Cryptocurrency Price Prediction Using Deep Learning

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Abstract:- Cryptocurrency is a type of digital or virtual currency that uses cryptography to secure and verify transactions as well as to control the creation of new units, it uses Blockchain properties for the same. Blockchain is a decentralized digital ledger technology that records transactions securely and transparently. Blockchain technology and cryptocurrency are closely connected. Cryptocurrencies rely on blockchain technology to operate, as blockchain serves as the decentralized ledger that records all transactions and ensures their security and transparency. [7] As the internet becomes more accessible and convenient, an increasing number of people and organizations are turning to digital transactions. Digital payment systems are significantly faster, less expensive, and more efficient. As a result, it's not unexpected that innovative digital payment system types are quickly emerging. No other approach even comes close to the colossus that is cryptocurrencies. Predicting cryptocurrency prices can be useful for a variety of reasons. For traders and investors, predicting cryptocurrency prices can help them make informed decisions about when to buy or sell cryptocurrencies, maximizing their profits or minimizing their losses. For prediction, the algorithms used are GRU (gated recurrent unit), LSTM (long-short-term memory), and Bi-LSTM (Bi-directional long-short-term memory) algorithms to predict the future price of a cryptocurrency. An ensemble model is also created using the three models, and prices could be accurately predicted using these models and displaying the obtained results.

Keywords: *Cryptocurrency; LSTM, Bi-LSTM, GRU, Ensambled;*

I. INTRODUCTION

Cryptocurrencies are a type of digital currency decentralized and not controlled by any government. Cryptocurrency is formed from two words - "crypto" (data encryption) and "currency" (medium of exchange). In the olden days, the exchange of goods happens with the help of a barter system, then realizing the values of each good differed and cannot be determined by another good, then exchange started with gold and later with coins. Then the transaction started with using deposited money there the user is not even seeing the money and an amount is transferred to the bank same then the idea of cryptocurrency evolved where money transfer happens digitally without intermediaries. Cryptocurrency does not exist in physical form (like paper money) and is typically not issued by a central authority.

[6] Cryptocurrencies have established themselves as essential financial software platforms. They are based on a secure distributed ledger data structure, and mining is essential to such systems. Mining provides records of previous transactions to the Blockchain distributed ledger, helping users to establish safe, strong consensus for each transaction. Mining also creates wealth in the form of new currency units. Because cryptocurrency was built as a peer-to-peer system, it lacks a central authority to mediate transactions.

[8] Virtual currencies are on the rise and so is money laundering. While there are efforts to combat money laundering through various intergovernmental bodies, many have expressed concern over the rise of virtual currencies. Some cryptocurrencies such as Bitcoin have played a major role in the proliferation of online money laundering as it possesses characteristics that criminals are fond of. Bitcoin and other cryptocurrencies are decentralized, anonymous/pseudonymous, and irreversible. They provide the means to skirt the Anti-Money laundering safeguards that have been put in place.

II. LITERATURE SURVEY

- *Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction*

The In this paper, [1] the authors study Bitcoin and explore features in its network that explain its price hikes. They gather data and analyze user and network activity that highly impacts Bitcoin price. They monitor the change in the activities over time and relate them to economic theories. a cryptocurrency's demand and supply dynamics.

Finally, they use machine learning methods to construct models that predict Bitcoin prices. Their regression model predicts Bitcoin price with 99.4% accuracy and 0.0113 roots mean squared error (RMSE). Used machine learning methods to construct models that predict Bitcoin price. Their regression model predicts Bitcoin price with 99.4% accuracy and 0.0113 roots mean squared error (RMSE), which provides a better understanding of the factors that influence the price of Bitcoin. This can be useful for investors, traders, and researchers interested in the cryptocurrency market.

- *A Decade Survey on Recent Advancements, Architecture, and Potential Future Directions*

This paper [2] Using artificial neural networks (ANNs), research provides a method for forecasting the conversion rate of Bitcoin to the US dollar. The authors collect historical Bitcoin-to-USD exchange rate data and use it to train ANNs to predict future exchange prices. The research examines the performance of several types of ANNs, such as feedforward neural networks, recurrent neural networks, and deep neural networks, in forecasting the exchange rate of Bitcoin to the US dollar. The authors also compare the performance of their suggested strategy to other known methods for forecasting Bitcoin exchange rates. The benefits of this article are that it employs a sophisticated technique for forecasting time-series data and provides prospective insights into the bitcoin market's behavior. Furthermore, the article proposes a mechanism for anticipating Bitcoin values that might be useful. However, this paper's weaknesses include its exclusive emphasis on Bitcoin and the lack of a complete examination of the suggested mechanism.

- *On-Chain Prediction with Deep Learning*

This paper [3] has used a deep learning model to predict the price of cryptocurrencies using on-chain data.

The authors of the paper have used a dataset of on-chain data related to cryptocurrencies. The dataset was collected from various sources such as blockchain explorers and cryptocurrency exchanges. The authors have used a deep learning model called Long Short-Term Memory (LSTM) to predict the price of cryptocurrencies. The LSTM model is a type of recurrent neural network that is capable of processing sequential data. The authors have also used a feature selection technique to select the most relevant features from the on-chain data.

The use of deep learning and on-chain data has several advantages in predicting the price of cryptocurrencies. The LSTM model is capable of processing sequential data, which is essential in predicting the price of cryptocurrencies as the price is dependent on historical data. The use of on-chain data helps in analyzing the transactions and activities related to cryptocurrencies, which can have a significant impact on the price of cryptocurrencies. The feature selection technique helps in selecting the most relevant features from the on-chain data, which can improve the accuracy of cryptocurrency price prediction.

- *Inter-Dependent Cryptocurrency Price Prediction*

This paper [4] has used a deep learning model to predict the price of cryptocurrencies using interdependent relations.

The authors of the paper have used a dataset of cryptocurrency prices and inter-dependent relations related to cryptocurrencies. The dataset was collected from various sources such as Yahoo Finance and Google News. The authors have used a deep learning model called Gated Recurrent Units (GRU) to predict the price of cryptocurrencies. The GRU model is a type of recurrent neural network that is capable of processing sequential data. The authors have also used inter-dependent relations to analyze the relationships between cryptocurrencies.

The use of deep learning and interdependent relations has several advantages in predicting the price of cryptocurrencies. The GRU model is capable of processing sequential data, which is essential in predicting the price of cryptocurrencies as the price is dependent on historical data. The use of inter-dependent relations helps in analyzing the relationships between different cryptocurrencies, which can have a significant impact on the price of cryptocurrencies. The paper provides a new approach to predicting the price of cryptocurrencies using inter-dependent relations, which can be useful for investors and traders in the cryptocurrency market.

III. METHODS

- *LSTM*

Designed to avoid the long-term dependency problem, it can remember information for long periods. Uses Three different gates for this process; forget gate, input gate, and output gate

- *Forget Gate:*

Removes information that is no longer useful in the cell state. Takes two inputs, the current cell and the previous cell, and they are multiplied with weight matrices followed by the addition of bias. The result is passed through an activation function which gives a binary output. If the output is 0, then the piece of information is forgotten and for output which is 1, the information is retained for future use.

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- *Input Gate:*

Adds useful information to the cell state. Information is regulated using the sigmoid function and filters the values to be remembered. Using input as the previous cell and current cell, a vector is created using the 1tanh function that gives an output from -1 to +1, which contains all the possible values from the previous cell and the current cell. Then values of the vector and the regulated values are multiplied to obtain the useful information

- *Output Gate:*

Extracts useful information from the current cell state to be presented as output. Vector is generated by applying the tanh function on the cell. Information is regulated using the sigmoid function and filtered by the values to be remembered using inputs previous cell and the current cell. Values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell.

➢ *Bi-LSTM*

Bi-LSTM introduces four gates, two for the forward LSTM and two for the backward LSTM, that control the flow of information and help the network selectively remember or forget information from past time steps. Uses Four different gates for this process; forget gate, input gate, output gate, and backward forget gate.

- *Forget Gate (Same as in LSTM):*

Controls how much of the previous cell state should be retained or forgotten.

- *Input Gate (Same as in LSTM):*

Determines which values from the current input should be added to the cell state.

- *Output Gate (Same as in LSTM):*

Controls how much of the current cell state should be output to the next layer.

- *Backward Forget Gate:*

passing the concatenation of the current input and the previous hidden state through a sigmoid activation function, which produces an output vector between 0 and 1. The output vector represents the degree to which the future cell state should be remembered or forgotten.

➢ *GRU*

Designed to avoid the vanishing gradient problem. The cell state is removed and used the hidden state to transfer information. Uses two different gates for this process; reset gate and update gate

- *Reset Gate:*

Controls the information that flows out of memory, and determines how much of the previously hidden state information should be forgotten or retained. If the gate value is close to 0, the GRU mostly forgets the previous hidden state and relies on the current input. If the gate value is close to 1, the GRU mostly retains the previous hidden state and incorporates it into the new hidden state

- *Update Gate:*

Controls information that flows into memory. Determines how much of the new input should be used to update the hidden state. It is a vector that decides which information to keep and which information to throw away. The output of the sigmoid function represents the amount of information to keep from the previous hidden state.

➢ *Ensemble*

The output of each model is used as an input to a higher-level model that learns to combine the outputs of the base models, and the predictions of each model are averaged together to form a final prediction. This can improve performance by reducing the prediction variance and increasing the model's stability.

➢ *Data Set:*

The analyzed dataset was collected from [5], an open-access website. It consists of a .csv file of many cryptocurrency coins and links for downloading the same are provided. The dataset used for this research paper is collected daily from 1 April 2015 to 1 April 2023.

Table 1 Data Set

Variable Name	**Variable Description**
Date	Date of Observation
Open	The open price of the given date
Low	The low price of the given date
High	The high of the given date
Close	The close price of the given date
Adj. Close	The Adjacent close price of the given date
Volume	The volume price of the given date

IV. RESULT AND DISCUSSION

10 different cryptocurrencies are used for this research paper. Three different algorithms which are LSTM, Bi-LSTM, and GRU are used and an ensembled model is also used for viewing the predicted results. Different users can choose the coin and model required accordingly the result will be displayed which will help the user to invest in the same.

All the attributes are used for training and testing purpose and the predicted result of all the attributes are obtained for the given date

The output obtained in the process of Bitcoin is discussed here:

➢ *LSTM Model*

```
Predicted prices for 2023-04-03:
Close: 29605.84
Open: 29434.47
High: 29889.27
Low: 28533.35
```

➢ *Bi-LSTM Model*

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Predicted prices for 2023-04-03:
Close: 28835.70
Open: 29059.22
High: 29475.48
Low: 28365.49
```

➢ *GRU Model*

```
Predicted prices for 2023-04-03:
Close: 28099.33
Open: 28019.08
High: 29160.90
Low: 27508.53
```

➢ *Ensemble Model*

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Predicted prices for 2023-04-03:
Close: 27307.72
Open: 27869.37
High: 27035.42
Low: 27251.24
```

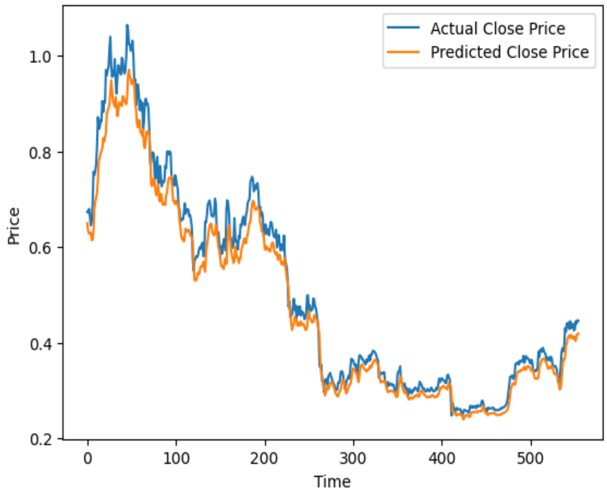

Fig 1 GRU Prediction of Close Price

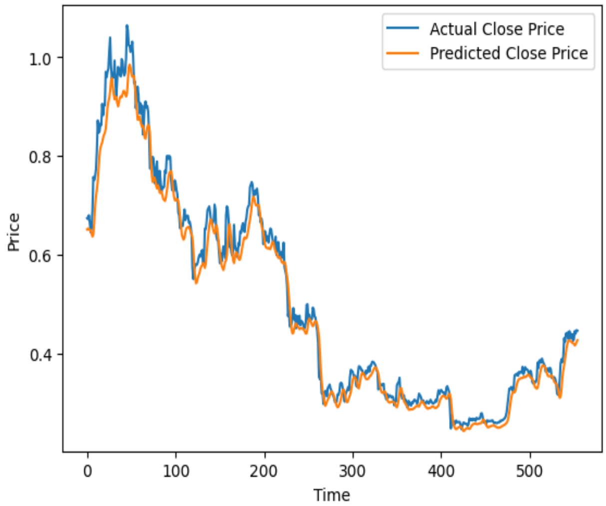

Fig 2 LSTM Prediction of Close Price

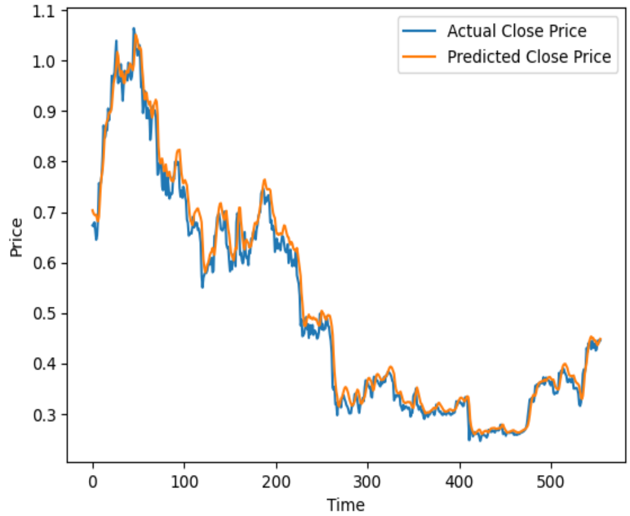

Fig 3 Bi-LSTM Prediction of Close Price

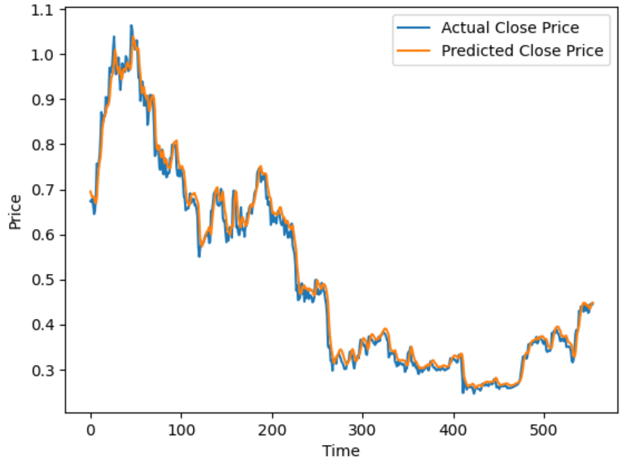

Fig 4 Ensemble Prediction of Close Price

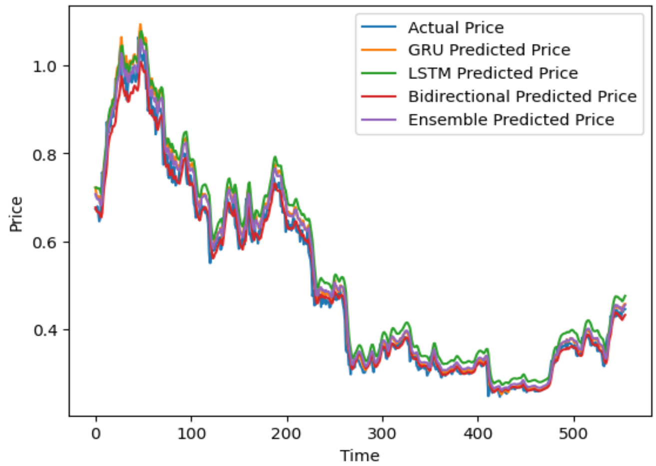

Fig 5 The Combined Result of all the Observation

Table 2 Mean Square Error Obtained while Prediction

MSE	
LSTM	0.0006063628663181186
Bi-LSTM	0.0013169118146140332
GRU	0.0013169118146140332
Ensemble	0.0005468361394868078

V. CONCLUSION

In this paper, three types of machine learning algorithms and ensemble models are used for predicting the prices of different types of cryptocurrency Deep learning is a powerful tool for cryptocurrency price prediction, but it requires careful preparation of data and a robust testing process to ensure accurate results. Cryptocurrency markets are highly unpredictable and can be influenced by a wide range of factors, so it is important to consider a wide range of relevant features when training a deep learning model. Fine-tuning the model by adjusting its hyperparameters can help to improve its performance, but it is important to be cautious when making changes to the model. Implementing the deep learning model in a production environment can be challenging.

Based on these findings, the GRU model for the cryptocurrencies under consideration may be regarded as efficient and dependable. This model is regarded as the best. However, Bi-LSTM is less accurate than GRU and LSTM with significant variations between real and forecasted pricing.

The ensembling model is a combination of GRU, LSTM, and Bi-LSTM. The accuracy of the model depends on which day the result is being predicted as the dates go far from the last day the prediction results will be good but the accuracy of the model decreases.

In future work, we would like to extract price trends from tweet posts and other social media platforms to increase the accuracy of the prediction.

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