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Bitcoin Price Prediction using Deep Learning

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Abstract: Bitcoin is a decentralized digital currency. It is a type of cryptocurrency because it uses cryptography to keep it safe. It is gaining popularity among individuals but it is still not common to use this technique because people still invest in traditional techniques like stock market. Additionally, there are various factors that affect the price of bitcoin such as total circulating supply, production costs, bitcoin mining, rules and regulations, and bitcoin sentiment. These factors and their combinations are used to determine which factor has the greatest influence on the price of bitcoin, and then use the studied factors and the history of the price of bitcoin to predict the evolution of bitcoin prices. Another emerging technique in computer science is deep learning, which is used for trend analysis. The models used are RNN, LSTM, and the model that gives the best result is selected for prediction.
Keywords: Bitcoin, cryptography, Deep Learning, RNN, LSTM.

I. INTRODUCTION

Bitcoin is a decentralized digital currency that enables secure peer-to-peer transactions without intermediaries such as banks or authorities. It was created in 2009 by an anonymous person or group using the pseudonym Satoshi Nakamoto. Unlike fiat money (INR, USD, Euro and other fiat currencies), Bitcoin is not regulated by any country. It's sort of the official currency of the Internet, and anyone with an Internet connection can own it. This makes it independent of corporate monopolies because everything in Bitcoin is controlled by a huge community of users like me, you and everyone else who uses it. The best thing about Bitcoin is how easy it is to transfer anywhere in the world with very low fees. For example, it costs only $2-$3 or less to transfer bitcoin from the US to India or Europe. Your event will also remain anonymous. Only the sender and recipient know who is involved in the transaction.

However, as a commodity, Bitcoin has the problem of high volatility. As observed in December 2017, Bitcoin reached an all-time high of nearly $20,000 before the Great Crash before falling to around $3,000 in December 2018. In April 2020, the US Federal Reserve announced a massive stimulus program to support the US economy during the pandemic. encouraging some investors to buy Bitcoin to protect against inflation, due to which it saw a second time high in January 2021, the value of Bitcoin continued to rise, reaching a new all-time high of over $40,000. This led to difficulty in predicting bitcoin prices. Many researchers have tried predicting the bitcoin prices by analysing the trends using different deep learning models, while few others have tried using correlation of different blockchain components for price prediction.

In order to contribute to the above mentioned work, the research chooses different features affecting the bitcoin prices and correlations between them were recorded to find which factors affect the most while determining the price. Using today's timestamp, it considers the previous 90 days price for prediction. In addition to a high-precision forecasting model, this study conducts an in-depth analysis of explanatory variables that determine the significance of Bitcoin prices and the relationship between forecasting accuracy and lags of explanatory variables. The forecasting models that were used are ANN, LSTM and RNN.

II. RELATED WORK

A deep neural network (DNN), a long short-term memory (LSTM) model, a convolutional neural network, a deep residual network, and their combinations are studied and compared for use in this paper in order to predict the price of bitcoin. According to experimental findings, whereas DNN-based models outperformed LSTM-based models significantly better for price classification (ups and downs), LSTM-based models performed slightly better for price regression (regression). Additionally, a straightforward examination of profitability revealed that classification models were superior to regression models for algorithmic trading. Overall, the proposed deep learning-based prediction models' performances were comparable. [1]

The cited study makes use of deep learning methods like RNN, LSTM, GRU, and MLP. The information was gathered in one minute and then reorganised to reflect it in hours. The input was taken into account over a period of 24 hours, and a prediction was made for the next hour. After comparing the models, it was determined that Multi-Layer Perceptron, or MLP, was not appropriate for the model due to lack of memory. [2]

For real-time datasets and models, an optimized RNN implementation employing LSTM was investigated. Deep learning was used to solve the real-time problem of predicting the price of digital currencies. By developing a GUI File Picker for user convenience and a wider range of applications, the implementations of the data pretreatment and filtering to deliver exact, sound, and consistent data were effectively carried out. Effective use of RNN was made utilizing the LSTM method. It was done to accurately depict the system architecture and to provide precise threshold outputs at the display unit. A graph was drawn, and outputs and observations were logged. [5]

Two deep learning methods, LSTM and GRU, are employed as prediction models in this research. According to the study, the GRU model is the more accurate and quicker to compile mechanism for time series bitcoin price prediction. Long-term dependencies are easier to detect with LSTM and GRU models. The root mean square error (RMSE) and mean absolute percentage error (MAPE), which are used to compare the accuracy of the proposed LSTM and GRU models, are found. [7]

The article forecasts the price using an LSTM model and compares it to a machine learning model to understand how accurate it is. In order to provide accurate forecasts, it thoroughly analyses the model. Due to the difficulty in predicting Bitcoin's relevance due to the use of blockchain technology, the authors employed machine learning models for testing and an LSTM model for more precise prediction. [8]

The LSTM deep learning model, which is used in the aforementioned paper and provides a trend accuracy of 93.9, is used. It also demonstrates how the predictive capability of the model is impacted by different cryptocurrencies, including ETH. The exchange trade volume, average transaction volume per block, and daily transaction volume were all considered by the authors as features for estimating the price of bitcoin. The meta-data also included labels for the open, close, high, low, and percentage change. [9]

III. PROPOSED METHODOLOGY

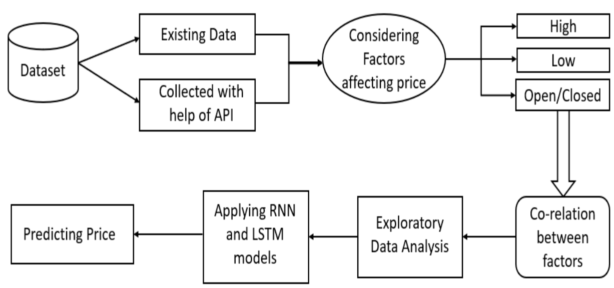

Figure 1. Architecture

A. Data and Pre-processing

Bitcoin is a decentralized digital currency that enables secure peer-to-peer transactions without intermediaries such as banks or authorities. It was created in 2009 by an anonymous person or group using the pseudonym Satoshi Nakamoto. Unlike fiat money (INR, USD, Euro and other fiat currencies), Bitcoin is not regulated by any country.

It is a sort of the official currency of the Internet, and anyone with an Internet connection can own it. This makes The datasets were collected from various trading venues that provided us with real-time bitcoin prices. The parameters looked at ranged from various blockchain components to the entire daily open and close of the cryptocurrency.

These parameters were applied based on their relationship to two datasets:

1) *Dataset 1:* It is collected from the Yahoo Finance website. The data period was observed from September 17, 2014 to March 6, 2023. It has attributes like open, high, close, low, volume and adjacent close. This dataset is used to predict Bitcoin price using RNN and LSTM models.
2) *Dataset 2:* It is collected from GitHub. The data period was observed from February 17, 2010 to January 31, 2018. The dataset consists of 23 properties related to the Bitcoin Blockchain network ranging from btc_market_price, btc_total_bitcoins, btc_volume till btc_estimated_transaction_volume and btc_estimated_transaction_volume_usd features. This material is used to understand and analyse the relationship between Bitcoin and its properties and how they would be used to predict the price of Bitcoin using an ANN model.

B. Exploratory Data Analysis

Both datasets were examined and visualized to better understand the distribution of the data and draw inferences from hidden patterns. As Dataset 2 consist of 23 features, the correlation between them with bitcoin price was found through a heatmap visualization (Figure 2.) that uses the Karl Pearson correlation coefficient to reduce the number of features as to avoid overfitting of the data and improve its quality. Only features with a correlation of >=0.8 were considered predictive of bitcoin price.
These were found to be 8 in number out of which difficulty and hash rate had same correlation value and were highly correlated by their definitions too.

So, only difficulty feature was used instead of hash rate. This resulted in total of 7 features which are listed below. These are:

1) market cap-1
2) trade vol-0.87
3) difficulty-0.92
4) minersrevenue-0.99
5) transaction fees-0.81
6) cost per transaction-0.82
7) transaction vol usd-0.97

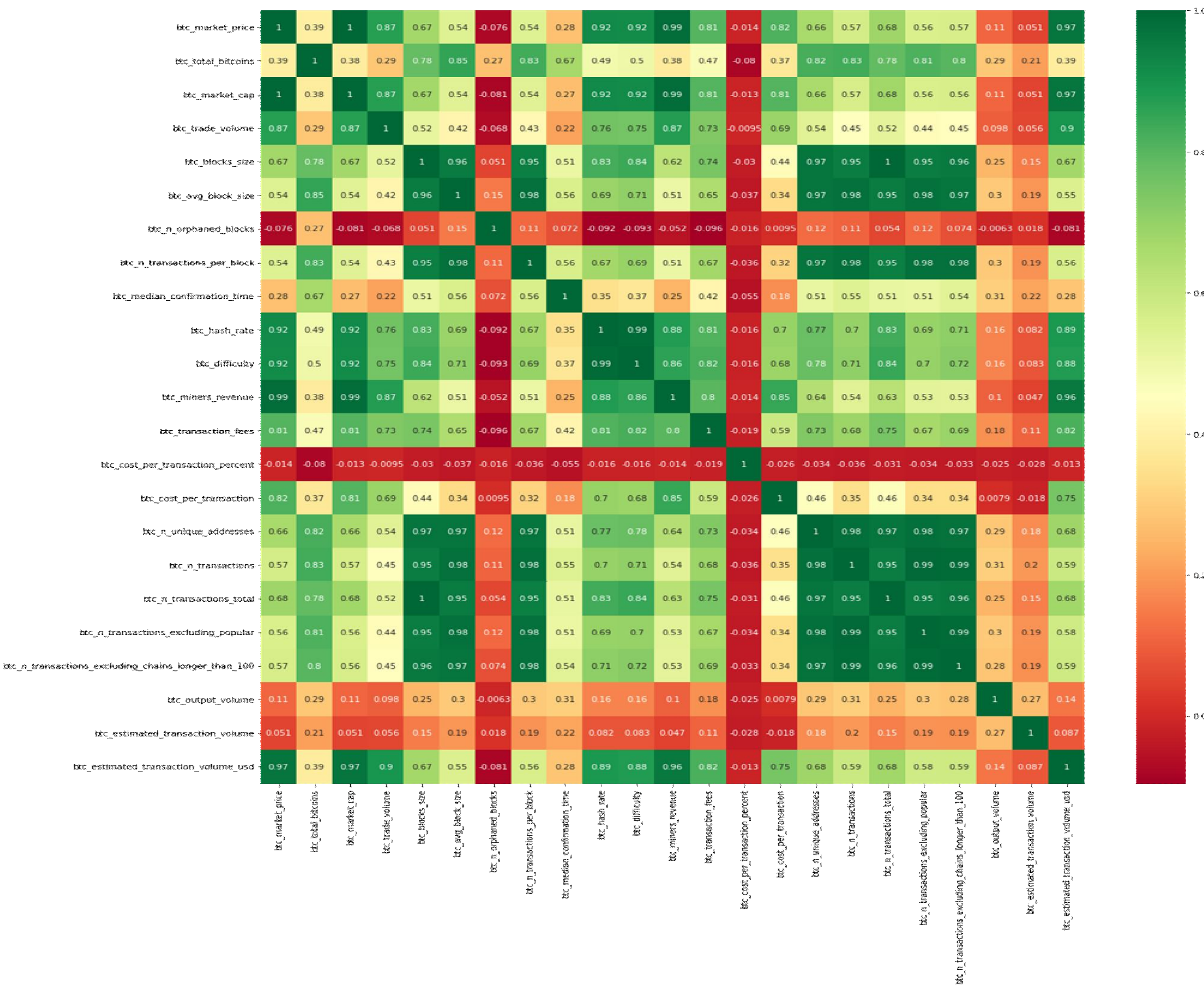

Figure 2. Heatmap Representation of blockchain features

Graphically, it can be analysed in Figure 3. that all these features show similar trends with the bitcoin price and are positively correlated. The trend line for difficulty and miners revenue show similar behavior.

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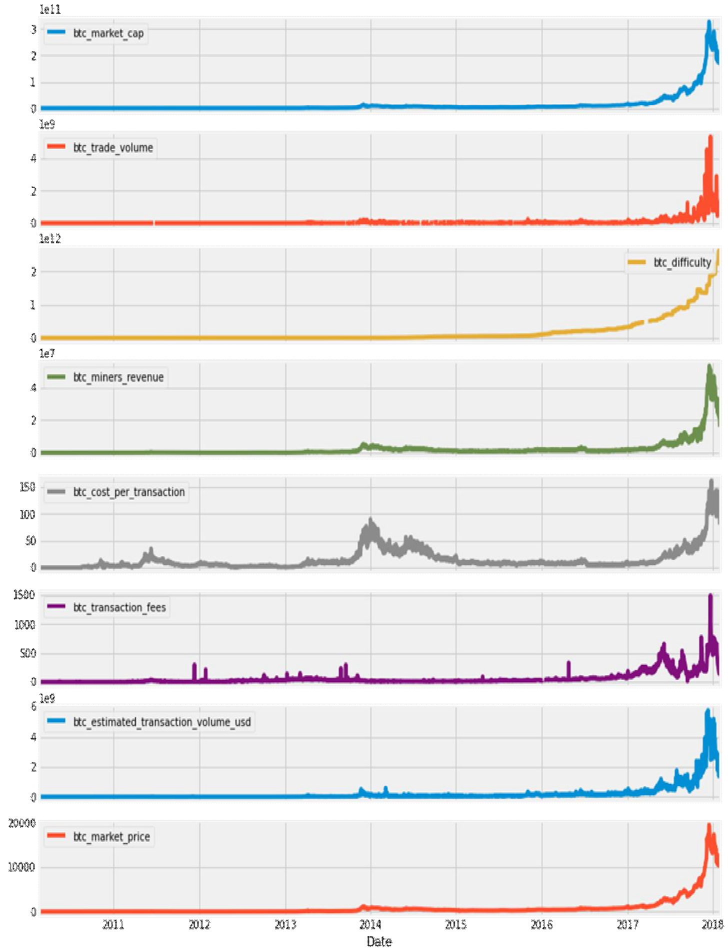

Figure 3. Correlation between the considered features

Similarly, Dataset 1 consisting of four salient features namely open, high, low and closed was analyzed graphically and for association with "Anova test". Figure 4. shows the evolution of bitcoin price over the period 2015-2023. The plot shows a positive trend, but there are also ups and downs.

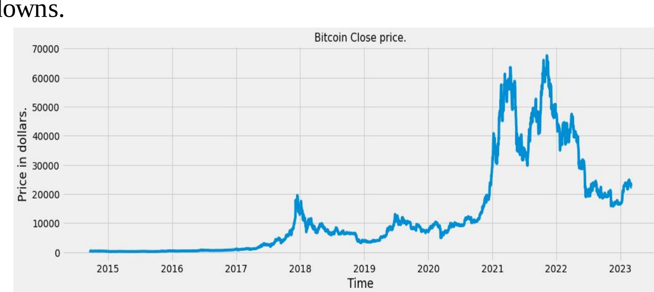

Figure 4. Close Price Variation

Figure 5 & 6. below shows that open, low, high and close prices of bitcoin are normally distributed graphically. Since these columns represent the same amount as the price, ‘ANOVA test’ was performed to determine if these characteristics differed significantly from each other by calculating the p-value.

Since the analysis showed a p-value of 0.41844, which is greater than the critical value mentioned above, the null hypothesis is accepted and that there is no significant difference between these properties, and any of them can be used to predict the price of bitcoin.

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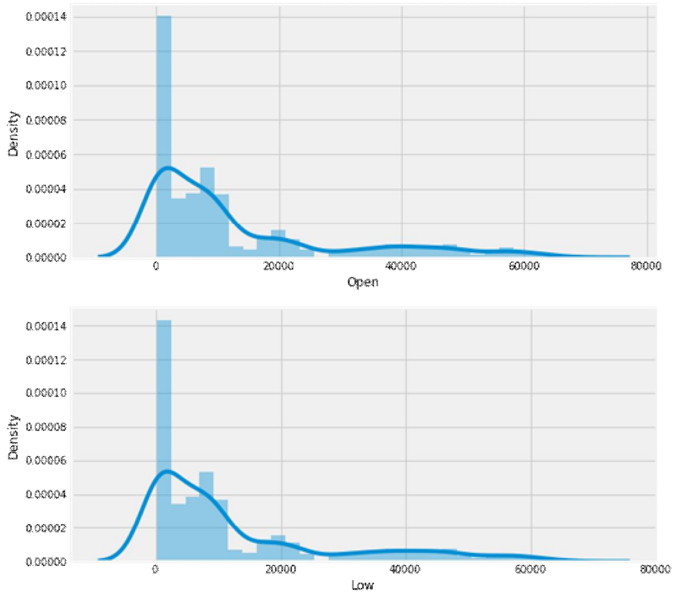

Figure 5. Normal Distribution of Open and Low

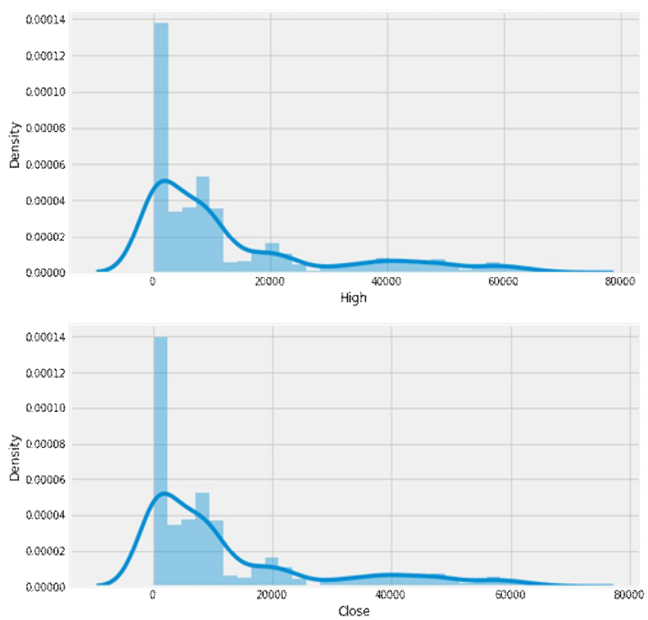

Figure 6. Normal Distribution of High and Close

From the images above, we can see that the data is positively skewed, which infers the number of deviations in bitcoin open, low, high and close prices. This can be attributed to the fact that there has been a huge fluctuation in the price of bitcoin over a very short period. Thus, only **close feature** was considered in **Dataset 1** for the prediction purpose as technical analysis like moving averages or chart patterns often use closing rates to identify trends and patterns in price action.

IV. RESULT AND ANALYSIS

A. ANN

The Dataset 2 was divided into 80% training and 20% testing sets. Because the price range varied so much, we used the StandardScaler Library to scale down the values and the Adam optimizer to optimize them. The summary of the model is as follows:

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Table 1. ANN Model's Summary

Sr. No	*Layers*	*Parameters*
Layer 1	ANN_1	units=6, activation='relu'
Layer 2	ANN_2	units=6, activation='relu'
Layer 3	ANN_3	units=6, activation='relu'
Layer 4	Dense	units=1

Table 2. ANN Evaluation metrics

Evaluation metric	*Value*
R Square value	0.9997238985920947
RMSE Value	65.262
MSE Value	4259.126

B. LSTM

In this case, Dataset 1 was separated into 90% and 10% training and test sets, respectively. MinMaxScaler library was utilised for price standardisation, while Adam optimizer was employed for optimisation.

The model's window size for the values it would evaluate for predicting the price was 90 days. The model's summary is given below, along with the prediction graph:

Table 3. LSTM Model's Summary

Sr. No	*Layers*	*Parameters*
Layer 1	LSTM_1	units=80
Layer 2	LSTM_2	units=80
Layer 3	LSTM_3	units=80
Layer 4	LSTM_4	units=80
Layer 5	Dense	units=1

Table 4. LSTM Evaluation metrics

Evaluation metric	*Value*
R Square value	0.8750911862141375
RMSE Value	1064.830
MAPE Value	0.043

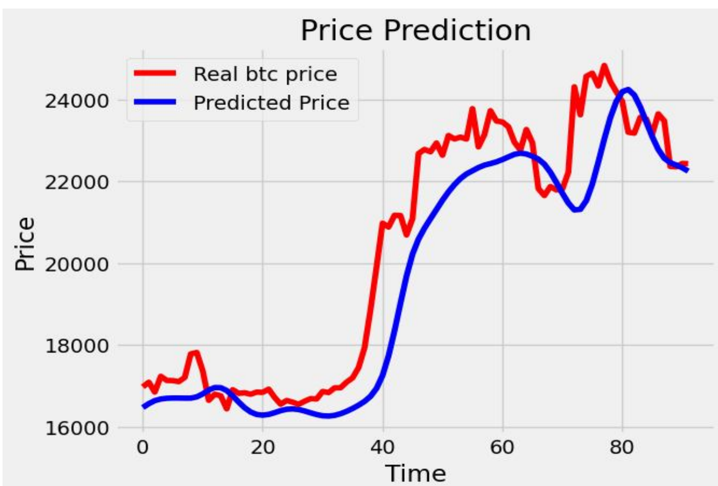

Figure 7. Predicted vs Real Price Prediction for LSTM

C. RNN

Similarly, MinMaxScaler was utilized here, but a different optimizer, rmsprop, was used. Again, the price forecast timeframe is 90 days. The model summary, as well as the prediction graph, are provided below.

Table 5. RNN Model's Summary

Sr. No	*Layers*	*Parameters*
Layer 1	RNN_1	units=32
Layer 2	RNN_2	units=32
Layer 3	Dense	units=1

Table 6. RNN Evaluation metrics

Evaluation metric	*Value*
R Square value	0.98182586609998
RMSE Value	504.568
MAPE Value	0.017

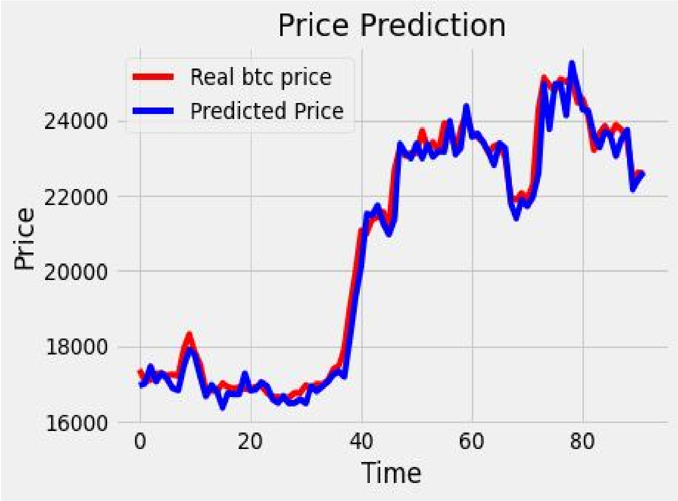

Figure 8. Predicted vs Real Price Prediction for RNN

In general, below table gives an overview of the metrics:

Table 7. Model Evaluation metrics Summary

Model	*R square value*	*RMSE value*
ANN	0.9997238985920947	65.262
LSTM	0.8750911862141375	1064.830
RNN	0.97195629855543	504.568

D. Graphical User Interface (GUI)

The GUI for predicting the bitcoin price in real time has been implemented with the help of streamlit app framework and yfinance module available in python.

Web applications are becoming an increasingly popular way to share data projects with other users. This is due to the emergence of easy-to-use Python libraries such as Streamlit and the ease of deploying web applications in the cloud for free.

Streamlit is an open-source Python framework for building machine learning and data science web applications [10]. With Streamlit, you can write an app just like you write python code and view results in a web application seamlessly.

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The screenshots of the web app are as follows:

Date	Open	High	Low	Close	Adj Close	Volume
2023-01-11 00:00:00	17,446.3594	17,934.8965	17,337.9941	17,934.8965	17,934.8965	18,372,283,782
2023-01-12 00:00:00	18,117.5938	19,030.0879	17,995.2031	18,869.5879	18,869.5879	34,971,338,710
2023-01-13 00:00:00	18,868.9063	19,964.3223	18,753.1641	19,909.5742	19,909.5742	29,225,029,694
2023-01-14 00:00:00	19,910.5371	21,075.1426	19,907.8281	20,976.2988	20,976.2988	38,967,784,639
2023-01-15 00:00:00	20,977.4844	20,993.748	20,606.9863	20,880.7988	20,880.7988	19,298,407,543
2023-01-16 00:00:00	20,882.2246	21,360.875	20,715.7461	21,169.6328	21,169.6328	26,792,494,050

Figure 9. Bitcoin's current price page with the price chart

Initially, the bitcoin price for the current day will be displayed at top, along with it the bitcoin price of the previous 90 days will be provided to the users for reference.

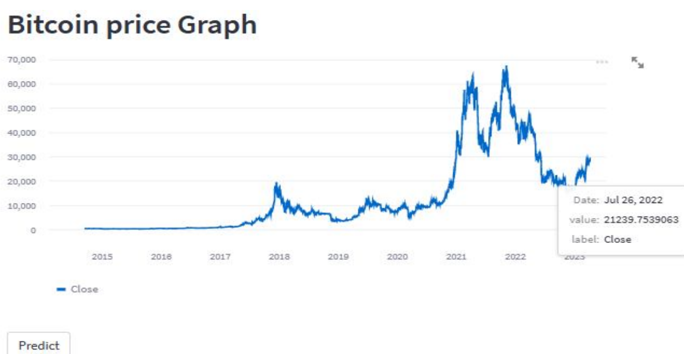

Figure 10. Bitcoin price graph page

After the price chart, an interactive graph will be displayed so that when the users hover over the graph, they can view the price and date for that particular day.

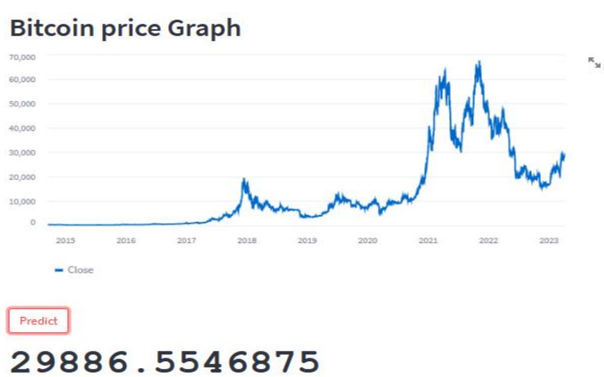

Figure 11. Bitcoin price prediction

When a user clicks on the Predict button the user will be provided with the bitcoin price which can be used by the users for their further decisions.

As it can be seen from the above GUI figures which display the price prediction of bitcoin, the model is predicting the price in a very close range with a minimal difference of 260.6 dollars. As the price of bitcoin is volatile in nature, hence fluctuations in the price are often seen due to which not exact prediction can be done.

V. CONCLUSION AND FUTURE WORK

Deep learning techniques were utilised in this work to handle the real-time challenge of predicting digital currency prices. Several data sets have been explored in order to forecast Bitcoin values. One that analyses multiple components of the blockchain and their link to price to anticipate the price, but because these values are not easily available, developing a perfect forecaster may cost money or require authorisation for scraping. However, this does not mean that such a forecaster cannot be developed in the near future. As previously indicated, for exploratory data analysis, we employed this dataset for price prediction using ANN, which yielded a 99% accuracy. The Open, High, Low, and Close prices of bitcoin are included in the other data set. Exploratory data analysis was performed on this data set to infer the hidden patterns of bitcoin price fluctuations during the covid period, and ANOVA was also performed to conclude that all of these price volumes have no significant difference between them and any column can be used to build a model; additionally, data processing and filtering were performed effectively to obtain accurate, reliable, and consistent information. The RNN and LSTM deep learning models are used to generate a forecast based on the closing price of Bitcoin over a 90-day period. It was shown that the RNN model outperformed the LSTM with accuracy of 0.97 versus 0.87 and RMSE of 504.568 versus 1064.830. Finally, a graphical user interface (GUI) was made available to users, enabling an interactive experience for real-time bitcoin price prediction.

To improve the functionalities, the following features can be enhanced and added:

1) Anyone with access to values like the closing price of bitcoin or any other coin can use the forecaster to anticipate the price for the very following day.
2) One can use hourly bitcoin price data to examine a different viewpoint and increase accuracy.
3) A recommendation system for several crypto currencies can be created to help people make smart financial decisions.

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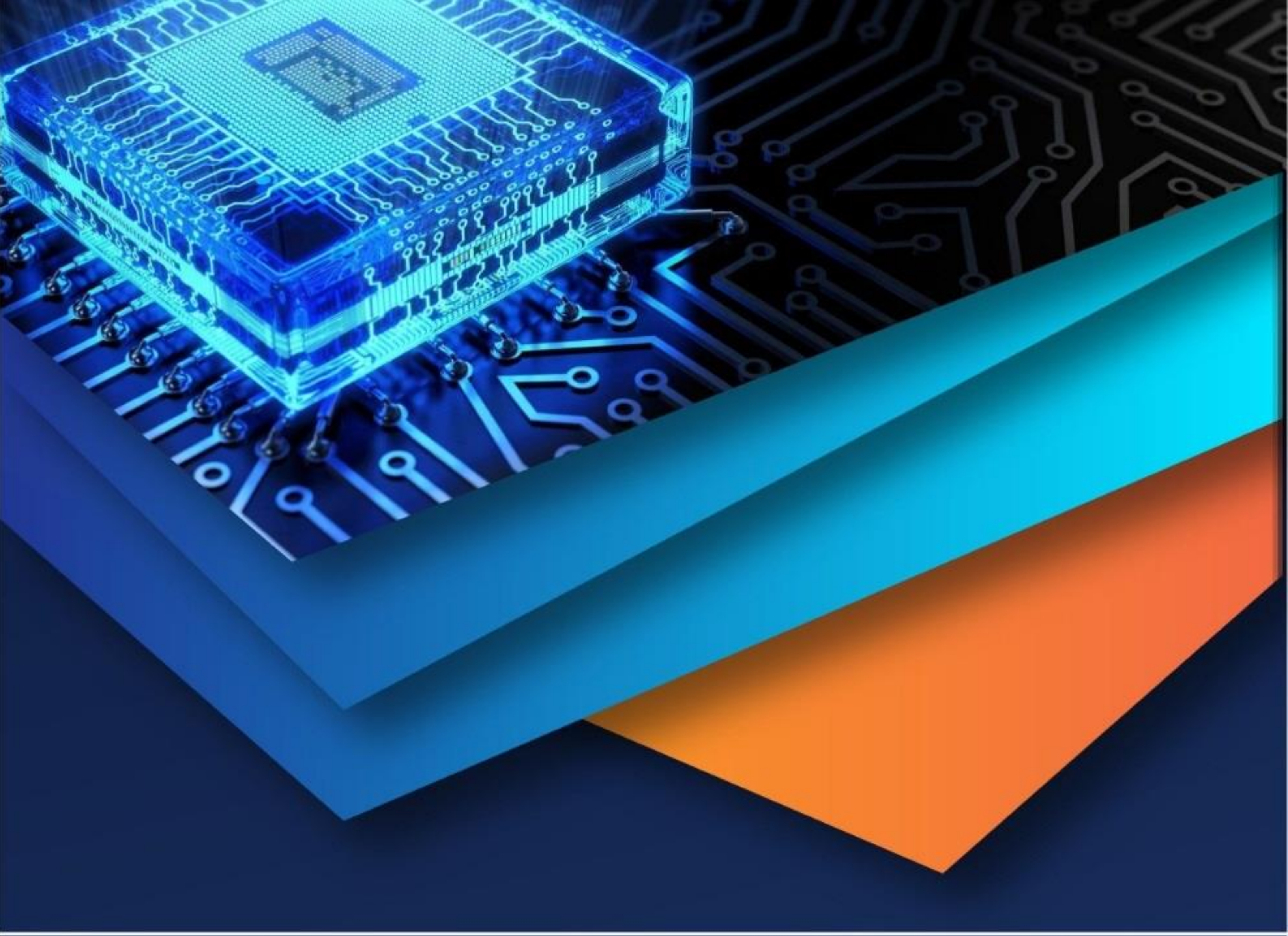

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