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Predictive Modelling of Bitcoin and Ethereum: A deep Dive into LSTM and Bi-LSTM

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Abstract

Cryptocurrencies have seen a meteoric rise in popularity, embodying a new era of financial innovation and decentralized digital assets. The inherent volatility and intricate price behaviors in cryptocurrency markets pose significant forecasting challenges. This paper conducts a comprehensive comparative analysis of two leading cryptocurrencies, Bitcoin and Ethereum price dynamics utilizing predictive modeling techniques. The cryptocurrencies have been implemented using LSTM and Bi-LSTM models to predict price movements by identifying linear and non-linear relationships in historical price data. The performance of these models is assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), which serve as benchmarks for predictive accuracy. The findings underscore the effectiveness of these models in predicting prices and provide insights into their operational efficiency, thereby enhancing real-time trading strategies and investment decisions. This research makes a substantial contribution to the financial technology sector by enhancing the understanding of how predictive models can effectively navigate the complexities of cryptocurrency markets, thus aiding investors and policymakers in making informed decisions.

Keywords: Bitcoin, Ethereum, Cryptocurrency, LSTM, Bi-LSTM, Predictive Modeling, Data Preprocessing, MSE, RMSE, MAE, Time-Series Analysis.

1. Introduction

Cryptocurrency is often termed as crypto which is depicted as alternate form of money which exist virtually or digitally and employed cryptography for secured transitions [1)]. In last few years, cryptocurrencies are measured as a universal awareness for considerable number of users attributable to its various functionalities like decentralization, immutability and many more. However, cryptocurrencies like bitcoin can become speculative investments with volatile prices and can lead to boom and bust periods for traders. In October 2008, an individual or group operating under the pseudonym Satoshi Nakamoto [2)] introduced a revolutionary system known as blockchain technology, which was accompanied by the invention of the first digital currency, BTC. There are different types of cryptocurrencies which includes Litecoin, Dogecoin, Ethereum, XRP (Ripple), Bitcoin, BNB, cardona and many more [3)]. These different types of cryptocurrency varies in terms of different aspect like privacy, scalability and functionality.

Owing to the incremental expansion and desirability of the cryptocurrency, they are used in exchange of cash flows and goods. Congruently, due to the approachability of high frequency of data and rapid flow of information results in employing Deep Learning (DL) and Machine Learning (ML) techniques for forecasting the price of cryptocurrencies, as Artificial intelligence (AI) techniques in recent years have received lot of reputation in crypto market. Therefore, price

forecasting for cryptocurrency is considered as an essential step while making a crucial financial decision like optimization of portfolio, assessment or evaluation of risk or trading, in spite of that, cryptocurrency market is considered to be complex, unpredictable due to strong fluctuations. Hence, different studies have employed different ML and DL based approaches for predicting the price of cryptocurrency. Here in this research, two different DL models are used for forecasting the price of Bitcoin and Ethereum by employing LSTM and BiLSTM.

1.1 Related Work

Various existing studies for predicting the price of cryptocurrencies have been reviewed in the subsequent section.

The price of cryptocurrency is considered to be volatile and dependent on different aspects like trends involved in market, transactional cost and other aspects. Therefore, prediction of cryptocurrency is important. Hence, suggested study has focused on predicting the non-familiar cryptocurrencies like monero and litecoin. In order to predict the price of cryptocurrency, recommended employed LSTM and GRU based hybrid model for prediction. Further, the model was evaluated using different metrics like RMSE, MAE, MAPE and MSE for monero and litecoin [4)]. Similarly, existing paper has also employed different DL models for predicting the precise price of two different cryptocurrencies like Zcash and Litecoin. In order to fetch the desired outcome, the model was trained with the data of the last 5 years and then, it was tested on real-time data. Further, the outcome obtained by the proposed model was compared with actual prices [5)].

Extremely precise price predictions of cryptocurrency are considered as dominant to investor and researchers. Moreover, assessment of discrete nature of time series data have been difficult due to nonlinearity approach of the cryptocurrency market. Hence, different methods have been used by various studies for predicting the price of cryptocurrencies. Likewise, the recommended study has employed LSTM, BiLSTM, and GRU for predicting the price of cryptocurrencies such as LTC (Litecoin), ETH (Ethereum), and BTC (Bitcoin). Three models employed in the recommended paper were primarily used for exchange rate predictions of the 3 cryptocurrencies. Out of the existing 3 models, BiLSTM model resulted in delivering the desired outcome when compared to LSTM or GRU. The recommended model primarily assisted investors and traders in different aspects as the implementation of DL algorithms in the suggested paper provided an efficient outcome for predicting the prices of cryptocurrencies than the conventional models [6)].

Different models were used for forecasting the price prediction of different cryptocurrencies like bitcoin, litecoin and ripple. In order to detect the future of cryptocurrencies, effective models should be implemented. Therefore, existing paper has utilized LSTM, simple RNN and GRU for predicting the price of cryptocurrency. The prediction power of the recommended model could be improved by employing Google trends data to the input of RNN approach. However, from the experimental, it was identified that, GRU model delivered better outcome for predicting the prices of litecoin and bitcoin [7)]. Similarly, recommended paper has utilized various DL methods like MLP and LSTM for forecasting the price trends of ethereum dataset. The methods were applied depending on historical data which was estimated as per min, hr and day wise. The dataset was sourced from CoinDesk repository. However, from the experimental outcome it was evaluated that, LSTM model delivered better outcome than the MLP marginally as LSTM model was sturdy and accurate for long term dependency when compared to MLP model [8)].

Bitcoin in recent years, have possessed greater reception by different bodies like trader, policy makers, scholars and even more. Hence, the prediction of cryptocurrencies helps in handling the price of volatility of bitcoin and performs in obtaining higher accuracy for the model. Therefore, recommended paper has employed the GRU and LSTM model in the suggested study, the process was proceeded by downloading the datasets, since the dataset is downloaded, the data has been employed for scaling by employing min-max normalization. The recommended LSTM model was used to overcome the vanishing gradient. The accuracy of the GRU and LSTM model was detected by using MAPE and RMSE metrics, in which from the experimental result, it was identified that GRU delivered better outcomes than the LSTM model [9)].

Cryptocurrency is considered as a newfangled kind of assets which has been emerged due to the progression of financial technology. However, forecasting the price of cryptocurrencies have been estimated as difficult process due to the dynamism and volatility nature of crypto. Hence, the suggested paper has employed 3 different types of RNN networks such as GRU, LSTM and BiLSTM for precisely predicting the prices of cryptocurrencies for BTC, LTC and ETH. The experimental outcome of the recommended paper has depicted that GRU has outperformed the prevailing algorithms with delivering MAPE rate of 0.2454% for BTH, 0.82% for ETH and 0.211% for LTC. Moreover, out of 3 algorithms, BiLSTM delivered less accuracy than LSTM and GRU models [10)]. Due to the constant fluctuation of prices in stock market, it is significant to build a dependable and accurate model for forecasting the process of cryptocurrencies, therefore, a multiple input cryptocurrency DL (MIC-DL) model was used for developing a precise and dependable model for prediction of crypto prices. The recommended MIC-DL model utilized different cryptocurrency data and handled them independently with the aim to exploit and process the information of cryptocurrency. The processed data then merged with the other data and resulted in delivering the final prediction [11)].

1.2 Organisation of the Paper

Section 2 discusses data collection, data characteristics, and dataset samples. Section 3 presents various prediction models such as LSTM and bi-LSTM for Bitcoin and Ethereum price prediction. Section 4 analyzes various features of the Bitcoin and Ethereum using preprocessing techniques, and discusses those features that we used to build prediction models. Also, this section presents experimental results under various performance evaluation metrics. Finally, Section 5 concludes and Section 6 discusses the future work.

2. Data Sets and Data Collection

We begin this section by detailing the sources of data collection and their attributes. The primary data for this research comprises historical price data of Bitcoin and Ethereum, including daily opening, closing, high, low, and volume figures. This data was meticulously gathered from established financial data services, ensuring a reliable foundation for analysis.

2.1 Data Source and Characteristics

In this study, we focus our analysis on two major cryptocurrencies based on their market capitalization and influence in the digital currency space: Bitcoin (BTC) and Ethereum (ETH). We collected the daily recorded data of each cryptocurrency's price against the US Dollar (USD) from established financial market databases, which offer comprehensive and reliable datasets. Each collected dataset contains several attributes with various data types as shown in Table 1, which are crucial for the analysis:

Table 1: Dataset Attributes

S.No.	**Attribute**	**Data type**	**Meaning**
1	Date	Date	Represents the date for each recorded price.
2	Open	Float	The opening price of the cryptocurrency for the trading day
3	High	Float	The highest price that the cryptocurrency reached during the trading day
4	Low	Float	The lowest price of the cryptocurrency during the trading day.
5	Close	Float	The closing price of the cryptocurrency at the end of the trading day.

Bitcoin data is available from the time of its first market appearance in 2009, providing a long historical range that helps to capture various market behaviors including bull and bear markets. Ethereum, introduced later, has data available from 2015, which covers significant market events including its rapid price increases and periods of volatility. Table 2 shows the Data Characteristics of collected datasets.

Table 2: Data Characteristics

Cryptocurrency	**Pairs**	**Start Date**	**End Date**	**No. of Records**
Bitcoin	BTC-USD	01-01-2018	31-05-2023	1974
Ethereum	ETH-USD	01-01-2018	31-05-2023	1975

Table 3(a): Bitcoin(BTC) Sample Dataset

S.No	**Date**	**Open**	**High**	**Low**	**Close**
1	01-01-2018	13996	14035	12860	13535
2	02-01-2018	13535	15217	12956	14770
3	03-01-2018	14770	15394	14589	15057
4	04-01-	15057	15395	14225	14921

	2018				
5	05-01-2018	14921	16909	14817	16828

This data's temporal span allows us to analyze the cryptocurrencies under different economic conditions, providing robust insights into their behavior and response to market stimuli. The characteristics of these datasets enable us to train predictive models effectively, using them to forecast future price movements and understand the intricacies of cryptocurrency market dynamics. The sample datasets of Bitcoin and Ethereum cryptocurrencies are shown in table 3(a) and 3(b) respectively.

Table 3(b): Ethereum(ETH) Sample Dataset

S.No.	Date	Open	High	Low	Close
1	01-01-2018	744.39	772.98	725.1	757.01
2	02-01-2018	757.01	879.9	758	864
3	03-01-2018	864	947.92	851	938
4	04-01-2018	938	988.99	905.01	942.04
5	05-01-2018	942.04	1009.84	900	958

3. Price Prediction using Machine Learning Models

This section explains the pre-processing and model development phases taken in the study. The significance of prediction models such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) lies in their ability to effectively capture and analyze sequential data, making them particularly valuable in time series forecasting tasks. To assess the effectiveness of our predictive models, we utilize three key statistical indicators: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics play a vital role in measuring the precision of both LSTM and Bi-LSTM models when forecasting the price movements of Bitcoin and Ethereum.

3.1 Pre-processing and model development

We conducted several pre-processing steps for each cryptocurrency data, starting from data imputation to handle missing values to data reshaped so that it can be processed by the deep learning methods applied in this study, namely LSTM, and Bi-LSTM. Firstly, out of six data attributes, we dropped the “crypto” attribute and focused on predicting the Close value as the target feature. Hence, rather than a univariate prediction approach, we used a multivariate prediction model in this study by incorporating the Close, Open, High, Low data attributes. Next, we checked for missing values found in the dataset and used a simple data imputation technique by replacing the missing values with their previous known records. Then, we normalized all data features using a MinMaxScaler transformation and reframed the dataset as a multivariate model. The next step is to split the data into training and test sets. We used an 80:20 ratio for training: test for each cryptocurrency. Lastly, we reshaped both those sets into 3D-array shapes to be further used in the deep learning model development phase.

In this study, we propose simple three layers networks architecture to be used in each deep learning model. We argue that simple networks architecture could achieve comparable performance results with deeper and complex ones, especially for regression tasks in the time series domain. In the LSTM model, a single LSTM layer with 256 neurons is employed, followed by a Dropout layer with a dropout rate of 20% to mitigate overfitting. Subsequently, a Dense layer with a single neuron is utilized for output generation. The architecture consists of a total of three layers, including the input layer. The LSTM layer captures temporal dependencies within the data, while the Dropout layer aids in regularization by randomly dropping 20% of the processed information during training. The model is compiled using the mean squared error loss function and the stochastic gradient descent optimizer. Training is conducted over 20 epochs, with a batch size of 64 samples per batch. On the other hand, the BiLSTM model incorporates two Bidirectional LSTM layers, each with 128 neurons, facilitating the capture of bidirectional temporal dependencies. These layers are followed by a Dense layer with a single neuron for output. Unlike the LSTM model, no explicit Dropout layers are included in the BiLSTM architecture. Therefore, no processed information is explicitly dropped due to dropout. The model is compiled using the same mean squared error loss function and stochastic gradient descent optimizer. Training parameters remain consistent with the LSTM model, comprising 20 epochs and a batch size of 64 samples per batch. The model was trained and run on Google Colab with a single core (two threads) Intel® Xeon® Processors @ 2.20 GHz, 12.69 GB RAM, and 107.72 GB disk spaces. In conducting the experiments, we used Python 3 and several core libraries, such as NumPy for numerical computing, Pandas for data processing and analysis, matplotlib for data visualization, Keras and scikit-learn (sklearn) for the deep learning application programming interface (API) in Python.

3.2 Prediction Models

A concise introduction to the predictive modeling techniques employed in this study will be provided. Specifically, we focus on two types of Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM). These models are well-suited for time series forecasting due to their ability to capture temporal dependencies and dynamics in price movements.

3.2.1 Long Short-Term Memory (LSTM)

In the realm of deep learning and time-series prediction, recurrent neural networks (RNNs) have established their significance by their ability to process sequences of data. They are particularly known for their use in modeling temporal dynamics [12)]. However, conventional RNNs are challenged by long-term dependencies due to the vanishing gradient problem. To overcome this, Long Short-Term Memory (LSTM) units were introduced as an enhancement to RNNs, capable of learning long-term dependencies [13)].

LSTMs are specifically designed with a memory cell that can maintain information in memory for long periods [14)]. The essential feature of the LSTM is its ability to regulate the flow of information through the cell state via gates—namely, the input, forget, and output gates are shown in figure 1. These gates control the extent to which information is saved, forgotten, or passed along to the next time step in the sequence to forecast the output of the network[15)]. This architecture makes LSTM particularly adept at applications such as time series forecasting, where understanding historical context is crucial.

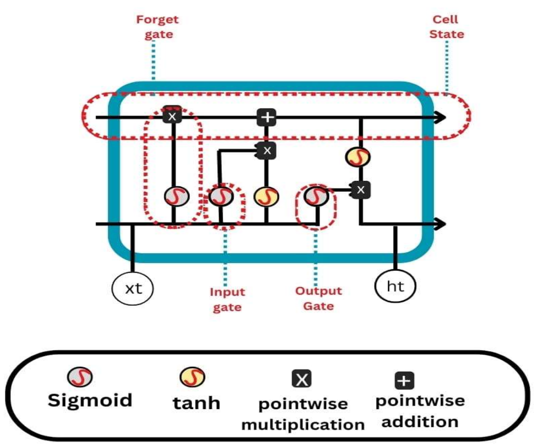


Fig. 1: LSTM Cell and its gate mechanism

$$f_{t} = \sigma(W_t h_{t-1} + U_f x_t + b_f) \quad (1)$$
$$i_{t} = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (2)$$
$$\widetilde{c}_{t} = \tanh(W_c h_{t-1} + U_c x_t + b_c) \quad (3)$$
$$c_{t} = f_t \,.\, c_{t-1} + i_t \,.\, \widetilde{c}_t \quad (4)$$
$$o_{t} = \sigma(W_o h_{t-1} + U_o x_t + b_i) \quad (5)$$
$$h_{t} = o_t \,.\, \tanh(c_t) \quad (6)$$

Here, $\widetilde{c}_t$ is the candidate cell state and c_t is the current cell state. All networks' weights are denoted as W_f, W_i, W_c, W_o, u_f, u_i, u_c, u_o and bias variables as b_f, b_i, b_c, b_o.h_t represents current hidden state value and x_t represents new information at the current cell. Two types of activation functions are used here, i.e; the sigmoid(σ) and the tangent hyperbolic (tanh) activation functions are shown in equations (1-6) [16)]. They are the most frequently used nonlinear activation functions in artificial neural networks.

3.2.2 Bi-directional LSTM (Bi-LSTM)

Furthermore, LSTM has been extended to Bidirectional LSTM (Bi-LSTM), which improves upon the standard LSTM by providing two-way processing of the data sequence. This bi-directional approach allows it to capture both past and future context by processing the data in both forward and backward directions. One of the key contributions of Bi-LSTMs was presented in the paper "Bi-directional Recurrent Neural Networks" [17)] in 1997, where they introduced the concept of using a forward and backward LSTM to model both past and future context for speech signal processing tasks.

Figure 2 shows that the Bi-LSTM network consists of two LSTMs that are applied in parallel: one on the input sequence as is and the other on a reversed copy of the input sequence. The outputs of both LSTMs are then combined to form the final output, providing a more enriched representation.

The Bi-LSTM is particularly useful in complex sequence prediction tasks where the context in both directions is essential for an accurate forecast [18)]. By preserving information from both the past and future at every point in time, Bi-LSTMs can offer a more profound understanding of the sequence patterns, which is crucial for the prediction of non-linear and volatile time series such as cryptocurrency prices [19)].

Both the LSTM and Bi-LSTM models serve as powerful tools in the prediction of time-series data, and their application in this study aims to capture the intricate patterns of cryptocurrency price movements, providing insights that are critical for robust predictive analysis. Figure 3 shows bidirectional will run the inputs in two ways, one from past to future and one from future to past while unidirectional LSTM runs backwards to preserve information from the future. A hybrid model combining LSTM, Attention mechanisms, and CNN outperformed the traditional ARIMA model for price forecasting using ten years of data. This model integrates historical trends and time-series signals, offering a robust alternative to conventional methods [20)]. This study [21)] developed two models to estimate the clearness index for meteorological stations in Dubai and Abu Dhabi over ten years. Neural network models showed superior performance, indicating strong agreement between estimated and measured values. The WAECN-BO model, combining CNNs with Bayesian Optimization, achieved a 99.98% accuracy rate on the UniMiB SHAR Dataset. This method excels in distinguishing highly correlated actions, enhancing HAR systems' performance [22)].

Based on the research provided, LSTM models have been extensively studied for predicting stock prices, including Bitcoin, with promising results in terms of accuracy [23,24)]. LSTM models, when paired with optimization techniques like Adam and Adamax, have shown to yield the least errors, making them suitable for stock price prediction tasks [25)]. Additionally, LSTM models have been compared to other models like MA and EMA, with LSTM consistently demonstrating more accurate predictions, especially for stock prices like those of General Electric Company [26,27)].

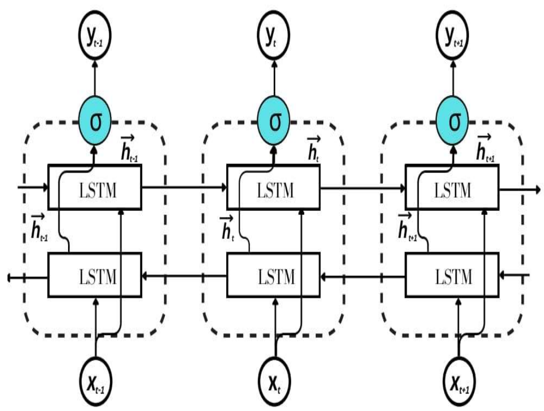


Fig. 2: Bi-LSTM Architecture

The LSTM and Bi-LSTM models have been utilized in various studies to analyze historical price data of cryptocurrencies like Bitcoin and Ethereum. The LSTM model has shown effectiveness in predicting Bitcoin and Ethereum prices, with findings indicating that larger batch sizes and the number of neurons impact prediction accuracy [28,29)]. Additionally, the Bi-LSTM model has been applied to Apple Inc. stock data, demonstrating the ability to capture both short- and long-term dependencies in the data, although it may struggle with sudden market changes [30)]. Furthermore, a study focusing on Ethereum price trends has proposed a novel system incorporating multiple data sources and market correlations, achieving accurate trend signal predictions by combining different types of data representations [31]. These models have identified key linear and non-linear relationships in the historical price data of Bitcoin and Ethereum, showcasing their potential in analyzing and predicting cryptocurrency trends.

The research findings from various studies on cryptocurrency price prediction using LSTM and Bi-LSTM models offer valuable insights for enhancing real-
time trading strategies and investment decisions. These studies demonstrate that LSTM models outperform

traditional methods like ARIMA, with LSTM achieving lower MAPE values and effectively capturing price movements [32,33,34)]. Additionally, the research highlights that simpler models can sometimes yield better results in predicting cryptocurrency prices, emphasizing the importance of model selection in trading decisions [35)]. By leveraging the accuracy and efficiency of LSTM and Bi-LSTM models in forecasting cryptocurrency prices, traders and investors can make more informed decisions, manage risks effectively, and potentially optimize their investment strategies in the dynamic and volatile cryptocurrency market, ultimately leading to improved financial outcomes.

Predictive modeling techniques, as highlighted in the research papers, play a crucial role in the financial technology sector by aiding investors and policymakers. These techniques, including machine learning models like penalized linear models and neural networks [36)], Decision Trees, Regression Analysis, and Neural Networks [37)], and deep learning methods combined with noise elimination techniques like Wavelet transform and Kalman filter [38)], provide accurate predictions for asset returns, creditworthiness assessment, and portfolio management. Moreover, the development of explainable artificial intelligence (XAI) models enhances trust and understanding in critical mission systems, such as healthcare and stock market predictions [39)]. By leveraging these predictive modeling tools, investors can make informed decisions, optimize operations, reduce risks, and increase revenue, while policymakers can utilize accurate projections for public health planning and response, offering valuable insights into unseen variables and hypothetical interventions [40)].

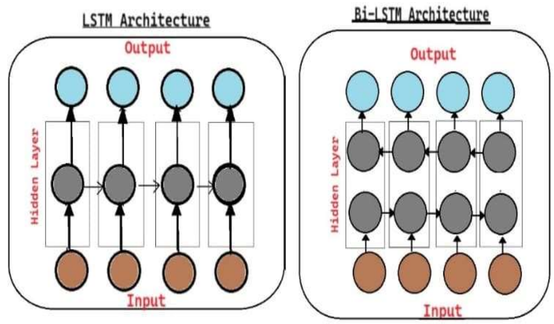


Fig. 3: LSTM versus Bi-LSTM architecture

Operational efficiencies in LSTM and Bi-LSTM models when applied to the dynamic and volatile nature of cryptocurrency markets include accurate price predictions and reduced errors. Studies show that Bi-LSTM outperforms LSTM and GRU in predicting cryptocurrency exchange rates, exhibiting lower MAPE values [41)]. Additionally, LSTM models demonstrate the ability to forecast future values of cryptocurrencies like Bitcoin, Ethereum, and Dogecoin based on historical data, aiding in understanding long-term trends and dependencies [42)]. Furthermore, MLP models are highlighted for their superior predictive results in cryptocurrency volatility forecasting, surpassing GARCH models and offering reduced computational complexity, making them suitable for highly nonlinear time series forecasts in the cryptocurrency market [43)]. These findings collectively emphasize the effectiveness of LSTM and Bi-LSTM models in enhancing prediction accuracy and operational efficiency in navigating the complexities of volatile cryptocurrency markets.

3.3 Performance Evaluation Metrics

To evaluate the predictive models' performance, we employ three statistical measures: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) [44)]. These metrics are crucial for gauging the accuracy of the LSTM and Bi-LSTM models in predicting the price dynamics of Bitcoin and Ethereum.

Mean Squared Error (MSE)- is calculated as the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value.

It is given by the formula:

$$\mathbf{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

where y_i is the actual observed value, y is the predicted value, and N is the number of observations.

Root Mean Squared Error (RMSE)- is the square root of the mean of the squared differences between the predicted and actual observations. It is expressed by the equation:

$$\text{RMSE}= \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y)^2}$$

This metric penalizes larger errors more than smaller ones due to the squaring of the error terms, hence is sensitive to outliers.

4. Results and Discussion

In this section, several examples of the prediction plot results of each Cryptocurrency are shown, followed by the performance results and analysis of this study.

4.1 Research Outcomes and Analysis

(i) LSTM Performance in the Bitcoin Dataset
(ii) Bi-LSTM Performance in the Bitcoin Dataset
(iii) LSTM Performance in the Ethereum Dataset
(iv) Bi-LSTM Performance in the Ethereum Dataset

4.1.1 LSTM Performance in the Bitcoin Dataset

The LSTM model's training process over 20 epochs shown in Table 4 indicates a consistent reduction in all three metrics—MAE, MSE, and RMSE—both in the training and validation datasets, which suggests the model is learning and improving its predictive accuracy with each epoch.

Looking at the MAE plot in fig. 4(a) shows there is a steep decline from the first epoch, which levels off as the model begins to converge to its minimum loss. The convergence of the training and test lines suggests that the model is not overfitting and generalizes well to unseen data.

The MSE plot in fig. 4(b) shows a similar trend with rapid improvement in early epochs and a steady convergence towards a minimal error rate as the epochs progress. This trend is a positive indicator of model reliability and its ability to predict the 'Close' price of Bitcoin accurately.

Table 4: All epochs Bitcoin LSTM

Epoch	Train_MAE	Train_MSE	Train_RMSE	Val_MAE	Val_MSE	Val_RMSE
1	0.1709	0.0673	1.2876	0.1386	0.0344	0.4592
2	0.1618	0.0399	0.9977	0.0993	0.0198	0.3483
3	0.1499	0.0317	0.8892	0.0867	0.0149	0.3023
4	0.134	0.0252	0.7891	0.0772	0.0117	0.2674
5	0.1199	0.0203	0.7107	0.0684	0.0089	0.2342
6	0.1056	0.0158	0.6268	0.062	0.0074	0.2134
7	0.0928	0.0127	0.5632	0.055	0.0058	0.1886
8	0.0816	0.0102	0.507	0.0485	0.0045	0.1656
9	0.0705	0.0078	0.4441	0.0425	0.0034	0.1447
10	0.0611	0.0061	0.3896	0.0384	0.0029	0.1323
11	0.0543	0.0052	0.3621	0.0333	0.0021	0.1138
12	0.0467	0.004	0.3219	0.0304	0.0018	0.1059
13	0.0414	0.0036	0.298	0.0279	0.0016	0.0992
14	0.0366	0.003	0.2768	0.0256	0.0014	0.0918
15	0.034	0.0028	0.2651	0.0238	0.0012	0.085
16	0.0302	0.0025	0.2507	0.0227	0.0011	0.0817
17	0.0286	0.0024	0.2424	0.0218	0.001	0.0778
18	0.0268	0.0023	0.2387	0.0213	0.0009	0.076
19	0.0249	0.0022	0.2339	0.0209	0.0009	0.0737
20	0.0242	0.0021	0.2308	0.0207	0.0009	0.0728

The RMSE plot in fig. 4(c) shows a further confirms these findings. The RMSE is generally higher than MAE because it squares the errors before averaging, thus giving a heavier penalty to larger errors. However, its reduction pattern over epochs mirrors that of MSE, showing significant improvement as training progresses.

In summary, the LSTM model demonstrates excellent performance in forecasting Bitcoin prices, as evidenced by the descending loss curves. The model's ability to achieve such low error rates—particularly indicated by the final MAE of 0.0207, MSE of 0.000873, and RMSE of 0.02955—suggests that it has learned to capture the underlying patterns and dynamics of the cryptocurrency's price movements effectively.

Lastly, the visual comparison of predicted versus actual values shows a close match, which visually confirms the quantitative metrics and suggests that the model could be a valuable tool for predicting Bitcoin prices, assuming similar market conditions continue.

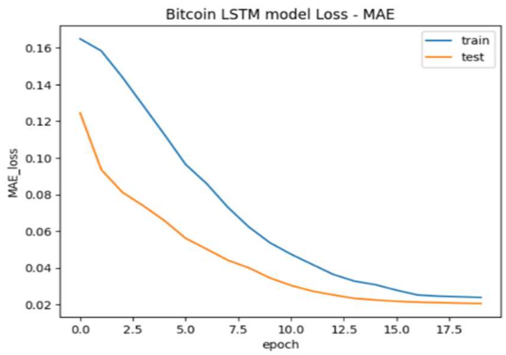
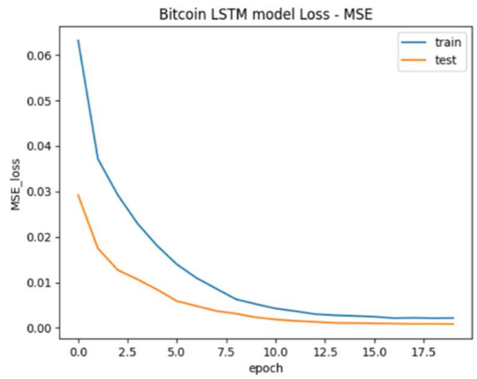


Fig. 4 (a) Loss in MAE plot for LSTM Bitcoin Dataset



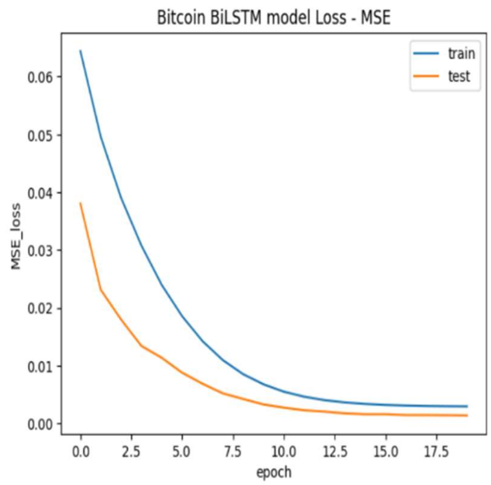


Fig. 4 (b) Loss in MSE plot for LSTM , Bitcoin Dataset

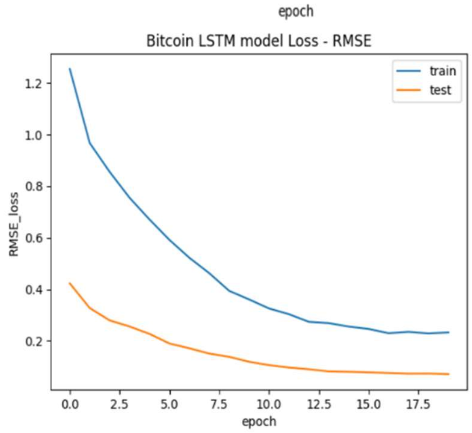


Fig. 4 (c) Loss in RMSE plot for LSTM , Bitcoin Dataset

Fig. 4: Loss in MAE, MSE and RMSE plot for LSTM , Bitcoin Dataset: Figures- 4(a), 4(b), 4(c)

4.1.2 Bi-LSTM Performance in the Bitcoin Dataset

The Bi-LSTM model exhibits a commendable performance in forecasting Bitcoin prices, as evidenced by the declining error metrics—MAE, MSE, and RMSE—across the training epochs in Table 5. Initially, the model starts with high error rates, which is expected due to the random initialization of weights. However, as the training progresses, a significant improvement is observed, particularly in the initial five epochs where the largest gains in learning are made. This early trend of sharp declines in error rates indicates that the model is rapidly learning the underlying patterns in the data.

The plots provided corroborate a consistent learning trajectory, with both training and validation loss metrics converging. This convergence is a positive indicator, suggesting that the model is not merely memorizing the training data (overfitting) but generalizing well to new, unseen data. By the 20th epoch, the model achieves MAE, MSE, and RMSE values of 0.0278, 0.0015, and 0.0941 on the validation set, respectively, which underscores the high accuracy of the model's predictive capabilities.

Table 5: All epochs Bitcoin Bi-LSTM

Epoch	Training MAE	Training MSE	Training RMSE	Validation MAE	Validation MSE	Validation RMSE
1	0.1715	0.0736	1.5103	0.1479	0.0421	0.5082
2	0.1996	0.0576	1.1938	0.1196	0.0288	0.42
3	0.1827	0.0464	1.0742	0.1087	0.0236	0.3808
4	0.1621	0.0373	0.9651	0.0955	0.018	0.3326
5	0.1442	0.0297	0.8613	0.0846	0.0139	0.2918
6	0.1273	0.0234	0.7666	0.0744	0.0105	0.2534
7	0.1111	0.0182	0.6721	0.0669	0.0086	0.229
8	0.096	0.0141	0.5915	0.0593	0.0067	0.2029
9	0.0826	0.011	0.5212	0.0524	0.0053	0.1799
10	0.071	0.0086	0.4645	0.0456	0.004	0.1571
11	0.0613	0.0068	0.4122	0.041	0.0034	0.1435
12	0.0524	0.0056	0.3705	0.0365	0.0027	0.1291
13	0.046	0.0047	0.3421	0.0337	0.0024	0.1209
14	0.0402	0.0041	0.318	0.0314	0.002	0.1113
15	0.0365	0.0037	0.3031	0.0302	0.0019	0.1066
16	0.0335	0.0035	0.2918	0.0294	0.0018	0.1048
17	0.0307	0.0033	0.2954	0.0287	0.0016	0.0986
18	0.0295	0.0032	0.2931	0.0284	0.0015	0.0956
19	0.0286	0.0031	0.2803	0.028	0.0015	0.0949
20	0.0274	0.0031	0.2744	0.0278	0.0015	0.0941

Furthermore, the close values of loss metrics between the training and validation sets towards the end of the epochs imply that the model maintains its performance on both seen and unseen data. Although the error rates are already low, suggesting the model has potentially reached an optimal state, there might still be scope for marginal gains with further tuning of hyperparameters or model architecture.

In practice, the model's accuracy suggests that it can be a valuable tool for stakeholders looking to predict Bitcoin price movements. However, given the inherent unpredictability of the cryptocurrency market, predictions should be approached with caution. Overall, the Bi-LSTM model has proven to be an effective and well-fitting model for this application, as evidenced by the steady decrease in loss and error metrics (shown in fig.5(a), fig.5(b), fig. 5(c),) and their eventual stabilization, suggesting that further training might yield diminishing returns.

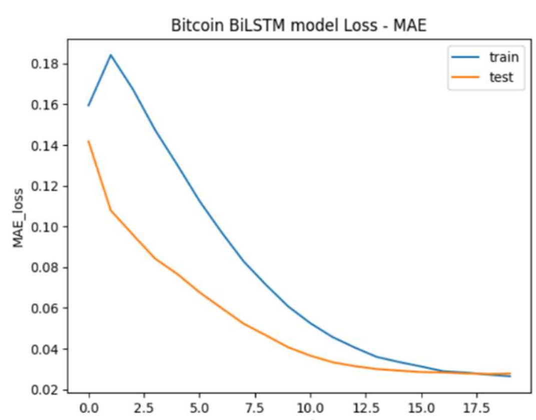


Fig.5(a) Loss in MAE plot for Bi-LSTM , Bitcoin Dataset

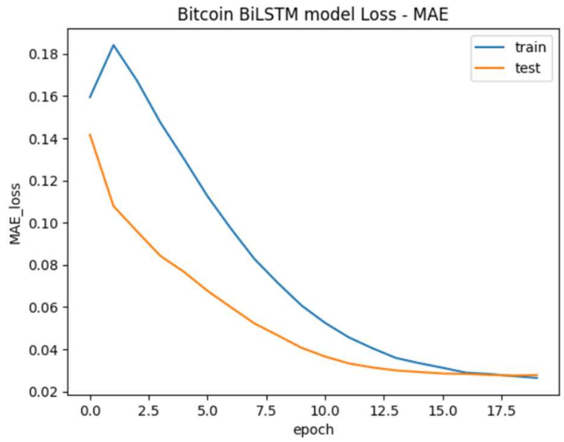


Fig.5(b) Loss in MAE plot for Bi-LSTM , Bitcoin Dataset

Fig.5(c) Loss in RMSE plot for Bi-LSTM , Bitcoin Dataset

Fig. 5: Loss in MAE, MSE and RMSE plot for Bi-LSTM , Bitcoin Dataset: Figures- 5(a), 5(b), 5(c)

4.1.3 LSTM Performance in the Ethereum Dataset

Analyzing the LSTM model across 20 epochs based on the provided epoch results and the uploaded plots for MAE, MSE, and RMSE in Table 6. From the start, the LSTM model exhibits significant errors, as expected in the early learning stages. As training progresses, we observe a consistent decrease in the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) in fig.6(a), fig.6(b) and fig.6(c) respectively signaling that the model is learning and improving its predictive capabilities.

The plots show that the training loss (both MAE and MSE) starts higher and decreases sharply in the initial epochs before gradually leveling off. This typical pattern indicates that the model rapidly learns from the training data early on but experiences diminishing returns on learning as it approaches a more optimized state.

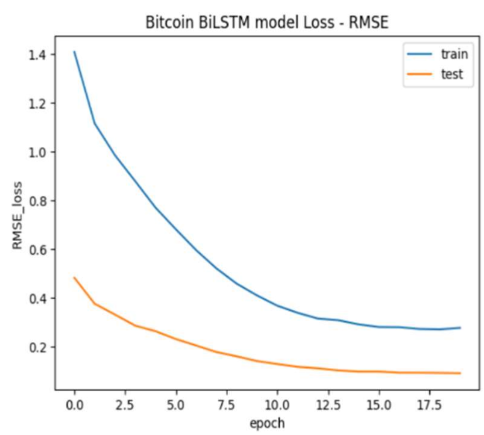


Table 6: All epochs Ethereum LSTM

Epoch	MAE_train	MSE_train	RMSE_train	Val_MAE	Val_MSE	Val_RMSE
1	0.2096	0.08	1.4025	0.1804	0.0335	0.449
2	0.1696	0.0429	1.0331	0.198	0.0402	0.4914
3	0.1534	0.0347	0.9298	0.1912	0.0374	0.4739
4	0.1382	0.028	0.833	0.1705	0.0297	0.4227
5	0.1251	0.0229	0.7541	0.1474	0.0223	0.3659
6	0.1111	0.0184	0.6762	0.1367	0.0192	0.3393
7	0.1002	0.015	0.6081	0.1174	0.0142	0.2918
8	0.0891	0.012	0.547	0.1061	0.0116	0.2639
9	0.0782	0.0093	0.4803	0.0924	0.0088	0.2302
10	0.0692	0.0073	0.4265	0.0769	0.0062	0.1925
11	0.0624	0.0062	0.3961	0.0695	0.0051	0.1746
12	0.0575	0.0054	0.3695	0.0601	0.0039	0.1522
13	0.0501	0.0042	0.3237	0.0487	0.0026	0.1253
14	0.045	0.0036	0.3026	0.0417	0.002	0.1091
15	0.0417	0.0032	0.2819	0.0365	0.0016	0.0976
16	0.0383	0.0029	0.2691	0.0319	0.0013	0.0877
17	0.0366	0.0028	0.2623	0.0275	0.001	0.0788
18	0.0335	0.0025	0.2478	0.0243	0.00088	0.0724
19	0.0328	0.0024	0.2451	0.0207	0.00073	0.0658
20	0.031	0.0023	0.2394	0.016	0.00056	0.058

By the 20th epoch, we note that the MAE has reduced significantly from 0.2096 to 0.0310, the MSE from 0.0800 to 0.0023, and the RMSE from 1.4025 to 0.2394 on the training data. The validation losses also show a similar pattern of decline, with the final MAE at 0.0160, MSE at 0.00056485, and RMSE at 0.0580. The closeness of the final training and validation metrics suggests the model has achieved a good balance, avoiding overfitting while maintaining its ability to generalize well to new data.

Fig.6 (a) Loss in MAE plot for LSTM , Ethereum Dataset

In summary, the LSTM model has learned to predict the data with increasing accuracy over time, as evidenced by the consistently decreasing error metrics and the loss plots converging to lower values. The model appears to have a good generalization capability, which is crucial for making reliable predictions on unseen data in the volatile cryptocurrency market. However, it's important to note that such models should be continuously monitored and retrained as needed to maintain their predictive performance in the ever-changing market.

Fig.6(b) Loss in MSE plot for LSTM , Ethereum Dataset

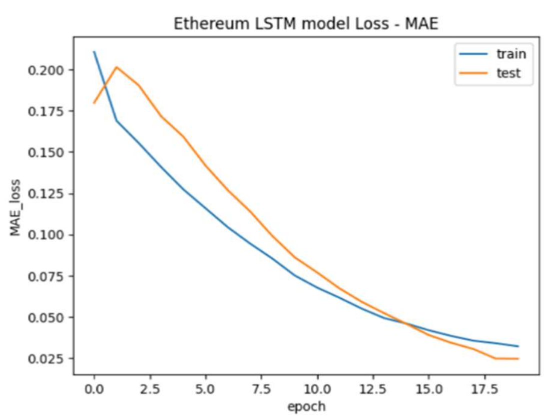


Fig.6(c) Loss in RMSE plot for LSTM , Ethereum Dataset

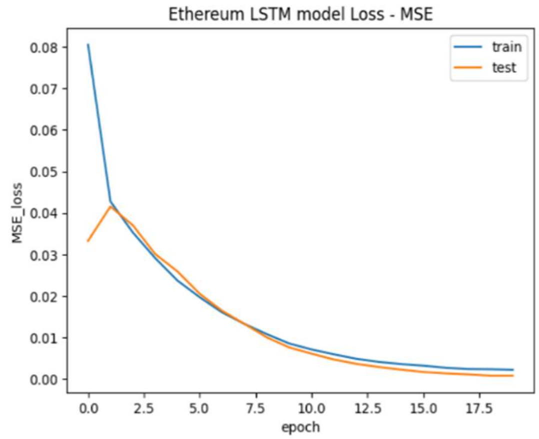


Fig. 6: Loss in MAE, MSE and RMSE plot for LSTM , Ethereum Dataset: Figures- 6(a), 6(b), 6(c).

4.1.4 Bi-LSTM Performance in the Ethereum Dataset

The BiLSTM model's performance over 20 epochs can be analyzed based on the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) as shown in the training and validation loss plots in Table 7.

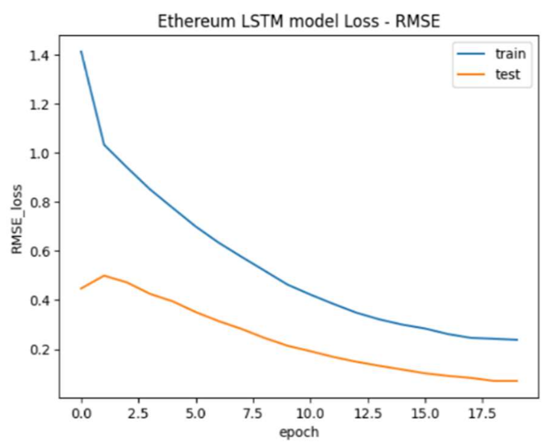


Table 7: All epochs Ethereum Bi-LSTM

Epoch	MAE (Train)	MSE (Train)	RMSE (Train)	MAE (Validation)	MSE (Validation)	RMSE (Validation)
1	0.1673	0.0591	1.3482	0.2004	0.0414	0.4985
2	0.1707	0.0436	1.043	0.2118	0.046	0.5256
3	0.1559	0.0357	0.9433	0.1898	0.037	0.4712
4	0.1407	0.0293	0.8568	0.1738	0.031	0.4316
5	0.1271	0.0239	0.7708	0.1539	0.0244	0.3826
6	0.1142	0.0194	0.6947	0.1353	0.0189	0.3369
7	0.1022	0.0157	0.6241	0.1177	0.0144	0.2939
8	0.0914	0.0127	0.5594	0.0969	0.0099	0.2432
9	0.0813	0.0103	0.5059	0.086	0.0078	0.2169
10	0.0724	0.0084	0.4565	0.0783	0.0066	0.1988
11	0.0648	0.0069	0.4135	0.0712	0.0055	0.1822
12	0.0589	0.0058	0.3794	0.0572	0.0037	0.1496
13	0.053	0.0049	0.3516	0.048	0.0028	0.1292
14	0.048	0.0043	0.3288	0.046	0.0026	0.1255
15	0.0448	0.0039	0.3129	0.0386	0.002	0.11
16	0.0417	0.0036	0.2988	0.0323	0.0016	0.0977
17	0.0394	0.0033	0.2894	0.0253	0.0012	0.0851
18	0.0371	0.0032	0.2808	0.0226	0.0011	0.0811
19	0.0359	0.0031	0.2804	0.0186	0.0009	0.0754
20	0.0346	0.003	0.2756	0.0178	0.0009	0.0747

Initially, the model starts with higher errors, which is typical as it begins to learn the underlying patterns within the data. Over time, the model demonstrates a significant improvement in its predictions, as indicated by the declining trend in the MAE, MSE, and RMSE values shown in fig.7(a), fig.7(b) and fig.7(c). This decline is steep at the beginning, illustrating the model's rapid learning curve, and then it starts to plateau, indicating the model is approaching its optimal performance level.

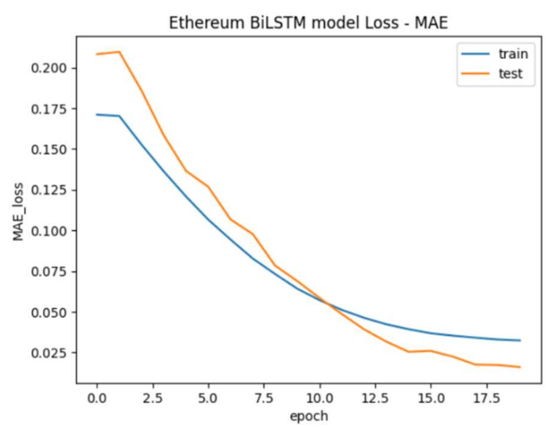


Fig.7(a) Loss in MAE plot for Bi-LSTM , Ethereum Dataset

By the 20th epoch, the training and validation errors have converged considerably, suggesting that the model is generalizing well and not overfitting to the training data. This is an excellent sign of a well-trained model, as it implies that the predictions made on new, unseen data will be reliable.

The final MAE, MSE, and RMSE values are quite low, indicating that the model's predictions are

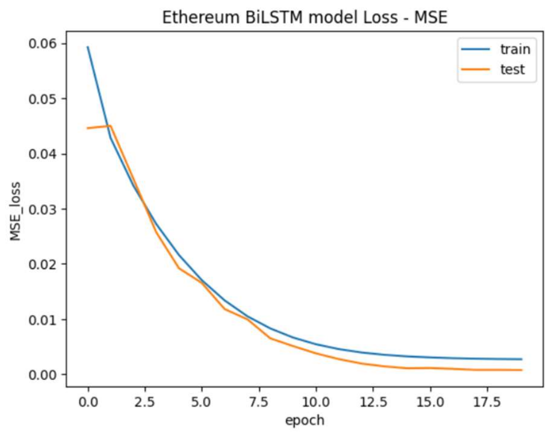


Fig.7(b) Loss in MSE plot for Bi-LSTM , Ethereum Dataset

quite close to the actual values. The training and validation loss plots for MAE, MSE, and RMSE visually demonstrate these points, with both the training and validation lines converging and flattening out as the epochs increase. The close alignment of the training and validation lines towards the end of the training indicates a balance between the model's bias and variance, showing it has learned well without overfitting or underfitting.

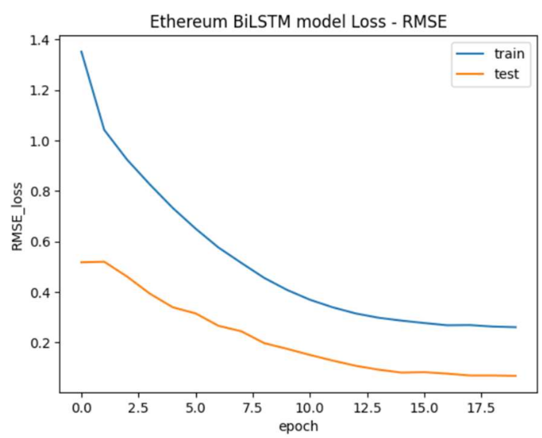


Fig.7(c) Loss in RMSE plot for Bi-LSTM , Ethereum Dataset

Fig. 7: Loss in MAE, MSE and RMSE plot for Bi-LSTM , Ethereum Dataset: Figures- 7(a),7(b),7(c)

In conclusion, the BiLSTM model has shown an ability to capture the complexities of the cryptocurrency price movements accurately, making it a potentially valuable tool for predictive analyses in this domain. However, given the inherent volatility of cryptocurrency markets, caution should be exercised when interpreting these results, and the model's predictions should be one of several tools used in decision-making.

4.2 Comparative Analysis of Predictive Models

Table 8 shows a comparative analysis of the performance of Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models on Bitcoin and Ethereum cryptocurrency prediction. The effectiveness of the models is measured using three common statistical metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Table 8. Comparative analysis of the performance of LSTM over Bi-LSTM

S.No.	Cryptocurrency	Model	MAE	MSE	RMSE
1	Bitcoin	LSTM	0.0206	0.0008	0.0295
		Bi-LSTM	0.0277	0.0014	0.0382

2	Ethereum	LSTM	0.0221	0.0007	0.0274
		Bi-LSTM	0.0257	0.0009	0.0306

The comparative analysis of LSTM and Bi-LSTM models for Bitcoin and Ethereum cryptocurrency prediction reveals that the LSTM model outperforms the Bi-LSTM model across all metrics. For both Bitcoin and Ethereum, LSTM exhibits lower MAE, MSE, and RMSE, indicating tighter average errors and generally more accurate predictions.

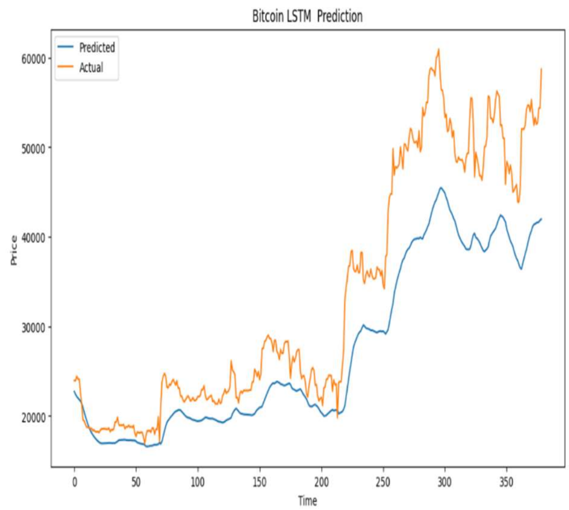


Fig. 8: Actual Vs Predicted Values of LSTM for Bitcoin

While the simplicity of the LSTM architecture seems effective for capturing the trends and volatility of cryptocurrency prices in this dataset, the choice of model should be informed by the specific characteristics of the dataset and the nature of the prediction task. LSTM is the most successful and widely used algorithm for prediction, so many authors have used it and improved the prediction accuracy. While LSTM proves superior in this scenario, Bi-LSTM models may offer better results in other contexts, considering their ability to capture bidirectional patterns. Figures 8 and 9 show graphs of predicted versus actual values of the LSTM model on both the cryptocurrencies Bitcoin and Ethereum.

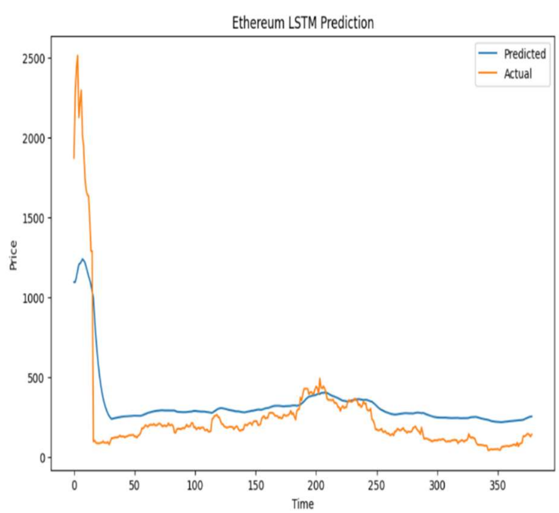


Fig. 9: Actual Vs Predicted Values of LSTM for Ethereum

5. Conclusion

This study provided a comprehensive analysis of Bitcoin and Ethereum price dynamics through advanced predictive modeling techniques. Utilizing LSTM and Bi-LSTM networks, the research addressed the forecasting challenges inherent in the volatile cryptocurrency market. The models' performances were meticulously evaluated against Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) benchmarks, which confirmed their effectiveness in capturing the complex temporal patterns of price movements. Our results showcase the LSTM and Bi-LSTM models as powerful tools in predicting cryptocurrency prices with a high degree of accuracy. These models are capable of identifying both linear and nonlinear relationships in historical price data, proving invaluable for real-time trading strategies and investment decisions. The insights derived from this study significantly contribute to the financial technology sector by providing a deeper understanding of the applicability and efficacy of predictive models in navigating cryptocurrency markets.

In conclusion, the LSTM model outperforms the Bi-LSTM model across all three metrics for both Bitcoin and Ethereum in this dataset. This suggests that for these specific datasets, the simpler LSTM architecture might be sufficient to capture the trends and volatility of cryptocurrency prices effectively. However, while LSTM appears to yield more accurate predictions in this case, it is important to consider that Bi-LSTM models may provide better results in other scenarios or with different datasets, as they are designed to capture patterns that span forward and backward in time, which might not be as relevant in this particular context. The choice of model should always be informed by the specific characteristics of the dataset and the nature of the prediction task at hand.

The research has demonstrated that with a rigorous preprocessing approach and appropriate model selection, it is possible to forecast cryptocurrency prices with reasonable accuracy, thus aiding stakeholders in making more informed decisions. Such forecasting models are vital for investors looking to optimize their portfolios and for policymakers concerned with the stability and oversight of financial markets.

6. Future Work

Looking ahead, future research avenues to expand upon the findings of this study include exploring Convolutional Neural Networks (CNN) for cryptocurrency prediction, leveraging their ability to extract features from time series data. Integrating sentiment analysis from social media and news sources could enhance prediction models by capturing market sentiment. Additionally, expanding the dataset to include more cryptocurrencies and financial indicators can provide a comprehensive view of market dynamics. Hybrid models combining LSTM or Bi-LSTM with other techniques may offer improved predictive accuracy. Implementing models in real-time data streaming environments enables live predictions for immediate decision-making. Moreover, assessing the impact of regulatory changes and incorporating blockchain analytics can further refine prediction capabilities. By addressing these areas, future research aims to enhance the accuracy and reliability of cryptocurrency market predictions, facilitating more informed trading strategies and contributing to the maturation of this evolving financial landscape.

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