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An Empirical Analysis on Price Forecasting of Bitcoin Using Deep Learning Models

Abstract: - Cryptocurrencies are among the most actively traded financial assets in the world, making price prediction a key concern for investors today. Currently, one kind of stock market investing is Bitcoin, a sort of cryptocurrency. Numerous things impact the stock market. Among the many cryptocurrencies that have surged in value recently is Bitcoin, which sometimes drops sharply without anybody realizing its impact on the stock market. An automated technique to forecast Bitcoin on the stock market is required due to its swings. The dataset, which was preprocessed, analyzed, and visualized using cryptocurrencies, was utilized for this study. The study suggests a CNN-GRU model that uses Gated Recurrent Units for sequence prediction and Convolutional Neural Networks for feature extraction. The current literature on price prediction is fragmented, inaccurate, and focused mostly on short-term forecasts. Training and testing the CNN-GRU model on the existing dataset to generate a long-term prediction is the innovative aspect of this study. Some measures of performance include decision accuracy, R2 Score, MSE, RMSE, and MAE. As a comparison, the best training performance for period 2 is 0.9988 with an RMSE of 562.08, MAPE of 0.0451, and R2 score of 0.9907. On the other hand, the best testing performance for period 2 is 0.9907 with an RMSE of 846.18, MAPE of 0.0134. Although it requires more time to build, the CNN-GRU model is determined to be the superior mechanism for time-series Bitcoin price prediction.

Keywords: Bitcoin,cryptocurrency, financial market, Price Prediction, machine learning and CNN-GRU model.

1. Introduction

These days, investors all across the world are on the lookout for assets that might reduce their portfolio risk while yet providing significant returns. As time has progressed, Bitcoin has gained more and more acceptance and recognition as a viable financial alternative. This change is due to the fact that institutional and ordinary investors alike have been captivated by the remarkable performance of cryptocurrencies. Actually, due to the increasing demand for cryptocurrency, a number of stockbrokers have started offering cryptocurrency ETFs, with a heavy emphasis on Bitcoin ETFs, which aim to monitor the price fluctuations of the most famous cryptocurrency [1][2]. Bitcoin is a decentralized digital money that functions without interference from banks or the government. It was created in 2008 under the pseudonym Satoshi Nakamoto by an individual or group. Security is guaranteed by the use of cryptography. Transparency and traceability are made possible via the blockchain, a public database that records Bitcoin transactions. Bitcoin's decentralized structure allows for quick worldwide transactions that are free of central bank control. As a consequence, Bitcoin has become popular as both a means of trade and a store of wealth [3][4].

The significant price volatility of Bitcoin is the main issue with the Bitcoin exchange rate. To successfully forecast the price of Bitcoin, one must take measures to account for its very volatile value. Telling people about Bitcoin's future price and gaining their confidence and acceptance on a global scale requires knowledge of the forecasting activity. The international connections of nations and the impact of their political systems, public relations, and market policies on different market tactics are two of many variables that might affect Bitcoin's economic function. As a conclusion, there is no formal roadmap; yet, there are a number of persistent difficulties and advancements in bitcoin prediction due to the lack of a detailed explanation of the exchange platform where buying and selling activities are unregulated[5][6].In an effort to understand Bitcoin's evolution, researchers have tried several methods. Some have investigated if there is a correlation between the price of Bitcoin and the price of crude oil, stock market indexes, or gold. However, prior studies have only shown weak links connecting Bitcoin to these more conventional assets [7][8][9].

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Machine learning has the ability to greatly enhance the accuracy of Bitcoin price predictions, making it a crucial tool in this field. Algorithms trained with ML can swiftly adjust to shifting market circumstances, evaluate massive datasets, manage complicated and non-linear connections, and discover and capitalize on complex patterns in Bitcoin price data [10][11]. In order to effectively manage risk and develop investment strategies, accurate Bitcoin price forecasts are crucial. Traders and investors may use machine learning models to evaluate the risks and rewards of various trading actions. Trading algorithms powered by machine learning may also automate trades, allowing investors to capitalize on market inefficiencies and increase their potential profits. The use of ML methods for Bitcoin price forecasting advances scholarly studies in economics and finance[12].This article aims to minimize risks for decision-makers and investors by utilizing deep learning models to create more exact Bitcoin price forecasts. In this research, itprovide a new way to build prediction models utilizing a deep learning strategy. Due to the deep learning model's consideration of the non-linear character of pricing, the suggested method outperformed the machine learning models used for prediction. The findings confirm the model's usefulness and point investors in the direction of potential uses of deep learning methods in decision-making.

1.1 Motivation and Contribution of the Study

This study uses the CNN-GRU algorithm to forecast Bitcoin prices since, in the background, it is necessary to mitigate Bitcoin price risk. This research uses state-of-the-art ML algorithms to make substantial progress in forecasting Bitcoin values.Integrating a CNN-GRU model, it enhances the accuracy of forecasts through effective feature extraction and sequence prediction.

- Implemented smoothing techniques and normalization with MinMaxScaler to improve data consistency and reduce noise, ensuring reliable model performance.
- Utilizes a CNN-GRU hybrid model for accurate Bitcoin price predictions, leveraging CNNs for feature extraction and GRUs for sequence learning.
- Evaluates model accuracy using R2 Score, MSE, MAE, RMSE, and Decision Accuracy (DA), providing a thorough assessment of forecasting capabilities.
- Offers insights for investors and analysts in making informed decisions, managing risks, and developing effective trading strategies in cryptocurrency markets.
- The work's innovation lies in its use of the existing dataset to train and test the CNN-GRU model, which yields a long-term prediction.

1.2 Paper organizations

This is how the remainder of the paper is arranged: In Section 2, the methods and approaches currently in use to forecast Bitcoin prices are covered. The research approaches used in this study are presented in Section 3.Discuss the experiment's outcomes and the study project's evaluations in Section 4. Section 5 contains the conclusions of their research study and recommendations for further work.

2. Literature Review

This section reviews and examines previously published papers about Bitcoin prediction research utilizing various machine learning and deep learning methodologies. The assessment took into account papers from the previous five years. They are further explained below:

Ahmadchitkara et al. (2023)execute and evaluate five distinct ML and statistical algorithms for predicting the price of Bitcoin the day after tomorrow. This study makes use of a variety of methods, including RF, LSTM models, Ridge regression, Lasso regression, and SVR. From November 2021 through February 2023, the daily trading data was used in this study. Based on the results of the trials, they can say that the LSTM model and Lasso regression both accurately estimate the value of Bitcoin the following day with a 97.88% accuracy rate. RF and SVM come in second and third, with 94.65% and 94.40% accuracy rates, respectively. Nevertheless, the Ridge regression achieves the best accuracy at 98.02%[13].

Ahmed et al. (2023)examine several techniques used by ML regression models to determine the system capable of producing the most accurate and efficient estimates of Bitcoin values based on various criteria. Careful analysis and preprocessing of the dataset followed by the use of various machine learning regression models—

including XGBoosting, GBR, Hist Gradient Boosting Regressor, RF, Linear Regression, SVR, Neural Network Regressor, DT, GPR, and KNN Regressor—to predict the price of Bitcoin. The most notable results were an R-squared (R2) of 99.497 percent (nearly 99.5%), an RMSE of 0.01281, and an MAE of 0.005755 using the GBR model[14].

Sonare et al. (2023)investigate, using a variety of historical data sets, how well ML models can forecast the price of Bitcoin. For the purpose of determining the most effective ML algorithms for both the short- and long-term prediction of Bitcoin prices, they compare and contrast their accuracy levels[15].

The three-category challenge is characterized by Yan, Lei and Wang (2022) as using the change rate over big Bitcoin price to predict the fluctuations for a few days. LSTM, and GRU are two DL models used to investigate the expected outcomes, with LSTM outperforming the GRU along with a highest AUC value of 0.701[16].

Ramani et al. (2023)executed sentiment analysis, XGBoost, LSTM, Autoregressive Integrated Moving Average, Prophet, and DL on Bitcoin data. Predicted measures such as RMSE, MAE, and R2 are used to compare the outcomes of the algorithms that were trained on live streaming financial data. Out of all the algorithms tested, sentiment analysis paired with LSTM produced the best results for predicting the price of Bitcoin[17].

Aggarwal et al. (2019)RMSE is used in a comparative analysis of the factors influencing Bitcoin price prediction. Various DL models, such as CNN, LSTM, and GRU, are used. The impact of the gold price on the Bitcoin price has been investigated[18].

Kumar.a, Pv and Jackson, (2023)development also focused on creating a reliable time series model that uses ML to forecast the price of BTC. Bitcoin price fluctuations necessitated the development of LSTM forecasting theory, which yields impressive accuracy. Comparing the LSTM to similar time-series models in this proposed research shows that it is effective in predicting cryptocurrency prices[19].

Dimitriadou and Gregoriou(2023)use a GRU model, an ANN based on DL, to make accurate predictions about the future price of Bitcoin using the existing previous price data. The most important metrics for evaluating the accuracy of forecasts are the RMSE and the MAPE[20].

To address this requirement,Malhotra et al. (2022)this article examines the relative efficacy of several ML algorithms on the popular cryptocurrency (Bitcoin). They tested the performance of several ML models to find out how accurate they were for Bitcoin. The findings demonstrate that among the models tested, ARIMA had the best performance and the lowest MAE[21].

Nesakumar et al. (2022)offered a complete account of their work, stating the way they utilized tree regressions for evaluating the Bitcoin prices, the evaluation with ARIMA-based models, and finally, LSTM models. The ARIMA model's R is flat at 0.94, whereas the LSTM model's R is flat at 0.49. They may thus see that the deep learning (DL) model outperforms the machine learning (ML) model[22].

Freeda, Selvan and Hemanandhini(2021)suggested method that improves upon previous approaches by using DL to forecast Bitcoin prices using a RNN model trained on time series data. The value of Bitcoin in 2021 is forecasted in this piece of writing. Based on comparisons with different ML algorithms, such as RF, SVM, GNB, and KNN, the suggested study demonstrates that the RNN model achieves a better accuracy of 76.99%[23].

The following Table 1 presents the comparative analysis of the related study on Bitcoin price prediction using multiple techniques.

Table 1: Related study on Bitcoin price prediction through the machine and deep learning methods

Ref	Models	Source	Accuracy	Limitation
Ahmadchitkara et al. (2023)	RF, SVR, Ridge Regression, Lasso Regression, LSTM	Daily traded data from November 2021 to February 2023	LSTM and Lasso: 97.88%, Ridge: 98.02%, RF: 94.65%, SVR: 94.40%	• Limited period; • need for validation with larger datasets over a longer period to confirm consistency and reliability.

Ahmed et al. (2023)	XGBoosting, GBR, Hist Gradient Boosting, RF, Linear Regression, SVR, Neural Network,DT, Gaussian Process, KNN Regressor	Meticulously analyzed and preprocessed dataset	GBRegressor: R^2 = 99.497%, RMSE = 0.01281, MAE = 0.005755	• Extensive model comparisons; • need for further analysis on computational complexity and real-time prediction capabilities.
Yan, Lei and Wang (2022)	LSTM, GRU	Change rate over big Bitcoin price	LSTM: AUC = 0.701	• Limited to few days of fluctuation prediction; • Requires exploration of longer-term predictions and additional evaluation metrics.
Freeda, Selvan and Hemanandhini(2021)	RNN, RF, Gaussian Naïve Bayes, SVM, KNN	Time series data	RNN: 76.99%	• RNN model shows improved accuracy but overall lower accuracy compared to other studies; • need for comparison with more advanced models like LSTM or GRU.
Nesakumar et al. (2022)	Tree Regressions, ARIMA, Long Short-Term Memory (LSTM)	Information gathered from Bitcoin Sets	DT: R^2 = 0.67, ARIMA: R^2 = 0.94, LSTM: R^2 = 0.49	• LSTM underperforms compared to ARIMA; • need for hybrid models combining strengths of both ML and DL approaches for improved accuracy.

2.1 Research gaps

The examination of a variety of Bitcoin price prediction models exposes both their strengths and weaknesses. The lack of consistency over longer periods is a cause for worry since some models attain great accuracy but are constrained by tiny datasets. Complex models sometimes lack real-time testing and are linked with high computing complexity, yet producing outstanding results. Some models excel at making short-term forecasts, but very little is known about how to foresee the future. A combination of deep learning and more conventional time series models may provide better results in some cases. In general, they need to keep improving, fix the problems with their datasets, and find a happy medium between too complicated models and their real-world applications.

3. Research Methodology

The suggested technique finds and evaluates important variables to anticipate the daily price of bitcoin using two prediction models based on DL. Using ML techniques, this research intends to forecast Bitcoin values.In this study, use python simulation tool and its packages such as Pandas, numpy, matplotlib, plotly, Min-MaxScaler, etcThe methodology involves several key steps: data collection focuses on acquiring a raw dataset containing daily financial and blockchain metrics, with emphasis on Bitcoin (BTC) data such as Date and BTC_Close. The first step in data preparation is to improve the data quality by employing smoothing techniques like moving averages and deleting extraneous characteristics like weekday names. Thus, it is preprocessed using MinMaxScaler in order to bring all the features to a common scale and structure them into a picture. The decoupling of data means splitting the dataset with start and finish dates into two parts: the training sample and the test sample. For feature extraction from raw input data the CNN-GRU uses feature extractors, which are the Convolutional Neural Networks (CNNs). For the sequence prediction, it uses Gated Recurrent Units (GRU), which is very effective in handling the sequential data. MSE, MAE, RMSE, DA, R2 Score, and out-of-bag accuracy are among the Performance evaluation metrics useful in determining of general forecasting ability of a model for Bitcoin price. In the following Figure 1 is showing, flow of data in the format of different steps and phases.

3.1 Data collection

For bitcoin price prediction, use Github[2]Dataset. The dataset corresponds to daily financial and blockchain data, Bitcoin (BTC) being at the center together with other crypto-assets and classic financial indexes. Squashing Bitcoin data that has only Date and BTC_Close columns into a new data structure.

3.2 Data preprocessing

A high-quality and analytic-ready dataset begins with thorough pre-processing of data. For their prediction models to be more accurate, it must eliminate any errors or discrepancies in the data. This study involves different preprocessing key steps. First, the dummy column with weekday names was removed to reduce noise. After that, the data was smoothed using methods such as moving averages to bring out patterns and minimize noise; the total length of the data set is 2557. Finally, the data was converted into a structured format, and the features were normalized for consistency. These steps collectively improved the dataset's suitability for training.

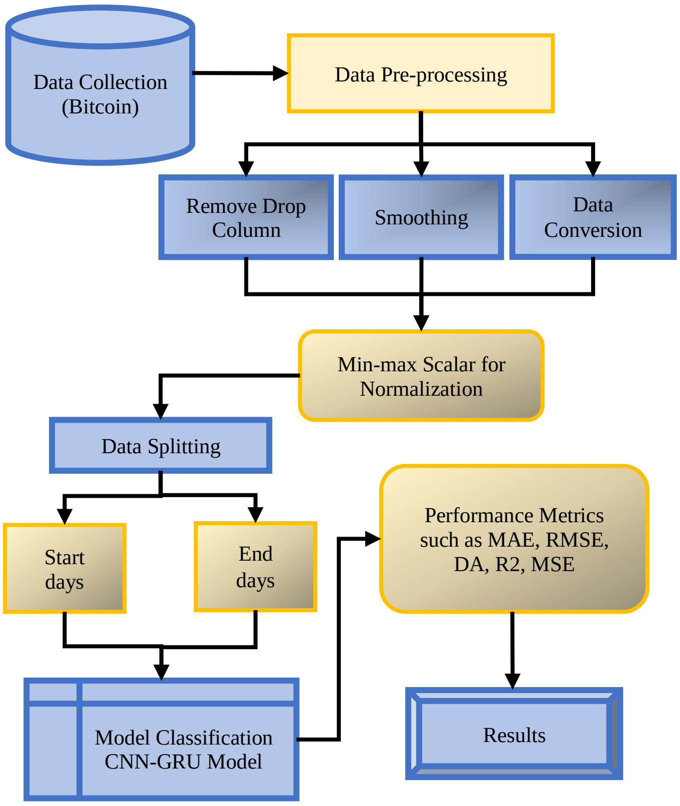

Figure 1: Proposed flowchart for Bitcoin price prediction

3.3 Min-MaxScaler for Normalization

Normalization, or Min-Max scaling, is a commonly used method. To make values lie between 0 and 1, this approach adjusts and rescales the values. By using the Equation (1), the transformation is accomplished.

$$x' = \frac{(x - x_{min})}{x_{\max} - x_{min}} \quad (1)$$

When X' stands for the normalised value, Xmax and Xmin are the maximum and lowest values of the corresponding feature, and X represents the original value.

3.4 Data splitting

[2]https://raw.githubusercontent.com/shiitake-github/jrfm-2156907-data/main/jrfm-2156907.csv

Data splitting is essential because it allows us to accurately gauge the model's performance, which in turn helps us choose the best model, and it confirms that the model can generalize well. The dataset was divided according to the start and end days of this investigation.

3.5 Proposed CNN-GRU model

Image identification and classification were the first applications for convolutional neural networks (CNNs), but these networks have already found applications in several other domains of computer science, such as semantic segmentation, localization, object detection, image super-resolution, and many more [24][25]. This design primarily lessens the need for manually produced features since CNNs are so good at learning problem-specific characteristics from raw input data.

GRU—an updated version of LSTM—consists of update (zt) and reset (rt) gates[26][27]. The LSTM network is optimized using GRU without sacrificing LSTM performance. One may adjust the amount of past information being brought into the present instant by using the update gate, and one can adjust the amount of past information being ignored by using the reset gate. The amount of prior information to be preserved and the method by which fresh input is merged with the last memory are determined by rt and zt, respectively. Equations (2–5) allow us to describe rt and zt, which are new memories (hti) and hidden states (ht), respectively:

$$r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right) \tag{2}$$

$$z_t = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right) \tag{3}$$

$$h_{ti} = tanh = (r_t \ o \ Uh_{t-1} + \ Wx_t) \tag{4}$$

$$h_t = (1 - z_t)o \ h_{ti} + z_t \ o \ h_{t-1} \tag{5}$$

where σ(…) is a sigmoidal function, and W(r) and W(z) are weight matrices, while o is the element-wise product.The proposedCNN-GRU model train with 32 batch size, 100 epochs and 3 lookbacks.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 2, 200)            600

 gru (GRU)                   (None, 2, 200)            241200

 gru_1 (GRU)                 (None, 2, 200)            241200

 gru_2 (GRU)                 (None, 200)               241200

 dense (Dense)               (None, 1)                 201

=================================================================
Total params: 724,401
Trainable params: 724,401
Non-trainable params: 0
```

Figure 2: Model summary of CNN-GRU

The proposed model CNN-GRU summary is shown in Figure 2.The CNN-GRU architecture combines Conv1D layers for feature extraction with multiple GRU layers for sequence prediction. The model has 724,401 trainable and total parameters with 0 non-trainable parameters, making it robust for complex prediction tasks.

4. Results and Discussions

In this section, provide the experimental outcomes and data analysis results for bitcoin price perdition using machine learning methods. The experimental results were obtained from an HP laptop, Core i7 8th generation, 64 GB RAM, and also from hardware devices. The machine learning models implement on python tool with google colab, jupyter notebook simulation tools. The results are compared during training and testing for period 1 and period 2 with performance measures such as RMSE, MAPE, DA, MSE, and R2 score. The Extract data insight knowledge with graphs are present below.

4.1 EDA (Exploratory Data Analysis)

An exploratory data analysis technique looks beyond formal modelling or hypothesis testing tasks to explore what the data might tell us. The four main components of EDA analysis are measures of central tendency (mean, mode, and median), measures of spread (standard deviation and variance), distribution shape, and outlier presence. These components aid in the analysis of the data sets to provide a summary of their statistical properties.A discussion of these important elements of EDA on the Bitcoin dataset using the seaborn and matplotlib tools is provided in the following paragraphs.

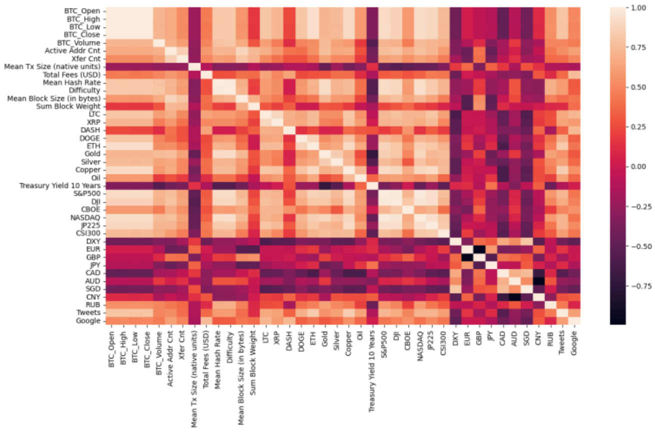

Figure 3: Plotting correlation heatmap

The following Figure 3 shows the correlation heatmap uses colored squares to show relationships between variables: dark red for strong positive correlations, and dark blue for strong negative ones. It's crucial in finance to understand how assets or indicators move together, aiding in risk management and investment strategies.

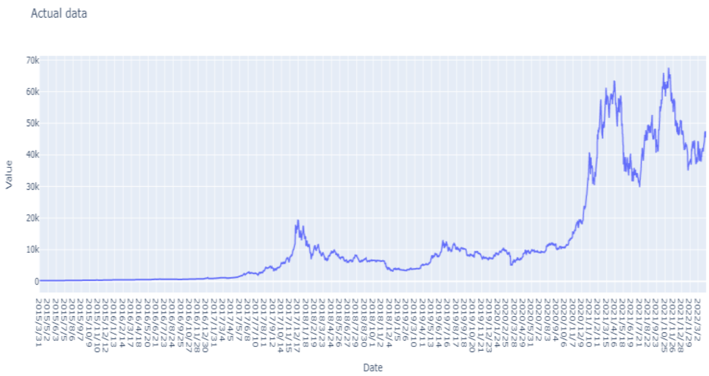

Figure 4: Sets the index based on the Date column.

The above Figure 4 shows the line Plot for Date column. In this figure, the x-axis represents dates ranging from 2014 to 2022. y-axis denotes the values, which reach a peak of approximately 70k.

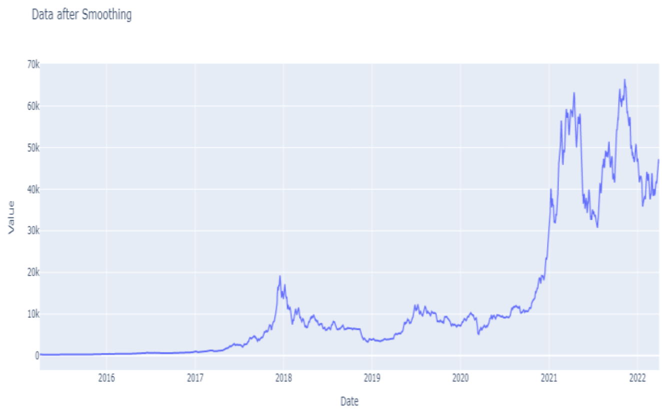

Figure 5: Making a windowed dataset for Period 1

Figure 5 displays the line plot of the smoothed data values over the same time frame. The X-axis represents dates, ranging from 2016 to 2022, and the Y-axis shows values up to around 70k.

4.2 Performance Metrics

It is necessary to have metrics in order to evaluate an ML model's performance. R2 Score, MSE, MAE, MAPE, RMSE, and Decision Accuracy (DA) are the metrics put to use in this investigation. The accuracy or misleadingness of regression models may be assessed using these validation measures.

MAE:The MAEmeasures how much the actual values depart from the expected values. As a measure of inaccuracy between two observations of the same phenomena, it has another possible definition. Mathematical representation for MAE Equation (6).

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|y_j - \bar{y}_j\right| \quad (6)$$

RMSE:A RMSE is calculated as the average of the squared differences between the target value and the model's projected value. The Equation is (7).

$$RMSE = \frac{1}{N}\sum_{j=1}^{N}\left(y_j - \bar{y}j\right)^2 \quad (7)$$

R squared (R^2):The R squared performance indicator shows the degree to which actual values are consistent with well-predicted values. The Equation is R^2 (8) is given below:

$$R^2 = 1 - \frac{\sum(y_i - \bar{y}_i)^2}{(y_i - \bar{y}_j)^2} \quad (8)$$

MSE:The error score is calculated as the average of the squared deviations of the projected and expected values. The mathematical expression is Equation (9)

$$MSE = \frac{1}{N}\sum_{i=1}^{N} y_i - \hat{y}_i)^2 \quad (9)$$

DA: decision as one in which there is a one-to-one correspondence between the factors that affect a decision and those that affect experience. The mathematical expression is Equation (10):

$$DA = \frac{m}{t=1} a(t) x 100\% \quad (10)$$

MAPE:(MAPE), which stands for mean absolute percentage deviation (MAPD), is a statistical metric that assesses the precision of a forecasting technique. Then, MAPE is defined as Equation (11)

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \quad (11)$$

4.3 Experiment results

The training and testing experiment results of proposed CNN-GRU modeldiscussionis presented in this section. The performance analysis based on the performance metrics for period 1 and period 2.

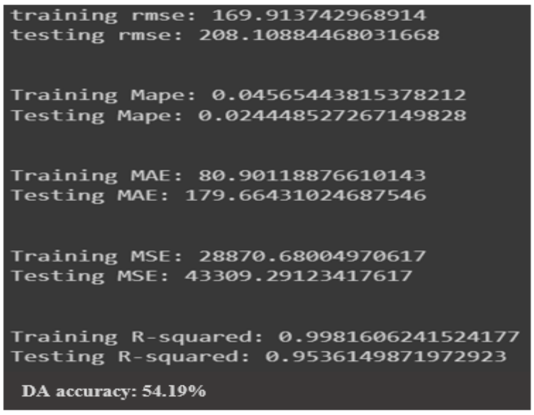

Figure 6: Performance analysis for period 1

The following Figure 6 displays the training and testing performance for period 1. The training and testing RMSE are 169.91 and 208.11, MSE are 28870.68 and 43309.29. MAPE value is0.0457 training and 0.0244 testing, and MAE is 80.90 for training and 179.66 for testing. The decision accuracy is 54.19 correctness of the model's prediction based on the change of direction (positive or negative) rather than the specific values. These metrics indicate high training accuracy and slightly lower testing performance, suggesting good model fit with some generalization issues.

Figure 7: Plotting the Actual v/s Predicted value for Period 1

Plot graph for Actual v/s Predicted value for Period 1 shown in Figure 7.The x-axis (ranging from January 2015 to July 2018). The y-axis represents the value, likely ranging from 0 to 20,000. The Actual values peak slightly higher than the Predicted values around early to mid-2017.

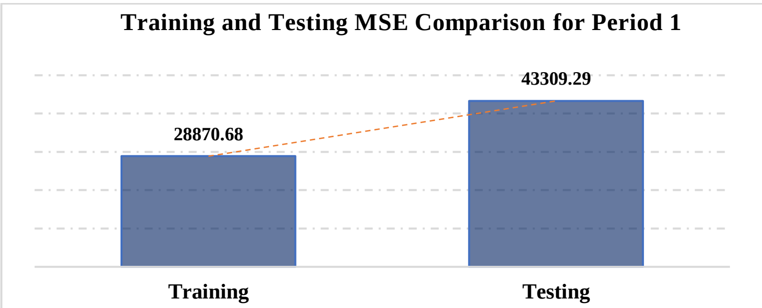

Figure 8: MSE comparison between training and testing for Period 1

The bar graph in Figure 8 illustrates the comparison between MSE values during training and testing. The training phase MSE value of 28870.68, and the testing MSE value of 43309.29.

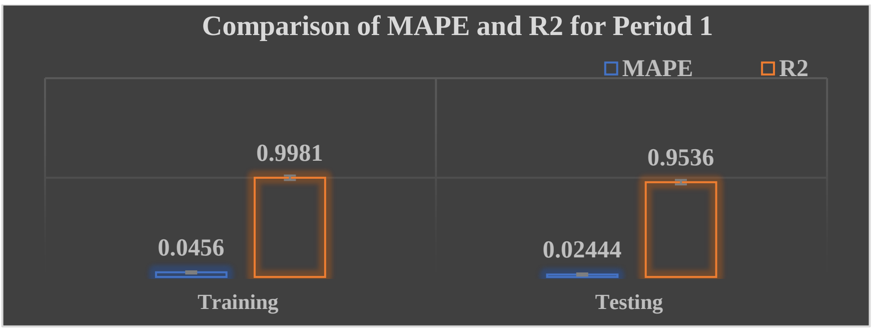

Figure 9: MAPE and R2 score comparison for Period 1

The training and testing comparison between MAPE and R^2 score is displayed in Figure 9. In this figure, training and testing MAPE are 0.0456 and 0.02444. The R2 Score for training 0.9981 and 0.9536 for testing.

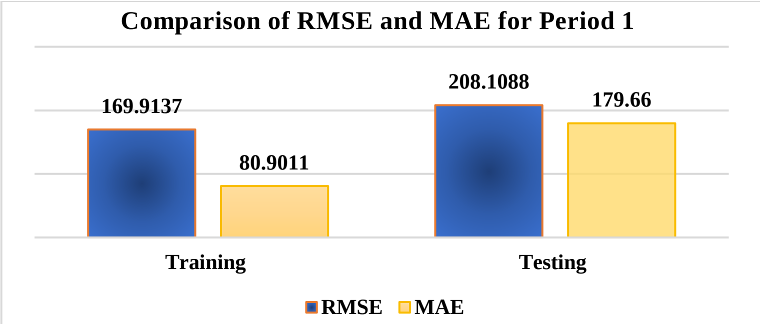

Figure 10: MAPE and R2 comparison between Period 1

The following Figure 10 shows the MAPE and R2 comparison during training and testing. RMSE is 169.91 and MAE is 80.90 for training data. For testing data, RMSE is 208.11 and MAE is 179.66.

```
training rmse:  562.0781840503206
testing rmse:  846.1763969576216


Training Mape:  0.045090276321090667
Testing Mape:  0.013380581533430278


Training MAE:  462.5658009582145
Testing MAE:  654.7243657914333


Training MSE:  315931.88498530607
Testing MSE:  716014.4947681824


Training R-squared:  0.9988397954004236
Testing R-squared:  0.9907372667128284


DA accuracy:  67.98%
```

Figure 11: Performance analysis for period 2

Figure 11 displays the training and testing Performance analysis for period 2. Training and testing RMSE are 562.08 and 846.18, MAE are 0.0451 and 0.0134, MSE are 462.57 and 654.72, R2 are 0.9988 and 0.9907.The R-squared values indicate how well the model generalizes new data. The DA accuracy is 67.98%.

Figure 12: Plotting the Actual v/s Predicted for Period 2

line graph comparing the actual values to the predicted values for Period 2 display in Figure 12. The x-axis spans from January 2015 to July 2018, indicating a time series. The y-axis represents a quantity ranging from 0 to 20k. The actual values peak slightly higher than the predicted values.

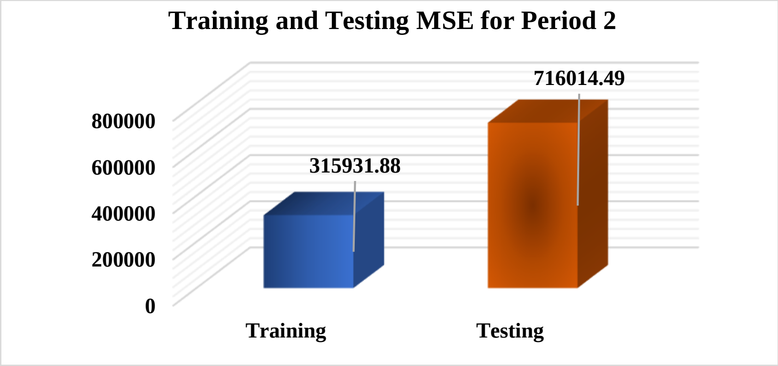

Figure 13: Performance of MSE for Period 2

The MSE for period 2 is shown in Figure 13. The MSE compares Training and Testing. The MSE is 315931.88 for training and 716014.49 for testing.

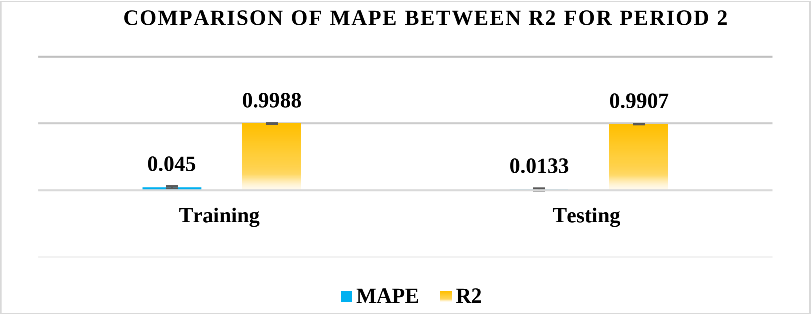

Figure 14: Comparison of MAPE and R2 during training and testing

The training and testing comparison between MAPE and $R^2$are shown in Figure 14. The MAPE values for training and testing are 0.045 and 0.0133. The 0.9988 R2 score for training and 0.9907 for testing.

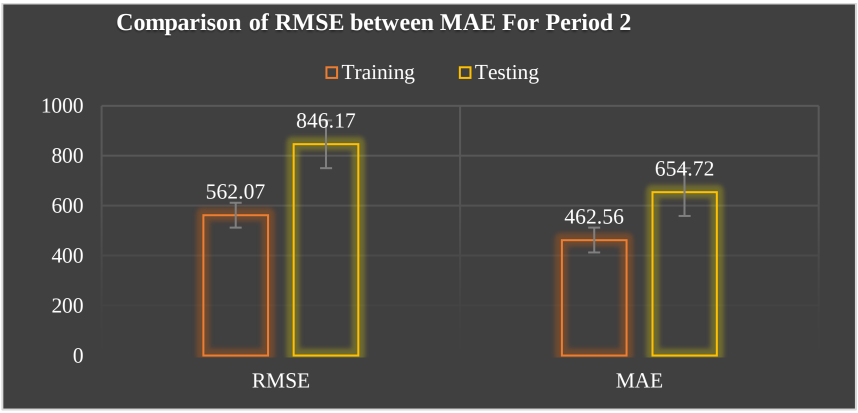

Figure 15: Comparison of RMSE and MAE during training and testing

A comparison of RMSE and MAE during training and testing is shown in Figure 15 above. RMSE Training is 846.17, and Testing is 562.07. In MAE, Training is 654.72, and Testing is 462.56, respectively.

The overall performance analysis for periods 1 and 2 indicates that while the models perform well during training, there are notable discrepancies in testing performance. The testing results underscore the need for improved generalization to enhance prediction reliability on unseen data.

4.4 Comparative Analysis

The following Table 2 provides the comparison between the existing random forest regressor (RFR) model and the proposed CNN-GRU model for the bitcoin price prediction on the GitHub dataset in terms of RMSE, MAPE, and DA accuracy.

Table 2: Comparison between proposed and existing models for bitcoin prediction

Parameters	Period 1		Period 2	
	Proposed	Existing	Proposed	Existing
	CNN-GRU	RFR	CNN-GRU	RFR
RMSE	208.10	320.37	846.17	2076.99
MAPE	0.024	0.0333	0.013	0.032
DA Accuracy	54.19	53.59	67.98	51.93

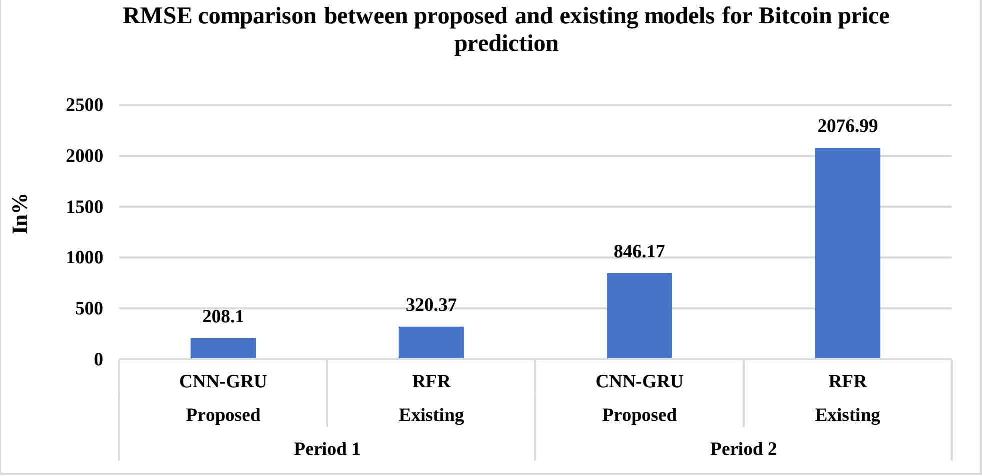

Figure 16: Bar graph of RMSE comparison between proposed and existing models for Bitcoin price prediction.

Figure 16 displays the RMSE for both the proposed CNN-GRU model and the existing RFR model across Period 1 and Period 2. In Period 1, the CNN-GRU model achieved an RMSE of 208.10, significantly outperforming the RFR model, which had an RMSE of 320.37. This trend continued into Period 2, where the CNN-GRU model maintained a lower RMSE of 846.17 compared to the RFR model's 2076.99. The lower RMSE values indicate that the CNN-GRU model offers better predictive accuracy and consistency, particularly in the more volatile Period 2.

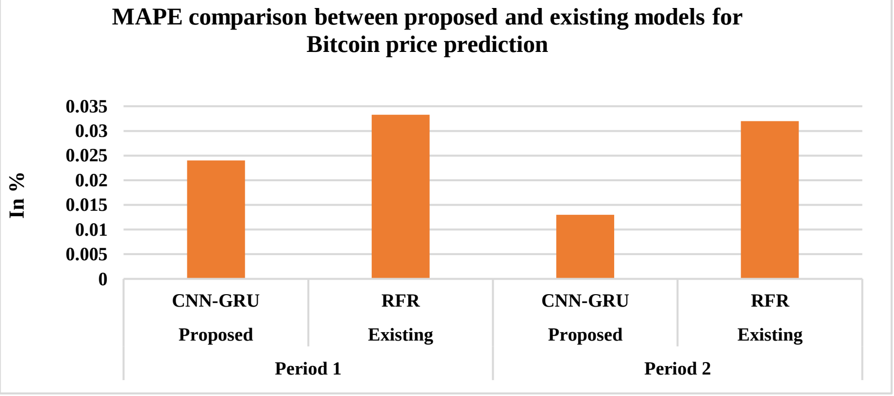

Figure 17: Bar graph of MAPE comparison between proposed and existing models for Bitcoin price prediction.

Figure 17 compares the Mean Absolute Percentage Error (MAPE) for both models in the same periods. In Period 1, the CNN-GRU model had a MAPE of 0.024, while the RFR model had a slightly higher MAPE of 0.0333. In Period 2, the CNN-GRU model demonstrated a substantial improvement in accuracy with a MAPE of 0.013, whereas the RFR model's MAPE remained higher at 0.032. This also shows that the proposed CNN-GRU model achieves a smaller absolute error on a test dataset and has less variance in consecutive time points.

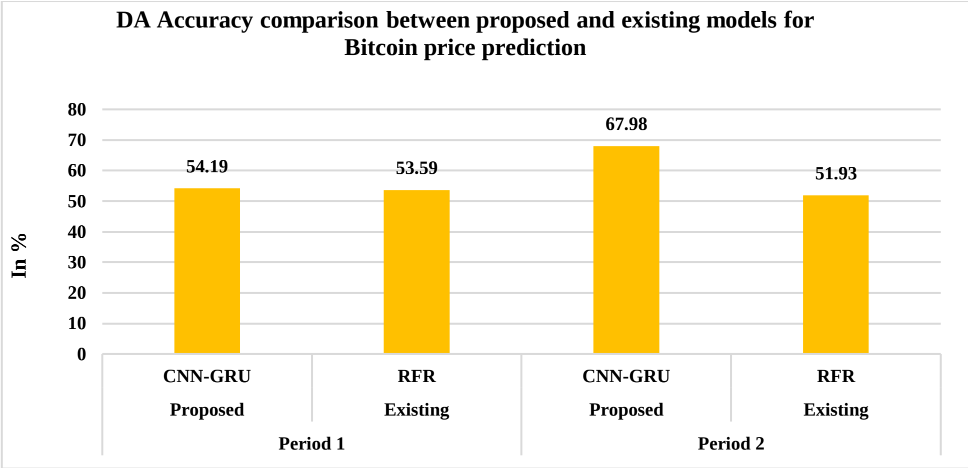

Figure 18: Bar graph of DA Accuracy comparison between proposed and existing models for Bitcoin price prediction.

Figure 18 shows Directional Accuracy, which summarizes how well the models predict the direction of a price movement. At Period 1, the proposed method CNN-GRU has 54.19% of DA accuracy which is slightly higher than the accuracy of using the RFR model, 53.59%. This enhancement was observed in Period 2, which saw the CNN-GRU model's DA accuracy rise to 67.98%, while the RFR model's was 51.93%. This massive gap asserts that the CNN-GRU model outperforms the benchmark of providing directionality of BTC prices.

Specifically, the proposed CNN-GRU model achieves better results than the existing RFR model in terms of all the evaluation metrics (RMSE, MAPE, and DA Accuracy) for the two periods. This implies that the CNN-GRU model is the best for the prediction of the Bitcoin price since it has lower error rates and tends to be highly directional hence more reliable in the analysis of the markets.

5. Conclusion and Future Work

A common area of study in the fields of AI and finance is the use of ML methods to forecast future changes in the price of Bitcoin. This research looked at ML techniques that forecast Bitcoin prices using sample dimensions and attributes. The suggested method examines and pre-processes the widely used dataset in an innovative way. The experimental results showed high training performance, with the highest training R2 score of 0.9988, RMSE of 169.91, and MAPE of 0.0457 for period 1, and R2 score of 0.9988, RMSE of 562.08, and MAPE of 0.0451 for period 2. The major problem is the difference between the training accuracy and test accuracy, which points at overfitting and poor ability to generalize on unseen data. Besides, the CNN-GRU model seems to have higher computational complexity, and its scalability and real-time prediction may be a restriction. To avoid these shortcomings, additional advanced investigations are needed regarding how to increase the model's generalization, the inclusion of a diverse data source, and more efficient algorithms. Applying more variables to the classification, including additional data with the Bitcoin rates, expanding the time horizon, and taking into account outside factors affecting the price can increase the model's reliability. However, reducing the complexity of the model architecture while not effecting the quality of the outcomes might also improve the aspects of scalability and real time application. Further studies in these fields will lead to considerably more accurate methods for forecasting bitcoins' price.

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