

# An artificial neural network (ANN) model for predicting HIV infection among adolescents in Adamawa State

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## Abstract:

Global health concern acquired immunodeficiency syndrome (AIDS) is brought on by the retrovirus known as Human Immunodeficiency Virus (HIV), which compromises immunity. The study's objective is to create a model of an artificial neural network (ANN) that can anticipate adolescent HIV infection. The study identified specific features related to HIV infection among adolescents and used the Analytical Hierarchy Process (AHP) to rank the importance of these features to improve the accuracy of prediction. This is because the input features used in the previous studies did not achieve the desired accuracy. Therefore, the study makes use of 14 characteristics that the literature analysis found to be linked to HIV infection in adolescents. Professionals used a systematic Likert scale with six alternatives to determine the infection's severity. The most important factors influencing HIV infection in adolescents were found by using the data collected to rate the infections. In the study, the ANN was modeled using the Keras Sequential Classification model package. A confusion matrix was used to assess the model's performance after the ideal number of hidden layers and neurons for each hidden layer were established. The model is a feed-forward multi-layer perceptron that is optimized via the back propagation algorithm and is implemented using the supervised learning approach. Accordingly, three hidden layers with 128 neurons, 128 neurons, and 64 neurons each using rectified linear unit (ReLU) activation functions are produced by the model. The model's accuracy in predicting adolescent HIV infection was 95%. Consequently, this study examined the model that can accurately predict HIV infection in Yola North LGA, Adamawa State, Nigeria. For practical application, the research suggests enlarging the dataset and raising the number of training epochs to further increase accuracy.

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## 1. Introduction

The Human Immunodeficiency Virus (HIV) is a retrovirus that infects immune cells like CD4 cells, reducing the bodies to fight against illness and infection. Acquired immune deficiency syndrome (AIDS) is caused by the immune system of an infected person gradually deteriorating. HIV/AIDS has emerged as a major public health concern. Since the discovery of HIV more than three decades ago in the early 1980s, HIV has been the leading cause of death worldwide [1]. Although HIV is mainly passed from person to person, it can also be passed from mother to child through breastfeeding, childbirth, and contact with contaminated blood [2]. Consequently, the virus does not currently have a therapy. However, by preventing the virus from replicating, certain medications can control and delay the virus's spread, resulting in a drop in the blood's viral load. It is observed that an estimated 76 million people have been infected by the HIV epidemic globally, and it has claimed 33 million lives. While AIDS-related mortality has declined, HIV incidence has only

dropped by 17%, meaning that the proportion of persons living with HIV has significantly increased [3]. In order to tackle this problem, the UNAIDS "Fast-track" aims to accomplish the following by 2030: making sure that 95% of persons living with HIV are informed of their status, that 95% of those receiving treatment are on antiretroviral therapy (ART), and that 95% of those receiving treatment effectively suppress their virus [4].

Furthermore, because HIV-1 impairs the immune system and increases mortality in the absence of therapy, acquired immune deficiency syndrome (AIDS) and HIV infection continue to be major public health concerns. The World Health Organization (WHO) advises antiretroviral medication (ART) for all people who test positive for HIV. The "treatment as prevention" strategy—which focuses on comprehensive diagnosis and treatment support—was born out of this emphasis on HIV medical care and attempts to bring an end to the HIV epidemic. In the world, 38.4 million people have HIV/AIDS as of 2021, of which over 28.7 million were receiving antiretroviral therapy

(ART). The majority of HIV/AIDS cases come from low- and middle-income nations; 53% of cases are found in Eastern and Southern Africa. According to a recent study from the Nigerian government, the country's HIV prevalence among adults between the ages of 15 and 49 is 1.4%, down from the previous estimate of 2.8%. The National Agency for the Control of AIDS (2019) and UNAIDS both estimate that 1.9 million people in Nigeria are HIV positive [4].

According to Consejo, *et al.* [5], adolescence is a critical time for making decisions about oneself that can have a big impact on one's future health. Adolescent people are particularly exposed to HIV/AIDS, with one-third of new infections occurring among those between the ages of 15 to 24. The global population of adolescents living with HIV has risen by 30% significantly between 2005 and 2016, highlighting the urgent need to address these urgent challenges and risks faced by adolescents in the context of HIV/AIDS.

From the existing literature, the detection of AIDS in 1981, has affected around 78 million people and caused the death of about 35 million worldwide. These digits and the actions taken by régimes in different republic have given rise to several concerns on the issue and highlighted the urgent need for a comprehensive survey into the nature and spread of HIV [6]. Many studies such as Tunduny [6], Yu [7], Simone [8] and Danaila, *et al.* [9] have used ANN to predict HIV infection among adolescents, for investigating antibody-antigen interaction, breadth of CD4bs and viral load. Nevertheless, the input features used in the previous survey did not attain the anticipated precision levels, ranging from 72.5% to 93.76%. Thus, these findings would rather prefer a different set of inputs to improve the accuracy of predicting HIV infection among adolescents. Also, the Analytical Hierarchy Process was remarkably not utilized in rating the input features. The results gap is the condition for further evaluation into the performance of neural networks, especially Multilayer Perceptron (MLP) networks, in medical categorization jobs. To attend these problems, the researcher developed an integrated ANN

model to predict HIV infection among adolescents in Adamawa State and the utilization of an Analytical Hierarchy Process (AHP) to frequency the input features.

The Human Immunodeficiency Virus (HIV) is a retrovirus that infects immune cells like CD4 cells, reducing the body's capacity to fight against illness and infection. Adolescents refer to individuals in the development stage between childhood and adulthood. This stage typically covers the ages between 10 to 19 years. Adolescence is a crucial phase of natural, thinking, responsive, and collective development [6].

## 1.1 How HIV Infects the Body

When the blood of an HIV-negative individual comes into direct contact with the HIV pathogen, HIV infection results. Activities including sharing contaminated needles or syringes, having unprotected sex with an HIV-positive person, or coming into touch with infected blood from an HIV-negative person's open wound can all lead to this. The main ways that HIV can spread are through tainted blood products, through sexual interaction (where there is a larger risk for homosexuals than heterosexuals), and from mother to child. HIV infection can only be definitively determined by blood or saliva testing because HIV symptoms are nonspecific and can mimic those of other illnesses. As a result, HIV tests for adolescents detect the presence of antibodies supplied in rejoinder to the infection. Fast examines are regularly used, but their accuracy depends on the time passed since exposure. Currently, fast examiners can detect the virus within two weeks of possibility disclosure. Immediately human immunodeficiency virus arrives the blood, it aims and duplicates inside the CD4+ cells, also known as T-helper cells, which are essential for the body's immune response. This duplication process, the immune system is compromised, causing in a deteriorated natural defense system. Figure 1 provides a visual version of how HIV infects CD4+ cells [6].

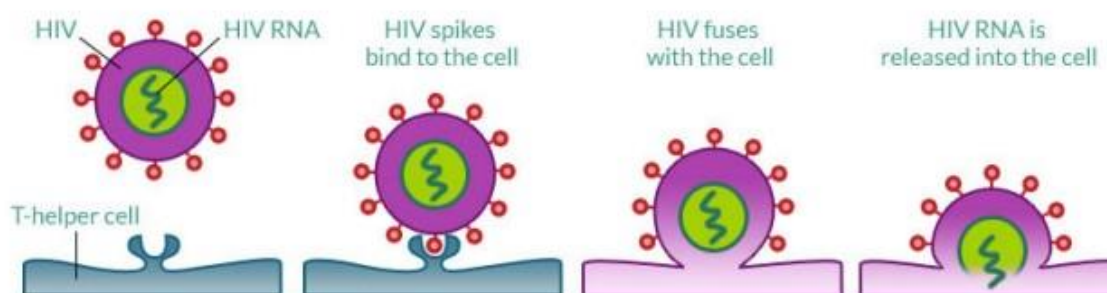


Figure 1: human immunodeficiency virus poisons the CD4+ cell. Sources: [6]

Reverse transcription is the method via which HIV penetrates CD4+ cells and uses the reverse transcriptase enzyme to change its RNA into DNA. With the aid of the integrase protein, the newly created DNA is subsequently incorporated into the cell's DNA, creating a persistent

infection. New HIV viruses are created by the infected cell, but they leave the cell before they have had time to fully mature. These immature viruses can infect other CD4+ cells and gain necessary proteins outside of the cell [20]. Antiretroviral treatment regimens aim to target different

stages of the HIV lifecycle, including obstructing the virus's ability to fuse with CD4+ cells, stopping the integration of HIV DNA into a cell's DNA, and preventing the conversion of HIV RNA to DNA. These involvements benefit stop lasting HIV disease [10].

## **1.2 Antiretroviral Therapy Adherence**

Faithfulness to antiretroviral medication is crucial for HIV-positive patients to efficiently control the virus, reduce drug resistance, and increase overall health and survival, as stated by Aids [11]. Absence of treatment observance can result in limited treatment choices because of drug challenge. Evaluating observance, however, can be difficult. Tunduny [6], identifies four techniques: self-reporting by patients, patients' reports of missed pills, drug level assays, and electrical monitoring systems. Each approach has its constraints. Personality-reportage may be inaccurate as patients may overstress their adherence, and it is only effective in the short span. Patient role reports of missed pills can be affected by the rejection of medication packaging and intentional pill-dumping. Medication level assays can be expensive and may provide wrong results if patients take drug before clinic visits. Automated examining methods assume that a dose is taken every time the medication bottle is commenced, which may not reflect actual adherence if multiple doses are taken at once. Studies by Ippolito [12]. Highlight the value of high observance to maintain viral suppression and optimal clinical outcomes for HIV-positive individuals. Particularly, underline that maintaining an observance level of 95% or higher is crucial for viral accomplishment.

## **1.3 Factors Affecting ART Adherence**

Several factors influence non-adherence to antiretroviral therapy (ART), including social factors and drug side effects. Reasons to identify include perceptions about antiretroviral therapy (ART), religious and ritual views, whisky consumption, lack of family care, economic trials, distance to access medication, stigma and discrimination, short prescription periods, gender disparities, and insufficient medication packet. Sexual category differences were particularly emphasized in a study handled in Nepal, where socio-cultural and economic restraints affect females' access to treatment. Short prescription periods, usually lasting one or two months, are influenced by financial factors, which may result in missed refills for individuals living far from distributing places. Adolescent age and binge consumption were consistently associated with lower adherence to antiretroviral therapy (ART). However, it is cautioned that not all studies have found associations between non-adherence and early stages, female gender, low educational level, or substance abuse history [12].

## **1.4 Impact of ART resistance in HIV-Positive Patients**

Antiretroviral therapy (ART) non-adherence is caused by a variety of circumstances, such as social issues and drug adverse effects. There are several reasons why this is the case, including attitudes against ART, religious and

ceremonial beliefs, drinking, the absence of family support, financial difficulties, and the distance to obtain medicine. HIV treatment resistance and elevated viral loads might arise from noncompliance with antiretroviral therapy [18]. Resistance can result in reduced survival, increased mortality rates, cross-resistance, and the spread of drug-resistant HIV strains, according to Aids [11]. Therefore, resistance strains may be transferred to the fetus in cases of mother-to-child transmission, which may limit the child's access to future treatments. Furthermore, within the same drug class, cross-resistance might result in second-line regimens losing some of their potency.

## **1.5 Artificial Neural Network**

According to Narayana [13] ANN is a mode of machine learning algorithm that mimics the nervous system discovered in animals. Its main goal is forecast, and with the exact structure, it can acquire from and adapt to data to achieve very high accuracy. ANNs are made up of associated neurons displayed in levels, just like real neurons. Effective computation and complicated problematic solving are made viable by this parallel-distributed construction. Analogous neural network (ANN) can be trained on data to find models and provide projections by varying levels and input data weights. Complete guidance, ANN mimic the ability of the human brainpower to detect forms and learn innovative one claims [14].

Amri [15] observed that in a review that ANNs can produce forecasts that are trustworthy and precise. On the other hand, if there is inadequate amount or poor quality of data available to prepare the network, the accuracy of these predictions may suffer. He further points out that the Feed Forward Neural Network has shown to be an effective forecasting tool because of how easy it is to build.

ANN could predict and simulate the functions of the human brain. ANNs can autonomously learn and effectively perform assigned tasks, mimicking the biological brains of animals. In research, ANN are advantageous because they can handle unclear and incomplete data, showcasing their fault tolerance. ANN are also fast and commonly used for data classification and pattern recognition, as noted by [16].

Consejo [6] assert that, machine learning, including Artificial Neural Networks, presents various potential and is relatively easy to implement. This ease of execution opens numerous opportunities for utilizing machine learning as a powerful tool. In the perspective of software program design, Deb [17] suggests that ANN is a valuable device for forecasting. ANN are composed of handling neurons, also called nodes or perceptron. These nodes are organized into input, hidden, and output layers. The participation level can consist of single integer or real numbers, with separate input having a weight value. These responses are processed to produce an output value. Furthermore, the output of one node can function as the input for additional node in the consequent level.

Therefore, neural networks are models composed of interconnected nodes that are used to solve various classification problems [5]. These systems accept input

data and compute the weights for the features to reduce errors involving actual and predicted groupings. The loads are in the beginning set to chance values and are regulated iteratively to correct accuracy [18].

According to Trifonov [19], ANN can identify and comprehend nonlinear relationships within input data sets. By employing the appropriate network topology and weights for connections between neurons, ANN can be trained to approximate functions that express the correlation between inputs and outputs using specific learning algorithms. The effectiveness of neural networks is greatly affected by issues such as the selection of input variables, data pre-processing, and the construction of the network itself.

ANN is a computational model that takes inspiration from the functioning of neurons in the central nervous

system. The central nervous system is responsible for processing and integrating sensory information, including inputs from the visual, auditory, somatic, gustatory, olfactory, and vestibular systems. The nervous system is made up of the spinal cord and the brain, which houses around 10 billion electrically active neurons. Neurons transmit and process information through electrical and chemical processes, which are facilitated by synapses that connect them. When a neuron cell receives input through its dendritic branches, it determines if the input surpasses a certain threshold. If it does, an electrical pulse is generated and travels through the soma (cell body) and down the axon. At the end of the axon, the electrical pulse is transferred to another neuron cell through the release of neurotransmitters. These neurotransmitters are chemicals that bind to the next neuron cell [2].

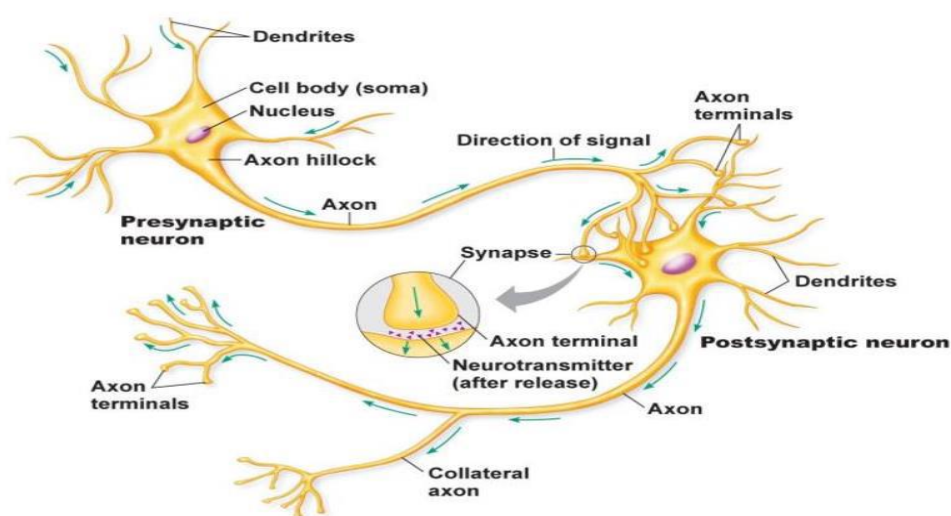


Figure 2: A Representation of 2 Biological Neuron. Dendrites Accepts Inputs and Fire Electronic Impulses Beside the Way Displayed by the Arrows. Outputs From the Axon Propagates in a Junction Called Synapse. Source: Amri [15]

## 1.6 Aim and scope of the Study

The paper aim to develop an Artificial Neural Network Model that predicts HIV infection among Adolescents. The paper covers predicting HIV infection among adolescents using an Artificial Neural Network (ANN). The Input features, such as the number of HIV infection symptoms reported from the State Specialist Hospital Yola, were analyzed by experts from the ART departments to uncover the relative importance of the predictive model.

## 2. Methodology

### 2.1 Study Area

The research area is the Yola-North Local Government Area in Adamawa State, Nigeria. The study area was selected due to its high population of adolescents in Yola-North, making it a target area.

### 2.2 Sample Technique

The method adopted in this finding involves all staff members contributing in the managing of HIV infection among adolescents. This includes various roles such as the ART Coordinator/Doctors, Nurses/TB DOT, and Case

Managers. By including all these employees' members, we aim to gather comprehensive data and insights into the various aspects of HIV management with adolescents. This permits for a more holistic recognizing the challenges, successes, and best systems in providing care and support to this specific population [6].

### 2.3 Procedure for ANN Design

The collection of input features for the model is built on earlier research and includes clinical phase 1 (Recurrent Headache, fatigue, aching muscles, sore throat, swollen lymph node, fever, ulcers(esophagus, anus or genitals)), clinical phase 2 (unexplained weight loss <10%, fungal infection, respiratory tract infection, recurrent oral ulceration), clinical phase 3 (unexplained weight loss >10%, diarrhea, persistent fever, pulmonary tuberculosis, severe bacterial infection, joint infection, unexplained anemia), clinical phase 4 (HIV wasting syndrome, recurrent bacteria, invasive cervical carcinoma, Central nervous system toxoplasmosis). These features were assessed and ranked employing the Analytical Hierarchy Process prior to being input into the model. The model was guided by



employing the back propagation algorithm, which is a supervised learning method. This approach is needed to capture the non-linear relationships in the data. The back-propagation procedure varies the weightiness in the model until the mistake is decreased to an acceptable level. The model procedure of the ANN model, as outlined by Maitha [20] involves several steps.

### 2.3.1 Methods of Data Collection

The paper involved a thorough review of literature from different sources and input from key stakeholders familiar with HIV infection among adolescents in the study area, including staff from Hope centers and HIV clinicians at Specialist Hospital Yola. The Data for this study was collected from these sources to inform the research.

### 2.3.2 Pre-Processing Data

In this paper, efforts were made to address missing data in the collected data, which was normalized and randomized. Various data pre-processing techniques were used, including global constant, noise removal, data transformation, and removal of outlier data. Data normalization was performed using the MinMaxScaler function from the scikit-learn library in Python to avoid outliers of large numbers over small ones and saturation of hidden nodes [13].

### 2.3.3 Building the Network

At this phase of the study, the network design process initiated. This requires identifying the number of layers in the network, selecting appropriate activation functions, determining optimization techniques, selecting an appropriate loss function, and determining the initial weights [13].

### 2.3.4 Activation Function

The paper employed both sigmoid and ReLu activation functions. These activation tasks are regularly utilized in the back-propagation training of Artificial Neural Networks (ANN) to represent the replacing state of the network. Balaji [21] shows that, the input layer of the network gets the data and applies the sigmoid function to transform it. The administered data is then handed to the hidden layer, which sums the inputs and transfers them to the following layer where the output data is computed. The sigmoid activation function is mathematically represented as follows:  $(x) = \frac{1}{1 + e^{-x}}$  Where  $(x)$  is the sigmoid value that varies from 0 to 1 and  $(x)$  is the value of the input values.

### 2.3.5 Training the Network

The exercising procedure of the Multi-Layer Perceptron (MLP) concerns iteratively altering the weights to minimize the argument amongst the actual output and the target output. This adjustment is achieved using the back propagation algorithm, which involves multiple iterations.

## 2.4 Back propagation Algorithm

The reason of applying back propagation is to decrease the network's mistake. The technique suggests propagating the fault, which is the disagreement between the genuine outputs and the target productions, back through the layers of the network. This action happens layer by layer, initial from the last layer and working backward until reaching the initial layer. The term "back propagation" is derived from the in reverse propagation of the mistake. Zilouchian, [22] provided a detailed explanation of the rule as follows:

For a single neuron

$$a = \omega_0 + \omega_1 + i_1 + \omega_2 + i_2 \dots + \omega_n + i_n \quad (1)$$

In a matrix form

$$a = \omega o + wTl \quad (2)$$

Where

W is the weight

I represent input vectors

a is the activity level of neuron

$\omega o$  is called the bias value.

Suppose the desired value of the output is "d" then error e can be denoted as

As

$$s = 12(d - o)^2 \quad (3)$$

Suppose the weight is j it is updated as

$$(new) = w(old) + \frac{Dw}{l} = 0, 1, 2, 3 \dots n \quad (4)$$

## 2.5 Testing

During the model trying point, numerous metrics were computed to evaluate the performance of the model. The paper outline three (3) metrics comprise Root Mean Square Error (RMSE), Binary Cross Entropy Error, and Mean Bias Error (MBE). The reasons is to minimize the training and authorization mistakes because a lower loss indicates a more accurate estimation [20]. Additionally, the precision proportion is computed after the training process to assess the model's performance.

## 3. Results

This research rated the input features based on the rating of the experts such that every feature is assigned a single rating of the saaty scale.

Table 3 displays experiment results on the model. The table includes variables such as HL (Hidden Layer), NPL (number of neurons per layer), HLA (hidden layer activation function), OLA (output layer activation function), OPT (optimizer), BN (Batch Normalization), ACC (accuracy), and L (loss).

Table 3: ANN Experimentation Trials

Trial	HL	NPL	HLA	OLA	OPT	BN	ACC%	L
1	2	64, 64	ReLU, ReLU	Sigmoid	Adam	No	85.00	2.1844
2	3	128, 64, 32	ReLU, ReLU, ReLU	Sigmoid	Adam	Yes	90.00%	1.6645
3	2	128,64	ReLU, ReLU	Linear	Adam	Yes	85.00%	2.7894
4	4	256, 128, 64, 32	ReLU, tanh, ReLU	Sigmoid	Adam	Yes	89.00%	1.2876
5	3	64,32, 16	ReLU, Linear ReLU	Sigmoid	Adam	No	87.00%	1.6516
6	4	4, 4, 16, 32	ReLU, ReLU, ReLU, ReLU	Sigmoid	Adam	No	81.00%	0.8505
7	3	16,64,32	ReLU, ReLU, sigmoid	Sigmoid	Adam	Yes	87.00%	2.1844
8	3	128, 128, 64	ReLU, ReLU, ReLU	Sigmoid	Adam	Yes	95.00%	0.9430

#### 4. Conclusion

The HIV is a retrovirus that weakens the body's immune system by infecting immune cells such as CD4 cells. This cause acquired immune deficiency syndrome (AIDS), which is a severe condition. Many studies such as Tunduny [6], Simone and Martin [8] and Danaila and Buiu [9] have used ANN to predict HIV infection among adolescents. Nevertheless, the input features used in the previous survey did not attain the anticipated precision levels, ranging from 72.5% to 93.76%. Thus, these findings would rather prefer a different set of inputs to improve the accuracy of predicting HIV infection among adolescents. Also, the Analytical Hierarchy Process was remarkably not utilized in rating the input features. To adopt the need for forecasting HIV infection among adolescents and combat its devastating impact, this research used an artificial neural network model as a dependable apparatus. The multilayer perceptron accomplished a remarkable precision of 95%, representing that the research objective was accomplished. Subsequently, the model can be applied for making forthcoming predictions of HIV infection among adolescents. The study also recognized 14 precise signs and conditions of HV among adolescents. Furthermore, it is recommended that further evaluation methods can be used to assess the model's performance.

#### Recommendation

The input attributes of HIV among adolescents should be measured a pointed factor in predicting HIV infection, as research has shown that adolescents are more affected. It is proposed to incorporate the use of artificial neural networks (ANN) in predicting HIV infection among pediatric patients, thus building a hybrid model.

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