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Effective Price Prediction of Cryptocurrencies using CNN-Based Dual Directional Model

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ABSTRACT

In recent days, predicting cryptocurrency trends has become essential for most individuals, including stockholders and traders, as it aids them in making better-informed selections regarding the digital asset market's future. Predicting the price of the cryptocurrency leads to profitability in trading strategies. Therefore, the main objective of the study is to create an effective deep learning architecture using forecasting models such as recurrent neural networks (recurrent NN), Convolutional neural networks (convolutional NN) and Long Short-Term Memory (LSTM) for predicting Bitcoin and Ethereum prices. The model utilizes CNN to extract features from historical price data. Where, CNN has the ability to detect complex patterns in price movements and incorporates bidirectional LSTM (Bi-LSTM) layers to capture both past and future price trends. Moreover, Bi-LSTM effectively manages the temporal dynamics and makes it suitable for financial time series, which demonstrate non-linear behavior. Experimental results on a dataset of major cryptocurrencies demonstrate the efficacy of the proposed model in forecasting cryptocurrency prices with high accuracy. The dual-directional model outperforms traditional time series forecasting methods and single-directional models, showcasing its potential for improving price prediction in the cryptocurrency stock market.

Keywords: Bitcoin and ethereum; Bidirectional LSTM; Cryptocurrency; Convolutional Neural Networks; Long short-term memory; Price prediction

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1. Introduction

Cryptocurrencies act as a secure form of digital money for direct transactions between individuals. The transactions are also kept in a block, which is called blockchain [1]. The security peculiarities have made cryptocurrency a widely used and recognized trading podium for stakeholders. Cryptocurrencies have seen significant growth, increasing in both popularity and market value. Bitcoin, created by Satoshi Nakamoto [2], is the initial decentralized digital currency and is now the most valuable cryptocurrency globally. Bitcoin is a P2P money transfer system that offers investors the ability to send digital currency online without the need of intermediaries [3].

Predicting cryptocurrency prices is speculative and can be impacted by factors like market sentiment, regulations, technological advancements, and macroeconomic trends. Predicting the future price of cryptocurrencies is challenging. However, analysts utilize different tools and methods to forecast price changes. Potential forms of analysis could comprise technical analysis, fundamental analysis, sentiment analysis, and machine learning algorithms. Investors should carefully research and do their due diligence before investing in the cryptocurrency market [4]. They should keep in mind that past performance will not guarantee future results, and investment in cryptocurrencies can to lead huge levels of risk and instability. Consulting with a financial advisor or investment professional prior to investing in cryptocurrency is always advisable [5].

There are several restrictions to the present techniques used for predicting the stock market. Predicting stock values exactly is hypothetic because of the unpredictable nature of their instability. Historical data and technical indicators often utilized in these tactics might not encompass every relevant factor. Moreover, the intricacy of stock market information presents difficulties when trying to develop precise forecasting models [6]. The problem of vanishing gradients is a major challenge for modern models, particularly in recurrent neural networks. Furthermore, the arrival of new investors in the stock market contributes to the unpredictability of predictions. To address these restrictions, adding financial news, stock forum data, and social media sentiments can enhance the precision of stock prediction approaches [7]. In finance and trading industries, forecasting the value of digital currencies through machine learning methods is a normal one. Numerous methods can be utilized to estimate cryptocurrency prices through machine learning, including regression models, time series analysis, and deep learning algorithms. A famous strategy involves applying past price data to train regression models like linear regression, support vector regression, or random forest regression [8]. The model can be exploited for forecasting future value changes by analyzing past data. Employing time series analysis tools like ARIMA or Prophet to study and forecast the time-based trends in cryptocurrency prices is another approach [9]. These models can understand the forms in the data to progress forecasts. DL methods like RNNs with LSTM networks are also used in predicting cryptocurrency prices. These models possess the ability of identifying intricate designs in the data and producing very precise calculations, particularly for time series data. It should be stressed that estimating cryptocurrency values with ML is tough due to the market's high unpredictability and non-linear characteristics [10]. Using correct data pre-processing, feature selection, and model evaluation techniques is important for increasing strong and accurate prediction models. Various deep learning methods, like Deep Learning Long Short-Term Memory (LSTM) models, have established encouraging consequences in predicting stock market prices.

To predict the prices of the cryptocurrency, in artificial intelligence and machine learning, some more advanced models can be made to enhance the prediction. A widely recognized model that has been receiving significant attention is the Dual Directional Model, which is based on a Convolutional Neural Network (CNN). A CNN teaches how to identify and inspect patterns in past price details while forecasting cryptocurrency prices. Utilizing a convolutional neural network aids the model in understanding intricate connections between variables and enhances its forecasting accuracy. The dual-directional feature permits the model to evaluate price changes in both upward and downward directions. The model can estimate both future price rises and potential downward trends, thus providing a more complete market outlook. The CNN-based Dual Directional Model's main strength is effectively managing vast amounts of data. Prices in cryptocurrency markets are known to fluctuate rapidly, showcasing high volatility. The model is built to predict large data sets quickly to handle and enables traders to make informed selection in real time. Moreover, the model can be effortlessly retrained and updated with fresh data, enabling it to adjust to evolving market conditions. Flexibility is crucial in the rapidly changing world of cryptocurrency trading, as market trends can change swiftly.

1.1 Research contribution

The contribution of the research in the proposed model comprises:

1. To forecast the price of cryptocurrencies of Ethereum and Bitcoin to eradicate the short-term financial crises by employing CNN-based dual directional feature prediction for Bitcoin and Ethereum cryptocurrencies.

2. To perform an internal comparison to assess the efficacy of the proposed framework with existing LSTM and BiLSTM models.

3. To estimate the performance and efficiency of the proposed model by employing different performance metrics such as MAE, MSE and RMSE.

1.2 Paper organization

The paper is organized with the following sections: Section II exposing the existing system's review by suitable problem identification. This is tracked through Section III by the proposed phases. The results obtained by the implementation of the proposed system are presented in Section IV. Finally, the inclusive research is resolved in Section V with conceivable future works.

2. Literature Review

Hybrid architectures with deep neural network components have many layers. Whereas, local features are obtained through a convolutional layer, and the weights linked to intuitive features are determined through the group-wise enhancement technique. Following the introduction of the enhanced context vector into the bidirectional layer to capture universal characteristics, the attention device with a fully linked layer was utilized. The results of the experiment have shown that the newly designed architecture performs better than the existing architecture, by obtaining an accuracy of 93.77% [11]. Additionally, a hybrid model based on deep learning that integrates Gated Recurrent Units (GRU) and Long Short Term Memory (LSTM), has been used to predict the prices of Litecoin and Zcash while considering the influence of the parent coin. The recommended approach would be suitable for real-time situations, being trained and assessed with datasets [12, 13]. The research glances at three types of Recurrent Neural Networks (RNNs) for predicting the exchange rates of 3 different crypto currencies such as (Bitcoin) BTC, (Ethereum) ETH, and (Litecoin) LTC [14, 15].

The Python package 'YFinance' has collected our cryptocurrency data, and the relative strength index that could be utilized to evaluate the cryptocurrencies[16]. The study applied seasonal decomposition on the dataset prior to execution of the model, and the augmented Dickey-Fuller test shows significant seasonality in the dataset. Moreover, the AR model is specific in forecasting prices of BTC, ETH, LTC, and Tether-token, through accuracies of 97.21%, 96.04%, 95.8%, and 99.91%, respectively [17]. Using the SDAE-B method to analyze bitcoin price for prediction is related to using traditional machine learning methods, such as LSSVM with BP, to predict the price of bitcoin. The SDAE-B prediction price has a MAPE as 0.016, RMSE as 131.643, and a DA as 0.817, according to the prediction results [18, 19]. A hybrid cryptocurrency prediction scheme is suggested, utilizing both Long Short Term Memory and GRU approaches, with a precise focus on Litecoin and Monero. The outcome shows that the suggested method effectively forecasts prices with precision, indicating its potential for use in predicting the prices of different cryptocurrencies [20, 21]. The use of a Multi-layer perceptron (MLP) with LSTM contributes to the forecasting of Ethereum's price trends. These methods have been utilized using historical data calculated on a daily, hourly, and minute-by-minute basis. The information is obtained from the CoinDesk repository [22, 23].

Additionally, GRU also shows the best forecast for LTC, with MAPE rates for BTC, Eth, and LTC [24, 25]. The CNN-LSTM model for multiple cryptocurrencies considers the significance of correlations between various frequencies and currencies, to reduce risk of investment by making simultaneous predictions for multiple currencies [26]. Optimized techniques employing deep learning algorithm and convolutional neural network are used for forecasting cryptocurrency. The analysis results show that the suggested approach accurately predicts prices at a rate of approximately 98.75% [27]. To mitigate this risk, a system must be in place to forecast bitcoin prices using data mining techniques such as CNN and LSTM. The information utilized consists of the closing prices of Bitcoin between January 1, 2017, and April 26, 2023. The MAPE value for the evaluation of prediction results is 0.037 in the CNN algorithm, compared to 0.065 in the LSTM algorithm [28, 29]. The Bitcoin price data from 2017 to 2020 are selected as the training with prediction sets. The experimental findings indicate that ensemble models can reach a prediction accuracy of 95.12%, outperforming the benchmark models [30]. The LSTM model successfully forecasted both the direction of Bitcoin and the value of Bitcoin prices during the chosen time frame. This study demonstrates that LSTM still excels in forecasting Bitcoin prices accurately, even when compared to the advanced ARIMA model [31].

2.1 Problem Identification

Certain limitations are identified in the implementation of the existing methods that are represented below.

- Reduced outcomes and less accuracy have been delivered by existing model for the price prediction of cryptocurrency [22].
- Reduction of economic crises is measured to be short term in the prevailing study [28, 29].

3. Proposed Methodology

In the proposed methodology, the cryptocurrency prices are predicted by using the CNN-based Dual-Directional Model. Initially, historical price of the cryptocurrency dataset with Ethereum and Bitcoin is used. First, the dataset is loaded and preprocessed using various preprocessing techniques for examining the missing values, removal of irrelevant and unwanted data, and eradicating the noisy data, which affects the quality of the dataset. Further, data encoding is employed in the proposed model. Subsequently, preprocessing the model splits the data into train and test splits. When the model splits, a regression process takes place to predict the value of crypto currencies. The proposed model utilizes a CNN-based dual-directional feature prediction for forecasting the prices of crypto currencies such as Bitcoin and Ethereum. The CNN model utilized in the proposed model incorporates the BiLSTM model with attention mechanism (AM), as the BiLSTM has the capability to learn the bidirectional sequential features that help in improving the accuracy of the model for calculation and the capability of AM helps in assigning the weights according to the

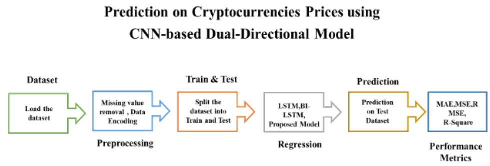

Fig. 1. Overall structure of CNN-based dual-directional model.

significance of the information. Further, AM is employed in the proposed framework to assist in reducing the effect of the terminated data on predicting the value of crypto through conveying better weights. Fig. 1 illustrates the overall structure of the CNN-based Dual-Directional model.

3.1 Pre-processing

The chronological collection of the price data can be predicted and it is obtained from the cryptocurrency exchanges databases. Here, there is an occurrence of removal of missing and irrelevant data. It is significant in the pre-processing step, which refers to the process of altering categorical or textual data into arithmetical format. This is used for identifying the design in the information and making predictions based on those patterns.

3.2 Train test split

The overall data which is preprocessed and sent for the feature section using optimal algorithms are divided in terms of train and test data respectively. The initial, train data are used in training the model. Whereas, the latent, test data are used in the model validation or in testing the respective model. The data will be separated in the ratios of 80:20 for train and test data, respectively.

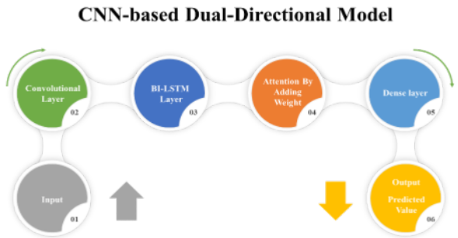

Fig. 2. Illustration of proposed CNN-based dual-directional model.

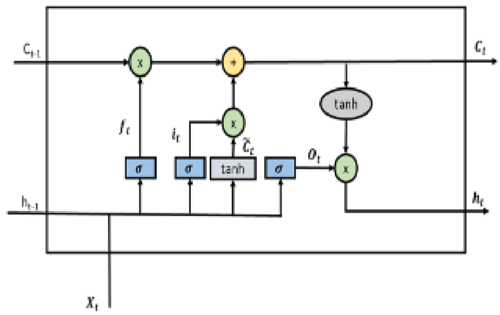

Fig. 3. Architectural diagram of LSTM model.

3.3 Proposed regression – CNN based dual directional model

In the proposed CNN based Dual Directional Model, after the train and test split, the obtained data is fetched into the convolution layer where the CNN model is used to extract the Bitcoin and Ethereum. Subsequently, it is processed by the BiLSTM layer where the model is trained by the local features that are extracted from CNN with the intention to learn the inner vibrant variation form. Hence, BiLSTM with CNN is used for learning the bidirectional serial features from the information of features which are extracted against CNN layer and completely achieve the long-term structures of the instance data aimed at learning which eventually helps in better price prediction of crypto values. Furthermore, assigning different weights based on the different features assists with discarding the irrelevant information for improving the efficacy of the information processing via differentiated weight assignment and aids in solving the issues associated with information loss, which can be caused by long sequences in the BiLSTM model. Finally, the output obtained in the previous step is passed via a dense layer in the CNN model. The dense layer is considered as a simple layer of neurons, herein each neuron gets input from all other neurons of the existing layer, and it is expressed in Fig. 2.

From Fig. 3, the memory storage unit of LSTM comprises the forget gate, the input gate, and the output gate. The forget gate processes the previous layer's output, choosing important data and removing unnecessary information. The input gate assesses the significance of data and modifies the unit's state based on crucial information. The output gate decides which unit status can be passed to the next layer's unit. Forget gate can be stated by Eqs. 3.1-3.3 in [32]:

$$r_t = \sigma(M_r \cdot [h_{t-1}, a_t] + a_r), \tag{3.1}$$

$$k_t = \sigma(M_j \cdot [h_{t-1}, a_t] + a_j), \tag{3.2}$$

$$\widetilde{C}_t = (M_C \cdot [h_{t-1}, a_t] + a_C). \tag{3.3}$$

Now, a unique unit status h_{t-1} is updated towards h_t, and it is given in Eq. 3.4.

$$D_t = r_t \times D_{t-1} + k_t \times \widetilde{D}_t. \tag{3.4}$$

The output gate regulates the output over the sigmoid function that is stated through the ensuing Eq. 3.5.

$$o_t = \sigma(M_o[h_{t-1}, a_t] + b_o), \tag{3.5}$$

$$h_t = o_t \times \varphi(D_t). \tag{3.6}$$

Fig. 4 shows the attention based BiLSTM network toward powerful prediction of price after historical data. Here, the enhanced BiLSTM and AM model evaluate

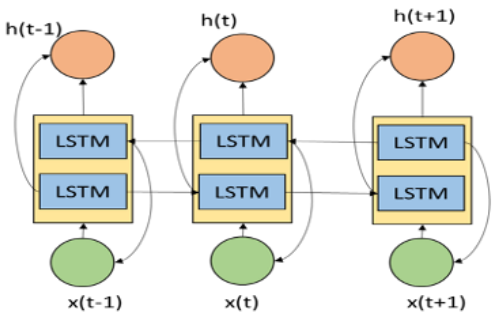

Fig. 4. Graphical representation of Bi-LSTM architecture.

prevailing exploration difficulties that depend on progressive feature classification with forecasting. The evaluation of the forward LSTM (first hidden layer) along with the backward LSTM (second hidden layer).

3.3.1 Forward LSTM (First hidden layer)

$$j_x = \sigma(M_j[q_{x-1}, a_x] + p_j), \quad (3.7)$$
$$m_x = \sigma(M_m[q_{x-1}, a_x] + p_m), \quad (3.8)$$
$$o_x = \sigma(M_0[q_{x-1}, a_x] + p_0) \quad (3.9)$$
$$d \sim x = \tau(M_c[q_{x-1}, a_x] + p_c) \quad (3.10)$$
$$d_x = m_x \circ c_{x-1} + j_x \circ c \sim t \quad (3.11)$$
$$\overrightarrow{q}_x = o_x \circ \tau(c_x). \quad (3.12)$$

3.3.2 Backward LSTM (Second hidden layer)

$$j_x = \sigma(W_j[q_{x+1}, a_x] + p_j), \quad (3.13)$$
$$m_x = \sigma(M_m[q_{x+1}, a_x] + p_m), \quad (3.14)$$
$$o_x = \sigma(M_o[q_{x+1}, a_x] + p_0), \quad (3.15)$$
$$d \sim x = \tau(M_c[q_{x+1}, a_x] + p_c), \quad (3.16)$$
$$d_x = m_x \circ d_{x+1} + j_x \circ d \sim x, \quad (3.17)$$
$$\overrightarrow{q}_x = o_x \circ \tau(c_x). \quad (3.18)$$

Whereas, jt, ft, and ot are utilized to signify three gates, a sigmoid function (σ), a tangent function (τ), and Hamdard product ($\circ$); the weight metrics are Mm, Mo, Mc, and Mc. The $qt1$ and $qt + 1$ signify the former and upcoming hidden states,pi, pf, po, pc means the bias vector, $d \sim x$ signifies the candidate value, dt shows the cell state, while $dt1$ and $dt + 1$ shows the former and upcoming state of the cell.

3.3.3 CNN-BiLSTM architecture

The proposed model takes the input data that can be in the form of sequential data. Where, the CNN part is utilized to extract high-level features against the input data. Besides, the CNNs contain multiple convolutional with pooling layers, which learn to perceive patterns and features in the input data. After that, the output from the CNN layers is handed to a BiLSTM network which can capture long-term dependencies in sequential data. Moreover, the bidirectional feature permits the model to aspect at the input data both forwards and backwards, by refining the model's capacity towards the reorganization of the input data. Finally, the output from the BiLSTM network is utilized for regression and it is shown in Fig. 5.

Fig. 5, shows that BiLSTM is an RNN variant that may resolve the gradient vanishing problem by integrating a pass selection procedure as in Eq. 3.19.

$$d_t = \sigma(M_f \times [p_{t-1}x_t] + a_f), \quad (3.19)$$
$$j_t = \sigma(M \times [p_{t-1}x_t] + a_i), \quad (3.20)$$
$$\widetilde{D_t} = \varphi(M \times [p_{t-1}x_t]) + a_c), \quad (3.21)$$
$$D_t = d_t \times D_{t-1} + j_t \times \widetilde{D_t}, \quad (3.22)$$
$$z_t = \sigma(W_z \times [p_{t-1}x_t] + b_z), \quad (3.23)$$
$$p_t = z_t \times \varphi(D_t), \quad (3.24)$$

where the input at the time (t) is given by x_t indicates, the implied state of layer on preceding instant(p_{t-1}), D_{t-1} reveals the

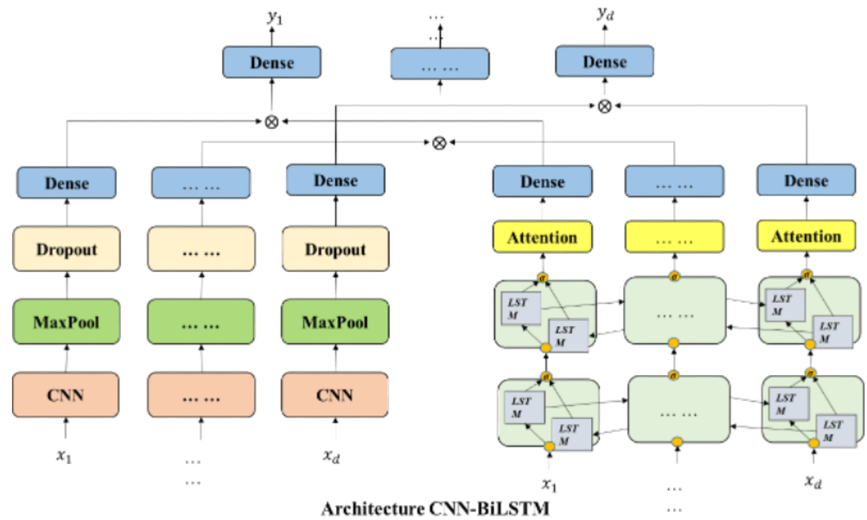

Fig. 5. Framework of CNN-BiLSTM architecture.

memory state in the former moment, Det remains as a transitory state of memory at instant t, along with ft, jt, Dt controls the magnitude of data formed in gates, along with memory part. M signifies the weights along with biases utilized in the training process.

Additionally, the related data is acquired in the chronological statement of complete input and BiLSTM incorporates the data in ways and functions and it is given in Eq. (3.14).

$$\overrightarrow{p_t} = \overrightarrow{LSTM}(p_{t-1}x_t, c_{t-1}), t \in [1, Y], \quad (3.25)$$

$$\overleftarrow{p_t} = \overrightarrow{LSTM}(p_{t-1}x_t, c_{t-1}), t \in [1, Y], \quad (3.26)$$

$$N_t = [\overrightarrow{p_t}, \overleftarrow{p_t}]. \quad (3.27)$$

Here, $\overrightarrow{p_t}$ specifies the forward layer's hidden state at the moment of t, $\overleftarrow{p_t}$ remains as the backward layer's hidden state at (t), while N_t indicates the BiLSTM's hidden state at time t.

4. Results and Discussion

This section focuses on the results and discussion during which the dataset description, EDA, performance metrics, performance analysis, experimental results and comparative analysis are discussed in detail.

4.1 Dataset description

Crypto, short for cryptocurrency, is a digital currency meant to be used as a medium of exchange. It utilizes a secure ledger system and strong cryptography to record coin ownership, control coin creation, and verify coin transfers. According to a report from Crypto.com, there were 106 million crypto users globally in January, with a 16% increase in participants from the previous month. A different study by financial advisory firm deVere revealed that 70% of its clients who were 55 and older had either invested in digital currencies or were considering doing so in 2021, even though digital currencies like Bitcoin are typically linked to younger millennial investors. The dataset

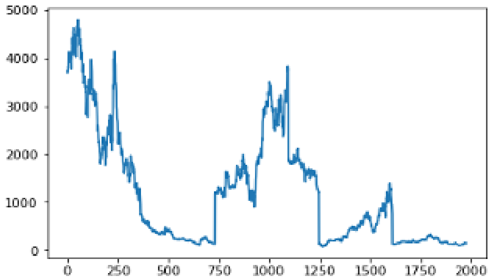

Fig. 6. Representation of data collected for prediction.

link is provided in the following link: https://www.kaggle.com/datasets/adityamhaske/cryptocurrency-price-analysis-dataset?select=BTC.csv

4.2 EDA

This section exploits the EDA for the prediction of cryptocurrencies such as Bitcoin and Ethereum. The dataset contains the date of the cryptocurrency prices, the open and closing prices with the respective dates, the highest and lowest price with the date, along with the volume of the cryptocurrency. Fig. 6 illustrates the data that are collected for price prediction.

Fig. 6 indicates the data collection for the year (2018-2023) which is utilized for the price prediction of Bitcoin and Ethereum cryptocurrency. The Bitcoin price prediction during the open and close state is specified in Fig. 7.

Fig. 7 shows the volume of the predicted price for the open and closed state of Bitcoin between the years 2018 and 2023. The graph indicates the variations in the price prediction, and it reveals that the years 2021 and 2022 had the highest predictive value when compared with the other years. Fig. 8 delivers the plotted graph for the prediction price for Bitcoin.

From Fig. 8, it can be seen that price prediction is more at 1000 as well as in

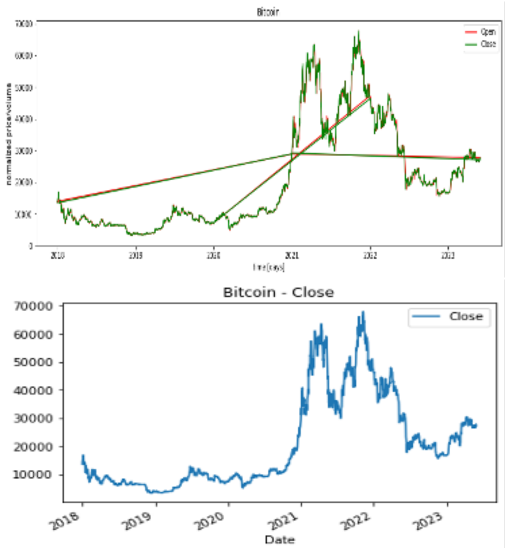

Fig. 7. Illustrates the volume of price prediction at the open and close state of bitcoin for the year (2018-2023).

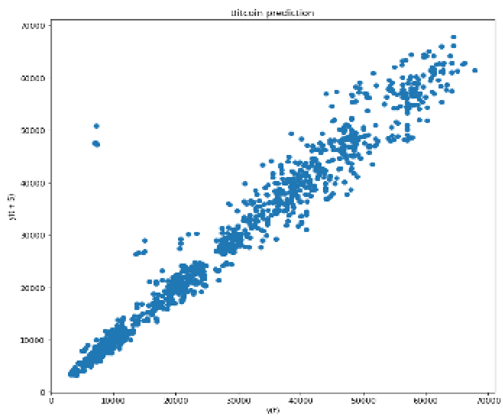

Fig. 8. Representation of price prediction of bitcoin using plotted graph.

25000. Besides, some may be predicted at 60,000. The price prediction of Ethereum is illustrated in Fig. 9.

Fig. 9 shows the volume of the predicted price for the open and close states of Bitcoin during the years 2018-2023. The graphical image considers variants in the price prediction, and it shows that years 2021 and 2022 have a higher predictive

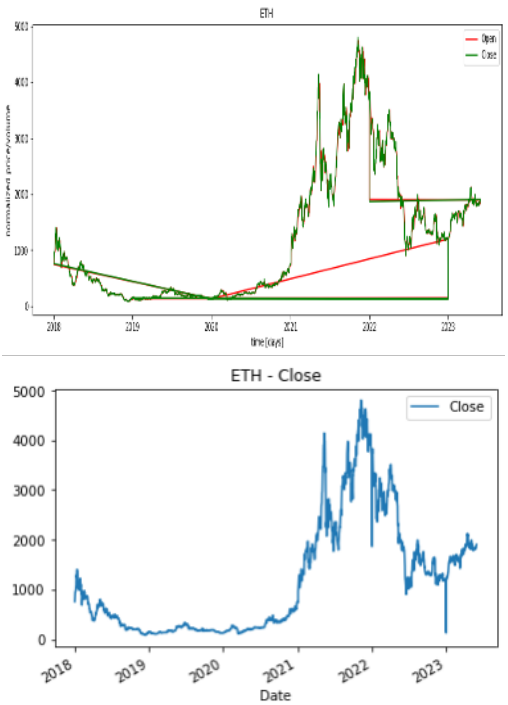

Fig. 9. Illustrates the volume of price prediction at the open and close state of eth for the year (2018-2023).

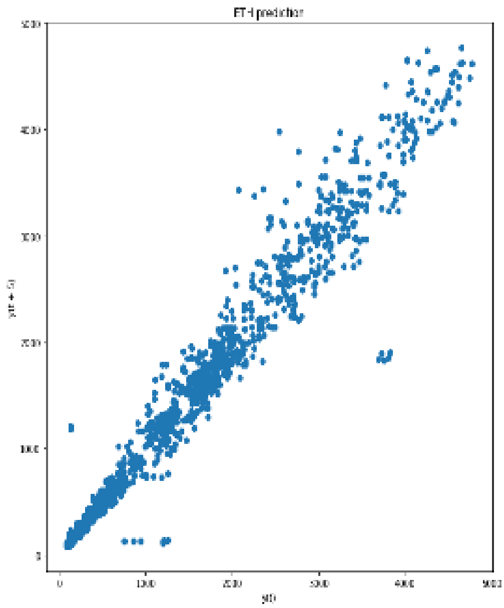

Fig. 10. Representation of price prediction of eth using plotted graph.

value when compared with the other years. Fig. 10 shows the plotted graph for the prediction price for Ethereum.

From Fig.10, it can be seen that price prediction is more at 1000 as well as in 25000. Besides, some may be predicted at 60,000.

4.3 Performance metrics

The performance metrics such as Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE) are described as follows.

4.3.1 Root Mean Square Error (RMSE)

RMSE is one of the parameters used in the evaluation of the quality of the prediction made by the respective model. It represents the quantity of deviation from the actual measured true values, including the Euclidean distance. This is represented using Eq. 4.1.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted - Actual)}{2}}. \tag{4.1}$$

4.3.2 Mean Absolute Error (MAE)

MAE processes the average of the errors' degree among the projected along with definite values. The formula of MAE is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{N}|y_i - \hat{y}_i|. \tag{4.2}$$

Here, n is the observation number, y_i denotes the ith observation of the actual value and $\hat{y}_i$ represents the ith observation of the predicted value.

4.4 Performance analysis

The performance of the LSTM, BILSTM and the proposed model is measured by using performance metrics such as MAE, MSE and RMSE value, and it is illustrated in Fig. 11.

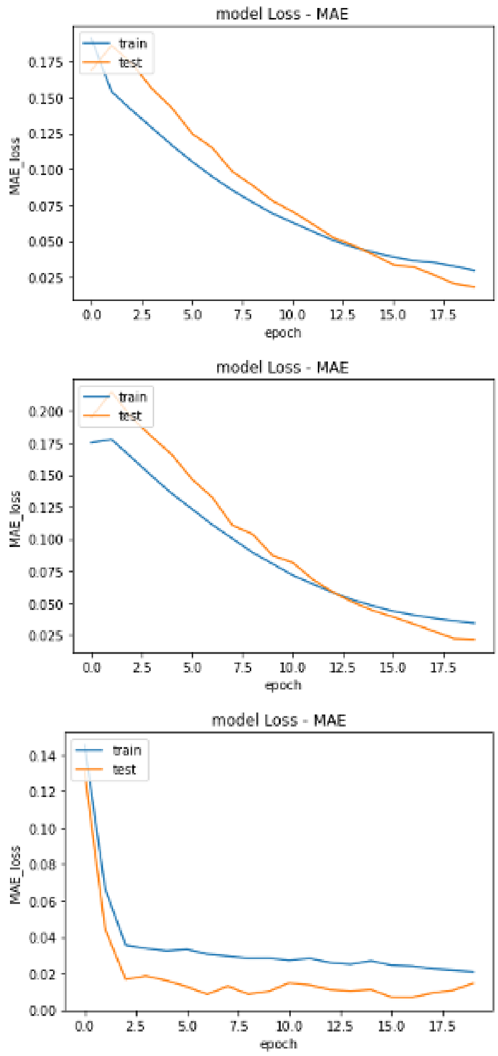

Fig. 11. Performance of MAE for LSTM, BiLSTM and proposed model for bitcoin.

Fig. 11 shows the train and test data of the LSTM, BiLSTM and the proposed model. Moreover, the MAE of the proposed model shows that both the test and train converge in the same manner.

Fig. 12 shows the performance of MSE of LSTM, BiLSTM and the proposed model. Here, the train and test data converge equally, whereas in LSTM and BiLSTM both test and train data give the same value.

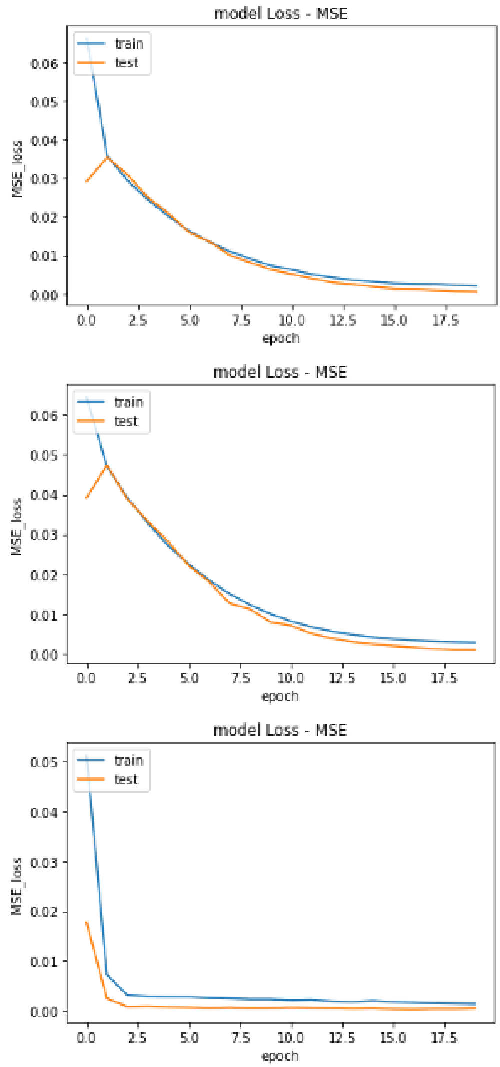

Fig. 12. Performance of MSE for LSTM, BiLSTM and proposed model for bitcoin.

The performance of RMSE of the above models, such as LSTM, BiLSTM, and the proposed model are given in Fig. 13. The train and the test data converge in a linear manner and then it is found that the proposed model works effectively.

Fig. 14 shows the train and test data

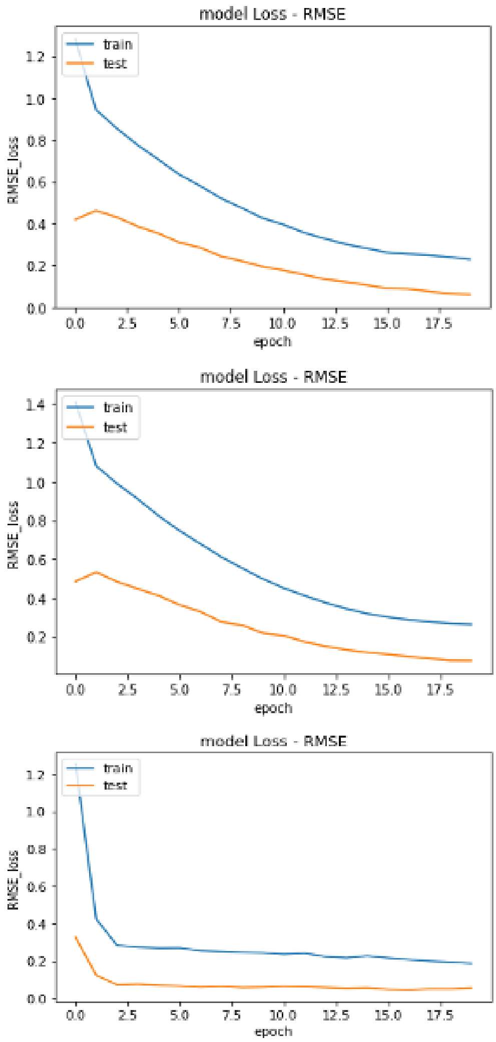

Fig. 13. Performance of RMSE for LSTM, BiLSTM and proposed model for bitcoin.

of the LSTM, BiLSTM and the proposed model for Ethereum . Moreover, the MAE of the proposed model shows that both the test and train converge in the same manner.

Fig. 15 illustrates the performance of MSE of LSTM, BiLSTM, and the proposed mode for Ethereum. Here, the train and test data converge equally, whereas in LSTM and BiLSTM, both test and train data give the same value.

The performance of RMSE of the

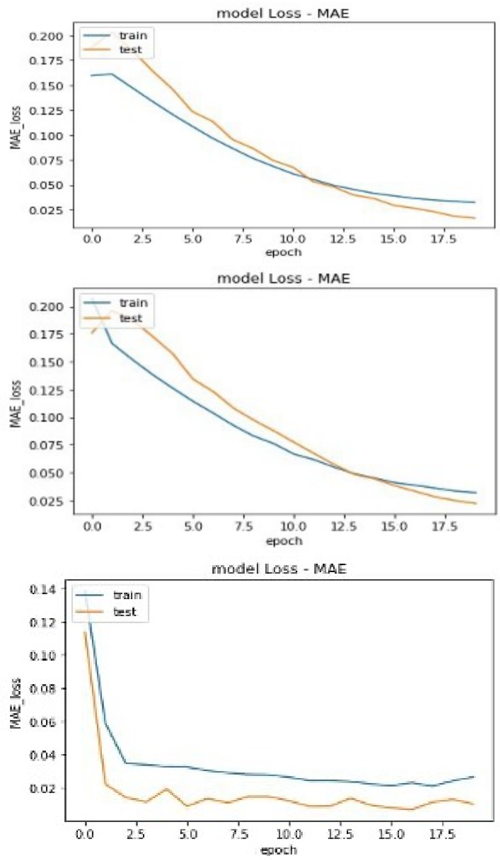

Fig. 14. Performance of MAE for LSTM, BiLSTM and proposed model for ethereum.

above models such as LSTM, BiLSTM and proposed model for Ethereum are given in Fig. 16. The train and the test data converge in a linear manner and then it is found that the proposed model works effectively. Table 1 and Fig. 17 show the MAE, MSE and RMSE values of LSTM, BiLSTM and the proposed model for Bitcoin, which is one type of cryptocurrency.

Table 1. Performance metrics of LSTM, BiLSTM and proposed model for bitcoin.

Model	MAE	MSE	RMSE
Lstm	0.019	0.0007	0.0249
Bi-lstm	0.024	0.0008	0.0317
Proposed	0.018	0.0005	0.0224

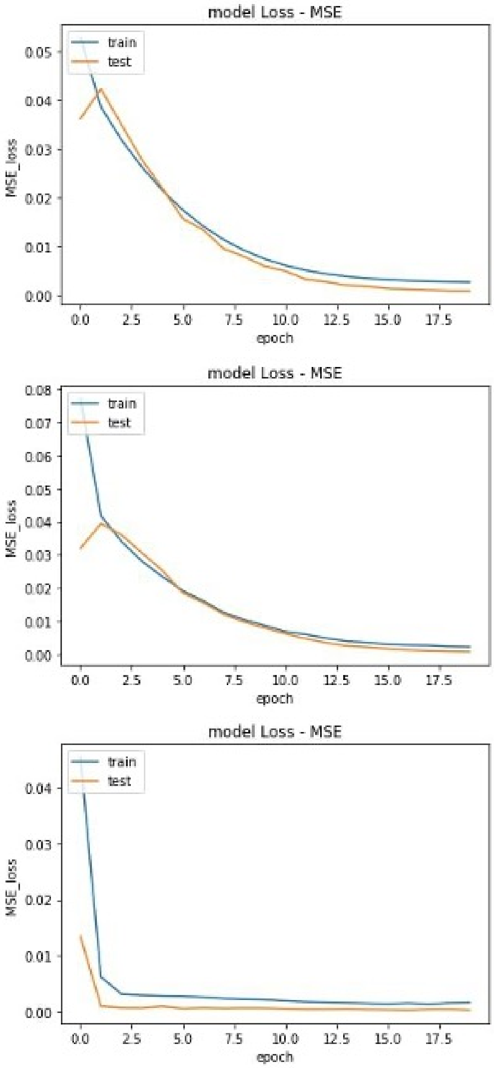

Fig. 15. Performance of MSE for LSTM, BiLSTM and proposed model for ethereum.

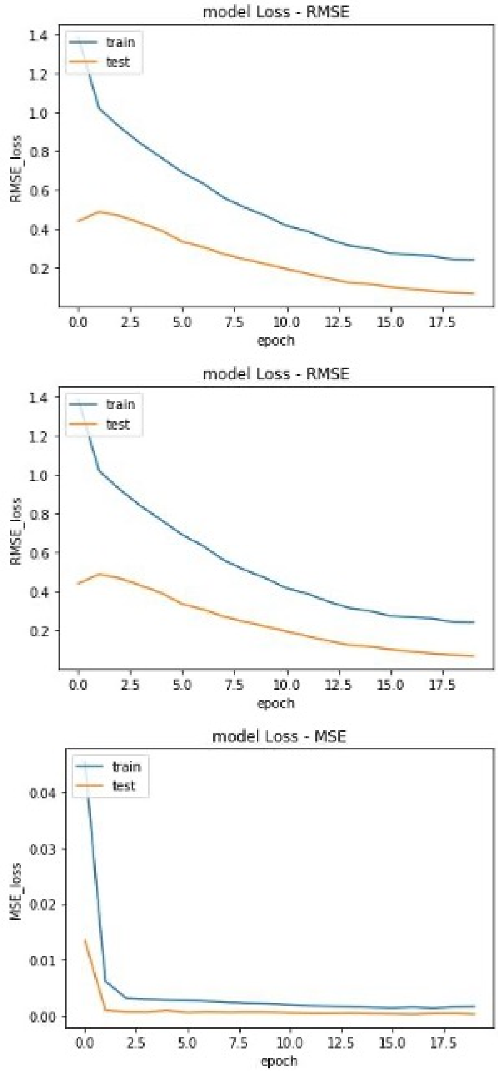

Fig. 16. Performance of RMSE for LSTM, BiLSTM and proposed model for ethereum.

From Table 1 and Fig. 17, it is observed that the proposed model has attained higher results than the LSTM and BiLSTM for the metrics, namely MAE, MSE, and RMSE values. Moreover, its values are 0.018, 0.0005, and 0.0224. Table 2 illustrates the MAE, MSE, and RMSE obtained by the LSTM, BiLSTM, and proposed model for the Ethereum cryptocurrency.

Table 2. Performance metrics of LSTM, BiLSTM and proposed model for ethereum.

Model	MAE	MSE	RMSE
Lstm	0.018	0.0006	0.0247
Bi-lstm	0.021	0.0009	0.0315
Proposed	0.014	0.0005	0.0225

From Table 2 and Fig. 18, it is observed that the proposed model has attained higher results than the LSTM and BiLSTM

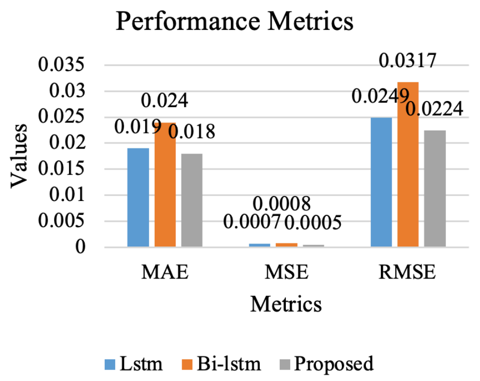

Fig. 17. Performance metrics of LSTM, BiLSTM and proposed model for bitcoin.

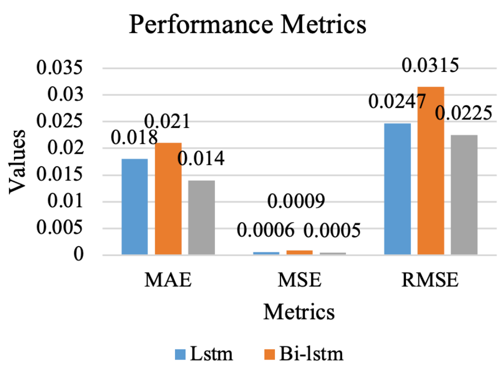

Fig. 18. Performance metrics of LSTM, BiLSTM and proposed model for ethereum.

for the metrics, namely MAE, MSE and RMSE values. Moreover, its values are 0.014, 0.0005 and 0.0225.

4.5 Comparative analysis

The proposed model is compared with the existing model for Bitcoin and Ethereum cryptocurrency and it is discussed in detail in the illustrative Table 3 and Fig. 19.

From Table 3 and Figure 19 [33], it is perceived that the RMSE value of the proposed model for Bitcoin is low when compared with the RMSE value of the other prevailing models. Hence, it is observed that

Table 3. Comparison of RMSE value of proposed model with conventional models for bitcoin [33].

Model	**RMSE**
ARIMA	43.954
Simple RNN	44.003
Facebook Prophet	805.169
GRU	43.998
LSTM	45.687
CNN-LSTM	47.537
Bidirectional LSTM	332.886
XGBoost	1477.181
1DCNN-GRU	43.933
Proposed	**0.0225**

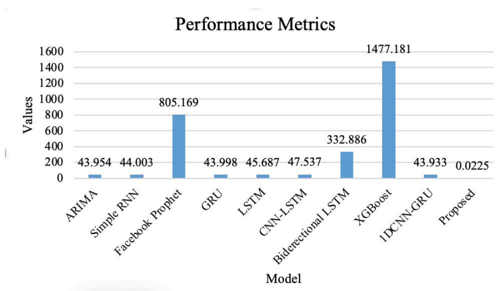

Fig. 19. Comparison of RMSE Value of Proposed Model with Conventional Models for Bit-Coin [33].

a lower RMSE value can provide a better model and also be able to predict the values accurately. Besides, table 4 illustrates the RMSE value of the conventional model with the proposed model, and it is depicted.

Table 4 and Fig. 20 show the RMSE values achieved by a proposed model and the prevailing models. Moreover, from Table 4, it is observed that a lesser RMSE value can increase the efficiency of the proposed model, and there is an occurrence of accurate prediction. Besides, Table 5 and Figure 21 have illustrated the MAE and RMSE values of the proposed model with the classical model for Bitcoin and Ethereum. The model has attained the min-

Table 4. Comparison of RMSE value of proposed model with conventional models for bitcoin [33].

Model	RMSE
ARIMA	3.516
Simple RNN	3.517
Facebook Prophet	157.046
GRU	3.512
LSTM	3.636
CNN-LSTM	3.516
Bidirectional LSTM	43.414
XGBoost	101.36
1DCNN-GRU	3.511
Proposed	**0.0224**

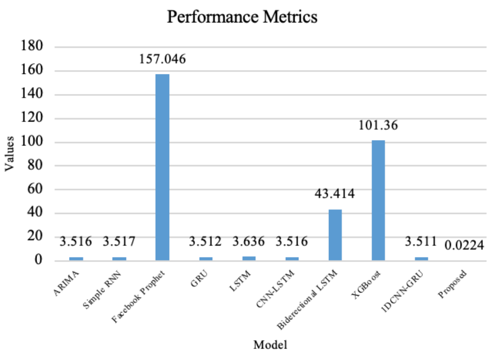

Fig. 20. Comparison of RMSE Value of Proposed Model with Conventional Models for Ethereum [33].

imal values of MAE and RMSE.

From Table 5 and Fig. 21 [34], it is seen that the MAE and RMSE values of the proposed model for Bitcoin have attained less value, and it is compared with the MAE and RMSE values of the other models. Henceforth, it is observed that lower RMSE and MAE values deliver an enhanced model and are also capable of predicting the values more precisely. Besides, the table illustrates the RMSE value of the conventional model with the proposed model and it is depicted.

Furthermore, Table 6 and Fig. 22 exploit MAE and RMSE values of the conventional model with the proposed model for Ethereum.

Table 5. Comparison of MAE, RMSE Value of Proposed Model with Prevailing Models for Bitcoin [34].

Model	MAE	RMSE
ARIMA	172.681	253.051
RF	283.246	372.773
SVM	236.284	330.389
Informer	257.918	333.124
AutoInformer	319.257	402.196
LSTM	193.817	275.958
GRU	180.501	260.502
EMD-AGRU-LSTM	181.721	223.556
VMD-ALL-AGRU	132.127	167.144
VMD-ALSTM-ADD	127.996	165.222
VMD-GRU-ADD	123.571	153.818
Proposed	**0.018**	**0.0224**

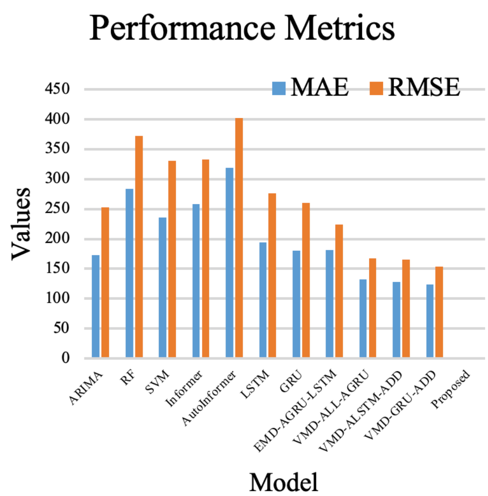

Fig. 21. Comparison of MAE, RMSE Value of Proposed Model with Prevailing Models for Bitcoin [34].

Table 6 and Fig. 22 reveal that the MAE and RMSE value is achieved by the projected model and the prevailing model. Furthermore, from the table, it is detected that less significant MAE and RMSE values can proliferate the efficacy of the model and there is an existence of exact prediction.

Table 6. Comparison of MAE, RMSE Value of Projected Model with Prevailing Models for Ethereum [34].

Model	MAE	RMSE
ARIMA	11.205	15.979
RF	12.089	17.751
SVM	12.35	18.549
Informer	19.666	24.685
AutoInformer	27.642	35.633
LSTM	16.126	23.129
GRU	14.054	20.062
EMD-AGRU-LSTM	6.269	8.238
VMD-ALL-AGRU	6.87	8.619
VMD-ALSTM-ADD	7.287	9.286
VMD-GRU-ADD	7.287	7.241
Proposed	**0.014**	**0.0225**

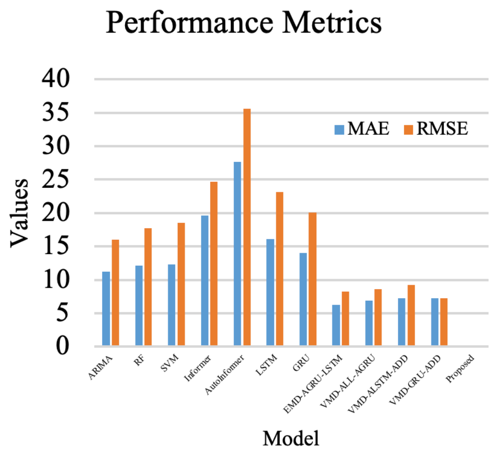

Fig. 22. Comparison of MAE, RMSE Value of Projected Model with Prevailing Models for Ethereum [34].

Table 7. Comparison of MAE, RMSE Value of Proposed Model with Prevailing Models for Bitcoin [10].

Model	MAE	RMSE
Linear (BTC)	2.24	3.36
RF (BTC)	2.42	3.46
SVM (BTC)	2.98	4.25
Proposed	**0.018**	**0.0224**

Table 7 and Fig. 23 has exposed that the proposed model has attained less MAE

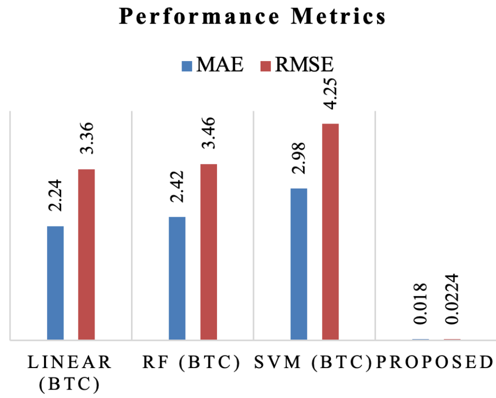

Fig. 23. Comparison of MAE, RMSE Value of Projected Model with Prevailing Models for Bitcoin [10].

and RMSE value when compared with other existing models for Bitcoin.

Table 8. Comparison of MAE, RMSE Value of Proposed Model with Prevailing Models for Ethereum[10].

Model	MAE	RMSE
Linear (ETH)	3.65	5.2
RF (ETH)	3.79	5.19
SVM (ETH)	3.71	5.28
Proposed	**0.014**	**0.0225**

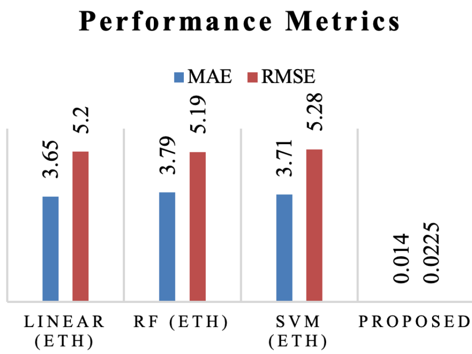

Fig. 24. Comparison of MAE, RMSE Value of Projected Model with Prevailing Models for Ethereum[10].

From Table 8 and Fig. 24, it is inferred that the MAE and RMSE values of the proposed model for Ethereum have achieved less value, and it is related with the MAE and RMSE values of the conventional models. Then, it is experiential that lesser RMSE and MAE values provide an enhanced model and are also capable of predicting the values more accurately.

5. Conclusion and Future Recommendations

Significantly, predicting the price of cryptocurrencies is highly speculative and can be influenced by a variety of factors, including market sentiment, regulatory developments, technological advancements, and macroeconomic trends. As a result, it was challenging to accurately forecast the future value of any cryptocurrency. However, ML techniques can provide insights and predictions for cryptocurrency price movements. The creation and execution of a dual-directional model using CNN for predicting cryptocurrency prices have displayed encouraging outcomes. By using convolutional neural networks trained with historical price data, the model could detect intricate patterns in the cryptocurrency market and accurately forecast future price changes. Taking into account both past and future price movements, the dual-directional method improved prediction accuracy by offering a holistic understanding of market dynamics. Besides, the method differentiates the model from conventional price prediction techniques, providing a more dependable forecast for traders and investors. While the model has performed well in backtesting and validation tests, additional research and testing are necessary to evaluate its strength and applicability in various cryptocurrency markets. Moreover, enhancing the model's predictive power and efficiency could be achieved by integrating supplementary features and data sources. In general, the dual-directional model based on CNN signifies notable progress in cryptocurrency price forecasting and has considerable possibilities for use in trading, investment, and risk control. The advancement of blockchain technology would rely on advanced predictive models to assist market participants in navigating the unpredictable cryptocurrency market. In the future, external factors such as macroeconomic indicators, geopolitical events, and regulatory changes will impact cryptocurrency prices and include these factors in multiple prediction ensemble models.

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