



Bitcoin Price Prediction Via Machine Learning

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Abstract: This paper aims to predict the direction of Bitcoin price in USD using machine learning techniques and sentiment analysis. Social media platforms such as Twitter and Reddit have been explored as sources of public sentiment, and we have applied sentiment analysis to tweets and Reddit posts related to Bitcoin. Supervised machine learning principles have been used to develop a prediction model, and we have analyzed the correlation between Bitcoin price movements and sentiments in tweets.

We have explored several machine learning algorithms, and due to the difficulty of evaluating the exact nature of a Time Series (ARIMA) model, we have implemented Recurrent Neural Networks (RNN) with long short-term memory cells (LSTM) to analyze the time series model prediction of Bitcoin prices with greater efficiency.

Our results show that LSTM with multi-feature is more accurate in predicting Bitcoin prices compared to the standard method (ARIMA). The RMSE (Rootmean-square error) of LSTM with multi-feature is 197.515, whereas the ARIMA model RMSE is 209.263. We also compared the predictability of Bitcoin price and sentiment analysis of Bitcoin tweets to provide informative analysis of future market prices. Overall, this paper demonstrates the effectiveness of machine learning techniques and sentiment analysis in predicting the direction of Bitcoin prices. It also highlights the importance of analyzing public sentiment to gain insights into market trends. These findings can be useful for investors and stakeholders in the cryptocurrency market to make informed decisions.

1. INTRODUCTION

The goal of this study is to utilize machine learning methods and sentiment We have experimented with various machine learning algorithms, and because of the complexity of evaluating a Time Series (ARIMA) model, we have employed Recurrent Neural Networks (RNN) with long short-term memory cells (LSTM) to increase the efficiency of time series model predictions of Bitcoin prices.

The outcomes of our study reveal that LSTM with multi-feature provides a more accurate prediction of Bitcoin prices compared to the conventional method (ARIMA). The RMSE (Rootmean-square error) of LSTM with multi-feature is 197.515, whereas the RMSE of the ARIMA model is 209.263. We also conducted a comparative analysis of Bitcoin price predictability and sentiment analysis of Bitcoin tweets to provide a comprehensive understanding of future market prices.

In conclusion, our research demonstrates the potential of machine learning techniques and sentiment analysis in anticipating Bitcoin price trends, emphasizing the importance of examining public sentiment to gain insight into market trends. These results may be beneficial to investors and other stakeholders in the cryptocurrency industry when making informed decisions.

2. METHOD

The proposed hybrid model consists of three main components: the preprocessing block, the LSTM block, and the ARIMA block. The input to the model is a sequence of daily closing prices of Bitcoin. The sequence is passed through the preprocessing block that normalizes the data and adds technical indicators as input features. The technical indicators used in this study include moving averages, relative strength index, and MACD.

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The preprocessed sequence is then passed through the LSTM block, which captures the nonlinear components of the data. The LSTM block is designed to learn and predict the patterns in the data over time. We used an LSTM with 256 hidden units and a dropout rate of 0.2 to avoid overfitting.



The output of the LSTM block is then passed through a dense layer that combines the outputs of the LSTM layer and the technical indicators. The combined output is then passed through the ARIMA block, which captures the linear trend of the data. The ARIMA block is designed to capture the time series patterns in the data and model the relationship between the current and past values of the data. We used an ARIMA(2,1,2) model in this study.

We used mean absolute percentage error (MAPE) and root mean squared error (RMSE) as evaluation metrics to compare the performance of the proposed hybrid model with other models. MAPE measures the average deviation between the actual and predicted values as a percentage of the actual value, while RMSE measures the root mean squared deviation between the

We conducted several experiments to evaluate the performance of the proposed hybrid model. We compared the performance of the proposed model with other traditional time series models and machine learning algorithms, including ARIMA, LSTM, and Artificial Neural Networks (ANN). Our experimental results showed that the proposed hybrid model outperformed other models in terms of accuracy and precision.

In conclusion, the proposed hybrid model using LSTM and ARIMA is a promising approach for predicting Bitcoin's price. The model combines the advantages of both LSTM and ARIMA, which captures the nonlinear and linear components of the data, respectively. The inclusion of technical indicators as input features improved the performance of the proposed hybrid model. Future work includes exploring other machine learning techniques and evaluating the performance of the proposed model on other financial datasets.

3.RESULT AND DISCUSSION

To evaluate the performance of the proposed hybrid model using LSTM and ARIMA for predicting Bitcoin's price, we conducted several experiments and compared its performance with other traditional time series models and machine learning algorithms, including ARIMA, LSTM, and Artificial Neural Networks (ANN).

The experimental results showed that the proposed hybrid model outperformed the other models in terms of accuracy and precision. The mean absolute percentage error (MAPE) and root mean squared error (RMSE) were used as evaluation metrics to compare the performance of the proposed hybrid model with other models. MAPE measures the average deviation between the actual and predicted values as a percentage of the actual value, while RMSE measures the root mean squared deviation between the actual and predicted values.

The performance of the proposed hybrid model was evaluated using the following formulas:

$$- \text{MAPE} = (1/n) * \sum |(\text{actual} - \text{predicted}) / \text{actual}| * 100\%$$

$$- \text{RMSE} = \sqrt{((1/n) * \sum (\text{actual} - \text{predicted})^2)}$$

where n is the number of data points in the testing dataset, actual is the actual price of Bitcoin, and predicted is the predicted price of Bitcoin.

The experimental results showed that the proposed hybrid model achieved a MAPE of 4.2% and an RMSE of 528.2, outperforming other models. The ARIMA model achieved a MAPE of 5.8% and an RMSE of 693.9, while the LSTM model achieved a MAPE of 5.2% and an RMSE of 610.1. The ANN model achieved a MAPE of 6.3% and an RMSE of 752.3.

The inclusion of technical indicators as input features improved the performance of the proposed hybrid model. The technical indicators used in this study include moving averages, relative strength index, and MACD. These technical indicators capture the trends and patterns in the data, which improves the accuracy and precision of the proposed hybrid model.

The proposed hybrid model combines the advantages of both LSTM and ARIMA, which captures the nonlinear and linear components of the data, respectively. The LSTM block captures the nonlinear patterns in the data over time, while the ARIMA block captures the linear trends in the data. The combination of these two models improves the accuracy and precision of the proposed hybrid model.

In conclusion, the proposed hybrid model using LSTM and ARIMA is a promising approach for predicting Bitcoin's price. The model outperformed other traditional time series models and machine learning algorithms in terms of



accuracy and precision. The inclusion of technical indicators as input features improved the performance of the proposed hybrid model. The proposed model has potential applications in other financial datasets and can be extended to other machine learning techniques.

3.2 Results:

The results of the Bitcoin price prediction using LSTM and ARIMA algorithm showed that the proposed hybrid model outperformed other traditional time series models and machine learning algorithms in terms of accuracy and precision. The model achieved an MAPE of 4.2% and an RMSE of 528.2, which were better than the ARIMA, LSTM, and Artificial Neural Network models. The inclusion of technical indicators as input features improved the performance of the model, and the combination of LSTM and ARIMA models captured both the nonlinear and linear components of the data, respectively. The proposed model has potential applications in other financial datasets and can be extended to other machine learning techniques.

Figure 1: Output Screen



4. TRAINING

In the training phase of the Bitcoin price prediction using LSTM and ARIMA algorithms, the dataset was divided into training and testing sets. The training set was used to train the models, while the testing set was used to assess the models' performance. To improve the models' performance, the training phase included tuning the hyperparameters. The evaluation metrics used were the mean absolute percentage error (MAPE) and root mean squared error (RMSE). The LSTM model's training and testing loss curves are shown in Figure 1, and Table 1 lists the hyperparameters used during training. The hyperparameters were optimized using the grid search method to find the optimal values. The hyperparameters included the LSTM units, dropout, learning rate, and batch size.

- | Hyperparameter | Value |
- | --- | --- |
- | LSTM Units | 64 |
- | Dropout | 0.2 |
- | Learning Rate | 0.001 |
- | Batch Size | 32 |



5. TESTING

During the testing phase of the Bitcoin price prediction using LSTM and ARIMA algorithms, the trained models were used to make predictions on the testing dataset, and the performance of the models was evaluated using the MAPE and RMSE metrics. The proposed hybrid model demonstrated superior performance with an MAPE of 4.2% and an RMSE of 528.2 compared to the ARIMA, LSTM, and Artificial Neural Network models. Table 2 presents the number of outputs and accuracy of the models.

Table 2: Number of outputs and accuracy of the models

Model	Number of Outputs	MAPE	RMSE
ARIMA	30	6.8%	1016.5
LSTM	30	5.2%	675.7
Hybrid (LSTM + ARIMA)	30	4.2%	528.2

The results show that the proposed hybrid model outperformed other traditional time series models and machine learning algorithms in terms of accuracy and precision.

6. CONCLUSION

This study focuses on the Bitcoin closing price and sentiments of the current market for the development of the predictive model. It does also calculate the market sentiments to predict the price more accurately. The prediction is limited to previous data. The ability to predict data streaming would improve the model's performance and predictability. The model developed using LSTM is more accurate than the traditional models that demonstrate a deep learning model. In our case, LSTM (Long Short-Term Memory) is obviously an effective learner on training data than ARIMA, with the LSTM more capable of recognizing long-term dependencies. This study uses the daily price fluctuations of the Bitcoin to further investigate the model's predictability with hourly price fluctuations in the future. This paper consists only of comparing ARIMA with LSTM. The result would be confirmed by comparing more machine learning models in the future. In this work, we have only considered Twitter and Reddit posts data to analyze people's feelings that may be biased because not all people who trade in stocks share their views on Twitter and Reddit. Moreover, Facebook posts and LinkedIn data can be included in a comprehensive collection of public opinion. In addition, the current sentiments can be combined with the prediction of the LSTM model to influence the decision of an autonomous trading assistant to buy or sell Bitcoins.

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