Forex Price Prediction After Economic News with Boomerang Strategy and Machine Learning

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ABSTRACT— **The Forex (Foreign Exchange) market is the largest and most liquid market in the global financial system; its daily trading volume reaches trillions of dollars. This market has a complex structure with high volume and sudden changes in direction, where international currencies are priced against each other. Therefore, making short-term price predictions is an extremely challenging problem for investors and algorithmic trading systems. In this study, three different deep learning models (LSTM, GRU, and BiLSTM) were used comparatively together with the Boomerang Strategy based on technical analysis for short-term exchange rate prediction in the Forex market. The models input historical OHLC (Open, High, Low, Close) data and are trained to predict the price movement in the next minute. The models' predictions were analyzed for performance evaluation using Mean Squared Error (MSE), F1 Score, and price direction accuracy rate (%). The results revealed that the models achieved accuracy rates ranging from approximately 51% to 63% in predicting the price direction. These rates show that deep learning models have demonstrated significant success despite the difficulty of the short-term Forex prediction problem.**

*KEYWORDS—***Forex price prediction, Boomerang Strategy, LSTM, GRU, BiLSTM**

I.INTRODUCTION

The Forex (Foreign Exchange) market is a global financial market with a daily trading volume of trillions of dollars and the highest liquidity in the world [1]. Currencies of some countries traded in this market, metals (Gold-Silver), indices, and oil prices, which can be currency pairs, exhibit sudden and difficult-to-predict fluctuations due to multidimensional factors such as economic trends and indicators, political developments, and investor psychology [2]. In particular, the EUR/USD currency pair is the most widely used parity in terms of having one of the highest volumes in the Forex market and the popularity of currencies, and investors frequently prefer it. Making short-term price predictions in the Forex market is always strategic and critical for financial decision-making [3]. Generally, two basic approaches stand out in market analysis: Fundamental and technical analysis. Fundamental analysis tries to predict price movements by evaluating countries' macroeconomic data, interest rate decisions, and geopolitical events. In contrast, technical analysis focuses on predicting future price behaviors using graphical and statistical methods based on past price and volume data [4].

Short-term price forecasting in financial markets is a complex problem due to high volatility, sudden information flows, and behavioral factors. Especially in the foreign exchange market, it is observed that classical statistical methods and approaches based on linear models cannot adequately represent this complex structure and are inadequate [5]. This situation reveals the need for more flexible, data-driven, and adaptable methods for forecasting problems.

Deep learning models can exhibit stronger forecasting performance than classical methods thanks to their capacity to learn sequential dependencies in time series [6]. In this study, short-term price forecasting was performed in the Forex market using three different deep learning models based on Recurrent Neural Networks (RNN) architecture: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Bidirectional LSTM (BiLSTM). All models were trained with real market data; their forecasting performances were compared using the Mean Squared Error (MSE) metric. In addition, the direction of the predicted prices was compared with the actual price movements, the direction accuracy rate (%) was calculated, and the degree to which the models reflected market behavior was analyzed visually and numerically [7].

Many studies conducted in recent years have shown that deep learning algorithms provide higher accuracy rates in financial time series compared to traditional models. In particular, it has been frequently reported in the literature that architectures such as LSTM and GRU are successfully applied in financial forecasting tasks due to their ability to model long-term dependencies [8]. It is emphasized that bidirectional network structures such as BiLSTM provide advantages, especially in determining trend direction. In this study, these architectures are comparatively evaluated for short-term exchange rate forecasting purposes by blending them with technical analysis.

II.RESEARCH METHOD

A. *Boomerang Strategy*

The Boomerang Strategy, the technical analysis approach used in this study, is an original method developed by an individual investor who trades in financial markets. Fibonacci correction levels and the Boomerang Strategy have been integrated to enrich machine learning-based prediction models with technical analysis components. Fibonacci levels, which are widely used in technical analysis, predict at what rates and prices the price may regress after a certain movement. In this context, the Fibonacci levels calculated in the study are defined as 0 (Low), 0.5 (medium level), and 1 (High) based on the highest and lowest values of the 1-minute news candle formed at 08:30 news hour. However, the Boomerang Strategy, which is based on the adverse reaction that the price may have after the news, has been implemented to determine strategic entry levels. The basic assumption of the strategy is that the price tends to correct in the opposite direction depending on the direction of the news candle. In this direction, the rising or falling candle formation is determined according to the opening and closing levels of the candle. Accordingly, target areas are based on correction levels such as Fibonacci 1.25, 1.5 (for rising candles) or -0.25, -0.5 (for falling candles).

In addition, by taking into account the liquidity zones, Fair Value Gap (FVG), and sweet spot critical price areas in this strategy, the models aim to produce numerical estimates and estimates based on meaningful structures related to strategic price zones. Figure 1 shows an example of a transaction where a sell position is assumed to have been entered at the Fibonacci 1.5 level after the rising 1-minute candle that came at the news hour.

Figure 1. An Example of a Trade Taken with the Boomerang Strategy

B. *Recırremt Neural Networks (RNN)*

Recurrent Neural Networks (RNN) are deep learning architectures used in processing sequential data structures such as time series, natural language processing, and signal analysis [9]. RNNs enable learning based on past information by transferring the hidden state obtained at each time step to the next steps. Thanks to this architectural structure, time-dependent relationships that traditional artificial neural networks have difficulty modeling can be represented more effectively and meaningfully. However, classical RNN structures can encounter a problem known as gradient fading, especially regarding long consecutive sequences. This causes the network to lose its sensitivity to past information over time and its learning performance to weaken [10].

The devaluation of information over time is undesirable, especially in applications where historical data is critical, such as financial time series. To overcome this problem, gate mechanisms that provide the capacity to learn longer-term dependencies have been developed in structures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), which are advanced architectures of RNN [11]. In this study, time series-based exchange rate forecasting was performed using LSTM, GRU, and bidirectional LSTM (BiLSTM) models, which are RNN-based architectures. Figure 2 shows the structure of the RNN Architecture.

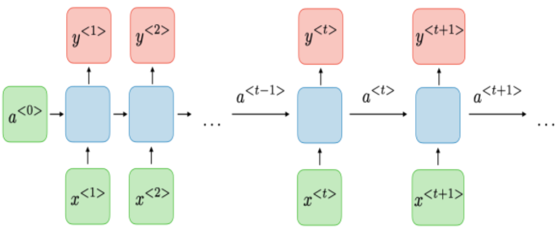

Figure 2. RNN Architecture[24]

C. *Long Short-Term Memory (LSTM)*

Long Short-Term Memory (LSTM) is a special structure developed due to the inadequacy of the classical Recurrent Neural Network (RNN) architecture in learning long-term dependencies [11]. LSTM cells have an internal mechanism that can keep information in memory longer than classical RNNs. Thanks to this structure, stronger contextual relationships can be established with past data in time series; this makes LSTM a widely preferred architecture in application areas such as financial time series forecasting, natural language processing, and speech recognition [12].

The LSTM architecture's main difference lies in its three gate mechanisms. These gates are called Input Gate, Forget Gate, and Output Gate. Input Gate: Decides how much new information will be taken into the cell. Forget Gate: Determines how much of the previous information will be deleted. Output Gate: Regulates which data will be transferred out of the cell. Thanks to this gate structure, LSTM cannot only keep important information in its long-term memory but also filter out irrelevant or noisy data and forget it. This feature provides a critical advantage, especially in terms of modeling the effect of past sudden price movements on subsequent price fluctuations. Figure 3 shows the structure of the LSTM architecture.

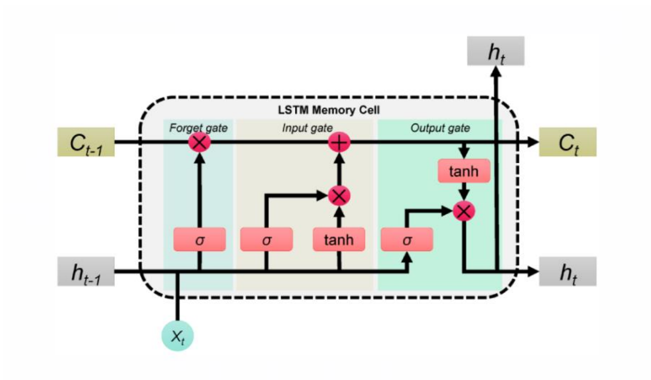

Figure 3. LSTM Architecture[25]

D. *Gated Recurrent Unit (GRU)*

Gated Recurrent Unit (GRU) is an alternative structure developed similarly to the Long Short-Term Memory (LSTM) structure to overcome the difficulties experienced by the classical RNN architecture in learning long-term dependencies [13]. The most striking feature of GRU, which has a simpler and faster architecture than LSTM, is that it reduces computational complexity and can work with fewer parameters by reducing the three-gate mechanism in LSTM to two gates [14].

There are two gates in the GRU architecture: the Update Gate and the Reset Gate. Update Gate: Determines to what extent the cell will carry past information. Reset Gate: Controls to what extent the new information will be blended with the past. Thanks to this gate structure, GRU can provide faster learning and achieve significant advantages in training time.

In addition, in some cases, especially in small and medium-sized data sets, it can achieve similar accuracy rates to LSTM with lower computational costs [15]. In this study, GRU was applied to high-frequency time series data from the foreign exchange market; the model was evaluated comparatively with other architectures in terms of its capacity to learn short-term price movements. The structure of the GRU architecture is shown in Figure 4.

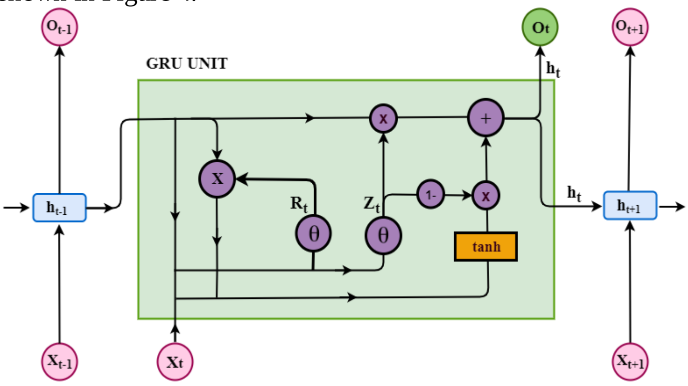

Figure 4. GRU Architecture[26]

E. *BiDirectional Long Short-Term Memory (BiLSTM)*

BiDirectional Long Short-Term Memory (BiLSTM) is an advanced variant of the classical LSTM architecture. It is a deep learning structure that aims to obtain richer contextual information by processing data sequences both from past to future and from future to past [16]. While traditional LSTM only considers past information, BiLSTM overcomes this limitation with bidirectional information flow and ensures that each unit in the time series gains meaning according to its previous and next context [17].

In the BiLSTM structure, two different LSTM layers are run in parallel at each time step. One processes the data forward, and the other processes it backward in time. The output vectors obtained from both methods are combined, creating a more holistic representation. Thanks to this architectural structure, BiLSTM can work more accurately than one-way models, especially in cases where data points gain meaning according to past and future contexts, such as financial signal prediction, natural language processing, and biomedical time series analysis [18].

In this study, BiLSTM was evaluated comparatively with LSTM and GRU models in terms of its potential to use context information more effectively in the context of exchange rate prediction problems. The structure of the BiLSTM architecture is shown in Figure 5.

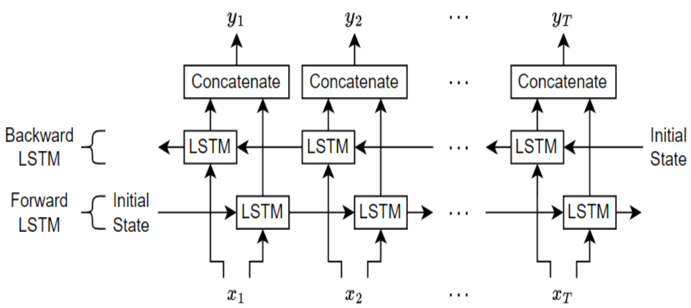

Figure 5. BiLSTM Architecture[27]

F. *Data Set*

The dataset used in this study belongs to the EUR/USD currency pair and was created by considering the days when high-impact USD news was announced between August 25, 2024, and February 15, 2025. Since the news usually causes sudden and high-frequency price movements in the foreign exchange market, only these days were specially filtered and included in the analysis.

The data was collected in a 90-minute time frame between 08:30 and 10:00 local time in New York, for a total of 90 minutes. In this context, only the candlestick data corresponding to the specified time frame were evaluated; thus, an analysis focused on the impact of price movements after the news was made.

Price information used in the forecast models is obtained in the classical OHLC data structure format consisting of opening (Open), highest (High), lowest (Low) and closing (Close) values. The data engineering process has been carried out meticulously, and only meaningful and high-information time intervals have been selected and included in the model training and analysis processes. A portion of the data set used is displayed in Figure 6.

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Date,Open,High,Low,Close,Volume
2024-09-17 08:30:00,1.1134,1.11415,1.11251,1.1141,973
2024-09-17 08:31:00,1.11414,1.11436,1.11274,1.1129,840
2024-09-17 08:32:00,1.11289,1.11297,1.11233,1.11276,762
2024-09-17 08:33:00,1.11277,1.11289,1.11227,1.11233,1208
2024-09-17 08:34:00,1.11232,1.11261,1.11211,1.11253,1323
2024-09-17 08:35:00,1.11252,1.113,1.11252,1.11297,904
2024-09-17 08:36:00,1.11296,1.11298,1.11248,1.11278,1373
2024-09-17 08:37:00,1.11278,1.11281,1.11249,1.11272,1284
2024-09-17 08:38:00,1.11272,1.11294,1.11254,1.11294,698
2024-09-17 08:39:00,1.11292,1.11292,1.11209,1.11213,1400
2024-09-17 08:40:00,1.11211,1.11248,1.11201,1.11234,1446
2024-09-17 08:41:00,1.11232,1.11257,1.11227,1.11248,1347
2024-09-17 08:42:00,1.11248,1.11256,1.11228,1.11254,941
2024-09-17 08:43:00,1.11254,1.11262,1.11212,1.11221,203
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Figure 6. First 15 Data of Filtered Dataset

G. *Data Preprocessing*

Before proceeding to the modeling process, various preprocessing steps were applied to the raw data. In the first stage, the OHLC format consisting of only the opening (Open), highest (High), lowest (Low), and closing (Close) values was preferred. To ensure more effective operation of deep learning models, these data were scaled to the range of [0, 1] using the Min-Max Normalization (MinMaxScaler) method for each feature separately [19]. This process increases the stability of the learning process by ensuring a balanced update of the weights during the training process of the neural networks.

This scaled data was then transformed into input (X) and target (Y) sets based on a specific window length (sequence length) to create the sequential patterns required for time series prediction. This study determined the window length as 10-time steps; therefore, the model tried to predict the OHLC values in the next minute by considering the past 10-minute price movement. This structure is critical in learning past-dependent patterns frequently encountered in time series and directly affects the model's prediction capacity.

H. Deep Learning Architectures

Each model used in this study takes OHLC (Open, High, Low, Close) data containing 10-time steps from the past as input and produces four-dimensional (opening, highest, lowest, and closing) price estimates for the next time step based on this historical information. Model architectures generally consist of two consecutive recurrent layers (LSTM, GRU, or BiLSTM) and a Dense(4) output layer following these layers. In the first recurrent layer, the "return_sequences=True" parameter is activated so that the output can be transferred sequentially to the second layer; thus, the models can better learn dynamic structures over time.

During training, all models were optimized with the Mean Squared Error (MSE) loss function due to the continuous value estimation problem. For parameter updates, the Adam optimization algorithm, which is a widely preferred and momentum-based method, was used [20]. Each model was retrained 20 times with different epoch and batch size combinations. As a result of these iterations, the hyperparameter combinations that reached the lowest average MSE value were selected. Thanks to this systematic experimental structure, optimum performance was achieved in model configurations.

I. Evaluation Metrics

Three basic metrics were used to evaluate model performance: Mean Squared Error (MSE), direction estimation accuracy rate (%), and F1 Score. MSE is an error measurement criterion commonly used in regression problems, calculated by taking the average of the square of the differences between the predicted and actual values [21]. The MSE formula is expressed as follows:

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

Here, y_i represents the real values, and $\hat{y}_i$ represents the values predicted by the model. In this study, the MSE values of all models were calculated; each model was run with different iterations, and the average MSE and the corresponding standard deviation values were reported. Thus, not only the error levels of the models but also their stability were evaluated.

For the performance analysis not limited to numerical prediction accuracy alone, the direction accuracy rate (%) was also calculated to show how accurately the models predicted the direction of price movements [22]. The direction accuracy rate formula is as follows:

$$\frac{Number\ of\ Correct\ Direction\ Predictions}{Total\ Number\ of\ Predictions}\times 100 \tag{2}$$

This ratio shows the extent to which the change directions (increase or decrease) of closing prices in consecutive time steps coincide between the forecast and actual data. Thus, the differences in price levels and the trend following performance are analyzed holistically.

In addition, the F1 Score metric was also used to evaluate the direction prediction performance in a more balanced and reliable way [23]. The F1 score expresses the classification success by taking into account the precision and recall rates together and is calculated as follows:

$$2\times\frac{Precision\times Recall}{Precision+Recall} \tag{3}$$

This metric provides a more reliable performance measure, especially in cases with data imbalance, and holistically evaluates the correct prediction rate of the model and its prediction accuracy.

III. RESULTS

A. Average MSE Results

This study's LSTM, BiLSTM, and GRU models were run in 20 different iterations on exchange rate forecasting. The Mean Squared Error (MSE) values obtained from each iteration were recorded. The prediction performance of each model was evaluated in terms of the mean error value and statistical consistency (standard deviation).

As a result of the comparison, although all models showed similar average MSE values, the LSTM model had the lowest average MSE value and a relatively lower standard deviation than the other two models. Thus, it shows that LSTM makes accurate predictions and provides a more stable and repeatable performance. Figure 7 shows the graphs of the model comparisons.

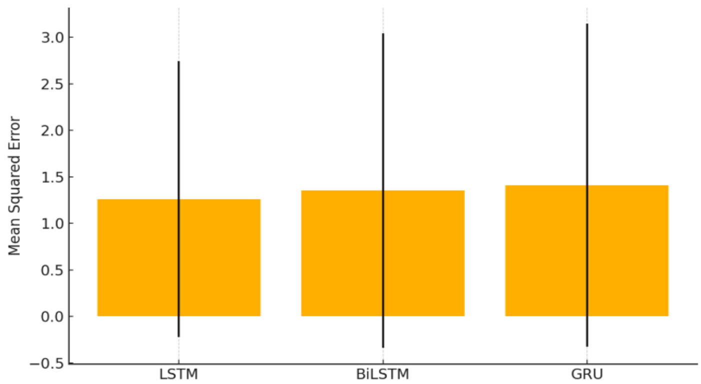

Figure 7. Model Comparison – Mean MSE and Standard Deviation

B. Direction Estimation Accuracy Rate

It is not enough to predict price levels correctly; it is also very important for the model to predict whether the price will go up or down in financial forecasting. The direction of the closing prices predicted by each model (increase/decrease) was compared with those in the actual data. In this way, direction accuracy rates were calculated.

While calculating the direction accuracy, the increases and decreases in consecutive closing prices were coded as "+1" and "-1". The correspondence between the direction predicted by the model and the actual direction was evaluated as a percentage. As a result of the comparison, The LSTM model showed the highest direction estimation performance with an average accuracy rate of 57.33%. Despite its bidirectional data processing feature, the BiLSTM model showed slightly lower performance in direction estimation than LSTM (54.67%). The GRU model had the lowest direction accuracy rate (51.38%).

These results show that the LSTM model performs better than the other two models, not only in terms of MSE but also in terms of correctly predicting the price direction.

C. *Graphs of Actual and Forecast Data*

To evaluate the performance of the models not only with numerical metrics but also visually, real market data and model predictions were compared on samples selected from different days. In this context, three different graphs are presented for each test day.

They are shown as candlestick charts of real market data (08:30–09:30), candlestick charts of prices predicted by the LSTM model, and line charts of real and predicted “Close” prices superimposed on each other.

These visuals show the general trends of the models and make it possible to observe how accurately they predict the direction and timing of price fluctuations.

Figure 8 – Graph of Actual Data as of November 14, 2024

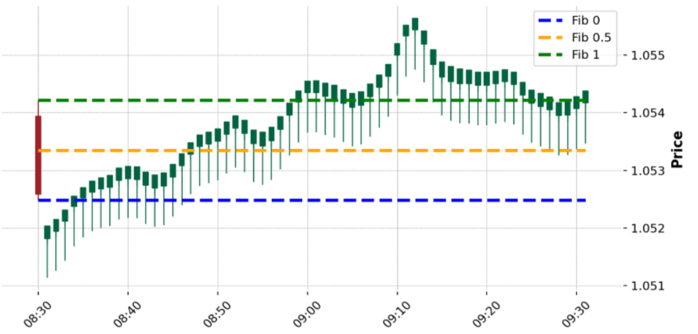

Figure 9 – Estimated Prices Chart as of November 14, 2024

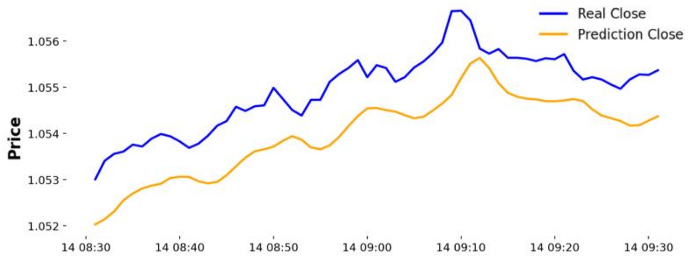

Figure 10 - Line Graph of Actual and Estimated Close Values as of November 14, 2024

The model's direction prediction accuracy rate for November 14, 2024, was 63.33%. This rate shows that approximately two-thirds of the model's predictions about whether the price will increase or decrease are correct. In addition, the F1 Score value calculated to evaluate the direction prediction performance more balanced in classification accuracy was found to be 0.6237. This score reveals the accuracy rate of the model's direction predictions and its capacity to produce stable predictions.

As a result of visual analysis, it was observed that the model could follow the general trend. However, it was observed that there was a deviation in some micro-level price fluctuations. The upward movement that started after the model, in particular, captured 08:45. However, the estimated Close values were generally below the real values.

Figure 11 – Graph of Actual Data as of October 31, 2024

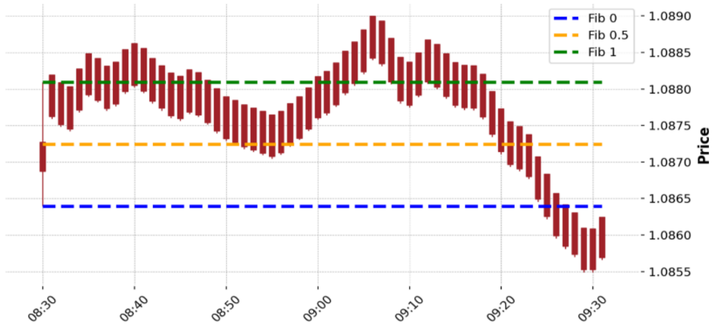

Figure 12 –Estimated Prices Chart as of October 31, 2024

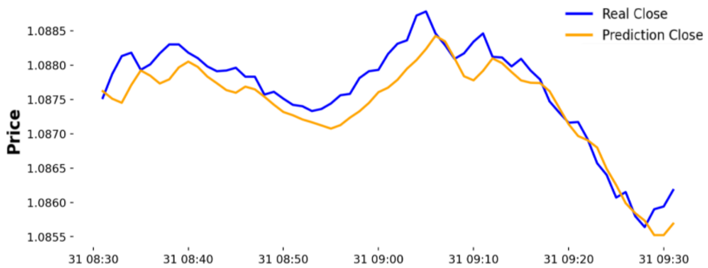

Figure 13 – Line Graph of Actual and Estimated Close Values as of October 31, 2024

The direction prediction accuracy rate for October 31, 2024, was 61.67%. This means that the model was successful in predictions at a rate of approximately 3/5. In addition, the F1 Score value calculated for a more balanced evaluation of direction prediction performance in classification performance was obtained as 0.5769. This result reveals that the model performed reasonably in determining the price direction, not only in terms of accuracy but also in terms of prediction consistency.

The model followed the general trend, especially after 09:05; it reacted to the downward movement. However, the model's predictions were sometimes delayed in response to the price momentum. The deviation in the Close values became especially evident at the turning points of the trend. Although there was a general similarity between the actual and forecast graphs, the forecast curve generally moved slightly below the price.

Figure 14 – Graph of Actual Data as of December 20, 2024

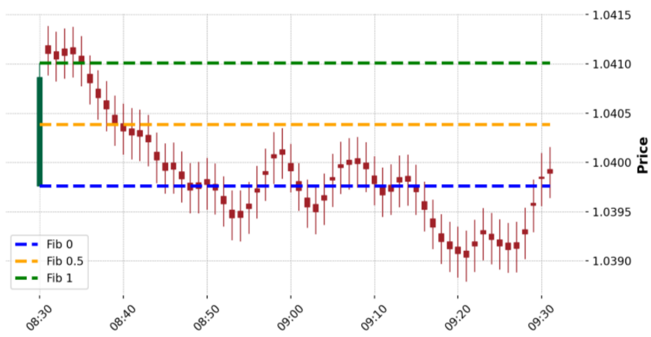

Figure 15 – Estimated Prices Chart as of December 20, 2024

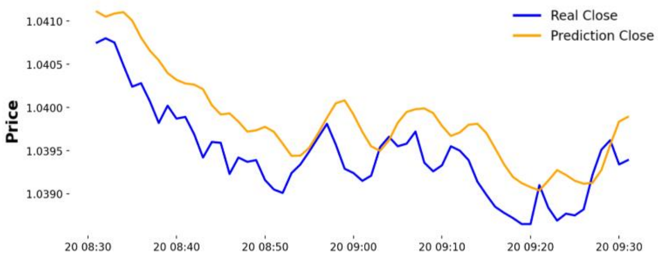

Figure 16 - Line Graph of Actual and Estimated Close Values as of December 20, 2024

The direction accuracy rate for today was calculated as 51.38%. This value is an accuracy rate that shows that the model makes almost chance-based predictions. In addition, the F1 Score value calculated for a more balanced evaluation of direction classification performance was 0.4236. This score indicates that the model performs poorly in terms of accuracy and consistency in price direction predictions.

The model caught the downtrend in the chart's first half; however, it could not accurately predict the direction changes due to the prices' micro-movements. Especially between 08:35 and 09:00, the model estimates drew the price down with a softer course, while the actual price showed sharper ups and downs. Although the model generally caught the trend after 09:05, when the price tended to recover, there were shifts in terms of timing.

Visual comparisons of actual and forecasted data reveal how well the models can capture price trends and micro-level fluctuations and movements.

As a result of these observations, the LSTM model has shown an above-average performance in predicting the trend direction. It has been observed that the model's predictive power is not very high in the post-news periods with high volatility. It also performs better on days when the direction is more obvious. Line charts show that the model's closing value predictions are often below or above the actual prices - just like a shadow.

On the other hand, it would be correct to say that there are intersections in certain regions. As a result, instead of making price predictions alone, using directional accuracy and similar complementary metrics provides a more meaningful framework when evaluating model success.

IV. **CONCLUSIONS**

In this study, short-term price predictions were made on days when high-impact news was announced using minute time series data for the EUR/USD parity. The data set created with the technical analysis-based Boomerang Strategy and filtered data at certain time intervals was evaluated with three RNN-based models: LSTM, BiLSTM, and GRU. Each model was trained for 20 iterations and analyzed with performance measures such as Mean Squared Error (MSE) and directional accuracy rate. According to the findings, the LSTM model gave the most successful results in terms of both average error and stability.

Not only error metrics but also direction prediction performance were considered; the rate of models correctly predicting the direction of price movements varied between 51% and 63%. These rates show how complex a problem direction prediction is in volatile market conditions. While the results reveal the applicability of deep learning-based approaches in financial markets, it was understood that the LSTM architecture, particularly, exhibited a more stable performance in trend following. Combining these architectures with different technical or fundamental analysis indicators in future studies can further increase prediction performance..

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