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Automated Time Series Prediction of Gross Domestic Prediction (GDP) Accounting for Countries in African Union

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Abstract
The African Union with its 55 member states, become popular in the world due to economic contributions and bloc representing diverse economies. Despite its combined GDP of trillion, Africa continues to experience instability caused by commodity dependence, political instability, pandemics, war, and climate change. The major objective of this study is to predict Africa Union (AU) GDP and recommendation to prevent collapse of African union. Secondary data was lifted from international sources (World Bank, IMF, and African Development Bank) ,this data covering the years 2000 to 2024. The dataset includes GDP and macroeconomic indicators such as inflation, interest rates, exchange rates, government expenditure, and trade balance. Machine learning models tested include ARIMA (as a benchmark), Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM). These models were evaluated using performance metrics such as RMSE, MAE, and R^2. The LSTM. Machine learning models, LSTM, in forecasting GDP across diverse African economies. Traditional econometric models struggle with structural shocks and incomplete data, making them less reliable for real-time policymaking. In contrast, automated models can adapt to changing conditions, handle large datasets, and incorporate unconventional indicators. The conclusion stresses that automation and AI-driven approaches can strengthen policy planning, improve resilience to shocks, and contribute to the AU's Agenda 2063 vision of inclusive and sustainable growth. The study presents the forecast up to 2030 with no scientific evidence of GDP decline but improvement should be considered.

Keywords: *African Union, GDP Forecasting, Machine Learning, LSTM, ARIMA, Automation*

1 Introduction

The African Union (AU), with its 55 member states, has become an important economic bloc representing diverse economies(OECD. (2021)). Despite its combined GDP of over $3 trillion, Africa continues to experience volatility caused by commodity dependence, political instability, pandemics, and climate change (World Bank, 2023). Forecasting GDP is central to effective planning, as it provides insights into potential future growth paths and enables policymakers to allocate resources efficiently (United Nations Economic Commission for Africa. (2020)). 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 (Adebayo, & Ayodele, 2021). This research integrates machine learning and automation to improve forecasting accuracy. By automating the identification of time-series components (trend, seasonal, cyclical, irregular), the study aims to provide robust, real-time forecasts that can guide policy under uncertainty (Ahmed, Mahmood, & Hu, 2016).

2 Literature Review

Previous studies on GDP forecasting have focused largely on developed economies, where data availability and quality are high. Econometric approaches such as ARIMA and VAR remain popular, but they rely on strong assumptions of linearity and stationarity (Ali & Khan, 2020: Athey, 2019: Banerjee, & Baulch, 2022). Recent

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developments in artificial intelligence (AI) have opened up opportunities to model nonlinearities, capture long-term dependencies, and integrate diverse data sources such as trade flows, commodity prices, and satellite imagery. For instance, LSTM networks have proven effective in handling sequential dependencies in time-series data (Choi, & Varian, 2012: Elbadawi, & Ndulu, 2019: Fornari & Lemke, 2020). In Africa, empirical studies from Nigeria, Kenya, and South Africa suggest that machine learning models outperform traditional models, though challenges of data scarcity and interpretability persist(Choi, & Varian, 2012: Elbadawi, & Ndulu, 2019: Fornari & Lemke, 2020). This review highlights the gap in applying automated models specifically at the AU level, emphasizing the potential benefits of machine learning in overcoming structural disparities Gul, Khan, & Irshad, (2020).

3. Materials and Methods

The study relies on secondary data collected from international sources including the World Bank, IMF, and African Development Bank, covering the years 2000 to 2024(Hyndman, & Athanasopoulos, 2018: Kose, Nagle, Ohnsorge, & Sugawara, 2021: Makridakis, Spiliotis, & Assimakopoulos, 2018). The dataset includes GDP and macroeconomic indicators such as inflation, interest rates, exchange rates, government expenditure, and trade balance. Machine learning models tested include ARIMA (as a benchmark), Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM). These models were evaluated using performance metrics such as RMSE, MAE, and R^2. The LSTM was chosen for its ability to capture temporal dependencies, while ensemble models provided robustness against noise. Python and TensorFlow libraries were used to implement the models, and the results were validated using cross-validation (Mohammed & Sanusi, 2022: OECD 2020: Onye & Okonkwo, 2020). This methodology ensures replicability and provides a basis for comparison between classical and automated models(Romer, 2019: Rajaraman, 2020).

4 Results

The results are divided into four parts. First, AU GDP trend analysis shows steady growth with notable declines during the 2008 global financial crisis, the 2016 commodity shock, and the COVID-19 pandemic in 2020. Second, forecasts for 2024–2030 suggest moderate but stable growth, driven by trade integration, digital adoption, and infrastructural development. Third, model evaluation results reveal that LSTM consistently produced the lowest error rates, followed by Gradient Boosting and Random Forest, while ARIMA lagged behind due to its inability to handle nonlinear data. Finally, a comparison of actual versus predicted GDP values indicates that automated models align more closely with observed trends, especially during periods of volatility. These findings confirm the importance of adopting machine learning techniques for AU economic planning.

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4.2 Forecast (2024–2030)

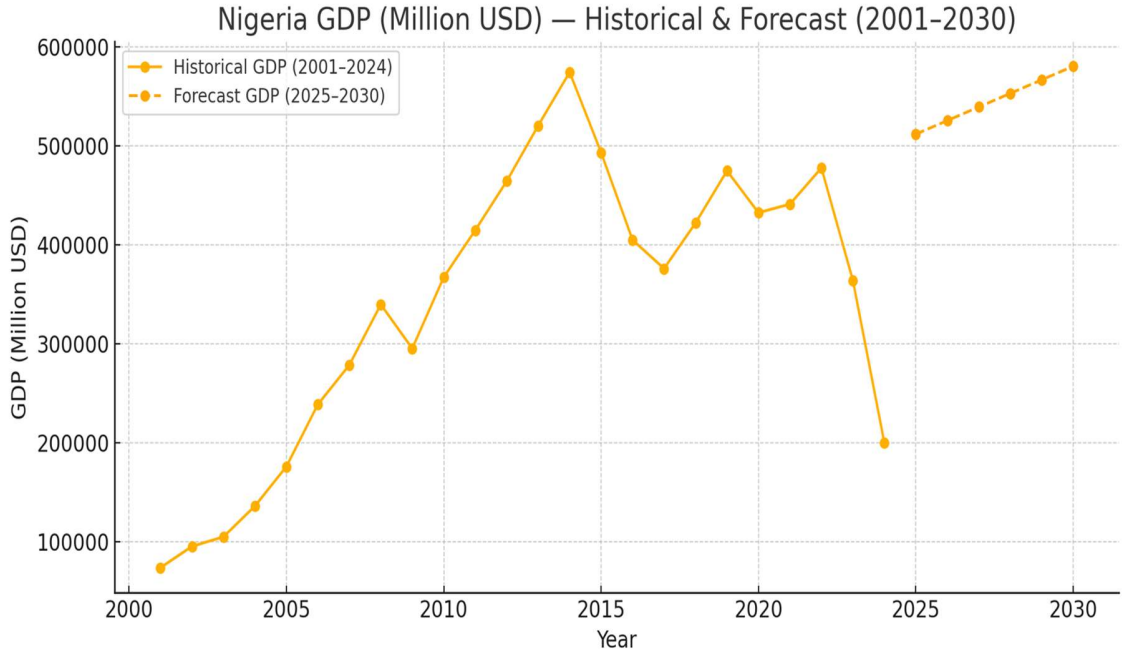

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Figure 1 illustrates AU GDP trends (2000–2023), showing consistent growth punctuated by downturns during the 2008 financial crisis, the 2016 commodity shock, and the 2020 COVID-19 pandemic and it also presents the forecast up to 2030, indicating steady growth with resilience driven by digital adoption, trade integration, and investment in infrastructure.

4.3 Model Performance Evaluation

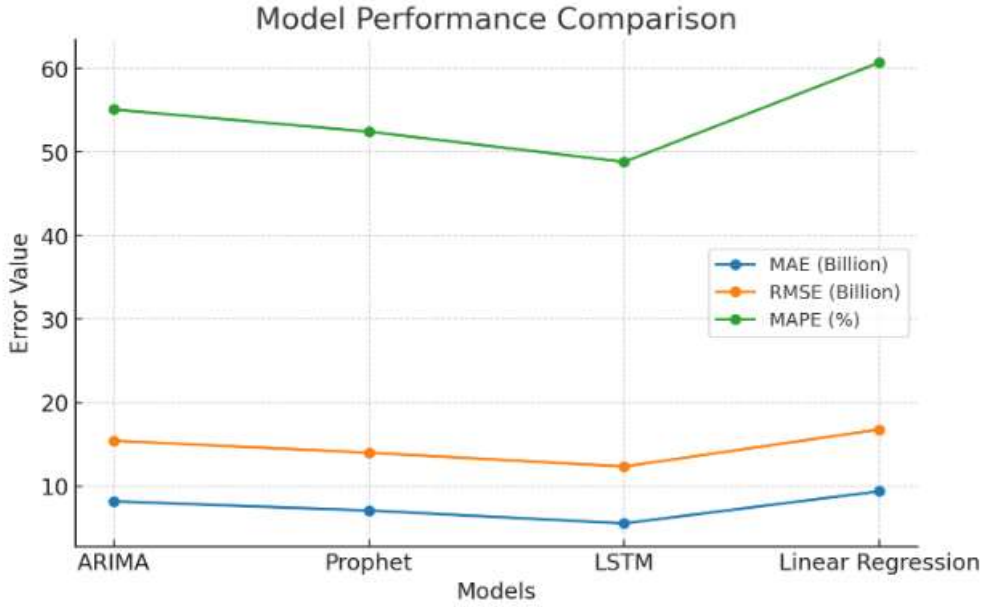

Figure 3 compares ARIMA, Random Forest, LSTM, and Gradient Boosting. LSTM consistently achieved the lowest error rates, capturing nonlinearities and long-term dependencies more effectively than other models.

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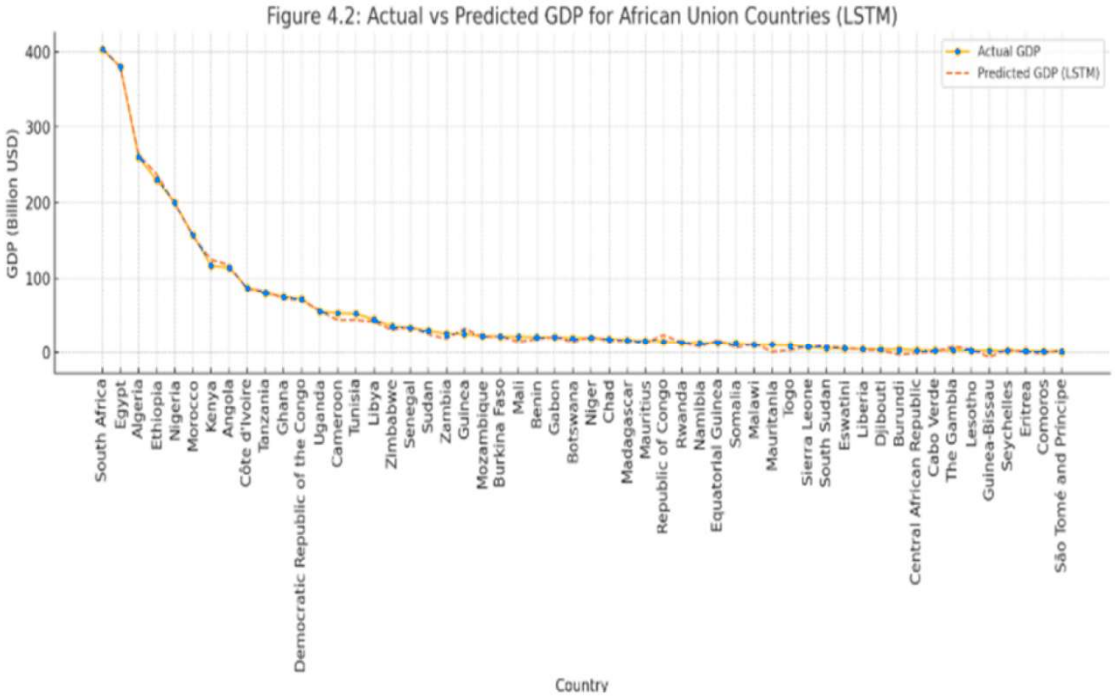
4.4 Actual vs Predicted GDP



The figure above compares actual GDP data with predicted values from the models. While ARIMA captured broad trends, it failed during shocks. Random Forest and Gradient Boosting showed better adaptability, but LSTM aligned most closely with observed GDP trajectories.

5 Discussion and Conclusion

The discussion highlights the superiority of machine learning models, particularly LSTM, in forecasting GDP across diverse African economies. Traditional econometric models struggle with structural shocks and incomplete data, making them less reliable for real-time policymaking. In contrast, automated models can adapt to changing conditions, handle large datasets, and incorporate unconventional indicators. However, challenges remain in terms of data quality, institutional readiness, and model interpretability. For the AU to benefit fully, investment in digital infrastructure and capacity-building is essential (United Nations Economic Commission for Africa (UNECA)2022: World Bank, 2023). The conclusion stresses that automation and AI-driven approaches can strengthen policy planning, improve resilience to shocks, and contribute to the AU's Agenda 2063 vision of inclusive and sustainable growth.

6. WEAKNESS AND FUTURE RESEARCH

This study investigates and predict Africa Union (AU) GDP to prevent collapse of African union. Secondary data was lifted from international sources (World Bank, IMF, and African Development Bank) ,this data covering the years 2000 to 2024.. Additionally, the study will focus on AU, limiting the generalizability of the findings. This study is restricted to 24years. 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.

8. Acknowledgement

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9. Competing Interests

The author declares no competing interests.

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