Optimizing Bitcoin Price Prediction with LSTM: A Comprehensive Study on Feature Engineering and the April 2024 Halving Impact

Panji Satria Taqwa Putra Purnama*

Ahmad Dahlan University, Yogyakarta, Indonesia

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Abstract

This research aims to develop a Bitcoin price prediction model using machine learning techniques, with a specific focus on Long Short-Term Memory (LSTM) neural networks. The Bitcoin market is characterized by unique features such as high volatility and the influence of various external factors, which differ significantly from traditional financial markets. As such, precise feature engineering is crucial for accurately modelling Bitcoin prices. Utilizing historical Bitcoin price data from 2014 to 2023, this study extensively evaluates LSTM models. The results indicate that LSTM models provide highly accurate predictions, with a Mean Squared Error (MSE) of 0.0001798 and a Mean Absolute Error (MAE) of 0.0101322. These results demonstrate that LSTM effectively captures the complex and dynamic patterns of Bitcoin prices, outperforming other methods. The findings have significant implications for financial market analysis, especially within the rapidly evolving domain of crypto assets. By leveraging machine learning methodologies, this research enhances understanding of the complexities of the crypto market and offers potential strategies for smarter investment decisions. The success of the LSTM model in improving Bitcoin price prediction accuracy underscores its importance in navigating the volatile and dynamic nature of the crypto market. Overall, this study highlights the substantial potential of machine learning approaches, particularly LSTM models, in analyzing and predicting crypto market behavior. It contributes to the growing academic discourse on the application of advanced technologies in finance and can stimulate further discussionson how machine learning can address challenges and opportunities in the crypto market.

Corresponding Author:
Email: panjisatriataqwa.putrapurnama@gmail.com

INTRODUCTION

The emergence of Bitcoin as a leading cryptocurrency has garnered significant attention in the global financial landscape. Known for its substantial price volatility, Bitcoin presents both opportunities and challenges for investors and researchers aiming to understand market behavior This study focuses on predicting Bitcoin prices using machine learning techniques, particularly Long Short-Term Memory (LSTM) neural networks [1], by analyzing historical data, this research aims to provide valuable insights to stakeholders for making informed investment decisions in the dynamic crypto market. Since its inception in 2009 by an anonymous entity known as Satoshi Nakamoto, Bitcoin has undergone tremendous growth and faced numerous challenges, achieving widespread adoption among investors and general users alike [2]. The cryptocurrency has attracted interest from a diverse audience, including financial market speculators and leading technologists. The introduction of blockchain technology and cryptocurrencies has significantly altered the financial world. Amongthese, Bitcoin remains the most prominent and widely discussed. Operating without a central authority, Bitcoin has intrigued various groups, from retail investors to large financial institutions [3]. The significant price

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fluctuations of Bitcoin have become a focal point for market participants, investors, and financial observers. Despite its volatility, Bitcoin has shown remarkable growth, rising from negligible initial value to thousands of US dollars per coin today. This study aims to implement anLSTM-based neural network model to predict Bitcoin prices, with particular emphasis on the Halving event in April 2024.

Halvings, occurring approximately every four years, reduce the rewards for Bitcoin miners by half, historically impacting Bitcoin's price significantly. By leveraging historical price data surrounding the Halving event and considering factors like volatility and fundamentals, this research seeks to develop a prediction model to aid investors and market participants in making better-informed decisions. The research will delve into the application of LSTM models for Bitcoin price predictionand explore how specific events, such as Halving, influence price forecasts. Furthermore, it includes a comprehensive analysis of various factors affecting Bitcoin prices, including volatility, correlations, and fundamental factors [4]. This study aims to provide significant insights for market participants and contribute to a deeper understanding of Bitcoin price behavior in the context of the 2024 Halving event and the broader growth of crypto assets. Since Bitcoin's introduction, it has revolutionized digital finance, offering transformative potential in transactions, value storage, and financial concepts. However, its high price volatility poses challenges for investors and market observers. Predicting Bitcoin price movements is crucial for stakeholders in the crypto ecosystem, necessitating sophisticated analytical tools and techniques. In this context, data modelling approaches like LSTM neural networks, capable of capturing complex patterns in financial data, have proven effective in forecasting Bitcoin prices.

METHODS

This research uses quantitative research, which relies on the analysis of historical Bitcoin price data and related external factors using the LSTM (Long Short-Term Memory) method. Figure 1 shows the journey of this research. Starting from problem identification, literature review, hypothesis research, data collection, data pre-processing, model development, and model performance evaluation. activities0.0, 0.1, 0.2, 0.3, 0.4, and 0.5 refer to steps or sub-steps in the research process. These are steps such as"Problem Identification", "Hypothesis Formulation", "Data Collection", "Data Analysis", "Result Interpretation", and so on. Each number after the decimal point (.) indicates a sub-step within the mainstep. For example, 0.0 might refer to the "Problem Identification" step, while 0.1 might be the first sub-step within the "Problem Identification" step, and so on. His kind of numbering helps organize and determine the order of the steps that need to be done in the research process, making it easier to understand and implement the research methodology.

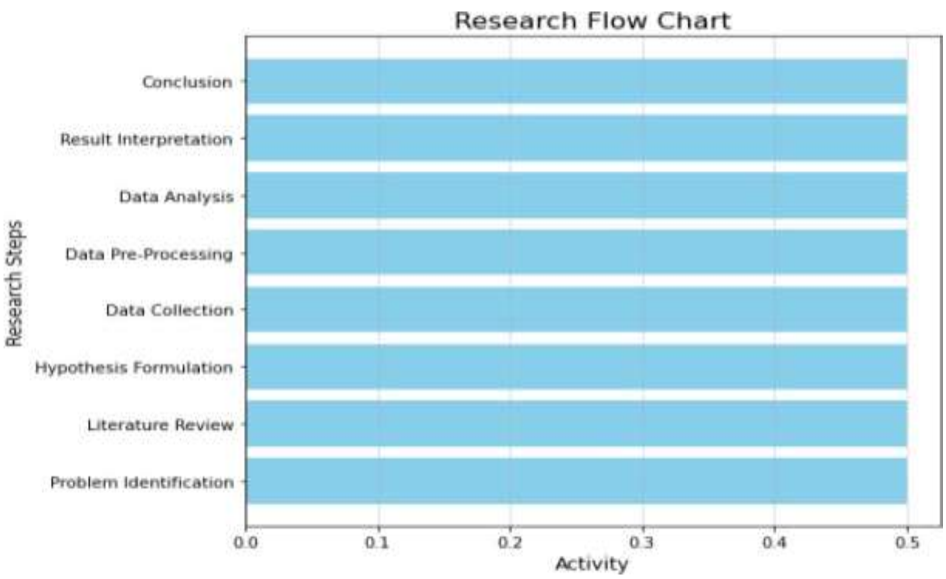


Figure 1. Research Flow Diagram

Data Collection

Bitcoin price data is obtained from trusted sources such as Yahoo Finance and Coin Gecko. The time period for the data collected was from January 2014 to December 2023. The data was then prepared for use in modeling with normalization steps and division into training and testing data sets.

	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	17/09/2014	465.864.013.671.875	46.817.401.123.046.800	4.524.219.970.703.120	4.573.340.148.925.780	4.573.340.148.925.780	21056800
3	18/09/2014	4.568.599.853.515.620	4.568.599.853.515.620	41.310.400.390.625	42.444.000.244.140.600	42.444.000.244.140.600	34483200
4	19/09/2014	4.241.029.968.261.710	4.278.349.914.550.780	3.845.320.129.394.530	3.947.959.899.902.340	3.947.959.899.902.340	37919700
5	20/09/2014	3.946.730.041.503.900	4.232.959.899.902.340	38.988.299.560.546.800	40.890.399.169.921.800	40.890.399.169.921.800	36863600
6	21/09/2014	4.080.849.914.550.780	4.124.259.948.730.460	3.931.809.997.558.590	3.988.210.144.042.960	3.988.210.144.042.960	26580100
7	22/09/2014	3.991.000.061.035.150	4.069.159.851.074.210	3.971.300.048.828.120	4.021.520.080.566.400	4.021.520.080.566.400	24127600
8	23/09/2014	4.020.920.104.980.460	4.415.570.068.359.370	3.961.969.909.667.960	4.357.909.851.074.210	4.357.909.851.074.210	45099500
9	24/09/2014	4.357.510.070.800.780	43.611.199.951.171.800	4.211.319.885.253.900	4.232.049.865.722.650	4.232.049.865.722.650	30627700
10	25/09/2014	423.156.005.859.375	4.235.199.890.136.710	4.094.679.870.605.460	4.115.740.051.269.530	4.115.740.051.269.530	26814400
11	26/09/2014	4.114.289.855.957.030	41.493.798.828.125	4.000.090.026.855.460	40.442.498.779.296.800	40.442.498.779.296.800	21460800
12	27/09/2014	4.035.559.997.558.590	40.662.298.583.984.300	39.737.200.927.734.300	3.995.199.890.136.710	3.995.199.890.136.710	15029300
13	28/09/2014	39.947.100.830.078.100	4.010.169.982.910.150	3.743.320.007.324.210	3.771.809.997.558.590	3.771.809.997.558.590	23613300
14	29/09/2014	3.769.280.090.332.030	38.521.099.853.515.600	372.239.990.234.375	3.754.670.104.980.460	3.754.670.104.980.460	32497700
15	30/09/2014	3.760.880.126.953.120	39.097.698.974.609.300	3.734.429.931.640.620	3.869.440.002.441.400	3.869.440.002.441.400	34707300
16	01/10/2014	387.427.001.953.125	3.913.789.978.027.340	3.807.799.987.792.960	383.614.990.234.375	383.614.990.234.375	26229400
17	02/10/2014	3.839.880.065.917.960	38.549.700.927.734.300	3.729.460.144.042.960	3.750.719.909.667.960	3.750.719.909.667.960	21777700
18	03/10/2014	3.751.809.997.558.590	37.769.500.732.421.800	3.578.590.087.890.620	3.595.119.934.082.030	3.595.119.934.082.030	30901200
19	04/10/2014	3.598.919.982.910.150	36.448.699.951.171.800	325.885.986.328.125	3.288.659.973.144.530	3.288.659.973.144.530	47236500
20	05/10/2014	3.289.159.851.074.210	3.418.009.948.730.460	2.892.959.899.902.340	320.510.009.765.625	320.510.009.765.625	83308096
21	06/10/2014	3.203.890.075.683.590	3.451.340.026.855.460	30.255.999.755.859.300	3.300.790.100.097.650	3.300.790.100.097.650	79011800
22	07/10/2014	3.305.840.148.925.780	33.924.700.927.734.300	32.048.199.462.890.600	33.618.701.171.875	33.618.701.171.875	49199900
23	08/10/2014	3.361.159.973.144.530	354.364.013.671.875	32.718.798.828.125	35.294.000.244.140.600	35.294.000.244.140.600	54736300
24	09/10/2014	35.274.798.583.984.300	38.272.601.318.359.300	34.768.701.171.875	3.650.260.009.765.620	3.650.260.009.765.620	83641104

bitcoin_data_2014_2023

Figure 2. Yahoo Finance Datasets

LSTM - Model Development

The LSTM (Long Short-Term Memory) model is used to model and predict Bitcoin prices. LSTM was chosen because of its ability to handle complex time series problems and its ability to learn long-term patterns. The LSTM model architecture used includes developing an LSTM model for Bitcoin price analysis by adopting an architecture consisting of two LSTM layers[4]. Each LSTM layer has 128 units, with a ReLU (Rectified Linear Unit) activation function applied to each layer. The training process is carried out with the Adam optimization algorithm, which helps in adjusting the model parameters efficiently. Apart from that, to increase convergence, this training uses a learning rate value of 0.001. With this specification, we hope to obtain an effective model for modelling and predicting Bitcoin prices based on the data provided, which is adjusted to the characteristics of the data and the complexity of the problem.

LSTM - Model Training

The LSTM model is trained using a previously prepared training data set. The training process involves repeated iterations of feeding data into the model, calculating loss values, and adjusting model parameters using optimization algorithms. The evaluation criteria used during training include mse, mae, volatility level, correlation level, generalization, and noise robustness, aiming to ensure the quality and performance of the resulting model.

Model Evaluation

The model is evaluated using previously unseen test data sets. Model evaluation is carried out by calculating a number of performance metrics, such as Mean Squared Error (MSE) and Mean Absolute Error (MAE). These metrics provide an idea of how well the model can predict the price of Bitcoin based on the data provided.

Evaluation of Result

The results of the model evaluation are used to evaluate the performance and accuracy of predictions. Additional analysis is performed to understand the patterns and trends detected by the LSTM model, as well as to identify external factors that may influence Bitcoin price movements.

RESULT AND DISCUSSION

Analyze Bitcoin price behavior based on historical data and related external factors and develop an LSTM model that can accurately predict Bitcoin price movements. In this section, the results of the analysis and evaluation that have been found are presented.

Clustering-Analysis

Data grouping is used as an initial stage in achieving goals by grouping data objects into clusters based on similar features or characteristics. To find hidden structures in the data using the K-Means algorithm in Figure 3, the results of Bitcoin price data clustering were carried out to identify hidden patterns or structures in price leaks. The resulting scatter plot displays data points whose coloring corresponds to the clusters they are grouped into. The x-axis shows the difference between opening and closing prices, reflecting price volatility, while the y-axis shows the difference between the highest and lowest prices, focusing on maximum and minimum price gains. By providing a different color for each cluster, you can differentiate the data groups that are formed.

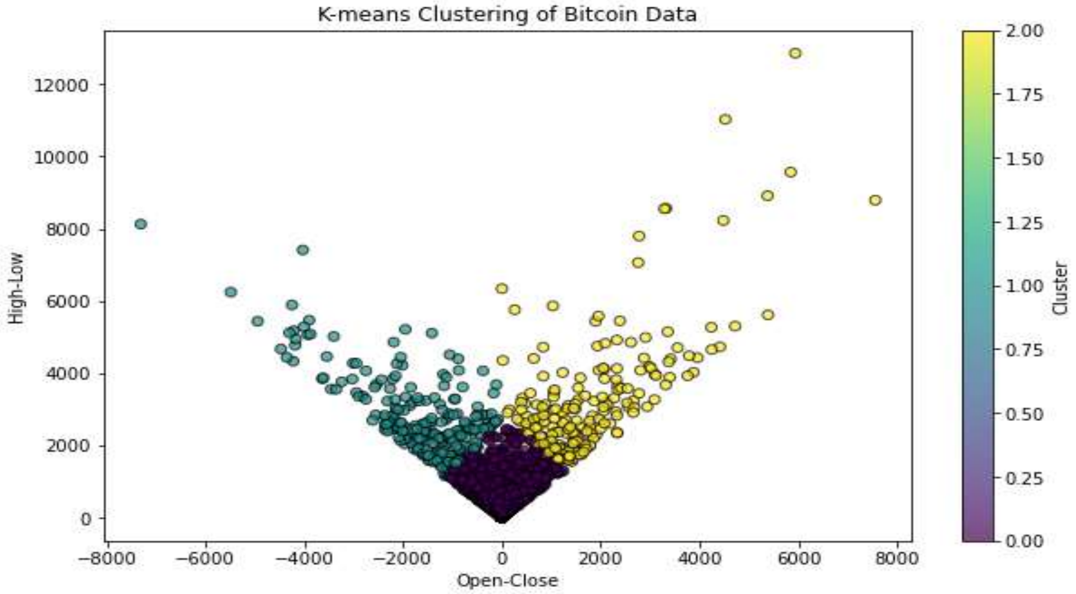
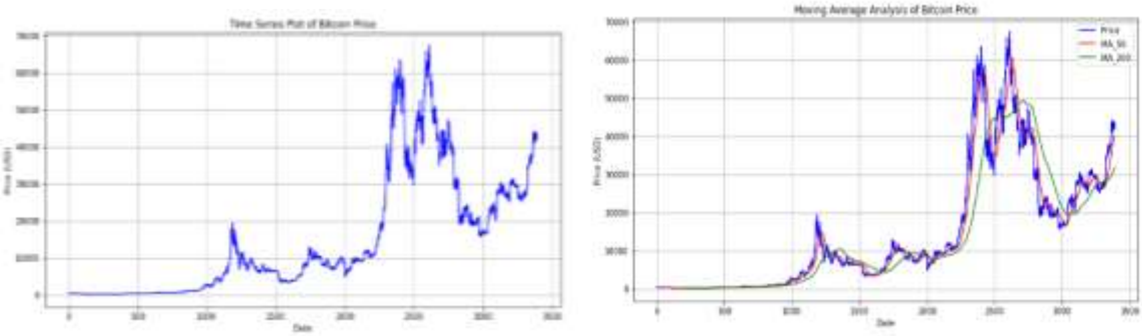


Figure 3. Clustering Analysis Results

Time series-Analysis

Statistics are used to understand patterns and behavior of data collected sequentially over a certain period of time. A predictive model is used to forecast future values based on historical data, as shown in Figure4 (a), a time plot displaying the closing price of Bitcoin throughout the observed period. This gives an idea of price fluctuations over time. Meanwhile, (b) moving average with a time window of 50 and 200 days. This chart shows the price of Bitcoin as well as the 50 and 200-day moving averages in one image.The difference between the actual price and movement of bitcoin helps identify short-term and long-termtrends. This is a useful tool for spotting Bitcoin price patterns and trends. In the context of Bitcoin price prediction, time series analysis shows significant upward price patterns that may occur in the future basedon historical data.



(a) (b)

Figure 4. Time Series Analysis Results (b) Moving Average Analysis Results

Correlation-Analysis

Correlation analysis on Bitcoin data provides a deep understanding of the relationship between variousfeatures that affect Bitcoin price. By visualizing the correlation matrix using a heatmap, we can identify features that have a strong relationship and can be used to build a more accurate prediction model [5].

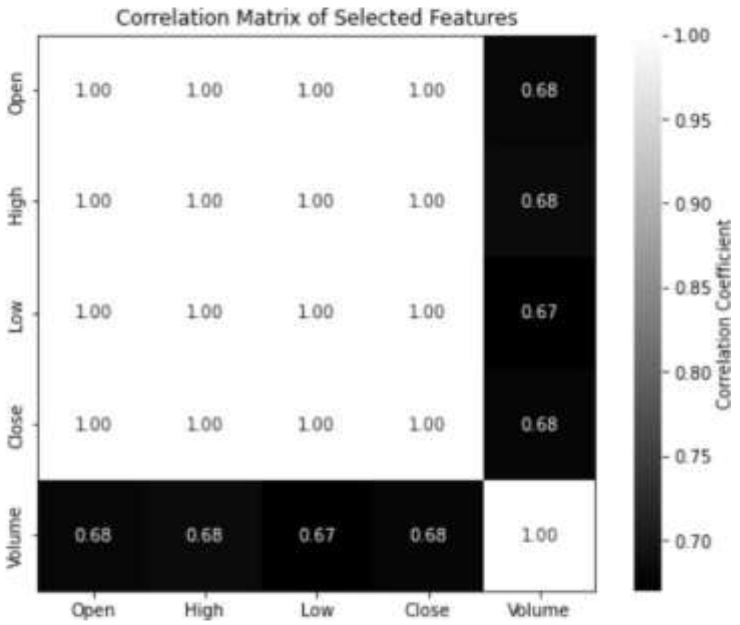


Figure 5. Correlation Analysis Results

Feature engineering is the process of transforming raw data into more informative and relevant features, which aims to improve the performance of machine learning models. In Bitcoin analysis, frequently used features include the opening price (Open), which is the price at which an asset was first traded at the beginning of a certain period; the highest price (High), which shows the highest price reachedby the asset during the period; the lowest price (Low), [6] which shows the lowest price reached during the period; the closing price (Close), which is the last price at which the asset was traded at the end of the period; and trading volume, which reflects the number of units of the asset traded during the period.

A correlation value of 1 indicates a perfect relationship between two variables. In a correlation matrix,a value of 1 appearing on the main diagonal indicates that each feature has a perfect correlation with itself,which makes sense mathematically since a feature always has an identical relationship with itself, resulting in a perfect positive correlation of 1. In Bitcoin analysis, heatmaps help identify strong positivecorrelations, Heatmaps are an effective visualization tool for depicting correlations between variables where an increase in the value of one feature is usually accompanied by an increase in the

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other; negativecorrelations, where an increase in one feature tends to be accompanied by a decrease in the other; and uncorrelated features, where changes in one feature do not provide meaningful information about the other. These heatmaps are very useful in the process of effective feature selection, as well as in identifyingfeatures that may be redundant or not contribute much to the model [7].

LSTM Models Architecture

This LSTM model architecture diagram illustrates the data flow in a sequence-based neural network model. The initial data, which is a time sequence with the shape (samples, time_steps, features), is fed into the first LSTM layer with 50 units and return_sequences=True, allowing the model to process the complete sequence and output the results to the next layer [8]. This layer is followed by a dropout with a rate of 20% to prevent overfitting. This process is repeated with the second and third LSTM layers, each with 50 units, where the third layer only outputs the last part of the time sequence[9]. Dropout is also applied between these layers to reduce the risk of overfitting. Finally, a Dense layer with 1 unit produces the final output in the form of predictions from the input data, which are then evaluated for model performance. This diagram provides a clear guide on how the data is processed through each LSTM layer, and the final prediction output is produced.

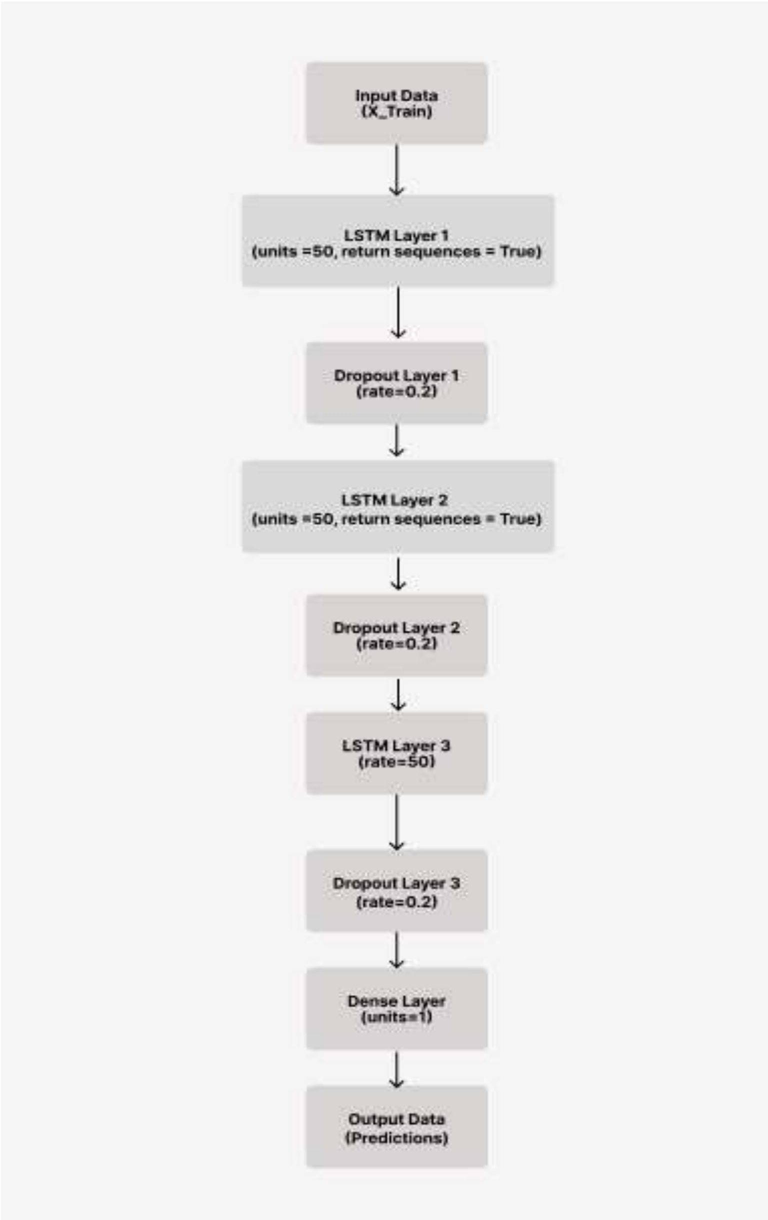

Figure 6. LSTM Models Architecture

Volatility-Analysis

Trading volatility refers to the degree of price fluctuation of an asset within a certain time period. In the context of Bitcoin, high trading volatility indicates that the Bitcoin price experienced large changes ina short period of time, [10]while low volatility indicates more stable price changes [11]. Bitcoin trading volatilityanalysis through Figure 6 In this context, Bitcoin price volatility describes how much the Bitcoin price fluctuates within a 30-day period, indicating higher price stability.

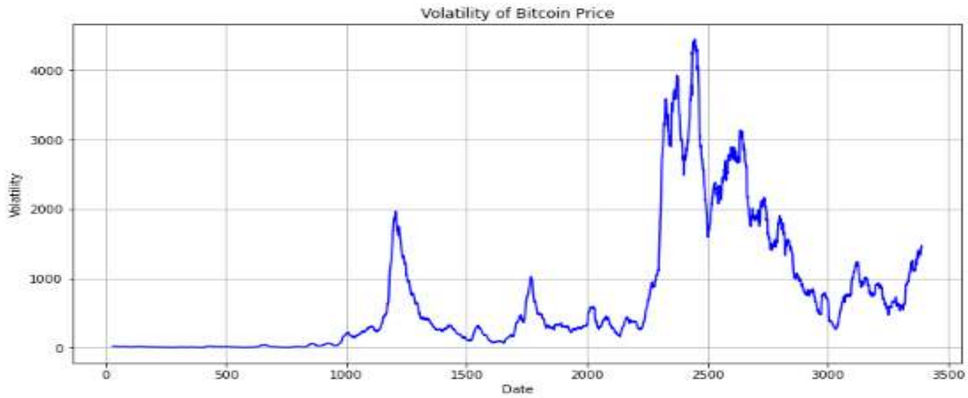

Figure 7. Volatility Analysis Results

Technical-Analysis

Bitcoin is a step asset. Moving averages (MA) are used to help identify asset price trends. In the context of Bitcoin, plotting daily closings in Figure 7 Technical results. Bitcoin shows the green line along with two moving averages, namely the 50-Day MA red line and the 200-Day MA green line. The 50-day MA represents short-term price trends, while the 200-day MA represents long-term price trends. When the closing price crosses the 50 MA from bottom to top, this indicates a buy signal because it indicates a possible uptrend. [12] Conversely, if the closing price crosses the 50 MA from top tobottom, this signals a sell signal as it indicates a potential downtrend

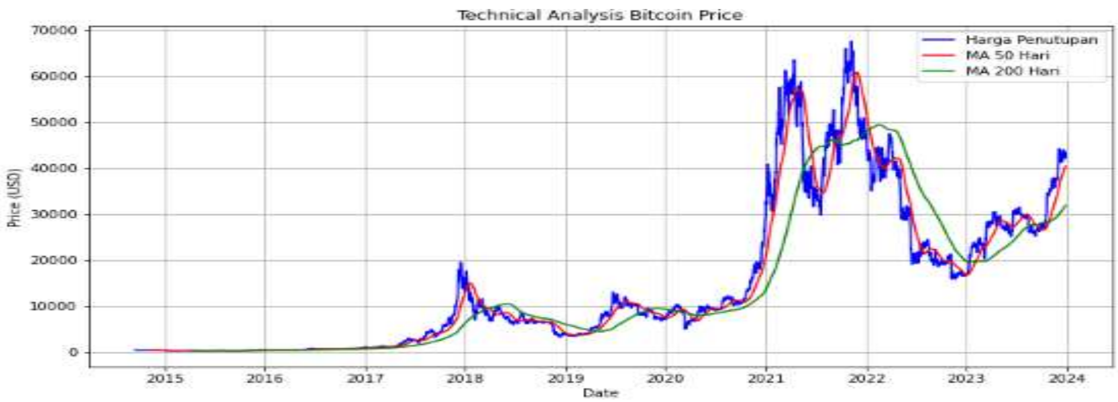

Figure 8. Technical Analysis Results

Fundamental-Analysis

Bitcoin fundamental analysis involves assessing factors related to Bitcoin fundamentals. We use the Coingecko API to find the latest Bitcoin price in US dollars. Via the get_bitcoin_price() function. Bitcoinhas a daily closing value that continues to change over time and to understand trends and fluctuations inprice [13]. Bitcoin's daily closing price within a certain time period can change. In Figure 8, the results of Bitcoin closing prices [14]The x-axis shows the price, while the y-axis shows the date Bitcoin closed in dollars. A moving line chart shows Bitcoin price fluctuations over time.

In terms of predictions, you can see the general trend of Bitcoin price movements and identify certain periods where prices tend toexperience correction before experiencing an increase ahead of the halving.

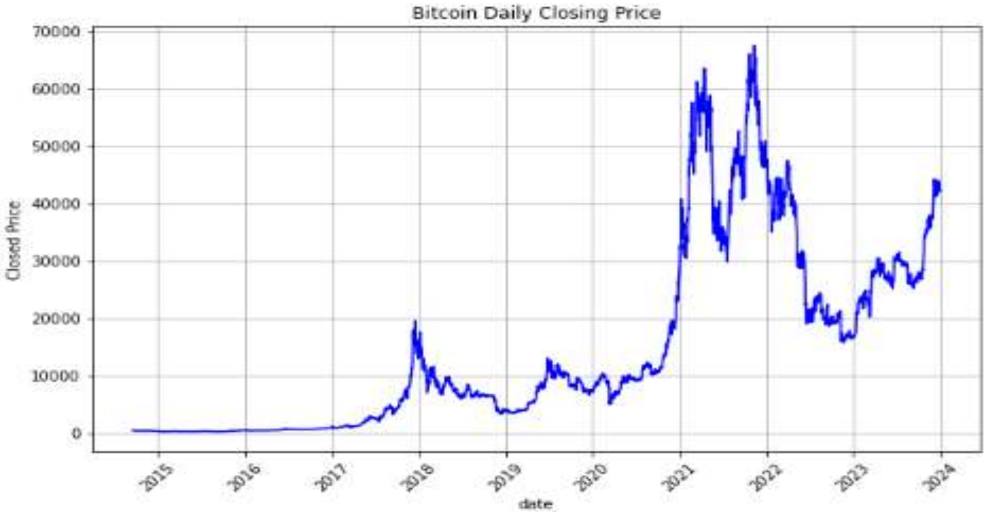

Figure 9. Fundamental Analysis Results

Analysis Bitcoin-Opening And Closing Prices

The process of examining trends and patterns that occur in prices as trades begin and end within a certain time period. In this analysis, the opening and closing prices are used as the main reference points.The opening price is the first price at the beginning of a trading session, while the closing price is the lastprice at the end of a trading session [15]. Regarding the closing and opening prices of Bitcoin, Figure 9 showsthe upward trend in Bitcoin prices over a certain period of time. This can be seen from the red line patternof closing prices which are consistently above the blue line of opening prices. This increase reflects increased interest from buyers [16], which drives closing prices to be consistently above opening prices. Thisanalysis provides an indication that the market tends to be bullish, where Bitcoin prices tend to increase over time.

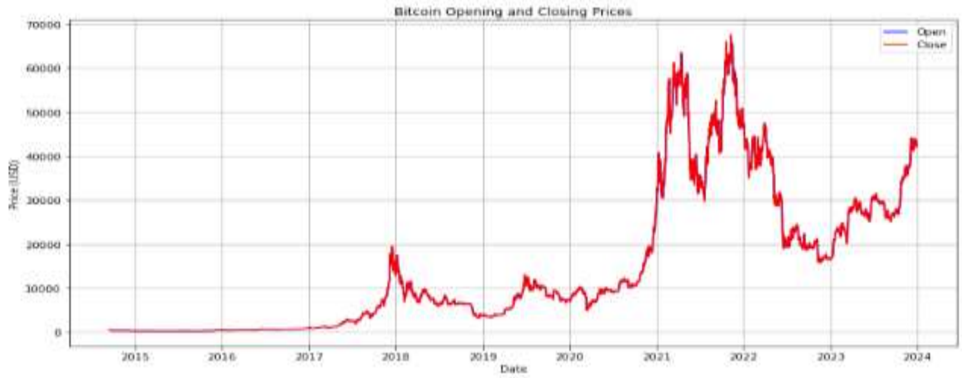

Figure 10. Bitcoin Closing And Opening Price Analysis Results

Training Models – Validation Loss

Training loss and validation loss are two important metrics used to evaluate model performance in theartificial neural network training process. Training loss reflects how well the model learns the patterns contained in the training data. Ideally [17], training loss should decrease as the epoch progresses.

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In Figure 10 Training and Validation loss indicates that the model is getting closer to the optimal representation of thetraining data. Validation loss measures a model's performance on validation data that was not used duringthe training process [4]. Low validation loss indicates that the model is able to make good predictions on newdata that has never been seen before, while high validation loss can indicate overfitting. By monitoring these two types of loss during the training process, we can evaluate the overall performance of the modeland ensure that the model not only learns well from the training data but can also generalize well to newdata [18].

```
83/83 [==============================] - 14s 172ms/step -
loss: 7.5208e-04 - val_loss: 2.0688e-04
Epoch 96/100
83/83 [==============================] - 14s 168ms/step -
loss: 7.2535e-04 - val_loss: 0.0013
Epoch 97/100
83/83 [==============================] - 14s 172ms/step -
loss: 7.1159e-04 - val_loss: 1.9495e-04
Epoch 98/100
83/83 [==============================] - 14s 169ms/step -
loss: 7.3841e-04 - val_loss: 1.9359e-04
Epoch 99/100
83/83 [==============================] - 14s 171ms/step -
loss: 6.7899e-04 - val_loss: 1.9077e-04
Epoch 100/100
83/83 [==============================] - 14s 169ms/step -
loss: 7.1618e-04 - val_loss: 3.5397e-04
```

(a)

(b)

Figure 11. (a) Epoch Training And Validation Loss Results (b) Graphich Training And Validation Loss Results

Model Performance-Evaluation

The trained LSTM model can predict the closing price of Bitcoin very well based on historical patterns from the processed data.

```
83/83 [==============================] - 39s 474ms/step - loss: 4.1213e-04 - val_loss: 7.6818e-04
Epoch 192/200
83/83 [==============================] - 40s 485ms/step - loss: 4.3366e-04 - val_loss: 3.4056e-04
Epoch 193/200
83/83 [==============================] - 38s 463ms/step - loss: 5.1719e-04 - val_loss: 1.3887e-04
Epoch 194/200
83/83 [==============================] - 38s 460ms/step - loss: 4.1313e-04 - val_loss: 1.7138e-04
Epoch 195/200
83/83 [==============================] - 39s 471ms/step - loss: 4.4009e-04 - val_loss: 1.3406e-04
Epoch 196/200
83/83 [==============================] - 39s 476ms/step - loss: 4.1221e-04 - val_loss: 3.0451e-04
Epoch 197/200
83/83 [==============================] - 40s 485ms/step - loss: 5.1740e-04 - val_loss: 3.2732e-04
Epoch 198/200
83/83 [==============================] - 39s 468ms/step - loss: 4.3331e-04 - val_loss: 1.5429e-04
Epoch 199/200
83/83 [==============================] - 38s 456ms/step - loss: 3.6955e-04 - val_loss: 1.4116e-04
Epoch 200/200
83/83 [==============================] - 40s 484ms/step - loss: 4.2801e-04 - val_loss: 1.7982e-04
```

Figure 11. Epoch Evaluate Performance Model Results

The performance of the model, by paying attention to the val_loss value at each epoch, in Figure 10, the results of the last epoch of the 200th epoch, the val_loss value is 1.7982e-04. This value shows that the LSTM model performs well in predicting Bitcoin's closing price based on processed data. Val_loss shows that the difference between the price predicted by the model and the actual price is relatively low, with the epoch value being relatively low. Hence, the model is able to provide accurate estimates. This model can predict the closing price of Bitcoin with a high level of confidence, which can indicate that the model is able to generalize well to new data so that it can be used to predict Bitcoin prices in the future.

Model Performance-Evaluation

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```
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Epoch 192/200
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Epoch 194/200
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Epoch 195/200
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Epoch 196/200
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Epoch 197/200
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Epoch 198/200
83/83 [==============================] - 39s 468ms/step - loss: 4.3331e-04 - val_loss: 1.5429e-04
Epoch 199/200
83/83 [==============================] - 38s 456ms/step - loss: 3.6955e-04 - val_loss: 1.4116e-04
Epoch 200/200
83/83 [==============================] - 40s 484ms/step - loss: 4.2801e-04 - val_loss: 1.7982e-04
```
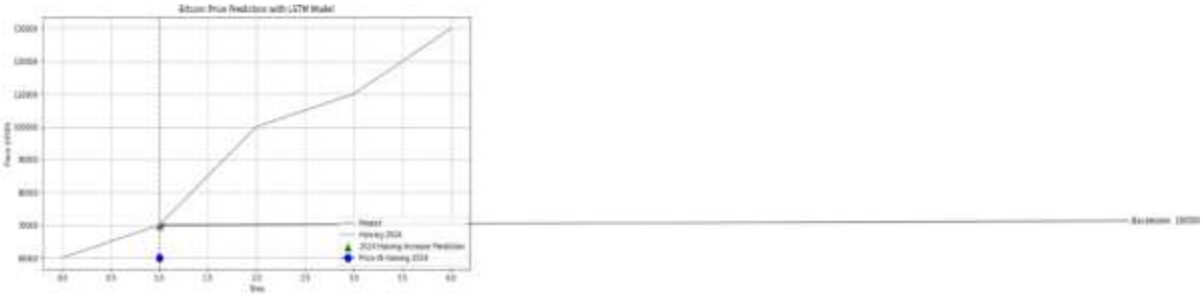

Figure 12. Epoch Evaluate Performance Model Results

April 2024-Halving Predictions

Bitcoin halving is an event where the amount of reward given to Bitcoin miners for each new block mined becomes half of the previous one. This event occurs periodically every 210,000 blocks or about once every four years. With the halving, the number of Bitcoins produced each day also decreases, which can affect the availability of new Bitcoin supply on the market [22].

Based on the Bitcoin price prediction graph using the LSTM model, it can be seen that the predicted price increase after the halving in Figure 12 and the prediction results for 2024 can reach a significant point. The green dot shows the predicted increase in Bitcoin prices ahead of the halving in 2024, which will most likely reach 70,000 USD or even exceed that figure after Bitcoin makes a correction [23]. This can be interpreted as a potentially significant increase in the value of Bitcoin before the halving and after the halving event occurs [24].



```
Prediction of Increase Ahead of Halving Price 2024: 70000
Current Bitcoin supply: 21000000.0
Fundamental Analysis of Bitcoin:
- Bitcoin Price: $58034.72820553373
```

Figure 13. Predictions Results

MSE and MAE

Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used to evaluate the performance of LSTM models in predicting Bitcoin prices [25]. LSTM models have the ability to maintain long-term information and overcome the problem of gradients that often disappear in neural networks. [26] The developed LSTM model shows satisfactory results in modeling Bitcoin prices, as seen in Figure 12 (a) which shows the model evaluation results have a low Mean Squared Error (MSE), in the following calculation formula:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(yi - yi)^2$$

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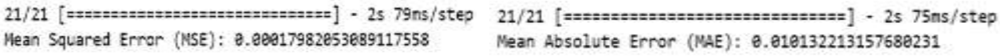
Mean Absolute Error (MAE) is an evaluation metric used to measure the average of the absolute difference between the predicted value and the actual value, in Figure 13 (b) it gives an idea of how close the model prediction is to the actual value. The lower the MAE value, the better the model performance in predicting the data [27].



(a) (b)

Figure 14. (a) Mean Squared Error (MSE) results (b) Mean Absolute Error (MAE) Results

MSE, MAE And RMSE

In evaluating the performance of a prediction model, there are several metrics commonly used to measure how well the model predicts the actual value. Three of them are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). At the end of model training, the results of the last epoch showed that during the training process, the `loss` and `val_loss` values showed fluctuations but generally decreased, indicating that the model was getting better at predicting the training data and validation data. Specifically, at the 100th epoch, `loss` reached 6.7193e-04 and `val_loss` reached 2.6036e-04. After training was completed, the evaluation metrics for the model showed a Mean Squared Error (MSE) value of 0.000260, which measures the average squared error of the prediction. The Mean Absolute Error (MAE) was recorded at 0.0124, indicating the average absolute difference between the predicted and actual values. Finally, the Root Mean Squared Error (RMSE) of 0.0161 provides a measure of error in the same units as the data. It emphasizes large errors, reflecting the level of accuracy of the model in prediction by giving more weight to more significant errors.

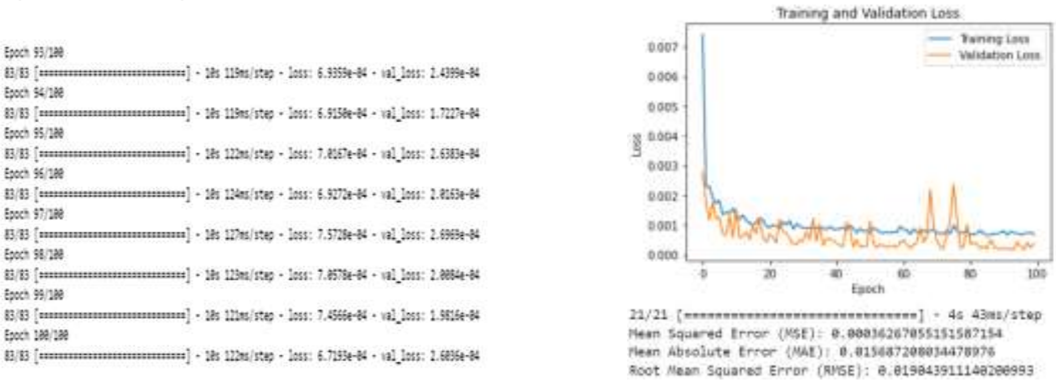


Figure 15. (a) The Last Epoch (b) Graphich Training Model Accuracy Level

LSTM – Models Upgrade

Before improving the LSTM model, the loss on the training data had an average of 7.0533, while theloss on the validation data had an average of 2.0971. After improvements were made to the LSTM model, there was a significant decrease in both values. The average loss on training data fell to 4.2801, while the average loss on validation data fell to 1.7982. This change shows that improvements to the LSTM model succeeded in improving model performance by reducing losses in the dataset [28].

Table 1. Comparison Table

Enhancement	Loss Training(average).	Val Loss (average).
Before	7.0533e-04	2.0971e-04
After	4.2801e-04	1.7982e-04

CONCLUSION

Based on the results of research that have been carried out, a thorough analysis of Bitcoin prices provides a deep understanding of Bitcoin's behavior and growth potential in the market. From various analysis methods, such as opening and closing price analysis and clustering, to predictions using the LSTM (Long Short-Term Memory) model. The developed LSTM model shows promising performance in predicting Bitcoin prices. The developed LSTM model shows satisfactory results in modelling Bitcoin prices. The LSTM model provides a clear visual of how Bitcoin price responds to the halving period. This significant upward pattern could be a valuable opportunity. However, it is important to remember that halving is not the only factor influencing the price of Bitcoin, and other factors, such as market news, also play an important role in determining price movements. Overall, this research provides deeper insight into Bitcoin price behavior and the factors that influence it. By using a holistic analytical approach and utilizing technology such as LSTM, we hope to make a valuable contribution to the understanding of the crypto market and help market players make better decisions.

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