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Short-term Prediction of Bitcoin Price Based on Generative Adversarial Network

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Abstract

Background and Objectives: Investment has become a paramount concern for various individuals, particularly investors, in today's financial landscape. Cryptocurrencies, encompassing various types, hold a unique position among investors, with Bitcoin being the most prominent. Additionally, Bitcoin serves as the foundation for some other cryptocurrencies. Given the critical nature of investment decisions, diverse methods have been employed, ranging from traditional statistical approaches to machine learning and deep learning techniques. However, among these methods, the Generative Adversarial Network (GAN) model has not been utilized in the cryptocurrency market. This article aims to explore the applicability of the GAN model for predicting short-term Bitcoin prices.

Methods: In this article, we employ the GAN model to predict short-term Bitcoin prices. Moreover, Data for this study has been collected from a diverse set of sources, including technical data, fundamental data, technical indicators, as well as additional data such as the number of tweets and Google Trends. In this research, we also evaluate the model's accuracy using the RMSE, MAE and MAPE metrics.

Results: The results obtained from the experiments indicate that the GAN model can be effectively utilized in the cryptocurrency market for short-term price prediction.

Conclusion: In conclusion, the results of this study suggest that the GAN model exhibits promise in predicting short-term prices in the cryptocurrency market, affirming its potential utility within this domain. These insights can provide investors and analysts with enhanced knowledge for making more informed investment decisions, while also paving the way for comparative analyses against alternative models operating in this dynamic field.

Introduction

The unpredictable nature of Bitcoin prices presents a specific challenge for investors making decisions in the cryptocurrency market [1]. Anticipating short-term in Bitcoin's price is crucial for investors, providing a perspective on whether the value of Bitcoin is poised to rise or fall [2]. This foresight is valuable for guiding strategic investment decisions within cryptocurrency investing.

In the field of cryptocurrency prediction, utilizing deep learning methods, especially neural networks, has shown promise in improving forecasting accuracy. Deep learning models utilize multiple layers of artificial neural networks to independently extract intricate patterns and dependencies within extensive datasets. This capability makes them proficient at capturing the inherent complexities of Bitcoin price dynamics. The use of deep learning in predicting Bitcoin not only enhances predictive capabilities but also allows adaptation to changing market conditions. This establishes Deep learning as a valuable tool in the quest for more accurate and agile forecasting models within the dynamic landscape of cryptocurrency markets [3].

Exploring GANs for short-term prediction of Bitcoin prices is an uncharted domain, despite the diverse methods employed in predicting financial market changes [4]. This research is driven by recognizing the absence of exploration in tackling this specific issue and acknowledging the potential of GANs. GANs have great potential to predict Bitcoin prices because they have proven to be effective in forecasting stock prices in traditional financial markets [5]-[7].

In the field of Bitcoin prediction, GANs have emerged as an innovative and cutting-edge approach. Proposed by Ian Goodfellow and colleagues, GANs consist of two neural networks—the generator and the discriminator—engaged in a competitive yet collaborative learning process [8]. The generator's objective is to create synthetic data resembling authentic Bitcoin price patterns, while the discriminator strives to differentiate between genuine and generated data [9]. Through adversarial training, this process facilitates the development of a generator capable of producing data indistinguishable from actual market behavior [10]. GANs offer a unique advantage in Bitcoin prediction by capturing complex temporal dependencies within prices and generating realistic future scenarios. GANs ability to create realistic data and understand complex patterns adds a new and dynamic aspect to forecasting in the cryptocurrency market [5].

This research aims to introduce a novel approach for short-term Bitcoin price prediction. While the use of GANs in financial prediction is not unprecedented and has been used in the stock market, this study pioneers a unique application by concentrating on the cryptocurrency domain, an area that has not been explored with such approaches. The lack of specific modifications to the GAN model underscores its adaptability to the distinct characteristics of cryptocurrency data.

Differing from conventional prediction models, our proposed approach enhances its predictive capacity by tapping into a wide range of data sources. This comprehensive approach encompasses fundamental data, technical data, technical indicators, and supplementary information, including tweet counts and Google trends. By integrating these diverse sources, our model aims for a comprehensive understanding of the factors shaping cryptocurrency market dynamics, striving for a detailed prediction strategy.

The main goal of this paper is to advance the knowledge in cryptocurrency prediction by introducing a method that can be compared to existing approaches. Moving forward, the proposed model creates opportunities for benchmarking against traditional methods and enables potential refinements to improve its predictive accuracy. Through this research, we seek to develop a deeper comprehension of the dynamics of Bitcoin prices, offering a valuable tool for investors navigating the intricate landscape of cryptocurrency markets.

In this study, we applied the Generative Adversarial Network (GAN) model to forecast short-term Bitcoin prices in the cryptocurrency market. The GAN architecture comprised a Generator using Gated Recurrent Units (GRU) for synthetic data generation and a Discriminator with a one-dimensional Convolutional Neural Network (CNN-1D) for distinguishing real from generated data. We curated a dataset with 738 Bitcoin-related features, applying the Gray Wolf algorithm for feature selection. The GAN model, trained on 70% of the dataset, demonstrated strong predictive capabilities, validated by low Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) values. This affirms the GAN model's effectiveness in short-term Bitcoin price prediction within the cryptocurrency market.

The structure of the continuation of this paper is as follows: In the second section, we will provide a review of relevant studies. The third section will elaborate on the methodology employed in this research. In the fourth section, we will describe the data used in this study and the operations conducted on them. In the subsequent section, we present the obtained results and the accuracy of the model. Finally, we conclude and outline the sources utilized.

Literature Review

So far, numerous works have been conducted in the field of cryptocurrency price prediction using various methods and models [11]-[14]. Some researchers have employed machine learning or deep learning approaches for this prediction, while others have utilized sentiment analysis methods in this domain. Additionally, a group of researchers has undertaken such predictions using traditional statistical methods. In the following, we will examine some examples of the works carried out in this area.

Alonso-Monsalve et al. investigated the applicability of Convolutional Neural Network (CNN) as an alternative to the traditional Multilayer Perceptron (MLP) in the realm of classification, specifically focusing on the cryptocurrency market trends through high-frequency technical analysis [15]. They gathered and processed data for six widely used cryptocurrencies (Bitcoin, Dash, Ethereum, Litecoin, Monero, and Ripple). The analysis, based on one-minute exchange rates, spanned a three-month period (July 1, 2018, to September 30, 2018). Utilizing 18 technical indicators, they evaluated the model's performance using the Sensitivity metric. Their results indicated that, overall, CNN exhibited superior performance compared to MLP, particularly for Bitcoin and Ethereum, showing promising outcomes. Litecoin, Dash, and Ripple also demonstrated incremental improvements, while Monero did not achieve satisfactory results.

Oyedele et al. explored the feasibility of predicting closing prices for various cryptocurrencies (Bitcoin, Ethereum, Litecoin, Binance Coin, Dogecoin, and Stellar) using three deep learning techniques (CNN, GRU, and DFNN), along with three tree-based techniques (Adaptive Boosting, GBM, and XGB) [16]. The study employed VIF for feature selection. Prediction accuracy was assessed using datasets from multiple sources, including Yahoo Finance (January 1, 2018, to December 31, 2021), UK Investing (July 1, 2021, to March 2, 2022), and Bitfinex (January 1, 2021, to July 6, 2021). The datasets encompassed five closing price features, such as closing price, highest price, lowest price, opening price, and daily volume for each cryptocurrency, along with weighted average and two technical indicators, SMA, and EMA. Evaluation metrics included NSE, EVS, t-test, and MAPE. The researchers concluded that, overall, predictions made by deep learning models, especially Convolutional Neural Network models, outperformed tree-based models.

Nakano et al. investigated Bitcoin investment using an Artificial Neural Network (ANN) that extracted trading signals from past time series data every 15 minutes, enabling the prediction of Bitcoin prices in the next 15 minutes [17]. In this study, they explored an artificial neural network model with varying numbers of layers, different activation functions, multiple classification types (3 classes, 4 classes, and 5 classes), and different inputs (to assess the impact of technical indicators). The authors collected Bitcoin price data, including closing price, highest price, lowest price, and volume, from the cryptocurrency exchange Poloniex at 15-minute intervals spanning from July 31, 2016, at 15:00 (GMT) to January 21, 2018, at 7:30 (GMT). They utilized cumulative returns for model performance evaluation. Ultimately, they concluded that predictive performance improves with an increase in the number of layers, the use of the Leaky ReLU activation function, a reduction in the number of classes in classification, and the incorporation of technical indicators as inputs.

Hansun et al. employed three methods—LSTM, Bi-LSTM, and GRU—to predict the next day's prices for several cryptocurrencies, including Bitcoin, Ethereum, Binance Coin, Cardano, and Tether [18]. The data used in this study comprised the maximum daily data available for each cryptocurrency collected from Yahoo Finance. Each dataset included historical features such as Open, Close, High, Low, and Volume for the respective cryptocurrency. They innovatively utilized a multi-variable approach and compared three models: LSTM, Bi-LSTM, and GRU. Performance evaluation metrics included MAE, MAPE, and RMSE. They iteratively developed and evaluated each deep learning network (LSTM, Bi-LSTM, and GRU) ten times and concluded that GRU emerged as the preferred deep learning method among the three considered.

Serafini et al. investigated the predictive power of sentiment analysis on the network, exploring statistical and deep learning methods for forecasting the future price of Bitcoin [19]. They analyzed financial features and sentiments extracted from economic data and crowd-sourced data, demonstrating how sentiments play a crucial role in predicting market movements for Bitcoin. The data used in this study were collected from April 2017 to October 2019, spanning a total of 944 days. Each sample in the dataset comprised daily Bitcoin volume features, weighted Bitcoin price, Bitcoin tweet sentiments, and Bitcoin tweet volume. The authors compared two models, ARIMAX and LSTM (a type of RNN), for predicting Bitcoin prices. They used the mean squared error as their evaluation metric and found that both models achieved optimal results in new predictions due to the inclusion of sentiment features (with a mean squared error of less than 0.14%). However, they noted that the ARIMAX model outperformed the LSTM, with a mean squared error of 0.00030187 in new predictions.

Zou et al. proposed a multi-faceted model for predicting extreme prices in Bitcoin [20]. This model takes input from related assets (Ethereum and gold), technical indicators, and Twitter content. The study aimed to investigate whether social media discussions among the public about Bitcoin have predictive power for significant price changes. For this purpose, a dataset of 5,000 daily tweets (containing the keyword "Bitcoin") from 2015 to 2021 was collected, amounting to a total of 9,435,437 tweets in the study. A new dataset included tweets, candlestick data, prices of related assets (Ethereum and gold), and a set of technical indicators collected from January 1, 2015, to May 31, 2021. In the presented model, FinBERT embeddings were used to represent the complete content of tweets at the sentence level. These embeddings were then combined with a convolutional neural network to create a predictive model for significant market movements. The goal of the study was to optimally utilize the content of social media beyond sentiment scores. To evaluate the performance of their model and demonstrate its practical application, the authors proposed a simple but long trading strategy and reported Backtesting results. They stated that the superior performance of the combined model presented in the paper is confirmed with a threshold of 0.95 in risk-adjusted measures such as the Sortino ratio and maximum drawdown.

Methodology

Certainly, the domain of cryptocurrency prediction has seen the rise of deep learning approaches, particularly neural networks, as a promising pathway for improving forecasting accuracy. Deep learning models, utilizing multiple layers of artificial neural networks, can independently identify complex patterns and relationships within large datasets. This feature makes them effective in grasping the inherent complexities of Bitcoin price dynamics [21].

Indeed, the use of deep learning in Bitcoin prediction not only enhances predictive capabilities but also enables adaptation to evolving market conditions. This positions deep learning as a valuable tool in the pursuit of more accurate and responsive forecasting models within the dynamic landscape of cryptocurrency markets [22].

In this paper, we have delved into short-term price prediction of Bitcoin using the GAN model, a methodology not yet explored in the cryptocurrency domain.

The aim of this article is to investigate the usability of the GAN model in the cryptocurrency market.

The GAN (Generative Adversarial Network) is a type of artificial neural network architecture consisting of two main components: the Generator and the Discriminator. These components engage in a competitive yet collaborative learning process. The Generator is responsible for predicting future Bitcoin prices using historical Bitcoin data it receives as input. These predictions should resemble real price patterns of Bitcoin. Subsequently, this generated data is presented as input to the Discriminator. The Discriminator is responsible distinguishing between real data and data generated by the Generator, and endeavors to differentiate between actual and generated data. Throughout the training process, the Generator and Discriminator networks iteratively improve in a reciprocal manner. In essence, the Generator attempts to produce data that the Discriminator cannot distinguish from real data, while the Discriminator strives to always provide the best possible discrimination. This adversarial training process enhances the quality of the data generated by the Generator [23], [24].

Each of the two components, Generator and Discriminator, is itself a neural network. In this study, we utilized GRU as the Generator and CNN-1D as the Discriminator. The architecture of the GAN model used in this research is show in Fig. 1.

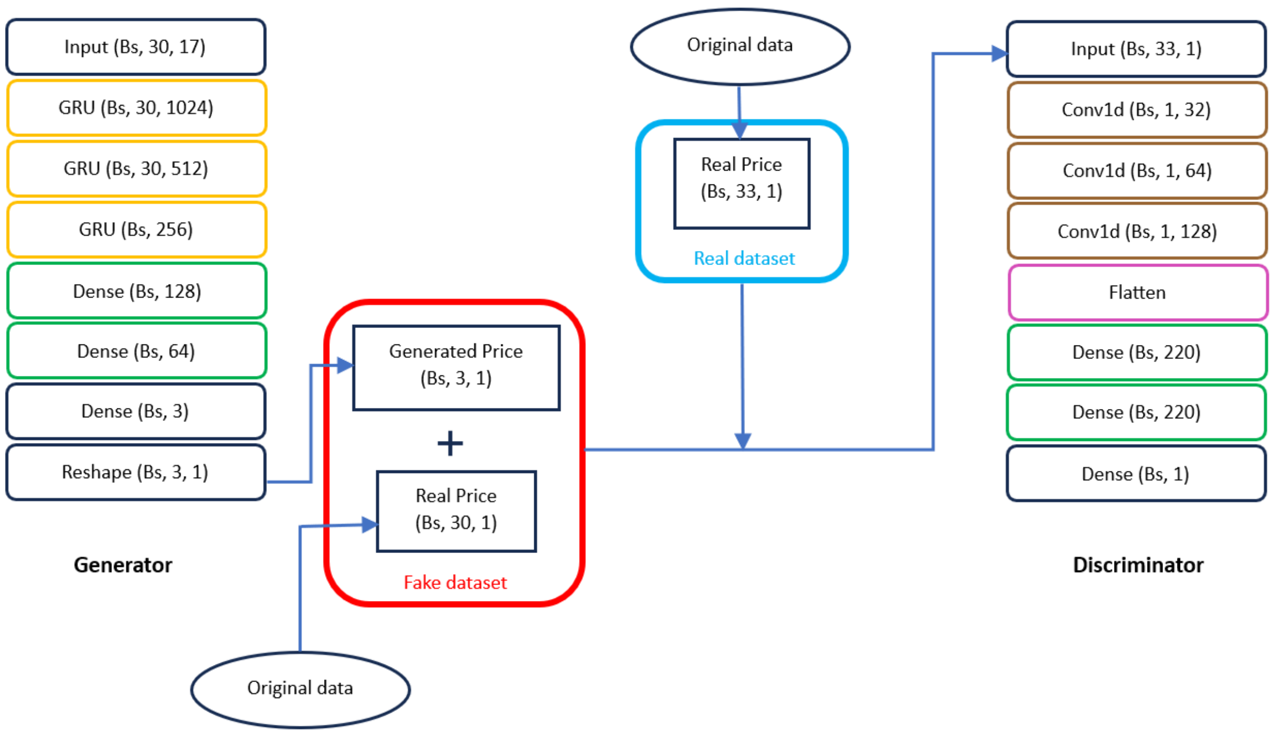

Fig. 1: GAN Architecture.

As illustrated in Fig. 1, historical Bitcoin data, which represents real values, is given to the Generator as input. In this study, GRU is utilized as the Generator. The details related to the data are thoroughly explained in the "Data Collection and Preprocessing" section. Then, the GRU, considering historical Bitcoin data and learning patterns related to them, predicts future values of Bitcoin prices. We combined values generated by the Generator with the real Bitcoin prices, and the result was considered as input for the discriminator. This combination process leads to an increase in the length of the data and, consequently, enhances the discriminator's accuracy in learning classification.

In this study, we train the Generator to minimize its objective function, defined as (1) [25].

$$Minimize \log(1 - D(G(z))) \quad (1)$$

Additionally, the objective of the Discriminator is to maximize the probability of assigning correct labels to samples, and its objective function is defined according to (2) [25].

$$Maximize \log(D(x)) + \log(1 - D(G(z))) \quad (2)$$

where z is the input data for generator, x is the target from the real dataset, G(z) is the generated data by the generator.

This study employs cross-entropy for calculating the loss for both Generator and Discriminator in the presented GAN model structure. The loss function for the Generator is defined according to Equation 3, and for the Discriminator, it is defined according to (3) [25].

$$-\log(1 - D(G(z))) \quad (3)$$

$$-\log(D(x)) - \log(1 - D(G(z))) \quad (4)$$

whatever loss function value minimizes during the training process, the better results obtained.

Generally, in the context of (1) to (4), where z represents the input data for the generator, x denotes the target from the real dataset, and G(z) indicates the data generated by the generator. Subsequently, this generated data serves as input for the discriminator, denoted by D(G(z)). In fact, G and D represent the generator and the discriminator respectively.

Every model of machine learning algorithms has a specific set of parameters, such as the number of layers, learning rate, the number of neurons, and some other parameters. These parameters need to be defined through the training process for achieving the highest performance score of the model [26].

In this study, Bayesian Optimization has been employed in the training process that utilize Bayes' Theorem to finding parameters that can create minimize or maximize the given objective function score.

Hyperparameters Tuning

This section outlines the specific configuration of key hyperparameters in the experimental design of the study, shedding light on the choices made to fine-tune the Generative Adversarial Network (GAN) model for predicting short-term Bitcoin prices.

1. Learning Rate Range (Hyperparameter Tuning): The learning rate, a critical hyperparameter in training neural networks, was meticulously chosen within the range of 0.00003 to 0.00016. This deliberate range selection reflects a systematic exploration of different learning rates. The learning rate is pivotal in determining the step size during optimization, influencing how quickly or slowly the model adapts to the dataset. The specified range indicates a nuanced approach to finding an optimal balance between convergence speed and model stability.

2. Number of Epochs (Training Iterations): To capture the dynamics of the learning process, the number of epochs, or complete passes through the dataset, was varied between 150 and 300. This parameter is crucial in gauging the model's exposure to the dataset and its learning capacity over time. The range chosen suggests a comprehensive investigation into the model's performance across different durations of training, offering insights into convergence patterns and potential trade-offs between underfitting and overfitting.

3. Batch Size (Data Processing Units): The batch size, set at 128, determines the number of data samples processed in each iteration during training. This parameter balances computational efficiency and model generalization. A batch size of 128 indicates a pragmatic choice, as it is commonly used in practice. It strikes a balance between leveraging computational efficiency, especially in parallel processing, and facilitating the model's ability to generalize patterns from the data.

By explicitly detailing these hyperparameters, the section not only provides transparency regarding the experimental setup but also offers valuable information for reproducibility and comparison with future studies. The meticulous selection of these parameters reflects a thoughtful approach to optimizing the GAN model for accurate short-term Bitcoin price prediction [27].

Data Collection and Preprocessing

The required data for this research was collected from the website https://bitinfocharts.com [28] using a web scraper written in Python 3.11.4. The collected data consists of 738 features related to the Bitcoin cryptocurrency that overall encompass technical data, fundamental data, technical indicators, and additional data such as the number of tweets and Google trends. The data has been collected daily in the time range from

October 1, 2014, to October 14, 2023.

The study employs a set of technical indicators to enhance the analysis of Bitcoin (BTC) price time series features. These indicators encompass diverse metrics such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Weighted Moving Average (WMA), Standard Deviation (STD), Variance (VAR), Triple Moving Exponential (TRIX), and Rate of Change (ROC). Computed across various periods, including end-of-day, 7, 30, and 90 days, these technical indicators provide nuanced insights into BTC price dynamics.

The raw features, constituting the foundation for these indicators and presented in Table 1, are derived from end-of-day closing prices, serving as fundamental reference values. These indicators transcend the inherent characteristics of raw features, unveiling intricate properties such as variances and standard deviations over time.

Specifically, they illuminate the relationship between BTC price and critical factors like the standard deviation of transactions or hashrate over 30-day periods. This nuanced approach moves beyond raw transaction and hashrate data, offering a refined understanding of BTC price dynamics through the perspective of calculated technical indicators.

Table 1: Raw features from which the technical indicators are created

Features	Discription
Transactions	The number of sent and received Bitcoin payments
Block size	Transactional information is cryptographically linked within the blockchain, with the maximum block size presently established at 1 megabyte
Sent from addresses	These are distinct Bitcoin addresses from which payments are made everyday
Difficulty	The daily average mining difficulty. The difficulty is computed by the network after a specified number of blocks have been created so that the time it requires to mine a block remains around 10 min
Average transaction value	The average value of the transactions in Bitcoin
Mining profitability	The profitability in USD/day for 1 terahash per second (THash/s)
Sent BTC	The total Bitcoins sent daily
Fee-to-reward ratio	The ratio of the fee sent in a transaction to the reward for verifying that transaction by the other users
Median transaction fee	The median of transaction fees in Bitcoin
Average transaction fee	In each transaction, the sender can include a transaction fee, and this fee is received by the miners who verify the transaction. Transactions offering higher fees serve as incentives for Bitcoin miners to prioritize and process them more promptly compared to transactions with lower fees
Block time	The time required to mine one block. Usually, it is around 10 min but can fluctuate depending on the hashrate of the network
Hashrate	The total daily computational capacity of the Bitcoin network, known as hashrate, signifies the speed at which a computer can perform operations
Median transaction value	The median value of the transactions in Bitcoin
Active addresses	The number of unique addresses participating in a transaction by either sending or receiving Bitcoins
Top 100 to total	The ratio of Bitcoins stored in the top 100 accounts to all the other accounts of Bitcoin

Once the data was collected, and obtaining clean and processable data, we added a label column to the data as a classification format (0, 1). In this format, 0 indicates a decrease in price compared to the previous day, and 1 indicates an increase in price compared to the previous day.

Next, we utilized the Gray Wolf optimization algorithm as a feature selection algorithm [29]. This led to identifying 17 influential features out of the 738 available features for predicting Bitcoin prices.

Table 2 displays 17 features obtained from running the Gray Wolf algorithm, along with some associated values.

Table 2: Selected features of Gray Wolf algorithm

Selected features by Gray Wolf algorithm
bitcoin-transactions
mediantransactionvalue-btc
transactions-btc-ema-7
transactions-btc-wma-7
size-btc-rsi-7
size-btc-std-14
transactionvalue-btc-trx-14
fee-to-reward-btc-roc-3
confirmationtime-btc-var-30
hashrate-btc-ema-14
hashrate-btc-trx-3
hashrate-btc-mom-7
mediantransactionvalue-btc-var-90
mediantransactionvalue-btc-mom-7
top100cap-btc-rsi-14
price-btc-ema-14
price-btc-rsi-90

As evident from Table 2, the features obtained from running the Gray Wolf algorithm, selected as the most influential features among the collected 738 features, are listed in Table 2.

After running the Gray Wolf algorithm and obtaining the influential features, we divided the data into a 70-30 ratio for training and testing, respectively. In fact, we have utilized 70% of the data for model training and the remaining 30% for testing the model.

This model employs a method for preparing the dataset for supervised learning by dividing it with a rolling window set to 1. Fig. 2 provides an illustration of this process. The original dataset, which is two-dimensional, undergoes a reshaping operation to transform it into three dimensions based on the specified timesteps.

Fig. 3 presents the output of the dataset generated by the generator, where the number of output units is set to 1. In our model, adjustments to the time step can be made in Fig. 2, while modifications to the output step can be implemented in Fig. 3. This paper has constructed a many-to-many model with a timestep of 30 and an output step of 3.

The time window used in this study is structured in a way that it leverages the past 30 days of Bitcoin data to predict its price for the next 3 days.

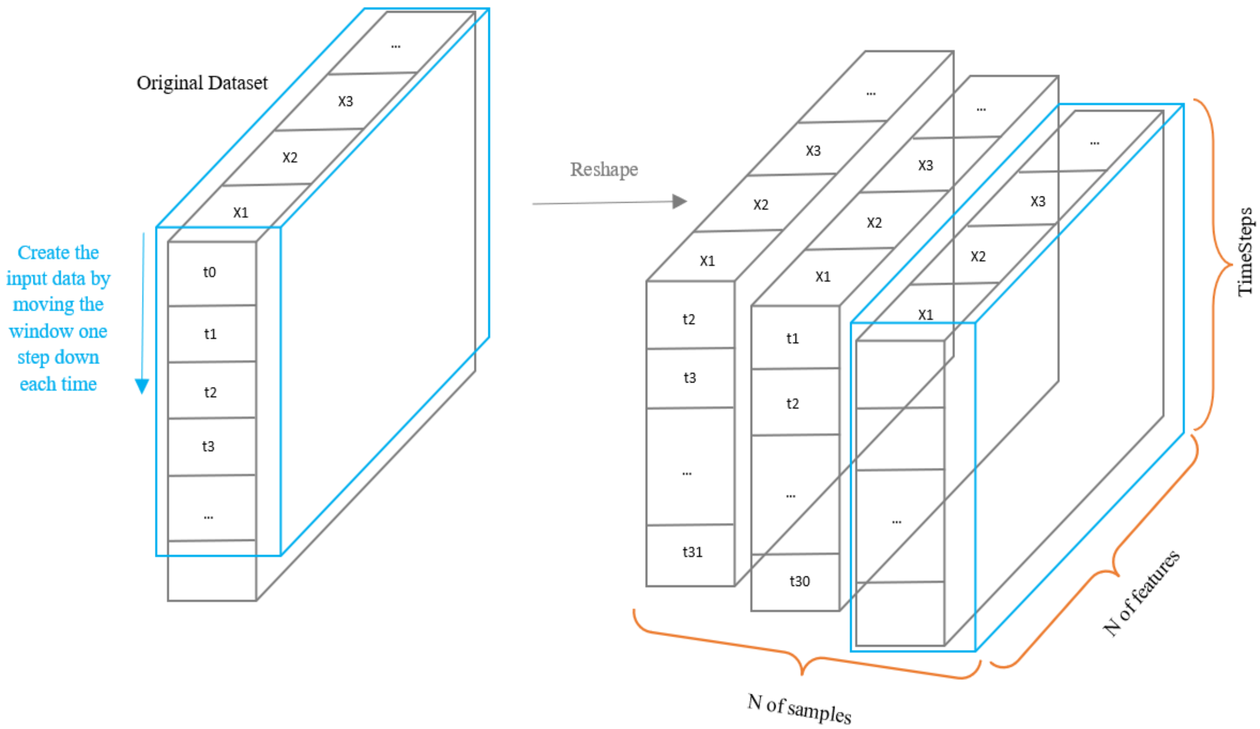

Fig. 2: Input data.

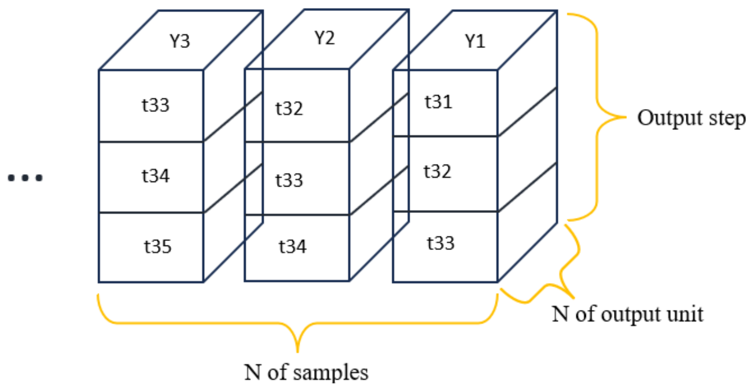

Fig. 3: Output data.

Evaluation and Result

In this paper, for evaluating the performance of the presented GAN model, we have employed the RMSE, MAE and MAPE metrics, defined by (5)-(7) respectively [30].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{N}} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{6}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{7}$$

In (5)-(7), N represents the number of data points, x_i denotes the actual Bitcoin price, and $\hat{x}_i$ represents the predicted Bitcoin price.

Fig. 4 and Fig. 5 illustrate the model's performance accuracy during the training and testing processes, respectively.

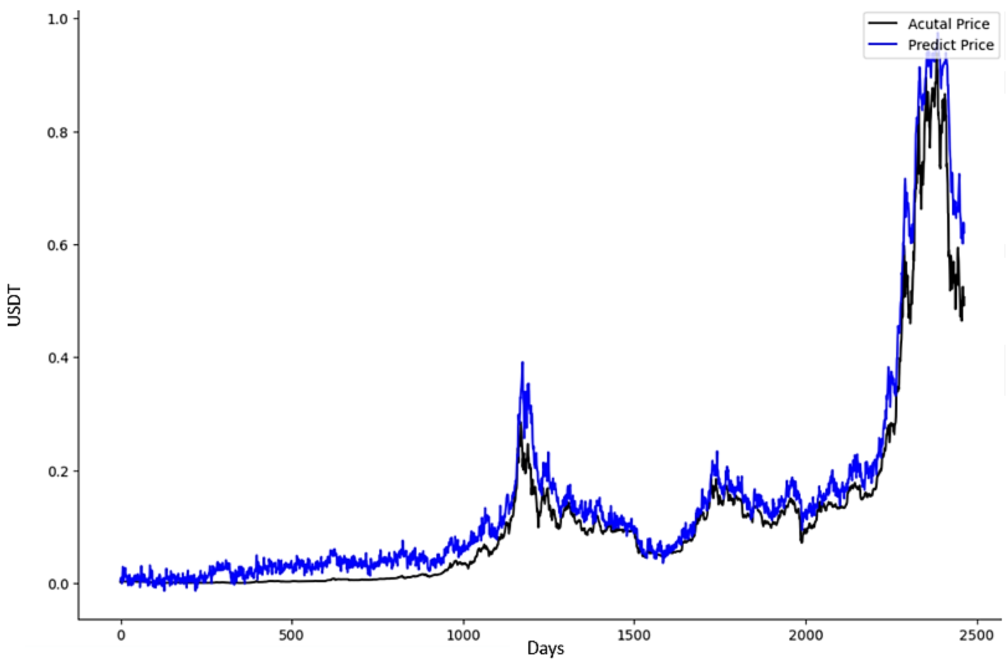

Fig. 4: The performance of the GAN model during the training phase.

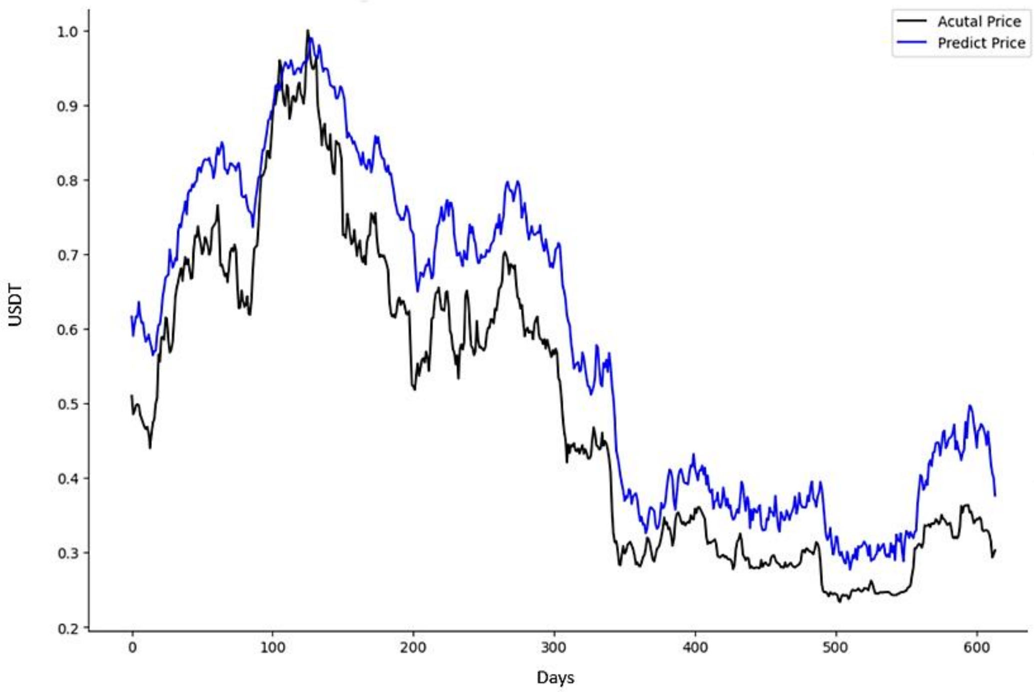

Fig. 5: The performance of the GAN model during the testing phase.

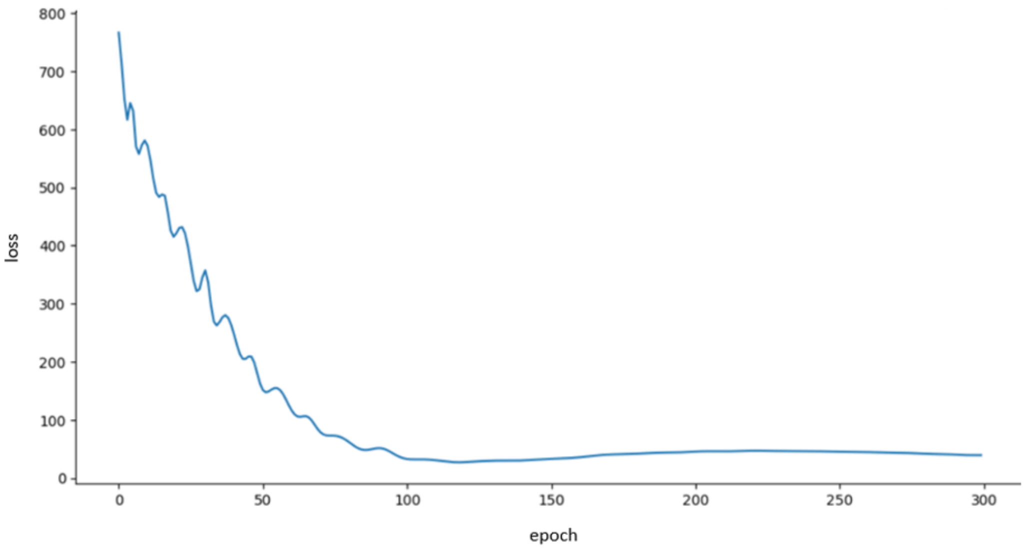

Fig. 6: GAN Loss Plot.

Fig. 4 illustrates the performance of the GAN model during the training process, and Fig. 5 displays its performance in the testing phase. The horizontal lines in Fig. 4 and Fig. 5 represent days, while the vertical lines denote the Bitcoin prices on each respective day. The black line in Fig. 4 and Fig. 5 represents the actual Bitcoin prices for each day, while the blue line depicts the predicted prices for Bitcoin on each day.

The RMSE, MAE and MAPE values obtained are also presented in Table 3, Table 4, and Table 5 respectively.

As indicated in Tables 3-5, these values indicate that overall, the GAN model has demonstrated good performance in predicting short-term Bitcoin prices, suggesting its potential utility in the cryptocurrency market. Fig. 6 shows the trend of loss reduction in this study.

As Fig. 6 illustrates, the loss value has significantly decreased from the beginning of the training process to around epoch 100, after which it has stabilized with minor fluctuations.

Table 3: RMSE values in GAN model

Stage	RMSE
Training	0.046
Testing	0.099

Table 4: MAE values in GAN model

Stage	MAE
Training	0.033
Testing	0.077

Table 5: MAPE values in GAN model

Stage	MAPE
Training	33.52%
Testing	75.24%

Conclusion and Future Suggestions

In this research, our primary focus was on examining the viability of implementing the Generative Adversarial Network (GAN) model within the cryptocurrency market. Specifically, we employed the GAN model to forecast short-term Bitcoin prices, utilizing a neural network architecture comprising two essential components: Generator and Discriminator, both functioning as distinct artificial neural networks. The Generator, responsible for producing synthetic data, was constructed using Gated Recurrent Units (GRU), while the Discriminator, designed to distinguish between real and generated data, employed a one-dimensional Convolutional Neural Network (CNN-1D). To conduct a thorough investigation, we amassed a dataset containing 738 features related to Bitcoin, spanning technical, fundamental, and additional data such as tweet counts and Google trends, collected daily from 01/10/2014 to 14/10/2023.

To pinpoint the most influential features within this extensive dataset, we applied the Gray Wolf algorithm. Subsequently, we partitioned the dataset, allocating 70% for training the GAN model and reserving the remaining 30% for assessing its predictive capabilities. The model's performance was then quantified using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) metrics. The experimental results, underscored by low RMSE values (0.046 during training and 0.099 in testing), validate the GAN model's efficacy in short-term Bitcoin price prediction. This substantiates the model's potential utility within the cryptocurrency market, opening avenues for comparative analyses against alternative models operating in this dynamic domain.

Through comparisons, architectural explorations, hyperparameter optimization, and training process refinements, researchers can discover strategies to boost the GAN model's effectiveness in the dynamic and complex cryptocurrency market.

1. Model Comparison: The first recommendation is to compare the GAN model with a variety of other models such as GRU, CNN, LSTM, Bi-LSTM, ARIMAX, etc. This comparative analysis aims to provide a deeper understanding of the relative strengths and weaknesses of each model. By evaluating how well the GAN model performs in comparison to these alternatives, researchers can gain insights into which model may be more suitable for specific scenarios or market conditions.

2. Exploring Different Architectures: The paragraph suggests exploring different artificial neural networks as both Generator and Discriminator. This means considering alternative configurations or types of neural networks for these crucial components of the GAN model. By experimenting with different architectures, researchers can identify which combinations yield the most accurate and reliable predictions. This exploration could involve testing variations in network depth, width, or incorporating novel neural network structures.

3. Optimizing Hyperparameters: The success of machine learning models heavily relies on choosing appropriate hyperparameters. Therefore, the paragraph highlights the importance of fine-tuning hyperparameters for the GAN model. This involves systematically adjusting parameters like learning rates, batch sizes, and layer configurations to optimize the model's performance. Bayesian Optimization, as mentioned earlier, is one approach that can be employed for this purpose.

4. Refining Training Processes: Continuous refinement of the training process is crucial for improving model performance. Researchers may consider experimenting with different optimization algorithms, regularization techniques, or introducing advanced training strategies. Bayesian Optimization, mentioned earlier in the context of hyperparameter tuning, can also be applied to refine the training process.

Author Contributions

Everyone contributed equally

Conflict of Interest

The authors declare that the authors have no competing interests as defined by JECEI, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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