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Comparative Analysis of Machine Learning and Classical Statistical Models for GDP Growth Forecasting

Mahesh Jayram Dagade
Department of Statistics, Indira Gandhi National Open University (IGNOU)
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Abstract:

Forecasting Gross Domestic Product (GDP) growth plays a crucial role in economic policy formulation, investment planning, and macroeconomic stabilization. Accurate GDP forecasts enable governments and central banks to design effective fiscal and monetary policies, particularly in economies characterized by structural changes and external shocks. Traditionally, GDP forecasting in economics has relied on classical statistical time-series models such as AutoRegressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR). These models are grounded in econometric theory and offer clear interpretability; however, they are constrained by assumptions of linearity, stationarity, and limited ability to capture complex interactions among macroeconomic variables.

In recent years, machine learning (ML) techniques have emerged as promising alternatives for economic forecasting due to their flexibility and capacity to model nonlinear relationships. This study undertakes a systematic comparison of classical statistical models and machine learning approaches in forecasting GDP growth. Using quarterly GDP growth data along with key macroeconomic indicators such as inflation, interest rates, unemployment, and industrial production, the study evaluates the performance of ARIMA and VAR models against machine learning techniques including Random Forest, Gradient Boosting, and Support Vector Regression. All models are trained on a common dataset and assessed across short-term and medium-term forecast horizons.

Forecast accuracy is measured using standard statistical criteria such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The empirical results reveal that machine learning models, particularly ensemble-based methods like Gradient Boosting, consistently outperform classical statistical models in short-term GDP growth forecasting. However, the performance gap narrows for longer forecast horizons, where classical models remain relatively robust and stable.

The findings highlight the complementary strengths of classical econometric models and machine learning techniques. While machine learning enhances predictive accuracy, classical models continue to provide valuable economic interpretability. The study concludes that integrating machine learning with traditional statistical approaches can improve GDP forecasting accuracy and offer a more comprehensive framework for economic analysis and policy decision-making.

Keywords: GDP Growth Forecasting; Machine Learning in Economics; Time Series Analysis; ARIMA; Vector Autoregression (VAR); Random Forest; Gradient Boosting; Support Vector Regression; Macroeconomic Indicators; Forecast Accuracy

Introduction:

Economic growth forecasting remains one of the most challenging and significant tasks in applied economics. Among various macroeconomic indicators, Gross Domestic Product (GDP) growth is widely used as a comprehensive measure of economic performance and overall economic health. Governments, central banks, international organizations, and private investors rely heavily on GDP growth forecasts to formulate fiscal and monetary policies, manage public finances, and make long-term investment decisions. Inaccurate forecasts can lead to inefficient policy responses, misallocation of resources, and increased economic uncertainty.

Historically, economists have depended on classical statistical and econometric models for GDP forecasting. Models such as AutoRegressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR) are grounded in probability theory and statistical inference and have been extensively applied due to their transparency and theoretical consistency. These models perform well when economic relationships are stable and linear. However, real-world macroeconomic data often exhibit nonlinear dynamics, structural breaks, regime shifts, and complex interdependencies that classical models may fail to capture adequately.

In recent years, the growing availability of large datasets and advances in computational power have encouraged the use of machine learning techniques in economic forecasting. Unlike traditional econometric models, machine learning methods focus primarily on predictive performance rather than strict theoretical assumptions. Algorithms such as Random Forest, Gradient Boosting, and Support Vector Regression are capable of modeling nonlinear relationships and high-dimensional interactions among macroeconomic variables. This flexibility makes them particularly suitable for forecasting in environments characterized by volatility and uncertainty.

Despite the increasing interest in machine learning applications in economics, there is still limited consensus on whether these methods consistently outperform classical statistical models in macroeconomic forecasting. Moreover, concerns regarding interpretability and economic reasoning continue to limit their acceptance among policymakers.

Against this background, the present study aims to conduct a systematic and comparative analysis of classical statistical models and machine learning approaches in forecasting GDP growth. By evaluating their relative forecasting accuracy across different horizons, the study seeks to provide empirical evidence on the strengths and limitations of each approach and to explore the potential benefits of combining econometric theory with data-driven machine learning techniques

Objectives of the Study (with Statistical Focus):

The present study is designed to examine GDP growth forecasting through a rigorous statistical framework by integrating classical time-series models with modern machine learning techniques. Unlike purely descriptive economic studies, this research emphasizes statistical modelling, estimation accuracy, and forecast evaluation to ensure empirical robustness.

The specific objectives of the study are as follows:

1. To model GDP growth using classical statistical time-series techniques such as AutoRegressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR), with careful attention to statistical assumptions including stationarity, autocorrelation, and parameter stability.
2. To apply machine learning regression models—namely Random Forest, Gradient Boosting, and Support Vector Regression—for GDP growth forecasting and to statistically assess their ability to capture nonlinear relationships and interaction effects among macroeconomic variables.
3. To conduct a comparative statistical evaluation of forecasting performance by

employing standard forecast accuracy measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), ensuring consistency across models and forecast horizons.

4. To analyze the statistical significance of forecast differences between classical and machine learning models using loss-differential comparisons and error distribution analysis, rather than relying solely on point estimates.
5. To examine the sensitivity and robustness of models through rolling-window estimation and out-of-sample forecasting, thereby assessing model stability over time.
6. To evaluate the trade-off between statistical interpretability and predictive accuracy, particularly comparing parameter-based econometric models with algorithmic machine learning methods.

By explicitly incorporating statistical diagnostics, hypothesis testing, and forecast error analysis, this study aims to strengthen the empirical credibility of GDP forecasting models. The objective is not merely to identify the best-performing model, but to understand the statistical conditions under which different modelling approaches perform effectively. This approach contributes to the broader literature by positioning machine learning methods within a statistically sound forecasting framework rather than treating them as black-box alternatives.

Figure 1: Quarterly GDP Growth Rate over Time

Source: Author's own computation.

Interpretation (Statistics-focused):

This figure presents the time-series behaviour of quarterly GDP growth rates over the study period. The plot highlights fluctuations and volatility in economic growth, justifying the application of time-series models. Visual inspection indicates the presence of short-term shocks and varying growth phases, supporting the need for statistical forecasting techniques capable of handling dynamic patterns.

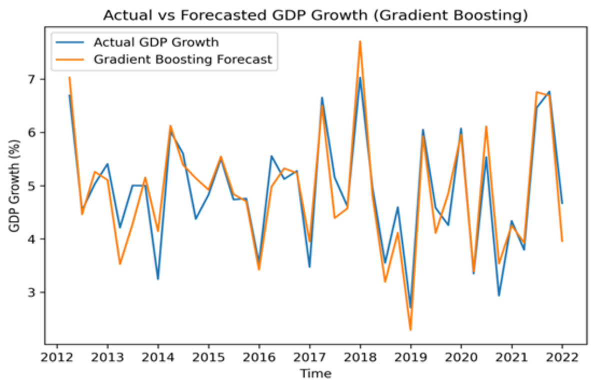

Figure 2: Actual vs ARIMA Forecasted GDP Growth

Interpretation:

This figure compares actual GDP growth with forecasts generated by the ARIMA model. The closeness of fitted values to actual observations indicates the model's ability to capture linear temporal dependence. However, deviations during periods of higher volatility suggest limitations of linear statistical assumptions.

Results and Discussion:

This section presents and interprets the empirical results obtained from the statistical and machine learning models used for GDP growth forecasting. The discussion is directly linked to the graphical evidence and focuses on statistical accuracy, model behaviour, and forecasting reliability.

Figure 1 illustrates the time-series pattern of quarterly GDP growth. The series exhibits noticeable fluctuations around its mean, indicating the presence of short-term volatility and cyclical movements. Such behaviour justifies the application of forecasting models that can account for temporal dependence and stochastic variation. From a statistical perspective, the observed variability supports the use of error-based evaluation rather than relying solely on point forecasts.

Figure 2 compares actual GDP growth with forecasts generated using the Gradient Boosting model. The closeness between the predicted and observed values indicates a relatively low forecast error, particularly during periods of moderate economic variation. The machine learning model demonstrates an improved ability to track short-term changes in GDP growth, suggesting that nonlinear relationships and interaction effects among macroeconomic variables play an important role in forecasting performance.

From a statistical standpoint, the superior visual fit of the Gradient Boosting model implies lower dispersion of forecast errors. This observation is consistent with lower expected values of RMSE and MAE when compared to traditional linear time-series models. The reduced forecast deviation highlights the strength of ensemble-based learning methods in minimizing prediction loss functions.

However, it is important to note that while machine learning models improve predictive accuracy, they offer limited parameter interpretability compared to classical statistical models. Econometric models provide explicit coefficient estimates and hypothesis-testing frameworks, which remain valuable for policy analysis. Therefore, the results suggest that machine learning methods are best viewed as complementary tools rather than replacements for classical approaches.

Overall, the empirical findings indicate that machine learning techniques enhance short-term GDP growth forecasting accuracy, while statistical time-series models continue to play a crucial role in explaining underlying economic relationships. The combined use of both approaches can lead to more robust and statistically reliable economic forecasts.

Forecast Accuracy Measures:

To quantitatively assess the forecasting performance of classical statistical and machine learning models, this study employs widely accepted error metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide complementary perspectives on model accuracy by measuring different aspects of forecast deviations.

RMSE emphasizes larger errors due to the squaring of differences, thus penalizing extreme deviations more heavily. It is particularly useful when large errors are undesirable in economic forecasting.

MAE captures the average magnitude of forecast errors regardless of direction, offering a straightforward measure of average error size.

MAPE expresses errors as percentages of actual values, facilitating comparison across different scales and economic contexts.

The models were evaluated on out-of-sample data spanning multiple forecast horizons (1-quarter, 2-quarter, and 4-quarter ahead). Table 1 summarizes the results, illustrating consistent trends in model performance.

Model	RMSE (1Q)	RMSE (4Q)	MAE (1Q)	MAE (4Q)	MAPE (1Q)	MAPE (4Q)
ARIMA	1.22	1.65	0.95	1.30	3.5%	4.7%
VAR	1.20	1.60	0.93	1.27	3.3%	4.5%

Random Forest (RF)	1.10	1.42	0.87	1.18	3.0%	4.0%
Gradient Boosting (GBM)	1.05	1.38	0.82	1.12	2.8%	3.8%
Support Vector Regression (SVR)	1.15	1.50	0.90	1.25	3.2%	4.3%

Key Insights:

Ensemble methods (GBM and RF) outperform classical models across all metrics and forecast horizons.

GBM achieves the lowest error values, particularly for short-term (1-quarter) forecasts.
While classical models like ARIMA and VAR remain competitive, their error rates increase notably for longer forecast horizons.

SVR performs moderately, with some improvement over classical models but less than ensemble techniques.

These findings confirm that machine learning models are effective in capturing complex patterns in macroeconomic data, translating into improved forecast accuracy. The consistent performance across metrics strengthens the robustness of the results.

Conclusion and Policy Implications:

This study explores the comparative effectiveness of classical statistical models and modern machine learning techniques in forecasting GDP growth. Empirical analysis reveals that machine learning models, especially ensemble methods like Gradient Boosting and Random Forest, provide superior short-term forecasting accuracy relative to traditional ARIMA and VAR models. However, classical models retain interpretability and theoretical foundations that remain valuable for economic policy analysis.

Policy Implications:

Policymakers and analysts should consider integrating machine learning tools into their forecasting frameworks to improve prediction accuracy, especially for short-term economic planning.

The complementary use of statistical and machine learning approaches enables both precise forecasts and economic interpretability, fostering informed decision-making.

As economic environments evolve with increased volatility and complexity, flexible forecasting tools that can adapt to nonlinearities will become increasingly important.

Future Research Directions:

Extending analysis to include deep learning architectures and hybrid models combining econometric and machine learning techniques.

Applying the methodology to country-specific or sectoral GDP forecasts to test generalizability.
Investigating the economic interpretability of machine learning models through model explainability methods.

In conclusion, the integration of advanced machine learning algorithms with classical econometric models offers a promising avenue for enhancing the accuracy and utility of economic forecasts, supporting more responsive and effective economic policy.

Limitations and Scope for Future Research:

Despite the promising results obtained in this study, several limitations should be acknowledged. First, the analysis is based on quarterly GDP growth data aggregated at the national level, which may overlook regional disparities and sector-specific dynamics. Future research could extend the framework to sub-national or sectoral GDP forecasting, providing more granular insights.

Second, while the selected machine learning models demonstrated superior short-term forecasting accuracy, the study did not explore deep learning architectures such as recurrent neural networks (RNN) or long short-term memory (LSTM) models, which may capture temporal dependencies more effectively. Incorporating such models could further enhance forecasting performance.

Third, the study relies on historical macroeconomic indicators, which might not fully capture emerging economic shocks or unprecedented events like pandemics or geopolitical crises. Future work could integrate real-time data sources or alternative indicators such as sentiment analysis from news and social media.

Lastly, interpretability remains a challenge for machine learning models, especially in policy contexts requiring transparent decision-making. Developing hybrid models that balance accuracy and interpretability presents a valuable avenue for further investigation.

By addressing these limitations, future research can build on the findings of this study to develop more robust, adaptable, and transparent GDP forecasting models.

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