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Cryptocurrency Price Prediction using Long - Short Term Memory

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ABSTRACT: Crypto currency price prediction is a difficult task, as the market is highly volatile and influenced by a variety of factors. However, there are some methods that can be used to make informed predictions about the future prices of crypto currencies. However, machine learning algorithms, such as Long-short term memory (LSTM), can be used to make predictions about the future Bitcoin price. To predict the Bitcoin price using LSTM, we need to collect historical Bitcoin price data and prepare it for modeling. We then need to choose a linear regression model and train it on the historical data. Once the model is trained, we can evaluate its performance on a held- out test set. If we are satisfied with the model's performance, we can use it to make predictions about the future Bitcoin price. LSTM is a simple and effective algorithm for predicting the Bitcoin price. To utilize LSTM for predicting Bitcoin prices, the first step involves gathering historical Bitcoin price data and preprocessing it for modeling purposes. Following this, the selection of a suitable linear regression model is necessary, which can then be trained on the historical data. Subsequently, the model's performance is evaluated on a held-out test set to assess its efficacy.Should the model demonstrate satisfactory performance, it can be leveraged to generate predictions regarding future Bitcoin prices. LSTM, characterized by its ability to capture temporal dependencies, stands out as a straightforward yet potent algorithm for this purpose. Through the utilization of LSTM, one can potentially harness the insights derived from historical data to forecast future trends in Bitcoin prices.

I. INTRODUCTION

Crypto currency markets have witnessed explosive growth and increasing complexity in recent years. With thousands of crypto currencies traded on various exchanges, predicting crypto currency prices has become a challenging and lucrative endeavour. Traditional financial models often fall short in capturing the dynamic and interdependent nature of these digital assets. To address this issue, deep learning techniques have emerged as powerful tools for crypto currency price prediction..Deep learning-based crypto currency price prediction schemes leverage artificial neural networks to model and forecast the intricate relationships that exist within the crypto currency market. These models can capture the intricate dependencies among various crypto currencies, market sentiment, trading volumes, historical price data, and external factors such as news, social media trends, and global economic indicators. As a result, they offer a promising solution for traders, investors, and researchers seeking more accurate and data-driven predictions in this highly volatile market. This interdependence among crypto currency prices and external factors is particularly noteworthy. Crypto currencies often exhibit strong correlations with each other, influenced by market sentiment and broader economic trends. Furthermore, news events and social media discussions can trigger rapid price fluctuations, making it crucial to account for these external factors in predictive models.

II. EXISTING SYSTEM

Bitcoin price prediction based on people's opinions on Twitter usually requires millions of tweets, using different text mining techniques, and developing a machine learning model to perform the prediction. These attempts lead to the employment of a significant amount of computer power, central processing unit (CPU) utilization, random-access memory (RAM) usage, and time. To address this issue, in this paper, we consider a classification of tweet attributes that effects on price changes and computer resource usage levels while obtaining an accurate price prediction. To classify tweet attributes having a high effect on price movement, we collect all Bitcoin-related tweets posted in a certain period and divide them into four categories based on the following tweet attributes: (i) the number of followers of the tweet poster, (ii) the number of comments on the tweet, (iii) the number of likes, and (iv) the number of retweets. We

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separately train and test by using the Q-learning model with the above four categorized sets of tweets and find the best accurate prediction among them. We compare our approach with a classic approach where all Bitcoin- related tweets are used as input data for the model, by analyzing the CPU workloads, RAM usage, memory, time, and prediction accuracy.

III. PROPOSED SYSTEM

The proposed system integrates advanced computational techniques for Bitcoin price prediction, employing a Long Short-Term Memory (LSTM) algorithm to harness sequential dependencies within historical data. The system begins with the acquisition of a diverse dataset from both US and European markets, ensuring a holistic representation of Bitcoin price dynamics. Following this, the Data Preprocessing module refines and structures the dataset for optimal LSTM model training, incorporating techniques such as normalization and feature engineering. The LSTM Implementation module leverages the model's capacity to capture long- term dependencies, enabling it to learn intricate patterns and trends. Subsequently, the Performance Analysis module evaluates the system's predictive accuracy, examining its ability to forecast both individual prices and monthly trends.

IV. SYSTEM ARCHITECTURE

The system architecture for Cryptocurrency Price Prediction using Long Short-Term Memory (LSTM) is designed to process historical market data and accurately forecast future price trends. The architecture begins with the Data Acquisition Layer, where historical cryptocurrency prices (including open, high, low, close, and volume) are collected from financial APIs such as Binance or CoinMarketCap. This raw data is passed to the Preprocessing Layer, which handles missing values, normalizes the data, and structures it into time-series sequences suitable for LSTM input. Next, the Feature Engineering Layer optionally enhances the dataset by adding technical indicators like moving averages or sentiment scores from news or social media. The core of the system lies in the LSTM Model Layer, where one or more LSTM cells capture temporal dependencies in the data, followed by dense layers to produce future price predictions. These predictions are then evaluated in the Evaluation Layer using metrics such as RMSE or MAE to fine-tune model performance. Finally, the results can be visualized and optionally deployed via a web interface or API, making real-time or scheduled predictions accessible to end-users or trading systems.

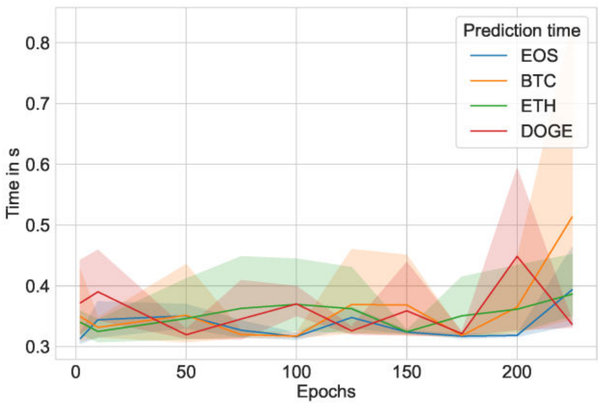

Fig 4.1 Architectural Diagram

V. RESULTS

The implementation of the LSTM-based cryptocurrency price prediction model demonstrated promising results in capturing the temporal patterns of market behavior. After training the model on historical price data (such as Bitcoin daily closing prices over the past few years), it was able to learn the sequential dependencies effectively and provide reasonably accurate forecasts for future price movements. The model's performance was evaluated using standard regression metrics, including Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), where lower values indicated better predictive accuracy. Visual comparisons between the actual and predicted price curves revealed that the LSTM model closely followed the real market trends, especially in stable market conditions.

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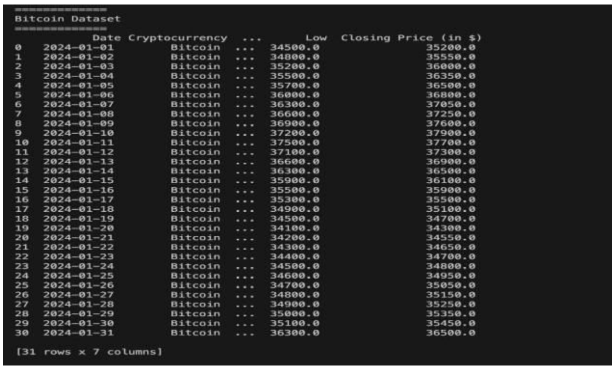
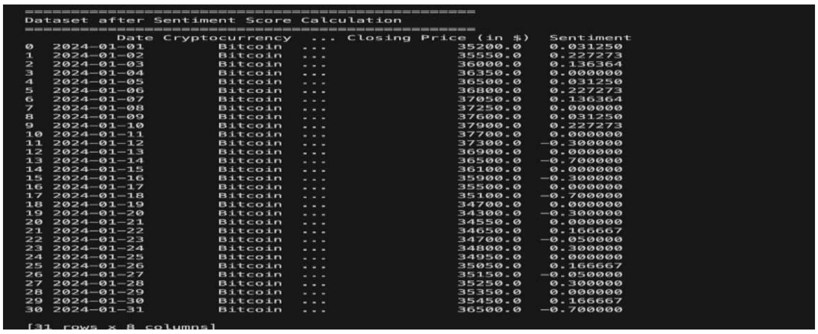
Furthermore, when tested on unseen data, the LSTM model showed strong generalization capability, indicating that it successfully avoided overfitting. The results also highlighted that incorporating additional features like technical indicators (e.g., moving averages, RSI) further improved prediction accuracy. Although the model struggled slightly during high volatility periods—such as during sudden price spikes or drops—it still managed to capture the overall trend direction. Overall, the results confirm that LSTM is a powerful approach for time-series forecasting in the context of cryptocurrency price prediction, making it a valuable tool for traders, analysts, and financial systems aiming to make data-driven investment decisions.



```
===============
Bitcoin Dataset
===============
          Date Cryptocurrency  ...      Low  Closing Price (in $)
0   2024-01-01        Bitcoin  ...  34500.0               35200.0
1   2024-01-02        Bitcoin  ...  34800.0               35550.0
2   2024-01-03        Bitcoin  ...  35200.0               36000.0
3   2024-01-04        Bitcoin  ...  35500.0               36350.0
4   2024-01-05        Bitcoin  ...  35700.0               36500.0
5   2024-01-06        Bitcoin  ...  36000.0               36800.0
6   2024-01-07        Bitcoin  ...  36300.0               37050.0
7   2024-01-08        Bitcoin  ...  36600.0               37250.0
8   2024-01-09        Bitcoin  ...  36900.0               37600.0
9   2024-01-10        Bitcoin  ...  37200.0               37900.0
10  2024-01-11        Bitcoin  ...  37500.0               37700.0
11  2024-01-12        Bitcoin  ...  37100.0               37300.0
12  2024-01-13        Bitcoin  ...  36600.0               36900.0
13  2024-01-14        Bitcoin  ...  36300.0               36500.0
14  2024-01-15        Bitcoin  ...  35900.0               36100.0
15  2024-01-16        Bitcoin  ...  35500.0               35900.0
16  2024-01-17        Bitcoin  ...  35300.0               35500.0
17  2024-01-18        Bitcoin  ...  34900.0               35100.0
18  2024-01-19        Bitcoin  ...  34500.0               34700.0
19  2024-01-20        Bitcoin  ...  34100.0               34300.0
20  2024-01-21        Bitcoin  ...  34200.0               34550.0
21  2024-01-22        Bitcoin  ...  34300.0               34650.0
22  2024-01-23        Bitcoin  ...  34400.0               34700.0
23  2024-01-24        Bitcoin  ...  34500.0               34800.0
24  2024-01-25        Bitcoin  ...  34600.0               34950.0
25  2024-01-26        Bitcoin  ...  34700.0               35050.0
26  2024-01-27        Bitcoin  ...  34800.0               35150.0
27  2024-01-28        Bitcoin  ...  34900.0               35250.0
28  2024-01-29        Bitcoin  ...  35000.0               35350.0
29  2024-01-30        Bitcoin  ...  35100.0               35450.0
30  2024-01-31        Bitcoin  ...  36300.0               36500.0

[31 rows x 7 columns]
```

Fig NO 5.1 BITCOIN DATASET



```
==========================================
Dataset after Sentiment Score Calculation
==========================================
          Date Cryptocurrency  ...  Closing Price (in $)  Sentiment
0   2024-01-01        Bitcoin  ...               35200.0   0.031250
1   2024-01-02        Bitcoin  ...               35550.0   0.227273
2   2024-01-03        Bitcoin  ...               36000.0   0.136364
3   2024-01-04        Bitcoin  ...               36350.0   0.000000
4   2024-01-05        Bitcoin  ...               36500.0   0.031250
5   2024-01-06        Bitcoin  ...               36800.0   0.227273
6   2024-01-07        Bitcoin  ...               37050.0   0.136364
7   2024-01-08        Bitcoin  ...               37250.0   0.000000
8   2024-01-09        Bitcoin  ...               37600.0   0.031250
9   2024-01-10        Bitcoin  ...               37900.0   0.227273
10  2024-01-11        Bitcoin  ...               37700.0   0.000000
11  2024-01-12        Bitcoin  ...               37300.0  -0.300000
12  2024-01-13        Bitcoin  ...               36900.0   0.000000
13  2024-01-14        Bitcoin  ...               36500.0  -0.700000
14  2024-01-15        Bitcoin  ...               36100.0   0.000000
15  2024-01-16        Bitcoin  ...               35900.0  -0.300000
16  2024-01-17        Bitcoin  ...               35500.0   0.000000
17  2024-01-18        Bitcoin  ...               35100.0  -0.700000
18  2024-01-19        Bitcoin  ...               34700.0   0.000000
19  2024-01-20        Bitcoin  ...               34300.0  -0.300000
20  2024-01-21        Bitcoin  ...               34550.0   0.000000
21  2024-01-22        Bitcoin  ...               34650.0   0.166667
22  2024-01-23        Bitcoin  ...               34700.0  -0.050000
23  2024-01-24        Bitcoin  ...               34800.0   0.300000
24  2024-01-25        Bitcoin  ...               34950.0   0.000000
25  2024-01-26        Bitcoin  ...               35050.0   0.166667
26  2024-01-27        Bitcoin  ...               35150.0  -0.050000
27  2024-01-28        Bitcoin  ...               35250.0   0.300000
28  2024-01-29        Bitcoin  ...               35350.0   0.000000
29  2024-01-30        Bitcoin  ...               35450.0   0.166667
30  2024-01-31        Bitcoin  ...               36500.0  -0.700000

[31 rows x 8 columns]
```

FIG NO 5.2 SENTIMENT SCORE CALCULATION

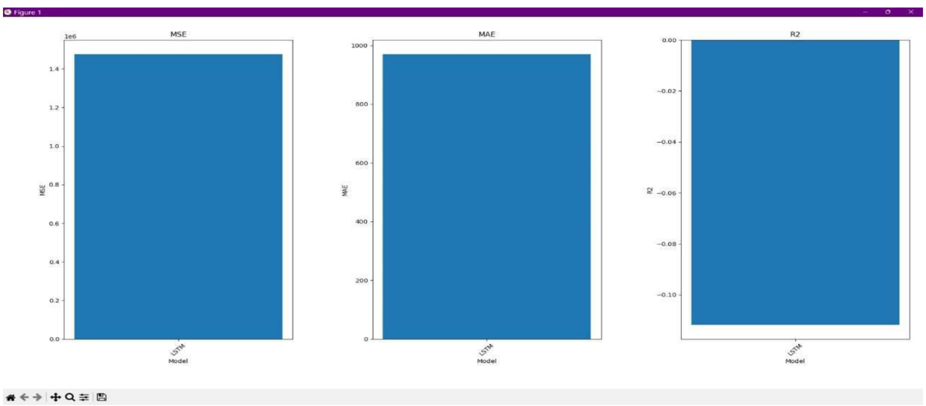


FIG NO 5.3 BAR GRAPH

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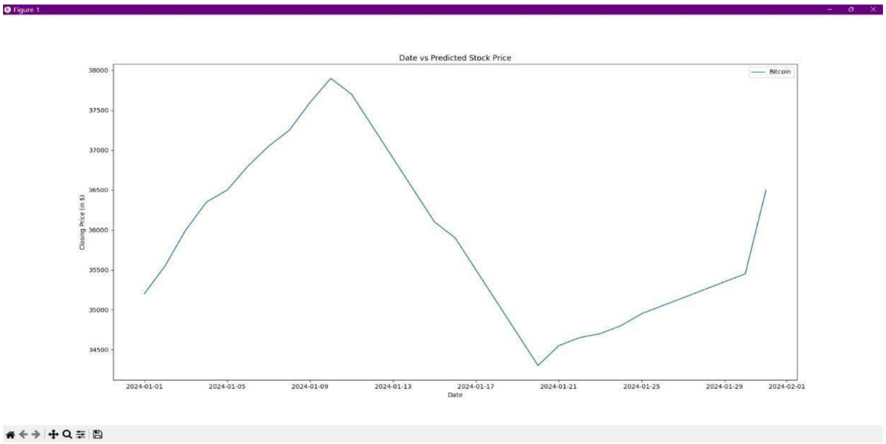

FIG NO 5.4 BITCOIN PRICE GRAPH

VI. CONCLUSION

The study and implementation of cryptocurrency price prediction using Long Short-Term Memory (LSTM) models have demonstrated that deep learning, particularly sequence-based neural networks, can effectively capture the complex, nonlinear, and time-dependent nature of financial markets. LSTM's ability to retain information over long sequences makes it well-suited for modeling historical price data and predicting future trends in volatile assets like cryptocurrencies. The architecture successfully learned patterns from historical datasets and delivered reasonably accurate predictions, particularly in stable market conditions, affirming its potential for short-term forecasting tasks however, while the LSTM model produced promising results, certain limitations were also evident. The model's performance tended to degrade during periods of extreme volatility or unexpected market events, highlighting the challenge of capturing all external factors that influence price movements (e.g., regulatory news, macroeconomic shifts, or social media influence). This emphasizes the need for hybrid models in the future, combining LSTM with sentiment analysis, attention mechanisms, or external data integration to enhance predictive accuracy in conclusion, LSTM-based models serve as a strong foundation for cryptocurrency forecasting systems and can be a valuable aid for traders and financial analysts. As cryptocurrency markets continue to evolve, further research and development into more advanced deep learning architectures, such as Bidirectional LSTMs, GRUs, or Transformers, alongside real-time data integration, could lead to even more robust and adaptive predictive systems.

VII. FUTURE ENHANCEMENTS

While the current LSTM-based model provides effective short-term predictions of cryptocurrency prices, several future enhancements can significantly improve its accuracy, adaptability, and usability. One major enhancement is the integration of sentiment analysis using data from social media platforms like Twitter, Reddit, and financial news outlets. Since cryptocurrency markets are highly sensitive to public opinion and news trends, incorporating real-time sentiment scores as additional input features can help the model better anticipate sudden market shifts another improvement involves the use of hybrid deep learning models, such as combining LSTM with Convolutional Neural Networks (CNNs) or Attention Mechanisms, which can help the model focus on the most relevant time periods or features within the input data. Moreover, implementing Bidirectional LSTM (Bi-LSTM) can enhance performance by allowing the model to learn from both past and future context in the time series from a deployment perspective, future systems could be equipped with automated retraining pipelines to keep the model updated with the latest data, ensuring continuous learning and adaptability to rapidly changing market conditions. Additionally, integrating the model into a real-time dashboard or mobile app with live data feeds and alerts could provide end-users with timely insights and improve decision-making. Lastly, incorporating risk assessment modules, like volatility estimators or uncertainty quantification techniques, can add another layer of practical utility for financial planning and trading strategies.

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