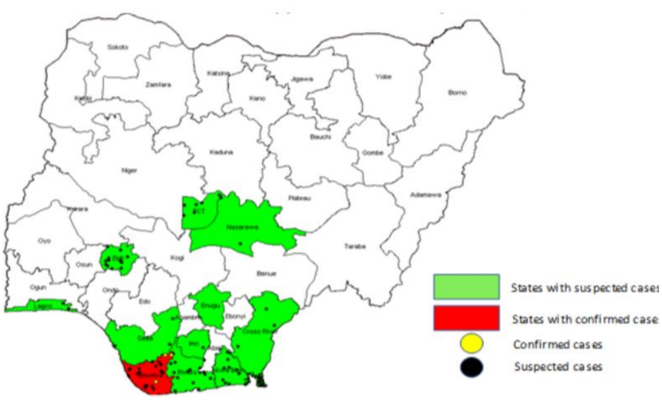


Fig.1. Distribution of Monkeypox Cases in Nigeria by State, 2017 [1].

### A. *Prevalence of Monkeypox in Nigeria*

With the advent of human monkeypox there also arise hypothetically serious health concerns for the Nigerian government and the citizens alike not excluding other African countries. This, of course, is steadily becoming a global health issue given the monkeypox outbreak in the United States in 2003 signalling the capability of the virus to blowout to new animal reservoirs outside central Africa where it is known to emanate from. In Nigeria since the onslaught of monkeypox, 74 suspected cases have been recorded in 11 States including the Federal Capital Territory as shown in figure 1. States most affected are Balyesa, Rivers, Ekiti, Akwa Ibom, Lagos, Ogun and Cross Rivers [1]. According to a study conducted by [1], the male to female ratio of suspected cases of monkeypox is 3:1 (see figure 2) and the most affected age group is 21-30 years. Although the highest age-specific incidences and the greatest number of cases occur among persons younger than 15 years, a trend toward increasing incidence among persons aged 15-30 years has been seen in recent years [2].

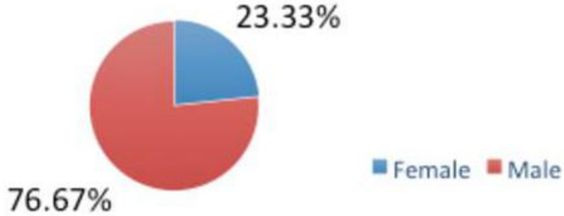


Fig. 2. Gender distribution of suspected cases of monkeypox in Nigeria in 2017[1].

Key indicators of the prevalence of monkeypox in Nigeria are presented in table I.

Table I
KEY INDICATORS OF MONKEYPOX PREVALENCE IN NIGERIA

| Key Indicators | Number |
|---|---|
| Total suspected cases | 74 |
| Total Deaths | 0 |
| Total samples received for diagnosis | 66 |
| States that have reported at least one suspected case | 11 |
| Number of contacts under follow-up | 204 |
| Confirmed cases | 3 |

### B. *Artificial Intelligence and the Fight against Diseases*

In the event of outbreaks of monkey pox diseases, close contact with infected persons or animals is the most significant risk factor for transmission of infection and therefore not advised. For this reason it is pertinent to explore avenues of diagnosis of monkey pox virus without contact with the patients. Surveillance measures and rapid identification of new cases is critical for outbreak containment. Suffice it to say that even though the human diagnostician's intelligence is sufficient to achieve satisfactory results in many diagnostic problems, certainly, this performance cannot be relied upon as it is based only on non-reproducible processes such as guessing or intuition. There must be some mechanism to support diagnosis suitable for reproducible formalization and automation. The identification of such structure and associated methods is a key goal of medical AI.

The two predominant approaches used in medical diseases diagnosis are heuristics based approach and model based diagnosis. The heuristic based solution is based mostly on formalization of experiences of experts in the field using sophisticated knowledge representation techniques. The mappings of diagnoses to their symptoms are hardly ever one-to-one considering their medical cause-effect relationships hence differentiation of diagnoses that share an overlapping range of symptoms is therefore inherently difficult. Observation of the symptoms of diseases is fraught with errors and correcting these errors requires assumptions that are seemingly only theoretically possible but not in practice. Also, the observations required for the diagnosis is conducted discretely. As a result health worker including diagnosticians or physicians are still having problems arising from elusive conjectures about diagnosis. Though, the model based diagnosis approaches derive the observed symptoms from assumed diagnoses, they simulate the established association between the symptoms and diagnosis thereby determining the cause ultimately. This understanding is developed from model based approaches' ability to learn and in the process secure an innate knowledge of the diseases characterization and uses models to mimic the functioning of diagnosed diseases.

Currently, there is no computerized system to help in this diagnostic problem. In this paper, a system for assisting physicians and the Nigeria Centre for Diseases Control (NCDC) in the diagnosis of monkeypox diseases is proposed.

### C. *Fuzzy Logic Approach to Medical Diagnosis*

Fuzzy set theory helps a lot with heuristic diagnosis. Knowledge and the resulting diagnoses are beclouded by uncertainty. Conventional expert knowledge therefore abounds with imprecise formulations. This imprecision is not because of the incompetence of the medical expert, but an intrinsic part of expert knowledge acquired through laborious experience. Any formalism that does not provide uncertainty handling is therefore not suitable to capture this knowledge

Fuzzy set theory on the other hand was conceived with the formalization of vague knowledge in mind. Together with appropriate rules of inference it provides a powerful framework for the combination of evidence and deduction of consequences based on knowledge specified in syllogistic form.

There is a fundamental necessity for fuzziness in diagnostic models. This requirement is in part due to complexities in biological systems and other natural systems where imprecision abound. Due to this, the need for a change from traditional approaches cannot be overemphasized. Hence, we must accept that there is substantial degree of fuzziness in the description of the behaviour of biological systems as well as in their characterization.

This fuzziness is the price for the ineffectiveness of precise mathematical techniques in dealing with systems comprising a very large number of interacting elements or involving a large number of variables in their decision trees." [3]. The majority of fuzzy set theories allow literally all models, as well as the ontologies within which they are created, to be fuzzified; as long as there is/are provision(s) for handling uncertainty that lies at the crossing between qualitative and quantitative methods.

Medical knowledge is simply a direct relation between the set of symptoms and the set of diseases [4]. Because medical knowledge is inherently fuzzy and the degree to which the symptoms are present as well as the degree to which the diagnoses apply can be mapped to a scale from 0 to 1, it seems a natural choice to regard the set of symptoms found in a patient, the relation representing the medical knowledge, and the set of diagnoses derived, as fuzzy sets.

## II. LITERATURE REVIEW

There are many of the model based methodologies (forming the center of interest in this paper) each characterized by a level of suitability in its application as a tool for medical diagnosis. In this section, we present a review of literature on the concept of Expert System (ES) and describe major tools for building systems with adaptation capability.

### A. *Techniques used in Modeling Intelligence*

AI has found widespread applications in manufacturing, oil exploration, construction, health and other services system automations [6]. AI mimics the human intelligence and deploys same on machines to handle complex imprecise tasks bringing speed and performance of the computer to bear. The notable problems in AI include reasoning, programming, artificial life, belief revision, how to representation knowledge, machine learning, natural language understanding, and computational theory [7, 8]. Fuzzy Logic, Neural Networks, and Genetic Algorithms, are techniques used in modeling intelligence. They are categorized as soft computing tools.

*Soft computing tools*:

The intervention of soft computing tools (techniques) in medical analysis has greatly reduced the cost of human support and medical diagnosis, with increase in accuracy of diagnosis results. Fuzzy Logic, Neural Networks, and Genetic Algorithm are common tools adopted in developing ESs [9].

***(1) Fuzzy logic***

Fuzzy Logic (FL) is one of AI techniques first introduced by Zadeh in 1965 [10] that deals with uncertainty in knowledge and simulates human reasoning in an incomplete or fuzzy data. It is impossible to cover all aspects of current developments in the field of the fuzzy logic. The aim of this sub-section is to provide its basic concepts. A more complete summary can be found in [11]. Fuzzy logic was proposed as an extension of classical logic. A classical logic set is a set with a crisp boundary. In contrast, a fuzzy set is a set without a crisp boundary. The transition from ''belonging to a set'' to ''not belonging to a set'' is gradual, and this smooth transition is characterized by membership functions that give fuzzy sets flexibility in modeling linguistic expressions.

For example, if $\mathbb{C}$ is a classical set of objects denoted generically by x, then a fuzzy set $\mathcal{F}$ in $\mathbb{C}$ is defined as a set of ordered pairs:

$$\mathcal{F} = \{(x, \mu_{\mathcal{F}}(x)) | x \in \mathbb{C}\} \tag{1}$$

where $\mu_{\mathcal{F}}(x)$ is called the membership function (MF) for the fuzzy set $\mathcal{F}$. The MF maps each element of $\mathbb{C}$ to a membership grade between 0 and 1. FL theory provides a mathematical strength to capture uncertainties associated with human cognitive processes, such as thinking and reasoning.

The central idea of the fuzzy logic is to model the imprecise aspects of the behaviour of the system through fuzzy sets and fuzzy rules. System variables are defined as linguistic variables and their possible values are linguistic terms (expressed as fuzzy sets). In fuzzy set theory, linguistic terms are used to illustrate the correlation of Membership Function (MF) which describes the membership of an element within the base of a fuzzy set. Each element has a unit value that characterizes the grade of membership of a set and such element can simultaneously belong to another set, possibly, at varying degrees. Reference [12] emphasize that a number of different types of MFs have been proposed for fuzzy control systems though [13] concluded triangular and trapezoidal MFs as the mostly used. Triangular MF is a particular case of MF that is specified by three parameters (a, b, c) and shows the degree of membership of each class of a linguistic term as possibility distribution [14].

A triangular MF is specified by three parameters {a, b, c} as in Eq. 2.

$$trimf(x; a, b, c) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ \frac{c-x}{c-b} & if\ b \le x \le c \\ 0 & if\ x \ge c \end{cases} \tag{2}$$

A trapezoidal MF is specified by four parameters {a, b, c, d} and can be determined using Eq. (3).

$$tramf(x; a, b, c, d) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{b-a} & if\ a \le x \le b \\ 1 & if\ b \le x \le c \\ \frac{d-x}{d-c} & if\ c \le x \le d \\ 0 & if\ x \ge c \end{cases} \tag{3}$$

Fig. 3a represents a typical Triangular MF of input and output variables while Fig. 3b uses four parameters to describe the membership of an element in a fuzzy set using Trapezoidal MF.

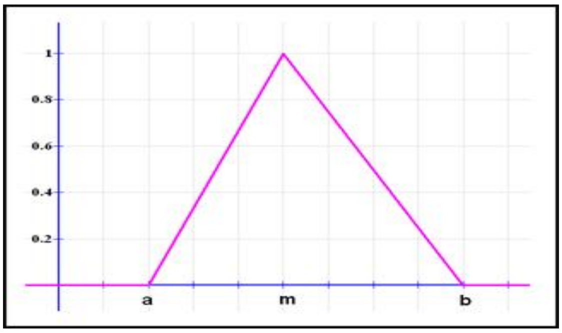


Figure 3a Triangular MF of input and output variables.

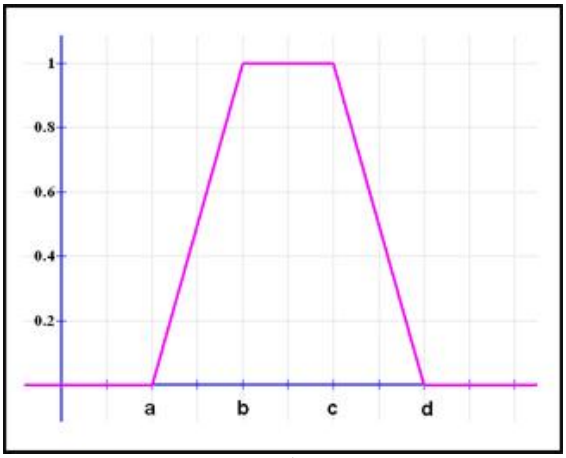


Figure 3b Trapezoidal MF of input and output variables

***(2) Neural network***

Neural Network (NN) is a group of interconnected artificial neurons that mimic the properties of biological neurons. It follows analog and parallel computing system made up of simple processing elements that communicate through a rich set of interconnections with varying contributory weights. Artificial Neural Network (ANN), is synthetic nervous systems loosely inspired to simulate functions of human brain [15]. ANN attempts to abstract the complexity of biological nervous system so as to focus on what may hypothetically matter most from an information processing point of view.

Medicine has always benefited from forefront of technology as it has boosted medicine to extraordinary levels of achievement. ANN has been successfully used in various areas of medicine such as biomedical analysis, imaging systems and drug development but extensively used in diagnosis to detect ailments such as cancer and heart problems in human [16]. The term network in ANN arises because of the function f(x) defined as a composition of other function gi(x) which are further used as composition of more functions. Fig. 4 shows a simple NN which comprises of three layers.

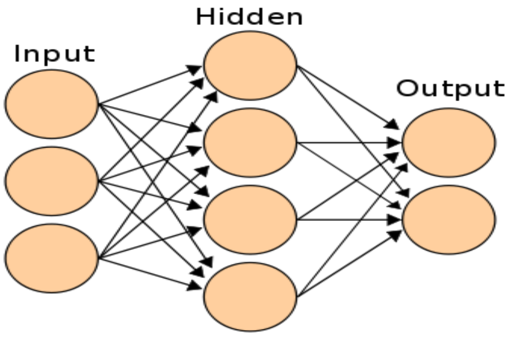


Fig. 4. Structure of a Simple Artificial Neural Network

The figure comprises of input units connected to hidden units which in turn is connected to a layer of ‘‘output” units. The activity of the input unit represented the raw information that is fed into the network; the activity of the hidden units is determined by the activity of the input units and the weights between the hidden and output units. The hidden units are free to construct their own representation of the input; the weights between the input and hidden units determine when each hidden unit is active and so by modifying the weights, a hidden unit can choose what it represents.

ANN employs learning paradigm that includes supervised, unsupervised and reinforced learning. One good thing is it does not require details on how to recognize disease but it has a self-learning and self-tuning feature which helps it to attain that [17]. Finally, it cannot handle linguistic information and vague information. The basis for adoption of neuro-fuzzy technology in this paper can be deduced from table II.

TABLE II
COMPARISON OF NEURAL CONTROL AND FUZZY CONTROL

| Neural Networks | Fuzzy Systems |
|---|---|
| no mathematical model necessary | no mathematical model necessary |
| learning from scratch | apriori knowledge essential |
| several learning algorithms | not capable to learn |
| black-box behavior | simple interpretation and implementation |

### *B. Related Work*

There have been many research works carried out on the application of Information Technology to Medical care. These research works can be classified into medical information management, telemedicine under which m-health and e-health reside and also expert system. In this section of the research, review of expert system related works will be considered.

The authors in [5] reported that the coverage of tuberculosis disease (with HIV prevalence) in Nigeria rose from 2.2% in 1991 to 22% in 2013 and the orthodox diagnosis methods available for Tuberculosis diagnosis were faced with a number of challenges which can increase the spread rate; hence, there is a need for aid in diagnosis of the disease. As a solution, they proposed a technique for intelligent diagnosis of TB using Genetic-Neuro-Fuzzy Inferential method to provide a decision support platform that can assist medical practitioners in administering accurate, timely, and cost effective diagnosis of Tuberculosis. An evaluation of their work showed sensitivity and accuracy results of 60% and 70% respectively which are within the acceptable range predefined by domain experts.

Reference [18] proposed a Web-Based model ES for typhoid fever driven by Fuzzy Logic. The system comprises 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. An experimental study of the their system showed that the results of the study were within the range of predefined limit as examined by medical experts. while [20] for malaria diagnosis, and lastly, [21] developed a diagnostic ES for cardiovascular diseases.

In [19], the use of Fuzzy Cluster Means was applied to diagnose HIV/AIDS shortly after [22] proposed the use of fuzzy sets for diagnosing low back pain in computer users.

Reference [14] proposes a personalized recommender system driven by fuzzy logic technique. The proposed system, though not in the area of medical diagnosis, intelligently mines information about the features of laptop computers and provides professional services to potential buyers by recommending optimal products based on their personal needs. Fuzzy Near Compactness (FNC) concept is employed to measure the similarity between consumer needs and product features in order to recommend optimal products to potential buyers. Experimental result of the proposed system proves its effectiveness.

Reference [23] developed a rule based expert system for diagnosing fever. This was implemented using VB.Net while the rules within the knowledge base were Boolean rules and not fuzzy rules hence; drawing of inference as performed by this system could not have a high degree of human like way of reasoning.

In reference [24] a framework for the construction of a fuzzy expert system to diagnose viral infection for mobile users was proposed. However, it was just a proposal and no attempt was made in executing the proposed work. Based on the objective of the work, actual implementation will need connection of the mobile through the internet for accessibility. If this is the case, the system is bound to be a partially used system.

A work on fuzzy expert system for the management of malaria (FESM) was executed in [25]. They claimed that the system was capable of providing decision support to medical doctors in malaria endemic regions. The developed system used a triangular typed membership function for the fuzzification of scalar inputs, a fuzzy inference method of root sum square (RSS) and finally, the defuzzifier employed center of gravity method of defuzzification.

In reference [26], a medical decision support system for diagnosing malaria using analytic hierarchy process was carried out. This system that used Knowledge components: chemotherapy, patient characteristics, patient information, patient examination, symptom intensity and medical history, was able to determine the priority order of basic malaria diagnosis criteria.

However, most literatures on expert system for medical diagnosis of diseases do not include monkeypox and if there are, they are just mere proposals or in non-fuzzy form of inference available medical knowledge just as we have in references [26] and [27].

# III. RESEARCH METHODOLOGY

## *A. Materials used in the MDiNFIS Model*

The materials used in the development of MDiNFIS include hardware and software tools. The hardware tools include an HP Laptop System with Intel Pentium T4400 @ 2.20GHz and installed memory of 6GB. The software tools include: Matlab 2008 on Windows 8 Operating System.

## *B. MDiNFIS Architecture*

This section presents the system's architecture and procedures performed by each component of the architecture during diagnosis. Components of the architecture, as presented in Fig. 5, are Knowledge Base, Neuro-Fuzzy Inference Engine, and Decision Support Engine.

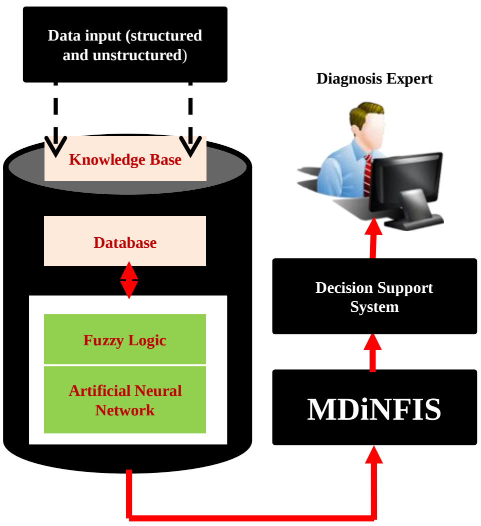


Fig. 5. Architecture of the proposed **MDiNFIS** system

*(1) Fuzzy logic*

The diagnosis process harnesses the strength of fuzzy logic component in the following operational sequence:

*(i) Fuzzification of input variable:*

Given a fuzzy set A, defined as Eq. (4), represents monkey pox (symptoms) diagnosis variables with elements denoted by $x_i$, the fuzzification process involves transforming raw input value of each variable to a fuzzy term obtained from set [very mild, mild, moderate, severe, very severe] defined over the variables. That is, such values are derived from functions defined to determine the degree of membership of each variable in the fuzzy set.

$$A = \{(x_i, \mu_A(x_i)) | x_i \in V, \mu_A(x_i) \in [0,1] \} \quad (4)$$

Fuzzification is done using function defined in Eq. (5)

$$trimf(x; a, b, c) = \begin{cases} 0 & if\ x_i \le a \\ \frac{x_i - a}{b - a} & if\ a \le x_i \le b \\ \frac{c - x_i}{c - b} & if\ b \le x_i \le c \\ 0 & if\ x_i \ge c \end{cases} \quad (5)$$

where $\mu_A(x_i)$ is the MF of $x_i$ in A using triangular MF while $\mu_A$ is the degree of membership of $x_i$ in A. a, b and c are the parameters of the MF governing its triangular shape and each attribute is described with linguistic terms.

In this paper, we considered eighteen symptoms associated with monkeypox according to the interviewed medical experts, symptoms obtained from the Nigeria Centre for Disease Control and other literatures about monkeypox diagnosis but in implementing the model only three symptoms were selected for the simulation. These symptoms: fever, sweating, rash, chills, headache, malaise, muscle ache, nausea/vomiting, lymphadenopathy, abdominal pain, back pain, wheeze, sore throat, runny nose, Pruritis, mouth ulcer, rash and diarrhea [1], are medically believed to be the symptoms associated with monkeypox. However, these symptoms are specific to some patients hence this list of symptoms is not exhaustive. In this research, each symptom is treated as a universe of discourse from where interval-valued fuzzy sets are obtained. Each fuzzy set is constituted by an interval-valued membership function. Here, for a given element, $x_i$= p, its grade of membership in a fuzzy set A i.e. μA(p) is the membership interval [α1, α2].

If malaise is considered as a universe of discourse with patients having malaise as symptom, an interval-valued fuzzy set (A) is extracted as follows:

A= {(mild, 0.1 ⩽ μA (mild) <0.3), (moderate, 0.3 ⩽ μA (moderate) < 0.6) (severe, 0.6 ⩽ μA (severe) < 0.8), (very severe, 0.8 ⩽ μA (very severe) ⩽ 1.0)}

We generalize fuzzy set (A) and other symptoms by fuzzification of their intervals using triangular membership functions as shown in figure 6.

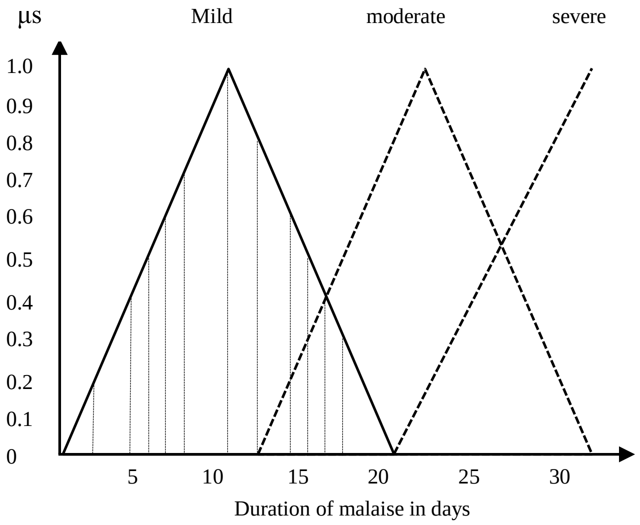


Fig.6. Triangular Membership Functions for the Fuzzy Set Mild

*Fuzzy Set by Symptoms*

The ordinary fuzzy set for the membership function for each symptom given each membership interval in set(A) was stated as follows:

mild = {(1, 0.1), (2, 0.2), (3, 0.2), (4, 0.3), (5, 0.4), (6, 0.5), (7, 0.6), (8, 0.7), (9, 0.8), (10, 0.9), (11, 1.0), (12, 0.9), (13, 0.8), (14, 0.7), (15, 0.6), (16, 0.5), (17, 0.4), (18, 0.3), (19, 0.2), (20, 0.1}

The same idea as in the ordinary fuzzy set for mild above was applied to moderate, severe and very severe linguistic variables.

*(ii) Fuzzy inference engine:*

This is the part of the fuzzy system that regulates the decision making logic. It applies suitable structured procedures from the rule base to values of variable inputs received. In the inference engine, structured procedure is applied on the inputs to produce desired output, and Root Mean Square Error (RMSE), is applied to measure the differences between values predicted by our model and the values actually observed. This represents errors in the fireability of the rules indicating the accuracy of the model. It is computed with Eq. (6).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \qquad (6)$$

*(iii) Defuzzification of output values:*

Defuzzification of output values is carried out. It involves a mapping of fuzzied results from the inference engine into appropriate crisp values required by medical experts for proper analysis and interpretation, this aids efficient diagnosis. This research employs Centroid of Area (CoA) technique for its defuzzification. This interface receives the output of inference engine as its input and finalizes computation by applying Eq. (7).

$$Z^* = \frac{\int \mu_A(x_i).x_i dx}{\int \mu_A(x_i)\text{dz}} \qquad (7)$$

where $\int$ denotes an algebraic integration and $\mu_A(x_i)$ degree of the $i$th symptom of monkeypox in a membership function and $x_i$ is the center value in function. The computational simplicity and intuitive plausibility of this approach gives rise to its adoption. For a complete medical evaluation of monkeypox disease, the variables considered after consultations with medical experts and other standard literal sources are categorized as presented in Table III.

Table III
Symptoms in Rule Base and Abbreviations

| S/N | Symptom | Abbreviation |
|---|---|---|
| 1 | Fever | Fev |
| 2 | Chills | Chs |
| 3 | Lymphadenopathy | Lym |
| 4 | Sweats | Swt |
| 5 | Headache | Hde |
| 6 | Abdominal pain | Abd |
| 7 | Muscle ache | Mul |
| 8 | Back pain | Bkp |
| 9 | Cough | Cou |
| 10 | Wheeze | Whz |
| 11 | Sore throat | Sot |
| 12 | Runny nose | Rns |
| 13 | Nausea/vomiting | Nav |
| 14 | Diarrhea | Drh |
| 15 | Pruritis | Pru |
| 16 | Malaise | Mal |
| 17 | Mouth ulcer | Mul |
| 18 | Rash | Rsh |

*(2) Knowledge Base*

Here, formalized knowledge extracted from human expert knowledge is presented in a computer understandable form. The rule base for monkeypox diagnosis is characterized by a set of IF–THEN rules in which the antecedents (IF parts) and consequents (THEN parts) involve linguistic variables as demonstrated in figure 7. The rules were formulated with assistance of experts in the management of monkeypox and on reference to existing standard literature. A rule can only fire if any of its precedence parameters such as mild, moderate, severe, and very severe evaluates to TRUE, otherwise it does not fire.

*(3) Neural Network*

Information elicited from patients is fed into NN through the input layer to train and test the fuzzy system. This is to optimize the performance of the overall system and impact of participation of each symptom is determined at a hidden layer of the network using:

$$Output_i = \sum_{i}^{n} sym_i * W_{sym_i} \qquad (8)$$

$sym_i$ is the $i$th diagnosis symptom variable with connection weight $W_{sym_i}$ and $n$ is the number of symptom variables considered in the diagnosis.

| Rule No | Fev | Chs | Lym | Swt | Hde | Abd | . . . | Rns | Nav | Drh | Pru | Mal | Mul | Rsh | Inference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | . . . | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) |
| 2 | Ml(0.4) | Md(0.2) | Md(0.3) | Md(0.4) | Md(0.2) | Md(0.4) | . . . | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.1) | Md(0.4) | Ml(0.4) | Md(0.4) |
| 3 | Se(0.4) | Ml(0.6) | Md(0.3) | Md(0.2) | Se(0.3) | Md(0.4) | . . . | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.1) | Md(0.4) | Md(0.4) | Md(0.4) |
| 4 | Se(0.4) | Ml(0.6) | Md(0.3) | Md(0.2) | Ml(0.3) | Md(0.2) | . . . | Md(0.4) | Se(0.2) | Ml(0.4) | Md(0.4) | Md(0.1) | Md(0.4) | Md(0.4) | Se(0.4) |
| 5 | Se(0.4) | Ml(0.6) | Md(0.5) | Md(0.2) | Md(0.3) | Md(0.2) | . . . | Md(0.4) | Se(0.4) | Ml(0.6) | Md(0.4) | Md(0.5) | Md(0.2) | Md(0.4) | Se(0.3) |
| 6 | Ml(0.4) | Ml(0.6) | Md(0.5) | Md(0.2) | Md(0.3) | Md(0.2) | . . . | Md(0.4) | Se(0.4) | Ml(0.6) | Md(0.4) | Md(0.5) | Md(0.2) | Md(0.4) | Md0.5) |
| 7 | Se(0.4) | Ml(0.6) | Md(0.5) | Md(0.2) | Md(0.6) | Md(0.2) | . . . | Md(0.4) | Se(0.4) | Ml(0.6) | Md(0.4) | Md(0.5) | Md(0.2) | Md(0.4) | Md0.5) |
| 8 | Ml(1.0) | 0 | 0 | 0 | 0 | 0 | . . . | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Ml(0.1) |
| 9 | Se(0.8) | Vs(0.6) | Se(0.6) | Md(0.4) | Se(0.4) | Md(0.4) | . . . | Md(0.3) | Vs(0.4) | Md(0.4) | Md(0.4) | Vs(0.4) | Md(0.6) | Md(0.4) | Vs(0.6) |
| 10 | Md(0.3) | 0 | 0 | 0 | Ml(0.4) | 0 | . . . | Ml(0.3) | Ml(0.3) | Ml(0.3) | Ml(0.3) | Ml(0.3) | Ml(0.3) | Ml(0.3) | Ml(0.3) |
| 11 | Ml(0.2) | Ml(0.2) | Ml(0.2) | 0 | Ml(0.2) | Ml(0.2) | . . . | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) |
| 12 | Se(0.5) | 0 | Se(0.6) | Md(0.4) | Se(0.3) | Md(0.2) | . . . | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Se(0.3) |
| 13 | Se(0.4) | Se(0.1) | Se(0.1) | Md(0.6) | Vs(0.3) | Md(0.2) | . . . | Se(0.1) | Se(0.8) | Md(0.2) | Md(0.2) | Se(0.1) | Md(0.2) | Vs(0.3) | Vs(0.6) |
| 14 | Se(0.5) | 1 | Se(0.6) | Md(0.4) | Se(0.3) | Md(0.2) | . . . | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Md(0.4) | Se(0.3) |
| 15 | Vs(0.4) | Se(0.1) | Se(0.1) | Md(0.6) | Vs(0.3) | Md(0.2) | . . . | Se(0.1) | Se(0.8) | Md(0.2) | Md(0.2) | Se(0.1) | Md(0.2) | Vs(0.3) | Vs(0.6) |
| 16 | Vs(0.4) | 0 | Vs(0.1) | 0 | Se(0.7) | Ml(0.2) | . . . | 0 | Md(0.4) | Md(0.6) | 0 | Se(0.1) | 0 | 0 | Vs(0.6) |
| 17 | 0 | 0 | Ml(0.3) | Ml(0.1) | Ml(0.1) | Ml(0.2) | . . . | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.1) | Ml(0.2) | Ml(0.1) | Ml(0.2) |
| 18 | Vs(0.3) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Vs(0.3) | Ml(0.2) | . . . | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Ml(0.2) | Vs(0.3) | Vs(0.3) |

Fig.7. Few contents of Fuzzy Rule Base

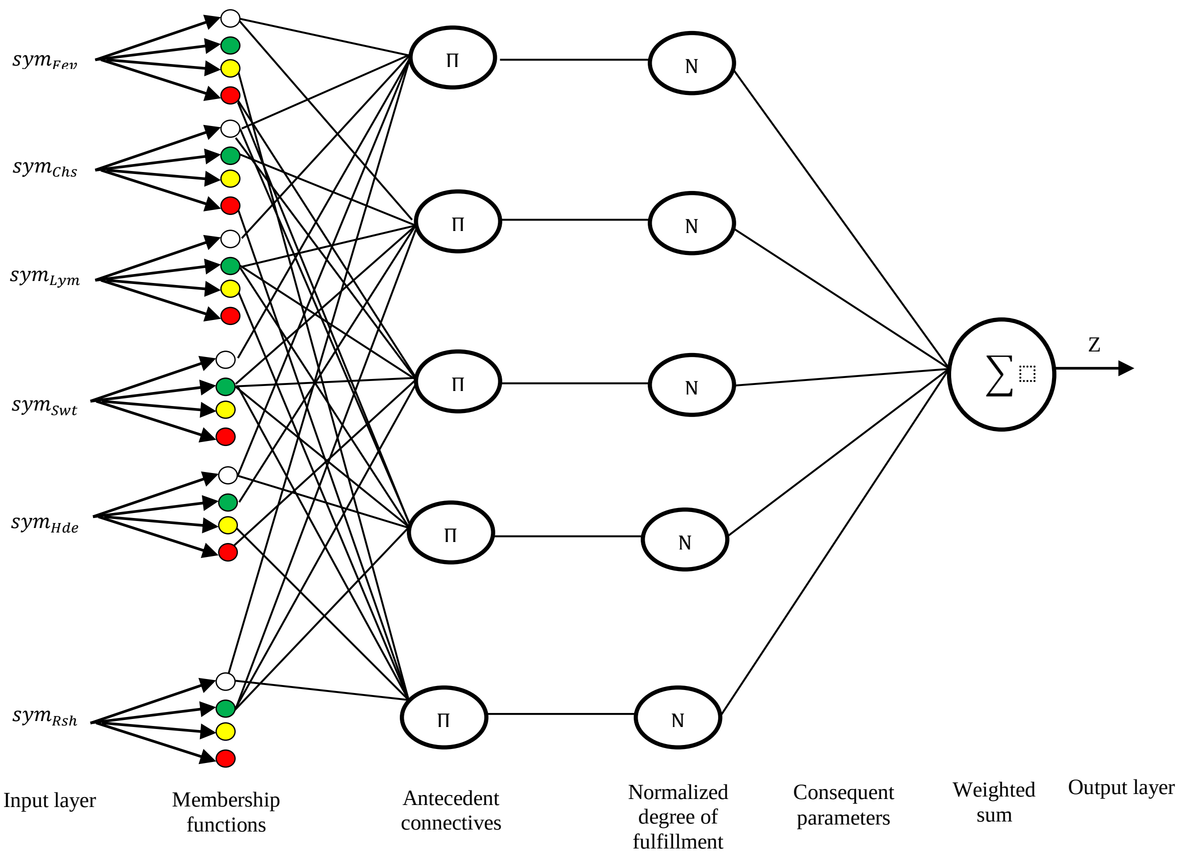


Fig. 8. A Neuro-Fuzzy Network representation of few rules at the computational level

Result of the output layer represents an overall output of diagnosis by the Artificial Neural Network (ANN) component of the architecture shown in Fig. 5.

### *C. Neuro-fuzzy Engine (NFE) Architecture*

A typical fuzzy classification rule $R_i$, which demonstrates the relation between the input feature space and classes, is as follows:

$R_i$: if $sym_{s1}$ is $x_{i1}$ and … $sym_{sj}$ is $x_{ij}$ … and $sym_{sn}$ is $x_{in}$ , then class is $C_k$

where $sym_{sj}$ is the *j*th symptom or input variable of *s*th diagnosed patient. $x_{ij}$ denotes the fuzzy set of the *j*th symptom in the *i*th rule and $C$ is the result of diagnosis for the patient diagnosed of monkeypox disease. In the NFE, we partitioned the symptom space into subspaces by fuzzy if-then rules. The NFE architecture is a multilayer feed-forward network (MLF) made up of the input, fuzzy membership, fuzzification, defuzzification, normalization, and output layers. Figure 8 depicts an NFE with symptoms and one output and some of the fuzzy rules are shown in figure 7.

### *D. Development of MDiNFIS*

Neuro-Fuzzy Inference System (**MDiNFIS**) is an inferential technique proposed to integrate ANN and Fuzzy Logic in the architecture to provide a self-learning (from ANN) and adaptive (from FL) system for handling uncertainty and imprecision in the data for diagnosis of monkeypox. Feed forward propagation technique made up of seven layers of neurons is engaged by the inference system as shown in Fig. 8. The inference engine's reasoning is goaded by the production rules based on Mamdani's Inference Mechanism. In the membership function layer, membership grades are determined as:

$$L_{mf}(sym_{si}) = \mu_{x_i}(sym_{si}) \quad (9)$$

The fuzzy value of each variable is computed using triangular MF, given as:

$$\mu_{x_i}(sym_{si}) = \frac{x_i - a}{b - a} \quad (10)$$

where a and b are the left and right bounds of the triangular MF variables such that $a \le x_i \le b$ . The output at the antecedent connectives layer which the firing strength of the rules is computed as:

$$L_{AtC}(sym_s) = \mu_{x_i}(sym_{si}) * \mu_{x_i}(sym_{sj}) * \dots * \mu_{x_i}(sym_{sn}) \quad (11)$$

At the normalized layer, the degree of fulfillment of a rule is passed through normalization since the values must be kept in the range (0, 1). The normalized strength of a *k*th rule is determined as:

$$L_{cp}(sym_s) = \frac{w_k}{\sum_{j=1}^{4} w_j} \quad (12)$$

where $W_k$ is the weight of the symptom and $W_j$ is the individual weights of the respective membership functions. Next, the symptom's contribution to the diagnosis processes is determined by taking the product of normalized firing strength of a rule and its corresponding output value. This is obtained using:

$$C_{sym} = L_{AtC}(sym_s) * L_{cp}(sym_s) \quad (13)$$

The weighted sum layer is a single fixed node representing the **MDiNFIS** output. This is the cumulative sum of all signals at its input as shown in Eq. (14).

$$Z = \sum_{i=1}^{n} C_{sym_i} \quad (14)$$

The crisp result obtained in Eq. (14) is hence classified to get the patient's final diagnosis result using Eq. (15)

$$output = \begin{cases} mild & Z \le 0.3 \\ moderate & 0.3 \le Z \le 0.6 \\ severe & 0.6 \le Z \le 0.8 \\ very\ severe & 0.8 \le Z \le 1.0 \end{cases} \quad (15)$$

## IV. SIMULATION AND EVALUATION

### *A. Simulation*

The proposed model was simulated in Matrix Laboratory (MATLAB) 2008 version environment. In order to evaluate the model, 74 patients' data were formulated based on the information obtained from NCDC. This formulation adequately reflected the state of health of the patients with respect to monkeypox diseases stored as rules in a database. Each rule consists of eighteen (18) input variables representing the symptoms of the monkeypox diseases and one (1) output variable representing the result for the diagnosed patient. A symptom's contribution to monkeypox diseases is determined by the symptom's severity.

The output from fuzzification of variables was directed as input to the ANN. To train the network all hidden and output layer neuron transformation, Back-propagation algorithm with sigmoid function was used. The NN trained by the subsystem consists of 18 nodes at the input layer, each representing unique monkeypox variables considered in this study. Membership function plots for headache and fever symptoms are shown in figure 9 and figure 10.

The fuzzy results were used as input to the neural network as shown in the architecture in figure 8 above. The Neuro-Fuzzy application was development using Java version 1.8 on NetBeans IDE version 8.0.2. Figure 11 – 14 give some snapshots of the developed monkeypox diagnosis system.

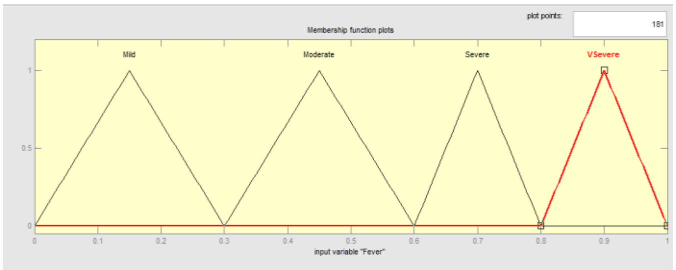


Fig. 9. Membership Function for Fever symptom

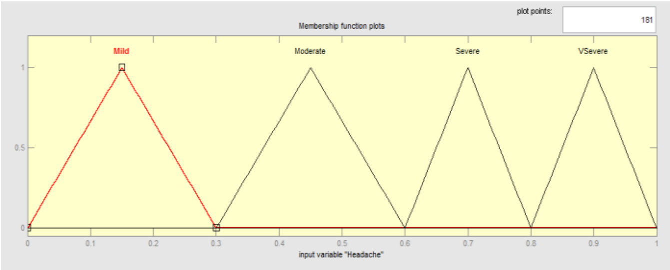


Fig.10. Membership Function for Headache symptom

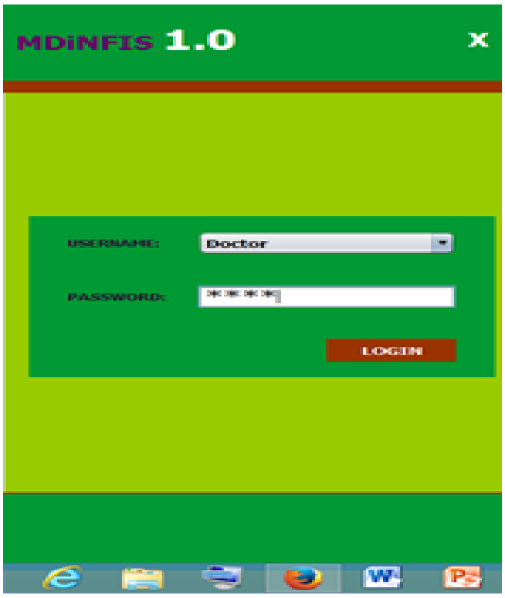


Fig. 11. **MDiNFIS** Login Screen

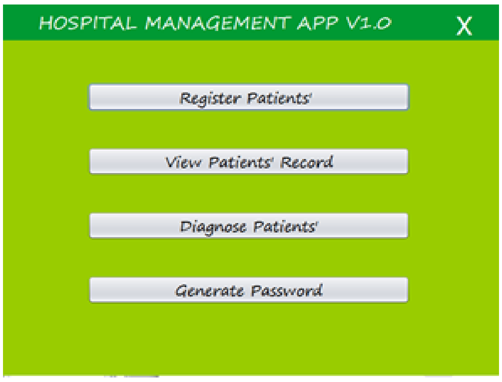


Fig. 12. **MDiNFIS** main menu

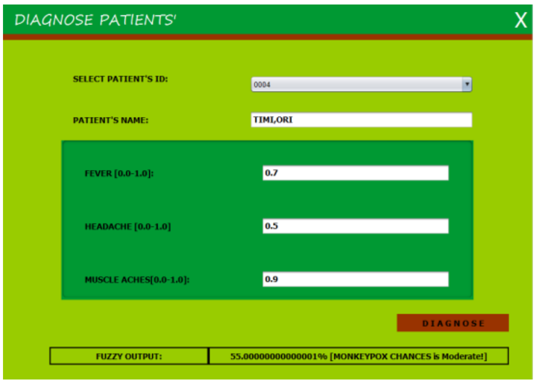


Fig. 13. MDiNFIS diagnose process Screen showing 3 symptom input

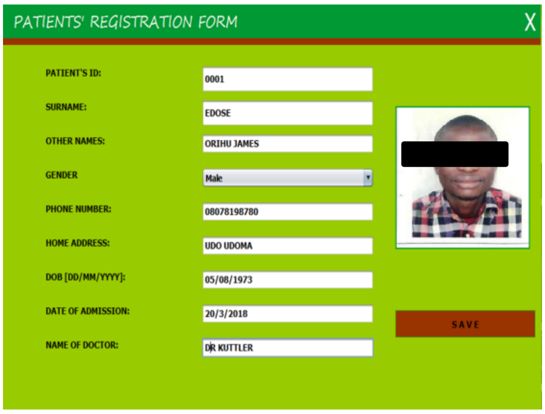


Fig. 14. MDiNFIS Patient Registration Screen

### *B. Evaluation of the Proposed Neuro-Fuzzy Logic Model*

Given the following set of input: 0.7, 0.5 and 0.9 for Fever, Headache and Muscle aches respectively, the following inference can be deduce:

**Fever**

$\mu_{mild}(0.7) = 0.0$
$\mu_{moderate}(0.7) = 0.0$
$\mu_{severe}(0.7) = 1.0$
$\mu_{vsevere}(0.7) = 0.0$

**Headache**

$\mu_{mild}(0.5) = 0.0$
$\mu_{moderate}(0.5) = 0.66$
$\mu_{severe}(0.5) = 0.0$
$\mu_{vsevere}(0.5) = 0.0$

**Muscle Aches**

$\mu_{mild}(0.9) = 0.0$
$\mu_{moderate}(0.9) = 0.0$
$\mu_{severe}(0.9) = 0.0$
$\mu_{vsevere}(0.9) = 1.0$

**Inference**

For the given set of input, rule number 38 got fired. i.e;
*If Fever is Severe And Headache is Moderate And Muscle Aches is vsevere then MonkeyPox Chances is Moderate.*
Using Mamdani method and keeping all other symptoms at mild, this yield;

And (1.0, 0.66, 1.0) = 0.66 Moderate.

$$\frac{(0.40+0.45+0.50+0.55+0.60+0.65+0.70)*0.66}{7*0.66} = \frac{2.541}{4.62} = 0.55$$

Hence for the given set of inputs, the chance of MonkeyPox is 55%.

### *C. System Limitations*

The result obtained here and the reliability of it is subject to the number of input used in the actual sense rather than the 18 inputs analysed in principle during analysis. For real life implementation of this proposed system it is recommended all the symptoms be included in the set of inputs. This will ensure better quality of the disease diagnosis.

## ACKNOWLEDGMENT

The lead author of this paper wishes to acknowledge Dr Mbosowo Etukudo currently Head of Department of Botany, Federal University, Otuoke, Nigeria for spurring up my resolve to publish this paper against all odds.

Also worthy of acknowledgement is Professor B. K. Alese of Computer Science Department, Federal University of Technology, Akure, Nigeria. He has been a motivator and a mentor who supervised my Masters and PhD thesis. Dr (Mrs.) Aderonke F. Thompson HOD of Cyber Security, Federal University of Technology, Akure, Nigeria also deserves commendation for being there for me. I say thank you so much.

## V. CONCLUSIONS

This study has attempted the development of a neuro-fuzzy based system that diagnoses the dreaded monkeypox virus taking care of degree of uncertainties supposed in the field of medicine by the human experts. This study has created lots of awareness with regards to the disease in case study. Now in Nigeria and other countries of the world, monkeypox outbreak have caused panic in homes hence the importance providing a mechanism for early diagnose of the zoonotic diseases cannot be overemphasized. In this paper, we leverage on the uncertainty handling capability of fuzzy logic systems (FL) and the learning capability of artificial neural networks (ANN) to build a system capable of diagnosing monkeypox diseases reliably. Monkeypox diseases can be transmitted from human to human through physical contact. This fact calls for a contactless methodology to diagnose presence of the virus in a patient without physically touching the patient. This system is a standalone system and does not require internet connectivity or any special machine to run. It is easy to use by doctors and paramedical health workers as it does not warrant any special training for implementation in diseases diagnosis. This makes this application to attain general accessibility and usability.

The proposed system can also serve as a decision support system for young medical practitioners who may want to acquire more knowledge on the diagnosis of monkeypox if properly implemented. A partial or full implementation of the developed neuro-fuzzy system can ensure efficient and effective diagnosis tool for monkeypox.

## REFERENCES

[1] Nigeria Centre for Disease Control (NCDC) Monkeypox Outbreak in Nigeria Situation Report (No. 002), October 16, 2017.

[2] Z Jezek, M. Szczeniowski, KM. Paluku, and M. Mutombo. Human monkeypox: clinical features of 282 patients. J Infect Dis.156 : 293-298. 1987.

[3] LA Zadeh, Biological application of the theory of fuzzy sets and systems, in: Proc. Int. Symp. Biocybernetics of the Central Nervous System (Little, Brown & Co., Boston 1969) 199–212.

[4] E Sanchez "Medical diagnosis and composite fuzzy relations" in: MM Gupta, RK Ragade, RR Yager (eds) *Advances in Fuzzy Set Theory and Aplications* (North-Holland, Amsterdam 1979) 437--444.

[5] M. O. Omisore, O. W. Samuel, E. J. Atajeromavwo A Genetic-Neuro-Fuzzy inferential model for diagnosis of tuberculosis. Applied Computing and Informatics (2017) 13, 27–37.

[6] S.A. Oke, A literature review on artificial intelligence, Int. J. Inf. Manage. Sci. 19 (4) (2008) 535–570.

[7] Y. Peng, X. Zhang, Integrative data mining in systems biology: from text to network mining, Artif. Intell. Med. 41 (2) (2007) 83–86.

[8] H.G. Sol, Expert systems and artificial intelligence in decision support systems, in: Proceedings of the Second Mini-Euro Conference, 17–20 November 1985, Springer, Lunteren, TheNetherlands, 1987, pp. 1–2.

[9] N. Mehdi, Y. Mehdi, Designing a fuzzy expert system for diagnosing the hepatitis B intensity rate and comparing it with adaptive neural network fuzzy expert system, in: Proceedings of the World Congress on Engineering and Computer Science (WCECS), vol. 11, San Francisco, USA, 2009.

[10] Zadeh L. Fuzzy sets. Inform Control 1965;8:338–53.

[11] Jang J-SR, Sun C-T, Mizutani E. Neuro-fuzzy and soft computing. A computational approach to learning and machine intelligence. Matlab curriculum series. Upper Saddle River, NJ: Prentice-Hall; 1997.

[12] B.K. Bose, Modern Power Electronics and AC Drives, Prentice-Hall, Upper Saddle River, NJ, 2002, pp 44.

[13] J. Zhao, B.K. Bose, Evaluations of membership functions for fuzzy logic controlled induction motor drive, in: Proceedings of the IEEE, 2002.

[14] B.A. Ojokoh, M.O. Omisore, O.W. Samuel, T.O. Ogunniyi, A fuzzy logic based personalized recommender system, Int. J. Comp. Sci., Inf. Technol. Sec. 2 (5) (2012) 1008–1015.

[15] A. Barwad, P. Dey, S. Susheilia, Artificial neural network in diagnosis of metastatic carcinoma in effusion cytology, Cytomet. B Clyn Cytom. 82 (2012) 107–111.

[16] P. Dey, A. Lamba, S. Kumari, N. Marwaha, Application of an artificial neural network in the prognosis of chronic myeloid leukemia, Anal. Quant. Cytol. Histol. 33 (6) (2012) 335–339.
[17] K. Vahid, A.M. Gholam, Artificial Intelligence in Medicines, Information Technology Department, School of Engineering, Terbiat Moderas University Tehran, Iran, 2009.
[18] O.W. Samuel, M.O. Omisore, B.A. Ojokoh, A web based decision support system driven by fuzzy logic for the diagnosis of typhoid fever, Exp. Syst. Appl. 40 (2013) (2013) 4164–4171.
[19] A. Imianvan, F. Anosike, C. Obi, An expert system for the intelligent diagnosis of HIV using fuzzy cluster means algorithm, Glob. J. Comp. Sci. Technol. 11 (12) (2011) 73–80.
[20] T.O. Oladele, J.S. Sadiku, R.O. Oladele, Coactive neuro-fuzzy expert system – a framework for diagnosis of malaria, Afric. J. Comput. ICT 7 (2) (2014) 174–188.
[21] O.U. Obot, F.M. Uzoka, O.C. Akinyokun, J.J. Andy, A neurofuzzy decision support model for therapy of heart failure, Int. J. Med. Eng. Inform. 6 (4) (2014) 319–334.
[22] A. Kadhim, A. Alam, H. Kaur, Design and implementation of fuzzy expert system for back pain diagnosis, Int. J. Innov. Technol. Creat. Eng. 1 (9) (2011) 16–22.
[23] S. Tunmibi, O. Adeniji, A. Aregbesola, and A. Dasylva, "A Rule Based Expert System for Diagnosis of Fever", International Journal of Advanced Research, 2013, 1(7), pp. 343-348.
[24] A. O. Adetunmbi, A. Oguntimilehin, and S.O. Falaki, "Web-Based Medical Assistant System for Malaria Diagnosis and Therapy", GESJ: Computer Science and Telecommunications, 2012, 1(33), pp. 42-53.
[25] World Health Organization, "Guidelines for the treatment of malaria", 2nd Edition, retrieved on 06/01/2011, from http://whqlibdoc.who.int/ publications/2010.
[26] F. M. E. Uzoka, O. U. Obot and K. Barker, "A performance comparison of Fuzzy Logic and AHP as engines for the development of Intelligent Medical Diagnosis Systems" Nigeria Computer Society 23rd National Conference, 2009, pp. 135- 150.
[27] M. Patel, and P. Virparia, "Designing Mobile Based Fuzzy Expert System Framework for Viral Infection Diagnosis", International Journal of Current Research and Review, 2012, 4 (12), pp. 139-146.
[28] M. O. A. Olufemi, "Mobile Phone-Based Expert System for Disease Diagnosis", retrieved on 22/05/2015, from http://www.irma-international.org/412224158/A-Mobile-Phone-Based-Expert-System-for-Disease-Diagnosis.pdf.