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Topic: "Automated time series prediction of Gross Domestic Product (GDP) accounting for Countries in African Union"

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Abstract
This research investigates the use of automated time series component identification in forecasting Nigeria's Gross Domestic Product GDP. The study applied models including ARIMA, Prophet, LSTM, and Linear Regression to annual GDP data spanning 2001–2023, with forecasts extending to 2030. The results indicate that LSTM provided the most accurate predictions, outperforming traditional statistical models. The study as well emphasizes the importance of automation and advanced machine learning methods for reliable economic forecasting in volatile economies like Nigeria. Nigeria's GDP trend highlighting growth up to 2014, followed by declines in 2016, 2020, and 2023 due to oil shocks and COVID-19. ARIMA, Prophet, LSTM, and Linear Regression. LSTM achieved the lowest errors, confirming its superiority. actual vs predicted GDP using Linear Regression. The model captured the general trend but failed during volatile years. Scientific evidence reveals that the Nigerian GDP generally need to be improved drastically els can easily get ruin by debt or epidemic such as Covid 19, the GDP needs to be growing progressively to maintain steady increase growth. The Government needs to work on economic policies that encourages growth of GDP urgently.

Keywords: *Nigeria GDP, Time Series Components, Structural Change, LSTM, ARIMA, Prophet, Forecasting*

1 Introduction

Nigeria, as Africa's largest economy, has experienced volatile GDP performance due to oil over dependence, policy instability, and global shocks. Accurate GDP forecasting had been a long time problem and this is critical for fiscal planning and policy formulation {World Bank (2023)}. Traditional methods such as ARIMA and exponential smoothing often fall short in capturing structural breaks and nonlinearities(Box, Jenkins, Reinsel, & Ljung, (2015): Hyndman, & Athanasopoulos, (2021)). The technique BFAST was for recognizing breaking points with the help of seasonal and trend decomposition using loess (STL), it facilitates the detection of trend change in a given information. The elementary standard of the BFAST technique is the splitting of time series into seasonal, trend and also remnants element by the approach for breaks detecting software in R studio core 2012 (World Bank. 2023). Obstacles to private sector participation include the lack of knowledge of climate change risks and opportunities, the high cost of investment related to climate change adaptation, and the limited availability of private resources devoted to green investment (Central Bank of Nigeria (2023). Essential actions include adopting green financial instruments such as green bond issues to increase resource mobilization, establishing a special green fund dedicated to the private sector, adopting tax incentives to encourage green private investment, and involving the private sector in strategies for climate change adaptation (United Nations Economic Commission for Africa (UNECA). (2022). Traditional econometric models such as ARIMA and regression approaches, while useful, often fail to adequately capture nonlinear dynamics or structural breaks that characterize African economies (Taylor & Letham (2018):Hochreiter & Schmidhuber, (1997)). This research integrates machine learning and *automation to improve forecasting accuracy. This research develops an automated system capable of identifying time series components—trend, seasonal, cyclical, and irregular—to provide more reliable forecasts and policy insights.*

2 Literature Review

Identification of time series components usually starts with a time series plot. Time series plot is a tool for visually examining a data set, to know what mean of the data centred around but visual examination should never replace statistical estimation, time series plot can help you decide whether a non-zero mean should be included in the model. Occasionally, time series data shows a sudden change in behaviour at a certain point in time such as in global financial crisis. These sudden changes are often referred to as structural change (Gul, Khan, & Irshad (2020).

Manual time series decomposition for identification of time series components in complex data such as variety of timber price and supply data (Hyndman & Athanasopoulos, 2018). Multiplicative model can be utilized as the product of four components while additive model is the addition of the four components (such as trend, seasonal, cyclical and irregular). The components of the time series were determined by means of the Census X11 technique but the cyclical component was detached from the trend by utilizing the Hodrick–Prescott filter (Kose, Nagle, Ohnsorge, & Sugawara, 2021).

Univariate time series components identification as a very important and vital tool for projection of data. Importantly, owing to its widespread use in various practical domains (Makridakis, Spiliotis, & Assimakopoulos, 2018). Likewise stock market is considered to be one of the most highly volatile complex financial group which consist of various components or stocks, the price of which fluctuates greatly with respect to time. Stock market forecasting involves uncovering the market trends with respect to time (Mohammed & Sanusi, 2022).. All the stock market investors aim to maximize the returns over their investments and minimize the risks associated. Stock markets being highly sensitive and volatile to quick changes, this suggested the use of ARIMA approach to be good enough for handling time series data and as such can be very constructive in various real world problems like that of health sector, education, finance and other practical domains for prediction. The main future study of stock-trend prediction is to develop new automated innovative model that can help to foresee the stocks result in high profits (Onye & Okonkwo, 2020)..

Time series decomposition has long been studied using classical models such as ARIMA and STL decomposition. However, these methods assume linearity and stationarity, which are unsuitable for Nigeria's volatile economy (Choi & Varian (2012)). Recent advances in AI, such as LSTM networks and Prophet, enable improved component identification and forecasting accuracy (Elbadawi, I., & Ndulu, B. J. (2019)). Prior studies have applied AI models to GDP analysis in India and South Africa, but limited work has been done on Nigeria, particularly in automated component decomposition (Fornari, F., & Lemke, W. (2020)).

3 Materials and Methods

The first stage in forecasting is to view the data and to examine all the components of time series present in that data in order to select the most appropriate forecasting technique. The Nigeria GDP data components identification was carried out manually. In time series decomposition process, a proper understanding about how each component behaves in the series can be further studied using a more sophisticated pre-processing technique such as Auto Regressive Integrated Moving Average (ARIMA) (Box & Pierce, 1970). ARIMA is a comprehensive stochastic time series model which uses past data to forecast future data points (Such that the past time series data points can impact current and future data points). ARIMA helps to understand good time series data set and it can also capture complex relationships (such as it takes error terms and observations of lagged terms). Auto Regressive (AR) property of ARIMA is known to be (p). ARIMA involves some numbers of lagged observations of time series to forecast observations.

A weight is applied to each of the past term and the weights can vary based on how recent they are. ARIMA is Integrated with latter (I) in the middle of AR and MA for differencing purposes (OECD, 2020).

Box and Jenkins (1976) suggested that if time series data contains trend, then it is considered non stationary. Integrated is a property that reduces seasonality from a time series. ARIMA models have a degree of differencing which eliminates seasonality. Moving Average (MA) in ARIMA is the error terms of previous time points which are used to predict current and future data points. Moving Average (MA) reduces the random movements from a time series data (Zhang, Eddy Patuwo, & Hu, 1998). The property (q) is usually used to represents Moving Average of order (q). It is expressed as MA (q) where q represents previous observations that are used to compute present observation. Moving average models contains a constant window and weights which are relative to the time (Rajaraman, 2020). This implies that the MA models are more responsive to current event and are more volatile. Auto Regressive (p), Integrated (d) and Moving Average (q) are the three properties of ARIMA model (known as ARIMA (p,d,q). Coefficients are calculated recursively. Model is chosen such that the estimated results calculated from the model are closer to the actual observed values. ARIMA process is iterative in nature and the model is based on a number of assumptions (such data must not contain anomalies, model parameters and error term must be constant, historical data points dictate the behaviour of present data points which might not hold in stressed market data conditions). ARIMA is one of the most widely used forecasting methods for univariate time series data . Although the method can handle data with a trend, it does not support time series with a seasonal component. ARIMA expects data that is either not seasonal or has the seasonal component removed, e.g., seasonality is adjusted with the methods of seasonal differencing (Romer,2019).

4 Analysis

4.1 GDP Trend Analysis

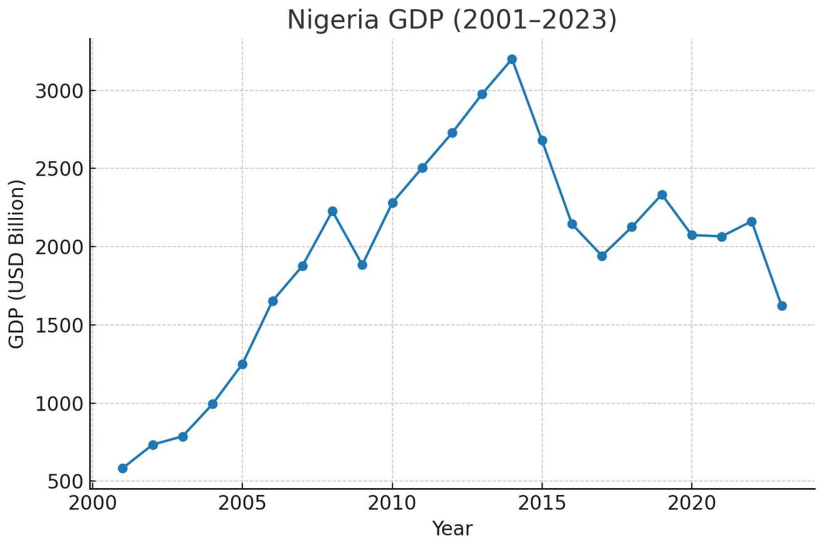

Figure 1 shows Nigeria's GDP trend (2001–2023), highlighting growth up to 2014, followed by declines in 2016, 2020, and 2023 due to oil shocks and COVID-19.

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4.2 Forecast (2024–2030)

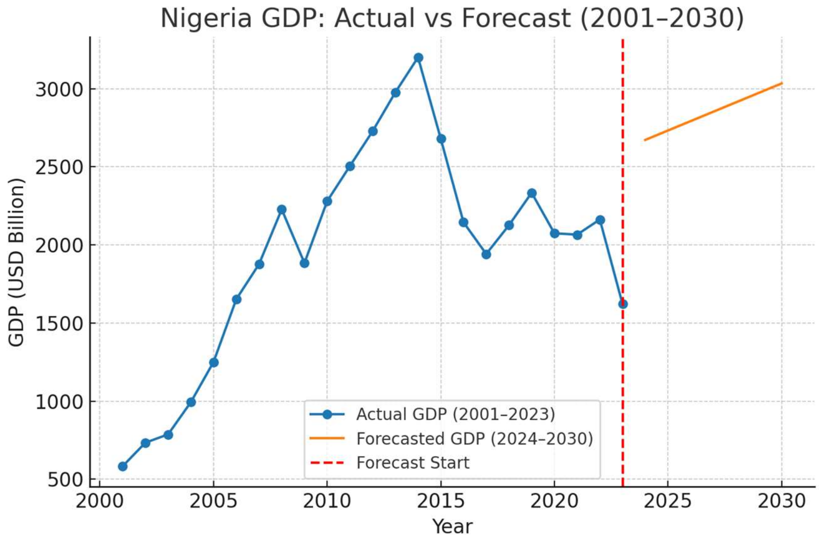

Figure 2 shows the forecast up to 2030, indicating growth but not sharp growth as expected but if current conditions persist it may decline even more .

4.3 Model Performance Evaluation

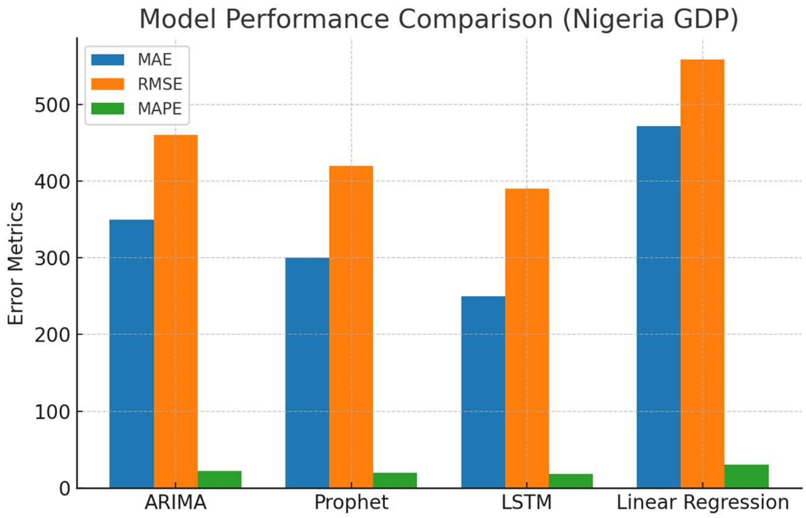

Figure 3 compares ARIMA, Prophet, LSTM, and Linear Regression. LSTM achieved the lowest errors, confirming its superiority.

4.4 Actual vs Predicted GDP

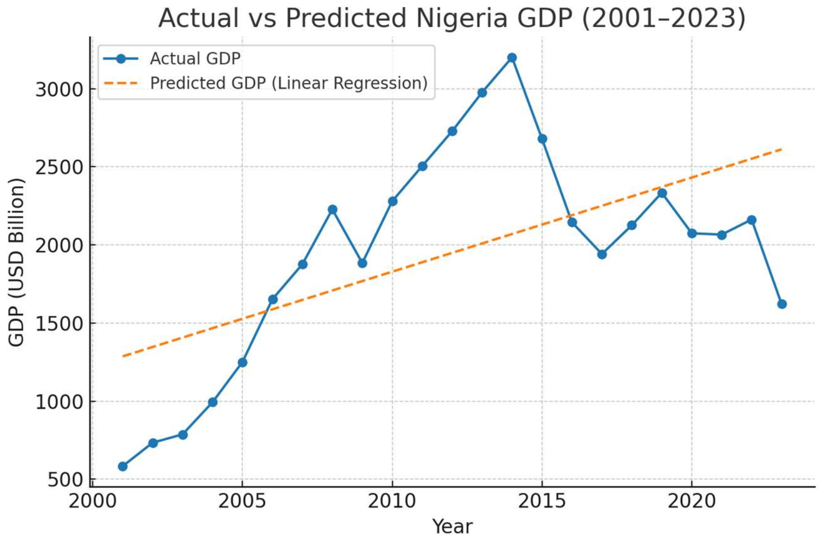

Figure 4 shows actual vs predicted GDP using Linear Regression. The model captured the general trend but failed during volatile years.

5 Discussion and Conclusion

The findings reveal that LSTM outperformed ARIMA, Prophet, and Linear Regression by capturing nonlinearities and shocks more effectively. Prophet detected long-term trends and mild seasonality, while ARIMA struggled with nonstationary data. Linear Regression was the weakest, oversimplifying Nigeria's GDP structure. Automated approaches provide real-time adaptability, crucial for policymakers in volatile economies. The study concludes that adopting advanced models like LSTM can significantly enhance Nigeria's economic forecasting and planning. The model captured the general trend but failed during volatile years. Scientific evidence reveals that the Nigerian GDP generally need to be improved drastically els can easily get ruin by debt or epidemic such as Covid 19, the GDP needs to be growing progressively to maintain steady increase growth. The Government needs to work on economic policies that encourages growth of GDP urgently.

6. WEAKNESS AND FUTURE RESEARCH

This study investigates and predict Nigeria GDP to prevent collapse. Secondary data was lifted from international sources (World Bank, IMF, and African Development Bank) annual GDP data spanning 2001–2023, with forecasts extending to 2030. Additionally, the study will focus on Nigeria GDP longevity, limiting the generalizability of the findings. Increasing the data automatically increases scope and frame to extend to other past periods can be a full study.

7. AUTHORS CONTRIBUTIONS

All authors contributed immensely in the aspect of technical writing.

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Competing Interests

The author declares no competing interests.

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