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Diagnosis of Human Immunodeficiency Virus (HIV/AIDS) Using Optimized ANFIS with Particle Swarm Optimization (PSO) Algorithm

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Abstract— *One of the significant bottlenecks in applying ordinary neural network to the clinical field is that it is extremely challenging to decipher, in a truly significant manner, on the grounds that the learned information is mathematically encoded in the prepared synaptic loads. This research Diagnosis of Human Immunodeficiency Virus (HIV/AIDS) Using Optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) with Particle Swarm Optimization (PSO) Algorithm expects to foster a further developed model joining ANFIS with PSO Algorithm to aid the health workers acquire exact and dependable outcome. The PSO is utilized to train inputs and optimize ANFIS for better, improved performance of the Adaptive Neuro-fuzzy Inference System (ANFIS). The symptoms of HIV/AIDS incorporate headache, chronic cough, diarrhea, swollen glands, lack of energy, and loss of appetite, weight loss, frequent fevers, frequent yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body and short-term memory loss. The data collected was split into two for training and testing, rules were generated. The system used the symptoms as input to make the decision. MATLAB 15a was utilized to examine and train the input and developed the model in this experiment; Gaussian membership function was utilized to evaluate the linguistic variables. In the meantime, two distinct advancement optimization methods for ANFIS are analyzed Genetic Algorithm GA-ANFIS Train is 0.300 and Test 0.320, Differential Evolution DE-ANFIS Train is 0.315 and Test is 0.400. The normal RMSE of ANFIS-PSO Training and Testing was 0.028 and 0.0416 respectively. This outcome shows that PSO execution can conquer the customary deduction framework and joined with other advancement optimization methods considerably. The framework will offer likely help to clinical professionals and the medical services area in settling on a brief choice during HIV/AIDS diagnosis.*

Keywords— *ANFIS: Diagnosis: HIV/AIDS: Optimization: PSO.*

I. INTRODUCTION

The Human Immunodeficiency Virus (HIV) is a retrovirus that infects immune system helper T cells or lymphocytes, resulting in Acquired Immune Deficiency Syndrome (AIDS). HIV is spread mostly through contact with tainted bodily fluids, particularly blood and sperm. Sharing infected sharp items and blood transfusions are two other ways to spread HIV. Headache, chronic coughs, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers and yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss are all symptoms of HIV. HIV is a virus that affects CD-4 cells, a type of immune cell that is a subset of T cells. AIDS is a syndrome that can manifest itself in the advanced stages of HIV infection or not (Amosa, Adisa, Ateku & Ugwu 2018). Although HIV infection can lead to the development of AIDS, it is also possible to contract HIV without developing AIDS. HIV can progress without treatment, and in the vast majority of instances, it will eventually lead to AIDS. HIV, on the other hand, can be transmitted through;

a. Sexual transmission: This can occur when infected sexual fluids are in contact with each other (rectal, genital, or oral mucous membranes). This can happen when you have intercourse without using a condom, such as vaginal, oral, or anal sex, or when you share sex toys with someone who has HIV. In Nigeria, the majority of HIV transmission occurs through sexual transmission. Over 90% of HIV transmission occurs through unprotected sexual contact between heterosexuals. HIV transmission is aided by homosexual sex, and the prevalence of HIV in this population is considerable, approaching 35 percent (NASCP, 2016).

b. Perinatal transmission: During birthing, pregnancy, and through breastfeeding, a mother can transmit HIV to her child. The likelihood of such transmission is 15-45 percent in the absence of measures. The National Association of State Colleges and Universities (NASCP) published a report in 2016. The majority of HIV-positive children under the age of 15 are infected through Mother-to-Child Transmission (MTCT).

c. Blood transmission: In developed nations, the risk of HIV infection through blood transfusion is extremely low, thanks to careful screening and safeguards. However, sharing and reusing syringes, as well as contact with a sharp piercing device used for scarification, tattoos, and surgical procedures, are all common among people who inject drugs. It is exceedingly dangerous to be contaminated with HIV-infected blood. This transmission's rate of occurrence is not documented.

At the end of 2020, 37.7 million [30.2 million - 45.1 million] persons worldwide would have been infected with HIV since the outbreak began. In 2020, 1.5 million [1.0 million - 2.0 million] persons were newly infected with HIV, despite the fact that the epidemic's burden varies greatly between nations and regions. Sub-Saharan Africa continues to be the most badly impacted region, with approximately one in every 25 adults

(4.2%) living with HIV, accounting for nearly two-thirds of all HIV patients globally (World Health Organization, 2021).

These statistics were collaborated by the most recent insights on the situation with the AIDS plague. In the report it was expressed that; at the finish of December 2020, 27.5 million [26.5million - 27.7million] individuals were getting to antiretroviral treatment, up from 7.8 million [6.9million - 7.9 million] in 2010. 37.7 million [30.2 million – 45.1 million] individuals around the world were living with HIV in 2020, 1.5 million [1.0 million – 2.0 million] individuals turned out to be recently contaminated with HIV in 2020, 680 000 [480 000 – 1.0 million] individuals kicked the bucket from AIDS-related diseases in 2020, 79.3 million [55.9 million – 110 million] individuals have become infected with HIV since the beginning of the pandemic and 36.3 million [27.2 million – 47.8 million] individuals have passed on from AIDS-related sicknesses since the beginning of the pestilence. As presented in the report kids were not left out on the grounds that in 2020 be 1.7 million [1.2 million – 2.2 million] kids (0-14 years) were living with HIV. 53% surprisingly living with HIV were ladies and young ladies. 84% [67 >98%] surprisingly living with HIV knew their status in 2020. Around 6.1 million [4.9 million - 7.3 million] individuals didn't realize that they were living with HIV in 2020. The result of HIV contamination is reported in (UNAIDS, 2020).

Adaptive Neural Fuzzy Inference System (ANFIS)

An ANFIS (Adaptive Neuro-Fuzzy Inference System) is a type of Artificial Neural Network (ANN) that works with the Takagi–Sugeno fuzzy inference system. The system was designed at the turn of the century (Jang, 1991). It has the ability to capture the benefits of both ANN and Fuzzy Logic principles in a single framework because it incorporates both. Its Fuzzy Inference System (FIS) is a set of fuzzy rules (IF-THEN) with a learning proclivity for approximating nonlinear functions. The most useful parameters taken by Genetic Algorithms can be used to practice the ANFIS more efficiently and optimally. (Tahmasebi & Hezarkhani (2012). In the network structure, there are two sections that may be distinguished: the basis and the consequence parts. The architecture is made up of five layers in total. The first layer receives the input, determines the membership functions that refer to the input values. This lnput layer is called the fuzzification. The premise parameter set, namely a,b,c, is used to calculate the membership degrees of each function. The second layer is in charge of determining the rules' firing strengths. The second layer is referred to as the "rule layer" because of its responsibilities. By sinking each value for the total firing strength, the third layer normalizes the measured firing strengths. The fourth layer uses the normalized values as input and the outcome parameter set p,q,r as output.

The values produced by this layer are defuzzified, and they are also sent to the final layer to replace the final output. (Dervis & Ebubekir, 2018). A deep landscape of ANFIS architecture is depicted in Figure 1. The Gaussian membership function was utilized in the model, and HIV symptoms were assessed and used as inputs to the system.

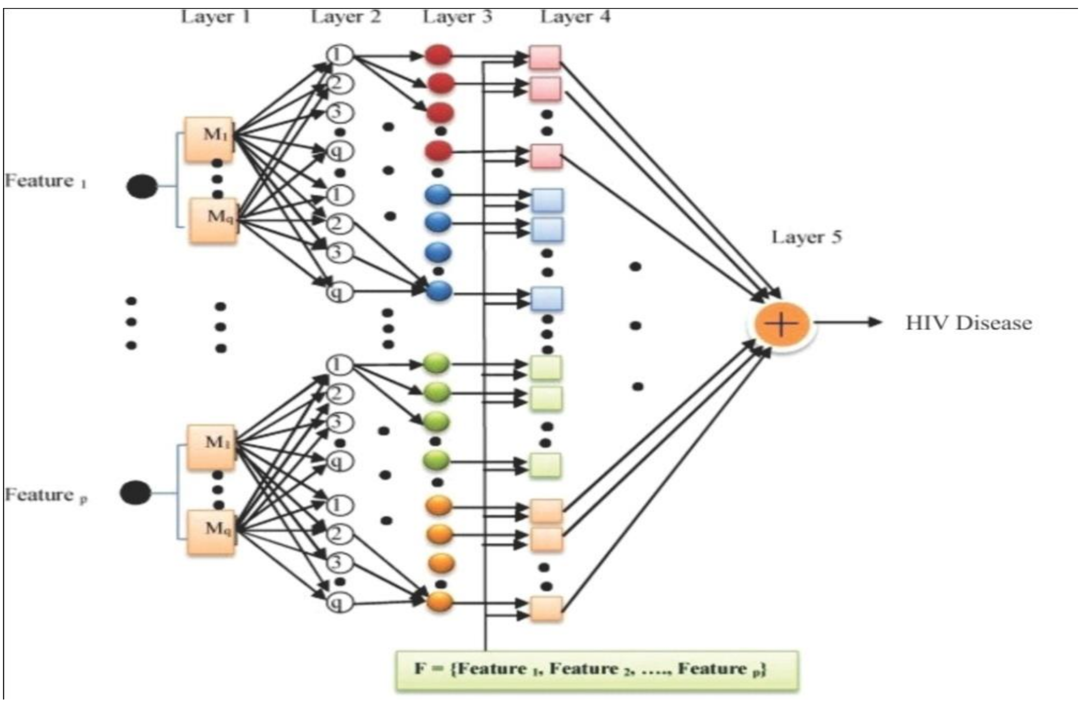

Fig. 1. The five layers Architecture of an Adaptive Neuro-Fuzzy Inference System (Jang, 1993)

Particle Swarm Optimization (PSO) is a populace based optimization approach, where individual particles are gathered into a swarm. Every particle in the swarm addresses a candidate solution to the optimization issue. The training in PSO is that every candidate or particle "streams" through a multidimensional pursuit space, changing its situation as per its experience and the encounters of its adjoining particles. The exhibition of every particle is estimated by a predefined

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wellness work. The target of PSO is to display straightforward behaviors and nearby associations with the climate, to such an extent that each moves towards its nearest neighbor and moves back to the express that the individual has encountered to be simply awesome. The result of demonstrating this social conduct is that the pursuit interaction includes particles that stochastically return towards the beforehand effective areas in the inquiry space. Uses of PSO incorporate capacity estimation, bunching, advancement of mechanical constructions (like neural organizations), tackling framework conditions, game learning, power frameworks, plan, booking, information mining, bioinformatics, signal preparing, AI, and adaptation control. (Jianchao, Jing, and Zhihua, 2004).

A unique hybrid technique for HIV diagnosis is proposed in this study. Particle Swarm Optimization (PSO) and the Adaptive Neuro-fuzzy Inference System (ANFIS) are used in this approach. The PSO is employed in this approach to improve the performance of ANFIS by providing a more accurate and trustworthy outcome. This system will give a self-learning and adaptive system capable of handling uncertainties and imprecise data to assist medical practitioners in making decisions.

Building the Proposed ANFIS-PSO

It is realized that the ANFIS scheme is computationally proficient and well-versatile with optimization and adaptive techniques. This scheme can likewise be joined with master frameworks and rough sets for different applications, just as utilized with different frameworks to deal with more perplexing parameters. One more benefit of ANFIS is its speed of activity, which is a lot quicker than in other control techniques. The difficult undertaking of training membership functions capacities is acted in ANFIS utilizing metaheuristic improvement algorithms (because of the nature of fuzzy frameworks). A methodology presented in this exploration that joins Adaptive Neuro-Fuzzy Inference System (ANFIS) and Particle Swarm Optimization (PSO). PSO was utilized to work on the presentation of ANFIS by changing the membership functions and limiting the error.

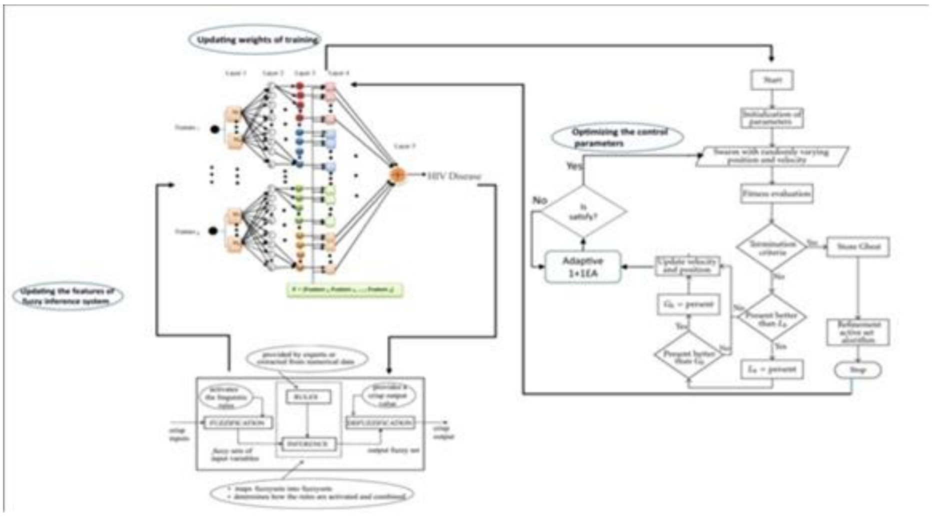

Fig. 2. Depict the Architecture of ANFIS/PSO.

II. Review of Related Works

There is no question about the various investigations that have been carried out in the space of Artificial Intelligence in medicine. Colossal progression in programming and equipment businesses has given freedoms to PC specialists to investigate each part of Artificial Intelligence strategies and procedures in building applicable frameworks and gadgets for medical Practitioners. Optimized ANFIS with Particle Swarm Optimization is a soft computing method that consolidates the provisions of ANFIS and PSO prompting having a half breed framework. It utilizes a managed learning algorithm that has the usefulness of the Takagi Sugeno model (Varinder, 2015).

EL-Hasnony *et al.*, (2020) designed an Optimized ANFIS Model for Parkinson's disease Prediction in an IoT Environment using Hybrid Metaheuristic Algorithms. A proposed fog-based ANFIS+PSOGWO model for Parkinson's disease prediction is proposed in this paper. With the use of a chaotic tent map for initialization, the suggested model takes advantage of the advantages of Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) for adjusting the Adaptive Neuro-Fuzzy Inference System (ANFIS) parameters. Many assessment criteria were employed in comparison to other optimization methods, including the Root Mean Square Error (RMSE), Mean Square Error (MSE), Standard Deviation (SD), and accuracy, as well as five standard datasets from the UCI machine learning, the proposed approach outperformed the Grey Wolf Optimization (GWO), the Particle Swarm Optimization (PSO), the Differential Evolution (DE), the Genetic Algorithm (GA), the Ant Colony Optimization (ACO), and the basic ANFIS model using machine learning. Furthermore, the proposed ANFIS+PSOGWO was used to predict Parkinson's disease and had an accuracy of 87.5 percent. In comparison to PSO, GWO, GA, ACO, DE, and some current literature for Parkinson's disease prediction, the proposed ANFIS+PSOGWO produced more positive outcomes. The

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proposed model surpassed its nearest competitors in all algorithms by 7.3 percent for Parkinson's disease prediction accuracy.

Balasubramanian and Ananthamoorthy (2020) proposed an Improved Adaptive Neuro-Fuzzy Inference System for medical diagnostics based on a Modified Glowworm Swarm and a Differential Evolution optimization technique. The study develops a model for detecting neurological disorders such as glaucoma and Parkinson's disease, as well as carcinogenic diseases such as breast cancer. The proposed method uses a Modified Glowworm Swarm Optimization Algorithm to improve the efficiency of the Adaptive Neuro-Fuzzy Inference System (ANFIS) (M-GSO). The DE–GSO–ANFIS model was compared to the classic ANFIS model, the Genetic Algorithm-ANFIS (GA-ANFIS), Particle Swarm Optimization-ANFIS (PSO-ANFIS), Lion Optimization Algorithm-ANFIS (LOA-ANFIS), Differential Evolution-ANFIS (DE-ANFIS), and Glow-worm Swarm Optimization models (GSO). The DE–GSO–ANFIS outperforms and outperforms similar approaches in terms of predicting medical conditions, according to their findings. The proposed approach was employed for prediction rather than diagnosis.

Abikoye, Popoola, Aro and Popoola (2017) utilize an Adaptive Neuro-fluffy induction framework for HIV/AIDS analysis, clinical staging, and routine prescription. The data gotten was parted into two sections, 70% was utilized for training and 30% for testing. The dataset was stacked into the ANFIS model by providing the info factors stacked through the MATLAB work area. An absolute number of nineteen ascribes and one gathering name were stacked into the ANFIS model. The parametric setting of the fuzzy inference framework was finished utilizing the subtractive bunching techniques. The test results was applied to think about the objective which is the normal output to the anticipated output of the model. A complete number of 75 dataset was utilized to test and the model had the option to order accurately 70 and grouped 5 inaccurately. Disarray grid and framework assessment was led to outline the varieties between the anticipated yield by the ANFIS model and target (Expected output). The outcome shows a genuine positive pace of 0.93333 and bogus negative rate 0.6667 with 93.33% of data classified accurately and 6.667 % of data arranged inaccurately by the ANFIS model.

A hybrid Adaptive Neural Fuzzy expert system based on Particle Swarm Optimization (PSO) was revealed in Matlab's Simulink to discriminate Liver disease and health condition in a paper by Mina, Masoumi, and Ajam (2019). When compared to the ANFIS based on the dataset, the accuracy of classification was raised by 10% using this proposed technique. Statistical analysis was used to determine the establishment of meaningful qualities and fuzzy rules. The potentiality is revealed by the importance of selecting significant and important fuzzy rules without the assistance of specialists.

Jayakumar, Sayeed, Hossen, Yusof, and Samraj (2017) proposed a Fuzzy Logic with Particle Swarm Optimization approach that supports RDF, OWL, and rule inference engine and is implemented using the Jena framework. In addition, the Jena framework is used to develop and apply fuzzy logic with the Particle Swarm Optimization (PSO) training pattern. The quality and correctness of ontology are factors in its evaluation. Performance is measured using standard measures like as recall, accuracy, and F-score. Let S represent the size of the ground truth value, D represent the number of right values extracted by the proposed system, and N represent the total number of values returned by the proposed system.

Amosa et al. (2018) designed an Adaptive Neuro-fuzzy expert framework for diagnosing HIV where HIV symptoms were used. The point of convergence was to depict and represent the use of the fuzzy logic framework to the diagnosis of HIV. It involves sequences of methodological and analytical decision steps that enhance the quality and which means of the logic produced. The framework dispenses with the uncertainties often associated with the investigation of HIV test data. The software utilized for the advancement of necessary Graphic User Interface (GUI), for fuzzy modeling, fuzzy interface framework editors, membership function editors, rule editorial manager GUI; a sort of an Adaptive Neural fuzzy inference framework was used for building and analyzing Mamdani.

Soft Computing Techniques were used in the diagnosis of tropical diseases by Samuel, Uzoka, Obot, Ekong, and Ejodamen (2020). The findings suggest that nations in Africa, Asia-Pacific, and Europe have done more research in areas focusing on the application of soft computing techniques in the diagnosis of tropical diseases, followed by countries in the Americas. Malaria, dengue fever, skin illnesses, and other tropical diseases are among the twelve (12) most regularly studied. The soft computing classifiers were evenly distributed between single and hybrid paradigms. The vast majority of the arrangement engines were based on fuzzy logic (15), neural organization (5), support vector machine (4), and decision tree (4).

III. Materials and Methodology

Essential Data were collected through interview, Discussion and perception at Numan General Hospital, Local Action Committee on AIDS (LACA) with the wellbeing professional to realize the parameters needed for HIV diagnosis and the etymological factors of each parameter. This was done to get a top to bottom information on how the framework functions.

The secondary data was gathered from course books, online articles, Journals both Local and International to empower the specialist see commitments in alternate points of view and strategies for approach which were planned to have superior information on finding of HIV.

HIV symptoms incorporate Headache, chronic coughs, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers and yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss. The dataset was stacked into the ANFIS/PSO model by providing the input values and the membership function for each input is shown in Figure 3 up to Figure 15. The sources of input incorporates headache, this input variable is characterize dependent on three (3) semantic factors (Migraine, Cluster and Tension-type). Chronic cough was separated into four (4) fuzzy sets (Dry, Croup, Whooping and Wet). Diarrhea saliently affects the outcome and can transform it without any problem. The Diarrhea field has two

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(2) fuzzy sets (Acute and Chronic). A swollen gland, the field is one of the main factors in this framework that changes the outcome. In this framework we have four (4) phonetic factors (Armpit, Others, Neck, and Groin). Lack of energy has two (2) fuzzy sets (True or False) and Loss of appetite has two (2) fuzzy sets (True or False). Weight loss has two (2) values (True or False). frequent fevers have four (4) fuzzy sets (Typhoid, Malaria, FUO and Others). Frequent yeast infection comprise of four (4) fuzzy sets (Oral, Others, Vagina, and Male). Skin rashes have two (2) values (0, 1) and sets (True or False). Pelvic/stomach cramps have two (2) values (0, 1) and sets (True or False). sores on specific pieces of the body, this information field is isolated into three (3) fuzzy sets (Mouth, Throat, and Others). Short-term memory loss has two (2) values (0, 1) and one fuzzy set (valid). On the off chance that the specialist decides the activity test for the patient worth 1 will be entered into the framework in any case esteem 0 will be entered. At long last, the HIV test result depends on three etymological factors Not HIV infected, Might be HIV infected and HIV infected.

IV. System Design

The Design of the ANFIS/PSO system that will analyze HIV will be considered under the followings: sources of input and output, linguistic rules, the parts of the fuzzy logic and the rule base.

I. The Inputs and Output boundaries The decision of the input(s) and output(s) is a key and essential piece of the plan since different pieces of the design relies upon what the sources of input and the output are ;

a. Inputs: The capacity of the regulator is to analyze HIV which can be dictated by manifestations Headache, chronic coughs, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers and yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss
b. Output: In this research The ANFIS/PSO framework proposed one output which is the HIV Result and is characterize dependent on three (3) phonetic factors which are Not HIV infected, Might be HIV infected and HIV infected

II. *Fuzzification*: The fuzzification of the data sources gives how much each piece of the forerunner has been fulfilled for each standard "belongingness". Since the predecessor of the standards utilized in the determination of HIV status utilizing fluffy rationale is more than one section, the fuzzy administrator "AND" is applied to get one number that addresses the result of the precursors for that standard. This number will then, at that point, be applied to the yield work. The contribution to the fuzzy administrator is thirteen participation esteems from fuzzified input variables. The output is a solitary truth value. In fuzzy system, each rule has a weight (a number somewhere in the range of 0 and 1) which is applied to the number given by the precursor. Nonetheless, in the exploration work, a load of 1 is relegated to each rule. Subsequent to allocating the loads to each standard, the ramifications technique is then carried out. A resulting is a fuzzy set addressed by a membership function, which weighs fittingly the semantic qualities that are credited to it. The resulting is reshaped utilizing an enrollment work related with the precursor. The contribution for the ramifications cycle is a solitary number given by the predecessor, and the output is a fuzzy set. From that point, suggestion is executed for each rule.

III. Fuzzification interface: The fuzzification interface converts the input data into appropriate linguistic variables, such as headache, chronic cough, diarrhea, swollen glands, lack of energy, and loss of appetite, weight loss, frequent fevers, frequent yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss into sweet able linguistic variables. The input range variables are shown as equivalent universes of discourse in a scale mapping using the Gaussian membership function.

Decision Making Logic: The Decision Making Logic surmises a system of rules through the fuzzy operator 'AND' and produces a solitary truth value which decides the result of the guidelines (deduced fuzzy control activity).

IV. Defuzzification interface: During fuzzification, the fuzzy input variable, every one of the manifestations will be changed over into their linguistic factors. The Gaussian membership function is utilized to perform the scale mapping.

d. Rule base: The conduct of the control surfaces is characterized by the rules that consolidate the fuzzy factors. Every one of the rules will be introduced generally speaking rule base matrix, where the predecessors are the Headache, chronic coughs, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers and yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss. And the consequence of the guidelines is 'HIV Result'.

V. Input Membership Functions of the Experiment

1. Headache membership function has three linguistic variables, which are Migraine, Cluster and Tension type. Migraine has the lowest level and Tension Type has the highest level as shown in Figure 3 below.

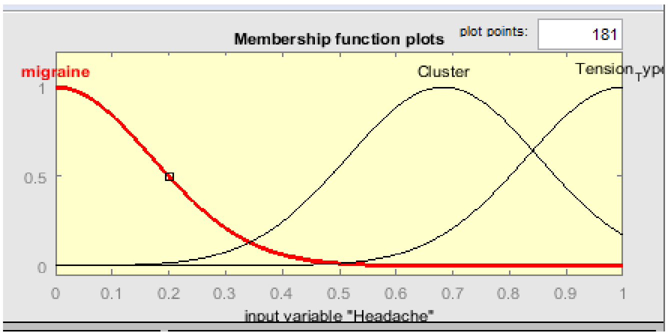

Fig. 3. Membership Function of Headache

2. Chronic Cough membership function has four linguistic variables, which are Dry, Wet, Whooping and Croup as shown in Figure 4 below.
3. Diarrhea membership function based on two linguistic variables, which are Acute and Chronic as shown in Figure 5 below.
4. Swollen Glands membership function based on four linguistic variables, which are Armpit, Others, Neck and Groin as shown in Figure 6 below.

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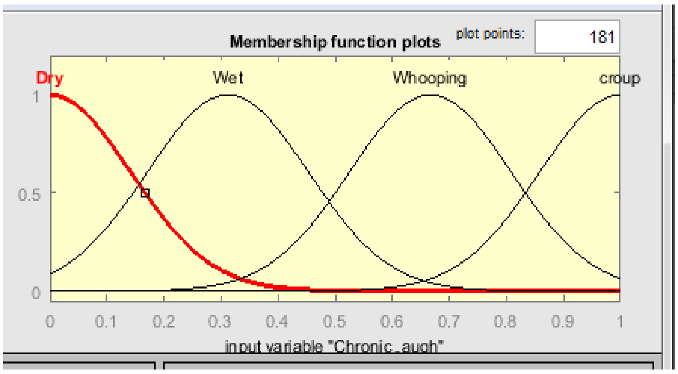

Fig. 4. Membership Function of Chronic Cough

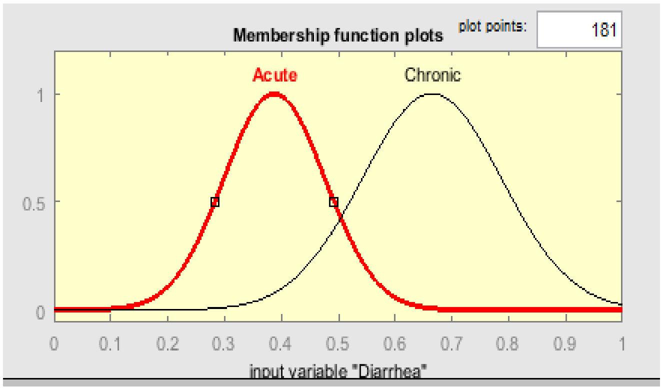

Fig. 5. Membership Function of Diarrhea

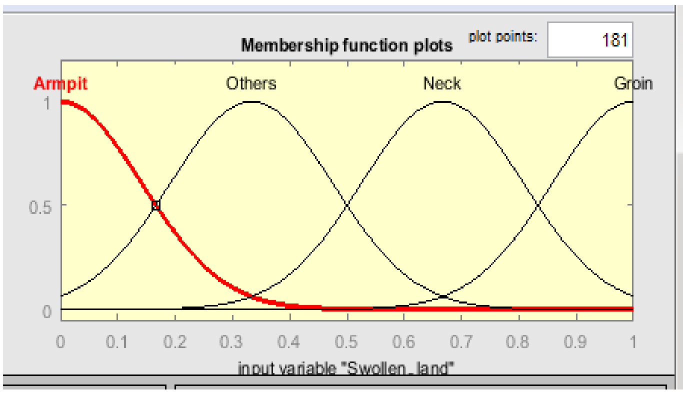

Fig. 6. Membership Function of Swollen Glands

5. Loss of Appetite membership function with two linguistic variables, 'True and False' as shown in Figure 7 below.

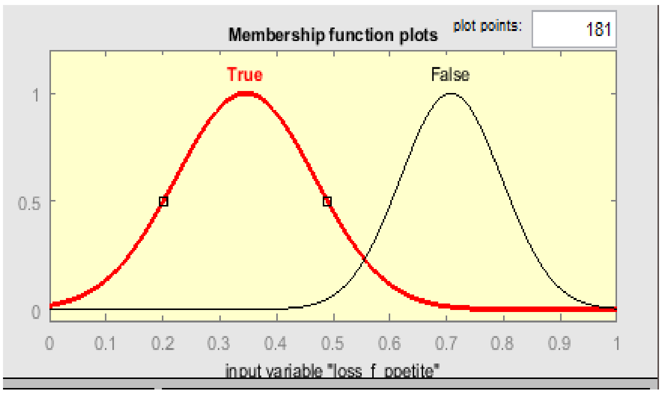

Fig. 7. Membership Function of Loss of Appetite

6. Weight Loss membership function having two linguistic variables, which are True and False as shown in Figure 8 below.

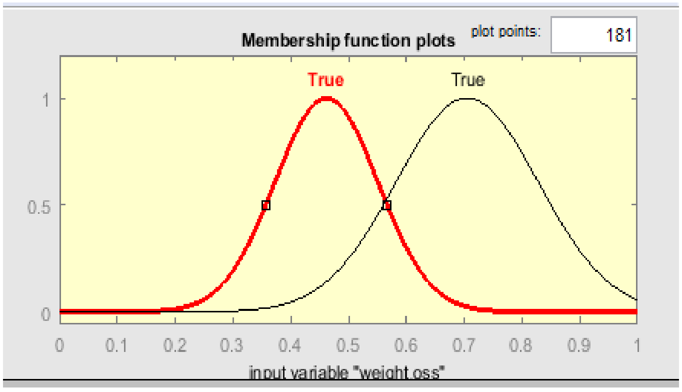

Fig. 8. Membership Function of Weight Loss

7. Frequent Fever membership function is described based on four linguistic variables, which are Malaria, Typhoid, FUO and Others as shown in Figure 9 below.

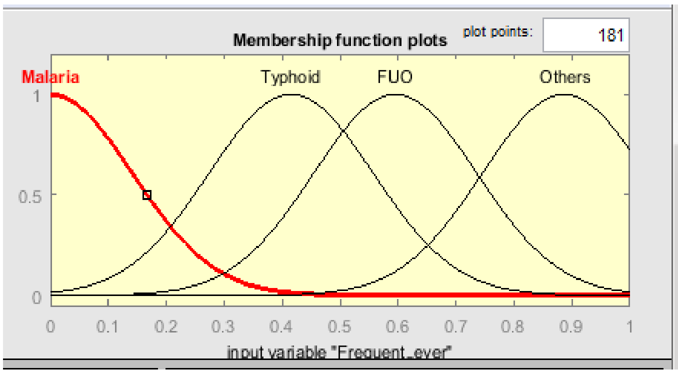

Fig. 9. Membership Function of Frequent Fever

8. Frequent Fever membership function has four linguistic variables, which are Oral, Vaginal, Male and Others as shown in Figure 10 below.

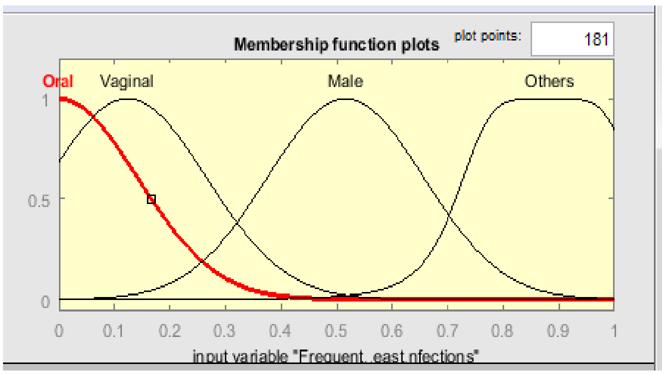

Fig. 10. Membership Function of Frequent Yeast infection

9. Skin Rash membership function is addressed based on two linguistic variables, which are True and False as shown in Figure 11 below.

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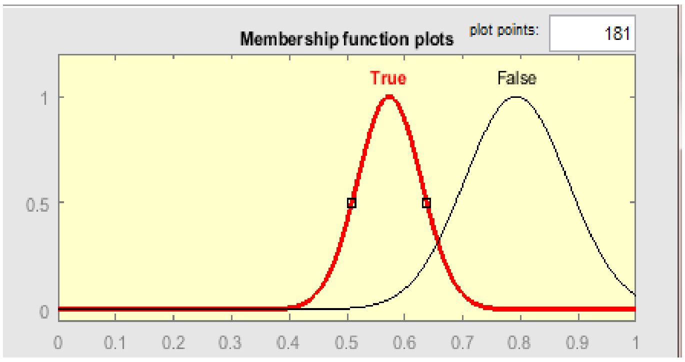

Fig. 11. Membership Function of Skin rash

10. Pelvin/Abdominal Cramp membership function defined based on two linguistic variables (True and False) Chronic as shown in Figure 12 below.

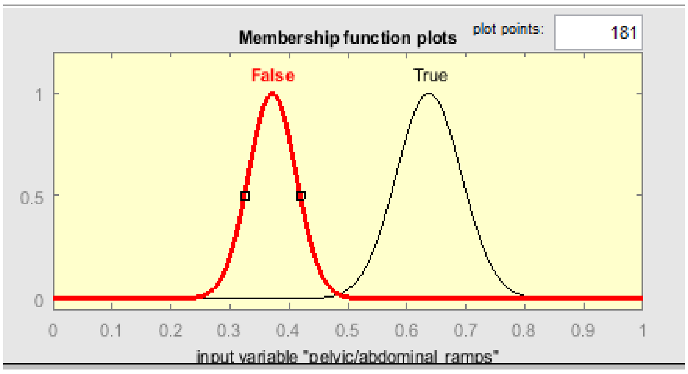

Fig. 12. Membership Function of Pelvin/Abdominal Cramp

11. Sores in Certain Part of the Body membership function has two linguistic variables, which are True and False as shown in Figure 13 below.

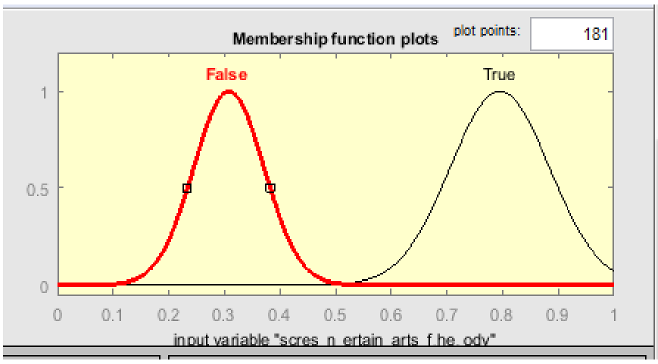

Fig. 13. Membership Function of Sores in Certain Part of the Body

12. Short term memory membership function is presented based on two linguistic variables, which are True and False as shown in Figure 14 below.
13. Lack of Energy membership function is presented with two linguistic variables, which are True and False as shown in Figure 15 below.

Output Variable The "goal" field refers to the presence of HIV disease in the patient. In this system, we have considered a different output variable, which divides into 3 fuzzy sets (Not HIV Infected, Might be HIV Infected and HIV Infected). Membership functions of 'Not HIV Infected', ' Might be HIV Infected' and 'HIV Infected' fuzzy sets are Gaussian membership functions, as shown in Figure 16 below.

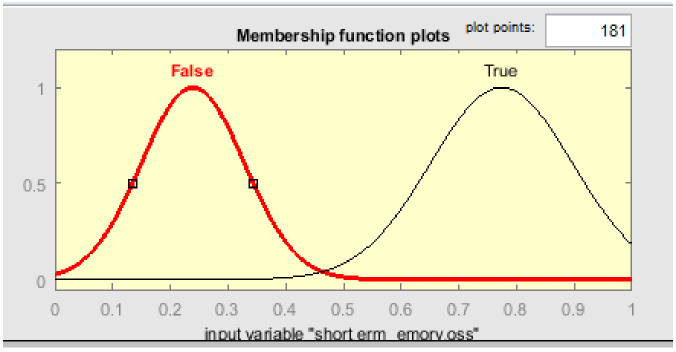

Fig. 14. Membership Function of Short term memory loss

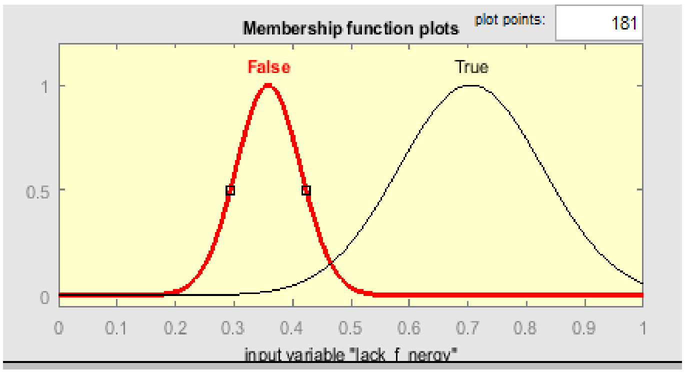

Fig. 15. Membership Function of Lack of Energy

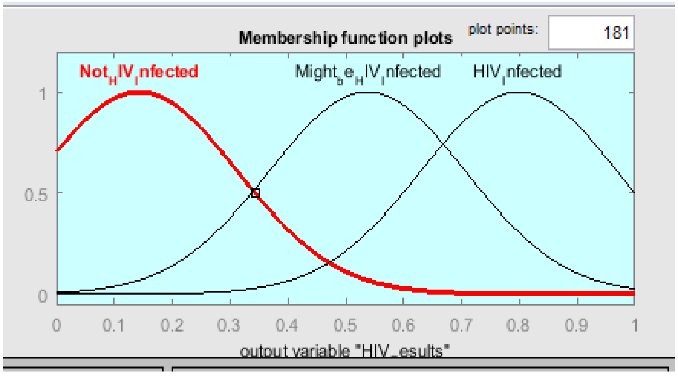

Fig. 16. Membership Function of Output

Generated rules by the subtractive clustering method. The rules generated are shown in Figure 17and Figure 18

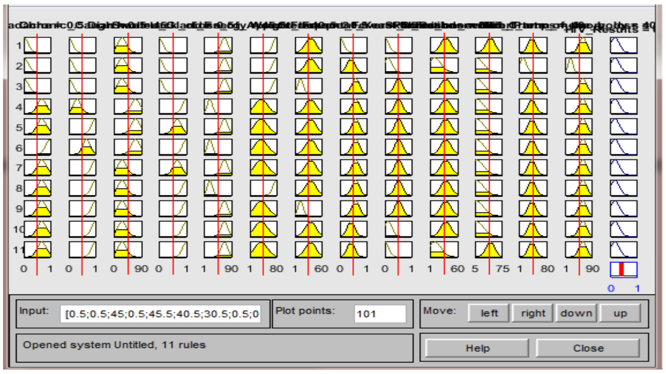

Fig. 17. Rule viewer

Myada Miriam Elias, Yusufu Gambo, and O. Sarjiyus, " Diagnosis of Human Immunodeficiency Virus (HIV/AIDS) Using Optimized ANFIS with Particle Swarm Optimization (PSO) Algorithm," *International Research Journal of Advanced Engineering and Science*, Volume 6, Issue 4, pp. 116-124, 2021.

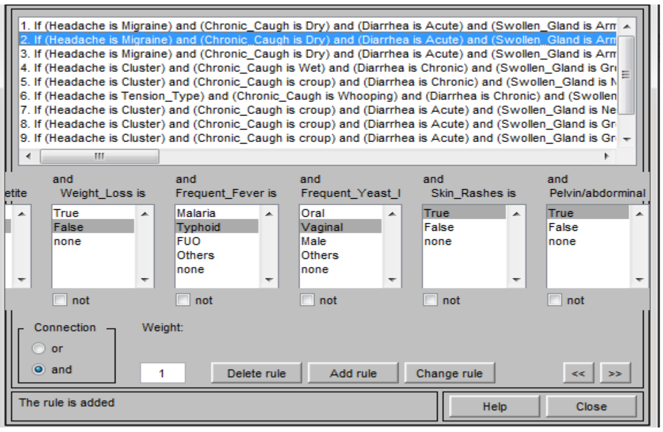

Fig. 18. Generated Rules

Figure 19 shows the data used in training the ANFIS/PSO model. 35 cases were used to train the ANFIS/PSO model

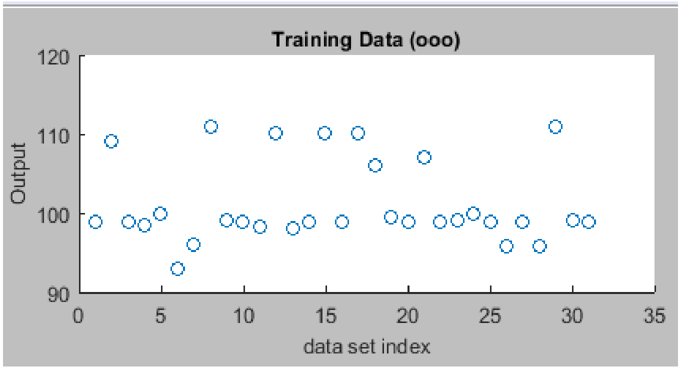

Fig. 19. Training Dataset Set Loaded into the ANFIS/PSO model

The effect of 'Headache' is plotted against another variable 'Cough' in Figure 20, it can be seen that the higher the Cough and Headache, the higher the level of HIV. Also, in Figure 21 the effect of Diarrhea was plotted against Headache.

Figure 22 Shows the fuzzy inference engine. The fuzzy inference engine contains the fuzzification layer, rule layer and defuzzification layer.Fuzzy inference engine with a total number of thirteen inputs, sugeno engine and one output.

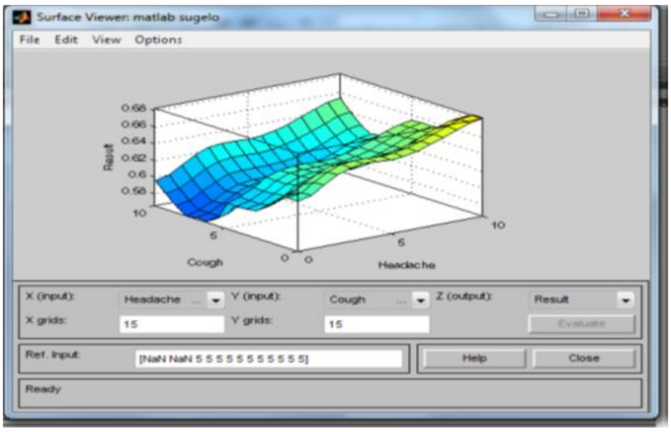

Fig. 20. Surface Viewer and Simulation for cough and headache

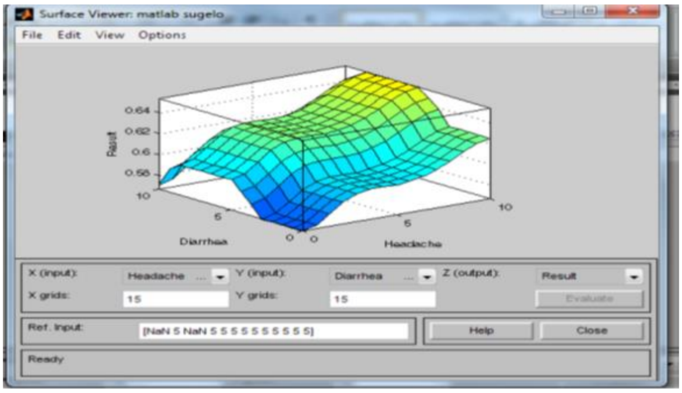

Fig. 21. SurfaceViewer and Simulation for Diarrhea and headache

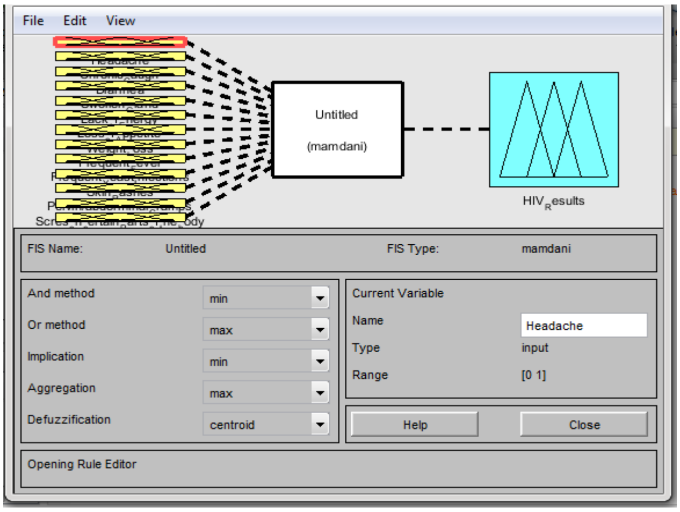

Fig. 22. FuzzyInference

Adaptive Neuro-fuzzy Inference System Model

The architecture of the Adaptive Neuro Fuzzy Inference System model is shown in Figure 23.

Headache, persistent cough, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers, frequent yeast infections, skin rashes, pelvic/abdominal cramps, lesions on certain parts of the body, and short-term memory loss are among the thirteen inputs. These were the signs and symptoms that were used to diagnose HIV.

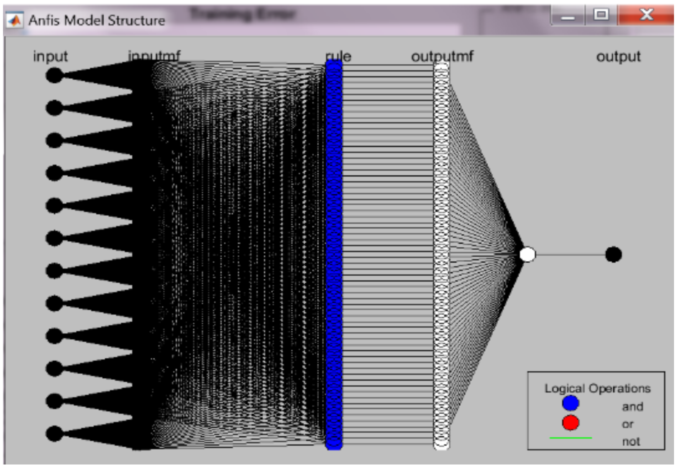

Fig. 23. Adaptive Neuro-Fuzzy Inference System Model

TABLE I. The statistical results based on RMSE for ANFIS Compared with other hybrid ideas

	ANFIS		GA-ANFIS		DE-ANFIS		ANFIS-PSO	
	Train	Test	Train	Test	Train	Test	Train	Test
Max	0.277	0.483	0.290	0.360	0.380	0.480	0.050	0.080
Min	0.284	0.360	0.310	0.280	0.250	0.320	0.006	0.0032
Average	0.280	0.421	0.300	0.320	0.315	0.400	0.028	0.0416

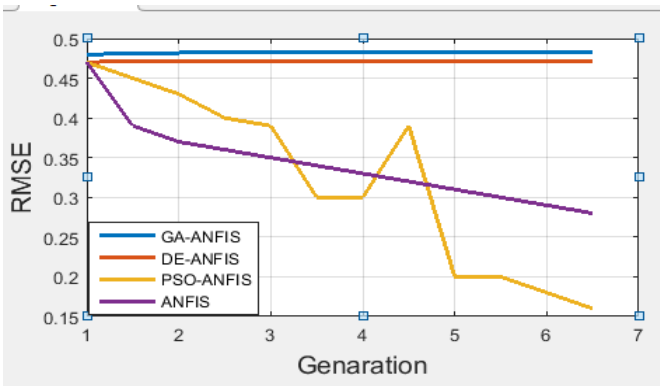

Fig. 24. The performance of PSO to tune the FIS Parameters and reduce the RMSE

VI. Discussion

In this research an ANFIS/PSO model was designed for diagnosing HIV. Thirteen symptoms Headache, chronic coughs, diarrhea, swollen glands, lack of energy, loss of appetite, weight loss, frequent fevers and yeast infections, skin rashes, pelvic/abdominal cramps, sores on certain parts of the body, and short-term memory loss on specific parts of the body, and transient cognitive decline were utilized in diagnosis of HIV with ANFIS/PSO model. The connection between the side effects and the diagnosis of HIV are shown plainly in figures 20 and 21. Huge measure of research has been conducted on HIV diagnosis using conventional ANFIS .The takagi sugeno model which was utilized to demonstrate the standard layer of the ANFIS/PSO framework. Our model consolidates both Adaptive Neuro-Fuzzy Inference System and Particle Swarm Optimization and this makes it more impressive than other ordinary strategies for determination. The investigations created admirable outcomes in the determination of HIV. Anyway the result from our concentrate as displayed in Fig. 24 has shown that ANFIS/PSO is better contrasted with ANFIS, Genetic Algorithm GA-ANFIS Train is 0.300 and Test 0.320, Differential Evolution DE-ANFIS Train is 0.315 and Test is 0.400. The average RMSE of ANFIS-PSO Training and Testing was 0.028 and 0.0416 diagnostics precision of HIV respectively.

VII. Conclusion

In this paper we designed an ANFIS-PSO structure for diagnosing HIV and it yielded a magnificent outcome. The ANFIS-PSO model had an exactness of 96.9%, which is higher than different models used in diagnosing HIV. The execution of this ANFIS-PSO system will aid the specialist in diagnosis of the disease. Instead of other optimized frameworks, ANFIS-PSO framework utilizes phonetic variables which facilitates with human portrayal utilizing their regular language. The outcomes are entrusting and promising dependent on the adaptability and instance of adaptability.

References

1. Abikoye, O. C., Popoola, E. O., Aro, T. O., & Popoola, V.O. Adaptive Neuro-Fuzzy Inference System for HIV/AIDS Diagnosis, Clinical Staging, and Regimen Prescription. *Computer Science and Telecommunication*, *1*(51), 62–76. 2017
2. Amosa, B. M. G., Adisa, S. P., Ateku, B. C., & Ugwu, J. I. Adaptive Neuro-Fuzzy Expert System for Diagnosis HIV. *International Journal of Scientific Research in Computer Science, Engineering & Information Technology*, *3*(5), 254–265. Retrieved from https://pdfs.semanticscholar.org/7256/633657a5c3553ab521d1dbf1cf4ab b4360d0.pdf. 2018
3. Balasubramanian K. and Ananthamoorthy N.P Improved adaptive neuro-fuzzy inference system based on modified glowworm swarm and differential evolution optimization algorithm for medical diagnosis .*Neural Computing and Applications (2021) 33:7649–7660*https://doi.org/10.1007/s00521-020-05507-0. 2020(0123456789()
4. Dervis, K., & Ebubekir, K.. Adaptive Network-Based Fuzzy Inference System (ANFIS) Training Approaches A Comprehensive Survey. *Artificial Intelligence Review*, *52*(4), 1–31. https://doi.org/10.1007/s10462-017-9610-2.2018
5. EL-Hasnony I.B., Barakat S. I., and Moatafa R.R.Optimized ANFIS Model Using Hybrid Metaheuristic Algorithms for Parkinson's Disease Prediction in IoT Environment.Digital Object Identifier 10.1109/ACCESS.2020.3005614. 8(1), 119252-119270. 2020
6. Jang, R. J.-S. Fuzzy Modeling Using Generalized Neural Networks and Kalman Filter Algorithm. *Proceedings of the 9th National Conference on Artificial Intelligence*, *91*, 762–767. Retrieved from http://www.aaai.org/Library/AAAI/1991/aaai91-119.php. 1991
7. Jang, J.S.R. "Anfis adaptive-network-based fuzzy inference system".Systems, Man and Cybernetics, IEEE Transactions on, Vol.23, pp. 665–685.1993
8. Jayakumar, V., Sayeed, S., Hossen, J., Yusof, I., & Samraj, A. Real-Time Face Recognition for Attendance Monitoring System. *Journal of Theoretical and Applied Information Technology*, *95*(1), 24–30.2017
9. Jianchao, C. Z., Jing, J., & Zhihua, H. C. Particle Swarm Optimization Algorithm. *Science and Technology*, *4*, 294–301. 2004
10. Tahmasebi, P., & Hezarkhani, A. A Hybrid Neural Networks-fuzzy Logic-Genetic Algorithm for Grade Estimation. *Computers and Geosciences*, *42*, 18–27. https://doi.org/10.1016/j.cageo.2012.02.004.2012
11. Mina, R., Masoumi, A., & Ajam, A. Adaptive Neuro Particle Swarm Optimization Applied for Diagnosing Disorders. *Preprint*. 2019
12. NASCP. *National AIDS, Viral Hepatitis and STIs Control Programme*. 2016
13. UNAIDS'AIDSinfo' [Accessed July 2020]
14. Varinder, P. Fuzzy Expert System for Medical Diagnosis. *International Journal of Scientific Research Publications*, *5*(1), 1–7. 2015
15. World Health Organization. (2021). HIV/AIDS.

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