Deep Learning Model for Predicting Economic Growth from Relative Depth of Financial Sector in Nigeria

Alabi Nurudeen Olawale & Okoro Ndubuisi Obuka
Department of Mathematics and Statistics, The Federal Polytechnic, Ilaro, Nigeria
Corresponding author email: nurudeen.alabi@federalpolyilaro.edu.ng

Introduction

Economic growth is crucial for national development, influencing employment, poverty reduction, and investment. Accurate forecasting is essential for policymakers and financial institutions. Traditional models like ARIMA and VAR often fail to capture the nonlinear complexities of financial time series. In Nigeria, indicators such as private sector credit, broad money supply (M3), and market capitalization reflect economic health. However, previous research has often overlooked dynamic dependencies. Deep learning models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), offer improved methods for capturing sequential patterns in financial time series. LSTM captures long-term trends, while GRU ensures computational efficiency. This study aims to enhance forecasting accuracy, providing valuable insights for policymaking and financial stability.

Materials and methods

This study examines Nigeria's financial and economic data (1982–2022) from the Central Bank of Nigeria, the National Bureau of Statistics, and the World Bank. It analyzes the impact of financial indicators on GDP using deep learning models like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). LSTM maintains long-term dependencies using memory cells, while GRU merges input and forget gates for efficiency. Both models use activation functions like Swish, ReLU, and Leaky ReLU. The streamlined GRU architecture enables faster training and effectively captures sequential financial patterns, enhancing forecasting accuracy for economic policymaking and financial stability.

Results and discussion

Table 1: Performance Comparison of LSTM and GRU Models

Architecture	TRAINING				VALIDATION			
	MSE	**MAE**	**RMSE**	**R^2**	**MSE**	**MAE**	**RMSE**	**R^2**
LSTM	0.1006	0.2581	0.3141	0.9824	0.1115	0.2814	0.3316	0.9795
GRU	0.02174	0.1141	0.1459	0.9962	0.02432	0.1221	0.1544	0.9955

GRU outperforms LSTM in forecasting economic growth, achieving lower error measures and higher accuracy. During training, GRU records lower MSE (0.02174 vs. 0.258), MAE (0.1148 vs. 0.258), and RMSE (0.1455 vs. 0.3125), with a higher R^2 (0.9951 vs. 0.9799). Validation results confirm GRU's superiority with smaller MSE (0.02432 vs. 0.2814), MAE (0.1221 vs. 0.2814), and RMSE (0.1544 vs. 0.3316), and a higher R^2 (0.9955 vs. 0.9795). GRU generalizes better, making it the preferred model. Figure 1 shows both models capture trends well, but GRU exhibits tighter clustering around the best-fit line, indicating greater accuracy and stability.

Conclusions

This research confirms that deep learning models, and GRU more particularly, are appropriate for predicting economic growth from financial sector data. GRU outperformed LSTM with smaller prediction errors and greater explanation of variance. Its strength in being able to capture temporal dependencies in time-series data is its advantage. LSTM, though, is also relevant for this kind of task, but the more straightforward architecture and gating mechanism of GRU enhance performance by reducing overfitting and easing generalization. These findings place GRU at the centre stage as a viable tool for economic forecasting, especially for large and complex datasets.