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Cryptocurrency Price Prediction Using LSTM Neural Networks

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Abstract -As the markets for cryptocurrencies have risen rapidly in recent years, there is more interest in forecasting their prices. The use of Long Short-Term Memory (LSTM) neural networks for cryptocurrency price prediction is examined in this paper. The model is trained to predict the price using historical data on the cryptocurrency exchange rate with the currencies of G20 nations. The pre-processed data collection is divided into training and testing sets. Then, using the training set and testing set, the LSTM model is trained. To assess the model's performance, it is put up against the time series model known as Autoregressive Integrated Moving Average (ARIMA). The outcomes show that the LSTM model performs better in terms of accuracy and offers more trustworthy forecasts of the cryptocurrency exchange rate than the ARIMA model. These results imply that LSTM neural networks are a potential method for predicting the price of cryptocurrencies and may be used to help traders and investors make wise choices.

I. Introduction

Digital assets known as cryptocurrencies are traded over decentralized networks, and they utilize encryption to protect financial transactions and regulate the generation of new tokens. Cryptocurrency are emerging as the new way for people to invest their excess money and make profits from it either in the long term or short term. One of the major reasons for the emergence of the cryptocurrency market is that it is not a centralized market, it is decentralized.

For several months in a row in 2017, the market capitalization of cryptocurrencies climbed significantly, greatly enhancing their popularity.

Prices peaked in January 2018 at a little under $800 billion.Cryptocurrency prices are difficult to forecast because of their distinctive traits, such as significant volatility, a dearth of historical data, and a lack of regulation. Although machine learning approaches like neural networks have demonstrated promising results, conventional financial analysis techniques may not be effective in predicting bitcoin values. The article proposes a Long Short-Term Memory (LSTM) neural network model that is designed to handle time series data in order to forecast bitcoin values. Long-term dependencies may be learned, and the LSTM model can spot data patterns that conventional machine-learning models would overlook.

II. Literature Survey

The LSTM neural network [1, 2, 4] for prediction of the cryptocurrency market shows how LSTM networks improve upon the earlier approaches (regression, conventional neural networks, and basic recurrent neural networks), [2] forecasts the prices of multiple cryptocurrencies using transformers and long-short term neural networks (LSTM)

The CatBoost model and BigData-based prediction [3] technique for the cryptocurrency market outperforms gradient propulsion, support vector machines, and linear regression algorithms.

We employ Long Short Term Memory networks and Hidden Markov Models to characterise historical cryptocurrency movements and forecast future movements. Comparing our suggested model to conventional LSTMs and ARIMA time-series forecasting models, it was found to be more effective.

To evaluate the price fluctuations of Bitcoin, Ethereum, and Ripple, we employ cutting-edge artificial intelligence frameworks called fully connected Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Networks [5]. We discover that LSTM typically relies more on short-term dynamics, while ANN typically relies more on long-term history.

[6] Verifying whether the addition of technical indicators to the traditional macroeconomic variables improves the ability to anticipate Bitcoin price changes by comparing a restricted and an unrestricted Bitcoin price categorization [6].

Several machine learning methods [7], including Support Vector Machine (SVM), XGBoost (XGB), a Convolutional Neural Network (CNN), and a Long Short Term Memory (LSTM) neural network, were used to implement the goal.

By utilising various machine learning methods, such as Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, and XGBoost [8], it is possible to forecast the daily price behaviour of the main 4 cryptocurrencies, including Bitcoin, XRP, Ethereum, and Stellar.

Our tests demonstrate that in predicting the precise closing price, the Ridge regression model works better than more intricate prediction models like RNNs and LSTM [9]. However, LSTM is more adept than others at predicting the course of the price of cryptocurrencies.

LSTM models and GRUs (Gated Recurrent Units) are both used [10]. These are used with three significant cryptocurrencies: OMG Network, Ripple (XRP), and DOGECoin. The outcomes demonstrate that LSTM and GRU are capable of accurately forecasting these coins' daily closing values.

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Most forecasting methods presented have some degree of error and are unable to anticipate prices with accuracy owing to randomness [11].

The additional research into cryptocurrency price prediction using an ARIMA model [12] that has been trained on the entire dataset and a small portion of the price history. A model for estimating bitcoin prices that integrates long-term and short-term learning and analyses a significant amount of past price dataWhile for the shorter time, we are concentrating on price-related accuracy, we are only paying attention to up and down for the longer length [13, 14].

The purpose of this study is to enhance the stock market strategy and attempt to apply it to bitcoin price prediction. In this study, a straightforward three-layered feedforward artificial neural networks model was used to forecast the daily movements of bitcoin prices.Measures of centrality can help anticipate the short-term volatility of bitcoin prices more accurately.

III. Proposed Work

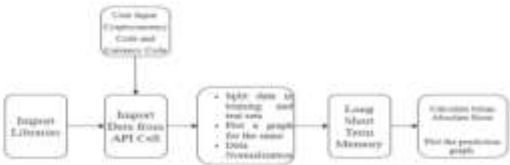

Fig 1.Architecture diagram of the model

The figure describes the architectural flow of the proposed work. We at first import the all the necessary libraries and we collect the data from api calls that are made on the demands of the user such that the user/ customer can choose which cryptocurrency they want and in which global currency they want. The dataset is then divided into two sets in the percent slot of 80% and 20% of the dataset we are using for the model. The data is being normalized, when preparing data for machine learning, normalization is a common approach used. The goal of normalisation is to maintain the ranges of value discrepancies while converting the numerical columns' values to a common scale.

LSTM - Long Short Term Memory algorithm is applied to the dataset and the model is being trained to predict the future values of the cryptocurrency. Last step is to calculate the Without accounting for their direction, mean absolute error determines the typical magnitude of errors across a set of projections..It is the test sample's average of the absolute differences between observed events and predicted events, with equal weight assigned to each difference individually. The prediction model graph is obtained in the conclusion, allowing us to assess the efficacy of our model.

TABLE 1. Information about the Data Set

time	high	low	open	volumefrom	volumeto	close
2021-11-02	64283.87	60677.48	60960.88	38008.86	2.380738e+09	63260.06
2021-11-03	63553.52	61057.89	63260.06	29518.09	1.852234e+09	62929.93
2021-11-04	63102.88	60749.84	62929.93	23030.57	1.420788e+09	61448.47
2021-11-05	62021.37	60799.18	61448.47	20540.58	1.262030e+09	61019.88
2021-11-06	61594.18	60130.85	61019.88	15432.25	9.395301e+08	61529.78
2021-11-07	63309.07	61406.58	61529.78	14937.90	9.298720e+08	63302.78
2021-11-08	67755.48	63302.78	63302.78	39774.17	2.814940e+09	67549.14
2021-11-09	68514.28	66312.42	67549.14	32745.53	2.209552e+09	66930.24
2021-11-10	68978.64	63196.28	66930.24	50881.31	3.388487e+09	64826.08
2021-11-11	65585.88	64130.37	64826.08	21475.87	1.393819e+09	64820.80

The table 1 gives us some information about the data set. It tells us about the the high and low price of the cryptocurrency, the open and close value of the cryptocurrency and the from which volume to which volume the currency has been traded in a specific day.

IV. Implementation

The model is connected to a web page, where the user can access and choose their cryptocurrency and the currency they are willing to get the future prediction of the cryptocurrency

Fig 2. Website design where user can access this model

As the user sets both the value, the prediction model gets called by the API (Application Programming Interface), the API carries the coin code and the currency code with it and hands it over to the model in a json format.

The datatset is fetched from an API which has historical data of cryptocurrency, the dataset is divided into the training and testing sets and the model is trained.

Fig 3. Line Plot for Training and Test Dataset

After The data is being normalized, when preparing data for machine learning, normalization is a common approach used. The goal of normalisation is to maintain the ranges of value discrepancies while converting the numerical columns' values to a common scale.

LSTM stands for long short-term memory, due to the problem that the recurrent neural networks had was that they didn't have a long memory to remember things. LSTM helps us solve this problem as it is the advanced version of RNN, the traditional RNN having short-term memory and in addition to it we add a long-term memory in which we store only the keywords that we need to remember in order to make the prediction.

In order to judge whether to discard the long-term memory keywords or to keep and add more long-term memory keywords we need to do this during the training of our model.

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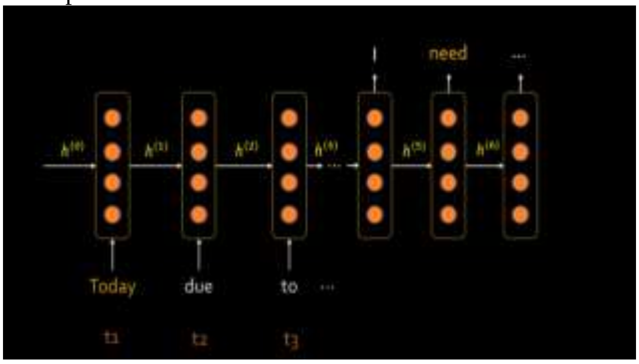

Fig 4. RNN layer at different period of time

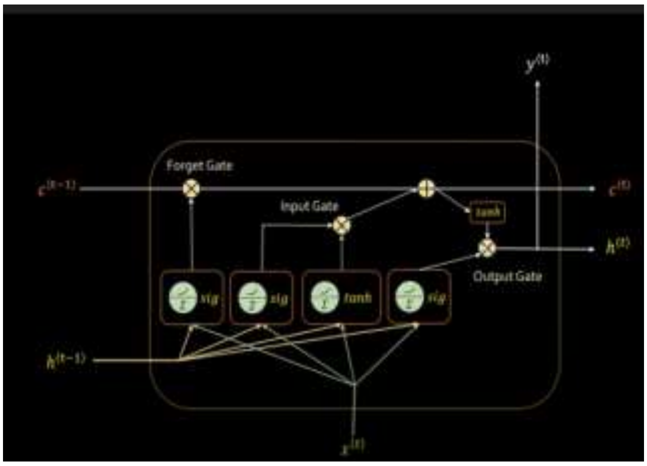

Fig 5. Representation of LSTM execution

Using particular gates, each LSTM layer can access data from both layers above and below it. After passing through a number of gates (such as the forget gate, input gate, etc.) and various activation functions, the data is sent through the LSTM cells (such as the tanh function, relu function). The main advantage of this is that it allows each LSTM cell to store patterns for a finite amount of time. The LSTM may remember important information while simultaneously forgetting less significant information, it should be emphasised.

V. Results

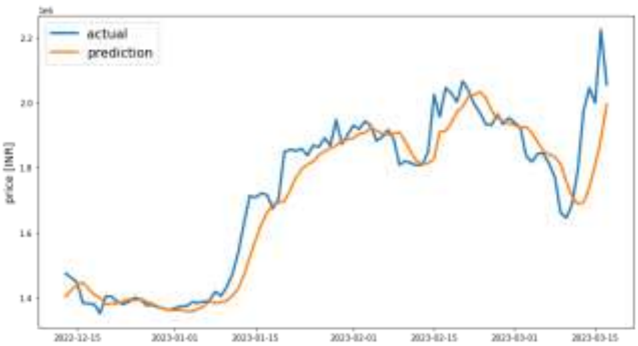

Fig 6. Prediction graph of the model

The figure 6, gives us a graph which shows us two lines one which shows the actual value of the cryptocurrency which has been entered by the user and the other plot shows us the predicted value of the same cryptocurrency. Since both the lines have been inter crossing each other very frequently and almost the value is near to equal.

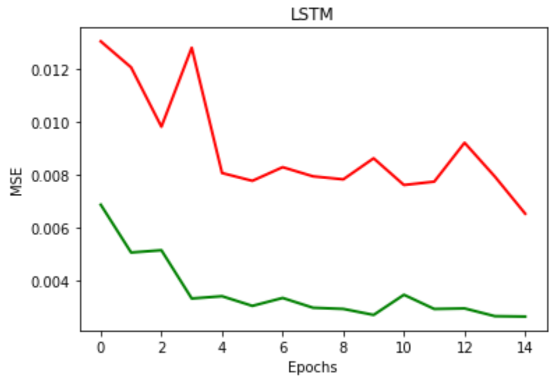

Fig 7. Variation of MSEvs the number of epochs for training and test data

The (coefficient of determination) regression score function for our model is 0.5404267415746096.

The value of mean squared error for the model is 0.0026295476654835987.

The value of Mean Absolute Error for our model is 0.03298679237232304

Conclusion

For time series prediction, the deep learning method known as Long Short-Term Memory (LSTM) is frequently utilised., including the cryptocurrency market. LSTM can capture long-term dependencies and relationships between data points that traditional machine learning models may miss, making it particularly effective for predicting volatile and complex financial data. As we moved further with the training, testing and prediction we found out that the mean absolute error for the model turns out be 0.0839027 for the model.

The use of LSTM in cryptocurrency price prediction is becoming increasingly popular as it offers significant advantages over traditional statistical methods. LSTM models can take into account a wide range of factors that can impact cryptocurrency prices, including market trends, trading volumes, and news sentiment, among others.

In conclusion, LSTM neural networks have proven to be effective in predicting cryptocurrency prices, and as the market continues to evolve and become more complex, the use of deep learning algorithms such as LSTM will become increasingly important in understanding and forecasting cryptocurrency trends.

References

[1] L. K. Priya, S. Kolanupaka, U. M. Ganta, B. Prakash Karing, and S. Yallanuru, "Predicting the Prices of Cryptocurrencies using Deep Learning," 26th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 76-80, 2022.

[2] A. Tanwar, and V. Kumar, "Prediction of Cryptocurrency prices using Transformers and Long Short term Neural Networks," 2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP), 2022, pp. 1-4,doi:10.1109/ICICCSP53532.2022.9862436.

[3] X. Ye, Y. Li, X. Feng, and C. Heng, "A Crypto Market Forecasting Method Based on Catboost Model and Bigdata," 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP), 2022, pp. 686-689, doi: 10.1109/ICSP54964.2022.9778789.

DOI: rp-9788770040723.130
[4] I. A. Hashish, F. Forni, G. Andreotti, T. Facchinetti, and S. Darjani, “A Hybrid Model for Bitcoin Prices Prediction using Hidden Markov Models and Optimized LSTM Networks,” 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2019, pp. 721-728, doi: 10.1109/ETFA.2019.8869094.

[5] W. Yiying, and Z. Yeze, “Cryptocurrency Price Analysis with Artificial Intelligence,” 2019 5th International Conference on Information Management (ICIM), 2019, pp. 97-101, doi: 10.1109/INFOMAN.2019.8714700.

[6] N. Uras, and M. Ortu, “Investigation of BlockchainCryptocurrencies’ Price Movements Through Deep Learning: A Comparative Analysis,” 2021 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER), 2021, pp. 715-722, doi: 10.1109/SANER50967.2021.00091

[7] L. Li, A. Arab, J. Liu, J. Liu, and Z. Han, “Bitcoin Options Pricing Using LSTMBased Prediction Model and Blockchain Statistics,” 2019 IEEE International Conference on Blockchain (Blockchain), 2019,
pp. 67-74, doi: 10.1109/Blockchain.2019.00018

[8] Rajesh, M., &Sitharthan, R. (2022). Image fusion and enhancement based on energy of the pixel using Deep Convolutional Neural Network. Multimedia Tools and Applications, 81(1), 873-885.

[9] A. Armin, A. Shiri, and B. Bahrak, “Comparison of Machine Learning Methods for Cryptocurrency Price Prediction,” 2022 8th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), Behshahr, Iran, Islamic Republic of, 2022, pp. 1-6, doi: 10.1109/ICSPIS56952.2022.10043898.

[10] A.A. Encean, and D. Zinca, “Cryptocurrency Price Prediction Using LSTM and GRU Networks,” 2022 International Symposium on Electronics and Telecommunications (ISETC), Timisoara, Romania, 2022, pp. 1-4, doi: 10.1109/ISETC56213.2022.10010329.

[11] J. Aravindan, and R. K. V. Sankara, “Parent Coin based Cryptocurrency Price Prediction using Regression Techniques,” 2022 IEEE Region 10 Symposium (TENSYMP), Mumbai, India, 2022, pp. 1-6, doi: 10.1109/TENSYMP54529.2022.9864452.

[12] D. K, B. S. P, D. J, I. C, and A. R, “Cryptocurrency Exchange Rate Prediction using ARIMA Model on Real Time Data,” 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 914-917, doi: 10.1109/ICEARS53579.2022.9751925.

[13] D. Yu, “Cryptocurrency Price Prediction Based on Long-Term and Short-Term Integrated Learning,” 2022 IEEE 2nd International Conference on Power, Electronics and Computer Applications (ICPECA), Shenyang, China, 2022, pp. 543-548, doi: 10.1109/ICPECA53709.2022.9718963.

[14] Pazhani. A, A. J., Gunasekaran, P., Shanmuganathan, V., Lim, S., Madasamy, K., Manoharan, R., &Verma, A. (2022).Peer–Peer Communication Using Novel Slice Handover Algorithm for 5G Wireless Networks.Journal of Sensor and Actuator Networks, 11(4), 82.