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Forecasting Turkish Lira (TRY)/US Dollar (USD) Interest Exchange Rates Using Machine Learning Methodologies

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ABSTRACT Machine learning algorithms have become increasingly popular in recent years for analyzing financial data and predicting the exchange rate system. The aim of this paper was to construct an investment appreciation rate estimation model based on machine learning by estimating the Turkish lira/US dollar exchange rate. The forecasting model was developed using foreign exchange market data, namely the exchange rates in TL and USD at specific periods. The proposed model was estimated using machine learning methods such as Multilayer Perceptron (MLP), Linear Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Local Weighted Learning (LWL). The model's validity was established using TRY interest rates and the USD exchange rate. The data were analyzed using mean absolute error (MAE), directional accuracy (DA), mean square error (MSE), and root mean square error (RMSE). These metric results show that the proposed model is suitable for both prediction and investment data.

KEYWORDS: Machine Learning, Exchange Rate Prediction, Regression, MLP, SVM, RF, and LWL.

1. INTRODUCTION

The exchange rate is one of the most important economic indicators of a country's economy. When it comes to making financial decisions, investors and businesses pay close attention to exchange rates. International investors pay close attention to the exchange rate when making investment decisions because it has the potential to cause financial damage. Many factors, such as the international trade balance, central bank fiscal policies, and exchange rates, affect the value of foreign currency rates. Cryptographic forecasting is very important in the economic field and has been studied for quite some time [1]. In this capacity, forex market forecasts are critical to investors and businesses [2] [3]. Financial data analysis can be divided into two distinct categories: fundamental and technical analysis. Fundamental analysts use macroeconomic difficulties to forecast problems in financial markets, while models based on historical data focus only on past data. Fundamental macroeconomic analysis and sound technical financial analysis are two commonly used types of financial analysis. While the former focuses on the crucial market characteristics, the latter is much more extensive and detailed [4]. Technical analysis assumes that the behavior of a financial market reflects the emotions of investors. In sound technical financial research, various techniques are used to determine how an investor's sentiment evolves over time. For example, "moving averages" represent trends within a particular investment. On the other hand, macroeconomic fundamental analysis is based on the idea that changes in the macroeconomic environment will lead to changes [5]. Pricing methods based on model characteristics are notoriously difficult to forecast. As a result, investors know that such investments require some risk while they actively seek the maximum potential return. As research on the potential downsides of private equity, venture capital, and other illiquid investments has shown, risk-averse investors are better served by investing in more liquid investments. These investors may be looking for the highest potential return on their investments. Because of the unpredictability of these investments, some believe that the risk is always greater than the potential gain [6]. According to the technical analysis, well-known statistical models such as the autoregressive moving average and generalized autoregressive conditional change in variance (GARCH) [7] [8] do not satisfy the nonlinearity of time series data. They also do not account for recurrent trends in time series data. Recurrent neural architecture models can represent recurrent patterns in time series data by using time series based gradient descent learning. Several advanced machine learning technologies (ML) [9-12] have recently led to better results in predicting time series. Artificial neural networks are one of them (ANN). For financial time series data, ANN has proven to be an excellent choice [10]. The success of ANNs is largely attributed to the fact that they find a nonlinear relationship without prior understanding of the information and have the ability to train and predict themselves. Machine learning has changed the game [11]. ANN is essentially a network of nodes organized into layers and connected by links with associated weights. To train the network, some training data is fed into the network. This training helps in selecting a decision function from a set of functions represented by the ANN structure. This decision function can be determined by assigning sufficient weights to the network. The error is reduced if the weights are chosen correctly [12]. Backpropagation Neural Network is a typical approach for error reduction, where the error is fed backwards to change the weights, resulting in error minimization [13].With good features and a suitable network model, such as a forward or backward model, high accuracy can be achieved. The aim of this project is to develop a machine learning model to predict the exchange rate of the Turkish Lira to the US Dollar using machine learning techniques. The main purpose is to develop an intelligent model that incorporates critical variables such as the TRY crude interest rate and the USD price index. The exchange rate is particularly susceptible to fluctuations in investor sentiment as it reacts to macroeconomic developments. Therefore, we have adopted an ML approach that is immune to sensitivity changes. Our data set includes nonlinear time-dependent data sets. The years 2010 to 2021 are covered by these datasets. The dataset has ten matched columns: Date, one-month Turkish lira interest rates, three-month Turkish lira interest rates, six-month Turkish lira interest rates, one-year Turkish lira interest rates, one-month USD interest rates, three-month Turkish lira interest rates, six-month USD interest rates, and one-year USD interest rates are all included [14].

The remainder of the article is organized as follows: Section 2 discusses the proposed methodology, algorithm, and procedures; Section 3 explains the experimental work and results; and Section 4 discusses the conclusion.

2. PROPOSED METHODOLOGY

Due to its ability to handle nonlinearity and adapt to noise, ANN has been widely used as an alternative for autonomous prediction in recent years [1] [15]. ANN -based forecasting has been offered as a very effective method for financial forecasting. The main objective of the study is to develop a forecasting model that can predict exchange rate fluctuations. The paper proposes the use of ML algorithms-based time series forecasting models. After studying the data and comparing it with many other machine learning techniques, we found that LR is the best acceptable model for the forecasting problem. The dataset containing the interest rates between the Turkish lira and the dollar in certain time intervals and in certain periods, as well as the buying and selling information of dollars, is used in this model. Figure 1 summarizes the proposed approach to predict the USD-TRY conversion rate and interest rates between 2010 and 2021. The software Weka [16] was used for the analysis carried out here.

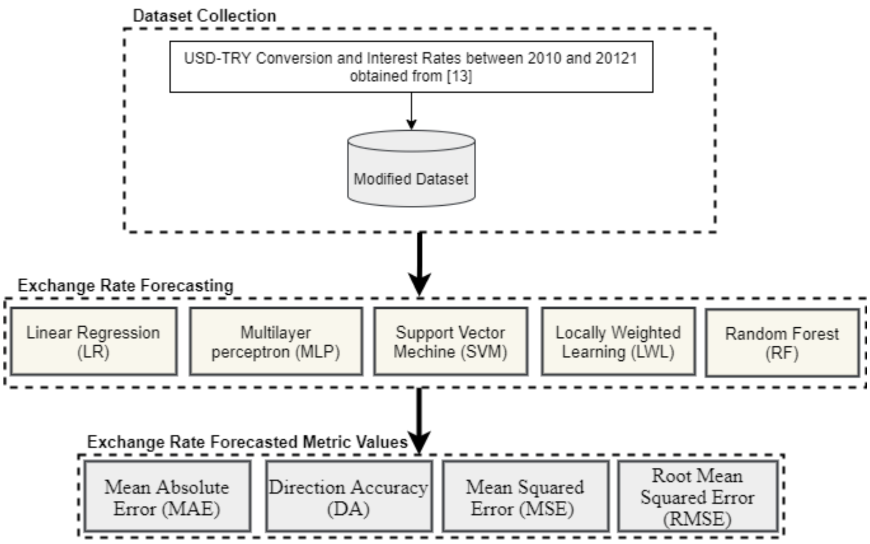

Figure 1. The overview of the proposed methodology

In this paper, ML techniques are used to estimate the exchange rate between the Turkish lira and the US dollar using time series analysis, focusing on exchange rate estimates. Estimation is a statistical technique for predicting future values in a time series using past data. The purpose of estimation is to offer values for future data that are uncertain. These projections and estimates can then be used to prepare for the future, make forecasts, and create budgets for future revenues and expenses. The proposed solution is based on a machine learning model that forecasts the future interest rate of the currency using data from [14]. The input data consists of the changes in the interest rates for the USD and the Turkish lira over the last 1, 3, 6, and 12 months. The downward forecast is based on the change in the buying and selling rates of the dollar.

2.1 Dataset

The data used here is from the Kaggle website [14]. From this resource, changes and details about the data can be obtained. It is a dollar buy/sell dataset that illustrates how individuals respond to changing circumstances as a function of TL/dollar interest rates. The data used ranges from July 2010 to July 2021 and consists of 134 rows and 11 columns (characteristics). These include the following: 1-month Turkish lira interest rates, 3-month Turkish lira interest rates, 6-month Turkish lira interest rates and 1-year Turkish lira interest rates, 1-month USD interest rates, 3-month USD interest rates, 6-USD interest rates and 1-year USD interest rates. It is composed of the USD/TRY buy and sell conversion ratios [14].

2.2 Random Forest

Random forests are collections of tree predictors where each tree is determined by the values of a uniformly distributed random vector. As the number of trees in a forest increases, the generalization error approaches a threshold. The generalization error of a forest of tree classifiers depends on the strength of the individual trees in the forest and their relationship to each other. Random forests are an efficient tool for prediction. They are not subject to overfitting by the law of large numbers. Because of their moderate predictability, they are accurate classifiers and regressors. In addition, the framework provides information about the predictive ability of the random forest, such as the strength of each predictor and their correlations. By using out-of-bag estimates, one can obtain actual numbers for strength and correlation that would otherwise have remained speculative [17]. It is calculated as in Eq. 1.

$$RF = E_{X,Y}(Y - h(X)^2 \tag{1}$$

Random forests are generated for regression by growing trees based on a random vector such that the tree predictor h(x,) contains numerical values rather than class labels. The output values are numerical, and we assume that the training set is randomly selected from the distribution of the random vector Y, X. The mean squared generalization error for each numerical predictor h(x) is computed by averaging the trees h (x, k) over k.

2.3 Linear Regression

Linear regression is a modeling and analysis tool for many different types of interactions between two or more variables. This variable may be the price of a stock in the financial market, the growth of a biological species, or the possibility of the discovery of a gravitational wave. A linear regression model describes the relationship between one or more independent variables, X, and a dependent variable, y. The dependent variable is also called the response variable. Continuous predictor variables are also called covariates, and categorical predictor variables are called factors. The design matrix is usually referred to as the X matrix of observations on the predictor variables [9].

2.4 Multi-layer Perceptron

A multilayer perceptron (MLP) is a variant of a feedforward neural network. As shown in Figure 2, this network has an input layer, an output layer, and a hidden layer. As in a feedforward network, data in an MLP is passed from the input layer to the output layer. The MLP neurons are trained using the backpropagation learning method. MLPs are supposed to be able to estimate any continuous function and solve problems that are linearly inseparable [18][19].

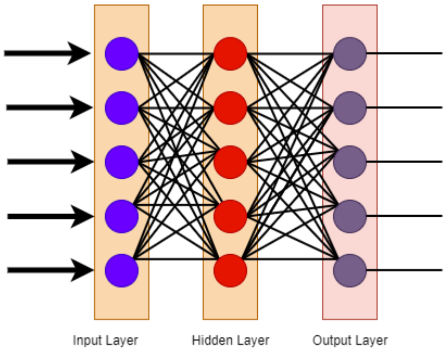

Figure 2. An MLP with a single hidden layer is shown schematically.

During the training phase, neurons in each layer are connected to neurons in the next layer by a weighted connection. In the buried layer, activation functions are used to accurately evaluate the features of the input data. Backpropagation training is a method for solving a variety of estimation problems using supervised learning. The following is an example of the output of an ANN layer.

$$a^i = f(\sum_{j=1}^{N} w_{ij}x_j + b^i) \tag{2}$$

Where w_{ij} and b denote the weights and bias values, respectively, N denotes the number of input neurons, and f denotes the activation function. More information about the MLP technique can be found here [20].

2.5 Support Vector Machine

Support Vector Machine (SVM) is one of the most widely used supervised learning algorithms in machine learning for classification and regression applications. Vladimir Vapnik [21] and colleagues first proposed SVM analysis in 1992, and it is a well-known machine learning technique for classification and regression. The goal of SVM is to find the optimal line or decision boundary for classifying the n-dimensional space, so that more data points can be classified easily in the future. SVM selects endpoints or vectors that help in forming the hyperplane. These extreme states are called support vectors, and the technology is called support vector machines. Since it is based on kernel features, SVM regression is a non-parametric approach. See [22] for more details.

2.6 Locally Weighted Learning

Locally weighted regression (LWR) is a nonparametric, memory-based regression technique that performs regression around a point of interest using only "local" training data. The techniques monitor and analyze the training data to make predictions. It is a method of fitting all training data to the domain around a query sample. Processing of the training data is often postponed until the target value of a query sample needs to be determined, as LWR is a type of lazy learning [23] [24].

2.7 Evaluation Metrics

Numerous metrics have been used to measure the efficiency of learning algorithms used to effectively predict the direction of the forex market. We evaluated the data in this study using four metrics: MAE, DA, RMSE, and MSE. These criteria can be used to evaluate investment data in terms of the performance of the algorithms used to estimate TL and USD exchange rates in the proposed model.

2.7.1 Mean Absolute Error (MAE)

Mean absolute error (MAE) is the most important indicator for measuring predictive accuracy. Unlike relative error, absolute error is the difference between expected and actual values. The MAE of a continuous variable is used to evaluate its accuracy. The mean absolute error of a prediction indicates the magnitude of the error that, on average, can be expected in the prediction. The mean absolute error estimates the average magnitude of error in a collection of predictions regardless of their direction. The MAE of a sample is defined as the average of the absolute differences between predicted and observed values, with all individual deviations weighted equally. The MAE and the RMSE can be used to characterize the model prediction error with respect to the target variable [25] [26]. This error is the average estimated error without considering the directions of the predicted values. Each estimated difference has the same weight and can be determined in the following way.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{3}$$

Absolute errors are defined as "$|y_i - \hat{y}_i|$" and are the sum symbol.

2.7.2 Directional Accuracy (DA)

Measures of directional accuracy (DA) include both realized and magnitudes of directional changes in exchange rates. These metrics are robust to outliers and provide an economically interpretable loss/gain functional framework in a critical decision-theoretic environment for traders and investors.

DA is a metric that measures the predictive accuracy of a forecasting method. It compares the expected direction (up or down) with the actual direction. The following formula is used to define DA [27] [28].

$$DA = \frac{1}{N}\sum_{t} 1_{sign\,(A_t - A_{t-1})} = \\ = sign(F_t - A_{t-1}) \tag{4}$$

Where A_t is the current value at time t and F_t is the predicted value at time t. N is the number of prediction points. Sign is a function.

2.7.3 Mean Squared Error (MSE)

The mean squared error (MSE) can be used to measure the degree of fit between a regression curve and a collection of points. The MSE statistic is used to quantify the uncertainty associated with statistical models. It is defined as the difference in mean squared values between the observed and expected values. As the accuracy of the model decreases, so does its value. For example, the mean squared error reflects the mean squared residual of the regression [29]. The MSE is calculated using the following formula.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

Where, y_i is the i-th observed value. $\hat{y}$ is the corresponding predicted value. N is the number of observations.

2.7.4 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is commonly used to quantify the discrepancy between what a model predicts and what is actually observed in the environment under study. The RMSE converts these individual variances into a single measure of predictive capacity, the residuals. The RMSE is a statistic that indicates the magnitude of the difference between two sets of data. In other words, the root mean square error is used to determine the difference between a predicted outcome and an actual outcome. You can use this metric to determine the average accuracy of your predictions [28] [29]. Calculate it using the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{6}$$

In this case, y_i represents the actual data, while $\hat{y}_i$ represents the predicted data. N is the number of observations.

3. EXPERIMENTAL WORKS AND RESULTS

The data used in these experiments cover the period from July 2010 to July 2021 and include historical interest rates and USD/TRY conversion rates. Using the data from the experiments conducted in our research, we performed a financial sensitivity analysis [14]. Based on the performance of the algorithms used to analyze the data, various metric calculation results were evaluated and presented in the form of a table (Table 1). In this study, all the data were analyzed as training data and the results were compared in this way. 1, 3, 6 months, 1-year Turkish lira and USD interest rates as well as USD/TRY purchase conversion rate and USD/TRY sale conversion rate consist of the data used in the proposed model and calculated periodically as time series. The table shows the evaluation indicators for the models that perform best.

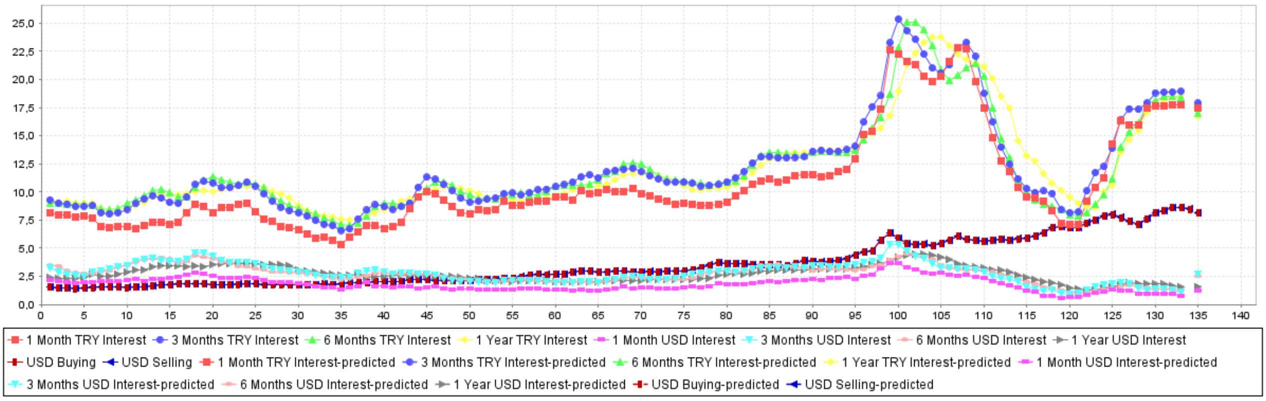

Figure 3. Future forecast for: 1 Month TRY Interest, 3 Month TRY Interest, 6 Month TRY Interest, 1 Year TRY Interest, 1 Month USD Interest, 3 Month USD Interest, 6 Month USD Interest, 1 Year USD Interest, USD Buying, USD Selling

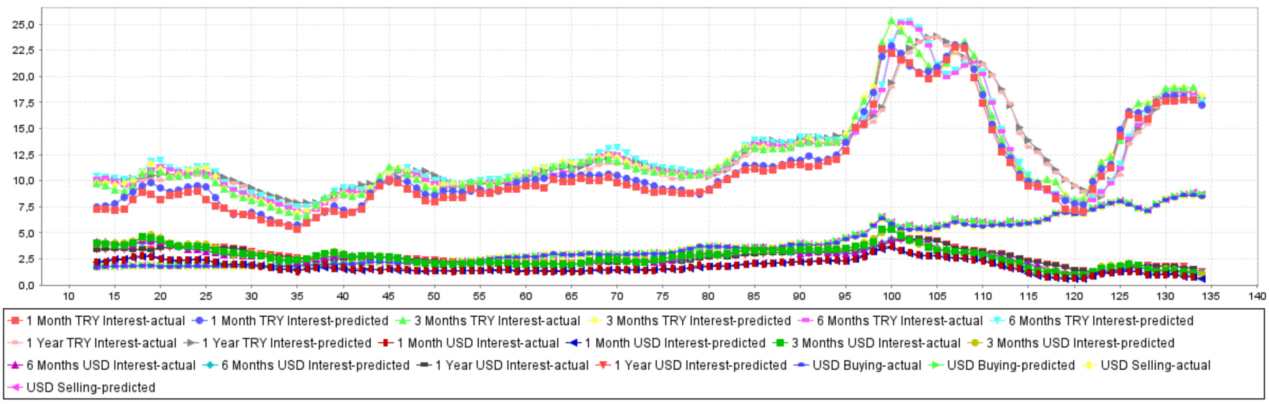

Figure 4. 1 step ahead predictions for: 1 Month TRY Interest, 3 Month TRY Interest, 6 Month TRY Interest, 1 Year TRY Interest, 1 Month USD Interest, 3 Month USD Interest, 6 Month USD Interest, 1 Year USD Interest, USD Buying, USD Selling

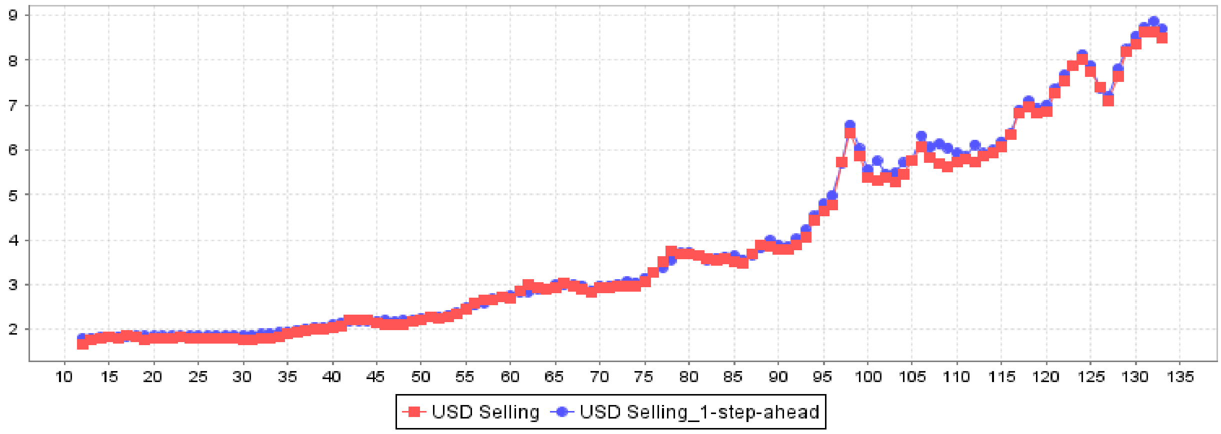

Figure 5. 1step-ahead prediction for USD Selling

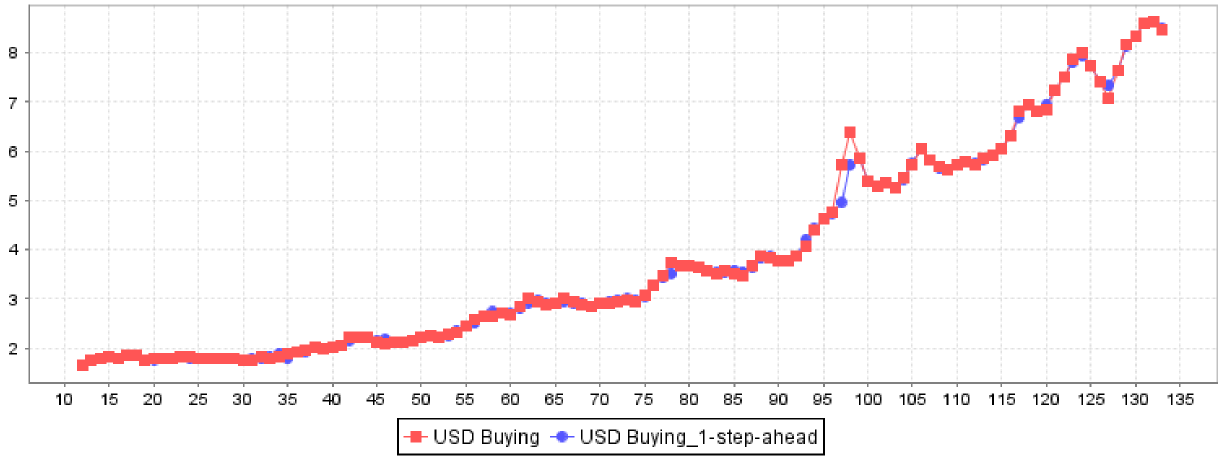

Figure 6. 1step-ahead prediction for USD Buying

The effectiveness of the algorithms was evaluated in this study using the computational results of the forecasting model DA, MAE, MSE and RMSE for time series data on dollar and TL interest rates. The future forecast is shown in Figure 3, while the 1-step forecast is shown in Figure 4. In Figure 5, USD selling is predicted by one step, while in Figure 6, USD buying is predicted by one step ahead. According to these figures, interest in buying and selling USD is steadily increasing. Long-term interest rates in both TL and USD are higher than short-term rates. By and large, the six-month USD rate is the ideal rate. Table 1 shows descriptive statistics for all datasets that illustrate the effectiveness of the learning methods used here, as well as the prediction rates for dollar purchases and sales. When we consider the performance of the algorithms in predicting the change in TRY and USD interest rates, "Linear Regression" yields the best results (100%). The realized estimate for dollar purchases was obtained by Random Forest with 85.53%, MLP with 70.48%, SVM with 84.3% and LWL with 75.06%. For sales in USD, RF achieved 76.95%, LR 100%, MLP 69.22%, SVM 83.47% and LWL 76.85% success. The table also includes the results obtained for various predictive metrics (MAE, RMS, RMSE) and time series. These are additional results of exchange rate estimation. All models show that MAE, RMS and RMSE decrease when sensitivity is included in the model.

Table 1. Evaluation on training data

Algorithms		1 Month TRY Interest	3 Month TRY Interest	6 Month TRY Interest	1 year TRY Interest	1 Month USD Interest	3 Month USD Interest	6 Month USD Interest	1 year USD Interest	USD Selling	USD Buying
Random Forest	**MAE**	0.2108	0.2106	0.209	0.1181	0.0345	0.0526	0.0437	0.0288	0.0459	0.0509
	DA	87.5	89.16	88.33	93.33	86.6	88.33	91.26	86.67	**76.95**	**80.53**
	MSE	0.3332	0.3172	0.3371	0.1643	0.047	0.0771	0.0579	0.0401	0.0709	0.0843
	RMSE	0.1111	0.1006	0.1136	0.027	0.0022	0.0059	0.0034	0.0016	0.005	0.0071
Linear Regression	**MAE**	0	0	0	0	0.0797	0	0	0	0	0
	DA	97.5	100	100	98.33	58.43	98.33	96.67	93.33	**100**	**100**
	MSE	0	0	0	0	0.1001	0	0	0	0	0
	RMSE	0	0	0	0	0.01	0	0	0	0	0
Multi-layer Perceptron	**MAE**	0.4353	0.2145	0.3067	0.3508	0.0718	0.102	0.0769	0.0415	0.0932	0.0931
	DA	75	87.5	83.33	82.5	63.33	75	81.67	78.34	**69.22**	**70.48**
	MSE	0.5204	0.2695	0.3646	0.4017	0.091	0.1248	0.0967	0.0562	0.1248	0.1247
	RMSE	0.2708	0.0727	0.1329	0.1613	0.0083	0.0156	0.0093	0.0032	0.0156	0.0156
Support Vector Machine	**MAE**	0.1675	0.1042	0.0645	0.0585	0.0456	0.0411	0.0302	0.0205	0.0348	0.0354
	DA	79.67	89.17	91.66	95	73.34	85.84	83.32	81.66	**83.47**	**84.3**
	MSE	0.3833	0.2474	0.1185	0.129	0.096	0.1188	0.0663	0.0427	0.1016	0.103
	RMSE	0.147	0.0612	0.0141	0.0166	0.0092	0.0141	0.0044	0.0018	0.0103	0.0106
Locally Weighted Learning	**MAE**	0.0397	0.0418	0.0386	0.0386	0.0049	0.0076	0.007	0.0062	0.0286	0.0264
	DA	87.5	94.16	93.33	90.83	93.33	93.34	91.66	89.16	**76.85**	**75.06**
	MSE	0.0599	0.0577	0.0565	0.0562	0.008	0.0116	0.0113	0.0103	0.0405	0.0351
	RMSE	0.0036	0.0033	0.0032	0.0032	0.0001	0.0001	0.0001	0.0001	0.0016	0.0012

4. CONCLUSION

The exchange rate is an important economic indicator of the health of a country's economy. Many elements affect the value of exchange rates, including the balance of international trade, central bank fiscal policy, and exchange rates themselves. Forecasts for the foreign exchange market are critical for investors and companies operating in this sector. According to technical analysis, the activity of a financial market reflects the emotions of investors. The aim of this paper is to build a machine learning model to predict the exchange rate of the Turkish lira against the US dollar using technical analysis. The prediction model has been built based on data from the foreign exchange market, namely the exchange rates of the Turkish lira and the US dollar over certain periods of time. Machine learning techniques such as MLP, LR, SVM, RF and LWL are used to estimate the proposed model. The data was analyzed using MAE, DA, MSE and RMSE. Hence, we believe that our research will benefit risk averse investors by providing basic macroeconomic analysis data that will help investors to make decisions on private equity, venture capital and other illiquid investments.

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