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ETHEREUM PRICE PREDICTION USING MACHINE LEARNING TECHNIQUES – A COMPARATIVE STUDY

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***Abstract*— In recent years, popularity and use of cryptocurrencies has been rising along with their prices and Ethereum is the second most famous cryptocurrency after Bitcoin. Cryptocurrencies are based on blockchain, which is a distributed and empowered technology that has the power to transform any banking systems. It has become an attractive investment for traders as well as individuals looking to invest. The price of Ethereum varies and is controlled by different factors, such as the crypto market in which it is sold, supply and demand. Ethereum is so valuable because it could be used as cash, we could also pay a portion or part of Ethereum to someone in exchange and it is easily guaranteed by the blockchain. Unlike stocks, Ethereum price is much more variable, as it has a trading time of 24-hours a day without any close time. The paper compares the results of three different models, namely Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs) and Bi-directional Long Short-Term Memory (Bi-LSTMs). The dataset consists of the closing price for the last 2000 days that is used to predict both short-term (30 days) and long-term (90 days) Ethereum prices. These prices are being fetched from an API which is in JSON format and are updated every day.**

***Keywords*— Blockchain, Cryptocurrency, Ethereum, Machine Learning, Neural Network, Regression.**

I. INTRODUCTION

Blockchain is an empowered technology that is able to retrieve any financial or banking systems. With its diverse nature, it has acquired interest from computer science, cryptography and the proliferation of communications. Blockchain technology can provide a platform to exchange money / money without any mediator such as government or other banking organizations.

Cryptocurrency is one such application built on the Blockchain and has an impact created in the banking sector. Various countries across the world such as the USA, Canada and Europe have accepted crypto as a legal tender, whereas there are some countries which have banned crypto currencies as well. India is neutral in this decision and has not regulated it properly, although they have allowed people to buy, sell and trade cryptocurrencies and are exploring the crypto regulations for the country.

There are various traditional statistical time series models for the prediction of prices, which are capable and good enough. With the advancement in Machine Learning and Deep Learning, the capture of long-term information for prediction has improved drastically and produces much better results. Although machine learning has become successful in predicting stock market prices by various time models, using for predicting cryptocurrency prices has been less effective. The reason for this is obvious as the prices of cryptocurrencies depend on many factors such as technological advances, internal competition, pressure on delivery markets, economic problems, security issues, politics etc. innovation strategies are adopted. Unfortunately, due to a lack of indicators, cryptocurrencies are not as reliable as traditional financial speculations such as the stock market.

The rest of the paper is organized as follows. Related Work is explained in section II. Methodology is presented in section III and Implementation in section IV. Experimental Results are explained in section V and the Concluding remarks are given in section VI.

II. RELATED WORK

The paper titled “Prediction of Bitcoin Price Change using Neural Networks” [1] predicted the short- and long-term Bitcoin price changes accurately. They had used Multilayer Perceptron (MLP) and Recurrent Neural Networks (RNN) for the prediction. The results of their paper were that the longer-term prediction had better result with MLP as compared to RNN with approximately 80% accuracy and the future scope was to improvise the short-term prediction as well.

Another paper titled “Bitcoin price prediction using Deep Learning Algorithm” [2] gave the near prediction of

Bitcoin prices from the available data using Bayesian Recurrent Hierarchical Neural Network (RNN) and a Long-Short Term Memory network (LSTM) and provided a comparative study of different methods such as RNN, LSTM, ARIMA and GRU for accuracy and error. They concluded that GRU models have better results than LSTM when High, Close and Open Prices were considered.

The authors of the paper "Enhancing Bitcoin Price Fluctuation Prediction Using Attentive LSTM and Embedding Network" [3] introduced three types of price prediction features, which includes basic features and autoencoders. The feature was tested using the Attentive LSTM Network and the Embedding Network (ALEN). An LSTM network was used to capture the time-based value of Bitcoin and the embedding networks were used to include hidden submissions from related cryptocurrencies. The LSTM was adopted because it found outstanding performance in time series forecasting. The conclusion was that the proposed ALEN model achieved high technological performance on all foundations.

The paper "Performance Evaluation of Machine Learning Algorithms for Bitcoin Price Prediction" [4] predicts the value of Bitcoin using Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Linear Regression (LR). The RNN model with LSTM apparently was more efficient at Bitcoin predictions and forecasts than regression model because it could detect long-term dependencies.

"A Comparative Study of Bitcoin Price Prediction Using Deep Learning" [5] mentions various high-level methods, such as DNNs, LSTMs, CNN, ResNets, which is done by combining CNN and RNN (CRNN), and their integrated Bitcoin pricing models. Various types of in-depth forecasts were used in studying Bitcoin price indexing problems and categories and the results were compared. The conclusion was that DNNs were more accurate than other methods.

The paper "Predicting Price Changes in Ethereum" [6] is a research paper from Stanford University that provides a comparative study of various Machine Learning models to predict prices of Ethereum such as Logistic Regression, Naive Bayes, Support Vector Machines, Random Forest and ARIMA and tabulated the accuracies. The paper concluded that ARIMA gave better predictions for time series than other machine learning models mentioned above.

"Deep Learning Ethereum Token Price Prediction with Network Motif Analysis" [7] paper speaks about using LSTMs for predicting the token value of Ethereum and further utilizes network motif analysis for improvised results. The work concludes that the current market value of cryptocurrencies is more than 230 billion dollars. Ethereum has the second highest currency value on the market and also supports much more performance as compared to Bitcoin. While the price is a bit limited in published documents, further technological performance could cause the Ether price forecast to be significantly different from that of Bitcoin.

The authors of the paper "Advanced CNN-LSTM Model for Cryptocurrency Forecasting" [8] uses convolution neural networks along with LSTMs in a combined manner for better prediction of three cryptocurrencies, i.e., Bitcoin, Ethereum and Ripple. The paper concludes that mixed cryptocurrency data in fully-connected deep neural networks provide better results than if they were computed individually.

Another paper "Ether Price Prediction Using Gated Recurrent Unit" [9] develops a prediction model to predict Ethereum prices using Gated Recurrent Unit (GRU). GRU is similar to LSTM, but the model is simpler and can remember long-term memory. The paper provides good results as compared to other methods and says that in future, information leakage can be prevented for better accuracy.

"Bitcoin Price Prediction Based on Other Cryptocurrencies Using Machine Learning and Time Series Analysis" [10] talks about various methods such as analysis of the time series, various neural networks and machine learning algorithms. Bitcoin prices were predicted based on other three famous cryptocurrencies, Ethereum, Zcash and Litecoin and it concluded that Zcash had best performance in forecasting Bitcoin's prices as compared to the other two currencies.

Another paper "Ethereum analysis and predictions utilizing deep learning" [11] talks about providing cryptocurrency market data analysis using the LSTM network, Stacked LSTM network, the Bidirectional LSTM network, and the Gated Recurrent Unit network. Six types of neural networks have been used to evaluate the effects of the selected types and to conclude. This paper concluded that LSTM and GRU gave 71% accuracy and was the highest as compared to other models.

The authors of the paper "Predicting the Trends of Price for Ethereum Using Deep Learning Techniques" [12] learned as to how in-depth Learning strategies such as Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) helped predict Ethereum pricing styles. Everyday data consisted of 1000 data samples and hourly data contained 1500 information samples and minute data contained 400000 data lines. Multi-Layer-Perceptron and Long Short-Term Memory models were used for predicting Ethereum value and Mean Absolute Percentage (MAPE) Errors.

Another paper titled "Cryptocurrency forecasting with deep learning chaotic neural networks" [13] uses deep learning techniques to predict the values of the three best-selling digital currencies namely, Bitcoin, Digital Cash and Ripple. The implementation of Lyapunov's closest neighbor rating, flexible analysis, hurst exponent and longer-term memory study of neural networks and general neural regression networks were performed and Root Mean Square Error (RMSE) was calculated for each cryptocurrency prediction.

The paper "Predicting the Price of Bitcoin Using Machine Learning" [14] gets the accuracy of Bitcoin price predictions in US dollars. The authors used the optimized Bayesian Recurrent Neural Network (RNN) and the Long Short-Term Memory (LSTM) network. LSTM achieved the highest accuracy of 52% and RMSE as 8%. ARIMA, a popular model for predicting time series prediction is compared to deep

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learning models. As expected, these learning methods surpasses ARIMA's speculative performance. Finally, both deep learning models were marked for both GPU and CPU and GPU training time which improved CPU implementation by 67.7%.

"Bitcoin Price Prediction using Machine Learning" [15] understood and identified everyday trends in the Bitcoin market by gaining insight in the positive aspects surrounding the Bitcoin price and predicting the everyday price change indicator with the higher accuracy. Two methods have been used by the authors, the Bayesian Regression and the Random Forest algorithms. After establishing a framework for learning and completing the standard, they used the above methods and chose the best way to solve the problem of Bitcoin prediction.

III. METHODOLOGY

The techniques used in this project are RNN, LSTM and Bidirectional LSTM and the comparison of these techniques for better performance in terms of accuracy.

A. RNN –

Recurrent Neural Network (RNN) is a group of neural networks that help to create a sequential data model. Based on the feedforward networks, RNNs reflect the same mechanism of action of the human brain. Because of their internal memory, RNNs can remember important things by capturing their findings, allowing them to be more accurate in predicting future events. This is why it is the preferred algorithm for successive data such as text, timeline, speech, financial data, video, audio, weather, etc. We can view RNN as a sequence of neural networks that we train in sequence with backpropagation.

B. LSTM –

Long Short-Term Memory (LSTM) network is a recurrent neural network that relies on learning system on problems that are predictable. The Long Short-Term Memory Network is complex version of RNN, that allows data to persist. It could handle the loss of gradient problem that the RNN faces. At a large-level, LSTM works much better than a RNN cell. The LSTM has three parts and each part does specific job.

The first part is known as the Forget Gate which selects if the data from the previous gate should be remembered or considered invalid and ignored. The second part or Input Gate try to learn new data from the input in the particular cell. Finally, the third part or Exit Gate transfers the updated data from the present time stamp for the next time stamp.

The equation for the forget gate is as follows:

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \quad - (1)$$

The equations for the input gate are as follows:

$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right) \quad - (2)$$

$$\hat{C}_t = tanh(x_t U^g + h_{t-1} W^g) \quad - (3)$$

$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \hat{C}_t\right) \quad - (4)$$

The equations for the output gate are as follows:

$$o_t = \sigma(x_t U^o + h_{t-1} W^o) \quad - (5)$$

$$h_t = tanh(C_t) * o_t \quad - (6)$$

W is a link that will recur from the before hidden cell and the present hidden cell. U is weight matrix that would connect input to the hidden layer. C is the internal memory, which is a combination of memory, multiplied by the forgot gate, and a new hidden state, multiplied with the input gate.

C. Bidirectional LSTM –

Bidirectional LSTMs expand regular LSTMs that could improve the performance of the model in successive phases. In case all steps of the input time are available, Bidirectional LSTM will train two LSTM sequences instead of one, where the first one of the sequences as it is and second one as a reverse copy of the sequence. This could give more context to the network and could lead to a faster and more better learning for the problem.

IV. IMPLEMENTATION

Python is selected as the programming language to code this project as it is an easy, user-friendly language and has a lot of libraries that support machine learning and deep learning implementation. While complex algorithms and various functions work after machine learning and AI, Python's simplicity and ease of use allow developers to write reliable programs.

A. Data Preprocessing

Min-max scalar (using sci-kit learn) transforms the given data into the range [0,1], which means the minimum and maximum value of a particular feature under consideration can be 0 and 1, respectively.

Min-max scalar technique is used for the normalization of the 'closing price' which is used to predict the prices.

B. Error metrics to evaluate the results

Mean Absolute Percentage Error (MAPE) - The Mean Absolute Percentage Error (MAPE) is the average of the absolute percentage errors of forecasts whose equation is as below:

$$MAPE = \left(\frac{100\%}{n}\right) \Sigma \left(\frac{|y-\hat{y}|}{|y|}\right) \quad - (7)$$

Root mean squared error (RMSE) - Root Mean Squared Error (RMSE) is the root of the mean of the squares of all the errors. The formula is as below:

$$RMSE = \frac{1}{n}\sum_{t=1}^{n} \cdot \left|\frac{At-Ft}{At}\right| \qquad - (8)$$

Mean absolute error (MAE) – Mean Absolute Error measures the mean magnitude of the errors. The equation is as shown:

$$MAE = \sum_{i=1}^{n} \cdot \frac{|yi-xi|}{n} \qquad - (9)$$

V. EXPERIMENTAL RESULTS

The result shows that Bidirectional LSTM is an extremely good model to study the trend of crypto currency prices and their variations for longer durations of time. The prediction charts of RNN, LSTM and Bidirectional LSTM along with the actual price are given below:

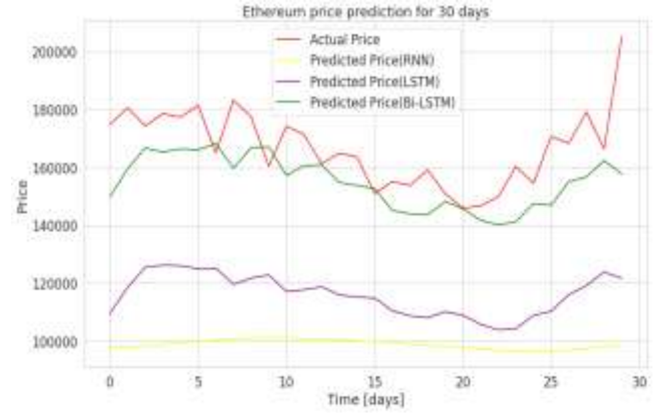


Fig. 3: 30-day price prediction

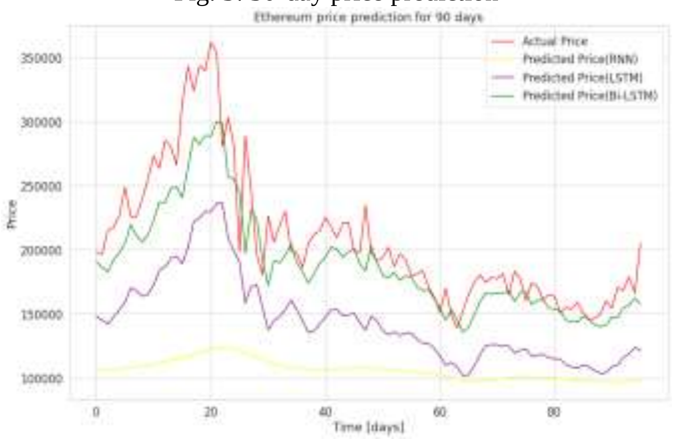
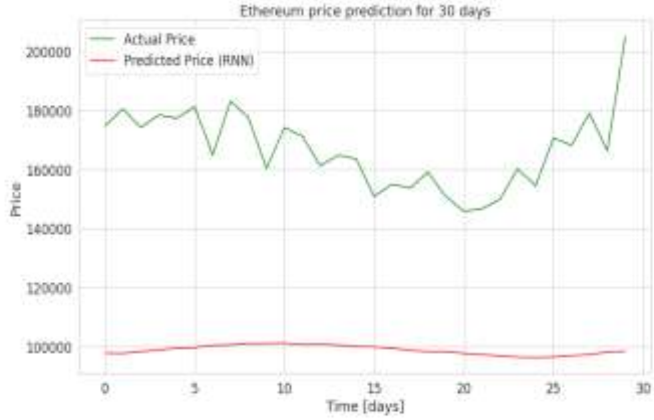
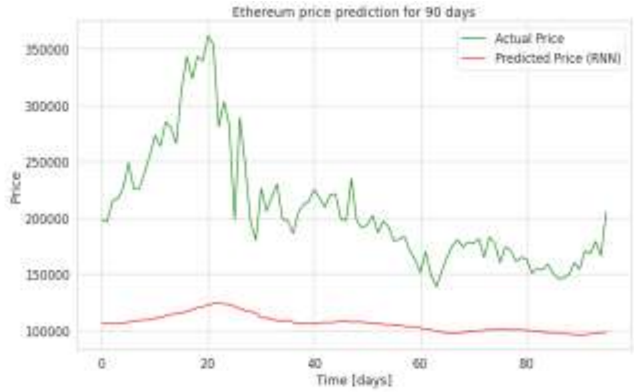


Fig. 4: 90-day price prediction

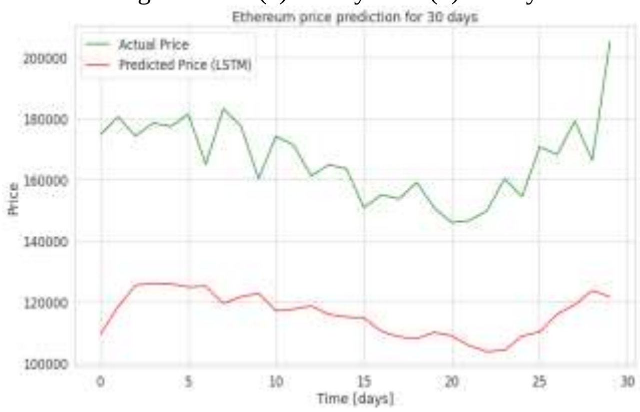


(a)

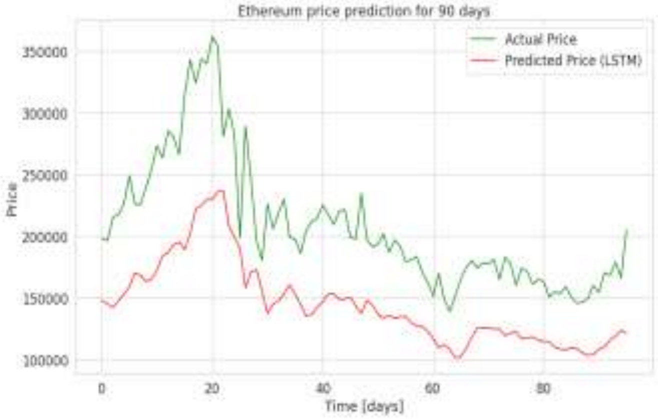


(b)

Fig. 5: The Actual Price and Predicted Price of Ethereum using RNN for (a) 30 days and (b) 90 days

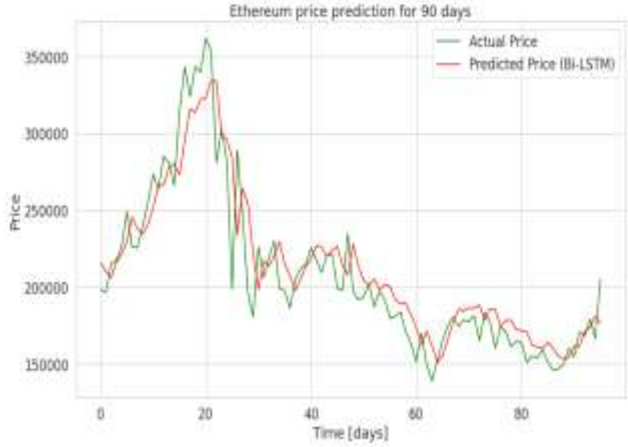


(a)



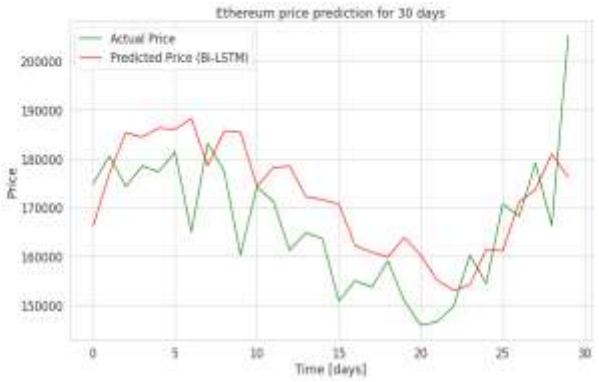
(b)

Fig. 6: The Actual Price and Predicted Price of Ethereum using LSTM for (a) 30 days and (b) 90 days



(b)

Fig. 7: The Actual Price and Predicted Price of Ethereum using Bidirectional LSTM for (a) 30 days and (b) 90 days



(a)

Metrics			**Methodologies**			
	Simple RNN		**LSTM**		**Bidirectional LSTM**	
	30 days	90 days	30 days	90 days	30 days	90 days
MAPE (%)	40.46	46.76	30.02	27.38	7.26	9.57
RMSE (Rs)	69271.59	111641.93	50500.4	61983.62	15800.94	29056.2
MAE (Rs)	68055.17	101613.66	49334.33	57835.78	12583.79	21908.86

Table - 1. Error Metrics of Ethereum prediction using Simple RNN, LSTM and Bidirectional LSTM for 30 days and 90 days

Table 1 gives the quantitative measure of the error metrics for various models used for comparison in the project. It is observed that Mean Absolute Percentage Error (MAPE) is larger for Simple RNN, lesser for LSTM and least for Bidirectional LSTM for both 30 days and 90 days categories.
The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) also is larger for Simple RNN, least for Bidirectional LSTM and intermediate for LSTM. Among 30 days and 90 days, the error metrics are larger for 90 days as compared to 30 days, which concludes that short term prediction is more accurate than long term predictions.

VI. CONCLUSION

The proposed model compares different price prediction models and concludes that bidirectional LSTM is the best model among RNN, LSTM and Bi-LSTM to forecast the price of Ethereum. The model uses the 'closing price' as the parameter to predict the price. When it comes to the financial market, getting to know the trends is very important. This model gives a good trend of the prices for longer periods of time (preferably 90 days). The model is also easily scalable and the accuracy can further be improved with some tweaks.
As noticed above, RNN fails in predicting the prices. LSTM and Bi-directional LSTM succeed in predicting the price of Ethereum but the better one is bidirectional LSTM. It achieves its purpose of predicting the prices and forecasting the price trends with a reasonable accuracy. The model can further be enhanced by considering more parameters and changing various hyper parameters. There's a lot of scope and things to further explore with better models coming up each day.

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