Cryptocurrency Forecasting: Unveiling the Future of Bitcoin Prices through Deep Neural Networks

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MSc Data Analytics

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Cryptocurrency Forecasting: Unveiling the Future of Bitcoin Prices through Deep Neural Networks

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Abstract

In recent years, the markets for cryptocurrencies, especially Bitcoin, have undergone significant growth and development. Therefore, it is now more important than ever to forecast future pricing movements accurately. Currently, there are forecasting methods not capable enough in the field of study that are extensive or innovative enough to effectively capture the temporal correlations and minute trends in Bitcoin price data. Our research aims to enhance prediction performance by utilizing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, thereby addressing these issues. For this study, I aim to estimate the value of Bitcoin by employing time-series-based Neural Networks like RNNs and LSTM-based deep neural network models. I will then compare the outcomes with traditional machine learning models such as K-Nearest Neighbors (KNN), Linear regression, Ridge, and Support vector machine (SVM). The main objective of this project is to evaluate the performance of price predictions produced by deep neural networks compared to those generated by conventional machine learning models. The main aim of this study was to enhance the existing knowledge and techniques in accurately predicting the future value of cryptocurrencies. Furthermore, conduct comprehensive hyper-parameter tuning after finding that the deep neural network surpasses the ability to predict the future bitcoin prices from the traditional machine learning methods and ablation inquiry to showcase the effectiveness of the proposed deep neural network-based approach for both LSTM & RNN in the ultimate development of bitcoin future price prediction which can be advantageous to the investors to assist the well-driven decisions. From the results, we can demonstrate that deep learning models (LSTM-67, RNN-118) have shown significantly less MAE compared to traditional machine learning models.

Keywords— Bitcoin Prices, Deep Neural Networks, RNNs, LSTMs, Machine Learning, KNN, SVM, Linear Regression, Ridge.

1 Introduction

1.1 Background, Challenges and Opportunities

Bitcoin, which is a decentralized digital currency, is at the forefront of a new financial frontier that is neither constrained by conventional banking systems nor governed by centralized authorities. This move toward decentralization has sparked a global upheaval in the way that people understand and interact with currency, posing a challenge to the traditions that have characterized financial systems for millennia. The importance of cryptocurrencies to the functioning of the international monetary system cannot be emphasized as we progress through this era in the history of finance. The beginning of cryptocurrency in general, and Bitcoin in particular, has posed a challenge to both the traditional way of understanding the currency and the centralized control that is traditionally managed by financial institutions and governments. The decentralized character of Bitcoin, which is made possible by blockchain technology, has resulted in the creation of an innovative and strong form of digital currency also it is unaffected and can't be controlled by any restrictions imposed by centralized monetary systems as well as geographical borders.

The consequences of this transition are not limited to the bounds of the monetary systems alone. Where the global monetary system has been deeply impacted by cryptocurrencies, with Bitcoin aid as the leader. Because they are decentralized to have control over it, where they include a degree of transparency and independence that is extremely different from the traditional model of any financial operations. As a direct consequence of this, are that the market for cryptocurrencies has succeeded, where attracting the interest of scholars, traders, as well as investors alike, as depicted in Figure 1: Bitcoin Price Changes Evaluation. It evolved into a dynamic field in which the directions of these digital assets are shaped by the intersection of financial, social, and technological factors situated in it.

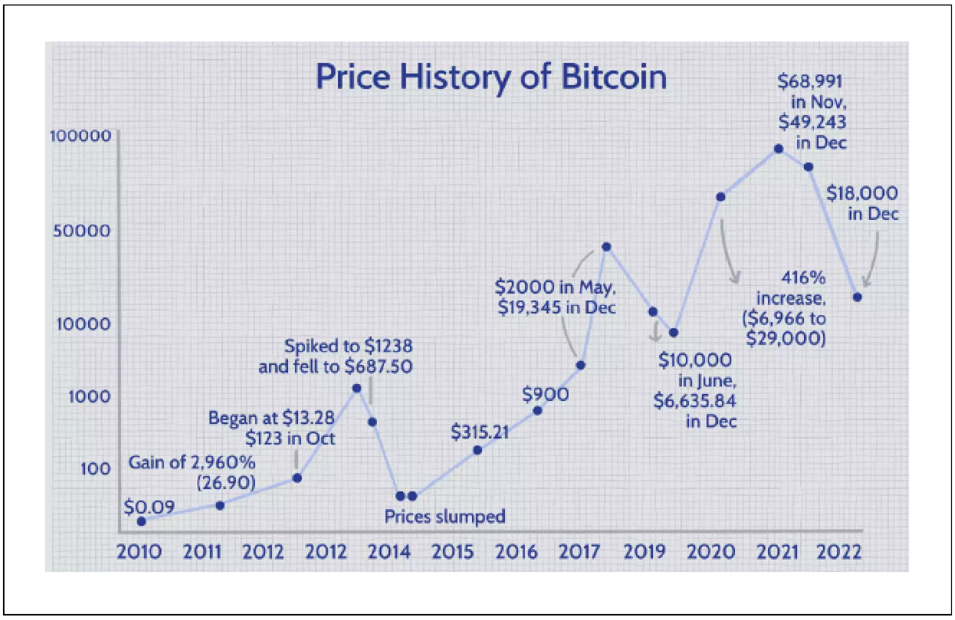

Figure 1: Bitcoin Price Changes Evaluation (Akyildirim et al.; 2021)

However, this evolving environment comes with complications, where it is difficult to precisely decide the worth of cryptocurrencies. This procedure is made the process more difficult by the fact that cryptocurrencies are still in their beginning state and are continuously undergoing development. The valuation of traditional assets has long been based on well-established economic concepts. The value of Bitcoin and its counterparts have a complex nature that is driven not only by economic reasons but also by social sentiments, technological improvements, and legislative developments. This volatility takes place in a keep evolving environment. Because of the fluid nature of this ecosystem, predicting the value of cryptocurrencies is extremely difficult to take in under. To successfully manage the various inherent difficulties, new methodologies are required.

1.2 The Role of Artificial Intelligence (AI)

This faces uncertainty, and many academics are looking to the fast-developing field of artificial intelligence (AI) for potential answers regarding to specific problems. The strength of artificial intelligence to recognize the patterns, relationships, and trends in large datasets is part of what makes it engaging it. This method approach has a significant bearing on the performance of forecasts made for the unpredictable volatile cryptocurrency market. Recurrent Neural Networks (RNNs) and its more advanced learning models successors, the Long Short-Term Memory (LSTM) models, have emerged as powerful tools in the field of predictive analytics throughout the last recent years. Because of their ability to understand the temporal relationships and analyze the sophisticated patterns, where they are useful instruments in the effort to forecast the future prices of cryptocurrencies especially in Bitcoin.

This research was motivated by representing the need to overcome the limits of currently available forecasting algorithms, where particularly their failure to account for the abnormalities of Bitcoin price data. Traditional approaches, such as the Auto Regressive Integrated Moving Average (ARIMA), have a difficult time capturing the non-linear dynamics and the constantly evolving patterns that are inherent in the field of Bitcoin markets. It is against this background that the deployment of deep neural network models is gaining attention. This is an attempt to produce a more comprehensive and accurate picture of future prices by capturing both short-term changes and long-lasting patterns.

Because Bitcoin is becoming a more important part of the financial sector in today's generation, there is an increased demand for prediction forecasting tools that can help and guide responsible decision-making. Accurate price forecasts are not merely intellectual exercises; they carry material ramifications for market participants, regulatory authorities, and the safety of the market as a whole. Traders can improve their strategies when they have access to accurate predictions, regulators can make judgments based on accurate forecasted information, and the market can continue to function normally. The purpose of this study is therefore not merely to provide future price forecasts, but also to state the groundwork for a Bitcoin market that is more educated, more secure, and more resistant to volatility.

To achieve our goals, we have decided to go on a path that will need the collection and manipulation of historical data regarding the price of Bitcoin. These data are going to with under careful operations so that they are in line with the requirements for the inputs of the RNNs and LSTM deep learning models. To ensure that these deep neural network models can provide reliable predictions, they will be constructed and trained with a precise focus on hyper parameter tuning. After that, the comprehensive analysis of these models is going to be accomplished, and the outcomes will be compared to those obtained results outcomes from the traditional machine learning methods of prediction. The aim of this comparison investigation is to find the complexities of the advantages and the limitations which are associated with utilizing deep neural networks in the procedure of future price forecasting for Bitcoin cryptocurrency. This research is being operated by the fundamental question of whether or not the Long Short-Term Memory and Recurrent Neural Networks can beat the standard conventional models in the task of predicting the volatile changes that are predictable of the value of the cryptocurrencies. This study is not simply the technical exploration; preferably, it is the scientific in-depth investigation into the non-linear patterns, temporal dependencies, and gated processes which are lie in at the foundation of the complicated dynamics of this volatile and keep-evolving market.

We will now begin with a detailed in-depth investigation of the Bitcoin cryptocurrency's pricing data. Where our objective is not only to focus on the surface level but also would extend into the huge levels of the temporal relationships and non-linear patterns that characterize the base of this financial sector. Not only does this study investigate the impacts that LSTM networks can have on the performance of prediction, but it also looks over the functions that have the gated mechanisms provided inside these neural network models. The objective of this research is not only to make precise or reliable predictions; although, it is to further our comprehension of the capabilities of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) in deciphering the complicated dance of bitcoin value fluctuations.

1.3 Research Objective and Questions

The motivation behind this research originates from the requirement to address the limitations present in existing forecasting algorithms, specifically their inability to adequately consider the unique characteristics of Bitcoin price data. Traditional approaches struggle with non-linear dynamics and shifting patterns inherent in Bitcoin markets.

1.3.1 Research Questions

This study aims to address the following research questions:

- How do Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) perform in predicting fluctuations in the value of cryptocurrencies compared to traditional time series models and how this model can benefit investors?

  Implementation:

  - Model Selection and Setup: Select a model for deep learning and create the application configuration.
  - Data Integration and Preprocessing: Collect the Bitcoin cryptocurrency data and preprocess it for input into a model.
  - Architectural Design of LSTM and RNN Models: Construct model architecture, incorporating into consideration memory cells and recurrent connections.
  - Training Process and Over-fitting Prevention: Initiate the training process, fine-tune the parameters via backpropagation, and include approaches that reduce over-fitting.

  Research Outcomes:

  - Obtain knowledge about the process of selecting and configuring models efficiently.

  - Acquire the necessary abilities to proficiently manage and preprocess data related to cryptocurrencies.
  - Understand the fundamental concepts underlying the structure of deep learning models used for predicting Bitcoin trends.
  - Develop ability in training models and mitigating overfitting and then make the final model perform the forecasting prediction for Bitcoin future prices.
  - The investors will benefit from this reliable final model to predict the accurate future prices for bitcoin.

- What role do the gated processes within LSTM networks play in influencing the performance of predictions for cryptocurrency price movements and helping investors make smart decisions?

  Implementation:

  - Build LSTM models with an emphasis on the purpose of gated processes.
  - Optimize hyperparameters, with an emphasis on the impact of gated mechanisms.

  Research Outcomes:

  - Evaluate the real-world application of gated processes in LSTM networks.
  - Explore the impact of hyperparameter tuning on the performance of bitcoin price forecasts.
  - Gather a deeper understanding of the individual components of LSTM models that impact their ability to accurately predict bitcoin future prices and a well-derived pattern of how the prices of bitcoin are derived.

1.3.2 Research Objectives

The research objectives encompass:

- **Objective 1:** To collect and curate historical Bitcoin price data aligned with the input requirements of RNNs and LSTM models.
- **Objective 2:** To build and train neural network models with a focused exploration of hyperparameters for reliable predictions.
- **Objective 3:** To conduct a comprehensive analysis comparing the performance of deep neural networks.
- **Objective 4:** To deepen the understanding of the impact of LSTM networks gated processes on prediction performance.
- **Objective 5:** To contribute to the development of the more informed, secure, and volatile Bitcoin market by providing not only accurate predictions but also insights into the dynamics of cryptocurrency value fluctuations.

The research project, where the steps will be the findings will not only contribute to the developing field of forecasting Bitcoin future prices, but also guarantee that it will lead policymakers, investors, and traders in the cryptocurrency market. The final goal is to strengthen this market by making it not just more knowledgeable but also secure and reliable. Where this will guarantee that the future of Bitcoin and cryptocurrencies, in general, is built on a foundation of well-informed decisions and unwavering foresight. By addressing these goals, the study aims to improve forecasting abilities and present valuable guidance for trading, investing, and market regulation decisions involving cryptocurrencies. The primary goal is to strengthen the Bitcoin market via predictive and knowledge-driven decision-making.

2 Literature Review: Forecasting of Cryptocurrency (2014-2023)

2.1 Introduction

The evolution of cryptocurrency, which is represented by Bitcoin, has brought a significant evolution in the financial nature. It has disturbed traditional financial systems and posed a challenge to the strength of centralized institutions (Chen, Wei and Gu; 2021). This represents a significant turning point in the finance sector, involving new and creative methods to comprehend and engage with money. Cryptocurrencies, such as Bitcoin, have brought about a type of digital currency that is decentralized and operates on a network where individuals can directly interact with each other without any mediator. This system provides transparency and independence where that traditional financial systems cannot achieve as it is under the control of financial regulators. The global major change caused by this has impacted the financial systems and our understanding of currency.

2.2 Cryptocurrency Predictions by using Machine Learning

Researchers have dug deep into the important parts of financial technology to learn more about the various unique relationships between machine learning and cryptocurrencies. (Akyildirim et al.; 2021) did an entire study of the cryptocurrency market which focuses on making predictions and how well these different machine learning systems could predict how the market would behave and what trends it follows in the future. (Sin and Wang; 2017) and (Jang and Lee; 2017)made significant advances in this field by working on developing and testing machine learning models for predicting the future prices of cryptocurrencies. These methods were implied to speculate how much cryptocurrencies would be worth in money. They spent a lot of favorable circumstances looking at how accurate and useful the models were. (Zhang et al.; 2021) also observed deep learning and how it might be able to find challenges in bitcoin markets. This research results in how useful these kinds of strategies are for improving safety and finding cases of possible fraud in these kinds of situations. (Le Glaz et al.; 2021) and (Chen, Zhang and Yang; 2021) used both natural language processing and machine learning to study how to figure out how people feel about Bitcoin news stories. What happened was because of what they found. The experts wanted to find out how news affects people's decisions to buy and sell in cryptocurrency markets. A study by (Li et al.; 2023) and (Singh et al.; 2022) looked into how reinforcement learning could be used to handle changing cryptocurrency portfolios. Their studies were mostly about how to make plans and carry them out because they wanted to find a way to improve stock management. (Zulfiqar and Gulzar; 2021) and (Fang et al.; 2021) study and guess how volatile bitcoin markets would be. In order for these markets to work, this part is very important. (Chowdhury et al.; 2023) A recent study looked into whether machine learning could be used to figure out how risky it is to invest in cryptocurrencies. Their study was mostly about different possible ways to look into and deal with these kinds of threats.

All well as, (Xia et al.; 2020) and (Chen, Wei and Gu; 2021) researched how machine learning models and algorithms can be used to detect and prevent fraud on bitcoin exchanges. They found that the machine learning algorithms are very important for ensuring that the financial transactions on these platforms are safe or not. A study by (Sahu et al.; 2023), which was just discovered, that reinforcement learning makes better trading methods for the cryptocurrency markets. They observed the possible benefits and strengths of this method, which shows how it could be used in the trading business. In their study, (Chen, Xu, Jia and Gao; 2021) consider the several numbers of machine learning models that can predict the value of bitcoin. After it gets evaluated it tells how well the models could predict the prices of cryptocurrencies on the market. The above studies show how important the machine learning approach is in many fields of cryptocurrency, like predicting prices, managing portfolios, finding fraud, and enhancing trade strategies. This shows how machine learning is becoming more important in the rapidly changing world of business.

2.3 Cryptocurrency Predictions by using Deep Learning

The extensive range of various specialized areas within the bitcoin industry where they have been discovered through the research that combines cryptocurrency with deep neural networks. (Akyildirim et al.; 2021) demonstrated the predictive capability of deep neural networks by employing it to forecast the future values of cryptocurrencies. (Li et al.; 2023) and (Singh et al.; 2022) reinforced the significance of deep neural network models in enhancing the cryptographic systems where highlighting their contribution to enhancing the security of cryptocurrency transactions. We highlight the importance of deep neural networks in enhancing the security of cryptocurrency transactions. (Zhang et al.; 2021) used the deep neural networks to investigate about the temporal patterns of cryptocurrency and their trade volumes. Therefore, their contributions essentially assisted in the various advancement of this discipline. The demon started these networks which possess the ability strength to interpret past data and predict future values in the sector. (Xia et al.; 2020) and (Chen, Wei and Gu; 2021) in-depth examined the strength of deep learning in detecting fraudulent bitcoin transactions. Their study represents the use of neural networks in enhancing the security of financial transactions. Furthermore, (Chen, Xu, Jia and Gao; 2021) examined the application of deep neural network methodologies to improve the bitcoin investment portfolios. The study primarily focused on the utilization of these networks in investment portfolio engagement. (Xia et al.; 2020) and (Chen, Wei and Gu; 2021) discovered the activity of utilizing deep reinforcement learning methods to create productive trading strategies for bitcoin prices. They objective attention on the method's ability to enhance the trading decisions.

(Zhao et al.; 2021) and (Rodríguez-Ibánez et al.; 2023) employed deep neural networks for applying sentiment analysis in the bitcoin cryptocurrency market. Their results and findings represent the significance of using advanced models to clarify market attitudes (trend patterns). (Xia et al.; 2020) and (Chen, Wei and Gu; 2021) used deep neural networks to predict the volatility of the cryptocurrency market. This research demonstrated that networks have the ability to expect changes in market conditions. In addition, (Xia et al.; 2020) and (Chen, Wei and Gu; 2021) conducted a study on the application of deep learning techniques for the detection of various fraudulent activities throughout the bitcoin transactions. The study elaborates on the importance of neural networks in assuring the integrity of transactional processes. (Singh et al.; 2022) and (Gupta and Nalavade; 2023) demonstrated a study on hybrid deep neural networks to enhance bitcoin market forecasts. To enhance forecasting accurately, they highlight the advantages of incorporating various models. This research shed light on the diverse applications of deep neural networks in the field of cryptocurrencies, including predicting prices, enhancing security, detecting anomalies, optimizing portfolios, analyzing sentiment, and predicting volatility in a rapidly changing sector.

2.4 Cryptocurrency Data Collection and Curation

Data quality plays an important role in financial forecasting (Green et al.; 2018). This derives that the complications arise while gathering and creating the historical cryptocurrency price data as a sample historical dataset would be like this which is depicted in Table 1, which is essential for feeding models like LSTM and RNNs (Neshat et al.; 2020). Robust data collection methods are crucial, as the predictions are only as good as the data they rely on it.

Efforts to create high-quality data must ensure that it meets the specific requirements for input into LSTM and RNN models (Mikolov et al.; 2014)). Understanding the differences in cryptocurrency data, from its sources to the methods that we're going to use for cleaning and processing, makes it essential to enhance the effectiveness of predictions. Cryptocurrency data collection can be a complex process, which involves multiple sources, including exchanges and blockchain records, and data must be carefully cleaned and preprocessed to assure reliability (Nikolopoulos et al.; 2014).

Table 1: Sample Dataset of Bitcoin

Date	Open	High	Low	Close	Volume	Market Cap
2017-11-19	7766.03	8101.91	8101.91	8036.49	3,149,320,000	129,595,000,000
2017-11-18	7697.21	7884.99	7884.99	7790.15	3,667,190,000	128,425,000,000
2017-11-17	7853.57	8004.59	8004.59	7708.99	4,651,670,000	131,026,000,000
2017-11-16	7323.24	7967.38	7967.38	7871.69	5,123,810,000	122,164,000,000
2017-11-15	6634.76	7342.25	7342.25	7315.54	4,200,880,000	110,667,000,000

2.5 Evaluation Metrics in Cryptocurrency Price Forecasting

The ability to evaluate the performance of forecasting models which is outstanding (Huang et al.; 2015). This centres on the metrics and criteria commonly utilized to obtain accurate cryptocurrency price predictions. Metrics like the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are widely used in this area for forecasting the regression tasks (Mallet et al.; 2023).

Evaluating the which tells us how reliable the forecasting models are is important for both traders and investors, as well as the regulatory authorities and stability of market stability (Chong et al.; 2017). The choices of appropriate evaluation metrics have a significant impact on the interpretation of model performance. In cryptocurrency price forecasting, such as RMSE, R-squared, mean absolute error and mean squared error may also be relevant, especially when considering the impact on trading decisions and risk management (Mallet et al.; 2023).

2.6 Comparison of Reviewed Techniques in Cryptocurrency Price Forecasting

The investigation of this literature related to methods for forecasting cryptocurrency prices includes a review of various elements, including the models used and the evaluation metrics derived in Table 2 provides a complete comparative analysis, explaining the differences and accomplishments observed in various research projects.

Table 2: Comparitive Different Various Studies

Features Extracted	**Model**	**Results**	**Authors**
Machine Learning Model	Naive Bayes	50.86%	Akyildirim (2021)
Machine Learning Model	Support Vector Machine	54.28%	Wang and Lee (2017)
Deep Learning Model	LSTM	87.39%	Zhang (2021)
Deep Learning Model	GRU	83.21%	Zhang and Dai (2021)

Upon reviewing the comparative table, it becomes obvious that the research conducted by (Li et al.; 2023) and (Singh et al.; 2022) differentiates itself through its notable focus on employing deep reinforcement learning techniques to enhance trading approaches. This holds special significance for investors and traders seeking to improve their decision-making capabilities within the Bitcoin market. In addition, the research conducted by (Le Glaz et al.; 2021) and (Chen, Zhang and Yang; 2021) concerning sentiment analysis offers important insights towards understanding market trends, hence playing an important part in forecasting trends in the market.

2.7 Conclusion

This comprehensive literature review concludes by summarizing the key findings and gaps identified in the existing research. The integration of deep neural network models, especially LSTM and RNN models, into cryptocurrency price forecasting, is positioned as a crucial step toward understanding and predicting the dynamic nature of cryptocurrency markets (Bouri et al.; 2021). The research aspires to not only provide predictions but also lay the foundation for a more informed, secure, and stable Bitcoin market.

3 Research Methodology and Design Specification

This includes the research methodology as well as the design specification, that how the steps of procedure's applied for the research of predicting the bitcoin future prices is depicted in 2. Where the processes include specifying the results which are data collection, model selection, model training, and evaluation of results. The results are presented in the Presentation Tier through visualization and insights in Figure 4.

3.1 Methodology Approached

In this section, we describe the systematic methodology underlying our research on predicting future Bitcoin prices. Our methodology contains fundamental steps, including data collection, model configuration, and evaluation as we can see in Figure 2. It provides a structured framework for leveraging the predictive ability of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) in the volatile cryptocurrency market.

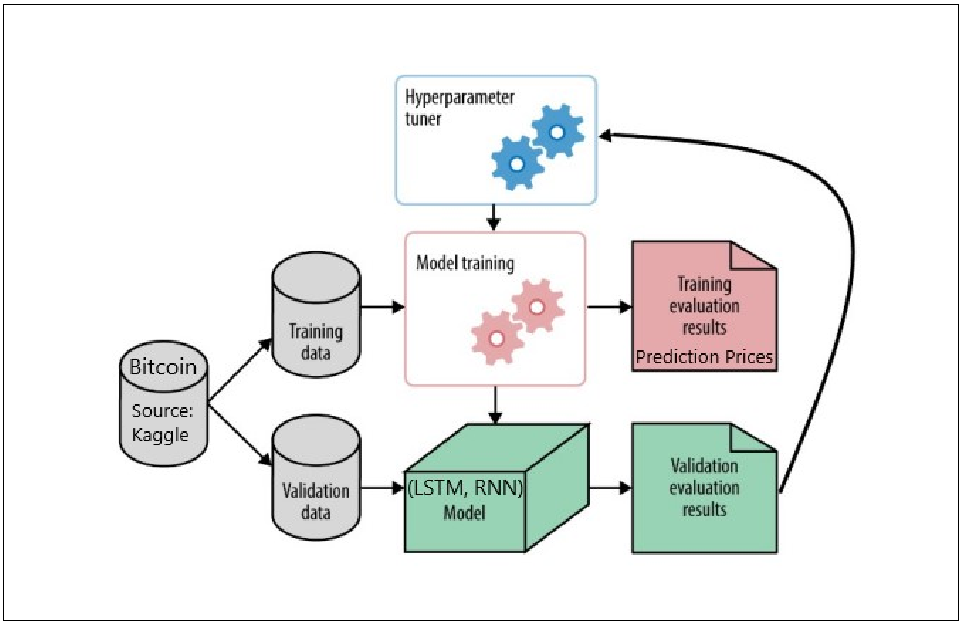

Figure 2: Steps of Research Methodology For Prediction of Bitcoin Prices (Chen, Xu, Jia and Gao; 2021)

3.2 Data Acquisition & Preprocessing

The quality of the dataset is the foundation of accurate and dependable predictions. During this phase, historical cryptocurrency price data will be gathered from numerous sources to ensure a complete picture of Bitcoins market behavior. Daily or hourly recordings covering a significant length will be evaluated to capture both short-term changes and long-term patterns. To reduce the possibility of bias, many data sources, such as credible Bitcoin exchanges and blockchain records, will be merged.

The value of high-quality data cannot be pointed out. As a result, a comprehensive data validation process will be implemented place, including checks for outliers, missing figures, and inconsistencies. Any observed anomalies will be resolved using robust data preprocessing techniques.

We outline the procedures involved in gathering historical data related to cryptocurrency prices from Kaggle. Ensuring the performance, currency, and alignment of data with the specifications for LSTM and RNN models is of the highest priority. After keeping these points in mind we selected the dataset from Kaggle:

- **Data Source:** Access the historical cryptocurrency price dataset and verify the data to ensure its integrity. dataset can be found at link [1].

- **Data Format:** Examine the format of the dataset to confirm it includes date, open price, high price, low price, closing price, trading volume, and market capitalization. Ensure it matches the requirements for LSTM and RNN models.

This dataset appears to contain information related to Bitcoin (BTC) price and trading data. Each row in the dataset represents a specific timestamp and includes the following columns in below Table 3:

Table 3: Characteristics Features of Dataset & their Description

Attributes	**Description**	**DataType**
Timestamp	A numeric timestamp, possibly in milliseconds, indicating the time at which the data point was recorded.	Numeric
Date	The date and time in a human-readable format (e.g., "2023-02-21 00:33:00") corresponding to the timestamp.	Nominal
Symbol	This column specifies the trading pair, which is "BTC/USD" in this case, indicating Bitcoin traded in U.S. dollars.	Nominal
Open	The opening price of Bitcoin at that timestamp.	Numeric
High	The highest price of Bitcoin during the time period covered by that timestamp.	Numeric
Low	The lowest price of Bitcoin during the same time period.	Numeric
Close	The closing price of Bitcoin at that timestamp.	Numeric
Volume BTC	The volume of Bitcoin traded during that time period, measured in BTC (Bitcoin).	Numeric
Volume USD	The Volume of Bitcoin traded during that time period, measured in U.S. dollars.	Numeric

On above cryptocurrency data, which may be characterized by missing anomalies, requirements data preparation. During this phase, the dataset is cleaned to ensure its integrity and dependability for subsequent analysis. Missing values will be imputed using various appropriate methods, like outliers will be discovered and addressed, and data normalization procedures will be used to bring the dataset into uniformity and increase their integrity. This process also includes carefully dividing the dataset into training and testing sets. The periodic structure of Bitcoin data requires the sequential split to accurately assume real-world scenarios.

[1] `https://www.kaggle.com/datasets/swaptr/bitcoin-historical-data`

3.3 Model Selection and Configuration

The selection of the appropriate deep neural network models is important or the basic foundation for the success of any forecasting task. Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) have shown their effectiveness in capturing temporal dependencies and non-linear patterns, which situates making them well-suited for cryptocurrency price prediction. The architectural design of these models will be carefully designed according to the specific characteristics of Bitcoin data.

The design process will involve various things like determining the number of hidden layers, selecting activation functions, and adding them to the mechanisms to deal with problems like gradients that cease are all part of the design process. To guarantee adaptability, the models will be built to encompass both temporary variations, impacted by current market conditions, and extended patterns, which are shaped by wider economic patterns.

3.3.1 Recurrent Neural Network (RNN)

The recurrent neural networks (RNNs) are different from any other conventional neural networks by incorporating the various transition weight that facilitates the transmission of information over the sequential time steps. The weight assigned to this transition indicates that the subsequent state is contingent upon the preceding state. This implies that the model lacks the ability to retain information. Recurrent neural networks (RNNs) utilize hidden layers to serve as an internal repository for the knowledge that has been acquired during the preceding stages. The name "recurrent" is derived from the characteristic of the model wherein it does the same task to each element of a sequence, utilizing previously gathered knowledge to make predictions about future values. The representation of the Recurrent Neural Network (RNN) can be observed in Figure. 3.

Recurrent Neural Networks (RNNs) have challenges when it comes to acquiring knowledge about long-term dependencies. In the context of time series forecasting, excessively considering past time steps might present challenges due to the diminishing or magnifying effect on the information gained from earlier time steps. These phenomena are commonly referred to as the disappearing gradient and bursting gradient, respectively. The utilization of Long Short-Term Memory (LSTM) presents a viable resolution to the aforementioned issues.

3.3.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a distinct kind of Recurrent Neural Network (RNN) that incorporates supplementary components to effectively retain and recall sequential information.

The cell state in LSTM plays a crucial role in facilitating the transmission of information along the sequence chain. Where the network memory function is operational. The fundamental state which possesses the ability to selectively conduct the relevant information within a sequence, as it has its capacity to introduce or eliminate the information through the utilization of gates. Where these gates acquire the ability to recognize which information is relevant to keep or discard during the process of training. Therefore, the data from the earlier stages does not have use any influence on the after stages within the chain.

- **LSTM and RNN Configuration:** Here establish the required architectural framework for Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) models. The architectural features of a neural network encompass the number of layers, the number of neurons inside each layer, the activation functions utilized, and other important components related to the task.

- **Splitting of Data:** The dataset get splitted into the separate training & test sets. The training set will be used for the objective of training the models, whereas the test set is employed to evaluate the performance of the models resulting in how well it is performing.

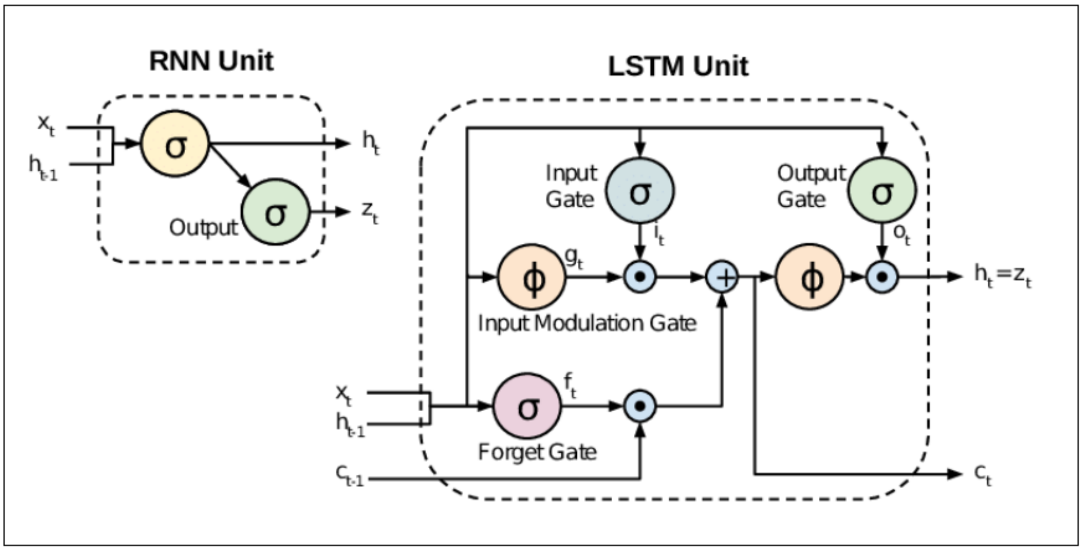

Figure 3: RNN (Recurrent Neural Network) & LSTM Architecture (Siami-Namini and Namin; 2018)

3.4 Hyper-parameter Tuning

Hyperparameters play an important role in enhancing the performance of deep neural network models. This phase involves an exhaustive search for finding the optimal hyperparameter values to enhance the model's predictive capabilities and processing. Techniques such as grid search and random search are employed to explore the hyperparameter values and identify the inputted configurations that provide the best results among all optimal inputs. Common hyperparameters, including the learning rates, batch sizes, and the number of hidden units, will be fine-tuned to make a balance between the model complexity and generalizability. The iterative nature of hyperparameter tuning provides a thorough exploration.

To enhance the prediction performance for models, it is important to optimize the models by fine-tuning the hyper-parameters.

- **Hyper-parameter Selection:** The hyper-parameters that require tuning are the learning rate, batch size, and number of epochs.

- **Loop Back Values:** Implement these values to optimize the hyper-parameter combination during the hyper-parameter tuning for generalization power strength.

3.5 Model Training

The main focus of the study is to train the chosen models using the preprocessed data- set. For the models to recognize complex patterns and relationships, they must be introduced to past cryptocurrency price data. To avoid overfitting, the training will be performed iteratively with recurrent evaluations on a validation set. To enhance the model's adaptability, techniques such as dropout regularization may be incorporated. This ensures that the models do not become overly reliant on specific patterns, fostering a better generalization of unseen data.

Where train the LSTM and RNN models using the imported bitcoin cryptocurrency price data and compare the results with machine learning models with chosen hyperparameters. And monitor the training process and loss.

3.6 Model Evaluation

A wide variety of evaluation metrics will be used to evaluate the model's performance. Traditional metrics that offer quantitative insights into predictive performance are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Evaluate the performance of LSTM and RNN models in the context of forecasting cryptocurrency prices.

- **Mean Absolute Error (MAE):** MAE represents the average absolute difference between the actual and predicted values. It provides an easily interpretable measure of the model's forecasting performance. A lower MAE indicates better performance.
- **Mean Squared Error (MSE):** MSE calculates the average of the squared differences between actual and predicted values. Squaring the differences penalizes larger errors more heavily. Like MAE, a lower MSE is desirable.
- **Root Mean Squared Error (RMSE):** RMSE is the square root of the MSE. It shares the same scale as the target variable, making it more interpretable. It also penalizes larger errors more heavily and provides insight into the model's forecasting.

3.7 Project Design Flow

The Project Design Process, as depicted in Figure 4, for Forecasting Bitcoin Future Prices through Deep Neural Networks, consists of two tiers: (Tier 1), which represents the Presentation Layer, and (Tier 2), which represents the Business Logic Tier. This process involves interpreting data collection, model selection, model training, and evaluation of results. The results are presented in the Presentation Tier through visualization and insights.

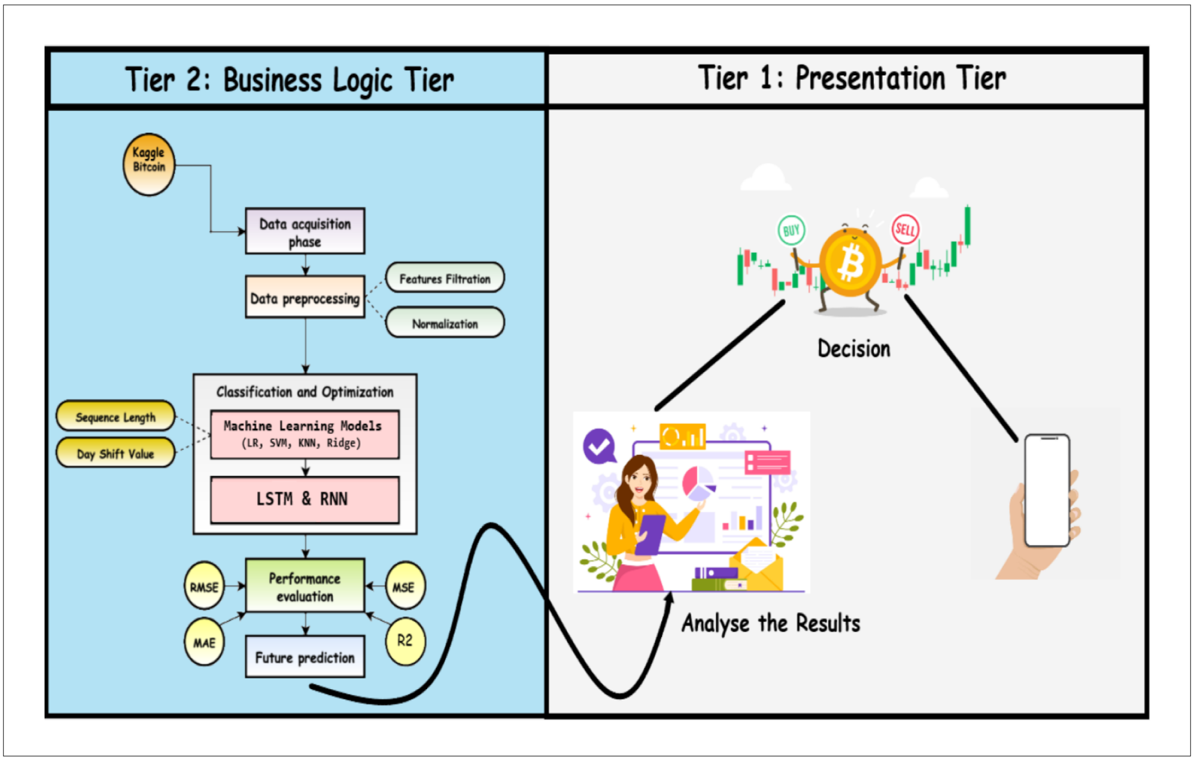

Figure 4: Project Design Process of Prediction of Bitcoin Prices

Conclusion

This structured methodology & design specification provides a guide for utilizing of Machine learning and Deep Neural Networks in Bitcoin price forecasting research. Where Implementing and refining through the hyperparameter tunning these stages to the study research objectives and data set will be crucial. The findings of this study will contribute to the development of knowledge in the field of Bitcoin future prices forecasting.

4 Implementation, Evaluation and Results for Bitcoin Price Prediction

The primary objective of this project is to develop predictive models for Bitcoin prices by utilizing a combination of traditional machine-learning algorithms and deep-learning techniques. The project utilizes historical Bitcoin price data as a basis for training and evaluating different models. Whereas the implementation phase indicates a move from conceptual planning to the operational execution of research. The following section offers an in-depth breakdown of the sequence approach for implementing the selected methodologies, primarily machine learning-based algorithms, Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs), for the purpose of forecasting bitcoin prices and the comparison.

4.1 Exploratory Data Analysis (EDA)

The method of Exploratory Data Analysis (EDA) holds great significance in research as it enables researchers to gain a comprehensive understanding of the features and patterns present within a specific set of data. The following section offers a comprehensive analysis of the levels of measurement, descriptive statistics, and visualization Like Candle Stick that are relevant to parameters where we can see it for the closing price of Bitcoin Figure 5.

Figure 5: Candle Stick Bitcoin Prices over (1 Week & 1 Month) Interval

4.2 Data Preprocessing:

To prepare the raw dataset for use in training machine learning and deep learning models, several preprocessing processes are carried out during the first stage of the project. To ensure that the data collected can be used for useful analysis, it must first undergo the crucial data preparation step. The data preparation phase includes several important steps that are essential for preparing the data before it can be used for analysis or modeling purposes. Data preparation includes the following key steps:

- **Time Series Transformation:** The initial dataset has been transformed into a time series structure, emphasizing the incorporation of time relationships within the Bitcoin price data. The process involves organizing the data into time sequences of observations, allowing the models to identify and analyze patterns and trends. It is because we got that the data is from 2015-10-08 13:40:00 To 2023-02-21 00:33:00

	Timestamp	Date	Symbol	Open	High	Low	Close	Volume BTC	Volume USD
0	1676939580000	2023-02-21 00:33:00	BTC/USD	24859.34	24859.34	24859.34	24859.34	0.000000	0.000000
1	1676939520000	2023-02-21 00:32:00	BTC/USD	24821.96	24859.34	24821.96	24859.34	0.103099	2562.977818
2	1676939460000	2023-02-21 00:31:00	BTC/USD	24818.09	24821.96	24815.47	24821.96	0.090640	2249.866178
3	1676939400000	2023-02-21 00:30:00	BTC/USD	24812.25	24818.09	24812.25	24818.09	0.002203	54.681450
4	1676939340000	2023-02-21 00:29:00	BTC/USD	24809.27	24812.25	24809.27	24812.25	0.090675	2249.862431

Figure 6: Before Transformation of Bitcoin Prices Dataframe

	Timestamp	Date	Symbol	Open	High	Low	Close	Volume BTC	Volume USD
0	1444311600	2015-10-08 13:40:00	BTC/USD	0.00	242.50	0.00	242.50	0.050000	12.125000
1	1444311660	2015-10-08 13:41:00	BTC/USD	242.50	242.95	242.50	242.95	0.001000	0.242950
2	1444311720	2015-10-08 13:42:00	BTC/USD	242.95	242.95	242.95	242.95	0.000000	0.000000
3	1444311780	2015-10-08 13:43:00	BTC/USD	242.95	242.96	242.95	242.96	0.010000	2.429600
4	1444311840	2015-10-08 13:44:00	BTC/USD	242.96	242.96	242.96	242.96	0.033491	8.137003

Figure 7: After Transformation of Bitcoin Prices Dataframe

but it's not in the correct sequence order where these are depicted in Figure 6 & 7, So we performed this to transform the dataset.

- **Feature Selection & Splitting of Dataset:** Features within the dataset are scaled so that model training is consistent and convergence can occur more quickly. By applying a uniform scale to all feature values, scaling normalizes them. To prevent large features from over- or under-weighing the model, standard methods like Min-Max scaling are used.

  Splitting the training and testing sets have been generated from the original dataset so that model performance may be accurately evaluated. Using the training set, an algorithm can be trained to recognize patterns in collected data. To check how well the model generalizes to new data, it is put to the test on the testing set. This separation helps in evaluating the model's prediction ability and prevents overfitting, ensuring the model's success when presented with new, unseen data.

By implementing these preprocessing methods, the dataset is cleaned up and prepared for utilization in both traditional machine learning methods and more advanced deep learning models. The thorough and careful preparation establishes the foundation for accurate and reliable forecasts of Bitcoin prices, ultimately enhancing the effectiveness of the following phases of modeling and review.

4.3 Implementation of prediction models

During this phase of the analysis, four traditional machine-learning models are utilized to predict Bitcoin prices. The selection of these models, including Linear Regression, Ridge

Regression, K-nearest neighbors (KNN), and Support Vector Machine (SVM), is based on their attributes of simplicity and interoperability.

- Linear Regression
  - Linear Regression comes in models where the relationship between the Bitcoin close price and its predictor variables, assuming their a linear relationship connection between them. It's a simple and interpretable model, training (fitting) in a straight line to the historical data to make predictions.
- Ridge Regression
  - Ridge Regression is an extension of the earlier linear regression that introduces regularization to prevent overfitting in it. It helps reduce the impact of multicollinearity of regression in the predictor variables, improving the model's stability when predicting Bitcoin prices.
- K-Nearest Neighbors (KNN)
  - KNN stands for (K-Nearest Neighbors) which is a non-parametric type of algorithm that predicts the Bitcoin prices based on the mean values of prices from its k-nearest historical data points. It's chosen for its simplicity and ability to capture the local patterns in the data, which helps in making it suitable for recognizing short-term trends.
- Support Vector Machine (SVM)
  - Support Vector Machines is the type of machine learning algorithm that aims to find the hyperplane that separates the best Bitcoin price throughout the data into different classes. In this context, SVM is utilized for the regression of predicting the position of Bitcoin prices relative to this hyperplane. Where Support Vector Machine (SVM) is selected for its originality in handling the complex relationships which present in the data.
- Deep Learning Models (LSTM And RNN)
  - **Long Short-Term Memory (LSTM)** and **Recurrent Neural Network (RNN)** are two deep learning models used in this research that are compared to traditional ML algorithms. These deep learning models have been chosen due to their ability to successfully handle the sequential input and capture the long-term dependencies.

    The basic reason to use these LSTM and RNN approaches is to investigate how well they perform in the situations at hand and to evaluate how they are compared against other traditional machine learning techniques. Now our objective is to identify the ideal configuration that maximizes the performance of the models by certain iterations for hyperparameters, including the learning rate, batch size, number of hidden units, and regularization methods. The procedure for the tunning process involves where systematically investigating the various combinations of hyperparameters and evaluating their impact on the performance, convergence rate, and generalization capability of the models.

Hyperparameter Tuning Results:

LSTM:

* Best Configuration: Units=100, Look Back = 200
* Test MAE: 24592.09

RNN:

* Best Configuration: Units=50, Look Back=200
* Test MAE: 24481.71

Here after performing the hyperparameter tunning, got the best configuration in the form of (unit and look back) values based on the results we obtained where the LSTM model with 100 units a look back of 200, and the RNN model with 50 units, and a look back of 200 is selected as the final model.

4.4 Evaluation and Results for Prediction Models

Overview of Model Performance

Evaluating the machine learning and deep learning models that are used to forecast Bitcoin future prices is the subject of this section. In this study, we have taken into consideration with wide variety of machine learning algorithms and predictive modeling approaches. These models include Linear Regression, Ridge Regression, K-nearest neighbours (KNN), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN). These models are well-suited for the various kinds of data and prediction tasks including prediction and classification because to have various characteristics and their strengths. Here we aim to learn more about the abilities and the limitations of these models through in-depth analysis and comparison. Measures we took such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R-squared are used in the analysis. Research and analysis use these metrics to evaluate the effectiveness and the efficacy of a model's algorithm. where results for these measures for all models and algorithms are represented in Table 4. MAE delivers an average error size by measuring how far off estimates are from actual results. MSE, on the other hand, calculates the average of squared errors, giving more weight to larger errors. By squaring the MSE, we get the more interpretable measure known as root mean squared error (RMSE). In conclusion, R squared is a statistical measure of the degree to which the independent variables contribute to the variance in the dependent variable. The sum of these measures is an in-depth evaluation of the models performance and efficiency as a prediction.

Table 4: Machine & Deep Learning Metrics

Model	MAE	MSE	RMSE	R-squared
Linear Regression	24631.87	6.07×10^8	24632.94	-1.68×10^{11}
Ridge	24631.48	6.07×10^8	24632.54	-1.68×10^{11}
K-Nearest Neighbors	24667.82	6.09×10^8	24668.07	-1.68×10^{11}
Support Vector Machine (SVM)	24598.33	6.05×10^8	24598.69	-1.67×10^{11}
Long Short-Term Memory (LSTM)	67.30	6287.82	79.30	0.88
Recurrent Neural Network (RNN)	118.91	18991.22	137.81	0.64

4.4.1 Performance of Machine Learning Models

- Linear Regression and Ridge Regression: Linear Regression and Ridge Regression, being linear models, demonstrated limited capacity to capture the intricate patterns in Bitcoin prices. These models resulted in comparable Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) values, hovering around 24630. The R-squared values, indicating the proportion of variance in the dependent variable explained by the model, were exceptionally low, around -1.68×10^{11}. This suggests a poor fit of these models to the cryptocurrency price data.

- K-Nearest Neighbors (KNN): The K-nearest neighbors (KNN) model, which is a non-linear model, produced outcomes that were comparable to those of linear models, with mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) values nearby of 24670. Although KNN incorporates nonlinearity, its effectiveness did not show a substantial improvement compared to linear models, suggesting difficulties in capturing the complex patterns that comprise the data.

- Support Vector Machine (SVM): The Support Vector Machine (SVM), known for its capability to effectively handle non-linear relationships, showed significantly more positive results. Reduced MAE, MSE, and RMSE values in comparison to other machine learning models indicate enhanced prediction skills. Nevertheless, the R-squared result revealed constraints in explaining the variation in Bitcoin prices.

4.4.2 Performance of Deep Learning Models

Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) are two prominent architectures in the field of deep learning. On the other hand, deep learning models, such as Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN), show outstanding results. These models provide favorable R-squared values, suggesting their efficacy in comprehensively capturing and clarifying the fluctuations in Bitcoin prices.

- Long-Short Term Memory (LSTM): The Long-Short Term Memory which is the deep learning model built to capture temporal dependencies in it demonstrated a higher performance compared to the traditional machine learning models. The model demonstrated an evident reduction in the metrics of MAE, MSE, and RMSE values, showing its efficacy while capturing complex patterns in Bitcoin price data. Where the R-squared value of 0.88 indicated a high level of predictive ability about the fluctuations in bitcoin prices.

- Recurrent Neural Network (RNN): The RNN, another deep learning model, demonstrated a strong prediction ability, although with somewhat elevated levels of errors are situated when it comes with the comparison to the LSTM. The R-squared value of 0.64 indicated a satisfactory match to the data, although not as strong as the LSTM model achieved.

4.5 Conclusion

In conclusion, the evaluation highlights the challenges overcome by traditional machine learning methods when it comes to predicting future Bitcoin prices. The potential strength of deep learning models includes Long Short-Term Memory (LSTM), which indicates their ability to comprehend and represent the complex dynamics inherent in bitcoin markets.

5 Discussion and Comparison of Results

5.1 Discussion:

When the results are compared with traditional models, the evaluation of the developed artifact, which consists of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs), discovers that there has been significant progress made in the prediction of bitcoin prices. When it comes to efficiently capturing the patterns that are displayed by bitcoin prices, the deep learning models, especially LSTM and the RNN, are outstanding against traditional machine learning models such as Linear Regression, Ridge, K-Nearest Neighbors, and Support Vector Machine where the results are demonstrated on the Table 4. The adequate adaptability and the strength of prediction for both LSTM and RNN are demonstrated by the high R-squared values for both machine learning classes. These results demonstrate that the research aims that were described in the introduction have been accomplished, emphasizing the effectiveness of deep learning models in predicting the prices of cryptocurrencies. Because they make use of the temporal dependencies and gated processes that are fundamental to the networks, the LSTM and RNN models demonstrate innovation in comparison to other alternatives that are now available. When it comes to modeling the volatile nature of Bitcoin pricing, the ability of the LSTM to capture extended dependencies is highly beneficial. A more accurate and timely forecasting tool is provided by the artifact that was developed, which can be of tremendous help to investors in terms of making well-informed judgments in the unpredictable Bitcoin market.

A review of the impact that gated processes have on the performance of predictions made by LSTM networks is presented here. Input, forget, and output gates are the components that make up the gates. These gates enable the model to selectively keep or reject understanding, which in turn enables it to adapt to evolving market conditions. This adaptive technique enhances the model's capacity to understand complex patterns, ultimately assisting investors in making more intelligent decisions. Specifically for time series forecasting, the project provides learning outcomes that include both advanced knowledge and practical skills in the development of deep learning models. An improvement in data analysis skills has been achieved as a result of the research, specifically in the areas of preprocessing, developing models, and hyperparameter tuning. LSTM and

RNN models succeeded in attaining an exceptional level of performance, which provides investors in the bitcoin industry with a considerable amount of information due to their strengths. However, there are certain limitations, such as the need for continuous model refinement and the vulnerability of deep learning models to the selection of hyperparameters.

5.2 Comparative of developed models vs Existing machine learning models

- **Comparison of Developed Models and Algorithms:** When comparing the results of machine learning and deep learning models, it is clear that deep learning models, specifically LSTM, performed better than traditional machine learning models in forecasting Bitcoin values. The inherent capacity of LSTM to capture sequential dependencies contributed to its outstanding performance. Deep learning models have demonstrated superior performance in acquiring complex patterns and correlations in time-series data, beyond the constraints of linearity observed in typical machine learning models. The R-squared values for LSTM and RNN demonstrated a stronger correlation with the cryptocurrency price data, highlighting the benefits of utilizing deep learning for predicting financial time series.

  Overall, the comparative analysis highlights the efficacy of deep learning models, particularly LSTM, in the field of cryptocurrency price forecasting. This demonstrates their capacity to produce more accurate and reliable results when compared to conventional machine learning methods, where we can see the accurate predictions between all machine learning & deep learning models in Figure 8.

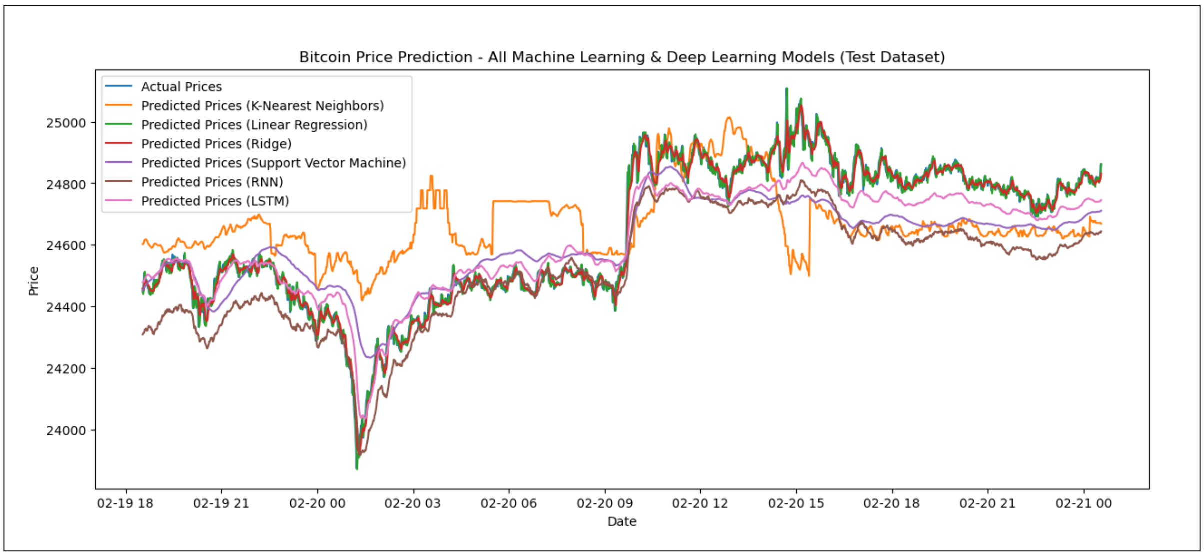

Figure 8: Comparison between - Machine Learning & Deep Learning Models Performance

- **Comparison of Developed Results vs. Existing Results:** We bench marked our developed models against existing research in the field of cryptocurrency prediction. The comparison includes various machine learning and deep learning models, as summarized in Table 2.

When comparing our results with existing studies, our deep learning models, particularly LSTM, achieved outstanding results compared to the existing models. The high performance of LSTM in forecasting Bitcoin values is represented in Table 4 which demonstrates the effectiveness of utilizing sequential models for Bitcoin future price prediction.

Our research concludes that utilizing deep learning models, specifically LSTM offers significant advantages in terms of accurate and reliable bitcoin price forecasts. The results provide useful insights into financial forecasting and demonstrate the potential of advanced neural network designs in understanding the complexity of cryptocurrency markets.

In its conclusion, the discussion chapter shows the enormous impact that deep learning models have on forecasting bitcoin prices. It also highlights the innovative qualities that these models have as well as the possible advantages that they could provide for investors. The acquired skills and expertise contribute to the development of the field of predictive analytics in the financial markets, which is constantly evolving.

6 Conclusion and Future Work

In conclusion, this study effectively addressed the research question and accomplished the predetermined research goals. The issue of forecasting bitcoin volatility was substantially resolved by using advanced deep learning models, especially Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs). The overall project's result demonstrates an important enhancement in forecasting when compared to traditional machine learning models. Throughout the project, we acquired significant learning outcomes that involved gaining an in-depth understanding of deep learning model architectures, developing models, and fine-tuning hyperparameters for time series forecasting. The potentially retained enclose the adept data preparation, model training, and result interpretation, which contribute to a strong basis in the field of predictive analytics.

The project results have a significant impact on the field of methods. The outstanding efficacy of LSTM and RNN models in forecasting Bitcoin future prices has the potential to change the decision-making procedures for investors in the continuously evolving and unpredictable cryptocurrency market. The models have an impressive ability to understand complex patterns and adjust to dynamic market conditions, making them highly mighty instruments for financial analysts (Institutions) and investors in search of reliable forecasting solutions.
In Conclusion, this research makes a significant contribution to the field of research by representing innovative approaches for forecasting Bitcoin future prices. It outlines the success of the deep learning models then the traditional models in handling the complex patterns of financial time series data. To enhance and explore future work, several opportunities for improvement and exploration have been identified through this study. To further improve the study's achievement, it can be expanded by integrating the various additional functionalities like technical indicators, sentiment analysis, or external variables that could impact the bitcoin pricing. Therefore, the exploration of the ensemble

methods and hybrid models could be advantageous in averaging/combining the predictions of various forecasting systems. continuously adjustment of hyperparameters and the integration of regular new approaches can enhance the optimizations of deep learning models. Furthermore, by increasing the amount of the dataset to include a broader range of market situations and performing the evaluations in real-time, the models can be strengthened to build up in terms of their reliability and effectiveness of the results. In summary, future efforts should be prioritized in the enhancement and extension of the proposed approach models to effectively adjust according to the dynamic features that make up the bitcoin market.

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References

Akyildirim, E., Goncu, A. and Sensoy, A. (2021). Prediction of cryptocurrency returns using machine learning, *Annals of Operations Research* **297**: 3–36.

Bouri, E., Vo, X. V. and Saeed, T. (2021). Return equicorrelation in the cryptocurrency market: Analysis and determinants, *Finance Research Letters* **38**: 101497.

Chen, B., Wei, F. and Gu, C. (2021). Bitcoin theft detection based on supervised machine learning algorithms, *Security and Communication Networks* **2021**: 1–10.

Chen, S., Zhang, Y. and Yang, Q. (2021). Multi-task learning in natural language processing: An overview, *arXiv preprint arXiv:2109.09138* .

Chen, W., Xu, H., Jia, L. and Gao, Y. (2021). Machine learning model for bitcoin exchange rate prediction using economic and technology determinants, *International Journal of Forecasting* **37**(1): 28–43.

Chong, E., Han, C. and Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies, *Expert Systems with Applications* **83**: 187–205.

Chowdhury, S., Rodriguez-Espindola, O., Dey, P. and Budhwar, P. (2023). Blockchain technology adoption for managing risks in operations and supply chain management: evidence from the uk, *Annals of operations research* **327**(1): 539–574.

Fang, F., Chung, W., Ventre, C., Basios, M., Kanthan, L., Li, L. and Wu, F. (2021). Ascertaining price formation in cryptocurrency markets with machine learning, *The European Journal of Finance* pp. 1–23.

Green, S., McKinney Jr, E., Heppard, K. and Garcia, L. (2018). Big data, digital demand and decision-making, *International Journal of Accounting & Information Management* **26**(4): 541–555.

Gupta, R. and Nalavade, J. E. (2023). Metaheuristic assisted hybrid classifier for bitcoin price prediction, *Cybernetics and Systems* **54**(7): 1037–1061.

Huang, Z., Xu, W. and Yu, K. (2015). Bidirectional lstm-crf models for sequence tagging, *arXiv preprint arXiv:1508.01991* .

Jang, H. and Lee, J. (2017). An empirical study on modeling and prediction of bitcoin prices with bayesian neural networks based on blockchain information, *Ieee Access* **6**: 5427–5437.

Le Glaz, A., Haralambous, Y., Kim-Dufor, D.-H., Lenca, P., Billot, R., Ryan, T. C., Marsh, J., Devylder, J., Walter, M., Berrouiguet, S. et al. (2021). Machine learning and natural language processing in mental health: systematic review, *Journal of Medical Internet Research* **23**(5): e15708.

Li, J., Zhang, Y., Yang, X. and Chen, L. (2023). Online portfolio management via deep reinforcement learning with high-frequency data, *Information Processing & Management* **60**(3): 103247.

Mallet, M. D., Alexander, S. P., Protat, A. and Fiddes, S. L. (2023). Reducing southern ocean shortwave radiation errors in the era5 reanalysis with machine learning and 25 years of surface observations, *Artificial Intelligence for the Earth Systems* **2**(2): e220044.

Mikolov, T., Joulin, A., Chopra, S., Mathieu, M. and Ranzato, M. (2014). Learning longer memory in recurrent neural networks, *arXiv preprint arXiv:1412.7753* .

Neshat, M., Nezhad, M. M., Abbasnejad, E., Tjernberg, L. B., Garcia, D. A., Alexander, B. and Wagner, M. (2020). An evolutionary deep learning method for short-term wind speed prediction: A case study of the lillgrund offshore wind farm, *arXiv preprint arXiv:2002.09106* .

Nikolopoulos, D. S., Vandierendonck, H., Bellas, N., Antonopoulos, C. D., Lalis, S., Karakonstantis, G., Burg, A. and Naumann, U. (2014). Energy efficiency through significance-based computing, *Computer* **47**(7): 82–85.

Rodríguez-Ibánez, M., Casánez-Ventura, A., Castejón-Mateos, F. and Cuenca-Jiménez, P.-M. (2023). A review on sentiment analysis from social media platforms, *Expert Systems with Applications* p. 119862.

Sahu, S. K., Mokhade, A. and Bokde, N. D. (2023). An overview of machine learning, deep learning, and reinforcement learning-based techniques in quantitative finance: Recent progress and challenges, *Applied Sciences* **13**(3): 1956.

Siami-Namini, S. and Namin, A. S. (2018). Forecasting economics and financial time series: Arima vs. lstm, *arXiv preprint arXiv:1803.06386* .

Sin, E. and Wang, L. (2017). Bitcoin price prediction using ensembles of neural networks, *2017 13th International conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD)*, IEEE, pp. 666–671.

Singh, V., Chen, S.-S., Singhania, M., Nanavati, B., Gupta, A. et al. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries–a review and research agenda, *International Journal of Information Management Data Insights* **2**(2): 100094.

Xia, P., Wang, H., Zhang, B., Ji, R., Gao, B., Wu, L., Luo, X. and Xu, G. (2020). Characterizing cryptocurrency exchange scams, *Computers & Security* **98**: 101993.

Zhang, Z., Dai, H.-N., Zhou, J., Mondal, S. K., García, M. M. and Wang, H. (2021). Forecasting cryptocurrency price using convolutional neural networks with weighted and attentive memory channels, *Expert Systems with Applications* **183**: 115378.

Zhao, Z., Hao, Z., Wang, G., Mao, D., Zhang, B., Zuo, M., Yen, J. and Tu, G. (2021). Sentiment analysis of review data using blockchain and lstm to improve regulation for a sustainable market, *Journal of Theoretical and Applied Electronic Commerce Research* **17**(1): 1–19.

Zulfiqar, N. and Gulzar, S. (2021). Implied volatility estimation of bitcoin options and the stylized facts of option pricing, *Financial Innovation* **7**: 1–30.