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DL-GuesS: Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction

RAJ PAREKH[1], NISARG P. PATEL[1], NIHAR THAKKAR[1], RAJESH GUPTA[1], (Student Member, IEEE), SUDEEP TANWAR[1], (Senior Member, IEEE), GULSHAN SHARMA[2], INNOCENT E. DAVIDSON[3], (Senior Member, IEEE), AND RAVI SHARMA[4]

[1]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat 382481, India
[2]Department of Electrical Engineering Technology, University of Johannesburg, Johannesburg 2092, South Africa
[3]Department of Electrical Power Engineering, Durban University of Technology, Steve Biko Campus, Durban 4001, South Africa
[4]Centre for Inter-Disciplinary Research and Innovation, University of Petroleum and Energy Studies, Dehradun 248001, India

Corresponding authors: Sudeep Tanwar (sudeep.tanwar@nirmauni.ac.in) and Gulshan Sharma (gulshans1@dut.ac.za)

ABSTRACT Cryptocurrencies are peer-to-peer-based transaction systems where the data exchanges are secured using the secure hash algorithm (SHA)-256 and message digest (MD)-5 algorithms. The prices of cryptocurrencies are highly volatile and follow stochastic moments and have reached their unpredictable limits. They are commonly used for investment and have become a substitute for other types of investment like metals, estates, and the stock market. Their importance in the market raises the strict requirement for a sturdy forecasting model. However, cryptocurrency price prediction is quite challenging due to its dependency on other cryptocurrencies. Many researchers have used machine learning and deep learning models, and other market sentiment-based models to predict the price of cryptocurrencies. As all the cryptocurrencies belong to a specific class, we can infer that the increase in the price of one cryptocurrency can lead to a price change for other cryptocurrencies. Researchers had also utilized the sentiments from tweets and other social media platforms to increase the performance of their proposed system. Motivated by these, in this paper, we propose a hybrid and robust framework, *DL-Gues*, for cryptocurrency price prediction, that considers its interdependency on other cryptocurrencies and also on market sentiments. We have considered price prediction of *Dash* carried out using price history and tweets of *Dash*, *Litecoin*, and *Bitcoin* for various loss functions for validation. Further, to check the usability of *DL-GuesS* on other cryptocurrencies, we have also inferred results for price prediction of *Bitcoin-Cash* with the price history and tweets of *Bitcoin-Cash*, *Litecoin*, and *Bitcoin*.

INDEX TERMS Cryptocurrency, complex systems, fusion of cryptocurrency, price prediction, VADER, sentiment analysis, deep learning, systems of systems.

I. INTRODUCTION

A cryptocurrency is a digital form of currency that was originally made as regular means of exchange. It uses cryptography algorithms such as SHA-256 and MD-5 to ensure security in financial transactions. In the existing scenario, the financial trades cannot be executed without the involvement of third-party organizations such as banks, whereas cryptocurrency eliminates those. Cryptocurrencies nowadays have become an integral part of society. It was first introduced as *Bitcoin* in 2008 to replace the entire cash exchange with a universal digital currency system [1]. This newly introduced financial system is independent of centralized financial institutions such as banks, governments, and other organizations to make the system transparent, secure, and distributed. Algorithms like proof-of-work (PoW), proof-of-stack (PoS), and other consensus algorithms were introduced to ensure system integrity and consistency. When it was developed, the Cryptocurrency exchange rates were very low. However, with time, its market starts to boom up by inheriting its volatile nature.

Nearly 4200 crypto coins are circulating in the market to date and their market cap is valued at $2.23 Billion (till April 2021). Some popular cryptocurrencies like *Bitcoin* and

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Ethereum are the biggest contributors with a share of 78% and 12%, respectively [2]. This boom in the cryptocurrency market attracts many individuals, investors, and companies to invest directly or indirectly [3]. The market boom of cryptocurrency is clumsy due to its volatile nature. The prices of cryptocurrencies fluctuate enormously with time. Within a decade, the *Bitcoin* price jumped from $0.08 in 2010 to $64000 during April 2021 [2]. The same trends were observed in *Ethereum*, as their prices increased from $0.67 in January 2018 to $2346 in April 2021 [2]. These trends justified the volatility of the cryptocurrency market. Moreover, there are several other factors like volume, mining difficulty, popularity, price of other crypto coins that make the prices of cryptocurrencies volatile.

Researchers across the globe have used hypotheses like the efficient market hypothesis (EMH) and alternate market hypothesis (AMH) to analyze the cryptocurrency market trends and volatility. The EMH hypothesis states that the prices at which the cryptocurrencies were traded are always fair and reflect every information piece. Moreover, when the complexity of the mining problem increases, the price of the corresponding cryptocurrency will also be increased [4]. Nevertheless, in a real scenario, this theory does not work, and to overcome the drawbacks of EMH, a new theory, i.e., AMH, was introduced with the inclusion of behavioral finance. Still, we can get good results by considering EMH as used by the authors of [5], but not accurate.

However, AMH works in practical scenarios as it combines EMH and behavioral finance principles to study the psychology and mindset of large investors. Individuals and small investors are dependent on the information provided by large investors and well-known analysts. They do not research their way out to make big decisions as the big investors do. Such a situation is the principal cause for herding phenomena in the market. Herding happened when most people started blindly following the limited information provided by big investors. This type of phenomenon creates a kind of human bias in the market in which the market is not operated ideally. Hence, EMH can fail as it considers the market frictionless and without any external bias. Since AMH includes human bias while checking the market efficiency that can be utilized in the cryptocurrency market. The authors in [19] concluded that there must be a systematic selection of features while determining the cryptocurrency price. They have also concluded that the performance of AMH is accurate in the cryptocurrency market. Combining two or more factors helps us in building a robust prediction model. The process of feature selection and integration is termed fusion. Many factors affect cryptocurrency prices, so combining factors is a significant concern. To understand the impact of additional factors on cryptocurrency prices, we studied extensively related published papers and analyzed their shortcoming and future scope to make the proposed framework powerful and robust.

Before we proceed further, we would like to bring attention to a factor that affects cryptocurrency prices: interdependency among cryptocurrencies. At present, there are nearly 4200 cryptocurrencies in the market, but most of them are derived from major ones like *Bitcoin* and *Ethereum*. Any change in *Bitcoin* and *Ethereum* changes the effectiveness of the derived cryptocurrencies. If we talked about Bitcoin, the cryptocurrencies such as *Litecoin* and *Bitcoin Cash* were forked from them with few additional changes [20], [21]. Further, a few of them exhibits hierarchical nature like *Dash*, which is a fork of *Litecoin*, so hierarchically, we can say that it is also dependent on *Bitcoin* [22].

The complexity of the cryptocurrency price prediction problem brings the attention of several researchers worldwide. Many researchers have worked on the price prediction of cryptocurrencies. For example, the authors in [11] proved that the volatility in prices of cryptocurrencies could be predicted using machine learning and sentiment analysis together. They implemented and compared the performance of multi-layer perceptron (MLP), support vector machine (SVM), and random forest (RF) for *Bitcoin*, *Ethereum*, *Ripple*, and *Litecoin* using their price history and tweets from Twitter. Then, the authors in [12] introduced a big-data and machine learning-based platform, i.e., Krypto-Oracle, for real-time cryptocurrency price prediction based on price history and Twitter sentiments [23]. They have used machine learning models to minimize the computational time for handling large queries.

After the emergence of deep learning algorithms like long short-term memory (LSTM) and gated recurrent unit (GRU) into their research work after the emergence of deep learning algorithms. Various deep learning-based price forecasting models had been introduced till now. An artificial neural network (ANN)-based prediction GASEN model was introduced in [7]. It was further improved using a genetic algorithm to avoid the convergence of weights to local minima. The genetic algorithm's inclusion improved the performance with a significant decrease in mean absolute percentage error (MAPE) loss. Then, the authors in [13] introduced an LSTM and GRU-based hybrid model for the price prediction of *Litecoin* and *Monero* coins. Their results achieved root mean square error (RMSE) as 2.2986 and 3.275 for 1-day prediction window, RMSE as 2.0327 and 5.5005 for 3-day prediction windows, and RMSE as 4.5521 and 20.2437 for the 7-day prediction window.

In [14], the authors have introduced a sentiment-driven model with statistical and deep learning approaches for cryptocurrency price prediction. They have used an autoregressive integrated moving average with explanatory variable (ARIMAX) and LSTM models for sentiment-based price prediction with different feature fusions [24]. Then, the authors in [14] concluded that ARIMAX has much better accuracy than the LSTM model with a final mean squared error (MSE) of 0.00030187. Based on the outcome, we can infer that the high number of features is not always substantial, but the quality of features is also essential. The other inference is that they got the best results for ARIMAX, which is less complex than LSTM. So, with the proper fusion of features, we can get good results through less computational power.

TABLE 1. Comparative analysis of state-of-the-art techniques for cryptocurrency price prediction with the proposed model.

Ref.	Year	Contribution	Expected result	Demerit
[6]	2017	Machine learning-based algorithms were used for price prediction of *Bitcoin*, *Litecoin*, and *Ethereum* with the sentiments of the news and social media.	Confusion matrix	Advanced models like LSTM and GRU were not explored. Data consideration was lesser in amount.
[7]	2018	ANN with its different variant was used for predicting the price of *Bitcoin*. There were 4 ANN methods used, and out of which the backpropagation neural network showed the best result.	MAPE	They only explored various types of ANN and did not explore sentiments and another deep learning-based model to find complex patterns.
[8]	2018	Different regression techniques had implemented for *Bitcoin* price prediction e.g.,theil-sen regression, huber regression, LSTM, and GRU	MSE = 0.00002, R2 = 0.992 (GRU)	Ignored impacting factors like sentiments and hybrid model also not explored.
[9]	2018	Machine learning-based algorithms like ANN, SVM, random forest and naive bayes were used for price prediction of different cryptocurrency.	Accuracy :- *Bitcoin* = 85%, *Ethereum* = 93.33%, *Bitcoin Cash* = 70%	Not considered deep learning based model to find complex patterns and sentiment of the cryptocurrency and hybrid model also not explored.
[10]	2019	They used hidden Markov models to show the historical data of cryptocurrencies and predicted future prices using the Long short-term memory model. This was the hybrid model-based approach.	MSE = 33.888 RMSE = 5.821 MAE = 2.510	They did not consider market sentiment as a feature, which can be used as means for prediction as it is important.
[11]	2019	Machine learning based algorithms were used with sentiments of the cryptocurrency for the prediction of price movment.	SVM Twitter and Market:- Accuracy = 0.66, Precision = 0.80, Recall = 0.67, F1 Score = 0.62	Not explored time-series-based models like LSTM and GRU.
[12]	2020	Introduced the novel big data platform for price prediction using sentiment and prices with classic machine learning models. Tweets from the twitter was collected in real-time.	RMSE	Deep learning models not considered for prediction such as RNN.
[13]	2020	LSTM-GRU's hybrid model was implemented for price prediction of *Litecoin* and *Monero* with different window sizes. The hybrid-based model helped to reduce the loss.	MSE RMSE MAE MAPE	Interdependence amongst cryptocurrency and sentiment as a feature not explored.
[14]	2020	ARIMAX and LSTM-based RNN experimented for price prediction of cryptocurrency.	MSE = 0.00030187	Hybrid models are not explored and feature fusion and sentiment were not considered.
[15]	2020	CNN-LSTM based hybrid model used for *Bitcoin's* price prediction with variations in the CNN models. Direction prediction and value prediction were also done.	MAE RMSE MAPE for value prediction, and precision recall F1 for direction prediction	Sentiment regarding cryptocurrencies in the market not considered.
[16]	2021	A hybrid LSTM and GRU-based deep learning model outperformed the state-of-the-art techniques, to predict the price of *Litecoin* and *Zcash* by the influence of the major coins like *Bitcoin*.	MSE	The sentiment of major crypto coins is not considered to predict the price of an influenced cryptocurrency.
[17]	2021	An ensemble model of LSTM, GRU, and TSN (Temporal Convolutional Networks) was used to predict the price of Ether based on its historical price data.	Accuracy:- 1-day = 84.2%, 1-week = 78.9%	Interdependence amongst cryptocurrency and sentiment is not considered as a feature for price prediction of Ether.
[18]	2021	To predict the price of *Bitcoin*, *Ethereum*, and *Litecoin*, the author proposed a system with LSTM and GRU. The price prediction was performed on two types of a data sample of *Bitcoin*, *Ethereum*, and *Litecoin*.	RMSE, MAE	One of the most important factors of market analysis is sentiment analysis, which is not considered, and interdependence among currencies is not considered.
Proposed	2022	Author proposed a new framework named DL-GuesS and it's performance evaluation was done by predicting prices of *Dash* and *Bitcoin Cash*. The price history of similar cryptocurrency i.e. Bitcoin and Litecoin, along with the twitter sentiments for each of them were used to predict the prices of *Dash* and *Bitcoin*	Dash MSE = 0.0185, MAE = 0.0805, MAPE = 4.7928 Bitcoin Cash MSE = 0.0011, MAE = 0.0196, MAPE = 4.4089	-

The authors in [15] presented a hybrid CNN and LSTM-based model to predict cryptocurrency prices, which gave a mean absolute error (MAE) of 209.89, RMSE of 258.31, and MAPE of 2.35. The precision, recall, and F1 score are calculated as 0.64, 0.81, and 0.69, respectively, to classify whether the prices will go up or down. However, the output loss is quite high. From the aforementioned discussion, we can infer that many factors affect cryptocurrencies' prices (ups and downs). Choosing more factors is not a concern; instead, choosing the right attributes to predict prices and build a robust model is of prime concern. From the literature, we have analyzed that authors either used Tweets or deep learning approaches to improve performance. Nevertheless, none of them considered it together for predicting the cryptocurrency prices and market sentiment together. Table 1 shows a relative comparison of various state-of-the-art models with the proposed model.

The aforementioned discussion motivated us to propose the idea of fusion, where we consider both cryptocurrency interdependence and sentiments from social media. This paper proposed a fusion-based model for cryptocurrencies price prediction, i.e., *DL-GuesS*. It aims to predict the price of a specific coin considering their price history and tweet sentiments of the other dependent or alternate coins.

A. RESEARCH CONTRIBUTIONS

Following are the major contributions of the paper.

- We present a comparative study of the state-of-the-art schemes for price prediction considering both historical prices and twitter sentiments.
- A deep learning (i.e., LSTM and GRU) and Twitter sentiments-based hybrid model, *DL-GuesS*, is proposed to predict the cryptocurrency prices considering the window sizes, i.e., 1, 3, and 7 days. We have also considered the inter-cryptocurrency dependencies to improve the performance of the proposed model *DL-GuesS*.
- Performance evaluation of *DL-GuesS* considering the evaluation matrices such as MSE, MAE, and MAPE for *Dash* coin and *Bitcoin-Cash* and compared it with the traditional approaches.

B. ORGANIZATION

The rest of the paper is organized as follows. Section II presents the system model and problem formulation. Section III describes the proposed *DL-GuesS* approach. Experimental results are presented in Section IV and finally, the paper is concluded as well as future directions suggested in Section V.

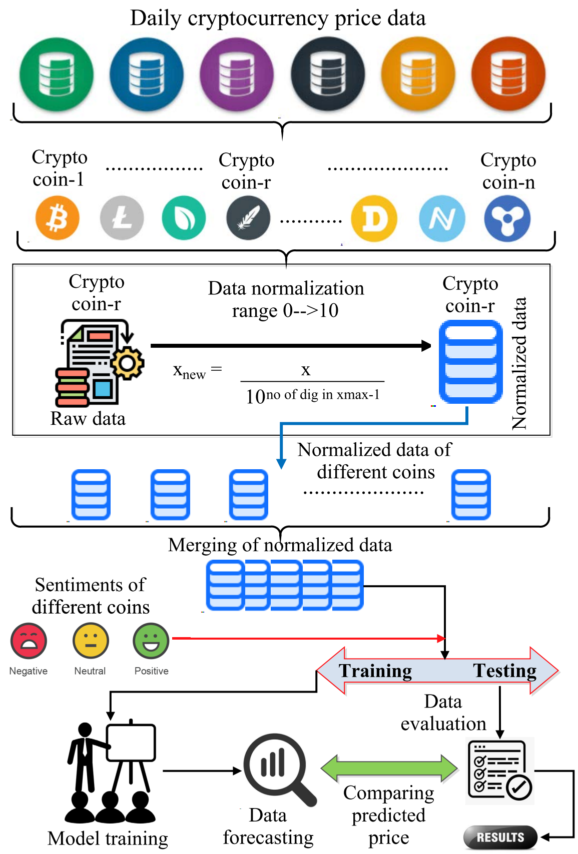


FIGURE 1. ***DL-GuesS*: system model.**

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section layouts the *DL-GuesS* system model and problem formulation for improving the cryptocurrency price prediction considering their interdependencies on other cryptocurrencies and twitter sentiments.

A. DL-GuesS: SYSTEM MODEL

FIGURE 1 shows the working of *DL-GuesS* system model. For training, the price history of data is collected from [25] and nearly 100 tweets are gathered from Twitter. After pre-processing, the normalization is carried out via division operator. Let x be the current price and x_{max} be the maximum price till now, y is the difference between the number of digits in x_{max} and 1, and x_{new} be the normalized prize which is calculated as follows:

$$x_{new} = \frac{x}{10^y} \tag{1}$$

$$y = Number\ of\ digits\ in\ x_{max} - 1 \tag{2}$$

Eq. (1) normalizes the price values in the range of 0 to 10. After pre-processing, the merging of data is done according to (9) to make an input tuple. Then, the data is further divided into two parts, i.e., training and testing data. The Model weights are trained using training data and their performance is evaluated using testing data. To predict price for the i^{th} day, we need to enter the past w days (window length) data for all the dependent cryptocurrencies such as *Bitcoin*, *Litecoin*, and *Dash* and their present-day tweets. Then, the forecasted price was fed as an input to the model with past $(w-1)$ days of cryptocurrency prices to predict the $(i+1)^{\text{th}}$ days price consequently. We repeat this process until the number of iterations equals the prediction window length. The new w days price is compared with the test data to evaluate its performance. The proposed scheme uses a hybrid GRU and LSTM-based model to prevent the vanishing gradient problem.

B. PROBLEM FORMULATION

In *DL-GuesS*, there are two types of inputs, i.e., past days prices and present-day tweets for each cryptocurrency price prediction. To analyze the performance of *DL-GuesS*, we have considered the price prediction of *Dash* with an input of past single-day price of *Bitcoin*, *Litecoin*, and *Dash* and their present-day tweets. The price forecasting problem is a supervised learning regression problem. The system model consists of two supervised learning phases where the first phase task is to get the polarity of tweets through VADER

TABLE 2. Dataset features and its descriptions.

Dataset Feature	Description
Bitcoin Price	The historical price data of *Bitcoin* to assist the price prediction of target cryptocurrency (*Dash*, *Bitcoin-Cash*)
Bitcoin Tweet	The tweet data that represent the sentiment of *Bitcoin* in the current market
Litecoin Price	The historical price data of *Litecoin* to assist the price prediction of target cryptocurrency (*Dash*, *Bitcoin-Cash*)
Litecoin Tweet	The tweet data that represent the sentiment of *Litecoin* in the current market
Dash Price	The historical price data of *Dash* to assist the price prediction of *Dash*
Dash Tweet	The tweet data that represent the sentiment of *Dash* in the current market
Bitcoin-Cash Price	The historical price data of *Bitcoin-Cash* to assist the price prediction of *Bitcoin-Cash*
Bitcoin-Cash Tweet	The tweet data that represent the sentiment of *Bitcoin-Cash* in the current market

API [26], which is formulated as follows:

$$inp_t = [t_b,\ t_l,\ t_d] \tag{3}$$
$$n = min(\ len(t_b),\ \ len(t_l),\ \ len(t_d)\ ) \tag{4}$$
$$t_b = t_b[0:n],\quad t_l = t_l[0:n],\ t_d = t_d[0:n] \tag{5}$$
$$s_b = fn(t_b),\quad s_l = fn(t_l),\ s_d = fn(t_d) \tag{6}$$

where t_b, t_l, and t_d are the tweets related to *Bitcoin*, *Litecoin*, and *Dash* retrieved from Twitter, respectively. The minimum number of tweets among t_b, t_l, and t_d are assigned to variable n. The polarity extractor from VADER API [26] is denoted as fn. For each tweet, fn returns a tuple of length three consisting of polarity score as positive, neutral, and negative sentiments. The result of t_b, t_l and t_d from fn is stored in s_b, s_l and s_d, respectively.

After the processing of tweets to get their sentiments or polarity score, the data can pass to the second phase. It requires the sentiments of tweets and past single day price to predict the current price of the given cryptocurrency. Lets consider the present day as i^{th} day and the mathematical equations for forecasting models are stated below:

$$p_b = fp(pb_{i-1})\ p_l = fp(pl_{i-1}),\quad p_d = fp(pd_{i-1}) \tag{7}$$
$$inp_b = [p_b,\ s_b]\ inp_l = [p_l,\ s_l]\ inp_d = [p_d,\ s_d] \tag{8}$$
$$inp = [inp_b,\ \ inp_l,\ \ inp_d] \tag{9}$$
$$op = \hat{p_i} \tag{10}$$

where pb_{i-1}, pl_{i-1} and pd_{i-1} are the previous day prices of *Bitcoin*, *Litecoin*, and *Dash*, respectively. The previous day prices are assigned in pb_{i-1}, pl_{i-1}, and pd_{i-1} and are normalized using (1), and then assigned to p_b, p_l, and p_d,respectively. The output of first phase is concatenated with the normalized prices of respective cryptocurrency and assigned it to inp_b, inp_l, and inp_d. The final input tuple is created using the concatenation of inp_b, inp_l, and inp_d, which is assigned to inp. The output of model is the forecasted price of *Dash* cryptocurrency for the i^{th} day, which is represented by variable op.

The objective of *DL-GuesS* is to minimize the prediction loss and increase the performance of forecasting model with (9) as input and predicted price for given cryptocurrency (10) as an output. The *DL-GuesS* objective function using MSE is as follows:

$$loss_{min} = \frac{1}{T}\sum_{i=0}^{D}(\hat{y}_i - y_i)^2,\quad \forall\{y_i, \hat{y}_i, T\} \geq 0 \tag{11}$$

where T is total number of input-output pairs. The actual price and predicted price is represent by y_i and $\hat{y}_i$, respectively.

III. *DL-GuesS*: THE PROPOSED MODEL

This section describes the architecture of the proposed *DL-GuesS*. It starts with the insights of the dataset used in *DL-GuesS*. Since the data is in raw format, it is mandatory to do pre-processing. The proposed *DL-GuesS* is divided into two phases, where the first phase calculates the sentiments from tweets, and the second phase utilizes the price history along with the extracted features from the first phase to predict the price of the cryptocurrency. Here, we consider a scenario of predicting the price of *Dash* coin considering tweets and the price history of *Dash*, *Bitcoin*, and *Litecoin*.

A. DATASET DESCRIPTION

The data price is collected from the global portal [25] for research purposes. It provides real-time data like the news and analysis of the financial market. The daily price data for *Bitcoin*, *Dash*, and *Litecoin* are filtered from it with the following features:

- *Price*: Average price of each cryptocurrency
- *Open*: The opening price of each cryptocurrency
- *High*: Highest price of each cryptocurrency
- *Low*: Lowest price of each cryptocurrency

Tweets for *Bitcoin*, *Dash*, and *Litecoin* are collected using Twitter API through *Tweepy framework* [27] in Python. Through this framework, a maximum of 100 tweets in the English language were retrieved for each cryptocurrency. The collected tweets must be posted on the day before the forecasting period.

Table 2 has the features that are used in the proposed model and its descriptions. As per the proposed model *Bitcoin*, and *Litecoin* is used to assist the model in accurately predicting the price of *Dash* and *Bitcoin-Cash*. To predict the price of *Dash*, the historical price data of *Bitcoin*, *Litecoin*, and *Dash* with the market sentiment of these cryptocurrencies, that are extracted through tweet dataset, used as a key feature of the proposed model. In the same manner, to predict the price of *Bitcoin-Cash*, the *Dash's* historical data and tweet data is replaced by the *Bitcoin-Cash's* data.

B. DATA ANALYSIS

In this subsection, the authors have analyzed and given insights into the data being used for the proposed model. There are two types of data used over here:

- Time Series data:- The price history of Dash, Litecoin, Bitcoin, and Bitcoin Cash are considered numeric time-series data.
- Sentiments data:- Sentiments for each of the cryptocurrencies are scrapped from Twitter using Twitter API through *Tweepy framework*, and they are considered as Unicode strings. After preprocessing and predicting sentiments labels, the data is propagated further with corresponding cryptocurrency price history into the forecasting model.

Now, to determine which cryptocurrencies suits best to predict the prices of Dash and Bitcoin Cash, we must look upon the correlation matrix with other cryptocurrencies. FIGURE 2 represents the correlation matrix as a heatmap. After looking upon the correlation score, Litecoin shows good similarity score with Dash and Bitcoin Cash (BCH_USD in FIGURE 2), and Litecoin is derived from Bitcoin. Because of this, authors had used Litecoin and Bitcoin for price prediction of Dash and Bitcoin Cash.

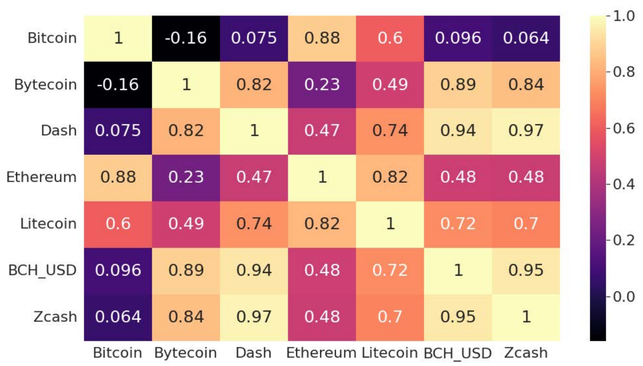


FIGURE 2. Heat map representing the correlation among various cryptocurrencies.

C. PRE-PROCESSING

The price range for *Bitcoin* is quite high compared to the *Dash* and *Litecoin*. The difference in cryptocurrency price change can affect the training time and performance of *DL-GuesS*. To overcome this, we can use either min-max normalization or Gaussian normalization. To normalize the cryptocurrency prices in *DL-GuesS*, we have used a custom normalization technique represented in (1). Since the Twitter tweets are scrapped directly from Twitter thus, there is a need to pre-process the data before usage. The tweets that contain hashtags, special symbols, emojis, and much other unwanted stuff have been removed from the Twitter dataset. It also uses a regular expression to eliminate the unwanted characters.

D. SENTIMENT ANALYSIS MODEL

To extract the polarity of positive, negative, and neutral sentiments, the proposed *DL-GuesS* uses a VADER algorithm to achieve promising results [26]. The output is a three-dimension vector consisting of polarity for each type of sentiment for a single tweet. The value of each polarity lies between 0 and 1. The sentiment for the input tweet is classified based on its polarity score, higher the polarity value, and higher the probability for that particular sentiment. The outputs of VADER were concatenated with the prices of their respective cryptocurrencies as mentioned in (8). Algorithm 1 shows the detailed working of the proposed model.

Algorithm 1 Twitter Sentiments

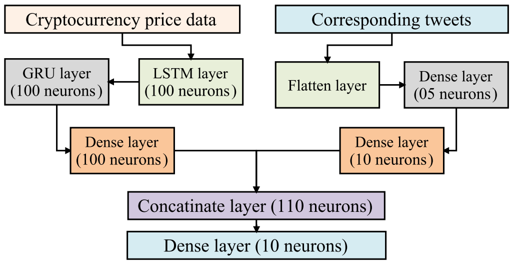
Input: $N \in$ {tweets of required cryptocurrencies}
Output: $S_x \in$ {sentiments}

procedure PROCESS_DATA(N)
  $tweet\_size \leftarrow count(N_1)$ ▷ *count* is the number of tweets
  $S_x \leftarrow \emptyset, \forall x \in N$
  for $\alpha = 2, 3 \ldots, N$ **do**
    $tweet\_size \leftarrow min(count(N_{alpha}), tweet\_size)$
  end for
  for $\alpha = 1, 2 \ldots, N$ **do**
    $S_{x_\alpha} \leftarrow \emptyset$
    for $\beta = 1, 2, \ldots, tweet\_size$ **do**
      $\mathcal{D}_x \leftarrow$ VADER(N[α][β]) ▷ $\mathcal{D}_x$ is temporary variable
      for dox_α and VADER is function from VADER API
        $S_{x_\alpha} \rightarrow append(\mathcal{D}_x)$
      end for
      $S_x \rightarrow append(S_{x_\alpha})$
    end for
    $\Re(S_x)$ ▷ $\Re$ returns the S_x values
  end for
end procedure

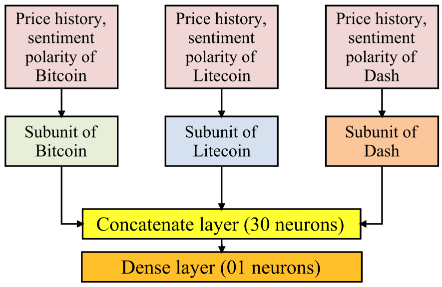
As discussed above, the VADER algorithm is the most promising for sentiment extraction from textual data. We have collected the tweets for each cryptocurrency for a particular day and fed them as an input to algorithm 1 and produced the output as a three-dimension vector. Our goal is to find the cryptocurrency with a minimum number of tweets and apply the VADER algorithm to each cryptocurrency's same number of tweets. First, we assign the number of tweets retrieved for cryptocurrency-1 to *tweet_size* and compare it with other cryptocurrencies. If the number of tweets for a specific cryptocurrency is low compared to *tweet_size*, then the present value of *tweet_size* can be updated. Now, we apply the VADER algorithm for *tweet_size* number of tweets for a cryptocurrency and then store all the output in a temporary variable $S_{x\alpha}$, and passed it to the other variable S_x. Then, make this temporary variable null and repeat the same for other cryptocurrencies. At the completion step, we pass the S_x as an output to our sentiment analysis model.

E. PRICE PREDCITION MODEL

FIGURE 3 shows the proposed *DL-GuesS* model. FIGURE 3a shows the subunit of architecture, which comprises of two phases, where the first phase consists of daily prices of given cryptocurrency as input, which is propagated to 100 neurons of LSTM, followed by 100 neurons of GRU, and at last



(a) Sub Model



(b) Final Model

FIGURE 3. Proposed architecture.

100 neurons of Dense with the rectified linear unit (ReLU) as an activation function. The mathematical formula for ReLU is given in (12) [28]. The second phase is used to get a latent feature from the polarity score calculated from tweets by the VADER algorithm. A flattening layer is applied to a vector consisting of a polarity score with a motive to convert an n-dimensional vector to a 1-dimensional vector. It is followed by a five neurons dense layer and a dense layer of ten neurons. Both dense layers use ReLU as an activation function. The last layer of both model is concatenated through the concatenation layer. The output from the concatenation layer is passed to a dense layer of 10 neurons. The output dense layer of the subunit is also activated using ReLU as an activation function.

FIGURE 3b shows the final phase of *DL-GuesS*, which consists of 3 subunits each for *Bitcoin*, *Litecoin*, and *Dash* cryptocurrencies. The outputs of all subunits are concatenated through the concatenation layer and further passed to the output layer, as follows:

$$F(x) = max(x, 0) \tag{12}$$

where F is a ReLU activation function and x is its input. Whenever the value of x is less than 0, F becomes 0; else keep it as it is if the value is greater than or equal to 0.

After getting the output of the sentiment analysis model, we have to restructure the data to make data in a form our model *DL-GuesS* accepts as an input. To achieve the same objective, Algorithm 2 is designed, which converts the raw data into a required input format. As we got the *tweet_size* in Algorithm 1, in a same way we will get the *sample_size* as well. This *sample_size* is based on a minimum number

Algorithm 2 Structuring Data

Input: $P \in$ {normalized prices of all cryptocurrencies}, $N \in$ {number of required cryptocurrencies}, $S \in$ {sentiments for each each cryptocurrencies}
Output: $P_x \in features$, $P_y \in target$

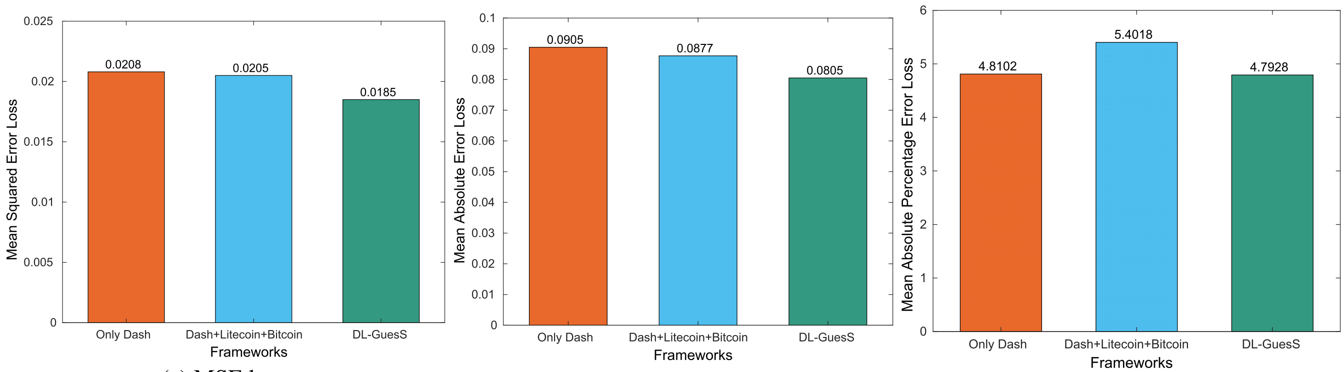
procedure PROCESS_DATA(P, N)
  $sample\_size \leftarrow len(P_1)$ ▷ *len* is the input data length
  $P_x \leftarrow \emptyset, \forall P_x \in P_{Training \rightarrow Features}$
  $P_y \leftarrow \emptyset, \forall P_y \in P_{Target}$
  for $\alpha = 2, 3 \ldots, N$ **do**
    $sample\_size \leftarrow min(len(P_{alpha}), sample\_size)$
  end for
  for $\alpha = 1, 2 \ldots, N$ **do**
    $P_{x_\alpha} \leftarrow \emptyset$
    $P_{y_\alpha} \leftarrow \emptyset$
    for $\beta = 1, 2, \ldots, sample\_size - 1$ **do**
      $\mathcal{D}_x \leftarrow$ P[α][β] ▷ $\mathcal{D}_x$ is temporary variable for x_α
      $\mathcal{D}_y \leftarrow$ P[α][$\beta + 1$] ▷ $\mathcal{D}_y$ is temporary variable for y_α
      $P_{x_\alpha} \rightarrow append(\mathcal{D}_x)$
      $P_{y_\alpha} \rightarrow append(\mathcal{D}_y)$
    end for
    $P_x \rightarrow append((P_{x_\alpha}, S[\alpha]))$
    if $\alpha == 1$ **then**
      $P_y \leftarrow P_{y_\alpha}$
    end if
  end for
  $\Re(P_x, P_y)$ ▷ $\Re$ returns the P_x, P_y values
end procedure

of data available for each cryptocurrency price. Here, input for Algorithm 2 is normalized price value of cryptocurrency-P according to (1), number of cryptocurrency considered-N, and sentiment for N cryptocurrency as S. Now, we will start with the target cryptocurrency as our first crypto coin from input for further process. We will take two temporary variable $P_{x\alpha}$ and $P_{y\alpha}$, which stores the value for N cryptocurrency one-by-one. Another two temporary variables D_x and D_y, which stores the values of the particular day and next day price, respectively, and append the values to $P_{x\alpha}$ and $P_{y\alpha}$ for *sample_size-1* times. Only for the first time, we will assign the final $P_{y\alpha}$ value to P_y as it contains the price of target cryptocurrency. For the rest of the cryptocurrencies, we will not change the value of P_y. On other side, $P_{x\alpha}$ with sentiments from Algorithm 1 *S[α]* appends to P_x, where *S[α]* contains the sentiments of cryptocurrency. At the end, the P_x and P_y will be given as output of the Algorithm 2.

IV. PERFORMANCE EVALUATION OF *DL-GuesS*

This section discusses the performance evaluation of *DL-GuesS* comparing it with the traditional prediction models. The deep learning models are trained using TensorFlow API's [28] over python 3.8.0 platform. For the sentiment analysis, the VADER algorithm [29] is used to analyze the tweets collected from Twitter API. *DL-GuesS* is trained for 50 epochs with *adam* as optimizer with batch-size of 16.

The performance of the *DL-GuesS* compared with two different models. The simple model has only Dash price as an



(a) MSE loss. (b) MAE loss. (c) MAPE loss.

FIGURE 4. **Comparative analysis of *DL-GuesS* with the *Dash* coin and dependency factors in terms of loss.**

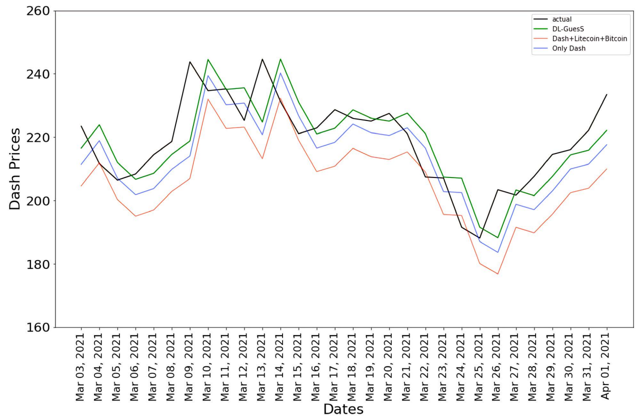


FIGURE 5. ***Dash* MSE prediction.**

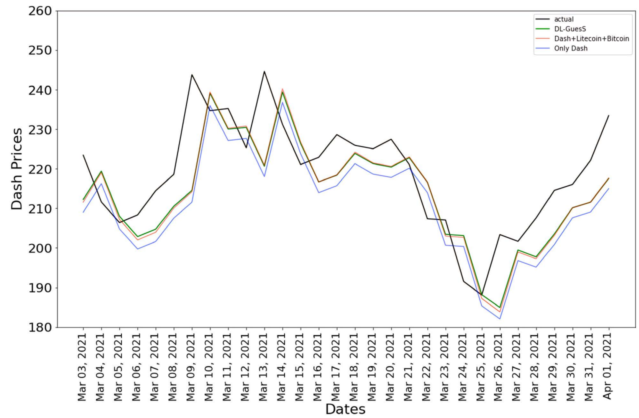


FIGURE 6. ***Dash* MAE prediction.**

input feature, wherein the second model uses the multi-level hierarchies among *Dash*, *Litecoin*, and *Bitcoin*. To predict the *Dash* coin price using a multi-level hierarchical model, the past prices of *Dash*, *Litecoin*, and *Bitcoin* are passed as an input feature with 1-day as the window size. To get a better idea of the performance of these models, we also considered the different loss values, e.g., MSE, MAE, and MAPE [30], [31], respectively. The loss values are calculated as follows:

$$MSE = \frac{1}{D}\sum_{i=0}^{D}(\hat{p}_i - p_i)^2 \tag{13}$$

$$MAE = \frac{1}{D}\sum_{i=0}^{D}|\hat{p}_i - p_i| \tag{14}$$

$$MAPE = \frac{1}{D}\sum_{i=0}^{D}\frac{|p_i - \hat{p}_i|}{p_i} \tag{15}$$

where D is the number of samples taken for consideration, p_i represents the true price of the *Dash*, and $\hat{p}_i$ represents the predicted price of the *Dash*.

A. SCENARIO 1: DASH PRICE PREDICTION

The simple model, having only *Dash* price as an input feature, has an MSE loss value of *0.0208* for forecasting the price of

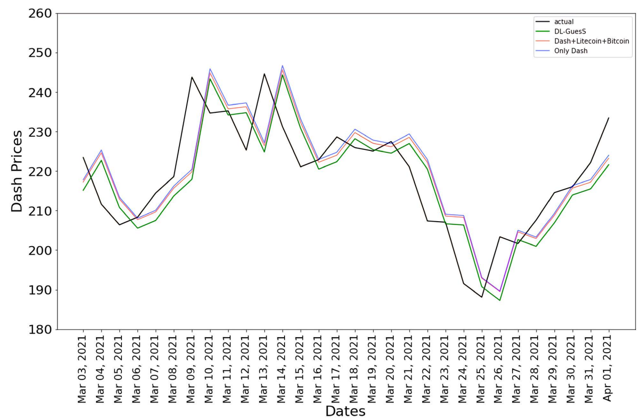
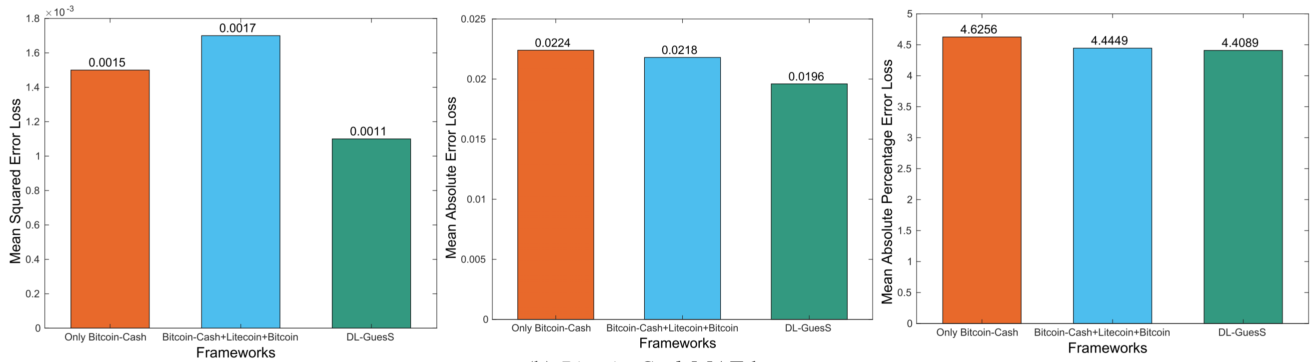


FIGURE 7. ***Dash* MAPE prediction.**

Dash. The model that considers the multi-level hierarchies among cryptocurrencies has an MSE loss value of *0.0205*. *DL-GuesS* has an MSE loss of *0.0185*, which is the least among all models. FIGURE 4a shows the comparison of these loss values for the different frameworks used to predict the price of *Dash*. FIGURE 5 shows the prediction done of *Dash* for the cycle of the next 30 days.



(a) *Bitcoin-Cash* MSE loss. (b) *Bitcoin-Cash* MAE loss. (c) *Bitcoin-Cash* MAPE loss.

FIGURE 8. **Comparative analysis of *DL-GuesS* with the *Bitcoin-Cash* and dependency factors in terms of loss.**

The simple model, having only *Dash* price as an input feature, has an MAE loss value of *0.0905* for forecasting the price of *Dash*. The model that considers the multi-level hierarchies among cryptocurrencies has an MAE loss value of *0.0877*. *DL-GuesS* has an MAE loss of *0.0805*, which is the least among all models. FIGURE 4b shows the comparison of these loss values for the different frameworks used to predict the price of *Dash*. FIGURE 6 shows the prediction done of *Dash* for the cycle of the next 30 days.

The simple model, having only *Dash* price as an input feature, has a MAPE loss value of *4.8102* for forecasting the price of *Dash*. The model that considers the multi-level hierarchies among cryptocurrencies has a MAPE loss value of *5.4018*. *DL-GuesS* has a MAPE loss of *4.7928*, which is the least among all models. FIGURE 4c shows the comparison of these loss values for the different frameworks used to predict the price of *Dash*. FIGURE 7 shows the prediction done of the price of *Dash* for the cycle of the next 30 days. Table 3 shows the loss value for different loss functions and different model architectures.

TABLE 3. ***Dash* model-loss comparison.**

Model	Loss		
	MSE	MAE	MAPE
Only *Dash*	0.0208	0.0905	4.8102
Dash+Litecoin+Bitcoin	0.0205	0.0877	5.4018
DL-GuesS	**0.0185**	**0.0805**	**4.7928**

B. SCENARIO 2: BITCOIN-CASH PRICE PREDICTION

To provide the evidence of *DL-GuesS's* usability on cryptocurrencies other than *Dash*, we predict the price of *Bitcoin-Cash* using the same approach, which is followed for price prediction of *Dash*. *Bitcoin-Cash* is dependent on *Bitcoin*, and its alternate coin is *Litecoin*. The price prediction of *Bitcoin-Cash* is carried out through the price history and sentiments of the *Bitcoin-Cash*, *Litecoin*, and *Bitcoin*. This subsection discusses the result obtained in this second scenario.

The simple model, having only *Bitcoin-Cash* price as an input feature, has an MSE loss value of *0.0015* for forecasting the price of *Bitcoin-Cash*. The model that considers the price of all three cryptocurrencies to predict the *Bitcoin-Cash's* price has an MSE loss value of *0.0017*. *DL-GuesS* has an MSE loss of *0.0011*, which is the least among all models. FIGURE 8a shows the comparison of these loss values for the different frameworks used to predict the price of *Bitcoin-Cash*. FIGURE 9 shows the prediction done of the price of *Bitcoin-Cash* for the cycle of the next 30 days.

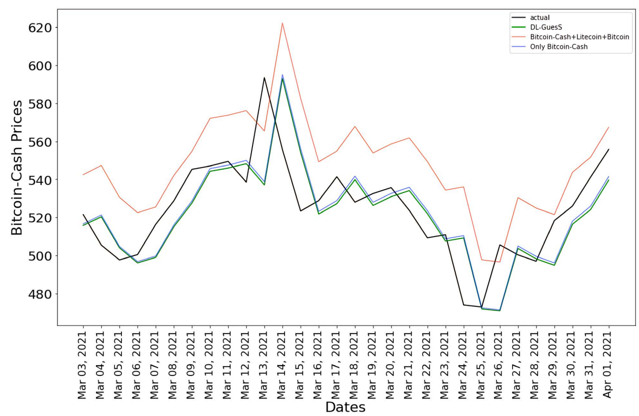


FIGURE 9. ***Bitcoin-Cash* MSE prediction.**

The simple model, having only *Bitcoin-Cash* price as an input feature, has an MAE loss value of *0.0224* for forecasting the price of *Bitcoin-Cash*. The model that considers the price of all three cryptocurrencies to predict the *Bitcoin-Cash's* price has an MAE loss value of *0.0218*. *DL-GuesS* has an MAE loss of *0.0196*, which is the least among all models. FIGURE 8b shows the comparison of these loss values for the different frameworks used to predict the price of *Bitcoin-Cash*. FIGURE 10 shows the prediction done of the price of *Bitcoin-Cash* for the cycle of the next 30 days.

The simple model, having only *Bitcoin-Cash* price as an input feature, has a MAPE loss value of *4.6256* for forecasting the price of *Bitcoin-Cash*. The model that considers the price of all three cryptocurrencies to predict the *Bitcoin-Cash's* price has a MAPE loss value of *4.4449*. *DL-GuesS* has a

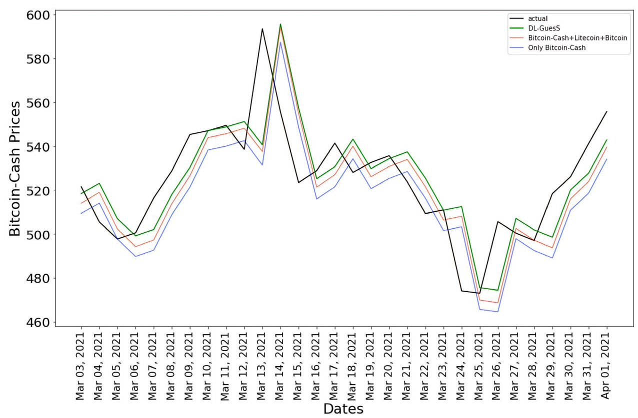


FIGURE 10. ***Bitcoin-Cash* MAE prediction.**

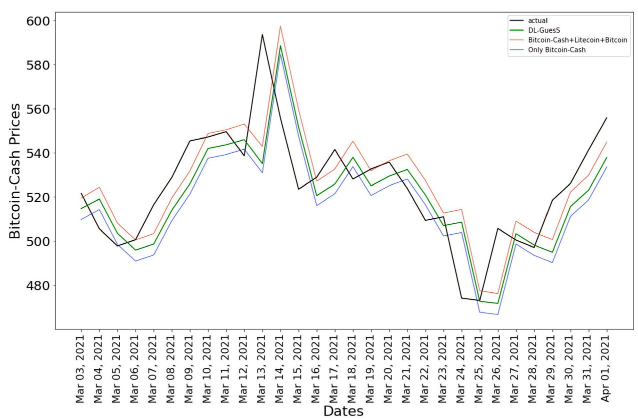


FIGURE 11. ***Bitcoin-Cash* MAPE prediction.**

TABLE 4. ***Bitcoin-Cash* model-loss comparison.**

Model	Loss		
	MSE	MAE	MAPE
Only *Bitcoin-Cash*	0.0015	0.0224	4.6256
Bitcoin-Cash+Litecoin+Bitcoin	0.0017	0.0218	4.4449
DL-GuesS	**0.0011**	**0.0196**	**4.4089**

MAPE loss of *4.4089*, which is the least among all models. FIGURE 8c shows the comparison of these loss values for the different frameworks used to predict the price of *Bitcoin-Cash*. FIGURE 11 shows the prediction done of the price of *Bitcoin-Cash* for the cycle of the next 30 days. Table 4 shows the loss value for different loss functions and different model architectures.

V. CONCLUSION AND FUTURE DIRECTIONS

This section will conclude the paper and provide future directions for improving the forecasting model performance to the research community.

A. CONCLUSION

In this paper, we analyzed the existing systems for cryptocurrency price prediction. Many of them are being utilized by fin-tech companies leveraging the advantages of cryptocurrency price prediction models. However, the volatile nature and many dependent factors make the prediction quite challenging. Inspired by the existing work, in this paper, we present a hybrid model, i.e., *DL-GuesS* for cryptocurrency price prediction considering price history and recent twitter sentiments. To describe the robustness of *DL-GuesS*, we have carried out the performance evaluation of *DL-GuesS* for two different cryptocurrencies and compared the results, i.e., loss functions with the existing works. The proposed *DL-GuesS* outperforms the traditional systems in predicting the cryptocurrency prices. *DL-GuesS*.

B. FUTURE DIRECTIONS

1) PROPER UTILIZATION OF FORECASTING MODEL

Currently, to predict the price of a single cryptocurrency, the forecasting model uses a single model trained on data of the specific cryptocurrency. In this paper, we have proposed a system where the price of a single cryptocurrency is predicted by data of itself and other data as well. This architecture can be carried forward by which a single forecasting model will predict the prices of all the known cryptocurrencies. Through this, the computational resources, as well as system intelligence, can be used efficiently.

2) ARCHITECTURE ADVANCEMENT

The pace of introduction to the new architectures for machine learning and deep learning is rapid. And each of them performs way better than the previous one. The same concept or the new concepts by other research fellows can experiment with new architectures like transformers, federated learning models as data is increasing at rapid rates, and many others to get better results on forecasting algorithms

3) INCLUSION OF OTHER FACTORS

DL-GuesS use the price history of similar cryptocurrency and their tweets for price predictions. Similarly, through the inclusion-exclusion principle, other factors with the amalgamation of *DL-GuesS* concept can increase the performance of forecasting models significantly.

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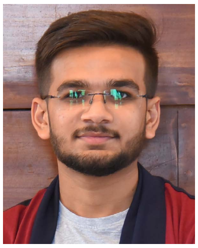
RAJ PAREKH is currently pursuing the B.Tech. degree in computer science and engineering with the Institute of Technology, Nirma University, Ahmedabad, India. His research interests include blockchain, federated learning, machine learning, and deep learning.



NISARG P. PATEL is currently pursuing the B.Tech. degree with the Institute of Technology, Nirma University, Ahmedabad, Gujarat, India. His research interests include data science, deep learning, and federated learning.

NIHAR THAKKAR is currently pursuing the B.Tech. degree in computer science and engineering with the Institute of Technology, Nirma University, Ahmedabad, India. He is working in the deep learning domain. His research interests include blockchain, machine learning, and deep learning.

RAJESH GUPTA (Student Member, IEEE) received the Bachelor of Engineering degree from the University of Jammu, India, in 2008, and the master's degree in technology from Shri Mata Vaishno Devi University, Jammu, India, in 2013. He is currently pursuing the Ph.D. degree with the Computer Science and Engineering Department, Nirma University, Ahmedabad, Gujarat, India. He has authored/coauthored some publications, including papers in SCI Indexed journals and IEEE ComSoc sponsored international conferences. Some of his research findings are published in top-cited journals, such as IEEE Transactions on Network Science and Engineering, IEEE Transactions on Green Communications and Networking, IEEE Transactions on Computational Social Systems, *IEEE Network*, *IEEE Internet of Things Magazine*, *Computer Communications*, *Computers and Electrical Engineering*, *IJCS* (Wiley), *ETT* (Wiley), *Physical Communication*, and many more. His research interests include device-to-device communication, network security, blockchain technology, 5G communication networks, and machine learning. He is an Active Member of ST Research Laboratory (www.sudeeptanwar.in). He is a recipient of the Doctoral Scholarship from the Ministry of Electronics and Information Technology, Government of India, under the Visvesvaraya Ph.D. Scheme. He was a recipient of the Student Travel Grant from WICE-IEEE to attend IEEE ICC 2021 held in Canada. He has been awarded the Best Research Paper Awards from IEEE ECAI 2021 and IEEE IWCMC 2021. His name has been included in the list of Top 2% scientists worldwide published by Stanford University, USA.

SUDEEP TANWAR (Senior Member, IEEE) received the B.Tech. degree from Kurukshetra University, India, in 2002, the M.Tech. degree (Hons.) from Guru Gobind Singh Indraprastha University, Delhi, India, in 2009, and the Ph.D. degree in wireless sensor network, in 2016. He is currently working as a Professor with the Computer Science and Engineering Department, Institute of Technology, Nirma University, India. He is also a Visiting Professor with Jan Wyzykowski University, Polkowice, Poland; and the University of Piteşti, Piteşti, Romania. He is also leading the ST Research Laboratory, where group members are working on the latest cutting-edge technologies. He has authored two books, edited 13 books, and more than 270 technical articles, including top journals and top conferences, such as IEEE Transactions on Network Science and Engineering, IEEE Transactions on Vehicular Technology, IEEE Transactions on Industrial Informatics, IEEE Wireless Communications, *IEEE Network*, ICC, GLOBECOM, and INFOCOM. He has initiated the research field of blockchain technology adoption in various verticals, in 2017. His H-index is 50. He actively serves his research communities in various roles. His research interests include blockchain technology, wireless sensor networks, fog computing, smart grid, and the IoT. He is a Final Voting Member of the IEEE ComSoc Tactile Internet Committee, in 2020. He is a member of CSI, IAENG, ISTE, and CSTA. He is a member of the Technical Committee on Tactile Internet of IEEE Communication Society. He has been awarded the Best Research Paper Awards from IEEE IWCMC-2021, IEEE GLOBECOM 2018, IEEE ICC 2019, and Springer ICRIC-2019. He has served many international conferences as a member for the organizing committee, such as the Publication Chair for FTNCT-2020, ICCIC 2020, and WiMob2019; a member of the Advisory Board for ICACCT-2021 and ICACI 2020; the Workshop Co-Chair for CIS 2021; and the General Chair for IC4S 2019 and 2020 and ICCSDF 2020. He is also serving the editorial boards for *Computer Communications*, the *International Journal of Communication Systems*, and *Security and Privacy*.

GULSHAN SHARMA received the B.Tech., M.Tech., and Ph.D. degrees. He is currently working as a Senior Lecturer with the Department of Electrical Engineering Technology, University of Johannesburg, Johannesburg, South Africa. He is a Y Rated Researcher from NRF South Africa. His research interests include power system operation and control and application of AI techniques to the power systems. He is working as an Academic Editor of the *International Transactions on Electrical Energy Systems* (Wiley). He is a Regional Editor of *Recent Advances in E & EE* and *Bentham Science*.

INNOCENT E. DAVIDSON (Senior Member, IEEE) received the B.Sc.Eng. (Hons.) and M.Sc. (Eng.) degrees in electrical engineering from the University of Ilorin, Nigeria, in 1984 and 1987, respectively, the Ph.D. degree in electrical engineering from the University of Cape Town, Rondebosch, South Africa, in 1998, and the Postgraduate Diploma degree in business management from the University of KwaZulu-Natal (UKZN), in 2004. He was an Associate Professor of electrical engineering and a Research Coordinator with the University of Namibia, Namibia, from 2012 to 2014. He was the Director of the Eskom Centre of Excellence in HVDC Engineering, UKZN, from 2014 to 2016. He is currently a Full Professor and the Chair of the Department of Electrical Power Engineering, the Director of the Centre of Excellence in Smart Grids, and the Project Leader of the Space Science Program, Durban University of Technology, Durban, South Africa. He has graduated eight Ph.D. and 42 master's students. He has managed over R45million in research funds. He has authored/coauthored of over 300 papers in accredited journals, peer-reviewed conference proceedings, and technical reports. His current research interests include HVdc power transmission, grid integration of renewable energy, innovation for smart cities, and power system planning and economics. He is a fellow of the Institute of Engineering and Technology, U.K.; and the South African Institute of Electrical Engineers. He is a Chartered Engineer, U.K.; and a Registered Professional Engineer (P.Eng.) of the Engineering Council of South Africa. He is a member of the Western Canada Group of Chartered Engineers (WCGCE), the Institute of Engineering and Technology (IET Canada) British Columbia Chapter, the IEEE Collabratec Communities on Smart Cities, and IEEE (South Africa Chapter). He has received the Associate Certificate in sustainable energy management (SEMAC) from the British Columbia Institute of Technology, Burnaby, BC, Canada, in 2011; and the Course Certificate in artificial intelligence from the University of California at Berkeley, Berkeley, CA, USA, in 2020. He was a recipient of numerous awards, including the Best Paper Award from the International Conference on Renewable and Energy Research and Applications Conference, Birmingham, U.K., in November 2016, for the paper titled "Harmonic Distortion of LCC-HVDC and VSC-HVDC Link in Eskom's Cahora-Bassa HVDC Scheme;" and the Best Paper Award (Third Place) from Clemson University Power Systems Conference, Clemson, SC, USA, in March 2020, for the paper titled "Modeling and Assessment of the Fault Ride-Through Capabilities of Grid Supporting Inverter-Based Microgrids." At DUT's Annual Research and Innovation, he was a recipient of the Top Impact Author Award, in November 2020, the "Top Faculty Researcher of the Year (Platinum Category)," in November 2019, and the "Faculty Researcher of the Year," in November 2018.

RAVI SHARMA is currently working as a Professor with the Centre for Inter-Disciplinary Research and Innovation, University of Petroleum and Energy Studies, Dehradun, India. He is passionate in the field of business analytics and worked in various MNC's as a leader of various software development groups. He has contributed various articles in the area of business analytics, prototype building for startup, and artificial intelligence. He is leading academic institutions as a consultant to uplift research activities in inter-disciplinary domains.