An Efficient Artificial Intelligence Model to Predict the Values of Cryptocurrencies

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Article Info
Page Number: 6351-6365
Publication Issue:
Vol. 71 No. 4 (2022)

Article History
Article Received: 25 March 2022
Revised: 30 April 2022
Accepted: 15 June 2022

Abstract

At present, all smart applications are being made with the use of data. These applications can become more effective by insights of cleaned data and will have a great effect on the research department of every industry. With the revolution of data science together with the internet, a large amount of data is produced daily. The data are heavily used by various industries. The data available is raw data cleaned by the researchers to produce better results. There needed some actions to make them even better. The paper presents the predictions of the values of cryptocurrencies by preparing the data set efficiently. Cryptocurrency is regarded as a perplexing subject in finance due to its high volatility. This paper aims to use the model to forecast the prices of cryptocurrencies. The goal of this article is to use Artificial intelligence machine learning algorithms and models to anticipate and forecast the closing price of the cryptocurrency, making it easier for users to trade these currencies.

Keywords: Bitcoin, Data Science; Deep Neural Networks [DNN]; Neural Networks; Virtual Currency.

1. Introduction: -

Cryptocurrencies have become a worldwide phenomenon in the economic sector. They are one of the most widely operated monetary products on the planet. These are the virtual currencies used in the market [1]. These currencies are not distributed by the banks rather they are decentralized and are converted by cryptographic methods. The distribution of these currencies is secured by blockchain technologies. It is very difficult to forecast its value due to dynamism [2][14]. Bitcoin is a type of cryptocurrency that is defined as a digital form of currency that is created and maintained using complex encryption techniques, which is known as cryptography. It is intended to serve as a modern-day medium of exchange. Bitcoins are a popular cryptocurrency. It was established in 2009. It is getting so much attention in computer science research as cryptocurrency values are very unstable [3]. There are many kinds of cryptocurrencies that are being used all over the world. In this paper, we are presenting results based on the three most popular cryptocurrencies and comparing the results with the previously published works. Bitcoin (BTC), Litecoin (LTC), and Ethereum (ETH) are the three common cryptocurrencies. Higher machine learning algorithms, deep learning algorithms, and neural networks are used in the presented study. It is very crucial to make assumptions about cryptocurrency valuations.

2. Related Work:

Artificial Intelligence (AI), is a subfield or the main technology, which comes under computer science. It focuses on making the model or making the machine at the top-notch level. Machine learning evolved as a subclass of artificial intelligence in the mid-twentieth century. It uses machine learning to provide a new technique to deal with AI challenges. It has also played a significant part in AI design by drawing on a conceptual understanding of how the human brain operates. It learns how to make important judgments in the same way that humans do. It may be accomplished by using a strong dataset to train our machine learning model and then applying the best neural networks [4][13]. Deep neural networks, together with advances in traditional machine learning and scalable general-purpose GPU and Tensor Processing Unit (TPU) computing, have become essential components of artificial intelligence, enabling many of these unexpected outcomes[15] [12].

Virtual Currencies are playing a great role in the current stock market. In the graph shown in fig1, the expansion of the market of cryptocurrencies in the past 10 years is presented[15].

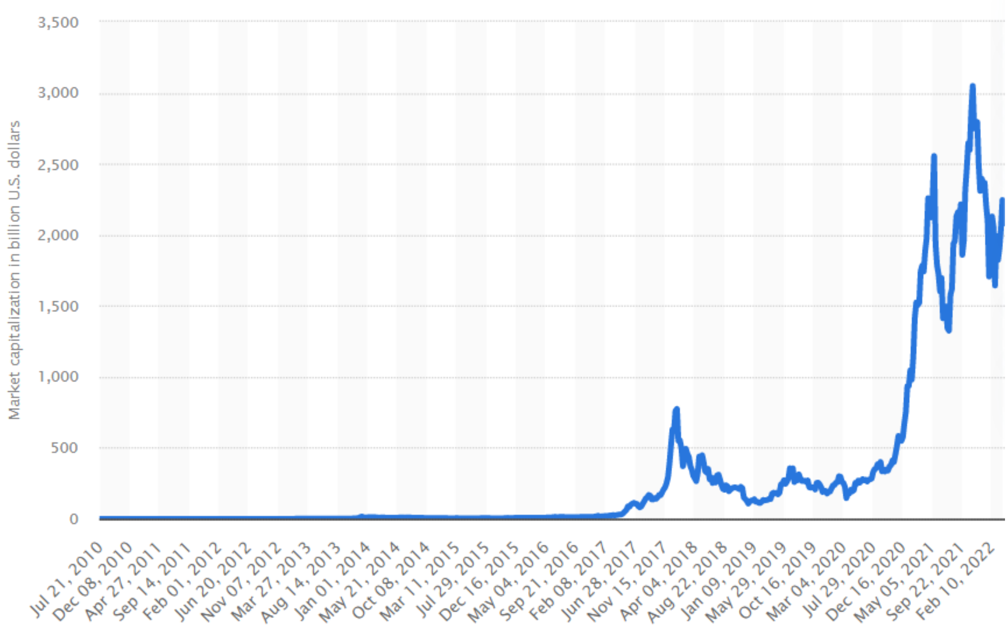

Fig1: Market Trend in Cryptocurrencies

We can also see that prices dropped significantly between December 2018 and April 2019. Prices continue to rise from April to August 2019, with some swings in July and August. Prices have been steadily falling since September 2019. The intriguing aspect of this price fluctuation is that prices are low in the middle of the year and then rise in the second half of the year.

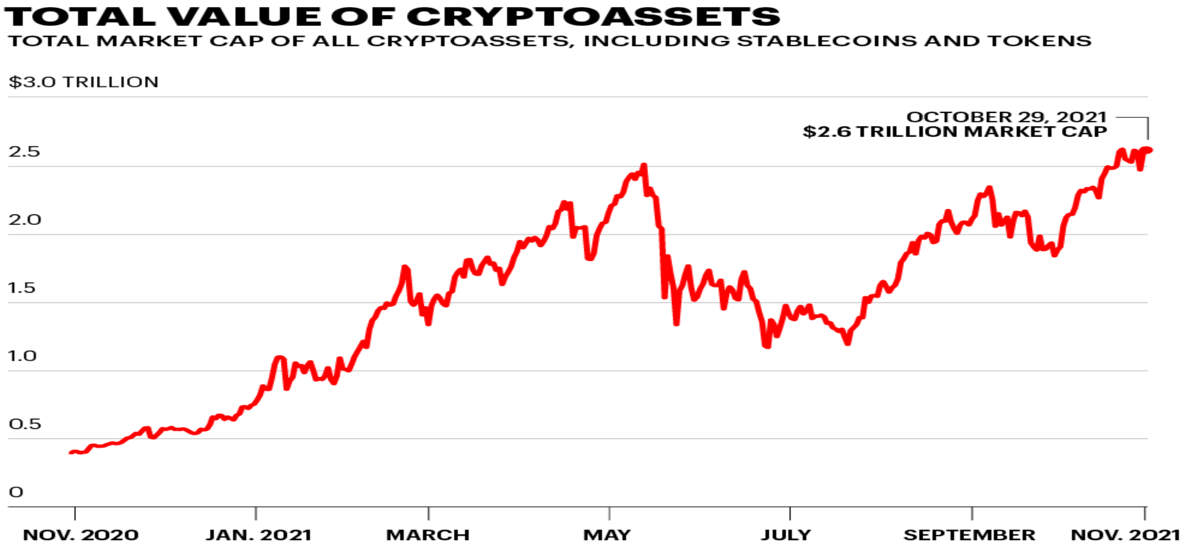

Fig2: Market Capital of Crypto Assets

Fig 2 shows the total market capital of crypto assets in the year 2021. It is 2.5 trillion dollars and Fig3: graph shows the shareholdings of leading companies in the cryptocurrency market [16].

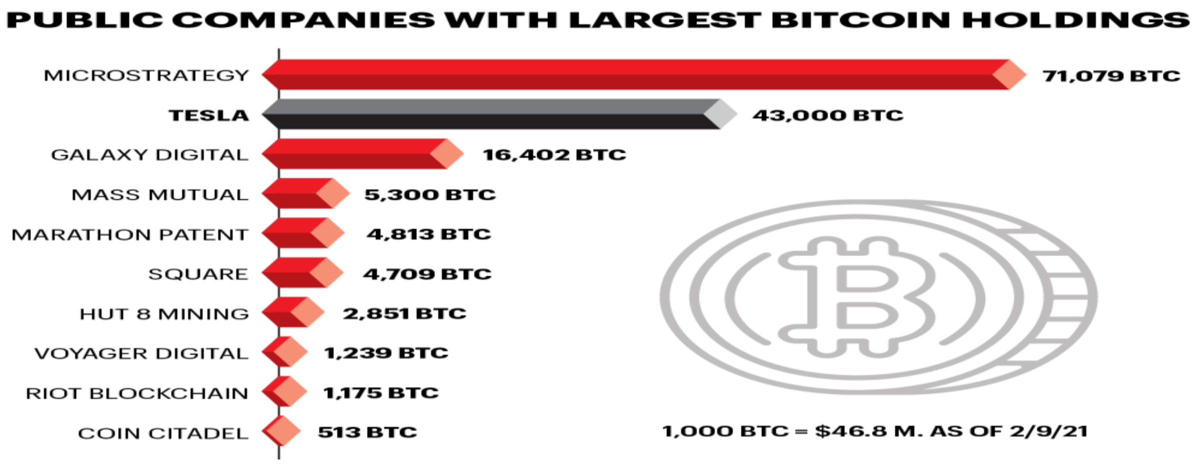

Fig 3: Major companies invested in Cryptocurrencies

The popularity of cryptocurrencies soared in 2017 as their market value grew exponentially for several months in a row. In January 2018, the prices reached a high of almost $800 billion. Although machine learning has been successful in predicting stock market prices using a variety of time series models, it has been limited in its use in predicting cryptocurrency prices. The explanation for this is self-evident. Cryptocurrency prices are influenced by a variety of variables, including technological advancements, internal competitiveness, market pressure to provide, economic issues, security concerns, political influences, and so on. Their extreme volatility means there's a lot of room for profit if you use smart inventing tactics.

Cryptocurrencies are, unfortunately, less predictable than traditional financial instruments due to their absence of indexes[17] [18]

Evans et.al (2021) take into consideration, the financial uncertainty associated with bitcoins trading volume specific to the Google trends as potential factors behind the return and exchange of Bitcoins. because of this uncertainty, it will create a lot of problems for the investors in crypto digital market assets. Talking about Bitcoin returns with the probable drivers of Bitcoin volatility, we take into account macroeconomic and financial factors, which are univariate. Bitcoin shows common factors with both gold and the dollar. This would help us classify the crypto market and analyze it as a separate asset class [6]. A hybrid cryptocurrencies-based prediction model is presented in [7]. It is focused on Monero and Litecoin cryptocurrencies. Paper [8] presented the use of linear regression and vector machine to forecast the values of bitcoins. The authors of [9] presented the use of a multiple linear regression model and deep learning methods with a conjugate gradient mechanism to predict the values of bitcoin. The paper [10] uses the LTSM model and through Yahoo finance, it predicts the values of bitcoins. The paper research [11] presents the use of Bayesian optimized RNN and LTSM for BTC price prediction. The study discovered that LTSM produces better outcomes, with a 52 percent accuracy and an 8 percent Root Mean Square Error. LTSM, GPU, and bi LTSM were applied to three popular cryptocurrencies, Bitcoin(BTC), Litecoin(LTC), and Ethereum(ETH) (ETH). This article refines data more thoroughly and obtains outcomes in order to present a more accurate and dependable model than[22].

3. Problem Formulation:

The big problem in investing in digital currencies is the uncertainty in Cryptocurrencies. These digital assets have no steadiness. it can be crashed at any time. it depends on the market trend of the current time. The model presented in this article would let the machine predict the value of particular cryptocurrencies. This model will help clients to invest in cryptocurrencies such as bitcoin, Ethereum, and LTC. It will make the digital process easier for investors. The forecasts made by the presented model are based on trade characteristics such as price, volume, open, high, and low values.

4. Methodology- To reach the goal of the article, an artificial Intelligence Model is developed and applied to three types of cryptocurrencies. First, the historical data set has been collected, and then a model is built by following the steps mentioned in Fig 4. By comparing the results to the model described in the study[22], the presented model is evaluated.

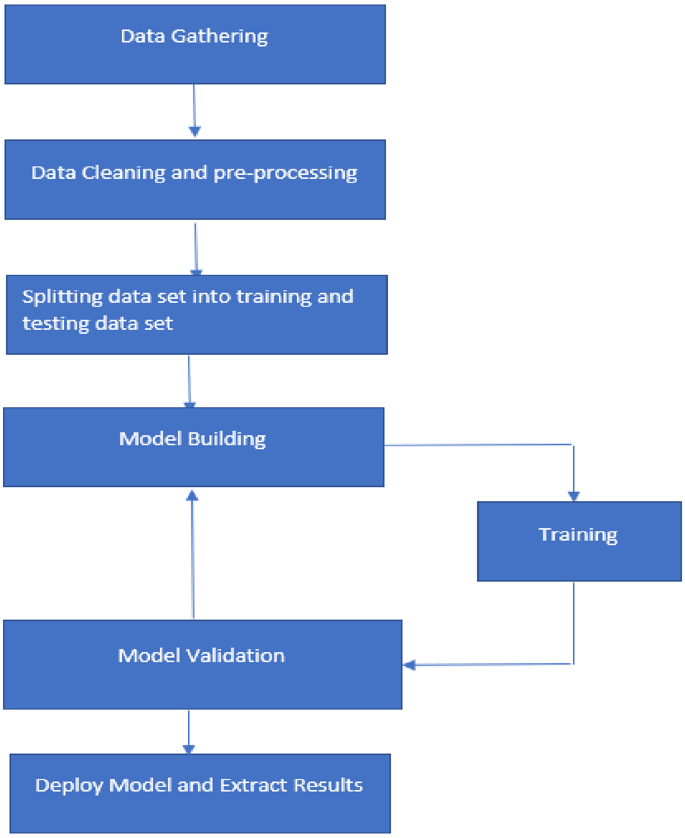

Fig 4: Steps for Model building and Making predictions

In this article presented results are based on real-time data from the Crypto Compare website (**https://data.cryptocompare.com/**). There are six features are present in the dataset, as shown in Fig 5. The details for them are as follows:

time	high	low	open	volumefrom	volumeto	close
2020-11-16	22138.63	20949.48	21122.26	103.70	2245691.48	22031.02
2020-11-17	23527.98	21788.12	22031.02	145.60	3299013.64	23269.27
2020-11-18	24238.26	22695.94	23269.27	180.84	4236777.74	23380.27
2020-11-19	23909.74	22959.77	23380.27	99.93	2353690.67	23452.37
2020-11-20	24459.67	23402.73	23452.37	157.70	3806209.07	24358.34
...	...	...	...	...	...	...
2021-02-19	70785.62	64521.64	65501.44	203.48	13801194.08	70756.32
2021-02-20	72772.90	68591.72	70756.32	170.69	12127421.54	71257.32
2021-02-21	73175.84	70390.14	71257.32	100.83	7264400.39	72326.14
2021-02-22	72326.14	58885.95	72326.14	273.54	18461117.53	68332.46
2021-02-23	68332.46	56403.47	68332.46	323.94	19725515.77	61490.86

Fig 5 Screenshots of Dataset

1) Close Price – This is the currency market's close price for that day.

2) High Price – This is the day's highest currency price.

3). Low Price — This is the day's lowest currency price.

4). Open Price — This is the currency market's open price for that day.

5) Volume from - The amount of currency traded from on that particular day.

6). Volume to — The total amount of currency traded on that particular day.

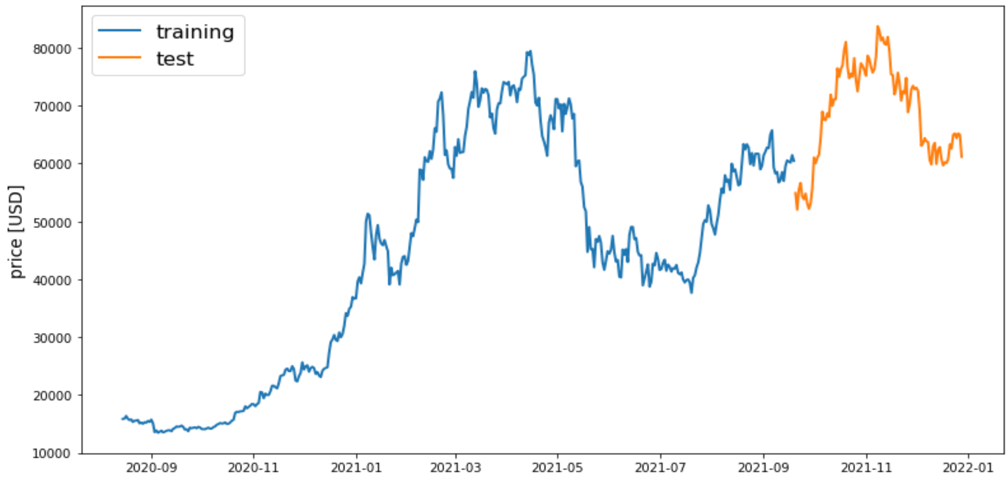

Fig 5 Training and Testing Data set

The data set has been separated into training and testing data, as shown in fig 5. Presented results are based on Neural network models LTSM, GPU, and bi LTSM.

As shown in Fig 6, A neural network (NN) is a system that approximates the operation of the human brain by modeling the neuronal structure of the cerebral cortex on a much smaller scale. The input, hidden, and output layers comprise a Neural Network. [21].

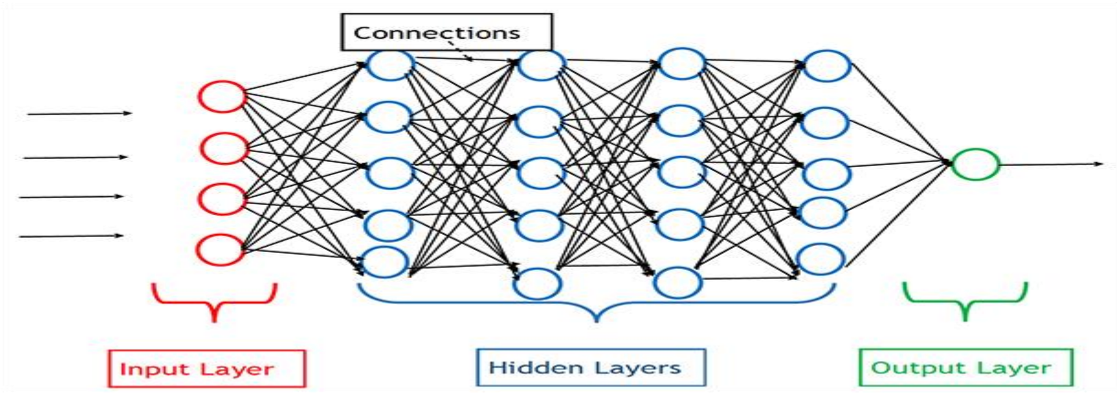

Fig 6: Deep Neural Network

4.1 LSTM:

It works by allowing each LSTM layer to take information from both, previous layers and the present layer using specific gates [19] [20]. The data is sent via the LSTM cells after passing through multiple gates (forgetting gate, input gate, etc.) and various activation functions (tanh function, relu function, etc.). The key benefit of this is that each LSTM cell can recall patterns for a set amount of time. It's worth noting that LSTM can remember crucial information while forgetting irrelevant information.

The following equations can be used to model the LSTM's forward training process:

$$i_t = \sigma(a_b \cdot [\![h_{t-1}, x_t]\!] + j_f)$$

$$e_t = \sigma(a_b \cdot [\![h_{t-1}, x_t]\!] + j_e)$$

$$d_t = f_t * d_{t-1} + i_t * \tanh(a_d \cdot [\![h_{t-1}, x_t]\!] + df)$$

$$k_t = \sigma(w_o \cdot [\![h_{t-1}, x_t]\!] + j_o)$$

$$h_t = k_t * \mathrm{tabh}(c_t)$$

where it, kt, and et signify the input gate, output gate, and forget gate activations, respectively; dt and ht denote the activation vector for each cell and memory block, respectively; and W and b denote the weight matrix and bias vector, respectively. Furthermore, $\sigma(\circ)$ stands for the sigmoid function [19].

5. Results

5.1 Results of Bitcoin:

Results for the prediction of the values of Bitcoin using models LTSM, GRU, and bi-LTSM are tabulated in Table-1 and the resulting graph is shown in Fig7, Fig 8, and Fig 9 respectively.

Table -1 Results of Bitcoin

Sr. No.	Cryptocurrency	Paramenters	Results
1	Bitcoin	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.2098% RMSE: 150.545
			LSTM MAPE: 1.098% RMSE: 390.676
			bi-LSTM MAPE: 4.987% RMSE: 2870.617

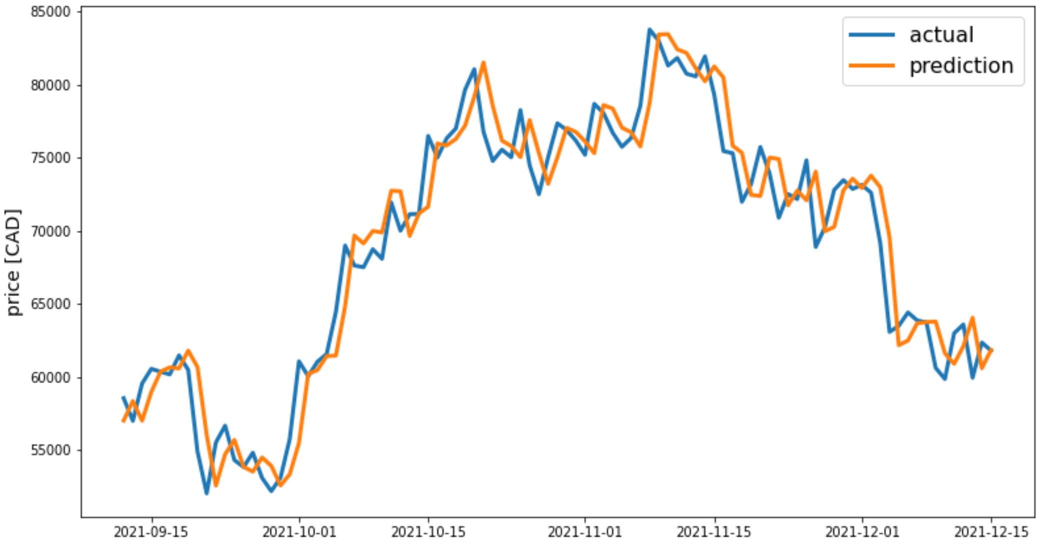

Fig 7: Bitcoin Predicted vs Actual Using LTSM Model

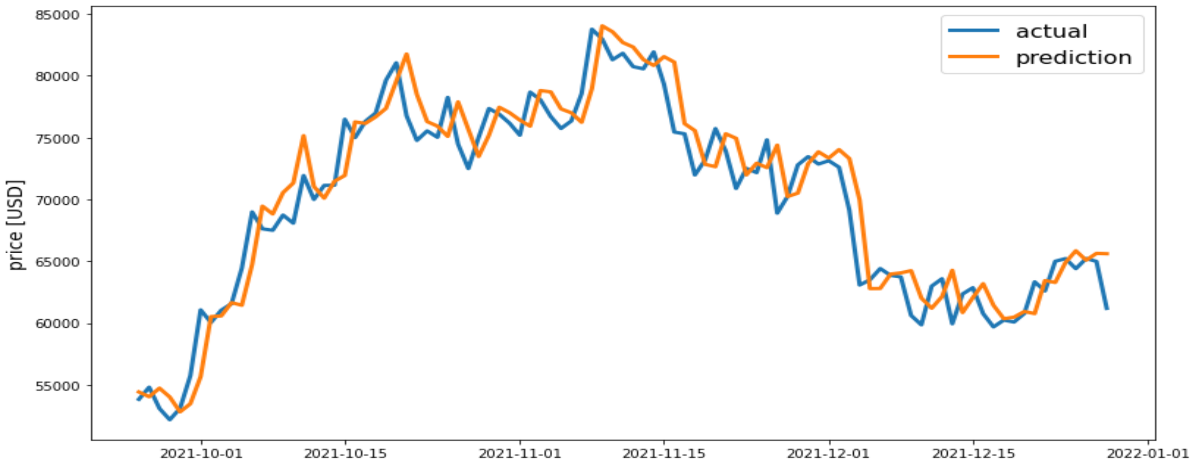

Fig 8: Bitcoin Predicted vs Actual Using GRU Model

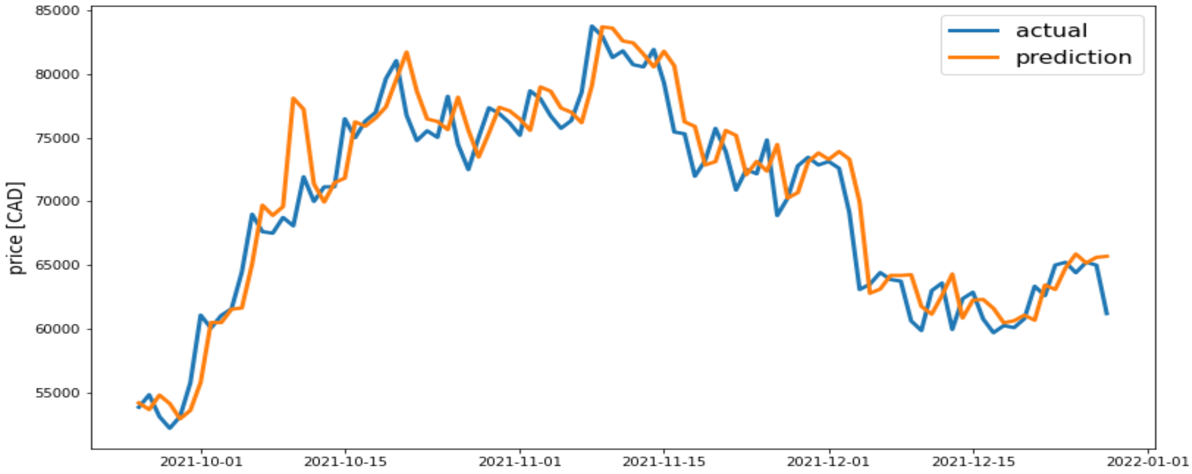

Fig 9: Bitcoin Predicted vs Actual Using bi-LTSM Model

Table-1 lists the accuracies of these models for BTC coins. The results in Figures 7, 8, and 9 compare the current and forecast BTC prices. Over the whole interval, the anticipated and actual prices are nearly identical, as shown in the graph. The MAPE and RMSE values of the GRU model are the lowest at 0.2098 percent and 150.545 percent, respectively, as shown in Table-1. As a result, GRU outperforms LSTM and bi-LSTM in predicting BTC trends. The discrepancy between the projected and actual price is almost non-existent along with the testing set, with very slight variances in the top few peaks of the time series, as shown in Fig 8. Hence this model is proven to be the best.

5.2 Result of Ethereum [ETH]:

Results for the prediction of the values of Ethereum using models LTSM, GRU, and bi-LTSM are tabulated in Table-2 and the resulting graph is shown in Fig10, Fig 11, and Fig 12 respectively.

Table -2 Results of Ethereum

Sr. No.	Cryptocurrency	Paramenters	Results
1	ETH	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.7454% RMSE: 39.89
			LSTM MAPE: 1.0897% RMSE: 56.456
			bi-LSTM MAPE: 5.78% RMSE: 305.698

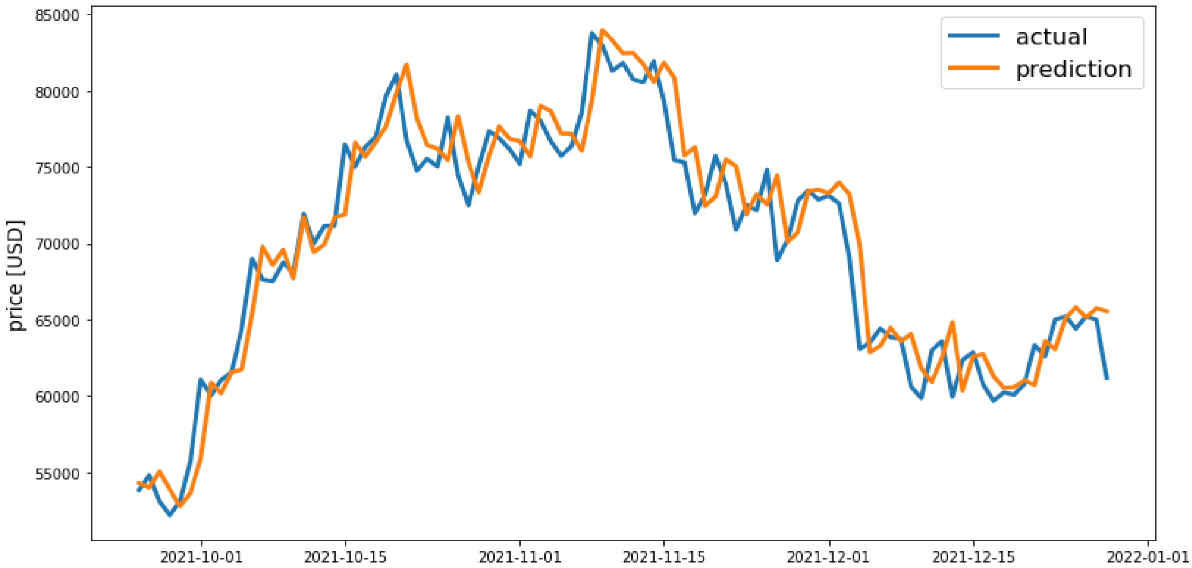

Fig 10: Ethereum Predicted vs Actual price Using LTSM Model

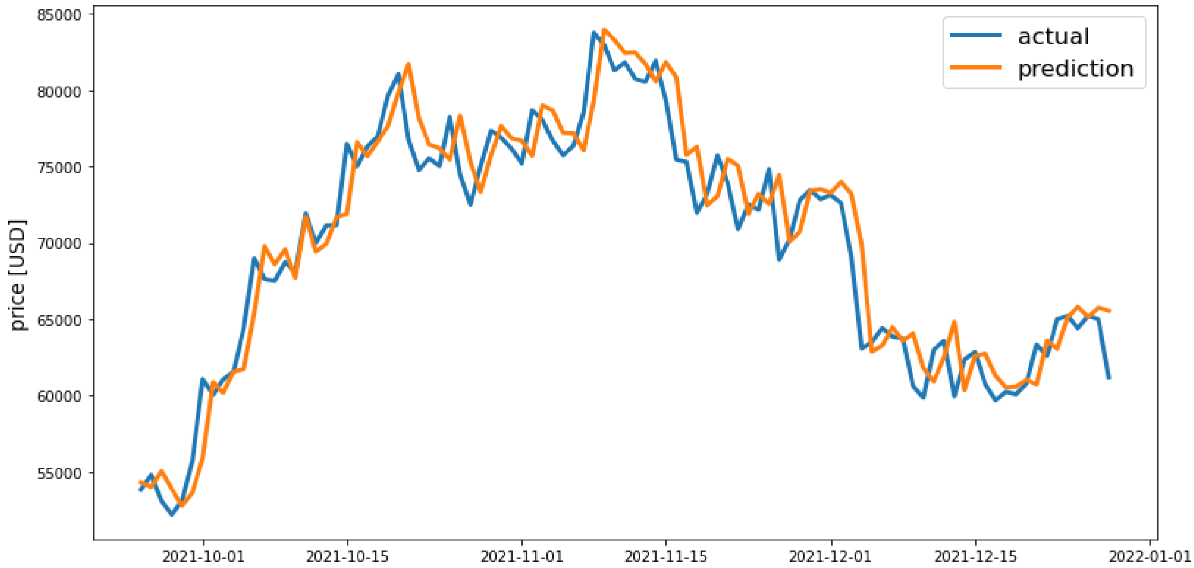

Fig 11: Ethereum Predicted vs Actual price Using GRU Model

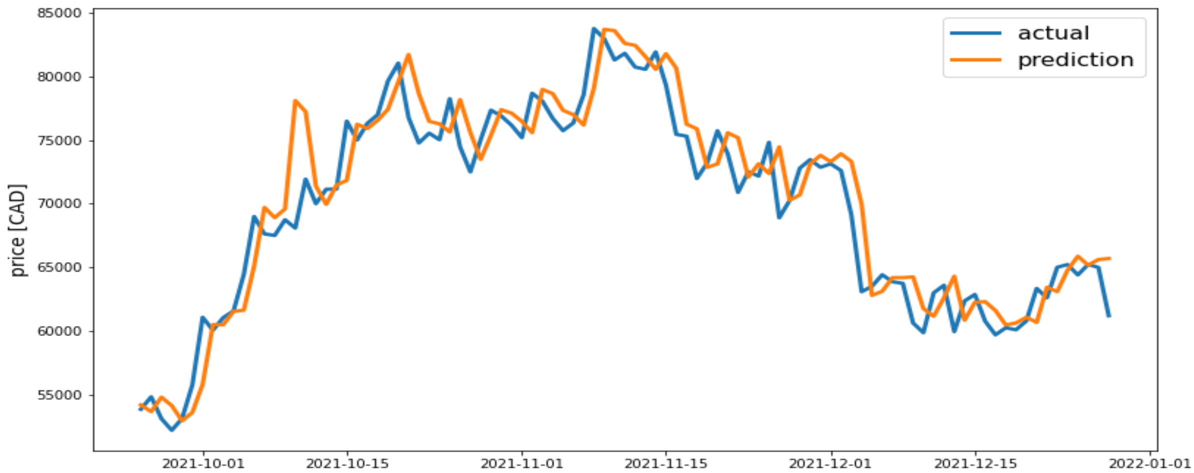

Fig 12: Ethereum Predicted vs Actual price Using bi-LSTM Model

Table-2 shows the accuracy of these models for the ETH cryptocurrency. The results in Figures 10, 11, and 12 compare the current and forecast price of ETH. Over the whole interval, the anticipated and actual prices are nearly identical, as shown in the graph. The MAPE and RMSE values of the GRU model are the lowest at 0.7454 percent and 39.89 percent, respectively, as shown in Table-2. As a result, GRU outperforms LSTM and bi-LSTM in predicting ETH movements. The gap between the projected and actual price is almost non-existent along with the testing set, with very slight deviations in the top few peaks of the time series, as shown in Fig 11. Hence this model is proven to be the best.

5.3 Result for LTC:

Results for the prediction of the values of LTC using models LTSM, GRU, and bi-LTSM are tabulated in Table-3 and the resulting graph is shown in Fig13, Fig 14, and Fig 15Respectively.

Table -3 Results of LTC

Sr. No.	Cryptocurrency	Paramenters	Results
3	LTC	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.1476% RMSE: 0.765
			LSTM MAPE: 0.6478% RMSE: 2.897
			bi-LSTM MAPE: 2.098% RMSE: 3.676

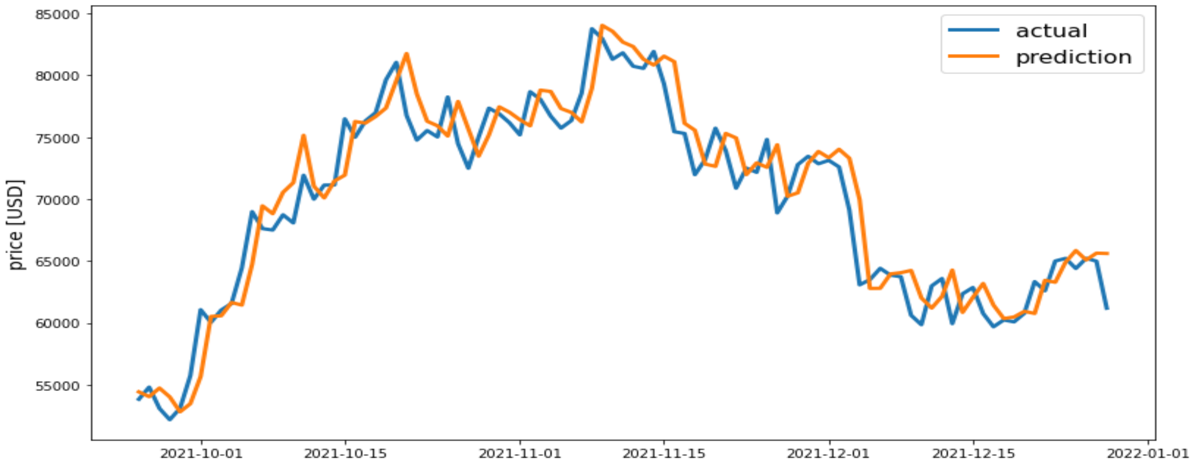

Fig 13: LTC Predicted vs Actual price Using LTSM Model

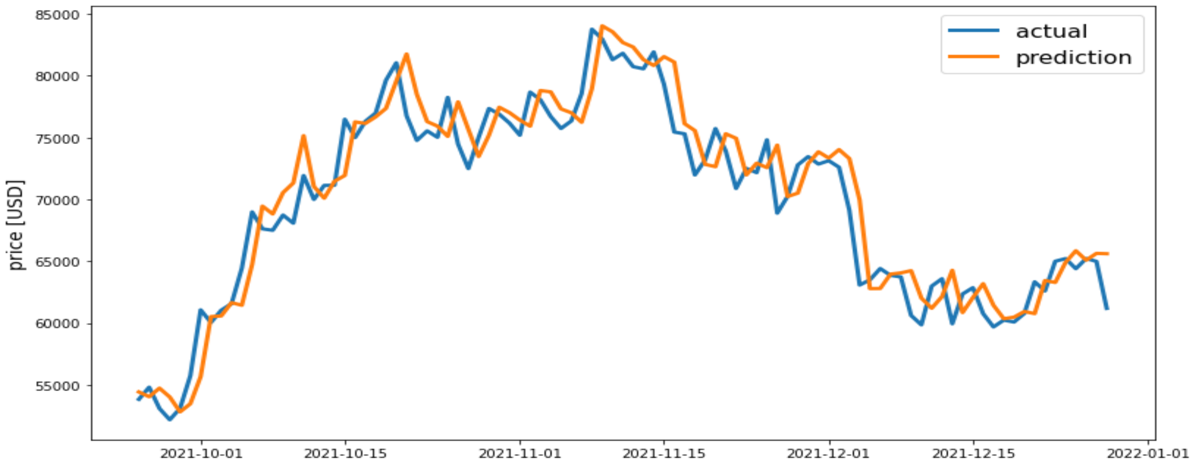

Fig 14: LTC Predicted vs Actual price Using GRU Model

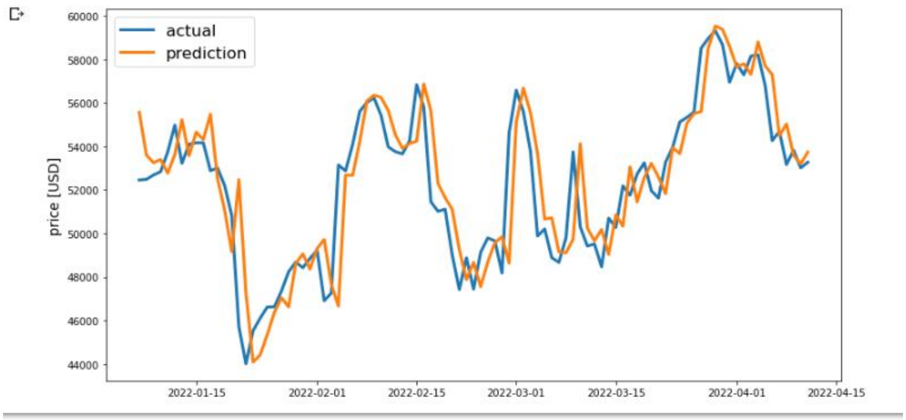

Fig 15: LTC Predicted vs Actual price Using bi-LTSM Model

Table-3 lists the accuracies of different models for the LTC cryptocurrency. The results in Figures 13, 14, and 15 compare the current and expected pricing of LTC. Over the whole interval, the anticipated and actual prices are nearly identical, as shown in the graph. The MAPE and RMSE values of the GRU model are 0.1476 percent and.765, respectively, as shown in Table-2. As a result, GRU outperforms LSTM and bi-LSTM in predicting LTC trends. The discrepancy between the projected and actual price is almost non-existent along with the testing set, with very slight variances in the top few peaks of the time series, as shown in Fig 14. Hence this model is proven to be the best.

5.4 Comparision with previous Work –

The comparison of the LTSM, GRU, and bi-LTSM model applied to three cryptocurrencies is tabulated in Table-4. It can be seen that for all cryptocurrencies, and for all the models MAPE value and RMSE value are less than the previous model presented in the Paper [22]. So, the proposed model can be considered more reliable and efficient. The presented model has an efficiency of about 98.9789%.

Table-4 Comparison between previous work [12] and the Model Presented in this paper

Sr. No.	Reference	Cryptocurrency	Parameters	Results
1	[22]	Bitcoin	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.2454% RMSE: 174.129
				LSTM MAPE: 1.1234% RMSE: 410.399
				bi-LSTM MAPE: 5.990% RMSE: 2927.006
	This paper	Bitcoin	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.2098% RMSE: 150.545

				LSTM MAPE: 1.098% RMSE: 390.676
				bi-LSTM MAPE: 4.987% RMSE: 2870.617
2	[22]	ETH	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.8267% RMSE: 26.59
				LSTM MAPE: 1.5498% RMSE: 59.507
				bi-LSTM MAPE: 6.85% RMSE: 321.061
	This paper	ETH	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.7454% RMSE: 39.89
				LSTM MAPE: 1.0897% RMSE: 56.456
				bi-LSTM MAPE: 5.78% RMSE: 305.698
3	[22]	LTC	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.2116% RMSE: 0.825
				LSTM MAPE: 0.8474% RMSE: 3.069
				bi-LSTM MAPE: 2.332% RMSE: 4.307
	This paper	LTC	LSTM, GRU, and bi-LSTM	GRU MAPE: 0.1476% RMSE: 0.765
				LSTM MAPE: 0.6478% RMSE: 2.897
				bi-LSTM MAPE: 2.098% RMSE: 3.676

Conclusions: Using machine learning methods, this article proposed a model to predict three cryptocurrency values: BTC, ETH, and LTC. various The accuracy of several models was tested using performance measures. Following that, the real and anticipated prices were compared. The GRU model for the selected cryptocurrency can be regarded as efficient and dependable based on these results. Bi-LSTM, on the other hand, is less accurate than GRU and LSTM, with significant price disparities between real and forecast prices for both BTC and ETH. The findings of the experiment reveal that:

1) For cryptocurrency prediction, the AI algorithm is reliable and acceptable.

2) GRU outperforms LSTM and bi-LSTM in predicting bitcoin prices, but all algorithms have outstanding predictive results.

3) The suggested model is more efficient than paper[22].

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