CHAPTER 4

ESTIMATION OF BITCOIN PRICE USING LONG SHORT-TERM MEMORY (LSTM) BY FEATURE SELECTION WITH GENETIC ALGORITHM

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ABSTRACT

Bitcoin (BTC) is a well-known cryptocurrency traded in financial markets based on blockchain technology. In recent years, bitcoin draws more attention than other financial investment instruments due to its capabilities of 24-hour trading, high volatility, and high profit potential with the price of high risk. The aim of the study is to estimate bitcoin price using 26 variables which consists of blockchain information, macroeconomic factors and global currency ratio variables such as average block size, cost per transaction, hash rate, gold futures, USD/EUR. Classical methods for estimation may not be appropriate when there are multicollinearity between variables and their level of stationary is not in the same order. Thus, LSTM will be used instead of classical methods for estimation which doesn't effected above mentioned restrictions.

Three machine learning based regression models are developed for estimating bitcoin prices for the 1 day, 7 days and 30 days ahead. The time series dataset to be used in the study is from 7/19/2010 to 7/19/2022. First of all, genetic algorithm is used to select relevant variables that affects bitcoin prices for the 1st, 7th and 30th days, respectively. For each set of variables, datasets are chronologically divided into training, and test data. Afterward, the bitcoin price is estimated by using the selected variables with LSTM. The performance of the models are assessed with R square, MAE, and RMSE metrics to compare the performance of Bitcoin estimation models.

Among constructed models one day ahead model has the highest R2 (0.98), and lowest RMSE (8204.57) and MAE (6341.62). As the estimation period gets longer R2 tends to get lower (0.96 for seven days ahead and 0.90 for thirty days ahead), RMSE and MAE tend to get higher. This is because it becomes harder to make estimation for further in time as uncertainty gets higher. Also in the case of Bitcoin, prices increased suddenly in the test data set which makes it difficult for the models to catch it when the time interval increased. This sudden increase in the Bitcoin prices also resulted the LSTM model estimation to be lower than the actual values.

In conclusion, it is stated that the bitcoin price using LSTM for the 1^{st}, 7^{th}, and 30^{th} days are estimated with low error and models can detect the changes in bitcoin price adequately.

Keywords: Bitcoin, Genetic Algorithm, Long Short-Term Memory, Feature Selection, Price Estimation

1. Introduction

The ownership and movements of money have been transferred to the electronic environment through financial institutions and banks by the integration of advanced digital technologies into financial markets. Transactions such as money transfers, commercial transactions, and payments have also been transferred to the digital environment and become faster and more reliable. Blockchain technologies and cryptocurrencies have emerged from these advanced technological developments. Blockchain technology, which constitutes the software architecture of cryptocurrencies, plays an essential role in the new monetary regulation that emerges due to the decreasing use of paper money day by day with the expenditures being made largely through digital currencies and digital platforms.

Developments in blockchain technology have led to a reshaping of the procedures, especially in the execution of traditional financial assets and transactions between parties. Blockchain is expressed as a distributed ledger that allows transactions between parties to be completed. In other words, it is a system that has encryption methods, enables the tracking of encrypted transactions, has high-security features, and keeps a record of all money exchanges. All parties on the blockchain network can view and share the transaction data that is collectively stored by this technology. Therefore, the use of Blockchain not only facilitates the execution of transactions but also reduces fraud by providing information transfer and transparency. This technology, which is also effective in domestic and foreign trade, allows for the automating and digitizing of trade finance procedures at the international level, making it easier to finance the supply chain. However, the efficiency of international trade can be increased with Blockchain technology and smart contracts. This increase can be achieved by reducing transaction costs, increasing the security of international payments, utilizing digital currencies and peer-to-peer cross-border payments, and creating unified ownership of commercial records and border procedures. Sonderegger (2015) argues that reductions in transaction costs at the local level will encourage the development of small businesses by encouraging low-value transactions and fostering access to financial services in countries where financial services are underdeveloped (J. Wang & Ngene, 2020).

Bitcoin, one of the most well-known blockchain applications and cryptocurrencies, was first introduced in 2008 by Satoshi Nakamoto. In a study published by Nakamoto in 2008 “Bitcoin: A Peer-to-Peer Electronic Cash System”, Bitcoin was defined as a digital currency and it was stated that money transfers between financial institutions and individuals could be made over the internet with this digital currency (Nakamoto, 2008). Bitcoin is a digital

currency that is not dependent on any central authority and can be transferred directly over the internet network without the need for intermediaries such as end-to-end banks. The most important feature is that it does not require a third party such as the state or central bank and can be exchanged directly between the buyer and seller in a digital environment. It also provides the owner with advantages such as financial independence, secure and confidential of transaction information, high transaction speed, elimination of intermediaries, and minimization of expenses such as protection from inflationary effects, taxes, bank expenses, and low transaction costs. In addition to these advantages, in general, cryptocurrencies such as Bitcoin do not dependent on any central authority such as a government or institution, which leads to the absence of the need for an intermediary and causes the transaction costs to be lower than the alternatives (Alpago, 2018). Moreover, cryptocurrencies such as Bitcoin, which can be worth millions of dollars, can be stored on a very small memory card for ease of transportation. In traditional online transactions using payment systems such as PayPal or credit cards, the seller needs to use third-party services when the buyer needs to return the money. In cryptocurrency systems such as Bitcoin, security problem doesn't occur because such a thing as a refund is not to happen. From the buyer's point of view, since cryptocurrency technology such as Bitcoin has a peer-to-peer (P2P) system, in other words, it works directly between peers without any intermediary, transactions such as money transfers and payments between accounts can be carried out faster, more reliable, and cheaper (Özkul & Bas, 2020).

In addition to these advantages, there are also disadvantages such as high volatility, hacking, and high electricity consumption. The fact that cryptocurrencies such as Bitcoin are not under the control, supervision, and dominance of any central authority may lead to illegal transactions such as money laundering and etc. For example, since the sender and receiver information are kept confidential in the transfer of these funds, it may pave the way for illegal transactions such as arms trafficking, drugs, money laundering, and financing terrorist organizations to take place through this system. The vulnerability of cryptocurrencies can be high due to sudden increases and decreases in price during the buying and selling process. Furthermore, although the use of cryptocurrencies such as Bitcoin does not have an inflationary effect, it can have a deflationary effect as the supply level of these currencies is predetermined (Carkacioglu, 2016). Therefore, a lack of supply in case of an increase in demand can cause prices to fall.

Bitcoin, which has a digital and distinctive structure, differs from other currencies. However, the digital nature of Bitcoin and other cryptocurrencies also brings some risks. These risks include market and transaction risks, regulatory and legal risks, operational risks,

the problem of a shallow market, privacy-related risks, and counterparty risks (Böhme et al., 2015). These risks significantly affect the volatility of Bitcoin by causing increases and decreases in the price. Therefore, the increased risk in the Bitcoin market also increases uncertainty. Estimating this uncertainty with various methods provides important information to investors who invest in cryptocurrencies such as Bitcoin, which offers high returns. Therefore, finding the optimal forecasting method to estimate Bitcoin volatility and return is of great importance for investors who invest in cryptocurrencies such as Bitcoin. Investors have increasingly embraced cryptocurrencies such as Bitcoin to protect themselves against global risk and uncertainty and to diversify their portfolio risk (Bouri et al., 2017).

Bitcoin has attracted worldwide attention since the day it was introduced, and cryptocurrencies such as Bitcoin have developed rapidly in recent years and new cryptocurrencies have emerged. However, Bitcoin has attracted and continues to attract more attention than other cryptocurrencies. It has also stood out among other cryptocurrencies in terms of market size, number of users, and acceptance as a payment tool. The Bitcoin market and its prices have expanded significantly, despite being as low as just a few USD cents in its early years (2009-2010) and having been very volatile since 2009. Bitcoin prices, which showed extreme volatility between 2013-2019, increased by almost 1900 percent in 2017 but lost almost 72 percent in 2018. Bitcoin prices have shown extraordinary fluctuations and have been shown to regain their value even in the period of crisis or high uncertainty after these drops (Mudassir et al., 2020). Although there has been a downturn in the value of digital assets, the total market capitalization of cryptocurrencies is still high at around USD 835 billion by the end of 2022, down 62% from around USD 2.2 trillion by the end of 2021 (Coinbase Institutional, 2023). Although Bitcoin also continued to fluctuate in 2021 and started the year with a low of 29,359, there were periods of peaks, reaching a high of 67,527 within the year (*Bitcoin Historical Data*, 2023). Especially during this period, investor interest in Bitcoin has increased even more. Investors, asset management experts, news media, financial analysts, policymakers, and academicians have also increased their interest in Bitcoin and other cryptocurrencies, and numerous studies on the subject have taken part in academic research and reports. 2023 started relatively strong, reaching a total market capitalization of $1.2 trillion in the first quarter of the year. As of July 2023, it is seen to be approximately 31,000. Compared to 2022, it can be said that it has achieved a recovery of 48.9% (406 billion dollars) in absolute terms, considering that it completed this year with 829 billion dollars (CoinGecko, 2023).

Bitcoin was the best-performing asset among other cryptocurrencies in the first quarter of

2023, up 72.4%. Bitcoin was followed by the NASDAQ index and gold by 15.7% and 8.4% respectively. All major asset classes, with the exception of crude oil, which fell by around 6.1%, completed the first quarter of the year with an increase. Crude oil initially fell as low as 17.2% due to the US banking crisis and the decline in oil demand as stated in the US inflation report, but recovered towards the end of March (CoinGecko, 2023) According to Coinmarketcap, as of June 2023, the value of the global crypto market reached $1.21 trillion and the total crypto market volume reached $27.4 billion. Among cryptocurrencies, Bitcoin continues to dominate with 49.61% (*CoinMarketCap*, 2023a).

Cryptocurrencies such as Bitcoin, which have started to be accepted as legal assets, have also started to be used in transactions such as futures, investments, and money transfers in some major stock exchanges. In 2017, Bitcoin futures were officially listed and traded on the Chicago Mercantile Exchange (CME). In 2020, Federal Reserve Chairman Powell acknowledged that Central Bank Digital Currencies could have an improving impact on US payment systems. In the same year, the Swiss Financial Markets Supervisory Authority authorized InCore to develop, transfer and store digital assets, making it the third digitally enabled bank in the world (Luo et al., 2022). The demand for cryptocurrencies causes these currencies to function as an alternative currency.

The Covid-19 pandemic not only caused disruptions in macro and microeconomic balances but also led to greater uncertainty and volatility in non-economic variables. This crisis, which caused the economic conditions all over the world, also had an impact on financial markets. While concerns about how to mitigate the financial risks that increased with the pandemic continued, new problems emerged during and after the pandemic. For example, monetary policy factors and serious problems in the supply chain, increasing inflation and interest rates, policy uncertainties in economies, and market volatility have revealed the importance of variables that characterize the business cycle and have a significant impact on asset prices in estimating Bitcoin prices (Basher & Sadorsky, 2022; Chevallier, 2020). During this period, unpredictable and sudden changes occurred in Bitcoin prices, and significant decreases were experienced in the US, European, and Asian stock markets. Nevertheless, there has been an increase in public demand for crypto assets as a hedge against high inflation due to the large amounts of liquidity created by the pandemic, and many of the cryptocurrencies have generated high returns and significant increases in trading volumes in the process (Park & Yang, 2023).

Most asset prices, which generally move cyclically, increase when inflation is consistent, stock market volatility is low and interest rates are low. In risk diversification and hedging,

counter-cyclical assets can be beneficial. If the crypto asset prices such as Bitcoin are affected by the business cycle conditions, the variables in the business cycle appear as important determinants. Conversely, if the prices of these assets are not affected by business cycle conditions, the variables in the business cycle are not significant determinants. In addition, models and forecasts should be updated according to whether the importance of these variables changes over time. If not updated, the accuracy of forecasts is questionable and wrong investment decisions may be made. Moreover, it is important to know which macroeconomic variables are more important when estimating the prices of crypto assets such as Bitcoin. For instance, can the price estimation of a variable like gold and an asset like Bitcoin be compared in the same model over a common time period? For example, are the macroeconomic variables important in estimating the Bitcoin price the same as the macroeconomic variables in estimating the gold price? If they are the same, similar portfolio diversification can be done for Bitcoin as for gold. In this case, gold and Bitcoin could be interchangeable (Basher & Sadorsky, 2022).

The theoretical basis for the predictability of price direction stems from behavioral finance Behavioral finance, based on investment psychology and arbitrage limits, states that true arbitrage is not possible in an investment situation where profits after costs are earned with zero risk. In investor psychology, it is known that not all investors act rationally at all times. This can lead to behavioral bias when market prices differ from fundamental values. Behavioral bias and arbitrage limits can lead to inaccurate pricing of assets that can be determined in the price direction (Basher & Sadorsky, 2022). The importance of forecasts for predictable price direction may be due to the importance of market timing. Fund managers and investors are more concerned with signs than actual values in determining how to allocate assets (Pesaran & Timmermann, 2002).

The Bitcoin market has a much higher volatility than other asset markets such as gold, stocks, etc (Baur et al., 2018). The Bitcoin market, which offers high risk and return, is also characterized by frequent and sharp declines. In order to cope with the high uncertainty and volatility in the Bitcoin currency market, many inputs are needed, such as financial variables as well as macro-level variables. Since the Bitcoin market also has regulatory deficiencies compared to financial assets, heterogeneous inefficiencies can be observed in this market. Since these uncertainties also lead to high volatility in the Bitcoin market, forecasting techniques alone are not sufficient. For instance, following a bull market surge in 2017, Bitcoin prices peaked in December 2017, but collapse in the following year with an eighty percent loss (Park & Yang, 2023).

The financial crisis that had an impact on the world financial system, had also an impact on the cryptocurrency market and therefore on Bitcoin prices. Global financial markets struggling with inflation, which can lead to recession, pose a risk to all investment instruments, including cryptocurrencies. Under these circumstances, it is difficult to estimate how the cryptocurrency market will evolve (CoinMarketCap, 2023b). Estimating the prices of crypto assets like Bitcoin is important to make the right decisions regarding the market trends of these assets. Accurate estimations of crypto asset prices will support investors and policymakers in making the right decisions and establishing regulatory policies by providing support in terms of portfolio and risk management. Although there are many studies in the literature that estimate the prices of crypto-assets such as Bitcoin with a wide variety of methods, there are also several important gaps in the literature that lead to research questions. For example, how important are macroeconomic variables such as inflation, interest rates, and market volatility when estimating the price of crypto-assets such as Bitcoin? Which methods give more accurate results? In this context, methods such as deep learning (DL), machine learning, support vector machines (SVM), artificial neural networks (ANN), Long Short-Term Memory (LSTM) have been used for risk management, quantitative investment, financial areas, and price estimations of cryptocurrencies in both academic literature and reports of a number of organizations.

The aim of this study is to estimate the bitcoin prices by using blockchain information variables, macroeconomic factors and currency rates. First of all, Genetic Algorithm (GA) is used to select the most important factors that effects bitcoin prices for 1 day, 7 days and 30 days ahead models. LSTM models are constructed by using the selected variables for each time periods. The conventional methods don't perform well to estimate Bitcoin prices because of the vast increase in the prices from 2010 to 2022. On the other hand, LSTM is a flexible method, which can be efficiently use to estimate Bitcoin prices.

2. Literature Review

Bitcoin has come into prominence among other cryptocurrencies, with its market size, the number of users, and beginning to be accepted as a means of payment. The fact that it has added value by expanding its transaction volume since 2009 has caused it to be the subject of many studies in the literature. These studies generally focus on estimating Bitcoin prices by using various methods. A number of studies have investigated whether Bitcoin prices are forecastable by using Bitcoin-related technical indicators. The results of these studies generally showed a significant return predictability existence. Moreover, the other studies analyzed the end-of-day price forecast and price increase/decrease forecasting by applying

various machine learning-related methods. Some of the studies in the literature also considered social media attention. The results of these studies demonstrated that for instance, the number of Tweets can affect Bitcoin trading volume for the day after. Some studies examined the influence of users' comments on online platforms on price fluctuations and the number of transactions of cryptocurrencies. These studies, found that Bitcoin especially correlated with the number of positive comments on social media.

McNally et al. (2018), investigated what accuracy the Bitcoin price can be forecasting applying the machine learning methods and they made a comparison of the parallelization methods implemented in multi-core and GPU environments. They used a Bayesian-optimized recurrent neural network (RNN) and a Long Short Term Memory (LSTM) network. They found that while LSTM acquires 52% accuracy, RMSE achieves 8% and the nonlinear deep learning methods outperform the poorly performing ARIMA estimation.

Mudassir et al. (2020), predicted movements of Bitcoin prices in medium and short terms in their study. They used high-performance machine learning-based classification and regression models and focus on the time series forecast of Bitcoin prices. While machine learning-based classification was used for only a one-day time frame in the previous works, they used a one, seven, thirty, and ninety days time frame. In accordance with their results, although, it is harder to estimate the Bitcoin price rise and fall, the actual Bitcoin price could be estimated with very low error rates. Moreover, the results of their findings indicated that the presented models in daily closing price forecasts and price increase-decrease estimation outperform the existing models in the literature.

Mehta and Sasikala (2020) used Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) and Random Forest algorithm to forecast Bitcoin prices. They compared the accuracy of the two models for the indicated best-choice algorithm used for Bitcoin price estimation. Their results showed that while Random Forest gave an accuracy of 84%, the Long Short-Term Memory (LSTM) RNN gave an accuracy of an outstanding 92%. Thus, they offered the best choice algorithm used for forecasting Bitcoin price.

Lei and Lin (2022) proposed an LSTM-based estimation model. They analyzed the Bitcoin and gold price estimations depending on the LSTM model. According to the results of the simulation, they stated that the model could successfully forecast the trend of the future price of gold and Bitcoin within the admissible error range, which aids in improving portfolio optimization. Additionally, they indicated that the loss function chosen to describe the accuracy of the estimation model is the Root Mean Square Error (RMSE).

Rathore et al. (2022) aimed to employ the Fbprophet model as the main model because it performs better than LSTM and ARIMA while also avoiding the pitfalls that arise from those models when examining cryptocurrency data. They offered an approach for forecasting Bitcoin's future price that does not only rely on past data by the reason of seasonal effects in historical data. They emphasized that even when seasonal data was available, the overall gap between actual values and estimated is lower by comparison to other models. They also remarked that applying the FBprophet Model when the data is stationary, smooth, and consistent can improve the outcomes.

Wardak and Rasheed (2022) estimated the Bitcoin price by considering several factors that effecting its value as accurately as possible by applying the Recurrent Neural Network (LSTM). The data they used in their study includes daily records updates on numerous facets of the price of Bitcoin across a five-year span. Given how volatile Bitcoin data is, they applied an efficient pre-processing method to possess better results of estimations. Hereby, they achieved a 95.7 accuracy and a 0.05 RMSE. On the basis of accuracy and performance, they also contrast their study with other existing methodologies. As a result of the comparison, they indicated that one of the most effective methods for estimating cryptocurrency prices is to use LSTM with sufficient hyperparameter tuning.

Zhang et al. (2022) applied an LSTM-P neural network model to estimate the prices of Bitcoin and gold using the historical price series for both from 9/11/2016 to 9/10/2021. Based on the model results, they indicated that the model estimates future prices with a high accuracy degree. Additionally, they also stated that, in the sense of precision and accuracy, the LSTM-P model performs better than both the traditional LSTM models and other time series estimating models.

Seabe et al. (2023) employed three different deep learning algorithms LSTM, GRU, and Bi-LSTM to forecast the prices of BTC, ETH, and LTC, as determined by their market capitalization. They used two scores, RMSE and MAPE, to assess the models' performance. According to their results, Bi-LSTM outperformed LSTM and GRU in terms of estimation for three cryptocurrencies and was considered the best algorithm. Moreover, when compared with GRU and LSTM, Bi-LSTM offered the most accurate estimation was made. Consequently, they stated that the algorithms of deep learning are effective in forecasting the price of cryptocurrencies.

Goodell et al. (2023) suggested and created a framework for explainable artificial intelligence (XAI) that combines a new feature selection technique with the game-theory-based SHapley Additive exPlanations methodology and a framework for forecasting. They tested

this experimental methodology on the cryptocurrency market and utilize an enhanced method of feature selection based on the value of SHAP to forecast the price of Bitcoin. FS-SHAP combined the benefits of Extra trees and features crucial for developing the estimation. Their findings showed that FS-SHAP enhances model generalization and explainability in addition to forecasting. Taking into account the findings, they revealed several conclusions. One of their conclusion is that, depending on the FS-SHAP value acquired multivariate regression, they indicated that between OLS regression and complicated models, LSTM provides the highest Roos and Extra trees followed it. They also stated that the crucial inflection points of the daily financial and macroeconomic factors that determine the transitions between high and low daily prices are revealed by modeling.

By keeping the data set multi-directional, particularly in terms of the variables employed, and applying a genetic algorithm to optimize the model's performance in selecting these variables, this study differentiates from other studies in the literature. Furthermore, the majority of studies in the literature on forecasting the price of Bitcoin concentrate on identifying the model that forecasts the price the most accurately. In this study, the variables that affect bitcoin price are forecasted as well as the model that provides the most accurate predictions. Our study varies from other studies in the literature in this regard.

3. Dataset

Dataset contains 26 variables measured daily from 7/19/2010 to 7/19/2022. Bitcoin measured in BTC/USD is the dependent variable of the study. Macroeconomic factors and currency rates are effective on Bitcoin prices because Bitcoin is an alternative investment instrument for stock markets, gold prices, and currency rates. Blockchain information variables are directly related with the bitcoin prices. Thus, the independent variables are selected from three main categories namely blockchain information variables, macroeconomic factors, and global currency ratios.

Average Block Size, Cost per Transaction, Cost % of Transaction Volume, Number of Transaction per Block, Hash Rate, Difficulty, Number of Unique Bitcoin Addresses Used, Bitcoin USD Exchange Trade Volume, and are the blockchain information variables all of which are gathered from NASDAQ - Quandl database.

Crude Oil WTI Futures, Gold Futures, Crude Oil WTI Spot US Dollar - WTI/USD, Gold Spot Us Dollar - XAU/USD, Nikkei225, S&P500, DOW30, NASDAQ, EUROSTOXX50, FTSE100, CBOE, and VIX are considered as the macroeconomic factors, and they are obtained from investing.com and Reuters – Datastream.

USD/EUR, USD/GBP, USD/CHF, USD/CNY, and USD/JPY are exchange rates between the USA and the European Union, the United Kingdom, Switzerland, China and Japan respectively. All these variables are considered as global currency ratios and extracted from investing.com. The list of variables, brief description and abbreviations are given in Table 1.

Table 1: Description of the variables in the study.

Variable Name	**Description**
btc	Bitcoin (BTC/USD)
block	Average block size
cost_per_trans	Cost Per Transaction
trans_vol	Cost % of Transaction Volume
trans_per_block	Number of Transaction per block
hash_rate	Hash Rate
diff	Difficulty
unique_address	Number of Unique Bitcoin Addresses Used
btc_trade_vol	Bitcoin USD Exchange Trade Volume
crude_oil	Crude Oil WTI Futures
gold	Gold Futures
crude_oil_spot	Crude Oil WTI Spot US Dollar - WTI/USD
gold_spot	Gold Spot US Dollar - XAU/USD
nikkei225	Nikkei225
sandp500	S&P500
dow30	DOW30
nasdaq	NASDAQ
eurostoxx50	EUROSTOXX 50
ftse100	FTSE100
cboe	CBOE
vix	VIX
usd_eur	USD/EUR
usd_gbp	USD/GBP
usd_chf	USD/CHF
usd_cny	USD/CNY
usd_jpy	USD/JPY

4. Material/Method

4.1. Study Design

The main aim of this study is to estimate bitcoin prices for the next day (1 day), for the next week (7 days) and for the next month (30 days). Thus, the datasets are constructed in such

a way that all the independent variables are lagged for 1 day, 7 days and 30 days resulting in three different datasets which will be denoted with D_1, D_7, and D_{30} respectively. The Bitcoin prices will be estimated in the USD for the next period.

The first step of the analysis is to decrease the number of independent variables as some of them have no or little effect on estimating Bitcoin prices. For this purpose, Genetic Algorithm (GA) method is employed to select the optimal subset of independent variables for each of D_1, D_7, and D_{30}. For each set of variables, D_1, D_7, and D_{30} are split into 80% training set (7/19/2010 - 3/2/2020) and 20% test set (3/3/2020 - 7/19/2022) according to their chronological order. The Long Short-Term Memory (LSTM) method is employed to estimate Bitcoin prices. The performance of the models is assessed with R square, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

4.2. Variable Selection with Genetic Algorithm

Variable selection is an important preprocess step before modeling the dataset especially when the number of independent variables is high. Bozdogan (2004) stated that there are millions of possible models when the number of candidate variables are over 20 and there are billions of possible models when the number of candidate variables are over 30. Efficient search algorithms to find the ideal subset of variables are required to optimize the performance of the model. One such method is the Genetic Algorithm (GA).

A GA is based on concepts of biological evolution and natural selection and can be applied to solving problems where vast numbers of possible solutions exist (Bozdogan, 2004). GA has been used in operation management, multimedia, wireless networking (Katoch et al., 2021), in engineering (Boopathi et al., 2023), economics (Chung & Shin, 2020; Y. Huang et al., 2021), game theory (Paritosh et al., 2019), computational sciences (Frank et al., 2020; Rajinikanth & Rama, 2023), marketing (Robles et al., 2020) and medicine (Rabipour & Asadi, 2023). GA also widely preferred for variable selection in different studies (Ali & Ahmed, 2019; Gümüşçü et al., 2020; Y. P. Huang & Yen, 2019; Kek et al., 2022; Maleki et al., 2021; Sayed et al., 2019; X. Wang & Wang, 2019). GA does not require to calculate the gradient of the objective function so it is unlikely that GA will be stuck in the local optima which gives an edge to GA compared to the conventional optimization approaches.

Information is treated as a binary string where each different string is a different solution for the optimization problem. A string should be evaluated with some kind of fitness metric to measure the ability to solve the problem. By using the fitness metric on everyone only the fittest individuals are allowed to reproduce and pass their genetic information to their

offspring. Thus, this behavior is like natural organisms in a competitive environment. In GA, two important terms should also be mentioned: exploration and exploitation. Exploration is the creation of population diversity by exploring the search space and is obtained by mutation and crossover. Crossover uses part of the information from two parents to form new offspring whereas mutation randomly alters the genetic information of a parent. On the other hand, Exploitation aims at reducing the diversity in the population by selecting at each stage the individuals with higher fitness (Scrucca, 2013). This is called an elitist strategy by allowing the best fitted individuals persist in the next generation even if they did not survive. The algorithm stops when a convergence is achieved or when a maximum number of iterations is reached.

Three different GA is employed on D_1, D_7, and D_{30} for variable selection. Although there are different fitness values used with the GA, Akaike Information Criteria (AIC) (Akaike, 1998) is preferred in this study. The basic formula for the AIC is $AIC = 2K - 2ln(\hat{L})$ where K is the number of independent variables used and L is the log-likelihood estimate. The GA package (Scrucca, 2013) in the R programming language (R Core Team, 2022) is used to perform variable selection.

4.3. Modeling with Long Short-Term Memory

Long Short Term Memory (LSTM) networks are a special kind of Recurrent Neural Networks (RNN), capable of learning long-term dependencies. RNNs allow previous information to persist by using a loop. But RNNs also have a drawback. They can't handle long-term dependencies which leads to LSTM networks (Hochreiter & Schmidhuber, 1997). The main difference between a RNN and LSTM is that RNN has a very simple chain of repeating modules of neural network such as a single activation layer whereas LSTM has four interacting layers.

Figure 1 gives the basic form of the LSTM. The linear line from c_{t-1} *to* c_t denotes the modifications from the previous cell state to the current one. These modifications are done through multiplication and addition operations or through the gates. Gates are a way to optionally let information to flow. Each gate composed of a sigmoid function (σ) and pointwise multiplication operation (×).

The first gate is called as the *forget gate* (f_t) and it determines how much of the information will be discarded from the cell state. This is done with a sigmoid layer (σ). σ takes x_t and h_{t-1} as inputs and outputs a number between 0 and 1 for each element in c_{t-1}. represents all the information should be reserved and 0 represents no information will be transferred.

Forget gate is formulized with the following

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

where sigmoid function is defined as

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

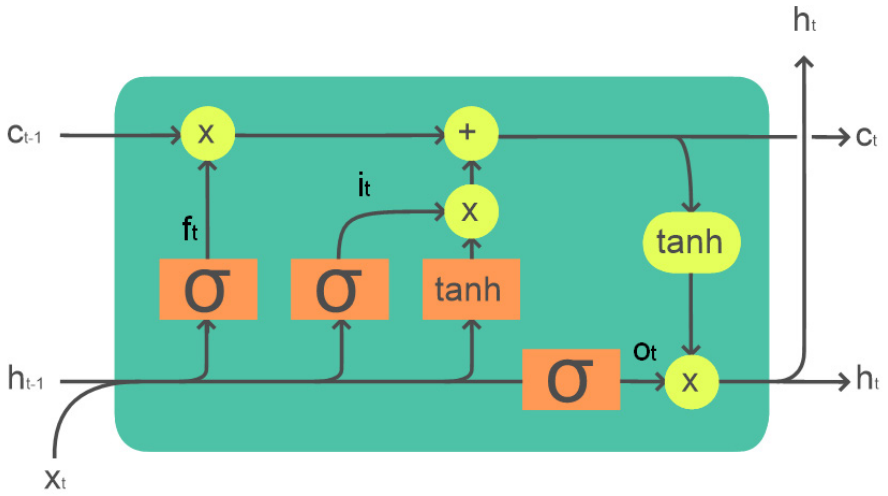


Figure 1: A basic LSTM schema, σ is the sigmoid function, tanh is the hyperbolic tangent function, f is the forget gate, i is the input gate, o is the output gate, h is the hidden state, c denotes the cell state, x is the input vector at time t. Source: Modified from https://commons.wikimedia.org/wiki/File:LSTM_Cell.svg

The second gate is called as the input gate (i_t) and it is used to update the cell states with the help of sigmoid layer (σ) and hyperbolic tangent function (tanh). This is done in two steps. In the first step, σ decides which values should be updated. In the second step, tanh creates a vector of new candidate values $\tilde{C}_t$ that potentially will be combined with C_t. These steps are given with:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

where

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

The update process is done by

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \tag{6}$$

Equation (4) tells new C_t is determined by a combination of forget gate, previous cell state, input gate and candidate values.

The third gate is called as the *output gate* (o_t). o_t is a filtered version of the C_t and determines which part of the C_t will be used in the output. This is again done with a two-step process.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \otimes tanh(C_t) \tag{8}$$

In this study, Keras and Tensorflow packages from Python programming language is used to perform LSTM analysis. For convenience, data is scaled into [0-1] range before conducting LSTM and rescaled into original range after analysis. The hyperparameters such as batch size, hidden units, number of LSTM layers, dropout, epochs, optimization algorithm, learning rate are optimized with grid search for the first model and the optimum values are used for the other models.

1.4. Evaluating Success in the Regression Models

The success of the model will be evaluated with the Coefficient of Determination (R^2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

R^2 is the measurement of model fit between the real and the estimated values. It takes values between 0 and 1 where values close to 0 indicates no explanatory power and values close to 1 indicates perfect explanatory power for the model. The formula for the R^2 is given with

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{9}$$

Here, SS_{res} is the sum of squares of residuals indicating total error made in the model, and SS_{tot} is the total sum of squares which are calculated with

$$SS_{res} = \sum_i (y_i - \hat{y}_i)^2 = \sum_i e_i^2 \tag{10}$$

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \tag{11}$$

Here $\hat{y}_i$ is the estimation for the y_i, $\bar{y}$ is the average of y, and e_i is the error.

MAE is the average of absolute difference between the real and the estimated values. Lower values of MAE indicates lower error and better model fit. MAE is calculated with

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n} \tag{12}$$

Here $\hat{y}_i$ is the estimation for the y_i, n is the number of observations, and e_i is the error.

RMSE is the standard deviation for the errors. It is calculated first by obtaining errors for each observation by subtracting real values from the estimations. Then, squares of errors are summed and divided into total number of observations which gives mean square error (MSE). Finally, square root of MSE is calculated to obtain RMSE. The formula for RMSE can be given with

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{13}$$

Lower RMSE values indicates lower error thus better model fit.

5. Results

An overview of the results can be followed through Figures 2-4. First, GA are employed to determine the variables with the most effect on estimating the Bitcoin prices for the D_1, D_7, and D_{30} separately. For all three GA, the population size is selected 50, number of generations is selected 100, crossover and mutation probability is selected as 0.8 and 0.1, respectively. The algorithms is processed for 100 iterations.

For D_1, one day lagged bitcoin prices (btc_{t-1}), one day lagged cost per transaction ($cost_per_trans_{t-1}$), one day lagged difficulty ($diff_{t-1}$), one day lagged WTI/USD – Crude Oil WTI Spot US Dollar ($crude_oil_spot_{t-1}$), one day lagged S&P500 ($sandp500_{t-1}$), and one day lagged NASDAQ ($nasdaq_{t-1}$) (Figure 2) are survived after GA. For D_7, one week lagged bitcoin prices (btc_{t-7}), one week lagged cost per transaction ($cost_per_trans_{t-7}$), one week lagged number of transaction per block ($trans_per_block_{t-7}$), one week lagged difficulty ($diff_{t-7}$), one week lagged Crude Oil WTI Futures ($crude_oil_{t-7}$), one week lagged WTI/USD – Crude Oil WTI Spot US Dollar ($crude_oil_spot_{t-7}$), one week lagged Nikkei225 ($nikkei225_{t-7}$), one week lagged S&P500 ($sandp500_{t-7}$), one week lagged DOW30 ($dow30_{t-7}$), one week lagged NASDAQ

($nasdaq_{t-7}$) and one week lagged USD/JPY (usd_jpy_{t-7}) (Figure 3) are survived after GA. For D_{30}, most of the independent variables are survived through the GA. All the variables other than one month lagged average block size ($block_{t-30}$), one month lagged cost % of transaction volume ($trans_vol_{t-30}$), one month lagged number of unique Bitcoin addresses used ($unique_address_{t-30}$), and one month lagged EUROSTOXX50 ($eurostoxx50_{t-30}$) are used in LSTM model for estimating Bitcoin prices for D_{30} (Figure 4).

After determining the candidate variables for affecting Bitcoin prices, three LSTM models are constructed. Three LSTM models with the batch size 72, hidden units 50, hidden LSTM layers 1, dropout 0.01, epochs 50, learning rate 0.001 are constructed. Adamax optimizer with $beta_1$ 0.9 and $beta_2$ 0.999 is used in all of the models. The performance of the model is evaluated with R^2, MAE and RMSE values of the test model. Table 2 presents the performance metrics for each model and for both the test and training sets.

Table 2: LSTM model performance for each time steps and for train and test data.

Model	Train			Test		
	RMSE	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
Model 1 (1 day)	715.59	423.64	0.96	8204.57	6341.62	0.98
Model 2 (7 days)	809.78	499.99	0.95	12732.37	10263.91	0.96
Model 3 (30 days)	1128.30	698.66	0.91	18128.23	14655.56	0.90

Among three models Model 1 (1 day) has the highest R^2 (0.98), and lowest RMSE (8204.57) and MAE (6341.62). As the estimation period gets longer R^2 tends to get lower (0.96 for Model 2 and 0.90 for Model 3), RMSE and MAE tend to get higher. This is because it becomes harder to make estimation for further in time as uncertainty gets higher. Also in the case of Bitcoin, prices increased suddenly in the test data set which makes it difficult for the models to catch it when the time interval increased. Figure 5 also presents, the actual and estimated values for the Bitcoin in each model.

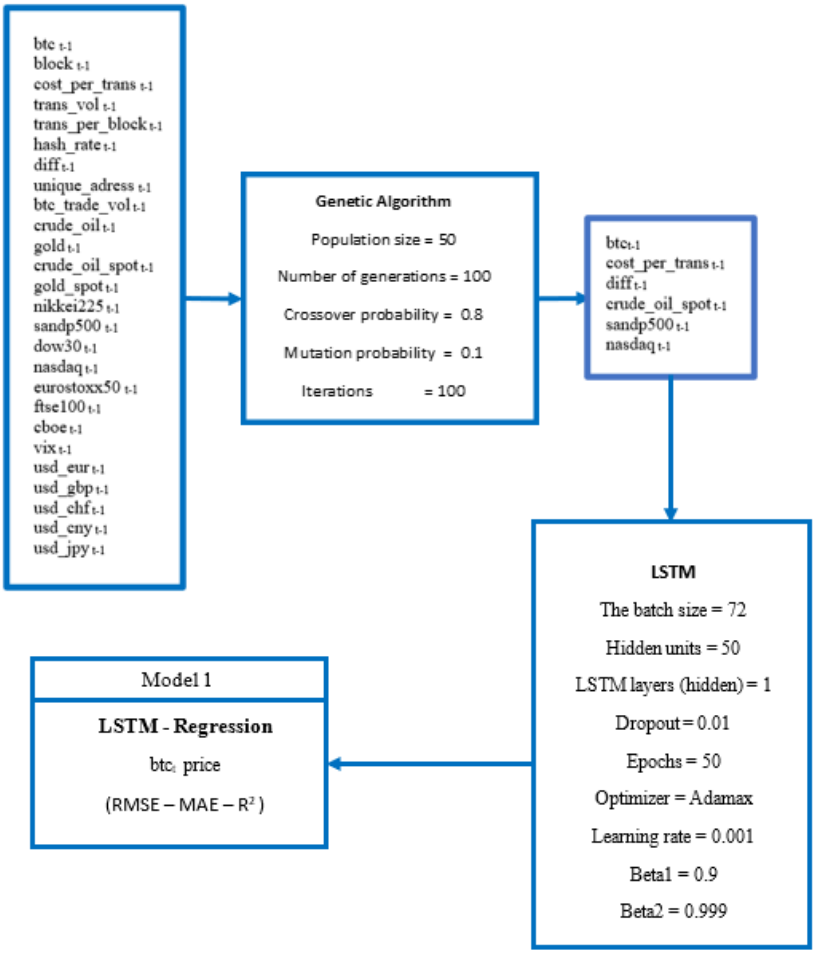


Figure 2: Flowchart for estimation of one day ahead (D_1)

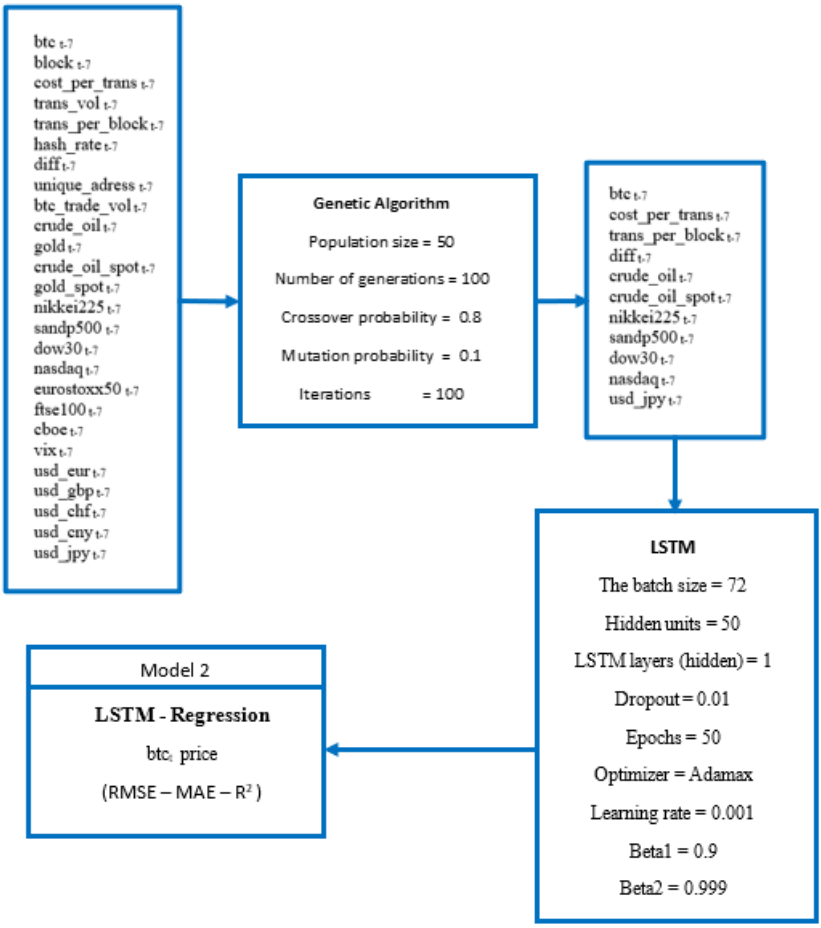


Figure 3: Flowchart for estimation of one week ahead (D_7)

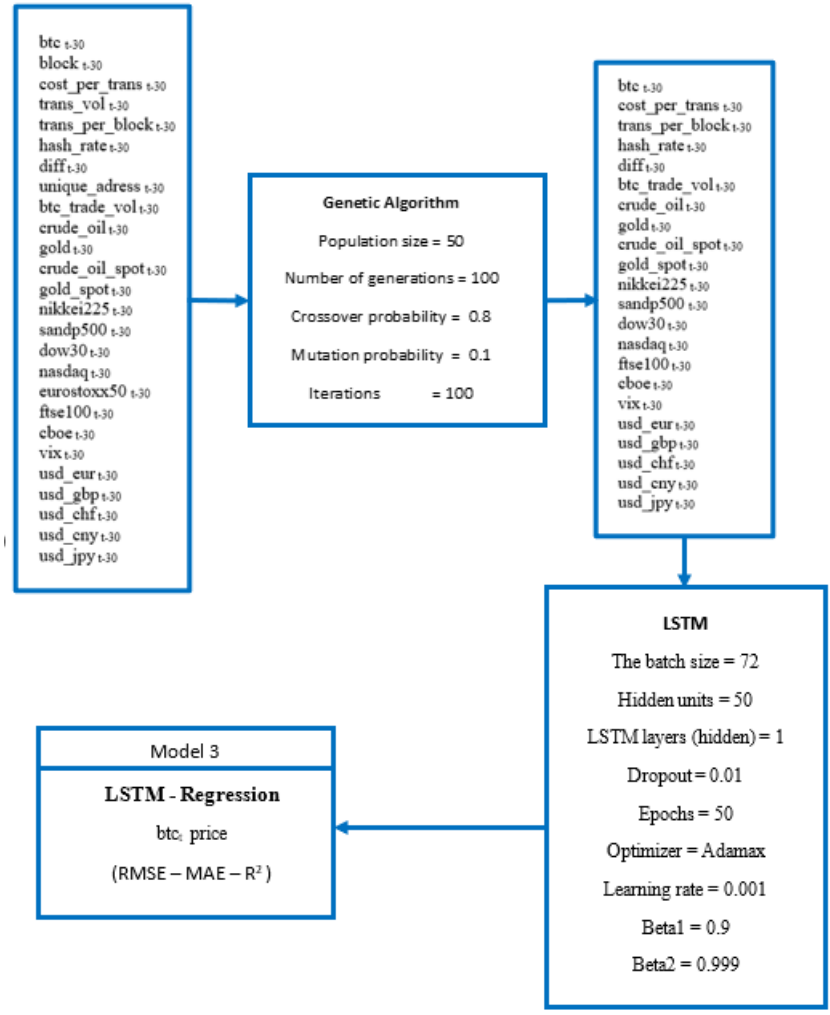


Figure 4: Flowchart for estimation of one day ahead (D_{30})

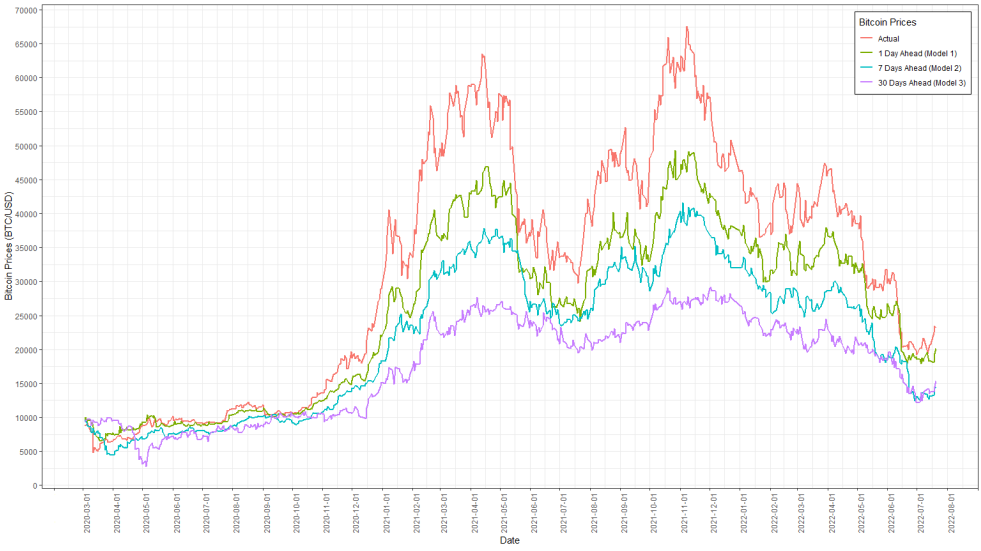


Figure 5: LSTM Model Estimations for Actual Values, 1, 7, and 30 days ahead models

For the Model 1, Bitcoin prices can be estimated adequately with one day lagged data. The trend of the actual Bitcoin prices is also can be observed in the estimations. Even small fluctuations in the prices are captured in Model 1. When the estimation interval is increased to a week rather than a day, the performance of the model starts to decline (Model 2), yet it can still catch the overall pattern and trend. For Model 3, the performance of the model is worse than other models, although the general pattern is visible, it is hard to determine minor fluctuations any more. Also we should note that, all three models are under estimated Bitcoin prices. The main reason for this is the sudden increase in the bitcoin prices inside the test dataset in which the LSTM models failed to catch effectively.

6. Discussion

In this study, since a solution for price estimation of the time series Bitcoin data containing daily prices between 19.07.2010 - 19.07.2022 and the indicators affecting the price is emphasized, performance evaluation has been made by processing the data with appropriate models. For this purpose, genetic algorithm and LSTM models are used.

Feature selection is important to optimize the performance of the model in identifying indicators that affect the Bitcoin price for different time series. Genetic algorithm methods were used to select optimal features and R-squared, MAE, RMSE were used to compare model performances. In this context, three models, Model-1, Model-2, and Model-3, were developed to estimate Bitcoin prices for the next 1 day, 7 days, and 30 days, respectively.

The models are different in terms of their performance and differ from each other in terms of their strengths and weaknesses.

Among the models, the model with the highest R square with 0.98 and the lowest RMSE and MAE with 8204.57 and 6341.62, respectively, was determined as Model-1. Therefore, our findings suggest that it may be possible to estimate the actual Bitcoin price (Model-1) with very low error rates. In other words, our study shows that short-term estimations are better than long-term. Among the three models, in Model 1, where Bitcoin prices are estimated with one-day delayed data, more accurate estimations about Bitcoin prices are obtained. Although the performance of the model starts to decline when the estimated interval is increased to seven days (Model-2), there are common indicators between Model-1, which estimates Bitcoin prices with one-day lagged data, and Model-2, which estimates with seven-day lagged data. For example, although the indicators that affect the Bitcoin price such as cost-per transaction, difficulty, oil spot, S&P500, NASDAQ, Nikkei225 give better results in Model-1, Model-2 can also give estimations at a level that can catch the overall pattern and trend. In Model-3, where the performance is worse than other models, it is difficult to detect small fluctuations.

When the studies on Bitcoin price estimation in the literature are examined, for example, Albariqi and Winarko (2020) applied baseline neural network models, MLP, and RNN models, to forecast changes in long and short-term Bitcoin prices. They used a total of 1300 data which consist of Bitcoin blockchain data between the period August 2010-October 2017 with two days period. They generated models to estimate both short and long-term Bitcoin price change from 2 days until 60 days. According to their results, the estimation for the long term gave a better result than the estimation for the short term.

Contrary to the studies of Albariqi and Winarko (2020), our results show that short-term forecasts with one-day-lagged data give better results than long-term forecasts. This differentiation may be related to the time period considered by Albariqi and Winarko and the use of the period of 2, 4, and 6 days until 60 days in their study. Moreover, the range they define for short-term price forecasting in their study is between 2 days and 30 days.

Wardak and Rasheed (2022) considered several factors that affect the Bitcoin value and estimated its price with the highest possible accuracy by applying the LSTM. Wardak and Rasheed (2022) found an accuracy of 95.7% with an error loss of RMSE value of 0.00065 and 0.05. In terms of accuracy and performance, as a result of comparing ARIMA, RNN, MLP, and other LSTM models with other methods, he stated that the most appropriate method to estimate Bitcoin price is to use LSTM with the appropriate hyperparameter setting.

7. Conclusion

In order to protect assets and make new investments, it is important to know the future value of the financial assets that are investing in. Bitcoin, which is among the new and popular investments, which caused a radical change in financial assets and entered our lives in 2008 and has followed a very fluctuating course with very high gains and losses until today, has attracted and continues to attract the attention of old and new investors. Bitcoin is different from other financial assets by its nature. Therefore, the parameters that determine the value of Bitcoin also differ from other financial assets. For this reason, traditional forecasting methods are insufficient for estimating financial assets with very high volatility and volatile values such as Bitcoin. In this study, three different models were developed using LSTM and the genetic algorithm model to estimate the Bitcoin price and identify the variables affecting the Bitcoin price.

The prices of crypto assets such as Bitcoin can be volatile a lot, as they can change on a daily or even hourly basis. This volatility leads to high uncertainty and risk. Despite the high risks and volatility, these assets also offer high returns, making them attractive to investors, who may be fearful of missing out. Therefore, despite these price fluctuations, it is important for investors to consider how to seize the opportunity and when to buy.

This study differs from other studies in the literature by keeping the data set versatile, especially in terms of the variables used, and using a genetic algorithm to optimize the performance of the model in the selection of these variables. Moreover, most of the studies in the literature on estimating the price of Bitcoin focus on finding the model that best estimates the price. In this study, not only the model that best estimates Bitcoin price but also the variables that have an impact on Bitcoin price are estimated. In this respect, our study differs from other studies in the literature.

Estimating and modeling actual prices can also be useful in identifying the effects of external factors such as global events, global financial risks, fraudulent activities, artificial pumping, etc. Future research may focus on models for making these determinations. In this context, machine learning-based price models can be used to assess and estimate the stability of crypto assets.

Although investments and forecasts in crypto assets are widely debated, interest in these assets continues to grow. However, expectations for crypto-assets and national policies can influence the value of these assets. Therefore, the accuracy of estimations about the future value of crypto-assets will help investors and policymakers to make the right decisions and make regulatory policies.

References

Akaike, H. (1998). Information theory and an extension of the maximum likelihood principle. In *Selected papers of hirotugu akaike* (pp. 199–213). Springer.

Albariqi, R., & Winarko, E. (2020). Prediction of bitcoin price change using neural networks. *2020 International Conference on Smart Technology and Applications (ICoSTA)*, 1–4.

Ali, W., & Ahmed, A. A. (2019). Hybrid intelligent phishing website prediction using deep neural networks with genetic algorithm-based feature selection and weighting. *IET Information Security*, *13*(6), 659–669. https://doi.org/10.1049/iet-ifs.2019.0006

Alpago, H. (2018). From Bitcoin to Selfcoin the Cryptocurrency. *Journal of the International Scientific Researches*, *3*(2), 411–428.

Basher, S. A., & Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? *Machine Learning with Applications*, *9*, 100355.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance Research Letters*, *25*, 103–110.

Bitcoin Historical Data. (2023). https://tr.investing.com/crypto/bitcoin/historical-data

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, *29*(2), 213–238.

Boopathi, D., Jagatheesan, K., Samanta, S., Anand, B., & Jaya, J. (2023). Application of Genetic Algorithm-Based Controllers in Wind Energy Systems for Smart Energy Management. In *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments* (pp. 139–160). Springer.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87–95.

Bozdogan, H. (2004). Intelligent statistical data mining with information complexity and genetic algorithms. In *Statistical data mining and knowledge discovery* (pp. 15–56). Chapman & Hall/CRC Boca Raton, Fla, USA.

Carkacioglu, A. (2016). Crypto-Currency Bitcoin. *Capital Markets Board of Turkiye, Research Report*, 1–68.

Chevallier, J. (2020). COVID-19 pandemic and financial contagion. *Journal of Risk and Financial Management*, *13*(12), 309.

Chung, H., & Shin, K. (2020). Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction. *Neural Computing and Applications*, *32*, 7897–7914.

Coinbase Institutional. (2023). *2023 Crypto Market Outlook* (Issue December 2022).

CoinGecko. (2023). *2023 Q1 Crypto Industry Report*. https://www.coingecko.com/research/publications/2023-q1-crypto-report

CoinMarketCap. (2023a). https://coinmarketcap.com/

CoinMarketCap. (2023b). *Crypto Market Recap Q1, 2023: Growth and Opportunities*. https://coinmarketcap.com/community/articles/642e95e08c9497781ca880b5/

Frank, M., Drikakis, D., & Charissis, V. (2020). Machine-learning methods for computational science and engineering. *Computation*, *8*(1), 15.

Goodell, J. W., Ben Jabeur, S., Saâdaoui, F., & Nasir, M. A. (2023). Explainable artificial intelligence modeling to forecast bitcoin prices. *International Review of Financial Analysis*, *88*, 102702. https://doi.org/10.1016/j.irfa.2023.102702

Gümüşçü, A., Tenekeci, M. E., & Bilgili, A. V. (2020). Estimation of wheat planting date using machine learning algorithms based on available climate data. *Sustainable Computing: Informatics and Systems*, *28*. https://doi.org/10.1016/j.suscom.2019.01.010

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.

Huang, Y., Gao, Y., Gan, Y., & Ye, M. (2021). A new financial data forecasting model using genetic algorithm and long short-term memory network. *Neurocomputing*, *425*, 207–218.

Huang, Y. P., & Yen, M. F. (2019). A new perspective of performance comparison among machine learning algorithms for financial distress prediction. *Applied Soft Computing Journal*, *83*, 105663. https://doi.org/10.1016/j.asoc.2019.105663

Katoch, S., Chauhan, S. S., & Kumar, V. (2021). A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications*, *80*, 8091–8126.

Kek, X. Y., Chin, C. S., & Li, Y. (2022). Multi-Timescale Wavelet Scattering with Genetic Algorithm Feature Selection for Acoustic Scene Classification. *IEEE Access*, *10*, 25987–26001. https://doi.org/10.1109/ACCESS.2022.3156569

Lei, J., & Lin, Q. (2022). Analysis of gold and bitcoin price prediction based on LSTM model. *Academic Journal of Computing & Information Science*, *5*(6), 95–100. https://doi.org/10.25236/ajcis.2022.050614

Luo, C., Pan, L., Chen, B., & Xu, H. (2022). Bitcoin price forecasting: an integrated approach using hybrid LSTM-ELM models. *Mathematical Problems in Engineering*, *2022*, 1--17.

Maleki, N., Zeinali, Y., & Niaki, S. T. A. (2021). A k-NN method for lung cancer prognosis with the use of a genetic algorithm for feature selection. *Expert Systems with Applications*, *164*(July 2019), 113981. https://doi.org/10.1016/j.eswa.2020.113981

McNally, S., Roche, J., & Caton, S. (2018). Predicting the price of bitcoin using machine learning. *2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP)*, 339–343.

Mehta, P., & Sasikala, E. (2020). Prediction of Bitcoin using Recurrent Neural Network. *International Journal of Recent Technology and Engineering (IJRTE)*, *8*(6), 1303–1307. https://doi.org/10.35940/ijrte.f7808.038620

Mudassir, M., Bennbaia, S., Unal, D., & Hammoudeh, M. (2020). Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach. *Neural Computing and Applications*, 1–15.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*.

Özkul, F. U., & Bas, E. (2020). Digital Age Technology Blockchain and Cryptocurrencies: Financial Evaluation Within the Framework of National Legislation and International Standards. *Accounting and Auditing Review*, *20*(60), 57–74.

Paritosh, P., Kalita, B., & Sharma, D. (2019). A game theory based land layout optimization of cities using genetic algorithm. *International Journal of Management Science and Engineering Management*, *14*(3), 155–168.

Park, S., & Yang, J.-S. (2023). Intelligent cryptocurrency trading system using integrated AdaBoost-LSTM with market turbulence knowledge. *Applied Soft Computing*, 110568.

Pesaran, M. H., & Timmermann, A. (2002). Market timing and return prediction under model instability. *Journal of Empirical Finance*, *9*(5), 495–510.

R Core Team. (2022). *R: A language and environment for statistical computing, R Foundation for Statistical Computing,*. https://www.r-project.org/.

Rabipour, S., & Asadi, Z. (2023). Application of Genetic Algorithm in Predicting Mental Illness: A Case Study of Schizophrenia. In *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments* (pp. 161–183). Springer.

Rajinikanth, V., & Rama, A. (2023). Evaluation of Underwater Images Using Genetic Algorithm-Monitored Preprocessing and Morphological Segmentation. In *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments* (pp. 231–245). Springer.

Rathore, R. K., Mishra, D., Mehra, P. S., Pal, O., HASHIM, A. S., Shapi'i, A., Ciano, T., & Shutaywi, M. (2022). Real-world model for bitcoin price prediction. *Information Processing and Management*, *59*(4), 102968. https://doi.org/10.1016/j.ipm.2022.102968

Robles, J. F., Chica, M., & Cordon, O. (2020). Evolutionary multiobjective optimization to target social network influentials in viral marketing. *Expert Systems with Applications*, *147*, 113183.

Sayed, S., Nassef, M., Badr, A., & Farag, I. (2019). A Nested Genetic Algorithm for feature selection in high-dimensional cancer Microarray datasets. *Expert Systems with Applications*, *121*, 233–243. https://doi.org/10.1016/j.eswa.2018.12.022

Scrucca, L. (2013). GA: A package for genetic algorithms in R. *Journal of Statistical Software*, *53*(4), 1–37. https://doi.org/10.18637/jss.v053.i04

Seabe, P. L., Moutsinga, C. R. B., & Pindza, E. (2023). Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach. *Fractal and Fractional*, *7*(2), 1–18. https://doi.org/10.3390/fractalfract7020203

Sonderegger, D. (2015). A regulatory and economic perplexity: Bitcoin needs just a bit of regulation. *Washington University Journal of Law & Policy*, *47*, 175–216.

Wang, J., & Ngene, G. M. (2020). Does Bitcoin still own the dominant power? An intraday analysis. *International Review of Financial Analysis*, *71*, 101551.

Wang, X., & Wang, B. (2019). Research on prediction of environmental aerosol and PM2.5 based on artificial neural network. *Neural Computing and Applications*, *31*(12), 8217–8227. https://doi.org/10.1007/s00521-018-3861-y

Wardak, A. B., & Rasheed, J. (2022). Bitcoin Cryptocurrency Price Prediction Using Long Short-Term Memory Recurrent Neural Network. *European Journal of Science and Technology*, *38*, 47–53. https://doi.org/10.31590/ejosat.1079622

Zhang, X., Zhang, L., Zhou, Q., & Jin, X. (2022). A Novel Bitcoin and Gold Prices Prediction Method Using an LSTM-P Neural Network Model. *Computational Intelligence and Neuroscience*, *2022*, 1643413. https://doi.org/10.1155/2022/1643413