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Enhancing Financial Predictions Based on Bitcoin Prices using Big Data and Deep Learning Approach

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ABSTRACT

An increasingly popular alternative investing strategy, trading digital money is gaining traction daily. In terms of technological implementation, Bitcoin is among the most prominent digital currencies. Bitcoin is decentralised and doesn't answer to any government, but that hasn't stopped many investors from trading in it and stimulating the economy. The purpose of this study is to forecast the next day's bitcoin price using five separate statistical and ML methods and to evaluate and contrast them. The ever-changing cryptocurrency industry, however, makes Bitcoin price prediction an increasingly important task. This study examines the effectiveness of several MLP, RNN, ARIMA, and SVM-based models in predicting Bitcoin prices. When applied to the historical price data, an MLP model turned out to be the most efficient, with an R^2 at 95.9%, while ARIMA was at 90.31%, SVM at 67.3%, and RNN at only 50.25%. The 60-day evaluation proved the proposed MLP model's accuracy in capturing short-term price movements, thus supporting the concept of a good fit. This work is then useful to establish sound guidelines in including ML and DL strategies in financial prediction, showcasing MLP model to improve decision-making during turbulence. More improvements can include other market factors and better configurations for improved precision and capacity.

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1. 1. Introduction

Internet accessibility has rapidly increased and brought with it a host of new approaches and processes in the real world. Cryptocurrency is one type of cash which is becoming established on the Internet as an alternative to the monetary system. Electronic money or virtual money is defined as an emerging way to exchange or transfer value electronically. Bitcoin has observed high volatility at large, which depends upon different factors associated with market sentiment, macroeconomic factors, and technological factors. Therefore, achieving correct price estimates is crucial for hedge and leverage on the volatility in the cryptocurrency area. The topic of how to forecast the future value of Bitcoin has been quite the focus of interest for quite some time now. When it comes to the total market valuation of cryptocurrencies, none is more important than Bitcoin, the pioneer of the blockchain monetary renaissance.

The traditional methods of financial forecasting are insufficient to identify the inherent nonlinearity and complexity of the dynamics in the prices of Bitcoins. A huge leap forward in the capacity to forecast financial outcomes has been achieved by the combination of sophisticated AI methods with big data analytics. Using the historical market data, social sentiment analysis and other factors, researchers, therefore, seek to develop accurate models for not only predicting Bitcoin price but also exploring and explaining drivers for market volatility. This work seeks to examine research questions touching on ways in which DL and big data would enhance Bitcoin price forecasts to reduce risks in the volatile crypto markets. There have been instances of ML and DL methods making use of massive datasets to improvise and glean insights from the data.

In contrast, DL models allow real-time projection updates, as well as dynamic consideration of new data when it appears. Another advantage of the DL models, which makes it possible to steadily enhance its accuracy as well as dependability, consists of flexibility. It is possible to analyse Bitcoin price history and predict future price patterns.

Significance and Contribution of Study

The important implication is increasing the reliability of the forecasted financial data within the uncertain environment of cryptocurrencies focusing on Bitcoin price. By integrating advanced data pre-processing techniques, feature selection, and robust forecasting models, it addresses the inherent challenges of noisy and unstructured data. This framework leverages big data and deep learning approaches to provide actionable insights for traders, investors, and financial analysts [9]. Additionally, the evaluation of multiple models and the use of performance metrics ensure a comprehensive and systematic approach to identifying the most reliable forecasting model, which is critical in financial decision-making. The contributions are as follows:

To develop a systematic pipeline for enhancing financial predictions using Bitcoin price data.

To implement data pre-processing techniques, including data cleaning, and Min-Max normalisation, to ensure high-quality inputs for model training.

To employ multiple forecasting models, including MLP, RNN, ARIMA, and SVM, for predicting Bitcoin prices.

To evaluate model performance using error metrics such as RMSE, MSE, and R^2, ensuring an accurate performance comparison.

Structure of the paper

The study is structured as follow: In Section II the existing literature on Bitcoin Prices using Big Data in section III methodology utilised to compile the data for this study. Section IV provide the results and analysis of text classification. At last, Section V provide the conclusion provides the conclusion.

Literature Review

The purpose of this section is to review the literature on the topic of financial prediction of bitcoin prices using the use of DL in the context of ML in finance.

In this study, Mohanty et al. (2018) used LSTM and Twitter data to forecast the public's sentiment and the future value of cryptocurrencies such as Bitcoin. Incorporating both social and market sentiment into the model training process, as the price of bitcoin exhibits mixed features, is a result of extensive research into the impact of social media data on the price of bitcoin. Their model provides 60% precision and 50% accuracy. In this instance, accuracy is not given as much attention as it should because of the extremely volatile market.

In this research, Phaladisailoed and Numnonda et al. (2018) aim to evaluate various ML algorithms in order to determine the most effective model for predicting the value of Bitcoin. Bitstamp, a Bitcoin exchange platform, collected trading data at 1-minute intervals from January 1, 2012, to January 8, 2018, and various regression models utilising the scikit-Iearn and Keras libraries were tested. The most promising findings demonstrated an MSE of less than 0.00002.

In this study, McNally, Roche and Caton et.al. (2018) It is the Bitcoin Price Index that provides the price data. Implementing a Bayesian optimised RNN and LSTM network allows for the objective to be accomplished, though to varied degrees of success. With a RMSE of only 8%, the LSTM attains the best classification accuracy (52%). In order to compare the DL models, the widely used ARIMA model is applied to time series forecasting. Compared to the ARIMA forecast, the non-linear DL algorithms naturally get better results.

In this study, Gao, Lin and Wang et.al. (2018) using stock data for the purpose of making deep learning-based predictions about stock values for the future. In order to foretell how stock values will move in the future, this article use deep learning. This study suggests a CRNN-based architecture, Conv LSTM, which makes use of RNN's long and short-term memory since stock trends are typically tied to the previous stock price. Structure with LSTM. The accuracy and stability of predictions are both enhanced by LSTM, which enhances the long-term dependency of classical RNNs. Using a total of ten stocks' worth of historical data, this study tests its hypotheses and finds an average RMSE of 3.449.

This research Radityo, Munajat and Budi, (2017) used a range of ANN methods to forecast Bitcoin's market value, a prominent cryptocurrency. A model to forecast Bitcoin's closing value the following day (next-day prediction) will be constructed using approaches. The four ANN approaches compared in this study are GANN, GABPNN, GANN, and NEAT. Accuracy and complexity are the two metrics used to assess the methods. The experimental results demonstrated that BPNN outperformed the other methods with a MAPE of 1.998 ± 0.038 % and a training time of 347 ± 63 seconds.
Below, Table I provides a summary of the literature review of Financial Predictions based on Bitcoin Prices with dataset approaches, results and limitations for text dataset classification.

Author	**Methods**	**Dataset**	**Key Findings**	**Limitations & Future Work**
Mohanty et al. (2018)	LSTM, sentiment analysis using Twitter data	Historical Bitcoin price data, Twitter data	Combined market and social sentiment, achieved 60% precision and 50% accuracy.	Low accuracy attributed to market volatility. Future work could involve more sophisticated sentiment analysis or integration of additional data sources.
Phaladisailoed & Numnonda (2018)	Regression models (various algorithms using scikit-learn and Keras libraries)	1-minute interval trading data from Bitstamp (January 1, 2012 – January 8, 2018)	Achieved the lowest MSE of 0.00002 for Bitcoin price prediction.	Model evaluations limited to MSE; future research could involve robustness testing under volatile market conditions and other forecasting metrics.
McNally, Roche & Caton (2018)	Bayesian optimised RNN, LSTM, ARIMA	Bitcoin Price Index data	LSTM had highest classification accuracy (52%) and RMSE (8%); deep learning outperformed ARIMA.	LSTM still produced limited accuracy. Future research could improve optimisation techniques and incorporate additional features like macroeconomic indicators or trading volumes.
Gao, Lin & Wang (2018)	ConvLSTM (CRNN-based architecture), deep learning	Historical stock price data from 10 stocks	Achieved 3.449 RMSE, demonstrating improved prediction accuracy and stability with ConvLSTM.	Focused on stocks, not cryptocurrencies. Future research could validate the model on Bitcoin or other volatile assets and improve interpretability.
Radityo, Munajat & Budi (2017)	BPNN, GANN, GABPNN, NEAT	Historical Bitcoin data	BPNN outperformed other methods with MAPE of 1.998 ± 0.038% and training time of 347 ± 63 seconds.	Future work could involve testing with larger datasets and exploring hybrid ANN approaches to improve prediction reliability.

Methodology

The research design for enhancing financial predictions based on Bitcoin prices involves several systematic stages. The following steps are illustrated in Figure 1. It begins with collecting Bitcoin price data, followed by data pre-processing, including data cleaning and Min-Max normalisation to improve data quality. Relevant features are then selected to optimise model performance. The data is split into 80% for training and 20% for testing. Various forecasting models, such as MLP, RNN, ARIMA, and SVM, are employed to predict future Bitcoin prices. Model performance is evaluated using error metrics like RMSE, MSE, and the Coefficient of Determination (R2) . Finally, results are generated to compare model performance, enabling the selection of the most accurate forecasting approach. This Figure1 block diagram of pipeline leverages big data and deep learning to provide a robust framework for predicting cryptocurrency prices.

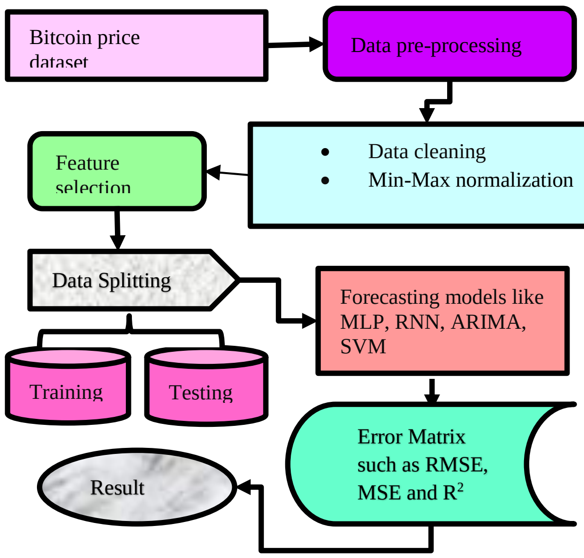

Fig. 1. Flowchart for Bitcoin price prediction

The outline of a flowchart for Bitcoin price prediction is explained below:

Data collection

This study makes use of a dataset containing bitcoin price data from 2012 all the way up to 2017. Anyone can access and download the dataset from Kaggle. It contains seven CSV files with a combined size of 877 MB. The dataset consists of individual files that represent bitcoin trade in many currencies on different bitcoin exchange sites. The correlation matrix of data is shown below:

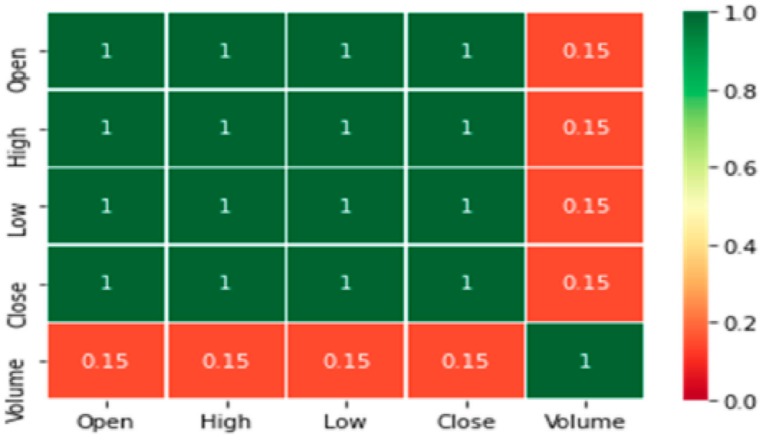

Fig. 2. Correlation matrix for features

Figure 2 shows that the Bitcoin data contains five crucial qualities. The goal of using the correlation technique was to find associations between these characteristics. Bitcoin cryptocurrency and the connections between its features.

Data preprocessing

An essential part of every data mining or machine learning project is the data preprocessing phase, which handles cleaning, organising, and normalising the raw material. The research utilised the following strategies for data preprocessing:

- **Data cleaning:** Problems with inconsistencies, gaps, and noise in the dataset are addressed during data cleaning. To ensure that the dataset was free of missing or inconsistent values, this study used the interpolation function.

Min-Max normalisation

This method applies a scale to a characteristic such that it falls inside a predetermined range, often from 0 to 1, as shown in (1):

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

where min(x) and max(x) are the dataset's minimal and maximum values, respectively, and x represents the original value. Figure 3 shows the following normalisation graph.

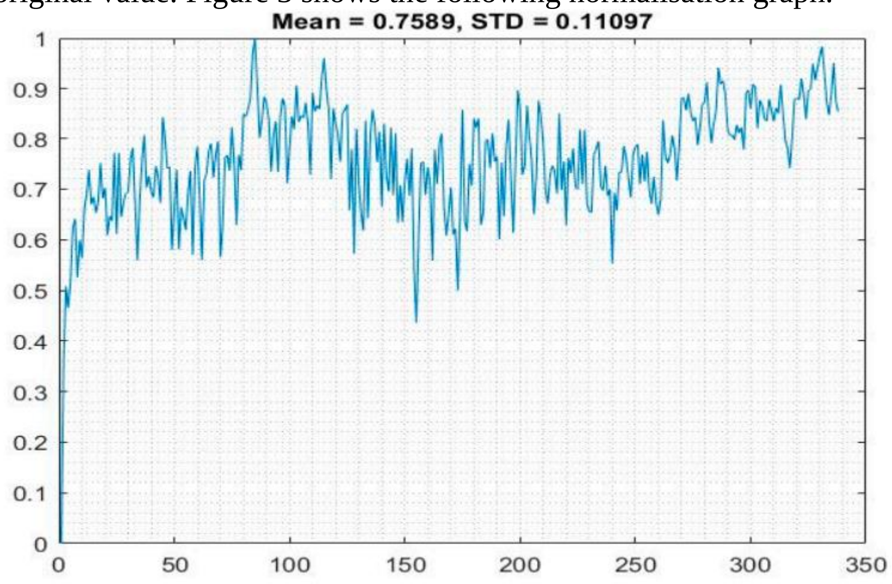

Fig. 3. After data normalisation

Figure 3 shows a mean of 0.7589 and a standard deviation of 0.11097, indicating that the data has been centralised with a relatively small spread. The line plot reveals significant fluctuations, reflecting variability in the normalised data, without a clear upward or downward trend, suggesting that the variations are largely random.

Feature selection

An important principle that has a significant influence on the model's performance is feature selection. They can improve accuracy, decrease training time, and decrease overfitting by picking just the most relevant features.

Data splitting

The data was divided into two sections: test data, which made up 80% of the total, and unseen data, which made up 20%, and these were utilised to train the model.

Prediction with MLP model

MLPs are computer systems that attempt to mimic human brain functions like learning, inferring new knowledge from existing data, and discovering new information independently. Researchers in the field of AI believe that it is feasible to create a computer with processing power comparable to that of the human brain and even more control over vast amounts of data. Biological neural networks are incredibly talented in terms of both performance and potential. The goal of applying MLP is to give computers this skill. Using equation (2), they can get the variables for output, input, and bias:

$$C_i = \sum_{i=1}^{n} E_{ij} IN_i + B_i \qquad (2)$$

The variables $E_{ij}, IN_i\ and\ B_i$ re represent the weights, inputs, and bias, respectively. If you want to activate two target classes, you can use the sigmoid function, which is defined as (3):

$$S_i = \frac{1}{1+e^{c_j}} \qquad (3)$$

For the output variable's final value, they can use the formula (4):

$$O_i = S_i(\sum_{i=1}^{n} E_{ij} IN_i + B_i \quad (4)$$

Performance metrics

This work develops a precise evaluation equation by evaluating the multiple performance indicators using the MSE, RMSE, and R2-score:

Mean Squared Error (MSE)

The discordance between the expected and actual values is averaged, and its square root is then used. A model that performs better has a lower MSE; if it is zero, it is completely forecasting with no mistake, which is very uncommon and challenging but feasible. It is computed by applying formula (5):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{Y}_i\right)^2 \quad (5)$$

$$MSE\ percentage = \left(\frac{MSE}{Mean\ of\ the\ actual\ values}\right) \times 100 \quad (6)$$

Coefficient of determination(R^2)

The model's fit is evaluated using R^2. The figure displays the ratio of the target feature's anticipated variance to that of all other features. The value of R^2 is consistently between zero and one. R^2 values closer to 1 are desirable, and 1 indicates that the model fits exactly. The formula is used to compute it:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (7)$$

Where:

- SSres is a residual sum of squares, representing an error between observed and predicted values.
- SStot is a total sum of squares, representing the variability in the observed data relative to the mean.

Root mean square error (RMSE)

A common metric for evaluating models is the root-mean-squared error (RMSE). Based on n observations y (yi, i = 1, 2,..., n) and n matching model predictions ˆy, it is calculated using the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_{iexp} - O_{irep./pred})^2} \quad (8)$$

Where, O_{iexp} and O_{irep} represent the experimental and predicted outputs, respectively.

Result Analysis And Discussion

The primary goal of this experiment is to predict on Bitcoin Prices using ML and DL models. The following MLP model is compared with existing machine learning models such as RNN, ARIMA and SVM compared (see Table III) across the performance matrix. The price data of Bitcoin is used to train the following models. Table II provides the MLP performance for Price prediction with error parameters like RMSE, MSE and R-square.

TABLE I. FINDINGS OF MLP MODEL ON BITCOIN PRICE DATASET FOR PRICE PREDICTION

Performance Parameters	Multilayer Perceptron (MLP)
R2	95.9
MSE	0.000109
RMSE	0.0104

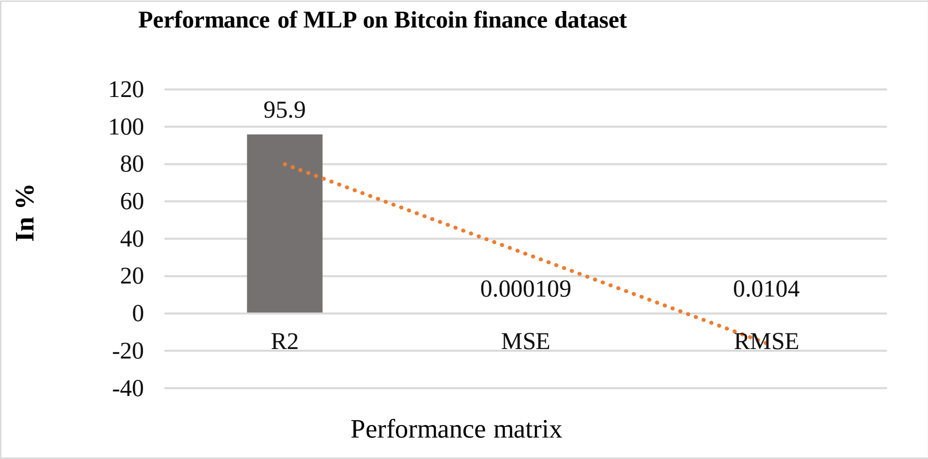

Fig. 4. MLP Model Performance

The above Table II and Figure 4 show the model performance for Bitcoin price prediction. In this figure, the MLP model achieves excellent performance with an R2-score of 95.9%, MSE of 0.000109 and RMSE of 0.0104, indicating strong classification ability.

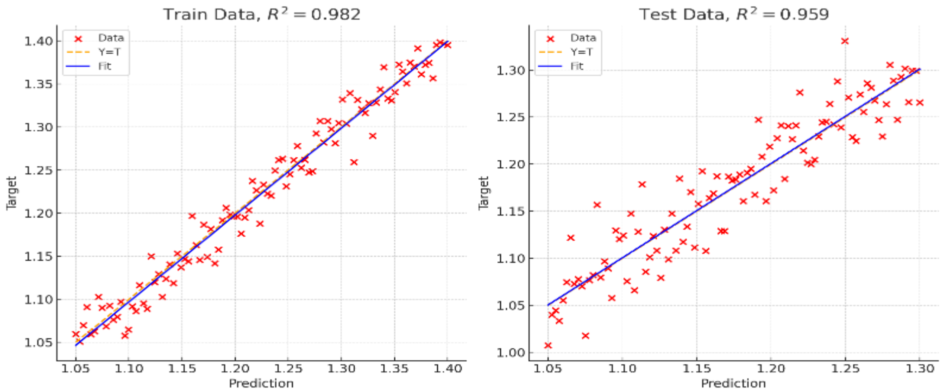

Fig. 5. Train and Test R-square of MLP model

Figure 5 shows excellent performance with very high R-squared values for both the training (R^2=0.982) and test (R^2=0.959) sets, indicating a strong correlation between forecasted and actual values. However, the slight difference among the training and test R-squared values suggests minor underfitting, where the model may not have fully captured all data nuances, leading to slightly reduced generalisation to unseen data.

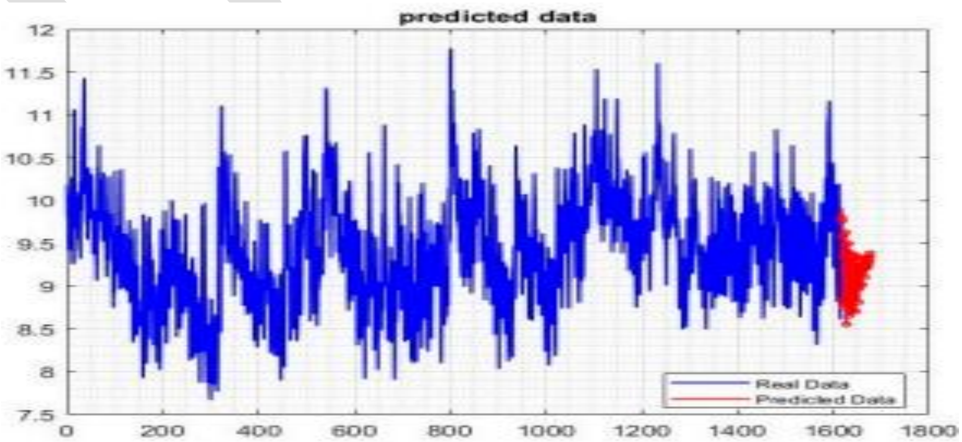

Fig. 6. Plot of time-period in 60 days of MLP model

The success of the MLP models in forecasting the value of the Bitcoin cryptocurrency over a 60-day period is displayed in Figure 6. The price of bitcoin has been declining, it was noted. Blue colour shows the real data while red colour shows the predicted data.

TABLE II. R-SQUARE COMPARISON BETWEEN MLP AND ANOTHER MODEL FOR BITCOIN PRICE PREDICTION

Models	R2-score
Multi-Layer Perceptron (MLP)	95.9
Recurrent Neural Network (RNN)	50.25
AutoRegressive Integrated Moving Average (ARIMA)	90.31
Support Vector Machine (SVM)	67.3

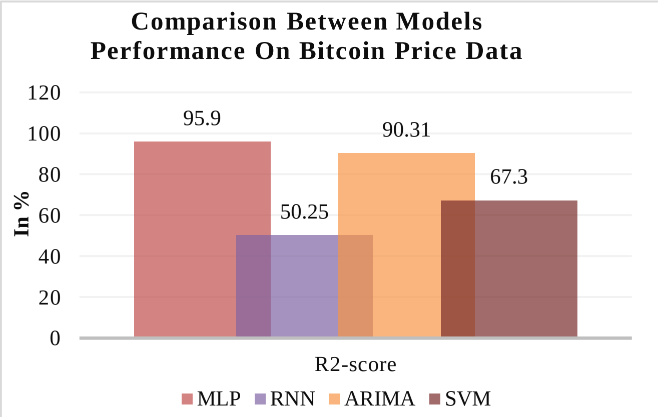

Fig. 7. Models Performance Comparison

The comparison between the performance of MLP and other models, including RNN, ARIMA, and SVM, highlights a significant difference in prediction accuracy shown in Figure 7 and Table III. MLP outperforms the other models with an impressive R^2 of 95.9%, indicating highly accurate and reliable predictions. In contrast, the ARIMA model achieves an R^2 of 90.31, SVM model has an R^2 of 67.3 and the RNN model shows an R^2 of 50.25. These results suggest that MLP significantly outperforms the other models in terms of both explained variance and prediction error.

Conclusion And Future Work

Bitcoin is a digital currency that does not rely on any one clearinghouse or bank to function. Bitcoin transactions are handled directly between participants, thanks to blockchain technology, eliminating the need for intermediaries. This study's evaluation of methodologies led to the development of a process for modelling and predicting bitcoin prices. A comparison of ML and DL models for forecasting a price of Bitcoin was reported in this paper. The results indicate that the MLP model was slightly more accurate than the other models with R^2 of 95.9% and corresponding MSE of 0.000109 and RMSE of 0.0104. Lower performance was observed in ARIMA, SVM and RNN with the corresponding R^2 values of 90.31%, 67.3% and 50.25% respectively. The high R^2 values for the training set of 98.2%, as well as that for the 95.9% test set, provide clear evidence that the MLP model excelled at capturing even the most subtle pattern of in the features relating to Bitcoin prices. The 60-day temporal assessment proved that MLP model followed the actual Bitcoin price patterns and is effective in short-term price prediction. This brings out the strength of the MLP model over the traditional ML models to give a proper framework for cryptocurrency prediction and financial decisions. Subsequently, future work may consider integrating other factors from the market and selecting more appropriate hyperparameters to increase the model's accuracy and expansibility.

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