IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5384~5392
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5384-5392

Generating market performance predictions employing machine and deep learning methods

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Article Info

Article history:

Received Jul 22, 2025
Revised Aug 7, 2026
Accepted Aug 1, 2026

Keywords:

Autoregressive integrated moving average
Deep learning
Foreign exchange
Machine learning
Prediction

ABSTRACT

One of the numerous difficult issues facing the artificial intelligence research community now is product-market forecasting. Acquisition methods in the stock market are intricate and rely on studying vast volumes of data. Unlike traditional methods, machine learning techniques evaluate and enhance market forecasts. This interest stems from the fact that stock prices fluctuate over time, making their prognoses crucial for data mining and a focus of considerable attention and work in recent decades. The ingrained qualities of time row data, such as its dimensionality, continuous updates, and volume, make this task challenging. To improve the efficacy of conventional techniques, researchers have investigated machine learning and deep learning techniques. The goal in this paper is to predict the products market at the end of the trading day using several machine learning approaches in the "EUR/USD" dataset and to dissect the models' predictions.

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1. INTRODUCTION

Global and domestic economic conditions, geopolitical events, industry trends, and stock market success are just a few of the many internal and external factors that interact to affect changes in foreign currency rates. The most important factor influencing these swings, nevertheless, continues to be historical trends in the Foreign exchange (Forex) rate itself. These observations emphasize the significance of comprehending the mechanisms that underlie Forex changes since they offer helpful data for evaluating the stability of the macro and micro-economies [1].

Forex is the most fluid and most extensive market after debt because it is where so-called substitutable currencies, or money pairs, are exchanged against one another at continuously fluctuating business rates. There are no physical boundaries or locations for this worldwide market. It is possible to execute the same transaction concurrently in London, Paris, Hong Kong, Zurich, or New York at any moment. In fact, during the 2000s, Forex trading volumes have increased consistently.

Forex is an over-the-counter demand in which the buyer and seller conduct their business directly with one another. In other remarks, the purchase or sale of banknotes is a voluntary activity that is carried out

by both the buyer and the seller, one in which solely free volition is the narrative. Marked by substantial bid-ask spreads and intermediation fees [2] as well as intermediation. Due to its volume of business, Forex is one of the needs that economic actors, institutional operators, and markets most need. Because of this, it is susceptible to economic investment, including budget deficits and recovery plans in Western countries, as well as the economic policies of the major central banks around the globe.

The literature suggests several approaches and strategies [3]–[5] for forecasting business rates in the Forex market. Yong *et al.* [6] investigated the impact of several kinds of information. It has been demonstrated that the type of data used for Forex price prediction is an important factor that cannot be ignored after learning how the closing price and technical indicators derived from price affect the Forex trend smart machine wisdom module predictions indicates that the accuracy of forecasting Forex prices improved by incorporating trading powers and specialized analysis, as carried out by the technological analyst, in the first stage of the predicting algorithm.

Dash *et al.* [7] suggested approach in this study seeks to forecast stock prices using a novel, fine-tuned support vector regression model. To explain each stage of this procedure, an appropriate dataset is used, and missing attributes are handled effectively by applying preprocessing methods. The optimal kernel function and its associated parameters are determined via a grid search technique over the training dataset. For the empirical evaluation, the suggested approach is trained using 4,163 records and validated with 1,800 records. Model performance is assessed using root mean squared error (RMSE) for the training phase and mean absolute percentage error (MAPE) for the validation phase. Qi *et al.* [8] sought to forecast future price movements using activity data, parts from previous data, technical analysis indicators, and artificial intelligence approaches. To anticipate prices at retracement points, this study developed a long short-term memory (LSTM) model architecture and a training data selection module.

Reinforcement learning (RL) in goods/Forex trading is yet in its infancy, and more research is required to establish it as a dependable technique in this field, according to a review of all recent studies that employed RL as their machine learning method for stock/Forex trading or prediction [9]. The arrangement of the forecasting models via the use of serious learning. Predicting the stock market is a challenging task, and data scientists frequently encounter challenges while attempting to develop a forecasting model. The query is how to predict if the cost of specific products will increase or decrease over the upcoming year. This study employs machine learning and deep learning techniques. Generally speaking, several scholars used time series to forecast prices using machine learning and deep learning procedures. To help investors in making well-informed determinations regarding closing prices, this study offers advice.

The following is how this paper is structured: after providing an overview, this paper examines the literature study in section 2 and different machine learning techniques in section 3. Then present an interview that focuses on long-term memory in deep learning in section 3. Following that, the research methodology is outlined in section 4. The experimental results are then presented and discussed in section 5. Lastly, concluding remarks are provided in section 6.

2. LITERATURE REVIEW

Time series financial analysis has recently made use of device learning techniques and algorithms, which have been proven highly effective in various domains, including biomedicine, image and discourse analysis, and machine translation [10]–[12]. Support vector engines [13] and other artificial neural network (ANN) architectures [14] are illustrations of the most popular machine learning techniques used in financial prediction. Pahlevi *et al.* [15] employed LSTM and gated recurrent unit (GRU) algorithms and evaluated them on multiple dataset partitions to predict currency patterns. A data collection of 4,979, divided into identical parts—80% for exercise, 10% for confirmation, and 10% for testing—produces the most accurate results. This method yields a coefficient of determination (R^2) of 97% and an RMSE of 0.054.

In a different study [16], the prices of Litecoin (LTC) and Monero worked a mixture strategy that incorporated LSTM and GRU networks. When comparing this hybrid strategy to a single LSTM technique, the results showed that the mixed model was more accurate at predicting the prices of the designated cryptocurrencies. The use of machine learning-based ensemble approaches, including ANN, k-nearest neighbors (KNN), gradient-boosted trees, and a mixed getup model, to forecast the values of nine well-known cryptocurrencies was investigated [17]. The results displayed that the model with the lowest prediction error was the ensemble-learning model.

Based on recent advances in RL, Carapuço *et al.* [18] constructed a new method for short-term prediction in the Forex market. They found that knowing in the training data collection is stable, and several validation learning curves show that the Q-network can identify associations in financial data that relate to constructing decisions outside of the sampling. It demonstrated that the model produced during the exercise process could be used to trade profitably in the A test dataset.

3. ALGORITHMS

3.1. Random forest regressor

One getup learning strategy for classification and regression situations is random forest (RF) [19]. Decision trees can be found inside forests thanks to bootstrap augmentation and random feature selection. To combine the clarity of numerous decision trees, RF generates a class manner for classification and a mean forecast for regression. Widely employed, the RF has many advantages, which include low variance, strong generalization, clarity, and longevity.

3.2. Stochastic gradient descent regressor

A machine-learning technique called SGDRegressor uses stochastic gradient descent to generate predictions. An objective function selected for its smoothness characteristics is iteratively optimized using the SGDRegressor approach. Because samples are chosen at random or shuffled to evaluate gradients, it is stochastic. SGD is a stochastic approximation of gradient descent optimization of this randomness. SGDRegressor is a simple yet powerful discriminative learning technique that is frequently applied to convex loss processes, such as those in linear support vector and logistic regression [20].

3.3. Bagging regressor

Bagging is for bootstrap aggregation, one of the numerous popular and successful ensemble techniques [21]. The basic principle of bagging [22] is straightforward. Building many classifiers and combining them is the aim of bagging. As a result, it is a straightforward classifier approach that trains the ground classifiers using exercise datasets. Bagging [23] consists of selecting random samples from an exercise dataset using a weak learning strategy.

3.4. Linear regression

This study uses linear regression to predict the market. The mathematical formula for linear regression in this case is in (1). The conditional variable is w, and the independent variable is y. The interceptor is c, and the slope is b. A fundamental method for supervised learning is linear regression. Specifically, linear regression is a helpful method for forecasting numerical solutions [24].

$$w = bc + y \tag{1}$$

3.5. Adaptive boosting regressor

The machine learning approach known as adaptive boosting or AdaBoost, is exploited to enhance the enactment of weak classifiers. More weight to the observation of the previous underachievers [25]. With a root and a related child based on finding variables, a level-one determination tree often corresponds to a decision stub. This study resamples the samples and create a new model for each iteration, focusing the attention of later classifiers on the instances where the previous classifier was unable to correct the forecast. Samples predicted to lose weight. Excessive sample weights were not accurate. The last prediction is the outcome of a weighted accounting of the model's predictions.

3.6. Long short-term memory

LSTM modules are another type of recurrent neural network (RNN) module. Hochreiter and Schmidhuber [26] invented LSTM, which has since been invented and popularized by numerous researchers [27]. Similar to the RNN, the LSTM is composed of recurrently consistent modules. An improved RNN known as LSTM has different associations between its hidden layers.

4. MATERIALS AND TECHNIQUES

4.1. Dataset

The open, high, low, and close (OHLC) properties within the utilized dataset represent the daily price metrics of the EUR/USD currency pair. The dataset spans a continuous ten-year period from July 7, 2015, to July 9, 2025, with no missing values or information gaps, thereby ensuring data integrity. For illustrative purposes, a representative sample of the raw dataset is presented in Figure 1, while the overall historical trajectory of the EUR/USD closing price is visualized in Figure 2.

4.2. Methodology

This study employed machine learning and deep learning methods after downloading the data, including LSTM, RF, AdaBoost, SGDRegressor, and linear regression. The closing values of EUR/USD were forecasted using autoregressive integrated moving average (ARIMA) and LSTM. This study compared

the results of the various algorithms operated, delivering suggestions to inform well-informed decisions regarding closing expenses.

To evaluate and compare the performance of various models, this study employs a single standardized accuracy metric. The comprehensive research methodology is illustrated in Figure 3, which consists of four core stages. First, the data acquisition stage involves gathering historical datasets containing the daily prices of the EUR/USD currency pair. Second, the model implementation stage utilizes a variety of machine learning techniques, LSTM architectures, and ARIMA models to train and generate predictions. Third, the predict closing prices stage generates the forecasted values for the EUR/USD currency pair. Finally, the comparative analysis stage evaluates and compares the different closing price estimates against the actual values.

Date	Open	High	Low	Close
2015-07-09 00:00:00+01:00	1.107236	1.111620	1.102290	1.107101
2015-07-10 00:00:00+01:00	1.106305	1.122000	1.105620	1.106305
2015-07-13 00:00:00+01:00	1.112904	1.119759	1.100770	1.112904
2015-07-14 00:00:00+01:00	1.098515	1.107400	1.096850	1.099046
2015-07-15 00:00:00+01:00	1.100897	1.104000	1.093610	1.100800
...	...	...	...	...
2025-07-03 00:00:00+01:00	1.180025	1.181335	1.172086	1.180025
2025-07-04 00:00:00+01:00	1.177149	1.178689	1.175668	1.177149
2025-07-07 00:00:00+01:00	1.178078	1.179009	1.171907	1.178078
2025-07-08 00:00:00+01:00	1.173654	1.176484	1.168470	1.173654
2025-07-09 00:00:00+01:00	1.172883	1.173296	1.169454	1.171234

Figure 1. The EUR/USD dataset

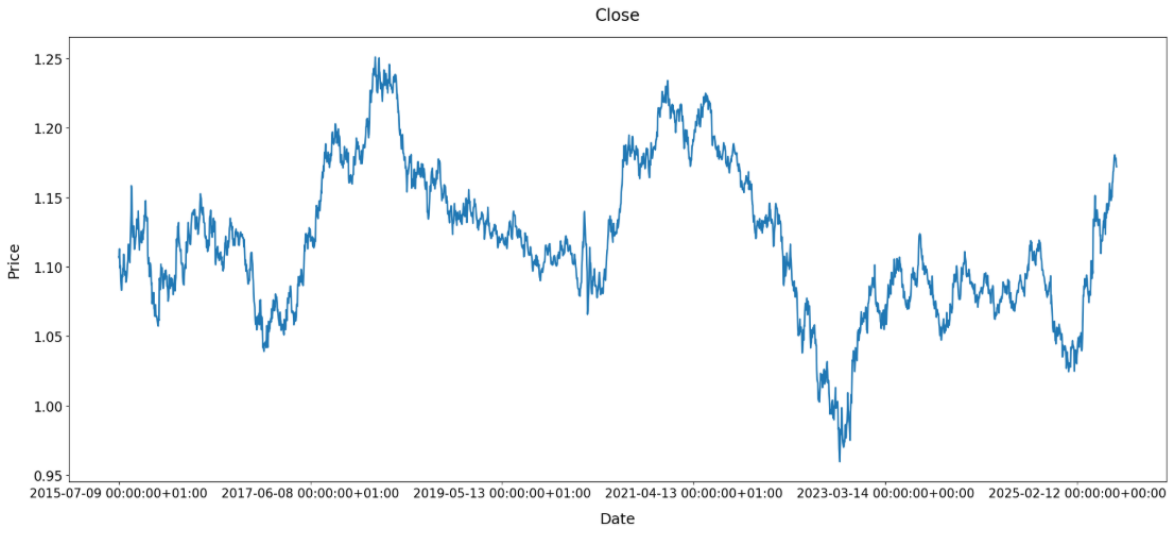

Figure 2. Close EUR/USD

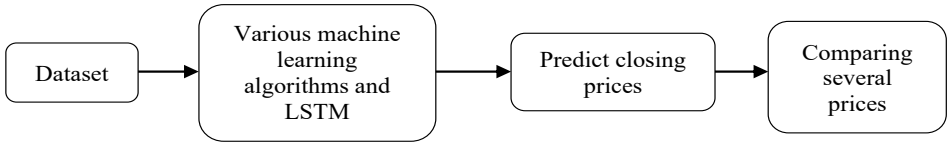

Figure 3. The proposed architecture

4.3. Evaluation metrics

To compare the several machine learning and deep learning techniques described above, three metrics include R^2, RMSE, and MAE. The formulas are in (2) to (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y - y_t)^2}{n}} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \quad (4)$$

5. RESULTS AND DISCUSSION

A predictive study of short-term memory and distinct machine learning methods is applied to the EUR/USD database in this part. The examination was carried out using a single database, analyzing the predictions created by each architecture, and comparing the results. By examining real-time stock market quotes, this study employs several methods to apply artificial intelligence to predict future and assess potential hazards. Consequently, the system determines when to enter and depart the market. This database includes numerous LSTM topologies and machine learning techniques. Analyze the predictions and the outcomes produced by the LSTM, ARIMA, linear regression, SGDRegressor, and other practices. This study helps investors construct informed decisions about closing prices. Utilize the different deep learning and machine learning techniques shown in Figures 4 through 10.



Figure 4. Prediction using linear regression



Figure 5. Prediction using bagging regressor



Figure 6. Prediction using RF



Figure 7. Prediction using AdaBoost



Figure 8. Prediction using SGDRegressor



Figure 9. Prediction using LSTM

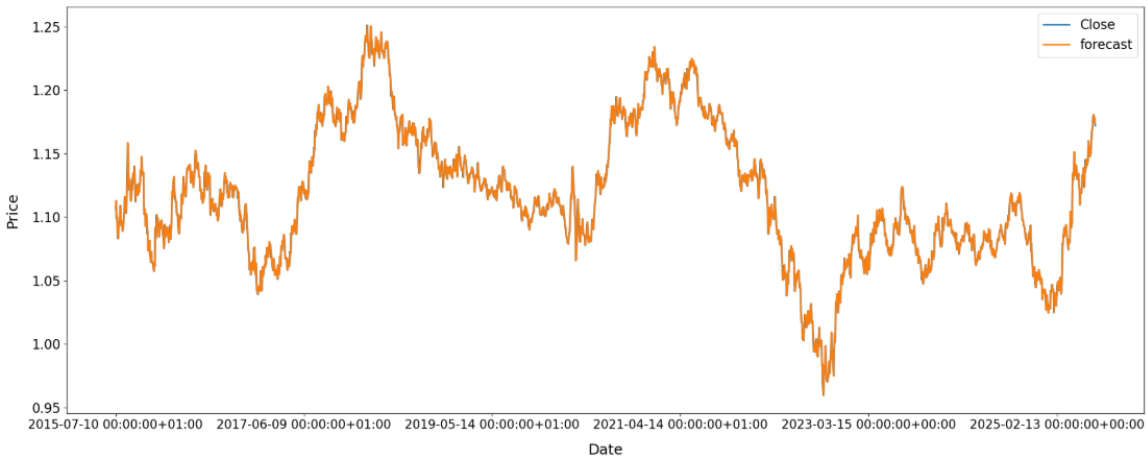

Figure 10. Prediction using ARIMA

In Figure 4, this study used a linear regression model to compare the predicted and real prices. As you can see, the accuracy of bagging reaches 99.97% in Figure 5, and the RF is 99.98% in Figure 6. The adaptive accuracy is 99.45% in Figure 7. The SGDRegressor is 99.98% in Figure 8, whereas the exactness of the LSTM is 99.35% in Figure 9. Using the ARIMA model, this sudy show the predicted and real prices in Figure 10.

The results in Table 1 show that the linear model outperforms other techniques in terms of accuracy. Table 1 shows that the RF algorithm arrives second with an accuracy of 99.98%, and the linear model forecasts the ending price of the EUR/USD with an accuracy exceeding 99.99%. The effort results in a

superior method to predict EUR/USD in the future. This study correlated the accuracy and RMSE of the examination with those of previous studies Table 2. The results obtained are limited to EUR/USD. The availability, quality, and variety of technical indicators used in our article's currency pair EUR_USD predictions are its strengths. Each of these factors affects forecasting accuracy.

Table 1. Performance comparison of various forecasting models based on error metrices and R^2 score

Model name	MAE	RMSE	R^2
Bagging regressor	0.0017	0.0032	0.9997
AdaBoost	0.0102	0.0141	0.9945
RF	0.0013	0.0026	0.9998
Linear regression	0.0004	0.0005	1
SGDRegressor	0.0013	0.0026	0.9998
LSTM	0.0013	0.0024	0.9935

Table 2. Comparison of the proposed approach with previous studies

Study	RMSE	R^2 (%)
Pahlevi *et al.* [15]	0.054	97
Proposed approach	0.0004	99

6. CONCLUSION

By comparing LSTM and various machine learning models for stock market tendency prediction, this study advances the field. The main goal of this effort is to examine the state of the art and incorporate it into a database to produce and evaluate forecasts. The latter made it attainable for our algorithms to pinpoint their benefits and drawbacks and enhance the forecasts. This study used several algorithms to forecast closing EUR/USD prices. In the next effort, this study plan to apply algorithms to other stock exchanges.

FUNDING INFORMATION

The authors state that no funding was involved in the research, authorship, or publication of this article.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Ethical approval was not required for this study, as it involved only the analysis of publicly available financial market data and did not involve human participants or animals.

DATA AVAILABILITY

The data used in this study were obtained from Yahoo Finance and are publicly available at https://finance.yahoo.com/quote/EURUSD=X.

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