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An Optimized Machine Learning Model for Population Growth Prediction Using Artificial Neural Network and Genetic (Neuro-Genetic) Algorithm

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ABSTRACT

With the global population growth reaching over seven billion persons on the planet, issues of desertification, famine, global warming and climate change are presently in the front burner of global discourse as the need for proper and more accurate population prediction for economic and national development become expedient. This paper therefore proposes' the optimization of machine learning model for population prediction in Nigeria using artificial neural network and genetic algorithm. The model was adopted to dataset for the national population commission (NPC) containing annual population growth from 1950 – 2021. The Agile Software Development Methodology (SDM) was applied to real-life data to evaluate the efficiency of the model. An iterative approach was adopted to time series data in other to examine the applicability of the proposed model. The model was implemented in Java Apache NetBeans using 70% of the dataset for training and 30% as test data. The model yielded an accuracy of 76% with a Root mean squared errors (RMSE) of 8.21%, mean Absolute percentage errors (MAPE) of 6.4%. Mean squared errors (MSE) of 5.67%, MEA of 23.29% and MAD of 49.23% when compared to existing models in literature.

1. INTRODUCTION

The population projection is important in both national planning and decision making for socioeconomic and demographic development. Population projection has emerged as one of the most pressing issues of discourse in global politics. Population sizes and growth in a country have a direct impact on the economy, policy, culture, education, and environment of that country, as well as the exploration and cost of natural resources. Countries across the globe do not want to wait until there is population explosion that would affect the available national resources as it will be counter-productive for national growth, stability and sustainability. In order to plan for the future, every government and collective sector must have a precise idea of the future size of various entities, such as population, resources, demands, and consumptions. To get this information, statisticians and mathematicians analyzed the behavior of the connected variables based on previous data, and then make future projections based on the conclusions drawn

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from the analysis. Social, environmental, and economic development are all threatened by the effects of population growth (Yahaya et al., 2017).

According to Nwokoye (2009), the current population growth rate in the world is estimated at 1.33 percent. As a result, United Nations Fund for Population Activities (UNFPA) reports that the world's population is growing at an annual rate of 78 million people. In developing countries, including Nigeria, the population is growing at a rate of over 95 percent per year. U.N. Population Agency (UNFPA) estimates that the world's population will reach 8.9 billion by 2050 (United Nations Population Fund [UNPF], 1999). The current global population is estimated to be 7.5 billion people. According to research, more than 85 million people are added to the world population each year, with developing countries accounting for more than 83 percent of this net increase. When compared to developed countries, the population of developing countries is growing at a geometric rate.

The choice of population estimate and prediction should be a data-driven decision at the heart of long-term planning as the adoption of population prediction and estimate based on a desired outcome rather than one based on accurate facts and historical patterns is one of the most common errors to avoid. However, very optimistic projections can lead to long-term infrastructure commitments that jeopardize other local objectives. Forecasts that are more conservative are thought to be less risky. Many decision-makers worry that they will be stranded with a projection for the next two decades, but jurisdictions could track population growth as it happens and make appropriate modifications at the next periodic review (Simpson, 2016).

Developing nations of the world especially in Sub-Saharan Africa, Nigeria inclusive are facing a massive population growth problem which have adversely affected the socioeconomic development in the countries. The problem of over population has negatively impacted on the provision of basic amenities that would hitherto have improved the lives and livelihood of the population. To this end there is need for the development of machine learning model to automatically forecast and predict population growth to enable policy and development planners make a more sustainable policy and development decision that would accommodate both present and future population growth pattern. With the advent of computer technology and artificial intelligence population prediction and estimation could the enhanced to endure high degree of prediction accuracy with lower error margin to promote sustainable development. This paper therefore, proposed the development of an improved machine learning model for population prediction and estimation using artificial using artificial neural network and genetic algorithm for the prediction of the Nigerian population growth rate.

2. LITERATURE REVIEW

The growth in the global population has pulled a lot of string on both human and natural resources leading to grave ecological danger on humanity as green areas and forest reserves are deliberately destroyed to meet the housing and nutritional need of people on the planet thereby resulting to the continuous depletion of existing natural resources like land, water (Rivers, Seas, Creeks, Oceans, e.tc) and air. It is evidence that globally that population growth has contributed immensely to global warming as the need to carter sustainably for this astronomical growth in population bites hard of global leadership, Nigeria inclusive.

Population forecasts and scenarios are valuable planning and risk-management tools for governments, businesses, non-governmental organizations, and individuals. Governments require short-term and mid-term scenarios to estimate the need for schools, hospitals, and other public services; to help inform long-term infrastructure investments; and to plan for the necessary skills to invest wisely in health research and development resources; and to provide skills and knowledge for the future workforce.

Long-term scenarios are necessary for governments to understand potential environmental, military, geopolitical, and other risks, as well as to develop prevention and mitigation strategies. Businesses engaged in long-term investments, such as those in the retails, banking, hospitality, entertainment, pharmaceutical industry, must consider population scenarios as well as well as in industries related to large-scale infrastructure projects. Individuals may also be concerned about the future population: will there be enough workers to pay taxes to support pension and health benefits for the retired? Will demographic change improve global and national security and stability, or will it put societies in jeopardy?

Understanding future population patterns is critical for anticipating and planning for changing age structures, resource and health-care needs, and environmental and economic landscapes. Future fertility patterns are an important input in estimating future population size, but they are surrounded by significant uncertainty and diverging estimation and forecasting methodologies, resulting in significant differences in global population projections. Changes in population size and age structure may have far-reaching economic, social, and geopolitical consequences in many countries (Vollset et al., 2020).

Nigeria has one of the highest population densities among developing countries. Because of its large population, Nigeria is often referred to as the "Giant of Africa". Nigeria is the most populous country in Africa and the seventh most populous country in the world, with a population of approximately 184 million people. Nigeria has one of the world's largest youth populations (Ogbuabor et al., 2018). Furthermore, Tartiyus et al (2015) avers that Nigeria is one of the world's fastest growing countries, with a population growth rate of 2.8 percent per year between 1952 and 1991. It is home to one in every five Sub-Saharan Africans. Nigeria's population has been rapidly increasing for at least the last five decades due to extremely high birth rates, quadrupling during this time with an exponential growth rate. According to the 2018 UN estimates, Nigeria's current population is 194,623,929 which represents an estimated 2.57 percent of the world's total population (Ogbuabor et al., 2018).

In spite of this, there is no consensus in the empirical literature about the impact of this growing population on economic development. The massive growth in the population of countries in Sub-Saharan Africa including Nigeria has its own set of issues as earlier stated. A large population size exhibits a pattern of behaviour when it get closer to its carrying capacity, or maximum sustainable population size (Tarsi and Tuff, 2012), this may result on all manner of agitation and unrest as witnessed in Nigeria in recent times as issues of resources control and herdsmen invasion and migration or more becomes common when populations are close to their carrying capacity.

Predicting human population patterns is a difficult task. There are a number of unknowns related with any country's population. If the population of a country were used as a predict variable and, it would be discovered that there are a number of possible predictors. Some predictors may be highly connected with the predict and, while others may not be. Furthermore, the kind and number of predictors differ per country. Some societal or political changes can cause a shift in the predictors' trends. For these reasons, the authors of this research believe that a country's population should be viewed as a chaotic system. In this case, a tiny change in one of the conditioning elements can cause a significant change in the population at a particular moment in time (Bandyopadhyay and Chattopadhyay, 2006).

Though statistical methodologies have traditionally been used for the prediction and forecasting of population, to deal with the enormous uncertainty associated with a country's demography, statistical demographic prediction agencies provide two or more projections of fertility, mortality or both. Traditional statistical approaches, on the other hand, are not very effective in predicting a chaotic system like the population. To begin, statistical methods rely on certain assumptions that have been proved to be unreliable. Secondly, the inherent chaos cannot be dealt with by statistical population forecasting processes (Keilman et al., 2002). Irrespective of the successes achieved by the statistical methods in population prediction and analysis, the emergence of machine learning models which is a subset of artificial intelligence has shown greater predictive accuracy as it requires little or no human intervention to perform the given tasks.

2.1 Application of Machine Learning For Population Prediction

Machine learning is a branch of artificial intelligence (AI) that deals with collecting patterns from data and then using those patterns to allow systems to better themselves over time. This form of learning can assist computers in recognizing patterns and relationships in huge volumes of data and making predictions and projections based on their findings. Cowley (2021) posits that a machine learning model is a file that has been taught to recognize specific patterns. You train a model on a set of data by providing it with an algorithm that it may use to reason about and learn from that data.

Machine learning is already having a significant impact in a variety of industries. Machine learning is being utilized in the financial services sector to evaluate data for risk analytics, fraud detection, and portfolio management. In terms of travel, GPS traffic predictions are available.

The following are some notable machine learning models;

1) Artificial Neural Network
2) Support Vector Machine
3) Naïve Bayes Network
4) Regression Models
5) Deep Neural Network etc.

From the list of machine learning algorithms above we shall explore and use artificial neural network (ANN) algorithm for the prediction problem to be solved in this dissertation.

2.2 Artificial Neural Network

Artificial neural networks (ANNs) were first proposed on a theoretical platform by McCulloch and Pitts in 1943 (as cited in Sean, 2020), but their implementation was computationally infeasible and impractical until the 1980s. However, as computers became more efficient, interest in neural models resurfaced, and they quickly established themselves among other machine learning and artificial intelligence algorithms. Deep learning neural networks have become the most popular machine learning algorithms in recent years, with applications in computer vision and natural language processing. Basic multilayer feedforward networks are made up of various layers that contain a number of units (often referred to as neurons) that can be weighted to model nonlinear functions. Each unit is a linear combination of all units in the previous layer with a nonlinear function applied to it, as modelled mathematically as follows:

$$h_{i,j} = f\left(W_{i,j}^{T} X_{i-1} + b\right), \quad (1)$$

where $h_{i,j}$ is the *j*th unit of the network's *i*th layer, wi,j is the vector of linear weights, X_{i-1} is the vector of unit values in layer $i-1$, and b is a bias term $f\cdot$ is a nonlinear function in this case. The sigmoid $tanh$, or, more commonly the ReLU, a simple nonlinear function defined as:

$$ReLu(x) = max\ (0, x) \quad (2)$$

Except at zero, ReLU is a simple to calculate nonlinear function with a well-defined gradient. Many neural network models, particularly in computer vision applications, now include ReLU activations. Furthermore, ReLU avoids a common stumbling block for deep neural networks: gradient calculation. The gradient of the loss function must be propagated back through the various layers when networks are made up of many layers. Due to repeated multiplications of values less than 1, the gradient with sigmoid or $tanh$, activations becomes smaller as it propagates (Liu and Chung, 2014).

The derivative does not decay in the same way with ReLU: because the ReLU function's derivative takes on the values 1 or 0, the gradient will not decay as it is repeatedly propagated backward, unless the unit takes on a negative value, at which point the derivative will stop propagating for the iteration.

$$ReLu'(x) \begin{cases} 0 & x < 0 \\ 1 & x > 0 \end{cases} \quad (3)$$

If a zero is encountered, the gradient is usually computed as one or zero at random. The popularity of artificial neural networks is fuelled by a variety of factors, but for our purposes, we shall concentrate on one feature that makes them useful: "multilayer feed forward networks are universal approximators" (Hornik et al.,1989). When the exact form a function may take is unknown or highly complex, such as when predicting time-series data or a country's net migration, this feature of neural networks is extremely useful. Furthermore, specific network architectures, such as gated recurrent units (Chung et al., 2014), have been shown to perform well when predicting time-series data such as foreign exchange, stock and population prediction.

In summary ANN learns from previous data to uses the derived features to make prediction. The dataset presented to the ANN model is used for training the network to enable the model reduce and minimizes errors between the insertion and the estimation. The process fine-tunes the weights and potential bias for various interaction of the network neurons. Finally, when an optimal learning rate is attained the training process is then terminated (Demuth et al., 2017; Abraham et al., 2020). Figure 1 and 2 shows a typical ANN architecture and the neuron with activation function. The weighted inputs bias and the activation function of the network is represented mathematically as:

$$ne = \sum_{i=1}^{n} x_i\, w_i + b_i \quad (4)$$

$$uf = (ne) \quad (5)$$

Where, $x_1 \ldots . x_n$ is the input dataset or value, $w_1 \ldots . w_n$ are the weight of the network and b the bias or the activation threshold of the neuron potential ne.

And the activation function of the neuron as:

$$f(ne) = \frac{1 - e^{-\beta u}}{1 + e^{-\beta u}} \quad (6)$$

where β is the constant associated with the hyperbolic tangent function's slope, and the output values are in the range of -1 to 1.

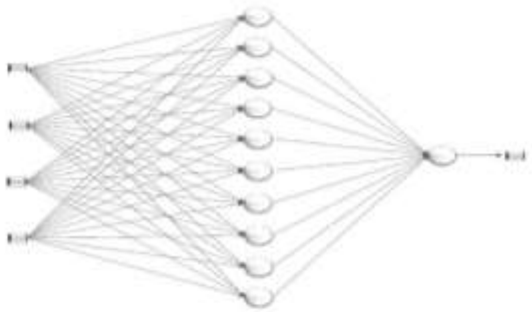

Figure 1: ANN Architecture (Source: Abraham et al., 2020)

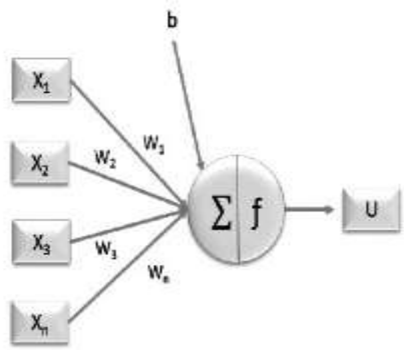

Figure 2: Artificial Neurone Showing Activation Function (Source: Abraham et al., 2020)

2.3 Optimizing Machine Learning Models

Most traditional techniques, particularly those with nonlinear objective functions, have failed to solve large-scale problems. One of the major issues with using traditional techniques to solve non-differentiable functions is that they require gradient information, which is difficult to obtain. These methods frequently fail to solve optimization problems with multiple local optima. It is necessary to develop more powerful optimization techniques in order to overcome these issues (Orkadi and Ojekudo, 2021). The goal of Machine learning main is to develop a model that performs well and makes accurate predictions in a specific set of scenarios. To achieve this goal there is need for the machine learning model to be optimized. The process of adjusting hyperparameters in order to minimize the cost function using one of the optimization techniques is known as machine learning optimization. The cost function must be minimized because it describes the difference between the true value of an estimated parameter and what the model predicts (Gavrilova, 2020).

Furthermore, Brownlee (2021) posits that machine learning process involves the use of an algorithm to learn and generalize from historical data in order to predict new data. This process can be described as approximating a function that maps input examples to output examples. The problem of approximating a function can be solved by framing it as function optimization. A machine learning algorithm defines a parameterized mapping function (e.g., a weighted sum of inputs), and an optimization algorithm is used to find the values of the parameters (e.g., model coefficients) that minimize the function's error when mapping inputs to outputs. This implies that whenever a machine learning algorithm is applied to a training dataset, we are solving an optimization problem.

According to Chauhan (2020), one of the most difficult challenges in the implementation of machine learning solutions is model optimization. The optimization of models has spawned entire branches of machine learning and deep learning theory. In machine learning, hyperparameter optimization aims to find the hyperparameters of a given machine learning algorithm that deliver the best performance on a validation set. Hyperparameter optimization returns an optimal model that reduces a predefined loss function and, as a result, improves the accuracy on given independent data by finding a combination of hyperparameters. To achieve maximum effectiveness, machine learning algorithms such as logistic regression and neural nets rely on well-tuned hyperparameters. The performance and cost of various hyperparameter optimization strategies varies (in time, money, and compute cycles.) Hyperparameters can affect the training of machine learning algorithms directly. It is therefore critical to understand how to optimize them in order to achieve maximum performance (Johnson, 2016; Chauhan, 2020). Some common hyperparameter optimization strategies include;

1. Manual hyperparameter tuning,
2. Grid search,
3. Random search,
4. Bayesian optimization
5. Gradient-based optimization and
6. Evolutionary optimization

In this paper we shall deploy genetic algorithm which an evolutionary computing and optimization strategy for optimizing the machine learning model to enhance the accuracy of the population prediction model.

2.4 Genetic Algorithm (GA)

The core notions of Darwinian evolution drove the development of GA. It's a heuristic approach to addressing computationally challenging problems (Zhu et al., 2006). When search spaces are very modal, discontinuous, or limited, GA outperforms several classic heuristic methods. It is the most often utilized type of evolutionary algorithm in a wide range of optimization problems (Kisi and Cengiz, 2013). It starts with an initial population made up of randomly generated rules that represent strings of bits (Han et al., 2012). GA is a search algorithm that, unlike other search algorithms, searches among a population of point and code parameters rather than using the parameters' valuesIt efficiently searches irregular spaces using objective function information rather than gradient information (Kabra and Bichkar, 2014). Soni (2018) adds that while GA can function as a standalone algorithm, it can also effectively serve as a complementary optimization role for other algorithms, facilitating an optimal starting point for other algorithms to begin. The GA's basic concept follows the process of creating an initial population, determining a fitness function, selection, crossover, and mutation.

At the inception, an initial population of individual chromosome is created and then the fitness function is further derived for each chromosome in the population furthermore, the selection process for the best fit chromosome is performed and the cross over process carries out. The crossover process could either be a single point or multi point cross over depending on the optimization need then the mutation is conducted and a new chromosome is formed, this process is repeated iteratively from the fitness function to the final state until an optimal solution is attained.

Kabra and Bichkar (2014), asserts opines that the GA framework would likely follow the progression as below:

a) Formulate or create initial population
b) Initialize the population randomly
c) Repeat the process
d) Evaluate the objective function
e) Find the fitness function
f) Apply genetic operators (Reproduction, Crossover and Mutation)
g) Repeat the process until the given criteria is met

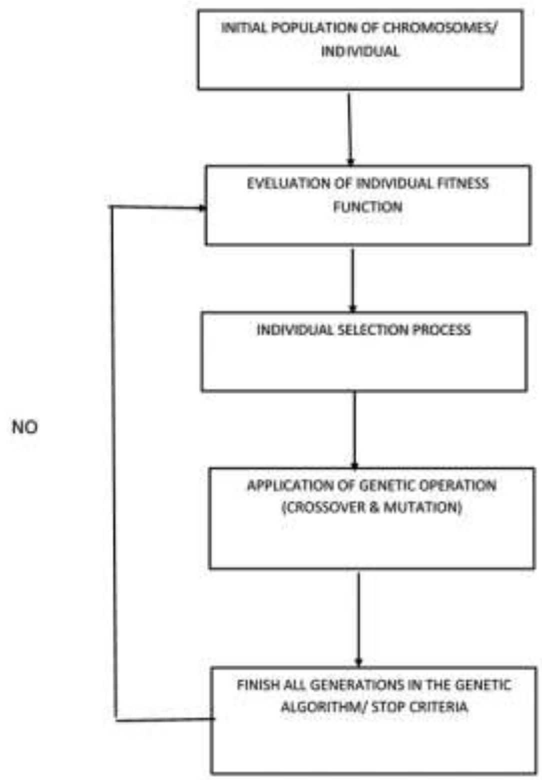

Figure 3: Genetic Algorithm Process Flow diagram

Genetic algorithms which mimic natural systems as they evolve from primitive to more complex structures, provide numerous opportunities in econometrics, particularly forecasting. They enable the creation of probabilistic models that include new information in a non-arbitrary way by performing reproduction, cross-over, and mutation operations on a randomly generated population. This method has proven to be efficient and particularly well-suited for simulating economic, human behaviour and trend analysis which has several relevant characteristics with evolutionary algorithms. Some of the most prominent advantages of genetic algorithms include their ability to deal with non-stationary data and the absence of the need to assume a specific data distribution. As a result, they have been successfully used to forecast trends and time series data such as FOREX, stock market, and commodity prices, as well as in hybrid applications with models such as artificial neural network (ANN) structures, adaptive neuro-fuzzy inference systems (ANFISs), or support vector machines (SVMs). They resulted in lower root-mean-square errors, mean absolute percentage errors, and higher R^2 values or directional correctness in numerous experiments.

2.5 Related Works

Jabrayilova (2019) built a fuzzy time series-based intelligent demographic forecasting system for predicting population growth in “Development of Intelligent Demographic Forecasting System”. The implementation of time series entails developing a mathematical model of time series observations of real-world phenomena. The author created an intelligent system that can forecast a population, and the forecast results for many indicators may be retrieved. The fuzzy time series, on the other hand, has the minimum AIC, and the diagnostic test run on the model using the Box-pierce test shows that the model is sufficiently suited for the data

Mwakisisile and Mushi (2019) in their paper “Mathematical Model for Tanzania Population Growth” implemented a mathematical model using using exponential and logistic population growth models to predict population growth in Tanzania with census data obtained from the national bureau for statistic between 1967 – 2012 to make projection for 2013 – 2035. The results show that the population is growing at a rate of 2.88 percent. According to the exponential model, the population in 2035 will be 87,538,767, while the logistic model predicts 85,102,504 people.

For the prediction of Malaysian economic growth Sanusi et al (2020) in their paper titled “Neural Network Analysis in Forecasting the Malaysian GDP” ptoposed an artificial neural network-based approach. The ANN algorithm was chosen because of its ability to deal with non-linear difficulties in Malaysia's growth statistics, as well as its ability to overcome multi-collinearity among variables. The research finding shows thst the neural network algotithm produces the smallest mean error of 0.81% with a total difference of 0.70%. This indicates that the neural network model is acceptable and relevant for forecasting Malaysia's economic growth.

Ding et al (2019) in "Predicting the Future Chinese Population using Shared Socioeconomic Pathways, the Sixth National Population Census, and a PDE Model" relied on a structural population data from China's Sixth National Population Census for provinces, prefectures, and counties. The population change parameters were explained using a population–development–environment model. On a nationwide basis, the population of 340 districts was revised, forecasted, and aggregated. From 2010 to 2050, the Chinese population is predicted to increase first, then drop, according to the five routes. The aging demographic structure is unaffected by any path, and the increase or decline in urban and rural populations between node years is largely tied to fertility rates and urbanization rates.

Fatih et al (2019) presented a presentation titled "Using Machine Learning Algorithms in Population Forecasting: The Case of Turkey" to forecast the population, they used various machine learning methods. The model was trained using 1595 different demographic statistics from 262 different nations between 1960 and 2017. When the models were compared, the ARIMA model was the most successful. After a thorough examination, the Machine Learning model outperformed the other demographic models. This suggests that Machine Learning Algorithms produce more meaningful findings when dealing with large datasets.

Ashioba and Daniel (2020) in the paper titled "Population Forecasting System Using Machine Learning Algorithm" asserts that census enumeration cost the Nigerian government a lot of money as census enumeration in the country has been marred by controversy. The Population Forecasting System was developed using linear regression model and Object-Oriented Analysis and Design methodology and the results obtained demonstrate that the model has smaller percentage error margins between 0.76% and 1.09 % than the Average Projection Model and the Nature Fund Growth Model, which have percentage error margins of 4.73 percent and 1.43 percent, respectively.

Tarasov et al (2018) in "Application of Nonlinear Autoregressive Neural Network with Exogen for Modeling Demographic Dynamics in Large Urban Agglomeration" proposed the implementation of artificial neural networks (ANN) for time series analysis in different fields. A nonlinear autoregressive exogenous neural network from the Matlab program is used to predict changes in the population and its sex-age composition, as well as the contribution of the migration factor. The forecast results yeilded an error margin of 3% from the actual data making the ANN model more reliable for forecasting population growth.

Riiman et al (2020) proposed the development of an artificial neural network (ANN) model for forecasting population growth of Alabama and 67 counties and they compared their work with a cohort of ANN and LSTM model. The model yielded RMSE, MAE and MAPE of 5,251, 3215 and 6.89% respectively. The model recorded also high false positive prediction.

Benzer (2015) in his paper titled "Population dynamics forecasting using artificial neural networks" deployed artificial neural networks (ANN) for the forecasting of population growth. The results of artificial neural networks and regression techniques are compared to the growth rates of fish taken in real environments and the von Bertalanffy growth model. It has been demonstrated that an artificial neural network is an effective tool for forecasting growth models. The use of ANNs as a forecasting tool demonstrates its availability and quite decent outcomes. Regression approaches produce good results and are strongly related to the quantity of observations.

Wang and Lee (2021) in their paper titled "Regional Population Forecast and Analysis Based on Machine Learning Strategy", identified the disadvantage of cohort-component type population forecasting by stating that it allows the analyst to specify future demographic rates, which, of course, tends to introduce a biased result in forecasting accuracy. They proposed a machine learning-based technique for objectively forecasting multi-regional population growth. Their research, which makes use of newly developed machine learning technology, attempts to analyze and forecast the population growth of Taiwan's major cities.

In the paper "Comparing the Performance of 17 Machine Learning Models in Predicting Human Population Growth of Countries" Otoom, (2021) stated that human population growth rate plays an important role in real-world planning. Areas with no historical data poses a major challenge to the planning process. Machine learning can help in these situations, but the variety of machine learning algorithms makes it difficult to choose the best approach. The study successfully demonstrates and compares machine learning techniques for predicting human population growth rate in scenarios where historical data and feature information are unavailable.

3. METHODOLOGY

The paper adopted the agile Scrum software development methodology which promotes a disciplined project management process that encourages frequent inspection and adaptation, a leadership philosophy that encourages teamwork, self-organization and accountability, a set of engineering best practices intended to allow for rapid delivery of high-quality software, and a business approach that aligns development with customer needs and organizational goals. Furthermore, the we developed a fusion of artificial neural network and genetic algorithm model for prediction of Nigerian population using population growth dataset in CSV format from the national population commission (NPC) from 1950-2021. The dataset was preprocessed and splits into 70% training and 30% test dataset for training and testing the efficiency of the model. Figure 4 shows the architecture of the proposed model. Finally, the model was developed using Java Apache Netbeans which is an open-source programming language of high repute and one that has been deployed across the industry for the development of world class user-friendly applications.

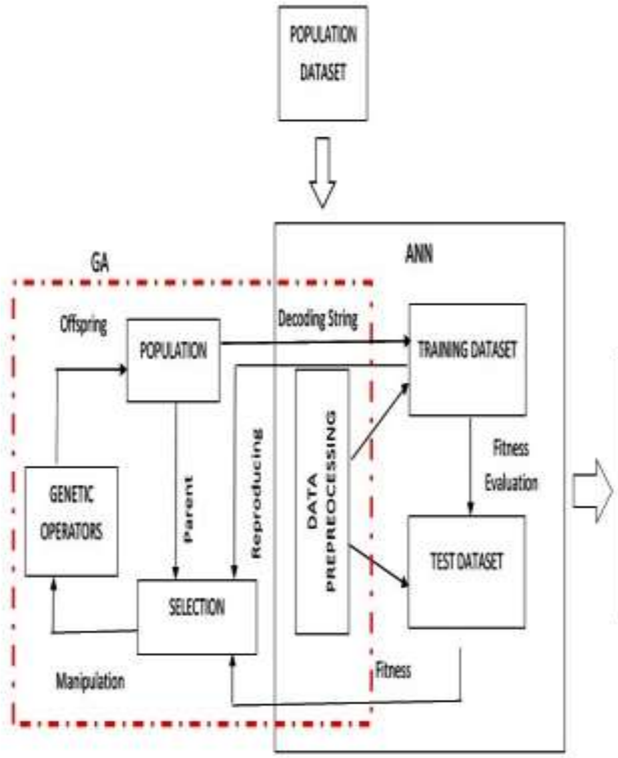

Figure 4: Architecture of Proposed System

4. RESULTS AND DISCOUSSION

The model was trained using historical population growth data from the repository of the national population commission (NPC). The dataset comprises of the population figures from the year 1950 – 2021 showing annual increase in population. The model was able to make prediction for the growth in the population using the dataset. Figure 5 shows the home page where the user can navigate to upload dataset using the dropdown menu. Also Figure 6 shows the dataset uploaded after preprocessing as a section of the dataset is used for the process of the computing the population.

Figure 5: Main Page showing dropdown menu

Figure 6: Computing Population Growth

Figure 7: Predicted Result

The process of computing the population include the use of time series data extracted from the national population commission (NPC) which is the authentic population prediction figure of Nigeria to train the model. With the figures from the 2017 population to 2021 population respectively the model make prediction. Figure 7 shows the prediction of the model with population projection for three decades from 2031 – 2051 respectively as shown in table 1

Table 1: Table of Predicted Population up to 2051

YEAR	POPULATION FIGURES
2017	190873244
2018	195874683
2019	200963599
2020	206400708
2021	211400708
PREDICTED POPULATION	
2031	221405932
2041	226494713
2051	231583494

The result of in this paper shall be discourseed by carrying out a comparative analysis of the newly developed model and the existing system with respect to result obtained from the forecasting task conducted ascertain the area of improvement with respect to the existing system.

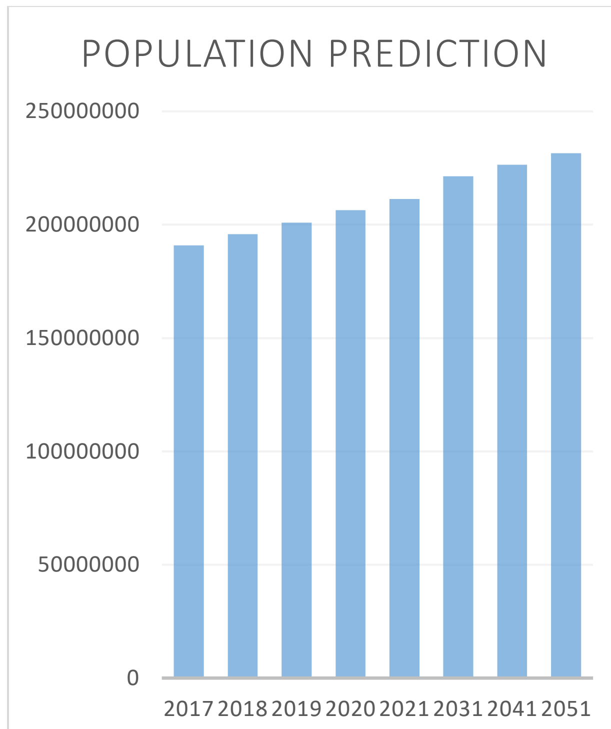

Figure 8: Chart of the Population Growth Prediction for 2017 – 2051

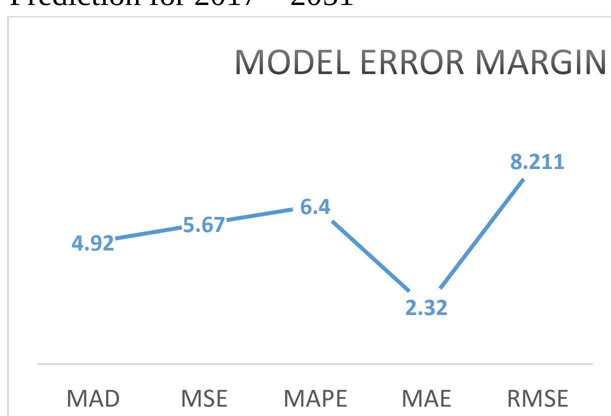

Figure 8: Error Margin Chart

The system used to evaluate the efficiency of the new system was developed by Riiman et al. (2020), which is an artificial neural model for the forecasting and prediction of population growth in 67 counties of the state of Alabama and yielded the following RMSE, MAE, MSE and MAPE of 9326, 5251, 3215 and 6.89% respectively. The new system trained with a dataset from the Nigeria national population commission (NPC) yielded an RMSE of 8211, MAPE 6.4%, MAE 2329, MSE 5675 and MAD of 4923 respectively. Table 2 and 3 shows the table of error margin in the existing and new system.

Table 2: The Error Margin for Existing System model

PARAMETER	ERROR MARGIN
MSE	3215
MAPE	6.89
MAE	5251
RMSE	9326

Table 3: The Error Margin for Existing System model proposed system model

PARAMETER	ERROR MARGIN
MAD	4923
MSE	5675
MAPE	6.4
MAE	2329
RMSE	8211

The comparative analysis of the existing and new system in Table 4 shows that the new system outperformed the existing system with respect to error margin. For the mean square error (MSE) the existing model error was lower than that of the new system with difference of 2.46, for mean absolute error (MAE) the new system outperformed the existing system with a difference of 2.92. The new system also performed better in the evaluation of the root mean square error (RMSE) with an error margin of 8211 as against the existing system error margin of 9326 which give a difference of 1.115 as the new system also recorded a lesser mean absolute percentage error (MAPE) of 6.40% as against the 6.89% achieved by the existing system. The existing system did not put into consideration the mean absolute deviation (MAD) of the model which is also a critical evaluation metrics for forecasting model but out model yielded 49.32% MAD. Figure 9 shows the comparative analysis chart of the new and existing system showing the variation in the error margin of the population prediction models.

Table 4: Estimated Error from Comparative Analysis of Existing and New System

ERROR EVALUATION METRICS	MAD	MSE	MAPE	MAE	RMSE
EXISTING SYSTEM		3215	6.89	5251	9326
NEW SYSTEM	4923	5675	6.4	2329	8211

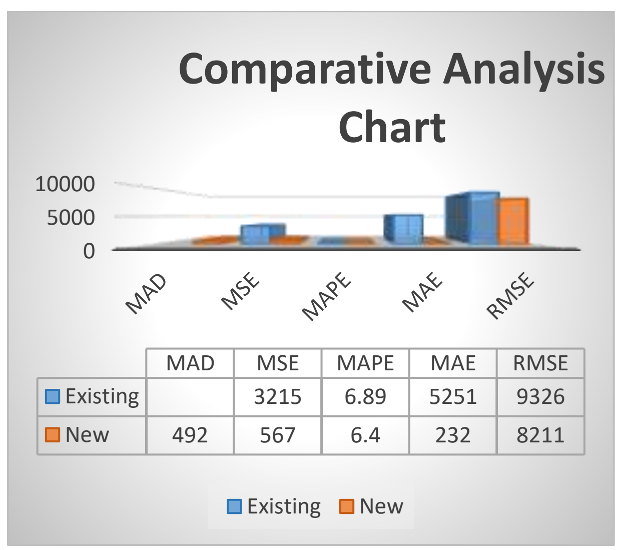

Figure 9: Comparative Analysis Chart for Existing and New System

5. CONCLUSION

This paper takes a dive at the machine learning approaches for predicting population growth rates in a data-constrained setting. Through a review of related works, we investigated the ability of demographic details from various areas around the world to predict population growth rates in any other area of the world, and proposes a hybrid machine learning model for population prediction by optimizing the artificial neural network (ANN) model with a genetic algorithm.In this dissertation, we improved on the machine learning model proposed by Riiman et al (2020) which developed an artificial neural network model for the forecasting the population trend in the 67 counties of the Alabama state and optimized the model with genetic algorithm. The improved neuro-genetic model for population prediction developed adopted an agile scrum methodology due to the fact that it emphasizes on the application of an empirical approach that enables for iterative and quick change in the program development and responds efficiently and successfully to changing customer requirement thereby boosting the morale of the development team. Finally the model developed in Java Apache Netbeans and trained with population dataset from the national population commission from 1950 – 2021 yielded an accuracy of 76% with a RMSE of 8.21%, MAPE of 6.4%. MSE of 5.67%, MEA of 23.29% and MAD of 49.23% respectively.

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