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Forecasting Art Coverage in Burundi Using the Artificial Neural Network Approach

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Abstract - In this research paper, the ANN approach was applied to analyze annual ART coverages in Burundi. The employed data covers the period 2000-2018 and the out-of-sample period ranges over the period 2019-2023. The residuals and forecast evaluation criteria (Error, MSE and MAE) of the applied model indicate that the model is stable in forecasting ART coverage in Burundi. The results of the study indicate that the ART coverage is likely to remain constant at around 83% over the period 2019-2023. Therefore the government is encouraged to increase HIV testing capacity and improve access to ART services for key populations in the country.

Keywords: *ANN, ART coverage, Forecasting.*

I. INTRODUCTION

Machine learning methods have been used in many fields such as engineering, agriculture, geography, environment science and epidemiology. These techniques can handle highly heterogeneous data differing from statistical models that form relationships based on assumptions such as homoscedasticity, normal distribution of errors and independent explanatory variables (Zhao et al, 2020). Machine learning can model complex interactions between variables without presupposing forms (Murphy, 2012; Breinman, 2001). Artificial neural networks, decision trees, K-nearest neighbors, support vector machine, gradient boosting and Naïve Bayes are frequently used (Nyoni et al, 2020; Gambhir et al, 2018, Guo et al, 2017; Scavuzzo et al, 2018; Althouse et al, 2011; Laureano-Rosario et al, 2018). The most widely used neural networks in time series forecasting is the Multilayer Perceptron (MLP) (Bishop, 1995). There is a lot of evidence suggesting that other neural network models can perform time series forecasting very well just like the MLP (Liu & Queck, 2007). The commonly applied neural networks are the MLP, generalized regression networks (GNN), radial basis function (RBF) and recurrent neural networks (RNN). The MLP is made up of 3 layers: input neurons, hidden neurons and output neurons (Fojnica et al, 2016; Zhang, 2003; Kaushiki & Sahi, 2018; Yan et al, 2018). In this type of framework the connections between neurons always feed forward. The type of training is supervised learning.

Radial basis function models are made up of three layers just like the MLP network. The difference is that the RBF model, hidden neurons operate on the basis of the Euclidean distance that separates the input vector X from the weight vector W which is stored by each one, a quantity to which a Gaussian radial function is applied in a similar way to the Kernel functions in the Kernel regression model (Bishop, 1995). The generalized regression neural network (GRNN) is made up of four layers of neurons: Input layer, pattern layer, summation layer and output layer. The number of input neurons depends on the number of predictor variables established. The GRNN allows for the estimation of the joint probability density function f(x, y) between a set of explanatory variable x and response or dependent variable y. The main advantage of this framework over the MLP is that it does not require an iterative training process. Recurrent neural networks (RNN) are useful in the representation of time relationships that may be established between input and outputs of the neural network (Elman, 1990).In this type of framework one layer of neurons has recurrent connections, many of the outputs of the neurons are temporarily stored and then sent as input signals to the same neurons or to other neurons in the neural network.

In this paper we applied the MLP to predict ART coverage in Burundi. The findings of this research work is expected to provide an insight of the future trends of ART coverage in Burundi and the progress towards achieving the global UNAIDS targets by end of 2030 of ending the HIV epidemic as a public health threat.

II. LITERATURE REVIEW

Bigelow & Verguet (2020) characterized the changes over time in antiretroviral therapy (ART) coverage in sub- Saharan Africa using growth curve models. This was a retrospective observational study. The research used publicly available data on

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ART coverage levels from 2000 to 2017 in 42 sub- Saharan African countries and developed two ordinary differential equations models, the Gompertz and logistic growth models that allowed for the estimation of summary parameters related to scale- up and rates of change in ART coverage. The research concluded that growth curve models can provide benchmarks to assess country performance in ART coverage evolution. They could be a useful approach that yields summary metrics for synthesizing country performance in scaling up key health services. They fitted non- linear regressions for the two models, assessed goodness of fit using the Bayesian information criterion (BIC), and ranked countries based on their estimated performance drawn from the fitted model parameters. Moyo et al (2017) examined changes and equity in ART use in Kenya and South Africa. The study analyzed national population based household surveys conducted in Kenya and South Africa between 2007 and 2012 for factors associated with lack of ART use among people living with HIV aged 15-64 years. The findings from the study revealed that ART use among PLHIV increased from 29.3% to 42.5% from 2007to 2012 in Kenya and 17.4% to 30.3% from 2008 to 2012 in South Africa. Areas needing improvement include rural Kenyans, students in South Africa and among young people and drug users in both countries. Barankanira et al (2016) investigated the spatial heterogeneity of HIV prevalence in Burundi and then assessed the association of social and behavioral characteristics with HIV infection accounting for the spatial heterogeneity. Methods: The study utilized data from the 2010 Demographic and Health Survey and analyzed the data with a geostatistical approach (which takes into account spatial autocorrelation) by i) interpolating HIV data using the kernel density estimation, ii) identifying the spatial clusters with high and low HIV prevalence using the Kulldorff spatial scan statistics, and then iii) performing a multivariate spatial logistic regression. The study results indicated that HIV infection was significantly associated with the female sex (posterior odds ratio [POR] 1.36, 95 % credible interval [CrI] 1.13-1.64), an older age (POR 1.97, 95 % CrI 1.26-3.08), the level of education (POR 1.50, 95 % CrI 1.22-1.84), the marital status (POR 1.86, 95 % CrI 1.23-2.80), a higher wealth index (POR 2.11, 95 % CrI 1.772.51), the sexual activity (POR 1.76, 95 % CrI 1.04-2.96), and a history of sexually transmitted infection (POR 2.03, 95 % CrI 1.56-2.64).

III. METHOD

The Artificial Neural Network (ANN), which we intend to employ; is a data processing system consisting of a large number of simple and highly interconnected processing elements resembling a biological neural system and has the capability of learning from an experimental or real data set to describe the nonlinear and interaction effects with great accuracy. ANN-based curve fitting method is one of the extensively applied artificial intelligence methods that are used for forecasting and prediction purpose. It consists of basically three layers i.e., input layer, hidden layer, and output layer, the present paper includes the number of years as input layer and the annual ART coverage in Burundi as output data for the network. In this research paper, our ANN is based on the hyperbolic tangent function.

Data Issues

This study is based on annual ART coverages (referred to as B series in this study) in all age groups in Burundi. The annual data covers the period 2000-2018 while the out-of-sample forecast covers the period 2019-2023. All the data employed in this research paper was gathered from the World Bank online database.

IV. FINDINGS OF THE STUDY

DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Mean	Median	Minimum	Maximum
25.947	19.000	0.00000	80.000
Std. Dev.	C.V.	Skewness	Ex. kurtosis
25.260	0.97350	0.79745	-0.50359
5% Perc.	95% Perc.	IQ range	Missing obs.
undefined	80.000	38.000	0

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ANN MODEL SUMMARY FOR ART COVERAGE IN BURUNDI

Table 2: ANN model summary

Variable	B
Observations	10 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	9
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.012381
MSE	0.302776
MAE	0.475700

Residual Analysis for the ANN model

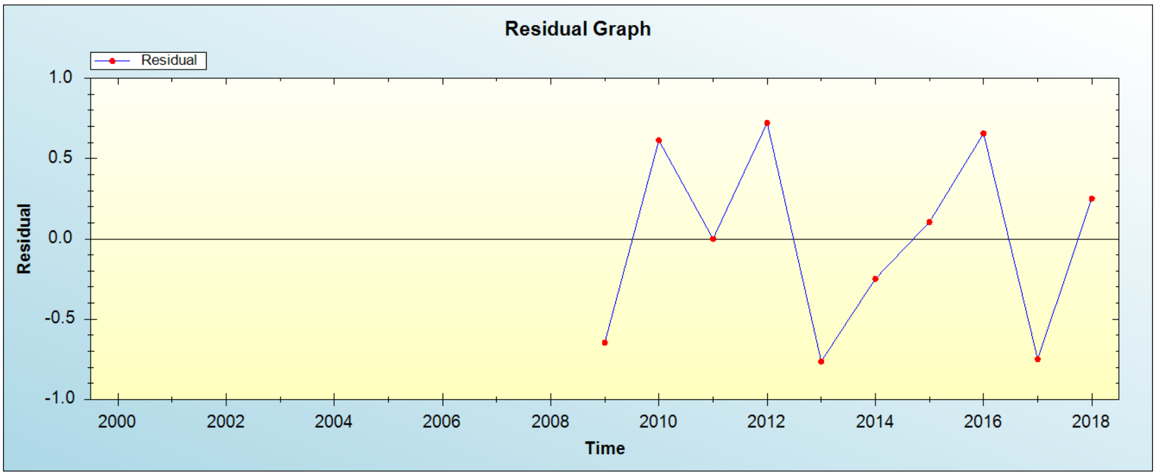

Figure 1: Residual analysis

In-sample Forecast for B

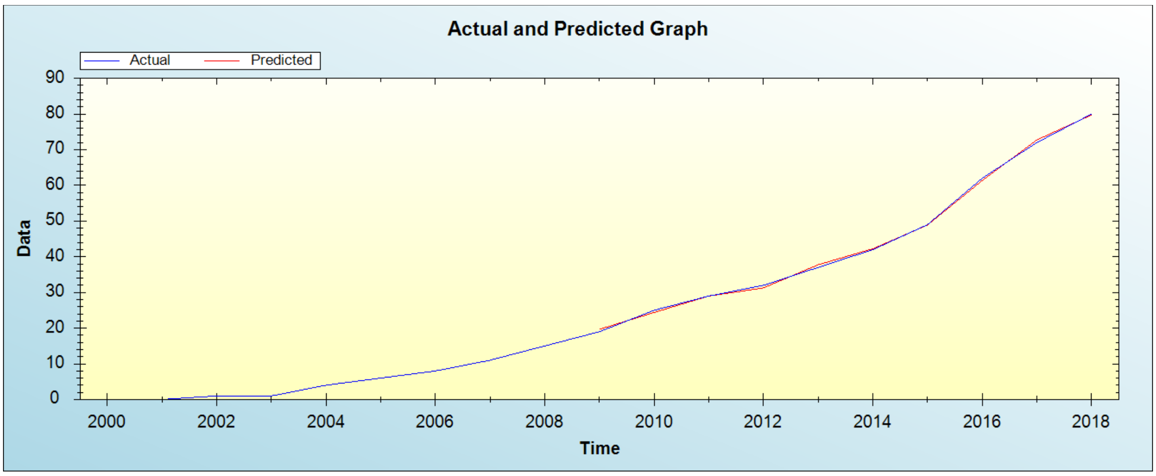

Figure 2: In-sample forecast for the B series

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Figure 2 shows the in-sample forecast for B series.

Out-of-Sample Forecast for B: Actual and Forecasted Graph

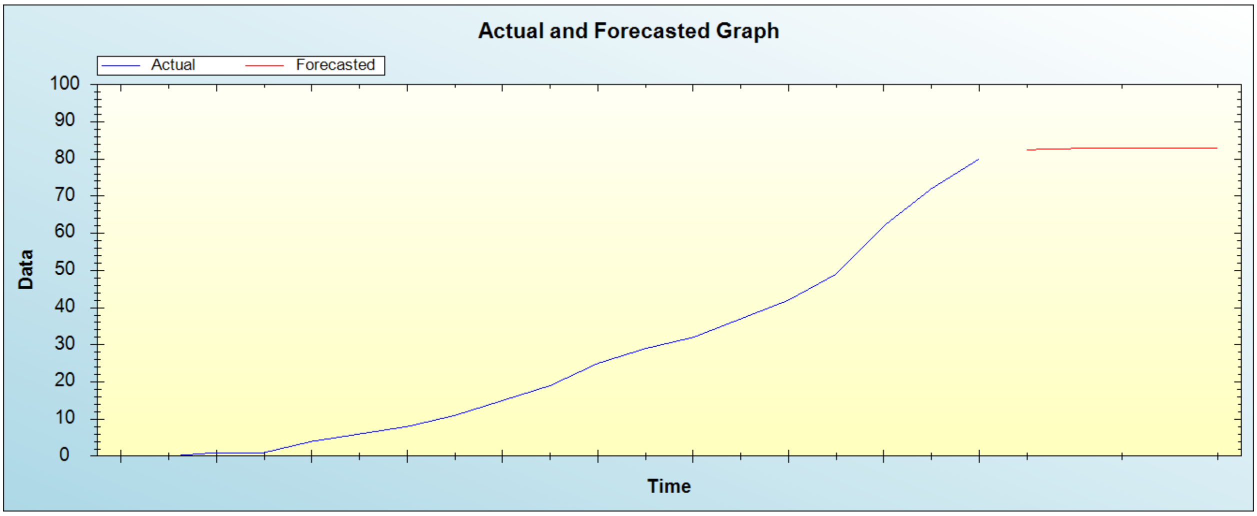

Figure 3: Out-of-sample forecast for B: actual and forecasted graph

Out-of-Sample Forecast for B: Forecasts only

Table 3: Tabulated out-of-sample forecasts

Year	Forecasted ART coverage
2019	82.4756
2020	82.8190
2021	82.9192
2022	83.0399
2023	82.8249

Over the study period, the minimum and maximum ART coverage was 0 and 80% respectively. The country recorded zeros in 2000 and 2001 because it commenced its National ART program in 2002The average ART coverage for the study period was 25.947 %. The data utilized by this study is not normally distributed i.e. it is positively skewed with an excess kurtosis of -0. 5035. The model evaluation criteria (Error, MSE, MAE) and residual graph indicate that the model is suitable and stable to forecast ART coverage in Botswana. The in-sample forecasts showed that the applied ANN (9, 12, 1) model simulates the observed data accurately. The projections from the employed neural network model suggest that the ART coverage is likely to remain constant at around 83 % throughout the out of sample period 2019-2023.

V. CONCLUSION & RECOMMENDATIONS

Burundi is committed to tackling the HIV epidemic in order to reduce morbidity and mortality due to HIV related conditions. Over the period 2018-2018 the country recorded a commendable upward trend in the ART coverage. The projections from the ANN (9,12,1) model revealed that the nation is likely to record a high ART coverage of approximately 83% throughout the period 2019-2023.Inorder to achieve the 90-90-90 global HIV targets the government is encouraged to increase HIV testing services and improving access to ART services for key populations in the country.

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