

# An Adaptive Neuro-Fuzzy Inference System for Diagnosis of EHF.

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## ABSTRACT

Ebola Haemorrhagic Fever (EHF) is a severe, often-fatal viral disease in humans and nonhuman primates with a fatality rate that has generally around the world raised from 50%–90%. Particularly in Africa, the outbreak is spreading at an exponential rate. Results of several studies show that Ebola is commonly under-diagnosed at the initial stage, especially in developing countries, because of the stigma associated with the disease, limited access to medical specialists, and laboratory data. In this paper, we present our initial efforts to develop an enhanced Adaptive Network-based Fuzzy Inference System (ANFIS) that formalizes the diagnosing process of EHF.

Five ANFIS classifiers were used to detect five EHF state using 34 clinical symptoms (parameters) and five EHF risk level as inputs. The Fuzzy cluster means framework comprises of some analytical decision steps that isolate data objects into homogeneous clusters using different types of similarity measures. ANFIS structure implements a Sugeno fuzzy inference method that facilitates learning, adaptation and optimization of results making the system less reliant on expert knowledge. The knowledge representation of the system is provided from an elevated level that is based on the perception of experienced physicians, health organizations, researchers and Ebola patients' commentary found in literature.

(Keywords: Ebola, fuzzy sets, diagnosis, neural network, expert system, fuzzy logic, neuro fuzzy system)

## INTRODUCTION

Ebola virus is a zoonotic (animal-borne) disease. Ebola viruses are rare and caused by infection with viruses in the genus *Ebolavirus* of the *Filoviridae* family (WHO, 2014) and are biosafety level-4 pathogens (BSL-4; risk group 4). The viruses are inactivated by gamma irradiation, are sensitive to sodium hypochlorite (bleach) and other disinfectants, and deactivated by heating for 60 minutes at 60 °C or boiling for five minutes. The viruses can survive in liquid or dried material for days (Piercy et al., 2010). It causes severe, often-fatal viral diseases in humans (i.e., 50%-90% fatality) and non-human primates (i.e., monkeys, gorillas, and chimpanzees) (Acute, 2014; C1NQ, 2014) with the number of cases currently doubling approximately every 3-4 weeks (Aylward, 2014). It is one of numerous Viral Hemorrhagic Fevers and is a deadly disease with several symptoms that are similar to other diseases.

EHF is caused by the following five genetically distinct members of the *Filoviridae* family, whose genomes can differ by 30-40%. These four have caused disease in humans: Ebola virus (*Zaire ebolavirus*) (ZEBOV); Sudan virus (*Sudan ebolavirus*) (SEBOV); Tai Forest virus (*Tai Forest ebolavirus*, formerly *Côte d'Ivoire ebolavirus*) (TEBOV); and Bundibugyo virus (*Bundibugyo ebolavirus*) (BEBOV). The fifth, Reston virus (*Reston ebolavirus*) (REBOV), has caused disease in nonhuman primates (WHO, 2014; CDC, 2014).

- Bundibugyo virus (*Bundibugyo ebolavirus*) (BEBOV) - Bundibugyo Ebola virus is responsible for most of the EHF outbreaks (Feldmann et al, 2005; Groseth, Groseth, 2007; Towner et al, 2008).

- Reston virus (*Reston ebolavirus*) (REBOV),- Reston Ebola virus has only caused disease in non-human primates (NHP) and was found in swine suffering from porcine reproductive and respiratory disease syndrome (Barrette et al., 2009; WHO, 2014; CDC, 2014).
- Sudan virus (*Sudan ebolavirus*) (SEBOV) - Sudan virus is responsible for most of the EHF outbreaks (Feldmann et al., 2005; Groseth, Groseth, 2007; Towner et al., 2008).
- Taï Forest virus (*Taï Forest ebolavirus*, formerly *Côte d'Ivoire ebolavirus*) (TEBOV) - *Côte d'Ivoire ebolavirus* has been associated with only one human case (Le Guenno et al., 1995).
- Ebola virus (*Zaire ebolavirus*) (ZEBOV) - Zaire, virus has caused disease in humans (Feldmann et al., 2005; Groseth, Groseth, 2007; Towner et al., 2008). It constitutes a particularly serious threat to both human and non-human primates in sub-Saharan Africa. The fatality ratio for ZEBOV infections is estimated to be between 44% and 90% (Banniste, 2010). There is a striking difference in viral load amongst non-survivors and survivors with high levels of viraemia associated with poor outcomes (Ksiazek et al., 1995).

EHF period between infection and first symptoms (incubation period) usually become evident between four to ten days, but can occur as early as two days to up to 21 days after exposure (Acute, 2014; CDC, 2014; WHO, 2012; State, 2014). Individuals infected may develop a diffuse erythematous maculopapular rash by day 5 to 7 (usually involving the face, neck, trunk, and arms) that can desquamate (Acute, 2014). After about 5 days, patients may develop gastrointestinal symptoms such as severe watery diarrhea, nausea, vomiting and abdominal pain.

Other symptoms includes: fever, lack of appetite, severe headache, anorexia, hiccups, rash, red eyes, fatigue, muscle pain, headache, and sore throat. The illness progression includes impaired organs function. In some cases, rash, internal and/or external bleeding can manifest as petechiae, ecchymosis/bruising, or oozing from venipuncture sites and mucosal hemorrhage, and death may occur (WHO, 2014; CDC, 2014). Pregnant women may also experience

spontaneous miscarriages. Clinical criteria include fever of  $\geq 99.5^{\circ}\text{F}/37.5^{\circ}\text{C}$  (Acute, 2014).

Although the clinical progression of infection and the transmissibility of the Ebola virus have always been similar to those in previous outbreaks, the present-day epidemic in West Africa is unparalleled in scale regardless of the progresses made in understanding the pathologies of the disease. Physicians and scientists have been working hard toward diagnosing and finding preventive and post-exposure treatments due to the significant threat the virus present (Teckman 2013; DB, 2014).

Mostly in the early stages of an outbreak, the presence of symptoms that are commonly associated with other diseases is problematic because it makes the disease difficult to diagnose (MacNeil and Rollin, 2012). Diseases which should be considered in the differential diagnosis of Ebola include typhoid fever, Marburg virus and other viral hemorrhagic fevers, malaria, fulminant viral hepatitis cholera, rickettsiosis, Chikungunya fever, meningococcal septicemia, typhus, plague, yellow fever, leptospirosis, anthrax, and shigellosis (WHO, 2014; DB, 2014; Feldmann et al., 2011; WHO, 2012).

Several treatment methods are being studied and presently several vaccines are identified in advance stages of development during the Ebola outbreak (WHO-1, 2014; Friedrich et al., 2010):

- BCX- 4430 prevents virus replication by constraining viral RNA polymerase function (Warren, 2014).
- cAd3-ZEBOV a non-replicative chimpanzee adenovirus type 3 vaccine containing the gene for the Zaire ebolavirus surface glycoprotein.
- ChAd3-ZEBOV a Chimpanzee adenovirus serotype 3 shows efficacy in primate pre-clinical trials (Aylward, 2014).
- Convalescent serum, hyperimmune globulin and antibodies (blood-derived products) from individuals who recovered from Ebola have been used lately to treat some aid workers (Aylward, 2014).
- rNAPc2, a nematode-derived anticoagulation protein, with 33% treatment efficacy in the treatment of macaque infected with Zaire

Ebola virus, weakens coagulation and inflammation (Geisbert et al., 2003).

- rVSV-ZEBOV, a recombinant vesicular stomatitis virus vaccine expressing a Zaire surface glycoprotein, prompts a Zaire ebolavirus specific immune response (Aylward, 2014).
- T-750 (favipiravir), a pyrazinecarboxamide derivative that inhibits influenza virus replication was effective in the treatment of Ebola virus disease in a mouse (Oestereich et al., 2014).
- RNAs and phosphorodiamidate morpholino oligomers may effectively prevent Ebola virus disease in nonhuman primates by targeting the Zaire Ebola virus RNA polymerase L protein (Warren et al., 2010).
- ZMapp, which is a mixture of three humanized mouse monoclonal antibodies (c13C6, h-13F6, and c6D8) have significantly protected rhesus macaques from a lethal challenge of Ebola virus (Olinger, 2012).
- TKM-Ebola has also been approved to treat patients infected with Ebola virus.

Research shows that in some instances, EHF has usually either been under-diagnosed or methods proffered to diagnose the disease have not been precise enough to discontinue the spread of infection (Spickler, 2014). A person with EHF exhibiting symptoms typical of common tropical diseases can be misdiagnosed and mistreated, and quarantine measures may not be taken, which poses a public health threat (Teckman 2013). The fact that there is a substantial difference amongst the incidence of physician diagnosed EHF and the incidence of related symptoms shows that the condition of the health systems needs support. Early diagnosis of EHF can help mitigate its spread, in both a natural outbreak and a deliberate attack.

In diagnosing EHF, which before now can only be done definitively in the laboratory, a number of different tests are performed to identify the virus, including enzyme-linked immunosorbent assay (ELISA) for immunoglobulin g and m (Nakayama et al., 2010), antigen detection tests, serum neutralization test, reverse transcriptase polymerase chain reaction (rT-PCR) assay, electron microscopy of clinical specimens and

virus isolation by cell culture (Wang et al., 2011). Problems with EHF patients are not easily discovered in a very early stage.

Prompt laboratory verification of suspected EHF is essential to implement appropriate control measures. Within a few days of symptom onset the following test are performed on conclusive diagnosis of suspected case (Nakayama et al., 2010; Yuan, 2012; Acute, 2014) antigen-capture ELISA testing for immunoglobulin g and m, IgM ELISA, blood for PCR and blood for virus isolation by cell culture.

Later in disease course or after recovery blood sample is taken for IgM and IgG antibodies. Later retrospectively in deceased patients' tissue for Immunohistochemistry testing, blood for reverse transcriptase polymerase chain reaction (rT-Pcr) assay and blood for virus isolation are collected and tested. Due to the rigours and risk involved in diagnosing EHF, many physicians require tools for evaluation.

Physicians generally make assertions about a type of disease after establishing facts about the disease symptoms, patients history and patients exposure routes. Merging fuzzy technique with an expert system will hasten and enhance EHF expert's knowledge in the diagnosing process of the virus in patients. An early diagnosis of EHF will increase patients' survival rate and reduce the distribution of the virus. The design of an effective diagnosis model is therefore an important issue in EHF treatment. In fuzzy logic applications, the uncertainties encountered in diagnosing a disease is often represented by linguistic terms which are often used to facilitate the expression of rules and facts.

In this paper, an appropriate computer based information and decision support for diagnosing EHF is proposed in order to: exclude the uncertainties associated with the analysis of clinical data, reduce cost for achieving clinical tests, reduce the effect of under-diagnosing EHF and eliminate the uncertainties associated with the analysis of EHF test. The disease is diagnosed based on the adaptive neuro-fuzzy inference system (ANFIS).

ANFIS structure implements a Sugeno fuzzy inference method that facilitates the learning of features contained in a data set, adjusting the system parameters according to a given error criterion and optimizing results by tracking the

given output data extracted from the dataset that best describes the system behavior, making the system less reliant on expert knowledge.

## MATERIALS AND METHODS

### Adaptive Neuro-Fuzzy Inferences System (ANFIS)

Fuzzy inference is a process of formulating the mapping from a given input to an output using the fuzzy set methods. The mapping provides a basis from which decisions can be made, or patterns discerned from a given set of data and information in which there are various forms of uncertainty.

Fuzzy inference process includes the use of linguistic terms to reason, membership functions, fuzzy logic operators, and if-then rules which connect multiple antecedent(s) with certain degree of membership between 0 and 1.

The fuzzy logical AND, OR and NOT operators are utilized to calculate the degree of firing strength of each rule. AND uses the minimum weight value of all the antecedents, OR uses the maximum value weight of all the antecedents while NOT subtracts a membership function from 1 to give the "complementary" function. The parameters of the fuzzy system are then optimized either manually or by means of an optimization technique which can be time consuming (Garibaldi and Ifeachor, 1999).

An approach for the fuzzy modeling procedure to learn information about a dataset is the adaptive neuro-fuzzy inference system (ANFIS) which has

been shown to provide a more accurate result compared to other fuzzy-neuro systems (Madu et al, 2005; Al-Daoud, 2010). In ANFIS, the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data are extracted from the dataset that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion.

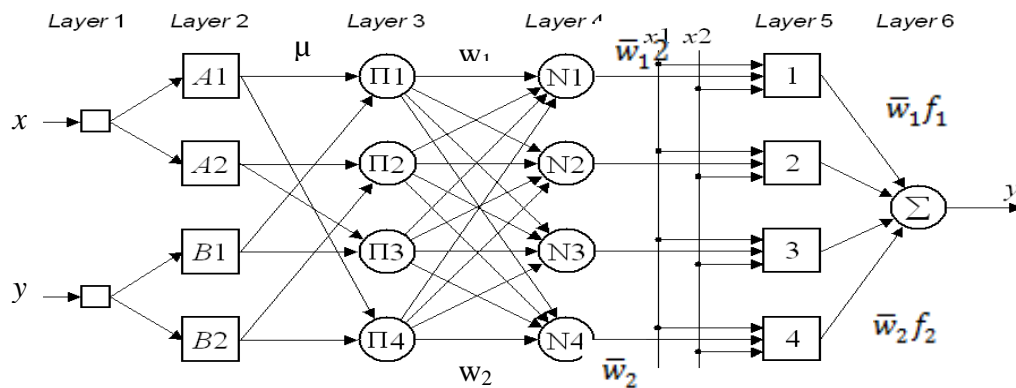
NFIS framework implements a Sugeno fuzzy inference system based on two fuzzy if-then rules that facilitates learning, adaptation and optimization of results making a system less reliant on expert knowledge (Jang, 1992; 1993; Al-Daoud, 2009). The two fuzzy rules are of the form:

Rule 1: If (x is  $A_1$ ) and (y is  $B_1$ )  
then ( $f_1 = p_1x + q_1y + r_1$ ).

Rule 2: If (x is  $A_2$ ) and (y is  $B_2$ )  
then ( $f_2 = p_2x + q_2y + r_2$ ),

where the two inputs, x and y, are first fuzzified to generate appropriate membership grades using the membership functions for the fuzzy sets,  $A_i$  and  $B_i$ .  $f_i$  are the outputs within the fuzzy region specified by the fuzzy rule.  $p_i$ ,  $q_i$  and  $r_i$  are the determined design parameters during the training process.

The ANFIS architecture contains a six layer feed-forward neural network that consists of adaptive nodes represented as squares and fixed nodes represented as circles as shown in Figure 1.



**Figure 1:** The ANFIS Architecture (Negnevitsky, 2005).

## THE DESIGN OF THE PROPOSED MODEL

To diagnose EHF, which is a class-4 pathogen, the patient's medical history is gotten by the physician, the patient is interviewed and physical examination is performed in a maximum containment facility. The physician also requests for further information about the patient's former state of health, living condition, past medical conditions and present symptoms. Patients response to questions asked, past medical history and symptoms are observed are then classified into the following five risk levels according to type of contact with (or without) an infected EHF patient (RRD, 2014; Acute, 2014): no risk, very low risk, low risk, intermediate risk and high risk.

**No-Threat** patients are those with no known exposures.

**Very-Low-Threat** patients are those who had contact with an asymptomatic person who had contact with a person with Ebola or patients who had contact with a person with Ebola before the person was showing symptoms or patients who had stayed for more than 21 days previously in a country with widespread Ebola virus transmission or patients who had been in a country where there is no widespread Ebola transmission and or had no other exposures to Ebola.

**Low-Threat** patients are those that have been in a country with widespread Ebola transmission within the previous 21 days and having no known exposure or was in the same room with an Ebola patients for a brief period of time (without direct contact but sharing a seating area or public transportation or receptionist tasks) while the Ebola patient was symptomatic or had a brief direct contact (e.g., shaking hands), while

Ebola patient was in the early stage of disease or had a direct contact with an Ebola patient while the patient was symptomatic or travel on an aircraft with an Ebola patient. It also includes patients who had been within approximately one metre of an EHF case or indoors in a care area for an extended period of time or in the case's room.

**Some-Threat** patients are those who live in countries with widespread Ebola transmission or who had direct or close contact (i.e. being within 3 feet of an Ebola patient for about an hour) with a person with Ebola while the person was symptomatic such as in a household, health care facility, or the community.

**High-Threat** patients are those who had direct contact with infected blood or body fluids of an EHF case (either suspected or confirmed) through needle stick, or splashes to eyes, nose, or mouth or skin or without appropriate personal protective equipment. High risk patients are also those who participated in funeral rites with direct exposure to human remains, bush meat or bats, rodents, primates, living or dead in/from affected areas. It also includes physicians handling body fluids, such as in a laboratory, without following the recommended safety precautions or those who traveled to countries with active Ebola outbreaks. A patient that have had a close face-to-face contact (e.g., within one meter) with a probable or confirmed case or who is coughing, vomiting, bleeding, or who has diarrhea or has had unprotected sexual contact with a case up to three months after recovery is also at high risk.

After ascertaining the risk level, a treatment plan is commenced by the physician. Diseases with similar symptoms such as malaria, cholera, and other viral hemorrhagic fever are excluded establishing persistent fever not responding to anti-malaria drugs or to antibiotics. Review of diagnosis is conducted several times if the patient fails to respond to treatment that would usually work.

In Table 1 based on domain experts' knowledge and literature, attributes are classified as T-1, T-2, T-3, T-4 and T-5 depending on the fatality effects on the patient, number of days since initial infection which has a direct effect on the rate of the disease transmission. T-1 denotes a non-fatal case and likelihood that the EHF is in its first six days, T-2 denotes Influenza-like syndrome and likelihood that the EHF is in its seventh and ninth day, T-3 denotes the likelihood that the EHF is in its 10<sup>th</sup> day, T-4 denotes the likelihood that the EHF is in its 11<sup>th</sup> day, and T-5 denotes the likelihood that the EHF is in its 12<sup>th</sup> day. The symptoms of EHF are presented in Table 2.

In the diagnosis of EHF, the above symptoms may appear from 2 to 21 days after exposure to an Ebola victim or a direct contact with THE fluid of an Ebola patient. The architecture of the proposed neuro-fuzzy system for the diagnosis of EHF (see Figure 2), is designed after series of consultations with literature and medical experts in the field.

**Table 1:** Diagnosis Categories of EHF.

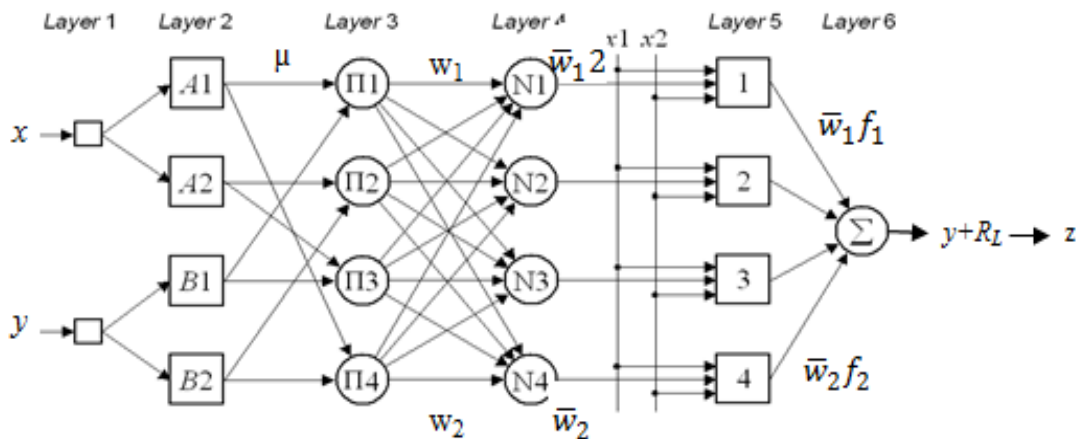
Diagnosis Categories	Clinical Signs and Symptoms
No-Threat (T-0)	Diffuse Erythematous Maculopapular Rash
	Fever
Very-Low-Threat (T-1)	Arthralgia
	Chills
	Sore throat
	Headache
	High Fever
	Joint pain
	Malaise
	Muscle soreness
	Myalgia
	Nausea.
Low-Threat (T-2)	Weakness
	Abdominal pain
	Anorexia
	Chest pain
	Intense fatigue
	Severe Watery Diarrhea
Some-Threat (T-3)	Vomiting blood
	Bleeding from anus
	Bleeding from nose
	Brain drain
High-Threat (T-4)	Headache confusion
	Cerebral edema
	Coma
	Conjunctival injection
	Hiccups
	Seizures
	Massive internal bleeding
	Organ failure
	Shock
	Shortness of breath

**Table 2:** Clinical Symptoms of EHF.

Symptoms	Linguistic term
Fever	S1
Severe headache	S2
Muscle pain	S3
Weakness	S4
Fatigue	S5
Diarrhea	S6
Vomiting	S7
Abdominal pain	S8
Unexplained hemorrhage	S9

In layer one the inputs are numeric values which represents the symptoms drawn from the different diagnosis categories. It passes external crisp signals to the next layer which is the fuzzification layer. All the nodes are adaptive nodes which denote inputs to the system. The fuzzification layer maps the crisp signal (value) into a fuzzy set. The fuzzifier contains a finite set of linguistic terms defined as  $\mathbf{x} = \{x_1, x_2, \dots, x_n\}$  and maps the input to their corresponding linguistic value  $f$ . Thus  $x_i$  represents an element in  $f$  which is a fuzzy set of diagnosis variables in  $F$  and  $n$  represents the number of input parameter in the first layer which represents the number of symptoms that are used for the diagnosis of EHF. The algorithm returns a list of  $c$  cluster centers  $F$ , such that  $F = F_i, i=1, 2, \dots, c$  and a partition matrix  $U$  such that  $U = U_{ij}, i=1, \dots, c; j=1, \dots, n$ . Where  $U_{ij}$  is a numerical value in  $[0, 1]$  that tells the degree to which the linguistic term  $x_j$  belongs to the  $i^{th}$  cluster.  $f$  is represented as Equation (1):

$$f = \{(x_i, \mu_f(x_i)) \mid x_i \in F, \mu_f(x_i) \in [0,1]\} \quad (1)$$



**Figure 2:** The Proposed ANFIS Architecture for the Diagnosis of EHF.

where  $\mu_f(x_i)$  is the membership function ( $M_f$ ) of  $x_i$  in  $f$  and it represents the degree of involvement of  $x_i$  to the outcome of the EHF diagnosis. The outputs of layer 1 are the fuzzy membership grade of the inputs which are represented in Equations 2 and 3 as:

$$f_i = \mu_{A_i}(x), \quad i = 1, 2 \quad (2)$$

$$f_i = \mu_{B_{i-2}}(y), \quad i = 3, 4 \quad (3)$$

where  $\mu_{A_i}(x)$  and  $\mu_{B_{i-2}}(y)$  can adopt any fuzzy membership function. In Figure 2, if the fuzzy sets  $A_1$  and  $A_2$  each has a membership function which is a bell curve (Clark et al., 2003) or bell shaped (Biganzoli et al., 1998), the membership function are obtained as represented in Equations 4 and 5:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[ \frac{(x-c_i)^2}{a_i^2} \right]^{b_i}} \quad (4)$$

$$\mu_{A_i}(x) = \exp \left\{ - \left( \frac{x-c_i}{a_i} \right)^2 \right\} \quad (5)$$

where  $a_i, b_i, c_i$  are the parameter set used to alter the shape of the membership function.

In the second layer, the nodes are fixed nodes, whose output is the product of the membership function grades (i.e., the incoming signals). The layer calculates the firing strengths of the rules as a product of the membership grades: The outputs of this layer are represented in Equation 6 as:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2 \quad (6)$$

In the third layer, each node is a fixed node and this is the rule layer, which calculates the ratio of the  $i^{\text{th}}$  firing strength rules to the sum of all firing strengths rules represented in Equation 7 as:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (7)$$

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model) from layer 3. Where  $\bar{w}_i$  denoted output of layer three and  $p_i, q_i,$  and  $r_i$  are the parameter set of the nodes. Parameters in this layer are referred to as consequent parameters. The outputs of this layer are characterized by a function of the form in Equation 8:

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \quad i = 1, 2 \quad (8)$$

Layer 5 is the defuzzification layer that yields the parameters of the consequent part of the rule. The single node in Layer 6 is a fixed node denoted as  $z$ , which computes the overall output as the sum of the contributions of each rule (i.e. the summation of all incoming signals and an extra decision facilitator). This is represented in Equations 9 and 10.

$$y = \sum_{i=1}^2 \bar{w}_i \cdot f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i}, \quad i = 1, 2 \quad (9)$$

$$Z = y + R_L \quad (10)$$

where  $R_L$  denotes the extra decision facilitator that is based on patient's type of contact with (or without) an infected EHF patient.

## DATA SAMPLE

The study data set was gotten through the use of research questionnaires and it contained cases of Ebola patient and patients suffering from fever, malaria and typhoid. The inputs into the ANFIS system are the clinical symptoms of EHF which are fever, headache, muscle pain, weakness, fatigue, diarrhea, vomiting, abdominal pain and hemorrhage.

The data gotten through the use of questionnaire was scaled using the following formula represented in Equation 11:

$$y' = \frac{y - y(\min)}{y(\max) - y(\min)} \quad (11)$$

and the scaled value of the parameters (symptoms) are mapped into the fuzzy set as shown in Table 3

## EXPERIMENTS

The computer simulation was carried out using MATLAB and Fuzzy Logic tool box. 50% of the dataset was used for training of the system and the training dataset was randomly permuted (i.e. mixing both Ebola patient and non-Ebola patient), 25% of the dataset was used to test the system while the remainder was used to check the system. The backward propagation was used to train the adaptive neuro fuzzy inference system

at a cut off at 0.2 with a linear output membership function.

**Table 3:** Fuzzy Set.

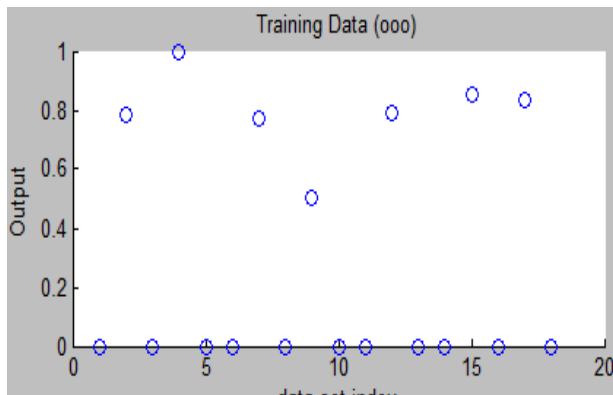
Diagnosis Categories	Fuzzy Values
Mild	$0.0 < x < 0.4$
Moderate	$0.41 < x < 0.7$
Severe	$0.71 < x < 1.0$

## RESULTS

The experiment and stimulation was conducted using different membership function and the result is shown below.

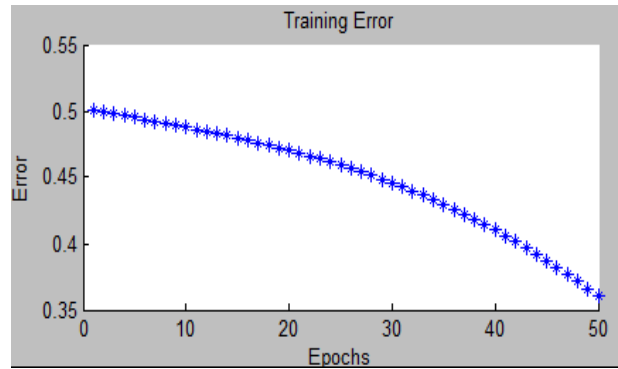
**Table 4:** Membership Functions.

Membership function	Output function	Training error	Testing error
Bell curve mf	Linear	0.368721	0.364222
trimf	Linear	0.5923302	0.532202
trapmf	Linear	0.642022	0.598832
Guass1mf	Linear	0.5232003	0.471783
Guas2mf	Linear	0.5432401	0.473366



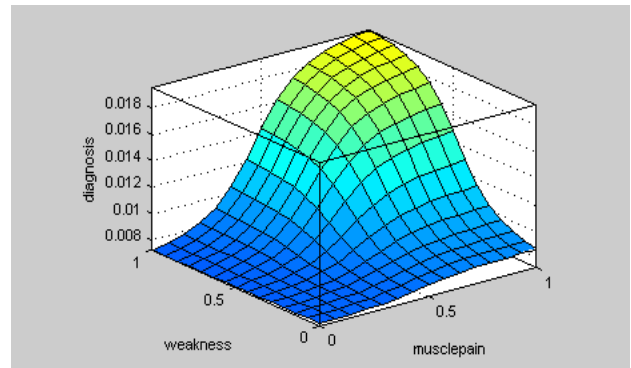
**Figure 3:** ANFIS Training Data.

The ANFIS training data (Figure 3), showing the partial distribution of training data from 0 to 1 on the output (Y axis) and 0-20 on the input (0-20), respectively.



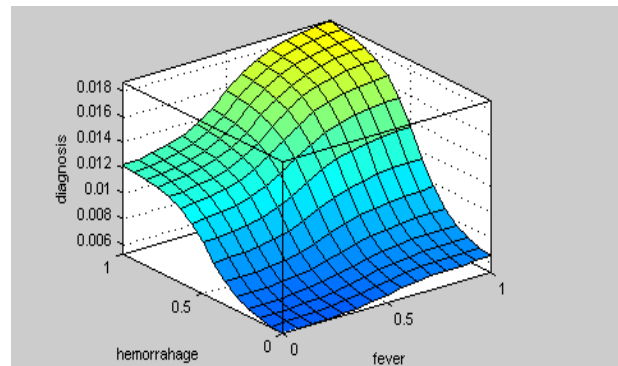
**Figure 4:** ANFIS Training Error.

The ANFIS training error (Figure 4) shows the relationship, declining gradually from error 0.5 through 0.45 down to error 0.35 at an epoch of 0-50, respectively.



**Figure 5:** ANFIS Surface Viewer 3.

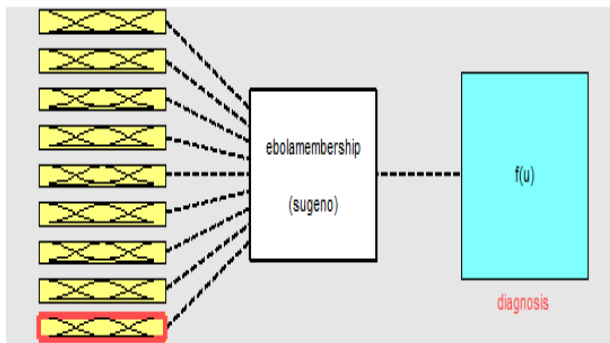
ANFIS surface viewer 3 (Figure 5) show the relationship between weakness and musclepain as regard Ebola diagnosis.



**Figure 6:** ANFIS Surface Viewer 4.



ANFIS surface viewer 4 (Figure 6) Showing the Relationship between hemorrhage and fever as regard Ebola diagnosis.



**Figure 7:** ANFIS Fuzzy Inference Editor.

The FIS editor (Figure 7) shows the input variables (varied symptoms of Ebola), the derived membership function and the output variable (diagnosed result).

## CONCLUSION

As the lack of an Ebola effective treatment protocol, limited access to medical specialist and laboratory data potentially threatens global health, the adoption of the enhanced Adaptive Network based Fuzzy Inference System that formalizes the diagnosing process of EHF using 9 clinical symptoms (parameters) will enhance the treatment process and prevent the spread of EHF that is already difficult to diagnose. From our experiment it was clearly shown that the membership function with a linear output function shows the least training error and at a cut off of 0.2 using the backward propagation learning algorithm.

The ANFIS framework which comprises of some analytical decision steps that isolates data objects into homogeneous clusters using different types of similarity measures implements the Sugeno fuzzy inference method and incorporated a decision facilitator that exist only in the EHF environment to enhance the learning, adaptation and optimization of results making the proposed system less reliant on expert knowledge and still capture the EHF domain.

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