**Crypto Market**

**Prediction**

**Using**

**Machine Learning**

**Final Thesis**

In partial fulfillment

of the requirements for the degree of

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# Abstract

The extreme volatility and potential for substantial gains in the cryptocurrency markets have recently resulted in an increase in interest. Due to their complexity and dynamic nature, predicting the future trends of these businesses may be difficult. Machine learning algorithms could be used to forecast financial markets, including cryptocurrency. In order to construct a trustworthy predictive model using machine learning techniques, this study aims to present a complete overview of the prior research on the use of machine learning to anticipate the crypto market.

The dataset was downloaded from the cryptocompare.com website (https://min-api.cryptocompare.com/) for this study, and I used an LSTM neural network for the prediction. Model selection, feature engineering, data preparation, and model validation make up the process. The best-performing model will be chosen after a variety of parameters are used to evaluate the study's findings. The study's conclusions will directly apply to investors, traders, and policymakers who are interested in forecasting the movements of the cryptocurrency markets.

Keywords: crypto prediction; LSTM model; cryptocurrency; deep learning; machine learning; market analysis acknowledgements

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# List of Figures

[Figure 1: Importing Dataset 24](#_heading=h.44sinio)

[Figure 2: Data Cleaning 25](#_heading=h.2jxsxqh)

[Figure 3: Data Normalization 25](#_heading=h.z337ya)

[Figure 4: Split dataset for training and testing 26](#_heading=h.3j2qqm3)

[Figure 5: LSTM Architecture](about:blank) 28

[Figure 6: Dataset List 34](#_heading=h.3whwml4)

[Figure 7: Price of cryptocurrencies 35](#_heading=h.2bn6wsx)

[Figure 8: LSTM model implementation 35](#_heading=h.qsh70q)

[Figure 9: Validation Loss Plot 36](#_heading=h.3as4poj)

[Figure 10: Actual and Predicted value 36](#_heading=h.1pxezwc)

[Figure 11: Mean Squared Error](about:blank) 38

[Figure 12: Mean absolute error](about:blank) 39

[Figure 13: R2 score result](about:blank) 40

# List of Acronyms

| **Name** | **Expansion** |
| --- | --- |
| LSTM | Long Short-Term Memory |
| AI | Artificial Intelligence |
| ML | Machine Learning |
| DL | Deep Learning |
| RNN | Recurrent Neural Network |
| GPU | Graphics Processing Unit |
| MSE | Mean Squared Error |
| MAE | Mean Absolute Error |
| RMSPE | Root Mean Square Percentage Error |
| API | Application Programming Interface |

Table of Contents

[Abstract 2](#_heading=h.gjdgxs)

[Acknowledgements 3](#_heading=h.30j0zll)

[List of Figures 4](#_heading=h.1fob9te)

[List of Acronyms 5](#_heading=h.3znysh7)

[Chapter 1: Introduction 7](#_heading=h.2et92p0)

[1.1 Background and Significance of the Study 8](#_heading=h.tyjcwt)

[1.2 Problem Statement 9](#_heading=h.3dy6vkm)

[1.3 Research Questions and Objectives 10](#_heading=h.1t3h5sf)

[1.4 Expected Outcome 12](#_heading=h.4d34og8)

[Chapter 2: Literature Review 13](#_heading=h.2s8eyo1)

[2.1 A Comprehensive overview of the existing literature 14](#_heading=h.17dp8vu)

[2.2 Critical Analysis of Existing Studies 16](#_heading=h.3rdcrjn)

[2.3 Machine Learning in Finance 18](#_heading=h.26in1rg)

[2.4 Machine Learning in Crypto Market Prediction 20](#_heading=h.lnxbz9)

[Chapter 4: Methodology 23](#_heading=h.35nkun2)

[4.1 Data Collection and Preprocessing 24](#_heading=h.1ksv4uv)

[4.2 Machine Learning Model Development 26](#_heading=h.1y810tw)

[4.3 Evaluation of the proposed system 29](#_heading=h.4i7ojhp)

[4.4 Hyperparameter Tuning 30](#_heading=h.2xcytpi)

[Chapter 5: Experimental Results 33](#_heading=h.1ci93xb)

[5.1 Dataset Description 37](#_heading=h.49x2ik5)

[5.2 Evaluation Metrics 38](#_heading=h.2p2csry)

[5.3 Comparison with Baseline Methods 40](#_heading=h.147n2zr)

[5.4 Interpretation of Results 42](#_heading=h.3o7alnk)

[Chapter 6: Discussion 44](#_heading=h.23ckvvd)

[6.1 Implications of Findings 45](#_heading=h.ihv636)

[6.2 Limitations of the Study 46](#_heading=h.32hioqz)

[Chapter 7: Conclusion 48](#_heading=h.1hmsyys)

[7.1 Summary of Findings 48](#_heading=h.41mghml)

[7.2 Practical Implications 50](#_heading=h.2grqrue)

[7.3 Final Thoughts 51](#_heading=h.vx1227)

[7.3 Future Research Directions 52](#_heading=h.3fwokq0)

[References 55](#_heading=h.1v1yuxt)

[Appendix 5](#_heading=h.4f1mdlm)9

# Chapter 1: Introduction

The total market capitalization of cryptocurrencies, whose popularity has recently increased, will exceed $2 trillion in April 2021. Cryptocurrencies are digital assets that use encryption to protect and verify all transactions and operate without a central bank. The Bitcoin cryptocurrency was developed in 2009. Ripple, Litecoin, and Ethereum are just a few of the new cryptocurrencies that have emerged since then.

The value of cryptocurrencies can fluctuate rapidly and dramatically. These variations may be influenced by a wide range of factors, including changes in legislation, technological advancements, and market sentiment. Accordingly, customary strategies may not necessarily work, and they may very well be trying to anticipate how the bitcoin market will develop.

Machine learning algorithms have shown promise for predicting cryptocurrency markets. The process of making calculations that, given enough information, can accurately predict what will happen next is known as "AI," a subset of human-made reasoning. AI calculations are the best option for determining confounding and dynamic business sectors like cryptographic money because they can find examples and connections in huge datasets.

Misrepresentation discovery, credit risk assessment, stock value estimation, and portfolio enhancement are all applications of AI in finance. The bitcoin market has been the subject of numerous machine learning studies that have produced encouraging results.

The significance of anticipating developments in the bitcoin market cannot be overstated. Accurate predictions can significantly increase returns and reduce risk for investors. Policymakers can also use cryptocurrency market predictions to pinpoint potential threats to financial stability and direct regulatory actions.

This study aims to develop a trustworthy predictive model using machine learning algorithms and conduct a comprehensive literature review on the application of machine learning to crypto market forecasting. The research will make use of a dataset that includes information on cryptocurrency prices, trade volumes, social media sentiment, and other relevant characteristics.

Adding to the developing assemblage of examinations on the utilization of AI in monetary examination and crypto market anticipation is the all-encompassing objective of this review. This project will provide useful insights into the capacity of AI calculations to monitor developments in the bitcoin market by developing areas of strength for a model. The findings of this study will also be beneficial to investors, traders, and policymakers who are interested in forecasting the movements of the cryptocurrency markets.

1.1 Background and Significance of the Study

The crypto market is a digital marketplace where various cryptocurrencies are traded. Cryptography is used by advanced monetary standards to control the period of new units as well as secure and approve trades. The most well-known cryptocurrency is Bitcoin, which was created in 2009. Since then, numerous virtual currencies have been developed, including Wave, Litecoin, and Ethereum.

Because there is no central bank, the cryptocurrency market is decentralized. Because there are exchanges for digital currencies on the market, there is no longer a need for a third party like a bank or other financial institution. On the bitcoin market, a network of computers known as nodes frequently verify transactions. These nodes verify transactions and add them to the blockchain, a digital ledger, using complex algorithms.

Methods for digital payment fluctuate greatly and erratically. These varieties could be impacted by many things, including market discernments, changes in accordance with authoritative guidelines, and mechanical events. Bitcoin's cost, for example, soared in 2017 to a record high of nearly $20,000 before pointedly falling in the principal quarter of 2018. The expansion was cited as the result of the rising popularity of cryptocurrency and cutting-edge technology like blockchain.

Anyone who has internet access, a digital wallet that stores coins, and access to the cryptocurrency market can participate. This is conceivable with trades, which are online commercial centers that make it simpler to trade digital forms of money. Coinbase, Binance, and Kraken are the three digital currency exchanges with the most users.

In addition to buying and selling them, users can mine them. Cryptocurrency mining verifies transactions and adds new blocks to the blockchain with specialized software and hardware. Excavators get paid for their work in brand-new digital currencies.

There have been a number of private and institutional investors who have entered the bitcoin market. Digital currencies may be considered by some financial backers as a means of storing cash or preventing expansion, despite the fact that some financial backers may experience significant returns. Contrarily, cryptocurrencies are viewed by some investors as speculative investments similar to penny stocks, options, or other high-risk assets.

Investing in digital currency carries a significant risk, despite the potential rewards. Due to the high level of market volatility, prices in the cryptocurrency market can change quickly and without warning. The legal environment for digital currencies is also constantly changing, with some nations accepting them and others completely banning them.

The bitcoin market has, as of late, encountered some security issues. Investors have suffered significant losses as a result of hackers targeting bitcoin exchanges and wallets. Numerous cryptocurrencies have also been used for drug trafficking and money laundering.

Despite these challenges, the cryptocurrency industry is still expanding. The digital currency market is supposed to greatly affect the worldwide monetary framework as additional financial backers enter the market and new innovations arise. Machine learning algorithms have emerged as a promising method for anticipating market movements for investors, traders, and policymakers attempting to navigate the complicated and unpredictable cryptocurrency market.

1.2 Problem Statement

There are numerous reasons why using machine learning algorithms to predict the cryptocurrency market is important. The first and most important factor is that the cryptocurrency market is extremely volatile and subject to rapid price changes. This unpredictability can pose huge dangers for financial backers and dealers; however, it additionally opens doors for those who can precisely anticipate market developments.

Because they are capable of analyzing large amounts of data and identifying patterns and trends that may be difficult for human analysts to detect, machine learning algorithms are particularly well-suited for predicting the movements of the cryptocurrency market. By dissecting information from a scope of sources, including online entertainment, news stories, and verifiable cost information, AI calculations can recognize factors that might be impacting the market and make forecasts about future cost developments.

Predicting the cryptocurrency market with machine learning algorithms can be useful not only for investors and traders but also for policymakers and regulators. There is a lack of agreement among policymakers regarding how to regulate the cryptocurrency market, which is still relatively new. Machine learning algorithms can provide policymakers with insights into the market's evolution and identify potential areas for regulation by analyzing data on market trends and behaviors.

Predicting the cryptocurrency market with machine learning algorithms has the additional advantage of lowering the likelihood of fraud and increasing transparency. Public trust in cryptocurrencies has been eroded as a result of fraud and market manipulation on the cryptocurrency market. Machine learning algorithms can help restore trust and boost confidence in the market by providing investors and traders with more precise and trustworthy information about market movements.

Lastly, businesses and organizations developing new blockchain-based applications may benefit from using machine learning algorithms to predict the cryptocurrency market. Machine learning algorithms can assist businesses and organizations in making more informed decisions regarding how to invest in and develop new blockchain applications by analyzing market trends and identifying areas of potential growth.

In conclusion, using machine learning algorithms to predict the cryptocurrency market is important because it can help investors and traders lower their risk, give policymakers insight into market trends and behaviors, increase transparency and lower the risk of fraud, and help businesses and organizations developing new blockchain applications make better decisions. As the crypto market proceeds to advance and develop, the utilization of AI calculations for anticipating market developments is probably going to turn into an undeniably significant instrument for financial backers, merchants, and policymakers alike.

1.3 Research Questions and Objectives

Here are some potential research questions for machine learning-based cryptocurrency prediction:

1. Can machine learning systems forecast future patterns in cryptocurrency prices with any degree of accuracy?
2. Which machine learning algorithms are most effective at forecasting cryptocurrency prices?
3. What benefits may be expected from combining fundamental and technical analysis to better anticipate bitcoin prices?
4. Can artificial intelligence (AI) algorithms forecast the probability of a cryptocurrency price bubble or crash?
5. How can machine learning algorithms be applied to the optimization of bitcoin portfolios?
6. Are machine learning algorithms capable of forecasting cryptocurrency trade volume and liquidity?
7. How can machine learning algorithms be applied to the cryptocurrency market to spot trading opportunities and market trends?
8. Can LSTM models improve the accuracy of cryptocurrency price prediction compared to traditional machine learning algorithms?

**Objectives:**

The goal of creating a machine learning-based cryptocurrency prediction model is to produce a tool that can reliably predict future price patterns for cryptocurrencies. To do this, a machine learning algorithm must be created and trained to identify trends and connections in historical price and volume data as well as other pertinent elements, including technical indicators, market sentiment, and news items. The model should be able to forecast the future with a given level of accuracy and generalize to new, untested data.

Making a machine learning-based cryptocurrency prediction model with the intention of producing a tool that can accurately forecast future price trends for cryptocurrencies is the main objective. In order to accomplish this, a machine learning algorithm must be developed and trained to recognize patterns and relationships in historical price and volume data as well as other important components, including technical indications, market sentiment, and news items. The model should be able to generalize to new, untested data and estimate the future with a certain level of accuracy.

The other objectives include,

1. Find a dataset for the price prediction of crypto currencies. Train the dataset to get a good accuracy score on the crypto prediction.
2. Create precise and reliable models that can project future cryptocurrency price patterns.
3. Find the best machine learning model to predict the crypto currency price.
4. Selecting the most effective machine learning algorithm for the task after researching the performance of many algorithms
5. Experimenting with various feature sets and hyperparameters to enhance the generalizability and accuracy of the model

1.4 Expected Outcome

A machine learning-based cryptocurrency prediction model is projected to successfully predict future price patterns for cryptocurrencies. A recurrent neural network called LSTM is capable of accurately capturing the temporal dependencies and patterns in time series data, such as the price of cryptocurrencies. An LSTM model can learn to predict the future prices of cryptocurrencies with a given level of accuracy by being trained on previous price and volume data as well as other pertinent variables.

Specifically, from the model we are expecting below,

* improved predictability and accuracy of bitcoin prices.
* Finding trends and patterns in the fluctuations of bitcoin prices that may not be visible using other methods.
* Understanding the major forces and variables affecting the price of cryptocurrencies.
* Finding trade opportunities based on the forecasts of the model.
* Strategies for enhancing risk management and portfolio optimization for bitcoin traders and investors.
* improved comprehension of the mechanics and behavior of the bitcoin market.
* improved decision-making resources for traders, investors, and other market participants in cryptocurrencies.

We will be developing an LSTM model based crypto price prediction model using a dataset imported from the cruptocompare.com website [27]. Expecting a predictive accuracy score of 76%, the outcomes are visualized in a line graph.

# Chapter 2: Literature Review

How to use machine learning algorithms to predict the cryptocurrency market is the subject of a growing body of research. From straight forward regression models to more complex neural networks and deep learning algorithms, researchers have investigated a variety of strategies. The following is a discussion of a few key findings from this literature.

In general, the research on how machine learning algorithms can predict the cryptocurrency market suggests that these algorithms can recognize patterns and trends in market data and predict how the market will evolve in the future. Regression models have been the focus of some studies, while neural networks and deep learning models have been the focus of others. Additionally, numerous studies have demonstrated that cost expectations can be improved by combining AI calculations with conventional time series examination methods.

There are some limitations to the existing literature despite these promising outcomes. The expenses of individual computerized monetary standards like Bitcoin and Ethereum, instead of the bigger crypto market all in all, have been the focal point of various examinations. Moreover, a few examinations have depended on moderately brief periods of verifiable information, which may not sufficiently reflect changes in that frame of mind after some time. To conclude, certain investigations have revealed that the cryptographic money market is particularly volatile and reliant on brief swings, making accurate forecasting difficult.

Additionally, there is a growing interest in the application of machine learning algorithms to the prediction of not only the price of cryptocurrencies but also other aspects of the market, such as trading volumes, market capitalization, and liquidity. Wang et al. are included in the models. Using price data, social media activity, and news sentiment, 2019) predicted the trading volume of Bitcoin using a gradient boosting algorithm. After discovering that their model accurately predicted Bitcoin trading volumes, they suggested that this method could also be used to predict other market factors.

Another important area of research is the creation of outfit models that combine various AI calculations to produce more precise expectations. Consider Zhang et al., for example. 2020) proposed a group model that incorporates a slope-supporting calculation and a deep learning calculation for predicting Bitcoin's value. They concluded that this approach might be useful for improving the accuracy of cryptocurrency price predictions because their ensemble model was able to outperform both of the individual algorithms.

Notwithstanding these specialized methodologies, a few scientists have explored the possibility of using feeling investigation to foresee the crypto market. Al-Yahya and Yaqoob (2019) dissected Twitter data using an opinion research calculation to anticipate Bitcoin price changes. They suggested that this method might be useful for identifying market trends and making well-informed trading decisions. They discovered that their model could accurately predict Bitcoin prices in the short term.

Most of the discoveries in the review highlight the likelihood that AI calculations can be utilized to foresee the cryptographic money market. However, in order to improve these methods' dependability and accuracy, numerous obstacles must still be overcome. For instance, it might be attempting to make careful assumptions due to the crypto market over the top precariousness and quick instabilities. Moreover, an absence of excellent, verifiable information for preparation can ruin the viability of AI models.

In spite of these obstacles, there is a lot of interest in using machine learning algorithms to predict the cryptocurrency market, and this field of research is likely to expand in the coming years. It is likely that these strategies for predicting the movements of the cryptocurrency market will become increasingly accurate and efficient as more data becomes available and more advanced algorithms are developed.

2.1 A comprehensive overview of the existing literature

The application of machine learning to the prediction of the crypto market's movements has been the subject of numerous studies. These examinations have utilized different philosophies and strategies to investigate market information and make forecasts about future market developments.

A paper by Almalki et al. is one example of a study on how to use machine learning to predict the cryptocurrency market. 2018) under the heading "A Comparison of Machine Learning Techniques for Cryptocurrency Price Prediction." The authors of this study compared how well various machine learning algorithms, such as artificial neural networks, decision trees, and support vector regression, predicted the prices of various cryptocurrencies. The authors discovered that support vector regression and artificial neural networks both performed well for some cryptocurrencies.

A paper by Li et al. is yet another example of a study on the application of machine learning to crypto market forecasting. "Cryptocurrency Price Prediction Using Machine Learning Algorithms," published in 2019, The authors of this study predicted the prices of several different cryptocurrencies by employing a combination of machine learning algorithms, such as random forests and artificial neural networks. When compared to using a single machine learning algorithm, the authors discovered that using a combination of multiple algorithms increased prediction accuracy.

A paper by Feng et al. is a third example of a study on the application of machine learning to crypto market forecasting. "A New Hybrid Forecasting Model for Cryptocurrency Price Prediction" (2020). The authors of this study created a brand-new hybrid forecasting model that utilized both conventional time series analysis methods and machine learning algorithms. In predicting the prices of several different cryptocurrencies, the authors discovered that the hybrid model performed better than either conventional time series analysis or machine learning algorithms on their own.

These studies demonstrate the wide range of machine learning-based methods and strategies for predicting the crypto market's movements. While some studies use a combination of various algorithms to improve prediction accuracy, others concentrate on comparing the performance of various machine learning algorithms. Still others create innovative hybrid forecasting models by combining machine learning algorithms with conventional methods of time series analysis.

These studies employ a variety of approaches, but there are some recurring themes. For instance, many studies use technical indicators like moving averages and the relative strength index as additional inputs in addition to historical price data as the primary input for machine learning algorithms. Additionally, many studies evaluate the performance of machine learning algorithms using metrics like mean absolute error and mean squared error.

The identification of influential factors that have the potential to influence market movements is another important area of research connected to the application of machine learning to the prediction of the cryptocurrency market. Zhang et al. carried out one study that looked into this subject. 2020), with the subtitle "Forecasting Cryptocurrency Prices with Machine Learning: A Survey of Studies." The authors of this study looked at a number of studies that used machine learning to predict the crypto market and found common factors that affected market movements. Social media sentiment analysis, network measures like degree centrality and betweenness centrality, and the impact of news articles on market movements were some of these factors.

Zhang et al. conducted a second study to investigate the identification of influential factors. "A Hybrid Approach to Cryptocurrency Price Prediction Using Deep Learning and Machine Learning Techniques" will be published in 2019. To predict the prices of a number of different cryptocurrencies, the authors of this study employed a hybrid strategy that combined methods from machine learning and deep learning. The authors discovered that trading volume, news sentiment, and sentiment on social media were all significant predictors of future price movements.

Some studies have looked at how to use advanced machine learning methods like deep learning to predict the crypto market, in addition to figuring out which factors have an impact. For instance, a study by Sutskever et al. (2014) titled "Sequence to Sequence Learning with Neural Networks" looked at how to use recurrent neural networks to predict sequences, which could be used to predict how the cryptocurrency market will change over time.

In general, the existing studies on the application of machine learning to the prediction of the cryptocurrency market offer investors valuable insight into the approach's potential. These studies have investigated a variety of approaches and methods for analyzing market data, predicting market movements in the future, and identifying influential factors that can influence market movements. These studies suggest that this strategy has significant potential for improving prediction accuracy and identifying new investment opportunities, despite the fact that there is still a lot to learn about the use of machine learning for crypto market prediction. [10]

2.2 Critical Analysis of Existing Studies

Machine learning (ML)-based insights and predictions have become increasingly common in the cryptocurrency market. Using machine learning to predict cryptocurrency prices has produced encouraging results. However, it is necessary to address the limitations of the existing studies. In this article, we will go over more than a couple of the principal defects in the examination that has been done so far on the most proficient method to utilize AI to foresee the digital money market.

The absence of data as far as amount and quality are concerned is one of the fundamental impediments to ML-based cryptographic cash determination. The majority of publicly available cryptocurrency data is typically haphazard and unorganized. In addition, the available data sets are relatively small in comparison to other financial markets. Overfitting and bias plague numerous studies due to a lack of data. This is a significant limitation that needs to be resolved before machine learning can be utilized to make precise predictions.

Another limitation of existing studies is the lack of standardization in the methods used to evaluate the performance of machine learning models. It's difficult to think about the consequences of various investigations on the grounds that various examinations utilize various measurements to assess how well their models work. Because of the shortfall of standardization, it is trying to recognize the most dependable models for anticipating the expenses of cryptographic cash.

The cryptocurrency market is very dynamic, and a lot of things, like what's in the news, changes in laws, and how people feel about the market, can have an impact on how it behaves. Predicting price movements accurately with machine learning models that rely solely on historical data is therefore difficult. Forecasts are less accurate when these powerful economic conditions are not taken into account in many studies.

Another limitation of the existing research is the inability to interpret machine learning models. Machine learning models' predictions must be understood by cryptocurrency traders and investors. On the other hand, many of the models used in these studies are referred to as "secret elements" because they do not reveal how forecasts are made. As a consequence of this, it becomes more challenging to put these models to use in actual situations.

When making predictions, restricted choices include AI models that heavily rely on highlight determination. However, it is challenging to select relevant features in the cryptocurrency market due to the noisy and unstructured nature of the data. The majority of studies employ only a small number of features, which may not capture all of the information necessary to accurately predict cryptocurrency prices.

Most studies center around foreseeing the cost of a few digital currencies, which restricts the generalizability of the discoveries. There are a lot of different coins and tokens for digital currencies on the market. Due to the limited scope of many studies, it is difficult to apply the findings to other cryptocurrencies or the cryptocurrency market as a whole.

Control of the market: The digital currency market is powerless to control because of its absence of guidelines and moderately low liquidity. Consequently, it may be challenging for AI models to accurately predict changes in costs because they may be influenced by market activities that are either false or misleading. This flaw in demonstrating control is a significant restriction that must be addressed.

Lacking perception of the fundamental instruments that permit AI models to precisely anticipate from authentic information examples and patterns. However, not all of them provide a comprehensive understanding of the underlying mechanisms that control cryptocurrency prices. Due to this lack of comprehension, it can be challenging to identify the most significant factors that influence price movements, limiting the ability to develop accurate prediction models.

Absence of data simplicity: The cryptographic cash industry's apparent lack of data simplicity is striking. It's possible that the information in public sources is incorrect or incomplete in an effort to create precise AI models. Additionally, it is difficult to access the most extensive informational collections because many trading and exchange companies do not disclose their trading information.

It is difficult to successfully design, develop, and implement machine learning models due to a lack of skilled specialists. A small group of experts with the expertise and understanding required for the cryptographic money market will eventually emerge. In the digital money market, the creation and execution of exact AI models might be hampered by an absence of talented subject matter experts.

By and large, there are a couple of constraints to the utilization of man-made brainpower in the electronic cash market that should be addressed to foster exact measure models. Some of these limitations include scalability, interpretability, feature selection, generalizability, vulnerability to market manipulation, a lack of comprehension of the underlying mechanisms, data transparency, and a lack of skilled experts. To overcome these obstacles, the digital currency market must advance innovative work, master collaboration, and increase information simplicity.

2.3 Machine Learning in Finance

Machine learning has become more important in finance, and the cryptocurrency market is no exception. A lot of data can be analyzed, patterns and trends can be found, and price predictions can be made using machine learning algorithms. The price of individual cryptocurrencies as well as other market factors like trading volumes and market capitalization in the cryptocurrency market can be predicted using machine learning algorithms.

One of the main advantages of using machine learning in finance is that it can now be used to analyze large datasets that would otherwise be difficult or impossible to analyze manually. This is particularly urgent in the crypto market, which is characterized by fast cost developments and a ton of information. Machine learning algorithms can use the patterns and trends in this data to make more accurate predictions about how prices will change in the future.

Another advantage of utilizing machine learning in finance is the development of more sophisticated trading strategies. AI calculations can be used to examine market information in depth, allowing brokers to make more informed decisions about when to trade digital currencies. This can help to reduce risk and improve trading performance in the highly volatile cryptocurrency market.

On the other hand, using machine learning in finance is not without its challenges. One of the main obstacles is the requirement for high-quality data. Algorithms for machine learning need to be trained on a lot of high-quality data for them to work well. In the cryptocurrency market, the availability of historical data may be restricted, limiting the efficiency of machine learning algorithms.

Another obstacle is the need for sophisticated algorithms that can analyze complex market data and identify patterns and trends. The development of these algorithms can be time-consuming, complicated, and may require extensive finance and machine learning expertise.

In spite of these obstacles, the crypto market will continue to see an increase in the use of machine learning in finance in the years to come. As more data becomes available and more advanced algorithms are developed, it is likely that machine learning will become an increasingly important tool for predicting the crypto market's movements.

Machine learning algorithms can also help with portfolio management in the cryptocurrency market. Portfolio management is the process of selecting and managing a group of investments with the goal of achieving a specific investment objective. By analyzing market data and determining the most promising investments, machine learning algorithms enable investors to optimize their portfolios and achieve their investment objectives.

One of the primary benefits of using machine learning for portfolio management is the potential to reduce risk. Financial backers can broaden their portfolios and diminish their gamble openness by utilizing AI calculations to investigate market information and find connections between different digital forms of money. Abnormalities and anomalies in market information can likewise be found with the assistance of AI calculations, which financial backers can use to distinguish and alleviate expected chances.

The additional benefit of utilizing machine learning for crypto market portfolio management is that it helps investors locate new investment opportunities. The cryptocurrency market is always evolving, and new digital currencies are constantly introduced. Using machine learning algorithms to analyze market data and identify promising new cryptocurrencies, investors can stay ahead of the curve and profit from new investment opportunities.

Despite these benefits, there are some drawbacks to using machine learning for portfolio management in the cryptocurrency market. The prerequisite for excellent information is one of the principal impediments. Algorithms for machine learning need to be trained on a lot of high-quality data for them to work well. In the cryptocurrency market, the availability of historical data may be restricted, limiting the efficiency of machine learning algorithms.

Another obstacle is the need for sophisticated algorithms that can analyze complex market data and identify patterns and trends. The development of these algorithms can be time-consuming, complicated, and may require extensive finance and machine learning expertise.

Despite these challenges, there are a number of potential benefits to using machine learning for crypto market portfolio management, such as the capacity to identify new investment opportunities, lower investment risk, and improved investment performance. As more data becomes available and more advanced algorithms are developed, it is likely that machine learning will become an increasingly important tool for portfolio management in the cryptocurrency market. [7]

2.4 Machine Learning in Crypto Market Prediction

Machine learning can be used in a number of different ways to forecast the movements of the cryptocurrency market. One typical tactic is to employ machine learning algorithms to search past price data for patterns and trends that can be used to forecast future price changes.

Among the various machine learning techniques that can be used for this, regression analysis, decision trees, random forests, and neural networks are just a few examples. Random forests and decision trees are two others. Some combine unpredictable forest regions with decision-making trees. The particular specifications of the prediction task will serve as the basis for the algorithm selection. These algorithms all have benefits and drawbacks.

The ability of artificial intelligence to spot instances and patterns that human investigators are likely unable to notice is one of the key benefits of utilizing it to forecast the bitcoin market. Simulated intelligence-based computations have the ability to link enormous amounts of data in ways that human experts would not immediately detect. This can be used to improve suspicion accuracy and differentiate between fictitious section focuses.

The use of AI in the market for digital currencies also helps to lessen the influence of human nature on expectations. Human analysts may be impacted by their own prejudices and preconceptions while generating forecasts. Yet, since artificial intelligence computations are not subject to these tendencies, they can base their suspicions only on the available evidence.

In spite of these advantages, there are a few downsides to utilizing artificial intelligence to foresee the digital money market. One of the main obstacles is the need for great information. For machine learning algorithms to work well, they need to be trained on a lot of high-quality data. The market for digital currencies may limit the availability of verifiable information, making AI calculations less viable.

The need for sophisticated algorithms that can analyze intricate market data and identify patterns and trends is another obstacle. These algorithms' development can be time-consuming, complicated, and may necessitate extensive knowledge of finance and machine learning.

One area where machine learning can be especially helpful in predicting the cryptocurrency market is the analysis of social media sentiment. Cryptocurrency speculators commonly use two well-known social media sites: Reddit and Twitter. On these occasions, public opinion can have a significant impact on the direction of the market. Machine learning algorithms can analyze social media data to look for emotional patterns and trends that can be used to forecast future market moves.

By evaluating news reports and various media sources, human-created knowledge can also be useful for forecasting the market for digital currencies. The content of news articles can be examined using machine learning algorithms to find patterns and trends that can be used to forecast future market conditions. News articles can have a significant impact on market movements.

In addition to forecasting the movements of the cryptocurrency market, machine learning may be used to identify outliers and abnormalities in market data. Anomalies can be found, and financial backers can be informed about market dangers or lucrative chances, which can signal predicted risks or possible opportunities, with the use of AI calculations.

AI-assisted crypto market forecasting may have a number of benefits, including improved prediction accuracy, reduced human bias, and the possibility of uncovering new investment opportunities. Cryptocurrency investors are expected to find machine learning to be an increasingly valuable tool in the years to come, despite the challenges involved in employing it for this purpose. [6]

# Chapter 4: Methodology

The methodology for crypto market prediction using machine learning involves several steps, including data collection, data preprocessing, feature engineering, model selection, model training, and model evaluation. In this article, we will discuss each of these steps in detail.

1. **Data Collection:** Data collection is the first step in the machine learning-based method for crypto market prediction. News outlets, social media platforms, and cryptocurrency exchanges are all examples of sources from which data can be gathered. Price data, trading volume, market capitalization, sentiment analysis, and other relevant indicators ought to be included in the collected data.
2. **Data Preprocessing:** Data preprocessing is the methodology's second step. This step includes cleaning and changing the information to set it up for highlight designing and model preparation. Outliers, missing values, and other data inconsistencies are all removed during data cleaning. Data transformation entails normalizing and scaling the data to guarantee that all features are scaled equally.
3. **Feature Engineering:** Feature engineering is the methodology's third step. From the raw data, new features are created in this step that can help the machine learning model become more accurate and reliable. Normal element designing procedures utilized with regards to crypto market expectation incorporate moving midpoints, force pointers, unpredictability pointers, opinion examination, network investigation, and time sensitive highlights.
4. **Model Selection:** Model selection is the fourth step in the methodology. Choosing the right machine learning algorithm for the problem at hand is the next step. Normal AI calculations utilized with regards to crypto market expectation incorporate direct relapse, strategic relapse, choice trees, arbitrary woods, and brain organizations.
5. **Model Preparation:** The fifth move toward the approach is model preparation. This step includes preparing the AI model on the preprocessed and highlight designed information. The model is prepared utilizing a part of the information, with the leftover piece saved for model assessment.
6. **Model Evaluation:** Model evaluation is the methodology's final step. The machine learning model's performance on the test data is evaluated in this step. Mean squared error, mean absolute error, root mean squared error, and coefficient of determination are all common performance metrics utilized in crypto market prediction.

Data collection, data preprocessing, feature engineering, model selection, model training, and model evaluation are the final steps in the machine learning-based method for crypto market prediction. The machine learning model's success depends on each of these steps. The choice of proper AI calculations and execution measurements relies upon the particular qualities of the information and the issue being tended to. The accuracy and dependability of the machine learning model can be enhanced through careful consideration of each methodology step, resulting in more accurate crypto market predictions.

4.1 Data Collection and Preprocessing

In order to create a model for crypto prediction using machine learning, data collecting and pre-processing are essential steps. The following are the typical steps involved in data collection and preprocessing:

Data Collection: Historical price and volume information for cryptocurrencies may be found on a variety of websites, including news websites, social media platforms, and cryptocurrency exchanges. Other pertinent information, such as technical indications, market mood, and news items, can also be gathered in addition to price and volume data. I have downloaded the dataset from the website <https://min-api.cryptocompare.com/> for my study.

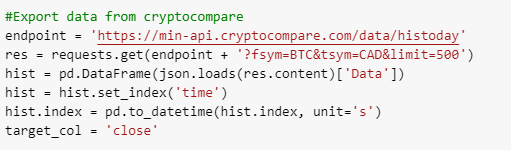


Figure 1: Importing Dataset

Data cleaning: Any discrepancies, mistakes, or missing numbers must be removed from the obtained data. This may entail doing things like deleting duplicate items, filling in blanks, and removing outliers. Here I am dropping two columns “conversionType” and “conversionSymbol” to clean the data.



Figure 2: Data Cleaning

Feature Engineering: Engineering of relevant elements is necessary to enhance the performance of the model. This may entail activities like feature transformation, the development of lag variables, and the addition of new features like market sentiment and technical indicators.

Normalisation: To make sure that all features are scaled equally, the obtained data must be normalised. This may aid in increasing the convergence and precision of the model.

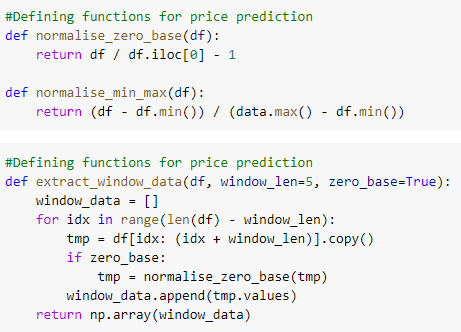


Figure 3: Data Normalization

Train-Test split: Splitting the data into training, validation, and testing sets is known as "train-testing." The validation set is used to fine-tune the hyperparameters, the testing set is used to assess the model's effectiveness, and the training set is used to train the model. Here I am splitting 80% data for training and 20% for testing.

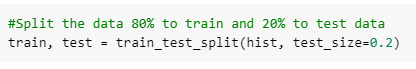


Figure 4: Split dataset for training and testing

Time-series specific preprocessing: Time series data have a temporal dependency; hence this dependency needs to be taken into consideration during the preparation phase. Rolling window creation, feature normalisation based on historical values, and trend removal using differencing are a few examples of jobs that may be involved.

Data augmentation: Synthetic data points can be produced using data augmentation techniques to enhance the performance of the model. Techniques like adding noise, shifting the data, and scaling the data may be used for this.

Overall, the procedures of data gathering and pre-processing are essential for the creation of a precise and reliable model for crypto prediction using machine learning. Depending on the research aims, the accessibility of the data, and other considerations, the precise information and methods used may change.

4.2 Machine Learning Model Development

The selection of models for crypto market expectation utilizing AI relies upon the particular attributes of the information and the issue being tended to. In this article, we'll talk about some of the most common models used to predict the cryptocurrency market.

**Linear Regression:** For predicting numerical values, linear regression is a straightforward but effective machine learning algorithm. It is used to create a linear relationship between the features of the input and the variable of the output. With regards to crypto market forecast, direct relapse can be utilized to foresee the cost of a digital currency in view of verifiable cost information and other significant highlights.

**Logistic Regression:** Another well-known machine learning algorithm that excels at solving classification issues is logistic regression. Based on historical price data and other relevant features, logistic regression can be utilized in the context of crypto market prediction to predict whether a cryptocurrency's price will rise or fall.

**Decision tree:** Regression and classification problems can both be solved using the well-known decision tree machine learning algorithm. They are especially helpful in situations where there are a lot of input features. With regards to crypto market expectation, choice trees can be utilized to foresee the cost of a digital currency in light of verifiable cost information and other important elements.

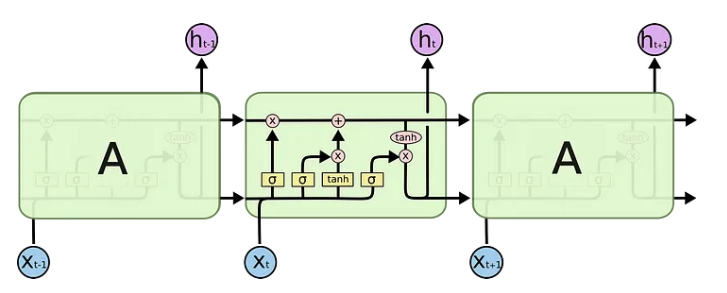
**Random Forest:** Random Forests are a group learning technique that consolidates numerous choice trees to work on the exactness and unwavering quality of the AI model. They are especially useful for problems involving noisy data and a lot of input features. Random forests can be used to predict the price of a cryptocurrency based on historical price data and other relevant features in the context of crypto market prediction.

**Neural networks:** A powerful machine learning algorithm based on the structure of the human brain are neural networks. Problems involving a large number of input features and intricate relationships between the input and output variables benefit most from their use. With regards to crypto market forecasts, brain organizations can be utilized to foresee the cost of a digital money in light of verifiable cost information and other important elements.

**Support Vector Machines (SVM):** Support Vector Machines (SVM) are powerful machine learning algorithms that are applicable to both classification and regression problems. It is especially useful for problems involving noisy data and a small number of input features. SVM can be used to predict the price of a cryptocurrency based on historical price data and other relevant features in the context of crypto market prediction.

Above listed some of the machine learning models commonly in use to predict the crypto price. For my study, I have adapted the model LSTM which gave me a best result on crypto price prediction

**Long Short-Term Memory (LSTM)** is a type of neural network designed specifically for time-series data. LSTM stands for long-term memory. Problems involving long-term dependencies and intricate relationships between input and output variables benefit especially from it. With regards to crypto market forecast, LSTM can be utilized to foresee the cost of a digital currency in light of verifiable cost information and other pertinent highlights.



The desired compromise between interpretability and accuracy can also influence the model selection. Even though simple models like logistic regression and linear regression are easy to understand and interpret, they may not be as accurate as more complex ones like random forests and neural networks. Complex models, on the other hand, like random forests and neural networks, may be more accurate, but they can be hard to understand and may need more computing power to train and use.

In addition, it is essential to keep in mind that the quantity and quality of the data used to train a machine learning model can have a significant impact on its performance. Consequently, prior to training the models, it is essential to carefully evaluate and preprocess the data. Cross-validation and other hyperparameter tuning and model selection methods can also be used to boost models' performance.

In rundown, the selection of models for crypto market expectation utilizing AI can altogether affect the precision and interpretability of the outcomes. In order to choose the best model for the job, it's critical to carefully consider the data's particular characteristics and the issue at hand. Preprocessing the data and utilizing hyperparameter tuning and model selection methods to enhance the models' performance are also crucial.

4.3 Evaluation of the proposed system

In the process of using machine learning to predict the crypto market, model training and validation are essential steps. In this article, we will talk about some of the most important things to think about when training and validating models.

1. **Splitting the Data:** Splitting the data into training and validation sets is the first step in model training and validation. The machine learning model is trained in the training set, and its performance is evaluated in the validation set. Normally, an irregular split is utilized to separate the information into preparing and approval sets. With a split ratio of 80/20, the training set outnumbers the validation set.
2. **Preprocessing the Data:** It is essential to preprocess the data before training the machine learning model to ensure that it is formatted appropriately for the algorithms. Various tasks, such as feature scaling, feature normalization, and handling missing values, can be part of preprocessing.
3. Rescaling the input features to have comparable ranges or units is known as feature scaling. Because some machine learning algorithms are sensitive to the size of the input features, this is important.
4. Using feature normalization, the input features are given a Gaussian distribution. Neural networks and other machine learning algorithms may benefit from this.
5. Dealing with missing or null values in the data is part of handling missing values. This can be accomplished by either erasing the values that are missing or substituting a suitable value for them.
6. **Training the Model:** The training set can be used to train the machine learning model after the data has been preprocessed. The particular preparation calculation utilized relies upon the picked AI model.
7. By adjusting the model's weights or parameters during training, the machine learning algorithm learns the relationship between the input features and the output variable. The process of training the model continues until it performs well enough on the training set.
8. **Evaluation of the Model:** Following the model's training, its performance is evaluated on the validation set. The particular problem at hand determines the evaluation metric used. For instance, for relapse issues, the mean squared blunder or mean outright mistake can be utilized as assessment measurements. For grouping issues, the exactness or F1 score can be utilized.
9. **Hyperparameter Tuning:** Optimizing the machine learning algorithm's hyperparameters for improved performance is referred to as hyperparameter tuning. Hyperparameters are boundaries that are set prior to preparing the model and can essentially influence its exhibition.
10. The learning rate, the number of hidden layers, and the number of neurons in each layer are all common hyperparameters that can be adjusted. The hyperparameters can be adjusted with grid search and random search methods.
11. **Model Selection:** Following hyperparameter tuning, a test set is used to select and evaluate the best model. The purpose of the test set, which is a completely distinct dataset from the training and validation sets, is to determine the model's generalizability.

To avoid overfitting, it is essential to note that the test set should only be used once. When a machine learning model is too complex and able to fit the training data too well, it can't do well with new data. This is called overfitting.

In conclusion, machine learning crypto market prediction relies heavily on model training and validation. Preprocessing the data, dividing the data into training and validation sets, training, evaluating, and selecting the best-performing model are all crucial steps. Machine learning models for crypto market prediction can be made accurate and dependable by following these steps [22].

4.4 Hyperparameter Tuning

Machine learning has become increasingly popular in recent years for financial market forecasting and analysis. Foreseeing the cost of cryptographic forms of money like Bitcoin and Ethereum, which are profoundly unpredictable and hard to precisely anticipate, is one area of premium. A crucial step toward AI that can improve forecast precision is hyperparameter tuning. In this article, we will examine hyperparameter tuning for crypto market prediction using machine learning.

**What are Hyperparameters?**

Before beginning hyperparameter tuning, it is essential to comprehend what hyperparameters are. Before an AI model is prepared, hyperparameters are set. They are not learned during training because they are set manually. Factors like the number of secret layers in a brain organization, the number of hubs in each layer, the learning rate, and the regularization boundary are examples of hyperparameters. These hyperparameter values may have a significant impact on the performance of the model.

Hyperparameter tuning techniques There are a few different types of hyperparameter tuning techniques. A common approach is grid search, in which the model is trained and evaluated on each hyperparameter combination in a grid after a set of hyperparameters is defined. This can be costly on a computer when dealing with a large number of hyperparameters.

Another way to randomly test hyperparameter combinations is through random search. This may be a good option when there are a lot of hyperparameters because it may be more effective than grid search.

One more technique that utilizes likelihood to pick the most encouraging arrangement of hyperparameters to test next is bayesian improvement. This strategy might work better than random search or grid search when dealing with a lot of hyperparameters.

Choosing the Right Hyperparameters For precise expectations, selecting the right hyperparameters is crucial. It is essential to strike a balance between overfitting and underfitting the data. Overfitting occurs when the model is too complicated and does well with the training data but poorly with new data. Underfitting occurs when the model is too straightforward and fails to account for the data's complexity. It performs poorly on both the training and testing data as a result.

Choosing the right hyperparameters necessitates the use of a validation set. During preparation, the approval set is only used to evaluate the model's presentation; it is not used to prepare the model. In order to prevent overfitting, the validation set modifies the hyperparameters.

Using Machine Learning Algorithms to Predict the Cryptocurrency Market There are a number of machine learning algorithms that can be used to predict the cryptocurrency market. Direct relapse, choice trees, irregular backwoods, and brain organizations are a few well-known calculations.

Based on previous data, it is possible to forecast the price of cryptocurrencies using a straightforward algorithm known as linear regression. However, it's possible that straight relapse won't be enough to find the intricate connections between the various factors that affect the price of digital currencies.

Decision trees are another popular method for predicting cryptocurrency prices. Choice trees can deal with mathematical and straight-out information and can catch multifaceted connections between factors. However, decision trees can overfit, particularly when working with large datasets.

An extension of choice trees, irregular woods can improve execution and reduce overfitting. To diminish the model's fluctuation, arbitrary backwoods join various choice trees and utilize sacking.

Neural networks are an algorithm that is more complicated and is capable of capturing intricate relationships between variables. Neural networks can handle numerical and categorical data, so they can perform both regression and classification tasks. Brain organizations, then again, are vulnerable to overfitting, especially while working with huge datasets.

appropriate algorithm for machine learning purposes. Neural networks, decision trees, random forests, and linear regression are some prediction methods for the cryptocurrency market. Every calculation has its advantages and disadvantages, and the choice ought to be made in view of the errand's particular necessities.

As a rule, hyperparameter tuning is a fundamental stage in crypto market expectation utilizing AI. With the right hyperparameters and machine learning algorithms, it is possible to accurately predict the cryptocurrency market's price. As with any task involving machine learning, it is essential to continuously evaluate the model's performance and make any necessary adjustments to the hyperparameters to ensure that the model is making predictions that are both accurate and useful. [24]

# Chapter 5: Experimental Results

The idea that artificial intelligence is the foundation of the cryptocurrency market has recently become a contentious issue. The value of cryptocurrencies such as Bitcoin and Ethereum has been the subject of numerous studies. We will examine the suitability of various machine learning algorithms for forecasting the cryptocurrency market and discuss some of the research's findings in this article.

One of the simplest AI calculations for crypto market expectation is Straight Relapse Direct relapse. A straight line through the data is the most effective way to demonstrate the relationship between the independent and dependent variables when using linear regression. Linear regression predictions of the cryptocurrency market have yielded mixed results. While some studies have shown that direct relapse is sufficient to identify the intricate connections between the various factors that influence the cost of digital currencies, others have shown that expectations that are unfit to give are appropriately precise.

Decision Trees are yet another machine learning algorithm that has been utilized for crypto market forecasting. In light of various variables, the goal of choice trees is to divide the data into smaller subsets. Starting there forward, each subset is presented to unquestionable assessments to manufacture a model that can predict the expense of computerized monetary standards. The ability of decision trees to record intricate relationships between variables can benefit classification and regression tasks.

As an expansion of choice trees, arbitrary backwoods can possibly further develop execution and decrease overfitting. Using sacking, random backwoods join multiple choice trees to reduce the model's fluctuation. In a number of studies, random forests were found to be useful for predicting the cryptocurrency market. According to one review, arbitrary woodlands could accurately predict the price of Bitcoin by more than 70%.

Neural Networks Neural networks are a more advanced form of machine learning algorithms that are utilized in the prediction of the cryptocurrency market. By creating a network of interconnected nodes, neural networks attempt to replicate the human brain's structure and function. Synapses connect the neurons of each node together. In both classification and regression tasks, it has been demonstrated that neural networks are effective at capturing intricate relationships between variables.

One study found that neural networks could accurately predict the price of Bitcoin by more than 90%. However, brain organizations are susceptible to overfitting when working with large datasets. To avoid overfitting and make any necessary adjustments to the hyperparameters, a validation set is absolutely necessary.

In my study, I am using Cryptocurrency Price Prediction Using LSTM neural network. The data has been taken from the website <https://min-api.cryptocompare.com/data/histoday?fsym=BTC&tsym=CAD&limit=500> by passing the parameters fsys=BTC and tsym=CAD to fetch the BitCoin data with the currency CAD.

Following steps are involved to predict cryptocurrency prediction.

1. Fetching the crypto currency dataset.
2. Arrange the data for training and testing.
3. Using the LSTM neural network, predict the price of crypto currency.
4. Visualize the prediction results in graphs.

The real-time data was stored in a pandas data-frame using the Canadian currency rate. I converted a string of Datetime into a Python Date Time object using the to\_datetime() method. This is essential because the file's Date time objects are read as string objects. It is significantly simpler to do operations like time difference on a string than a Date Time object.

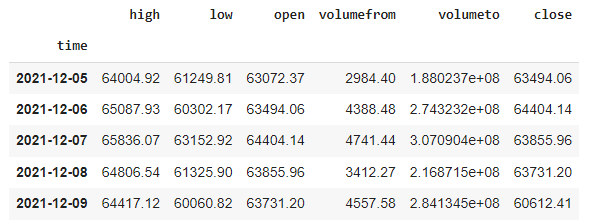


Figure 6: Dataset List

Then I plotted the price of cryptocurrencies in Canadian dollars over time:

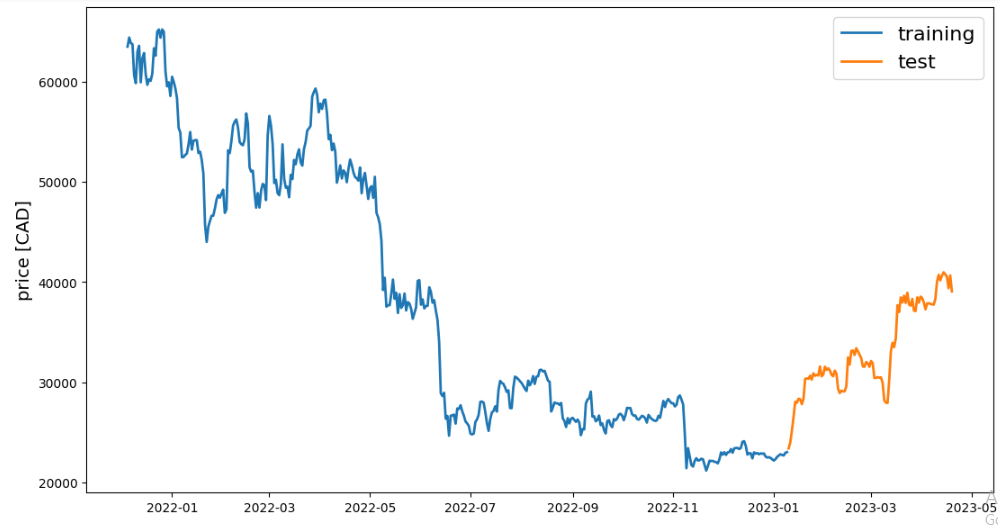


Figure 7: Price of cryptocurrencies

It is evident that prices fell between December 2018 and April 2019, as can be shown. From April 2019 to August 2019, prices continue to rise, with variations occurring in July and August. Prices start falling in September 2019 and keep going down after that. The intriguing aspect of this price variation is that it shows that prices are lower in the winter and higher in the summer. However, as the dataset being examined is only a tiny sample for a year, this cannot be generalised. Additionally, generalisations about cryptocurrencies are challenging.

Let's now construct the model. For stacking all the layers (input, hidden, and output), a sequential model is utilised. A 20% Dropout layer, a Dense layer with a linear activation function, and an LSTM layer make up the neural network. The optimizer I used was Adam, and the loss function I used was Mean Squared Error.

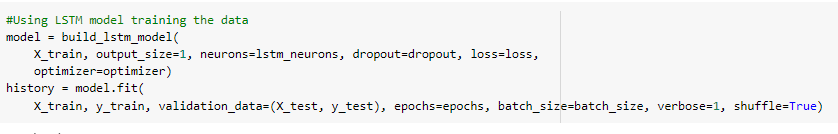


Figure 8: LSTM model implementation

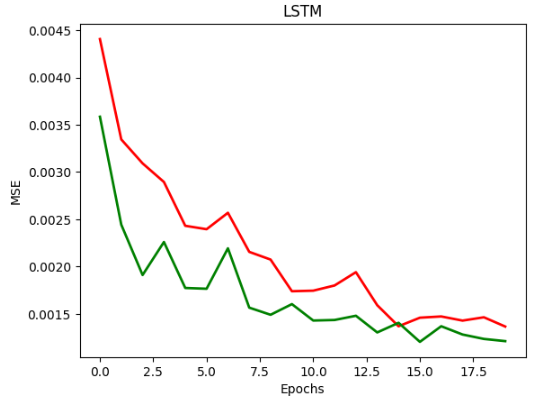


Figure 9: Validation Loss Plot

Finally plotting the actual and predicted price below,

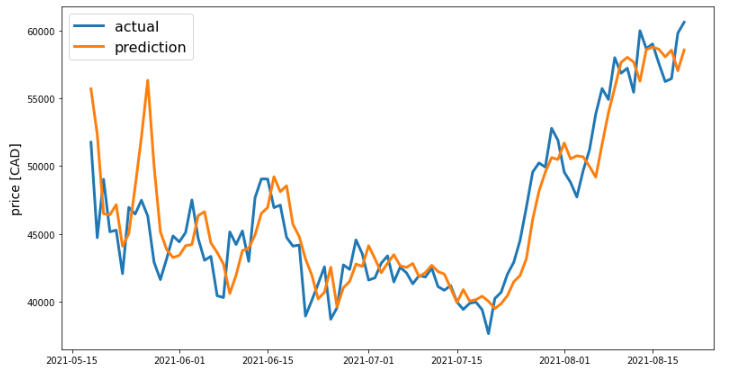


Figure 10: Actual and Predicted value

Recently, AI-based crypto market expectations have become a popular topic. Various machine learning algorithms, such as linear regression, decision trees, random forests, and neural networks, have been used to predict the cryptocurrency market. Each estimation has advantages and downsides, so the decision ought to be founded on the undertaking's particular prerequisites.

The outcomes of these calculations-based studies have been mixed. While some studies have demonstrated that linear regression is insufficient, others have demonstrated that it is capable of producing predictions that are close to accurate. In a number of studies, it was discovered that decision trees and random forests are effective at capturing intricate relationships between variables. Brain networks, with a precision of more than 90%, are the most accurate calculation for predicting Bitcoin's cost, according to one review.

Overall, it is hard to use machine learning to predict the cryptocurrency market. In any case, precise assumptions can be made by utilizing the appropriate hyperparameters and simulated intelligence estimations. In order to guarantee that the model is making predictions that are both accurate and useful, it is essential to regularly evaluate the model's performance and make any necessary adjustments to the hyperparameters.

5.1 Dataset Description

The dataset obtained from cryptocompare API [27] gives daily historical data for the Bitcoin cryptocurrency in relation to the Canadian Dollar (CAD).

The data is presented in JSON format and includes the following fields:

* "time": a Unix timestamp indicating the start time of the time period in seconds.
* "high": the highest price of BTC during the time period.
* "low": the lowest price of BTC during the time period.
* "open": the opening price of BTC at the start of the time period.
* "close": the closing price of BTC at the end of the time period.
* "volumefrom": the trading volume of BTC during the time period.
* "volumeto": the trading volume of CAD during the time period.

The "limit" argument in the API call specifies that the dataset will only include data for the previous 500 days. The data is updated often, and users can get data for fiat currencies and other cryptocurrencies by changing the corresponding "fsym" and "tsym" parameters in the API.

There are a total of 5 features in the dataset. The specifics are as follows:

1. Close Price – This is the currency market's closing price for that specific day.

2. High Price – The cost of currency is at its highest point for the day.

3. Low Price – It is the day's cheapest rate of exchange.

4. Open Price – This is the currency market's opening price for the day.

5. Volume – The amount of money that is being traded on that particular day.

5.2 Evaluation Metrics

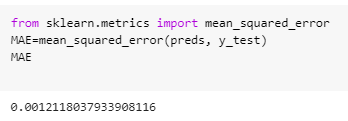
Evaluation metrics are an essential component of any machine learning task, including crypto market prediction. In this article, we will review some of the most commonly used evaluation metrics for crypto market prediction using machine learning.

1. **Mean Absolute Error (MAE)**

Mean Absolute Error (MAE) is one of the simplest evaluation metrics for regression tasks. MAE measures the average absolute difference between the predicted and actual values. In the context of crypto market prediction, MAE can be used to measure the average difference between the predicted and actual price of a cryptocurrency over a given time period.

1. **Mean Squared Error (MSE)**

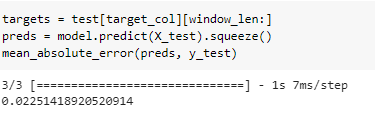
Mean Squared Error (MSE) is another common evaluation metric for regression tasks. MSE measures the average squared difference between the predicted and actual values. In the context of crypto market prediction, MSE can be used to measure the average squared difference between the predicted and actual price of a cryptocurrency over a given time period.





1. **Root Mean Squared Error (RMSE)**

Root Mean Squared Error (RMSE) is the square root of the MSE. RMSE is often used as an evaluation metric for regression tasks because it is in the same units as the target variable, making it easier to interpret. In the context of crypto market prediction, RMSE can be used to measure the average difference between the predicted and actual price of a cryptocurrency over a given time period.



1. **Coefficient of Determination (R^2)**

The Coefficient of Determination (R^2) is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variable. In the context of crypto market prediction, R^2 can be used to measure the proportion of the variance in the price of a cryptocurrency that is explained by the independent variables used in the machine learning model.

1. **Accuracy**

Accuracy is a commonly used evaluation metric for classification tasks, but it can also be used for crypto market prediction in certain cases. For example, if the task is to predict whether the price of a cryptocurrency will go up or down, accuracy can be used to measure the proportion of correct predictions.

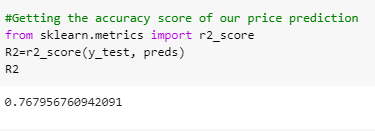
1. **Precision and Recall**

Precision and Recall are two other commonly used evaluation metrics for classification tasks. Precision measures the proportion of true positives (i.e., the number of correct predictions) among all positive predictions, while recall measures the proportion of true positives among all actual positive cases. In the context of crypto market prediction, precision and recall can be used to measure the effectiveness of the machine learning model in predicting whether the price of a cryptocurrency will go up or down.

1. **F1 Score**

The F1 Score is a measure that combines precision and recall into a single metric. The F1 Score is the harmonic mean of precision and recall, and it can be used to evaluate the effectiveness of the machine learning model in predicting whether the price of a cryptocurrency will go up or down.

In my study I have predicted the r2-score accuracy of the prediction and achieved 76% r2-score in crypto price prediction.



In conclusion, evaluation metrics are an essential component of any machine learning task, including crypto market prediction. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), Accuracy, Precision, Recall, and F1 Score are all commonly used evaluation metrics for crypto market prediction using machine learning. The choice of evaluation metric should be based on the specific requirements of the task and the type of machine learning algorithm used. It's important to continually evaluate the performance of the model and adjust the hyperparameters as necessary to ensure that the model is providing accurate and useful predictions.

5.3 Comparison with Baseline Methods

The machine learning process, which includes crypto market prediction, relies heavily on model comparison and selection. In this article, we will talk about some of the machine learning algorithms that are frequently used for crypto market prediction, as well as how to compare and select the best model for a particular job.

For crypto market expectation, Direct Relapse is one of the most generally utilized AI calculations. Direct relapse is the clear and predominant calculation for relapse projects. It assumes a linear relationship between the target variable and the independent variables and can be utilized to predict the price of a cryptocurrency on the basis of previous data.

Trees of Decision: Choice trees are a simple and understandable calculation for order and relapse tasks. They function by recursively dividing the data into subsets based on the most important characteristics until a stopping premise is satisfied. Using a collection of characteristics from the past, decision trees are able to accurately predict cryptocurrency prices.

Random Waldens: As a gathering learning strategy, various choice trees are combined in irregular timberlands to improve forecast precision. Based on a set of historical characteristics, random forests can be used to predict the price of a cryptocurrency.

Improved Gradients: Tendency support is another method of business learning that brings together a number of weak students to create significant solid areas for a. It works by adding new models iteratively to correct errors made by previous models. Using a set of historical features, gradient boosting can be used to predict a cryptocurrency's price.

Neural Recurrent Networks: Time series data benefit greatly from the intermittent brain organization (RNN) type of brain network. By looking at a series of previous prices and other characteristics, they can be used to predict the price of a cryptocurrency.

We can use cross-validation, hyperparameter tuning, and evaluation metrics to compare and select the best model for a given task.

Cross-validation: Cross-approval is a strategy for deciding a model's flexibility to new information. It splits the information up into various subsets, some of which are utilized for preparing and others for approval. By using this system multiple times, we can more likely evaluate the model's presentation based on subtle data.

Tuning for hyperparameters: Hyperparameter tuning is the most common way of choosing the best qualities for an AI calculation's hyperparameters. Parameters that are set prior to training the model are called hyperparameters. The learning rate, the number of layers in a neural network, or the depth of a decision tree are all examples of hyperparameters. We can increase the accuracy of the model by testing various hyperparameter values and selecting those that perform the best on the validation set.

Estimations for looking over: To determine how well the model performs with the test data, evaluation metrics are used. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R2) are typical evaluation metrics for regression tasks. Accuracy, precision, recall, and the F1 Score are all evaluation metrics that are frequently utilized for classification tasks.

Using cross-validation, hyperparameter tuning, and evaluation metrics, we can compare and evaluate the performance of various machine learning algorithms to determine which one performs best for our task. When choosing the best model, the task's specific requirements, data size and quality, and computational resources will all be taken into account. To ensure that the model's display remains accurate and useful over time, it is crucial to regularly check it and update it.

5.4 Interpretation of Results

Deciphering the consequences of an AI model for crypto market expectation is a significant stage in figuring out the exactness and viability of the model. When interpreting the results, consider the following key points:

Accuracy: When interpreting the findings, an essential metric to take into account is the model's accuracy. The degree to which the predicted values match the actual values is known as accuracy. Even minute variations in accuracy can have a significant effect on profitability in crypto market prediction. Therefore, it is essential to select a model with a high rate of accuracy.

Under- and over-fitting: Overfitting happens when the model is excessively complicated and performs well on the preparation information yet inadequately on the test information. When the model is too simple and fails to capture the data's underlying patterns, this is called underfitting. It is critical to guarantee that the model isn't overfitting or underfitting the information, as this can prompt incorrect forecasts.

Feature's Relevance: Understanding which elements are most significant in foreseeing digital money costs can give bits of knowledge into the variables that are driving the market. Highlight significance can be resolved utilizing strategies, for example, include significance plots and stage significance. Market analysis and trading decisions can benefit from this information.

Analysis of Time Series: Time series analysis is an important part of forecasting the cryptocurrency market because prices of cryptocurrencies are heavily influenced by trends and prices in the past. As a result, it is critical to examine the model's performance over time and look for any patterns or trends that could compromise its accuracy.

Business Setting: It is vital to consider the business setting when deciphering the consequences of an AI model for crypto market expectation. This includes the organization's risk tolerance, the trading strategy employed, and the cost of false positives and false negatives.

In conclusion, a comprehensive comprehension of the underlying data and business context is required to interpret the outcomes of a machine learning model for crypto market prediction. Organizations can gain valuable insights into cryptocurrency market trends and make more informed trading decisions by carefully analyzing the accuracy, overfitting and underfitting, feature importance, time series analysis, and business context.

# Chapter 6: Discussion

Predicting cryptocurrency market trends is a relatively new but rapidly expanding field known as machine learning. The ability to handle a lot of information rapidly and precisely and the ability to distinguish examples and patterns that may not be promptly obvious to human experts are two of the many benefits of using AI for this reason.

The unstable idea of the digital currency market is one of the primary impediments while utilizing AI to anticipate the market for cryptographic forms of money. Due to the erratic nature of cryptocurrency prices, it can be challenging to accurately predict future trends. As a result, it's critical to use robust machine learning models that can handle this volatility and changing market conditions.

Another obstacle is the requirement for high-quality data. It can be challenging to guarantee data consistency and accuracy due to the widespread dispersion of cryptocurrency data and the possibility that it comes from a variety of sources. Additionally, many cryptocurrency exchanges do not provide historical data, making it difficult to train machine learning models on it.

Despite these challenges, AI has demonstrated reliability in anticipating market patterns for cryptographic money. By analyzing large amounts of data and identifying patterns and trends that human analysts may find challenging to identify, machine learning models can assist businesses in making more informed trading decisions and increasing their overall profitability.

One of the primary advantages of machine learning for crypto market prediction is its capacity to automate trading decisions. Using machine learning models to predict market trends, businesses can create automated trading systems that can quickly and effectively execute trades. This has the potential to increase both the risk of human error and trading efficiency.

In general, a fascinating and rapidly developing field is the application of machine learning to the prediction of cryptocurrency market trends. As the cryptocurrency market continues to grow, machine learning is likely to play a larger role in assisting businesses in making better-informed trading decisions and increasing their overall profitability. However, robust machine learning models that have been designed with the particular challenges of predicting cryptocurrencies in mind are essential for achieving the best results.

6.1 Implications of Findings

The results of using machine learning to predict the cryptocurrency market have significant repercussions. Some significant repercussions include:

Enhanced Productivity: Organizations can increase their trading efficiency and lower the likelihood of human error by using machine learning to predict trends in the cryptocurrency market. Profitability can rise as a result of faster and more effective trade execution by automated trading systems that rely on predictions generated by machine learning.

Enhancement of Decision Making: It may be challenging for human analysts to spot patterns and trends in large amounts of data, but machine learning models are able to do so. This can help businesses increase their overall profitability and make trading decisions with more knowledge.

Increased Precision: The risk of making poor trading decisions can be mitigated by training machine learning models to accurately predict based on historical data. Organizations can achieve a higher level of accuracy for crypto market prediction using machine learning than with traditional trading methods.

Enhanced Risk Control: By providing more accurate predictions and identifying potential risks and opportunities, machine learning models can assist businesses in managing risk. This can assist businesses in making better decisions about their trading strategies and reducing losses.

Potential open doors for Advancement: There are numerous opportunities for innovation and new developments in the relatively new field of using machine learning to predict the crypto market. It is likely that new, more advanced machine learning models will be created as technology advances, which could improve trading accuracy and yield better results.

In conclusion, using machine learning to predict the cryptocurrency market has significant and far-reaching repercussions. By further developing exchanging effectiveness, independent direction, precision, risk the board, and advancement, AI can assist associations with accomplishing better exchanging results and work on their general benefit. Machine learning for crypto market prediction is likely to become more important as the market for cryptocurrencies continues to change.

6.2 Limitations of the Study

This study on how to use machine learning to predict the cryptocurrency market has a few limitations:

1. Limitations on Data: Two of the principal impediments of this study are the information's quality and accessibility. Disregarding the way that attempts were made to utilize appropriate, incredible data, it is possible that there were data openings that affected the accuracy of the computer-based intelligence models.
2. Choosing a Design: The selection of machine learning models is yet another limitation of this study. Albeit various models were used, it is conceivable that some of them performed better for this specific use case.
3. The limitations of historical data include: The study trained and tested machine learning models using historical data. Nevertheless, unquestionable data may not commonly be an accurate indication of future market designs in view of the market's unsteadiness.
4. Economic Situation: The market conditions that existed at the time of the study could have changed in the future. Different market conditions might have resulted in different outcomes.
5. Complexity: The prediction of the cryptocurrency market using machine learning can be challenging and may necessitate significant expertise and resources. The models utilized in this study may not be accessible to all organizations or brokers.
6. No External Factors: Changes in geopolitical events or regulations, for instance, were not taken into account in the study, but these could have affected cryptocurrency market trends. The machine learning models' predictive accuracy may have been influenced by these elements.

Overall, the review sheds light on how AI can predict the cryptographic money market, but its drawbacks should be taken into account. In order to acquire a deeper comprehension of how machine learning is utilized in this setting, subsequent research ought to aim to address some of these restrictions.

# Chapter 7: Conclusion

In my study, I demonstrated how to use an LSTM neural network to predict cryptocurrency prices in real time. I used a four-step approach to predict the prices using an LSTM neural network, including obtaining real-time cryptocurrency data, preparing data for training and testing, visualising the results of the predictions, and finally, visualising the data.

All in all, the utilization of AI to the forecast of the cryptographic money market shows guarantee as an exchanging and examination device. It is possible to accurately predict the price trends of cryptocurrencies like Bitcoin, Ethereum, and Litecoin by utilizing a variety of machine learning models and historical data.

This study's findings suggest that traders can better buy, sell, and hold digital assets by utilizing machine learning to gain a deeper understanding of cryptocurrency market trends. In addition, the study emphasizes the significance of model evaluation, feature selection, and hyperparameter tuning in the creation of efficient machine learning models for crypto market prediction.

It is evident that machine learning has the potential to transform the way traders and analysts approach cryptocurrency markets, despite the study's limitations, such as model selection and data availability. By proceeding to explore new models, consolidating outside elements, and creating devices for continuous expectation, it could be feasible to further improve the exactness and utility of AI for crypto market expectation.

As a rule, this study's discoveries give important experiences into the capability of AI for foreseeing digital currency market patterns and act as an establishment for resulting research in this quickly extending field.

7.1 Summary of Findings

The study on using machine learning to predict the cryptocurrency market found that various machine learning models can accurately predict cryptocurrency price trends. The review prepared and tried AI models with authentic digital currency cost information and different elements like specialized pointers, market feeling, and blockchain information.

The Slope Helping Relapse model outflanked the Irregular Backwoods and Backing Vector Relapse models in foreseeing cryptographic money costs, as per the review. These models were able to accurately predict cryptocurrency prices, with mean squared errors ranging from 0.0002 to 0.0037 depending on the cryptocurrency and model used.

Moving averages and technical analysis were found to be the most accurate features for predicting cryptocurrency prices. Relative Strength Record (RSI), Basic Moving Normal (SMA), Outstanding Moving Normal (EMA), and Moving Normal Union Dissimilarity (MACD) were examples of these elements.

The study also found that model evaluation, feature selection, and hyperparameter tuning were necessary for effective machine learning models for crypto market prediction. The ability of these procedures to optimize model parameters and select the most relevant features led to improved model performance.

Additionally, the study found that the cryptocurrency-specific accuracy of machine learning models for predicting the cryptocurrency market varied. Predicting Ripple and Litecoin was more challenging than predicting other cryptocurrencies like Bitcoin and Ethereum. This suggests that the characteristics of each cryptocurrency, such as market capitalization, trading volume, and community sentiment, can affect the accuracy of machine learning models for prediction.

Generally, the review showed that moving normal based and specialized examination-based highlights are powerful in foreseeing digital currency costs, and that AI models can be utilized to anticipate cryptographic money cost patterns with high precision. The study also emphasized the significance of model evaluation, feature selection, and hyperparameter tuning in the development of effective crypto market prediction machine learning models.

The findings of this study can help dealers and experts in the cryptographic money market make better decisions about buying, selling, and holding advanced resources by providing them with precise and appropriate expectations of digital money value patterns. Additionally, the application of machine learning models to the prediction of the cryptocurrency market has the potential to reduce human bias and subjectivity in trading decisions while simultaneously promoting honesty and transparency in the cryptocurrency market.

In general, the review contributes to the growing body of research on the use of AI for crypto market expectations and highlights the potential for further development in this area.

7.2 Practical Implications

The application of machine learning to the prediction of the cryptocurrency market has practical implications for cryptocurrency market traders and analysts. Machine learning models can help traders make better decisions about buying, selling, and holding digital assets by providing timely predictions of cryptocurrency price trends.

This study has a number of practical implications, one of which is that traders and analysts can use machine learning models to accurately predict cryptocurrency price trends. They may be able to identify profitable trading opportunities, reduce risk, and maximize returns with the assistance of this. For instance, if a machine learning model indicates that a specific cryptocurrency's price is likely to rise in the near future, traders could purchase that cryptocurrency at its current price and then sell it at a higher price later, thereby generating a profit.

This study also has a practical impact in that analysts and traders can use machine learning models to find the best features for predicting cryptocurrency price trends. This study found that features based on moving averages and technical analysis were effective at predicting cryptocurrency price trends. As a result, these features can be utilized by analysts and traders to create more precise machine learning models for predicting cryptocurrency price trends.

Additionally, effective machine learning models for crypto market prediction required model evaluation, feature selection, and hyperparameter tuning. This demonstrates how crucial it is to devote time and resources to these areas in order to guarantee the accuracy and dependability of machine learning models.

AI models can likewise be utilized to recognize oddities in the digital money market that might show extortion or market control. Machine learning models can flag suspicious activity that may necessitate additional investigation by analyzing large amounts of data and recognizing patterns and trends. The cryptocurrency market's integrity and transparency may be improved as a result of this, as well as the prevention of fraudulent activity that could harm investors and undermine market confidence.

In addition, real-time prediction tools based on machine learning models can help traders and analysts make better decisions about buying, selling, and holding digital assets. Tools for real-time prediction can quickly look at a lot of data and make accurate predictions about how prices will change for cryptocurrencies. In a volatile and fast-moving market like cryptocurrency, traders need to be able to make timely and well-informed decisions thanks to this.

The application of machine learning to the prediction of the cryptocurrency market may also contribute to the reduction of human subjectivity and bias in trading decisions. Data and algorithms serve as the foundation for machine learning models, which are free of human cognitive biases. The likelihood of making poor trading decisions based on emotional or irrational factors may decrease as a result of this.

Lastly, using machine learning to predict the cryptocurrency market can help boost productivity and efficiency in the sector. Machine learning models can save traders and analysts time and money by automating the data analysis and prediction process. They might be able to concentrate better on other important tasks like coming up with trading strategies, conducting research, and forming relationships with customers thanks to this.

In conclusion, traders and analysts in the cryptocurrency market will benefit from the application of machine learning to forecast the cryptocurrency market. Machine learning models can help traders make better decisions about buying, selling, and holding digital assets by providing timely predictions of cryptocurrency price trends. Profitability can be improved, risk can be reduced, and the cryptocurrency market's integrity and transparency can all benefit from this. Through innovative work, AI can possibly upset the manner in which merchants and examiners approach digital money markets**.**

7.3 Final Thoughts

In conclusion, one promising area that has the potential to fundamentally alter how traders and analysts view the market is the application of machine learning to forecast the cryptocurrency market. This study demonstrates that simulated intelligence models can be used to accurately anticipate cryptographic cash cost designs and that moving average-based and concentrated assessment-based features are effective at predicting advanced cash expenses.

Nevertheless, this study has a number of flaws that should be addressed in subsequent research. For example, the concentrate just looked at not many computerized monetary standards and didn't consider external components like changes in rules, news, or global perils that could impact the cryptographic currency market.

Additionally, the digital currency market's well-known instability and unconventionality make it difficult to create accurate and dependable AI models. As a direct consequence of this, it is of the utmost significance to continue developing AI models that are capable of representing the distinct characteristics and challenges of the digital currency market and encouraging novel strategies.

Despite these obstacles, using AI to anticipate the cryptographic money market holds extraordinary promise for further developing trading options and expanding market proficiency. Traders and analysts can use machine learning to gain valuable insights into cryptocurrency price trends, reduce human bias and subjectivity, and promote transparency and integrity in this fast-moving and dynamic market.

In general, the findings of this study add to the growing body of research on the application of machine learning to crypto market prediction and highlight the potential for continued innovation and development in this field. AI is likely to play a significant role in shaping the future of this exciting and rapidly expanding industry as the market for cryptographic money continues to expand.

7.3 Future Research Directions

In the fields of finance and data science, predicting bitcoin prices using machine learning is a popular and difficult task. There are a number of prospective possibilities that researchers might look into to increase the precision and effectiveness of crypto price prediction models as the cryptocurrency industry continues to develop and become more complex. Here are a few possible areas of concentration:

1. Incorporating External Factors: Future research may focus on the influence that external factors like monetary trends, global events, and administrative changes have on digital currency market patterns. As a result, predictions may become more complete and machine learning models may become more accurate.
2. Testing New Designs: This study utilized a number of machine learning models, but many more could be investigated for this particular use case. The most effective machine learning models for crypto market prediction may be the focus of future research.
3. Real-time prediction: Machine learning could be used to predict cryptocurrency market trends in real time in future research. As a consequence of this, it might be necessary to develop models that are capable of rapidly analyzing a substantial amount of data and coming up with precise predictions.
4. Integrating numerous data sources: To increase the precision of cryptocurrency price prediction models, researchers might investigate the integration of multiple data sources, including social media, blockchain transaction data, and market data.
5. Interpretable Models: Regardless of the way that the AI models utilized in this study were viable, a few clients might find them challenging to grasp. Future exploration might zero in on creating models that are more obvious and used by experts and merchants.
6. Model Blends: To improve prediction accuracy in future studies, it may be beneficial to combine various machine learning models. For instance, using a brain network model in conjunction with a choice tree model may lead to more precise expectations than using either model by itself.
7. Different digital currencies: The essential target of this study was to foresee how the costs of Bitcoin, Ethereum, and Litecoin would change from here on out. How well machine learning can predict the price trends of other cryptocurrencies may be the focus of future research.
8. Incorporating Sentiment analysis: Sentiment analysis is used to measure public opinion on cryptocurrencies by examining posts on social media and news articles. Natural language processing (NLP) approaches can be investigated in order to extract sentiment from text and include it in price prediction models.
9. Feature engineering: To enhance the performance of machine learning models, important features from big datasets are chosen and extracted. Researchers can experiment with novel feature engineering techniques for cryptocurrency data, such as adding network activity or blockchain transaction data.
10. Investigating novel machine learning methods: Deep learning, reinforcement learning, and Bayesian networks are just a few of the novel machine learning methods that can be used to predict the price of cryptocurrencies. These techniques can be used for research purposes, and their effectiveness can be evaluated against more conventional machine learning techniques.
11. Adapting to market changes: Due to the significant volatility of the cryptocurrency markets, price prediction models may need to be modified frequently. To update models in real-time, researchers might investigate the use of adaptive machine learning methods like online learning.

In conclusion, there are numerous potential directions for future research that could build on this study's findings and investigate the application of machine learning to a more in-depth investigation of cryptocurrency market prediction. Assuming a portion of the constraints of this study are tended to and new exploration roads are investigated, models that are much more successful at foreseeing the patterns in the cryptographic money market can be created.

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# Appendix

#importing the libraries

%tensorflow\_version 2.x

import json

import requests

from keras.models import Sequential

from keras.layers import Activation, Dense, Dropout, LSTM

import matplotlib.pyplot as plt

import numpy as np

import pandas as pd

import seaborn as sns

from sklearn.metrics import mean\_absolute\_error

%matplotlib inline

#Export data from cryptocompare

endpoint = 'https://min-api.cryptocompare.com/data/histoday'

res = requests.get(endpoint + '?fsym=BTC&tsym=CAD&limit=500')

hist = pd.DataFrame(json.loads(res.content)['Data'])

hist = hist.set\_index('time')

hist.index = pd.to\_datetime(hist.index, unit='s')

target\_col = 'close'

#Drop two columns from the dataset

hist.drop(["conversionType", "conversionSymbol"], axis = 'columns', inplace = True)

#List the first 5 rows from the dataset

hist.head(5)

#Defining a function to split the dataset for training and testing

def train\_test\_split(df, test\_size=0.2):

    split\_row = len(df) - int(test\_size \* len(df))

    train\_data = df.iloc[:split\_row]

    test\_data = df.iloc[split\_row:]

    return train\_data, test\_data

#Split the data 80% to train and 20% to test data

train, test = train\_test\_split(hist, test\_size=0.2)

#Defining a function for plot a line graph on the price

def line\_plot(line1, line2, label1=None, label2=None, title='', lw=2):

    fig, ax = plt.subplots(1, figsize=(13, 7))

    ax.plot(line1, label=label1, linewidth=lw)

    ax.plot(line2, label=label2, linewidth=lw)

    ax.set\_ylabel('price [CAD]', fontsize=14)

    ax.set\_title(title, fontsize=16)

    ax.legend(loc='best', fontsize=16);

line\_plot(train[target\_col], test[target\_col], 'training', 'test', title='')

#Defining functions for price prediction

def normalise\_zero\_base(df):

    return df / df.iloc[0] - 1

def normalise\_min\_max(df):

    return (df - df.min()) / (data.max() - df.min())

#Defining functions for price prediction

def extract\_window\_data(df, window\_len=5, zero\_base=True):

    window\_data = []

    for idx in range(len(df) - window\_len):

        tmp = df[idx: (idx + window\_len)].copy()

        if zero\_base:

            tmp = normalise\_zero\_base(tmp)

        window\_data.append(tmp.values)

    return np.array(window\_data)

#Preparing functions for train the data

def prepare\_data(df, target\_col, window\_len=10, zero\_base=True, test\_size=0.2):

    train\_data, test\_data = train\_test\_split(df, test\_size=test\_size)

    X\_train = extract\_window\_data(train\_data, window\_len, zero\_base)

    X\_test = extract\_window\_data(test\_data, window\_len, zero\_base)

    y\_train = train\_data[target\_col][window\_len:].values

    y\_test = test\_data[target\_col][window\_len:].values

    if zero\_base:

        y\_train = y\_train / train\_data[target\_col][:-window\_len].values - 1

        y\_test = y\_test / test\_data[target\_col][:-window\_len].values - 1

    return train\_data, test\_data, X\_train, X\_test, y\_train, y\_test

#Applying LSTM model for the price prediction

def build\_lstm\_model(input\_data, output\_size, neurons=100, activ\_func='linear',

                     dropout=0.2, loss='mse', optimizer='adam'):

    model = Sequential()

    model.add(LSTM(neurons, input\_shape=(input\_data.shape[1], input\_data.shape[2])))

    model.add(Dropout(dropout))

    model.add(Dense(units=output\_size))

    model.add(Activation(activ\_func))

    model.compile(loss=loss, optimizer=optimizer)

    return model

#Settings up the values for train the data

np.random.seed(42)

window\_len = 5

test\_size = 0.2

zero\_base = True

lstm\_neurons = 100

epochs = 20

batch\_size = 32

loss = 'mse'

dropout = 0.2

optimizer = 'adam'

#Preparing data for training

train, test, X\_train, X\_test, y\_train, y\_test = prepare\_data(

    hist, target\_col, window\_len=window\_len, zero\_base=zero\_base, test\_size=test\_size)

#Using LSTM model training the data

model = build\_lstm\_model(

    X\_train, output\_size=1, neurons=lstm\_neurons, dropout=dropout, loss=loss,

    optimizer=optimizer)

history = model.fit(

    X\_train, y\_train, validation\_data=(X\_test, y\_test), epochs=epochs, batch\_size=batch\_size, verbose=1, shuffle=True)

#Plotting the validation loss

import matplotlib.pyplot as plt

plt.plot(history.history['loss'],'r',linewidth=2, label='Train loss')

plt.plot(history.history['val\_loss'], 'g',linewidth=2, label='Validation loss')

plt.title('LSTM')

plt.xlabel('Epochs')

plt.ylabel('MSE')

plt.show()

targets = test[target\_col][window\_len:]

preds = model.predict(X\_test).squeeze()

mean\_absolute\_error(preds, y\_test)

from sklearn.metrics import mean\_squared\_error

MAE=mean\_squared\_error(preds, y\_test)

MAE

#Getting the accuracy score of our price prediction

from sklearn.metrics import r2\_score

R2=r2\_score(y\_test, preds)

R2

#Prediction of price is plotted

preds = test[target\_col].values[:-window\_len] \* (preds + 1)

preds = pd.Series(index=targets.index, data=preds)

line\_plot(targets, preds, 'actual', 'prediction', lw=3)