Forecasting Bitcoin Prices in the Context of the COVID-19 Pandemic Using Machine Learning Approaches

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Abstract. Using daily data from April 1st, 2016 to March 3rd, 2022, this study aims to explore the use and effectiveness of machine learning algorithms in forecasting the price of Bitcoin. The paper examines the forecasting performance based on different time lags within the selected periods: 1) Before Pandemic and 2) Including Pandemic. The second time frame is selected to examine the effect of the Covid pandemic on the Bitcoin market fluctuations. This research employs four machine learning models, including Linear Regression, Support Vector Regression, Extreme Gradient Boosting, and Long Short-Term Memory. These are refined and calibrated to produce the most accurate forecasts. The performance of the algorithms was measured and compared using regression metrics. The results show that before the pandemic, the linear regression model performed the best for next-day predictions, while Extreme Gradient Boosting performed best overall and for longer-term predictions. For the period including the pandemic, Extreme Gradient Boosting and linear regression performed the best, consistently outperforming Long Short-Term Memory and Support Vector Regression. The prediction models for data before the pandemic have demonstrated improved performance, whereas the selected model for the period including the pandemic exhibited satisfactory results. This is because bitcoin prices displayed the highest volatility during the Covid pandemic. The study finds that Extreme Gradient Boosting performs best overall and for longer-term predictions, while linear regression performs the best for next-day predictions before the pandemic. Moreover, the study reports satisfactory results for bitcoin price prediction for the period including the pandemic, despite the high volatility of prices.

Keywords: Cryptocurrency, Bitcoin Price, Time Series Forecasting, Machine Learning, Technical Indicators, Linear Regression, Support Vector Regression, Extreme Gradient Boosting, and Long Short-Term Memory

1 Introduction

Bitcoin, one of the most popular cryptocurrencies, was introduced by Satoshi Nakomoto in 2009 [1]. The principle of decentralisation is applied to cryptocurrency, while fiat currencies are based on central banking systems. Therefore, a cryptocurrency is not subjected to interference from a central banking authority. The global financial crisis in 2007-2008, known as the subprime mortgage crisis, followed by the eurozone debt crisis in 2011-2012 substantially increased people's distrust in their government and declined their faith in traditional financial institutions. As a result, Bitcoin with its promising and revolutionised features of a decentralised structure with no governmental and regulatory controls, was well received in the coming years [2]. Bitcoin and other

Cryptocurrencies are used in different ways, such as speculative trading assets, investment or simply as a payment method. Bitcoin, with its explicit speculative behaviour, is subjected to high volatility and bubbles [3]. The unusual price behaviour of Bitcoin has attracted many researchers to provide the most efficient models to predict the price.

Financial time series forecasting has been a subject of significant interest in economics, statistics, and computer science. A cryptocurrency is a digital currency that uses cryptography to make transactions securely [4]. All cryptocurrencies are traded across various exchanges 24/7, resulting in much volatility compared to traditional stock markets. The motivation behind predicting the price of Bitcoin using machine learning techniques was heavily inspired by increasingly better-performing ensemble algorithms and neural network architectures. Bitcoin recorded its all-time high in 2021 and experienced high fluctuations during the Covid pandemic attracting massive public attention. The high price volatility of bitcoin, especially during the pandemic, motivated this research to analyse the Bitcoin price behaviour before and during the Covid pandemic.

This study aims to examine the effectiveness of machine learning algorithms in forecasting Bitcoin prices before and during the COVID-19 pandemic. It uses a robust feature selection strategy to identify the most critical features for prediction and applies different machine learning algorithms to forecast Bitcoin prices. The models have been optimised and tuned to reflect the fluctuations as well. The paper considers forecasting performance on different lags within pre-selected periods. It evaluates the extent to which the prices of Bitcoin can be accurately predicted for the next day, 7th day, 15th day, and 30th day.

The rest of this paper is organised as follows. Section 2 discusses the literature review. The methodology and the machine learning models utilised in this paper are detailed in Section 3. Section 4 is devoted to the experimental result, and Section 5 concludes the paper.

2 Literature Review

The high volatility of Bitcoin price could be due to many factors from operating hours of the American, European, and Asian markets to different macroeconomic factors of the world economy, especially the leading economies. While regulatory implications and economic pressures led Bitcoin to be perceived differently in various countries, Bitcoin price volatility and its hedging capacity have been discussed in many studies, as Bitcoin-based portfolios can gain significant gains. Bitcoin has been considered a risk diversifier for the portfolio. In some cases, it proved to be the best hedge choice during financial crises helping the investor in the investment process [5].

Some studies suggested that Bitcoin should not be considered as a currency; they argued that due to Bitcoin's volatile price behaviour, it should be instead referred to as a speculative investment asset. Among the early studies on bitcoin price volatility, Mittal [6] found no fundamental explanation for Bitcoin's price movements and concluded that the primary determinant of Bitcoin price is the investors' speculation. Meanwhile, Buchholz et al. [7] argued that Bitcoin's price had bubble characteristics with no significant relation with other financial assets. He concluded that Bitcoin price movement was only derived from its own dynamics of supply and demand induced by the behaviour of speculative investors. Gronwald [8] examined if Bitcoin's price movements exhibited characteristics of commodities such as gold or oil and found that compared to the price fluctuation of traditional commodities, Bitcoin price was significantly more volatile.

As interest in Bitcoin grew during the initial years, some studies have used statistical and econometric model-based techniques to predict bitcoin prices [9]. Statistical model-based time-series forecasting is a method of estimating and predicting price values, but it has the drawback of requiring assumptions about the data distribution beforehand. Bitcoin prices are non-stationary, and this approach cannot be used to make accurate predictions as there are no seasonal effects with Bitcoin. Some studies recommended Autoregressive Integrated Moving Average (ARIMA) based model for predicting Bitcoin prices [10, 11]. Alahmari [12] used the ARIMA model to predict Bitcoin, Ripple and Ethereum based on daily, weekly, and monthly time horizons. Huang et al. [13] developed a classification tree-based model for predicting Bitcoin returns using 124 Technical indicators that indicate overlap, momentum, pattern etc. Their approach claimed that technical analysis of historical data could predict Bitcoin returns within narrow ranges as its value is believed to be driven by factors other than fundamental factors. The result could surpass the buy-and-hold strategy and significantly contribute to the newly emerging literature on technical analysis-based cryptocurrency price forecasting.

Machine learning can be referred to as an automated learning process from experience without the need for explicit programming. This motivated many researchers to study Bitcoin volatility and propose forecasting techniques using machine learning. Greaves and Au [14] applied linear regression, logistic regression, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) and achieved a 55% accuracy rate with ANN, outperforming the other models. They concluded that financial flow features from various exchanges would be an added advantage in predicting Bitcoin prices. Using only blockchain-based features for training and testing offers limited predictability. Madan et al. [15] addressed binary classification models like logistic regression and Random Forest. Results show that the Random Forest outperformed SVM as the former is not affected by high standard deviation and outliers within the data. The study by Radityo et al. [16] predicted next-day prices using the closing price of Bitcoin in USD. The research utilised four variations of Artificial Neural Network (Generic Algorithm NN, Backpropagation NN, Genetic Algorithm BPNN, and Neuroevolution of Augmenting Topologies) and compared the results based on Mean Absolute Percentage Error (MAPE) values and computational time complexity. Among the variants of ANN used, GABPNN showed the best results, whereas the performance of the genetic algorithm NN was unsatisfactory. The study by Yeh et al. [17] proposes an improved ensemble learning method for forecasting Bitcoin price movements. The method combines AdaBoost, Random Forest, and Extreme Gradient Boosting algorithms to enhance prediction accuracy. The authors evaluate the proposed method on real-world Bitcoin price data and compare it with other popular forecasting methods, including ARIMA and LSTM neural networks. The experimental results demonstrate that the proposed method outperforms other methods in accuracy and robustness. Authors in [18] present a hybrid deep learning framework for forecasting cryptocurrency prices, including Bitcoin. The framework combines CNN and LSTM to capture the complex temporal patterns of cryptocurrency price data. The experimental results show that the proposed framework achieves higher accuracy and lower error rates than other models. However, it is worth noting that these studies do not consider the pandemic period for Bitcoin price.

3 Methodology

A time series is a set of sequential data points for a specific successive time duration. It incorporates methods that relate time series with understanding the trend of data points within the time series or helps make predictions. This research concentrates on forecasting Bitcoin prices using multivariate time series and machine learning models, where the value of the target variable x at a future time point, *x^[t+s]=f(x[t],x[t-1],...,x[t-n]), with s>0*, represents the prediction horizon. The prediction forecast is evaluated for horizons of the next day, 7th day, 15th day, and 30th day. As shown in Figure 1, the implementation of a time-series-based forecasting method begins with creating a dataset. Then, machine learning models are trained for the specified prediction horizons. Technical indicators contributing to the bitcoin price have been scraped from open data sources.

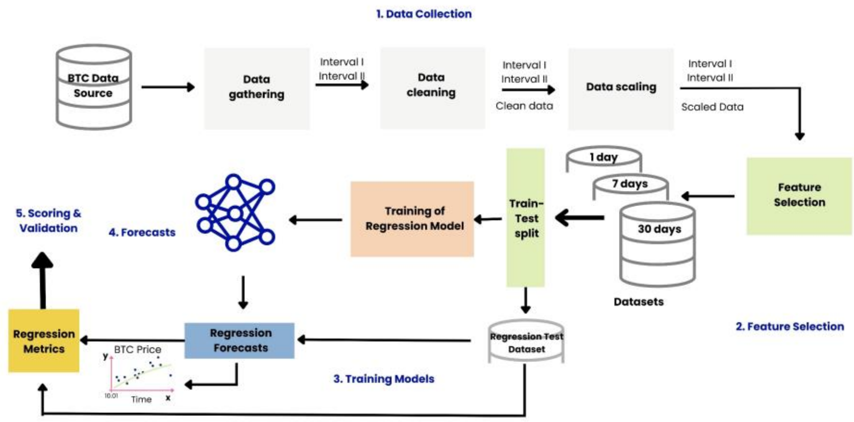

Fig. 1. Step-by-step model development

As a pre-processing step, the data is consolidated into a single data frame, cleaned, and scaled. The end-of-day close price is used to create datasets for the next day, 7th day, 15th day, and 30th day forecast for historical periods of data (i.e., from April 1st, 2016, to November 1st, 2019 and April 1st, 2016, to March 3rd, 2022). This results in four separate datasets for the two time periods specified. Feature extraction and feature selection are performed separately for each dataset. Over 900 derived features are created based on past time frames of 7 days, 30 days, and 90 days. Feature selection, which is a crucial step, is depicted in a figure and is performed to reduce the number of input variables, thereby reducing the dimensionality and computational complexity of the model. The top 10 features from each dataset are extracted using a Random Forest Regressor, followed by a training and testing split.

3.1 Data Collection

We have collected daily historical data from Yahoo Finance API (OHLC feature), blockchain-based features from Bitinfocharts [19], and Quandl [20] through web scraping techniques. We have 23 features excluding Date and Target variables. Table 1 represents the features that have been gathered.

Table 1. Features collected using Web Scraping.

Number of transactions per day in blockchain	Block Size	Miner Revenue
Number of sent by addresses	Number of active addresses	Open Price
Average mining difficulty	Average hash rate	Low Price
Average & Median Transaction fee	Average Block time	Volume
Mining Profitability	Sent coins	High price
Average and median transaction value	Tweets & Google trends per day	Number of coins in circulation
Average fee percentage in total block reward	Top 100 richest addresses to total coins	Close Price
Market Cap	Confirmation Time	

3.2 Feature Engineering Using Technical Indicators

The dataset was enriched with newly generated features based on technical indicators and lagged for 7, 30, and 90 days. These technical indicators added to the dataset by providing information that could not be obtained from the existing features. For instance, these new features addressed the need for more information regarding properties like variance and standard deviation, which were calculated from the raw features. This calculation allowed us to observe the relationship between prices and the standard deviation of hash rate for past 7, 30, and 90-day intervals rather than just the raw features. Table 2 represents the features extracted based on Technical Indicators.

Table 2. Extracted Features based on Technical Indicators.

Simple Moving Average	Weighted Moving Average
Exponential Moving Average	Double Exponential Moving Average
Triple Exponential Moving Average	Standard Deviation
Relative Strength Index	Rate of Change
Bollinger Bands	Moving Average Convergence Divergence

3.3 Feature Selection

When dealing with large datasets with many features, it can increase the complexity and time of computing an algorithm. The feature selection process can help identify which features have a more significant impact on the outcome by analysing the contribution of each feature, and reducing the dimensionality of the dataset, all the while retaining or improving the accuracy scores. A random forest regressor selects the top 10 features from the entire dataset. When working with extensive datasets that possess numerous features, the computational time and complexity of an algorithm can increase significantly. To address this issue, the feature selection process can be employed to identify the most impactful features by evaluating each feature's contribution. This process reduces the dataset's dimensionality while preserving or enhancing the accuracy scores. Therefore, we have applied the Random Forest Regressor method to identify the top 10 features represented in Table 3.

Table 3. Most frequently selected features across all horizons.

Features	Next Day	7	15	30
WMA 30 Number of coins in circulations	*	*	*	*
SMA 13 High	*	*	*	
EMA 90 Low	*		*	*
EMA 7 Number of coins in circulations		*	*	*
Close	*	*		
High	*	*		
WMA 7 Close	*	*		
EMA 7 Open	*	*		
DEMA 30 Close	*			*
DEMA 7 Market Cap	*	*		
EMA 30 Close			*	*

To determine relevant features for this study, we have identified new features using technical analysis and feature selection algorithms. Feature engineering revealed the extent to which features directly related to the blockchain impacted the price of bitcoin. For example, Miner revenue, which involves transaction fees and rewards, is correlated with the Bitcoin price. Similarly, Block size and the creation of new blocks also correlate with the number of transactions. More number of bitcoin transactions correlates with bitcoin price. More processing power in mining coins is the result of high difficulty, which is highly correlated with the hash rate.

3.4 Training and Testing

After the feature selection process, the next step is to allocate a portion of the data as the training set and another portion as the testing set. Due to the non-stationary nature of cryptocurrency prices, there is a conundrum of using too much or too little data for training. While the former makes the model irrelevant, the latter makes it prone to overfitting the model. This problem is usually solved by using the ideal ratio of 80% training data and 20% testing data based on the Pareto principle. However, we observed overfitting in the results obtained through time series split cross-validation. Therefore, we employed a sliding window approach which uses 10 consecutive data points to predict the 11th and 12th data points within the same sequence, as supported by previous research [21]. Essentially, the prediction of the next two days will be based on data from the preceding ten days, with the final metric being the average of the metrics computed for each split.

3.5 Machine Learning Algorithms

Four machine learning models have been implemented in this work including (1) Liniear Regression with Gradient Descent (LR), (2) Support Vector Regression (SVR), (3) Extreme Gradient Boosting (XGBoost), and (4) Long Short-Term Memory (LSTM). Table 4 shows a summary of the parameters chosen for each model. For all four models, all possible combinations of the hyperparameters were investigated during the hyperparameter tuning process and the combinations presented in table 4 produced the best results.

Table 4. Hyperparameter tuning for each model.

Model	Parameters	Value
LR	Loss function	squared_epsilon_insensitive
	Penalty	elasticnet
	Shuffle	True
	L1_ratio	0.15
	Epsilon	0.01
	Learning rate	adaptive
	Max_inter	1000
SVR	Kernel	Radial basis function
	c	1000
	gamma	auto
XGBoost	n_estimators	500
	max_depth	3
	learning_rate	0.01
	n_jobs	-1
LSTM	Monitor	root_mean_squared_error
	Verbose	1
	Mode	min
	Patience	3

For the LSTM model, a bidirectional layer of 500 cells was used followed by a dropout of 25% which is intern fed to another bidirectional layer of 600 cells, followed by dropout of 30%. In order to update network weights during training an optimizer algorithm was used. Adam optimizer is suitable for non-convex optimization problems with benefits like little memory requirements, efficient with noisy gradients and computationally efficient. Hence, Adam optimizer was adopted.

4 Experimental Results

The performance outcomes of the forecasting models are outlined in this section. We have developed all the steps explained in Section 3 using Python on the Google Colab platform. Two case studies have been conducted based on the following time frames:

- *Period 1: Before Pandemic (April 1st, 2016 to November 1st, 2019)*
- *Period 2: Including Pandemic (April 1st, 2016 to March 3rd, 2022)*

The models are evaluated using three metrics which are Root-Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). When evaluating models, it is ideal to have low values for the MAPE, RMSE, and MAE metrics. For instance, in the case of Bitcoin price prediction, a model with inconsistent values may result in a higher RMSE value, but it could still have lower MAPE or MAE values. Hence, it is crucial to assess the models using all three measures.

4.1 Period 1: Before Pandemic (April 1st, 2016 to November 1st, 2019)

In the second period, we examine forecasting bitcoin prices before the pandemic. Table 4 presents the outcomes of the machine learning models for the different time frames.

Table 4. Comparing Model Accuracy Across Time Frames.

Test metrics: 01 April 2016 – 01 November 2019				
Next Day				
	LR	SVR	XGBoost	LSTM
RMSE	261.6396	363.0427	288.9283	373.1148
MAE	244.5862	349.7400	272.1291	359.8107
MAPE	0.8746	5.9647	0.8746	0.8746
7th Day				
	LR	SVR	XGBoost	LSTM
RMSE	407.1737	389.4182	316.0947	399.7969
MAE	392.4431	376.1204	297.5931	386.8093
MAPE	1.4965	6.2503	1.4965	6.3994
15th Day				
	LR	SVR	XGBoost	LSTM
RMSE	398.0850	387.2883	326.3839	406.8071
MAE	383.5820	374.2908	309.8014	394.1188
MAPE	4.2807	6.1359	4.2807	6.6521
30th Day				
	LR	SVR	XGBoost	LSTM
RMSE	386.2755	389.6317	277.8465	423.1300
MAE	372.3106	374.5799	259.9288	408.9162
MAPE	0.8412	6.1730	0.8412	6.7438

During this period, Bitcoin prices displayed minimal fluctuation but saw a significant increase in early 2017, maintaining a stable trend for the remainder of the interval. Among the models for next-day predictions, LR achieved the lowest RMSE of 261.6396, followed by XGBoost, SVR, and LSTM. LR also had the best MAE of 244.5862, followed by XGBoost, SVR, and LSTM. In terms of MAPE, LR, XGBoost, and LSTM recorded 0.8746, with SVR coming in at 5.9647. Therefore, the LR model is the best performer among the four models mentioned (LR, XGBoost, SVR, and LSTM).

For the 7-day prediction, XGBoost showed the best performance, with the lowest RMSE of 316.0947, followed by SVR, LSTM, and LR. XGBoost also had the best MAE of 297.5931, followed by SVR, LSTM, and LR. In terms of MAPE, LR and XGBoost performed best with a value of 1.4965, followed by SVR and LSTM. For the 15-day prediction, XGBoost showed the best performance with an RMSE of 326.3839, followed by SVR, LR, and LSTM. XGBoost also had the best MAE of 309.8014, followed by SVR at 374.2908, LR at 383.5820, and LSTM at 394.1188. In terms of MAPE, LR and XGBoost performed best with a value of 4.2807, followed by SVR and LSTM. For the 30-day prediction, the best RMSE was achieved by the XGBoost model with a value of 277.8465, followed by LR, SVR, and LSTM. XGBoost also had the best MAE of 259.9288, followed by LR at 372.3106, SVR, and LSTM.

The results show that the LR model performs the best for next-day predictions with the lowest RMSE and MAE values. For the 7-day prediction, XGBoost outperforms the other models with the lowest RMSE and MAE values. Similarly, for the 15-day and 30-day predictions, XGBoost performs the best with the lowest RMSE and MAE values. For all prediction periods, LR and XGBoost also performed well in terms of MAPE values. In conclusion, the XGBoost model performs the best overall, while the LR model performs well for next-day predictions. Figure 2 presents a graph contrasting the actual and predicted data for the 15-day forecast utilising the XGBoost model.

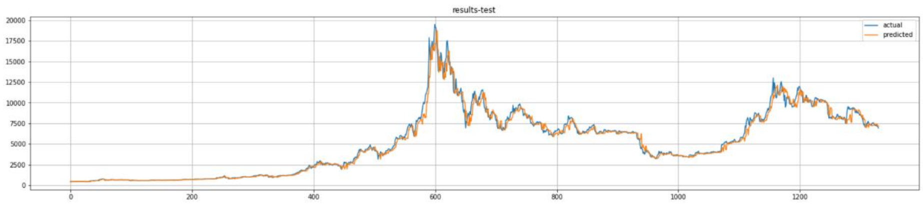

Fig. 2. Comparison of Actual vs Predicted Data for 15- Day Prediction using XGBoost Model.

4.2 Period 2: Including Pandemic (April 1st, 2016 to March 3rd, 2022)

In the second period, we examine forecasting bitcoin prices for the period that included the pandemic, characterised by an unusual level of volatility. This constitutes the core contribution of this research. Table 5 displays the results of the machine learning models for various time frames in this period.

Table 5. Comparing Model Accuracy Across Time Frames.

Test metrics: 01 April 2016 – 01 November 2019				
Next Day				
	LR	SVR	XGBoost	LSTM
RMSE	773.8296	981.2988	723.9742	890.0664
MAE	739.1618	952.5082	682.4402	859.1364
MAPE	0.3862	6.3134	0.3862	5.8114
7th Day				
	LR	SVR	XGBoost	LSTM
RMSE	989.5905	998.1517	734.0597	993.7988
MAE	958.2842	969.1428	691.8397	963.8020
MAPE	4.0497	6.362	4.0497	6.3729
15th Day				
	LR	SVR	XGBoost	LSTM
RMSE	976.8267	1008.8316	686.5598	1002.8917
MAE	944.8389	979.7016	648.2302	973.0593
MAPE	6.2047	6.3711	6.2047	6.4255
30th Day				
	LR	SVR	XGBoost	LSTM
RMSE	1007.7876	1029.7602	678.8905	1038.7840
MAE	966.5514	989.2436	633.0426	997.3399
MAPE	0.6291	6.3763	0.6291	6.5032

The results of the Next day prediction show that XGBoost achieved the lowest RMSE of 723.9742, followed by LR at 773.8296, LSTM at 890.0664, and SVR at 981.2988. XGBoost also had the best MAE of 682.4402, with LR, LSTM, and SVR following. LR and XGBoost had the best MAPE of 0.3862, while LSTM and SVR followed.

For the 7th day prediction, XGBoost had the lowest RMSE of 734.0597, followed by LR, LSTM, and SVR. XGBoost also reported the best MAE of 691.8397, followed by LR, LSTM, and SVR. LR and XGBoost had the best MAPE of 4.0497, followed by SVR and LSTM. For the 15-day prediction, XGBoost had the lowest RMSE of 686.5598, followed by LR, LSTM, and SVR. XGBoost also had the best MAE of 648.2302, followed by LR, LSTM, and SVR. LR and XGBoost had the best MAPE of 6.2047, followed by SVR and LSTM. For the 30-day prediction, XGBoost had the lowest RMSE of 678.8905, followed by LR, LSTM, and SVR. XGBoost also had the best MAE of 633.0426, followed by LR, SVR, and LSTM. LR and XGBoost had the best MAPE of 0.6291, while SVR and LSTM followed.

The results show that XGBoost outperformed the other models in all time frames regarding RMSE, MAE, and MAPE. LR also performed well, consistently achieving the second-best results. LSTM and SVR showed lower performance compared to XGBoost and LR. Overall, XGBoost and LR demonstrated the best results in predicting future outcomes based on the given dataset. The graph in Figure 2 compares the actual and predicted data using the XGBoost model for the period that includes the pandemic.

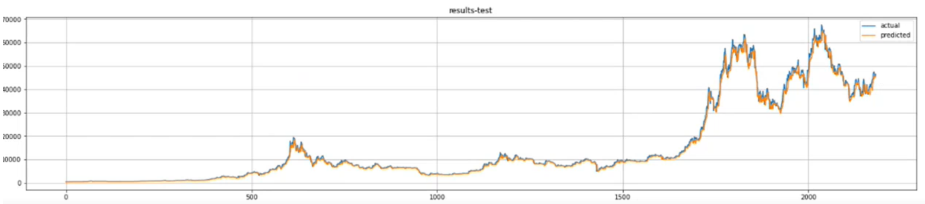

Fig. 2. Comparison of Actual vs Predicted Data using XGBoost Model for the period covering pandemic.

The four machine learning models (SVR, XGBoost, LR, and LSTM) used in the study differ in their underlying principles and have varying strengths and weaknesses. Regarding speed, SVR was the quickest at 3 seconds, followed by Linear Regression at 10 seconds, XGBoost at 90 seconds, and LSTM at 90 minutes for predicting next-day bitcoin prices in the second period. As LSTM had the longest runtime, the other models are recommended for their time-saving advantages.

5 Conclusion and Future Work

This study assessed the performance of four machine learning models, Linear Regression, Support Vector Regression, XGBoost, and LSTM, in predicting bitcoin price volatility during the COVID-19 pandemic using technical features and indicators. The results show that the models performed better before the pandemic compared to during the pandemic with high volatility. Despite this, the study still reports satisfactory results for bitcoin price prediction during the pandemic. The authors suggest that this remains a challenge for future studies.

The study employed a robust feature selection strategy to determine the most critical features. The random forest regressor recommended features for all defined horizons, which have been partially related to specified periods. For example, the number of coins in circulation has been selected for all horizons, while the close price has been only selected for the next day and 7th day horizons and not for the 15th and 30th day horizons. The study shows a satisfactory prediction of bitcoin prices over the selected horizons. The results showed that the accuracy of predictions for the next day, 15th day and 30th day was superior to that for the 7th day horizon in the second dataset. The reason could not be established as bitcoin prices are stochastic. The limitations of this study could include the following:

- The study only examines the period of April 1st, 2016 to March 3rd, 2022, and may not capture the full range of Bitcoin price fluctuations over a longer period.
- The study only focuses on four machine learning models, and other models may better predict Bitcoin price fluctuations.
- The study only uses technical features and indicators, and additional factors such as global economic conditions and regulatory changes may affect Bitcoin prices.

Future work could involve exploring other machine learning models or incorporating additional features to improve the performance of the models. Additionally, the study could be extended to other cryptocurrencies and compare the results with those obtained for bitcoin.

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