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Sentiment-Driven Exchange Rate Forecasting: Integrating Twitter Analysis with Economic Indicators

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Abstract

This study focuses on predicting the USD/TL exchange rate by integrating sentiment analysis from Twitter with traditional economic indicators. With the dynamic nature of global finance, accurate exchange rate forecasting is crucial for financial planning and risk management. While economic indicators have traditionally been used for this purpose, the increasing influence of public sentiment, particularly on digital platforms like Twitter, has prompted the exploration of sentiment analysis as a complementary tool. Our research aims to evaluate the effectiveness of combining sentiment analysis with economic indicators in predicting the USD/TL exchange rate. We employ machine learning techniques, including LSTM Neural Network, xgboost, and RNN, to analyze Twitter data containing keywords related to the Turkish economy alongside TL/USD exchange rate data. Our findings demonstrate that integrating sentiment analysis from Twitter enhances the predictive accuracy of exchange rate movements. This study contributes to the evolving landscape of financial forecasting by highlighting the significance of sentiment analysis in exchange rate prediction and providing insights into its potential applications in financial decision-making processes.

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Keywords: Twitter narratives, LSTM, XGBoost, RNN, USD/TL FX rate, Narrative economics.

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1. Introduction

In the dynamic landscape of global finance, the accurate prediction of exchange rates is a critical endeavor. This study focuses on the forecasting of the USD/TL (United States Dollar to Turkish Lira) exchange rate, utilizing a unique approach that integrates economic indicators with sentiment analysis derived from social media data.

Understanding and predicting currency movements is vital for financial planning, risk management, and policy formulation. Economic indicators traditionally play a pivotal role in such forecasts, providing valuable insights into the health of an economy. However, in an era dominated by digital communication, the influence of public sentiment on financial markets has gained prominence. Social media platforms, particularly Twitter, have become rich sources of real-time public opinion, reflecting sentiments that may impact economic behaviors.

This study is motivated by the belief that combining traditional economic indicators with sentiment analysis from Twitter can enhance the accuracy of exchange rate predictions. The amalgamation of these factors may provide a more comprehensive understanding of the intricate dynamics influencing currency markets.

The central question guiding this research is: Can sentiment analysis on social media, specifically Twitter, contribute significantly to the prediction of the USD/TL exchange rate? To address this, the study aims to achieve the following objectives:

- Evaluate the effectiveness of sentiment analysis in capturing market sentiment related to economic variables.
- Investigate the correlation between sentiment scores derived from Twitter data and fluctuations in the USD/TL exchange rate.
- Develop and assess machine learning models, including LSTM Neural Network, XGboost, and RNN, to predict exchange rate movements based on sentiment and economic indicators.

Throughout the study, it was observed that the LSTM model outperformed both RNN and XGBoost, achieving a prediction accuracy of 65% and a Mean Absolute Percentage Error (MAPE) of 35%. Notably, the robustness of the model was challenged by external factors, particularly interventions by the Central Bank of the Republic of Turkey. The observed accuracy suggests a significant predictive capability, even in the presence of interventions that may introduce artificial fluctuations in the exchange rate.

Through these objectives, we aspire to contribute insights into the evolving landscape of financial forecasting, showcasing the potential of sentiment analysis as a complementary tool in predicting currency exchange rates.

2. Literature Review

A range of studies have explored the role of economic indicators in exchange rate prediction. Panopoulou and Souropanis (2019) found that both technical indicators and macroeconomic predictors are valuable in forecasting exchange rates, with a combination of the two significantly improving forecast accuracy. However, Faust et al. (2003) cautioned that data revisions and changes in sample periods can significantly impact the predictability of exchange rates, suggesting a need for ongoing evaluation and refinement of forecasting models.

Kucuklerli and Ulusoy (2023) utilized the DCC-GARCH model to assess the relationship between narratives regarding the Turkish economy on Twitter and TL/USD FX rate movements. This choice was motivated by the non-normal and heteroskedastic nature of the Twitter and TL/USD FX rate data, alongside their varying conditional correlations across different lags. Subsequent analysis of delayed relationships up to 10 lags revealed that the 6th and 10th lags of 60-minute frequency 7-day Twitter data exhibited significant conditional correlation with 60-minute frequency TL/USD FX rate data. However, other lags and series were deemed statistically insignificant in elucidating the conditional correlation and dynamic relationship. the DCC-GARCH model indicated that volatility in Twitter data containing specific keywords, notably "Dolar," could precipitate volatility in the TL/USD rate at T+360 minutes and T+600 minutes, enabling investors to anticipate these fluctuations.

Research in sentiment analysis and its applications in finance has demonstrated promising outcomes. Souza et al. (2015) revealed that Twitter sentiment can exert a significant impact on stock returns and volatility in the retail sector, surpassing the predictive power of traditional news sources. Building on this, Jangid et al. (2018) took a step forward by developing a deep learning model for aspect-based sentiment analysis in the financial domain, achieving remarkable accuracy. Expanding the scope, Ravi et al. (2015) applied sentiment analysis to customer reviews in the educational sector, showcasing its effectiveness in evaluating program quality. In the realm of Chinese microblogs related to finance, Yan et al. (2018) proposed a method for sentiment analysis using a hybrid approach involving rule-based and classification methods. Together, these studies underscore the considerable potential of sentiment analysis in finance, offering valuable insights for both market analysis and customer feedback evaluation.

Moreover, an array of studies has delved into the intricate relationship between social media sentiment and market movements. Rao and Srivastava (2012) discovered a pronounced correlation between stock prices and Twitter sentiments, emphasizing the substantial impact of Twitter discussions on stock price dynamics. Yang et al. (2015) identified a distinct financial community on Twitter, whose sentiment exhibited a noteworthy correlation with the returns of major financial market indices. Examining public sentiments in tweets, Pagolu et al. (2016) found a robust correlation with stock market movements, particularly in response to positive news and tweets. Ranco et al. (2015) conducted a detailed investigation into the connections between Twitter sentiment and stock prices, revealing a significant dependence between Twitter sentiment and abnormal returns, especially during peaks of Twitter volume.

The integration of sentiment analysis into traditional forecasting models offers several advantages. Ren et al. (2019) and Nguyen and Shirai (2015) both demonstrate that it can significantly improve the accuracy of stock market movement predictions, with Ren reporting an 18.6% increase in accuracy. Dang et al. (2021) further highlights its potential in enhancing the performance of recommender systems, particularly in understanding user attitudes and emotions. However, Mishev et al. (2020) cautions that the effectiveness of sentiment analysis in finance is contingent on the use of domain-specific language and the availability of large labeled datasets. Despite these limitations, the potential for improved forecasting accuracy and performance in various applications makes the integration of sentiment analysis a promising area for further research and development.

Research has consistently shown a strong interplay between economic factors and sentiment. Benhabib (2017) found that sentiment, particularly expectations about national output growth, significantly influences future state economic activity. This was further supported by Baghestani and Palmer (2017), who demonstrated a dynamic relationship between consumer sentiment and economic policy assessment, with both influencing each other. Dergiades (2012) added to this by showing that investors' sentiment dynamics can significantly predict stock returns. These studies collectively highlight the importance of sentiment in shaping economic outcomes.

A range of machine learning models have been used to predict exchange rates, with varying degrees of success. Goncu (2019) found that Ridge regression offered accurate estimation, particularly for the US Dollar and Turkish Lira exchange rates. Chen et al. (2021) developed a two-stage approach for Bitcoin exchange rate prediction, using economic and technology determinants to achieve better performance than traditional methods. Pfahler (2021) used artificial neural networks and XGBoost models to make out-of-sample forecasts for ten currency pairs, demonstrating significant predictive power in directional forecasts. Tak and Logeswaran (2022) highlighted the potential of hybrid machine learning models, particularly those incorporating text mining for sentiment analysis, in predicting foreign currency exchange rates.

Ketkar (2017) stated Recurrent Neural Networks (RNNs) are a type of neural network that utilize recurrence, allowing them to use information from previous forward passes and they are characterized by internal loops that introduce delayed activation dependencies, creating recursive dynamics. Kaur and Mohta (2019) emphasized that RNNs are a key component of deep learning, capable of processing sequential data and preserving elements over time. Bisong (2019) highlighted they are particularly well-suited for tasks where past information is crucial for future predictions, such as language modeling and stock market prediction.

A range of studies have demonstrated the effectiveness of LSTM and XGBoost models in financial forecasting. Liwei et al. (2021) found that the LSTM-BO-XGBoost model outperformed both LSTM and RNN in stock price prediction.

Similarly, Qu et al. (2019) reported that the LSTM neural network model had smaller errors and more accurate predictions than the RNN model in foreign exchange price forecasting. In the context of volatility forecasting, Liu (2019) found that LSTM RNNs performed as well as v-SVR and outperformed the GARCH model. Tsang et al. (2018) further supported the use of LSTM-based models in stock market index prediction, demonstrating significant profitability. These studies collectively highlight the potential of LSTM and XGBoost models in financial forecasting.

A range of studies have explored the impact of central bank interventions on currency markets. Beine et al. (2007) found that both concerted and unilateral interventions can influence exchange rate dynamics, with the former affecting both currency components and the latter primarily impacting the central bank's currency. Pasquariello (2010) proposed a theory that the mere expectation of future interventions can affect exchange rate levels, volatility, and bid-ask spreads, with these effects being influenced by dealership competition, the central bank's policy trade-off, and the credibility of its threats. Nikkinen and Vähämaa (2009) further noted that central bank interventions can alter market expectations about future exchange rate movements, temporarily increasing correlations among major exchange rates.

In addition, Sağlam et al. (2019) introduced SWNetTR++, a Turkish sentiment lexicon crafted to encapsulate the sentiment orientations of approximately 49,000 Turkish words and word groups. This lexicon comprises polarity and tone values, serving as indicators of the directional sentiment associated with each word. Specifically, the polarity value of a word reflects a positive sentiment with a score of 1, whereas it indicates a negative sentiment with a score of -1. Moreover, the tone values of words fall within the continuous range of [-1, +1], offering nuanced insights into the intensity or strength of the associated sentiment. SWNetTR++ stands as a pivotal resource in the realm of sentiment analysis, furnishing researchers and practitioners with a comprehensive tool to decipher and interpret the intricate fabric of sentiment embedded within Turkish language expressions.

Given the limited research on Turkish sentiments in this domain and the absence of studies utilizing machine learning algorithms such as LSTM, RNN, and XGBoost for sentiment-based exchange rate predictions, our literature review serves the purpose of situating our research within the current scholarly landscape. This endeavor seeks to underscore the relevance of our approach, offering valuable insights to the evolving dialogue on exchange rate prediction.

3. Data and Methodology

The data were retrieved from Thomson Reuters EIKON and Twitter Inc. databases, encompassing tweets originating from Turkey containing keywords such as "economic crisis," "inflation," "unemployment," "economic recession," “refugee” and "#dollar," alongside TL/USD fx rate data. The data span from October 1, 2020, to April 11, 2023, comprising a total of 16,163,207 tweets.

With this Twitter data at hand, sentiment scores were assigned to each word of every tweet using the SWNET++ lexicon for sentiment analysis, followed by aggregation at the tweet level. R programming language was employed for these analyses. Subsequently, sentiment scores obtained for each tweet were aggregated over intervals of 15, 30, and 60 minutes, as well as 12 hours and 1 day, forming a time series dataset tailored for analysis.
Concurrently, TL/USD exchange rate data for the same periods were sourced from the Thomson Reuters EIKON database and merged with tweet data to construct a time series. Then, this dataset was subjected to analysis utilizing LSTM Neural Network, xgboost, and RNN techniques, with the USD/TL exchange rate serving as the dependent variable, and aggregated sentiment scores assigned to specific keywords ("economic crisis," "inflation," "unemployment," “refugee”, "economic recession," and "#dollar") across aggregated periods acting as independent variables. Descriptive statistical values for the variables are provided in Appendix 1 and Appendix 2.
In this study, three distinct machine learning techniques were employed for analysis: Long Short-Term Memory (LSTM) Neural Network, eXtreme Gradient Boosting (xgboost), and Recurrent Neural Network (RNN). These models were chosen due to their established effectiveness in handling sequential data and their applicability to time series forecasting tasks.
Prior to model implementation, the dataset underwent rigorous preprocessing steps to ensure compatibility with each respective model. This included data cleaning, normalization, and feature engineering to extract relevant information from the raw input data.

3.1 Recurrent Neural Network (RNN)

The Recurrent Neural Network (RNN) architecture was also employed to analyze the dataset. RNNs are particularly adept at capturing sequential patterns and have been widely utilized in various natural language processing and time series analysis tasks. In this study, RNNs were utilized to model the temporal dynamics of the data and make predictions based on historical trends.
Recurrent Neural Networks (RNNs) constitute a class of artificial neural networks particularly suited for sequential data analysis, including time series forecasting and natural language processing tasks. Unlike traditional feedforward neural networks, RNNs possess feedback loops that enable them to exhibit temporal dynamics by incorporating information from previous time steps into their computations.
The architecture of an RNN typically comprises three main components: an input layer, a hidden layer with recurrent connections, and an output layer. The key distinguishing feature of RNNs is the presence of connections that allow information to persist over time, making them well-suited for tasks involving sequential data.
The recurrent connections in an RNN enable it to maintain a form of memory, allowing past information to influence the network's current output. At each time

step, the hidden layer receives both the current input and the output from the previous time step, thus capturing temporal dependencies in the data.

Training an RNN involves optimizing its parameters to minimize a specified loss function, typically achieved through gradient-based optimization techniques such as backpropagation through time (BPTT). During training, the network learns to update its internal state based on both the current input and its previous state, allowing it to capture complex temporal patterns in the data.

Despite their effectiveness in modeling sequential data, RNNs have certain limitations, such as difficulties in capturing long-range dependencies and issues with vanishing or exploding gradients during training. These challenges have led to the development of more advanced architectures, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), which address some of the shortcomings of traditional RNNs.

As per Goodfellow et al. (2016), multilayer perceptrons (MLPs) are employed to approximate a function denoted as f^*. The concept underlying multilayer perceptrons involves learning the parameters θ of a mapping

$$y = f^*(\cdot, \theta) \tag{1}$$

Essentially, an MLP consists of a sequence of linear mappings and activation functions applied to the input data. For instance, a two-layer MLP can be mathematically represented by the following equations:

$$h = \varphi(W_{xhx} + bh) \tag{2}$$

$$y = W_{hyh} + by \tag{3}$$

In the context of multilayer perceptrons (MLPs), the weight matrices W_{xh} and W_{hy} are utilized in the input-to-hidden layer mapping and hidden-to-output layer mapping, respectively. Here, x represents a vector containing the input data, b denotes a bias vector, and φ signifies an element-wise applied non-linear activation function. MLPs possess the capability to approximate any mapping given adequate capacity. RNNs leverage the same set of weights across multiple time steps and incorporate recurrent connections. This characteristic, known as parameter sharing, empowers RNNs to effectively process data of varying lengths.

The introduction to the RNN, as outlined by Graves et al. (2013), describes a standard Recurrent Neural Network (RNN) architecture. In this setup, the RNN computes two sequences: the hidden vector sequence $h = (h_1, h_2, \ldots, h_T)$ and the output sequence $y = (y_1, y_2, \ldots, y_T)$. This computation unfolds iteratively over time t within the range $[1, 2, \ldots, T]$, governed by a set of equations.

$$ht = \varphi(W_{xhxt} + W_{hhht} - 1 + bh) \tag{4}$$

$$yt = W_{hyht} + by \tag{5}$$

where W_{xh} is a weight matrix applied to input layer, W_{hh} and W_{hy} are weight matrices applied to the output from the hidden layer at time $t-1$ and t respectively, x is input data, b denotes a bias vector and is a function applied to the hidden layer. In a simple RNN, the hidden layer function could be for example an element-wise application of the sigmoid function. The RNN is illustrated in Figure 1.

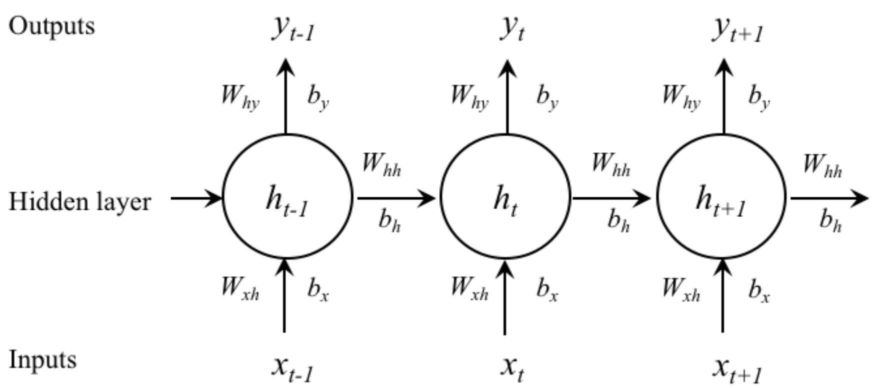

Figure 1: RNN Framework

To optimize the model parameters within a Recurrent Neural Network (RNN), conventional practice involves employing gradient-based backpropagation techniques over time, known as backpropagation through time (BPTT). The primary objective of this optimization process is to minimize an objective function, $L(y_t, \hat{y}_t)$, which quantifies the current error of the model. Here, $y_t$represents the target output, while $\hat{y}_t$ denotes the current output generated by the model. BPTT operates by computing the gradients of the model parameters relative to the error, beginning from the most recent time step and then systematically moving backward in time. Subsequently, the model parameters undergo updates via gradient descent. This iterative process continues until the error diminishes to an acceptable level or the parameters converge.

The update rules for the parameters in Backpropagation Through Time (BPTT) are as follows:

For the output layer, the gradient δ_t^y is computed as the partial derivative of the loss function $L(y_t, \hat{y}_t)$ with respect to the output y_t, given by:

$$\delta_t^y = \frac{\partial L(y_t, \hat{y}_t)}{\partial y_t} \tag{6}$$

These gradients are then propagated to the hidden layer according to:

$$\delta_t^h = \varphi'(\delta_t^y W'_{hy} + \delta_{t+1}^h W'_{hh}) \tag{7}$$

Where φ' represents the element-wise derivative of the activation function, and for the last time step T, the term $\delta_{t+1}^h W'_{hh}$ is zero.
Finally, the model parameters are updated using gradient descent based on these computed gradients.

$$W_{hy}^{i+1} = W_{hy}^i + s \sum_{t=1}^T \delta_t^y h'_t \tag{8}$$

$$b_y^{i+1} = b_y^i + s \sum_{t=1}^T \delta_t^y \tag{9}$$

$$W_{hh}^{i+1} = W_{hh}^i + s \sum_{t=1}^T \delta_t^h h'_{t-1} \tag{10}$$

$$W_{xh}^{i+1} = W_{xh}^i + s \sum_{t=1}^T \delta_t^h x'_{t-1} \tag{11}$$

$$b_h^{i+1} = b_h^i + s \sum_{t=1}^T \delta_t^h \tag{12}$$

Here, s represents a predefined learning rate, and i denotes the iteration number.

3.2 LSTM Neural Network

The LSTM Neural Network, a type of recurrent neural network with specialized memory cells, was implemented to capture temporal dependencies within the dataset. LSTM networks are well-suited for modeling sequential data, making them ideal for time series prediction tasks such as forecasting exchange rate movements. According to Hochreiter and Schmidhuber (1997), Long Short-Term Memory (LSTM) represents an advancement in Recurrent Neural Network (RNN) architecture. By introducing memory cells within the hidden layers, LSTM effectively manages temporal information in time series data. This structural enhancement enables the controlled transmission of information across various cells within the hidden layer via controllable gates, namely the forget gate, input gate, and output gate. Consequently, the extent of memory retention and forgetting pertaining to both previous and current information can be regulated. Unlike traditional RNNs, LSTM incorporates a long-term memory function, thus mitigating the issue of gradient disappearance which is called vanishing gradients.
In response to vanishing gradients, Schmidhuber and Hochreiter (1997) proposed a solution by introducing long short-term memory (LSTM) cells. These specialized cells can be integrated into RNNs by replacing the activation function in Equation 2 with a composite function.

$$i_t = \sigma(W_{xi} X_t + W_{hi} h_{t-1} + W_{ci} C_t - 1 + b_i \quad (13)$$

$$f_t = \sigma(W_{xf} X_t + W_{hf} h_{t-1} + W_{cf} C_{t-1} + b_f) \quad (14)$$

$$C_t = f_t C_{t-1} + i_t tanh(W_{xc} X_t + W_{hc} h_{t-1} + b_c) \quad (15)$$

$$o_t = \sigma(W_{xo} X_t + W_{ho} h_{t-1} + W_{co} C_{t-1} + b_o) \quad (16)$$

$$h_t = o_t tanh(c_t), \quad (17)$$

where

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (18)$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (19)$$

In the LSTM architecture, i, f, and o denote the input, forget, and output gate vectors, respectively. Additionally, c represents the cell vector, and each weight matrix applied to the cell-to-gate mapping is diagonal. Graves et al. (2013) visualize the LSTM cell structure is visually given the Figure 2 below.

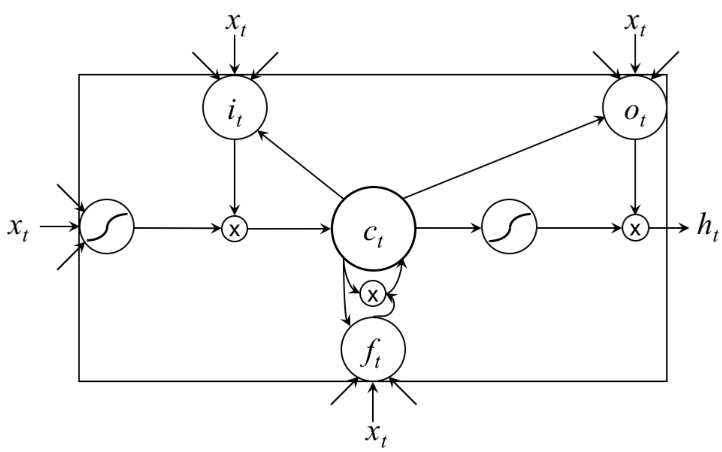

Figure 2: LSTM-NN cell structure

The LSTM RNN exhibits the capability to model dependencies with arbitrary time spans between the predictive signal and the target. Within the LSTM architecture, the memory cell c_t retains the temporal state values of the network, while the gates, characterized by elements ranging between 0 and 1, regulate the flow of information. For instance, when the elements of the input gate vector are zero, new information is prevented from being added to the temporal state. Similarly, the output vector governs the flow of information exiting the cell.

Extreme Gradient Boosting (xgboost) is a powerful ensemble learning technique

that combines the strengths of decision trees with gradient boosting algorithms. In this study, xgboost was utilized for its ability to handle complex, nonlinear relationships in the data and its robust performance in predictive modeling tasks with decision tree regression model with boosting.
Chen and Guestrin (2016) described XGBoost as;

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)\, , f_k \in F \tag{20}$$

Where K is the total trees and F is the total trees. The objective function is:

$$L = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{21}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \tag{22}$$

In the given context, L represents the loss function, while Ω denotes the regularization function utilized to mitigate overfitting. Additionally, T signifies the number of leaves per tree, and *w* denotes the weight associated with each leaf of the tree. ${\hat{y}_i}^{(t)}$ represents the predictive value after the t_{th} iteration, then:

$${\hat{y}_i}^{(t)} = {\hat{y}_i}^{(t-1)} + f_t(x_i) \tag{23}$$

Therefore, the objective function can be expressed as:

$$L^{(t)} = \sum_i l({\hat{y}_i}^{(t-1)} + f_t(x_i), y_i) + \Omega(f) \tag{24}$$

The second-order Taylor expansion of the objective function is:

$$L^{(t)} = \sum_i [\, l(y_i, {\hat{y}_i}^{(t-1)} + g_i f_t(x_i) + \frac{1}{2} h_i {f_t}^2(x_i))] + \Omega(f) \tag{25}$$

where:

$$g_i = \partial_{{\hat{y}_i}^{(t-1)}} l(y_i, {\hat{y}_i}^{(t-1)}) \tag{26}$$

$$h_i = {\partial_{{\hat{y}_i}^{(t-1)}}}^2 l(y_i, {\hat{y}_i}^{(t-1)}) \tag{27}$$

Ignore constant term could be written as:

$$L^{(t)} = \sum_i \left[g_i f_t(x_i) + \frac{1}{2} h_i {f_t}^2(x_i) \right] + \Omega(f) \tag{28}$$

Define $I_j = \{i | q(x_i) = j\}$ as the j_{th} leaf node and (28) can be written as:

$$L^{(t)} = \sum_i \left[g_i f_t(x_i) + \frac{1}{2} h_i {f_t}^2(x_i)\right] + \frac{1}{2}\lambda \sum_{j=1}^{T} {w_j}^2 \quad (29)$$

$$= \sum_{j=1}^{T} \left[\left(\sum_{i\in I_j} g_i\right) w_j + \frac{1}{2}\left(\sum_{i\in I_j} h_i + \lambda\right){w_j}^2\right] + \gamma T \quad (30)$$

When the derivative of the objective function reaches 0, the optimal weight is attained.

$${w_j}^{*} = - \frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda} \quad (31)$$

When $w_j = {w_j}^{*}$, the objective function is:

$$\tilde{L}^{(t)}(q) = -\frac{1}{2}\sum_{j=1}^{T} \frac{\left(\sum_{i\in I_j} g_i\right)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma T \quad (32)$$

If we define I_L as the collection of all left nodes post-split, and I_R as the set of all right nodes post-split, then following each split, the objective function's information gain is calculated as:

$$Gain = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma \quad (32)$$

4. Model Training and Evaluation

The correlation matrix provides insights into the relationships among the variables analyzed in the study. It indicates positive correlations between the USD/TL FX Rate and factors such as Unemployment, Economic Recession with RTE (where RTE refers to "retweet effect"), #Dolar with RTE, and Refugee with RTE. These findings underscore potential interdependencies among the variables examined, emphasizing their roles in economic dynamics and policy-making contexts. The Pearson correlation results measured between variables are presented in Appendix 3.

In delineating the training process for each machine learning model utilized in this study, a systematic approach was adopted to ensure optimal performance. Initially, the dataset was partitioned into training and testing sets to facilitate model evaluation and prevent overfitting. In the models where "RTE" (retweet effect) is incorporated, the sentiment score of tweets is multiplied by the number of retweets to enhance the predictive power of the sentiment analysis. This multiplication serves to amplify the impact of tweets that have been widely shared, under the assumption that highly retweeted tweets may exert a stronger influence on market sentiment and subsequently on exchange rate movements. By integrating the retweet count into the sentiment analysis, these models aim to capture the potential amplifying effect of social media activity on financial markets, thereby improving the accuracy of exchange rate predictions.

The training process for the machine learning models involved sequential processing of input data to capture temporal dependencies. In LSTM Neural Network models, backpropagation through time iteratively adjusted the network's weights to minimize loss and improve predictive accuracy. Hyperparameter tuning optimized parameters like layer count, hidden units, and learning rate. Similarly, SimpleRNN models processed data sequentially, albeit with a simpler architecture than LSTM, potentially limiting their ability to capture long-term dependencies. Nevertheless, hyperparameter tuning was employed to enhance predictive accuracy. XGBoost models refined decision trees iteratively, utilizing techniques such as grid search or random search to optimize parameters like tree depth and learning rate.

Throughout the training process for each model, validation techniques such as cross-validation were utilized to assess generalization performance and mitigate overfitting. Additionally, models were trained iteratively, with adjustments made to optimize performance metrics such as accuracy and precision.

Overall, the training process for each machine learning model aimed to maximize predictive accuracy and generalization capability, thereby enhancing the effectiveness of exchange rate forecasting.

In evaluating the performance of the machine learning models, Mean Absolute Percentage Error (MAPE) was utilized as a key metric. MAPE is a commonly used measure in forecasting tasks, particularly in financial forecasting, as it provides insights into the accuracy of predictions relative to the actual values. To calculate MAPE following formula is used.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - Y_{pred}|}{Y_i} \tag{33}$$

Where,

Y_i: is the actual value of the TL/USD FX Rate

Y_{pred}: is the forecasted value of TL/USD FX Rate

n is the total number of observations

By employing MAPE as a performance metric, this study sought to gauge the effectiveness of each machine learning model in accurately forecasting exchange rate movements while considering the magnitude of errors relative to the actual values. This approach enabled a robust assessment of model performance, facilitating informed comparisons and aiding in the selection of the most suitable model for exchange rate forecasting. The MAPE values measured for the models are provided in Appendix 4.

In evaluating the performance of each machine learning model in predicting exchange rate movements, several key metrics were utilized to provide a comprehensive assessment. The Mean Absolute Percentage Error (MAPE) served as a primary metric, quantifying the average absolute percentage difference between predicted and actual values. This metrics allowed for an evaluation of each model's predictive accuracy and effectiveness in capturing exchange rate dynamics. Among the models examined, those utilizing LSTM Neural Networks consistently demonstrated lower MAPE values and higher Prediction Power scores compared to other models, indicating superior performance in predicting exchange rate movements. Notably, the LSTM_NN_1day_rte model stood out with the lowest MAPE of 34.56% and the highest Prediction Power of 65.44%, highlighting its effectiveness in accurately forecasting exchange rates. Conversely, models employing SimpleRNN and XGBoost techniques generally yielded higher MAPE values and lower Prediction Power scores across various time intervals and tweet inclusion variations, suggesting comparatively poorer predictive performance. These findings underscore the importance of selecting appropriate machine learning techniques, such as LSTM Neural Networks, for achieving more reliable predictions in financial forecasting tasks.

5. Conclusion

In the dynamic realm of global finance, accurately predicting exchange rates is paramount. This study delves into forecasting the USD/TL exchange rate, employing a novel methodology that integrates economic indicators with sentiment analysis sourced from social media data. Understanding and forecasting currency movements are essential for effective financial planning, risk management, and policy formulation. While economic indicators traditionally offer valuable insights, the burgeoning influence of public sentiment, particularly on digital platforms like Twitter, has garnered significance in recent years.

Our study aims to enhance exchange rate predictions by combining traditional economic indicators with sentiment analysis from Twitter, aiming for a more comprehensive view of currency market dynamics. We ask: Can Twitter sentiment analysis significantly aid in predicting the USD/TL exchange rate? To answer this, we assess the effectiveness of Twitter sentiment analysis in capturing market sentiment on economic variables and develop and evaluate machine learning models like LSTM Neural Network, XGBoost, and RNN to forecast exchange rate movements using sentiment and economic indicators.

Throughout our study, we observed that the LSTM model consistently outperformed both RNN and XGBoost, boasting a prediction accuracy of 65% and a Mean Absolute Percentage Error (MAPE) of 35%. Notably, the model's robustness was tested by external factors, particularly interventions by the Central Bank of the Republic of Turkey. Despite these challenges, our findings underscore the model's significant predictive prowess, even in the face of interventions that may introduce artificial fluctuations in the exchange rate.

The implications of sentiment analysis in predicting exchange rates are profound. By leveraging sentiment analysis from social media platforms, financial institutions, policymakers, and investors can gain a more nuanced understanding of market sentiment and sentiment-driven behaviors. This, in turn, can aid in making informed decisions regarding currency trading, investment strategies, and policy adjustments. Moreover, the real-time nature of sentiment analysis allows for timely responses to market fluctuations, enhancing agility and responsiveness in the financial landscape. There are several avenues for future research in the realm of predicting exchange rates using sentiment analysis. Firstly, exploring the integration of sentiment analysis from multiple social media platforms can provide a more comprehensive understanding of market sentiment. Additionally, incorporating alternative data sources, such as news articles or economic reports, may further enhance predictive accuracy. Furthermore, refining sentiment analysis techniques to account for linguistic nuances and context-specific factors can improve the reliability of predictions. Finally, longitudinal studies tracking the effectiveness of sentiment analysis in different market conditions and geopolitical contexts can provide valuable insights into its robustness and applicability.

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Appendix 1: Descriptive Statistical Values for the Variables

Freq	Descriptive Stats	USD/TL FX Rate	Economic Crisis	Inflation	Unemployment	Economic Recession	#Dolar	Refugee
15 Min	Mean	13.22	(0.79)	1.97	(2.35)	(0.01)	4.31	(0.21)
	Standart Deviation	4.59	4.44	12.85	6.34	0.40	10.80	1.13
	Max	19.46	376.01	360.88	208.15	7.25	529.36	18.92
	Min	6.90	(162.29)	(577.77)	(347.29)	(90.98)	(231.51)	(65.54)
	Median	13.68	(0.15)	0.11	(0.95)	-	1.91	-
30 Min	Mean	13.22	(1.97)	4.93	(5.88)	(0.02)	10.12	(0.51)
	Standart Deviation	4.59	10.23	30.30	14.60	0.53	26.06	2.55
	Max	19.46	679.44	895.32	371.24	24.35	1,300.60	34.40
	Min	6.90	(358.67)	(1,100.08)	(452.64)	(40.98)	(171.56)	(124.39)
	Median	13.68	(0.60)	0.38	(2.56)	-	4.30	-
60 Min	Mean	13.22	(4.34)	10.84	(13.00)	(0.06)	23.65	(1.13)
	Standart Deviation	4.59	20.81	63.53	29.64	1.30	55.34	5.31
	Max	19.46	1,131.95	1,747.53	490.74	34.18	2,225.34	66.87
	Min	6.90	(630.48)	(2,438.05)	(617.09)	(105.31)	(223.01)	(200.37)
	Median	13.68	(1.48)	0.88	(5.92)	-	11.39	-
6 Hour	Mean	13.22	(28.00)	69.81	(83.63)	(0.36)	149.66	(7.25)
	Standart Deviation	4.60	103.51	320.27	140.93	5.18	299.32	27.56
	Max	19.45	1,576.79	5,121.45	1,273.86	61.58	7,384.89	78.25
	Min	6.90	(1,857.26)	(2,961.34)	(2,173.85)	(202.80)	(1,119.40)	(555.30)
	Median	13.70	(12.12)	8.54	(45.19)	-	83.61	(0.95)
12 Hour	Mean	13.22	(56.45)	141.12	(168.88)	(0.74)	302.75	(14.62)
	Standart Deviation	4.60	184.01	543.19	233.70	8.67	554.82	48.99
	Max	19.45	2,373.33	6,386.34	1,387.37	61.78	13,390.36	96.56
	Min	6.90	(2,161.95)	(3,761.92)	(2,249.15)	(261.35)	(1,638.43)	(783.01)
	Median	13.70	(28.25)	24.87	(113.30)	-	182.92	(3.19)
1 Day	Mean	13.24	(112.94)	282.53	(337.91)	(1.47)	607.06	(29.28)
	Standart Deviation	4.60	316.12	963.65	393.51	16.35	871.02	92.13
	Max	19.45	3,217.32	10,604.24	1,149.00	95.44	13,716.28	119.93
	Min	6.92	(2,509.17)	(4,518.33)	(2,873.08)	(420.38)	(649.80)	(1,397.30)
	Median	13.70	(60.67)	59.55	(240.53)	(0.09)	393.57	(10.28)

Appendix 2: Descriptive Statistical Values for the Variables (w/RTE)

Freq	Descriptive Stats	Economic Crisis w/RTE	Inflation w/RTE	Unemployment w/RTE	Economic Recession w/RTE	#Dolar w/RTE	Refugee w/RTE
15 Min	Mean	(372.64)	1,840.35	(252.43)	(1.50)	956.21	(102.10)
	Standart Deviation	18,999.22	47,773.01	9,674.32	101.85	10,554.32	1,827.54
	Max	2,736,040.46	4,992,801.00	915,071.60	6,388.00	600,918.90	8,115.55
	Min	(814,103.50)	(2,837,776.00)	(300,217.40)	(13,282.48)	(272,924.10)	(190,830.20)
	Median	(0.26)	-	(9.00)	-	15.22	-
30 Min	Mean	(914.29)	4,620.46	(604.57)	(3.16)	2,392.66	(256.05)
	Standart Deviation	44,261.31	117,772.61	24,272.31	217.30	25,670.52	4,362.96
	Max	4,931,931.07	9,978,586.44	2,078,188.02	21,454.03	1,229,895.80	9,376.13
	Min	(2,101,334.00)	(5,299,743.30)	(597,891.36)	(19,054.71)	(589,502.53)	(364,734.05)
	Median	(6.90)	-	(53.54)	-	74.88	-
60 Min	Mean	(2,102.40)	10,124.15	(1,366.53)	(7.54)	5,265.00	(562.83)
	Standart Deviation	86,640.41	240,527.38	50,112.35	471.85	54,893.92	9,287.05
	Max	8,288,862.00	13,139,768.90	3,660,150.40	30,493.22	2,217,505.40	15,859.40
	Min	(3,743,803.70)	(8,832,758.58)	(1,055,780.85)	(39,924.16)	(1,213,128.80)	(581,790.50)
	Median	(33.70)	-	(152.33)	-	233.49	-
6 Hour	Mean	(13,417.43)	65,662.31	(8,750.53)	(49.69)	33,941.97	(3,623.55)
	Standart Deviation	385,793.43	1,201,942.97	247,488.99	2,138.02	301,117.86	49,988.07
	Max	11,658,165.32	23,931,277.02	9,255,651.00	54,960.02	7,158,300.02	58,847.13
	Min	(8,184,615.80)	(23,865,069.54)	(2,336,652.41)	(94,366.07)	(6,807,545.97)	(1,617,722.25)
	Median	(636.30)	-	(1,647.51)	-	2,457.37	-
12 Hour	Mean	(26,391.56)	133,136.21	(17,612.96)	(100.09)	68,606.51	(7,294.12)
	Standart Deviation	715,272.96	2,071,273.99	408,090.79	3,534.12	573,300.33	87,608.06
	Max	18,113,571.01	41,049,326.32	9,990,469.05	54,960.22	13,235,985.89	109,237.02
	Min	(12,221,473.07)	(29,425,388.85)	(4,358,064.44)	(122,174.45)	(10,376,844.35)	(1,943,224.46)
	Median	(1,712.55)	814.51	(4,016.32)	-	6,757.88	-
1 Day	Mean	(52,981.78)	266,716.84	(35,197.19)	(203.89)	137,483.59	(14,644.36)
	Standart Deviation	1,227,364.64	3,620,264.92	648,105.65	7,237.74	862,000.50	169,366.89
	Max	24,416,786.60	59,694,433.50	9,212,065.17	84,730.56	14,807,306.62	176,761.46
	Min	(11,351,882.47)	(35,691,280.47)	(5,151,089.69)	(198,101.50)	(11,170,196.80)	(4,090,118.05)
	Median	(4,129.17)	2,174.17	(10,772.84)	(0.09)	18,147.54	(13.59)

Appendix 3: Pearson Correlations Between Variables

	USD/TL FX Rate	Economic Crisis	Inflation	Unemployment	Economic Recession	#Dolar	Refugee	Economic Crisis w/RTE	Inflation w/RTE	Unemployment w/RTE	Economic Recession w/RTE	#Dolar w/RTE	Refugee w/RTE
USD/TL FX Rate	1.0000	(0.0301)	0.0633	0.1126	(0.0092)	0.0673	(0.0782)	0.0006	(0.0009)	0.0243	0.0060	(0.0108)	(0.0380)
Economic Crisis	(0.0301)	1.0000	(0.0062)	0.0417	0.0075	(0.0496)	0.0157	0.7659	(0.0074)	0.0254	0.0030	(0.0907)	(0.0030)
Inflation	0.0633	(0.0062)	1.0000	0.0062	(0.0001)	0.0635	(0.0165)	0.0067	0.5100	0.0284	(0.0029)	0.0388	0.0127
Unemployment	0.1126	0.0417	0.0062	1.0000	0.0097	(0.0389)	0.0045	0.0073	(0.0041)	0.4073	0.0126	(0.0102)	0.0046
Economic Recession	(0.0092)	0.0075	(0.0001)	0.0097	1.0000	0.0068	(0.0006)	0.0034	0.0006	0.0054	0.7771	(0.0008)	(0.0011)
#Dolar	0.0673	(0.0496)	0.0635	(0.0389)	0.0068	1.0000	(0.0151)	(0.0163)	(0.0088)	0.0081	0.0322	0.7241	0.0087
Refugee	(0.0782)	0.0157	(0.0165)	0.0045	(0.0006)	(0.0151)	1.0000	0.0067	0.0059	(0.0049)	(0.0015)	(0.0031)	0.6852
Economic Crisis w/RTE	0.0006	0.7659	0.0067	0.0073	0.0034	(0.0163)	0.0067	1.0000	0.0006	0.0069	0.0003	(0.0508)	(0.0014)
Inflation w/RTE	(0.0009)	(0.0074)	0.5100	(0.0041)	0.0006	(0.0088)	0.0059	0.0006	1.0000	0.0208	(0.0002)	0.0168	0.0198
Unemployment w/RTE	0.0243	0.0254	0.0284	0.4073	0.0054	0.0081	(0.0049)	0.0069	0.0208	1.0000	0.0080	0.0021	0.0047
Economic Recession w/RTE	0.0060	0.0030	(0.0029)	0.0126	0.7771	0.0322	(0.0015)	0.0003	(0.0002)	0.0080	1.0000	0.0018	(0.0008)
#Dolar w/RTE	(0.0108)	(0.0907)	0.0388	(0.0102)	(0.0008)	0.7241	(0.0031)	(0.0508)	0.0168	0.0021	0.0018	1.0000	0.0013
Refugee w/RTE	(0.0380)	(0.0030)	0.0127	0.0046	(0.0011)	0.0087	0.6852	(0.0014)	0.0198	0.0047	(0.0008)	0.0013	1.0000

Appendix 4: The MAPE Values for the Models

Model	Mape_s	Prediction_Power
LSTM_NN_1day_rte	34.56%	65.44%
LSTM_NN_15min_tweet	35.48%	64.52%
SimpleRNN_1day	36.10%	63.90%
LSTM_NN_15min	36.73%	63.27%
LSTM_NN_1day	36.97%	63.03%
LSTM_NN_60min_tweet	37.05%	62.95%
LSTM_NN_1day_tweet	37.22%	62.78%
SimpleRNN_60min	37.25%	62.75%
SimpleRNN_15min_tweet	37.39%	62.61%
SimpleRNN_30min	37.56%	62.44%
SimpleRNN_30min_tweet	37.70%	62.30%
LSTM_NN_15min_rte	37.77%	62.23%
LSTM_NN_60min_rte	37.79%	62.21%
SimpleRNN_15min_rte	37.84%	62.16%
LSTM_NN_6hour_rte	37.88%	62.12%
SimpleRNN_1day_rte	37.90%	62.10%
SimpleRNN_15min	37.92%	62.08%
LSTM_NN_12hour_rte	37.93%	62.07%
SimpleRNN_1day_tweet	37.96%	62.04%
LSTM_NN_6hour	38.06%	61.94%
LSTM_NN_30min	38.16%	61.84%
LSTM_NN_30min_rte	38.16%	61.84%
SimpleRNN_60min_rte	38.16%	61.84%
SimpleRNN_30min_rte	38.17%	61.83%
LSTM_NN_30min_tweet	38.38%	61.62%
LSTM_NN_60min	38.44%	61.56%
SimpleRNN_60min_tweet	38.57%	61.43%
SimpleRNN_12hour_tweet	38.60%	61.40%
LSTM_NN_12hour_tweet	39.01%	60.99%
SimpleRNN_12hour_rte	39.21%	60.79%
SimpleRNN_12hour	39.33%	60.67%
LSTM_NN_6hour_tweet	39.49%	60.51%
SimpleRNN_6hour	39.95%	60.05%
SimpleRNN_6hour_rte	40.07%	59.93%
XGBoost_15min_tweet	40.22%	59.78%
SimpleRNN_6hour_tweet	40.28%	59.72%
XGBoost_15min_rte	40.63%	59.37%

Model	Mape_s	Prediction_Power
XGBoost_30min_rte	41.00%	59.00%
XGBoost_30min_tweet	41.00%	59.00%
XGBoost_15min	41.01%	58.99%
LSTM_NN_12hour	41.12%	58.88%
XGBoost_30min	41.65%	58.35%
XGBoost_60min_rte	41.91%	58.09%
XGBoost_60min_tweet	41.91%	58.09%
XGBoost_60min	42.37%	57.63%
XGBoost_12hour	42.93%	57.07%
XGBoost_6hour_rte	42.95%	57.05%
XGBoost_6hour_tweet	42.95%	57.05%
XGBoost_1day_rte	43.05%	56.95%
XGBoost_1day_tweet	43.05%	56.95%
XGBoost_12hour_rte	43.15%	56.85%
XGBoost_12hour_tweet	43.15%	56.85%
XGBoost_6hour	43.27%	56.73%
XGBoost_1day	43.37%	56.63%