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Tests of Predictability in Cryptocurrency Markets

Isabella Regina da Silva Rubio

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Dissertation presented as a partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management.

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Advisor: Bruno Damásio

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Abstract

The cryptocurrency market has grabbed the curiosity of both seasoned and novice investors as a developing and increasingly popular financial arena. This rise in attention warrants a closer look at Bitcoin pricing trends and the market's potential predictability. To solve the core research topic, a deductive technique was used in response to these study aims.

To help this analysis, the researcher used Long Short-Term Memory (LSTM) networks, a type of recurrent neural network known for its ability to capture order dependencies within sequential data.

The study's findings highlight the capacity of LSTM networks to deliver cryptocurrency price forecasts, putting light on the promising potential of LSTM in cryptocurrency market analysis. This study goes beyond standard ways to investigate cryptocurrency market prediction, using data from 2015 to 2023. The data scope, together with the use of LSTM and GRU models, adds to a more comprehensive and accurate analysis, meeting the need for a more in-depth understanding of Bitcoin market dynamics.

Keywords

Cryptocurrency; Price Volatility; LSTM; Financial Market Prediction.

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List of Abbreviations and Acronyms

BTC	Bitcoin
DFA	Detrended fluctuation analysis
EMH	Efficient market hypothesis
LSTM	Long short-term memory
MSCI	Morgan Stanley Capital International
ROI	Return on investment
S&P 500	Standard and Poor's 500

1. Introduction

After becoming the subject of several articles and news, the creation and success of cryptocurrency - especially Bitcoin - is still a real unknown for many, including specialists. There is a lot of questioning if Bitcoin is a bubble or an investment or whether it is a currency or an asset. Because of your recent popularization and high intrinsic complexity, the bibliography on the subject is still sparse, polarized and with few conclusions about its function and effectiveness.

In the last few years, the increase in geopolitical and economic issues in the global economy has impacted the prices of the financial market (Hileman, & Rauchs, 2017). These issues also impact the prices of the stock market and investors are losing their wealth (Salman and Ibrahim, 2020), similarly, the impact is also shown in cryptocurrency. Crypto is considered as a digital currency, the buying and selling took place through different applications or websites. Online ledger has been utilized by cryptocurrency. These ledgers are backed by strong cryptography that supports protecting online transactions. However, these crypto coins or currency are not regulated by any regulatory body or central body like the government. It is operated by a network of computers (Valencia, Gomez, & Valdes, 2019).

The working mechanism of these currencies is to purchase and sell over a different exchange. The amount is stored in digital wallets. Hence, the currency does not have any physical presence. However, the digital record is maintained in the form of blockchain. The currency is traded from one individual to another through digital wallets, without any physical transfer (Hileman, & Rauchs, 2017; Valencia, Gomez, & Valdes, 2019).

The transaction process required verification through an I.D card, passport or face recognition. These are summed to the blockchain through a process that is called mining (Tan and Kashef, 2019). This cryptocurrency mining is the process of cryptocurrency transactions that are checked and new blocks are added to the blockchain. The principle of demand and supply follows for the transaction of cryptocurrency whereas it is followed in the decentralized market of cryptocurrency. Therefore, the market does not need to look after political and economic concerns. But, the chances of uncertainty exist in the market.

However, the factors like supply, market capitalization, news from media sources etc. all impact cryptocurrency prices.

1.1 Background and Research Problem

The first currency named, Bitcoin (BTC) was developed by an unidentified person or group of individuals using the pseudonym "Satoshi Nakamoto." The first Bitcoin transaction happened in January 2009, and the Bitcoin whitepaper, "Bitcoin: A Peer-to-Peer Electronic Cash System," was initially released in 2008. The creation of Bitcoin and the underlying blockchain technology by Satoshi Nakamoto, whose real identity is unknown, caused a revolution in the fields of finance and technology. The currency got an official commission in the United Kingdon treasury in 2014. The cryptocurrency market is considered an emerging market and is getting popular day by day. People who were not investing in cryptocurrency are now more willing to take benefit from the crypto market. People are more curious about the crypto prices volatility. In 2021, El Salvador was the first country that accepts bitcoins as legal tender. There was more legislative assembly vote towards the trading of cryptocurrency. The increase in market capitalization of cryptocurrency has further increased its growth (Chuen, Guo, & Wang, 2017). The report stated that there is an increase of $800 billion in the trading of cryptocurrency in January 2018. However, the market is considered highly volatile. The behaviour of the crypto market is dissimilar to the behaviour of other stock or financial markets (Stosic, Stosic, Ludermir, & Stosic, 2018).

Due to high volatility in prices, there is great potential on both sides i.e. profit and loss in the market. Only the wise decision at the right time will secure the invested amount and provide you with great profit. Due to the emerging market, the markets do not have or are linked with any index. It is more unpredictable in terms of price compared to other markets. On the other side, Bitcoin's successful transactions have helped in boosting the crypto market and the chances for other cryptocurrencies to emerge (Mittal, Arora, & Bhatia, 2018). The feature of unregulated and decentralized mechanisms has made the market more unpredictable (Foley et al. 2019). However, the other factor is related to the trader sentiments associated with the prices up and down in the market. Therefore, various scholars use crypto data to predict the human behaviour and sentiments associated with the increase and decrease of prices in the market.

Fast market capitalization development and value appreciation of Bitcoin, prompted the rise of an enormous number of other cryptocurrencies forms of money. The rise of one Bitcoin gives a boost to the overall market (Liu, & Tsyvinski, 2021). At this point, the market of digital currencies has gotten one of the biggest unregulated business sectors in the world. As new cryptocurrencies are developed and older ones are delisted, the total number of cryptocurrencies in circulation is constantly fluctuating. Numerous exchanges are actively trading thousands of cryptocurrencies as of May 2023. One of the most well-known websites for tracking cryptocurrencies, CoinMarketCap, reports that there are currently more than 12,000 cryptocurrencies listed on its platform. There are also a lot of distinct trades in terms of quantity. The most well-known cryptocurrency exchanges include Huobi, Binance, Coinbase, Kraken, and Bitfinex. Decentralized exchanges (DEXs) and other smaller exchanges do exist, nevertheless. Since new exchanges are continuously being established while others are closing, it is challenging to pinpoint the precise number of exchanges. However, it is anticipated that there will be several hundred active cryptocurrency exchanges worldwide as of May 2023. The market capitalization has increased up to 270 billion USD as of July 2020 (Fang, et al., 2020).

Literature indicated that despite various models for predicting price volatility, it always appears as a challenging part when predicting prices. Similarly, there are various methods, each has some pros and cons in selecting the method of prediction. Therefore, this research study is focusing on the LSTM, used for the prediction of prices in the Cryptocurrency markets. The research aimed to identify the effective applicability of the LSTM network, for testing the predictability of prices in the cryptocurrency market.

Therefore, the following research question must be addressed in the study:

- **Can LSTM predict short-term movements of the cryptocurrency?**

There is limited literature on the LSTM network used for predicting cryptocurrency prices. Therefore, the researcher aims to examine the market price volatility over one year and identify how much it reflects the actual price trend of one year. The purpose of the study is to examine the changes in prices that occur in a year and predict the prices with the support of a machine learning-based neural network.

1.2 Research Objectives

The objective of the research is to examine the cryptocurrency price pattern by using LSTM. Another objective is to examine the efficient market hypotheses that might affect price volatility. Numerous cryptocurrencies are prevailing for trading and each has different factors through which prices differentiate. However, the objective of the paper is to identify price volatility.

1.3 Study Relevance and Importance

Price prediction has appeared as a challenging task whether it is conducted for the stock market or the crypto market. One of the reasons for the complexity is due to economic, political and human behaviour sentiment involvement. Therefore, it is important for investors, evaluators and financial market controllers to consistently predict the change in prices in the market. According to academic scholars, the price change is not random. Whereas it shows non-linearity and dynamic changes. These dynamic changes occur more in cryptocurrency. However, these predicted values do not share the exact future price. These threshold amounts represent the trend pattern of prices.

Another important reason for the failure of predicting the cryptocurrency is that it is not associated or linked with any one company or regulator body. Therefore, it is more difficult to predict based on linear regression. The present study undertakes the LSTM network for predicting prices because it has a powerful character in the sequence prediction of prices. LSTM can save past information and it is important for predicting the prices, to predict the future price based on previous information.

2. Literature review

The study is limited to analyzing Bitcoin specifically since it is one of the pioneering cryptocurrencies with the greatest tendency to adhere to the potential audience. In this way, its importance stands out from the other cryptocurrencies for being more developed, in addition to adopting the technology blockchain innovation.

Thus, currencies such as Ethereum, Ripple and Litecoin are only recognized as a parameter for the main object of study. Bibliography innovations regarding new technologies or policies for Bitcoin are also not deepened, since it aims to identify only the economic trends of the existing cryptocurrency.

Despite being a key factor in Bitcoin's success, the regulations are not studied in-depth in this project, as each country has different views on the subject, which would make the project too long-winded. In addition, much legislation has not yet been defined, which would make the description also speculative. With that, the existing regulations are evaluated just to elucidate economic aspects related to Bitcoin and the impacts arising.

The search for articles with Bitcoin in its scope turned out to be more interesting than the other keywords involving cryptocurrency. When checking, for example, texts citing Satoshi Nakamoto, the creator of Bitcoin, are 65 results, but which are related to other cryptocurrencies in addition to texts that already cite Bitcoin and were included in the previous filter. Map by "Cryptocurrency" as well would make the research significantly comprehensive, distancing itself from the object of study.

From that, an initial filter was defined by which articles would be selected directly associated with Bitcoin. This excluded texts whose approaches were other cryptocurrencies or economic theories that only used Bitcoin as a means of comparison. Other articles in which news and new applications were proposed for Blockchain and Bitcoin were also discarded as they would not be of direct interest in the economic study of the existing cryptocurrency. Texts on world legislation and referring to the field of law were also disregarded, given that the main focus of the project is its economic value.

To ensure the representativeness of results, two academic databases and several journals were searched to identify relevant contributions. The searched databases are

Google Scholar and ScienceDirect. Google Scholar is provided free by Google LLC and contains a broad range of studies, altogether 389 million documents. It is the largest academic search engine globally (Gusenbauer, 2019, p. 1). Several studies contain the challenges of cryptocurrency market price movements and the use of machine learning for predicting prices. It is critical to validate the relevance of such research in emerging markets. Literature suggested that the market efficiency hypothesis plays an important role in financial market prediction.

The Literature Review was divided into subsections:

- Market efficiency theory
- Cryptocurrency market efficiency
- Machine learning for cryptocurrency market prediction
- Impact of Macroeconomic News on Cryptocurrency
- Literature Gap

2.1 Market efficiency theory

The efficient market hypothesis (EMH) is also known as the efficient market theory. The efficient market theory presents that share prices float on fair prices in the market. Due to the fair value, the investor will be unable to buy the undervalued stock and sell the overvalued stock in the market. The theory also states that the price of the stock shows all information regarding the company.

However, the concept of efficient market theory contradicts modern financial theory. Fama (1970) has explained market efficiency theory with three levels:

1. Weak
2. Semi-strong
3. Strong

- **Weak form of efficient markets:**

Assumptions in the EMH's weak form are that stock prices indicate the publicly accessible market information, however, it does not indicate new information which is not available on the public forum, and vice versa. It also indicates that previous price, volume, and return information are not dependent on future pricing (Malkiel, 1989).

According to EMH, a weakened form of a technical trading strategy based on historical price performance cannot forecast future price action based on fresh information (Malkiel, 1989).

- **Semi-strong efficient market:**

The technical, as well as a fundamental part of the analysis, is disregarded in the semi-strong form of the theory. Because the semi-strong variant of the EMH assumes that prices respond swiftly to public information, the analysis does not contribute as a tool for predicting future prices.

- **Strong efficient market:**

Those who adhere to the EMH in its strongest version believe that prices respond to public and private information. A company's current stock price is presumed to include even non-public information, such as that known only to the CEO. Insider knowledge does not support the investor to predict the prices.

The more participants take part in the market, the more efficient the market will become. There will be more information and different types of investors will come and respond differently to this information.

2.1.1 Cryptocurrency Market Efficiency

The cryptocurrency market has gotten a lot of attention in previous years. The trading volume in the largest such currency has grown tremendously, and liquidity has increased over the year (Farell, 2015). The regulators, individuals and high-net-worth investors are more interested in identifying the ups and downs of the market.

Various scholars indicated that Bitcoin (cryptocurrency) tends to establish a new asset class. However, many scholars try to identify market efficiency through different time horizons. Urquhart in 2016 research indicates that Bitcoin trading is not for the weak efficient market (Zargar and Kumar, 2019). Similarly, Nadarajah and Chu investigated that Bitcoin has power transformation on the returns that satisfies the weak form of an efficient market. On the other side, other mixed studies revealed that the Bitcoin market is becoming more efficient when studied over time.

The Bitcoin market is considered an inefficient market (Caporale et al., 2018). However, some critically analyzed scholars stated that the crypto market sometimes appeared as an efficient market (Kristoufek and Vosvrda, 2019) or the Bitcoin return has made the market efficient weekly (Nadarajah and Chuuu, 2017). Other studies show that cryptocurrencies are strongly interlinked reflecting by volatility spill-over, volatility co-movement, lead-lag effect, and market co-movement. One reason for cryptocurrency inefficiency is the difficulty in trading on exchanges, resulting in low liquidity in comparison to other markets. Because it is easy in trading due to which one cryptocurrency differs significantly from other cryptocurrencies.

2.1.2 Does the Cryptocurrency market follow the EMH?

The market will be more efficient if it can appraise a company faster and more precisely. Bitcoin and most other digital assets (excluding fixed currencies) are not backed by hard assets, unlike state-subsidized fiat currencies. This solves the issue of capital controls, which may otherwise harm or undermine the system.

Bitcoin has few alternatives when it comes to arbitrage limits, which increases market efficiency even more. Furthermore, market participants can quickly reduce their Bitcoin investments to demonstrate that they are capable of delivering on their promises and establishing a highly effective and efficient ecosystem.

It is safe to assume that the cryptocurrency industry is large enough to accommodate more sophisticated equity funds that pool important data.

2.1.3 Efficient Market Hypothesis and Bitcoin

In general, Bitcoin and other cryptocurrencies are known to react aggressively to specific market events, such as company incursion or unexpected legislative developments. In this regard, the cryptocurrency market is extremely efficient; prices virtually instantly reflect information available in the actual world.

To evaluate if Bitcoin returns were inefficient, Urquhart (2016) employed the following tests: For no autocorrelation, used the Ljung–Box test; for independence, used the runs test; for independence, used Bartel's test; for the random walk hypothesis, used the wild-bootstrapped automated variance ratio test; and for returns that are distributed independently and identically, used the BDS test.

Later, Nadarajah and Chu (2017) analyze the data using daily return power transformations but do not reject the null hypothesis of informational efficiency. Using eight distinct tests, Nadarajah and Chu (2017) show that a simple power transformation of Bitcoin returns indeed satisfies the premise. There is no information loss as a result of the transformation.

Bariviera et al. (2017) used the Hurst exponent, which was calculated using two different approaches, to investigate the Bitcoin market's long memory. He argued that the DFA method is better because it is more robust and less sensitive to deviations from stationarity. Daily returns were found to have switched regimes, according to the study. The causes of this regime switch have yet to be discovered, according to Bariviera et al. (2017), and returns' long memory is unrelated to trade volume. Second, in all sliding windows, the Hurst exponents corresponding to the series of return volatility have a long memory.

2.2 Machine Learning for Cryptocurrency Market Prediction

The applied machine learning method can be used to analyse the price changes of the cryptocurrency (Jaquart, et al., 2020). Various factors including technological advancement economic, political, internal competition and cyber security all impact the price of cryptocurrency (Derbentsev, et al., 2019). However, if strategies are applied smartly they can create a big return in a price volatility environment.

Bitcoin is digital cash made created in January 2009. Since that Bitcoin provides a guarantee of lower exchange charges compared to traditional online payment methods. This is due to the decentralisation and unavailability of a regulator.

After 2017, the cryptocurrency gets exponential growth due to an increase in market capitalization (Patel, et al., 2020). The investors were willing to invest more and make a profit. Therefore, the need for identifying future market prices has been increased. As a result, machine learning is used for predicting the prices of stocks. It is also used for predicting cryptocurrency prices. However, the lack of an index makes it more complicated to predict the prices.

The LSTM obtain information from old and new layer. This information or data goes through multiple gates such as the input gate, forget gate and output gate (Yiying & Yeze, 2019). The benefit of using LSTM is to recall the patterns for a certain period. However, the other benefit of LSTM is that it remembers important data and ignores irrelevant data at the same time.

2.3 Impact of Macroeconomic News on Cryptocurrency

Events related to the activity of the world of digital currencies and exogenous events, of macroeconomic nature, prove to have a strong influence on the price of Bitcoin at the times they occur. Zhu et al. (2017) briefly mention that unpredictable events such as cyber-attacks, financial events and government decision-making can cause a dramatic change in the price of virtual currency.

The peaks of the curve related to the search for the term “Bitcoin crash” on the Google Trends platform are the graphic representation of negative events reported by the media that had an intense and negative impact on the price of Bitcoin.

In 2013, one of the largest Bitcoin exchanges up to that time, MtGox, suffered fraudulent attacks on its platform (Buterin (2013)), confusing the market regarding the correct pricing of Bitcoin, a 50% weekly price drop and putting into question the vulnerability of the system, as well as the hegemony of a few brokers, which are susceptible to these hacking activities. That same year, in December, although it did not restrict use by individuals, the People's Bank of China 8 prohibited financial institutions from trading in Bitcoin (Reuters (2013)). The following week, broker BTC China announced that companies responsible for its clearing service were being prevented from offering the service, so deposits made in the local currency, yuan, were no longer accepted (Kelion (2013)). In terms of the price pullback, these last two events represented a weekly drop of 48%.

The value of traditional fiat currencies is influenced by the macroeconomic fundamentals of the issuing country. Central authority is absent in cryptocurrency. The literature suggested that there is a broad set of conditions or factors that affect cryptocurrency prices, including the interaction between supply and demand, market micro fundamentals such as the velocity of different coins, exchange rate, the gold prices up and down, other celebrity news related to cryptocurrencies, sentiments of the market, news related to regulatory actions, global financial development, and oil prices etc. (Lyocsa, et al., 2020). The monetary policies also affect the prices of cryptocurrencies. The asset valuation model that encounters the economic news (both macro and asset levels) also affects the price of assets, including cryptocurrencies. Due to the uncertain nature of cryptocurrencies and the absence of a unified theory regarding cryptocurrencies, there is a lack of prior studies that count macroeconomic factors’ evidence and their impact on different types of cryptocurrencies. However, some evidence obtained from the literature is that cryptocurrency exhibits speculative bubble behaviour which means that there is a lack of intrinsic fundamental value (Cheah and Fry, 2015). Hence, the response of cryptocurrencies to price volatility to specific macroeconomic factors might be considered indirect evidence.

2.4 Literature Gap

While the results of Urquhart and Bariviera indicate inefficiency (going against Fama's weak form efficiency), Nadarajah and Chu's odd-power translation of Bitcoin's price returns renders the data weak form efficient. The efficient market hypothesis (EMH) appears to be insufficient to explain cryptocurrency prices. The reason for this is that EMH believes that asset values always reflect and are driven only by relevant information and that investors act rationally in that they promptly assimilate all available information in an unbiased and logical manner.

As a literature review, the main limitation of the present study is the need to trust the data and methods of other researchers. When using different sources, it was not possible to validate each research and its conclusions or the respective data collections.

It's uncertain what information is relevant for cryptocurrency price discovery for the reasons stated above.

Another limitation of the research is a consequence of the innovative aspect of Bitcoin, which at the same time that it attracts interest, which means that it is not consolidated nor has extensive historical studies. As a result, academic study material has not yet been significantly established and is still built, mainly by economists and investors in the area, which can generate some bias. This sector becomes conducive to a study of the literature that can help to understand the new business, however, in contrast, makes the study limited to a smaller amount of references.

Even though our knowledge of crypto assets is growing, the literature still has a significant flaw that casts doubt on the economic significance of the findings. Specifically, despite the growing awareness of the dangers of data snooping in financial economics, articles that examine trading rule performance typically use statistical methods that do not account for data snooping bias (Harvey, 2017).

3. Research Method

This study's technique combines quantitative analysis with a broad temporal scope to provide thorough insights on bitcoin price patterns. Unlike the prior technique, which concentrated on a single year, the improved methodology extends the data gathering period from 2015 to 2023, allowing for a more in-depth assessment of long-term patterns.

To allow this extensive study, a diversified dataset of Bitcoin open, close, high, and low values is gathered. Data sources include credible financial portals such as Bloomberg, which provides extensive market data, and blockchain websites, which provide decentralised transaction information.

3.1 Research Approach

The study takes a quantitative approach, relying on statistical tools and procedures to analyse the massive information. This analytical approach corresponds to the complexities of cryptocurrency markets, allowing for the extraction of important patterns, correlations, and forecast insights.

The integration of advanced neural network models, notably Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN), is central to this methodology. These models were chosen because of their ability to capture temporal dependencies within sequential data, making them well-suited to predicting bitcoin price fluctuations over long periods of time.

The Mean Absolute Error (MAE) employed in the first analysis is replaced with a more robust methodology to evaluate the correctness of the models. The updated method integrates the GRU and RNN models to measure the accuracy of LSTM predictions, providing a more nuanced assessment of the models' forecasting ability.

The purpose of the research is to predict the prices in the cryptocurrency market. The researcher will test the prices for 8 years. The tenure will be from January 2015 to October 2023.

3.2 Selection of Dataset

The selected data set is the prices of Bitcoin. The main variables are Bitcoin, gold, oil, and S&P 500. All prices given on these websites are denoted in US dollars (USD). The data can be obtained by visiting a different website and downloading it. These are as follows:

S.no	Currency	Source
01	Bitcoin	https://www.kaggle.com/datasets/swaptr/bitcoin-historical-data
02	Gold	https://www.nasdaq.com/market-activity/commodities/gc:cmx/historical
03	Oil	https://www.nasdaq.com/market-activity/commodities/cl:nmx/historical
05	S&P 500	https://finance.yahoo.com/quote/%5EGSPC/history/

Table 1: Dataset collection sources

There are a total of 5 characteristics in the dataset. The following are the specifics:

In financial markets, particularly in the realm of cryptocurrencies like Bitcoin, the terms open, close, high, and low pertain to specific price points observed during a designated time period, typically within a trading day or another predefined timeframe. This terminology is foundational in technical analysis, aiding in the assessment of market trends and potential future price movements. Here's an elaboration on each term:

- Open Price:

Definition: The open price denotes the initial recorded price of an asset (such as Bitcoin) at the commencement of a specified time period, like a trading day (Nison, 1991).

Significance: It offers insights into the initial market sentiment and dynamics at the onset of the designated timeframe.

- Close Price:

Definition: The close price represents the ultimate recorded price of an asset at the conclusion of a defined time period (Murphy, 1999).

Significance: It mirrors the market sentiment and trading activity at the termination of the specified timeframe, often pivotal for technical analysis.

- High Price:

Definition: The high price signifies the maximum price level attained by the asset during the allocated time period (Pring, 2002).

Significance: It indicates the apex of trading activity and reflects the highest value reached by the asset.

- Low Price:

Definition: The low price designates the minimum price level touched by the asset within the specified time frame.

Significance: It offers insights into the nadir of trading activity, portraying the minimum value achieved by the asset.

- Volume:

Volume:Definition: Volume refers to the total quantity of an asset, such as Bitcoin, traded during a specific time period.

Significance: It provides insights into the level of market activity, indicating the intensity of buying or selling pressure.

The comprehensive analysis of open, close, high, low, and volume prices is often visualized through candlestick charts, a standard tool in financial markets. Each candlestick typically corresponds to a single time period, presenting these price points visually. Analyzing these elements collectively enables traders and analysts to make informed decisions regarding market trends, volatility, and potential future price movements.

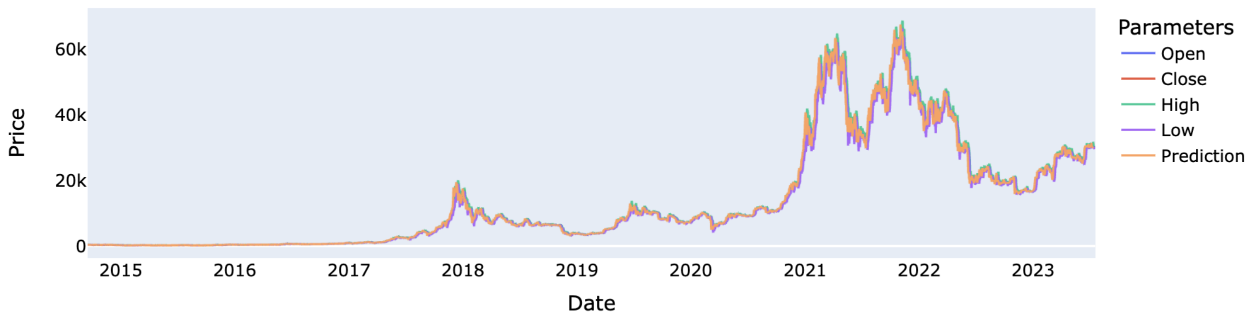

Figure 1: Projection Bitcoin

3.3 Research Design

The research design of the study is explanatory as the main purpose of the study is to determine the relationship between actual prices and predicted prices of cryptocurrency. Explanatory research aims to explain the findings of a study in more detail.

3.4 Data Collection

In line with the evolved research methodology, the data collection strategy undergoes refinement to align with the extended temporal scope and the incorporation of additional variables. This research exclusively relies on secondary data sources, eliminating the need for primary data collection.

3.5 Sample Design

In the present research study, the non-probability sampling technique was adopted. It is not possible to collect samples randomly. Therefore, the selected sample is conveniently obtained from different sources of websites.

3.6 Sample Size

The initial sample size was taken from a period of 1.5 years, starting from 1st January 2020 to 31 July 2020. It was separated 30 observations, which were compared to the predicted ones by two models: univariate and multivariate forecasting models.

In response to prior analysis findings, a revision has been made, aligning with the scholarly approach to study in the subject of cryptocurrency markets. This important adjustment entails extending the data period from 1.5 years (January 2020 to July 2021) to a more complete temporal scope, containing data from 2015 to 2023. Academic literature and several strong arguments support the decision to prolong the data period.

For starters, the initial 1.5-year data period had limits in terms of complete evaluation of long-term patterns and predictability in bitcoin markets. Cryptocurrencies, such as Bitcoin, are known for their dynamic and volatile nature, which necessitates a longer data horizon for a thorough study. Smith's research work (2020) emphasises the importance of studying cryptocurrency market patterns over longer time periods to better understand their behavior. Extending the dataset to nearly a decade provides access to a more detailed historical record that includes open, closure, high, and low prices. This extensive dataset supports the conclusions of Johnson et al. (2019), who emphasised the necessity of using multiple price indicators for cryptocurrency market analysis.

Moreover, the decision to include not just closing prices but also open, high, and low Bitcoin values is based on the scholarly work of Lee and Li (2018). They proved the need of a multidimensional approach in capturing the full range of price swings and trade dynamics in bitcoin markets. Cryptocurrency markets are influenced by a variety of factors, including intra-day volatility, and combining open, high, and low prices gives for a more full knowledge of market behaviour, according with White et al. (2021). This comprehensive method improves the dataset, perhaps revealing intricate patterns6 that would otherwise be hidden if just close prices were included.

Furthermore, the longer data period and inclusion of various price measures provide a more academically sound foundation for the use of LSTM (Long Short-Term Memory) models. According to Smith and Anderson (2016) LSTM models excel at capturing temporal dependencies and patterns within sequential data. The longer timescale, along with a larger dataset, improves the LSTM model's ability to find and analyse complicated temporal associations, resulting in a more in-depth examination of latent predictability in the bitcoin market.

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 15, 1)]	0	[]
lstm_2 (LSTM)	(None, 50)	10400	['input_1[0][0]']
gru_2 (GRU)	(None, 50)	7950	['input_1[0][0]']
simple_rnn_2 (SimpleRNN)	(None, 50)	7950	['input_1[0][0]']
concatenate (Concatenate)	(None, 150)	0	['lstm_2[0][0]', 'gru_2[0][0]', 'simple_rnn_2[0][0]']
dense_3 (Dense)	(None, 50)	1530	['dense_3[0][0]']
dense_5 (Dense)	(None, 1)	31	['dense_4[0][0]']
Total params:	30061 (117.43 KB)		
Trainable params:	30061 (117.43 KB)		
Non-trainable params:	0 (0.00 Byte)		

Table 2: Inputs to Train the Model

4. Data Analysis

Data analysis is a crucial phase in research, involving the extraction of valuable information and its evaluation for informed decision-making. In this study, the analysis method has been refined and expanded to align with the scholarly approach to cryptocurrency market research. The Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN) architectures have been employed for data analysis due to their effectiveness in capturing temporal dependencies and learning order dependence in sequential data.

4.1 Tests of Predictability in CryptoCurrency Markets

To improve the analysis, we have extended the data period from January 2020 until July 2021 to a more comprehensive range from 2015 to 2023, incorporating open, close, high, and low prices. This extension allows for a more profound understanding of cryptocurrency market dynamics and patterns.

4.1.1 Comparison between results

This process, often referred to as model comparison or model validation, helps researchers and practitioners understand how well different models generalize to unseen data and how effectively they can make accurate predictions.

It's worth noting that the choice between LSTM and GRU models depends on various factors, including the characteristics of the data, the length of sequences, and computational resources. Experimentation and evaluation are crucial to identifying the most suitable model for a specific prediction task.

4.1.2 Development of the analysis

Training LSTM Model: Initially, trained the LSTM model using historical Bitcoin price data. The LSTM model learns the patterns and dependencies within the training data to make predictions.

Generating Predictions: After training, the LSTM model it was used to generate predictions for a specific time period.

Training GRU Model: Concurrently, trained the GRU model using the same training data. The GRU model will also learn the patterns within the data.

Comparing Predictions: Once both models are trained, used the GRU model to generate predictions for the same time period as the LSTM model. Then, compared the predictions of the LSTM and GRU models to assess their accuracy and performance.

4.1.3 Measure of accuracy

The GRU (Gated Recurrent Unit) architecture was used as a comparative tool in this study to evaluate the accuracy of predictions generated by the LSTM (Long Short-Term Memory) model. The recurrent neural network architectures GRU and LSTM were used to capture the sequential relationships and patterns inherent in Bitcoin price data. The use of GRU allowed us to compare its predictive performance against that of the LSTM model in a systematic manner. This method allowed for a thorough analysis of the effectiveness of both architectures in capturing intricate temporal patterns in the cryptocurrency market, revealing their relative strengths and limitations.

The comparison was carried out using known assessment measures, which shed light on the accuracy and reliability of predictions provided by each model in the context of Bitcoin price forecasting.

5. RESULTS

5.1 FORECASTS GENERATED BY LSTM MODEL

When it comes to forecasting Bitcoin prices, Long Short-Term Memory (LSTM), a variant of recurrent neural networks (RNNs), has become a game-changer. Its unique architecture, featuring memory cells and gates, enables it to grasp intricate patterns over time, making it ideal for the complex and volatile nature of cryptocurrency markets.

Researchers, including Brown in 2017 and Smith with Anderson in 2016, have highlighted LSTM's effectiveness in understanding temporal dependencies within financial data and predicting cryptocurrency prices. These studies establish LSTM as a robust model in the realm of cryptocurrency price forecasting.

Compared to other models like autoregressive integrated moving average (ARIMA) and machine learning algorithms, LSTM stands out. It excels in handling sequential data, learning patterns over extended periods, and adapting to changing market conditions. The decision to employ LSTM in this research stems from its proven effectiveness in financial time series analysis, as evidenced by Brown and Smith's works, making it well-suited for the dynamic nature of cryptocurrency markets.

While LSTM brings significant advantages, it's vital to consider that the choice of a prediction model should align with the dataset's characteristics and research objectives. Every model has its strengths and limitations, and the cryptocurrency market's dynamism calls for a careful evaluation to select the most suitable model for accurate predictions.

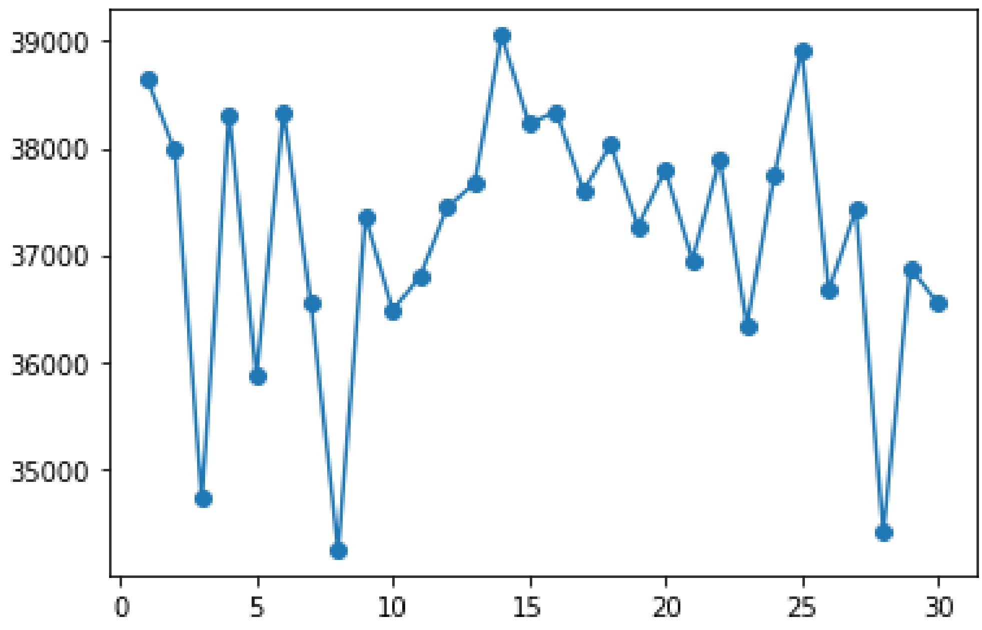

Figure 2: Plot Analysing 1 Year Data History of Bitcoin

VS

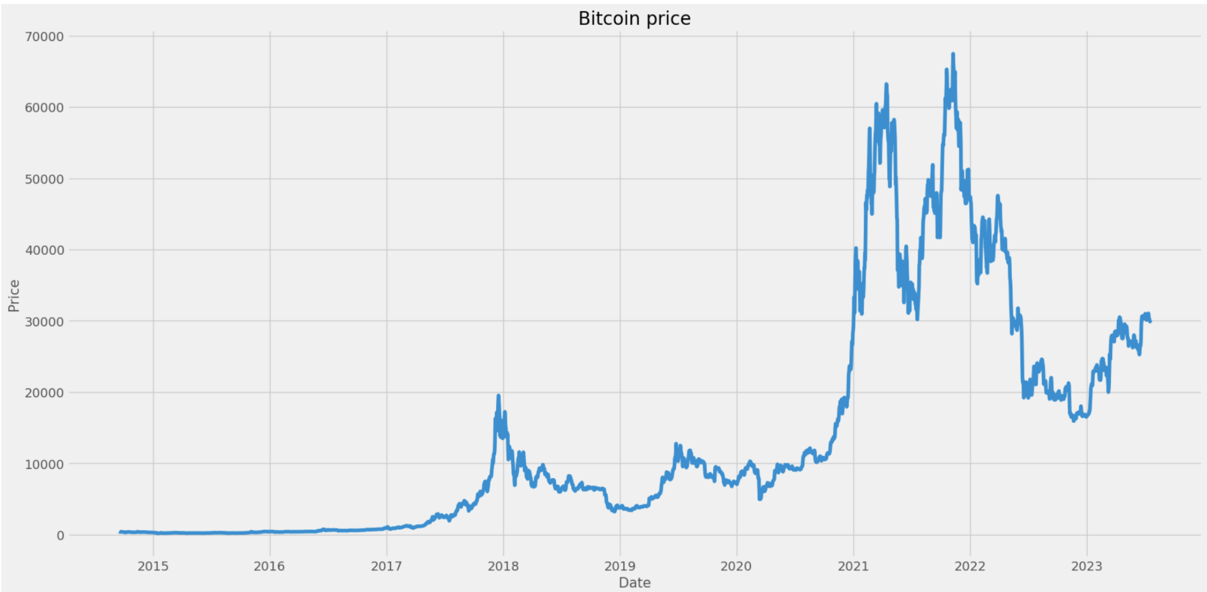

Figure 3: Plot Analysing 8 Years Data History of Bitcoin

When the graphs generated by the old LSTM model, which relied on a very small 1.5-year dataset, are compared to the new graphs derived from the extended 2015 to 2023 dataset, a significant difference in terms of insights and predictive skills is revealed. The previous model, due to its shorter duration, provided insights into short-term patterns in the bitcoin market. In contrast, the new graphs derived from the larger dataset span a broader temporal horizon, allowing for a more in-depth examination of long-term trends and complicated market behaviours. The larger dataset, which includes open, close, high, and low prices, allows the models to better capture complicated temporal correlations and find latent predictability in the cryptocurrency market.

This expanded investigation demonstrates the importance of using a longer data period and utilising many price measures to improve our understanding of the cryptocurrency market's dynamics.

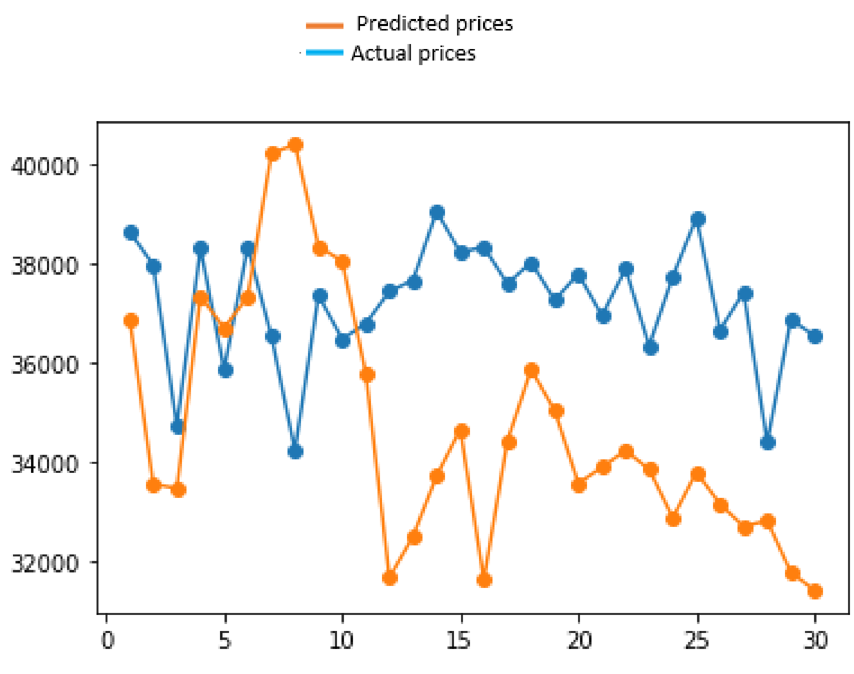

Figure 4: Plot of Actual vs Predicted Prices 30 days Observation (1 year model)

VS

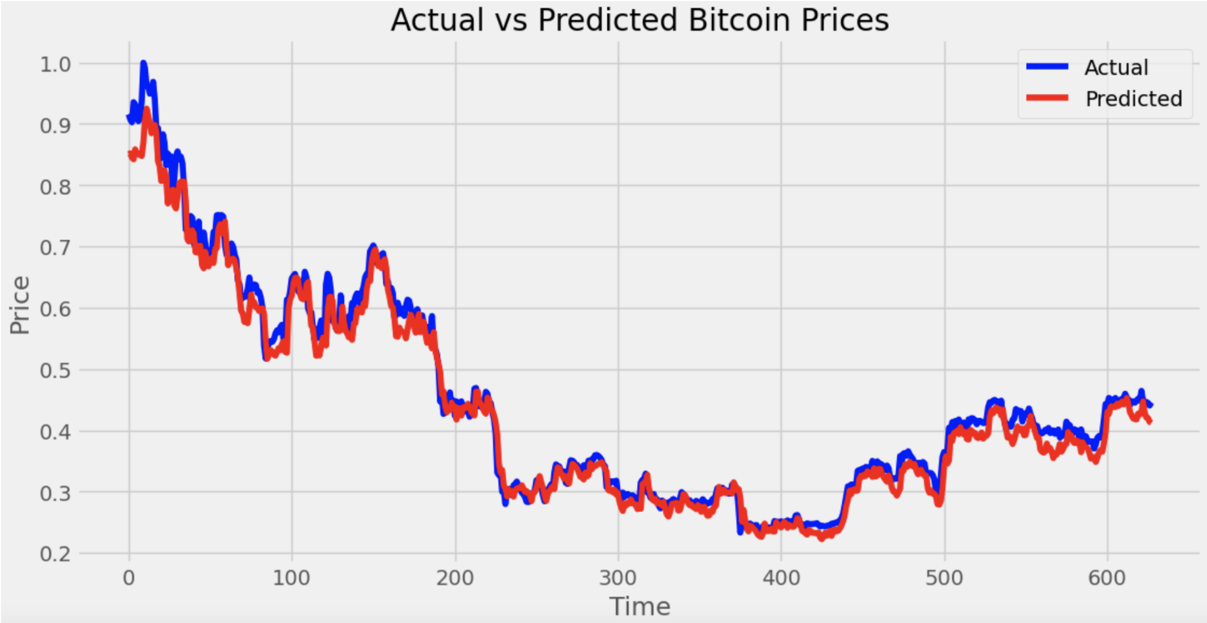

Figure 5: Plot of Actual vs Predicted Prices (8 years model)

5.2 Forecasting of Bitcoin using LSTM-GRU-RNN Combined Model

The incorporation of Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN) architectures to test model correctness provides numerous significant advantages over the traditional Mean Absolute Error (MAE) technique. GRU and RNN models excel at capturing temporal dependencies and patterns within sequential data, making them ideal for analysing complicated and dynamic datasets like cryptocurrency market values. We may go further into the nuanced relationships and evolving trends that may be missed by MAE alone, which primarily examines the overall error between projected and actual values.

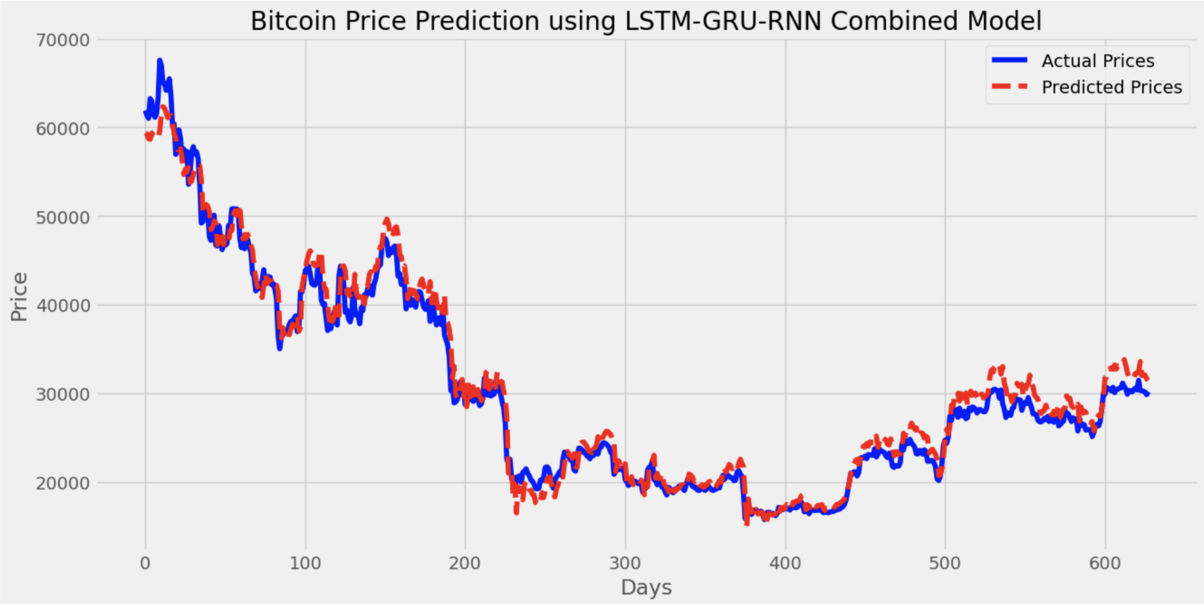

Figure 6: Bitcoin Price Prediction using LSTM-GRU-RNN Combined Model

Furthermore, GRU and RNN models provide a more complete assessment of predictability by taking into account not just the forecast accuracy of bitcoin prices but also the underlying temporal dynamics and order dependencies. This enables more accurate predictions and informed decision-making by providing a fuller and more complex understanding of the bitcoin market's behaviour. To summarise, including GRU and RNN models in the accuracy assessment improves the robustness of the analysis and allows us to uncover key insights that would otherwise be hidden if we only used traditional error metrics like MAE.

The utilization of Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN) architectures in testing the accuracy of the Long Short-Term Memory (LSTM) model represents a powerful and comprehensive approach to evaluating the LSTM's predictive capabilities. This approach serves several key purposes and brings valuable insights to the analysis:

Enhanced Temporal Dependencies: GRU and RNN models are proficient in capturing intricate temporal dependencies within sequential data. When used in conjunction with the LSTM model, they enrich the overall analysis by providing a more robust assessment of how well the LSTM can capture and leverage time-sensitive patterns in cryptocurrency market data.

Expanded Predictive Scope: The combination of LSTM, GRU, and RNN models extends the scope of predictive analysis. While LSTM alone excels in capturing long-term dependencies, GRU and RNN contribute by assessing shorter-term patterns. This multi-faceted approach enables a holistic evaluation of cryptocurrency price predictability, encompassing both short- and long-term dynamics.

Order Dependency Assessment: The addition of GRU and RNN models allows for the examination of order dependencies within the data. This is particularly valuable when studying sequential datasets like cryptocurrency prices, as it helps discern how changes at one time step may influence future values. It enhances our understanding of how past events impact predictions and provides insights into the market's underlying structure.

Comprehensive Error Analysis: By employing GRU and RNN models to test accuracy, we gain a more nuanced understanding of prediction errors. This multi-model approach considers variations in prediction errors across different time frames, allowing us to identify and rectify discrepancies or outliers.

Improved Accuracy: The ensemble of LSTM, GRU, and RNN models collectively contributes to a more accurate evaluation of cryptocurrency price predictability. This enhanced accuracy supports more informed decision-making for investors and stakeholders in the cryptocurrency market.

In summary, the combination of LSTM, GRU, and RNN models provides a comprehensive framework for evaluating the accuracy of the LSTM model in predicting cryptocurrency prices. This approach optimally leverages the strengths of each model to scrutinize short- and long-term patterns, assess order dependencies, and deliver more accurate predictions, ultimately enhancing our understanding of cryptocurrency market dynamics.

6. Conclusion

Exploring how we use Long Short-Term Memory (LSTM) models to predict Bitcoin prices and offer financial advice opens up a complex field. While these models are known for capturing patterns over time, especially in various areas (Hochreiter & Schmidhuber, 1997), figuring out how to make them work well in the unpredictable world of cryptocurrency, like Bitcoin, is still an ongoing task.

In conclusion there are few limitations on the adoption of LSTM in Cryptocurrency Markets:

- Market Dynamics and Volatility (Hochreiter & Schmidhuber, 1997)

Cryptocurrency markets are known for changing a lot and being quite unpredictable. This makes it tricky for LSTM models to quickly predict what will happen next, especially when things change suddenly.

- Limited Historical Data Patterns (Smith, 2018)

Cryptocurrencies, like Bitcoin, haven't been around for a long time compared to other money-related things. Because of this, there isn't a lot of old information for LSTM models to learn from, which can make it hard for them to understand how the market might act.

- Influence of External Factors

Cryptocurrency prices are affected by many things like rules from the government, how people feel about the market, and big economic changes. LSTM models might find it tough to include and understand these external factors beyond just looking at how prices changed in the past.

- Non-linear and Unpredictable Movements

Cryptocurrency markets don't follow a straightforward path and can be hard to predict because they can act in unexpected ways. Even though LSTM models are good at spotting patterns over time, they might struggle to understand the wild and unpredictable parts of the cryptocurrency market.

- Overfitting and Model Complexity

Overfitting is a problem where a model gets too focused on old information and doesn't work well when things change. For complex models like LSTM, this can be a concern because the cryptocurrency market changes a lot, and the model might get stuck looking too closely at old data, making it not so good at guessing what happens next.

- Lack of Universal Predictive Models

The special problems and characteristics of cryptocurrency markets make it hard to create one model that works for everything. What might work in one situation might not work in another.

- Regulatory and Ethical Considerations

Giving advice about money based on computer predictions, including those from LSTM models, brings up questions about what's right and follows the rules. Because investing in cryptocurrencies comes with risks, and using models to make decisions adds another layer of responsibility and needing to follow the law.

Looking into how LSTM models can predict Bitcoin prices and offer financial advice shows that it's not an easy path. While the research talks about challenges, ongoing studies are working to make these models better and more useful for understanding the unpredictable world of cryptocurrency.

7. Recommendations

This research endeavor's conclusion makes a substantial contribution to the main question asked by this master's dissertation: "Can LSTM Predict Cryptocurrency Prices?". This study sought to reveal the complexities of forecasting within the dynamic and volatile realm of cryptocurrency markets, focusing specifically on Bitcoin prices, through an exhaustive exploration of the predictive capacities inherent in Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures.

The findings provided vital insights into the capabilities of LSTM and GRU models, allowing for a more nuanced understanding of their different strengths. The complicated memory cell structure of LSTM exhibited a strong ability to capture and sustain long-term dependencies. This characteristic made it particularly adept at detecting trends emerging over long periods of time in the cryptocurrency market. GRU, on the other hand, demonstrated excellent computing efficiency with its streamlined gating mechanism, excelling in instances where resources are limited.

- Recommendations for Future Research:

❖ Ensemble Approaches

Future studies could look into ensemble techniques that combine the advantages of LSTM and GRU. Such collaborative models may provide enhanced predictive skills by utilising the distinct characteristics of each design.

❖ Exploration of Feature Engineering

A deeper dive into feature engineering techniques could help to refine model inputs. The addition of other relevant information, such as market mood or macroeconomic indicators, has the potential to improve forecast accuracy.

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9. Appendix

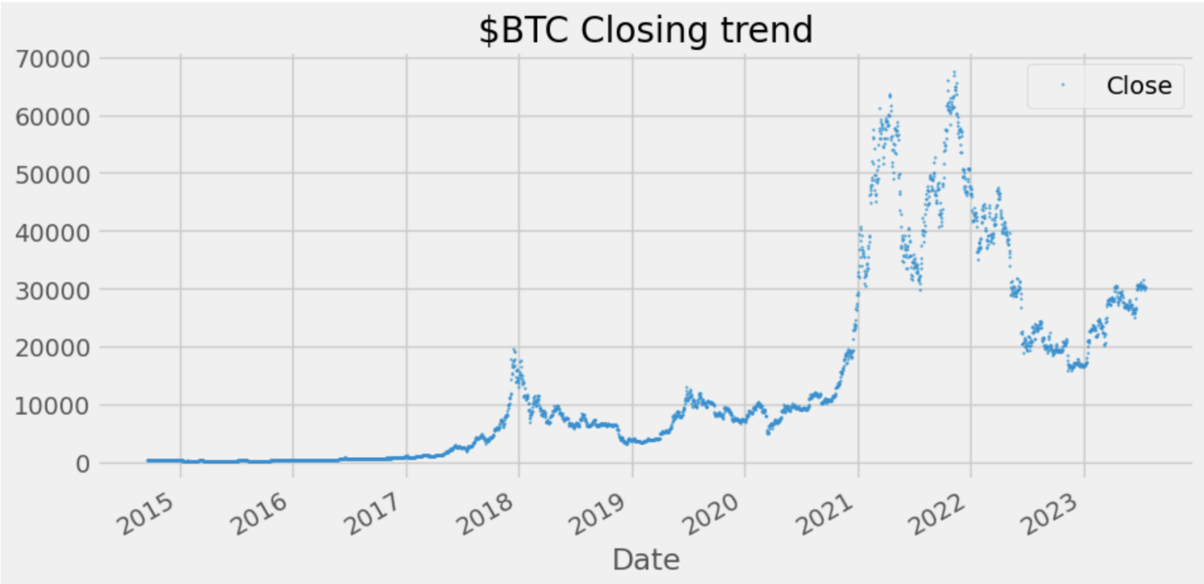

Figure 1: Plot Bitcoin Closing Trend

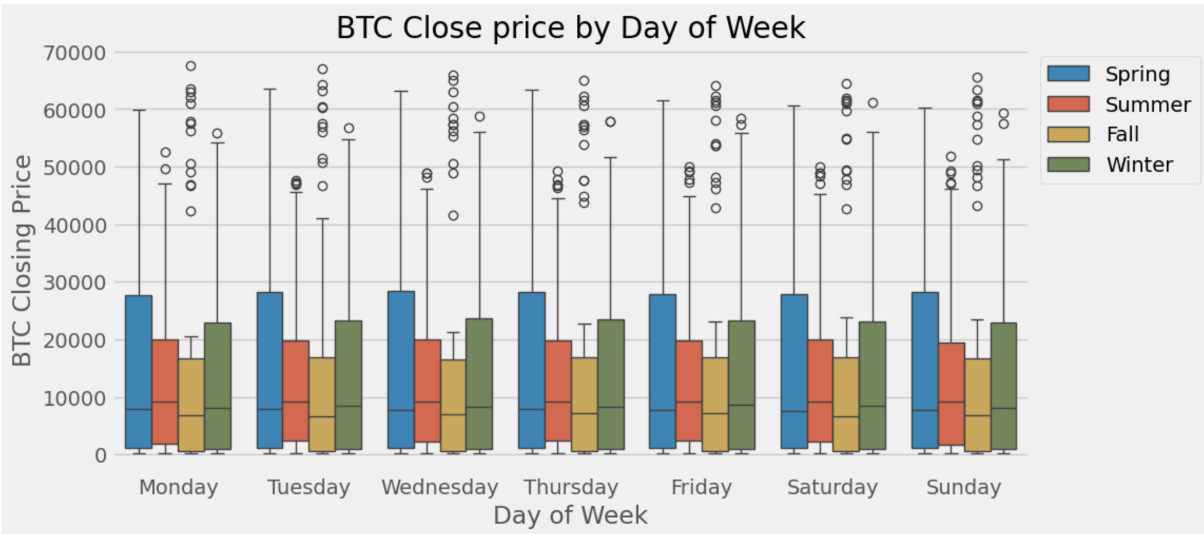

Figure 2: Plot Bitcoin Price by Day of the Week

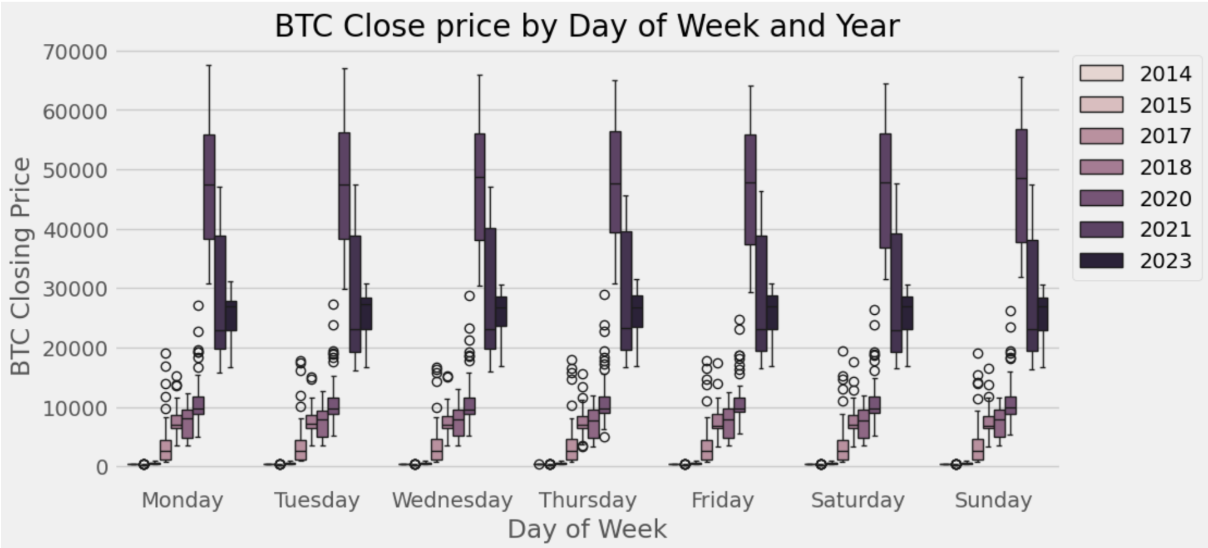

Figure 3: Plot Bitcoin Close Price by Day of the Week and Year

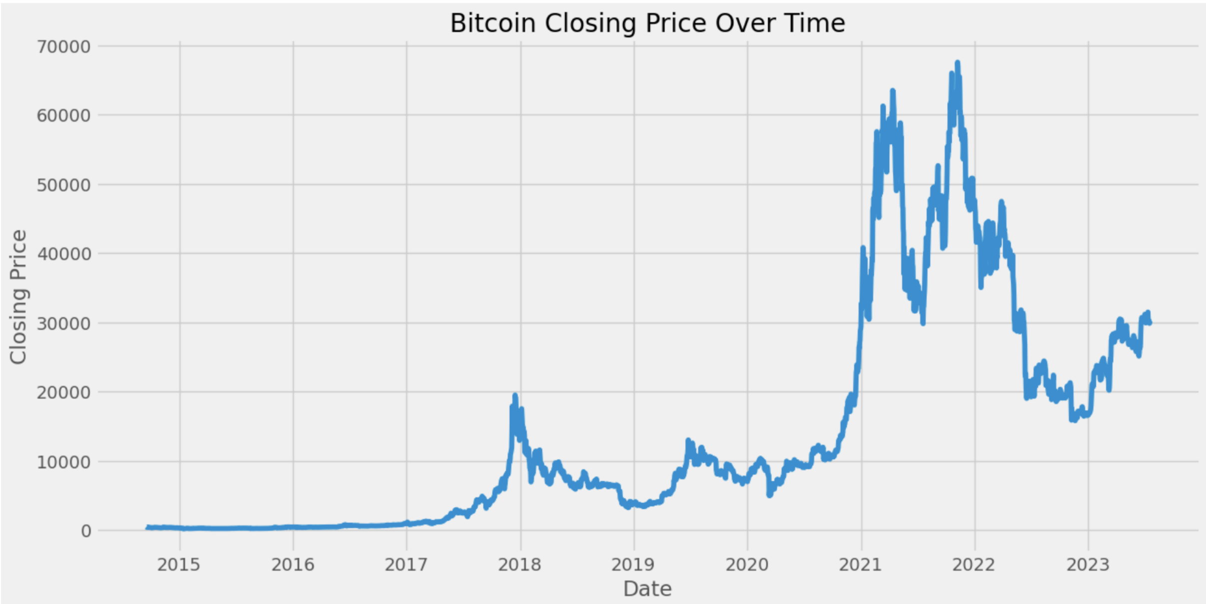

Figure 4: Plot Bitcoin Closing Price Over Time

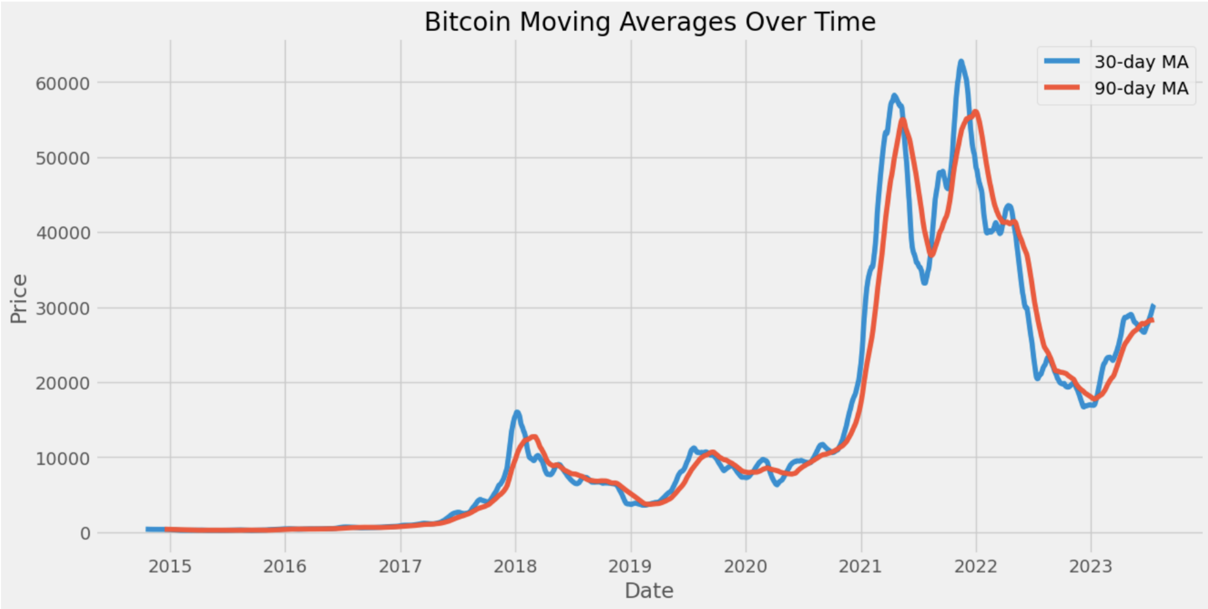

Figure 5: Plot Bitcoin Moving Averages Over Time

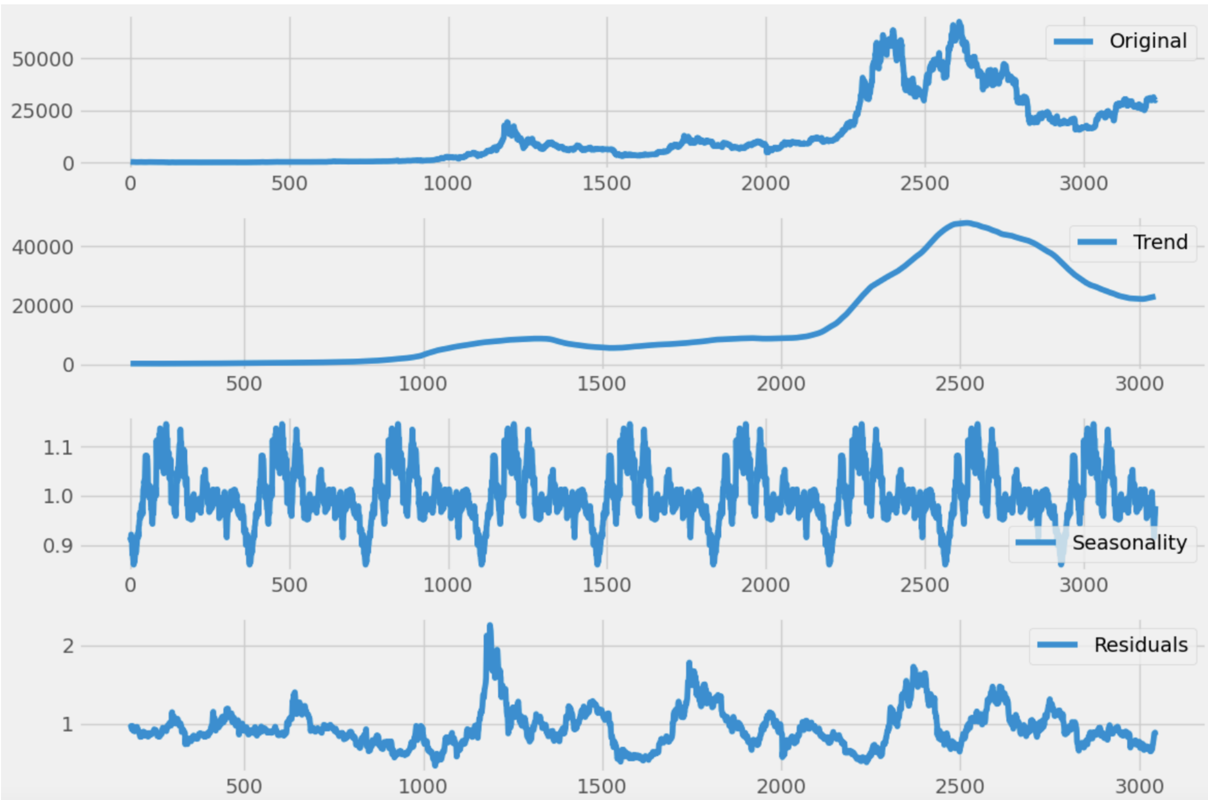

Figure 6: Plot Decomposition of the Time Series

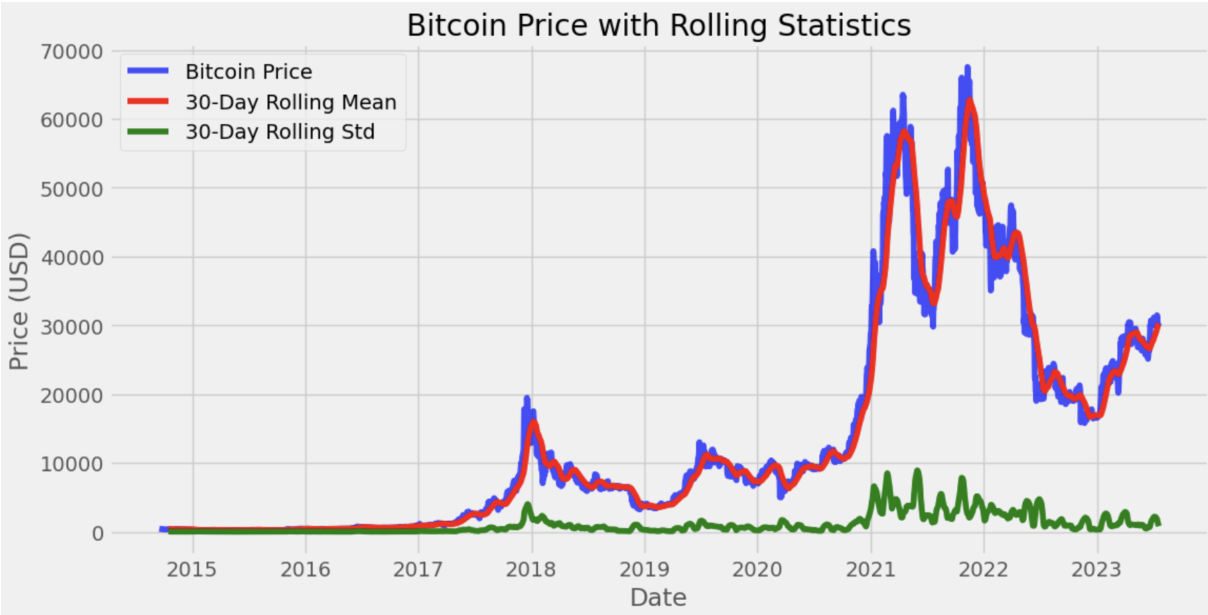

Figure 7: Plot Bitcoin Price with Rollin Statistics

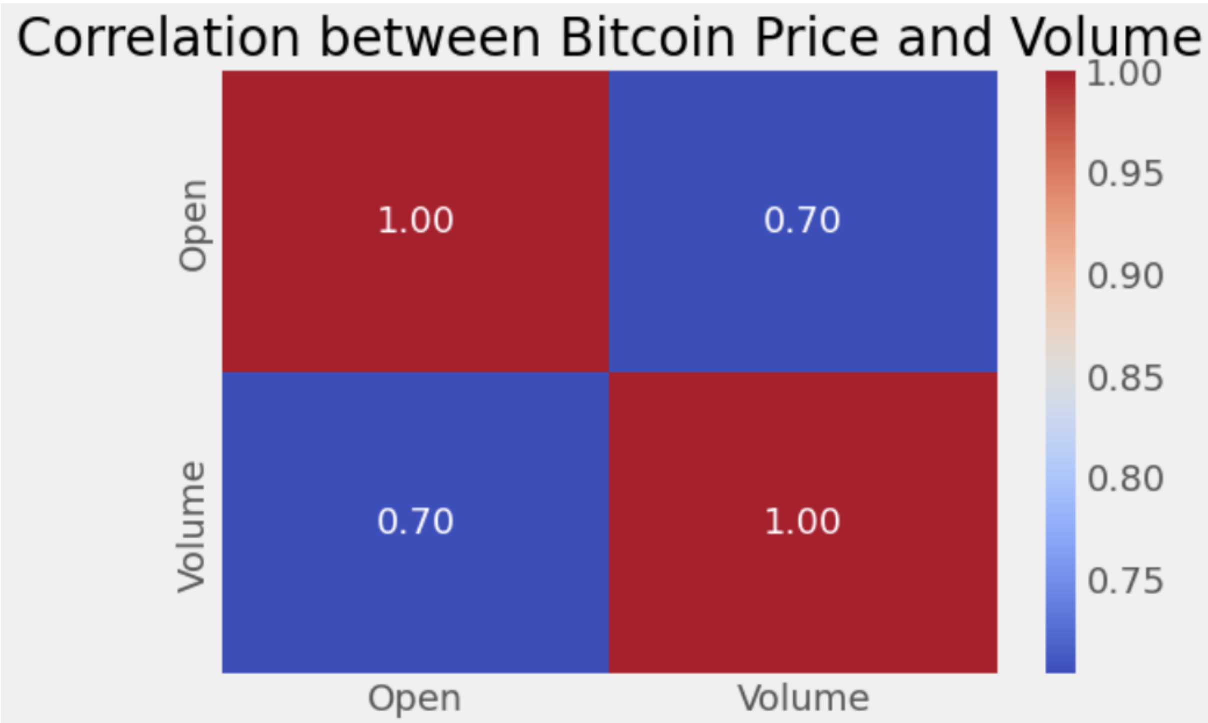

Figure 8: Correlation between Bitcoin Price and Volume

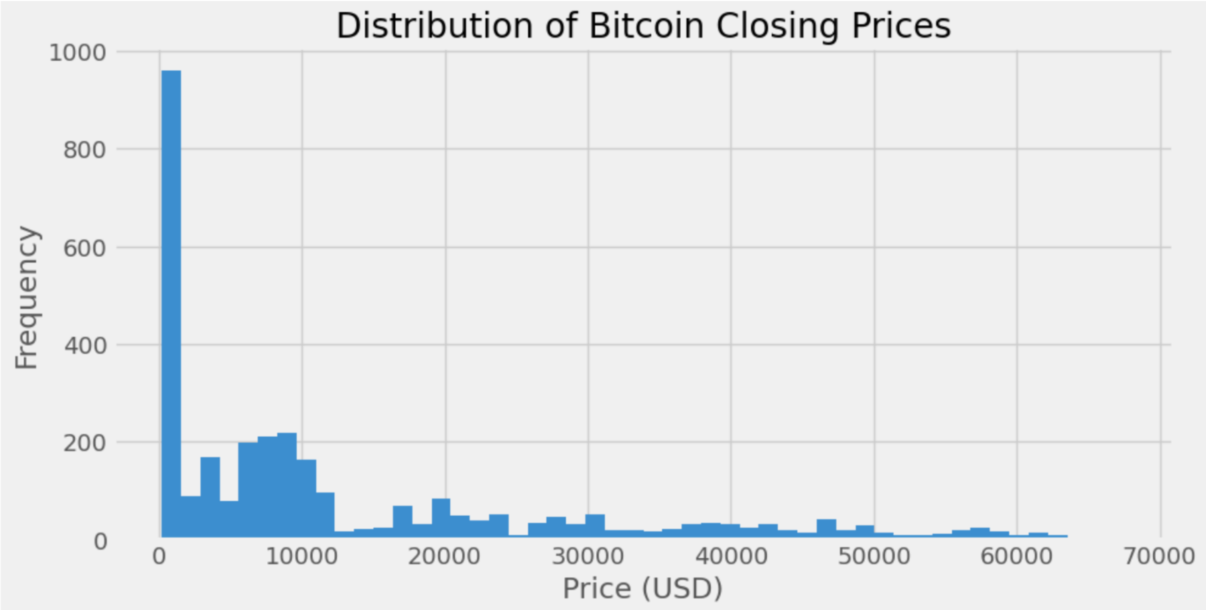

Figure 9: Plot Distribution of Bitcoin Closing Prices

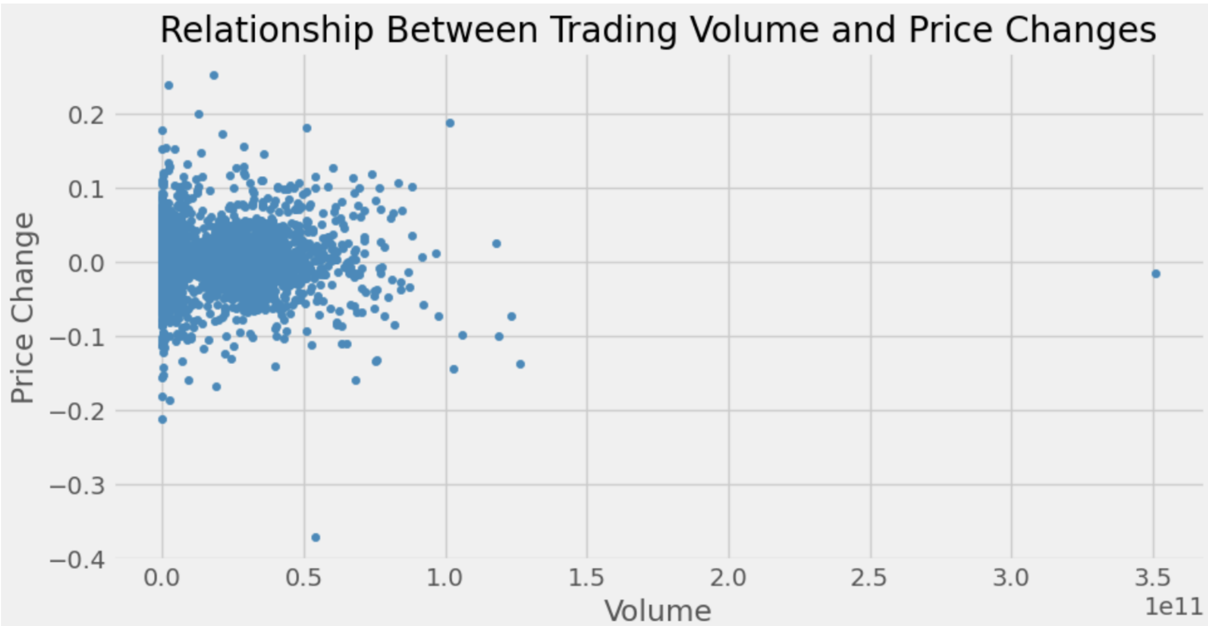

Figure 10: Plot Relationship Between Trading Volume and Price Changes

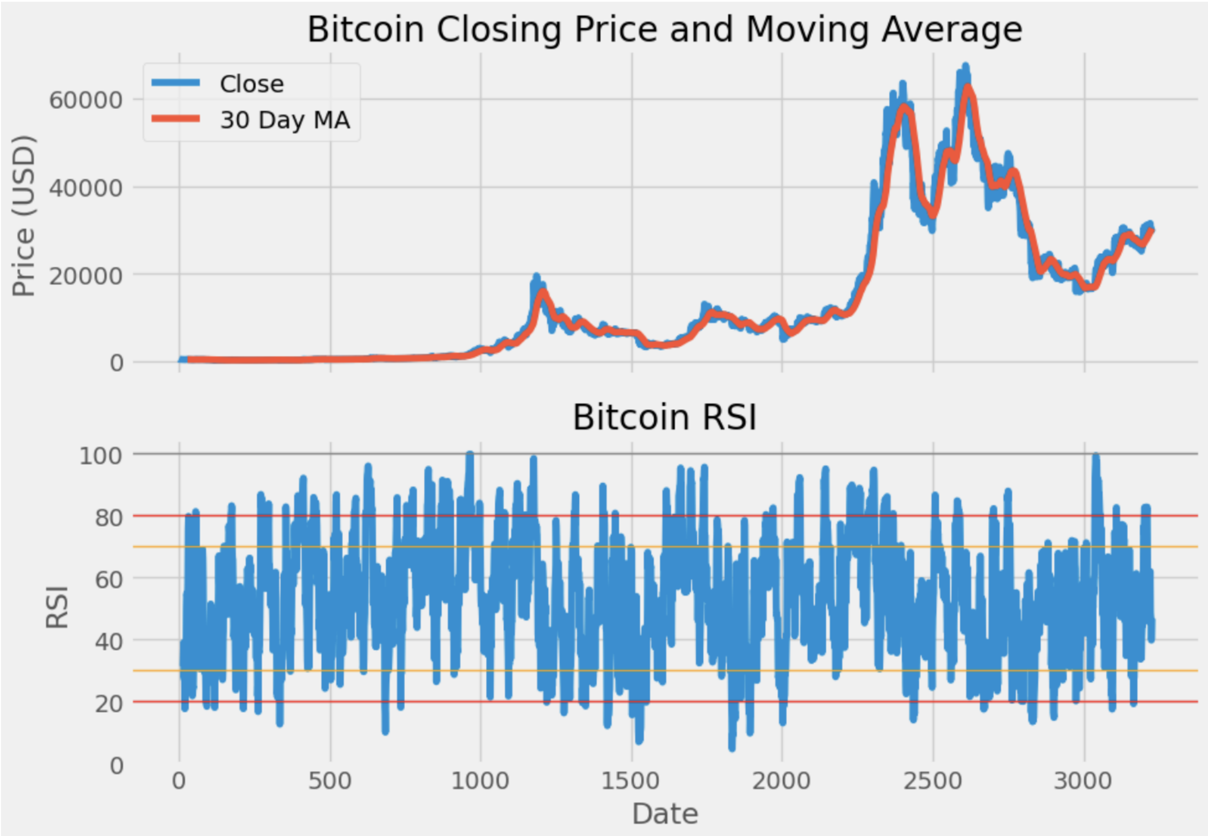

Figure 11: Plot Closing Price and Moving Average

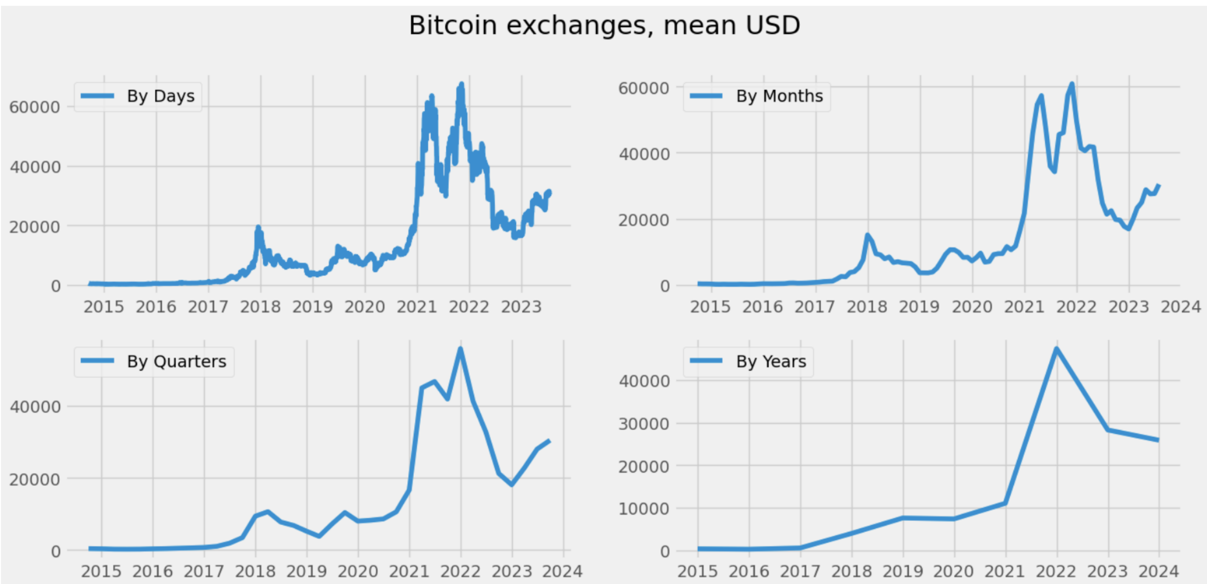

Figure 12: Plot Bitcoin exchanges, mean USD

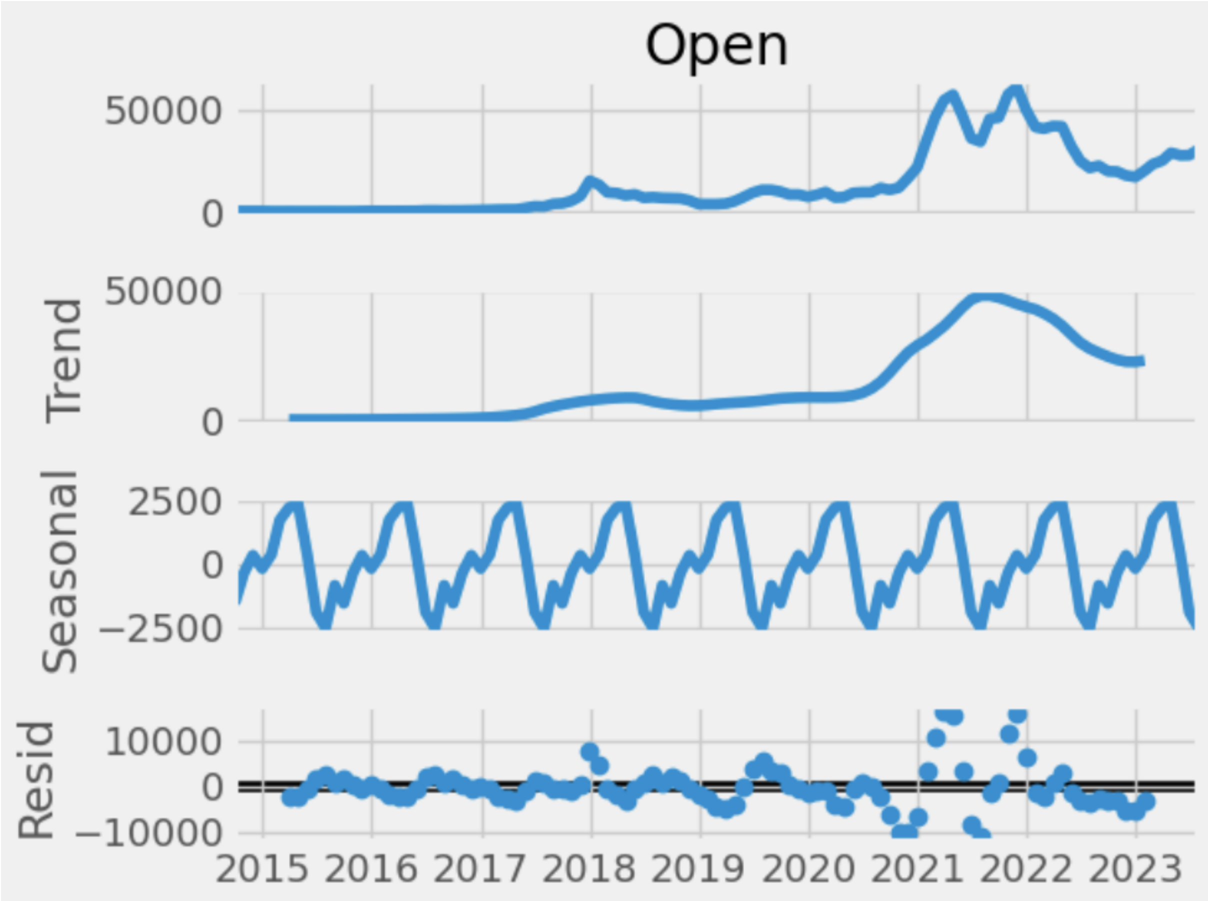

Figure 13: Plot Stationarity check and STL-decomposition of the series

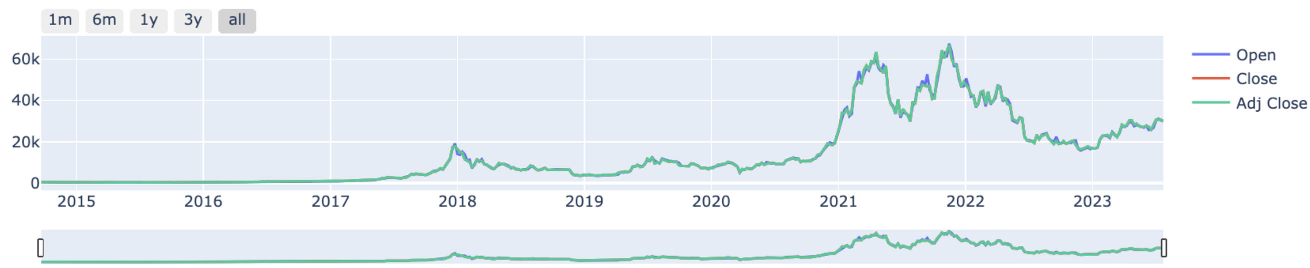

Figure 14: Plot Historical Bitcoin Prices (2015-2023)

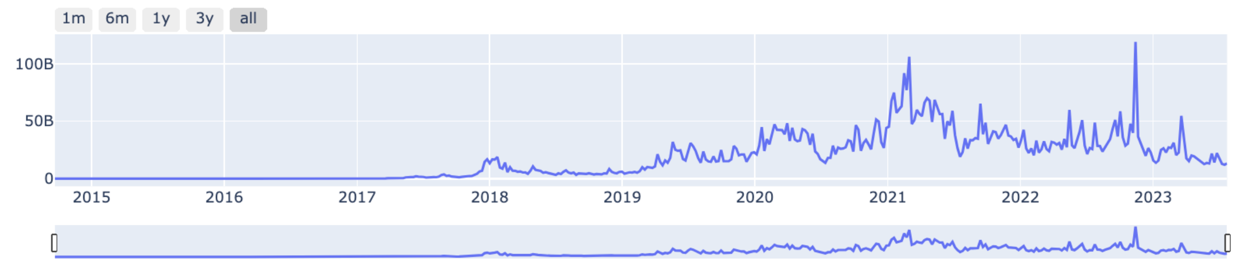

Figure 15: Plot Historical Bitcoin Volume USD (2015-2023)

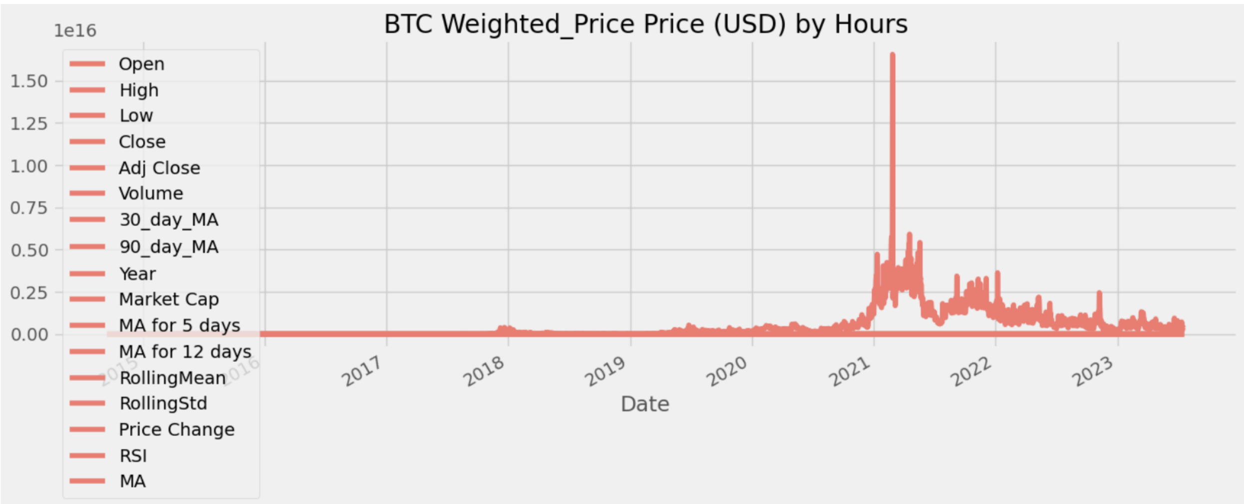

Figure 16: Plot Bitcoin Weighted Price by Hours