Machine Learning Techniques for Predicting and Classifying Exchange Rates between US Dollars and Japanese Yen

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ABSTRACT

The prediction of fluctuations in foreign exchange prices is a well-researched and well-known field in finance. Using machine-learning techniques to evaluate and forecast changes in the foreign exchange market has been examined in numerous research projects. This study examined multiple machine learning techniques, including random forest, Adaboost, logistic regression, gradient boosting, bagging, Gaussian naïve Bayes, extreme gradient boosting, decision tree, and a proposed ensemble method combining three models: logistic regression, extreme gradient boosting, and Gaussian naïve Bayes. The proposed method aimed at forecasting when to buy and sell dollars relative to the Japanese yen to make more profits. Various technical markers were included in the training dataset to improve accuracy. Experimental results showed that the proposed ensemble method performed better than competing techniques, yielding better prediction accuracy. The proposed method achieved an accuracy of 98.4%, which shows that it can help investors decide when to purchase and sell in the USD/JPY market and make wise judgments.

Keywords-forex; japanese yen; xgbclassifier; prediction

I. INTRODUCTION

Foreign exchange, also known as forex or FX, is the term used to describe the international exchange market. Players in this decentralized market, including banks, financial institutions, corporations, governments, and individual traders, buy and sell global currencies. The foreign exchange market is essential for international trade and investment because it allows the conversion of one currency into another. Interest rates, market sentiment, geopolitical developments, and economic indicators are some factors that affect exchange rates in the foreign exchange market [1].

In [2], machine learning was used to forecast changes in the price of Bitcoin [2]. In [3], a trading algorithm was proposed, which combined machine and deep learning methods to assist traders in the GBP/JPY currency to overcome challenges and draw conclusions quickly. The ideal time to buy or sell a currency pair is a very common question. This study used a variety of machine-learning approaches to schedule the purchase and sale of USD/JPY, developing a system to predict the best times for each action. The goal is to classify whether it is preferable to buy or sell the following day. This classification of technical metrics and characteristics, such as High, Open, Low, and Close, depends on factors that affect buying and selling decisions.

II. RELATED WORKS

In [4], three different kernel types were employed to forecast gold commodities using Auto-Regressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM). In [5], an automated stock trading strategy was proposed, which combined a closest-neighbor classification algorithm with trend analysis. This study integrated technical analysis tools such as the Relative Strength Index (RSI) filter, stop loss, and stop gain. This method reduces the risks related to market exposure while simultaneously increasing profitability. In [6], a mixed method was proposed, which combined the Long Short-Term Memory (LSTM) and GRU networks to predict the prices of LTC and Monero. The results showed that the combined model outperformed the single LSTM technique in predicting the prices of these cryptocurrencies. In [7], different dataset divisions were used to evaluate predictions on currency trends made using the LSTM and GRU techniques. A dataset of 4979 rows was divided into three parts, and 80% for training, 10% for validation, and 10% for testing achieved the most accurate results with 0.054 RMSE, 0.037 MAPE, and 0.97 R^2.

In [8], KNN, ANN, gradient-boosted trees, and a combined ensemble model were used to predict the prices of nine well-known cryptocurrencies. The results showed that the ensemble-learning model had the least prediction error. In [9], Stock Technical Indicators (STIs) and LSTM were used to forecast stock prices. Its objective was to provide investors with a dependable tool to make sustainable investments by combining deep learning techniques with technical indications. More stocks, more sophisticated optimization methods, a range of STIs, real-time data integration, and enhanced model interpretability were proposed as possible future enhancements. In [10], the association rule and LSTM were used to forecast gold prices. LSTM is a type of recurrent neural network that assesses long-term patterns. In [11], a novel approach was presented to accurately predict opening stock prices by fusing ensemble learning techniques with technical indicators.

This study uses a variety of technical indicators, including moving averages, Bollinger bands, and the RSI, to capture different aspects of market behavior. The forecasts from these indicators are combined using ensemble learning techniques such as Gradient Boosting (GB), Random Forest (RF), Support Vector Regressor (SVR), and the ARIMA model. Ensemble learning combines the knowledge of the learned features, employing many machine-learning algorithms that have produced unsatisfactory results to achieve knowledge and improve predictive performance through adaptive voting schemes [12].

III. METHODS AND MATERIALS

A. Dataset

This study classifies the projected buying and selling activities of the USD/JPY currency pair. The dataset, which includes daily pricing from July 21, 2021, to July 20, 2024, was collected continuously, yielding three years. Open, High, Low, and Close variables were included in the dataset. Figure I shows a sample of the dataset and Figure 2 depicts the close price of USD/JPY in the dataset.

Date	Open	High	Low	Close
2021-06-21 00:00:00+01:00	110.192001	110.328003	109.736000	110.200996
2021-06-22 00:00:00+01:00	110.385002	110.788002	110.221001	110.374001
2021-06-23 00:00:00+01:00	110.684998	111.091003	110.684998	110.653999
2021-06-24 00:00:00+01:00	110.986000	111.095001	110.709999	111.012001
2021-06-25 00:00:00+01:00	110.917000	110.974998	110.482002	110.920998
...	...	...	...	...
2024-06-14 00:00:00+01:00	157.128006	158.246994	156.899994	157.128006
2024-06-17 00:00:00+01:00	157.546005	157.951996	157.169998	157.546005
2024-06-18 00:00:00+01:00	157.699997	158.227997	157.524994	157.699997
2024-06-19 00:00:00+01:00	157.871002	157.945007	157.613007	157.871002
2024-06-20 00:00:00+01:00	157.975006	158.938004	157.916000	158.906998

Fig. 1. Sample of the USD/JPY dataset.

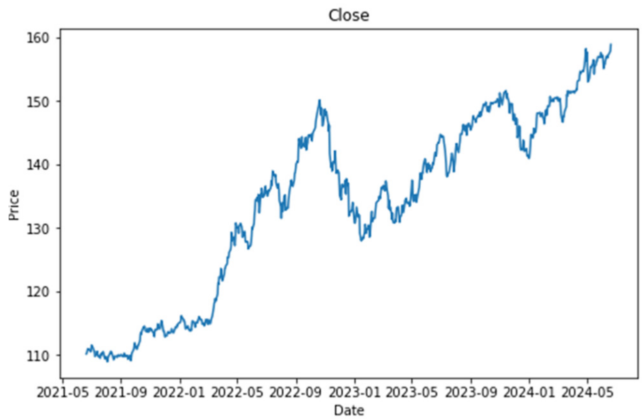

Fig. 2. Close price for USD/JPY.

B. Feature Engineering

Technical indicators are derived from past data and are used in the financial markets to predict stock prices. Table I contains the indicators and additional attributes. The precise amount that each attribute contributes to the anticipated outcomes varies. TargetClass verifies whether the price is increasing or decreasing, EMA monitors denote trend directions over time, TargetNextClose is assigned the future close price of USD/JPY, and RSI indicates whether a stock is overbought or oversold.

TABLE I. INDICATORS

Attributes	Description
EMA100	100-day exponential moving average
EMA150	150-day exponential moving average
EMA20	fifteen-day exponential moving average
RSI15	15-day relative strength index
TargetClass	Verifying if the price is increasing or decreasing
TargetNextClose	Next close price

C. Machine Learning Algorithms

1) Logistic Regression (LR)

LR is a supervised machine learning technique for binary classification and nonlinear datasets with categorical class variables [13] to forecast future probabilistic systems [14]. Using statistical analysis, the relationship between one or more independent factors, which may be categorical or interval-based, and a response (dependent) variable is established.

2) Bagging (BAG)

BAG is an ensemble learning model that combines the predictions of multiple basic classifiers to reduce overfitting and boost overall performance. BAG uses sample data from datasets split into training and testing subsets. This classifier produces distinct hypotheses or probability estimates and works together to identify a single precise value [15].

3) Adaboost (AB)

AB is an ensemble learning technique that trains trees sequentially. It focuses on improving the classification of data that the previous classifier misclassified by boosting to connect a series of weak classifiers. This method sequentially combines inefficient classifiers to generate an effective and robust classifier [16].

4) Extreme Gradient Boosting (XGB) Classifier

XGB is a machine-learning algorithm renowned for its outstanding performance and efficacy. The gradient tree-boosting technique has been introduced as part of this classifier [17].

5) Gaussian Naïve Bayes (GNB)

The GNB algorithm is a method for probabilistic classification based on the statistical Bayes theorem. To provide well-informed predictions, it accounts for the correlations between attributes within a dataset [18]. GNB is also based on the Gaussian distribution and uses the Bayes theorem to produce forecasts, assuming that the characteristics associated with each category have a distribution.

6) Decision Tree (DT) Classifier

DT is a supervised learning method for regression and classification tasks. Its primary objective is to forecast a target variable by creating unambiguous decision rules from the information and associated properties [19].

7) Random Forest (RF)

RF is used for regression and classification tasks [20]. During learning, it generates several decision trees. Regression uses the mean prediction and classes according to their mode. RF is a popular option in many applications because it improves the model's overall performance and robustness.

8) Gradient Boosting (GB) Classifier

Regression and classification models, frequently directed as nonlinear and generally recognized as decision or regression trees, can be better used with the GB algorithm [21].

D. The Proposed Approach

This study uses a voting classifier with three machine-learning methods to predict future buying and selling. The fundamental idea is to predict an output (class) with the highest probability after training on tree models. Figure 3 shows the various processes that make up the proposed method. The data was preprocessed using the MinMaxScaler library, and the NAN value was removed after calculating the technical indicators. The Close, High, Open, and Low indicators were also included in the dataset. Figure 4 shows an overview of modeling predictions.

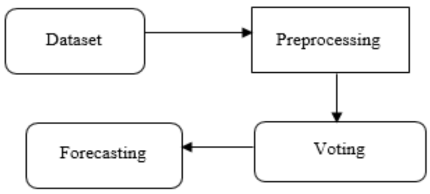

Fig. 3. The proposed method.

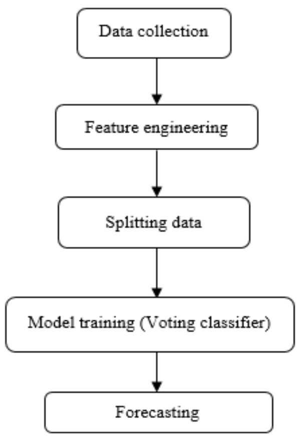

Fig. 4. An overview of modeling predictions.

The proposed ensemble model combined LR, XGB, and GNB. Soft voting was used to predict future purchases and sales, based on the three classifiers. Figure 5 shows the voting procedure. Soft voting is a straightforward technique that capitalizes on the fact that predictions made by many classifiers are frequently more accurate than those of a single classifier. Figure 6 shows a representation of the voting process.

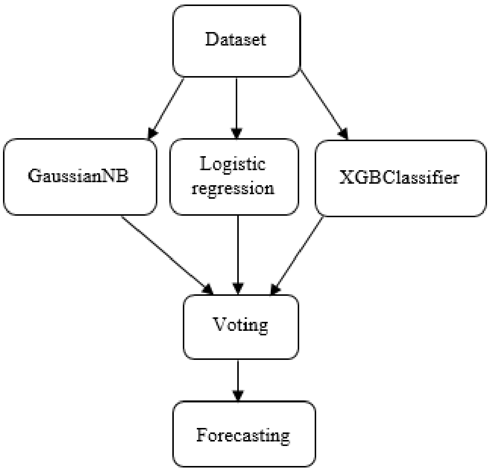

Fig. 5. The voting procedure (three models).

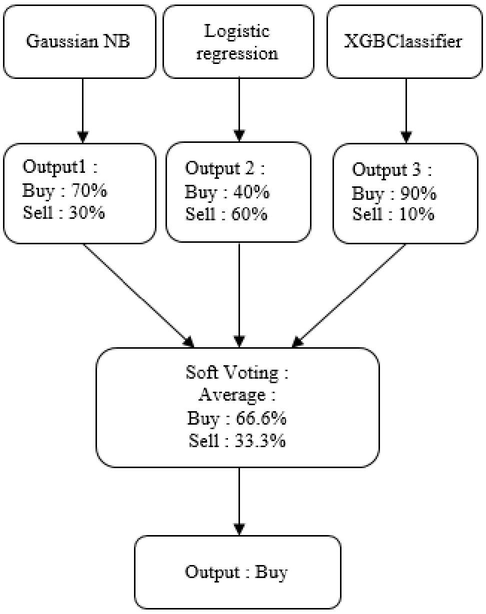

Fig. 6. Soft voting in the proposed method.

E. Performance Metrics

The proposed model was evaluated and compared using accuracy, precision, recall, F1 score, and ROC-AUC (Receiver Operating Characteristic - Area under the Curve). ROC-AUC can show how well the models distinguish between points in the positive and negative classifications. False Negatives (FN), True Negatives (TN), True Positives (TP), and False Positives (FP) are used to calculate these metrics. These measures are calculated as follows:

$$Accurracy = \frac{TP+TN}{TN+TP+FN+FP} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\ score = \frac{precision \times recall}{\text{precision} + \text{recall}} \times 2 \quad (4)$$

IV. RESULTS AND DISCUSSION

This study used the USD/JPY dataset, calculated a few technical indicators, and added a new attribute. The dataset was split into 80% for training and 20% for testing. Various machine-learning techniques was used during the modeling phase. Using the USD/JPY dataset, the AB classifier outperformed the other algorithms, with the BAG classifier coming second. Table III shows the results of the different models. The models' AUC-ROC values were around 0.9, which shows excellent differentiation between positive and negative cases. For example, the GNB classifier had 0.927, the DT classifier had 0.847, etc. Figure 7 shows the AUC-ROC metric for binary classification. The proposed model is shown in Figure 8.

TABLE II. PERFORMANCE METRICS

Algorithm	Accuracy	Precision	Recall	F1 score
XGB	91%	80%	75%	79%
AdaBoost	89%	70%	65%	70%
LR	90%	91%	85%	98%
RF	89%	67%	50%	67%
BAG	92%	70%	75%	80%
GNB	88%	78%	70%	71%
XGB	88%	98%	96%	90%
DT	90%	95%	95%	97%
Proposed method	98%	99%	97%	98%

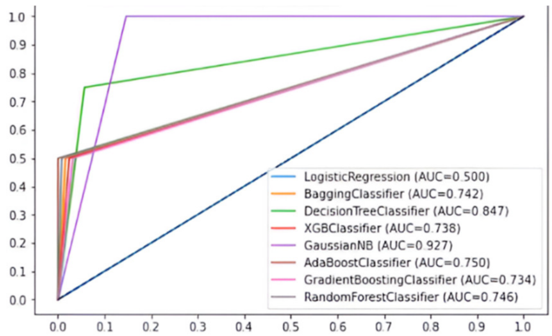

Fig. 7. ROC curve for USD/JPY prediction.

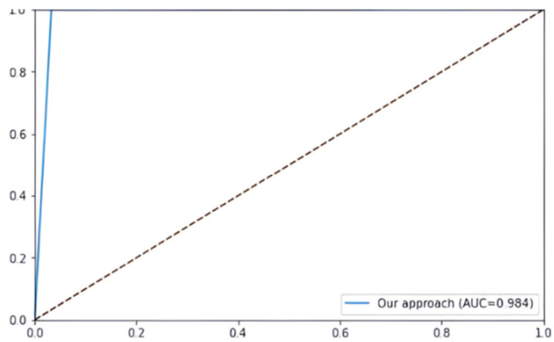

Fig. 8. ROC curve of the proposed method.

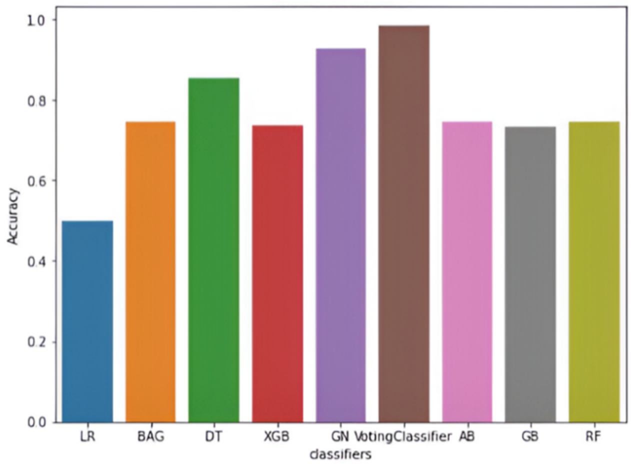

Fig. 9. Accuracy comparison.

The proposed approach demonstrates a dependable algorithm for predicting upcoming bying and selling activity in the USD/JPY currency pair, as shown in Figure 9. The confusion matrices in Tables III to V provide additional context for how well each method performed. For example, the proposed method correctly identified 119 positive cases, missed four cases, made zero incorrect identifications, and accurately identified four negative cases.

TABLE III. CONFUSION MATRIX FOR XGB CLASSIFIER

Prediction	**True**	
	Positive	Negative
Positive	120	3
Negative	2	2

TABLE IV. CLASSIFICATION MATRIX FOR GNB

Prediction	**True**	
	Positive	Negative
Positive	105	18
Negative	0	4

TABLE V. CLASSIFICATION MATRIX FOR THE PROPOSED ENSEMBLE METHOD

Prediction	**True**	
	Positive	Negative
Positive	119	4
Negative	0	4

The LR algorithm achieved 90% accuracy. Next, XGB and LR were combined, obtaining 92% accuracy. Then, GNB and LR were combined, achieving 91% accuracy. Finally, combining the three models achieved 98% accuracy. Finally, the proposed ensemble method was compared with the model in [22], as shown in Table VI.

TABLE VI. COMPARING THE ACCURACY OF THE PROPOSED METHOD WITH THAT OF THE METHOD IN [22]

Study	**Accuracy**
[22]	94%
Proposed method	98%

V. CONCLUSION

This study aimed to forecast future buying and selling signals for the USD/JPY currency pair using a variety of technical indicators. This study used several machine-learning algorithms along with an ensemble method. The proposed approach was tested and compared with other methods, achieving high-quality classification results with 98% accuracy, 99% precision, 97% recall, and 98% F1 score. These results demonstrate how well the proposed method predicts USD/JPY. The proposed method can help investors make informed decisions about their future USD/JPY transactions, allowing them to select the optimal times to buy and sell in the market. Future studies can use these technical markers and different deep-learning strategies to improve the precision of forecasts.

REFERENCES

[1] M. El Mahjouby, M. Taj Bennani, M. Lamrini, B. Bossoufi, T. A. H. Alghamdi, and M. El Far, "Machine Learning Algorithms for Forecasting and Categorizing Euro-to-Dollar Exchange Rates," *IEEE Access*, vol. 12, pp. 74211–74217, 2024, https://doi.org/10.1109/ ACCESS.2024.3404824.

[2] A. Muminov, O. Sattarov, and D. Na, "Enhanced Bitcoin Price Direction Forecasting With DQN," *IEEE Access*, vol. 12, pp. 29093–29112, 2024, https://doi.org/10.1109/ACCESS.2024.3367719.

[3] S. R. Thumu and G. Nellore, "Optimized Ensemble Support Vector Regression Models for Predicting Stock Prices with Multiple Kernels," *Acta Informatica Pragensia*, vol. 2024, no. 1, pp. 24–37, 2024.

[4] D. Makala and Z. Li, "Prediction of gold price with ARIMA and SVM," *Journal of Physics: Conference Series*, vol. 1767, no. 1, Oct. 2021, Art. no. 012022, https://doi.org/10.1088/1742-6596/1767/1/012022.

[5] A. A. Ariyo, A. O. Adewumi, and C. K. Ayo, "Stock Price Prediction Using the ARIMA Model," in *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*, Mar. 2014, pp. 106–112, https://doi.org/10.1109/UKSim.2014.67.

[6] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar, "A Deep Learning-based Cryptocurrency Price Prediction Scheme for Financial Institutions," *Journal of Information Security and Applications*, vol. 55, Dec. 2020, Art. no. 102583, https://doi.org/10.1016/j.jisa.2020.102583.

[7] M. R. Pahlevi, K. Kusrini, and T. Hidayat, "Comparison of LSTM and GRU Models for Forex Prediction," *Sinkron: jurnal dan penelitian teknik informatika*, vol. 7, no. 4, pp. 2254–2263, 2023.

[8] R. Chowdhury, M. A. Rahman, M. S. Rahman, and M. R. C. Mahdy, "An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning," *Physica A: Statistical Mechanics and its Applications*, vol. 551, Aug. 2020, Art. no. 124569, https://doi.org/10.1016/j.physa.2020.124569.

[9] M. Agrawal, P. Kumar Shukla, R. Nair, A. Nayyar, and M. Masud, "Stock Prediction Based on Technical Indicators Using Deep Learning Model," *Computers, Materials & Continua*, vol. 70, no. 1, pp. 287–304, 2022, https://doi.org/10.32604/cmc.2022.014637.

[10] L. Boongasame, P. Viriyaphol, K. Tassanavipas, and P. Temdee, "Gold-Price Forecasting Method Using Long Short-Term Memory and the Association Rule," *Journal of Mobile Multimedia*, pp. 165–186, 2023, https://doi.org/10.13052/jmm1550-4646.1919.

[11] J. Jose and P. Varshini, "Integrating Technical Indicators and Ensemble Learning for Predicting the Opening Stock Price," *International Journal of Information Technology, Research and Applications*, vol. 3, no. 2, pp. 1–15, Jun. 2024, https://doi.org/10.59461/ijitra.v3i2.96.

[12] X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma, "A survey on ensemble learning," *Frontiers of Computer Science*, vol. 14, no. 2, pp. 241–258, Apr. 2020, https://doi.org/10.1007/s11704-019-8208-z.

[13] H. Takci, "Improvement of heart attack prediction by the feature selection methods," *Turkish Journal of Electrical Engineering and*

Computer Sciences, vol. 26, no. 1, pp. 1–10, Jan. 2018, https://doi.org/10.3906/elk-1611-235.

[14] A. K. Chhotu and S. K. Suman, "Predicting the Severity of Accidents at Highway Railway Level Crossings of the Eastern Zone of Indian Railways using Logistic Regression and Artificial Neural Network Models," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14028–14032, Jun. 2024, https://doi.org/10.48084/etasr.7011.

[15] Y. P. Huang and M. F. Yen, "A new perspective of performance comparison among machine learning algorithms for financial distress prediction," *Applied Soft Computing*, vol. 83, Oct. 2019, Art. no. 105663, https://doi.org/10.1016/j.asoc.2019.105663.

[16] S. Misra and H. Li, "Noninvasive fracture characterization based on the classification of sonic wave travel times," in *Machine Learning for Subsurface Characterization*, Cambridge, MA, USA: Gulf Professional Publishing, 2019, pp. 243–288.

[17] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, USA, May 2016, pp. 785–794, https://doi.org/10.1145/2939672.2939785.

[18] P. Venkata and V. Pandya, "Data mining model and Gaussian Naive Bayes based fault diagnostic analysis of modern power system networks," *Materials Today: Proceedings*, vol. 62, pp. 7156–7161, Jan. 2022, https://doi.org/10.1016/j.matpr.2022.03.035.

[19] M. Nabipour, P. Nayyeri, H. Jabani, S. S., and A. Mosavi, "Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis," *IEEE Access*, vol. 8, pp. 150199–150212, 2020, https://doi.org/10.1109/ACCESS.2020.3015966.

[20] Z. Jin, J. Shang, Q. Zhu, C. Ling, W. Xie, and B. Qiang, "RFRSF: Employee Turnover Prediction Based on Random Forests and Survival Analysis," in *Web Information Systems Engineering – WISE 2020*, 2020, pp. 503–515, https://doi.org/10.1007/978-3-030-62008-0_35.

[21] A. Abraham, P. Dutta, J. K. Mandal, A. Bhattacharya, and S. Dutta, Eds., *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 2*, vol. 813. Springer Singapore, 2019.

[22] M. El Mahjouby, M. Taj Bennani, M. Lamrini, B. Bossoufi, T. A. H. Alghamdi, and M. El Far, "Machine Learning Algorithms for Forecasting and Categorizing Euro-to-Dollar Exchange Rates," *IEEE Access*, vol. 12, pp. 74211–74217, 2024, https://doi.org/10.1109/ACCESS.2024.3404824.