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RESEARCH ARTICLE

Machine Learning Algorithms for Forecasting and Categorizing Euro-to-Dollar Exchange Rates

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ABSTRACT Forecasting changes in foreign exchange rates is a well-explored and widely recognized area within finance. Numerous research endeavors have delved into the utilization of methods in machine learning to analyze and predict movements in the foreign exchange market. This work employed several machine-learning techniques such as Adaboost, logistic regression, gradient boosting, random forest classifier, bagging, Gaussian naïve Bayes, extreme gradient boosting classifier, decision tree classifier, and our approach (we have combined three models: logistic regression, random forest classifier, and Gaussian naive Bayes). Our objective is to predict the most advantageous times for purchasing and selling the euro about the dollar. We integrated a range of technical indicators into the training dataset to enhance the precision of our techniques and strategy. The outcomes of our experiment demonstrate that our approach outperforms alternative methods, achieving superior prediction performance. Our methodology yielded an accuracy of 0.948. This study will empower investors to make informed decisions about their future EUR/USD transactions, helping them identify the most advantageous times to buy and sell within the market.

INDEX TERMS Foreign exchange, prediction, logistic regression, random forest, Naïve Bayes.

I. INTRODUCTION

Foreign exchange, sometimes shortened to "forex" or "FX," describes the international exchange market. Participants in this decentralized market, which includes banks, financial organizations, businesses, governments, and individual traders, purchase and sell several global currencies. Because it allows one currency to convert into another, the foreign exchange market is essential to international trade and investment. Several variables, such as interest rates, market sentiment, geopolitical developments, and economic indicators, affect exchange rates in the foreign exchange market. To reduce risk or pursue speculative opportunities, players in the foreign exchange market try to profit from currency swings.

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Recently, machine learning methods and algorithms— which have shown to be very successful in several fields, including biomedicine, image and speech analysis, and machine translation [1]— have been used in the examination of time series financial [2], [3]. The prevailing machine learning algorithms utilized in financial prediction encompass support vector machines [4] and diverse architectures of Artificial Neural Networks (ANNs) [5].

Several researchers have utilized various approaches for forecasting time series data. In reference [6], an LSTM model was developed to predict stock prices. The proposed method forecasts agricultural productivity using RNN, CNN, and LSTM [7].

Research has shown that machine learning is employed to predict Bitcoin price changes, and it has become a powerful tool in this quest [8]. In reference [9], the authors wanted to help traders in the GBP/JPY currency pair overcome obstacles and make quick decisions. To this, a trading algorithm

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using an integration of deep learning and machine learning techniques. XGBoost classifier is employed to determine trading decisions.

The authors of reference [10] provided a reusable trading system that trained on historical data recorded at 4-hour intervals using candlesticks of six different currency pairings: two minor pairs, such as EUR/GBP and GBP/JPY, and four big pairs, such as GBP/USD, EUR/USD, USD/CHF, and USD/JPY.

In reference [11], the authors suggested a version based on compressed autoregression vectors for time series testing and prediction. They initially compressed a wide range of Forex data into a smaller format random compression. Next, to ascertain the loading of every randomly compressed datum and derive the overlapping parameters, they employed the Bayesian model averaging (BMA) approach. Their method can produce forecasts fourteen days ahead of the current date based on out-of-sample data. They concluded that their approach was unsuitable for projecting all 30 currencies used in foreign exchange. Undoubtedly, their suggested research surpasses the current benchmark for Bayesian autoregression.

The most common question researchers ask is, what is the best moment to purchase or sell a currency pair? This query is our inspiration to employ machine-learning methods to time the buying and sale of EUR_USD. This study used various machine learning techniques to develop a strategy for predicting optimal buying and selling points for the EUR/USD currency pair. The objective is to categorize whether it is advisable to buy or sell on the following day. This classification relies on computed technical metrics, fundamental features such as High, Open, Low, and Close, and additional attributes that influence mad purchasing and selling decisions. This study will empower investors to make informed decisions about their future EUR/USD transactions, helping them identify the most advantageous times to buy and sell within the market.

For price forecasting, researchers in this subject often employ machine learning and deep learning techniques mixed with time series data. Regarding the methods employed for examining the stock market's dynamics, some rely on artificial intelligence and machine learning approaches [12], while others are grounded in statistical methods [13]. In the field of literature, deep learning techniques have recently started gaining attention in financial research. Numerous implementations of deep learning, such as LSTM [14], Temporal Convolutional Networks (TCN) [15], and Convolutional Neural Networks (CNN), coexist with various machine learning techniques like the support vector machine [16].

In citation [17], the authors explored the utilization of RNN and CNN algorithms. The accuracy of these models was assessed by contrasting their effectiveness with actual stock market values. The researchers in [18] introduced a novel strategy for forecasting stock market trends, employing a combination of LSTM and GA methodologies. According to their research, this approach demonstrated

TABLE 1. EUR_USd sample dataset.

Date	Open	High	Low	Close
2021-01-11 00:00:00+00:00	1.218784	1.219959	1.213474	1.218621
2021-01-12 00:00:00+00:00	1.216160	1.217849	1.213887	1.216070
2021-01-13 00:00:00+00:00	1.220927	1.222494	1.215539	1.220889
2021-01-14 00:00:00+00:00	1.216175	1.217285	1.211314	1.216249
2021-01-15 00:00:00+00:00	1.215300	1.216249	1.208474	1.215126
...	...	...	...	...
2024-01-05 00:00:00+00:00	1.094739	1.099638	1.087985	1.094739
2024-01-08 00:00:00+00:00	1.094224	1.097815	1.092454	1.094224
2024-01-09 00:00:00+00:00	1.095170	1.096732	1.091262	1.095170
2024-01-10 00:00:00+00:00	1.093243	1.096972	1.092335	1.093243
2024-01-11 00:00:00+00:00	1.097514	1.099143	1.093147	1.097514

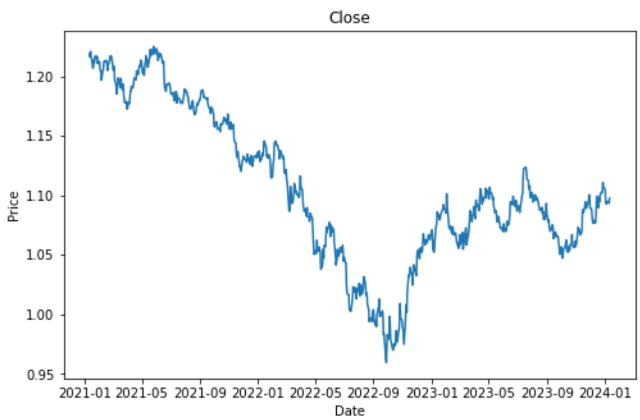

FIGURE 1. Close price for EUR_USD.

superior performance compared to the standard benchmark model. In reference [19], the authors applied a deep learning approach called stacked LSTM to predict the closing value of the NASDAQ Composite on the American Stock Exchange. The results of their research indicated an improvement in the accuracy of predictions when forecasting the stock price.

In reference [20], the authors introduced an ensemble learning approach where predictions from three primary learning methods are combined to generate ultimate predictions. They assessed their proposed methodology using a dataset covering Spain's energy consumption over nine years.

II. MATERIALS AND TECHNIQUES

A. DATA

This research categorized the prospective purchasing and selling activities related to the EUR_USD currency pair. The data, comprising daily prices spanning from January 11, 2021, to January 12, 2024, was gathered without any gaps, resulting in an extensive spanning three years. The dataset encompassed variables Open, High, Low, and Close. The

TABLE 2. Diverse technical metrics.

Attribute	An explanation
RSI15	For 15 days, the relative strength index
EMA20	exponential moving average for 20 days
EMA100	exponential moving average for 100 days
EMA150	exponential moving average for 150 days
TargetClass	TargetClass is confirming whether the price is rising or falling
TargetNextClose	Future close price

sample dataset is in Table 1, and Figure 1 displays the close price EUR_USD.

B. FEATURE ENGINEERING

The technical indicators are produced from historical data and employed for forecasting stock prices within the financial markets. This study employed some technical indicators and other attributes. The indicators and other attributes are in Table 2.

In detail, the contribution of each feature to the predicted results. RSI (Relative Strength Index) is an indicator that lets you know if a stock is overbought or oversold, EMA measures trend directions over some time, attributes TargetNextClose as the future close price of the EUR_USd, and TargetClass confirms whether the price is rising or falling.

C. MACHINE LEARNING

Machine Learning involves specialized algorithms for analyzing datasets to predict trends, categorize information, or establish distinctions [21].

1) LOGISTIC REGRESSION (LR)

LR is a method for supervised machine learning designed for nonlinear datasets featuring categorical class variables and is particularly well-suited for binary classification [22]. This statistical analysis approach establishes the connection among one or more separate factors, which can be either categorical or interval-based, and a response variable, referred to as the dependent variable [23].

2) ADABOOST CLASSIFIER (ABC)

AdaBoost is a method used in ensemble learning where trees are trained and applied sequentially. It utilizes boosting by linking a sequence of weak classifiers, focusing on improving the classification of samples that the prior classifier incorrectly classified. This approach effectively sequentially combines ineffective classifiers to produce a robust classifier [24].

3) GRADIENT BOOSTING CLASSIFIER (GBC)

The GBC Algorithm is utilized to improve the training of classification and regression models, often described as nonlinear and commonly identified as decision or regression trees [25]. It is associated with decision trees or regression trees in the model development.

4) RANDOM FOREST CLASSIFIER (RFC)

Both classification and regression tasks in the RF are used [26]. It creates a lot of decision trees during training to work. The classes are categorized based on their mode, while regression utilizes the mean prediction. This approach enhances the overall performance and robustness of the model, making Random Forest a popular choice in various applications.

5) BAGGING CLASSIFIER (BAGG)

A bagging classifier (BAGG) is an ensemble learning model that leverages the bagging technique. To decrease overfitting and increase overall performance, it integrates the predictions of several base classifiers. The bagging classifier method includes dividing sample data from datasets into training and testing subsets. This classifier generates specific hypotheses or probability estimates and collaboratively determines a single accurate value [27].

6) GAUSSIANNB (NB)

The Gaussian Naive Bayes algorithm, grounded in Bayes' theorem from statistics, is an approach for conducting probabilistic classification. It considers the relationships among attributes within a dataset to make informed predictions [28]. GaussianNB is a probabilistic classification algorithm based on the Gaussian distribution. It presupposes that the characteristics linked to each category have a distribution, and it utilizes Bayes' theorem to generate forecasts.

7) XGBCLASSIFIER (XGB)

The Extreme Gradient Boosting (XGBoost) Classifier, designed by Chen and Guestrin, is a robust machine-learning algorithm recognized for its effectiveness and superior performance. They introduced the gradient tree-boosting technique as a component of this classifier [29].

8) DECISION TREE CLASSIFIER (DTC)

The DTC is a supervised learning technique used for regression and classification assignments. Its main goal is to forecast a target variable by establishing clear-cut decision rules from the dataset and its corresponding attributes [30].

D. OUR METHODOLOGY

This research contributes by developing a predictive model that utilizes machine learning techniques to forecast future buying and selling prices of EUR/USD. Our objective is to introduce a classification model. We've employed diverse machine learning algorithms along with a voting classifier to forecast upcoming buying and selling actions. The fundamental concept behind our recommended model involves training on a combination of tree models and predicting an output

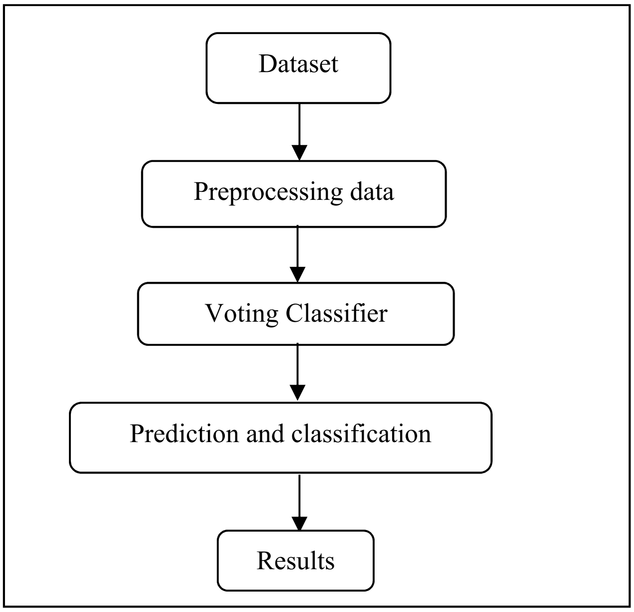

FIGURE 2. Proposed approach.

(class) based on the highest probability among the chosen classes. Our methodology comprises some phases, illustrated in Figure 2 below.

1) Dataset: The dataset consists of daily price data from January 11, 2021, to January 12, 2024, with no gaps or missing information. YFinance [31], a Python library, was used to obtain our dataset.
2) Preprocessing Data: In our datasets, we've incorporated the Close, High, Open, and Low, alongside the four technical indicators and other attributes. You can find further information on this process in the feature engineering section. After calculating technical indicators, we removed the nan value and utilized the library MinMaxScaler for preprocessing our data.
3) Voting Classifier: After completing the mentioned steps, which involve downloading the dataset, calculating technical indicators, incorporating additional attributes, and standardizing the data, we moved on to utilizing machine learning models. In particular, we employed the Voting classifier to predict future buying and selling actions. In our model, we have merged three models: logistic regression, random forest classifier, and Gaussian naive Bayes.
4) Prediction and classification: According to our model's performance, we noted the classification results for potential buying and selling actions concerning EUR_USD.
5) Results: Expectation of future buying and selling activities involving the EUR/USD currency pair.

We have integrated three models in our study to apply the suggested methodology: Gaussian naive Bayes, random forest classifier, and logistic regression. We have employed our approach with a voting classifier to forecast upcoming buying and selling actions. Our three models illustrated in Figure 3 below.

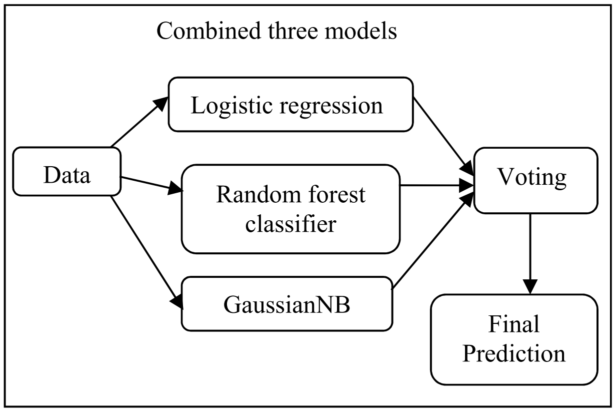

FIGURE 3. Our three models integrated (Voting).

We have selected 0 for the random state in logistic regression and the random forest classifier. We have chosen 50 for the n_estimators in the random forest classifier. After that, we combine several three models to produce the final prediction. For the voting classifier, we have used soft voting for the forecast with the highest total probability selected by adding the probabilities of each prediction in each model.

E. PERFORMANCE MEASURES

We use performance metrics to evaluate and compare our models. They based evaluations on measures such as accuracy and ROC-AUC. The ROC-AUC metric helps us assess whether our models can effectively distinguish between points in the negative and positive classes. 80% of the sample was used for training, whereas testing used the remaining 20% according to usual practice. We use symbols like fn (false negative), n (negative), tn (true negative), p (positive), tp (true positive), and fp (false positive) in the computation of that metric. Accuracy is by Equations (1) [32].

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \tag{1}$$

III. RESULTS AND DISCUSSION

In this research, we applied the EUR_USD dataset, computed some technical indicators, and incorporated an additional attribute. Then, the dataset split into training sets, which made up 80%, and testing sets, which made up 20%. Following these steps, we utilized various machine-learning methods mentioned earlier in the modeling phase. Among these algorithms, the AdaBoost Classifier demonstrated superior performance compared to others in predicting foreign exchange market trends using the EUR_USD dataset, with the bagging classifier ranking second in effectiveness. Table 3 displays the outcomes of various models.

Observing the AUC-ROC values of the models, it is evident that they are all around 0.9, indicating their excellent ability to differentiate between positive and negative cases. For instance, the GaussianNB Classifier has 0.935, the

TABLE 3. Comparison table.

Model Machine learning	Accuracy
Logistic Regression	0.906
Bagging Classifier	0.890
DecisionTreeClassifier	0.913
XGBClassifier	0.921
GaussianNB	0.882
AdaBoostClassifier	0.890
GradientBoostingClassifier	0.882
RandomForestClassifier	0.898
Our Work	0.948

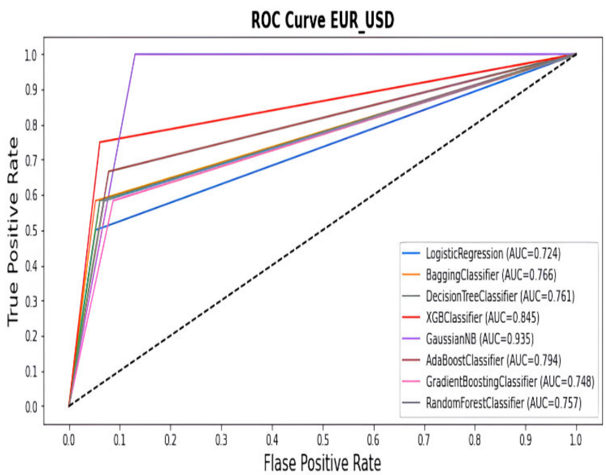

FIGURE 4. Roc-curve.

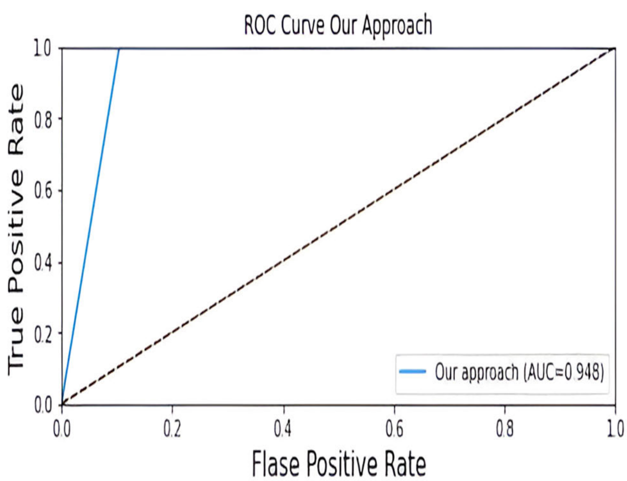

FIGURE 5. Our approach (Roc-curve).

XGBClassifier has 0.845, and so forth. Figure 4 displays the AUC-ROC evaluation metric designed for binary classification, with values ranging from 0 to 1. In conclusion, Figure 5 below depicts our proposed model.

Figure 4 displays the AUC-ROC of our method, providing a visualization of each model's effectiveness in accurately distinguishing between positive and negative examples. To further illustrate their performance, we present the corresponding confusion matrices from Table 4 to Table 6. For

TABLE 4. Classification matrix of gaussiannb.

Prediction	True	
	Positive	Negative
Positive	100	15
negative	0	12

TABLE 5. Classification matrix of xgbclassifier.

Prediction	True	
	Positive	Negative
Positive	108	7
negative	3	9

TABLE 6. Classification matrix of our approach.

Prediction	True	
	Positive	Negative
Positive	103	12
negative	0	12

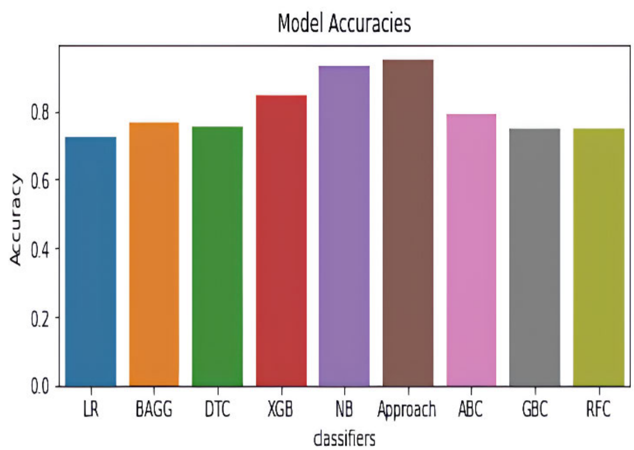

FIGURE 6. Comparison of our machine learning algorithms based on their accuracies.

instance, our approach correctly identified 103 positive cases, made 0 incorrect identifications, missed 12 identifications, and accurately identified 12 negative cases. This pattern persists for other instances outlined in the tables.

As depicted in Figure 6, our method proves a reliable algorithm for forecasting future buying and selling activities in the EUR/USD currency pair.

The generalization of our model involved using the logistic regression algorithm for implementation in the beginning, which produced 90% accuracy. Later, we combined two models—logistic regression and random forest classifier—to obtain 91% accuracy. Later, we combined two more models—logistic regression and GaussianNB—yielded an accuracy of 88%. Finally, we combined the three models to obtain 94.80% accuracy. Our model benefits from the most recent outcomes.

TABLE 7. Comparison of the accuracy of our study with that of the previous studies.

Study	Algorithms
In [32]	Adaboost classifier (76.10%)
Our work	Voting classifier (94.80%)

The various algorithms of machine learning utilized to provide the currency pair EUR_USD forecasting in our article, the factors that contribute to the accuracy of the predictions include the availability of data, quality of data, and different technical indicators used.

In machine learning algorithms, accuracy is a crucial metric. Based on the results, our techniques perform better accuracy than other machine learning algorithms, which is a benefit of our article. If the accuracy of our model and the algorithms is higher, it indicates that the model is better than the other models.

In Table 7, we have compared the accuracy of our study with that of the previous studies, and our work (voting classifier with three models) is a better algorithm to predict future buying and selling for EUR_USD.

IV. CONCLUSION

This paper created several machine-learning algorithms to classify future buy and sell signals for the currency pair EUR_USD using diverse technical indicators and additional attributes. Subsequently, we assessed the performance of these techniques by testing our approach yielded positive results in classification, achieving an accuracy score of 0.948. The results of this study will enable investors to choose the best times to purchase and sell in the market, enabling them to make knowledgeable judgments about their future EUR/USD transactions. In our future research, we intend to apply the same technical indicators along with alternative approaches to deep learning to enrich the accuracy of our predictions.

REFERENCES

[1] S. Patil and V. Phalle, "Fault detection of anti-friction bearing using ensemble machine learning methods," *Int. J. Eng. Trans. B Appl.*, vol. 31, no. 11, pp. 1972–1981, 2018, doi: 10.5829/ije.2018.31.11b.22.

[2] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "Statistical and machine learning forecasting methods: Concerns and ways forward," *PLoS ONE*, vol. 13, no. 3, Mar. 2018, Art. no. e0194889, doi: 10.1371/journal.pone.0194889.

[3] N. Kourentzes, D. K. Barrow, and S. F. Crone, "Neural network ensemble operators for time series forecasting," *Expert Syst. Appl.*, vol. 41, no. 9, pp. 4235–4244, Jul. 2014, doi: 10.1016/j.eswa.2013.12.011.

[4] Y. Peng, P. H. M. Albuquerque, J. M. Camboim de Sá, A. J. A. Padula, and M. R. Montenegro, "The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with support vector regression," *Expert Syst. Appl.*, vol. 97, pp. 177–192, May 2018, doi: 10.1016/j.eswa.2017.12.004.

[5] Y. Kara, M. Acar Boyacioglu, and Ö. K. Baykan, "Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul stock exchange," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 5311–5319, May 2011, doi: 10.1016/j.eswa.2010.10.027.

[6] M. Roondiwala, H. Patel, and S. Varma, "Predicting stock prices using LSTM," *Int. J. Sci. Res.*, vol. 6, no. 4, pp. 1754–1756, 2017.

[7] T. Mallika, S. D. Kavila, B. Pydi, and B. Rajesh, "A novel method for prediction of crop yield using deep neural networks," *Int. J. Intell. Syst. Appl. Eng.*, vol. 11, no. 4, pp. 308–315, 2023.

[8] A. Muminov, O. Sattarov, and D. Na, "Enhanced Bitcoin price direction forecasting with DQN," *IEEE Access*, vol. 12, pp. 29093–29112, 2024, doi: 10.1109/ACCESS.2024.3367719.

[9] S. R. Thumu and G. Nellore, "Optimized ensemble support vector regression models for predicting stock prices with multiple kernels," *Acta Inf. Pragensia*, vol. 13, no. 1, pp. 24–37, Apr. 2024.

[10] M. Fisichella and F. Garolla, "Can deep learning improve technical analysis of forex data to predict future price movements?" *IEEE Access*, vol. 9, pp. 153083–153101, 2021, doi: 10.1109/ACCESS.2021.3127570.

[11] P. Taveeapiradeecharoen, K. Chamnongthai, and N. Aunsri, "Bayesian compressed vector autoregression for financial time-series analysis and forecasting," *IEEE Access*, vol. 7, pp. 16777–16786, 2019, doi: 10.1109/ACCESS.2019.2895022.

[12] R. K. Nayak, D. Mishra, and A. K. Rath, "A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices," *Appl. Soft Comput.*, vol. 35, pp. 670–680, Oct. 2015, doi: 10.1016/j.asoc.2015.06.040.

[13] N. S. Arunraj and D. Ahrens, "A hybrid seasonal autoregressive integrated moving average and quantile regression for daily food sales forecasting," *Int. J. Prod. Econ.*, vol. 170, pp. 321–335, Dec. 2015, doi: 10.1016/j.ijpe.2015.09.039.

[14] K. Chen, Y. Zhou, and F. Dai, "A LSTM-based method for stock returns prediction: A case study of China stock market," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Oct. 2015, pp. 2823–2824, doi: 10.1109/BIGDATA.2015.7364089.

[15] S. Mehtab and J. Sen, "Stock price prediction using convolutional neural networks on a multivariate timeseries," Tech. Rep., 2020, doi: 10.36227/techrxiv.15088734.v1.

[16] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-based model to forecast stock prices," *Complexity*, vol. 2020, pp. 1–10, Nov. 2020, doi: 10.1155/2020/6622927.

[17] G. Rekha, D. B. Sravanthi, S. Ramasubbareddy, and K. Govinda, "Prediction of stock market using neural network strategies," *J. Comput. Theor. Nanoscience*, vol. 16, no. 5, pp. 2333–2336, May 2019, doi: 10.1166/jctn.2019.7895.

[18] H. Chung and K.-S. Shin, "Genetic algorithm-optimized long short-term memory network for stock market prediction," *Sustainability*, vol. 10, no. 10, p. 3765, Oct. 2018, doi: 10.3390/su10103765.

[19] S. O. Ojo, P. A. Owolawi, M. Mphahlele, and J. A. Adisa, "Stock market behaviour prediction using stacked LSTM networks?" in *Proc. Int. Multidiscip. Inf. Technol. Eng. Conf. (IMITEC)*, 2019, pp. 1–5, doi: 10.1109/IMITEC45504.2019.9015840.

[20] F. Divina, A. Gilson, F. Goméz-Vela, M. G. Torres, and J. Torres, "Stacking ensemble learning for short-term electricity consumption forecasting," *Energies*, vol. 11, no. 4, p. 949, Apr. 2018, doi: 10.3390/en11040949.

[21] R. Ali, M. M. Yusro, M. S. Hitam, and M. Ikhwanuddin, "Machine learning with multistage classifiers for identification of of ectoparasite infected mud crab *genus scylla*," *Telkomnika (Telecommun. Comput. Electron. Control.*, vol. 19, no. 2, pp. 406–413, 2021, doi: 10.12928/TELKOMNIKA.v19i2.16724.

[22] H. Takci, "Improvement of heart attack prediction by the feature selection methods," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 26, pp. 1–10, 2018, doi: 10.3906/elk-1611-235.

[23] T. Mantoro, M. A. Permana, and M. Anugerah Ayu, "Crime index based on text mining on social media using multi classifier neural-net algorithm," *TELKOMNIKA (Telecommun. Comput. Electron. Control)*, vol. 20, no. 3, p. 570, Jun. 2022, doi: 10.12928/telkomnika.v20i3.23321.

[24] S. Misra and H. Li, "Noninvasive fracture characterization based on the classification of sonic wave travel times," in *Machine Learning for Subsurface Characterization*. Amsterdam, The Netherlands: Elsevier, 2019, doi: 10.1016/B978-0-12-817736-5.00009-0.

[25] "Emerging technologies in data mining and information security," in *Advances in Intelligent Systems and Computing Emerging Technologies in Data Mining and Information Security*, vol. 2, 2019, doi: 10.1007/978-981-13-1498-8.

[26] Z. Jin, J. Shang, Q. Zhu, C. Ling, W. Xie, and B. Qiang, *RFRSF: Employee Turnover Prediction Based on Random Forests and Survival Analysis*. Wise, 2020.

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

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

[29] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 785–794, doi: 10.1145/2939672.2939785.

[30] 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, doi: 10.1109/ACCESS.2020.3015966.

[31] *Yfinance 0.2.38*. Accessed: Dec. 25, 2023. [Online]. Available: https://pypi.org/project/yfinance/

[32] M. EL Mahjouby, Y. Manzali, M. T. Bennani, M. Lamrini, and M. E. Far, "Machine learning technique to predict the right buying and selling for EUR_USD," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 16s, pp. 439–445, 2024.

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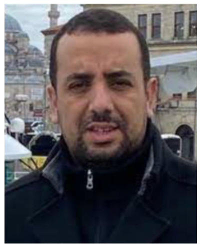

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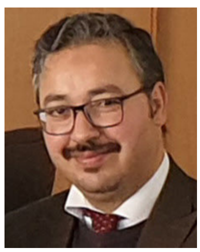

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