Indonesian Journal of Computer Science
ISSN 2549-7286 (*online*)
Jln. Khatib Sulaiman Dalam No. 1, Padang, Indonesia
Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

A Review of Bitcoin Price Prediction Based on Deep Learning Algorithms

Hanaa Tayib, Adnan M. Abdulazeez
Duhok University

Article Information

Submitted : 25 Mar 2024
Reviewed: 30 Mar 2024
Accepted : 20 Apr 2024

Keywords

Bitcoin, Deep Learning, CNN, LSTM, GRU

Abstract

This study provides a comprehensive analysis of the existing body of work on predicting the price of Bitcoin using deep learning techniques. It discusses the fundamental concepts behind deep learning and Bitcoin, including recurrent neural networks, convolutional neural networks, and long short-term memory networks. The study also examines the data sources used in training these models, including historical Blockchain transaction data, social media sentiments, and Bitcoin prices. The report also highlights the importance of metrics like mean absolute error, mean squared error, and root mean squared error for evaluating the effectiveness of various models. It also discusses future research topics, such as incorporating external factors into prediction models. The article offers valuable insights for academics, practitioners, and policymakers interested in cryptocurrency prediction.

A. Introduction

The markets for cryptocurrencies are characterized by a high degree of volatility, which is caused by several factors that go beyond the price moves that have occurred in the past [1]. Attempts to fathom this complexity using conventional methods are not without their challenges. A solution that is both compelling and effective is provided by neural networks. Because they can handle non-linear connections and derive insights from huge datasets, such as social sentiment and news, they are exceptionally well-suited for analyzing complicated dynamics. Furthermore, neural networks, particularly recurrent ones, have an outstanding capability of identifying patterns in time series data such as historical prices, which may potentially result in more accurate price projections [2]. This is because neural networks can recognize patterns so well. As the dynamic coin company continues to evolve, their adaptability helps them to continually gain new expertise and improve their talents [3].

The power of neural networks to navigate the complex nature of the market has contributed to the rise in importance and relevance of neural networks in the process of predicting the prices of cryptocurrencies. In addition to historical price data, neural networks can analyze a broad variety of criteria, such as the attitude expressed on social media platforms, the volume of trades, and the number of articles published in the news [4]. The fact that they are not typical procedures distinguishes them. Because of this, they can capture the intricate and subtle mechanisms that are responsible for the price of cryptocurrencies, including non-linear correlations in the market. Furthermore, specific neural network architectures like as long short-term memory (LSTM) networks have an outstanding competence in spotting patterns in time series data, which may result in more accurate price projections [5]. Given that neural networks have the power to continually learn information and improve performance via the incorporation of new data, the ability to adapt is vital in the ecosystem of the coin, which is always developing. The use of neural networks is a powerful tool for investors and researchers who wish to study and maybe forecast the future of Bitcoin values. Although it is difficult to achieve perfect prediction, neural networks are a formidable instrument for this purpose [6].

The field of neural networks and their use in predicting the value of coins are the subjects of investigation in this theoretical paper. The framework may begin with an introduction section that will explain the inherent volatility and complicated features of the crypto currency market, with a particular emphasis on the limitations of traditional methods. The next step of the research will include an investigation of the objectives, with a specific focus on the benefits of neural networks [7]. The capacity of neural networks to efficiently interpret non-linear connections and enormous datasets, such as those observed in social media and news, which influences the prices of crypto currencies, would be elucidated as a result of this. It is reasonably anticipated that the article would study certain structures, such as Long Short-Term Memory (LSTM), to evaluate historical price sequences, which has the potential to improve projections. In the end, the framework may be able to address the limitations of neural networks, such as over fitting, while simultaneously emphasizing the overall relevance and pertinence of neural networks in this dynamic market [8].

This article provides an analysis of the fundamental reasons and the inherent worth of cryptocurrencies. The process of doing a fundamental analysis entails conducting an exhaustive investigation of all the pertinent information that is associated with a coin. To do this, it makes use of both quantitative and qualitative metrics of financial outcomes. The determination of the value that is intrinsic to a coin is the ultimate goal of basic analysis [9].

The complicated structure of the human brain serves as a source of inspiration for neural networks, which are a kind of artificial intelligence. The processing of information is carried out hierarchically via neural networks, which are made up of interconnected nodes, which are also referred to as artificial neurons in some instances. It is via the process of training with huge datasets that these networks can gain knowledge of subtle patterns and relationships [10]. Back propagation, which alters the weights of connections between nodes to reduce the number of errors, and activation functions, which integrate non-linearity to solve more complicated challenges, are two examples of common approaches that are used in this context [11].

Neural networks are increasingly used in various industries due to their ability to understand complex patterns from large datasets. They are revolutionizing finance by identifying fraudulent activity through transaction patterns. They are also gaining interest in algorithmic trading and financial forecasting by predicting market trends. Neural networks also play a significant role in cryptography, evaluating and weakening existing encryption methods, and developing innovative, more resistant methods. They are also used in secure communication protocols and blockchain data analysis to identify system vulnerabilities. The study of neural networks is expected to continue, increasing its significance across various industries [12, 13].

The aim of this article review studies using deep learning algorithms to estimate Bitcoin price, analyzing techniques, methodologies, and performance metrics. It discusses challenges, opportunities, and potential areas for further study in cryptocurrency forecasting.

The rest of this paper is structured as follows: section 2 gives a comprehensive overview of the background and theory including Deep Learning, (RNNs), (LSTM),(GRU),(CNN), AlexNet, and GoogLeNet. Section 3 provides an overview of related works (literature review) conducted about the previous studies using a set of algorithms related to Bitcoin. The findings from the literature are thoroughly discussed in Section 4. Finally, Section 5 concludes this paper Summarize the main ideas derived from the models used to estimate Bitcoin prices.

B. Deep Learning (DL)

Artificial neural networks that are fashioned after the structure and function of the human brain are used in deep learning, which is an advanced branch of machine learning that focuses on interpreting and digesting massive quantities of data [14]. Deep learning is comprised of artificial neural networks. The several layers of interconnected neurons that are characteristic of deep learning architectures are what set them apart [15].

To forecast the price of Bitcoin, deep learning, which is a subcategory of machine learning, is a very efficient approach. It does very well when it comes to automatically recognizing intricate patterns and connections by analyzing vast volumes of historical data automatically. The analysis of historical Bitcoin price data and the forecasting of future price patterns may be accomplished via the use of deep learning techniques. These techniques include recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs) [16]. When it comes to predicting the price of Bitcoin, deep learning has a big advantage in that it can effectively capture the complex temporal dependencies and nonlinear correlations that are present in the data. Specifically designed to handle sequential data, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are well suited for modeling time-series data, such as Bitcoin values. These networks were developed with the express purpose of processing sequential data [17]. These networks can learn information from the sequential properties of the data, which enables them to recognize and comprehend patterns such as seasonality, trends, and other patterns that have the potential to influence price variations [18].

Furthermore, Convolutional Neural Networks (CNNs) have the potential to be used in the evaluation of Bitcoin price data in both the temporal and feature domains. CNNS can use convolutional filters to examine price data and identify relevant qualities and patterns that are associated with pricing fluctuations in the future. The use of this tactic in conjunction with other types of data, such as sentiment analysis or technical indicators, has the potential to provide exceptionally fruitful outcomes [19].

Moreover, deep learning models hold the potential to dynamically adapt and update their projections in real time as fresh data becomes available [20]. The flexibility of deep learning models allows them to constantly improve their accuracy and reliability over time. As a result, these models are extremely ideal for markets that are dynamic and unpredictable, such as Bitcoin. Nevertheless, it is of the utmost importance to note that deep learning models that are used to predict the price of Bitcoin may face challenges such as overfitting, restricted data availability, and the inherent volatility of financial markets [21, 22]. Consequently, to ensure the reliability and robustness of deep learning-based models for forecasting Bitcoin values, it is essential to validate and evaluate models rigorously [23].

A framework that is both strong and adaptive is provided by deep learning to forecast Bitcoin values. It does this by using complex neural network topologies and doing significant data processing to offer insightful predictions and useful information. Investing methods and judgments on risk management in the cryptocurrency market may be influenced by these forecasts, which can be used to guide investment plans [24].

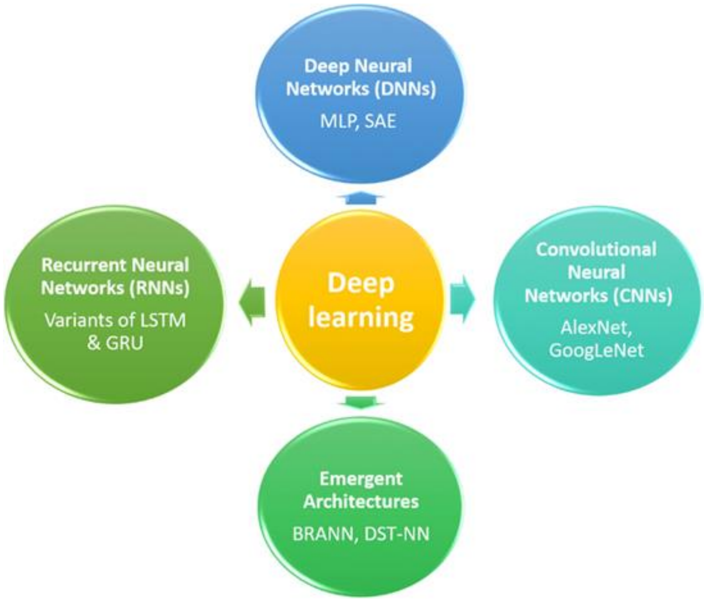

Figure 1: Deep Learning Algorithms

2.1 Recurrent Neural Networks (RNNs)

The Recurrent Neural Network (RNN) algorithm plays in the analysis and prediction of Bitcoin prices. RNNs, which stand for recurrent neural networks, are particularly well-suited for the analysis of time-series data, such as variations in the price of Bitcoin. This is because RNNs are particularly adept at capturing the links that exist between data points over time and recognizing patterns that occur in a certain sequence [25]. When it comes to predicting the price of Bitcoin, Recurrent Neural Networks (RNNs) can learn from historical price data to make predictions about future price variations. The research will look at several different reinforcement neural network (RNN) designs and methods that are used in Bitcoin price prediction competitions [26]. These include Gated Recurrent Unit (GRU) networks and long Short-Term Memory (LSTM) networks. The issue of vanishing gradients is resolved by these topologies, which also make it possible for RNNs to effectively learn from extensive sequences of data sources. In addition, the research will investigate the challenges that arise when attempting to forecast the price of Bitcoin using RNNs [27]. These challenges include the management of noisy data, the handling of non-stationarity, and the reduction of overfitting. The purpose of this research is to investigate the benefits and drawbacks of using RNN-based algorithms throughout the process of forecasting Bitcoin prices. The purpose of this study is to investigate the effectiveness of deep learning methods in the field of financial forecasting, with a special focus on the cryptocurrency markets [28].

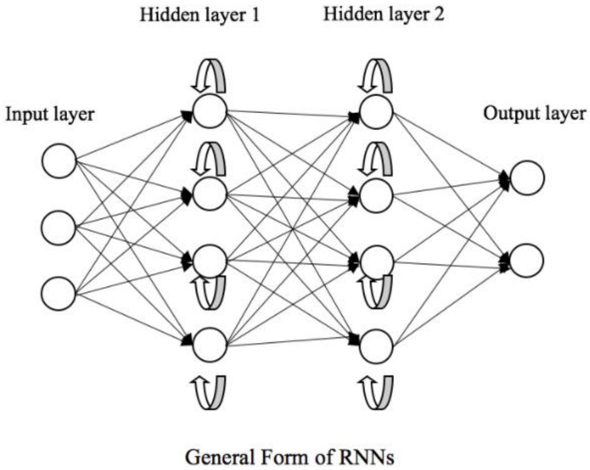

Figure 2: Recurrent Neural Networks

2.2 LSTM (Long Short-Term Memory)

When it comes to assessing and forecasting Bitcoin values, the LSTM algorithm is a very important component [29]. Long Short-Term Memory, often known as LSTM, is a special kind of Recurrent Neural Network (RNN) that was built expressly to address the problem of vanishing gradient. This problem frequently prevents regular RNNs from effectively capturing long-term associations in sequential data [30]. LSTM was developed to address this issue. As a result of the ephemeral quality of Bitcoin price data, LSTM networks are an excellent choice for modeling and forecasting price movements over some time. An examination of LSTM networks is the primary emphasis of this paper, which is conducted in the context of Bitcoin price prediction tasks. The investigation focuses on their organizational structure, training methodology, and assessment standards [31]. Because LSTM networks are so adept at gaining and preserving long-term connections in sequential data, they are particularly well-suited for deciphering the complicated patterns of Bitcoin price fluctuations. This is because LSTM networks can effectively acquire and maintain long-term connections. The research may also involve an investigation into the possibility of improving the accuracy of LSTM-based models for forecasting Bitcoin values. Approaches like feature engineering, hyperparameter tweaking, and ensemble techniques are examples of methodologies that might fall under this category [32]. The purpose of this study is to provide insights into the applicability and limitations of deep learning technologies in the analysis of cryptocurrency markets. This will be accomplished by conducting a thorough examination of the performance of LSTM networks in projecting Bitcoin prices [33].

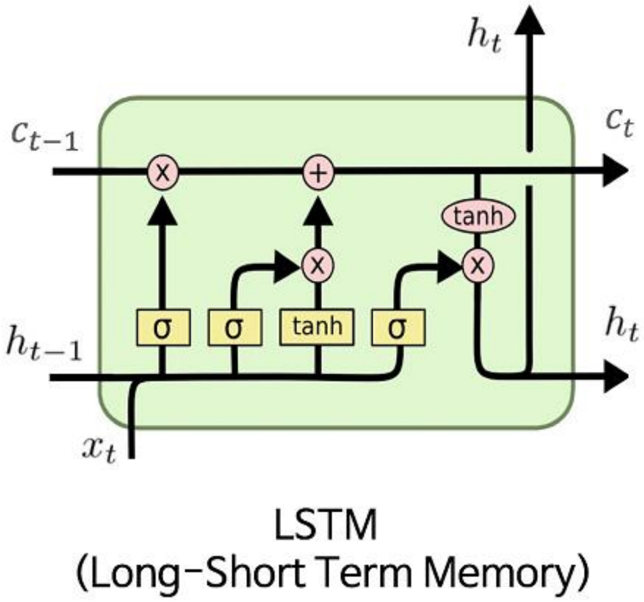

Figure 3: Long-Short Term Memory

2.3 Gated Recurrent Unit (GRU)

A significant amount of weight is given to the Gated Recurrent Unit (GRU) algorithm when it comes to the evaluation and analysis of models that are used to forecast Bitcoin values [34]. The Gated Recurrent Unit, often known as the GRU, is a particular kind of recurrent neural network (RNN) that was developed to address the problem of disappearing gradients and to facilitate effective learning from extensive sequences of data. GRU networks are very ideal for gathering and assessing the complicated patterns and linkages that are inherent in price fluctuations over time [35]. The ephemeral nature of Bitcoin price data, GRU networks are particularly suitable for this purpose. In this study, we will investigate the usage of GRU networks in tasks that are associated with forecasting Bitcoin values. We will also analyze the structure of these networks, as well as their training techniques and performance characteristics. GRU networks, which are distinguished by their streamlined architecture in comparison to Long Short-Term Memory (LSTM) networks, can effectively train and model abilities for time-series data, such as Bitcoin prices [36]. In addition to this, the essay will investigate the advantages and disadvantages of using GRU-based models in the process of forecasting Bitcoin values. Additionally, it may take into consideration the efficacy of these algorithms in contrast to other deep learning algorithms, such as LSTM, or traditional statistical methods. By evaluating the efficiency of GRU networks in predicting Bitcoin prices, the purpose of this study is to improve the understanding of deep learning techniques in the context of financial forecasting, especially in the context of cryptocurrency markets [37].

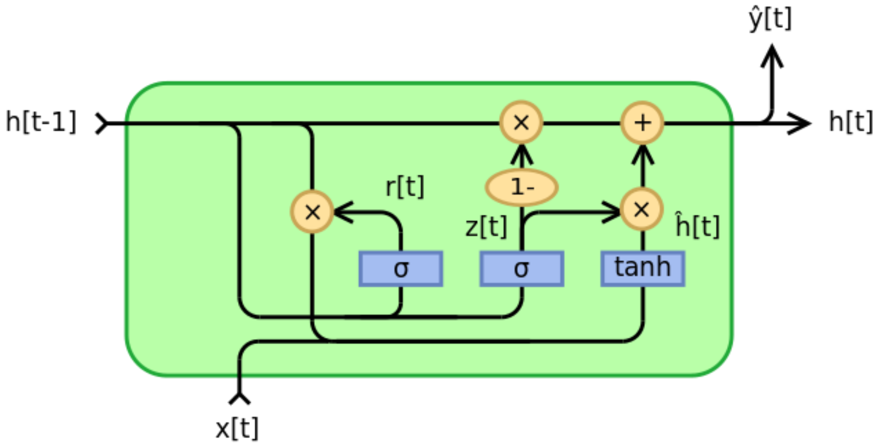

Figure 4: Gated Recurrent Unit (GRU)

2.4 Convolution Neural Networks (CNNs)

The Convolutional Neural Network (CNN) approach is a powerful instrument that can be used in the area of deep learning-based Bit-coin price prediction to evaluate and forecast the values of this cryptocurrency. The analysis of time-series data, such as the fluctuations in the price of bitcoin, is another potential use for convolutional neural networks (CNNs), which are often utilized for computer vision applications. When it comes to identifying relevant features from input data, convolutional neural networks (CNNs) perform very well, which enables them to make accurate predictions about future price movements [38].

Convolutional Neural Networks (CNNs) may be trained to anticipate the price of Bitcoin by utilizing historical price data, in addition to other relevant information such as trading volumes, market sentiment indicators, and technical analysis metrics. This allows CNNs to make more accurate predictions. By acquiring the capacity to discern patterns and relationships within the data, the CNN model can accurately capture the complicated dynamics of the fluctuations in the price of bitcoin over time [39].

When it comes to predicting the price of Bitcoin, the capacity of Convolutional Neural Networks (CNNs) to recognize and analyze spatial and temporal patterns within the data is a significant advantage since it allows for more accurate forecasting. By applying convolutional filters to the time series of Bitcoin prices across a wide range of periods, CNNs can effectively identify major traits and patterns in the history of Bitcoin prices. In addition, Convolutional Neural Networks (CNNs) have the potential to independently acquire hierarchical representations of the data, enabling them to capture both instant fluctuations and long-lasting trends in the price of Bitcoin [40]. Nevertheless, it is of the utmost importance to admit that Convolutional Neural Networks (CNNs) may have limitations when they are used to assess financial time-series data, such as Bitcoin prices. During the process of training models and attaining accurate predictions, the inherent noise and volatility in the data may provide challenges that need to be overcome. Additionally, Convolutional Neural Networks (CNNs) may have difficulty capturing the complex nonlinear connections that exist in the oscillations of Bit-coin values, particularly during periods of extreme volatility or market uncertainty. This is especially true when the market is unclear [41].

In conclusion, Convolutional Neural Networks (CNNs) have the potential to be an effective instrument for forecasting the price of Bitcoin by using deep learning methods. Using them, major insights and patterns in the data might be revealed with their assistance. On the other hand, the effectiveness of these strategies could be different depending on factors such as the quality of the data, the choice of model architecture, and the characteristics that are unique to the Bitcoin market. Therefore, when incorporating Convolutional Neural Networks (CNNs) into Bitcoin price forecasting models, it is essential to conduct exhaustive testing and validation [42].

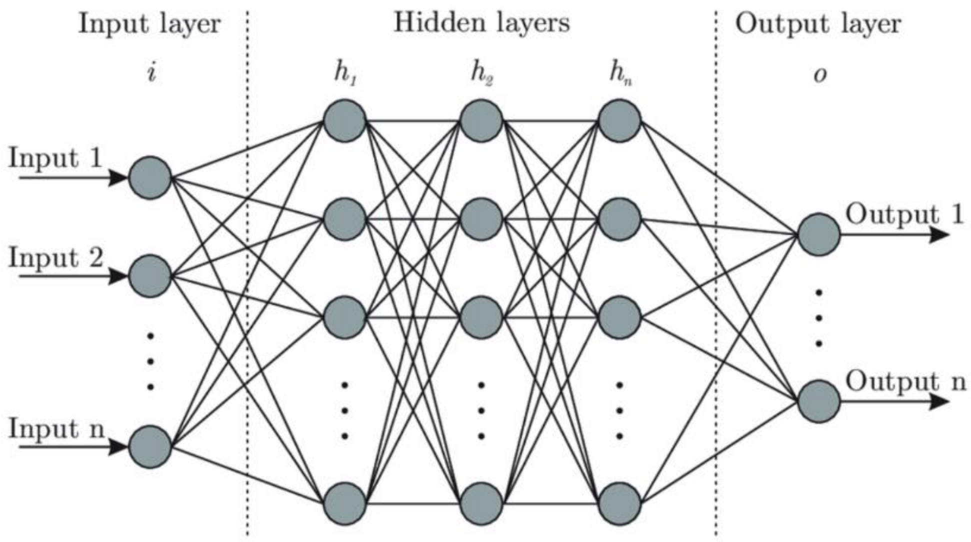

Figure 1

Figure 5: Convolution Neural Networks

2.5 AlexNet

AlexNet, a convolutional neural network (CNN) architecture, has significantly influenced deep learning, particularly in computer vision. Originally designed for image classification, AlexNet can be adapted to handle various data types, including time-series data, for Bitcoin price prediction [43]. The network's architecture, consisting of convolutional and pooling layers and fully connected layers, allows it to independently acquire hierarchical representations of input data [44].

To use AlexNet for Bitcoin price prediction, historical price data must be preprocessed and entered into the network. The network can then derive major features like trends, volatility patterns, or seasonal changes, which can be used as input for independent models like recurrent neural networks or fully connected neural networks [45].

Despite not being specifically designed for time-series data analysis, AlexNet's ability to acquire hierarchical representations and recognize detailed patterns may be useful in identifying relevant traits from Bitcoin price data. Transfer learning techniques can be used to fine-tune pretrained AlexNet models for better accuracy in forecasting prices [46].However, the use of AlexNet for Bitcoin price prediction may present challenges in model modification, data preprocessing, and feature extraction. Further research and simulations are needed to determine the feasibility and effectiveness of AlexNet's application in this context [47].

2.6 GoogLeNet

Also known as Inception-v1 is a convolutional neural network architecture developed by Google for photo classification jobs [48]. Its design aims to achieve high accuracy in photo classification jobs while maintaining low processing requirements. However, it can be modified for analyzing various types of data, such as time-series data, to make predictions about Bitcoin price [49]. GoogleNet extracts patterns and features from historical price data using a large number of convolutional layers and a module called "Inception" that uses simultaneous convolutional techniques [50].

To use GoogleNet for Bitcoin price prediction, historical price data must be preprocessed and input into the network. The network then recognizes key features like trends, volatility patterns, or seasonal swings, which can be used as input for a different model, such as a recurrent neural network or fully connected neural network [51].

GoogleNet's advantage is its ability to recognize complex patterns and correlations within the data while preserving computer system efficiency. However, it may face challenges in model adaptation, data preparation, and feature extraction. A comprehensive evaluation and comparison of GoogleNet-based models for Bitcoin price forecasting with other deep learning architectures is crucial [52].

2.7 Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) are a type of artificial neural network that is widely used for predicting Bitcoin's price using deep learning. These networks can identify intricate patterns in historical price data, allowing them to uncover seasonality and other factors that impact Bitcoin values. By analyzing large amounts of historical data, DNNs can acquire complex features at each level, helping them understand complex market dynamics [53].

One common method for training DNNs is to evaluate historical data, with the objective variable being the projected price movements. By constantly adjusting the network's parameters, DNNs can learn to correlate input attributes with the target variable, enabling them to accurately predict future price variations. However, DNNs face limitations such as high data demand, processing resources, and hyperparameter tuning. Additionally, they may struggle with interpretability, which can hinder their ability to understand the fundamental factors driving their predictions. Despite these challenges, DNNs offer valuable insights and forecasts that can influence investment strategies and risk management decisions in the constantly shifting and unpredictable cryptocurrency market [54, 55].

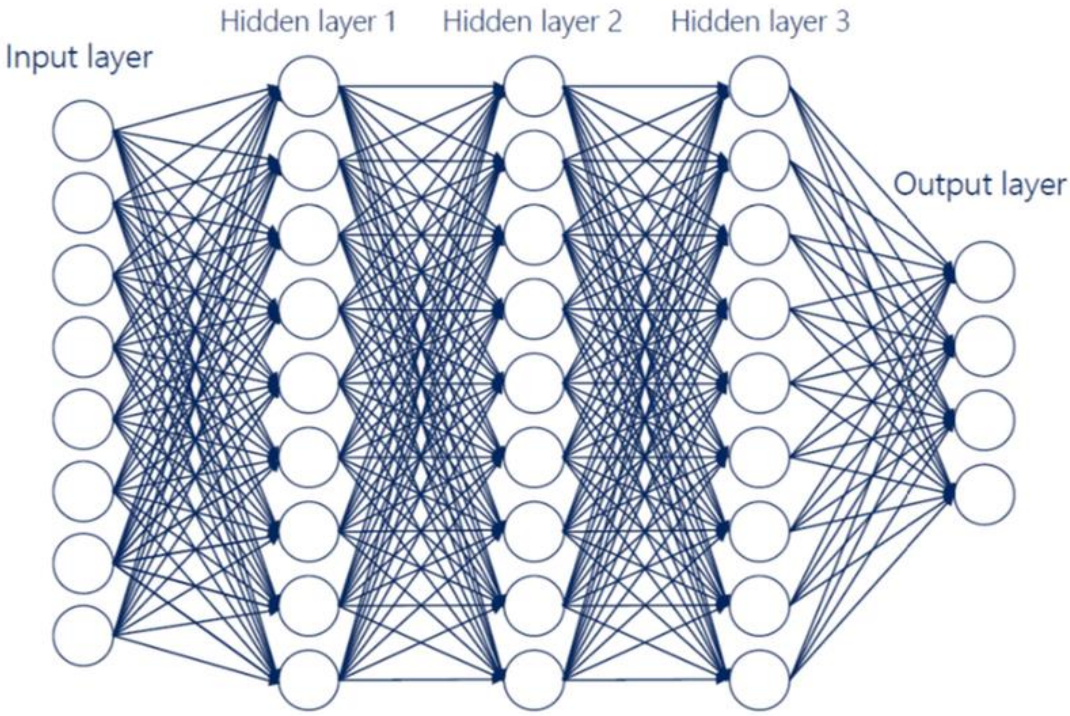

Figure 6: Deep Neural Networks

C. Literature Review

In [56], with the use of different machine learning algorithms, the purpose of this study was to identify the model that was both the most effective and accurate in predicting Bitcoin values. During the period beginning January 1, 2012, and ending January 8, 2018, a number of alternative regression models were tested using the scikit-learn and Keras libraries. These models were applied to trade data that had been collected at intervals of one minute on the Bitcoin exchange website known as bitstamp.

In [57], the aim of this research was to assess the degree of accuracy in forecasting the movement of Bitcoin price in USD. The price data was sourced from the Bitcoin pricing Index. The task was completed with varying degrees of achievement by using a Bayesian optimized recurrent neural network (RNN) and a Long Short Term Memory (LSTM) network. The LSTM model achieved a classification accuracy of 52% and a root mean square error (RMSE) of 8%. The ARIMA model, a commonly used method for time series forecasting, was constructed specifically for the aim of comparing it with deep learning models.

In [58], this study conducted a comparative investigation of many parameters that impacted the prediction of Bitcoin values. The study relied on the Root Mean Square Error (RMSE) measure and employed several deep learning models, such as Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU). The correlation between the price of gold and the price of Bitcoin was analyzed.

In [59], the study employed a multiple input LSTM-based prediction model and the Black-Scholes model to analyze Bitcoin option pricing. It predicted price volatility for the next 30 days based on on-chain and off-chain transactions, using Blockchain statistical data and social network trends. The model evaluated Blockchain wallet activity, active nodes, and platforms like Google, Reddit, and Twitter. Performance was compared with a baseline model without Blockchain statistical inputs.

In [60], the research used experimentation methods to analyze data from May 1, 2013, to June 7, 2019, utilizing data from www.coingecko.com. Preprocessing involved eliminating characteristics, conducting a stationary test, and applying data differentiation. The model candidate was determined using correlationogram methodology, and the Autoregressive Integrated Moving Average (ARIMA) method was used for accurate short-term forecasts.

In [61], the objective of this work was to assess and compare three separate machine learning models in terms of their capacity to forecast time series. For our time series analysis, we used the Bitcoin price information to construct forecasts and make our judgments. Based on the results, it could be inferred that the ARIMA model yielded better results than the regression models based on deep learning.

In [62], both Litecoin and Monero were the primary objectives of that study, which focused on a hybrid approach to cryptocurrency prediction. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures served as the conceptual foundations upon which the system was built. The results showed that the approach that was advised was capable of precisely anticipating prices with a high level of accuracy, which suggested that it could forecast the values of various cryptocurrencies to a substantial degree.

In [63], the study examined how global currencies such as the US Dollar and foreign exchange rates affected Bitcoin values, and investigated if Bitcoin had the potential to replace global currencies and become the primary means of exchange. The work sufficiently assisted in predicting price, achieving a 94.89% accuracy in predicting Bitcoin prices using a machine learning-based neural network. This led to a reduction of over 13.7% in price prediction in April 2020 during evaluation, considering all technical trade indications.

In [64], this research offered a prediction model based on deep learning to forecast and classify the price and movement direction of bitcoin. Due to the extreme volatility of cryptocurrency prices, it was difficult to perform these two tasks. The cryptocurrency trading market did not demonstrate ideal market characteristics, indicating that price movements were not fully random. This study showed that both the price value estimate and the classification of the direction of price movement were trustworthy. A prediction model using recurrent neural networks was constructed to perform regression and categorization of prices. The recommended approach achieved an unprecedented degree of performance in movement classification. This was achieved by using external dependable components and choosing dynamic features that were flexible.

In [65], this study introduced a hybrid model including deep learning techniques, namely Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM). The model was created to predict the prices of Litecoin and Zcash by considering the interrelationship with the main currency. The proposed model was extensively trained and evaluated using standard datasets, demonstrating its suitability for real-time applications. The findings showed that the recommended model outperformed other models in properly forecasting prices.

In [66], for the purpose of analyzing the market for digital currencies and forecasting the daily price of Bitcoin, this research made use of a model that contained both machine learning and deep learning. A daily examination of the data for 1,691 different cryptocurrencies was conducted, beginning in November 2017 and continuing through April of the following year. Using complex artificial intelligence algorithms in straightforward trading operations had successfully satisfied the conditions that were established, according to the research.

In [67], used ARIMA, FBProphet, and XG Boosting for time series analysis as machine learning approaches. assessed these models based on Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R2. After completing trials on three methodologies, time series analysis determined that ARIMA is the most effective model for predicting Bitcoin price in the crypto-market, with an RMSE score of 322.4 and an MAE score of 227.3. Moreover, this information might benefit investors in the cryptocurrency industry.

In [68], this study presented a prediction system using a genetic algorithm (GA) and XGBoost approach, with an enhanced feature engineering process. The process included expanding the feature set, preparing data, and selecting the optimum feature set using the hybrid GA-XGBoost algorithm. The study demonstrated the relevance of this feature engineering method in anticipating stock price direction through empirical validation, comparing generated feature sets with the initial dataset and improving prediction performance to outperform benchmark models.

In [69], within the confines of this essay, studied the uses of machine learning, as well as its weaknesses and ways to strengthen it, from the perspective of information technology security. We had a discussion about the possible areas of study that could be conducted in the future, and as a consequence, we created a roadmap for the hardware security community in general.

In [70], this research investigated Bitcoin manipulations using machine learning and statistical forecasting techniques. It assessed the impact of social media attitudes on manipulations and their correlation with price changes. The study investigated claims that prediction techniques used before the Covid-19 crisis were more effective. The Covid-19 epidemic was considered a global catastrophe, and relevant research was scrutinized.

In [71], users could have used this research to examine projected price trends of existing cryptocurrency coins, allowing them to make well-informed decisions and investments based on the cryptocurrency's value. We created a system that used two Machine Learning algorithm models, ARIMA and LSTM, to examine the daily price fluctuations of five cryptocurrencies: Bitcoin, XRP, Ethereum, Dogecoin, and SHIBA INU. Once connected, blockchain technology secured the database. When the user selected the currency and forecast date, the system provided data and a graph using Smart Contract code and Time Series Forecasting. This allowed the user to engage in the present financial cryptocurrency market. The technology enhanced bitcoin assessment by using machine learning methods to train and update its dataset.

In[72], this paper presented a self-attention-based multiple long short-term memory (SAM-LSTM) system for the prediction model. This system consisted of many LSTM modules for on-chain variable groups and the attention mechanism. Experiments were carried out utilizing actual Bitcoin price data and different approach configurations to showcase the effectiveness of the proposed framework in forecasting Bitcoin prices.

In [73], this study aimed to provide a Long Short-Term Memory (LSTM) algorithm designed to anticipate the values of four distinct cryptocurrencies. The cryptocurrencies mentioned included AMP, Ethereum, Electro-Optical System, and XRP. The LSTM model was evaluated using mean square error (MSE), root mean square error (RMSE), and normalized root mean square error (NRMSE) experiments. The gathered findings showed that the LSTM algorithm outperformed in predicting various coins. Therefore, it could be deemed the most efficient algorithm.

In [74], this research aimed to develop a predictive framework for cryptocurrency prices using two advanced deep learning architectures: BiLSTM and GRU. The current study utilized three public real-time bitcoin datasets obtained from "Yahoo Finance." Deep learning methods using Bidirectional Long Short-Term Memory and Gated Recurrent Unit were used to forecast the prices of three major cryptocurrencies: Bitcoin, Ethereum, and Cardano. The Grid Search approach optimized hyperparameters during operations.

In [75], automated identification of ancient Roman coins was established based on their features. The approach incorporated a CNN-based category classifier together with a hierarchical knowledge structure of coins. We focused on Roman Republic photo datasets for currency identification using the CNN AlexNet architecture. Recognition was the act of identifying comparable pictures by analyzing their intrinsic characteristics. Identifying and characterizing sites of interest was achieved by the use of local elements, such as their appearance.

In [76], this study presented the cryptocurrency exchange rate using the machine learning XGBoost algorithm and blockchain architecture to enhance the safety and transparency of the system. This system utilized data mining techniques for precise data analysis. XGBoost was the machine learning algorithm that was used for achieving the highest prediction accuracy performance. Various filters and coefficient weights were used in developing the prediction program. Cross-validation was used throughout the training phase to improve the system's overall performance.

In [77], the paper introduced DL-Gues, a robust and adaptable framework for forecasting cryptocurrency values. DL-Gues considered the interconnectedness between cryptocurrencies and market sentiments. We performed a price forecasting research for Dash using historical price data and tweets pertaining to Dash, Litecoin, and Bitcoin. We assessed the efficacy of many loss functions for the purpose of validation. Furthermore, we evaluated the efficacy of DL-GuesS on alternative cryptocurrencies by examining the price projection of Bitcoin-Cash based on its historical price data and tweets from Bitcoin-Cash, Litecoin, and Bitcoin.

In [78], this document detailed a system that identified several interconnected cryptocurrencies as data sources, aiming to enhance accuracy. To illustrate this concept, we analyzed the price projection of Dash cryptocurrency using past values of Dash, Litecoin, and Bitcoin. These cryptocurrencies exhibited hierarchical dependency at the protocol level. The proposed methodology effectively predicted prices with minimal error and high precision. The model could be utilized to evaluate various forecasts of digital currency expenses.

In[79], the study presented an ensemble learning approach for detecting fraudulent bitcoin transactions by combining convolutional neural networks (CNN) with long short-term memory (LSTM). This strategy was founded on the notion that these two methods were mutually beneficial. Accuracy and losses of off-the-shelf convolutional neural networks (CNN) and long short-term memory (LSTM), as well as ensemble CNN and ensemble LSTM employing bagged and boosted techniques, were compared while analyzing training and test datasets. The 10-fold cross-validation approach was used to evaluate the efficiency of the given methodology.

In [80], this research aimed to find the most effective model for forecasting Bitcoin and Ethereum values using Deephaven data curation. Data from both cryptocurrencies was retrieved, and correlated characteristics were identified. Models like Artificial Neural Networks, Long-Short Term Memories, and Gated Recurrent Units were trained using a trial-and-error approach. The models were then assessed using statistical measures like MAE, RMSE, and MAPE for both training and testing datasets. The study aimed to improve cryptocurrency forecasting.

In [81], this paper introduced a specialized deep-learning system created to classify Brazilian coins. Our proposed solution to address these problems utilized state-of-the-art convolutional neural networks (CNNs) in deep learning architecture. This presentation introduced an RFE-CNN model, which stood for Repetitive Feature Extractor Convolution Neural Network, designed to efficiently and precisely detect currency.

In [82], the study suggested using Long Short-Term Memory (LSTM) networks to predict cryptocurrency values. The LSTM model used historical price data and technical indicators to understand patterns and trends. To improve forecast precision, a Change Point Detection (CPD) approach using the Pruned Exact Linear Time (PELT) algorithm was added. This method identified significant fluctuations in cryptocurrency values and adjusted the LSTM model accordingly, enhancing forecasting capabilities.

In [83], the aim of this study was to create a forecasting model that was both more efficient and accurate. Our main objective was to enhance the accuracy of forecasting fluctuations in the Bitcoin price, given its significant implications for traders, investors, and the wider financial community. To achieve this, we first analyzed 14 unique data categories, including various types of information such as price and volume statistics, social media sentiments, and trending topics. This dataset was considered capable of representing the complexities of the Bitcoin market.

In [84], this research highlighted the need for using an approach that carefully balanced the complexity of models, their interpretability, and processing efficiency in order to accurately anticipate bitcoin values. Further investigation might have explored hybrid models that leveraged the benefits of many techniques, using external factors such as sentiment analysis and market dynamics to enhance the accuracy of predictions. This study laid the groundwork for future advancements in developing robust models for forecasting bitcoin values, facilitating informed decision-making in financial markets.

In [85], this paper introduced a hybrid model that combined Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks for the purpose of predicting Bitcoin prices. The model was built using the TensorFlow and Keras frameworks and evaluated using historical Bitcoin price data obtained from Yahoo Finance. The objective of our approach was to use the benefits of both LSTM and GRU architectures to enhance the accuracy of price predictions.

Table 1: Comparison of Bitcoin Price Prediction Based On Deep Learning

Ref	Author Name	Year	Algorithms	Results	Pros	Cons	Accuracy
[56]	(Phaladisailoed & Numnonda, 2018)	2018	(SVM), (LSTM), (RNN), (ARIMA)	The Gated Recurrent Unit model outperforms other machine learning models for Bitcoin value forecasting, suggesting data collection and updating should be prioritized.	The study explores machine learning models for Bitcoin price prediction strategies, offering insights into potential new methods or model changes for investors and traders.	Data limitations, biases, overfitting, and ethical concerns in bitcoin market may impact model accuracy, performance metrics, and interpretation in high-stakes financial decision-making.	(MSE)=0.00002, (R2)=99.2%.
[57]	(McNally et al., 2018)	2018	(RNN),(LSTM),(ARIMA)	The research introduces a hybrid model that integrates statistical and machine learning techniques for Bitcoin price forecasting, thereby filling a knowledge gap in digital currency trading.	Machine learning is being utilized to predict Bitcoin prices, aiding traders and investors, and potentially58developing new techniques for other financial markets and asset classes.	Machine learning algorithms' biases, overfitting, and interpretability issues can potentially skew bitcoin price projections, raising ethical concerns in volatile markets and potentially unsuitable in real-world scenarios.	RMSE=6.87% RMSE= 5.45% RMSE= 53.74%
[58]	(Aggarwal et al., 2019)	2019	(CNN),(LSTM) ,(GRU)	Deep learning models effectively predict Bitcoin price, with LSTM algorithm providing the lowest RMSE	This article utilizes deep learning to predict Bitcoin prices based on socio-economic factors, potentially	Socio-economic data challenges include data quality, accessibility, and overfitting in deep	RMSE for (CNN)=201.34 RMSE for (LSTM)=15.6

				figure. Twitter sentiment reflects pleasure and negativity, influencing price.	improving forecasts and introducing new research opportunities.	learning models, necessitating ethical considerations and market analysis for accurate predictions and financial decisions.	7 RMSE for (GRU)=179.23
[59]	(Li et al., 2019)	2019	(LSTM)	A multi-input LSTM-based prediction model offers risk-informed pricing for Bitcoin call options, reducing RMSE by up to 46.2% through Blockchain data analysis.	The paper introduces a novel Bitcoin option pricing method utilizing LSTM prediction models and blockchain data, which can identify intricate patterns in prior data.	Data quality, blockchain statistics, and opaque structure of LSTM models may affect model accuracy, overfitting, and application to other markets or cryptocurrencies, necessitating ethical considerations.	reduce the root-mean-square error (RMSE) by up to 46.2%.
[60]	(Wirawan et al., 2019)	2019	ARIMA	The proposed method accurately predicts prices with high precision, suggesting its potential for use in other cryptocurrencies.	The ARIMA model is utilized in this research to predict short-term Bitcoin values, providing a reliable and practical tool for traders and investors.	The ARIMA model's effectiveness may be hindered by the intricate nature and unpredictability of Bitcoin markets, which may not be accurately represented by linear trends and stationary data.	Least MAPE: 0.87 (1 day), 5.98 (7 days)
[61]	(Yamak et al., 2019)	2019	ARIMA, LSTM, GRU	The ARIMA model demonstrated superior results compared to deep learning-based regression models.	This paper compares ARIMA, LSTM, and GRU time series forecasting methods, highlighting their advantages and disadvantages, aiding in selecting the most suitable technique and improving understanding of	The article's findings may be limited by the need for fair model parameterization, dataset and evaluation criteria, and the time range analyzed, potentially affecting comparisons.	RMSE ARIMA: 302.53, LSTM: 603.68, GRU: 381.34

					their applications.		
[62]	(M. M. Patel et al., 2020)	2020	LSTM, GRU	High accuracy in price prediction is shown by the suggested technique, making it suitable to numerous cryptocurrencies.	The paper introduces a deep learning-based bitcoin price prediction system for financial institutions, enabling accurate market projections and smart investment decisions based on subtle bitcoin data patterns.	Deep learning models pose challenges in data accuracy, comprehension, and market volatility, while ethical concerns regarding their effectiveness and forecast accuracy need to be addressed.	RMSE: 1-day: L=2.2986, M=3.2715,3-days: L=2.0327, M=5.5005, 7days: L=4.5521, M=20.2437
[63]	(Khalid Salman & Abdu Ibrahim, 2020)	2020	Keras framework as the neural network model	The models demonstrated superior accuracy in forecasting Bitcoin values compared to other cryptocurrencies, with the most effective approach being a combination of technical trading indicators and machine learning.	This study explores the use of technical indicators and machine learning in predicting cryptocurrency prices in unstable markets, providing valuable insights for investors and traders.	Poor performance, overfitting, and opaqueness in machine learning models can be attributed to issues in data accuracy, feature selection, model comprehension, and market conditions.	94.89%
[64]	(El-Berawi et al., 2021)	2021	(RNN)	The study reveals that implementing an adaptive feature selection strategy significantly improves classification performance.	The paper introduces a deep learning method for classifying bitcoin price movements, improving market dynamics understanding and adapting to changing market conditions for real-time trading analysis.	The effectiveness of deep learning models should be evaluated for their potential issues in other cryptocurrencies or market conditions.	92% MAPE=2.4
[65]	(Tanwar et al., 2021)	2021	Gated Recurrent Units (GRU), Long Short Term Memory (LSTM)	The study indicates that the proposed model outperforms the current models in accurately predicting prices.	Deep learning is utilized to accurately predict bitcoin values, capturing intricate connections between	Deep learning models face challenges in data accuracy, comprehension, and applicability due to their black-	(LSTM) MSE=31126 MAE=130.29 RMSE=176.4

					cryptocurrencies and market conditions, thereby aiding investors and traders in making informed decisions.	box nature and the need for proper analysis for other market conditions or cryptocurrencies.	2 MAPE=9.41 (GRU) MSE=38166 MAE=141.44 RMSE=195.36 MAPE=10.22
[66]	(P et al., 2021)	2021	BILSTM	The model, with a 13% Mean Absolute Percentage Error, effectively tracked the test dataset, making it beneficial for users in making Bitcoin investment decisions.	The paper introduces a Bi-LSTM network for precise Bitcoin price predictions, utilizing deep learning algorithms to assist investors and traders in a rapidly evolving market.	Deep learning methods like Bi-LSTM networks face challenges in data pretreatment, model tweaking, interpretability, and success depend on data quality, feature selection, and hyperparameter adjustment.	Mean Absolute Percentage Error of 13%
[67]	(Iqbal et al., 2021)	2021	ARIMAX, XGBoost, and FBProphet	FBProphet outperformed all three models, achieving the lowest RMSE of 229.5 and the highest R2 score of 205.4	This article explores the use of machine learning in predicting the bitcoin market, highlighting its ability to identify and analyze price trends, aiding informed investment decisions	Issues in data accuracy, model selection, and application of machine learning models, as well as potential overfitting and inaccurate predictions due to laws and market sentiment.	RMSE=322.4, MAE=227.3, and R2=205.4
[68]	(Yun et al., 2021)	2021	hybrid GA-XGBoost	The study demonstrates that precise outcome prediction is achieved by combining feature engineering techniques with a foundational learning model,	The study employs genetic algorithms and XGBoost to predict stock values, improving accuracy through feature engineering and incorporating complex price	The technique's complexity, difficulty in scaling, and reliance on large computer resources may limit its suitability for specific stocks	validation accuracy=93.68% test accuracy= 93.82%,

				balancing the benefits and drawbacks of dimensionality.	trends for investors and traders.	or market conditions.	
[69]	(Liu et al., 2021)	2021	(DNNs)	The study highlights the advantages of machine learning in hardware security applications but also identifies areas that require further research for the development of reliable solutions.	This paper explores the potential of machine learning in hardware security, highlighting its potential to detect irregularities, enhance authentication, and mitigate system attacks.	Machine learning in hardware security applications faces challenges like adversary attacks, biases, and privacy concerns, necessitating ethical and efficient solutions.	RMSE of implied volatility=0.188 the minimum RMSE of 10% call option price is 82.012, and the minimum RMSE of 50% call option price= 38.794
[70]	(Akba et al., 2021)	2021	SVM , SARIMAX	The weekly successful sentiment analysis data was utilized to identify abnormalities in the research continuation.	The study uses prediction abnormalities to detect market deception in bitcoin, enhancing market monitoring, boosting investor confidence, and ensuring market integrity.	The effectiveness of manipulator detection systems in cryptocurrency markets depends on data quality, model accuracy, and detecting false positives, which can affect its applicability and legality.	93%
[71]	(Parab & Nitnaware, 2022)	2022	(ARIMA),(LSTM)	The goal of the technique is to improve the evaluation of bitcoin coins by using a machine learning approach to educate and update the dataset.	The study introduces a novel method for assessing bitcoin coins using machine learning and blockchain technology, offering transparency, reliability, and valuable insights for investors and regulators.	Cryptocurrency assessment methods rely on accurate data, machine learning models, and understanding bitcoin market dynamics, but challenges persist in data quality, accuracy, and interpretability.	99.87%
[72]	(Kim et al., 2022)	2022	(SAM-LSTM)	Empirical studies utilizing BTC price data and different approach setups show that the proposed	The study introduces a deep learning-based cryptocurrency price prediction model that utilizes	Deep learning models are crucial for cryptocurrency price forecasting due to their accuracy,	MAE= 0.3462 RMSE=0.5035

				framework predicts BTC price.	on-chain data to analyze intricate patterns, offering valuable insights for investors and traders.	applicability, and adaptability, which rely on on-chain data and market behavior.	MSE=0.2536 MAPE=1.3251
[73]	(Ammer & Aldhyani, 2022)	2022	(LSTM)	The study's results show that the proposed model demonstrated exceptional accuracy, with minimal prediction errors.	The study introduces a deep learning system for predicting bitcoin price fluctuations, enhancing investors' understanding of the cryptocurrency market and potentially increasing investment participation.	Challenges in deep learning models include data precision, model interpretation, and applicability. Factors like hyperparameter optimization, model architecture, and transparency affect prediction accuracy and effectiveness.	**Training Phase(96.73 %)** **Testing Phase(96.09 %)**
[74]	(Aljadani, 2022)	2022	(BiLSTM), (GRU)	The proposed framework demonstrated exceptional performance, achieving minimal Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values in the experimental findings.	The article introduces DLCP2F, a deep learning-powered framework for cryptocurrency price prediction, which enhances forecast accuracy and aids market decision-making by analyzing bitcoin price data.	DLCP2F faces challenges in data quality, model complexity, and interpretability due to noisy cryptocurrency price data and complex deep learning algorithms, requiring further examination and resolution.	(GRU) MSE=0.00029, RMSE=0.01711, MAE=0.02214, MAPE=0.07036 (BiLSTM) MSE=0.00210, RMSE=0.04582, MAE=0.03358, MAPE=0.10942
[75]	(Manzoor et al., n.d.)	2022	CNN Alex-net	A sophisticated convolutional neural network may produce considerable results using supervised learning, and coin	The study investigates the application of deep learning algorithms for the classification of	Ancient currency categorization using deep learning models faces challenges in data availability,	96%

				visuals are crucial to training and analyzing coin sizes.	ancient coins, highlighting their potential for enhanced accuracy and automation in numismatic research.	model resilience, and understanding, necessitating rigorous validation and improvement for reliability and relevance.	
[76]	(Shahbazi & Byun, 2022)	2022	XGBoost	The study aims to predict daily exchange rates of digital currency using a novel technique and utilizing diverse information.	The study employs machine learning pipelines to predict bitcoin exchange rates, enhancing market comprehension and aiding traders in devising investment strategies and risk management measures.	Issues in bitcoin exchange rate prediction include data quality, model complexity, and interpretability, necessitating validation and improvement for reliable and practical knowledge discovery.	MAE= 0.608 RMSE= 0.765 MAPE= 0.005
[77]	(Parekh et al., 2022)	2022	DL-Gues	The DL-GuesS model outperforms existing methods in accurately predicting bitcoin values.	DL-GuesS, a deep learning and sentiment analysis technique, enhances bitcoin price prediction by analyzing market trends and investor sentiment, potentially aiding traders and investors in investment strategies.	DL-GuesS, a deep learning model for cryptocurrency price prediction, faces challenges in data accuracy, model comprehension, and application due to noisy, biased, and complex data.	MSE = 0.0185 MAE = 0.0805 RMSE=4.7928
[78]	(N. P. Patel et al., 2022)	2022	LSTM,GRU	The research article introduces a deep learning model that utilizes fusion techniques to forecast bitcoin prices, combining LSTM and GRU units to extract characteristics from various cryptocurrencies.	This paper explores fusion bitcoin price prediction methods, highlighting their improved accuracy and robustness through ensemble learning, deep learning, and hybrid models, providing insights for sector advancement.	Fusion methods for bitcoin price prediction face challenges like data accessibility, model complexity, and processing resources, which must be addressed for feasibility and reliability.	MSE= 0.0187

[79]	(Umer et al., 2023)	2023	(CNN), (LSTM)	The bagged LSTM ensembled strategy outperforms other approaches in accuracy, with a statistically significant 96.4% accuracy.	The study introduces an ensemble deep learning technique for predicting fraudulent bitcoin transactions, enhancing accuracy and reliability in identifying complex patterns and anomalies in blockchain networks.	Ensemble deep learning effectively detects fraud in bitcoin transactions through accurate data, model comprehension, and addressing biases and incorrect positive results.	96.4%
[80]	(Syed et al., 2023)	2023	(ANN), (LSTM), (GRU)	The proposed approach's effectiveness could be enhanced by implementing neural network models on other cryptocurrencies like Binance, Tether, and Ripple.	This essay uses predictive deep learning algorithms and Deephaven data curation to predict bitcoin values quickly and reliably, providing traders with actionable data.	Deephaven's prognostic deep learning algorithms face challenges in model accuracy, data curation, and computational power, affecting real-time forecasting's scalability and addressing noise and biases.	MAE=0.079, RMSE=1.16, MAPE=0.0006
[81]	(Swain et al., 2023)	2023	CNN	Our proposed deep learning system provides a reliable and efficient method for categorizing coins in real-world scenarios.	The study introduces a deep learning method for Brazilian currency classification, enhancing numismatic research and coin identification, potentially improving collection management and conservation.	The proposed deep learning architecture for coin classification faces challenges such as data access, model interpretability, and efficiency varying based on coin types and conditions.	98.34%
[82]	(V. et al., 2023)	2023	(LSTM)	The study suggests that integrating LSTM with change point detection techniques could enhance cryptocurrency	The paper introduces a deep learning-based bitcoin price prediction model that enhances	The proposed cryptocurrency price forecasting system faces challenges in data accuracy, model	MSE = 846529.29 MAE = 920.07 RMSE=829.3

				price prediction accuracy, benefiting investors, traders, and analysts.	predictions by analyzing complex data patterns and trends, improving cryptocurrency market prediction modeling.	comprehension, and application due to noise, biases, and complex deep learning models.	6
[83]	(Muminov et al., 2024)	2024	(DQN)	Our findings serve as a foundation for future research on this intricate and constantly evolving field of study.	Deep Q-Networks (DQN) is utilized in a study to estimate Bitcoin values, improving market trend prediction and enhancing market forecasting modeling, potentially aiding informed decision-making.	DQN-based Bitcoin price direction forecasting requires addressing issues like data accuracy, model complexity, and result comprehension, as well as market conditions, to ensure reliability and feasibility.	95%
[84]	(Ahmed & Abdulazeez, n.d.)	2024	Random Forest, Linear Regression, SVM, LSTM, and GRU	The study reveals that combining order book data with historical volatility data improves the precision of short-term Bitcoin price volatility forecasts.	This study compares machine learning and deep learning models for predicting Bitcoin price, providing insights for future research and implementation in bitcoin trading.	Data accuracy, model selection, and applicability issues in Bitcoin price prediction research require attention to ensure reliability and relevance, despite potential limitations in real-world settings.	Random Forest (R^2=0.988) Linear Regression ($R^{2=}$ 0.842) SVM ($R^{2=}$0.945) LSTM ($R^{2=}$ 0.926) GRU ($R^{2=}$ 0.952)
[85]	(Salih & Abdulazeez, n.d.)	2024	(LSTM),(GRU)	The hybrid LSTM-GRU model effectively captures the intricate dynamics of cryptocurrency markets, overcoming the limitations of	The study utilizes LSTM and GRU models to predict Bitcoin prices, enhancing the accuracy of these predictions and providing valuable	Hybrid LSTM-GRU models face challenges in data quality, complexity, and interpretability, necessitating validation and	RMSE= 496.077

				traditional time-series analysis methods.	insights for investors and traders.	optimization for accurate and practical predictions of bitcoin price.	

D. Results and Discussion

This study aimed to explore the effectiveness of deep learning models in predicting Bitcoin's price using three fundamental designs: recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks. RNNs are known for their ability to identify sequential patterns in data, making them suitable for time-series prediction tasks like Bitcoin price forecasting. However, the vanishing gradient problem revealed their limitations in capturing long-term associations. Convolutional neural networks (CNNs), originally designed for image identification, were adapted for time-series analysis but showed potential in capturing local patterns but were unable to accurately capture long-term trends. Long short-term memory (LSTM) networks outperformed both RNNs and CNNs in forecasting Bitcoin price due to their ability to capture both short-term volatility and long-term trends in Bitcoin prices.

E. Conclusion

This article provides a comprehensive analysis of the use of deep learning algorithms to predict Bitcoin's price. It explores the fundamental concepts of deep learning architectures, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks. These models are well-suited for analyzing time-series data, such as Bitcoin prices. The study uses historical Blockchain transaction data, social media sentiment studies, and past Bitcoin price fluctuations as data sources. Evaluation metrics like mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) are also highlighted. The review suggests that further research could incorporate external factors affecting Bitcoin price fluctuations. Demand, supply, economic and political events, technology, legislation, and psychology affect Bitcoin's price. More individuals using it as payment or investment boosts its value. Economic crises, inflation, and political actions affect its value. The findings offer valuable insights for scholars, practitioners, and policymakers seeking to improve Bitcoin price prediction using deep learning techniques.

F. References

[1]. Jiang, X. (2019). Bitcoin price prediction based on deep learning methods. Journal of Mathematical Finance, 10(1), 132-139.

[2]. Jiang, W. (2021). Applications of deep learning in stock market prediction: recent progress. Expert Systems with Applications, 184, 115537.

[3]. Liu, M., Li, G., Li, J., Zhu, X., & Yao, Y. (2021). Forecasting the price of Bitcoin using deep learning. Finance research letters, 40, 101755.

[4]. Jagannath, N., Barbulescu, T., Sallam, K. M., Elgendi, I., Okon, A. A., McGrath, B., & Munasinghe, K. (2021). A self-adaptive deep learning-based algorithm for predictive analysis of bitcoin price. IEEE Access, 9, 34054-34066.

[5]. Kim, G., Shin, D. H., Choi, J. G., & Lim, S. (2022). A deep learning-based cryptocurrency price prediction model that uses on-chain data. IEEE Access, 10, 56232-56248.
[6]. Parekh, R., Patel, N. P., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., ... & Sharma, R. (2022). DL-GuesS: Deep learning and sentiment analysis-based cryptocurrency price prediction. IEEE Access, 10, 35398-35409.
[7]. Ye, Z., Wu, Y., Chen, H., Pan, Y., & Jiang, Q. (2022). A stacking ensemble deep learning model for bitcoin price prediction using Twitter comments on bitcoin. Mathematics, 10(8), 1307.
[8]. Shah, J., Vaidya, D., & Shah, M. (2022). A comprehensive review on multiple hybrid deep learning approaches for stock prediction. Intelligent Systems with Applications, 16, 200111.
[9]. Hu, Z., Zhao, Y., & Khushi, M. (2021). A survey of forex and stock price prediction using deep learning. Applied System Innovation, 4(1), 9.
[10]. Serafini, G., Yi, P., Zhang, Q., Brambilla, M., Wang, J., Hu, Y., & Li, B. (2020, July). Sentiment-driven price prediction of the bitcoin based on statistical and deep learning approaches. In 2020 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.
[11]. Kilimci, Z. H. (2020). Sentiment analysis based direction prediction in bitcoin using deep learning algorithms and word embedding models. International Journal of Intelligent Systems and Applications in Engineering, 8(2), 60-65.
[12]. Pintelas, E., Livieris, I. E., Stavroyiannis, S., Kotsilieris, T., & Pintelas, P. (2020). Investigating the problem of cryptocurrency price prediction: a deep learning approach. In Artificial Intelligence Applications and Innovations: 16th IFIP WG 12.5 International Conference, AIAI 2020, Neos Marmaras, Greece, June 5–7, 2020, Proceedings, Part II 16 (pp. 99-110). Springer International Publishing.
[13]. Koo, E., & Kim, G. (2021). Prediction of Bitcoin price based on manipulating distribution strategy. Applied Soft Computing, 110, 107738.
[14]. Amirshahi, B., & Lahmiri, S. (2023). Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies. Machine Learning with Applications, 12, 100465.
[15]. Zhang, C., Sjarif, N. N. A., & Ibrahim, R. B. (2023). Deep learning techniques for financial time series forecasting: A review of recent advancements: 2020-2022. arXiv preprint arXiv:2305.04811.
[16]. Roy, P. K., Kumar, A., Singh, A., & Sangaiah, A. K. (2023). Forecasting Bitcoin Prices using Deep Learning for Consumer Centric Industrial Applications. IEEE Transactions on Consumer Electronics.
[17]. Kim, G., Shin, D. H., Choi, J. G., & Lim, S. (2022). A deep learning-based cryptocurrency price prediction model that uses on-chain data. IEEE Access, 10, 56232-56248.
[18]. Ye, Z., Wu, Y., Chen, H., Pan, Y., & Jiang, Q. (2022). A stacking ensemble deep learning model for bitcoin price prediction using Twitter comments on bitcoin. Mathematics, 10(8), 1307.
[19]. Serafini, G., Yi, P., Zhang, Q., Brambilla, M., Wang, J., Hu, Y., & Li, B. (2020, July). Sentiment-driven price prediction of the bitcoin based on statistical and

deep learning approaches. In 2020 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.
[20]. Atrushi, D., & Abdulazeez, A. M. (2024). Human Gait Recognition Based on Deep Learning: A Review. Indonesian Journal of Computer Science, 13(1).
[21]. Arabo, W., & Abdulazeez, A. M. (2024). Facial Beauty Prediction Based on Deep Learning: A Review. Indonesian Journal of Computer Science, 13(1).
[22]. Fadhil, J., & Abdulazeez, A. M. (2024). Classification of Cancer Microarray Data Based on Deep Learning: A Review. Indonesian Journal of Computer Science, 13(1).
[23]. Kilimci, Z. H. (2020). Sentiment analysis based direction prediction in bitcoin using deep learning algorithms and word embedding models. International Journal of Intelligent Systems and Applications in Engineering, 8(2), 60-65.
[24]. Politis, A., Doka, K., & Koziris, N. (2021, May). Ether price prediction using advanced deep learning models. In 2021 IEEE International Conference on Blockchain and Cryptocurrency (ICBC) (pp. 1-3). IEEE.
[25]. Sibel Kervanci, I., & Fatih, A. K. A. Y. (2020). Review on bitcoin price prediction using machine learning and statistical methods. Sakarya University Journal of Computer and Information Sciences, 3(3), 272-282.
[26]. Khedr, A. M., Arif, I., El-Bannany, M., Alhashmi, S. M., & Sreedharan, M. (2021). Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. Intelligent Systems in Accounting, Finance and Management, 28(1), 3-34.
[27]. Thanvi, A., Sharma, R., Menghani, B., Kumar, M., & Jangir, S. K. (2021). Bitcoin exchange rate price prediction using machine learning techniques: A review. Information Management and Machine Intelligence: Proceedings of ICIMMI 2019, 635-642.
[28]. Kavitha, H., Sinha, U. K., & Jain, S. S. (2020, January). Performance evaluation of machine learning algorithms for bitcoin price prediction. In 2020 Fourth International Conference on Inventive Systems and Control (ICISC) (pp. 110-114). IEEE.
[29]. Kumar, D., & Rath, S. K. (2020). Predicting the trends of price for ethereum using deep learning techniques. In Artificial intelligence and evolutionary computations in engineering systems (pp. 103-114). Springer Singapore.
[30]. Khedr, A. M., Arif, I., El-Bannany, M., Alhashmi, S. M., & Sreedharan, M. (2021). Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. Intelligent Systems in Accounting, Finance and Management, 28(1), 3-34.
[31]. Hamayel, M. J., & Owda, A. Y. (2021). A novel cryptocurrency price prediction model using GRU, LSTM and bi-LSTM machine learning algorithms. Ai, 2(4), 477-496.
[32]. Nasirtafreshi, I. (2022). Forecasting cryptocurrency prices using recurrent neural network and long short-term memory. Data & Knowledge Engineering, 139, 102009.
[33]. Ateeq, K., & Khan, M. A. (2023). A Mechanism for Bitcoin Price Forecasting using Deep Learning. International Journal of Advanced Computer Science and Applications, 14(8).

[34]. Tanwar, S., Patel, N. P., Patel, S. N., Patel, J. R., Sharma, G., & Davidson, I. E. (2021). Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations. IEEE Access, 9, 138633-138646.
[35]. Gupta, A., & Nain, H. (2021). Bitcoin price prediction using time series analysis and machine learning techniques. In Machine Learning for Predictive Analysis: Proceedings of ICTIS 2020 (pp. 551-560). Springer Singapore.
[36]. Islam, M. S., Hossain, E., Rahman, A., Hossain, M. S., & Andersson, K. (2020). A review on recent advancements in forex currency prediction. Algorithms, 13(8), 186.
[37]. Kim, J., Kim, S., Wimmer, H., & Liu, H. (2021, September). A cryptocurrency prediction model using LSTM and GRU algorithms. In 2021 IEEE/ACIS 6th International Conference on Big Data, Cloud Computing, and Data Science (BCD) (pp. 37-44). IEEE.
[38]. Prajapati, P. (2020). Predictive analysis of Bitcoin price considering social sentiments. arXiv preprint arXiv:2001.10343.
[39]. Jagannath, N., Barbulescu, T., Sallam, K. M., Elgendi, I., Okon, A. A., McGrath, B., ... & Munasinghe, K. (2021). A self-adaptive deep learning-based algorithm for predictive analysis of bitcoin price. IEEE Access, 9, 34054-34066.
[40]. Li, Y., & Dai, W. (2020). Bitcoin price forecasting method based on CNN-LSTM hybrid neural network model. The journal of engineering, 2020(13), 344-347.
[41]. Samaddar, M., Roy, R., De, S., & Karmakar, R. (2021, February). A Comparative study of different machine learning algorithms on bitcoin value prediction. In 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) (pp. 1-7). IEEE.
[42]. Millikan, E., Subramanian, P., & Joseph, M. H. (2021). Bitcoin Vision: Using Machine Learning and Data Mining to Predict the Short-Term and Long-Term Price of Bitcoin. Technology.
[43]. Zhu, L., Li, Z., Li, C., Wu, J., & Yue, J. (2018). High performance vegetable classification from images based on alexnet deep learning model. International Journal of Agricultural and Biological Engineering, 11(4), 217-223.
[44]. Yuan, Z. W., & Zhang, J. (2016, August). Feature extraction and image retrieval based on AlexNet. In Eighth International Conference on Digital Image Processing (ICDIP 2016) (Vol. 10033, pp. 65-69). SPIE.
[45]. Abd Almisreb, A., Jamil, N., & Din, N. M. (2018, March). Utilizing AlexNet deep transfer learning for ear recognition. In 2018 fourth international conference on information retrieval and knowledge management (CAMP) (pp. 1-5). IEEE.
[46]. Aliyu, H. A., Razak, M. A. A., Sudirman, R., & Ramli, N. (2020). A deep learning AlexNet model for classification of red blood cells in sickle cell anemia. Int J Artif Intell, 9(2), 221-228.
[47]. Jiang, B., He, J., Yang, S., Fu, H., Li, T., Song, H., & He, D. (2019). Fusion of machine vision technology and AlexNet-CNNs deep learning network for the detection of postharvest apple pesticide residues. Artificial Intelligence in Agriculture, 1, 1-8.

[48]. Al-Qizwini, M., Barjasteh, I., Al-Qassab, H., & Radha, H. (2017, June). Deep learning algorithm for autonomous driving using googlenet. In 2017 IEEE intelligent vehicles symposium (IV) (pp. 89-96). IEEE.
[49]. Kim, J. H., Seo, S. Y., Song, C. G., & Kim, K. S. (2019). Assessment of electrocardiogram rhythms by GoogLeNet deep neural network architecture. Journal of healthcare engineering, 2019.
[50]. Teymournezhad, K., Azgomi, H., & Asghari, A. (2022). Detection of counterfeit banknotes by security components based on image processing and googlenet deep learning network. Signal, Image and Video Processing, 16(6), 1505-1513.
[51]. Zakaria, N., Mohamed, F., Abdelghani, R., & Sundaraj, K. (2021, November). VGG16, ResNet-50, and GoogLeNet deep learning architecture for breathing sound classification: a comparative study. In 2021 International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP) (pp. 1-6). IEEE.
[52]. Gurrib, I., & Kamalov, F. (2022). Predicting bitcoin price movements using sentiment analysis: a machine learning approach. Studies in Economics and Finance, 39(3), 347-364.
[53]. Lamothe-Fernández, P., Alaminos, D., Lamothe-López, P., & Fernández-Gámez, M. A. (2020). Deep learning methods for modeling bitcoin price. Mathematics, 8(8), 1245.
[54]. Cocco, L., Tonelli, R., & Marchesi, M. (2021). Predictions of bitcoin prices through machine learning based frameworks. PeerJ Computer Science, 7, e413.
[55]. Chen, J. (2023). Analysis of bitcoin price prediction using machine learning. Journal of Risk and Financial Management, 16(1), 51.
[56]. Phaladisailoed, T., & Numnonda, T. (2018). Machine Learning Models Comparison for Bitcoin Price Prediction. 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE), 506–511. https://doi.org/10.1109/ICITEED.2018.8534911
[57]. McNally, S., Roche, J., & Caton, S. (2018). Predicting the Price of Bitcoin Using Machine Learning. 2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP), 339–343. https://doi.org/10.1109/PDP2018.2018.00060
[58]. Aggarwal, A., Gupta, I., Garg, N., & Goel, A. (2019). Deep Learning Approach to Determine the Impact of Socio Economic Factors on Bitcoin Price Prediction. 2019 Twelfth International Conference on Contemporary Computing (IC3), 1–5. https://doi.org/10.1109/IC3.2019.8844928
[59]. Li, L., Arab, A., Liu, J., Liu, J., & Han, Z. (2019). Bitcoin Options Pricing Using LSTM-Based Prediction Model and Blockchain Statistics. 2019 IEEE International Conference on Blockchain (Blockchain), 67–74. https://doi.org/10.1109/Blockchain.2019.00018
[60]. Wirawan, I. M., Widiyaningtyas, T., & Hasan, M. M. (2019). Short Term Prediction on Bitcoin Price Using ARIMA Method. 2019 International Seminar on Application for Technology of Information and Communication (iSemantic), 260–265. https://doi.org/10.1109/ISEMANTIC.2019.8884257
[61]. Yamak, P. T., Yujian, L., & Gadosey, P. K. (2019). A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting. Proceedings of the 2019

2nd International Conference on Algorithms, Computing and Artificial Intelligence, 49–55. https://doi.org/10.1145/3377713.3377722
[62]. Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A Deep Learning-based Cryptocurrency Price Prediction Scheme for Financial Institutions. Journal of Information Security and Applications, 55, 102583. https://doi.org/10.1016/j.jisa.2020.102583
[63]. Khalid Salman, M., & Abdu Ibrahim, A. (2020). PRICE PREDICTION OF DIFFERENT CRYPTOCURRENCIES USING TECHNICAL TRADE INDICATORS AND MACHINE LEARNING. IOP Conference Series: Materials Science and Engineering, 928(3), 032007. https://doi.org/10.1088/1757-899X/928/3/032007
[64]. El-Berawi, A. S., Belal, M. A. F., & Ellatif, M. M. A. (2021). Adaptive Deep Learning based Cryptocurrency Price Fluctuation Classification. International Journal of Advanced Computer Science and Applications, 12(12). https://doi.org/10.14569/IJACSA.2021.0121264
[65]. Tanwar, S., Patel, N. P., Patel, S. N., Patel, J. R., Sharma, G., & Davidson, I. E. (2021). Deep Learning-Based Cryptocurrency Price Prediction Scheme With Inter-Dependent Relations. IEEE Access, 9, 138633–138646. https://doi.org/10.1109/ACCESS.2021.3117848
[66]. P, N., Tom, R. J., Gupta, P., Shanthini, A., John, V. M., & Sharma, V. (2021). Prediction of Bitcoin Price Using Bi-LSTM Network. 2021 International Conference on Computer Communication and Informatics (ICCCI), 1–5. https://doi.org/10.1109/ICCCI50826.2021.9402427
[67]. Iqbal, M., Iqbal, M., Jaskani, F., Iqbal, K., & Hassan, A. (2021). Time-Series Prediction of Cryptocurrency Market using Machine Learning Techniques. EAI Endorsed Transactions on Creative Technologies, 8(28), 170286. https://doi.org/10.4108/eai.7-7-2021.170286
[68]. Yun, K. K., Yoon, S. W., & Won, D. (2021). Prediction of stock price direction using a hybrid GA-XGBoost algorithm with a three-stage feature engineering process. Expert Systems with Applications, 186, 115716. https://doi.org/10.1016/j.eswa.2021.115716
[69]. Liu, W., Chang, C.-H., Wang, X., Liu, C., Fung, J. M., Ebrahimabadi, M., Karimi, N., Meng, X., & Basu, K. (2021). Two Sides of the Same Coin: Boons and Banes of Machine Learning in Hardware Security. IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 11(2), 228–251. https://doi.org/10.1109/JETCAS.2021.3084400
[70]. Akba, F., Medeni, I. T., Guzel, M. S., & Askerzade, I. (2021). Manipulator Detection in Cryptocurrency Markets Based on Forecasting Anomalies. IEEE Access, 9, 108819–108831. https://doi.org/10.1109/ACCESS.2021.3101528
[71]. Parab, L. J., & Nitnaware, P. P. (2022). Evaluation of Cryptocurrency coins with Machine Learning algorithms and Blockchain Technology. 2022 IEEE Region 10 Symposium (TENSYMP), 1–5. https://doi.org/10.1109/TENSYMP54529.2022.9864430
[72]. Kim, G., Shin, D.-H., Choi, J. G., & Lim, S. (2022). A Deep Learning-Based Cryptocurrency Price Prediction Model That Uses On-Chain Data. IEEE Access, 10, 56232–56248. https://doi.org/10.1109/ACCESS.2022.3177888

[73]. Ammer, M. A., & Aldhyani, T. H. H. (2022). Deep Learning Algorithm to Predict Cryptocurrency Fluctuation Prices: Increasing Investment Awareness. Electronics, 11(15), 2349. https://doi.org/10.3390/electronics11152349
[74]. Aljadani, A. (2022). DLCP2F: A DL-based cryptocurrency price prediction framework. Discover Artificial Intelligence, 2(1), 20. https://doi.org/10.1007/s44163-022-00036-2
[75]. Manzoor, S., Ali, N., Raees, M., Khan, K. A., Usama, M., & Ahmed, A. (n.d.). Ancient coin classification based on recent trends of deep learning.
[76]. Shahbazi, Z., & Byun, Y.-C. (2022). Knowledge Discovery on Cryptocurrency Exchange Rate Prediction Using Machine Learning Pipelines. Sensors, 22(5), 1740. https://doi.org/10.3390/s22051740
[77]. Parekh, R., Patel, N. P., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., Davidson, I. E., & Sharma, R. (2022). DL-GuesS: Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction. IEEE Access, 10, 35398–35409. https://doi.org/10.1109/ACCESS.2022.3163305
[78]. Patel, N. P., Parekh, R., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., Davidson, I. E., & Sharma, R. (2022). Fusion in Cryptocurrency Price Prediction: A Decade Survey on Recent Advancements, Architecture, and Potential Future Directions. IEEE Access, 10, 34511–34538. https://doi.org/10.1109/ACCESS.2022.3163023
[79]. Umer, Q., Li, J.-W., Ashraf, M. R., Bashir, R. N., & Ghous, H. (2023). Ensemble Deep Learning-Based Prediction of Fraudulent Cryptocurrency Transactions. IEEE Access, 11, 95213–95224. https://doi.org/10.1109/ACCESS.2023.3310576
[80]. Syed, S., Iqbal, A., Mehmood, W., Syed, Z., Khan, M., & Pau, G. (2023). Split-Second Cryptocurrency Forecast Using Prognostic Deep Learning Algorithms: Data Curation by Deephaven. IEEE Access, 11, 128644–128654. https://doi.org/10.1109/ACCESS.2023.3331652
[81]. Swain, D., Rupapara, V., Nour, A., Satapathy, S., Acharya, B., Mishra, S., & Bostani, A. (2023). A Deep Learning Framework for the Classification of Brazilian Coins. IEEE Access, 11, 109448–109461. https://doi.org/10.1109/ACCESS.2023.3321428
[82]. V., A., M.V.S., N., I., P., Reddy M., S., & G., A. K. (2023). A Cryptocurrency Price Prediction Model using Deep Learning. E3S Web of Conferences, 391, 01112. https://doi.org/10.1051/e3sconf/202339101112
[83]. Muminov, A., Sattarov, O., & Na, D. (2024). Enhanced Bitcoin Price Direction Forecasting With DQN. IEEE Access, 12, 29093–29112. https://doi.org/10.1109/ACCESS.2024.3367719
[84]. Ahmed, O. M., & Abdulazeez, A. M. (n.d.). Comparative Analysis of Machine Learning and Deep Learning Models for Bitcoin Price Prediction.
[85]. Salih, N. M., & Abdulazeez, A. M. (n.d.). Bitcoin Price Prediction Using Hybrid LSTM-GRU Models.