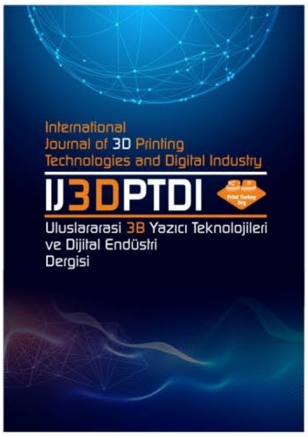

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FORECASTING CURRENT EXCHANGE AND GOLD RATES WITH HYBRID MODELS USING TIME SERIES AND DEEP LEARNING ALGORITHMS

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ABSTRACT

The flexibility and volatility experienced in exchange rates affect many financial activities in the world. In order to follow this situation, countries and multinational companies need to follow financial indicators in the world economy. There is a need for important decision systems that will follow all these systems with a reliable prediction model together with the developing technology. In this study, deep learning-based models that will accurately predict the movement of gold, dollar, and euro exchange rates are proposed. Time Series methods were used to analyze the data and make predictions. In addition to deep learning models such as LSTM, GRU, Bi-LSTM and RNN, hybrid models of these methods were also used to compare their prediction performances. The data set includes USD/TRY and EUR/TRY exchange rates and monthly prices of bullion gold in Turkish Lira. Data between the years 2000-2024 were included in the analyses, and a six-month future prediction of each rate was also made. In the study, the best results were obtained with a 98.39% f1 score in gold rate prediction with the GRU-RNN hybrid model. It was observed that hybrid models in particular provided higher accuracy in predictions in general. The findings show that optimizing model parameters has a significant impact on the success of financial forecasts.

Keywords: Deep Learning, Time Series Models, Artificial Intelligence, Foreign Exchange Prediction, Hybrid Models, Data Mining

1. INTRODUCTION

Exchange rates can be considered not only as an individual investment tool for companies that have close commercial relations with the outside world, but also as an important investment and economic indicator tool for the economies of countries. Countries and multinational companies can use exchange rates as one of the most important financial indicators to maintain their economic relations with the outside world [1]. This could bring the global foreign exchange market to a significant position in the world, so that exchange rates can respond quickly to market conditions [2]. While the Dollar and Euro are among the most used foreign exchange types in international trade and borrowing in Turkey, gold can stand out as an important store of value for both individual investors and central bank reserves. Fluctuations in exchange rates are among the critical factors that directly affect inflation, import and export balance in the Turkish economy. Gold is a widely preferred investment tool, but it also stands out as an asset that can be quickly affected by economic fluctuations and politics [3]. Gold, which has a wide range of uses in many industries such as electronics, aviation, medicine and jewelry, is considered a precious metal due to its properties as both a commodity and a monetary asset [4]. It also attracts great interest from individual investors, institutional investors and governments. As a result of changes in the exchange rate of a currency, the economy and trade are affected, inflation can increase, and the global economy is suppressed or stimulated.

The importance of disciplines such as machine learning (ML) and deep learning (DL) has been increasing over the years, and a lot of model inspired by these fields can supply solutions to today's complex problems as well as open the doors to new research areas. The innovations provided by these technologies, especially in financial markets, can be quite remarkable. As mentioned before, the foreign exchange market is easily affected by external conditions such as trade, peopolitical situations, economic indicators and market sentiment. This situation causes exchange rates to generally exhibit complex and fluctuating structures, makes difficult to achieve best accuracy rates in forecasting processes [5]. However, machine learning-based models can be important to overcome these difficulties.

In this study, it is aimed to estimate the value of dollar (USD), euro (EUR) and gold against Turkish Lira (TL) by using deep learning based methods for time series analysis. In addition to DL models such as Long Short Term Memory (LSTM), Recurrent Neural Networks (RNN), Closed Recycled Units (GRU) and Bi-LSTM, hybrid models of these methods will be used and their prediction performances will be compared. This provides a comprehensive framework to understand the advantages and disadvantages of existing methods. In addition, gaps in the literature will be illuminated by determining which model or hybrid approach performs better under which conditions. The lack of much information in the literature for performance of hybrid models provides a new reference point for this study. This study provides applicable results especially for market players, investors and financial analysts. The application of hybrid models in this study examines whether better results can be achieved compared to traditional approaches. The limited availability of information on the accuracy of hybrid models in the literature makes this study a new reference point. The findings of this research aim to provide practical insights, particularly for market participants, investors, and financial analysts.

1.1. Literature Review

Kilimci et al. [6] proposed to predict the final price of the BTC/USDT exchange rate in their study. Moreover, in addition they used statistical indicators, and considered data such as BB (Bollinger Band) and MA (Hourly Moving Average) as a feature set. Mohammad J. Hamayel et al [7] recommended three different RNN-based model to see the price of popular cryptocurrencies.

Table 1. Literature Review

Articles	Data	Method	Model	Rmse	Mae	Mape
[8]	USD	They proposed using sentiment analysis and time series analysis together.	ARIMA	-	0.0472	2.7144
[9]	GOLD	They proposed using time series analyzes.	LSTM Bi-LSTM GRU	61.728 76.711 87.425	48.85 61.53 71.24	3.48 4.24 4.91
[10]	VESTEL (share)	They proposed using deep learning methods.	RNN CNN	0.3263 0.086	- -	- -
[11]	ASELSAN (share)	They proposed using deep learning methods with time series algorithms.	ARIMA LSTM GRU	- - -	0,0836 0,0213 0,0205	- - -
[11]	AKBANK (share)	They proposed using deep learning models.	ARIMA LSTM GRU	- - -	0,1066 0,0317 0,0257	- - -
[12]	GOLD	They proposed using time series methods based on sentiment analysis.	CNN LSTM CNN-LSTM	- - -	0,0850 0,1042 0,0969	4,9630 5,9920 5,5944
[13]	BIST100 (share)	They proposed using memory based machine earning method.	LSTM GRU	- -	- -	- -

[14]	USD	They proposed using a dual-layer LSTM.	SL-LSTM TLS-LSTM	0.007465 0.004251	0.00656 0.00336	- -
[15]	GOLD	They proposed using LSTM with time series.	LSTM	-	-	0.4867
[16]	EUR	They proposed using LSTM.	LSTM	0.0015	-	0.12

2.MATERIAL AND METHOD

2.1. Time Series

Time series analysis is the process of examining and modeling data collected over a specific period of time [17]. Such data provides important clues for predicting future values using past observations. So that time series methods were used to analyze data and make predictions.

In time series analysis; Features such as trends, seasonal changes and random fluctuations in the data can be identified and future values can be predicted using these features.

2.2. Data Set

The data set was obtained through the Electronic Data Distribution System (EVDS) of the Central Bank of the Republic of Türkiye (CBRT) on November 15, 2024 [18]. The data set includes USD/TRY and EUR/TRY exchange rates and monthly prices of gold bullion in Turkish Lira. Data between 2000 and 2024 were included in the analysis and the data were recorded in Excel format.

Each data set contains 300 data points. During the data pre-processing phase, missing data were filled in using the linear interpolation method as it was suitable for the time series. USD/TRY data is visualized in Figure 1, EUR/TRY data is visualized in Figure 2, and gold price data is visualized in Figure 3

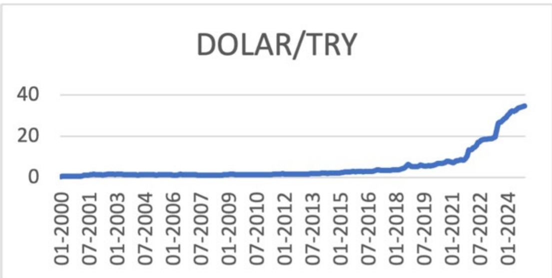


Figure 1. USD/TRY graph

Figure 2. EUR/TRY graph

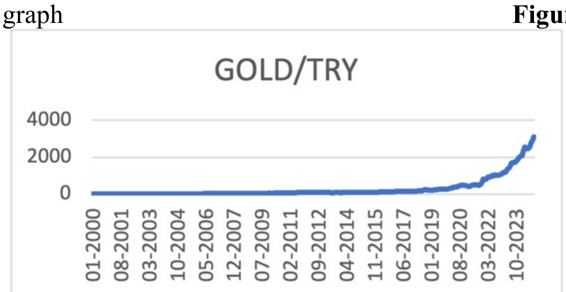


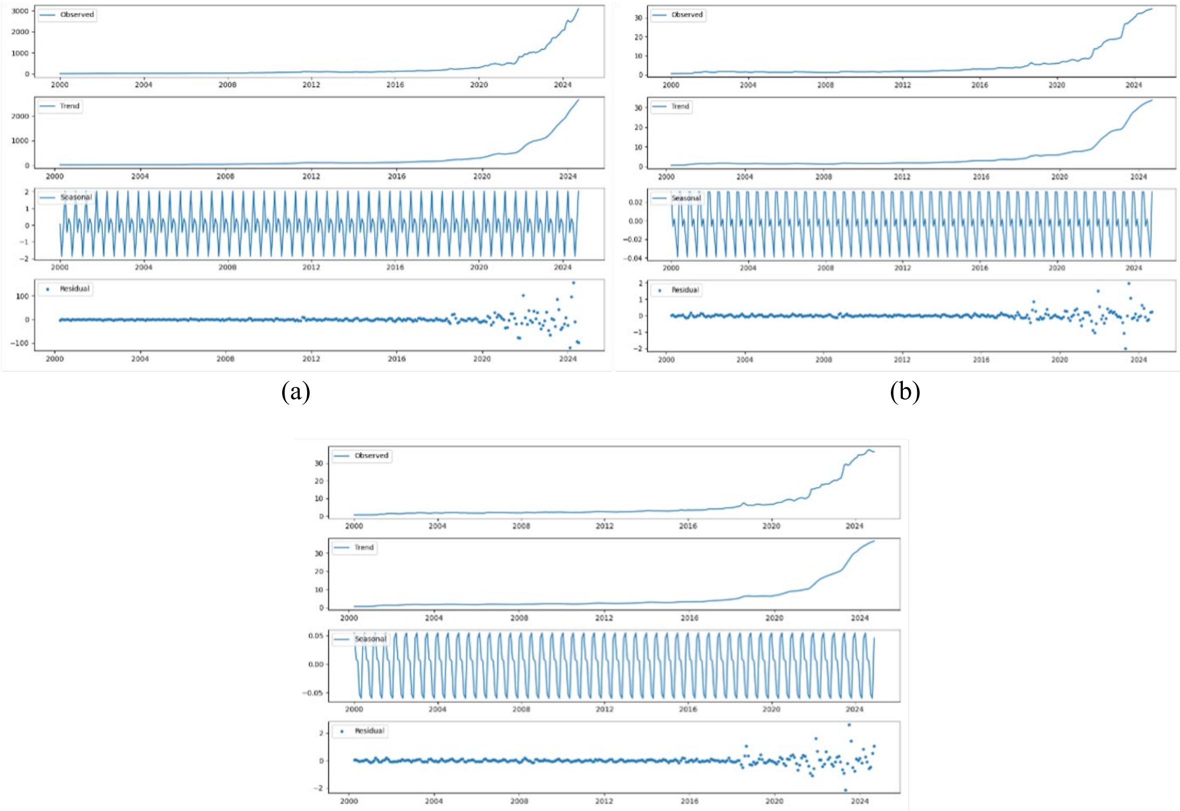
Figure 3. GOLD/TRY Graph

The graphs shown in Figure 4 decompose the trend, seasonality, and residual components of the GOLD/TRY, EUR/TRY, and USD/TRY time series. When examining the graphs, the trend component exhibits a sharp increase after 2020. The seasonal components display periodic fluctuations, reflecting the regular cycles in the foreign exchange market. The residual component represents minor deviations that the model cannot explain.

2.3. Deep Learning Models

In this study, deep learning models were used to analyze and predict dollar, euro and gold data. DL techniques such as LSTM, RNN and GRU were used in the predictions.

The layer structure of each model was designed using the layer sequence shown in Figure 5. The efficiency of the models was evaluated with the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) criteria.



(a) (b)

(c)

Figure 4. Trend, seasonality, and residual components of the Gold/TRY (a), USD/TRY (b) and EUR/TRY (c) time series

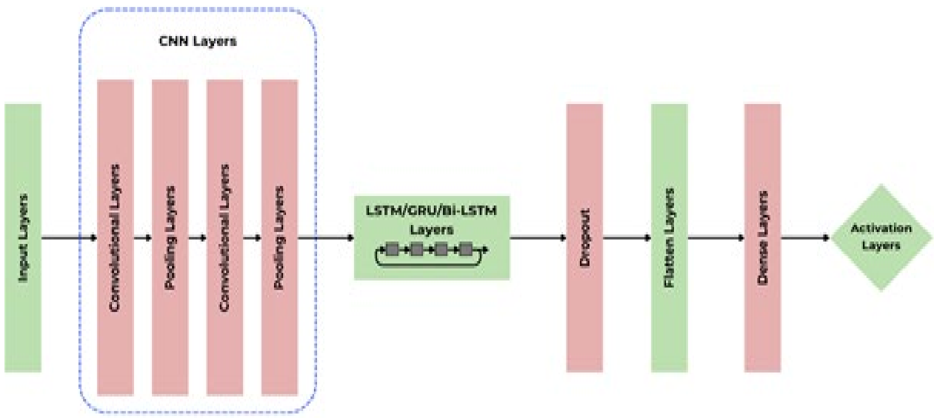


Figure 5. Model layers

The layers, parameters, optimization methods and functions used in this study are listed in Table 2. Adam was chosen as the optimizer within the scope of the study. The performance of each model was run for 100 epochs. In all models, the Tanh activation function is preferred for the output layer. The Tanh function generally gives results in the basic output range between -1 and 1 and is especially suitable for normalized time series.

Table 2. Hyperparameter Values of Deep Learning Models

Layers	Actıvatıon Function	Epochs	Optımızer	Batch sıze	Loss Function
Lstm(64) dropout(0.2) Lstm(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Bi-lstm(64) dropout(0.2) Bi-lstm(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Gru(64) dropout(0.2) Gru(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Rnn(64) dropout(0.2) Rnn(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Lstm(64) dropout(0.2) Bi-lstm(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Lstm(64) dropout(0.2) Gru(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Lstm(64) dropout(0.2) Rnn(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Bi-lstm(64) dropout(0.2) Rnn(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Gru(64) dropout(0.2) Bi-lstm(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE
Gru(64) dropout(0.2) Rnn(64) dropout(0.2) Flatten() dense(1)	Tanh	100	Adam	64	MSE

2.4. Deep Learning Time Series Models

In this study, LSTM networks, which are one of the most preferred recurrent architectures in the literature for the prediction of sequential data, were used. LSTM is a type of recursive neural network that has the capacity for learning long-term dependencies in time series data [19].

RNN were used to process sequential data. RNN is a type of artificial neural network designed for learning sequential dependencies in time series data [20]. These networks affect the out-put of the current step by processing information from previous steps and thus serve as a kind of memory. In general, it has an architecture that evaluates the information from previous steps by processing inputs at each time step and produces outputs [21].

Gate Controlled Recurrent Unit (GRU) was used for periodic data processing. GRU has a similar structure to LSTM, but offers a simpler architecture and can be more computationally efficient. It is also frequently used with LSTM in the literature. GRU includes two basic mechanisms to control cell states: the update gate and the forget gate. As shown in Figure 6, the LSTM structure includes mechanisms such as input, forget and output gate.

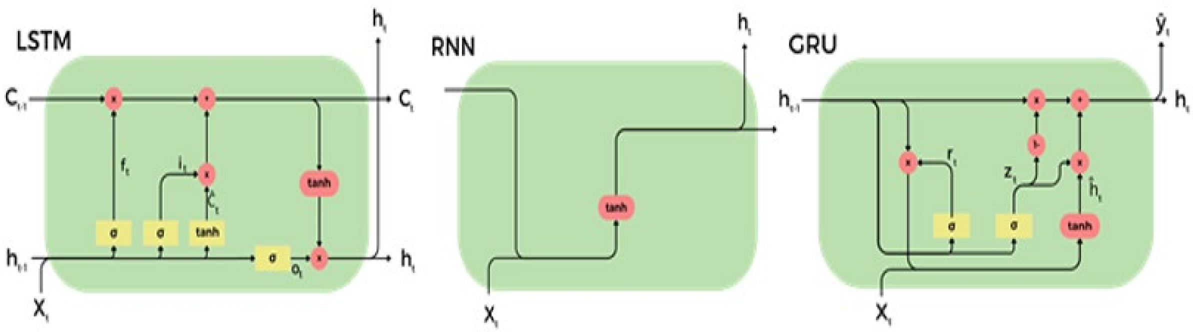


Figure 6. Basic structure of LSTM , RNN and GRU models.

Min-Max Normalization method was used to scale the data before model training. This method transforms each value in the data set into a certain range, ensuring that inputs at different scales are evaluated with equal importance by the model. Normalization contributes to the independent modeling of features and the stabilization of the learning process. Min-Max Normalization was performed by transforming each value according to the min and max value in the data set.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

RMSE metric was used for evaluation the model performance. RMSE is an error measurement criterion that is frequently used in the literature to measure the closeness of model predictions to the true values. With this metric, the square of the prediction errors is averaged and then the square root is calculated. The RMSE value indicates how much deviation there is in the model's predictions.

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

RMSE expresses the results depending on the scale of the dataset due to unit precision, and a low RMSE value means that the model's predictive performance is high. Using RMSE helps to understand full distribution of the errors [22].

MAE was used for evaluation as a metric the model's performance. MAE directly measures the magnitude of the prediction errors by averaging the absolute values of the differences between the model's predicted values and the actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \bar{y}_i| \quad (3)$$

MAE shows the average error in the model's predictions in units and makes it easier to interpret the magnitude of the error. Another metric, In addition to this in this study MSE, selected to evaluate the performance of the models which is more sensitive metric to the outliers compared to the MAE [23].

MSE measures the magnitude of the prediction error by averaging the squared differences between the model's predicted values and the actual values.

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

MSE shows the average error in the model's predictions in square units and is used as an effective metric to optimize model performance because it penalizes large errors.

In this study, the MAPE metric is used. MAPE calculates the percentage error rate of the model's predicted values compared to the actual values and expresses the results in percent units. This metric is widely used to measure prediction accuracy and compare error rates. Also, it is found to be commonly used in finance as profits and losses are relative terms [24].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (5)$$

MAPE provides an advantage in comparing the results of different data sets, as it provides an error rate in percentage terms.

However, the results may become sensitive when the y_i values are close to zero.

In addition, F1 Score calculates the harmonic mean of the accuracy and recall values to measure the classification success of the model. This metric is an effective part of evaluating model performance even in imbalanced data sets.

$$F1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \quad (6)$$

F1 Score can be especially useful in cases where it is important to correctly predict the positive class. It provides an advantage in summarizing the overall performance in model because it offers a balance between Precision and Recall.

3. RESULTS

In this study, LSTM, RNN, GRU, Bi-LSTM and hybrid models of these methods were used to estimate USD/TRY, EUR/TRY and bullion GOLD/TRY prices. While analyzing the performance of the models, 80% was separated as training and 20% as test data. In addition, a forward-looking forecast was made for each unit between 6 months.

When the graph of gold prices shown in Figure 7 is examined, it is seen that there is an increasing trend in gold prices in the 6-month forward forecast period. When the future forecasts of the GRU-RNN model, which showed the best performance, are examined, it is seen that it predicts gold prices as 3408,451 TRY at the end of the 6-month period.

The results of the GOLD/TRY data are presented in Table 3. According to the table, the best performance was obtained with the GRU-RNN hybrid model with an F1 score of 98.39%. The hybrid model closest to this result was the LSTM-GRU hybrid model.

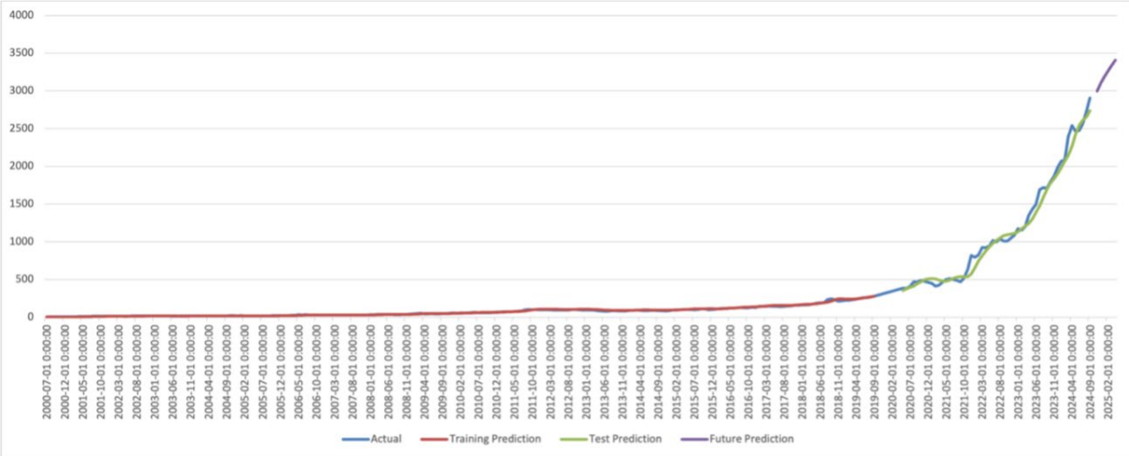


Figure 7. Gold/TRY test results.

Table 3. Gold/TRY test results

MODEL	RMSE	MSE	MAE	MAPE	F1
LSTM	0.0563	0.0032	0.0434	0.1146	0.9438
Bi-LSTM	0.0449	0.0020	0.0341	0.0931	0.9642
GRU	0.0427	0.0018	0.0318	0.0853	0.9677
RNN	0.0454	0.0021	0.0324	0.0801	0.9634
LSTM - GRU	0.0363	0.0013	0.0267	0.0809	0.9767
LSTM - RNN	0.0531	0.0028	0.0406	0.1067	0.9500
BiLSTM - RNN	0.0488	0.0024	0.0370	0.0974	0.9577
GRU - BiLSTM	0.0452	0.0020	0.0341	0.0942	0.9639
GRU - RNN	0.0301	0.0009	0.0220	0.0685	0.9839

The graph regarding dollar prices presented in Figure 8 reveals that there is a clear upward trend in dollar prices in the 6-month forecast period. According to the future data estimates obtained by the GRU-RNN model, the dollar exchange rate is predicted to be 37.33 TRY at the end of the 6-month period.The results of USD/TRY data are presented and evaluated in Table 4. According to the table, the best performance was obtained with the GRU-RNN hybrid model. The closest result to this model was provided by the LSTM-GRU model. This clearly shows the superiority of the hybrid model when it comes to USD prediction. When the RMSE values are examined, it is seen that the GRU-RNN hybrid model achieved the best result with a value of 0.0363. And achieved the highest result with an F1 score of 98.26%.

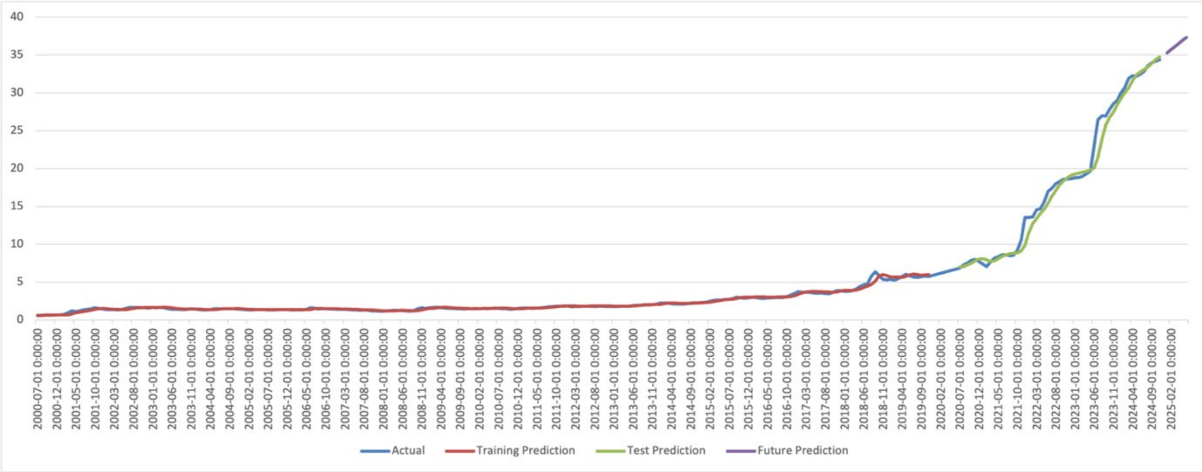


Figure 8. USD/TRY test results.

Table 4. USD/TRY test results.

MODEL	RMSE	MSE	MAE	MAPE	F1
LSTM	0.0555	0.0031	0.0392	0.0760	0.9595
Bi-LSTM	0.0643	0.0041	0.0497	0.0884	0.9456
GRU	0.0443	0.0020	0.0300	0.0607	0.9741
RNN	0.0666	0.0044	0.0542	0.0960	0.9417
LSTM-GRU	0.0412	0.0017	0.0289	0.0595	0.9777
LSTM-RNN	0.0565	0.0032	0.0421	0.0773	0.9581
Bi-LSTM-RNN	0.0584	0.0034	0.0446	0.0807	0.9551
GRU-Bi-LSTM	0.0612	0.0037	0.0460	0.0834	0.9507
GRU-RNN	0.0363	0.0013	0.0234	0.0501	0.9826

Figure 9 is examined, it is seen that the EUR/TRY results will tend to decrease in the future. Contrary to expectations, hybrid models generally performed worse than single models. The graph regarding euro prices presented in Figure 9 clearly reflects the downward trend in euro prices during the 6-month forecast period. According to these data obtained, the EURO price was estimated as 32.86 TRY according to the RNN model, which gave the best result at the end of the 6-month period. The estimates are especially important in terms of making predictions about the future direction of movements in the foreign exchange market.

The results of EUR/TRY data are presented and analyzed in Table 5. According to the analysis results, the best performance was obtained with the RNN model. The prediction success of the RNN model clearly shows its capacity to effectively learn patterns in the data set. The closest performance to this model was provided by the Bi-LSTM model.

RNN gives best results among the single models with the lowest RMSE 0.0448 and MSE 0.0020 values on Table 5. It is also quite successful in the MAPE 0.0619 and MAE 0.0340 metrics. The F1 score was the highest among all models with 0.9718. This shows that RNN performs better than other models in financial prediction tasks. Although Bi-LSTM has slightly higher RMSE 0.0489 and MSE 0.0024 values than RNN, it has achieved more successful results than other models. When the Bi-LSTM results are examined, it gives better results than LSTM with MAPE 0.0630 and MAE 0.0340 values, while it shows a performance close to RNN. The performance of GRU is similar to LSTM, but it gives slightly weaker results.

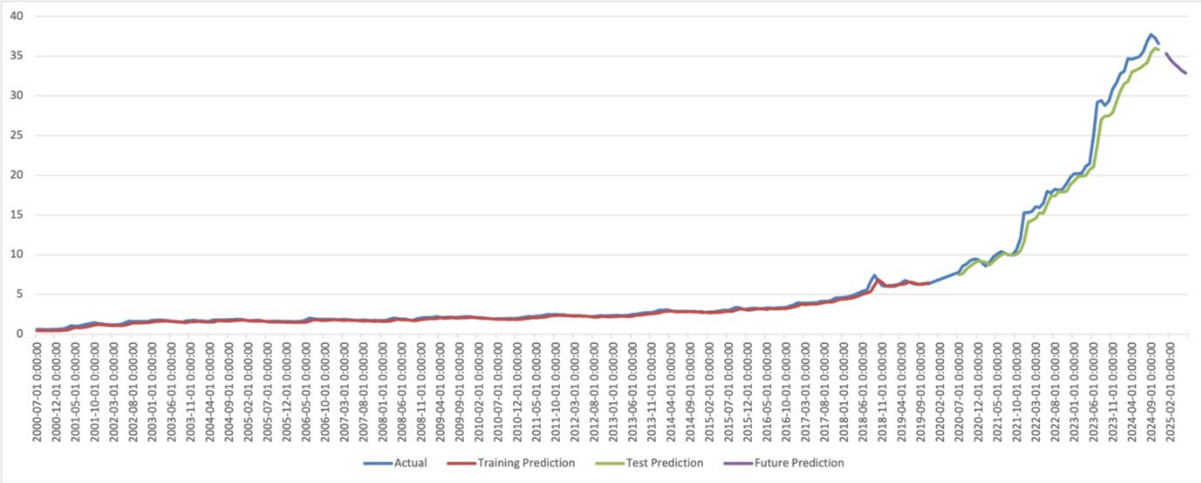


Figure 9. EUR/TRY test results.

Table 5. EUR/TRY test results.

MODEL	RMSE	MSE	MAE	MAPE	F1
LSTM	0.0517	0.0027	0.0346	0.0676	0.9625
BiLSTM	0.0489	0.0024	0.0340	0.0630	0.9665
GRU	0.0518	0.0027	0.0380	0.0736	0.9624
RNN	0.0448	0.0020	0.0340	0.0619	0.9718
LSTM-GRU	0.0599	0.0036	0.0449	0.0850	0.9497
LSTM-RNN	0.0593	0.0035	0.0442	0.0843	0.9508
BiLSTM-RNN	0.0690	0.0048	0.0553	0.0986	0.9333
GRU-Bi-LSTM	0.0629	0.0040	0.0478	0.0880	0.9445
GRU-RNN	0.0680	0.0046	0.0545	0.0985	0.9351

Today, the development of computers makes it possible to make future predictions in financial markets by processing large data sets. In this study; LSTM, RNN, GRU, Bi-LSTM and hybrid models of these methods were used to predict dollar, euro and gold prices.

4. DISCUSSION

Forecasting financial indicators such as exchange rates and precious metals is of great importance in determining economic policies worldwide, developing investment strategies and risk management policies. Therefore, there is an intense research interest in developing highly accurate artificial intelligence-supported forecasting systems. In recent years, deep learning-based time series models have come to the fore in this field. The application of hybrid models in this study shows whether better results can be obtained when compared to traditional approaches. There are different suggestions in the literature such as time series for forecasting gold prices [25,26], time series for USD/EUR exchange rate [27], models using LSTM and GRU Methods for Forecasting Gold Exchange Rate Against Dollar [28].Since the main purpose of the studies in this field is high accuracy and performance, hybrid models are more prominent. It is seen that the performance of the hybrid models reaches high accuracy values in USD/TRY and GOLD estimation. The performance of the models is evaluated with RMSE, MSE, MAE, MAPE and F1 Score metrics. In the study, the best results were obtained with the GRU-RNN hybrid model. It was observed that hybrid models in particular provide higher accuracy in estimates in general. The obtained findings show that optimizing the model parameters has a significant effect on the success of financial estimates. In the study conducted by İslam et al. using LSTM and GRU hybrid models to predict EUR/USD and GBP/USD currency pairs, MSE, RMSE and MAE results were reported as 0.00001, 0.00301 and 0.00224, respectively [29]. The performance of the hybrid models used in this study on USD/TRY and EUR/TRY was similar to the results in the literature, and low error values were obtained. In addition they worked in a shorter time period. An accuracy of 0.948 was achieved in the study that determined the most advantageous time for investors' future EUR/USD transactions [30].When the studies conducted are examined, it is seen that the data sets only use time series methods and do not make future predictions. In this study, the MSE, MAE and RMSE values of the results obtained in the data set and the test set as well as the results of the lower rates in the future are also included. In the bitcoin price prediction study conducted by Buslim et al. [31], the GRU model gave the best result with the Grid Search method and a MAE value of 0.0594 was obtained. Similarly, in this study, the use of GRU and hybrid models provided high accuracy for gold, dollar and euro prices, and it was particularly noteworthy that GRU provided a low error rate in the test data. In this study, GRU achieved a very successful result in EURO prediction with a MAE value of 0.0380. While only Bitcoin data were analyzed in the study conducted by Buslim et al., this study evaluated more than one financial unit and made a wider evaluation. The effect of the selected hyperparameters on the prediction results while training LSTM models and hybrid models was analyzed comparatively. The 98.39% F1 score obtained in this study shows how effective the model in question can be in financial forecasting. It is seen that the presented study is compatible with the literature and supported by current approaches. In this context, the study contributes to the literature both methodologically and practically. In the literature, Wang et al. [32] achieved 98.8% R^2 in foreign exchange rate forecasting with CNN-LSTM hybrid model, for USD/CNY. Similarly, the finding in this study that hybrid models show higher success in many models compared to single models supports this literature. In the study [33] conducted to determine the future value of the Chinese Yuan (CNY) against the US dollar, LSTM models and machine learning models were analyzed as hybrids. In the study, LSTM and XGBoost algorithms were compared and the results obtained were analyzed. It was seen that the LSTM model gave better results in the study. Although the LSTM model gave a result below the average among deep learning models in this study, it has a very high performance among time series algorithms. Finally, hyperparameter optimization also seriously affects the model performance. Therefore, meticulous optimization of the model parameters proposed in this study increases the reliability of the results.

5. CONCLUSION

In this study, LSTM, GRU, RNN, Bi-LSTM, and hybrid models were used to forecast USD/TRY, EUR/TRY, and bullion gold prices. When the obtained results are compared with other studies in the literature, they show similarities and differences in terms of both the data sets used and accuracy measures.In this study, batch size, number of hidden layers and epoch number were also effective in measuring model success. These parameters were specifically adjusted for the models as a result of experimental results. Parameter setting is very important for the performance of time series models, so the models were designed considering this. In the study, hybrid models were presented in addition to time series models and their performance values were analyzed comparatively. The limitations of the study are that the dataset only covers certain exchange rates. At the same time, future prediction time can be increased by making predictions over a wider time range. In future studies, longer-term prediction processes will be performed using different deep learning models. Performance results will be increased with large datasets and different hyperparameter combinations. This study is of a nature that will provide insight to investors with the future prediction results obtained by using recurrent neural network models.

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