6 COMPARATIVE ANALYSIS OF MACHINE LEARNING AND TRADITIONAL METHODS IN TURKEY'S GROSS DOMESTIC PRODUCT FORECASTING

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Abstract

In this study, the Gross Domestic Product (GDP) is forecasted using data from a sample of Turkey covering the period between 1991 and 2020. The aim of the study is to compare the forecasting performance of traditional econometric models and machine learning (ML) methods. In this way, in cases where the assumptions and limitations of traditional methods cannot be met, the potential of ML methods with fewer assumptions and constraints is evaluated as an alternative approach to be preferred by researchers. Among the traditional methods, ARIMA (AutoRegressive Integrated Moving Average) model is used in the study, while Artificial Neural Networks (ANN), Elastic Net, Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) models are used as ML methods. Error metrics such as R-squared, MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error) and Scatter Index were used to compare the prediction performance of the models. The results show that XGBoost performs the best with high prediction accuracy (R-square = 0.99999) and low error rates (RMSE = 0.00134, MAE=0.00071). In addition, the forecasting performance of other ML models is better than that of the traditional ARIMA model. This study shows that ML methods are more effective and flexible than traditional methods in forecasting macroeconomic indicators such as GDP.

Keywords: *Gross Domestic Product, Artificial Neural Networks, Elastic Net, Support Vector Machine, XGBoost.*

JEL Classification: *C22, C45, C53.*

1. Introduction

Economic growth is the main indicator of economic progress in a country or region (Tuncsiper, 2023). Economic growth, defined as the measure of the total income got from goods and services produced within the borders of a country in a certain period, is measured through the Gross Domestic Product (GDP) growth rate and is the basic component of a healthy economy (Vrbka, 2016; Kordanuli et al., 2017; Milačić,2017). GDP growth is affected by various factors, each with a different and potentially significant impact (Mladenovic et al.,2016; Lagat et al. 2018). Considering that economic growth is a complex process where many known and unknown factors

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come together, the structure of the factors that define economic growth is important not only in understanding the current economic situation but also in predicting future economic trends (Feng & Zhang, 2014; Milačić et al. 2017; Psimopoulos, 2020).

Economic growth forecasts help us understand current and future economic conditions, improving economic and financial stability, strengthening crisis resilience, and making policy interventions more effective (Christensen et al., 2018; Jung et al.,2018). That the effects of macroeconomic instruments (such as monetary policy) affecting economic growth on the economy have long and variable lags direct policy makers to use the current growth rates of macroeconomic quantities such as consumption and investment to make reliable economic forecasts (Tkacz, 2001). However, data deficiencies frequently observed sudden structural changes and economic shocks, especially in developing economies characterized by unstable financial systems, strengthen the tendency for forecast findings to be inconsistent (Oduor et al., 2017; Park & Yang, 2024). Considering the dynamic structure of the economic process, it becomes more important to choose the forecast model that can be tested with high accuracy.

Researchers and policy makers use various methods based on historical data periods and theoretical approaches to estimate economic growth. These methods, which are mostly based on time series techniques (such as Box-Jenkins techniques, Kalman filter, Brown's linear exponential smoothing method, piecewise regression, structural econometric models, ARIMA, GARCH etc.) use the data in the time series to predict future values. It is based on the classical linear system that converts the data into a linear function (Huang et al., 2007). The application of these approaches, called traditional methods, most times leads to an incomplete depiction of the nonlinear dynamics that characterize the forecasting process (Jahn,2020). This deficiency observed in traditional methods has made the use of nonlinear models more popular in the process of handling nonlinear situations and estimating time series data consistently (Chuku et al., 2019).

Higher computational power and new methods are needed to make more accurate forecasts using traditional economic models (Pérez, et al. 2021). These models are based on the principle of reconstructing a time series based on data samples to forecast future values in time series analysis (Huang et al., 2007). Although these techniques are powerful statistical tools, they perform poorly in forecasting macroeconomic variables such as economic growth, which are affected by various factors (Li & Ma, 2010). In contrast, ML techniques are defined as flexible and universal function approaches. These methods stand out as important tools in forecasting complex and multivariate economic processes (Kaastra & Boyd, 1996; Huang et al., 2007). This is because ML methods perform well, even with noisy data. They can learn directly from the data without requiring prior knowledge about input-output relationships (Shachmurove, 2002). In this context, although traditional econometric methods such as AutoRegressive Integrated Moving Average (ARIMA) appear to be successful tools in the process of forecasting time series based on linear relationships of past observations, the forecasting power of traditional models decreases in the nonlinear structure of complex and multilayered economic data (Ariyo et al., 2014). In contrast, ML methods such as ANN, ElasticNet, SVM, and XGBoost offer a more flexible and powerful approach in modeling multivariate, nonlinear, and complex relationships (Hsu et al., 2016; Athey & Imbens, 2019; Zhao et al., 2024). For instance, ANN is used as a research tool in many fields and allows working with large data samples without restrictive assumptions such as linearity (Moshiri & Cameron, 1999). Similar to ANN, ElasticNet stands out as a powerful regularization method that enables working with high-dimensional samples, improves variable selection during the analysis process, reduces multicollinearity, and increases forecast consistency (Zou & Hastie,2005). SVM is a powerful ML method that creates hyperplanes that separate different classes with maximum margin by selecting significant features in high-dimensional data, providing effective classification (Wang et al., 2022). XGBoost, besides being a powerful gradient boosting algorithm that manages missing data and provides high performance in forecasting complex datasets, also increases the interpretability of model forecast results by presenting the importance ranking of variables (Chen & Guestrin, 2016; Zhang et al., 2023).

This study makes three main contributions to the literature. First, it comparatively evaluates the growth forecasting performance of the ARIMA model, a traditional econometric method, and contemporary ML algorithms such as ANN, ElasticNet, SVM and XGBoost, using data for the Turkish economy for the period 1991-2020. In this respect, the study aims to provide guidance for researchers and policy makers in the choice of methods by revealing the strengths and weaknesses of traditional and modern methods. The second contribution is the focus on macroeconomic indicators of a developing country like Turkey, which is subject to frequent economic fluctuations. In this context, the findings provide generalizable implications for countries with similar economic structures. Thirdly, the superior performance of the ML algorithms used in the study compared to the traditional model with high accuracy and low error rates reveals that ML approaches can be used as an alternative and effective tool, especially when linear assumptions cannot be met. In these respects, the study makes a unique contribution from both methodological and applied perspectives.

In this context, this study's main purpose is to examine comparatively the forecast performances of the ARIMA model, a traditional time series forecasting method, and ML techniques using key macroeconomic indicators of the Turkish economy. The main reason for focusing this study on the Turkish economy is that Turkey, as a developing country, is frequently exposed to economic fluctuations and uncertainties. Therefore, this study on the Turkish economy aims to provide an original contribution to the macroeconomic forecasting literature, both methodologically and empirically. In this direction, macroeconomic data for the period 1990–2020 were used, and the ML algorithms ANN, ElasticNet, SVM, and XGBoost were evaluated comparatively with the ARIMA model, which is considered a traditional method. The study aims to reveal the limitations of traditional methods, particularly in forecasting nonlinear and multivariate indicators like economic growth, and empirically shows the potential contributions of ML-based approaches in these areas. Following the introduction, the second section of the study presents a literature review by examining previous research focusing on economic growth forecasting. In the third section, the dataset, and method used in the study are discussed, and the basic features of the ARIMA and selected ML algorithms are explained. In the fourth section, the forecast results got are comparatively evaluated, and the performance differences between the methods are discussed. Finally, the fifth section presents the general conclusions and evaluations based on the findings.

2. Literature Review

Considering that the economy comprises policymakers, households, and investors, it is important to reduce or eliminate uncertainty in the decision-making processes of these groups. Particularly in developing countries, ensuring optimal resource allocation and achieving sustainable growth targets are directly proportional to the predictive power of forecasts. Consistent and successful forecasts not only contribute to policymakers in ensuring economic stability and developing necessary strategies against cyclical fluctuations, but also enhance the realism of long-term growth targets and increase the potential realization of these growth forecasts. The significance attributed to consistent and successful forecasting processes has led to the development of a research area aimed at determining the most optimal forecasting technique, particularly with the advancement of ML methods.

In the literature, economic growth is estimated with linear econometric models, and these models serve as reference points for comparisons with non-linear or more complex methods. Conversely, Marcellino (2006) stated that linear time series models are successful in forecasting GDP growth and inflation compared to more complex models, and the results tested with the bootstrap algorithm show these models provide sufficient performance most of the time. Similarly, Huang et al. (2007) stated that ANNs have been widely used in finance and economic forecasting, but their performance has been mixed when compared to traditional models. The study emphasized that variable types, neural network models, and prediction success may vary depending on data, time horizon, and model type. Insel et al. (2010) stated that ARMA and ANN models show similar performance in predicting the main economic variables in the Turkish economy, but their prediction performances differ according to variable movements and data period length.

In the literature, these approaches frequently focus on comparing the performance metrics of ARIMA models, representing traditional econometric methods, and ANN models, representing ML methods. For instance, Alamsyah & Permana (2018), in their study forecasting economic growth for the Indonesian economy for the period 1970-2017, concluded that the ANN method was the best tool for predicting economic growth. Chuku et al. (2019), in their study forecasting economic growth for Kenya, Nigeria, and South Africa using quarterly data from 1970 to 2016, concluded that the ANN forecasting method outperformed structural econometric and ARIMA models. Hüsnüoğlu & Oda (2022), in their study examining the impact of information technologies on economic growth in the Turkish economy using ARIMA and ANN models, concluded that the forecasting results of the ANN model were superior to those of the time series model. Sun et al. (2023) emphasized that ANN models outperform traditional linear regression models in their study, in which they stated that accounting data got from the four components of income-based GDP calculation (Depreciation, Income, Salaries, and Value Added) can be used in GDP estimation. Tchoketch-Kebir & Madouri (2024) stated that ANN models, such as MLP and LSTM, outperform reference ARIMA models in economic growth forecasts. In their study, while MLP models presented the most successful results in the short and medium term (6–12 months) and LSTM models in the long term (18–24 months), ARIMA models exhibited the lowest performance in all time periods.

When the methods used in economic growth forecasting are examined in the literature, it is observed that ANN models exhibit superior performance compared to linear and non-linear traditional methods; however, this superiority varies depending on the data structure and analysis period.

Apart from these, some studies show that hybrid models combining ANN and traditional forecasting methods produce more consistent results. For example, González (2000) stated that ANN models outperformed linear regression models in predicting Canada's real GDP growth, both in-sample and out-of-sample predictions, but this improvement was not statistically significant and that ANN models were compared to standard econometric methods. He suggested it should be considered as a complementary approach. Demir et al. (2015) stated that hybrid ANN models outperformed multiple regression models in predicting Japan's GDP growth. Oduor et al. (2017) compared the performance of ANN with traditional time series and structural econometric models in forecasting GDP growth in selected African frontier economies between 1970 and 2016, and recommended the use of hybrid models to improve forecasting accuracy. Li & Zhang (2018) used ARIMA and ARIMA-XGBoost hybrid models in their study to forecast China's energy supply security level. In their analysis, they first made time series forecasts with the ARIMA model and then predicted the residuals of the ARIMA model using the XGBoost model. Finally, they got the final results by summing the forecast results of both models. In this way, while capturing the general trends of the time series with the ARIMA model, they used the XGBoost method to correct the model's errors and improve the accuracy of the forecast results. As a result, it was stated that the forecasts closest to the actual values were made with the ARIMA-XGBoost hybrid model.

Therefore, some studies in the literature compare the forecasting performances of different ML techniques alongside traditional econometric methods. For example, Tiffin (2016), in their study forecasting GDP for the Lebanese economy using quarterly data covering the periods 1996–2010 and 2011–2014, concluded that the ElasticNet method produced more consistent forecasts compared to the Random Forest method. Similarly, Martin (2019), in their study forecasting GDP for the South African economy using quarterly data for the periods 1992–2016 and 1992–2017, compared traditional econometric methods such as AR and VAR models with ML methods such as ElasticNet, SVM, and RNN. In the study, where performance metrics were compared, the ElasticNet model was found to have the lowest RMSE and highest correlation, while the Random Forest method performed relatively better than traditional forecasting methods, and the RNN model's forecasting performance was lower than traditional methods. Alim et al. (2020) compared the performance of ARIMA and XGBoost models in forecasting human brucellosis cases. They concluded the XGBoost model outperformed the ARIMA model and was more suitable for forecasting human brucellosis cases. Rahman et al. (2022) used ARIMA and XGBoost methods to model and make short-term forecasts of COVID-19 cases and related deaths in Bangladesh. In their study, they showed forecasts made with the ARIMA model yielded better results than those of the XGBoost model for both cases and deaths. Adewale et al. (2024), aiming to increase the accuracy of GDP forecasts for Nigeria, used Random Forest (RF), XGBoost, and Linear Regression ML techniques in their study. They showed that the best forecasting model belonged to the RF model, with an R-squared value of 0.96. For XGBoost and Linear Regression, the R-squared value was calculated as 0.94. Monar Aguilar (2022), in their study, compared the performance of classical algorithms and ML algorithms for GDP forecasting. For this purpose, they used VAR, XGBoost, LightGBM, and CatBoost models. In their study, where a one-step-ahead forecasting strategy was used for GBDT-based algorithms, XGBoost was identified as the model that exhibited the best performance. Another GDP forecast study conducted by Droogh (2022) aimed to compare the forecasting performance of traditional models (ARIMA and DFM – Dynamic Factor Model) and ML models (RF, XGBoost, LSTM – Long Short-Term Memory, and SVR). It was shown that ML methods had better forecast values compared to traditional methods. According to the MAE metric, the SVR model, and according to the RMSE metric, the XGBoost model exhibited the best forecasting performance.

In studies conducted with observations from different samples and periods, ML techniques, which focus on maximizing forecasting power, as stated in the literature, exhibit higher forecasting performance compared to traditional econometric models. In this context, considering the complexity of the model and the existence of non-linear characteristics, ML methods largely stand out as more consistent and successful forecasters.

3. Dataset & Method

The sample of the study consists of Turkey data. The data set includes 30 observations covering the period 1991-2020. Environmental, economic, global and sociological indicators are selected to predict Turkey's economic growth. The variables are taken from the World Bank (World Bank, 2025), KOF Swiss Economic Institute (KOF Swiss Economic Institute, 2025) and International Monetary Fund (IMF, 2025) database. The variables and scales used in the study are given in Table 1.

The explanatory variables used in this study have been selected by taking into account the main factors affecting economic growth in the literature. Gross Domestic Product (GDP) is the main indicator that measures the economic performance of countries and it is important that the variables used in the estimation of this indicator are based on theoretical and empirical foundations. Accordingly, fixed capital investments are included in the model as a factor that directly affects economic growth by increasing production capacity. Trade openness reflects the positive effects of openness on growth, while foreign direct investment plays a supportive role in economic growth through technology transfer and employment opportunities. The level of financial development is important for the efficiency of capital allocation and improving the investment climate. Renewable energy consumption is taken into account due to its potential impact on growth in relation to reducing energy dependence and sustainable development goals.

Globalization index may have indirect effects on growth by reflecting the level of integration of countries with the world economy. Urban population growth can affect economic activity by having an impact on infrastructure, consumption and the labor market. Finally, population growth rate can shape growth dynamics through labor supply and consumption demand. Since these variables are frequently used as determinants of economic growth in both theoretical and empirical studies, their inclusion in the model increases both explanatory power and forecasting accuracy.

The LABOR variable measured in millions of people and the GDP and GFC variables measured in millions of dollars were standardized by applying a Z-score transformation. This preserved the shape of their original distributions. No transformation was applied for variables measured in scaled and percentage changes. The variables are then included in the forecasting model and the forecasting model is constructed as follows.

$$ZGDP = \beta_0 + \beta_1 REC + \beta_2 GLO + \beta_3 ZGFC + \beta_4 TRADE + \beta_5 FINDEV + \beta_6 FDI + \beta_7 URBAN + \beta_8 POPULATION + \beta_9 ZLABOR + \varepsilon_i \quad (1)$$

In this study, the forecasting power of ML methods against traditional methods is compared. ARIMA method is used as traditional time series methods. On the other hand, ANN, ElasticNET, SVM and XGBoost methods were used as ML methods. R program (R Core Team, 2024) was used for all analyses in the study. In order to compare traditional and ML methods, MSE, RMSE, MAE and SI performance metrics were calculated for each method.

Table 1

The variables and their scales

Symbol	Variables	Scale	Database
GDP	Gross Domestic Product	Constant, 2015$	World Bank
REC	Renevable Energy Consumption	Share in total energy consumption (%)	World Bank
GLO	Globalization Rate	Scale, 0-100	KOF Swiss Economic Institute
GFC	Fixed Capital Formation	Constant, 2015$	World Bank
TRADE	Trade	Ratio of total imports and export to GDP (%)	World Bank
FINDEV	Financial Development Index	Scale, 0-1	International Monetary Fund
FDI	Foreign Direct Investments	Percentage change (%)	World Bank
URBAN	Urbanization	Percentage change (%)	World Bank
POPULATION	Population Growth Rate	Percentage change (%)	World Bank

Although ML algorithms are generally designed to work with larger datasets, some of the methods used in this study (e.g. algorithms with regularization and error correction mechanisms such as ElasticNet and XGBoost) are also applicable to small samples. Various measures have been taken to reduce the risk of overfitting due to limited samples in the methods applied in this study. Especially in ANN, SVM, ElasticNet and XGBoost models, hyperparameter adjustments and cross-validation methods were used to increase the generalizability of the model. For example, in the ANN model, the most appropriate hidden layer structure was determined with 10-fold cross-validation and the predictive power of the model was increased by optimizing the learning rate. Similarly, in the ElasticNet model, the optimal lambda value was determined by cross-validation and the contributions of Ridge and Lasso regressions were balanced. In SVM and XGBoost models, the hyperparameters were optimized with 5-fold cross-validation. In this way, the performance metrics show that despite the small sample size, the resulting models avoid overlearning and have high prediction accuracy. However, it should be kept in mind that the results obtained should be evaluated considering the limited data set and that increasing the data frequency in future studies (e.g. with quarterly or monthly data) may further improve model reliability.

The ARIMA model (Box et al., 2015) was developed to model and forecast time series data. For the ARIMA model, the stationarity of the variables is analyzed by Phillips-PP (Phillips-Perron) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) tests. The *tseries* library (Trapletti & Hornik, 1999) was used for the unit root test. For the variables that are non-stationary at the level value, the stationarity of the series is tested again by taking the first differences. After the series became stationary, the ARIMA model was constructed by determining the model parameters p (AR degree), d (Differencing degree) and q (MA degree). The ***auto.arima*** function in the *forecast* (Hyndman et al., 2009) library was used for the model parameters. This function automatically finds the optimal ARIMA model. The validity of the model is tested with Ljung-Box and Durbin-Watson tests. Thus, it is checked whether the error terms are independent and have zero mean.

ANN (McCulloch & Pitts, 1943) aims to process information like biological neurons with a theoretical artificial neuron model. In this way, it can learn patterns and relationships, analyze large and complex data sets, and make effective predictions. The *neuralnet* package (Fritsch et al., 2008) was used for ANN analysis. The data set was randomly partitioned into training (70%) and test (30%) data. The ANN model was trained with a 10-layer cross-validation method. Thus, the generalization ability of the model was increased and the risk of overfitting was reduced. At this stage, *caret* (Kuhn, 2007) package was used. After the hidden layer structure was determined, the ANN model was created. In the last stage, model predictions were made on the test data.

Elastic Net, a powerful regularization technique developed by Zou & Hastie (2005), addresses some of the shortcomings of more traditional techniques such as Ridge regression and LASSO (Least Absolute Reduction and Selection Operator). Elastic Net aims to improve the interpretability and predictive performance of models when working with high-dimensional data, especially when the predictor variables are highly correlated (Friedman et al., 2010; Teipel et al., 2017). In addition to imposing a constraint on the size of the coefficients (minimization), Elastic Net reduces dimensionality while preserving the structure of the dataset by combining L1 and L2 penalties to enable better selection between correlated features (Teipel et al., 2017; Zhu et al., 2018). In this study, the dataset was first subdivided into training (70%) and test (30%) data using the *caret* (Kuhn, 2007) package. Then, the model was trained using the *glmnet* (Friedman et al., 2008) package and the best lambda value was determined as a result of cross-validation. Using this lambda value, predictions were made on the test data.

SVMs, whose main application areas are classification and regression problems (Drucker et al., 1996), are a powerful ML technique due to their practicality and solid theoretical foundation. The advantages of SVMs are high accuracy, efficient results on nonlinear data thanks to the kernel function, and resistance to overlearning. For SVM, the *e1071* library (Meyer et al., 1999) was used for optimizing the hyperparameters, training the model and obtaining the prediction values. First, the dataset was randomly partitioned into training (70%) and testing (30%). Then the model hyper-parameters were determined using 5-fold cross-validation. At this stage, the ***tune*** function was used. Kernel function was also used linearly. After training the model with the determined parameters, prediction values were obtained.

XGBoost (Chen & Guestrin, 2016) is an efficient and fast ML algorithm. This algorithm uses the “boosting” technique, which improves the prediction performance by correcting the errors of the previous model in each new model. It also offers high accuracy by avoiding overfitting problems with measures such as data-specific adjustments and complexity penalties (Wang & Zhou 2023). As a first step in the analysis, the data were converted to DMatrix format using the ***xgb.DMatrix*** function, thus enabling the model to work more efficiently. *Matrix* (Bates et al., 2000) package was used for this process. In the next step, the *caret* package was used to obtain the hyperparameters to be used in the training of the model with 5-fold cross validation. Finally, the model was trained with the best hyper parameter combination and the prediction values were calculated. At this stage, *xgboost* (Chen et al., 2014) package was used.

4. Results

For ARIMA, the stationarity of the variables is decided according to their p-values. For the PP-test, if the p-value is <0.05, the null hypothesis stating that the series is non-stationary is rejected. In the KPSS test, the null hypothesis stating that the series is stationary cannot be rejected if the p-value is >0.05. The results of the stationarity analysis of the series at the level and after first differences are given in Table 2. When the stationarity analysis results for ARIMA are analyzed, it is seen that only URBAN variable is stationary at the level according to PP-tet. The stationarity tests were repeated by taking the first differences of the variables in the series. According to PP and KPSS test results, the entire series is stationary at I(1) level.

Table 2

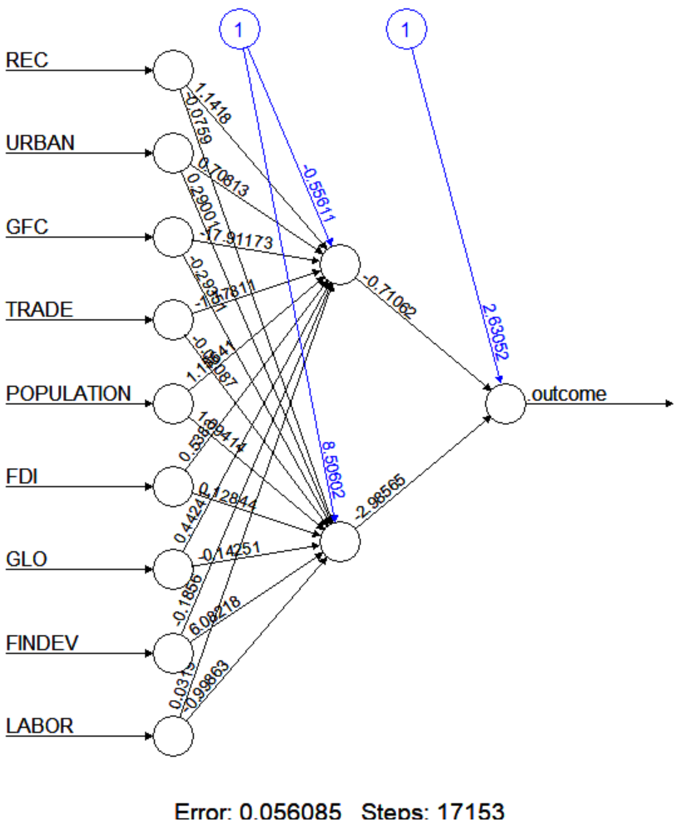
Stationarity test results

		Level		First Differance	
Variables	**Test**	**Statistic**	**P_Value**	**Statistic**	**P_Value**
GFC	PP	-8.4080	0.5872	-26.7601	0.0100
	KPSS	1.0203	0.0100	0.1151	0.1000
LABOR	PP	-4.5502	0.8418	-25.1931	0.0100
	KPSS	0.9732	0.0100	0.1960	0.1000
REC	PP	-3.8284	0.8894	-29.6602	0.0100
	KPSS	0.9832	0.0100	0.3439	0.1000
URBAN	PP	-22.9948	0.0101	-30.7117	0.0100
	KPSS	0.9750	0.0100	0.1196	0.1000
POPULATION	PP	-16.3323	0.0888	-32.2256	0.0100
	KPSS	0.7626	0.0100	0.0718	0.1000
TRADE	PP	-15.0194	0.1510	-24.3376	0.0100
	KPSS	0.8560	0.0100	0.0690	0.1000
FINDEV	PP	-13.9091	0.2242	-33.9789	0.0100
	KPSS	1.0617	0.0100	0.2216	0.1000
FDI	PP	-11.8006	0.3634	-25.2216	0.0100
	KPSS	0.4846	0.0451	0.0755	0.1000
GLO	PP	-7.3761	0.6553	-27.7483	0.0100
	KPSS	1.0440	0.0100	0.3403	0.1000
GDP	PP	-3.2754	0.9172	-25.3355	0.0100
	KPSS	1.0456	0.0100	0.3813	0.0852

The values of p, d and q for the ARIMA model are determined by the auto.arima function. This function automatically selects the most appropriate model according to the AIC or BIC criteria. The most appropriate model for the GDP series is ARIMA (1,1,0). In the tests for model validity, we find that there is no autocorrelation in the residuals according to the Ljung-Box test (p-value = 0.07465>0.05) and no first-order autocorrelation in the residuals according to the Durbin-Watson test (DW = 2.3392 ≈ 2; p-value = 0.8238>0.05). Moreover, according to the Shapiro-Wilk normality test (W = 0.96131; p-value = 0.354>0.05), the residuals fit the normal distribution and according to the Breusch-Pagan test (BP = 9.5974; p-value = 0.384>0.05), there is no heteroskedasticity problem in the residuals. As a result, the model is statistically valid and its forecasts are reliable. The performance metrics for ARIMA model forecasts show that the model can explain 90.03% of GDP (R-square = 0.90030) and provides a good fit. Moreover, the error metrics (MSE = 0.00108; RMSE = 0.03297; MAE = 0.02460) and the standard deviation of errors (Scatter Index = 0.02234) were found to be quite low. According to these results, the model predictions are close to the actual values and the model is consistent.

Figure 1

Graph of the ANN model



The number of hidden layers for the ANN was determined by 10-fold cross validation. The model was trained with 3, 2 and 1 hidden layers respectively. Model weights could not be calculated for hidden layer number 1. The R-square value was calculated as 0.9352. Error metrics were calculated as RMSE = 0.2879 and MAE = 0.2436. When the cross-validation results are analyzed, it can be said that the model is not overfitting and has a high predictive power. Since the sample is divided into sub-samples during cross-validation, the R-square and other metric values obtained are the average of the values of these sub-samples. In the study, the number of hidden layers for the ANN model was tested separately as (3,2), 3 and 2 and the model with the highest R-square value (hidden layer=2) was selected. Accordingly, the R-square value for the ANN model trained with 2 hidden layers and a learning rate of 0.01 was calculated as 0.97592. Error metrics were calculated as MSE=0.22203, RMSE=0.14900, MAE=0.12273 and Scatter Index=0.08963. The ANN graph is given in Figure 1. The weights in the model are given in Table 3.

The best lambda value for the Elastic NET model was obtained by cross-validation. Lambda is a regularization parameter and expresses the complexity of the model. Larger lambda values mean a simpler model (more regularization). Another issue to be considered here is the value of the alpha parameter. Since ElasticNet is a combination of Ridge and Lasso regressions, the weights of Ridge and Lasso in the model are determined by the alpha parameter. In the study, alpha=0.5 is taken. Thus, Ridge and Lasso regressions are weighted equally in the model. The best lambda value was obtained as 0.01554 for the lowest value of the model performance metric MSE (0.01783). In the next step, the best lambda value obtained was used to obtain the prediction results. For the model predictions, R-square=0.98093, MSE=0.01764, RMSE=0.13281, MAE=0.10771 and Scatter Index=0.08306.

In SVM analysis, especially in regression problems, two parameters play a critical role in determining the performance and characteristics of the model. These are cost and epsilon parameters. Cost parameter controls the fit of the model to the training data, while epsilon determines the error tolerance. In this study, the best values for these two parameters were obtained with the 5-fold cross-validation method. The cost values for cross-validation were set as 0.01, 0.1, 1, 10, 100 and the values for the epsilon parameter were set as 0.01, 0.1, 0.5, 1. After 5-fold cross-validation, the best cost value was 0.1 and the best epsilon value was 0.01. Thus, prediction values were obtained for the best model. The metrics for the performance of the SVM model were calculated as R-square=0.96644, MSE=0.03094, RMSE=0.17591, MAE=0.13978, Scatter Index=0.17732.

Table 3

ANN Model Weights

Hidden Layer 1 Weights			Output Layer Weights		Model Error and Steps	
Variable	**Hidden Noron 1**	**Hidden Noron 2**	**Variable**	**Output Noronu**	**Metrics**	**Value**
Intercept	-0.55611	8.50602	Intercept	2.63052	Error	5.61E-02
REC	1.14179	-0.07590	Hidden Noron 1	-0.71061	Threshold	8.11E-03
URBAN	0.70813	0.29001	Hidden Noron 2	-2.98565	Steps	1.72E+04
GFC	-17.91173	-0.29351				
TRADE	-1.17811	-0.02087				
POPULATION	1.15641	1.09413				
FDI	0.53829	0.12843				
GLO	0.44241	-0.14251				
FINDEV	-0.18560	6.08217				
LABOR	0.03190	-0.99863				

In order to make predictions with the XGBoost method, it is necessary to determine the parameters to be used in the model similar to other methods. To determine the hyperparameters, a parameter search space is defined as in the SVM method. According to this field, number of trees (nrounds = c(50, 100, 150)), maximum depth of trees (max_depth = c(3, 6, 9)), learning rate (eta = c(0.01, 0.1, 0.3)), minimum loss reduction (gamma = c(0, 0.1, 0. 2)), column sampling rate (colsample_bytree = c(0.6, 0.8, 1)), minimum child weight (min_child_weight = c(1, 3, 5)) and row sampling rate (subsample = c(0.6, 0.8, 1)). For the optimal hyperparameter values, 5-fold cross-validation method was used. In addition, RMSE was used as the error metric for the optimal values to be used in the model. After cross-validation, the optimal parameters were found as follows: nrounds = 150, max_depth = 9, eta = 0.3, gamma = 0, colsample_bytree = 0.6, min_child_weight = 3 and subsample = 1. Finally, these hyperparameters were used in the model for prediction and the performance metrics of the predictions were calculated. Accordingly, the R-square value for the XGBoost model was calculated as 0.99999. MSE value is 1.81984e-06, RMSE value is 0.00134, MAE value is 0.00071 and finally Scatter Index value is 0.00116. The importance matrix of the variables is given in Table 4. When Table 4 is analyzed, it is seen that the variables that contribute the most to the model performance are GLO, GFC, and LABOR variables with the highest gains. Although variables such as POPULATION, TRADE, and FDI have high coverage and frequency, they do not contribute much to the predictions of the model due to their low earnings. The graph showing the importance of the variables is given in Figure 2.

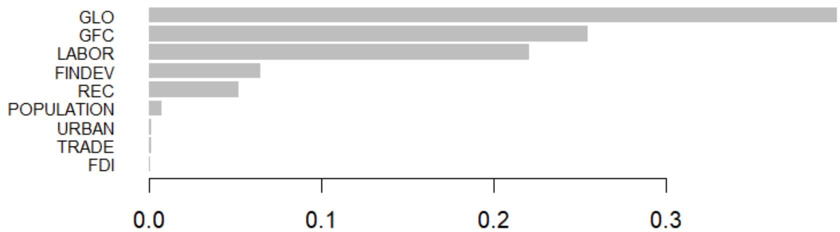
Table 4

Importance matrix

Feature	Gain	Cover	Frequency
GLO	0.399335	0.02804	0.0308057
GFC	0.254825	0.088638	0.0829384
LABOR	0.220528	0.101395	0.0971564
FINDEV	0.064351	0.084784	0.0734597
REC	0.051622	0.117209	0.1208531
POPULATION	0.006954	0.165449	0.1516588
URBAN	0.001162	0.094751	0.1137441
TRADE	0.00115	0.138073	0.1540284
FDI	7.33E-05	0.181661	0.1753555

Figure 2

Importance of variables



If the results are summarized, it is seen that all models have high prediction performance. The XGBoost model with the highest R-squared value and the lowest error metrics is the model with the highest prediction performance. Although the ARIMA model performance is in the last place compared to other models, it is seen that it has a good prediction performance with its high R-squared value and low error rate. The performance metrics for all models are given in Table 5. In addition, the graphs of the changes in the real and predicted values with respect to each other and with respect to time are given in Figure 3 as ARIMA, ANN, Elastic NET, SVM and XGBoost, respectively.

Table 5

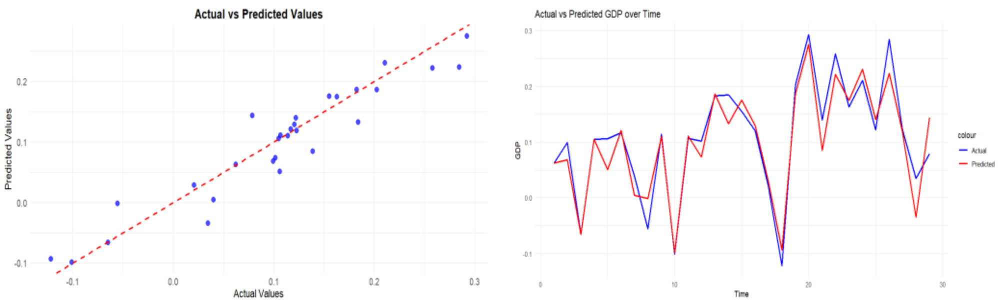
Performance metrics of models

Metrics	ARIMA	ANN	Elastic NET	SVM	XGBoost
R-square	0.90030	0.97592	0.98093	0.96644	0.99999
MSE	0.00108	0.22203	0.01764	0.03094	1.82E-06
RMSE	0.03297	0.14900	0.13281	0.17591	0.00134
MAE	0.02460	0.12273	0.10771	0.13978	0.00071
Scatter Index	0.02234	0.08963	0.08306	0.17732	0.00116

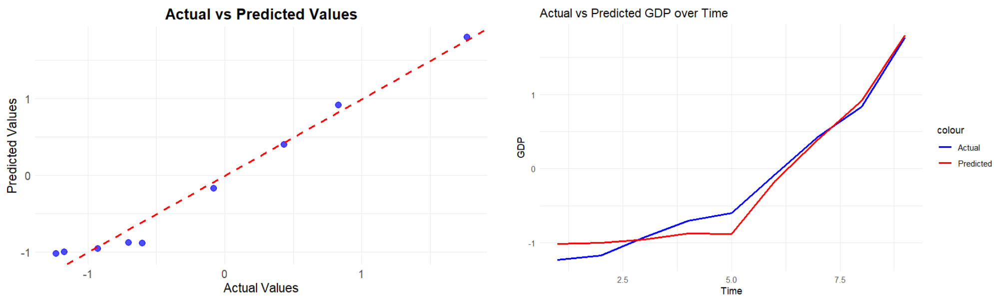
Figure 3

Graphs of Actual and Predicted values

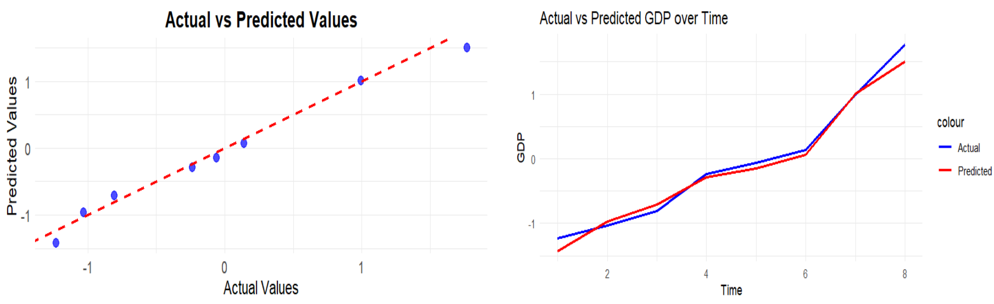
ARIMA



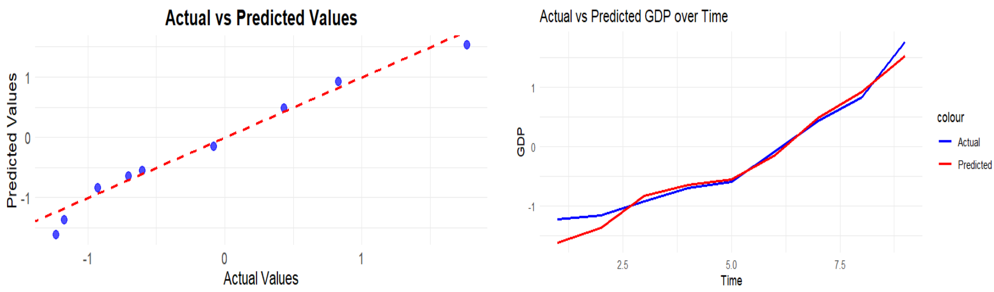
ANN



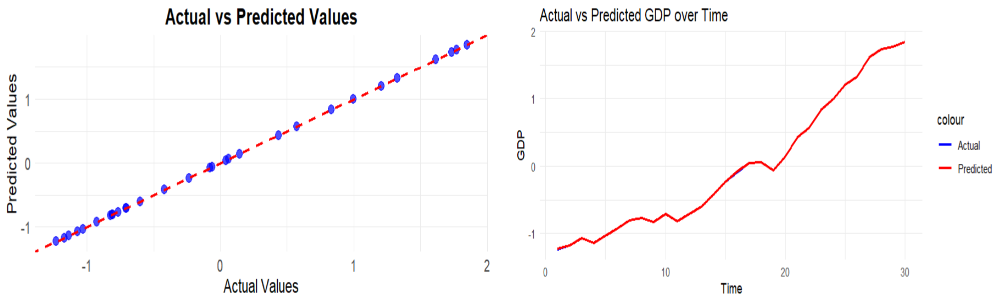
Elastic NET



SVM



XGBoost



5. Conclusion

The results of GDP forecasting models for Turkey clearly demonstrate the performance difference between traditional and ML methods. Traditional methods such as ARIMA are more limited in capturing nonlinear relationships in data. These traditional models are generally based on linearity and stationarity assumptions, but these assumptions may be difficult to meet in real-world economic data. In addition, these assumptions may not generally be valid in dynamic and complex time series data such as GDP, which can lead to inefficiencies and lower accuracy estimates. On the other hand, ML methods such as XGBoost, SVM, ANN, and Elastic Net exhibit better adaptation and performance. These models can capture nonlinear patterns in data and interactions between variables, which is often the case in GDP data such as macroeconomic time series data. In addition, these models do not require strict stationarity or linearity assumptions, making them more flexible and suitable for modeling real-time economic data. ML approaches also offer advantages in terms of computational efficiency and scalability. Once trained, these models can process large data sets and produce forecasts in real time, which is particularly important for tasks such as nowcasting where timely forecasts are critical. The ability to automatically learn from data and improve forecasts over time is a significant benefit in the context of uncertain and volatile economic environments.

As a result, ML techniques offer a promising alternative to traditional econometric models. The superior accuracy, flexibility, and ability to handle complex and nonlinear data of these models make them a valuable tool for forecasting GDP growth and other macroeconomic indicators. Therefore, the integration of ML methods into economic forecasting applications can significantly improve the quality and timeliness of forecasts.

The main limitation of this study is the relatively small dataset used. This may have a limiting effect on the generalization capacity of the model. However, technical measures such as cross-validation methods and hyperparameter optimization were taken to reduce this limitation. Nevertheless, it will be possible to test the model performance in a more reliable and generalizable way in future studies by increasing the sample size. In addition, only a few selected ML methods were compared in this study. Testing the performance of different deep learning methods (e.g. GRU, Bi-LSTM, etc.) or hybrid models in future studies can make a significant contribution to the literature. In addition, the interaction of variables can be examined in more detail by conducting different regional analyzes according to country groups

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