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Cryptocurrency Price Prediction Using Neural Networks and Deep Learning

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Abstract*—This rise in cryptocurrencies' value has contributed to the decentralization of authority, lowering control amongst countries. The wide price range of digital currencies highlights the need for reliable preparation for predicting the currency's price. A new model is a situation in which this paper presents a new way of forecasting digital value for money by considering several variables, such as stock market capitalization, volume, distribution, and high-end delivery. To include training results, active LSTM networks, and an overview of long-term organizations are considered. The proposed technique is used for the benchmark data sets. The results indicate the efficiency of the forecasting of digital currency.

***Keywords*—Crypto-Currency, Value Prediction, Bitcoin, Etherium, Gated-Recurrent-Unit, Time Stamp & Time Series**

I. Introduction

The traditional economic system relies primarily on the banks to operate transactions (such as banks). There are types of organizational intermediaries that ensure high-quality transactions. There is a vibrant economy. Cryptocurrency may have an impact on financial problems in a big way. This helps to improve life immensely when we have the chance to travel to Australia and About 98% of all cryptocurrencies are held in the top 15 funds.

It has been shown that a network of consensus is developed and enforced. Blockchain can be applied using proof-of-work techniques. The PoW is used to verify transactions and block creation. The P2P distributed money removes barriers to trust and transparency in the traditional financial system. The chain's apparent presence is only spread to all nodes in the network. When talking about digital currencies, it presents the concepts of a digital currency innovation termed "cryptocurrency."
Cryptocurrency is something that can be traded between individuals or groups. They are an organization that encrypts transactions using modern encryption techniques. Cryptocurrencies are designed around the characteristics of blockchain technology, such as "transparency and consistency." Cryptocurrencies, unlike traditional financial systems, have no "central authority." Enforcement algorithms calculate the trust in the method. Bitcoin is the first blockchain-based cryptocurrency developed by Satoshi Nakamoto. Numerous other currencies have been created as an alternative to Bitcoin. Some of the famous cryptos are Ethereum, Ripple, Monero, Stellar, Litecoin, and Dash. Cryptocurrencies are grouped into three major groups. For example, this is sponsorship, forum, and application.
With regard to monetary functions or as a medium of trade, cryptocurrencies exist. The network participants will help build various blockchain-based applications. Some frameworks that manage cryptocurrencies are introduced in specific fields. Cryptocurrency has been consistently common over the past three years. This study shows that the number of users of the blockchain fund steadily grew from 2012 to 2015. Bitcoin may have significant variations in value over short periods. Bitcoin and seven other assets make up the majority of all investment accounts. Figure 2 depicts the market's monetization, which is achieved during the year.

Bitcoins are more convenient to use than Altcoins. Monero is one of the top 15 financial groups in the world. Due to its unique and non-discounted transactions, it is regarded as a secret currency by the government. That demand will go up due to this. It aims to identify cryptocurrencies and to estimate their value for everyone in the world. The price of the digital computer This has been a big subject affecting scientists around the world. Cryptocurrency prices are different each time. The rate is unpredictable and unknown. For researchers, thus, a prediction is challenging. We recommend a reading-based hybrid system that uses LSTM and GRU to forecast unfamiliar cryptocurrency values such as Litecoin and Monero. We utilized digital currency historical prices for training the digital currency segment prediction segment to accomplish this. After that, we compare the model's accuracy that we suggested with the existing model to assess its usefulness.

These days, cryptocurrencies and digital currencies like Bitcoin have become a global phenomenon. Cryptocurrencies show an insight into a potential future due to increased accuracy, performance, and stability. Rate trends, however, are incredibly contentious and unpredictable. Academic literature on the usage of cryptocurrency has paid very little attention to niche cryptocurrencies such as currency litecoin, currency ripple, and cryptocurrency stellar. Litecoin is located in the top 10 currencies.

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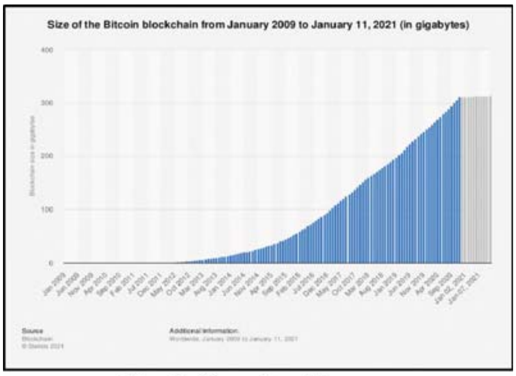

Fig. 1. Growth with years

Digital currency prices. Cryptocurrency market forecast issues are also discussed in Section 3. Section 4 outlines the processes of the proposed method.

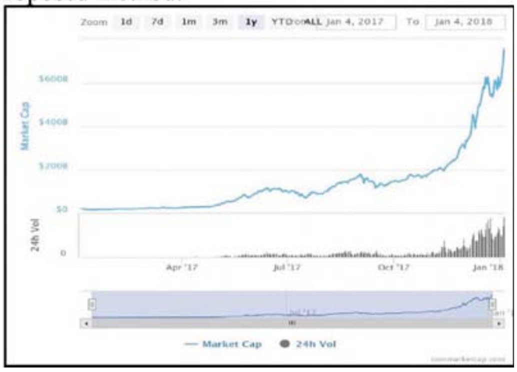

Fig. 2. Market Capitalization of all cryptocurrencies

A. *The significant contribution of this paper is as given below;*

Because of the business's uncertainty and instability, investing in digital currency is not a profitable activity. Analysis has solely concentrated on forecasting proven cryptocurrencies. Bitcoins or other cryptocurrencies are already available or no longer available. Many of the following are the paper's constructive goals. We give a detailed overview of available crypto-currency services. An in-depth analysis of the LSTM process and the GRU to reliably predict the valuation of cryptocurrencies.

B. *The organization of the paper is as follows;*

The structure of the paper is shown in Figure 3. LSTM hybrid price was taken into account the forecast model devised by GRU. Section 5 of this document deals with the evaluation requirements of our proposed model. Finally, Section 7 discusses how other related issues may be solved. Table 1 lists the document.

II. State-Of-The Art

Researchers are focusing on forecasting market values for digital currencies. Scientists have investigated several factors affecting CryptoFac's beliefs. They will collect their savings. These researchers have analyzed the connection between gold and oil price changes and bitcoin price, tether price, ether price, and litecoin price. They have calculated the Bitcoin RAM blockchain probability based on Bitcoin statistics. They have accurately predicted the existence of Bitcoin, Ethereum, and Dash. One of the most common forecasting techniques used by economists is ARIMA [8]. In a study, they used the ARIMA model. They forecast bitcoin prices [13]. They employed an SVM (Support Vector Machine) developed by Hitma et al. This method achieved a high-quality production. Employing an array of linear regression models, they use historical financial data to predict bitcoin's price more accurately [16]. Many researchers have used LSTM models to estimate or forecast the value of bitcoin. They used the supervised classification method [19].

The structure of the paper is shown in Fig 3. This paper is as follows. Integrated moving average (ARIMA) and Long Short-Term Memory (LSTM) learning. LSTM hybrid price was measured, including forecasting skills. Section 5 of the document addresses the assessment criteria of the model proposal. Finally, there are several problems listed in Section 7 to solve.

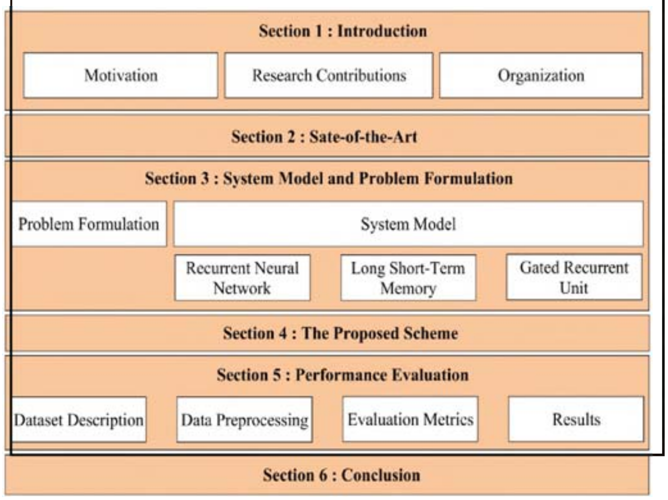

Fig. 3. Organization.

In essence, the prices for products are estimated using a Selective Neural Network Ensemble using the Genetic Algorithm (GASEN). Hashish et al. tried to research the effect of socioeconomic variables on bitcoin prices with hidden models [20].

Extended Short-Term Memory models with improved or enhanced performance may be applied. Evaluated technologies of Bitcoin, Ethereum, and Ripple using supervised and unsupervised machine learning models. Consumption and network actions and cost analysis were tied to pricing schemes. Several other variables may have also played a role in deciding rates, such as public opinion, supply and demand, and media attention.

III. System Model And Problem Formulation

An example of a digital currency pricing mechanism and issue-solving is mentioned in this section.

A. *Problem Formulation*

During digital history, the prices of digital currencies are calculated at regular intervals. Enable individual time-stamp prices of x such as p0, p1, p2, p3, p4, p5, etc.

The aim is to use the input vector containing past prices to predict the value of pi+1. The data are placed into output pairs, as is seen above.

B. System Model

As shown in Fig 4, the performance of the proposed scheme is perfect. Cryptocurrency forecasting equations and tables are frequently updated daily. Values will be set to 0 and 1 by Min-Max conversion during the step-by-step process. This dataset consists of two partitions: a training dataset and a research dataset. Using training data, the hybrid model is being trained. The final price from this form is supposed to be fed into the model, predicting the price tomorrow. It is also used to measure the expense the next day. This process is repeated at least four times as much as the size of the projected window. Test samples are used to do a background check of results. In the first hybrid model that integrates GRU and LSTM, networks are combined with the proposed system.
Once the prices were at a value between W hidden and W input, it was necessary to drive production by tanh. After the measurement, the secret state can be found.

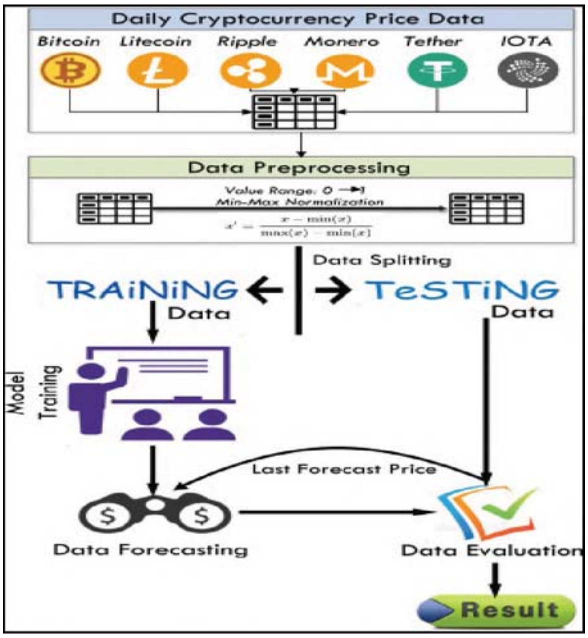

Fig. 4. System Architecture

C. Recurrent Neural Network

The renewal gate stipulates the sum of digital data that must be periodically transferred from the past to the future. The resetting of the brain causes to forget specific details. An LSTM recurrent neural network is a feed-forward neural network with internal memory. Compared to a regular neural network, where each neuron is self-isolated from others. In RNN, the performance of one category feeds into the next category. The odd temporary release capability property contributes to the odd temporary release capability feature.

Therefore summarizes the function of GRU and presents a simple recurrent neural network (SNN):

$$h_t = \theta(W_{hidden} h_{t-1} + W_{input} x_t)$$

$$y_t = W_{output} h_t$$

W input is the input neuron's weight, m hidden state, time dimension, input x, and activation function (tanh). The final hidden state is calculated from current and previous states. Typically, RNN is trained using backpropagation. The Space Elevator is not quickly installed and seems to have a problem with compliance with a bending function. The analysis of long-term dependence is somewhat tricky. RNN has a problem that LSTMs and GRUs can solve.

D. Long Short-Term Memory

Structure, as shown in Figure 5. There are four various forms of therapies. The basic architecture of LSTM consists of an input gate. A forget gate and an output gate. Equations (5), (6), and (6) illustrate the actual circumstances of the gate location (10). The cell is defined as follows.

$$i_t = \sigma(x_t V_i + h_{t-1} W_i)$$

$$f_t = \sigma(x_t V_f + h_{t-1} W_f)$$

$$o_t = \sigma(x_t V_o + h_{t-1} W_o)$$

$$\tilde{C}_t = tanh(x_t V_g + h_{t-1} W_c)$$

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

$$h_t = tanh(C_t) * o_t$$

E. Gated Recurrent Unit

Another choice to fix perishable gradients is GRU. GRU is similar to LSTM but has gates. "There is a reset gate and an update gate. The first step is to create the details first and have these models ready for feedback. Input is broken into output chunks. The RNN is an artificial neural network used to predict network behavior from incoming data. The renewal gate stipulates the sum of digital data that must be periodically transferred from the past to the future. The resetting of the brain causes you to forget specific details.

Following equations summarize the GRU.

$$u_t = \sigma(V_u x_t + W_u o_{t-1} + b_u)$$

$$r_t = \sigma(V_r x_t + W_r o_{t-1} + b_r)$$

$$i_t = tanh(V_o x_t + W_o(r_t \odot o_{t-1}) + b_o)$$

$$o_t = u_t \odot o_{t-1} + (1 - u_t) \odot i_t$$

If xt is the input, output, ut is the update gate output, rt is the exit gate reset says Hadamard's product and V, W, and b are weight parameters or matrices.

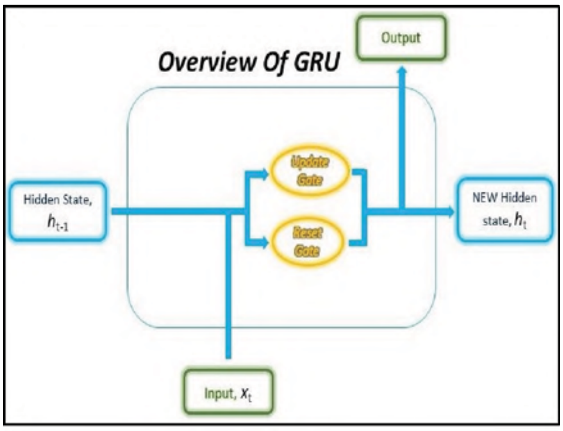

Fig. 5. Overview Of GRU

IV. The Proposed Scheme

This segment discusses the pricing forecasts for Litecoin (LTC) and Monero (XMR). GRU and LSTM models support this platform. We built RNNs so that we can display different series of data. They have a memory that repeats. In that context, current inputs were built up in tandem with past inputs and outcomes. By checking comprehension of sequential relationships makes them more straightforward and more accurate. However, the LSTM network also experiences gradient distortion. Many previous studies have shown the significance of LSTM and GRU in time series forecasting. That is, we propose to both push and pull.

A past valued map of output will be the input. The sequence of hyperparameters is the duration of this algorithm (n). We render [x0, x1, .. xn− 1] as one input and take the output to be [xn] as one output. The next step is training the model to fit the data. The model is a mixture of Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM). Both principles have their specific definitions, which cannot be found in the other. There is a GRU layer of 30 neurons in the GRU network. A stop layer to avoid an overdose is recommended. The waste is coated in a thin sheet. LSTM networks have 30 LSTM layers. To regulate unequal distribution, the LUNA layer must be added. An LSTM layer with 50 secret neurons also does. This layer's output is passed into a thicker layer. Outputs are mixed and moved on to a dense layer of both lines, which gives the extra return lines planned cost-benefit. ReLU used by Adam is identical to the activator. A model of a hundred seasons.

Predictions came after planning had been done. It is fair that the last view on a sequence is called input. Knowing the value of the last n-1 values, we can quickly generate the fixed expected value. In cycles of k, these projections take place, and Projection 2 has been discussed. The model shown in figure 8 was used for comparison and the mission. The model is optimized with the role of Adam and learning of ReLU. Without overfitting, the model can be adequately trained. To assess the program's viability and the valid attributes for instruction, we also built an assessment framework.

A. Dataset Description

The research uses data collected from Investing.com. It is a website that offers news and market data from global financial markets all over the world. Two cryptocurrencies collected the data.

There are five components of the data collected, the following being

- Cost: The average daily digital price
- Open: The starting price for the digital currency of the day
- Close: Regular currency digital closing price
- High: The highest per-day digital price
- Low: the lowest daily digital price
- Volume: The digital sum of money sold every day

There is regular information available. The following are individual descriptions of datasets.

- Litecoin: 24 August 2016 - 23 February 2020 (1279 data points)
- Monero: 30 January 2015 - 23 February 2020 (1851 data points)

The data preprocessing is as follows:

There is a significant variation of values within this data set. Standard charting research is carried out in this range. In preparation for functions, the Min-max norm is used to measure range.

B. Evaluation Metrics

Calculate how well the measure performs(RMSE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{p}_i - p_i\right)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{p}_i - p_i\right)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{p}_i - p_i\right|$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{p}_i - p_i}{p_i}\right|$$

For cycles of 1 day, three days and seven days. These predictions are all based on the validated model. The model was analyzed and tested to assess efficiency. The square of the correlation coefficient was used. Then correlations between Market Open and Market Value, Market Open and Market Close, Market Open and Market Low, and Market Open and Market High were calculated. All types of capital markets. There are many cryptocurrencies on the market at the moment. Millions of dollars are in circulation as a result of Bitcoin. It is a severe issue due to the lack of reliable models to forecast different currencies' rates.

V. High Volatility of Cryptocurrency Prices

There remains a broad spectrum of ambiguity in the valuation of digital currencies. Prices of buses are very similar to a random travel system, i.e., independent of time. Prices are primarily influenced by external factors that are entirely unexpected.

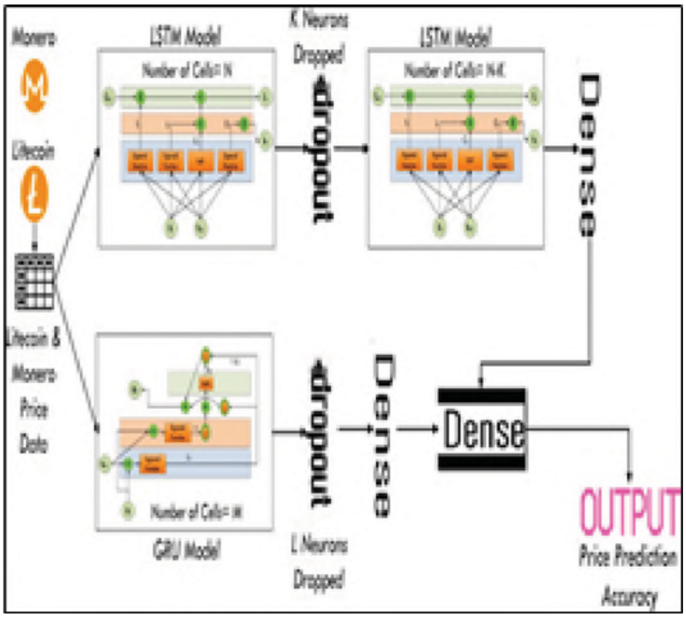

Fig. 6. LSTM Model Working

Input: $D \in \{normalized\ prices\ of\ cryptocurrency\}$
Output: $D_x \in features$, $D_y \in target$

1. procedure PROCESS_DATA($D, \varpi_{COUNT\ FEATURES}$)
2. $D_x \leftarrow \theta, \forall D_x \in D_{Training \rightarrow Features}$
3. $D_y \leftarrow \theta, \forall D_y \in D_{Target}$
4. $n \leftarrow Length(D)$
5. for $\lambda = 1,2,\ldots,n$ do
6. $\zeta \leftarrow \lambda + \varpi_{COUNT\ FEATURES}$
7. if $\zeta > (n-1)$ then
8. Break
9. end if
10. $T_x \leftarrow data[\lambda:\zeta]$
11. $T_x \leftarrow data[\zeta]$
12. $D_x \rightarrow append(T_x)$
13. $D_y \rightarrow append(T_y)$
14. end for
15. $R(D_x, D_y)$
16. end procedure

Algorithm 1. Data Preparation

Intput: $D_x \in features$, $D_y \in target$, $\rho_{Window} \in prediction\ window\ length$
Output: $\rho_{values} \in predicted\ prices$

1. procedure PREDICT_PRICE(D_X, D_Y, ρ_{Window})
2. $R \leftarrow \xi(D_x, D_y)$
3. $\rho_{values} \leftarrow \theta$
4. $\iota \leftarrow append(D_x \rightarrow_{Last\ Value})$
5. DELETE(ι, $D_x \rightarrow_{First\ Value}$)
6. $\iota \rightarrow append(D_y \rightarrow_{Last\ Value})$
7. for $\lambda = 1,2,\ldots,\rho_{Window}$ do
8. $P_{Values} \rightarrow append(R.\rho\iota)$
9. DELETE(ι, $Dx \rightarrow FirstValue$)
10. $\iota \rightarrow append(PValues.Dy \rightarrow LastValue)$
11. end for
12. $R(P_{Values})$
13. end procedure

Algorithm 2. Cryptocurrency Prediction Algorithm

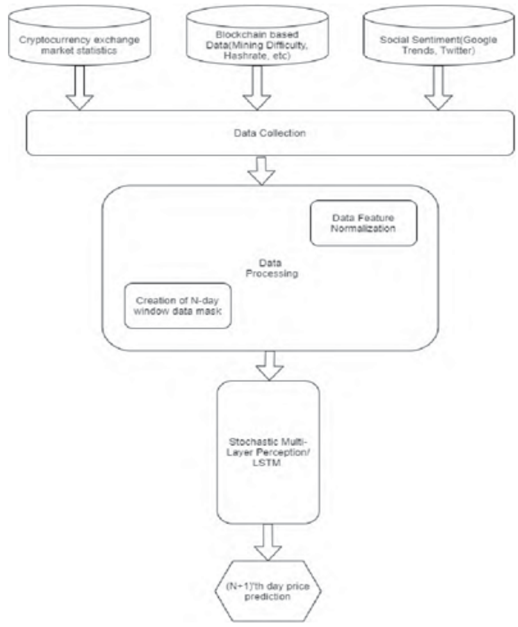

Fig.7. Price Prediction Model

Technology progresses, and as the time spent in each job decreases, the machinery's power increases continuously. This could trigger volatility in currency markets shortly. Feedback proves that public sentiment and prices have a strong connection. A modernized approach to researching emotions is a challenging aspect of this research. Cryptocurrencies are gaining in popularity worldwide, but they are still illegal in many other countries. No power of one's self-control. It impacts people's beliefs, which also affects prices for cryptocurrencies.

VI. Conclusion

Digital money pricing is a complicated problem to tackle. This is used to forecast the pattern of time series. Besides this, numerous machine learning, neural networks, and deep learning algorithms have been employed. In time-series data prediction, neural networks are showing promise. Digital currency is available for research in the complex neural network. The research of LSTM has shown that it is the finest. It is because they possess the capability to remember and remember the characteristics of very transient data. We suggest a pricing mechanism for cryptocurrencies using GRU and LSTM. Our developed system proved better than the current LSTM network.

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