APPLICATION OF MACHINE LEARNING ALGORITHMS IN ECONOMETRIC MODELING AND COMPARATIVE EVALUATION OF THEIR EFFECTIVENESS

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Abstract: This article examines the theoretical and methodological aspects and practical applications of machine learning algorithms in econometric modeling. It provides a comparative analysis of the characteristics, advantages, and limitations of classical econometric models and modern machine learning algorithms. The study compares linear regression and time series-based econometric approaches with machine learning algorithms such as Random Forest, Gradient Boosting, and XGBoost. The findings provide a methodological basis for selecting an appropriate modeling approach based on data characteristics and research objectives in the analysis of economic indicators.

Keywords: econometric modeling, machine learning, econometric model, Random Forest, Gradient Boosting, XGBoost, regression analysis, forecasting, comparative analysis, model accuracy, economic processes.

INTRODUCTION

The increasing complexity of modern economic processes, the strengthening of interrelationships among economic indicators, and the growing availability of large volumes of data require the application of new methods for economic analysis and modeling. Traditional econometric models serve as important tools for identifying quantitative relationships between economic phenomena, assessing the effects of various factors, and developing scientifically grounded forecasts. However, the presence of complex, nonlinear, and multidimensional relationships within datasets sometimes necessitates complementing classical econometric methods with modern computational approaches.

Econometric modeling integrates economic theory, mathematics, and statistical methods to provide a quantitative representation of economic processes. Linear and multiple regression models, time series analysis, ARIMA models, and other econometric techniques are widely used to identify patterns and trends in economic indicators. A major advantage of these approaches is their ability to provide economically interpretable parameter estimates, determine the direction and magnitude of relationships between variables, and test statistical hypotheses.

In recent years, advances in artificial intelligence technologies have significantly expanded the application of machine learning (ML) algorithms in economic data analysis. Machine learning algorithms are distinguished by their ability to automatically identify patterns in data, model complex and nonlinear relationships, handle large numbers of explanatory variables, and generate potentially accurate predictions. Accordingly, they are increasingly regarded as modern methodological approaches that complement traditional econometric modeling techniques.

In particular, algorithms such as Random Forest, Gradient Boosting, and XGBoost offer considerable opportunities for identifying complex relationships within economic datasets. Random Forest improves model stability by aggregating the predictions of multiple decision trees, while Gradient Boosting is based on sequentially reducing the errors of preceding models. XGBoost, in turn, applies optimized gradient boosting techniques and controls model complexity to achieve high predictive accuracy.

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Nevertheless, classical econometric models and machine learning algorithms differ in their objectives and the interpretability of their results. Econometric research often focuses on estimating relationships grounded in economic theory, testing the statistical significance of parameters, and explaining the relationships between explanatory variables and outcome indicators. In contrast, machine learning generally prioritizes predictive accuracy on previously unseen data and the generalization performance of models. Therefore, rather than treating these approaches as competing alternatives, it is scientifically important to identify their respective strengths and limitations and explore opportunities for their complementary application.

Another important application of machine learning methods in economic research is the assessment of the relative importance of explanatory variables. Techniques such as feature importance, permutation importance, and SHAP help identify which variables contribute most significantly to model predictions. However, these measures cannot be interpreted in the same way as regression coefficients or causal effect estimates in classical econometric models. This distinction highlights the need to consider methodological differences when comparing econometric and machine learning results.

When comparing models, attention should be paid not only to their goodness of fit but also to their ability to predict new observations. For this purpose, evaluation metrics such as the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE) can be employed. In machine learning, separating datasets into training and testing subsets and applying cross-validation techniques are essential for detecting overfitting and evaluating model generalization. For time series data, these procedures should also preserve the chronological order of observations.

The purpose of this article is to investigate the theoretical and methodological foundations of applying machine learning algorithms in econometric modeling, comparatively evaluate the capabilities of classical econometric models and modern machine learning algorithms, and identify effective approaches to their application in modeling economic processes. The study aims to systematize the characteristics of classical econometric approaches; assess the potential of Random Forest, Gradient Boosting, and XGBoost algorithms in economic modeling; compare these methods in terms of interpretability, the identification of nonlinear relationships, the assessment of variable importance, and predictive accuracy; and examine opportunities for integrating econometric and machine learning approaches.

The scientific and practical significance of the research lies in developing a comprehensive approach to analyzing economic processes by combining the advantages of econometric methods and machine learning algorithms. Such an approach makes it possible, on the one hand, to explain the economic meaning of relationships between variables and, on the other hand, to identify complex patterns and potentially improve predictive accuracy. Consequently, model selection in econometric analysis can be conducted in accordance with research objectives, data characteristics, and expected outcomes.

RESEARCH METHODOLOGY

This study employed a methodological approach aimed at identifying the potential applications of machine learning algorithms in econometric modeling and comparatively evaluating classical econometric methods and modern machine learning approaches. The fundamental principle of the research methodology was to compare the explanatory capabilities of econometric methods in analyzing economic processes with the ability of machine learning algorithms to identify complex relationships and generate predictions.

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The study employed systematic analysis, comparative analysis, statistical analysis, econometric modeling, machine learning, forecasting, and scientific generalization methods. Systematic analysis was used to examine the role, functions, and interrelationships of econometric modeling and machine learning in economic research. Comparative analysis focused on identifying the advantages, limitations, and conditions of application of these approaches.

The ordinary least squares (OLS) method was considered one of the principal techniques for estimating econometric model parameters. The coefficient of determination, adjusted coefficient of determination, Fisher's F-test, Student's t-test, and diagnostic indicators of model residuals were considered for evaluating model quality. These criteria make it possible to assess the overall statistical significance of the model and the statistical reliability of individual parameter estimates.

At the next stage of the research, the potential applications of machine learning algorithms in econometric modeling were examined. Random Forest, Gradient Boosting, and XGBoost algorithms were selected for comparative analysis. The selection of these algorithms was motivated by their ability to process multivariate datasets, identify complex and nonlinear relationships, and potentially improve predictive accuracy.

The Random Forest method is based on constructing multiple decision trees and aggregating their predictions. Each tree is developed using a particular subset of observations and features. Aggregating the predictions reduces the sensitivity of individual decision trees to random variations and can improve model stability. The Gradient Boosting algorithm is based on the sequential construction of predictive models. Each subsequent model is designed to reduce the prediction errors generated in the preceding stages. Consequently, this algorithm can progressively capture complex relationships within economic data.

The coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE) were used as criteria for comparative model evaluation. R^2 indicates the extent to which a model explains variation in the dependent variable, while MAE measures the average absolute difference between actual and predicted values. RMSE is more sensitive to large prediction errors and provides an overall measure of predictive error. In comparative evaluation, a higher R^2 value and lower MAE and RMSE values generally indicate better predictive performance.

However, model evaluation was not limited to predictive accuracy alone. An important advantage of classical econometric models is their ability to provide economically interpretable parameter estimates and support statistical inference. In machine learning algorithms, interpretability techniques such as feature importance, permutation importance, and SHAP can be used to assess the contributions of explanatory variables to model predictions. Nevertheless, feature importance in machine learning was distinguished from causal effects and regression coefficients, as these concepts do not have identical interpretations.

Within the comparative analysis methodology, econometric and machine learning approaches were evaluated according to the following criteria.

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Comparison criterion	Econometric approach	Machine learning approach
Main focus	Explaining relationships and drawing statistical inference	Prediction and identification of patterns
Linear relationship	High effectiveness	Can be identified
Nonlinear relationship	Requires specifying a model form	Can be identified more automatically
Interpretation of parameters	Relatively easy	Relatively complex
Testing statistical hypotheses	Broadly available	Not a primary objective
Assessment of factors	Regression coefficients and statistical tests	Feature importance, SHAP, and other methods
Risk of overfitting	Present	Higher, especially in more complex models
Predictive accuracy	Depends on the data and model	May be higher for complex relationships
Model selection	Based on economic theory and diagnostic tests	Greater emphasis on validation and test results

Figure 1. Comparative Evaluation Criteria for Econometric Models and Machine Learning Algorithms

The fundamental principle of the research methodology was not to establish the absolute superiority of any particular approach, but rather to determine the conditions under which each approach performs more effectively. When the primary objective of a study is to explain the economic effects of explanatory variables and test statistical hypotheses, classical econometric approaches offer significant advantages. Conversely, when the main objective is to identify complex relationships and achieve high predictive accuracy for previously unseen observations, machine learning algorithms provide additional opportunities.

RESULTS

The findings of the study indicated that econometric modeling and machine learning algorithms represent complementary methodological approaches to analyzing economic processes. Their main differences lie in modeling objectives, data requirements, methods for identifying relationships, interpretability of results, and forecasting mechanisms.

Classical econometric models enable the quantitative assessment of relationships between dependent variables and explanatory factors based on economic theory. Regression coefficients can be used to determine the direction and magnitude of the relationship between explanatory variables and the dependent variable. Student's t-test, Fisher's F-test, and other statistical criteria make it possible to examine the statistical significance of individual model parameters and the model as a whole. In this respect, econometric models offer important advantages in terms of the economic interpretation of results.

The main advantage of machine learning algorithms lies in their ability to identify complex and nonlinear relationships within datasets without requiring a strictly predefined functional form. Random Forest, Gradient Boosting, and XGBoost algorithms can capture complex interactions between multiple explanatory variables and the dependent variable. This capability is particularly valuable in economic processes where linear relationships are insufficient to adequately describe the underlying patterns.

The comparative analysis highlighted the potential of the Random Forest algorithm to produce relatively stable predictions by introducing randomness and aggregating the results of multiple decision

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trees. This algorithm is particularly useful for handling datasets with numerous explanatory variables and provides mechanisms for assessing feature importance. However, interpreting its results directly in economic terms is more challenging than interpreting classical regression coefficients.

An important characteristic of the Gradient Boosting algorithm is its ability to progressively reduce prediction errors by constructing successive models that address the shortcomings of preceding models. As a result, its capacity to identify complex patterns within datasets is enhanced. Nevertheless, inappropriate selection of model parameters may increase the risk of overfitting. Therefore, hyperparameters such as tree depth, number of trees, and learning rate should be selected through appropriate validation procedures.

The XGBoost algorithm is distinguished by its optimized implementation of the gradient boosting framework. Through model complexity control, regularization, and hyperparameter optimization, it is designed to achieve high predictive accuracy. However, the superior performance of XGBoost is not automatically guaranteed across all economic datasets. Its effectiveness depends on data volume, data quality, selected features, and model configuration.

RESULTS

The comparative findings indicated that there is no universal answer to the question of which model performs best. Model selection depends on the research objective. When the primary goal is to quantitatively assess the relationships between economic factors and the dependent variable, test the statistical significance of parameters, and draw economically meaningful conclusions, classical econometric models offer important advantages.

When the main objective is to improve predictive accuracy, handle numerous explanatory features, or identify complex nonlinear relationships, machine learning algorithms may be more appropriate. Their performance should be evaluated using consistent metrics, including R^2, MAE, and RMSE, on the same test dataset. A high R^2 value obtained from training data alone does not necessarily indicate that a model will accurately predict future observations.

The study also highlighted the importance of evaluating feature importance in machine learning algorithms. In Random Forest and boosting models, feature importance measures help identify the variables that contribute most significantly to predictions. The SHAP approach provides more detailed explanations of feature contributions at both the individual observation and overall model levels. However, these results should primarily be interpreted as indicators explaining the model's predictive mechanisms rather than as estimates of causal economic effects.

Another important finding concerns the possibility of applying econometric and machine learning approaches sequentially or in parallel. Initially, econometric models can be used to examine relationships consistent with economic theory and identify statistically significant explanatory variables. Subsequently, machine learning algorithms can be employed to investigate complex nonlinear relationships and assess predictive performance. Finally, all models can be compared using the same test data and evaluation criteria.

Overall, the findings suggest that machine learning algorithms should not be viewed as replacements for econometric modeling, but rather as complementary approaches that expand its analytical and predictive capabilities. Integrating the explanatory and statistical inference capabilities of econometric models with the pattern recognition and forecasting capabilities of machine learning provides a comprehensive methodological framework for analyzing economic processes.

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DISCUSSION

The comparative analysis demonstrated that econometric modeling and machine learning algorithms perform different methodological functions in economic research. Classical econometric approaches are distinguished by their ability to establish theoretically grounded relationships between economic indicators, estimate the direction and magnitude of associations between variables, and test statistical hypotheses. In contrast, machine learning algorithms primarily focus on identifying complex patterns in data and improving predictive performance on previously unseen observations.

The comparative advantage of the Random Forest algorithm lies in its ability to reduce the variability associated with individual decision trees by aggregating predictions from multiple trees. In addition, the algorithm provides mechanisms for assessing the relative importance of explanatory variables. This feature is particularly useful for identifying predictors that contribute significantly to forecasting performance among numerous economic indicators. Nevertheless, the identified feature importance cannot be directly interpreted as a causal economic effect.

The advantages of Gradient Boosting and XGBoost algorithms are associated with their sequential model improvement mechanisms and their ability to reduce prediction errors from preceding stages. Consequently, these algorithms may achieve high predictive accuracy when applied to datasets characterized by complex relationships. The availability of regularization and model complexity control mechanisms in XGBoost further expands its practical applications. However, because the performance of these algorithms is sensitive to hyperparameter selection, data volume, and data quality, evaluating them without appropriate validation is methodologically insufficient.

One of the important conclusions of the comparative analysis is that the coefficient of determination alone is insufficient for evaluating model performance. A model may achieve a very high R^2 value on training data while producing substantial prediction errors on previously unseen observations. Therefore, MAE and RMSE should be evaluated alongside R^2, while test-set performance and cross-validation results should also be considered. This approach provides a more objective assessment of a model's generalization ability rather than merely its goodness of fit to existing data.

One of the main challenges associated with applying machine learning algorithms in economic research concerns the interpretability of results. In classical econometric models, the sign and magnitude of regression coefficients often have a clear economic interpretation. In contrast, understanding how predictions are generated by complex machine learning models can be more challenging. Techniques such as feature importance, permutation importance, and SHAP partially address this limitation by identifying the explanatory variables that play important roles in model predictions. Nevertheless, these techniques do not automatically establish causal relationships.

The comparative analysis suggests that econometric and machine learning approaches should not be treated as mutually exclusive alternatives. Their effectiveness depends on the objectives of the research. When a researcher seeks to answer the question, "How and to what extent is variable X associated with outcome Y?", an econometric model grounded in economic theory and statistical inference may be more appropriate. If the primary question is, "How can the future value of Y be predicted as accurately as possible?", machine learning algorithms may offer additional advantages.

From this perspective, the integrated application of the two approaches may produce more effective results in economic research. Initially, dependent and explanatory variables are selected based on economic theory, and their relationships are estimated using econometric models. At the next stage, machine learning algorithms are employed to investigate nonlinear relationships, interactions, and

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predictive capabilities. Finally, all models are compared using the same test datasets and evaluation criteria.

CONCLUSIONS AND RECOMMENDATIONS

The comparative analysis demonstrated that econometric modeling and machine learning algorithms possess different yet complementary capabilities for studying economic processes. Classical econometric models offer important advantages in estimating the direction and magnitude of relationships between economic indicators, assessing the statistical significance of parameters, and providing economically meaningful interpretations. Machine learning algorithms, in turn, expand opportunities for identifying complex and nonlinear relationships, processing numerous explanatory features, and potentially improving predictive accuracy.

The comparative analysis established that integrating the strengths of econometric and machine learning methods is more appropriate than replacing one approach with another. Econometric models provide a framework for economic interpretation and statistical inference, while machine learning algorithms expand the ability to identify complex relationships and generate predictions. Accordingly, model selection should be based on research objectives, data volume and structure, and expected scientific outcomes.

Based on the findings, the following recommendations are proposed:

Integrate econometric and machine learning methods. An econometric model should initially be developed based on economic theory, followed by the application of Random Forest, Gradient Boosting, or XGBoost algorithms to examine complex and nonlinear relationships.

Prioritize research objectives in model selection. When the primary objective is to explain the direction and magnitude of relationships between economic variables, greater emphasis should be placed on econometric models. When predictive accuracy is the main priority, machine learning algorithms should receive greater consideration.

Compare models using consistent evaluation criteria. Forecasting-oriented comparisons should employ MAE and RMSE alongside R^2, with all metrics calculated using the same test period or validation procedure.

Control the risk of overfitting. Cross-validation, hyperparameter optimization, and regularization techniques should be employed to prevent machine learning algorithms from becoming excessively fitted to training data.

Improve the interpretability of machine learning results. Feature importance, permutation importance, and SHAP techniques should be used to identify the explanatory variables that contribute most significantly to model predictions. However, feature importance should not be equated with causal effects.

Consider data volume and quality. Complex machine learning algorithms do not necessarily produce superior results when applied to small datasets. Therefore, model complexity should be aligned with the number of available observations, and datasets should be expanded whenever feasible.

Preserve chronological order in time series modeling. Economic forecasting procedures should prevent future observations from entering the training process inappropriately and should employ validation methods specifically designed for time series data.

Develop hybrid modeling approaches. Future research should move beyond the parallel application of econometric and machine learning models toward developing hybrid frameworks that combine their

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outputs. Such approaches may improve the balance between economic interpretability and predictive accuracy.

The practical significance of this approach lies in integrating the explanatory capabilities of econometric models with the predictive capabilities of machine learning algorithms within a unified analytical framework. Consequently, it creates opportunities for a more comprehensive assessment of economic processes, the development of scientifically grounded model selection criteria, and the formulation of management decisions based on more reliable forecasts.

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