

# Intelligent Crypto Currency Price Predictor

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**Abstract** *The digital currency in which encryption techniques are used to regulate the generation of units of currency is said to be called cryptocurrency. The technology used here is used to explore the next day change in the price of cryptocurrency. It is a challenge for a common person to achieve with varying degrees of success. But this is achieved through the implementation of an optimized recurrent neural network (RNN) and a Long Short Term Memory (LSTM) network. This paper presents a deep learning approach for predicting the prices of cryptocurrencies. The proposed method uses a combination of Long Short-Term Memory (LSTM) neural networks and Recurrent Neural Networks (RNN) to analyze historical data and make predictions. The model was trained and tested using data from the Bitcoin market. The results showed that the proposed method outperformed other state-of-the-art models in terms of accuracy and robustness.*

**Keywords:** *Crypto currency, LSTM (Long-Short-Term-Memory), RNN (Recurrent-Neural-Network).*

## 1. INTRODUCTION

Cryptocurrencies are a digital currency where transactions can be done by online transactions, unlike the other common currencies, it is designed based on cryptography. Cryptocurrency was present since many years but nowadays it has become a trending topic across the world. We come to hear about it day in and day out touching new highs and lows. As crypto markets are influenced by many uncertainties factor such as political issue, the economic issue at impacted to local or global levels to interpretation key of success, predicting the price of them with accuracy and perfection is a complicated work. To solve this problem, regarding the fluctuations there's a need automation tool to predict its price and help the investors decide for better cryptocurrency market investment. Nowadays the automation tools are usually used in common stock market predictions, and we can do the same works and strategy on this domain. Researchers have done many works related to this topic. This paper studies all the previous research and all the other available resources to decide which technologies and methodologies will be the most efficient in making an automated tool for predicting the prices of crypto currencies. The aim of the proposed system is to study and analyze price of any crypto currency with the help of historical data using machine learning by constructing a training network, the model must be having less percentage of errors and higher accuracy as compared to the other existing models. And help the investors to make proper decisions while investing in cryptocurrencies. The model which is proposed here

not only predicts the price of bitcoin only but rather all the other cryptocurrencies as well like Ethereum, tether, dogecoin, etc.

## 2. LITERATURE SURVEY

Bitcoin: A peer-to-peer electronic cash system. In this paper we come across the idea of making an entirely peer-to-peer version of electronic cash that would allow online payments to be sent directly from one person to another without going through any centralized financial institution. They made it possible through 'Digital signatures' which provides a part of the solution, but the main benefits are lost if a trusted third person is still required to prevent double spending. Here they propose a solution to the double-spending problem using a peer-to-peer network. network timestamps transactions by hashing them into an ongoing chain of -based proof-of-work, forming a record that cannot be changed without redoing proof-of-work. The longest chain not only serves as proof of the sequence of witnessed, but proof that it came from the largest pool of CPU power. As a majority of CPU power is controlled by nodes that are not cooperating to attack the network, they'll generate the longest chain and outpace attackers. The itself requires minimal structure. Messages are broadcast on a best effort, and nodes can leave and rejoin the network at will, accepting the longest -of-work chain as proof of what happened while they were gone.

A Deep Learning-Based Action Recommendation Model for Cryptocurrency Profit Maximization. - To grab the success of cryptocurrency this paper was published. In this paper we have seen improvements in price prediction models. To improve the performance of price prediction methods they used deep learning-based models. However, most studies have focused on predicting cryptocurrency prices for the following day. Therefore, clients are inconvenienced by the necessity of rapidly making complex decisions on actions that support maximizing their profit, such as "Sell", "Buy", and "Wait". Furthermore, very few studies have explored the use of deep learning models to make recommendations for these actions, and the performance of such models remains low. Therefore, to solve these problems, they propose a deep learning model and three input features: sell Profit, buy Profit, and max Profit. Through these concepts, clients are provided with criteria on which action would be most beneficial at a given current time. These criteria can be used as decision-making indices to facilitate profit maximization. To verify the effectiveness of the proposed method, daily price data of six representative cryptocurrencies were used to conduct an

experiment. They claim that the proposed model showed approximately 13% to 21% improvement over existing methods and is statistically significant.

A deep learning-based cryptocurrency price prediction scheme for financial institutions. - A cryptocurrency is a network-based digital exchange medium, where the records are secured using strong cryptographic algorithms such as Secure Hash Algorithm 2 (SHA-2) and Message Digest 5 (MD5). It uses blockchain technology to make the transactions secure, transparent, traceable, and immutable. Due to these properties, the cryptocurrencies have gained popularity in almost all the sectors especially in financial sectors. Though, cryptocurrencies are getting recognition from the approval bodies, but still, the uncertainty and dynamism in their prices risk the investments substantially. Cryptocurrency price prediction has become a trending research topic globally. Many machine learning and deep learning algorithms such as Gated Recurrent Unit (GRU), Neural Networks (NN), and Long short-term memory (LSTM) have been used by the researchers to predict and analyze the factors affecting the cryptocurrency prices. In this paper, a LSTM and GRU-based hybrid cryptocurrency prediction scheme is proposed, which focuses on only two cryptocurrencies, namely Litecoin and Monero. The results depict that the proposed scheme accurately predicts the prices with high accuracy, revealing that the scheme can be applicable in various cryptocurrencies price predictions.

Forecasting and trading cryptocurrencies with machine learning under changing market conditions. - This study examines the predictability of three major cryptocurrencies—Bitcoin, Ethereum, and Litecoin—and the profitability of trading strategies devised upon machine learning techniques (e.g., linear models, random forests, and support vector machines). The models are validated in a period characterized by unprecedented turmoil and tested in a period of bear markets, allowing the assessment of whether the predictions are good even when the market direction changes between the validation and test periods. The classification and regression methods use attributes from trading and network activity for the period from August 15, 2015 to March 03, 2019, with the test sample beginning on April 13, 2018. For the test period, five out of 18 individual models have success rates of less than 50%. The trading strategies are built on model assembling. The ensemble assuming that five models produce identical signals (Ensemble 5) achieves the best performance for Ethereum and Litecoin, with annualized Sharpe ratios of 80.17% and 91.35% and annualized returns (after proportional round-trip trading costs of 0.5%) of 9.62% and 5.73%, respectively. These positive results support the claim that machine learning provides robust techniques for exploring the predictability of cryptocurrencies and for devising profitable trading strategies in these markets, even under adverse market conditions.

Short-term bitcoin market prediction via machine learning. - We analyze the predictability of the bitcoin market across prediction

horizons ranging from 1 to 60 min. In doing so, we test various machine learning models and find that, while all models outperform a random classifier, recurrent neural networks and gradient boosting classifiers are especially well-suited for the examined prediction tasks. We use a comprehensive feature set, including technical, blockchain-based, sentiment-/interest-based, and asset-based features. Our results show that technical features remain most relevant for most methods, followed by selected blockchain-based and sentiment-/interest-based features. Additionally, we find that predictability increases for longer prediction horizons. Although a quantile-based long-short trading strategy generates monthly returns of up to 39% before transaction costs, it leads to negative returns after taking transaction costs into account due to the particularly short holding periods.

Forecasting Cryptocurrency Prices Using Ensembles-Based Machine Learning Approach. - This paper is devoted to the problems of the short-term forecasting cryptocurrencies time series using machine learning approach. We applied two the most powerful ensembles methods: Random Forests (RF) and Gradient Boosting Machine (GBM). For testing models, we used the daily close prices of three the most capitalized coins: Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP), and as features were selected the past price information and technical indicators (moving average). To check the efficiency of these models we made out-of-sample forecast for three cryptocurrencies by using one step ahead technique. As the accuracy rate for our models, we were selected Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics. According to comparative analysis of the predictive ability of the RF and GBM both models showed the same order of accuracy for the out-of-sample dataset prediction, although boosting also was somewhat more accurate. Computer experiments have confirmed the feasibility of using the machine learning ensembles approaches considered for the short-term forecasting of cryptocurrencies time series. Built models and their ensembles can be used as the basis algorithms for automated Internet trading systems Prices Using Ensembles-Based Machine Learning Approach

Bitcoin price prediction using ensembles of neural networks. - This paper explores the relationship between the features of Bitcoin and the next day change in the price of Bitcoin using an Artificial Neural Network ensemble approach called Genetic Algorithm based Selective Neural Network Ensemble, constructed using Multi-Layered Perceptron as the base model for each of the neural network in the ensemble. To better understand the practicality and its effectiveness in real-world application, the ensemble was used to predict the next day direction of the price of Bitcoin given a set of approximately 200 features of the cryptocurrency over a span of 2 years. Over a span of 50 days, a trading strategy based on the ensemble was compared against a “previous day trend following” trading strategy through back-testing. The former trading strategy generated almost 85% returns, outperforming the “previous day trend following” trading strategy which produced an approximate 38% returns and a trading

strategy that follows the single, best MLP model in the ensemble that generated approximately 53% in return.

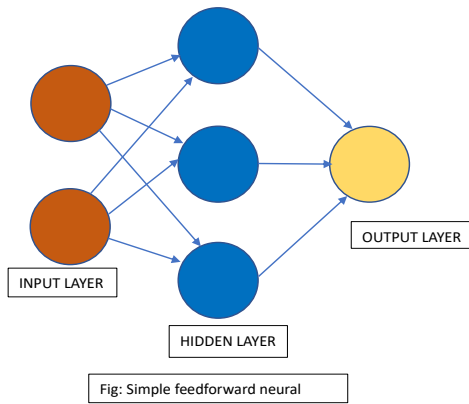
### 3. PROPOSED SYSEEM

By analyzing each and every study in the literature review we came to a conclusion that the best technique used in dealing with time series data are the artificial neural networks. In ANN the best neural network for extracting patterns in time series data are the recurrent neural networks. To get more accuracy and less percentage of errors we decided to use the upgraded version of RNN which is the best in terms of dealing with large amount of long time series data which is specially created to circumvent long-term dependency issues is Long short term memory or LSTM is also used in the proposed system.

#### Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNN) are a collection of machine learning methods. It is one of many types of artificial neural networks used for different applications and data types. RNN is widely used for deep learning algorithms specifically used for extracting patterns from temporal sequence[9], but RNN are not an effective solution for predicting the price of cryptocurrency as it is not capable of learning long term dependencies, this is an issue which is solved by the specialized version of the recurrent neural network that is the long-short term memory.

Fig-1: Simple feed forward neural network



#### Long Short-Term Memory (LSTM)

LSTM (Long Short-Term Memory) is another type of module provided for RNN. LSTM was created by Hochreiter & Schmidhuber (1997) [8]. It is a specialized version of the RNN that can learn long-term dependencies. Thus, these networks can remember information for long periods of time by default. It is widely used by the developer and researchers. It is basically an updated version of the recurrent neural network with a difference in the connection between the hidden layer in the recurrent neural network and the memory cell of structure hidden layer, whereas

the structure is same. In LSTM repeating modules have a different structure. Instead of single neural network it uses four layers which interacts with each other in a special way.

Fig-2: LSTM cell and its internal components

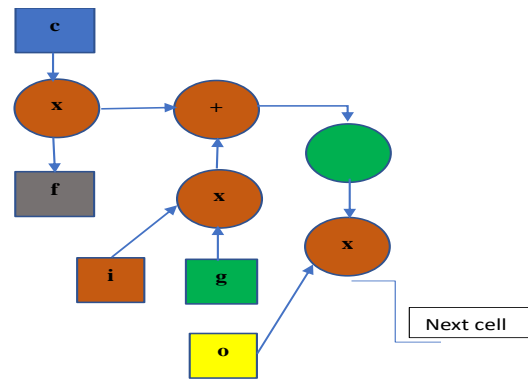


Fig : LSTM cell and its internal components

The proposed system is broadly divided into 3 phases:-

- 1.) Data Collection
- 2.) Data Processing
- 3.) Data Training

These phases are further implemented in 6 modules: -

#### 3.1. Module 1: Collection of Data

The developer collects the historical data of any crypto currency (e.g.: Bitcoin, Ethereum or any other crypto currency) by downloading it from websites like Yahoo Finance or Coin Market Cap. The data should have parameters such as opening price, closing price, highest price of that day, lowest price of that day, etc. More the data is collected more the model will be accurate in predicting the price of that cryptocurrency.

#### 3.2. Module 2: Pre-processing of Data

Some modification is done on the data before applying it to the algorithm like converting the data in to a proper format and proper type, by removing the inconsistencies from the data such as null and unnecessary values. Then the data is spited into a training data set, testing data set and a validation data set based upon the parameters. The training data set should at least be more than double of the testing data set. The last 40 rows are used as testing data set and the remaining will be used as training data set. The more the data is pre-processed the more will be the accuracy and the less will be the percentage of error.

**Table-1:Details of Data Collection**

Details of data collection						
Date	Open	High	Low	Close	Volume	Market cap
2017-11-19	7756.03	8111.91	7695.10	8037.49	3249320000	129585000000
2107-11-18	7687.21	7854.99	7464.44	7780.15	3657190000	128525000000
2017-17-17	7863.57	8014.59	7562.09	7709.99	4651570000	131036000000
2017-11-16	7333.24	7957.38	7177.58	7881.69	5125810000	122154000000

### 3.3. Module 3: Model Building (RNN) & Applying LSTM Algorithm

In this module the RNN model is implemented using the long-short term memory regression algorithm. RNN is basically an artificial neural network with temporal memory which is created to take the sequences. The parameters are chosen using methods such as grid search and then the data is reshaped into a three dimensional array, this preprocessed data prepared is finally fed to the LSTM regression model. This model consists of 2 hidden layers that are used for better computation and performance [10].

### 3.4. Module 5: Training the Model

In this module, the model is trained using the preprocessed training dataset prepared in the previous modules. The model can be trained in 10 epoch cycles, 50 epoch cycles, 100 epoch cycles or 1000 epoch cycles. More is the number of epoch cycles, more it is better inn terms of training and getting good accuracy and less percentage of errors.

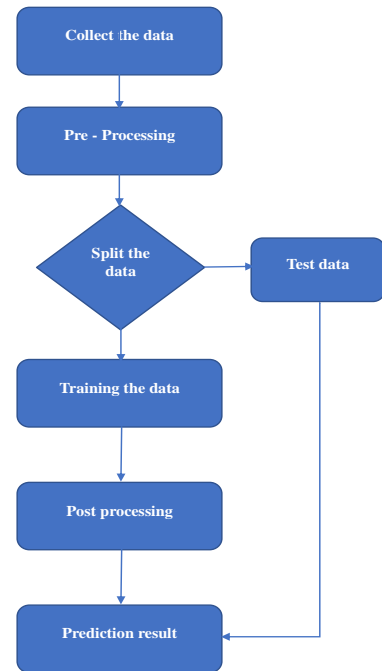
### 3.5. Module 6: Prediction of Result

The result is displayed in the form of a chart showing the plotted graph of the actual price in red color and the predicted price in green color of the crypto currency .we can analyze how accurate the trained model is by visualizing the graph of actual and predicted price.

### 3.6. Module 7: Analyzing the Accuracy

After predicting the results the last task to analyze the accuracy or the percentage error of the trained model using the root mean square error formula. The accuracy and the percentage error is dependent on the number of epochs. The more the number of epochs more will be the accuracy and less will be the percentage error.

**Fig-3: System Flow Diagram :-**



## 4. CONCLUSION

We can conclude that the best way to predict the prices of cryptocurrency is by using artificial neural networks. By studying all the literature review, various research papers and other available sources we found that to analyze the price of the cryptocurrency different neural networks are used, but the most effective among the all is Long-Short term memory which is the specialized version of the recurrent neural network. It provides us with a great accuracy and less percentage of errors as compared to the other models. As the prices of cryptocurrencies are highly volatile and is influenced by various outside factors and external social aspects we cannot directly depend on any model to predict the exact price but we can see how the prices can change in the actual time . This model performance can be improved by using more effective techniques and get better results.

## REFERENCES

- [1] Nakamoto, S. Bitcoin: A peer-to-peer electronic cash system. In Decentralized Business Review; Seoul, Korea, 2008; p. 21260. Available online: <https://www.debr.io/article/21260-bitcoin-a-peer-to-peer-electronic-cash-system>.
- [2] Park, J.; Seo, Y.S. A Deep Learning-Based Action Recommendation Model for Cryptocurrency Profit Maximization. Electronics 2022, 11, 1466.
- [3] Patel, M.M.; Tanwar, S.; Gupta, R.; Kumar, N. A deep learning-based cryptocurrency price prediction scheme for financial institutions. J. Inf. Secur. Appl. 2020, 55, 102583.

[4] Sebastião, H.; Godinho, P. Forecasting and trading cryptocurrencies with machine learning under changing market conditions. *Financ. Innov.* 2021, 7, 1–30.

[5] Jaquart, P.; Dann, D.; Weinhardt, C. Short-term bitcoin market prediction via machine learning. *J. Financ. Data Sci.* 2021, 7, 45–66

[6] Derbentsev, V.; Datsenko, N.; Babenko, V.; Pushko, O.; Pursky, O. Forecasting Cryptocurrency Prices Using Ensembles-Based Machine Learning Approach. In *Proceedings of the 2020 IEEE International Conference on Problems of Infocommunications. Science and Technology (PIC S&T)*, Kharkiv, Ukraine, 6–9 October 2020; pp. 707–712.

[7] Sin, E.; Wang, L. Bitcoin price prediction using ensembles of neural networks. In *Proceedings of the 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, Guilin, China, 29–31 July 2017; pp. 666–671.

[8] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735– 1780, 1997.

[9] Jang Huisu, Jaewook Lee, Hyungjin Ko, Woojin Le, aPredicting Bitcoin price using Rolling Window LSTM modela ,DSF, ACM ISBN 123-4567-24-^567/08/06, vol.4, pp.550- 580, 2018.

[10] Isaac Madan, Shaurya Saluja, Aojia Zhao, *Automated Bitcoin Trading via Machine Learning Algorithms*, Stanford: Department of Computer Science, Stanford University, 2015.