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PERFORMANCE COMPARISON OF MACHINE AND DEEP LEARNING METHODS IN USD/TRY EXCHANGE RATE FORECASTING

Ahmed İhsan ŞİMŞEK[1]

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Abstract

Accurate estimation of exchange rates is of great importance in terms of economic and financial analysis. Turkey has been faced with serious exchange rate fluctuations, especially in the recent period. At this point, accurate estimation of exchange rates is of critical importance for both individual and institutional investors. The aim of this study is to make a comparative performance analysis of different machine and deep learning methods used in USD/TRY exchange rate estimation. In the study, USD/TRY exchange rate estimation was performed using 149 months of data between January 2012 and May 2024. Total opened USD deposits, M3 money supply, total imports, total exports, unemployment rate, gold price, CPI, PPI and central bank net dollar reserves were used as input variables. Estimates were made with XGBoost, Random Forest, LightGBM, LSTM and SVR methods. In addition, the generalizability of the results was tested using the five-fold cross-validation method. According to the obtained results, the best estimation performance was produced by the Random Forest model in the training, test and cross-validation data sets. This study contributes to the literature by comparing the strengths and weaknesses of different methods in USD/TRY exchange rate forecasting.

Keywords: Exchange Rate, Deep Learning, Machine Learning, Decision Support, Random Forest.

Jel Codes: C45, C53, C87, F47

[1]**Sorumlu Yazar:** Dr. Öğr. Üyesi, Fırat Üniversitesi, ORCID: 0000-0002-2900-3032, aisimsek@firat.edu.tr.
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1. Introduction

Exchange rate forecasting is crucial in economic and financial analysis. Exchange rates are one of the key indicators which, directly affect a country's economic stability and possibilities to compete on an international economic field. Thus, the impact of the fluctuations in the rates on the macroeconomic variables can be regarded as crucial concern, practically for the developing countries like Türkiye. Even though the country has observed substantial volatility in the currency exchange rates for the last decade, the recent times tend to show even cruder changes in this respect. On the one hand, the direct effects are manifested in relation to inflation, imports and exports, foreign payment balance, and economic growth. However, from the viewpoint of forecasting, the precise prediction of currency exchange rates is rather significant. It should be noted that this extremely assists in planning country's public policies, as well as various organizations' business sector plans. Therefore, due to the economic planning and, consistently, risk-preventing reasons, conducting research on which factors impact exchange rate prediction is rather important. The exchange rate is the price of one currency in terms of another. It is one of the factors of the economy that have important consequences. Every change in the exchange rate affects the economics of importing, exporting, inflation rates, interest rates, and economic growth. Forecasting the fluctuations of currency exchange rates allows companies to develop plans for managing exchange risk more effectively, investors to reduce the risk in their portfolios, and governments to generate better economic policies. With regards to the Turkish economy, the USD/TRY exchange rate can be regarded as very important. Moreover, its swings have a range of implications. The implementation of machine and deep learning models in the exchange rate forecasting process brings multiple machine and deep learning benefits with regard to the precision and reliability of the forecasts. These types of models bring major benefits. They can capture the intricacies and patterns in an exchange rate's data, meaning these models allow for improved forecasting.

Claveria et al. (2022) stated that machine and deep learning methods are successful in foreign exchange rate prediction. Compared to traditional models, it can be said that machine and deep learning methods are much more successful in recognizing and using patterns in time series (Luo, 2024). In addition, deep learning and machine learning methods are successful in recognizing short- and long-term connections in time series of exchange rates (Rossi, 2013). In addition, the high adaptability of machine and deep learning methods to fluctuations in trends enables them to produce more accurate prediction results (Cao et al., 2020). In addition, machine and deep learning methods enable a deeper and more detailed examination of the factors affecting exchange rates thanks to the ability to combine different input variables (Safi et al., 2022). More accurate and reliable predictions can be made by improving the performance of models with machine and deep learning methods. From a broad perspective, these methods enable both individual and institutional investors to make more accurate decisions thanks to more accurate forecasts, better adaptation to market volatility, more in-depth analysis of the input variables used and up-to-date optimization techniques.

The aim of this study is to compare the performance of different machine and deep learning methods used in USD/TRY exchange rate forecasting. The study attempts to increase the accuracy of exchange rate forecasts by taking into account the fragility of the Turkish economy. This study examined the factors that influence the exchange rate between the US dollar (USD) and the Turkish lira (TRY). The variables considered include the amount of deposits opened in USD, the M3 money supply, the total value of imports and exports, the unemployment rate, the price of gold, the Producer Price Index (PPI), the Consumer Price Index (CPI), and the dollar reserves held by the Central Bank of the Republic of Turkey (CBRT). Analyses were conducted on a total of 149 months of data for these variables, spanning from January 2012 to May 2024. The study employed XGBoost, Random Forest, LightGBM, LSTM, and SVR techniques to forecast the USD/TRY exchange rate. Upon analyzing the research on predicting the USD/TRY exchange rate, it is evident that in addition to classic time series analysis approaches (Bağcı, 2020), machine and deep learning techniques (Ata & Erbudak, 2022; Tekin & Patır, 2023; Gümüş, 2024) have started to be employed. Ata & Erbudak (2022) utilized a dataset consisting of 1352 days of exchange rate data to forecast the exchange rate using four distinct machine learning techniques. Tekin and Patır (2023) conducted a study on the Dollar/TL forecast using the artificial neural networks method. They utilized a dataset spanning 156 months from 2009 to 2021. The study utilized interest rates, BIST100 index, gram gold price, M3 money supply, ounce gold price, and CPI variables to predict the exchange rate between the Dollar and TL. Gümüş (2024) employed an artificial neural networks model to forecast the exchange rate between the Dollar and TL. The model utilized monthly data spanning from May 2006 to August 2022. The study utilized many factors, including current account, CPI, gross dollar reserve, short-term debt stock, 2-year bond interest, net errors and omissions account, and M1 money supply, to estimate the exchange rate between the Dollar and TL. Upon reviewing the literature, it is evident that there is a scarcity of studies utilizing machine and deep learning techniques for predicting the Dollar/TL exchange rate. This study collected data on 9 characteristics to estimate the exchange rate between the Dollar and Turkish

Lira. The data was analyzed using five different machine and deep learning approaches. This study involved a comparison of various machine and deep learning approaches to determine which method yielded more beneficial outcomes. While machine learning uses simpler algorithms that work on structured data, deep learning has the ability to discover hidden patterns in large data sets through more complex and multi-layered structures. In this study, XGBoost, Random Forest and LightGBM were used as machine learning methods; LSTM and SVR were preferred as deep learning methods. Furthermore, the analysis incorporated data on 9 other variables that impact the Dollar/TL exchange rate in order to enhance the precision of the projections. During the literature review, it was noted that established approaches in time series analysis, such as LSTM, XGBoost, and Random Forest, have not been previously employed for calculating the Dollar/TL exchange rate. The purpose of using these models is to improve the accuracy of estimating the exchange rate between the Dollar and the Turkish Lira.

In the study, exchange rate estimates were made using Turkey's economic indicators and the performances of different methods were compared. These analyses aim to ensure that exchange rate estimates are more accurate for both individual and institutional investors. The methods used in this study, unlike the classical methods used in USD/TRY exchange rate estimates, have enabled machine and deep learning techniques to perform deeper analyses and increased the accuracy of estimates. The findings provide significant contributions to the methods used in exchange rate estimates in the literature.

2. Literature Review

Machine and deep learning methods are frequently used in predicting commodity prices (Karasu et al., 2018; Nas & Ünal, 2023; Gür, 2024). More specifically, studies using artificial intelligence-based methods in exchange rate forecasting are given below.

Plakandaras et al. (2015) used machine learning techniques to predict daily and monthly exchange rates. In the study, machine learning methods such as Support Vector Regression (SVR) and Artificial Neural Networks (ANN) combined with Empirical Mode Decomposition (EEMD) have achieved successful results in exchange rate predictions. This study compared traditional methods with machine learning techniques and revealed that SVR and ANN improved the exchange rate prediction performance.

Bao et al. (2017) presents a model using wavelet transforms, stacked autoencoders, and long-short-term memory (LSTM) in the deep learning framework for foreign exchange forecasting. The study uses wavelet transforms to purify financial time series from noise, and then deploys stacked autoencoders to extract features from these series. In the final stage, the extracted high-level features are transferred to LSTM to make a forecast for one step ahead of the time series. In the analyses, it has been observed that the proposed model is superior to other models in terms of both forecast accuracy and profitability. The study stands out with its ability to process complex structures in financial time series and its deep feature extraction capacity.

Ramakrishnan et al. (2017) tried to predict the Malaysian exchange rate based on commodity prices using machine learning techniques such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN). The results of the study revealed that commodity prices such as oil, gold and palm oil have a significant impact on the exchange rate and accurate predictions can be made with machine learning models. The findings show that machine learning techniques provide successful results in foreign exchange rate prediction and that commodity prices are important variables to be considered in these prediction processes.

Amat et al. (2018) examined the use of machine learning methods in exchange rate forecasts and revealed that it increases the predictive power of basic economic variables in short-term exchange rate forecasts. In the study, it was shown that in addition to basic economic indicators obtained from classical exchange rate models (such as PPP, UIRP) on the exchange rates of major industrialized countries between 1973 and 2014, variables based on the Taylor rule were also effective in exchange rate forecasts. Among the forecasting methods, machine learning techniques such as sequential ridge regression and exponential weighted average strategy were used and it was stated that these methods gave more successful forecast results than the OLS methods used in previous studies. It was determined that better performance was achieved than the "no-change" model in terms of root mean square error (RMSE), especially in short-term (1-month) forecasts.

Ranjit et al. (2018) compared different machine learning algorithms used in exchange rate prediction. The study aimed to predict the exchange rates of Nepalese Rupee (NPR) against US Dollar (USD), Euro (EUR) and British Pound (GBP) using Artificial Neural Network (ANN), Recurrent Neural Network (RNN) and various architectures of these networks. Especially Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures gave the best results compared to other methods. In the study, significant success was achieved in exchange rate prediction with ANN architectures using 1500-day data. LSTM provided the most successful results with the lowest error rate especially for all currencies.

Das et al. (2019) developed a hybrid machine learning model for exchange rate forecasting. In their study, they aimed to improve the performance of the model by using the Extreme Learning Machine (ELM) method with the self-adaptive multiple population-based Jaya algorithm. This hybrid framework was applied to forecast USD-INR and USD-EUR exchange rates and high accuracy forecast results were obtained compared to other methods. The main advantage of the ELM method is the high computational speed and the use of population-based optimization algorithms to increase the overall performance of the model. This study provides an important contribution to the potential of hybrid machine learning approaches in the field of exchange rate forecasting.

Kaushik & Giri (2020) compared VAR, SVM, and LSTM models for predicting the USD/INR exchange rate. In the study using data between April 1994 and December 2018, various macroeconomic variables were determined as input variables for exchange rate forecasting. The LSTM model yielded the most accurate prediction outcome, as indicated by the study's findings.

Zhang & Hamori (2020) used monthly data between 1980-2019 to forecast JPY/USD. US treasury yield, Japan treasury yield, PPI, CPO, M1 and Industrial production index variables were used as input in the study. It has been concluded that random forest, SVM and neural network models produce more accurate predictions when combined with traditional models.

Sun et al. (2020) used daily data between January 3, 2011 and December 29, 2017 to predict the dollar exchange rate of GBP, JPY, EUR and CNY. As a result of the analysis comparing 9 different methods, it was observed that the proposed LSTM-B ensemble deep learning method gave better results than other methods.

Abedin et al. (2021) proposed a new model to predict the dollar exchange rate of 21 national currencies for the period before and after Covid 19. It has been shown that this proposed model based on Bi-LSTM and Bagging Ridge Regression produces better prediction results than SVR, Regression Tree and Random Forest methods, which are traditional machine and deep learning methods.

Yilmaz & Arabaci (2021) compared 10 different models to predict the dollar exchange rate of Canada, Australia and England currencies. When the RMSE and MAE values obtained in the study were examined, it was revealed that the ARIMA-LSTM hybrid model gave better results than other time series, machine and deep learning methods.

Agarwal (2022) used export, import, FDI, DII, inflation variables for FX rate prediction. Estimates were made using 6 different methods using data between January 1, 2016 and December 31, 2018. According to the results obtained, the Scaled conjugate gradient method produced the best prediction result.

Safi et al. (2022) compared CNN, MLP, LSTM and EMD-CNN methods for exchange rate prediction using oil prices. As a result of the analysis, it was observed that the best result was produced by the EMD-CNN method according to the MSE, RMSE, MAE, R^2, MAPE and SSE statistical coefficients.

Yu et al. (2023) used data between June 2015 and December 2020 to predict the CNY/USD exchange rate and included a total of 30 variables in two categories. According to the RMSE, MAE and MAPE results of six different deep learning and machine learning methods, it was concluded that the best prediction performance was produced by the linear regression method.

Sumargo & Wasito (2024) used 7007 days of data for USD/IDR prediction and 6280 days of data for CNY/IDR prediction. As a result of the analyzes made with RNN, LSTM and GRU methods, it was observed that the RNN method gave better results than other methods.

When the literature was examined, a limited number of studies were found to predict the exchange rate of the Turkish Lira. These studies are given below.

Yasar & Kilimci (2020) combined sentiment analysis with artificial intelligence-based models to predict the Dollar/TL exchange rate. According to the results obtained, it was observed that the model proposed in this study gave better prediction performance than traditional models.

Ata & Erbudak (2022) used a data set consisting of 1352 data for USD/TRY prediction and analyzed this data set with decision tree, svr, gauss regression and linear regression methods. According to the RMSE, R^2, MAE and MSE values obtained as a result of the analysis, the best prediction performance was produced by the decision tree method.

Tekin & Patır (2023) used interest rate, BIST100 index, gram gold price, m3 money supply, ounce gold price and CPI variables to estimate the USD/TRY exchange rate. As a result of the study conducted using the artificial neural networks method, the MSE value was measured as 0.0019, the MAE value was 0.0173 and the MAPE value was 0.5137.

Gümüş (2024) used monthly data between September 2022 and October 2022 for USD/TRY forecast. In the study, current account, CPI, gross dollar reserve, short-term debt stock, 2-year bond interest, net errors and omissions account, and M1 money supply variables were used to predict the USD/TRY exchange rate. As a result of the analyzes performed using artificial neural networks, MAE and MAPE values were obtained for the training, testing and cross-validation data sets. Accordingly, the average MAE value was found to be 0.0912 and the MAPE value was 0.0308.

Gür (2024) compared SVM, XGBoost, LSTM and GRU methods for determining the EUR/TL exchange rate. As a result of the analysis conducted with monthly EUR/TL exchange rate data between January 2000 and October 2023, it was observed that the most accurate result was produced by the GRU method according to MAPE, RMSE, MAE and R^2 statistical coefficients.

3. Data & Methodology

This study has a time period of 149 months, spanning from January 2012 to May 2024. The analysis comprised 149 months of data on total deposits opened in USD, M3 money supply, total imports and exports, unemployment rate, gold price, PPI, CPI, CBRT dollar reserves, and USD/TL exchange rate. The study provides a comprehensive list of the variables used and the sources of the data in Table 1.

Table 1.

Sources of Variables

Variables	**Type**	**Source**
Total Opened USD Deposits	Input	evds.tcmb.gov.tr
M3 Money Supply	Input	evds.tcmb.gov.tr
Total Import	Input	tüik
Total Export	Input	tüik
Unemployment Rate	Input	tüik
Gold Price	Input	evds.tcmb.gov.tr
Producer Price Index	Input	tüik
Consumer Price Index	Input	tüik
Central Bank Net Reserve	Input	evds.tcmb.gov.tr
USD/TRY Rate	Output	evds.tcmb.gov.tr

The flow of the study is given in Figure 1.

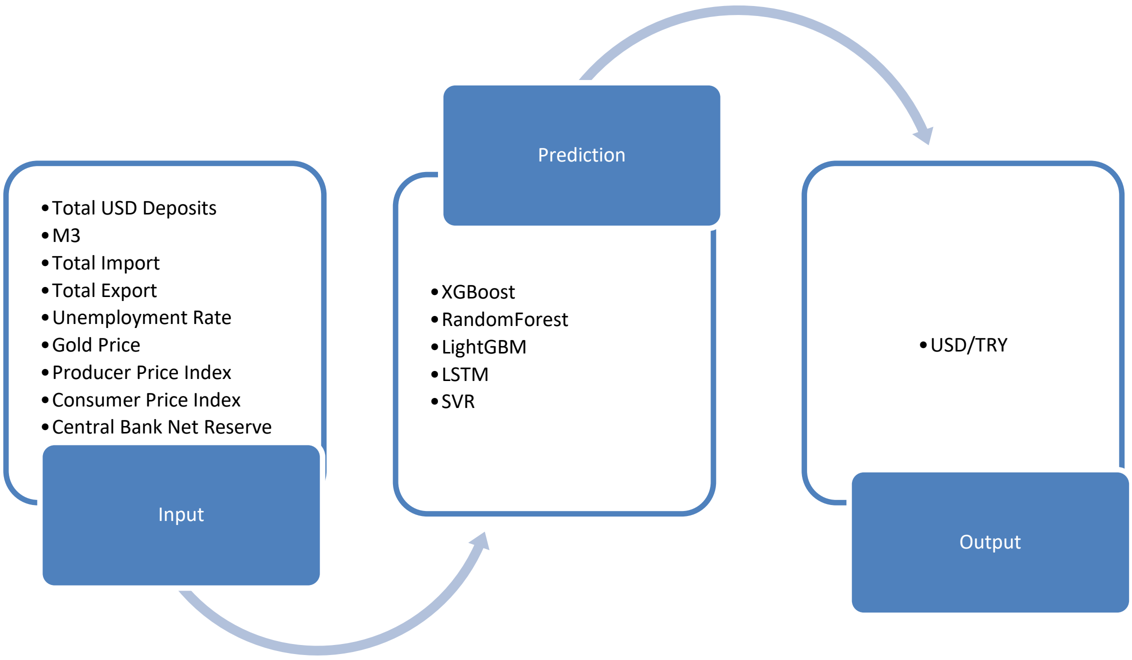

Figure 1.

Exchange Rate Forecasting Process Flow

The data was normalized before the analysis. This process was done to increase the accuracy of the model and to reduce the effects of extreme data values. In addition, the hyperparameter optimization process was carried out in the study to increase the performance of the model, eliminate incompatibility problems and ensure scaling of the data. This process was carried out especially by using the random search algorithm. Thanks to this method, over-learning was prevented, the training times of the model were shortened and a more accurate comparison of the performances of the models was provided. XGBoost, Random Forest, LightGBM, LSTM and SVR models were used in the analyses using the data shown in Table 1. The performance of each algorithm was measured with different metrics and comparative analysis was performed. Hyperparameter optimization was performed for the methods used in the study. In this way, model performances were increased, over-learning problems were eliminated, model training times were shortened and a more accurate comparison of the performances of the models was provided. Table 2 includes the hyperparameters used in the analysis.

Table 2

Hyperparameters

Model	**Hyperparameters**
XGBoost	{'colsample_bytree': 0.634336, 'gamma': 0.011092, 'learning_rate': 0.308899, 'max_depth': 6,

	'min_child_weight': 6, 'n_estimators': 308, 'subsample': 0.664114}
RandomForest	{'max_depth': 12, 'max_features': 'sqrt', 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 276}
LightGBM	{'colsample_bytree': 0.874540, 'learning_rate': 0.295214, 'max_depth': 11, 'min_child_samples': 8, 'n_estimators': 238, 'num_leaves': 40, 'reg_alpha': 0.156019, 'reg_lambda': 0.155995, 'subsample': 0.558084}
LSTM	{'units': 150, 'learning_rate': 0.01, 'epochs': 100, 'batch_size': 32}
SVR	{'kernel': 'linear', 'C': 1, 'gamma': 'scale'}

3.1. XGBoost Model

XGBoost, abbreviation for Extreme Gradient Boosting, is an effective machine learning method that has shown substantial growth in popularity in recent years. The system is a scalable tree boosting system that has gained extensive usage in diverse industries including finance, healthcare, and engineering. XGBoost operates by sequentially generating an ensemble of decision trees, with each tree aiming to rectify the mistakes made by the previous tree, resulting in a highly accurate predictive model. Chen (2016) presented XGBoost as a scalable tree boosting system that has demonstrated exceptional performance in managing extensive datasets and attaining remarkable prediction accuracy. The model's capacity to enhance the collection of decision trees by maximizing information gain has established it as a preferred option for numerous machine learning practitioners. Furthermore, the versatility of XGBoost in dealing with both classification and regression tasks has rendered it a flexible tool in predictive modeling. Equations 1-8 represent the implementation of the XGBoost algorithm.

$$\hat{y}_i = \emptyset(x_i) = \sum_{k=1}^{K} f_k(y_i), f_k \in \mathcal{F} \quad (1)$$

$$min\, L^{(t)}(\, y_i, \hat{y}_i{}^{(t)}) = min \left(\sum_{i=1}^{n} \iota\left(y_i, \hat{y}_i{}^{(t)} \right) + \sum_{k=1}^{t} \Omega(f_k) \right) \quad (2)$$

$$\Omega(\, f) = \gamma T + \frac{1}{2}\lambda w^2 \quad (3)$$

$$min\, L^{(t)} = min \left(\sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i) \right] + \Omega(f_t) \right) \quad (4)$$

$$g_i = \partial_{\hat{y}_i{}^{(t-1)}} l(y_i, y_i^{t-1}) \quad (5)$$

$$h_i = \partial^2_{y_i^{t-1}}\, l(y_i, y_i^{t-1}) \quad (6)$$

$w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda}$	(7)
$obj^* = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum g_i)^2}{\sum h_i + \lambda} + \gamma . T$	(8)

An ensemble of tree models is used to predict the outcomes of a dataset that consists of a n number of samples and m attributes. This model uses K additive functions, implied as $\boldsymbol{D} = \{(\boldsymbol{x_i}, \boldsymbol{y_i})\}(|\boldsymbol{D}| = \boldsymbol{n}, \boldsymbol{x_i} \in \boldsymbol{\mathcal{R}^m}, \boldsymbol{y_i} \in \boldsymbol{\mathcal{R}}$. Equation 1 denotes the collection of regression trees, where F represents this set. The variable $\boldsymbol{f_k}$ indicates the amount of underperforming learners, whereas K represents the total number of underperforming learners. The algorithm's target function at time t, denoted as $\boldsymbol{L^{(t)}}$, is precisely described by Equation 2. The parameter $\boldsymbol{l}(\boldsymbol{y_i}, \boldsymbol{\hat{y}_i}^{(t)})$ represents a set of loss functions used to solve particular challenges. Equation 3 shows a broadly used approach for measuring the extent of variance among the observed value ($\boldsymbol{y_i}$) and the predicted value ($\boldsymbol{\hat{y}_i}^{(t)}$), together with the overall complexity of the model, represented as $\sum_{k=1}^{t} \boldsymbol{\Omega}(\boldsymbol{f_k})$. During the tth iteration, the objective function is assessed by substituting the projected value (($\boldsymbol{\hat{y}_i}^{(t)}$) for the ith sample. Equation 4 demonstrates the implementation of the computation by employing the second-order estimation of the Taylor expansion at the anticipated value of y obtained from the prior step, denoted as ($\boldsymbol{\hat{y}_i}^{(t-1)}$). Equation 4 denotes the first and second derivatives of the loss function $\boldsymbol{l}(\boldsymbol{y_i}, \boldsymbol{\hat{y}_i}^{(t)})$ as $\boldsymbol{g_i}$ and $\boldsymbol{h_i}$, respectively. To compute the derivative, you can substitute the formulas labeled as Equation 4, Equation 5, and Equation 6 into Equation 2, as mentioned earlier. Equations 7 and 8 can be utilized to deduce solutions. The variable obj*, as defined by equations 7 and 8, reflects the numerical value of the loss function score. A lower score signifies a tree structure that is closer to an optimal condition. The symbol $\boldsymbol{w_j^*}$ signifies the most suitable option for the weights in the spesific situation being analyzed in the XGBoost model. The values for the other parameters are as follows: 'colsample_bytree': 0.634336, 'gamma': 0.011092, 'learning_rate': 0.308899, 'max_depth': 6, 'min_child_weight': 6, 'n_estimators': 308, 'subsample': 0.664114.

3.2. Random Forest Model

Breiman presented the random forest model in 2001, an ensemble learning technique that combines decision trees into random forests. The objective of this strategy is to improve the accuracy of predictions and address the problem of overfitting. The system operates by generating many decision trees during the training phase and determining the most frequent category for classification tasks or the average prediction for regression analysis (Chen, 2020).

Random Forest succeeds in its capacity to effectively handle both classification and regression tasks. Random Forest reduces the likelihood of overfitting and produces reliable predictions by constructing numerous decision trees using random subsets of data and features (Li et al., 2010). Random Forest model illustrated in Figure 2.

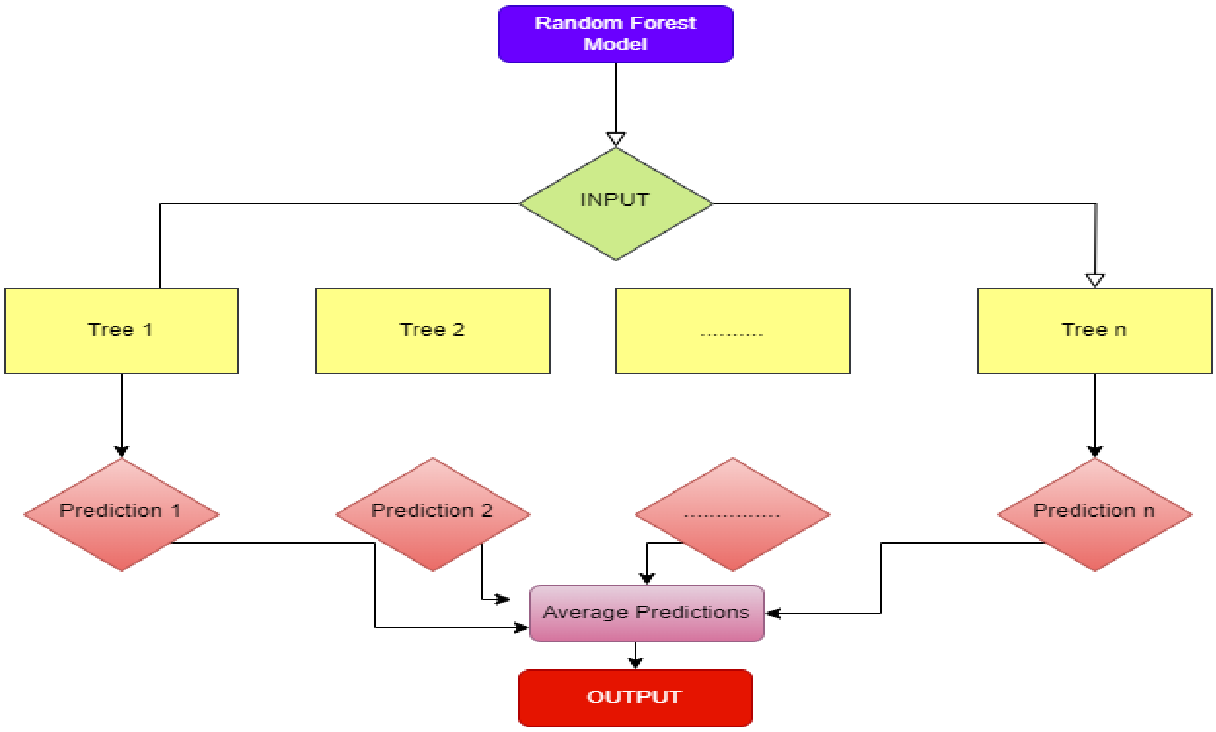

Figure 2.

Random Forest Model

The Random Forest model was generated with the following parameters: 'max_depth': 12, 'max_features': 'sqrt', 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 276. During the initial phase of the Random Forest model, data is gathered and then partitioned into several sets for training and testing purposes. Once the data has been appropriately modified, several decision trees are consolidated. Subsequently, various data points are allocated to distinct trees through the process of bootstrap sampling. A decision tree is constructed for each sampled dataset, resulting in the creation of decision and leaf nodes. Subsequently, the decision trees are merged. A test set is used to conduct an assessment of the Random Forest model, and performance metrics are measured.

3.3. LightGBM Model

Ke, et al. introduced the LightGBM model in 2017. LightGBM is a gradient boosting framework known for its speed, efficiency, and great performance. The approach is founded on the concept of ensemble learning, which involves the combination of numerous weak learners (decision trees) to form a powerful learner for tasks related to predictive modeling. The LightGBM model has advantages such as fast training performance (Luo, 2024), limited memory usage (Wang et al., 2022), and high accuracy (Park et al., 2021). In addition, it has disadvantages such as overfitting risk (Chen, 2023), sensitivity to noisy data (Chen, 2023) and hyperparameter tuning (Liu, 2023). The LightGBM methodology employs a leaf-wise approach to determine the leaf with the highest scattering gain among all current leaves and then split it. An issue with the Leaf-wise algorithm is that it has the potential to produce overfitting due to its tendency to create an extensive decision tree. LightGBM employs a leaf-wise approach with a specified maximum depth constraint to enhance efficiency and mitigate the risk of overfitting. Trees are cultivated using the level-wise tree growth approach, where each level is grown sequentially. This strategy involves the division of information by each node, with a focus on the nodes that are closest to the root of the tree (Shakeel et al., 2023). The LightGBM model was generated with the following parameters: 'colsample_bytree': 0.874540, 'learning_rate': 0.295214, 'max_depth': 11, 'min_child_samples': 8, 'n_estimators': 238, 'num_leaves': 40, 'reg_alpha': 0.156019, 'reg_lambda': 0.155995, 'subsample': 0.558084.

3.4. LSTM Model

Long Short-Term Memory (LSTM) is a specific type of recurrent neural network (RNN) that is specifically built to capture long-range dependencies in sequential input. LSTM, which was first introduced in 1997 by Hochreiter and Schmidhuber, has garnered considerable interest due to its capacity to surpass the constraints of conventional RNNs in capturing and preserving information over long durations. The major characteristic of LSTM is its memory cell, which has the ability to retain information throughout lengthy periods, making it highly suitable for jobs that include time series data, natural language processing, speech recognition, and other related applications (Nguyen & Kim, 2019). The LSTM architecture has memory blocks that communicate through different gates, such as input gates, forget gates, and output gates, enabling the network to control the information flow. LSTMs possess the ability to acquire and retain patterns within data sequences, rendering them very efficient for tasks that need the representation of intricate temporal connections (Wang et al., 2022). The implementation process of the Long Short-Term Memory (LSTM) approach is described in Equation 9-14 as follows:

$$f_t = \sigma_g \left(W_f x_t + U_f h_{t-1} + b_f \right) \tag{9}$$

$$i_t = \sigma_g \left(W_i x_t + U_i h_{t-1} + b_i \right) \tag{10}$$

$\Omega(f) = \gamma T + \frac{1}{2}\lambda w^2$	(11)
$C'_t = \sigma_c (W_c x_t + U_c h_{t-1} + b_c)$	(12)
$C_t = f_t \, x \, C_{t-1} + i_t \, x \, C'_t$	(13)
$o_t = \sigma_g (W_o x_t + U_o h_{t-1} + b_o)$	(14)
$w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda}$	(15)
$h_t = o_t \text{ x } \tanh(C_t)$	(16)

Equation 9 incorporates the variables $\boldsymbol{x_t}$, $\boldsymbol{h_{t-1}}$, $\boldsymbol{f_t}$, and $\boldsymbol{\sigma_g}$, which respectively specify the input of the time series, the previous hidden state, the output vector, and the activation function. The bias coefficient is generally denoted as $\boldsymbol{b_f}$, while the forget gates are assigned as $\boldsymbol{W_f}$ and $\boldsymbol{U_f}$. The output vector is connected to the forget gate. Equation 10 symbolizes this correlation. Equations 11 and 12 describe the connection among the precise point in the time series input, denoted as $\boldsymbol{x_t}$, and the hidden state, denoted as $\boldsymbol{h_{t-1}}$, from the previous time frame. The values of the coefficients $\boldsymbol{i_t}$ and $\boldsymbol{C'_t}$ within this gate are dictated by these variables. The calculation of these coefficients is performed using the activation function. The variables $\boldsymbol{W_i}$, $\boldsymbol{U_i}$, $\boldsymbol{W_c}$, and $\boldsymbol{U_c}$ denote the weight coefficients, while the symbols $\boldsymbol{\sigma_g}$ and $\boldsymbol{\sigma_c}$ signify the activation function. Equation 12 depicts the mechanism by which the cell state, referred to as $\boldsymbol{C_t}$, is updated. This method entails the multiplication of the input gate output, $\boldsymbol{i_t}$, with the cell candidate data, $\boldsymbol{C'_t}$, and the product of the prior cell state, $\boldsymbol{C_{t-1}}$, and the forget gate outcome, $\boldsymbol{f_t}$. The computation results in a depiction of the modified state of the cell, denoted as $\boldsymbol{C_{t-1}}$. The equation 13 demonstrates how the output vector $\boldsymbol{\sigma_t}$ is generated by transforming the input vectors $\boldsymbol{h_{t-1}}$, and $\boldsymbol{x_t}$ using the activation function $\boldsymbol{\sigma_g}$. The input gate is linked to the bias coefficient, $\boldsymbol{b_o}$, as well as the weighted values of the cell state, W_o and U_o. Once formed, the current sequential cell state, $\boldsymbol{C_t}$, is multiplied by the value of the output gate, $\boldsymbol{o_t}$. Equation 14 demonstrates the application of the tanh activation function to the output of the hidden layer. The LSTM model is configured with the parameters of 'units': 150, 'learning_rate': 0.01, 'epochs': 100, 'batch_size': 32.

3.5. SVR Model

Support Vector Regression (SVR) is a machine learning model that applies the ideas of Support Vector Machines (SVM) to solve regression problems. SVR, a robust regression technique, is designed to identify a regression plane that optimizes the distance between the data points and the regression plane. SVR, or Support Vector Regression, is a technique that effectively captures intricate relationships in data by optimizing a hyperplane to reduce the distance between the data points and the plane (Ulenberg et al., 2016). The SVR model is specifically designed to address regression problems, whether they are linear or non-linear in nature. It achieves this by employing the kernel technique, which allows for the mapping of data into higher-dimensional spaces. The goal of Support Vector Regression (SVR) is to reduce the discrepancy among the forecasted values and the actual target values, while also ensuring a specified margin of tolerance around the regression plane (Manurung et al., 2023). Equation 15-21 delineates the successive stages of the Support Vector Regression (SVR) approach.

$$f\,(x) = \widehat{\omega\,\Phi}\,(x) + b \tag{15}$$

$$\mathrm{L}(f\ (\mathrm{x}), \mathrm{y}, \varepsilon) = f(x) = \begin{cases} 0 & |\mathrm{y} - f\ (\mathrm{x})| \le \varepsilon \\ |\ y - f\ (\mathrm{x})| - \varepsilon & |\mathrm{y} - f\ (\mathrm{x})| > \varepsilon \end{cases} \tag{16}$$

$\begin{cases} Min. \dfrac{1}{2}\lVert\omega\rVert^2 + C\sum_{i=1}^{n}\xi_i \\ sub.t. \begin{cases} y_i - \omega\Phi(x_i) - b \le \varepsilon + \xi_i \\ -y_i + \omega\Phi(x_i) + b \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \end{cases}$	(17)
$\omega^* = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\,\Phi(x_i)$	(18)
$b^* = \dfrac{1}{N_{nsv}} \left\{ \sum_{0<\alpha_i<C}\left[y_i - \sum_{x_i \in SV}(\alpha_i - \alpha_i^*)K(x_i, x_j) - \varepsilon\right] + \sum_{0<\alpha_i<C}\left[y_i - \sum_{x_j \in SV}(\alpha_j - \alpha_j^*)K(x_i, x_j) + \varepsilon\right] \right\}$	(19)
$K(x_i, x_j) = \exp\left(-\frac{\lVert x - x_i\rVert^2}{2\sigma^2}\right)$	(20)
$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i, x) + b^*$	(21)

Support Vector Regression (SVR) seeks to determine a linear regression function, denoted as f(x), in a space with a large number of dimensions. Let x represent an element from the set of real numbers, and let it serve as the sample vector. The function's mapping has non-linear characteristics. The incorporation of a linear insensitivity loss function, represented as L(f (x), y, ε), enhances the robustness of the optimization problem. Equation 16 is a quantitative depiction of the loss function. Equation 17 entails the depiction of the input vector and output value using the variables x_i and y_i, correspondingly. The variables in question are associated with a certain serial number, indicated by the symbol i. The variables x_i and y_i belong to the set of real numbers, denoted as R. The input vector is d-dimensional. In this situation, the variable d represents the number of elements in an input vector. n denotes the number of training samples. The symbol ε denotes the degree of accuracy in regression analysis. The variable C represents a penalty factor that quantifies the severity of the penalty applied to a data sample when its mistake surpasses the threshold value ε. The slack variables ξ_i and ξ_i^* are used to penalize the complexity of the fitting parameters. To determine the values of variables a and b, it is imperative to address the optimization problem as delineated in Equation 18 and 19. The variable N_nsv represents the number of support vectors that have been explicitly identified. The Lagrange multipliers, represented by α_i and α_i^*, must satisfy the condition of being greater than or equal to zero. Equation 20 in this particular circumstance employs the kernel function, represented as K(x_i,x_j). The Gaussian kernel function, known for its exceptional capacity to generalize, is selected. Equation 21 denotes the ultimate regression function. The SVR model employed a kernel function. The parameters utilized were 'kernel': 'linear', 'C': 1, 'gamma': 'scale'.

4. Findings

This study has a time period of 149 months, spanning from January 2012 to May 2024. The analysis comprised 149 months of data on total deposits opened in USD, M3 money supply, total imports and exports, unemployment rate, gold price, PPI, CPI, CBRT dollar reserves, and USD/TL exchange rate. The study employed XGBoost, Random Forest, LightGBM, LSTM, and SVR techniques to predict the USD/TRY.

The study incorporated five distinct approaches. The prediction algorithms being considered are LSTM, XGBoost, SVR, RF, and LightGBM. The model's effectiveness was assessed using several statistical metrics, including RMSE, MAE, MSE, R^2, and MAPE. The statistical parameters are computed using mathematical equations denoted as Equations 22, 23, 24, 25, and 26.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)}{N}} \quad (22)$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{N} \quad (23)$$

$$MSE = \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)}{N} \quad (24)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \mu)^2} \quad (25)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| x100 \quad (26)$$

Training results for the methods used in the research are shown in Table 3.

Table 3.

Training Results

Model	R^2	**MAE**	**MAPE**	**MSE**	**RMSE**
XGBoost	0.9923	0.0143	0.0752	0.000511	0.0226
RandomForest	0.9981	0.0051	0.0172	0.000125	0.0112
LightGBM	0.9968	0.0084	0.0439	0.000215	0.0147
LSTM	0.9966	0.0105	0.0661	0.000224	0.015
SVR	0.9354	0.0608	0.5447	0.00431	0.0656

Upon examining Table 3, it becomes evident that the RandomForest model demonstrates superior performance based on the training outcomes. The model's coefficient of determination ($R2$ score) is 0.9981, indicating an exceptional match by accounting for 99.81% of the variability in the training data. The model's predictions are highly accurate, as evidenced by the very low errors, with an MAE value of 0.0051 and a MAPE value of 1.72%. In addition, the (MSE) is 0.000125 and the (RMSE) is 0.0112. These values suggest that the model's prediction mistakes are extremely small, indicating a high level of accuracy. The XGBoost model exhibits exceptional performance. The model achieved a $R2$ score of 0.9923, indicating that it can explain 99.23% of the variation in the training data. The (MAE) is 0.0143 and the (MAPE) is 7.52%, suggesting that the model's predictions are highly accurate. This model, boasting an MSE (Mean Squared Error) score of 0.000511 and an RMSE (Root Mean Squared Error) value of 0.0226, garners attention due to its impressively low error rates. The LightGBM model demonstrates excellent performance. The model achieved a $R2$ score of 0.9968, indicating that it can explain 99.68% of the variance in the training data. The MAE score of 0.0084 and the MAPE value of 4.39% suggest that the model's predictions are typically precise. The model has low error rates, as indicated by the MSE value of 0.000215 and the RMSE value of 0.0147. The LSTM model accurately accounts for 99.66% of the variability in the training data, as indicated by a high $R2$ value of 0.9966. The model demonstrates high accuracy in its predictions, as seen by its MAE value of 0.0105 and MAPE value of 6.61%. The model demonstrates good performance and low mistakes, as evidenced by the MSE value of 0.000224 and the RMSE value of 0.015. Conversely, the SVR model has inferior performance compared to other models. The $R2$ score of 0.9354 indicates that 93.54% of the variance in the training data can be explained. This particular model has greater error rates, as indicated by its (MAE) value of 0.0608 and (MAPE) value of 54.47%. The Support Vector Regression (SVR) model exhibits higher error rates and inferior performance compared to other models, as indicated by its (MSE) value of 0.00431 and (RMSE) value of 0.0656. Overall, the RandomForest model demonstrates superior performance, while the XGBoost and LSTM models exhibit similarly impressive performance. Although the LightGBM model has satisfactory performance, the SVR model exhibits inferior performance in comparison to other models.

Table 4 illustrated the test results of the methods used in the study.

Table 4.

Testing Results

Model	R^2	**MAE**	**MAPE**	**MSE**	**RMSE**
XGBoost	0.9887	0.0136	0.0662	0.000748	0.0273
RandomForest	0.9983	0.0067	0.0262	0.000109	0.0105
LightGBM	0.9926	0.0121	0.0457	0.000492	0.0222
LSTM	0.996	0.0107	0.0652	0.000264	0.0163
SVR	0.9244	0.0662	0.5735	0.004997	0.0707

Upon analyzing Table 4, it becomes evident that the RandomForest model exhibits the most superior performance. The model's $R2$ score is 0.9983, indicating that it accounts for 99.83% of the variance in the test data. The RandomForest model demonstrates exceptional predictive accuracy, as evidenced by its MAE value of 0.0067, MAPE value of 2.62%, MSE value of 0.000109, and RMSE value of 0.0105. These remarkably low error rates distinguish it from other models, confirming its outstanding success in making predictions. The LSTM model demonstrates exceptional performance. Having a $R2$ score of 0.996, it accounts for 99.6% of the variability in the data. The LSTM model demonstrates excellent performance with minimal error rates, as indicated by its MAE value of 0.0107, MAPE value of 6.52%, MSE value of 0.000264, and RMSE value of 0.0163. The XGBoost model exhibits excellent performance. The model's $R2$ score is 0.9887, indicating that it accounts for 98.87% of the variability in the data. XGBoost exhibits a (MAE) value of 0.0136, a (MAPE) value of 6.62%, a (MSE) value of 0.000748, and a (RMSE) value of 0.0273. Although XGBoost demonstrates marginally greater error rates compared to other models, it still achieves commendable performance. The LightGBM model has excellent performance. The model's $R2$ score is 0.9926, indicating that it accounts for 99.26% of the variability in the data. LightGBM stands out for its exceptional performance, as evidenced by its MAE value of 0.0121, MAPE value of 4.57%, MSE value of 0.000492, and RMSE value of 0.0222. These remarkably low error rates make it highly appealing. Nevertheless, the SVR model has inferior performance compared to other models. The $R2$ score of 0.9244 indicates that it accounts for 92.44% of the variability in the data. The Support Vector Regression (SVR) model exhibits higher error rates and inferior performance compared to other models, as indicated by its (MAE) value of 0.0662, (MAPE) value of 57.35%, (MSE) value of 0.004997, and (RMSE) value of 0.0707. Overall, the RandomForest model has the lowest error rates and demonstrates the maximum performance, while the LSTM and XGBoost models also exhibit commendable performance. Although the LightGBM model has satisfactory performance, the SVR model exhibits inferior performance in comparison to other models.

In this study, five-fold cross-validation method was used for the validation process of the models. This method was preferred to test the generalizability of the models and to prevent over-learning. With five-fold cross-validation, the performance of each model was evaluated and compared more accurately. Table 5 illustrates the five-fold cross-validation outcomes of the methods used in this study.

Table 5.

Kfold 5 Results

Model	R^2	**MAE**	**MAPE**	**MSE**	**RMSE**
XGBoost	0.9876	0.0199	0.113	0.00106	0.0325
RandomForest	0.9914	0.0103	0.034	0.000613	0.0236
LightGBM	0.9733	0.0199	0.0835	0.00209	0.0392
LSTM	0.9951	0.0112	0.0565	0.000308	0.0167
SVR	0.9283	0.0612	0.5515	0.00443	0.0663

RandomForest is the best performing model according to Kfold 5 results. The R^2 score is 0.9914, explaining 99.14% of the variance in the data. RandomForest, with its MAE value of 0.0103, MAPE value of 3.4%, MSE value of 0.000613 and RMSE value of 0.0236, has very low error rates compared to other models, which shows that the model is extremely successful in predictions. The LSTM model also shows very high performance. R^2 score is 0.9951, explaining 99.51% of the data variance. LSTM, with its MAE value of 0.0112, MAPE value of 5.65%, MSE value of 0.000308 and RMSE value of 0.0167, generally shows high performance with low error rates. In particular, MSE and RMSE values are quite low, emphasizing the accuracy of the model. The XGBoost model also performs well. R^2 score is 0.9876, explaining 98.76% of the data variance. With MAE value of 0.0199, MAPE value of 11.3%, MSE value of 0.00106 and RMSE value of 0.0325, XGBoost has slightly higher error rates compared to other models, but its overall performance is quite good. The LightGBM model also performs well. R^2 score is 0.9733, explaining 97.33% of the data variance. LightGBM, with its MAE value of 0.0199, MAPE value of 8.35%, MSE value of 0.00209 and RMSE value of 0.0392, attracts attention with its low error rates, but exhibits slightly lower performance compared to other models. The SVR model shows lower performance than other models. R^2 score is 0.9283, explaining 92.83% of the data variance. SVR, with its MAE value of 0.0612, MAPE value of 55.15%, MSE value of 0.00443 and RMSE value of 0.0663, has higher error rates and lower performance compared to other models. In general, RandomForest has the lowest error rates and shows the highest performance, while the LSTM model also performs quite well. The XGBoost and LightGBM models also perform well, but have slightly higher error rates compared to the RandomForest and LSTM models. The SVR model exhibits the lowest performance compared to other models.

When Tables 3, 4 and 5 are examined together, the RandomForest model shows the best performance in all three result sets. The LSTM model also generally exhibits high performance. The XGBoost and LightGBM models also perform well, but have slightly higher error rates compared to the RandomForest and LSTM models. The SVR model exhibits the lowest performance compared to other models.

5. Conclusion

Exchange rate forecasting plays an important role in economic and financial analysis. Especially in developing countries, the impact of exchange rate fluctuations on macroeconomic variables is quite evident. In developing countries like Turkey, exchange rate movements have a direct impact on many variables such as inflation rates, export and import balance, interest rates and economic growth. Effectively forecasting sudden changes in exchange rates provides a great advantage in planning countries' economic policies, developing risk management strategies in the business world and managing investors' portfolios. Therefore, studies on exchange rate forecasting have a wide range of interest both in academic and applied terms. From the perspective of the Turkish economy, the USD/TRY exchange rate stands out as an indicator that reflects the vulnerabilities of the country's economy and produces important results.

In recent years, the use of machine learning and deep learning techniques in exchange rate forecasting has gained importance due to its potential to increase forecast accuracy. These methods stand out with their ability to capture hidden patterns and complex relationships in time series. Thus, more successful results can be obtained in exchange rate forecasting than traditional methods. The use of machine and deep learning models in this field not only provides more accurate predictions, but also allows these models to examine the effects of variables on the exchange rate in more depth. Studies in the literature show that these methods are successful in exchange rate prediction. The aim of this study is to examine the relationships between Turkey's economic indicators and exchange rates and to evaluate the USD/TRY exchange rate prediction performance in the light of these indicators.

This study covers 149 months of data between January 2012 and May 2024. 149 months of data on total deposits opened in USD, M3 money supply, total imports and exports, unemployment rate, gold price, PPI, CPI, CBRT dollar reserves and USD/TL were included in the study. The study encompassed five separate methodologies. The candidate prediction algorithms under consideration are LSTM, XGBoost, SVR, RF, and LightGBM. The efficacy of the model was evaluated using various statistical indicators, such as RMSE, MAE, MSE, and R^2. Hyperparameter optimization was performed using the “randomsearch” algorithm for each model used in the study. In this way, in addition to higher accuracy and prediction performance, the risk of overfitting is prevented. According to the results obtained from the study, the best performance for training, testing and cross-validation sets was produced by the Random Forest model. Then comes the LSTM model. Although XGBoost and LightGBM models produced good predictions, they made predictions with higher errors than the results of Random Forest and LSTM models. The SVR model exhibited the poorest performance in the investigation. It has been observed that the results obtained from the study show better forecasting performance when compared to the studies on Dollar/TL exchange rate forecasting in the literature. In the study of Gümüş (2024), the average MAE value was obtained as 0.0941 and the MAPE value as 0.0326%. However, in this study, the RandomForest model showed better prediction performance by providing a much lower MAE value of 0.0103 and a MAPE of 0.034%. In addition, this model also obtained strong results in additional metrics with an MSE value of 0.000613 and an RMSE value of 0.0236. Similarly, in Tekin & Patır (2023) study, the USD/TRY exchange rate for the period 2009-2021 was estimated using an artificial neural network model. In this study, the MSE value was calculated as 0.0019355, the MAE value as 0.01738 and the MAPE value as 0.5137%. It was observed that the model exhibited a successful performance with an error rate of 0.5137% in exchange rate prediction, especially when the

MAPE value was taken into account. In this study, various machine and deep learning methods (XGBoost, Random Forest, LightGBM, LSTM and SVR) were used in the USD/TRY exchange rate prediction for the period 2012-2024. In particular, the Random Forest model showed the best performance in all metrics. Lower error rates were obtained than the artificial neural network model with an MSE value of 0.000613, a MAE value of 0.0103 and a MAPE value of 0.034%. In addition, the generalizability of the model was increased by using the K-Fold cross-validation method in this study. In the Tekin & Patır (2023) study, cross-validation was not applied. As a result, the Random Forest model used in this study showed superior performance than the Tekin & Patır (2023) artificial neural network model in terms of both lower error rates (MSE, MAE, MAPE) and generalizability with K-Fold cross-validation. In the study of Erbudak and Ata (2022), the Decision Tree model achieved successful results with values of R^2 = 1.00, MAE = 0.0097679, MSE = 0.00023164 and RMSE = 0.1522. However, cross-validation was not used in the model. The RandomForest model used in my study showed low error rates with results of R^2 = 0.9914, MAE = 0.0103, MSE = 0.000613 and RMSE = 0.0236. In addition, it provided stronger generalizability by testing with K-Fold cross-validation. It also provided higher accuracy in predictions by using MAPE, providing an error rate of 0.034%. As a result, the RandomForest model exhibited a more generalizable and consistent performance with cross-validation and low error rates.

As a result, it can be said that Random Forest and LSTM models for Dollar/TL exchange rate prediction produce better forecasting performance than both the other models used in this study and the studies conducted in the literature for Dollar/TL exchange rate forecasting. Forecasting exchange rates is essential in economic and financial analysis. Exchange rates are vital indicators that directly influence a nation's economic stability and its capacity to compete on the global stage. The effects of fluctuations in currency rates on macroeconomic variables is highly substantial, especially in developing countries such as Türkiye. The USD/TRY exchange rate is of great significance to the Turkish economy, and its fluctuations have far-reaching consequences. Utilizing machine learning and deep learning models in exchange rate forecasting offers several benefits that improve the accuracy and reliability of predictions. It is thought that the results obtained from this study will be useful for both investors and academics in predicting possible exchange rate movements. In particular, the Random Forest model can be used to forecast the Dollar/TL because it captures complex relationships between variables and has a low tendency to overfit. The performance of the SVR model can be increased by normalization and scaling of the data. Additionally, new and meaningful variables can be created by performing additional feature engineering in the data set. Economic indicators used in financial forecasting change over time. In future studies, the data set should be updated taking this situation into consideration. Additionally, the use of ensemble learning models can increase the success of predictions. Prediction performance can be improved with new hybrid models, especially where Random Forest and LSTM models, which gave the best results in this study, are used together.

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