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A Deep Learning-based Cryptocurrency Price Prediction Scheme for Financial Institutions

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ABSTRACT

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 form 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.

1. Introduction

Traditional economy systems solely rely on third party financial institutions (such as banks) to process the payment of any form, i.e., cash or electronic. These institutions are the mediators between the parties exchanging funds and have complete control over the transactions. It works well for financial transactions, but allows to transact only limited money and also lacks in trust, security, transparency, and flexibility. To address the aforementioned issues, we need a system that can entirely eliminate the mediators of the financial transaction, i.e., allow direct funds transfer between the parties, which brings a change in the way the economy works.

In 2008, an anonymous researcher named Satoshi Nakamoto unveiled a paper titled "*Bitcoin: A Peer-to-Peer (P2P) Electronic Cash System*" [1] with the concept of P2P cash transfer of online payments without the involvement of any intermediary financial institutions. He demonstrated the idea of a decentralized chain of valid transactions (chain of blocks), which are distributed among all peers in the network. It can be implemented using the proof-of-work (PoW) consensus mechanisms based on timestamps and hashes. A PoW algorithm is used to validate the transaction and generate a new block in the chain. This P2P distributed system eliminates the trust and transparency issues of the traditional financial system, as no third party is involved in the execution of a transaction. It is transparent in nature as the chain is distributed to all nodes or peers. This conceptualizes the new form of the digital currency known as cryptocurrency.

Cryptocurrencies are virtual currencies that can be exchanged between individuals or groups [2]. They are a network-based exchange medium that uses cryptographic algorithms to secure transactions. As cryptocurrencies rely on blockchain technology, they inherit the properties of blockchain, i.e., decentralization, transparency, and immutability. Unlike traditional systems, the transactions of cryptocurrencies are not in the control of any central authority. So, the procedure to validate or confirm the transaction is consensus algorithms, which solve the trust issues among the stakeholders of the system.

Bitcoin was the first cryptocurrency that was established based on

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the concepts of Satoshi Nakamoto's paper. Since then, many cryptocurrencies have been introduced for varied applications. Ethereum, Ripple, Monero, Stellar, Litecoin, and Dash are some of the famous cryptocurrencies which are heavily used along with the Bitcoin. These cryptocurrencies are broadly classified under the three major domains, i.e., currency, platform, and application. The cryptocurrencies which fall under the currency domain acts as a payment method or as an exchange medium. The ones falling under the platform category facilitates the infrastructure for building blockchain-based diverse applications. Some cryptocurrencies are used in specific industries and these fall under the domain of application.

Since its inception, cryptocurrency has seen a substantial rise in its usage, especially in the last 3 years. This is evident from the number of blockchain wallet users, that has increased nearly exponentially from 2012 to 2020, as shown in Figure 1. Bitcoin, from having no value at all in 2008, went to *$20,089.00* in 2017, its highest ever price recorded in its history. Since then, the price of bitcoin has not gone below *$3000*. As of February 2017, the total market capitalization of all the cryptocurrencies summed to approximately USD 19 billion. With this amount, the top 15 currencies constituted over *97%* of the market and seven currencies included accounted for *90%* of market capitalization [3]. Figure 2 shows the year-wise market capitalization of all cryptocurrencies in billion US dollars.

The price of the cryptocurrency has been a subject of curiosity for researchers across the globe. The prices of cryptocurrencies are volatile and are dependent on various factors such as transaction cost, mining difficulty, market trends, popularity, price of alternate coins, stock markets, sentiments, and some legal factors [4]. The aforementioned factors make the cryptocurrency prices unstable that change rapidly over time and also makes its prediction difficult. Hence, forecasting has been a very challenging and crucial task for the researchers.

In this paper, we propose a deep learning-based hybrid scheme using LSTM and GRU to predict the non-familiar cryptocurrencies (such as Litecoin and Monero) prices [5]. To accomplish this, we have used the historical cryptocurrency prices to train the classification model for cryptocurrency price prediction. Then, we compare the accuracy of our proposed model with the existing models to evaluate the proposed schemes performance.

1.1. Motivation

Nowadays, cryptocurrencies become a global phenomenon that attracts a significant number of users. Due to the properties like decentralization, immutability, and security, the cryptocurrencies shows a promising future. But, its prices are fluctuating a lot depending upon the parameters discussed above. Forecasting creates a matter of concern for researchers around the world. As per the literature, many researchers have tried machine learning and deep learning algorithms for cryptocurrency price prediction, but they have focused only on limited but famous cryptocurrencies such as bitcoin and Ethereum. But, there exist many other currencies such as Litecoin, Monero, and stellar that have the potential to be extensively adopted in the financial institutions. Litecoin stands in the top 10 currencies. It has a transaction time, which is four times faster than Bitcoin, which makes it a potential candidate to be extensively utilized in future applications. Monero falls into the list of top 15 currencies. It is labeled as a privacy coin owing to its transactions which are untraceable, unlinkable, and analysis resistant. Due to this property, it is highly likely that its demand will increase in future. This paper aims to target those cryptocurrencies and provide an appropriate scheme for their price prediction.

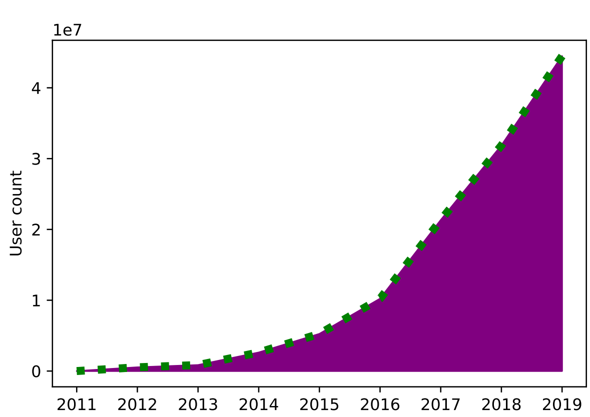


Fig. 1. Growth of wallet users with years

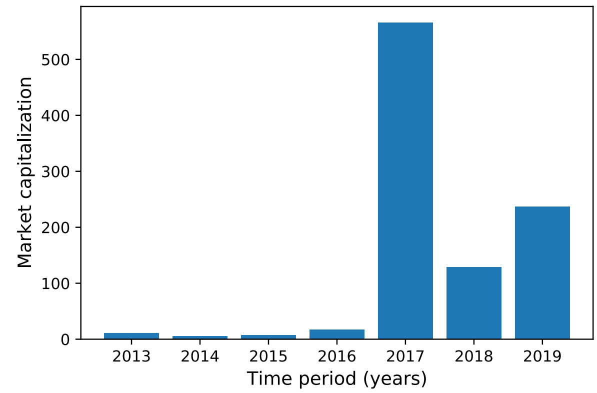


Fig. 2. Market Capitalization of all cryptocurrencies

1.2. Contributions

The cryptocurrency price prediction is a tedious task because of its price instability and dynamism. Researchers across the globe have worked on the prediction of known cryptocurrencies only. But, the other cryptocurrencies are still unusable in any form as currency or platform. In view of this, the following are the crisp objectives of the paper.

- We present a comprehensive study on the various existing schemes to predict the cryptocurrency prices.
- A new deep learning, i.e., LSTM and GRU-based hybrid model is proposed to predict the prices of *Litecoin and Monero* cryptocurrencies accurately within the stipulated window sizes, i.e., 1,3, and 7.
- Performance evaluation of the proposed hybrid model has been done using the evaluation matrices such as MSE, RMSE, MAE, and MAPE for Litecoin and Monero by comparing it with the traditional LSTM-based approaches.

1.3. Organization

The organization of paper is shown in Figure 3. Rest of the paper is organized as follows. Section 2 discusses the existing methodologies and models to predict the cryptocurrency prices. Section 3 discusses the system model and problem formulation for the cryptocurrency price predictions. Section 4 describes the workflow of the proposed hybrid LSTM and GRU-based prediction model. Section 5 discusses the performance evaluation of the proposed model. Section 6 discusses the various open issues and challenges. Finally, Section 7 concludes the paper. Table 1 shows the list of abbreviations used in the paper.

2. State-of-the-Art

A lot of research has been carried out to predict the cryptocurrency prices. Researchers worldwide have used various techniques and methodologies to find out the factors that affect the prices of cryptocurrencies. Many attempts have been made by the authors using various

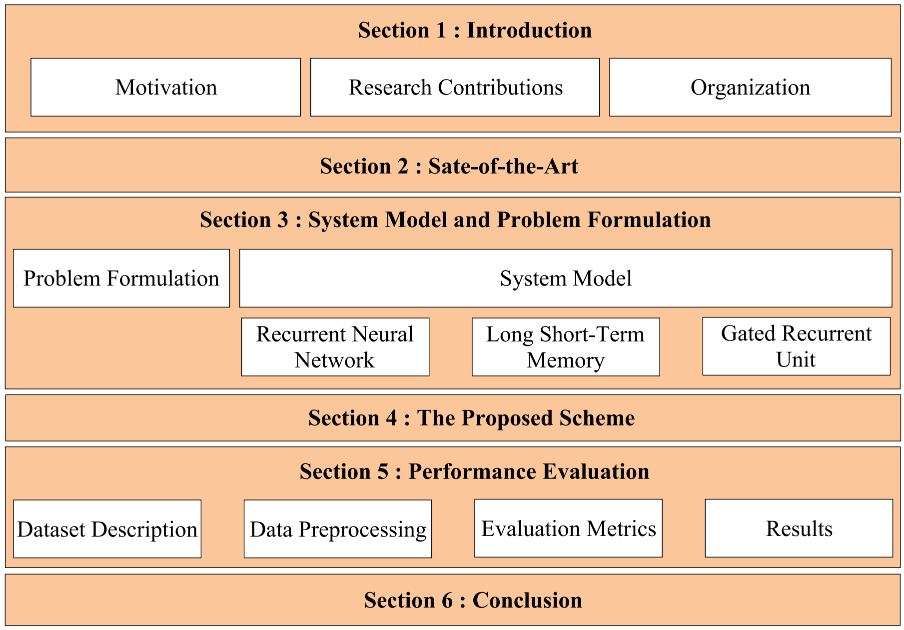


Fig. 3. Organization of the paper.

Table 1
Acronyms

ANN	Artificial Neural Network
AR	Autoregressive model
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
BPNN	Backpropagation Neural Network
GA	Genetic Algorithm
GABPNN	Genetic Algorithm and Backpropogation Neural Network
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GASEN	Genetic Algorithm based Selective Neural Network Ensemble
GRU	Gated Recurrent Unit
HMM	Hidden Markov Model
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
NEAT	Neuro Evolution of Augmented Topologies
PSO	Particle Swarm Optimization
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal AutoRegressive Integrated Moving Averages with eXogenous regressors
SVM	Support Vector Machine

machine learning and deep learning algorithms [6]. For example, Teker *et al.* [7] mapped the relation between changes in gold and oil prices and daily prices of Bitcoin, Tether, Ethereum, and Litecoin. Li *et al.* [8] predicted the global computing power of blockchain with the help of cryptocurrency prices. Peng *et al.* [9] have used Generalized Autoregressive Conditional Heteroskedasticity (GARCH) along with Support Vector Regression to predict prices of Bitcoin, Ethereum, and Dash and showed significant improvement. An Autoregressive Integrated Moving Average (ARIMA) has been one of the extensively used classical time-series analysis models. Garg *et al.* [10], Roy *et al.* [11], and Wirawan *et al.* [12] used ARIMA model to forecast the bitcoin prices. Hitma *et al.* [13] used Support Vector Machine (SVM) and enhanced it using Particle Swarm Optimization (PSO) [14]. The accuracy generated by this approach was an improvement over previous methodologies.

Later, Poongodi *et al.* [15] adopted linear regression and SVM based prediction model for Ethereum using time-series data. Rathan *et al.* [16] employed decision tree and linear regression to predict the prices of bitcoin using historical time series data and compared their accuracy. Wu *et al.* [17] used an LSTM model to forecast the bitcoin prices. Tandon *et al.* [18] used LSTM along with 10-fold cross-validation for prediction of bitcoin prices. Radityo *et al.* [19] used ANN with optimization using genetic algorithm. A genetic algorithm was used to optimize the initial weights of ANN to avoid achieving a local minimum result. Sin *et al.* [20] forecasted bitcoin prices using the ANN ensemble approach known as the Genetic Algorithm based Selective Neural Network Ensemble (GASEN). Aggarwal *et al.* [21] tried to map the impact of socio-economic factors on bitcoin prices. Hashish *et al.* [22] proposed a hybrid model using hidden Markov models and LSTM and improved results over traditional ARIMA and LSTM. Yiying *et al.* [23] analyzed the price dynamics of Bitcoin, Ethereum, and Ripple using ANN and LSTM. Saad *et al.* [24] analyzed user and network activity and related them to economic theories in order to forecast prices. All these approaches worked on historical data. There are other important exogenous factors like public sentiments, supply and demand, and media coverage which play a role in determining prices.

Sentiments are a very important factor that drives the prices of cryptocurrencies. How people perceive the currency is very important. Jain *et al.* [25] used tweets to perform sentiment analysis of cryptocurrency and use it for prediction. Wimalagunaratne *et al.* [26] used tweets and historical data to forecast prices of Bitcoin, Ethereum, and Bitcoin Cash. Smuts [27] employed a new approach to use Telegram Sentiment data and Google Trends data for Bitcoin and Ethereum price prediction. Cerda *et al.* [28] used historical prices and sentiments of influencer's as inputs to RNN and tried to improve results. Mittal *et al.* [29] tried to find a correlation between tweet volume, google search trends, and tweet sentiments and bitcoin prices. It was found that of the three tweet sentiment analysis displayed the least accurate results. Mohanty *et al.* [30] used daily generated data like price, block size, a number of transactions per block, and other 26 features of the bitcoin blockchain along with twitter data to predict fluctuations in bitcoin prices. A relative comparison of the proposed scheme with existing approaches of cryptocurrency price prediction is presented in Table 2.

3. System Model and Problem Formulation

This section describes the system model for cryptocurrency price

Table 2
Relative comparison of existing techniques for cryptocurrency price prediction.

Paper	Year	Objective	Methodology	Data Source	Cryptocurrency	Forecast duration	Results
[19]	2017	Study and compare performance of BPNN, GABPNN, and NEAT	BP2NN, GABPNN, NEAT	[31]	B	1 day	MAPE: BPNN: 1.998 ± 0.038, GABPNN: 1.883 ± 0.066, NEAT: 2.175 ± 0.096
[20]	2017	Demonstrate correlation between features of Bitcoin and change in price level of Bitcoin using GASEN	GASEN	[32]	B	50 days	Accuracy 58% - 63%
[33]	2018	Use ANN to forecast cryptocurrency close prices and study the difference in price change with the stock exchanges	ANN, Rprop algorithm	[31]	B, Bc, D	31 days, 150 hours	Accuracy: 75% to 97.3% for B
[25]	2018	Predict the price of cryptocurrencies using Social Factors	Multi-linear Regression	[34]	B, L	3 days	R2_score: 44% for L and 59% for B
[26]	2018	Assess how public perception, trading data and other factors affect currency prices and correlation between Bitcoin and Altcoin prices	ANN	[35], [36], [37]	B, E, Bc	3 months	Accuracy: B: 85%, E: 93.33%, Bc: 70%
[17]	2018	Develop a new method to forecast bitcoin prices and improve the problem of input variables selection in LSTM	LSTM, AR	[38]	B	71 days	RMSE: 247.33
[30]	2018	Predict prices of bitcoin using market and network related features along with sentiment data	Bi-directional LSTM, Word2vec	[32], [35], [39]	B	6 months	Accuracy: 50%Precision: 60.99%
[11]	2018	Predict price of bitcoin using ARIMA	ARIMA	[34]	B	10 days	ARIMA 90.31%, AR 89.25%, MA 87.58%
[40]	2018	Use ARIMA to forecast Bitcoin close prices	ARIMA	[34]	B	545 days	Accuracy: 60-70%
[16]	2019	Determine the accuracy of Bitcoin prediction using different ML algorithms and compare their accuracy	Regression, Decision tree	[41]	B	5 days	Accuracy: Decision Tree: 95.88013, Regression: 97.59812
[42]	2019	Compare ARIMA, LSTM and GRU for time series prediction	ARIMA, LSTM, GRU	[43]	B	492 days	RMSE ARIMA: 302.53, LSTM: 603.68, GRU: 381.34
[44]	2019	Use ANN and LSTM to predicatively model the price of several popular cryptocurrencies	ANN, LSTM	Unk nown	B, E, R, S, L, M	1, 10, 20, 30 days	RMSE : 53.30 (1 day), 67.99 (10 days), 91.41 (20 days), 45.71 (30 days) for B
[13]	2019	Show that SVM can be optimized using Particle Swarm Optimization for better forecasting	SVM with PSO	[45], [46]	B, E, L, N, R, S	1 year	B: 90.4, E: 97, L: 92.1, N: 57.8, R: 82.8, S: 64.5
[21]	2019	To do a comparative study of the various parameters affecting bitcoin price prediction	CNN, LSTM, GRU	[47], [48], [35]	B	1, 3 months	RMSE (Gold prices) CNN: 201.34, LSTM: 151.67, GRU: 179.23 (Twitter sentiments): LSTM: 32.98
[22]	2019	Understand Bitcoin price dynamics to optimize machine to machine payments	HMM, LSTM, GA	[49]	B	3 days	RMSE - LSTM: 7.006, HMM-LSTM: 5.821
[23]	2019	Use ANN and LSTM to analyse price dynamics of cryptocurrenies	ANN, LSTM	[32]	B, E, R	1, 3, 5, 7, 14 days	MSE: lowest: 1 day ≈ 2 for E, highest: 7 days ≈ 66 for R
[12]	2019	Predict bitcoin prices using ARIMA	ARIMA	[50]	B	7 days	Least MAPE: 0.87 (1 day), 5.98 (7 days)
Proposed Approach	2020	Use a hybrid approach using GRU and LSTM to predict cryptocurrency prices	GRU, LSTM	[38]	L, M	1,3,7 days	RMSE: 1-day: L=2.2986, M=3.2715,3-days: L=2.0327, M=5.5005, 7days: L=4.5521, M=20.2437

B:Bitcoin, L:Litecoin, R:Ripple, S:Stellar, E:Ethereum, M:Monero, N:Nem, Bc:BitcoinCash, D:Dash

prediction and problem formulation.

3.1. Problem Formulation

We have the historical data of the cryptocurrencies in the form of prices of cryptocurrency accounted on a daily basis.

Let the cryptocurrency prices at the individual timestamps be $\{p_0, p_1, p_2, p_3, p_4, \ldots, p_n\}$, where p_i denotes price at time stamp i. Let the input window length be w, the input vector be v, and the output be o, then v and o can be denoted as:

$$v = [p_{i-w+1}, p_{i-w+2}, p_{i-w+3}, \ldots, p_{i-1}, p_i] \quad (1)$$

$$o = [p_{i+1}] \quad (2)$$

The aim is to predict the p_{i+1} value using the input vector containing the past values. The data is arranged into multiple input-output pairs as shown above.

3.2. System Model

The working of the proposed scheme is as shown in Figure 4. The data is collected from the daily cryptocurrency prediction tables and then preprocess it. In the preprocessing step, the data is being normalized using *Min-Max normalization* to convert the values in the range of 0 to 1. After normalization, the data is further split into two sets named as training and testing datasets. The proposed hybrid model is trained using training data. For forecasting, the last w (input window length) are fed into the model, which predicts the next day price. This predicted price is again fed into the model to forecast the next day's price consequently. This process is repeated number of times equal to the prediction window length. The test data set is used to assess the performance after the prices have been forecasted. The proposed scheme uses a hybrid model combining GRU and LSTM.

3.2.1. Recurrent Neural Network

A recurrent neural network is a type of feed-forward neural network having internal memory. In contrast to the conventional neural network in which inputs and other outputs are independent of each other. In RNN, the outputs of one stage become the input to the next stage. Due to this property, RNNs have an extraordinary capability to extract temporal characteristics of data. An RNN appears like multiple neural networks arranged side by side with output from one network as input to another.

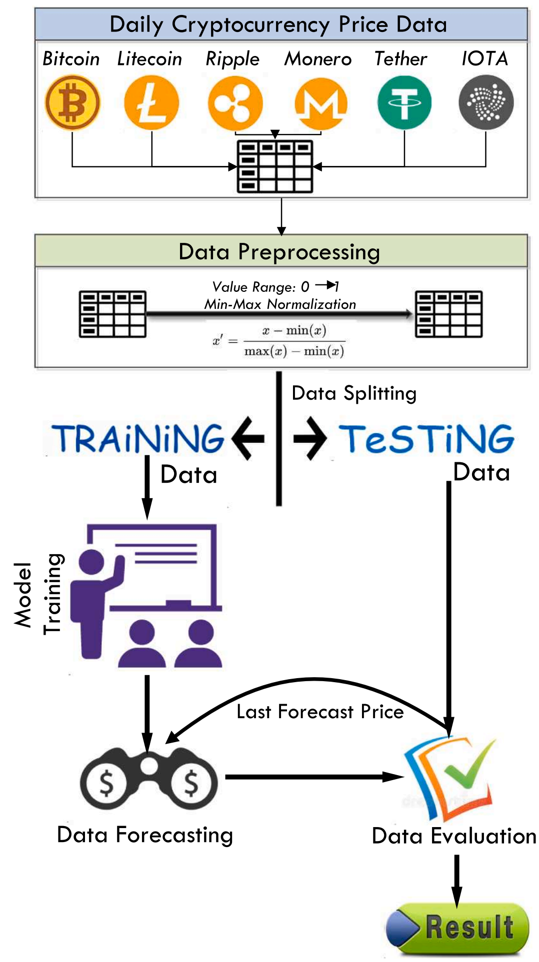


Fig. 4. System Architecture

A simple recurrent neural network can be defined as:

$$h_t = \theta(W_{hidden}h_{t-1} + W_{input}x_t) \tag{3}$$

where W_{hidden} is the weight of recurrent neuron, W_{input} is the weight of input neuron, h_t is new state, h_{t-1} is previous state, x_t is the current input, and θ is activation function, which is usually tanh. After calculating the current hidden state, the output state y_t is calculated as:

$$y_t = W_{output}h_t \tag{4}$$

RNN is usually trained using back-propagation. But due to its cyclic architecture, they are difficult to train, take longer to converge, and suffer from the problem of vanishing gradient. Therefore, learning long-term dependencies is not easier for an RNN [51]. This problem of RNNs is solved using LSTMs and GRUs.

3.2.2. Long Short-Term Memory

Long Short-Term Memory is a variant of RNN which can learn long term dependencies [52]. LSTMs have a structure similar to RNN, but the repeating unit has a comparatively different structure, as shown in Figure 5. Unlike having a single neural network layer, they have four that interact with each other.

A typical LSTM unit is made up of an input gate, a forget gate, and an output gate. The mathematical form of these gates are as shown in Eqs. (5), (6), and (10). These gates control the flow of information. The LSTM cell is characterized as follows.

$$i_t = \sigma(x_tV_i + h_{t-1}W_i) \tag{5}$$

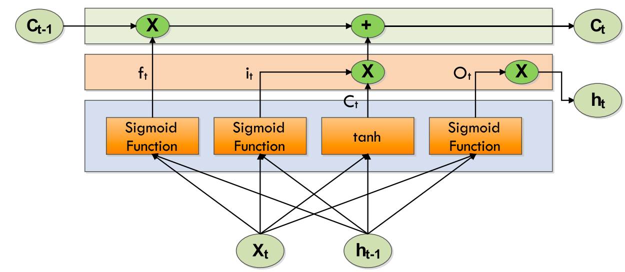


Fig. 5. LSTM cell structure

$$f_t = \sigma(x_tV_f + h_{t-1}W_f) \tag{6}$$

$$o_t = \sigma(x_tV_o + h_{t-1}W_o) \tag{7}$$

$$\tilde{C}_t = tanh(x_tV_g + h_{t-1}W_g) \tag{8}$$

$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right) \tag{9}$$

$$h_t = tanh(C_t) * o_t \tag{10}$$

where x_t is input, h_{t-1} is previous cell output, C_{t-1} is previous cell memory, h_t is current cell output, C_t is current cell memory, and W, V denote the weights.

3.2.3. Gated Recurrent Unit

GRU is another variant of RNN that solves the vanishing gradient problem. Introduced by Cho *et al.* [53], a GRU is similar to LSTM but has fewer gates, which is evident from Figure 6. It has two gates, namely, an update gate and a reset gate. Together these two gates control the flow of information through the network. The update gate determines the amount of information from the past that needs to be passed further. The reset gate determines the amount of information to forget.

Following Eqs. summarize a GRU.

$$u_t = \sigma(V_ux_t + W_uo_{t-1} + b_u) \tag{11}$$

$$r_t = \sigma(V_rx_t + W_ro_{t-1} + b_r) \tag{12}$$

$$i_t = tanh(V_ox_t + W_o(r_t \odot o_{t-1}) + b_o) \tag{13}$$

$$o_t = u_t \odot o_{t-1} + (1 - u_t) \odot i_t \tag{14}$$

where x_t is the input, o_t is the output, u_t is the update gate output, r_t is the reset gate output, $\odot$ denotes the Hadamard product and *V, W*, and *b* are the parameters or weight matrices.

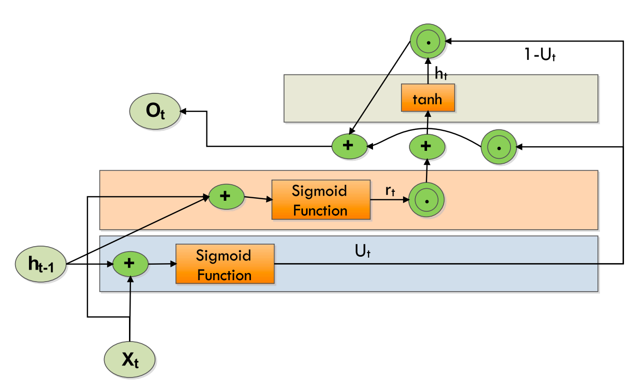


Fig. 6. Structure of a GRU.

4. The Proposed Scheme

This section introduces the proposed model for the price prediction of Litecoin and Monero cryptocurrencies, as shown in Figure 7. It utilizes the GRU and LSTM-based hybrid model.

RNNs are designed in such a way that they can model sequence data. They have what is known as sequential memory. Their structure is defined in a way that their output is a combination of current inputs and information that it has learned from previous inputs and outputs. This makes them efficient in sequence-related tasks such as time-series prediction. But they suffer from the problem of vanishing gradient, which makes them harder to train. LSTM and GRU are both variants of RNN designed in a way to overcome the vanishing gradient problem faced by RNN. Many previous researches([17], [30], [44], [24], etc.) have shown the supremacy of LSTM and GRU in time-series prediction. So we propose a method to use them both together to reap benefits from both models.

The first step is to prepare the data and make it suitable for input to the model [54]. The data is being divided into data into multiple input-output pairs. The input will be a sequence of past values or observations that will be mapped with an output value. The length of this sequence (n) is a hyperparameter. To generate the input-output pair we take $[x_0, x_1, \cdots, x_{n-1}]$ as one input and x_n as output for this input. For the next input, we take $[x_1, x_2, \cdots, x_n]$ and output as x_{n+1}. The dataset is prepared in this manner. The algorithm for creating the input-output pairs is discussed as Algorithm 1.

The next step is to train the model according to the data. The model is a hybrid of a GRU and an LSTM network. Both the models individually have a common input and both the networks are concatenated and passed through a dense layer, which gives the final output.

The GRU network consists of a GRU layer with 30 neurons. The layer is followed by a dropout layer to avoid overfitting. The output of the dropout is fed into a dense layer. Whereas, the LSTM network has an LSTM layer with 30 neurons. The LSTM layer is followed by a dropout layer to avoid an over-fitting problem. The layer is again followed by an LSTM layer having 50 neurons. The output of this layer is passed to a dense layer. The output from both networks is combined and passed through a dense layer, which gives the final predicted price. The activation function used is ReLU and the optimizer used is Adam. The model has been trained for 100 epochs.

After the training, the predictions are done. For predicting, the last n observations are taken as input, where n is the length of the input sequence of the model. Using this, the next value is predicted. Having obtained this value, the next input is prepared, consisting of the last *n-1* values and the predicted value. This process is carried out for *k-times, k* being the prediction window size. This process has been discussed as an Algorithm 2.

The model used for comparison is an LSTM network with LSTM layers having 50 neurons followed by a dense layer as represented in Figure 8. The model is compiled using Adam as an optimizer and ReLU as the activation function. The model is trained by running for 100 epochs.

5. Performance Evaluation

This section describes the features of data used for prediction for various cryptocurrencies and the data preprocessing phase. We also present the evaluation metrics to evaluate the performance of the proposed scheme, along with the training hyper parameters. Finally, the results obtained from the proposed scheme has been demonstrated.

5.1. Dataset Description

The data used in the research was collected from *Investing.com*. It is a global portal that provides an analysis and news about global financial markets. The data was collected for two cryptocurrencies: Litecoin and Monero. The data collected has five features, which are as follows.

- *Price:* Average price of cryptocurrency for the day
- *Open:* Opening price of cryptocurrency for the day
- *Close:* Closing price of cryptocurrency for the day
- *High:* Highest price of cryptocurrency for the day
- *Low:* Lowest price of cryptocurrency for the day
- *Volume:* Volume of cryptocurrency traded in the day

The data is available on a daily basis. The details of individual datasets are as follows.

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

The plot of prices (in USD) vs. time can be seen in Figure 9 and 10.

5.2. Data Preprocessing

The range of the data values varies widely and cannot be directly used. Normalization is performed to scale the data values to a particular range of values. Min-max normalization is used to prepare data that scales the data into range *0 to 1*.

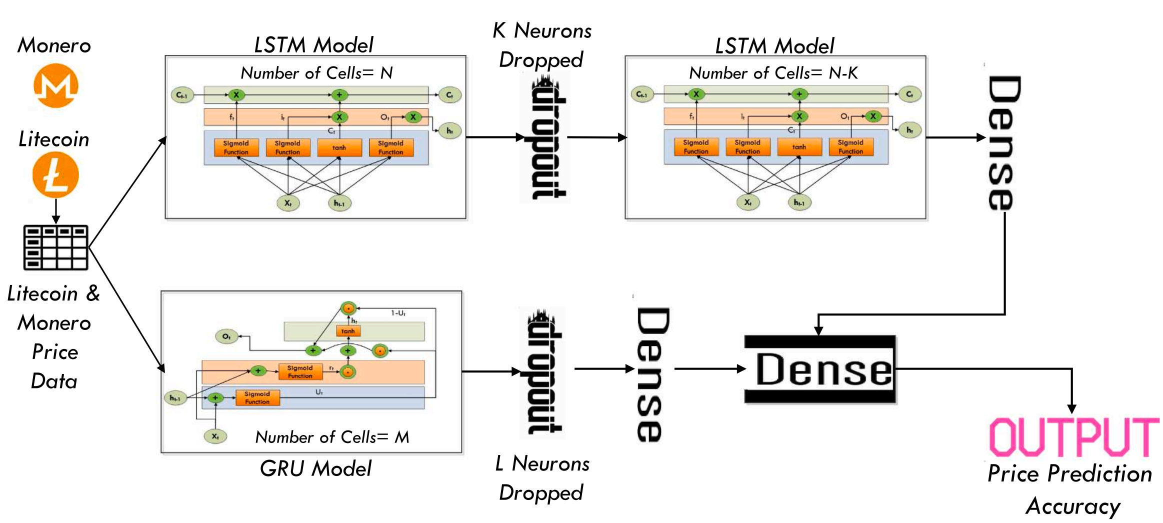


Fig. 7. The Proposed LSTM and GRU-based Hybrid Model

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

procedure PROCESS_DATA($D, \varpi^{Count}_{Features}$)
  $D_x \leftarrow \emptyset, \forall D_x \in D_{Training \rightarrow Features}$
  $D_y \leftarrow \emptyset, \forall D_y \in D_{Target}$
  $n \leftarrow \ell$ (D) ▷ ℓ is the input data length
  for $\lambda = 1, 2, \ldots, n$ **do**
    $\zeta \leftarrow \lambda + \varpi^{Count}_{Features}$
    if $\zeta > (n - 1)$ **then**
      break
    end if
    $\mathcal{T}_x \leftarrow$ data[$\lambda : \zeta$] ▷ $\mathcal{T}_x$ is temporary variable for x
    $\mathcal{T}_y \leftarrow$ data[ζ] ▷ $\mathcal{T}_y$ is temporary variable for y
    $D_{x \rightarrow append}(\mathcal{T}_x)$
    $D_{y \rightarrow append}(\mathcal{T}_y)$
  end for
  $\mathcal{R}(D_x, D_y)$ ▷ $\mathcal{R}$ is return the D_x, D_y values
end procedure

Algorithm 1. Data Preparation

Input: $D_x \in features, D_y \in target, \mathcal{P}_{Window} \in prediction\ window\ length$
Output: $\mathcal{P}_{Values} \in predicted\ prices$

procedure PREDICT_PRICE($D_x, D_y, \mathcal{P}_{Window}$)
  $\mathfrak{R} \leftarrow \xi(D_x, D_y)$ ▷ $\mathfrak{R}$ is trained model
  $\mathcal{P}_{Values} \leftarrow \emptyset$ ▷ $\mathcal{P}$ is the prediction
  $\iota \leftarrow append(D_{x \rightarrow lastValue})$
  DELETE($\iota, D_{x \rightarrow FirstValue}$)
  $\iota \rightarrow append(D_{y \rightarrow LastValue})$
  for $\lambda = 1, 2, \ldots, \mathcal{P}_{Window}$ **do**
    $\mathcal{P}_{Values} \rightarrow append(\mathfrak{R}.\mathcal{P}_\iota)$
    DELETE($\iota, D_{x \rightarrow FirstValue}$)
    $\iota \rightarrow append(\mathcal{P}_{Values}.D_{y \rightarrow LastValue})$
  end for
  $\mathcal{R}(\mathcal{P}_{Values})$
end procedure

Algorithm 2. Cryptocurrency Prediction Algorithm

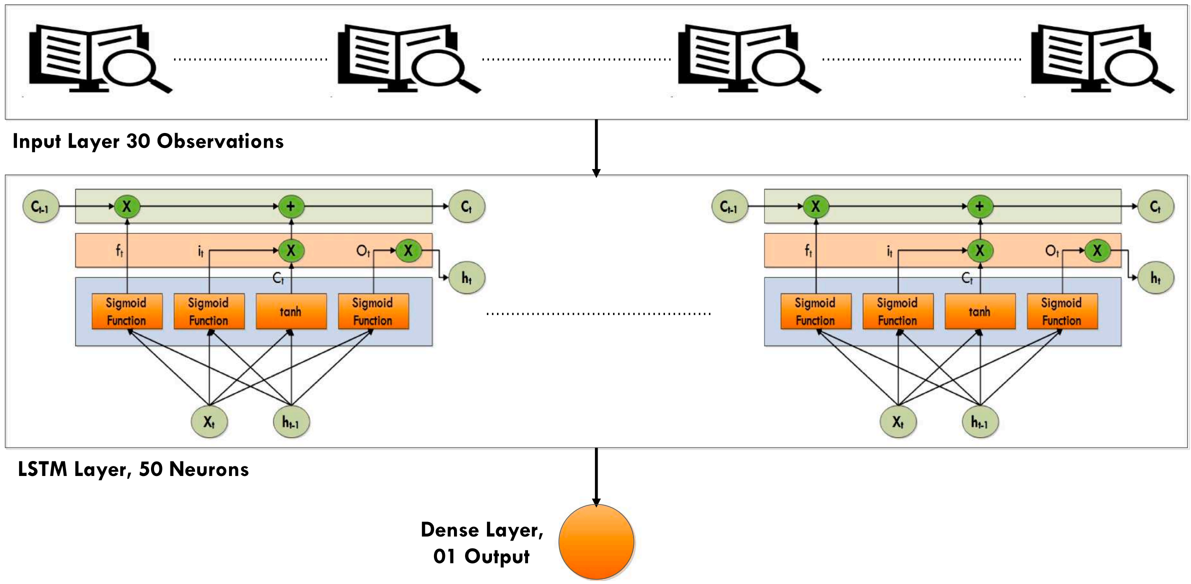


Fig. 8. LSTM Model

Fig. 9. Litecoin Price

$$x_{normalized} = \frac{x_{original} - x_{min}}{x_{max} - x_{min}} \tag{15}$$

We select price as our primary feature and train the model with the data of the past 30 days. After normalization, the data was converted into the form suitable for input in the model. We divide the data into input/output samples. The input will have 30-time steps, i.e., data of the past 30 days and 1-time step as output. This is done using the Algorithm 1.

5.3. Evaluation Metrics

The evaluation of the proposed scheme is done using mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE) and root mean squared error (RMSE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{p}_i - p_i\right)^2 \tag{16}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{p}_i - p_i\right)^2} \tag{17}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{p}_i - p_i\right| \tag{18}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{p}_i - p_i}{p_i}\right| \tag{19}$$

where $\hat{p}_i$ represents the predicted price, p_i represents the actual price and N is total number of observations.

5.4. Results

The price prediction has been made for different window lengths: *1 day, 3 days and 7 days*. In order to judge the actual performance of the

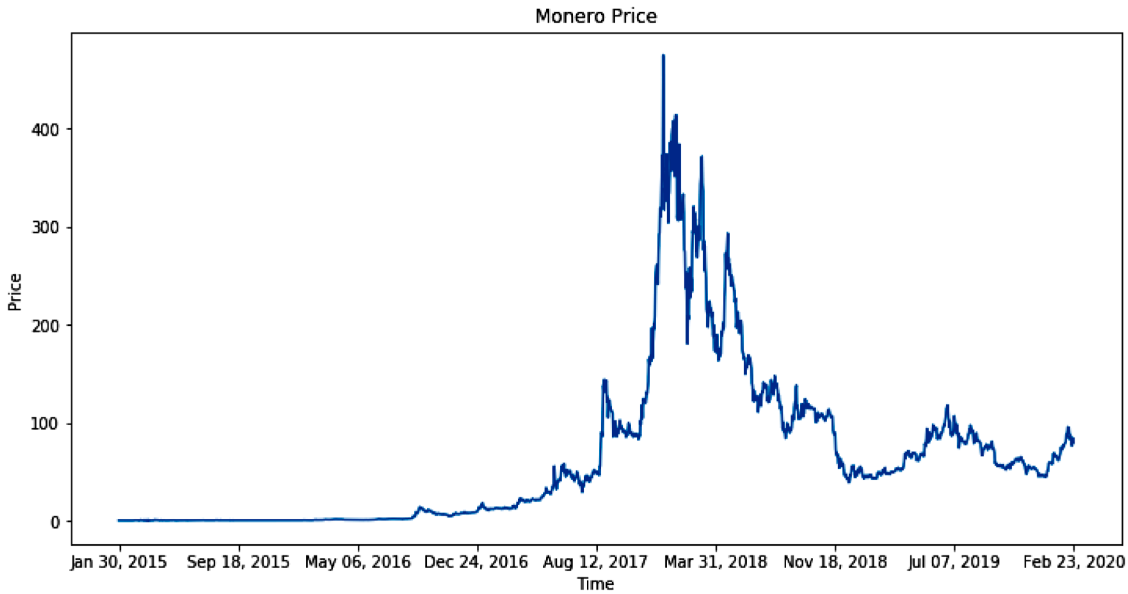


Fig. 10. Monero Price

proposed approach, these predictions are computed based on out of sample data that was not utilized to train model.

5.4.1. Scenario 1 - 1 day price prediction

For Litecoin, the model has been trained using the data of period August 24, 2016-February 22, 2020. The data contains *1278* data points. The trained model has been utilized to predict the price for the next day, i.e., February 23, 2020. Figure a shows the actual and predicted prices (in USD) with a prediction window of 1 day for Litecoin. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *2.2986*, whereas, for baseline LSTM model, it is *13.9461*.

For Monero, the model has been trained using the data of period January 30, 2015 - February 22, 2020. The data contains *1850* data points. The trained model has been utilized to predict the price for the next day, i.e., February 23, 2020. Figure b shows the actual and predicted prices (in USD) with a prediction window of 1 day for Monero. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *3.2715*, whereas, for baseline LSTM model, it is *15.1965*.

5.4.2. Scenario 2: 3 days price prediction

For Litecoin, the model has been trained using the data of period August 24, 2016 - February 20, 2020. The data contains 1276 data points. The trained model has been utilized to predict the price for the next 3 days, i.e., February 21, 2020 - February 23, 2020. Figure c shows the actual and predicted prices (in USD) with a prediction window of 3 days for Litecoin. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *2.0327*, whereas the baseline LSTM model is *5.2144*.

For Monero, the model has been trained using the data of period January 30, 2015 - February 20, 2020. The data contains 1848 data points. The trained model has been utilized to predict the price for the next day, i.e., February 21, 2020 - February 23, 2020. Figure d shows the actual and predicted prices (in USD) with a prediction window of 3 days for Monero. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *5.005*, whereas, for baseline LSTM model, it is *5.5507*.

5.4.3. Scenario 3: 7 days price prediction

For Litecoin, the model has been trained using the data of period August 24, 2016 - February 16, 2020. The data contains 1272 data points. The trained model has been utilized to predict the price for the next 7 days, i.e., February 17, 2020 - February 23, 2020. Figure e shows the actual and predicted prices (in USD) with a prediction window of 7 days for Litecoin. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *4.5521*, whereas, for baseline LSTM model, it is *16.9164*.

For Monero, the model has been trained using the data of period January 30, 2015 - February 16, 2020. The data contains 1844 data points. The trained model has been utilized to predict the price for the next day, i.e., February 17, 2020 - February 23, 2020. Figure f shows the actual and predicted prices (in USD) with a prediction window of 7 days for Monero. Using the specified step size and prediction window, the RMSE for prediction using our approach comes out to be *20.2437*, whereas, for baseline LSTM model, it is *22.8847*.

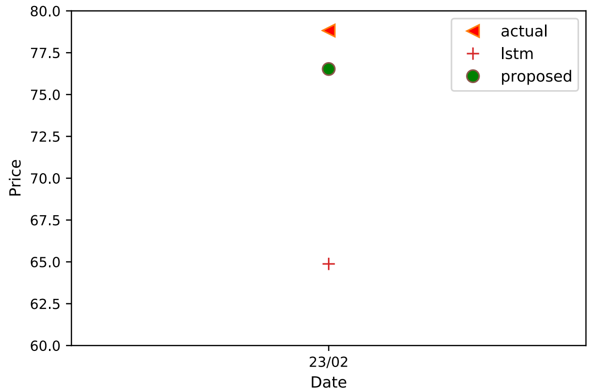
Tables 3, 4 and 5 show the comparison of errors in prediction by a simple LSTM network and our proposed approach.

The comparison of different errors has been shown in Figure 12 a, 12 b, 12 c, and 12 d. Figure 12 a shows comparison of MSE for predictions. The errors in prediction by the Proposed approach are very small as compared to an LSTM network. Figure 12 b shows that the RMSE for the proposed approach is less than half as compared to LSTM in all cases. Figure 12 c show the MAE errors. The MAE of the proposed approach is nearly one-third than that of LSTM. The MAPE (Figure 12 d) also shows that the error is less in case of proposed approach.

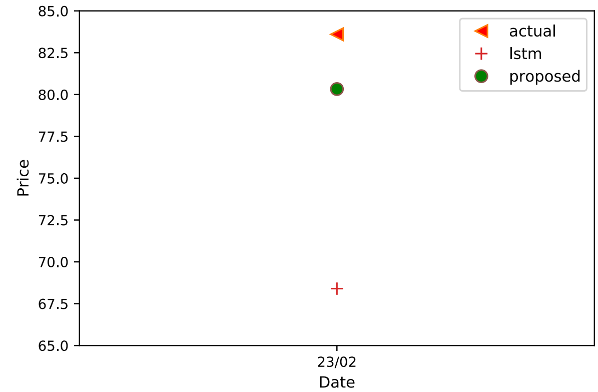
It is observable from the results that our proposed approach shows much lower errors as compared to an LSTM network for predictions for all three window sizes. The error difference between the two approaches is considerably high in the prediction of *1 day* prices, showing that the proposed approach is very effective in predicting next-day prices. Although, in both cases, it evident that the approaches are not very effective in predicting prices of the next *7 days*. This shows that these methods are useful for short term predictions and not much fruitful in long term predictions.

6. Open issues and research challenges

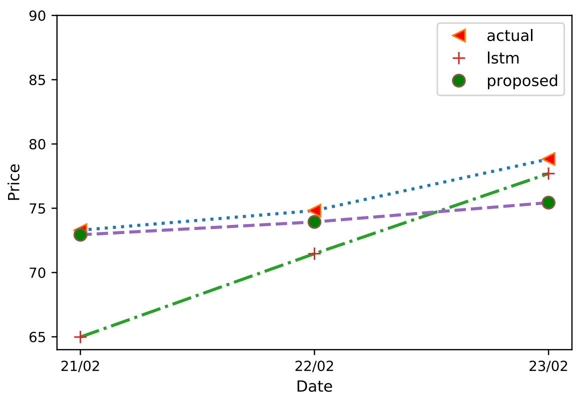
This section discusses the open issues and future research challenges in the domain of cryptocurrency price prediction. A brief description of these challenges is as follows.



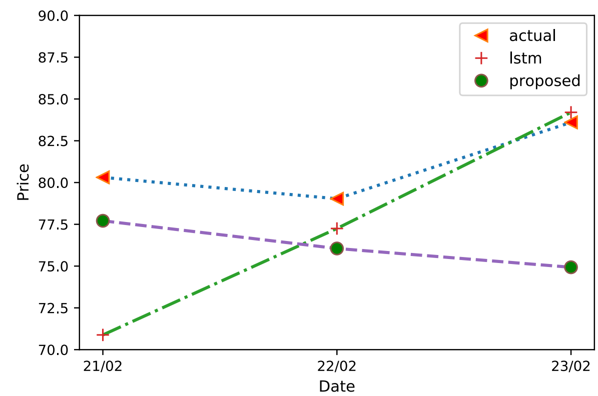
(a) Actual vs Predicted Litecoin prices for 1 day period



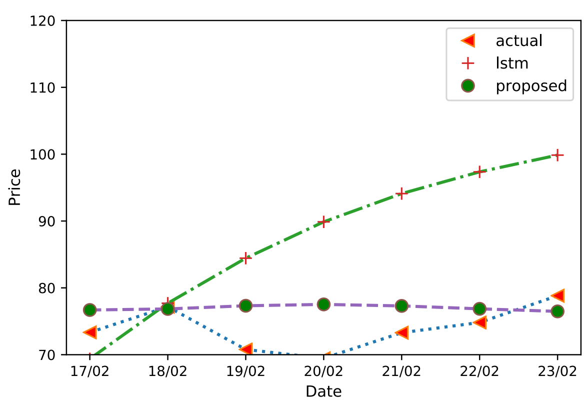
(b) Actual vs Predicted Monero prices for 1 day period



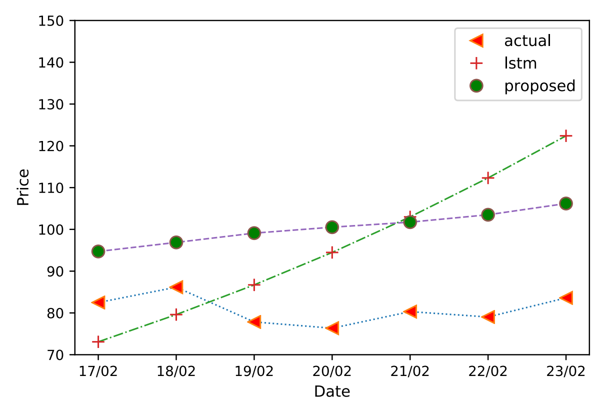
(c) Actual vs Predicted Litecoin prices for 3 days period



(d) Actual vs Predicted Monero prices for 3 days period



(e) Actual vs Predicted Litecoin prices for 7 days period



(f) Actual vs Predicted Monero prices for 7 days period

Fig. 11. Actual vs Predicted values by LSTM and Proposed Approach.

Table 3
Results of LSTM and Proposed Approach for 1-day prediction window

Model	Currency	MSE	RMSE	MAE	MAPE
LSTM	Litecoin	194.4952	13.9461	13.9461	21.4956
	Monero	230.9365	15.1965	15.1965	22.2161
Proposed	Litecoin	5.2838	2.2986	2.2986	3.0037
	Monero	10.7031	3.2715	3.2715	4.0727

Table 4
Results of LSTM and Proposed Approach for 3-days prediction window

Model	Currency	MSE	RMSE	MAE	MAPE
LSTM	Litecoin	27.1899	5.2144	4.2639	6.3109
	Monero	30.8105	5.5507	3.9370	5.4405
Proposed	Litecoin	4.1319	2.0327	1.5425	2.0581
	Monero	30.2559	5.5005	4.7478	6.2754

6.1. Vast availability of different cryptocurrencies

The number of cryptocurrencies available in the market is quite high. Thousands of currencies have come into existence since the release of Bitcoin. Therefore, building a system or model that is suitable for predicts prices of all type of currencies accurately is very challenging.

Table 5
Results of LSTM and Proposed Approach for 7-days prediction window

Model	Currency	MSE	RMSE	MAE	MAPE
LSTM	Litecoin	286.1674	16.9164	14.7071	15.9441
	Monero	523.7109	22.8847	19.6743	19.1254
Proposed	Litecoin	20.7219	4.5521	3.8135	4.9407
	Monero	409.8096	20.2437	19.5513	19.3493

6.2. High volatility of cryptocurrency prices

The prices of cryptocurrency show a great range of volatility. The prices, to some extent, resemble a random walk process, i.e., they are independent of time. The prices are greatly affected by external changes, which are quite unpredictable.

6.3. Technological innovations

The technology is continuously evolving and with it the computing power is increasing day by day with a decrease in time consumed. These advances affect the prices of different currencies differently and add to the already volatile nature of prices.

6.4. Public perception and acceptance

The way people perceive a currency highly affects the prices. If the currency is more popular, the prices are expected to be higher. Studies show there is a positive correlation between public opinion and prices. Real-time tracking of these sentiments and predicting is a challenging task.

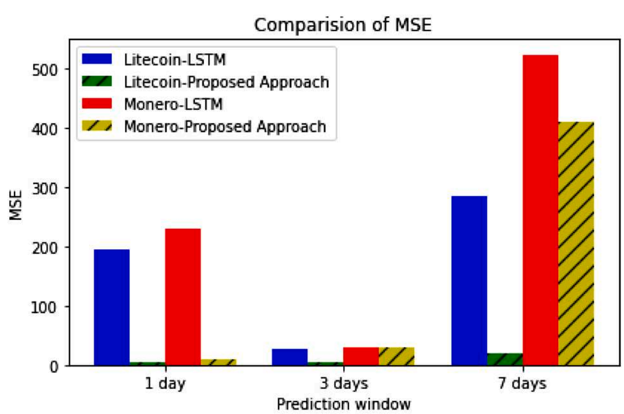
6.5. Legal aspects and issues

Cryptocurrencies are gaining a lot of recognition, but still, there are some countries where they are banned. There is no regulatory body in existence to control them. Even in places where it is accepted, it comes along with a lot of legal aspects. These factors affect the perception of people and hence the prices of cryptocurrencies as well.

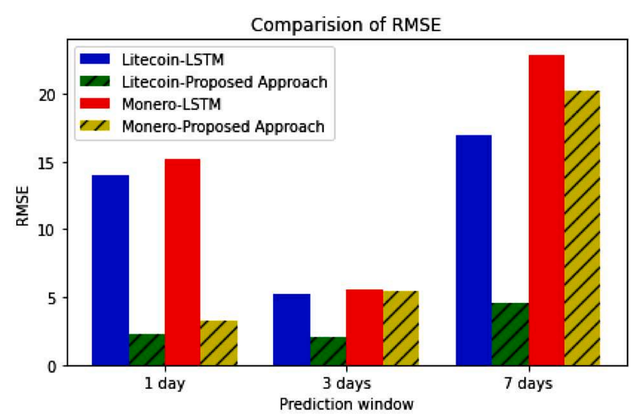
7. Conclusion

Cryptocurrency price prediction has been a very challenging task for researchers due to the external or exogenous social and psychological factors that affect its price prediction, as mentioned in Section 1. Traditional time-series models such as ARIMA, SARIMA, ARCH, and GARCH are often used for the analysis of various financial schemes. These are largely used for time series prediction but have limitations due to assumptions. Apart from these, many machine learning and deep learning algorithms have been used for prediction purposes. In recent times, neural networks have shown promising results in time-series data prediction. Many variants of neural networks are there to analyze cryptocurrency prices. Among all, LSTM has been proved to be the best in until now. This is due to their ability to remember and extract the temporal features of data. In this paper, we proposed a cryptocurrency price prediction scheme that utilizes a hybrid model of GRU and LSTM. Our proposed scheme has proved to be better than the LSTM network, which is evident from the errors of prediction.

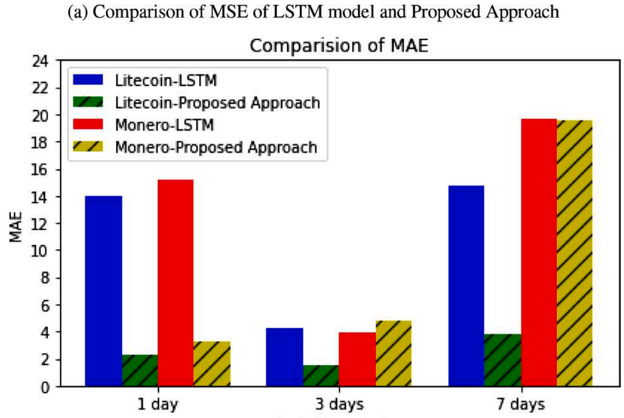
In the future, we will introduce a more complex model along with the incorporation of sentiment data, which can improve the prediction results for cryptocurrencies.



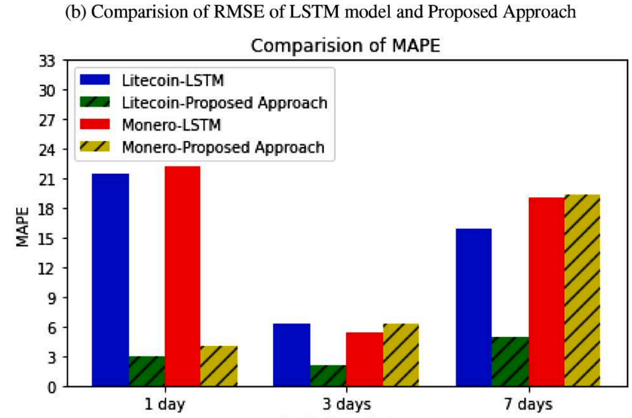
(a) Comparison of MSE of LSTM model and Proposed Approach



(b) Comparision of RMSE of LSTM model and Proposed Approach



(c) Comparision of MAE of LSTM model and Proposed Approach



(d) Comparision of MAPE of LSTM model and Proposed Approach

Fig. 12. Comparision of errors for LSTM and Proposed Approach.

Declaration of Competing Interest

Authors declare that there is no conflict of interest during the submission of the paper at this venue.

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