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A comparative analysis of exponential smoothing method and deep learning models for bitcoin price prediction

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ABSTRACT

Blockchain technology is the foundation of cryptocurrencies, which are virtual currencies. The decentralized nature of cryptocurrencies has resulted in a significant reduction of central authority over them, which has implications for global trade and relations. The need for an effective model to anticipate the price of cryptocurrencies is essential due to their wide variations in value. Due to the shortcomings of conventional production forecasting, in this work, four distinct models were used. The deep learning models are the long short-term memory (LSTM) and bidirectional long short-term memory (Bi-LSTM), and both the Facebook-Prophet and Silverkite support the exponential smoothing technique. Silverkite is designed to handle a wide range of time series forecasting tasks. Considering past bitcoin information from January 2012 to March 2021, a period of nine years, we looked at the models. The Bi-LSTM model yields a 7.073 mean absolute error (MAE) and a 3.639 root mean squared error (RMSE). The Bi-LSTM model identifies the deviations that might draw attention and avert any problems.

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1. INTRODUCTION

The decentralized network of computers that power cryptocurrencies collaborate to validate the log transactions. Therefore, the money is no longer subject to the rheostat of authority like a bank or the government. Cryptocurrency transactions are documented on a blockchain, an immutable, decentralized ledger [1], [2]. To enable private and secure transactions, public and private keys are employed. Lahmiri and Bekiros [3] testing the nonlinearity, produced data showing fractal dynamics, extended memory, and self-similarity in all digital currency time series. There is a cap on the total quantity of coins or tokens that may ever be issued for several cryptocurrencies. As an illustration, the maximum quantity of Bitcoin coins is set at 21 million, a measure intended to produce scarcity and perhaps boost value over time. Transactions with cryptocurrencies are often faster and may be less expensive than those using traditional banking systems, and it can be sent and received anywhere on the globe.

Cryptocurrencies are a popular investment option for investors. In addition to being used for online payments and remittances, digital assets are also utilized for other practices. According to Sun *et al.* [4], the prediction's performance is impacted by the cryptocurrency's overall strength. This can reduce risks and provide investors with excellent guidance when building a bitcoin portfolio. Nonetheless, the market for cryptocurrencies is renowned for its unpredictability, difficulties with regulations, and constant technical advancements [5]. Predictions may be used by traders and investors to create hedging strategies, which try to reduce total risk by offsetting possible losses in one area of the portfolio with profits in another. Predictions about cryptocurrencies might be useful to traders when deciding whether to enter or leave the market. This might be essential for optimizing gains or reducing losses under quickly shifting market circumstances [6]–[8].

In this work, long short-term memory (LSTM) and bidirectional-long short-term memory (Bi-LSTM) are employed that automatically extract pertinent characteristics. This is helpful because it enables the model to derive accurate depictions from the input data, especially when working with big and complicated datasets [9]. Similarly, the exponential smoothing methods Facebook-Prophet (FB-Prophet) and Silverkite are castoff; these models are straightforward and obvious methods that give historical observations exponentially diminishing weights.

2. RESEARCH METHODOLOGY

We are using the real time update provided by the Bitcoin exchange dataset. The dataset consists of the following eight parameters: timestamp, open, high, low, close, volume in currency, volume in bitcoin, and weighted price. The correlation heatmap of Bitcoin dataset is given in Figure 1. The timestamp data columns include no transactions or activity are occupied with not a number (NaNs). If a timestamp is absent, it may be due to an unanticipated technical fault in data reporting or collection [10]. From Kaggle contests, we amassed bitcoin historical data. Here, the historical bitcoin data is at 1-minute interludes.

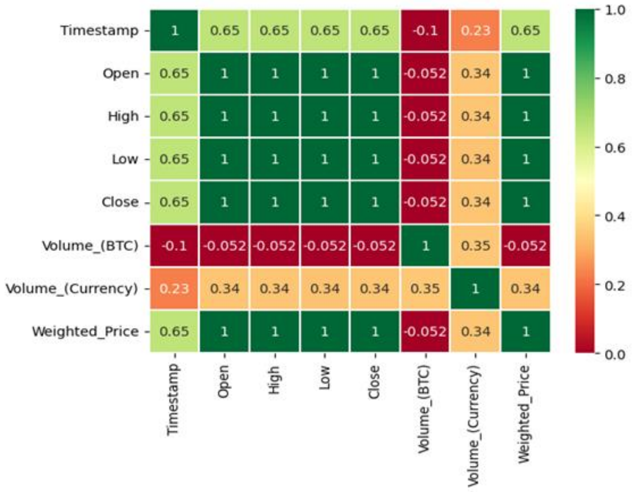

Figure 1. Correlation heatmap of bitcoin data

2.1. Long short-term memory

Prices of cryptocurrencies frequently show long-term patterns and interdependence. In order to overcome the vanishing gradient issue that plagues conventional recurrent neural networks (RNNs), LSTMs are made to be able to learn and retain data across longer sequences [11]. LSTMs do not require human feature engineering since they can automatically extract relevant characteristics from the input data [12]. For bitcoin prediction jobs involving complicated and high-dimensional data, this is advantageous. In (1) to (6) shows the simple LSTM formulations. Since LSTMs can tolerate varying intervals of time between observations, they are a good fit for data on cryptocurrencies, since price fluctuations may not happen at regular intervals. Where f_t is the forget gate, i_t is the input gate, o_t is the output, $\tilde{c}_t$ is the new candidate value, h_t is the hidden state, σ is the sigmoid instigation function, and tanh is the hyperbolic tangent instigation function.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{2}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{3}$$

$$\tilde{c}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{4}$$

$$c_t = f_t.c_{t-1} + i_t.\tilde{c}_t \tag{5}$$

$$h_t = o_t.\tanh(c_t) \tag{6}$$

2.2. Facebook-Prophet

Prophet can handle holidays and seasonality on a weekly and annual basis. This helps to capture recurrent trends and the possible influence of holidays or unique occasions on price movements in the context of bitcoin prediction [13]. Potential changepoints, or locations where the time series shows a notable shift in trend, are automatically detected by Prophet. In (7) to (9) shows the FB-Prophet formulations. This helps to record abrupt fluctuations in the price of cryptocurrencies. Because Prophet's settings are simple to understand and adjust, even individuals without a lot of experience with time series modelling may use it [14], [15].

$$s(t) = \sum_{i=1}^{N}(U_i.\sin\left(\frac{2\pi it}{Z}\right) + V_i.\cos\left(\frac{2\pi it}{Z}\right)) \tag{7}$$

Where $s(t)$ is the seasonality at time t, N is the number of seasonal components U_i and V_i are the coefficients for i^th component, Z is the period of seasonality.

$$g(t) = k(t) + \sum_{n-1}^{N}(\delta_n.h(t - T_n)) \tag{8}$$

Where $g(t)$ is the trend at time $t, k(t)$ is the baseline growth, N is the numeral of change points, δ_n is the magnitude of n-th change point. During model training, managing holidays entails defining holidays and how they affect the time series data. Prophet's architecture allows for the inclusion of holidays and other special occasions in the forecasting process. $y(t)$ is the observed value at time $t, g(t)$ is the leaning, $s(t)$ is the seasonality, $h(t)$ is the day off effect, and $\in_t$ is the fault term. The formulation for handling holidays is given in (9).

$$y(t) = g(t) + s(t) + h(t) + \in_t \tag{9}$$

2.3. Silverkite

LinkedIn releases the time-series prediction library Greykite to simplify forecasting for data scientists. The primary forecasting algorithm in this package is Silverkite, an automated prediction technique. LinkedIn developed Greykite to help employees make informed decisions using time-series forecasting models. A multitude of features are automatically generated by Silverkite, capturing various properties of the time sequence. Silverkite's incorporation of various periodic patterns, trends, and unique occurrences enables flexible forecasting. This adaptability helps to capture the dynamic and diversified character of the bitcoin markets. Because Silverkite is built to withstand outliers and missing data, it can produce accurate forecasts even in situations where the supplied data is incomplete. In (10) and (11) shows the Silverkite forecast formulation. By optimizing for forecast accuracy, Silverkite automatically chooses the optimal forecasting model from a group of candidate models. This can be helpful in the prediction of cryptocurrencies, where selecting a suitable forecasting model might be difficult. Where $\hat{y}_t$ is the calculated value at time t, b_0 is the intercept, b_i, b_j, b_k are coefficients, $\in_t$ is the error term.

$$\hat{y}_t = b_0 + \sum_{i=1}^{N} b_i . s_{i,t} + \sum_{j=1}^{N} b_j . h_{j,t} + \sum_{k=1}^{N} b_k . c_{k,t} + \in_t \tag{10}$$

$$m_s = a_m(\sum_{t=1}^{T}(y_t - \hat{y}_{m,t})^2) \tag{11}$$

2.4. Bidirectional-long short-term memory

The price fluctuations of cryptocurrencies frequently show long-term tendencies and relationships. Long-term trends in the historical pricing data may be found and used with Bi-LSTM's capacity to record knowledge gathered from current and future time steps [16]. Numerous variables impact cryptocurrency markets, and there may be nonlinear interactions between these elements. Being a kind of neural network, Bi-LSTM may adjust to the dynamic and frequently unpredictable character of cryptocurrency markets by learning intricate nonlinear correlations in the data [17], [18]. In (12) to (18) shows the Bi-LSTM forecast formulation.

$$\overleftarrow{f}_t=\sigma(R_{\overleftarrow{f}}^{L}[h_{t-1}^{L},h_t^{L-1}]+s_{\overleftarrow{f}}^{L}) \tag{12}$$

$$\overleftarrow{\imath}_t^{L}=\sigma(R_{\overleftarrow{f}}^{L}[h_{t-1}^{L},h_t^{L-1}]+s_{\overleftarrow{f}}^{L}) \tag{13}$$

$$\overleftarrow{o}_t^{L}=\sigma(R_{\overleftarrow{o}}^{L}[h_{n-1}^{L},h_t^{L-1}]+s_{\overleftarrow{o}}^{L}) \tag{14}$$

$$\overleftarrow{c}_t^{L}=\overleftarrow{f}_t^{L}.\overleftarrow{c}_{n-1}^{L}+\overleftarrow{\imath}_t^{L}.\overleftarrow{c}_{\overleftarrow{n}-1}^{L} \tag{15}$$

$$\overleftarrow{c}_t^{L}=\tanh\,(R_{\overleftarrow{c}}^{L}[h_{n-1}^{L},h_t^{M-1}]+s_{\overleftarrow{c}}^{L}) \tag{16}$$

$$\overleftarrow{h}_t=\overleftarrow{o}_t^{L}.\tanh\,(\overleftarrow{c}_t^{L}) \tag{17}$$

$$y_t=R\left[\overleftarrow{h}_t,\overleftarrow{h}_t\right]+s \tag{18}$$

3. PROPOSED MODEL

The dynamics of cryptocurrency marketplaces result in fluctuating values due to many variables. As additional data becomes available, deep learning models may update their internal representations to reflect the shifting market conditions [19]. Experts at automatically extracting pertinent characteristics from unprocessed data are deep learning algorithms. In the domain of cryptocurrency forecasting, where intricate correlations exist between attributes and price fluctuations, this is particularly advantageous [20], [21]. The proposed workflow diagram is given in Figure 2. Every data point in the collection has a time stamp or period attached to it that indicates the exact moment the observation was made. The consequences of the Dickey-Fuller test (DFT) are shown in Table 1.

Time series data may be studied to uncover underlying dynamics and forecast future values since it frequently shows patterns, trends, or seasonality. Cryptocurrency markets show intricate and non-linear interactions between several price-influencing elements [22]. Deep learning models can identify complicated patterns and correlations in the data because they can represent complex functions. Human feature engineering no longer be necessary as deep learning algorithms automatically extract relevant features from raw data. In the Bitcoin market, where pertinent aspects could be dynamic and complicated, this is useful [23]–[25].

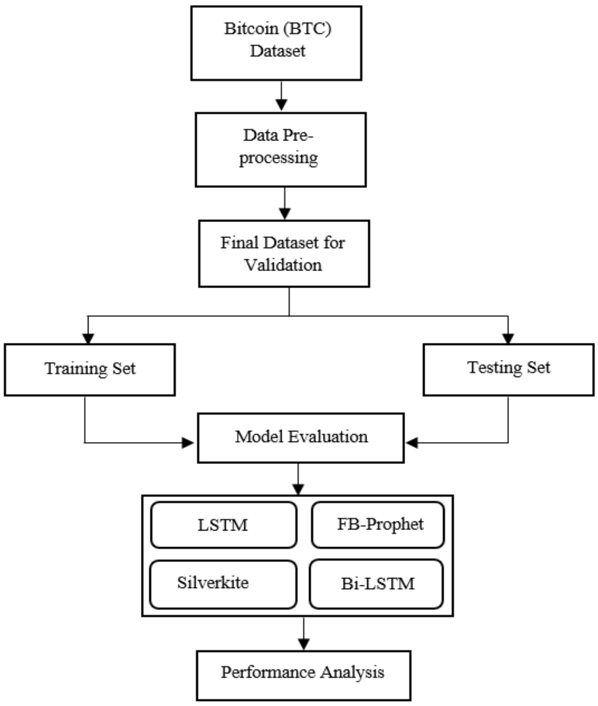

Figure 2. Proposed workflow diagram

Table 1. Fallouts of DFT

Parameters	Speed (rpm)
#Lags used	28.000000
Frequency of observations	3151.000000
Critical value (1%)	-3.531219
Critical value (5%)	-2.751343
Critical value (10%)	-2.657257
Data type	float64
Test statistic	-1.342317
p-value	0.584528

4. RESULTS ANALYSIS

Cryptocurrency forecasting can assist people and organizations in evaluating and controlling the risks brought on by price swings. Developing methods to mitigate risks is made possible by understanding possible price fluctuations. Predictions are a common tool used by investors to maximize their bitcoin holdings. They can modify their asset portfolios to enhance profits or reduce losses by forecasting market fluctuations. In this work we are taking four different models from two separate fields and making the comparison. When compared to other models, the Bi-LSTM model performs well. Figure 3 displays the LSTM anticipated price of bitcoin, whereas Figure 4 displays the FB-Prophet expected price of bitcoin. In a similar vein, Figures 5 and 6 illustrate the predicted prices for bitcoin by Silverkite and Bi-LSTM, respectively.

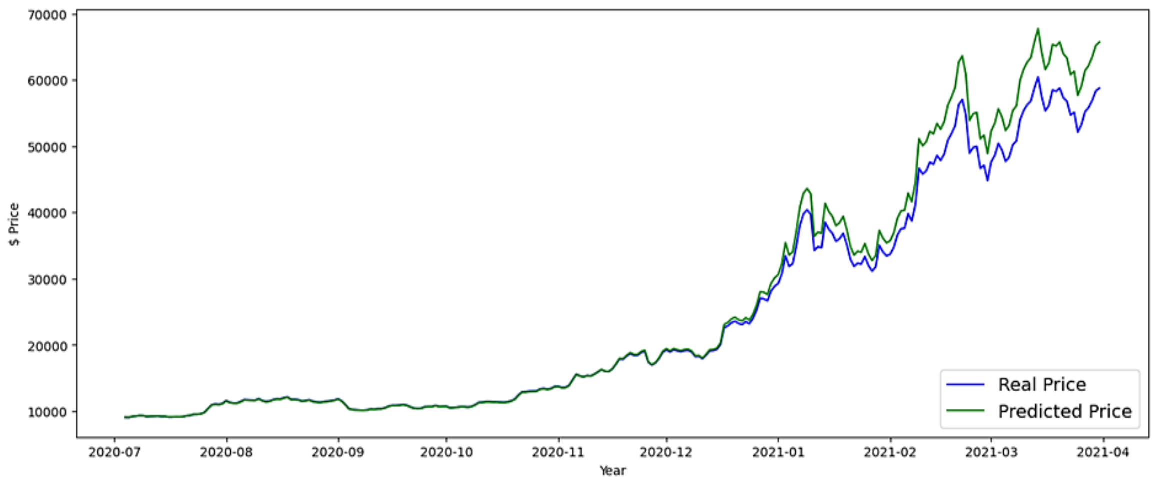

Figure 3. LSTM predicted BTC price

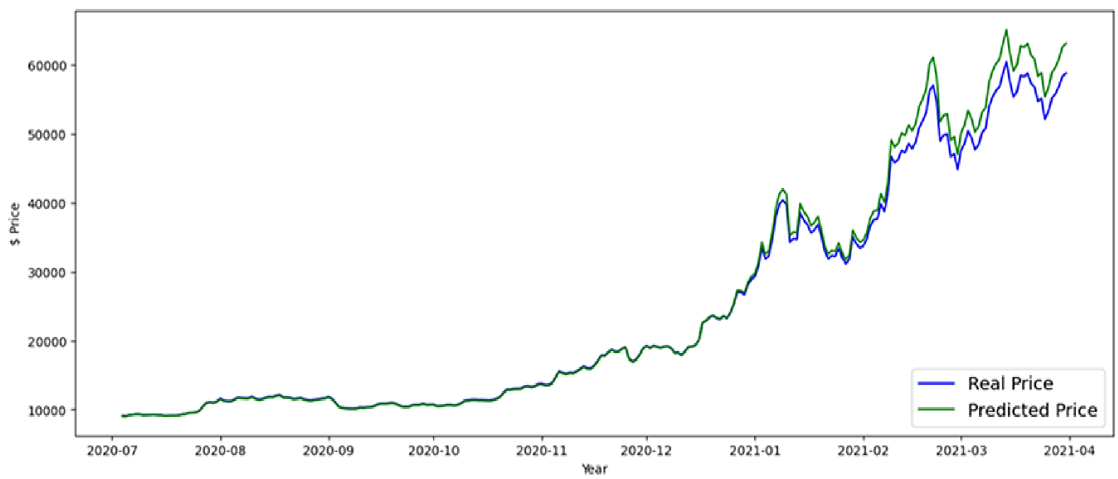

Figure 4. FB-Prophet predicted BTC price

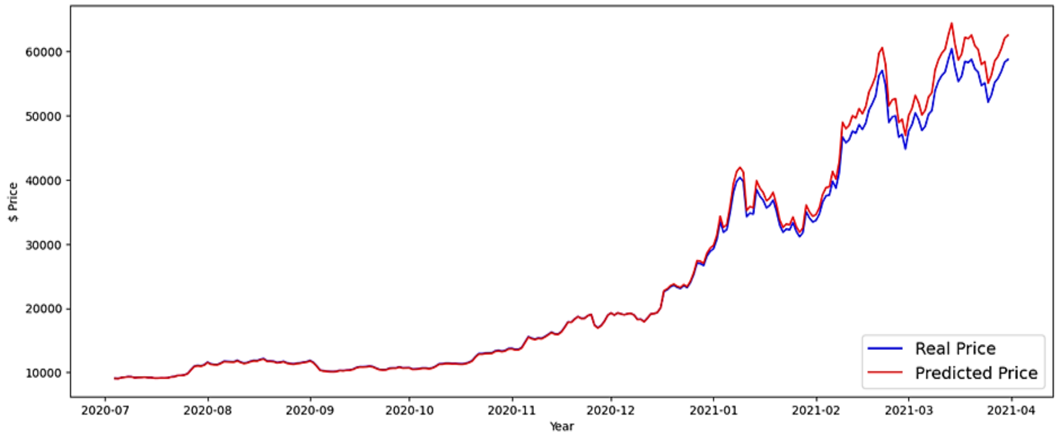

Figure 5. Silverkite predicted BTC price

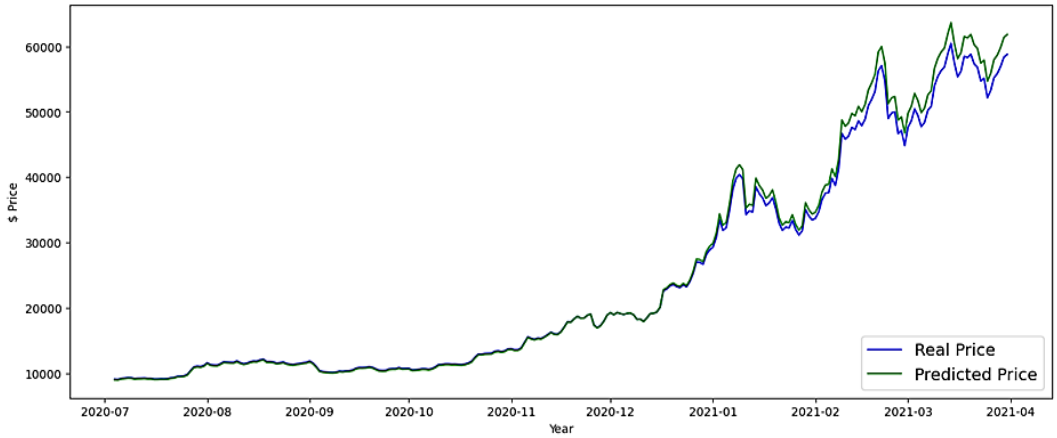

Figure 6. Bi-LSTM predicted BTC price

Table 2 displays the mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) scores of each model. The Bi-LSTM model has an RMSE score of 3.639 and a minimal MAE score of 7.073 when compared to the LSTM, FB-Prophet, and Silverkite models. By utilizing the capacity to recognize intricate trends in sequential data and to record long-term dependencies, the Bi-LSTM model provides various potential advantages for bitcoin price prediction. Prices of cryptocurrencies frequently show long-term trends and interdependence. As a variant of LSTM with bidirectional processing, Bi-LSTM models are able to more accurately represent long-term dependencies in the data by capturing data from both past and future time steps. Models' MAE, MSE, and RMSE scores are plotted in a bar diagram conspiracy in Figure 7. Prognoses for the future can be used by cryptocurrency-related businesses to put hedging plans into place. In order to provide some amount of risk management, this entails establishing positions to counter possible losses from unfavorable market fluctuations. Future projections can help businesses that adopt or use cryptocurrencies make wise decisions about financial planning, budgeting, and general company strategies. Forecasts for the future help raise awareness and educate people about the bitcoin industry. Entrepreneurs keep up with the dynamics of the ever-changing cryptocurrency industry by being aware of possible future developments.

Table 2. Error score of each model

Model name	MAE	MSE	RMSE
LSTM	14.728	26.525	5.471
FB-Prophet	8.357	15.354	3.917
Silverkite	7.662	13.948	3.834
Bi-LSTM	7.073	11.929	3.639

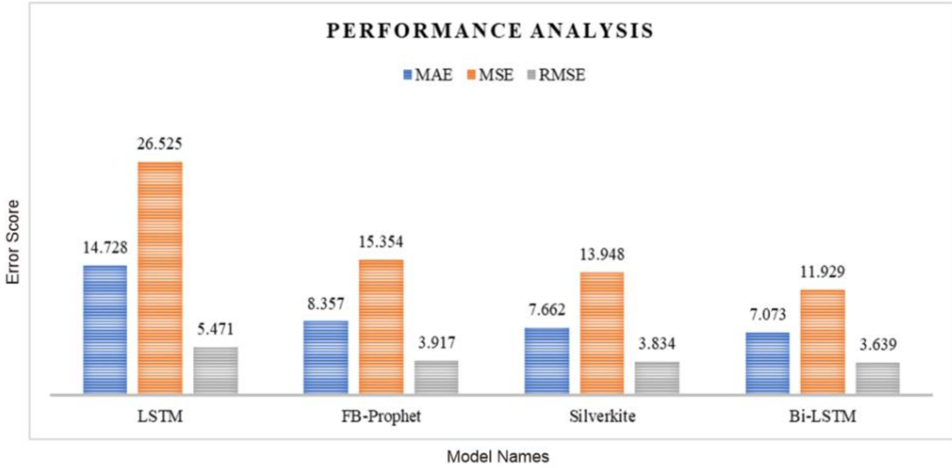

Figure 7. MAE, MSE, and RMSE result of models

5. CONCLUSION

Research and analysis of the market benefit from predictions. They offer perceptions of market mood, possible trends, and variables affecting bitcoin pricing. Using this knowledge to inform strategic decision-making is beneficial. Predictions can help organizations that deal with cryptocurrencies, including exchanges and payment processors, make choices. In this work against the LSTM, FB-Prophet, and Silverkite models, the Bi-LSTM model has a minimal MAE score of 7.073 and an RMSE score of 3.639. This might involve risk management, price tactics, and market fluctuation preparation. Predictions can be used by organizations that deal with cryptocurrencies, such as corporations and institutional investors, to create hedging strategies that would lessen the risk of losses brought on by market volatility. Financial markets are so dynamic and complicated that it is always difficult to forecast their movements, especially those of bitcoin values. Future developments in data science and a thorough comprehension of the dynamic cryptocurrency environment will probably be used to anticipate bitcoin prices. Scholars and experts in this domain will persist in investigating inventive methods to augment the precision and dependability of predictions for the bitcoin.

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