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Neural Network-based Time Series Forecasting of HIV Epidemics: The Impact of Antiretroviral Therapies in the Philippines

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Abstract

In the past ten years, the HIV epidemic in the Philippines has grown and changed rapidly. The rate of detected HIV infections has sharply grown to 32 cases per day, going from a low and gradual to a fast and furious epidemic. Thus, some modeling and forecasting methods are necessary for the country to predict the spread pattern and enforce mitigation measures. In this study, the researcher uses Artificial Neural Network in time series forecasting to determine the impact of Antiretroviral Therapies (ART) in the Philippines. The datasets extracted from the HIV/AIDS and ART Registry of the Philippines for the period March 2009 – February 2022 (156 months) are carefully examined for forecasting and analysis. Findings revealed that the cumulative cases in the country by December 2030 will reach 256,983, showing an upward linear trend, with the highest peak in March 2025 of 4,225 cases. The observed and predicted values of HIV epidemics are somewhat close and similar, as supported by the lower values of its RMSE, MAE, and MAPE and higher coefficient of determination. Further, findings showed that as per the United Nations' SDG-3 of Project 2030, the Philippines is still far from the goals for ending the HIV epidemic due to an increase in HIV incidence in the country. Thus, the Philippine government must continue to adopt the 90-90-90 UN targets and improve further its ART program.

Keywords— Antiretroviral Therapy, Artificial Neural Network, Forecasting, HIV/AIDS

I. INTRODUCTION

The Asia-Pacific region's HIV/AIDS epidemic is spreading quickly in the Philippines[1]. With an increase from 311 cases in 2007 to 11,427 cases in 2018 - a nearly 37-fold increase in new HIV incidence - national surveillance statistics reveal that the number of instances of new HIV infection in the nation has increased at a concerning rate [2]. With 76 percent of people living with HIV (PLHIV) aware of their status and 57 percent of those who are aware of their status and are receiving treatment, the Philippines is making slow progress toward the HIV/AIDS 90-90-90 goals, according to surveillance reports from the Joint United Nations Programme on HIV/AIDS (UNAIDS) [3].

Treatment as prevention is an important strategy to end AIDS. A priority is exploring novel approaches to retain PLHIV in care, supporting adherence, and reaching viral suppression [4]. Although the first case (2 cases) was detected in 1984, ART in the Philippines just started with 31% coverage last March 2009. The cost of first-line antiretroviral (ARV) medications is Php 7,230, while the cost of second-line ARV is Php 81,970 per patient per year, according to the Philippines' Department of Health (DOH) [5]. However, it can be difficult to persuade patients to test, develop high compliance levels with ART, and retain in care because of a lack of awareness, obstacles to receiving care, and pervasive stigma [6]. Poor outcomes for many HIV patients are caused by loss of follow-up, high rates of first-line therapeutic failure, and inadequate medication adherence, just like in many underdeveloped nations like the Philippines [4], [7].

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Health systems and politicians are significantly impacted by the predictions of HIV/AIDS transmission rate and models of its future values [8]. To recommend new public health responses and approaches and assess the effectiveness of already-enacted policies, policymaking relies on discernments created by prediction models [9]. The ability to predict epidemics like HIV is crucial. Knowing the spread's development trends will assist governments and medical professionals develop the best therapies, protections, and preventive methods possible [10]. To predict the spread of an epidemic, applying Artificial Intelligence (AI) techniques is a good substitute for conventional epidemic models [11].

For machine learning to predict the trajectory of the HIV epidemic, data sequences acquired over time are typically used as inputs. To anticipate the spread of HIV, a number of widely used methodologies have been put into practice. For instance, to match the HIV incidence data in Guangxi, China, from 2005 to 2016, Long Short-Term Memory (LSTM), Autoregressive Integrated Moving Average (ARIMA), Generalized Regression Neural Network (GRNN), and Exponential Smoothing (ES) models were all utilized [12]. When the value of N was 12, the LSTM model's Mean Square Error (MSE) was the lowest. When predicting HIV incidence in Guangxi, GRNN and ES models performed particularly badly. Using the ARIMA (1,1) model, a different study employed the ARIMA algorithm to forecast the number of HIV cases in Indonesia up to 2030 [13]. Using the same method for forecasting was also performed by the researchers in Finland [14], Nigeria [15], Korea [16], Brazil [17], Uganda [18], and various countries [19]. Although the model can generate a visually dynamic future forecast, the MAE values need further improvement. Other notable and recent AI and statistical applications for forecasting HIV epidemics are shown in Table I.

Table I: Other AI and Statistical Applications for HIV/AIDS Forecasting

Methods	Region	Pros	Cons	References
Generalized Growth Model (GGM)	Brazil	Denotes the early growth dynamics of the HIV epidemic.	It relies on AIDS incidence surveillance data.	[20]
Modes of Transmission Model (MoT)	Morocco	Provides mapping of HIV exposures.	It does not hold for heterogeneity.	[21]
Box-Jenkins	Philippines	The model is appropriate for the series.	Most of the ACF and PACF values are not significant.	[22]
Box-Jenkins "Catch-All"	Zimbabwe	Generally stable and acceptable for forecasting.	They are focused only on a local level.	[23]
Univariate Box-Jenkins	Philippines	Best model is SARIMA (2,1,0) (0,0,1) with drift.	Must use optimization.	[24]

With several AI strategies available, the Artificial Neural Network (ANN) has shown superiority over earlier suggested forecasting models in more desirable values for accuracy and precision [8]. ANNs can be created by replicating a network of model neurons on a computer, and they are influenced by the early theories of how the human brain processes sensory information. We may train the network to tackle various tasks using algorithms that

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closely resemble the operations of actual neurons [25]. It has been used to tackle problems like gene prediction, speech recognition, protein secondary structure prediction, and cancer categorization. It is the most popular and widely-used network paradigm in many applications such as forecasting [26]. The application of the ANN model in predicting HIV epidemics is shown in Table II.

Table II: ANN Implementations in HIV/AIDS Forecasting

Region	Problem Description	References
Guangxi, China	HIV/AIDS incidence data in Guangxi, China, for 2005-2016.	[12]
Niger Delta, Nigeria	HIV/AIDS prevalence and transmission in Rivers State, Nigeria's Niger Delta.	[27]
Egypt	Egypt's ART Coverage from 2000 to 2018.	[28]
China	Comparison of the ARIMA and BP ANN models' predictions for the incidence of HIV/AIDS.	[29]
Kenya	ART Coverage in Kenya Using the MLP Neural Network for 2000-2018.	[30]
South Africa	ART Coverage in South Africa Using the Multilayer Perceptron (MLP) Neural Network for 2000-2018.	[31]
Gweru District Hospital, Zimbabwe	New HIV infections in pregnant women in Zimbabwe.	[32]
Malawi	Use of the MLP for ART Coverage in Malawi from 2000 to 2018.	[33]

The table shows no recent study on predicting HIV cases in the Philippines using ANN. Also, there is no ANN model in the Philippine setting studying the impact of ART for 2009-2022.

In this study, ANN has been examined in-depth to forecast the monthly cases of HIV in the Philippines until 2030, the global target to end HIV/AIDS by adopting the 3rd Sustainable Development Goal (SDG-3) of Project 2030. With the ART program started in the Philippines in March 2009, the paper will study the program's impact by assessing the nation's progress towards achieving a decline of 90% between 2010 and 2030 of new HIV infections [34].

The study's primary objective is to create an ANN model to predict the number of monthly cases in the Philippines. Specifically, it intends to:

1. Validate whether the ART dataset is a good fit for the ANN model in forecasting;
2. Forecast the number of monthly and cumulative cases by the end of 2030;
3. Determine the nation's progress in the adoption of SDG-3 of Project 2030;
4. Compare the outcomes between the predicted and observed monthly cases of HIV epidemics in the Philippines; and
5. Determine the ANN model's performance measures using the following standard metrics for regression: RMSE, MAE, MAPE, and R^2.

II. MATERIALS AND METHODS

Data

The HIV/AIDS epidemic in the Philippines started in 1984 with 2 cases; however, the ART coverage began in 2009 [5]. Therefore, the dataset from March 2009 to February 2022 (156 months) will be used for forecasting to determine the impact of ART coverage in the Philippines. The San Lazaro Hospital STD/AIDS Cooperative Central Laboratory (SACCL) confirms the dataset sources, including the HIV/AIDS and ART Registry of

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the Philippines (HARP), the official database of all laboratory-confirmed diagnoses, HIV-related fatalities in the Philippines, and ART outcome status. Confirmed HIV-positive persons were reported to the DOH-Epidemiology Bureau (EB) and recorded to HARP. One hundred fifty-eight (158) major HIV care treatment facilities and treatment centers in the Philippines provide ART numbers, which are counts of HIV-positive adult and pediatric patients currently enrolled and receiving ARV medication during the reporting period.

Concept of the Study

The prediction of HIV/AIDS monthly cases in the Philippines until December 2030 was performed using the ANN model. This algorithm's forecasting and prediction is a multi-stage process (Fig. 1). The exact procedures used in the investigation are shown in Figure 1. First, monthly HIV cases were organized in order of occurrence. These data were further classified by focusing on the MATLAB environment's cell and row matrix. To obtain accurate results, an appropriate network is necessary. As a result, the three sequential layers of the neural net time series known as *ntstool*, which includes training, validating, and testing the outcome, were selected. The HIV data that had been gathered had been used for testing, training, and forecasting new HIV infections in the Philippines. Performance, final judgment, and optimum model structure design were evaluated using statistical techniques that are often used to assess prediction outcomes.

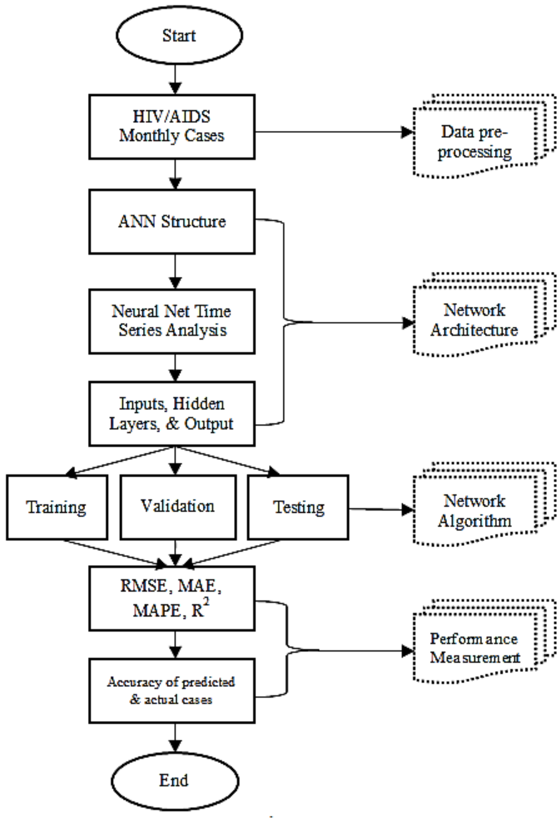

Fig. 1: Methodological Flowchart of Predicting HIV/AIDS Monthly Cases using ANN Model

Artificial Neural Network

In this work, an ANN forecasting model is used. It is a greatly condensed representation of the biological brain network's architecture. It has connected processing units that work together to perform pattern recognition[35]. Neural networks are designed to understand the link between inputs and output variables using cross-sectional data, much like regression. Time series analysis is how ANNs are most frequently used for predicting. Based on historical data, ANN models help predict future values. [36]. Input and output can be plotted in ANN models. When the weights and inputs flow through the appropriate neurons, it functions as a multiprocessor, parallel processor, and distributed system [37].

Fig. 2 shows a straightforward neural network model. It consists of three parts: a summing component, an activation function for limiting the amplitude of a neuron's output *f()*, and a collection of connecting links, or synapses, that

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pass input x linked to the neuron multiplied by the weight, $w_i x_i$. In fig. 2, $w_1, w_2 \ldots w_i$, are the set of weights that can be compared to signals or connection strengths, whereas, $x_1, x_2 \ldots x_i$, are the set of inputs. The weight will provide a high value if the input strength is strong; conversely, the weight will also be lower if the input strength is low. So the inputs are multiplied with weights and expressed in (1) – (4):

$$S = w_1 x_1 + w_2 x_2 + \cdots next, \\ = \sum w_i x_i \quad (1)$$

$$S = \sum_{i=1}^{n} (w_i x_i - \theta) \quad (2)$$

$$S = f(x) = x \quad (3)$$

$$\delta = b - s = b - x \quad (4)$$

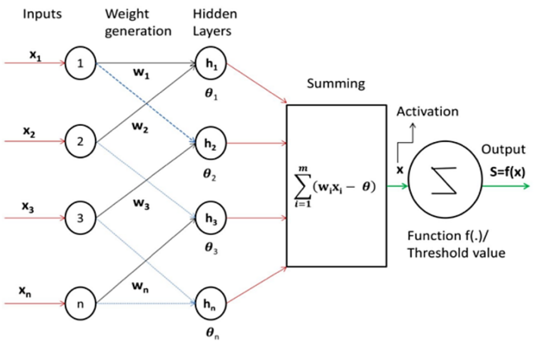

Fig. 2: Three Layers Make Up a Basic Neural Network Model: Input, Hidden, and Output

The above equation's summation value is crucial as it determines the threshold value. A neuron with the appropriate weight and threshold value generates an output in units of time because it has a single input and a single output. To compare the difference between input and output, the threshold function is necessary. The output will be 1 if the output sum *S(f(x))* weight is greater than this threshold value and 0 otherwise. One way to spell it is as follows

$$f(x) = 1, x > 0 \quad (5)$$

$$f(x) = 0, x \leq 0 \quad (6)$$

There are typically four threshold functions that are frequently used: the signum function, the piecewise linear function, the hyperbolic tangent function, and the sigmoid function. [38]. In the current investigation, a linear transfer function was employed between hidden and output layer neurons, while a tangent sigmoid function was used between input and hidden layer neurons. The mathematical equivalent of this function is *tanh* (*N*). In neural networks, where speed is important, this function has a suitable adjustment, and the precise value of the transfer function is consistent. [39].

MLP is the most well-liked and widely applied neural network design [40]. Future intelligence might be better structured with MLP networks' learning and perceptive abilities. The current work used a nonlinear autoregressive method coupled with a multilayer feed-forward neural network structure.

Future values of one or more time series are predicted using the past values of those time series, which is a type of dynamic filtering. Tapped delay lines are used in neural networks for nonlinear filtering and forecasting. A nonlinear autoregressive (NAR) tool is used in the study using MATLAB R2021a for time series problems in ntstool. Given the previous value of *y(t)*, it predicts the series time value of *y(t)*. In mathematics, it can be stated as

$$yt = f(y(t-1) + y(t-2) + y(t-3) \\ + y(t-m) \quad (7)$$

156-month data were used to train and test a model for forecasting monthly cases of the HIV epidemic in the Philippines. The MLP model was utilized, although either overfitting or underfitting is the main problem with employing MLP. Because of this, there are inconsistencies between the input and output layers. To cut down on these errors, the Stop Training Approach (STA) has been implemented. HIV monthly case data are collected and separated randomly into training, validation, and testing data.

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To obtain the intended result *(t)*, the target time series dataset was chosen. Because the target dataset "HIV monthly cases" is an *x* cell array of *x* matrix, indicating dynamic data *x* time steps of 1 element, the cell column as a time series row matrix was selected in the time step. 80 percent of the 156 months' worth of data are training data. The 124 HIV monthly cases time series data are split into 1 x 124 cell arrays of 1 x 1 matrices. In this case, training is linked to ANN's learning process. 20% of 156 data points are used for testing (10%) and validation (10%). This suggests that a 1 x 16 cell array of a 1 x 1 matrix is used to separate the time series data for 16 HIV monthly cases. The value of validation and testing can be changed from 5% to 35%, which automatically changes the selection ratio and affects the value of training. However, the optimal choice is 80/10/10, which is the default. Selecting the hidden layer is another crucial step that impacts the output accuracy. Here, ten (10) hidden layers have been picked. Feedback delays are set to 14, which means that to produce a suitable model, the training data must be subtracted by 14 monthly cases.

Evaluation Metrics

This study uses four metrics of regression, as shown in (8) to (11), to evaluate the performance of the ANN forecasting model using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2) [41]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N_s}(P_{yi} - Y_i)^2} \quad (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N_s}|P_{yi} - Y_i| \quad (9)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{yi} - Y_i}{YP_i}\right| \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - P_{yi})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2} \quad (11)$$

The lowest *RMSE*, *MAE*, and *MAPE* values are the best method. The higher value of R^2 indicates a better correlation for the technique [42].

III.RESULTS AND DISCUSSION

On Validity of ART Dataset as a Good Fit for the ANN Model in Forecasting

By altering the neurons of hidden layers during the training, testing, and validation processes, several structures have been confirmed. The least RMSE and highest R^2 values were found in the ANN structure 1-10-1 (Input-Hidden-Output), which was regarded as the best structure. The dataset describing ART implementation in the Philippines is appropriate for predicting monthly HIV/AIDS cases in the future when put into the suggested model. As a result, the training model's R-value is 0.99937, while the tested model's R-value is 1.0, indicating a very high prediction accuracy. The model's autocorrelation plot is shown in Figure 3. It is obvious that the values are getting closer to 0, which denotes a stronger positive correlation.

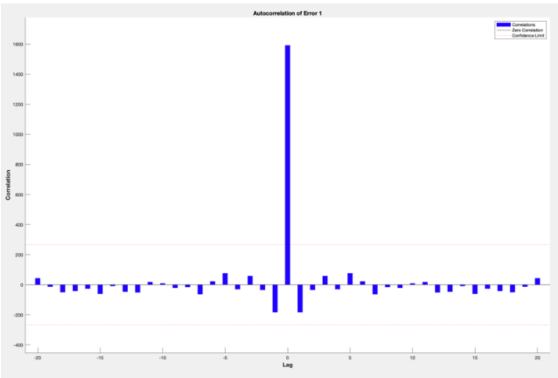

Fig. 3: Autocorrelation Plot of the Model

On the Predicted Future Values of Monthly and Cumulative Cases by the End of 2030

With the use of Table III, we can project the monthly and total incidence of HIV/AIDS cases in the country over the period of months 157 – 262 (March 2022 – December 2030). Predicted cumulative cases by the end of December 2030 is 256,983, nearly a 3-fold increase from the actual cumulative cases in February 2022 with

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93,557 cases. However, it is predicted that the monthly case will reduce to 317 only, a 69.92% decrease from the February 2022 actual case of 1,054. Furthermore, the seasonal peaks usually happen during March. The predicted highest new HIV infection in a month will be in March 2025, with 4,226 cases.

Table III: Sample Predicted Number of HIV/AIDS Cases in the Philippines for the Period January 2029 – December 2030

Month, Year	HIV Monthly Cases	Cumulative Cases	Month, Year	HIV Monthly Cases	Cumulative Cases
Jan-29	830	224,787	Jan-30	1,830	247,139
Feb-29	1,468	226,255	Feb-30	62	247,201
Mar-29	1,633	227,887	Mar-30	287	247,488
Apr-29	996	228,884	Apr-30	441	247,929
May-29	3,704	232,587	May-30	760	248,690
Jun-29	377	232,964	Jun-30	360	249,050
Jul-29	2,759	235,723	Jul-30	2,491	251,541
Aug-29	2,403	238,126	Aug-30	2,156	253,697
Sep-29	588	238,714	Sep-30	457	254,154
Oct-29	4,090	242,804	Oct-30	1,093	255,247
Nov-29	2,220	245,024	Nov-30	1,420	256,666
Dec-29	285	245,309	Dec-30	317	256,983

Interestingly, based on Fig. 4, the predicted values show random albeit cycles with upward and downward drifts. The amplitude or distance varies in length with sudden jumps. On the other hand, Fig. 5 still offers a linear upward trend, meaning the HIV/AIDS cases in the Republic of the Philippines will continue to increase.

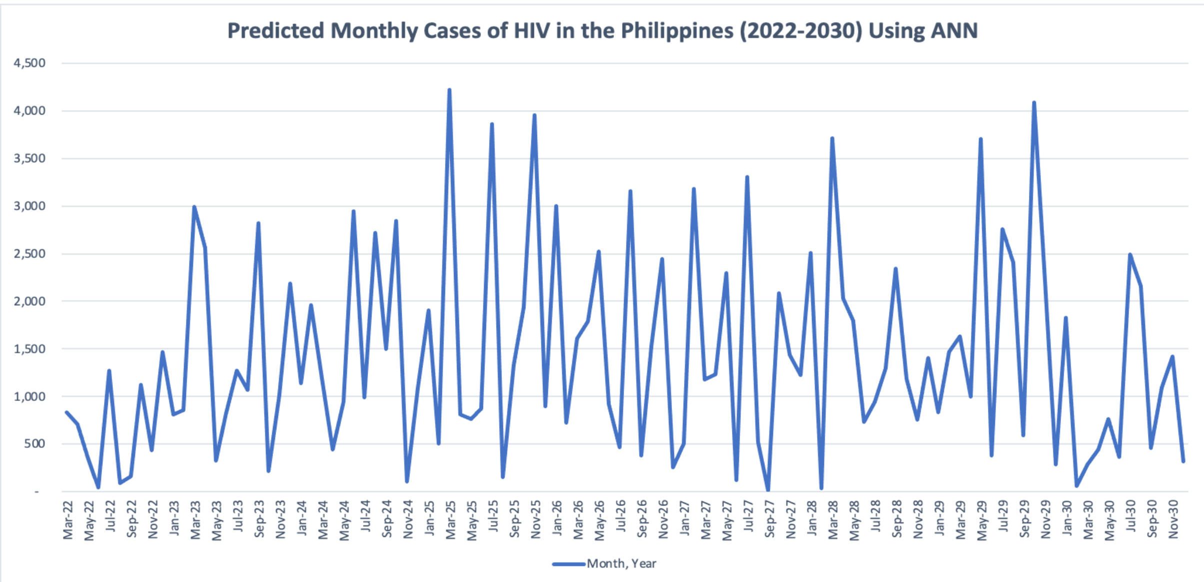

Fig. 4: Time Series Plot of HIV/AIDS Monthly Cases in the Philippines

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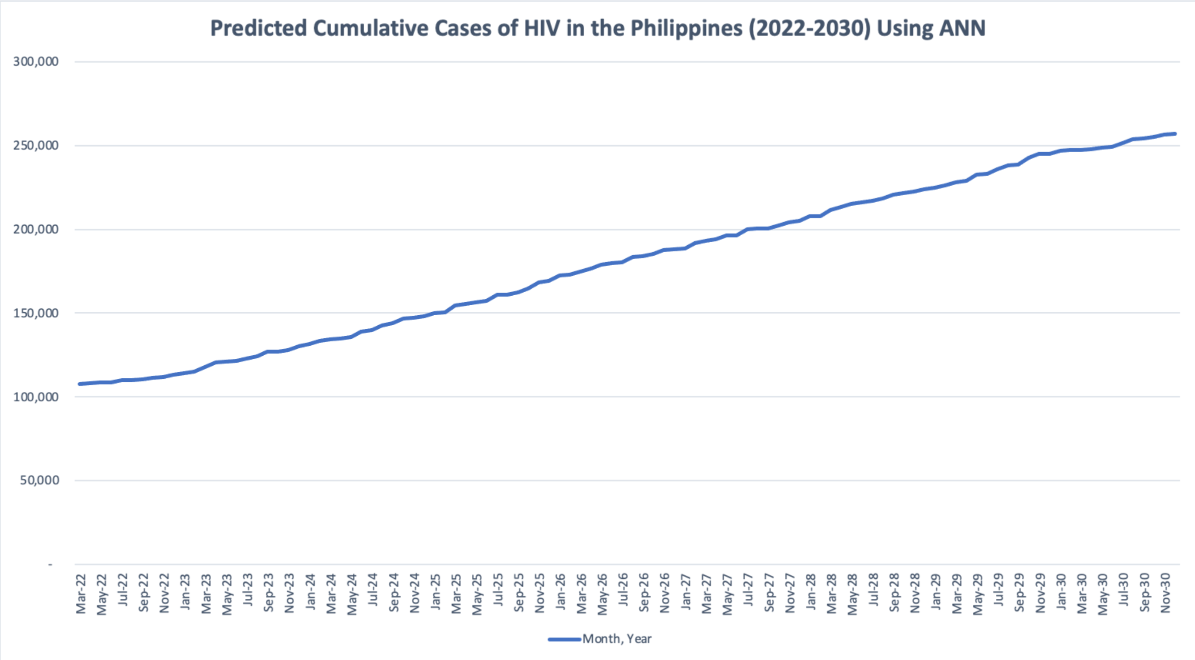

Fig. 5: Future Values of Cumulative Cases of HIV/AIDS in the Philippines

On Philippines' Progress in the Adoption of SDG-3 of Project 2030

"No one should be left behind"; this is the core principle of the 17 SDGs and the AIDS response. Without addressing the needs of PLHIV as well as the factors that determine vulnerability and health, the AIDS pandemic cannot be stopped. A goal and aspiration to eradicate HIV/AIDS by 2030 have been actively publicized by UNAIDS [43]. During a High-Level Meeting in 2016, the UN General Assembly discussed this problem, and the SDG-3 included a goal to end the HIV/AIDS pandemic by 2030 (Project 2030) [44]. A reduction in new HIV infections of 90% between 2010 and 2030 is the quantitative definition of Project 2030's success [45].

In December 2010, the Philippines recorded an actual new HIV infection of 174. Based on the ANN forecasting model, by December 2030, the new HIV incidence will reach 317, an 82.18% increase. Further, based on cumulative cases annually, the actual 2010 data shows new HIV incidence at 1,591, while the 2030 forecast shows that the case rises to 11,674, a 633.75% increase. Thus, the Philippines is still far from the goals of ending the HIV epidemic, despite rigid HIV testing and treatment cascade.

On Comparison between Observed and Predicted Values of HIV Epidemic

The neural network's training, validation, and testing results are compared to the observed and anticipated monthly rates of HIV/AIDS in Figs. 6 and 7. The training phase will further generalize and evaluate the structure that was learned from the prior target data points. The graph demonstrates some instances where there is a slight variation between the expected and actual HIV cases. Additionally, the outcome suggests that, in some circumstances, the values of projected and observed HIV/AIDS cases are near and comparable. As a result, the overall outcome can be regarded as noteworthy.

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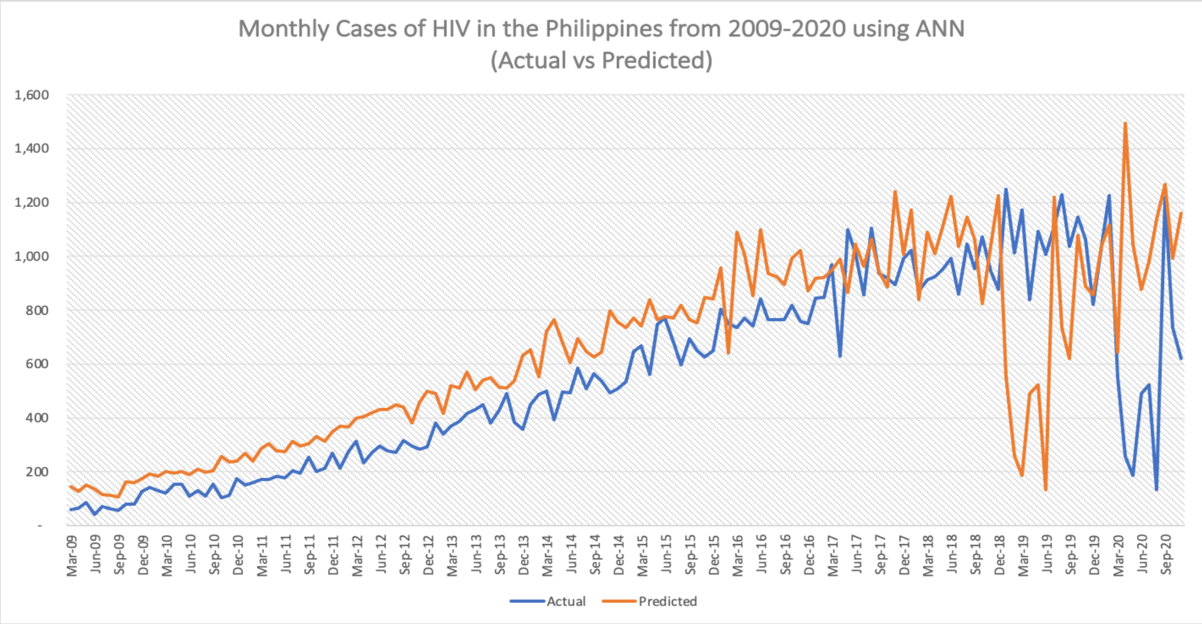

Fig. 6: Comparison Between the Predicted and Observed Monthly Cases of HIV/AIDS in the Philippines

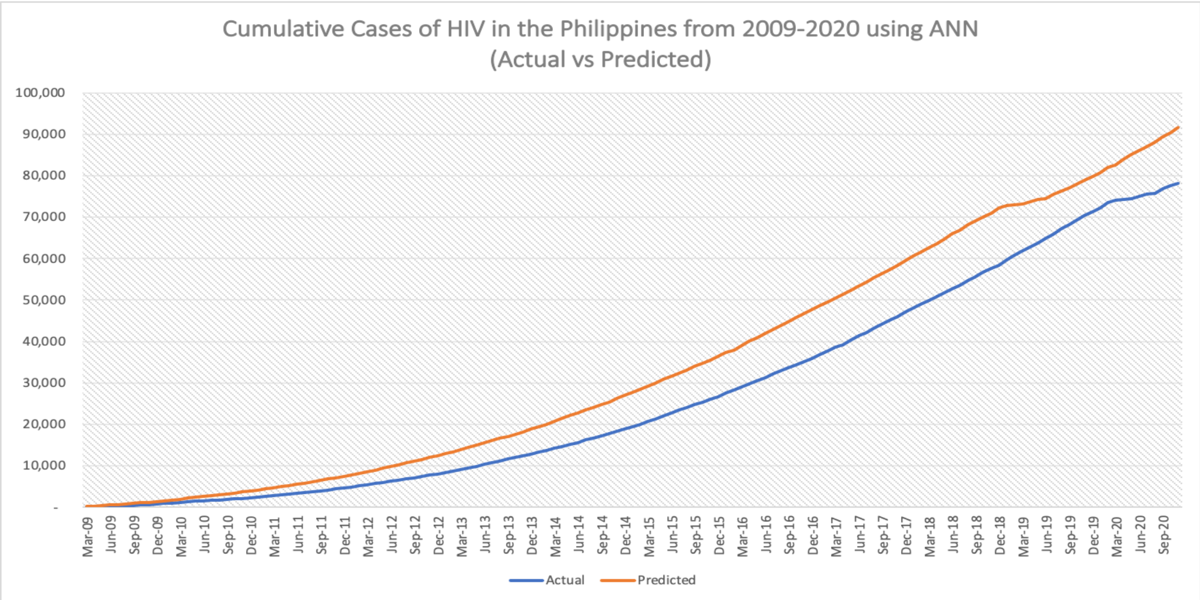

Fig. 7: Comparison Between the Predicted and Observed Cumulative Cases of HIV/AIDS in the Philippines

On the Performance Measures of ANN Forecasting Model

Table IV shows the accuracy of the model for trained and tested data. The *RMSE*, *MAE*, and *MAPE* output produced very low values, which means the method used is effective. On the other hand, based on Model Goodness-of-Fit, the ART datasets used to obtain a Pearson's R^2 = 0.5803 indicate a nearly perfect fit and, therefore, a highly reliable model for this forecast.

Table IV: Performance Measures of the Trained and Tested Model

Performance Measurement	Values
RMSE	5.61
MAE	164.78
MAPE	46.90
R^2	0.5803

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IV. CONCLUSION

The findings presented lead to the following conclusions:

1. The ART data sets used to train, validate, and test the model have been found applicable to forecasting future monthly HIV/AIDS cases.
2. By December 2030, monthly and cumulative cases in the country will reach 317 and 256,983, respectively, showing an upward linear trend with somewhat a cycle and seasonality. Also, the monthly trends show random albeit cycles with upward and downward drifts.
3. In compliance with SDG-3 of Project 2030, the Philippines is still far from the goals of ending the HIV epidemic, despite rigid HIV testing and treatment programs because of an increase in HIV incidence in the future, both monthly and annual data.
4. As a result of the substantial agreement between observed and anticipated values for HIV cases, the entire result may be deemed reliable.
5. Based on performance measures, the model produces accurate and reliable results.

REFERENCES

[1] L. M. A. Gangcuangco, "HIV crisis in the Philippines: urgent actions needed," *The Lancet Public Health*, vol. 4, no. 2. Elsevier Ltd, p. e84, Feb. 01, 2019. doi: 10.1016/S2468-2667(18)30265-2.

[2] Department of Health - Epidemiology Bureau, "HIV/AIDS & ART Registry of the Philippines, March 2019," 2019. Accessed: Apr. 28, 2022. [Online]. Available: https://doh.gov.ph/sites/default/files/statistics/HIV_STAT_2019MAR.pdf

[3] Joint United Nations Programme on HIV/AIDS (UNAIDS), "UNAIDS Data 2019," 2019. Accessed: Apr. 28, 2022. [Online]. Available: https://www.unaids.org/sites/default/files/media_asset/2019-UNAIDS-data_en.pdf

[4] C. Oconnor *et al.*, "Risk factors affecting adherence to antiretroviral therapy among HIV patients in Manila, Philippines: A baseline cross-sectional analysis of the Philippines Connect for Life Study," *Sexual Health*, vol. 18, no. 1, pp. 95–103, Mar. 2021, doi: 10.1071/SH20028.

[5] J. Kivela, "Cost-Benefit Analysis of HIV Prevention Programs for Filipino Seafarers 2010 - 2015," 2009. Accessed: Apr. 28, 2022. [Online]. Available: https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---ilo-manila/documents/publication/wcms_140905.pdf

[6] J. W. de Lind Van Wijngaarden, A. D. Ching, E. Settle, F. van Griensven, R. C. Cruz, and P. A. Newman, "'I am not promiscuous enough!': Exploring the low uptake of HIV testing by gay men and other men who have sex with men in Metro Manila, Philippines," *PLoS ONE*, vol. 13, no. 7, Jul. 2018, doi: 10.1371/journal.pone.0200256.

[7] A. Jiamsakul *et al.*, "Factors associated with suboptimal adherence to antiretroviral therapy in Asia," *J Int AIDS Soc*, vol. 17, May 2014, doi: 10.7448/IAS.17.1.18911.

[8] S. G. Fard, H. M. Rahimi, P. Motie, M. A. S. Minabi, M. Taheri, and S. Nateghinia, "Application of machine learning in the prediction of COVID-19 daily new cases: A scoping review," *Heliyon*, vol. 7, no. 10, Oct. 2021, doi: 10.1016/j.heliyon.2021.e08143.

[9] F. A. Binti Hamzah *et al.*, "CoronaTracker: World-wide COVID-19 Outbreak Data Analysis and Prediction," *Bulletin of the World Health Organization*, vol. 1, no. 32. World Health Organization, pp. 1–32, Mar. 01, 2020. doi: 10.2471/BLT.20.251561.

[10] M. Ali, D. M. Khan, M. Aamir, U. Khalil, and Z. Khan, "Forecasting COVID-19 in Pakistan," *PLoS ONE*, vol. 15, no. 11 November, Nov. 2020, doi: 10.1371/journal.pone.0242762.

[11] D. Ivanov, "Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case," *Transportation Research Part E: Logistics and Transportation Review*, vol. 136, Apr. 2020, doi: 10.1016/j.tre.2020.101922.

[12] G. Wang *et al.*, "Application of a long short-term memory neural network: A burgeoning method of deep learning in forecasting HIV incidence in Guangxi, China," *Epidemiology and Infection*, vol. 147, 2019, doi: 10.1017/S095026881900075X.

[13] M. D. Kurniasari, A. D. Huruta, H. T. Tsai, and C. W. Lee, "Forecasting future HIV infection cases: evidence from Indonesia," *Social Work in Public Health*, vol. 36, no. 1, pp. 12–25, 2021, doi: 10.1080/19371918.2020.1851332.

[14] M. Löytönen, "The Box-Jenkins Forecast of HIV Seropositive Population in Finland, 1991–1993," *Geografiska Annaler: Series B, Human Geography*, vol. 73, no. 2, pp. 121–131, Aug. 2017, doi:

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10.1080/04353684.1991.11879618.

[15] N. C. Umunna and S. O. Olanrewaju, “Forecasting the Monthly Reported Cases of Human Immunodeficiency Virus (HIV) at Minna Niger State, Nigeria,” *Open Journal of Statistics*, vol. 10, no. 03, pp. 494–515, 2020, doi: 10.4236/ojs.2020.103030.

[16] H. K. Yu, N. Y. Kim, S. S. Kim, C. Chu, and M. K. Kee, “Forecasting the Number of Human Immunodeficiency Virus Infections in the Korean Population Using the Autoregressive Integrated Moving Average Model,” *Osong Public Health and Research Perspectives*, vol. 4, no. 6, pp. 358–362, 2013, doi: 10.1016/j.phrp.2013.10.009.

[17] A. V. Campos Coelho, H. F. Campos Coelho, L. C. Arraes, and S. Crovella, “HIV-1 mother-to-child transmission in Brazil (1994–2016): a time series modeling,” *Brazilian Journal of Infectious Diseases*, vol. 23, no. 4, pp. 218–223, Jul. 2019, doi: 10.1016/j.bjid.2019.06.012.

[18] J. Rubaihayo, N. M. Tumwesigye, J. Konde-Lule, and F. Makumbi, “Forecast analysis of any opportunistic infection among HIV positive individuals on antiretroviral therapy in Uganda,” *BMC Public Health*, vol. 16, no. 1, pp. 1–11, 2016, doi: 10.1186/s12889-016-3455-5.

[19] L. Xie, “Analyzing and Forecasting HIV Data Using Hybrid Time Series Models,” *Asian Journal of Probability and Statistics*, vol. 2, no. 3, pp. 1–12, 2018, doi: 10.9734/AJPAS/2018/46566.

[20] L. Dinh, G. Chowell, and R. Rothenberg, “Growth scaling for the early dynamics of HIV/AIDS epidemics in Brazil and the influence of socio-demographic factors,” *Journal of Theoretical Biology*, vol. 442, pp. 79–86, Apr. 2018, doi: 10.1016/j.jtbi.2017.12.030.

[21] S. P. Kouyoumjian *et al.*, “Mapping of new HIV infections in Morocco and impact of select interventions,” *International Journal of Infectious Diseases*, vol. 68, pp. 4–12, Mar. 2018, doi: 10.1016/j.ijid.2017.12.013.

[22] A. M. A. Tatoy and R. F. Ceballos, “HUMAN IMMUNODEFICIENCY VIRUS (HIV) CASES IN THE PHILIPPINES: ANALYSIS AND FORECASTING,” *JP Journal of Biostatistics*, vol. 16, no. 2, pp. 67–77, Nov. 2019, doi: 10.17654/bs016020067.

[23] S. P. Nyoni and T. Nyoni, “Modeling and Forecasting New HIV Infections at Silobela District Hospital, Zimbabwe: Empirical Evidence From a Box-Jenkins’ Catch All’ Model,” *International Journal of Recent Engineering Research and Development*, vol. 19, no. 12, pp. 1–10, 2019, [Online]. Available: www.ijrerd.com

[24] R. E. Apa-Ap and H. L. Tolosa, “Forecasting the Monthly Cases of Human Immunodeficiency Virus (HIV) of the Philippines,” *Indian Journal of Science and Technology*, vol. 11, no. 47, pp. 974–6846, 2018, doi: 10.17485/ijst/2018/v11i47/121923.

[25] A. Krogh, “What are artificial neural networks?,” 2008. [Online]. Available: http://www.r-project.org/

[26] G. Zhang, B. E. Patuwo, and M. Y. Hu, “Forecasting with artificial neural networks: The state of the art,” 1998.

[27] B. Baridam and C. Irozuru, “The Prediction of Prevalence and Spread of HIV/AIDS using Artificial Neural Network-the Case of Rivers State in the Niger Delta, Nigeria,” 2012.

[28] S. P. Nyoni and T. Nyoni, “Forecasting Art Coverage in Egypt Using Artificial Neural Networks,” *International Research Journal of Innovations in Engineering and Technology (IRJIET)*, vol. 5, no. 3, pp. 156–160, 2021, doi: 10.47001/IRJIET/2021.503027.

[29] Z. Li and Y. Li, “A comparative study on the prediction of the BP artificial neural network model and the ARIMA model in the incidence of AIDS,” *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, Jul. 2020, doi: 10.1186/s12911-020-01157-3.

[30] S. P. Nyoni and T. Nyoni, “Forecasting Art Coverage in Kenya Using the Multilayer Perceptron Neural Network,” *International Research Journal of Innovations in Engineering and Technology (IRJIET)*, vol. 5, no. 3, pp. 161–165, 2021, doi: 10.47001/IRJIET/2021.503028.

[31] S. P. Nyoni and T. Nyoni, “Forecasting Art Coverage in South Africa Using the Multilayer Perceptron Neural Network,” *International Research Journal of Innovations in Engineering and Technology (IRJIET)*, vol. 5, no. 3, pp. 207–211, 2021, doi: 10.47001/IRJIET/2021.503034.

[32] S. P. Nyoni and T. Nyoni, “Analyzing New HIV Infections in Pregnant Women at Gweru District Hospital Using Artificial Neural Networks,” *International Journal of Innovations in Engineering Research and Technology*, vol. 7, no. 6, 2020.

[33] S. P. Nyoni and T. Nyoni, “Forecasting Art Coverage in Malawi Using the Multilayer Perceptron Neural Network,” *International Research Journal of Innovations in Engineering and Technology (IRJIET)*, vol. 5, no. 3, pp. 222–226, 2021, doi: 10.47001/IRJIET/2021.503037.

[34] Y. Assefa and C. F. Gilks, “Ending the epidemic of HIV/AIDS by 2030: Will there be an endgame to HIV, or an endemic HIV requiring an integrated health systems

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response in many countries?," *International Journal of Infectious Diseases*, vol. 100. Elsevier BV, pp. 273–277, Nov. 01, 2020. doi: 10.1016/j.ijid.2020.09.011.

[35] B. Yegnanarayana, *Artificial Neural Networks*. New Delhi, India: PHI Learning Pvt. Ltd., 2006.

[36] V. M. Adamović, D. Z. Antanasijević, M. Ristić, A. A. Perić-Grujić, and V. v. Pocajt, "Prediction of municipal solid waste generation using artificial neural network approach enhanced by structural break analysis," *Environmental Science and Pollution Research*, vol. 24, no. 1, pp. 299–311, Jan. 2017, doi: 10.1007/s11356-016-7767-x.

[37] S. A. Ali and A. Ahmad, "Forecasting MSW generation using artificial neural network time series model: a study from metropolitan city," *SN Applied Sciences*, vol. 1, no. 11, Nov. 2019, doi: 10.1007/s42452-019-1382-7.

[38] S. Rajashekaran and G. V. Pai, *Neural networks, fuzzy logic and genetic algorithm-synthesis and applications (with cd)*. 2003.

[39] T. P. Vogl, J. K. Mangis, A. K. Rigler, W. T. Zink, and D. L. Alkon, "Accelerating the Convergence of the Back-Propagation Method," 1988.

[40] A. Jain and S. Srinivasulu, "Integrated approach to model decomposed flow hydrograph using artificial neural network and conceptual techniques," *Journal of Hydrology*, vol. 317, no. 3–4, pp. 291–306, Feb. 2006, doi: 10.1016/j.jhydrol.2005.05.022.

[41] M. A. A. Al-qaness, H. Fan, A. A. Ewees, D. Yousri, and M. Abd Elaziz, "Improved ANFIS model for forecasting Wuhan City Air Quality and analysis COVID-19 lockdown impacts on air quality," *Environmental Research*, vol. 194, Mar. 2021, doi: 10.1016/j.envres.2020.110607.

[42] M. A. A. Al-Qaness, A. A. Ewees, H. Fan, and M. A. el Aziz, "Optimization method for forecasting confirmed cases of COVID-19 in China," *Journal of Clinical Medicine*, vol. 9, no. 3, Mar. 2020, doi: 10.3390/jcm9030674.

[43] Unaids, "2016 United Nations Political Declaration on Ending AIDS sets world on the Fast-Track to end the epidemic by 2030," 2016. Accessed: May 03, 2022. [Online]. Available: https://www.unaids.org/sites/default/files/20160608_PS_HLM_Political_Declaration_final.pdf

[44] United Nations, "The Sustainable Development Goals Report 2018," New York, 2018. Accessed: May 03, 2022. [Online]. Available: https://unstats.un.org/sdgs/files/report/2018/TheSustainableDevelopmentGoalsReport2018-EN.pdf

[45] Unaids, "90-90-90: An ambitious treatment target to help end the AIDS epidemic," 2020. Accessed: May 03, 2022. [Online]. Available: https://www.unaids.org/sites/default/files/media_asset/90-90-90_en.pdf

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