Forecasting Exchange Rate Volatility: A Machine Learning Approach for the TRY/USD Market

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1. Abstract

Exchange rate volatility is a significant concern in financial markets due to its implications for investment decisions, risk management, and economic policy formulation. This paper investigates methods to enhance volatility forecast accuracy in the TRY/USD foreign exchange market context. Drawing on a diverse range of data sources spanning economic indicators, market indices, and Google search trends, the study employs machine learning techniques to predict high and low volatility periods in the exchange rate. The methodology involves data preprocessing, feature selection, model training, and evaluation. Various classification models, including K-Nearest Neighbors, AdaBoost, Gradient Boosting, Random Forest, and others, are compared based on performance metrics such as accuracy, precision, recall, and AUC. The results reveal that the Gradient Boosting Classifier outperforms other models, exhibiting an accuracy of 74% and an AUC of 0.744. Further analysis, including ROC curves, confusion matrices, and feature importance plots, provides insights into the model's predictive capabilities and the factors driving exchange rate volatility. Overall, the study contributes to the literature by highlighting the effectiveness of machine learning techniques in forecasting exchange rate volatility and informing decision-making in financial markets.

2. Introduction

Exchange rate volatility is a crucial aspect of financial markets, significantly influencing investment decisions, risk management strategies, and macroeconomic policies. Therefore, the ability to accurately forecast exchange rate movements is paramount for market participants, policymakers, and researchers alike. Traditional econometric models have long been employed, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. However, with the advent of machine learning techniques and the availability of vast amounts of data, there has been a growing interest in exploring alternative methods for volatility prediction.

This paper contributes to the ongoing discourse by investigating the efficacy of machine learning models in forecasting exchange rate volatility, with a specific focus on the Turkish Lira/US Dollar (TRY/USD) exchange rate. Leveraging diverse datasets encompassing economic indicators, market indices, and Google search trends, we employ a comprehensive methodology involving data preprocessing, feature selection, model training, and evaluation. Our analysis encompasses a range of classification models, including K-Nearest Neighbors, AdaBoost, Gradient Boosting, Random Forest, and others, to identify the most effective approach for volatility prediction.

By comparing the performance of these models based on various metrics such as accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC), we aim to shed light on the strengths and weaknesses of different methodologies. Furthermore, through in-depth analysis, including ROC curves, confusion matrices, and feature importance plots, we seek to elucidate the factors driving exchange rate volatility and provide insights into the predictive capabilities of the selected models. Ultimately, our study contributes to the existing literature by offering practical implications for market participants and policymakers and methodological insights for researchers in financial forecasting.

3. Literature Review

Exchange rate volatility is a critical focus in financial research due to its profound implications for investment strategies, risk management, and economic policy formulation. Numerous studies have endeavored to estimate exchange rate volatility using traditional econometric models and machine learning approaches. Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to capture volatility clustering in financial time series. Within this framework, Bollerslev addressed the uncertainty of inflation rates through maximum likelihood estimation and testing. After that, In his 2003 study, Kim utilized Support Vector Machines (SVMs) to predict stock price indices, thereby effectively demonstrating the efficacy of neural networks in forecasting exchange rates. Furthermore, his research rigorously assessed the applicability of SVMs in financial forecasting by benchmarking their performance against backpropagation neural networks and case-based reasoning methods. Kim's findings indicate that SVMs offer a promising alternative for stock market prediction, underscoring their potential utility in financial forecasting. In summary, Kim's study highlights the effectiveness of neural networks in predicting exchange rates.

With advancements in computational power and data availability, machine learning models have gained substantial prominence in academic research. A significant study focused on the stock market, utilizing ten years of historical data from 2003 to 2012, compared four prediction models—Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest, and Naive Bayes—using two different data preprocessing techniques. The research revealed that the Random Forest model exhibited superior performance with continuous technical parameters, and all models demonstrated improved accuracy with trend-identifying data (Patel, Shah, Thakkar, & Kotecha, 2015).

In a study published in 2024, the ability of long short-term memory (LSTM) models to predict the implied volatility of EURUSD across the volatility surface was compared to random forest and various time series models, and it was observed that the huge and sudden changes in implied volatility, which are important for protecting against significant changes in exchange rates, were captured by the LSTM model. (Olsen et al., 2024)

Building on similar preprocessing techniques and machine learning models, this study aims to determine the most effective method to increase volatility forecast accuracy in the context of USD/TRY foreign exchange markets.

4. Methodology

4.1 Data Collection

The study utilized diverse data sources to ensure a robust analysis of the factors influencing the volatility of the TRY/USD exchange rate. The primary datasets included:

- **TRY/USD Exchange Rate**: Daily bid prices for the TRY/USD exchange rate were acquired from the Central Bank of the Republic of Türkiye (CBRT) via the Electronic Data Delivery System (EVDS) API, covering the period from December 31, 2004, to January 1, 2024.
- **BIST100 Index**: Daily adjusted closing prices and trading volumes of the BIST100 index were sourced from Yahoo Finance, encompassing data from December 1, 2004, to January 1, 2024.

- **VIX Index**: Daily closing prices of the VIX index were also obtained from Yahoo Finance for the same temporal scope as the BIST100 index.
- **Deposit Interest Rates**: Monthly interest rates for deposits in Turkish Lira (TRY), US Dollar (USD), and Euro (EUR) were procured from the CBRT via the EVDS API, spanning from December 31, 2004, to December 29, 2023.
- **Inflation Data**: Monthly inflation rates were similarly sourced from the CBRT via the EVDS API.
- **Gross National Product (GNP)**: Monthly GNP data sourced from the CBRT, covering the period from January 1, 2005, to January 1, 2024.
- **Google Trends**: Data on search queries related to the TRY/USD exchange rate was obtained from Google Trends. Queries included terms such as "dolar," "tl dolar," "dolar kaç," and "dolar kuru."

4.2 Data Preprocessing

Comprehensive preprocessing steps were undertaken to ensure data consistency and suitability for analysis:

1. **Date Parsing and Indexing**: All date columns were converted to datetime objects and set as indices for their respective dataframes. This facilitated time-series operations and ensured temporal alignment across datasets.
2. **Handling Missing Values**: Missing values were addressed through appropriate imputation strategies. Forward-filling was applied where temporal continuity was essential, while in other cases, missing data points were dropped to prevent skewed analysis.
3. **Resampling**: Daily data was resampled to a monthly frequency to align with the temporal granularity of macroeconomic indicators such as inflation and GNP. Aggregation methods were carefully chosen (e.g., mean for average values and last value for end-of-period indicators).

4. **Normalization and Scaling**: Numerical features were normalized or standardized using StandardScaler from the scikit-learn library. This step ensured that all features contributed equally to the analysis, preventing dominance by larger-scale variables.
5. **Feature Engineering**:
    - **Volatility Calculation**: Daily returns of the TRY/USD exchange rate were computed using the logarithmic difference of consecutive bid prices. Monthly volatility was then calculated as the standard deviation of daily returns, with annualized volatility derived subsequently.
    - **Lagged Features**: Lagged versions of each predictor variable were created to capture temporal dependencies, reflecting the delayed effects of economic indicators on exchange rate volatility.
    - **Categorical Transformation**: Google Trends data, initially continuous, was binned into discrete categories representing varying levels of search interest intensity. This transformation aimed to capture shifts in public sentiment and its potential impact on exchange rate fluctuations.

4.3 Feature Selection

An extensive set of features was curated to encompass a wide range of economic indicators potentially influencing the volatility of the TRY/USD exchange rate. The final feature set included:

- **BIST100_Value_mean:** Monthly mean value of percentage changes in the BIST100 index.
- **BIST100_Volume_mean:** Monthly mean value of percentage changes in the BIST100 index volume.
- **GNP(TRY):** Gross National Product in Turkish Lira.
- **Inflation(%):** Monthly inflation rate.
- **Deposit_Interest(TRY), Deposit_Interest(USD), Deposit_Interest(EUR):** Monthly percentage changes in deposit interest rates for TRY, USD, and EUR.
- **VIX:** Monthly percentage change in the Volatility Index.

- **Google_Trends:** Categorical representation of Google search interest levels.
- **Annualized_Volatility:** Annualized volatility of the TRY/USD exchange rate.
- **Lagged versions of the predictors above.** (The idea of putting lagged versions is keeping past data's predictable information into future data.

These features provide a holistic view of the economic landscape and its potential impacts on exchange rate volatility.

4.4 Model Selection and Training

Various classification models were evaluated to identify the most effective model for predicting high or low volatility levels in the TRY/USD exchange rate. The models included:

1. **K-Nearest Neighbors (KNN)**: A non-parametric method used for classification by identifying the k-nearest data points in the feature space.
2. **AdaBoost**: An ensemble method that combines multiple weak classifiers to create a robust classifier, enhancing performance through iterative learning.
3. **Gradient Boosting**: Another ensemble technique that builds a series of weak models, typically decision trees, to optimize prediction accuracy by correcting errors of previous models.
4. **Random Forest**: An ensemble learning method using multiple decision trees, offering robustness to overfitting and high accuracy.
5. **Logistic Regression**: A parametric model used for binary classification, leveraging the logistic function to model the probability of class membership.
6. **Decision Tree**: A non-parametric model that splits the feature space into regions based on decision rules inferred from the data.
7. **Naive Bayes**: A probabilistic classifier based on Bayes' theorem, assuming feature independence.
8. **Support Vector Machine (SVM)**: A model that finds the optimal hyperplane for separating data into different classes, particularly effective in high-dimensional spaces.
9. **Neural Network**: A custom neural network classifier developed and trained to capture complex patterns and interactions in the data.

For each model, hyperparameters were meticulously tuned using GridSearchCV with 10-fold cross-validation, optimizing for performance metrics such as accuracy, precision, recall, and F1 score.

4.5 Model Evaluation

The models were rigorously evaluated using a variety of metrics to assess their performance comprehensively:

- **Accuracy**: The proportion of correctly classified instances among the total instances.
- **Precision**: The proportion of optimistic predictions that were accurate.
- **Recall**: The proportion of actual positives that were correctly identified.
- **F1 Score**: The harmonic mean of precision and recall, providing a balance between the two.
- **AUC (Area Under the ROC Curve)**: A metric that measures the model's ability to discriminate between positive and negative classes.

5. Results

5.1 Model Performance Comparison

The performance evaluation of each classification model involved a meticulous assessment utilizing a variety of metrics, including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC). A summary of the performance metrics for each model is provided in Table 1, shedding light on their respective strengths and weaknesses.

Table 1: Performance Metrics for Each Model

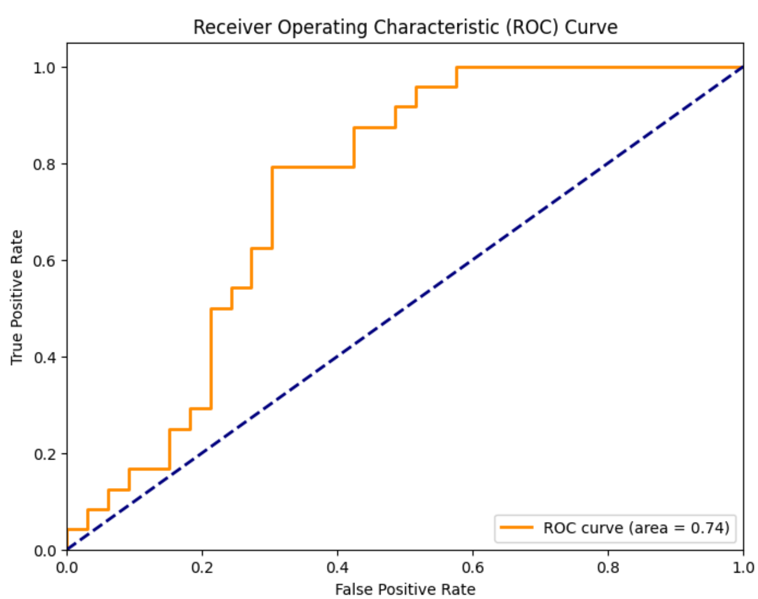
Model	Accuracy	Precision	Recall	F1 Score	AUC	TP	TN	FP	FN
Gradient Boosting	0,737	0,655	0,792	0,717	0,744	19	23	10	5
KNN	0,684	0,607	0,708	0,654	0,723	17	22	11	7
Random Forest	0,684	0,588	0,833	0,690	0,747	20	19	14	4
AdaBoost	0,649	0,550	0,917	0,688	0,727	22	15	18	2
Logistic Regression	0,649	0,559	0,792	0,655	0,760	19	18	15	5
Naive Bayes	0,614	0,525	0,875	0,656	0,766	21	14	19	3
Decision Tree	0,596	0,520	0,542	0,531	0,563	13	21	12	11
Neural Network	0,456	0,436	1,000	0,608	0,542	24	2	31	0

The tabulated results show that the Gradient Boosting Classifier exhibited the most promising performance across multiple metrics, boasting the highest accuracy of 74% and an impressive AUC score of 0.744. This underscores its efficacy in accurately discerning between high and low volatility periods for the TRY/USD exchange rate.

5.2 Detailed Analysis of the Best Model

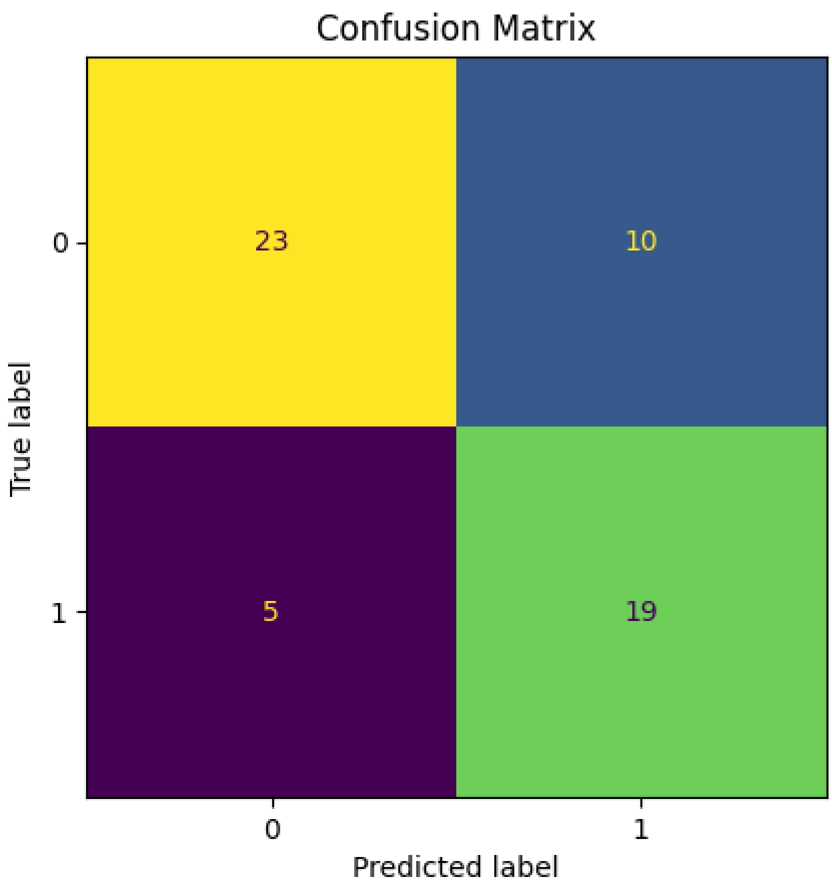
Given the standout performance of the Gradient Boosting Classifier, a deeper analysis was warranted to elucidate its effectiveness and glean insights into its predictive capabilities.

Figure 1: ROC Curve for Gradient Boosting Classifier



The receiver operating characteristic (ROC) curve provides a visual representation of the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity) for the Gradient Boosting Classifier. The pronounced area under the curve (AUC) of 0.74 attests to the model's robust discrimination ability, further validating its reliability.

Figure 2: Confusion Matrix for Gradient Boosting Classifier

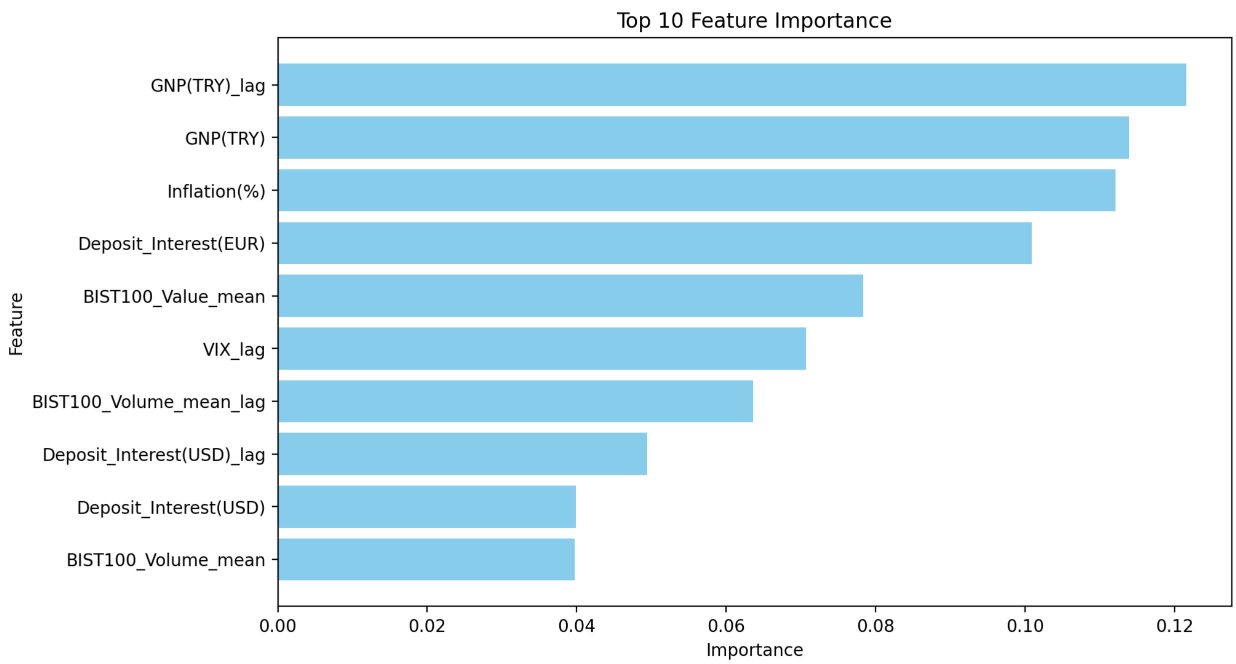


The confusion matrix furnishes a granular breakdown of the model's predictions, delineating the counts of true positives, true negatives, false positives, and false negatives. This matrix is a cornerstone for evaluating the model's classification performance and provides valuable insights into its predictive accuracy and error distribution.

Feature Importance Analysis

A feature importance analysis was conducted to gain a deeper understanding of the factors driving the predictive power of the Gradient Boosting Classifier.

Figure 3: Feature Importance Plot for Gradient Boosting Classifier



The feature importance plot showcases the significance of various economic indicators in influencing exchange rate volatility, with features such as BIST100_Value_mean, Inflation(%), and Deposit_Interest(USD) emerging as pivotal predictors.

Summary of Findings

In summary, the Gradient Boosting Classifier emerged as the top-performing model for predicting high and low volatility periods in the TRY/USD exchange rate. Its superior accuracy, robust discrimination ability (as evidenced by the AUC), and interpretability make it a compelling choice for financial forecasting applications. The feature importance analysis and decision tree visualization provided deeper insights into the economic factors shaping exchange rate dynamics, underscoring the multifaceted nature of currency market influences.

6. Conclusion

In conclusion, this study has explored the application of machine learning techniques in forecasting exchange rate volatility, with a specific focus on the TRY/USD exchange rate. Through a rigorous methodology encompassing data collection, preprocessing, feature selection, model training, and evaluation, we have compared the performance of various classification models in predicting high and low-volatility periods.

Our findings indicate that the Gradient Boosting Classifier emerges as the most promising model, exhibiting superior accuracy and discrimination ability compared to other methodologies. The model's robust performance, as evidenced by an accuracy of 74% and an AUC of 0.744, underscores its potential utility in forecasting exchange rate volatility. Furthermore, our analysis provides insights into the factors driving exchange rate dynamics, elucidated through feature importance plots and decision tree visualization. By highlighting the significance of economic indicators such as stock market indices, inflation rates, and interest rates, we contribute to a better understanding of the determinants of exchange rate volatility.

Overall, this study adds to the growing body of literature on financial forecasting by demonstrating the effectiveness of machine learning techniques in predicting exchange rate volatility. Our findings have practical implications for market participants, policymakers, and researchers, offering valuable insights for decision-making in financial markets and informing future research endeavors in exchange rate forecasting.

7. Comments

This study monitored the effectiveness of machine learning models in predicting the volatility of the exchange rate change of the TRY/USD currency pair. The evaluation of various classification models revealed that the Gradient Boosting Classifier is the most promising performing model, providing high accuracy and a solid area under the ROC curve. This situation reveals that machine learning can facilitate more informed decision-making processes in the field of forex trading and risk management by providing valuable information about volatility, one of the economic indicators that drives exchange rate dynamics.

In Ankita Garg's thesis titled "Forecasting exchange rates using machine learning models with time-varying volatility," Regression Trees, Random Forests, Support Vector Regression (SVR), Least Absolute Shrinkage and Selection Operator (LASSO), and Bayesian Additive Regression Trees (BART) methods were employed to demonstrate the ability of machine learning models to predict both daily and monthly frequencies of exchange rates. Similarly, our paper has reached conclusions similar to Garg's, emphasizing the importance of method accuracy in prediction.

8. References

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Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. Expert Systems with Applications: An International Journal, 42(1), 259–268.

Olsen, A., Djupskås, G., de Lange, P.E. *et al.* Forecasting implied volatilities of currency options with machine learning techniques and econometrics models. *Int J Data Sci Anal* (2024).

Garg, A. (2012). *Forecasting exchange rates using machine learning models with time-varying volatility*. (Master's thesis, Linköping University, Department of Computer and Information Science, Statistics.)

APPENDIX

Best parameters for each model:

Model	Best Model	Best Parameters
KNN	KNeighborsClassifier(leaf_size=10, n_neighbors=7)	{'algorithm': 'auto', 'leaf_size': 10, 'n_neighbors': 7, 'weights': 'uniform'}
AdaBoost	AdaBoostClassifier(learning_rate=0.01, n_estimators=200)	{'algorithm': 'SAMME.R', 'learning_rate': 0.01,
Gradient Boosting	GradientBoostingClassifier(learning_rate=0.05, max_depth=5, min_samples_leaf=2, min_samples_split=5, n_estimators=200)	{'learning_rate': 0.05, 'max_depth': 5, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 200}
Random Forest	RandomForestClassifier(max_depth=10, min_samples_leaf=4, min_samples_split=10, n_estimators=50)	{'bootstrap': True, 'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_estimators': 50}
Logistic Regression	LogisticRegression(C=10, penalty='l1', solver='liblinear')	{'C': 10, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblinear'}
Decision Tree	DecisionTreeClassifier(criterion='entropy', max_depth=20, min_samples_leaf=2, min_samples_split=10, splitter='random')	{'criterion': 'entropy', 'max_depth': 20, 'min_samples_leaf': 2, 'min_samples_split': 10, 'splitter': 'random'}
Naive Bayes	GaussianNB()	{}
Neural Network	<keras.src.engine.sequential.Sequential object at 0x7831ac3ed840>	{'layers': [256, 128, 64], 'dropout_rate': 0.4, 'learning_rate': 0.0001, 'regularization_rate': 0.001}

See the files that are uploaded to the system to see an example decision tree for the best model.