How Machine Learning Methods Unravel the Mystery of Bitcoin Price Predictions

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Abstract
Machine learning has a wide range of applications to meet the complexity of data and various expectations for prediction types. In this study, a comprehensive review of various machine learning approaches for Bitcoin price prediction will be proposed. After examining previous research on cryptocurrency prediction using Long-Short Term Memory (LSTM), Multi-layer Perceptions (MLP), and Support Vector Machine (SVM), with the focus on LSTM, it can be found that LSTM is a widely employed method in Bitcoin price prediction because of its advantages in incorporating both long-term and short-term dependencies. This paper reviews a series of research papers by comparing the differences between the methods they implemented, to a limited extent, based on their predictive power, replicability, and model limitations. Furthermore, some potential improvements and explored innovations for future studies also be discussed.

Keywords-*Neural Networks; Price Predicitons; Bitcoin; Price Predicitons*

1. INTRODUCTION

Nowadays, there has been a lot of interest in cryptocurrencies. A cryptocurrency is a digital currency, secured by cryptography. The blockchain technology involved brings advantages to cryptocurrencies: money transfers become cheaper and faster; and because the system is decentralized, it is difficult to break it down at one point. A great number of cryptocurrencies have emerged in recent years, as the market has evolved in different aspects. It is without doubt a hot market for investments in the financial industry. Moreover, some global companies have even started accepting cryptocurrencies as a form of payment [1]. However, cryptocurrencies are also more volatile in price than non-crypto currencies. In the case of Bitcoin alone, it has been seen that every new Bitcoin high is easily followed by a big drop. Therefore, it is difficult to make predictions about the price movement of cryptocurrencies in the long run. As a result, experts in the industry are trying to apply machine learning algorithms to analyze cryptocurrencies.

Machine learning methods are widely used for various types of predictions, and many researchers have been exploring different types of machine learning methods to predict the price and returns of cryptocurrencies. Research found on this topic are generally focused on Long-Short Term Memory (LSTM), Multi-layer Perceptions (MLP), and Support Vector Machine (SVM) models. The types of LSTM models discussed include Standard LSTM, LSTM with AR (2), Stochastic LSTM, Bayesian Optimized LSTM, Ensemble LSTM, and Gated Recursive Unit (GRU). In addition to these LSTM models, several MLP and SVM models are examined in comparison.

In this paper, the general literature on the empirical pricing of Bitcoin through machine learning methods are examined in four sections. In Section II. there is a brief introduction on the research method used in this paper. Next, Section III. presents an overview of the three types of machine learning algorithms, each with a brief introduction of the terminology and model structures. Then, Section IV. reviews a series of research papers by comparing the differences between the methods they implemented, to a limited extent, based on their predictive power, replicability, and model limitations.

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Following Section IV., a detailed discussion is included in Section V to compare the characteristics of the three methods in real-world scenarios. Finally, the paper concludes with a summary of different characteristics of the three methods and further presents potential changes and exploration of future topics in the field in Section VI.

2. Methodology

This paper is based on a comprehensive search for previous studies published between 2015 and 2021 that used machine learning methods to study Bitcoin price prediction. The databases used include Google Scholar, ScienceDirect, and Semantic Scholar. Keywords used in the search were all related to machine learning and cryptocurrencies, such as neural networks and bitcoin price prediction, machine learning and bitcoin price prediction, regression models and forecast in cryptocurrencies, and deep learning methods for cryptocurrency prediction. Only papers with more than 5 citations were included. LSTM, MLP, and SVM were the most frequently explored models in the field, so these papers were further categorized into the three types of models. For each type, model specifications were reviewed in details and the key results were organized using tables for a better comparative review.

3. Overview of Machine Learning Algorithms

3.1. Long-Short Term Memory (LSTM)

LSTM networks are a subtype of recurrent neural networks that are useful for learning both long-term and short-term dependencies. Recurrent neural networks usually consist of a chain of repeating modules of a neural network. LSTMs have four layers of neural networks in each module. The structure of an LSTM has two special components: the cell state and various gates. Each cell state carries relevant information through the process, and information will be added or removed to the cell state via the regulating gates. In most cases, information from previous time steps can be reused in subsequent time steps, minimizing the impact of short-term memory. The gates are neural networks that select the appropriate information for the cell state. These neural networks can be trained to learn what information is relevant to keep or discard. Fig. 1 shows a simplified structure of an LSTM neural network cell.

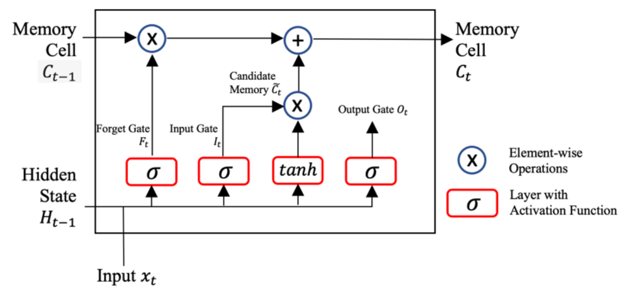

Figure 1. Cell Structure of an LSTM Neural Network

3.2. Multi-Layer Perceptions (MLP)

MLP are also a type of commonly used neural network architecture. MLPs can be used when the data is not linearly separable. This nonlinearity is achieved by using smooth activation functions that connect different layers, using a logistic function or a hyperbolic tangent function as the activation function. In addition, as a feedforward algorithm, each element of a given layer feeds back to all elements of the next layer. MLPs are typically trained with a backpropagation algorithm that propagates errors through the network and allows for the adjustment of hidden processing elements. Fig. 2 shows a simplified structure of an MLP neural network.

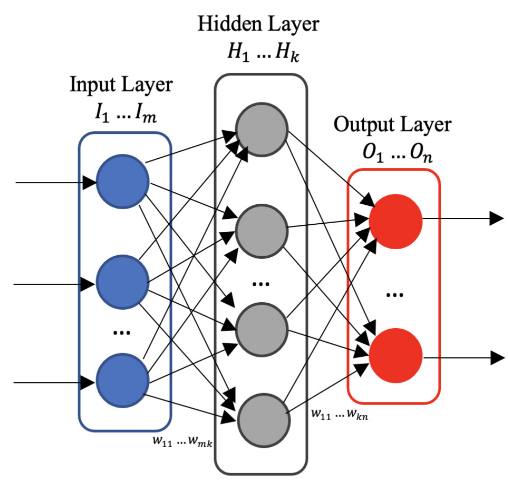

Figure 2. Structure of an Multi-layer Perceptions Neural Network Cell

3.3. Support Vector Machine (SVM)

SVM is a classifier to work in high dimensions. It is to solve problems ranging from pattern recognition to fault diagnosis. It provides a nonlinear and solid solution by implementing kernel functions to transform input space into a higher-dimensional space. To implement SVM technology, data is often plotted as a point in n-dimension. The hyper-plane to differentiate two classes were found by classification. The Fig. 3 is a classic linear example in two dimensions for finding a line, which is the decision boundary.

The optimal hyperplane is the solid blue line in Fig. 3 that splits the samples with two different labels (blue circles and red square 1), and the maximum margin is the distances between the negative and positive hyper-plane. The solid circles in both negative and positive hyper-plane are known as support vectors. If nonlinear data appears, the kernel trick will work to change to a higher-dimensional space.

The SVM has many advantages, including outperforming generalization models and performing well with small datasets. SVM's goal is to generate a classification hyperplane that distinguishes between two classes of data with the greatest possible margin.

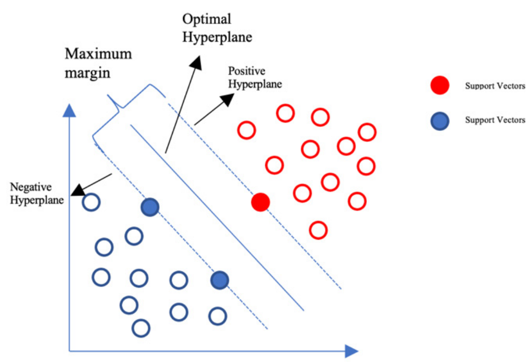

Figure 3. Structure of Support Vector Machine

4. Literature Review

4.1. Research in LSTM Neural Networks

Recent research on Bitcoin price predictions has implemented various machine learning algorithms such as neural networks. Among various neural network models, there is an increasing trend in the research effort done to anticipate the prices of cryptocurrencies using LSTM models. This section reviews a series of prediction models based on LSTM neural networks.

Alessandretti et al. [2] tested the performance of three models in predicting daily cryptocurrency prices. The gradient boosting decision trees (XG Boost) model was employed in the first two models, while LSTM neural network was used in the third model. The researchers constructed their LSTM neural network by selecting parameters that achieve geometric mean optimization or Sharpe ratio optimization. In the evaluation process, these three models were compared based on their return on investment generated from price predictions. The results showed that LSTM neural network consistently produced the best return on investment, with the most noticeable difference being that the LSTM neural network performed best when predicting based on approximately 50 days of data, whereas the other models predicted better using a short-term window of 5-10 days.

In addition to using optimization methods to construct an LSTM network, Wu et al. [3] built a forecasting framework for bitcoin price prediction by incorporating a time series model. In their study, the authors proposed an LSTM neural network with an AR (2) auto-regressive model that uses the autocorrelation function (ACF) and partial autocorrelation function (PACF) of bitcoin prices to find price lags and moving average periods and then uses translation volume as a predictor variable. The predictive performance of the model was compared with the conventional LSTM using four error metrics: Mean Squared Errors (MSE), Root Mean Squared Errors (RMSE), Mean Absolute Errors (MAE), and Mean Absolute Percentage Errors (MAPE). The results showed that the proposed LSTM with AR (2) model had smaller prediction errors than the conventional LSTM. This research also offered an LSTM application to help overcome and improve the input variable selection problem without relying on tight data assumptions.

In a study by Jay et al. [4], a stochastic process is introduced along with LSTM neural network to predict bitcoin prices to capture the market reaction to new knowledge. Their approach is based on the random walk theory, which is widely used to model stock prices in financial markets. The proposed model first incorporated cascading stochasticity into the observed feature activation of a neural network to model market volatility and learn the market response patterns. The parameter tuning process consisted of optimizing the error distribution by choosing the value of the perturbation factor that optimizes the error distribution. Their results showed that the stochastic LSTM neural network outperformed the deterministic model the most when the perturbation factor was set as a learnable parameter. In that case, the MAPE of the stochastic LSTM is improved by 0.398% over the deterministic neural network in the unnormalized data set.

McNally et al. [5] implemented a Bayesian optimization with an LSTM neural network to determine the accuracy of Bitcoin price direction in USD. In comparison with the LSTM neural network, the researchers applied the same optimization to a simple Recurrent Neural Network (RNN), which has different lengths of time windows. The models were evaluated in terms of accuracy and RMSE. The result showed that the Bayesian optimized LSTM achieved the highest accuracy of 52% and an RMSE of 8%. The RNN model achieved the lowest RMSE, and the second-highest accuracy, about 2.5% less than the accuracy of LSTM. In addition, an Auto-Regressive Integrated Moving Average (ARIMA) model was implemented as a comparison with time series models. Both of the deep learning approaches outperformed the ARIMA prediction, given their advantages in machine learning.

Unlike the previous single LSTM neural network models, an ensemble approach with various time windows was proposed for bitcoin price prediction in the research by Shin et al. [6]. The learning architecture consisted of three LSTM-based neural network models that reflect bitcoin price fluctuations in different time scales: short-term (minutes), medium-term (hours), and long-term (days). Based on the three individual LSTM models, an ensemble technique was applied to aggregate the results. Their experiments showed that each individual LSTM model provided different results when training on data with various time intervals, even though the datasets arrived at the same price with different time steps. The proposed joint model aggregated the LSTM neural network and predicted bitcoin price with the best performance in comparison with each individual model, especially during risky periods when bitcoin price showed deterministic changes. The ensemble of LSTM achieved the highest accuracy of 98.86 and the smallest RMSE of 31.60. In this case, the authors concluded that the ensemble model more accurately captured the real-world price fluctuations while providing high prediction accuracy.

In the research by Phaladisailoed et al. [7], they achieved an efficient and accurate prediction of bitcoin prices through Gated Recurrent Unit (GRU), a machine learning algorithm developed from LSTM. Compared to LSTM, GRU has a less complex structure, adapting the gates of the LSTM into reset and update gates. The reset gate is used to determine how much previous state data is available for the current input data, while the update gate is used to determine how much of the previous state is to be collected. This paper also included a Theil-Sen regression model and a Huber regression model to compare with the predictions using GRU and conventional LSTM. MSE and R-Squared were used to measure the accuracy, and the results showed that GRU and LSTM gave better results than Theil-Sen regression and Huber regression. GRU had the best results with an MSE of 0.00002 and an R-squared of 99.2%. However, in terms of efficiency, the computation time of the Huber regression was much less than that of LSTM and GRU, but GRU was more efficient than LSTM neural network due to its improvement in the gate structure.

Table 1 below summarizes the LSTM models discussed in this study.

TABLE 1. LSTM MODEL SUMMARY

Article	Model	Functionality	Model Optimization	Model Advantages	Other Model(s)	Results
[2]	Standard LSTM	Prediction of Bitcoin based on the values of the ROI in a previous time window	Choose parameters that either achieve geometric mean optimization or Sharpe ratio optimization	Capable of learning long-term dependencies; stable against price volatility	XG Boost	Performed best when predicting based on approximately 50 days of data; other models predicted better using a short-term window of 5-10 days
[3]	LSTM with AR (2)	Forecasting Bitcoin daily price	Use ACF and PACF to find price lag period and moving average period, and use the translation volume as the predictive variables	Overcome and improve the input variable selection problem without relying on tight data assumptions	Conventional LSTM	Smaller prediction errors than conventional LSTM MSE: decreased by 4574.12 RMSE: decreased by 9.08 MAE: decreased by 9.75 MAPE: decreased by 0.15
[4]	Stochastic LSTM	Prediction of Bitcoin price using a stochastic module to	Choose the value of the perturbation factor that optimizes the	Propose stochastic behavior in MLP to simulate market volatility,	Deterministic LSTM	Best performance with the perturbation factor was set as a learnable parameter. MAPE improved by

		capture markets' reaction to new knowledge	error distribution	solve the problem of price fluctuations		0.398% in the unnormalized data set.
[5]	Bayesian optimized LSTM	Prediction of Bitcoin price	RMSprop optimizer to improve on stochastic gradient descent	Use Bayesian optimization to optimize the selection of dropout	ARIMA and RNN	Bayesian optimized LSTM: highest accuracy of 52% and an RMSE of 8% RNN: lowest RMSE, and the second-highest accuracy
[6]	Ensemble-based LSTM	Predict Bitcoin price recognizing instantaneous price fluctuations	-	Aggregates the LSTM networks with ensemble techniques	ARIMA Minute LSTM Hour LSTM Day LSTM	The ensemble of LSTM achieved the highest accuracy of 98.86 and the smallest RMSE of 31.60.
[7]	GRU	Predict Bitcoin prices in a most accurate and efficient ML model	Adjust gate in LSTM by resetting and updating the gate to use precious state data with current input data	Less complex structure than LSTM	Theil-Sen Regression, Huber Regression, LSTM	GRU had the best results: MSE = 0.00002 R-squared = 99.2% Huber regression had the least computation time. GRU was more efficient than LSTM neural network.

4.2. Research in MLP Neural Networks

Franco et al. [8] proposed the use of machine learning tools and available social media data to predict the price movement of the Bitcoin market. Their paper used Twitter and market data as input features to compare MLP neural networks with SVM and Random Forest (RF) models. Their MLP neural network used hyperbolic tangent activation functions to obtain the best optimization results. The research showed the prediction results of cryptocurrency prices using both machine learning and sentiment analysis. MLP neural network outperformed other models for the prediction of Bitcoin. The accuracy of the MLP model was 0.72, which was the highest among the three tested models. It also had a precision of 0.76, a recall value of 0.72, and an F1 score of 0.72. Among all four-evaluation metrics, the MLP model has been shown to outperform the SVM and the RF models.

In the same research paper that Jay et al. [4] derived the stochastic LSTM neural network, they also proposed a stochastic version of the MLP neural network. Therefore, the model pertains to the same stochasticity as mentioned for LSTM neural networks. The stochastic MLP neural network was also compared with the deterministic MLP based on MAPE, MAE, RSE, MAPE, MAE, RMSE, and MSE. The results showed that the stochastic MLP outperformed the deterministic MLP model, and the most significant improvement was also achieved by setting the perturbation factor as a learnable parameter. In this case, the MAPE of the stochastic MLP model was improved by 16.44% over the deterministic neural network in the unnormalized data set.

To understand how bitcoin characteristics, affect the next-day price level change of bitcoin, Sin et al. [9] utilized an artificial neural network (ANN) ensemble approach to construct a Genetic Algorithm-based Ensemble of Selective Neural Networks (GASEN). The ensemble was used to forecast the direction of the Bitcoin price's next-day change. The GASEN model used five MLPs of the same specification, but with different numbers of nodes in each layer, and it selectively chose small ANN ensembles with low generalization error and low computational cost. The model was trained with the Levenberg-Marquardt algorithm to improve speed and accuracy. This ensemble approach was able to predict Bitcoin prices with a stable accuracy of 58%-63%, with a back test accuracy rate of 64%. The GASEN approach was also tested against the single best MLP model in the set. The back test for the single model had an accuracy rate of 60%. Therefore, the ensemble MLP model had a higher back testing accuracy than the single model.

Table 2 below summarizes the MLP models discussed in this study.

TABLE 2. MLP MODEL SUMMARY

Article	Model	Functionality	Model Optimization	Model Advantages	Other Model(s)	Results
[8]	MLP	Prediction of Bitcoin price movement using social media data and market data	Hyperbolic tangent activation function	Use sentiment analysis with a machine learning approach to improve the precision	SVM RF	MLP achieved best performance Accuracy: 0.72 Precision: 0.76 Recall: 0.72 F1 score: 0.72
[4]	Stochastic MLP	Prediction of Bitcoin price using a stochastic process to capture markets' reaction to new knowledge	Choose the value of the perturbation factor that optimizes the error distribution	Address the problem of fluctuations in the prices of Bitcoin by proposing stochastic behavior in MLP to simulate market volatility	Deterministic MLP	MAPE improved by 16.44% over the deterministic neural network in the unnormalized data set.
[9]	GASEN	Understand how features of bitcoin affect the next day's change in the price level of Bitcoin	Trained with the Levenberg-Marquardt algorithm to improve speed and accuracy	Selectively choosing a smaller ANN ensemble with lower generalization error and computation cost	Single MLP	GASEN: a stable accuracy of 58%-63%, with a back test accuracy rate of 64% single MLP model: 60% back test accuracy.

4.3. Research in Support Vector Machines (SVM)

Valencia et al. [8] use available social media data like Twitter or market data to predict Bitcoin price movements. SVM technique is to construct a hyperplane and maximize the distance between the hyperplane and the training example. The SVM kernel use the Gaussian radial basis function to improve its accuracy. Valencia et al. [8] showed the accuracy was 0.55 with 0.31 precision, 0.56 Recall, and 0.40 F1 Score. The result is better than a random forest model using the same data but still needs to be improved by training more data.

Also, Colianni et al. [10] modeled the prediction using Twitter data. They also applied several machine learning algorithms, like naive Bayes, logistic regression, and SVM. From the results, SVM technology, with L1 norm soft margin, is easily used for text classification as well as sentiment analysis. The result, however, shows lower accuracy than the other models. It shows the accuracy of using the tweet as a feature vector is 83% and using sentiment as a feature vector is only 53.5%.

Other researchers use SVM by implementing more optimized algorithms like Particle Swarm Optimization. Hitam et al. [11] forecast the future bitcoin prices by an optimized Support Vector Machine based on Particle Swarm Optimization. The PSO can reduce the fitness of Mean square error to predict more accurate future prices. The result shows around 90% accuracy for the model, compared to the original SVM, it is much higher and shows good performance. Table 3 below summarizes the SVM models discussed in this study.

TABLE 3. SVM MODEL SUMMARY

Article	Model	Functionality	Model Optimization	Model Advantages	Other Model(s)	Results

[8]	SVM	Prediction of Bitcoin price movement using available social media data like Twitter and market data	Gaussian radial basis function	Randomly improve accuracy by market and twitter data.	Random Forests, MLP	SVM shows poorer performance than MLP. Accuracy: 0.55 Precision: 0.31 Recall: 0.56 F1 score: 0.40
[10]	SVM-L1 Norm Soft Margin formulation	Prediction of Bitcoin prices based on twitter sentiment analysis	L1 Norm Soft Margin Model	The model using L1 Norm Soft Margin is easier for sentiment analysis as it is trained with text classification or sentimental feature vectors	Logistic Regression, Naive Bayes	The model does not show higher accuracy than other models. Accuracy Using Tweet as Feature Vector:83%; Accuracy Using Sentiment as Feature Vector:53.5%
[11]	Optimized SVM-PSO model	Forecasting future bitcoin prices	Particle Swarm Optimization	The SVM with PSO reduce the fitness of Mean Square Error	SVM	The model shows higher accuracy than the original one. Accuracy: 90.4%

5. DISCUSSION

The review in the previous section has investigated various machine learning methods in Bitcoin price predictions. Most of the models implemented in previous studies tend to combine machine learning models with other methods or algorithms to exploit the predictability of these neural networks while optimizing the choice of structure or model parameters.

LSTM neural networks appeared to be the most popular models used in studying bitcoin price predictions. LSTM neural networks have better performance when forecasting based on data with longer time intervals, as they capture not only short-term but also long-term dependencies. They have also proven to be more resistant to price fluctuations, and therefore are particularly well suited for volatile financial products like Bitcoin. Considering multiple time windows, this approach may elicit a more comprehensive understanding of bitcoin price movements and has also proven to be suitable for more volatile financial products. In addition, the hyperparameter tuning process of LSTM includes the selection of input variables, which requires the researcher's knowledge and trial and error to determine the best choice of a set of input variables. Therefore, hybrid models using LSTM methods determine the best input variables using the time series graphical features of Bitcoin to build LSTM time series forecasting models without the trial-and-error process. Time-series methods alone are often used to predict price movements of financial products, but the statistical assumptions required make it impossible to predict bitcoin prices when the data is a non-stationary time series. Another variant of the LSTM method is GRU. Similar to LSTM models, GRU models can achieve high accuracy in predicting the bitcoin price. However, they are more efficient than LSTM models in terms of training and computation time because they have fewer tensor operations in their structural design. Another point worth noting is that whether GRU produces better prediction results than LSTM may depend on the choice of data used and the number of features included.

In addition to LSTM models, another type of widely used neural network model is the MLP-based model, and some studies have shown that MLP neural networks with sentiment analysis can be used to predict bitcoin prices with high accuracy. Recent research has shown that both LSTM and MLP models can be extended with stochastic and ensemble methods. The use of stochasticity with neural networks aims to observe the market's response to information and to form a pattern that exhibits the market behavior when new information is widely available. According to Brock et al, this pattern must be stochastic to accommodate the multiplicity of all possible outcomes when new knowledge arrives. The results show that the stochastic model is effective in deciphering market volatility and outperforms the deterministic version. The ensemble method is an aggregation of multiple LSTM or MLP models to make predictions. LSTM-based learning using longer time interval data facilitates the prediction of deterministic shifts in Bitcoin value over time, while LSTM-based learning using shorter time interval data is helpful in predicting more moderate shifts. Thus, the aggregated results of multiple single LSTM-based learning procedures can lead to more accurate predictions based on ensemble techniques. Similarly, an MLP-based GASEN (an ensemble approach) has been shown to be effective in producing smaller ensembles with low generalization error and computation cost.

The SVM classification models are also used for the cryptocurrency area. Most machine learning applications in predicting Bitcoin prices are based on sentiment analysis and market data. SVM becomes a popular choice for financial forecasting and stock market prediction. From examples for SVM, including those optimized SVM techniques, SVM is found to be resistant to over-fitting, and is more suitable to be used in high dimensional spaces effectively. This feature can be used for better text classifications and sentiment analysis. However, previous research also showed that text classification sometimes could limit SVM accuracy and cause small errors. For further improvement, there are ways to create sets of words that are highly correlated with cryptocurrency market movement and use them as the basis for training the model. By resources found in the research, an SVM is an efficient technique compared to other classification models for forecasting prices, though the original SVM models in general have less accuracy than optimized ones.

Last but not least, some of the models examined in this paper still have limitations. First, some models simply use the average daily price, rather than considering the effects of intra-day price fluctuations. In addition, most models made theoretical assumptions that the supply of bitcoin is infinite, and the volume of transaction tested will not affect the overall market. In the future, further research can be carried out in several directions. Some models like decision trees also perform well with high accuracies, but more data is needed for testing. Future work can concentrate on finding more optimized parameters for the models and increasing data amount to improve accuracy. Systematic feature selection or optimization could also be performed to find the most suitable subset of features for the best bitcoin price prediction accuracy, as irrelevant input features may introduce noise and reduce the accuracy of the predictions.

6. CONCLUSIONS

Overall, this paper presents a review of previous studies in Bitcoin price predictions using machine learning methods. The main focus is to compare various models based on LSTM, MLP, and SVM methods. Most of the models have shown to be effective in forecasting bitcoin price movement, and in general, have better accuracy than other models compared on a similar basis. The general applicability of each type of model were also discussed, along with certain models' limitations in their data sources and choice of optimization. Therefore, future works may be expected to focus on finding more effective methods to optimize parameters for the models and increasing the amount and type of data used in the process.

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