Simple RNN-LSTM hybrid deep learning model for Bitcoin and EUR_USD forecasting

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ABSTRACT

The popularity of deep learning in time series prediction has significantly increased compared to the past. In this article, we utilize deep learning methods, which encompass long short term memory (LSTM) networks, simple recurrent neural network (SimpleRNN) networks, and gated recurrent units (GRU) networks. This research introduces a hybrid foundational model for forecasting future closing prices of EUR_USD in financial time series and Bitcoin, combining SimpleRNN with LSTM, referred to as SimpleRNN-LSTM. To improve the precisions of our hybrid model, we incorporate twenty-one technical indicators into the training data. Then, we compute four measures to evaluate the performance of various prediction models. When predicting currency pairs EUR_USD and Bitcoin, our hybrid foundational model outperforms SimpleRNN, LSTM, and GRU models.

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1. INTRODUCTION

Cryptocurrencies are digital forms of money that rely on encryption for security. In contrast to conventional government-issued currencies like the US dollar or the euro, cryptocurrencies function on decentralized networks underpinned by blockchain technology. Cryptocurrencies employ cryptographic methods to safeguard transactions and regulate the generation of additional units. It is prices can be highly volatile. Cryptocurrencies can be transferred and received globally with relative ease, making them useful for cross-border transactions and remittances.

Bitcoin stands out as one of the most widely embraced cryptocurrencies. It operates as a decentralized digital currency, free from the control of a central bank or any singular authority figure. Remarkably, its creation traces back to an enigmatic individual or collective entity known as Satoshi Nakamoto, who concealed their true identity. This pioneering digital currency was introduced to the public as open-source software back in 2009 [1].

Over the past few years, the continuous investigation of forecasting stock prices has been a prominent area of focus in computational finance research. The substantial difficulty in predicting stock prices arises from their highly unpredictable and dynamic behavior. Price fluctuations appear to be largely unpredictable, and accurately capturing these changes presents a formidable challenge. Given the effectiveness of artificial neural networks (ANN) in various prediction endeavors, researchers are increasingly inclined toward utilizing advanced machine learning techniques to construct improved forecasting models [2].

Artificial intelligence and machine learning are subsets of deep learning, concentrating on instructing ANN to execute tasks without direct programming. It derives its inspiration from the configuration and operation of the human brain, particularly neural networks, which consist of interconnected units (neurons) responsible for processing and transmitting information. Deep learning is a subfield of artificial intelligence and machine learning that focuses on teaching ANN to perform tasks without the need for direct programming. It derives its inspiration from the configuration and operation of the human brain, particularly neural networks, which consist of interconnected units (neurons) responsible for processing and transmitting information.

Several researchers have utilized various approaches for forecasting time series data. In research by Roondiwala *et al.* [3], an long short term memory (LSTM) model was developed to forecast stock prices. Jose *et al*. [4] presented a novel approach to accurately predict opening stock prices by fusing ensemble learning methods with technical indicators. Saad *et al.* [5] utilized machine learning techniques to construct models to predict Bitcoin prices. They explored a multivariate regression approach, relying on highly linked characteristics, and a deep learning mechanism incorporates the conjugate gradient method alongside linear search to forecast Bitcoin's price. Mahjouby *et al.* [6] looked at different machine learning approaches and suggested an ensemble approach that combined three models: Gaussian naïve Bayes, logistic regression, and extreme gradient boosting. The proposed approach sought to predict the best times to buy and sell US dollars to the Japanese yen to increase earnings.

Predictions of currency trends utilizing the LSTM and gated recurrent units (GRU) algorithms were evaluated in [7] using various dataset partitions. The best accurate findings, with 0.054 root mean square error (RMSE), 0.037 mean absolute percentage error (MAPE), and 0.97 R-squared (R^2), were obtained by dividing a dataset of 4979 rows into three parts: 80% for training, 10% for validation, and 10% for testing. Machine learning was employed in [8] to predict the price of Bitcoin.

Today, everyone discusses when to buy or sell the cryptocurrency bitcoin or EUR/USD. Several researchers have developed articles and research to address this issue. In this context, we utilized diverse deep-learning models and introduced a hybrid approach to predict the future values of EUR/USD and Bitcoin. Our purpose is to forecast the following day. This forecasting on fundamental characteristics: open, high, low, close, and twenty-one technical indicators.

The paper's structure is as follows: the second section provides an overview of the literature and clarifies relevant studies. In the third section, we will introduce the recurrent neural networks (RNN) utilized in our work. The fourth section will detail the methods used. The fifth section will elaborate on the performance metrics relevant to this domain. The sixth section will present and analyze the results, while the final section will the final remarks.

2. LITERATURE REVIEW

A review of the previous literature is covered in this section. Chen *et al.* [9] forecasted the closing prices of several businesses using a combination of convolutional neural network (CNN), bidirectional LSTMs (BiLSTM), and an attention-based model. They used CNN to derive characteristics from the input data and enhanced the network's predictive capabilities by integrating an efficient channel attention mechanism with BiLSTM for stock price forecasting.

Sayavong *et al.* [10] utilized a CNN to predict the closing price and trend of three firms listed on the Thai stock exchange. They employed a sliding window approach with a window size matching the input size. In each iteration of the sliding window, there was no overlap between consecutive windows as they moved to the right. The outcomes revealed that the CNN model exhibited excellent performance in forecasting the current day's data.

Fabbri and Moro [11], utilized an LSTM model for forecasting the closing price of the Dow Jones index for the next day. They conducted a comparison between the results obtained from the LSTM model and those from a feed-forward neural network (FFNN). The results obtained indicated that the LSTM model outperformed the feed-forward neural network in terms of predictive accuracy.

Ojo *et al.* [12] utilized a deep learning technique known as stacked LSTM to forecast the closing price of the NASDAQ composite on the American stock exchange. The outcomes of their study demonstrated an enhancement in predictive accuracy when forecasting the stock price. Lin *et al.* [13] utilized a LSTM model to forecast the closing price using historical stock data Taiwan stock exchange (TWSE). The primary objective was to substitute the RNN model with the LSTM model because of its capability for long-term memory retention, as the RNN struggled to maintain data over extended periods.

Makala and Li [14] investigated gold commodity forecasting using auto regressive integrated moving average (ARIMA) and support vector machine (SVM), and three types of kernels were employed in this paper. Bitcoin is a commonly utilized cryptocurrency in the present day, and as a result, there are only a limited number of prediction models accessible. McNally *et al.* [15] use RNN coupled with LSTM to achieve 52% classification accuracy and an RMSE of 8%. The authors assert that the utilization of RNN in conjunction with LSTM yields superior performance compared to conventional RNN and ARIMA models.

Bitcoin price prediction is conducted through empirical investigation [16]. The Bayesian neural network is compared to proven non-linear and linear benchmark methods in this study, which gives useful insights. Sun *et al* [17] discerned daily trends in the Bitcoin market while considering the semantics and insights related to factors influencing Bitcoin's price. They also forecasted changes in Bitcoin's daily price, employing both Random Forest and Bayesian regression methods as part of their research.

3. NEURAL NETWORKS

We looked at the various deep learning models used in this work in this part. Deep learning neural networks (DLNN) organize enormous amounts of data by arranging complicated data structures that an ANN cannot [18]. A deep neural network is a parallel processing architecture made up of interconnected neurons organized in a layer network. The primary structure of a deep neural network is composed of three important components: input, output, and one or more hidden layers of hidden units [19].

3.1. Recurrent neural networks

Human comprehension of each scene in a movie relies on grasping the context established by preceding scenes. Conventional neural networks are incapable of accomplishing this, posing a significant challenge. RNNs tackle this problem by incorporating loops, enabling them to retain and utilize information over time. RNNs find utility in various applications involving sequential data, including tasks like generating captions for images or videos, natural language processing such as predicting words, translating languages, and recognizing speech.

Figure 1 illustrates a neural network element labeled as "A." This element accepts an input denoted as "X_t" and produces an output value referred to as "h_t." The inclusion of a loop enables the exchange of information between various steps within the network. You can envision a recurrent neural network as having multiple instances of "A" within the network, where each instance sequentially sends information to the next one, as depicted in Figure 1.

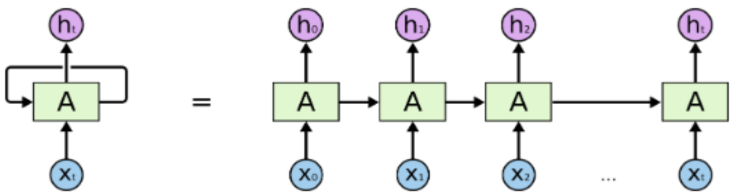

Figure 1. An unrolled representation of a recurrent neural network

In situations where the distance between pertinent information and the point where it is required is minimal, RNNs can acquire the ability to make use of past information effectively. However, situations can occur where a broader context becomes essential, and in these cases, the distance between the required information and the moment it is needed can significantly increase. In practical terms, RNNs tend to struggle with this latter scenario, as noted in references [20].

3.2. Long short term memory

LSTM networks tackle the issues of diminishing and skyrocketing gradient problems that frequently occur in extended recurrent neural networks (ERNNs) and more generally, in traditional RNNs [21]. LSTM networks retain the identical overall architectural layout as ERNNs but distinguish themselves by having a different configuration for the internal module or cell. LSTM is a type of RNN that handles and predicts data with recurrent time series in an effective manner. Time series forecasting, speech recognition, and natural language processing are just a few of the many domains it finds use.

3.3. Gated recurrent units

Initially presented in Cho *et al.* [22], GRUs represent a simplified version of LSTM and consequently, fall within the category of gated RNNs. GRUs set themselves apart from LSTMs by consolidating two key functionalities, which are regulated by the forget gate and the input gate, into a single gate. This type of cell ultimately incorporates only two gates, leading to a more concise architecture when contrasted with LSTM, which, in contrast, employs three gates. GRU is a type of gated RNN that is used to alleviate the prevalent problem of gradient vanishing in traditional RNNs [23].

4. MATERIALS AND METHODS

4.1. Data

In this study, we used deep learning technology to anticipate the forthcoming EUR/USD and Bitcoin closing price using our approach. The datasets consists of daily prices data collected from August 30, 2013, to August 31, 2023 for EUR_USD and from 17/09/2024 to 13/10/2023 for Bitcoin, with no gaps or missing information. Consequently, the total cumulative observation period spans a decade, encompassing data for high, open, low, and close prices.

4.2. Feature engineering

The data we have available comprises the following characteristics: date, high, low, open, and close. We perform computations for 21 technical indicators. Table 1 provides an overview of the technical indicators' descriptions.

Table 1. A number of technical indications

Technical indicators	Description
EMA10	Exponential moving average for 10 days
EMA30	Exponential moving average for 30 days
EMA200	Exponential moving average for two-hundred days
ROC10	Rate of change for 10 days
ROC30	Rate of change for 30 days
MOM10	Price momentum for 10 days
MOM30	Price momentum for 30 days
RSI10	Relative strength index for 10 days
RSI30	Relative strength index for 30 days
RSI200	Relative strength index for 200 days
%K10	Stochastic indicator for 10 days
%D10	Stochastic indicator for 10 days
%K30	Stochastic indicator for 30 days
%D30	Stochastic indicator for 30 days
%K200	Stochastic indicator for 200 days
%D200	Stochastic indicator for 200 days
MA21	Moving average for 21 days
MA63	Moving average for 63 days
MA252	Moving average for 252 days
Upper_band	Bollinger upper line
Lower_band	Bollinger lower line

Next, we included a target column that holds the closing price for the following day.

4.3. Proposed hybrid SimpleRNN-LSTM base model

The most critical and valuable deep neural models emerge when various network types hybrid models. We suggested a hybrid model that uses SimpleRNN and LSTM to forecast future EUR/USD and Bitcoin closing prices utilizing 21 technical indicators, as seen in Figure 2. The architecture of the hybrid model we used to forecast Bitcoin and EUR_USD is in Figure 2.

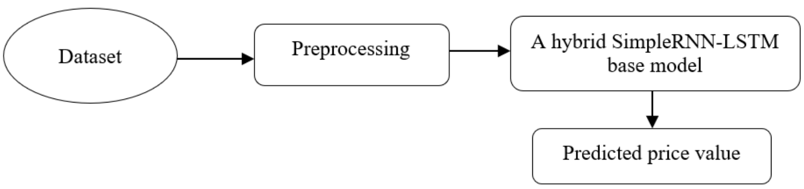

Figure 2. Architecture of our hybrid model

5. EVALUATION MEASURES

This section presents the four metrics utilized in the study. The authors employ multiple well-chosen models that consistently demonstrate higher accuracy [24].

5.1. Error in absolute percentage mean

The efficiency of prediction methods is typically assessed using MAPE. In the field of machine learning, MAPE measures prediction accuracy and is often represented as a percentage. In (1) depicts its mathematical expression [25].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \quad (1)$$

In this formula, A_t stands for the real value and F_t for the anticipated (predict) value. In the equation, the absolute difference between these numbers is calculated and divided by A_t. The total amount of data points is divided by the sum of this absolute difference for all anticipated values. After that, the result is multiplied by 100 to become a percentage.

5.2. Mean absolute error

The difference between two values is measured using the mean absolute error (MAE). In the field of machine learning, the MAE, which stands for the average difference between anticipated and actual values, is a standard metric for evaluating prediction accuracy. You can find its formula in (2) [25], [26]:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \quad (2)$$

In this formula, A_t stands for the real value, and F_t is the projected value. The equation calculates the absolute difference between these values, divides the result by n (the number of samples), and then sums these absolute differences for each forecasted value.

5.3. Root mean square error

RMSE is used in regression analysis as a standard deviation indicator for prediction mistakes. The difference between actual values and a predictive model is quantified by prediction errors, sometimes referred to as residuals, which also show how the residuals are spread across the model. This statistic reveals how data points congregate around the most suitable model. Average squared discrepancy between predictions and real observations is used to calculate RMSE [12]. The (3) can be used to represent the formula:

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

5.4. R-squared

A statistic called R^2 is used to assess the effectiveness of a linear regression model. It is a numeric value within the range of 0 to 1, representing the precision with which a statistical model forecasts an outcome. The calculation formula for R^2 is as (4):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

where, $\bar{y}$ is mean of the metric and $\hat{y_i}$ is forecasted outcome.

6. EXPERIMENT FINDINGS

In this part we show experimental findings for predicting future EUR_USD and Bitcoin closing values.

6.1. Results of EUR_USD

In this study, the EUR/USD dataset was used, 21 various technical indicators were computed, the other attribute target was used. Dataset subsequently separated into test and training sets, with sets for training representing 80% of the total and testing collections representing for 20%.

EUR/USD utilized to apply LSTM, SimpleRNN, GRU, and our hybrid SimpleRNN-LSTM base model. The results acquired offer an extensive prediction and comparative analysis. The models' performance is displayed in Table 2.

Table 2 illustrates a comparative performance assessment of diverse deep-learning algorithms. The hybrid model distinguishes itself by achieving lower RMSE, MAPE, and MAE values while attaining higher R^2 values. This dominance of the hybrid model over other models reinforces the efficacy of combining SimpleRNN and LSTM. Figures 3 to 6 show the forecast price versus the actual prices.

Table 2. Comparison table (EUR_USD)

Model	RMSE	MAE	MAPE	R^2
LSTM	0.009	0.007	0.007	0.964
SimpleRNN	0.011	0.009	0.008	0.943
GRU	0.013	0.011	0.010	0.918
SimpleRNN-LSTM	0.007	0.005	0.005	0.980

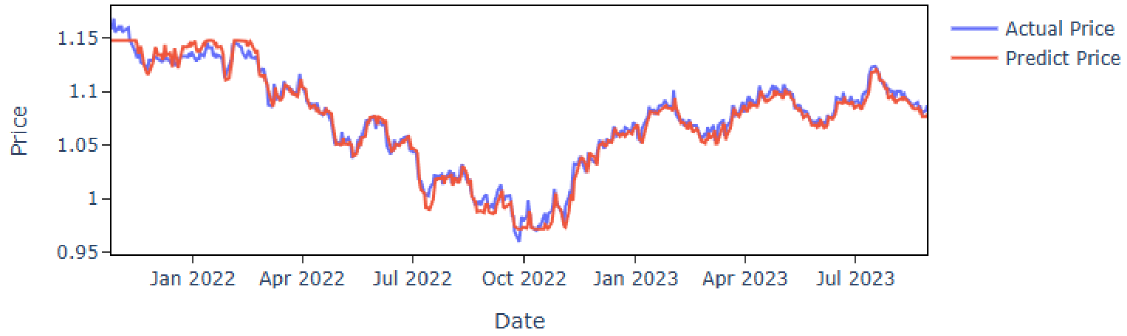

Figure 3. Predicted prices using LSTM of EUR_USD

Figure 4. Predicted prices using GRU of EUR_USD

Figure 5. Predicted prices using SimpleRNN of EUR_USD

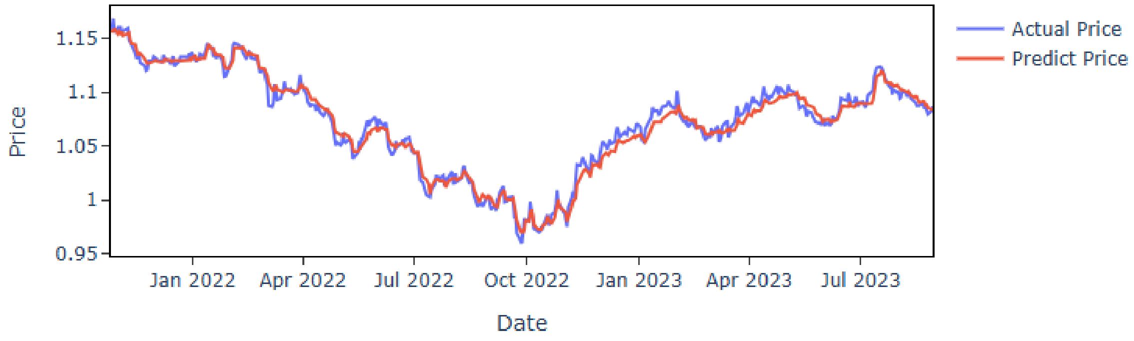

Figure 6. Predicted prices using hybrid SimpleRNN-LSTM base model of EUR_USD

6.2. Results of Bitcoin

In this study, the Bitcoin dataset was used, 21 various technical indicators were computed, the other attribute target was used. Dataset subsequently separated into test and training sets, with sets for training representing 80% of the total and testing collections representing for 20%. Bitcoin utilized to apply LSTM, SimpleRNN, GRU, and our hybrid SimpleRNN-LSTM base model. The results acquired offer an extensive prediction and comparative analysis. The models' performance is displayed in Table 3.

Table 3 illustrates a comparative performance assessment of diverse deep-learning algorithms. The hybrid model distinguishes itself by achieving lower RMSE, MAPE, and MAE values while attaining higher R^2 values. This dominance of the hybrid model over other models reinforces the efficacy of combining SimpleRNN and LSTM. Figures 7 to 10 show the forecast price versus the actual prices.

Table 3. Comparison table (Bitcoin)

Model	RMSE	MAE	MAPE	R^2
LSTM	1345.846	1019.729	0.037	0.968
SimpleRNN	1835.372	1465.797	0.057	0.94
GRU	1841.563	1366.1	0.054	0.94
SimpleRNN-LSTM	1237.259	833.667	0.032	0.973

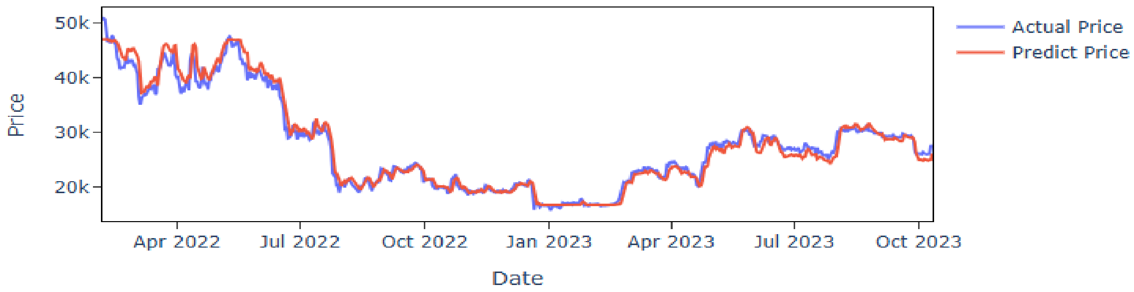

Figure 7. Predicted prices using LSTM of Bitcoin

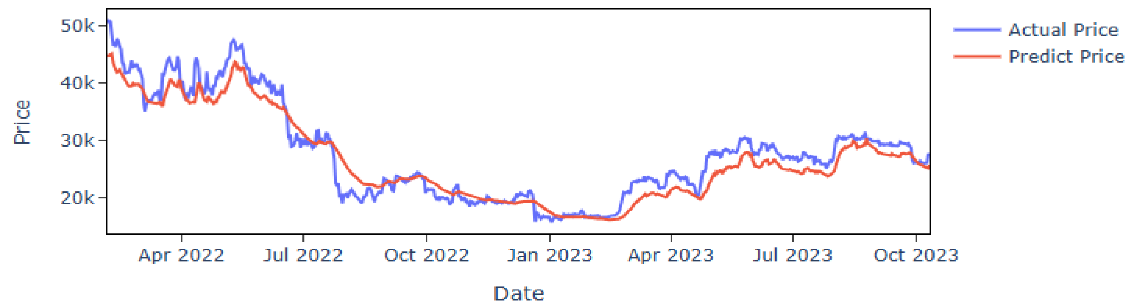

Figure 8. Predicted prices using GRU of Bitcoin

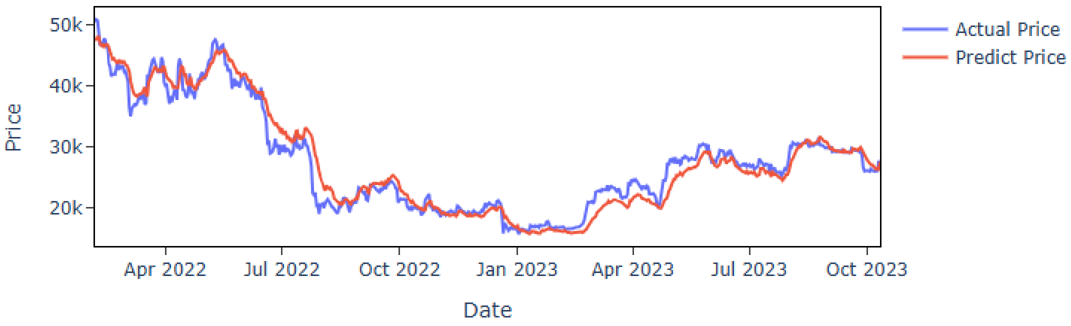

Figure 9. Predicted prices using SimpleRNN of Bitcoin

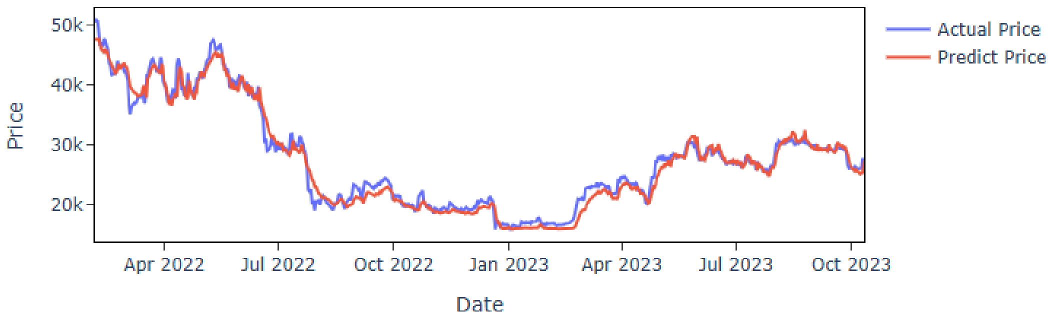

Figure 10. Predicted prices using hybrid SimpleRNN-LSTM base model of Bitcoin

Our suggested hybrid SimpleRNN-LSTM base model outperforms LSTM, SimpleRNN, and GRU when forecasting the currency pair EUR/USD and Bitcoin. The forecast closely matches the actual trends, showcasing the effectiveness of the hybrid model. The proximity of these two lines serves as an indicator of how well the model performs.

We compared our study's accuracy, RMSE, and MAPE to those of earlier research Table 4, and our work produces a better algorithm to predict EUR/USD going forward. The study limit is consequences obtained are exclusive to the EUR/USD data. The strengths to provide the currency pair EUR_USD forecasting in our article are the availability, quality of data, and different technical indicators used. All of these factors contribute to the accuracy of the predictions.

Table 4. Comparison of our analysis with that of the last studies

Study	RMSE	MAPE	R^2
Pahlevi *et al.* [7]	0.054	0.037	0.97
Our approach	0.007	0.005	0.98

7. CONCLUSION

We have suggested a hybrid SimpleRNN-LSTM base model for forecasting future closing prices for our datasets with 21 technical indicators to help investors make decisions to buy or sell EUR_USD based on future prices. When predicting the target, the proposed hybrid base model outperforms the LSTM, SimpleRNN, and GRU models. In the future, we recommend using algorithms and our hybrid model on other currency pairs and the stock markets.

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