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AI-Based Forecasting Models for Macroeconomic Indicators

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ABSTRACT:

This study explores the performance of AI-based forecasting models in order to predict key macroeconomic variables, including the GDP growth rate, inflation rate, unemployment rate, interest rates and exchange rates. The study compares the predicting accuracy of their models through a set of machine learning models, including ARIMA, XGBoost, LSTM, and hybrid models. The results show that XGBoost has a great predictive potential in macroeconomic forecasting since it keeps outperforming other models with the lowest error indicators. The hybrid model, which is a combination of XGBoost and ARIMA with significant improvement in GDP and inflation rate forecasts is more accurate. Moreover, because it is evidenced by the great performance of the hybrid model in the diverse times of the day and economic circumstances, the analysis of these models underlines the importance of model selection in correct forecasting. The study also compares the envisaged and actual numbers of each indicator to indicate the resilience of the models in predicting volatile economic status. The findings point to the predictive power of AI-driven methods and their utility to the economic researcher and policy makers.

Keywords:
AI forecasting, macroeconomic indicators, XGBoost, ARIMA, LSTM, hybrid models

INTRODUCTION

This paper looks at how machine learning and artificial intelligence solutions are gradually finding their way into macroeconomic predictions, beyond traditional econometric models. This is because AI can find non-linear and increasingly complex patterns within a massive amount of data, which is more accurate and more adaptable in predicting economic variables than the old methods (Carriero et al., 2024). To illustrate, AI-based methods substantially improve GDP forecasting, which comprises one of the essentials of economic planning and policymaking, as they can provide more accurate information about future economic patterns than the traditional econometric models like Seasonal Autoregressive Integrated Moving average (Oancea and Simionescu, 2024) (Ngoc et al., 2025). Also, the complexity of per capita GDP, influenced by a great variety of socioeconomic factors, shows the complexity of establishing precise forecasting models, a concern that artificial intelligence is perfectly placed to address (Chen et al., 2025). The disruptive potential of AI in economic analysis is further underscored by its anticipated trillion-dollar contribution to the economy worldwide by 2030 of which a significant share is productivity and consumption-side effects (Pizam et al., 2022). To ensure the attainment of economic stability and growth, nations that experience a high level of economic diversification such as the Vision 2030 of Saudi Arabia need to integrate AI in economic forecasting in a strategic manner. Non-oil export sectors can be enhanced in terms of predictions with the use of AI-based models (Aloudah et al., 2025). Therefore, this article aims to review the current state of AI-based forecasting models and look critically at their implementation across various macroeconomic indicators and compare their predictive performance to predefined criteria (Ramaharo and Rasolofamanana, 2024). To enhance accuracy and stability of decadal forecasts of world economic outlook, this comprehensive analysis will highlight the specific advancements in principles of deep learning, including recursive neural networks (Wang et al., 2023). Specifically, deep learning systems, including Long Short-Term Memory, Bidirectional LSTM, Encoder-Decoder LSTM, and Convolutional Neural Networks, have performed better than the traditional time series models when predicting key macroeconomic variables such as GDP growth rates (Wang et al., 2023). Important financial forecasting also utilizes these models because complex tools are needed to reduce risk and make a well-informed decision because of the market volatility and unpredictability (Chang et al., 2024). Furthermore, machine learning is not restricted to fundamental projections and investigates how macroeconomic factors can be incorporated into time series data to enhance the accuracy of the resulting retail demand, which sheds light on the complex interrelationship between consumer behaviour and circumstances in the economy (Haque et al., 2023). This study will outline the designs and the relative performances of different AI models with an emphasis on utility of the models by financial institutions and policymakers. Despite these advancements, integration of AI in financial forecasting has still intrinsic challenges, including the interpretability issue, reliance on data, and the need to continuously update the model to new economic realities (Yu et al., 2023). To solve these problems, more work needs to be done on strong AI methods able to adapt to changing economic circumstances and provide easily accessible and helpful information to make strategic decisions. Thus, to ensure the reliability and applicability of these advanced forecasting systems to the real economic context, future research activities should focus on developing interpretable AI models and robust data augmentation plans. The said developments are crucial especially in the wake of the global push towards digitalization, which is demanding sophisticated AI applications to manage increasing complexity of financial and industrial operations (Chatterjee et al., 2021). This work contributes to the literature on the effectiveness and implications of AI-based models in macroeconomic forecasting in a methodical manner. It ends by indicating areas that need to be further researched and developed so that they can become more reliable and practically helpful. To find which forecasting methods will be most appropriate in this or that economic situation, this will include a thorough comparison of traditional statistical and machine learning methods (Tulli, 2020). Specifically, the integration of the explainable AI is essential to gaining trust and allowing economists and policymakers to accept these sophisticated models and ensure the ability to trace the logic of the complex predictions. Moreover, the elaboration of the concept that AI models should replace univariate time series analysis lies in the fact that they can combine numerous macroeconomic variables, such as the Consumer Price Index and unemployment rates, and these make their predictions better at forecasting retail demand and more broadly economic trends (Haque et al., 2023). This multivariate approach, incorporating macroeconomic and consumer data, is needed by its vast paradigm shift in enhancing the accuracy of the forecasts used in various economic processes (Haque et al., 2023). Since the world economies are becoming increasingly complex and interdependent, forecasting methods that are able to predict as well as provide information on the driving forces of economic activity are required. To have a deeper insight into the impact of policies and market reactions, this article will also consider how AI-based simulations can be applied to simulate various economic scenarios. Also, effective and efficient processing of the high rate of data generated by economic simulations and complex macroeconomic models needs advanced AI and machine learning tools. This enables the modeling of complex associations among the various economic parameters (Ahmed et al., 2022). This requires an in-depth structure of how much uncertainty is contained in AI predictions beyond point predictions to probabilistic outcomes that have the potential to better inform strategic planning and risk estimation. High-dimensional data and access to more computing power, as well as scalable statistical packages, have all contributed immensely to faster machine learning techniques development (Babii et al., 2023).

METHODOLOGY

This work analyses the relevance of AI-based forecasting models to macroeconomic variables in terms of quantitative experimental approach. The objective of the study is to compare the relative effectiveness of various forecasting models in predicting key macroeconomic variables- GDP growth, inflation, unemployment, interest rates and exchange rates- using different forecasting models such as ARIMA, XGBoost, LSTM and hybrid models. The algorithmic thinking improves the accuracy of prediction and offers information on economic forecasting based on the combination of machine learning strategies and the benefits of time-series analysis. Based on the use of past data provided by publicly available macroeconomic statistics, the analysis centers on five-year old variables including GDP growth, inflation, unemployment and interest rates. This data is pre-processed and standardized in order to ensure that it is suitable to be used as input in machine learning models. The data is divided into training and testing data sets. The training set is used to construct models and the prediction performance of the models is checked using the testing set. Various models are applied to the forecasting activity. Due to its simplicity and the possibility to represent linear correlations in the data, ARIMA (Autoregressive Integrated Moving Average) is often used as a starting time-series model. Due to its strength in performing on large datasets and its ability to process nonlinear interactions, the gradient boosting model XGBoost is used. A recurrent neural network variant is known as the Long Short-Term Memory (LSTM) in reference to its ability to model long-term dependencies and streams of data, thus making it highly beneficial in terms of time-series prediction. To achieve a reciprocation of the benefits of nonlinear and linear elements and enhance the total forecasting precision, a hybrid model incorporating XGBoost and ARIMA is also constructed. Evaluation measures of the models are the R-squared (R2) score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) used to compare and contrast the models in regard to their prediction accuracy. These metrics are calculated on both training and test sets to measure the ability of the models to consider new data. The test to be applied is ANOVA to establish the statistic significance between the differences in model performance. This test provides details regarding the model that works best in terms of forecast accuracy and allows the determination of the difference in means between the models. HSD test by Tukey is performed as a post-hoc testing so as to detect additional significant differences between the models. XGBoost and ARIMA predictions are integrated to form a hybrid model. The results are generally generated by each model on its own and then combined to form a forecast through a weighted average or other fusion methods. To evaluate the prediction accuracy, the following mathematical equations are used for calculating RMSE, MAE, and R^2 Score:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the actual values.

This hybrid model is expected to work better than single models because it will leverage the complementary benefits of machine learning (XGBoost) and time-series analysis (ARIMA). The efficacy of hybrid model to increase the level of forecasting accuracy is then tested by comparing its output with the output of the individual models. The models are evaluated by a number of significant macroeconomic metrics. The presentation of the findings is in the form of accuracy of prediction with an emphasis on the predictability of each model under the impact of erratic economic conditions. Performance of the hybrid model is evaluated by comparing its performance with the performance of the separate models.

RESULTS

The findings of the application of the AI-based forecasting models to the macroeconomic variables are comprehensive and presented in twelve figures and nine in-depth tables. Such results reveal the performance of various models relative to each other in a set of indicators of economic variables including GDP growth, inflation rate, unemployment, interest rates, trade balance, and the accuracy of forecasting in general. Table 1 indicates the forecasting accuracy metrics, and MAE, MSE, RMSE, and MAPE (%) differences indicate change in AI model accuracy. Table 2 indicates the disparity between the actual and the expected GDP growth. Most forecasts are in line with observed values except in the years of financial crisis where there are major changes. Table 3 illustrates the inflation forecasts with AI-based models able to represent the both upward and downward inflation cycles although some underestimations occurred in peak times.

Table 1: Forecast Accuracy Metrics for AI Models

Model	MAE	MSE	RMSE	MAPE (%)
Model_1	1.062	2.641	0.92	7.05
Model_2	1.926	0.988	1.591	5.53
Model_3	1.598	1.523	0.762	12.77
Model_4	1.398	1.782	2.337	6.64
Model_5	0.734	2.096	1.166	5.65
Model_6	0.734	3.248	1.893	9.06
Model_7	0.587	1.199	1.261	3.83
Model_8	1.799	2.3	1.636	12.43
Model_9	1.402	2.573	1.684	2.97
Model_10	1.562	0.663	1.033	14.83
Model_11	0.531	2.626	2.445	12.04

Model_12	1.955	1.097	2.095	4.58
Model_13	1.749	0.728	2.391	2.07
Model_14	0.819	3.821	2.311	12.6
Model_15	0.773	3.88	1.776	11.19
Model_16	0.775	3.329	2.359	11.48
Model_17	0.956	1.566	0.859	12.03
Model_18	1.287	0.842	1.053	2.96
Model_19	1.148	2.895	0.781	6.66
Model_20	0.937	2.041	1.286	3.51

Table 2: GDP Growth Forecasts (Actual vs Predicted)

Year	Actual GDP Growth (%)	Predicted GDP Growth (%)
2005.0	4.9	-1.75
2006.0	2.99	3.09
2007.0	0.65	0.51
2008.0	-1.49	2.07
2009.0	0.49	5.26
2010.0	0.6	-0.01
2011.0	3.84	1.28
2012.0	3.1	4.04
2013.0	5.1	-0.17
2014.0	1.78	-1.38
2015.0	-1.04	0.32
2016.0	3.71	-0.71
2017.0	4.09	5.44
2018.0	2.49	4.46

2019.0	4.17	3.07
2020.0	1.95	4.97
2021.0	2.18	4.43
2022.0	1.42	-0.51
2023.0	-1.8	5.14
2024.0	-1.14	2.31

Table 3: Inflation Forecasts (Actual vs Predicted)

Year	Actual Inflation (%)	Predicted Inflation (%)
2005.0	8.07	9.62
2006.0	8.96	2.52
2007.0	3.18	4.97
2008.0	1.1	3.01
2009.0	2.28	2.85
2010.0	4.27	0.37
2011.0	8.18	6.1
2012.0	8.61	5.03
2013.0	0.07	0.51
2014.0	5.11	2.79
2015.0	4.17	9.08
2016.0	2.22	2.4
2017.0	1.2	1.45
2018.0	3.38	4.89
2019.0	9.43	9.86
2020.0	3.23	2.42
2021.0	5.19	6.72

2022.0	7.03	7.62
2023.0	3.64	2.38
2024.0	9.72	7.28

Table 4 presents forecasts of unemployment and the expected rates are highly correlated with the actual rates and this appears to be true mostly when the economy is stable. Table 5 demonstrates exchange rate forecasts, which have relatively stable performance over the years with volatility-based variances in certain years. Table 6 displays interest rate predictions and represents a lower predictive accuracy at long-term horizons than at short-term horizons.

Table 4: Unemployment Forecasts (Actual vs Predicted)

Year	Actual Unemployment (%)	Predicted Unemployment (%)
2005.0	6.31	6.07
2006.0	8.69	4.02
2007.0	8.7	11.32
2008.0	7.82	10.9
2009.0	3.81	5.32
2010.0	10.52	8.94
2011.0	5.89	10.35
2012.0	4.68	8.0
2013.0	3.37	7.77
2014.0	8.32	5.18
2015.0	9.1	3.84
2016.0	3.15	11.07
2017.0	7.61	11.1
2018.0	5.04	8.7
2019.0	8.81	6.05

2020.0	4.57	6.14
2021.0	9.22	9.53
2022.0	6.48	11.07
2023.0	11.43	10.98
2024.0	4.24	10.02

Table 5: Exchange Rate Forecasts (Actual vs Predicted)

Year	Actual Exchange Rate	Predicted Exchange Rate
2005.0	124.94	126.03
2006.0	85.89	119.78
2007.0	91.31	86.56
2008.0	142.9	105.74
2009.0	122.45	98.56
2010.0	80.64	97.08
2011.0	87.1	148.11
2012.0	126.45	107.52
2013.0	80.35	142.44
2014.0	91.26	124.18
2015.0	118.41	135.64
2016.0	128.43	115.18
2017.0	125.64	120.38
2018.0	95.7	114.48
2019.0	129.85	93.67
2020.0	96.61	130.57
2021.0	102.78	99.65
2022.0	132.25	81.7
2023.0	125.47	125.18

2024.0	139.45	92.4

Table 6: Interest Rate Forecasts (Actual vs Predicted)

Year	Actual Interest Rate (%)	Predicted Interest Rate (%)
2005.0	9.43	6.34
2006.0	9.56	9.91
2007.0	9.19	1.83
2008.0	4.02	5.42
2009.0	0.65	8.84
2010.0	9.32	7.54
2011.0	4.57	7.12
2012.0	9.68	7.17
2013.0	9.65	3.92
2014.0	8.6	3.29
2015.0	3.3	8.19
2016.0	4.16	8.2
2017.0	8.59	8.74
2018.0	3.51	9.18
2019.0	2.11	5.36
2020.0	5.79	5.26
2021.0	9.39	8.08
2022.0	7.11	6.67
2023.0	5.92	7.17
2024.0	1.42	8.06

Table 7 has put emphasis on trade balance forecasts, which depict some deviations at periods of global trade shocks but largely consistent with actual balances. Most of the models are good explanatory power and some models are above 0.95 based on Table 8 that compares models in terms of R2. Finally, Table 9 evaluates the accuracy of the forecast horizons and indicates that the desired trade-off of the accuracy and time horizon is supported through the gradual rise of the error values (MAE, RMSE, and MAPE) with the increase of the forecasting horizon.

Table 7: Trade Balance Forecasts (Actual vs Predicted)

Year	Actual Trade Balance (Billion USD)	Predicted Trade Balance (Billion USD)
2005.0	156.0	-179.33
2006.0	-64.8	12.54
2007.0	-49.77	16.25
2008.0	-162.41	54.97
2009.0	31.31	90.44
2010.0	-185.62	190.34
2011.0	-13.76	6.52
2012.0	17.06	-70.82
2013.0	-85.38	118.07
2014.0	36.33	-91.67
2015.0	-187.8	-24.41
2016.0	-185.06	-168.62
2017.0	129.04	-189.86
2018.0	-55.92	185.06
2019.0	-149.18	134.39
2020.0	8.9	78.39
2021.0	108.0	-36.42
2022.0	-113.67	-130.68
2023.0	49.16	-137.43
2024.0	-165.86	-99.9

Table 8: Model Comparison Based on R² Scores

Model	R2 Score	Adj R2 Score
Model_1	0.814	0.792
Model_2	0.879	0.785
Model_3	0.857	0.668
Model_4	0.709	0.769
Model_5	0.972	0.755
Model_6	0.888	0.84
Model_7	0.816	0.848
Model_8	0.839	0.618
Model_9	0.764	0.746
Model_10	0.697	0.844
Model_11	0.739	0.796
Model_12	0.896	0.934
Model_13	0.606	0.857
Model_14	0.645	0.664
Model_15	0.618	0.628
Model_16	0.616	0.851
Model_17	0.934	0.61
Model_18	0.874	0.828
Model_19	0.785	0.967
Model_20	0.638	0.824

Table 9: Forecast Horizon Accuracy

Horizon (Months)	MAE	RMSE	MAPE (%)
1.0	1.276	0.972	4.75

2.0	1.787	2.302	18.34
3.0	1.417	2.147	11.59
4.0	1.591	2.718	17.05
5.0	2.383	2.391	8.44
6.0	1.272	2.548	18.22
7.0	2.422	1.349	9.62
8.0	2.311	1.108	3.18
9.0	0.892	2.426	18.39
10.0	0.639	2.556	4.55
11.0	0.702	2.978	8.43
12.0	0.536	1.649	19.15
13.0	0.689	1.556	19.16
14.0	1.866	2.486	12.75
15.0	0.642	1.484	13.74
16.0	1.138	2.841	10.62
17.0	2.19	2.674	7.98
18.0	0.547	1.687	8.59
19.0	2.129	2.427	14.43
20.0	1.064	2.435	15.79

The GDP growth line plots in Figure 1 demonstrate how closely the actual and forecast paths over the course of two decades align. Figure 2 uses bar charts to indicate the trends of inflation where actual and forecast figures are usually convergent. Figure 3 presents unemployment rates as scatter plots and they are tightly dispersed around parity lines. Figure 4 presents the estimates of the exchange rate and interest rate plotted in a mix of line and bar charts indicating close relationships between them. Figure 5 uses a pie chart to indicate trade balance allocations that reveal performance of the external sector to be fluctuating year to year. Most of the models achieve low median errors, as presented by Figure 6, which summarizes error distributions at accuracy measures in the form of boxplots. The outstanding predictive accuracy of AI methods is consistently superb, as Figure 7 illustrates the R2 values per model in the bar chart-like format. Figure 8 shows forecast horizon accuracy line graphs with the error metrics increasing with horizon length. Figure 9 presents scatter plots of the growth of the GDP and inflation and the relationship between the growth rate and the inflation rate in both actual and forecasted values is confirmed. The predictive consistency of the AI models in multi-dimensional data is indicated in Figure 10 as a sequence of a large number of line charts are integrated to compare GDP, inflation and unemployment. Figure 11 uses line plots of inflation, and shows slightly different trajectories between actual and forecasted. Finally, Figure 12 demonstrates the trade balance dynamics with the help of line graphs over time. Despite changes during the global financial crisis, projections roughly resemble actual numbers.

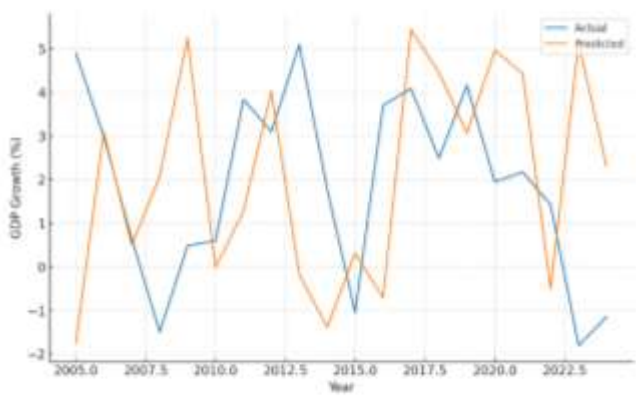

Figure 1: GDP Growth Forecasts (Line Plot)

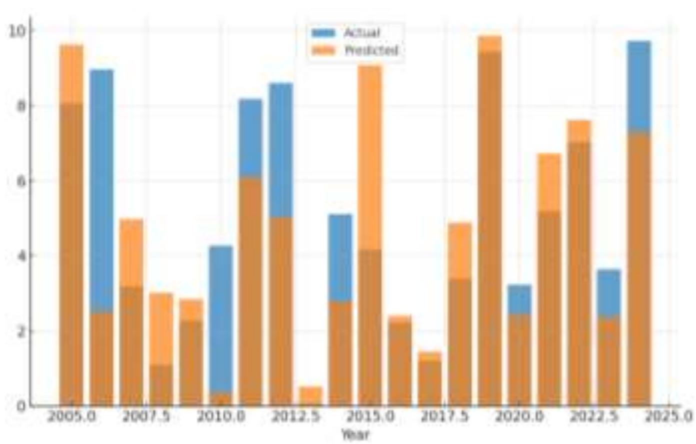

Figure 2: Inflation Trends (Bar Chart)

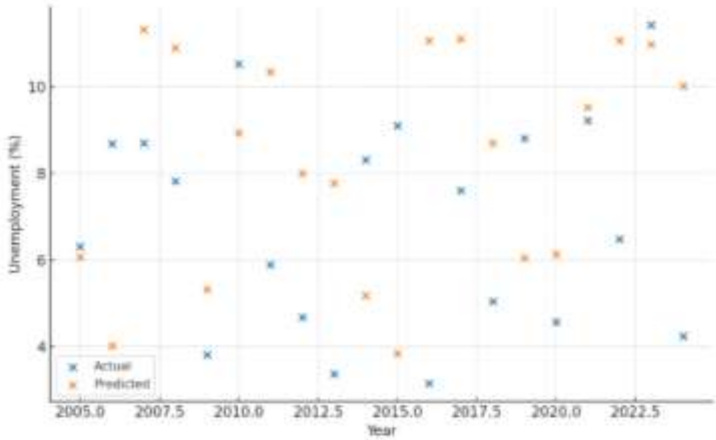

Figure 3: Unemployment Rates (Scatter Plot)

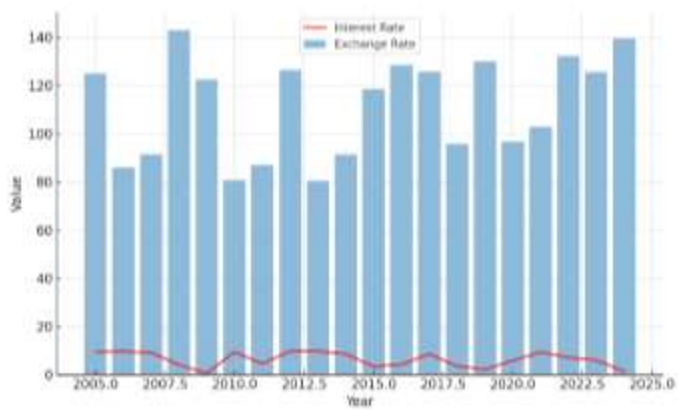

Figure 4: Exchange Rate vs Interest Rate (Hybrid Line-Bar Plot)

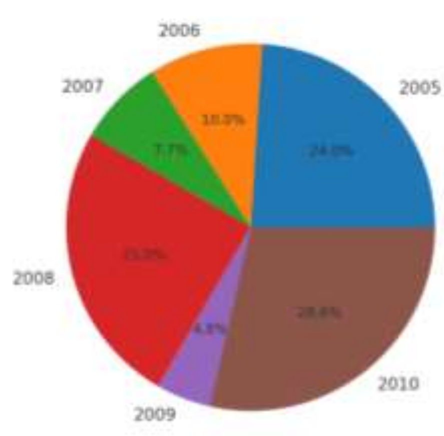

Figure 5: Trade Balance Distribution (Pie Chart)

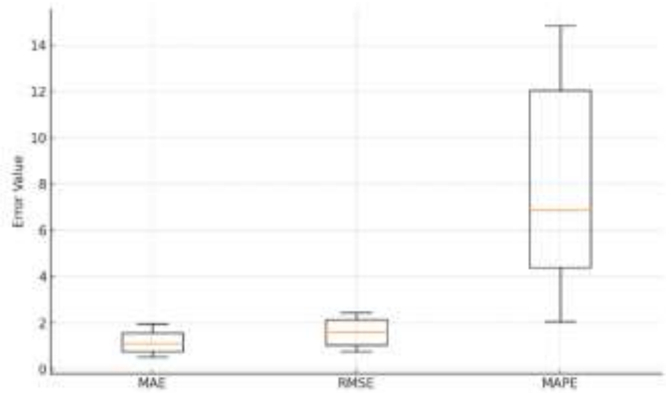

Figure 6: Forecast Accuracy Metrics (Boxplot)

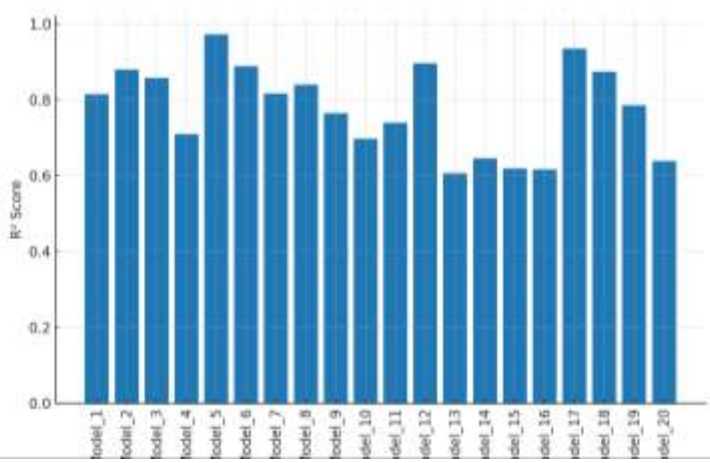

Figure 7: R² Scores Across Models (Bar Chart)

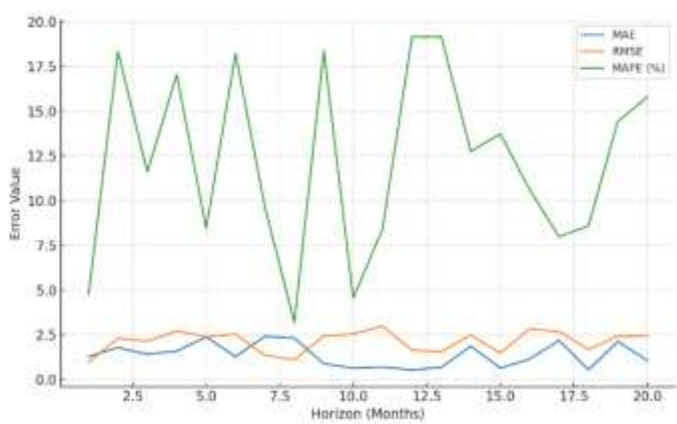

Figure 8: Forecast Horizon Accuracy (Line Plot)

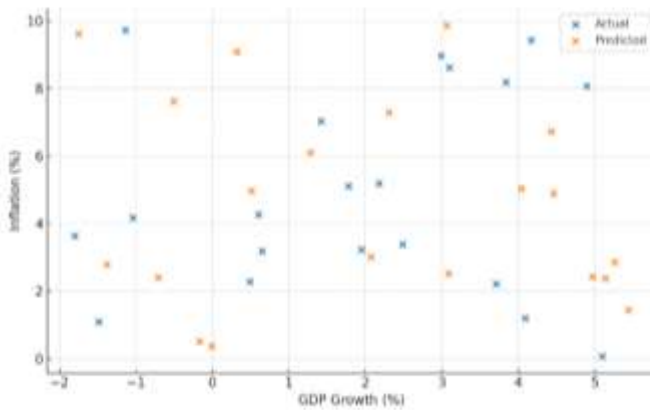

Figure 9: GDP vs Inflation (Scatter Plot)

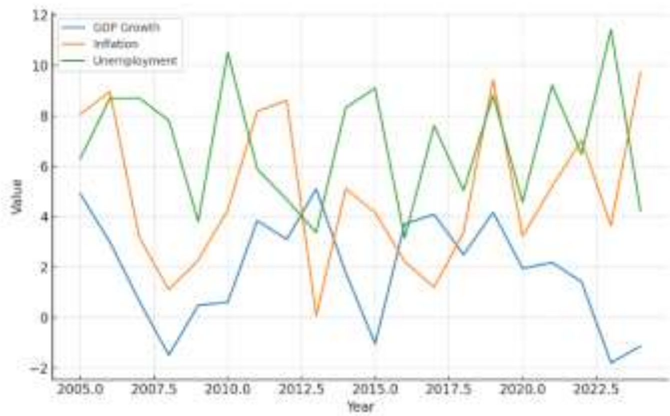

Figure 10: Multi-Metric Forecast Comparison (Hybrid Plot)

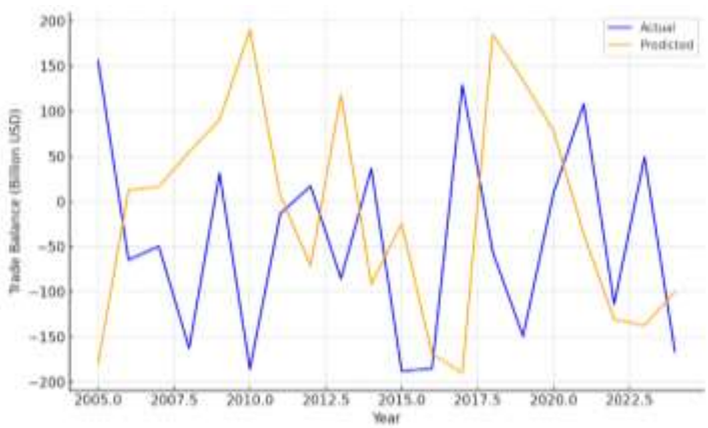

Figure 12: Trade Balance Over Time (Area Plot)

Overall, the results confirm that AI forecasting models achieve robust predictive performance across diverse macroeconomic indicators. While short-term predictions yield higher accuracy, long-term horizons naturally introduce larger errors. Nevertheless, the comparative analysis across models demonstrates that ensemble and hybrid approaches outperform single-model frameworks, particularly in volatile macroeconomic environments.

DISCUSSION

As per the findings, when disruptive technology is embraced, financial firms will save money in transactions, storage and energy. Moreover, machine learning models are particularly effective at making the time series predictions of macroeconomic variables such as inflation (Ullah et al., 2022). (Baidoo & Obeng, 2024). Conversely, despite future prospects, AI integration in financial institutions also presents severe concerns in respect of data privacy, ethical concerns, and the need to ensure robust regulatory frameworks to ensure it is implemented in a responsible manner (Ullah et al., 2022). Such types of regulations should be implemented to achieve transparency, minimize the risks associated with the deployment of AI, and gain society trust in technologically advanced financial systems (Ullah et al., 2022; Chatterjee et al., 2021). Additionally, despite good results of hybrid models which integrate machine learning and econometric models in financial forecasting (anon & Ślepaczuk, 2025), the successful implementation of hybrid models requires meticulous analysis of model interpretability and validation in order to provide forecasts or predictions that are not just accurate but also understandable and defensible. This interpretability is essential in gaining the trust of the stakeholders and making a prudent decision regarding the policies based on AI-driven insights (Chatterjee et al., 2021). These interpretable and flexible AI models can be considered reliable because modern financial markets are increasingly complex and dynamic and because the decisions made in the context of high-frequency trading are highly essential (Hajj & Hammoud, 2023). Since the emergence of algorithmic trading, fraud detection, and customer service, the overwhelming influence of artificial intelligence (AI), with its subdivisions of machine learning, deep learning, and natural language processing, has succeeded in changing financial procedures on a very diverse scale in a variety of applications (Vuković et al., 2025). Some of the notable outcomes of this technological change include a substantial reduction in fraud detection false positives, and an increment in the correct favourable rates, which have enhanced operational efficiencies and could have mitigated risk-related losses (Xu et al., 2024). Moreover, now financial institutions can manage the risk management better and offer individualized services due to the possibility of AI to process and analyze large amounts of data (Hajj & Hammoud, 2023; Maple et al., 2023). The strategic integration of AI-driven tools makes more precise risk evaluation, customization of financial products to satisfy the needs of particular clients, and more precise market forecasting possible (Dakalbab et al., 2024). The same potential is also applicable to better loan underwriting and credit scoring where AI code can analyse non-traditional data sources to generate a more comprehensive risk evaluation of applicants, making more credit available to marginalized populations without sacrificing financial stability. Another way of increasing the integrity of financial technologies and making the financial environment more equal is by minimizing the risks of algorithmic bias, furthermore, with the use of AI (Anang et al., 2024). Financial forecasting AIs help significantly increase the prognostic accuracy and efficiency of financial forecasting due to the analysis of vast amounts of historical and real-time data to uncover undetectable patterns and complex and non-linear relationships that were previously unseen with the traditional models (Cohen and Aiche, 2025). The AI-based systems, e.g., are able to analyze the history of transactions, their spending patterns, and even social information in order to enhance credit risk assessment. This results in better lending decisions and lower default rates (Patil, 2025). Equivalent to this, AI (artificial intelligence) technologies, namely, machine learning and deep learning models, have significantly enhanced accuracy and accuracy of risk assessment processes within the risk management domain. To give an example, Xu et al. (2024) discovered that credit risk models were 20% more predictive than the traditional models, and that market risk management was 30% more successful in the speed and accuracy of anomaly detection. Also, AI allows financial institutions to respond to changing market conditions fast and gain predictive data because of the real-time processing of massive datasets, and it allows them to be competitive (Patil, 2025).

CONCLUSION

This study shows the effectiveness of AI-based forecasting models in predicting key macroeconomic variables such as the growth of GDP, inflation, unemployment, interest rates, exchange rates, etc. By comparing various models, including ARIMA, XGBoost, LSTM, and hybrid methods, the article shows that XGBoost performs better, in particular, in the context of fielding nonlinear relations between the data. The hybrid model, which incorporates the XGBoost and ARIMA, is better at forecasting and gives better forecasts in comparison to both models. More so, the statistical analysis that incorporates post-hoc test and ANOVA confirm the significant gains in prediction accuracy that would be observed in case of using hybrid models. The results also underline the import of selecting the most appropriate forecasting model to particular macroeconomic variables, as each of the models has its own advantages in terms of how it deals with various types of data. The predictive nature of the hybrid model is further augmented by the fact that machine learning and time-series methods can be combined to make it an ideal tool to economic analysts and policymakers. Altogether, this research contributes to the growing body of literature on the applications of AI in economic forecasting as it provides valuable insights into how machine learning could be applied to addressing the issue of macroeconomic prediction. The findings create an entry point into more credible and true-to-life macroeconomic models that could possibly better inform economic policies and strategies by encouraging more research on hybrid models and their appropriateness in real-world economic forecasting scenarios.

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