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Deep Learning-Based Cryptocurrency Price Prediction Scheme With Inter-Dependent Relations

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ABSTRACT Blockchain technology is becoming increasingly popular because of its applications in various fields. It gives an edge over the traditional centralized methods as it provides decentralization, immutability, integrity, and anonymity. The most popular application of this technology is cryptocurrencies, which showed a massive rise in their popularity and market capitalization in recent years. Individual investors, big institutions, and corporate firms are investing heavily in it. However, the crypto market is less stable than traditional commodity markets. It can be affected by many technical, sentimental, and legal factors, so it is highly volatile, uncertain, and unpredictable. Plenty of research has been done on various cryptocurrencies to forecast accurate prices, but the majority of these approaches cannot be applied in real-time. Motivated from the aforementioned discussion, in this paper, we propose a deep-learning-based hybrid model (includes Gated Recurrent Units (GRU) and Long Short Term Memory (LSTM)) to predict the price of *Litecoin* and *Zcash* with inter-dependency of the parent coin. The proposed model can be used in real-time scenarios and it is well trained and evaluated using standard data sets. Results illustrate that the proposed model forecasts the prices with high accuracy compared to existing models.

INDEX TERMS Cryptocurrency, price prediction, Litecoin, Zcash, Long Short-Term Memory, Gated Recurrent Unit, inter-dependencies, direction algorithm, parent coin's direction.

I. INTRODUCTION

Modern monetary systems are based on fiat money, which has many advantages because of its divisibility, transfer-ability, durability, and scarcity [1]. However, there are a couple of problems with it such as the currency is not backed by anything, so governments have control over money. It can lead to many issues, such as hyperinflation and income inequality [2]. Yugoslavia, Peru, and Venezuela are suffering from hyperinflation because the current system has failed [3]. The second problem with the current system is the vulnerability of existing ledgers, which keep the record of all transactions. The modern financial system says that money is just an entry on these ledgers, but they can be manipulated and violated. The third problem is the way people transact money. Everyone transacts money with a cheque, wire transfers, credit cards, or online applications such as G-pay or Amazon Pay, etc. The payment goes through a financial institution or intermediaries such as credit card companies, clearinghouses, and financial institutions. The average cost of transferring money from one country to another ranges from 6% to 10% and can sometimes take up to one week to complete the transaction.

People have lost control and ownership of their data because of the monopoly of these intermediaries. People trust these institutions because of their accountability and predictability. Based on trust, more than 6 billion people transact 200 trillion worth of money every year [4]. This trust is backed by the government regulations and legal contracts, but it is easily breakable and the world has witnessed many

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instances of trust breach, such as the crash of the dot-com bubble in the 1990s and the real-estate bubble in 2008, which had wiped out trillions of dollars [5].

A question arises how people trust the current financial system, which has a threat of hyperinflation, the ledgers are not tamper proof, and the intermediaries can also be failed. So there is a need to develop a model, which establishes the trust among all the stakeholders.

On 31 October 2008, Satoshi Nakamoto proposed a system that revolutionized the current system with the invention of a technology called Blockchain having first digital currency *Bitcoin* [6]. *Bitcoin* is a peer-to-peer (P2P) money transferring system that allows users to transact digital money over the public internet without intermediaries [7]. Blockchain stores all the transactions in the forms of blocks and all the blocks have their unique key. A block contains cryptographically encoded data locked by its key and the data of the previous block. In this manner, it creates the whole chain of blocks. It becomes nearly impossible to tamper any existing record or to get the control of this ledger, so it is a secure, immutable, and tamper proof ledger running on a decentralized network of computers. The integrity of the system is maintained by all the users through consensus algorithms, public-key cryptography methods, smart contracts, hashes, and digital handshakes [8].

Using cryptocurrencies people can transfer money anytime at minimal cost instantly. Also, this technology can help to reduce inflation and income inequality. It has the potential to close the ever-increasing trust gap between investors and sellers. It can solve the double-spending problem and detect fraud and users can achieve true data democracy with the help of it [9], [10].

Many cryptocurrencies entered into the crypto market after *Bitcoin*, for example, *Ethereum*, launched in 2015, is the second-largest cryptocurrency with a $410 billion market capitalization [11]. More than 5,600 different cryptocurrencies are traded in around 1,100 exchanges and *Ripple*, *Tether*, *Cardano*, *Stellar*, *Litecoin*, and *Zcash* are the most popular digital currencies. Back in June 2016, the total market capitalization of all cryptocurrencies was approximately 12.22 billion dollars and it fluctuated in 2017. It increased to $1.75 trillion in June 2021 [12], with an all-time high of $2 trillion. It will reach nearly $8 trillion by 2030. The daily volume of the crypto market is around $117 billion and more than 100 million people are using these currencies [13].

The Crypto market is attracting more people with its high returns and rapid growth. Cryptocurrencies have become an intangible digital assets for many individual investors and traders to invest in them [14]. It is a new investment opportunity for financial institutions, hedge funds, and corporate companies [15]. This market can grow exponentially and its growth is also evident after August 2020 during the COVID-19 pandemic [16]. Also, the researchers, companies, start-ups, and universities across the globe are working to make this new technology more reliable, mature, and secure. Many researchers are working to make crypto mining more efficient, cheaper [17], [18] and to prevent cryptojacking [19].

Predicting the accurate price of cryptocurrencies is always challenging because of their volatility and complexity. The price of crypto depends on more than 25 technical factors and market sentiment. Many cryptocurrencies, such as *Litecoin* and *Zcash*, are dependent on major cryptocurrencies, such as *Bitcoin*. Moreover, government and international regulations and plenty of legal factors can affect their prices [20]–[22]. Because of all these factors, many cryptocurrencies have shown more than 30% of growth in a single day, which is highly unpredictable and unreliable for the investors. However, with the use of various Machine Learning (ML) and Deep Learning (DL) algorithms, forecasting has become a little bit easier than past [23]. Plenty of research has been done in this area and many investors and financial institutions are trading with their price prediction system [24]. Motivated from the aforementioned discussions, in this paper, we propose a deep learning-based scheme to predict the accurate price of *Litecoin* and *Zcash*. We have trained the proposed model with the data of the last five years, tested it in the real-time, and compared its results with actual prices.

A. PRELIMINARIES

Cryptocurrencies are gaining popularity in recent days. The crypto market grew nearly ten times between June 2020 and May 2021. Nowadays, investments in cryptocurrencies are more reliable than before. For example, many researchers are working on the security of cryptocurrencies to prevent cryptojacking [19], [25]. Plenty of research is already carried out to make crypto mining efficient by reducing the mining cost [26]. Miners are trying to reduce the carbon footprint by replacing traditional energy sources with renewable energy.

Many researchers have already used various ML and DL algorithms to forecast the price of cryptocurrencies. However, most of them focused on the top ten coins in terms of market capitalization rather than the growth potential, technology, and purpose of the coin. The growth potential of *Litecoin* and *Zcash* is enormous, but they have not been exploited to their full potential. *Litecoin* is one of the fastest crypto-chains and it is also popular among investors from the beginning. It has a market capitalization of $11.14 billion, making it the eleventh-largest cryptocurrency in the world.

Litecoin is four-time faster than Bitcoin as its transaction validation time is only 2.5 minutes. It has a higher number than Bitcoin in terms of quantity, with 84 million total coins. Another advantage of *Litecoin* is that the transaction fees of its blockchain are lower than many other popular blockchains, including Bitcoin. From its creation in 2011 till the present day its blockchain has faced no major issues in terms of security. However, there are several disadvantages of this coin too. For example, *Litecoin* is quite similar to Bitcoin and is struggling to differentiate itself. Another drawback is that it still uses an energy-intensive consensus algorithm, which is the 'Proof of Work algorithm. Finally, the *Litecoin* ecosystem is improving and developing at a slower rate than the ecosystem of *Ethereum* based coins. The market trends of *Litecoin* showed that it is volatile like other currencies. It was first listed at the price of $30, and then it increased to just over $350 in December of 2017 before decreasing to just $23 in 2019. It increased significantly after May 2020 and reached its all-time high price, which was nearly $370. This coin has a huge potential to grow further.

Zcash uses the most advanced and complex cryptography techniques and overall, it is very similar to *Bitcoin*. *Zcash* provides complete anonymity as it does not reveal the information of users while validating transactions, which is possible because of using zero-knowledge proofs (zk-SNARKs). It is a very secure crypto-chain. On the other hand, governments see this functionality as a threat because they would fail to trace any criminal activity that involves *Zcash*, such as tax evasion or money laundering. However, this issue can be solved by imposing certain regulations on the transactions as per the guidelines of the Security and Exchange Commission (SEC) and other government authorities. *Zcash* was first mined in 2016 and reached nearly $3,000 in the same year. After that, it decreased to just over $20 in 2017 before increasing dramatically to $900 in January 2018. Between the years 2018 and 2021, the price of *Zcash* fluctuated between $50 and $320.

Another issue in forecasting is that many crypto coins are dependent on the parent currency, but often, these inter-dependencies, which play an important role in the price prediction, are not included in the forecasting models. Omitting the parent coin's direction may lead to poor prediction results. In this paper, we propose an appropriate and accurate deep learning-based model for the price prediction of these two currencies with the direction of the parent coin.

B. RESEARCH CONTRIBUTIONS

Following are the research contributions of the paper.

- **Research Community**: This paper can contribute to the existing literature because of its novel approach in the price forecasting domain. The paper can be set as a basic scheme that can be vertically expanded by adding more technical factors such as market capitalization, sentimental factors such as Twitter posts, and legal factors such as the economic policy and regulations to produce better results. There is also a possibility of expanding the proposed scheme horizontally by applying it to different cryptocurrencies. This article can be useful to the research community for future work in one of the fastest-growing fields of cryptocurrencies and blockchain.
- **Scientific Rationale**: To propose an LSTM-GRU based hybrid scheme with the direction of parent coin. This model can easily derive the inter-dependency between two coins by appending direction algorithm with historical data. The hybrid scheme can contribute to better performance than the existing and widely used basic LSTM and simple GRU model. The main scientific contribution of the paper is to enhance the deep learning-based models and time-series algorithms by considering hybrid features. For better comprehension, the mathematical formulation of the proposed model is also described. The model predicts the price of *Litecoin* and *Zcash* with four window sizes, i.e., 1, 3, 7, and 30 days.
- **Economic Rationale**: We have focused on cryptocurrencies, namely *Litecoin* and *Zcash*, that have less market capitalization, investor's attention, and popularity in the media but have unique features, cutting edge technology, and huge growth potential. The main motive of this is to reduce the polarization in the market, to eliminate the monopoly of big coins, such as Bitcoin and Ethereum, and to make low and mid-market cap coins more reliable by forecasting their accurate prices. These small coins will build trust among investors and will drive the market in the future. In the next two decades, the crypto market will be extremely mature and regulated, so the coins, which are unique and superior in technology, will grow significantly over the coins that are totally sentiment-driven.
- **Society and Industry Applications**: The proposed model considers not only technical factors, such as the average price but also uses the direction of the parent coin, which is important to understand the market sentiment, in the price prediction. Because of these functionalities, the proposed model can be used to detect the bullish or bearish nature of the coin at a particular time instance. So, retail investors and financial institutions can use this scheme to decide their hedging strategy and also for short-term investments.
- A detailed study on existing forecasting techniques, including the latest work of 2020-2021, with their results, merits, and demerits with a comprehensive study that includes various aspects of *Litecoin* and *Zcash* such as differences, advantages, disadvantages, and market trends.
- We have used Mean squared error (MSE) to evaluate the performance of the proposed hybrid model for *Litecoin* and *Zcash*.

C. ORGANIZATION

The rest of the paper is organized as follows. Section II illustrates a detailed study on the existing methodologies that predict cryptocurrency prices. Section III explains the system architecture and problem formulation. Section IV describes the proposed model. In Section V, the performance evaluation of the proposed model is discussed and finally, Section VI concludes the paper.

II. RELATED WORK

Many researchers have tried to predict the crypto market using various techniques and algorithms. They have considered different technical and sentimental parameters to come up with the best strategy. Some have worked to find the influence of various parameters on the price of cryptocurrencies.

TABLE 1. Acronym used.

Acronyms	Meaning
ALSTM	Attention-Based Long Short-Term Memory
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BiLSTM	Bidirectional Long Short-Term Memory
BPNN	Backpropagation Neural Network
CNN	Convolutional Neural Networks
DL	Deep Learning
GABNN	Genetic Algorithm and Backpropogation Neural Network
GANN	Genetic Algorithm Neural Network
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Squared Error
OLS-SVM	Optimal Least Square Support Vector Machine
PSO	Particle Swarm Optimization
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SVM	Support Vector Machine
VARIMA	Vector Autoregressive Integrated Moving Average

For example, Okorie *et al.* [45] gave evidence of a correlation between the volatility of cryptocurrencies and crude oil prices. Huynh *et al.* [46] explored the connection between the Bitcoin returns and the US oil market by using three different approaches, including Clayton copulas, Normal copulas, and Gumbel copulas. Chuen *et al.* [47] found out the influence of cryptocurrencies on the economy. In [48], the authors derived the correlation between gold and cryptocurrency and their effect on the Thai stock market in various situations. Huynh *et al.* [49] showed that gold can also be used as a hedging tool to predict the crypto market. Huynh *et al.* [50] also derived a relation between Bitcoin movement and the ratio of gold to platinum prices.

As mentioned earlier, legal factors plays an important role in the crypto market. Yuneline *et al.* [51] analyzed the nature of cryptocurrency based on characteristics of money, legal perspective, and the economic perspective of different countries. Foglia *et al.* [52] examined the connection between economic policy uncertainty (EPU) of different countries and cryptocurrency uncertainty indices between the years 2013 and 2021.

The price of cryptocurrencies can be affected by various technical factors, such as the popularity of a coin, mining cost, market trends, and buying behavior. Sovbetov *et al.* [53] considered many technical factors that influence the prices and trading volume of *Bitcoin*, *Ethereum*, *Dash*, *Litcoin*, and *Monero*. Many sentimental factors can also affect the bearish and bullish nature of traders. Narman *et al.* [54] described how positive and negative comments on social media affect the prices of cryptocurrencies. Rothman *et al.* [55] used videos and posts on YouTube, Facebook, Telegram, and Reddit for sentimental analysis of cryptocurrencies. Kraaijeveld *et al.* [56] analyzed public Twitter sentiment, including Twitter bots, to predict the prices of nine different cryptocurrencies, and Zhang *et al.* [57] examined the relationship between investor attention and cryptocurrencies using Google Trends. Burggraf *et al.* [58] examined the relationship between investor sentiment on Bitcoin return by considering household-level and market-level sentiment using Google's search engine. Aggarwal *et al.* [59] described the impact of social factors on the cryptocurrency market. Social media posts of celebrities and the media coverage of a particular coin can also affect the prices of cryptocurrencies. For example, Ante *et al.* [60] analyzed to what extent Elon Musk's Twitter posts affect short-term returns and volume. Huynh *et al.* [61] represented an analysis of how the movements of the Bitcoin market correlate to tweets of US President Donald Trump by considering nearly 14,000 tweets from January 2017 to January 2020.

Nowadays, with the usage of various ML algorithms, price forecasting has become easier. For example, Sebastião *et al.* [62] used the classical ML models, such as SVM and random forest, and evaluated their performnce in real-time using MAE and RMSE. Koker *et al.* [17] used a direct reinforcement ML technique to reduce the downside risk of *Bitcoin*, *Ethereum*, *Litecoin*, *Ripple*, and *Monero*. Hitam *et al.* [29] demonstrated how an optimized SVM based on Particle Swarm Optimization (PSO) is better than the simple SVM algorithms for crypto price prediction. Many researchers combine technical and sentimental factors to obtain better prediction results. For example, Nair *et al.* [63] used SVM, random forests, neural networks, and the components from Twitter to predict the behavior of the crypto market.

Different time-series analysis approaches are also helpful to improve the prediction accuracy [64]. Gupta *et al.* [65] used various time series analysis techniques, such as ARIMA, with different ML and DL algorithms to predict the price of *Bitcoin*. Anupriya *et al.* [66] predicted the close prices of *Bitcoin* using the ARIMA model. Widiyaningtyas *et al.* [67] also employed the ARIMA model for short-term prediction of *Bitcoin* prices and evaluated the results using MAPE. The authors of [68] used a novel parameter optimization of VARIMA models to forecast the price of cryptocurrencies.

DL techniques are used extensively to forecast the movement of the crypto market. Ortu *et al.* [69] used four different DL algorithms, namely MLP, CNN, LSTM, and ALSTM, with social media indicators for prediction. Vanderbilt *et al.* [40] considered three RNN models to predict the price of *Bitcoin*, *Ripple*, and *Litecoin* and determined which one was performing better, but they found out that none performed significantly better than others. Radityo *et al.* [29] developed a model to forecast the close price of *Bitcoin* in the next day using the ANN method and compared the results of all four ANN methods, namely BPNN, GANN, GABPNN, and NEAT, and found that BPNN is the best method for prediction [70].

LSTM is the most successful and widely used algorithm for prediction, so many authors have used it and improved the prediction accuracy [71]. For example, Pintelas *et al.* [72] employed three models based on DNN, namely LSTM,

TABLE 2. A relative comparison of state-of-the-art approaches for cryptocurrency price prediction with the proposed scheme.

Ref.	Year	Contribution	Expected result	Merit	Demerit
[27]	2017	Price prediction of cryptocurrency with GASEN algorithm	Accuracy = 58% - 63%	Classification tasks are performed with GASEN	Systematic feature selection is not used in GASEN
[28]	2017	Compared four different ANN methods to get the best prediction for *Bitcoin*	MAPE	BPNN is the best method compared to others	Fuzzy logic and support vector machine is not explored
[29]	2019	Cryptocurrency forecasting using SVM along with PSO	Performance accuracy of optimized SVM-POS: *Bitcoin*=90.4% *Ethereum*=97% *Litecoin*=92.1%	SVM-PSO algorithm is better than normal SVM algorithms	Sentimental data is not used in preprocessing
[30]	2019	Price prediction of *Etherium* using LR and SVM	Accuracy = 99%	In immediate rise and drop in price algorithm performs accurately	Other cryptocurrencies are not explored
[31]	2019	Cryptocurrency price prediction by LSTM - RNN along with 10-fold cross-validation	MAE = 0.0043s	Accuracy increases due to the combination of cross-validation, RNN, and LSTM	No use of data noise reduction method in preprocessing
[32]	2019	Comparative study of parameters which affect cryptocurrency price prediction using DL approach	RMSE	Twitter sentimental analysis shows positive correlation	No use of live dataset input
[33]	2019	*Bitcoin* price prediction using HMM and GA-LSTM to allow M2M payments	RMSE-LSTM = 7.006 HMM-LSTM = 5.821	HHM-LSTM algorithm outperforms traditional ARIMA model	No use of internal details of bitcoin transactions
[34]	2019	Analyzed the price dynamics of cryptocurrency with ANN and LSTM	MSE	Different length of memory for prediction was used	Optimization is not tested well
[35]	2019	*Bitcoin* price prediction with neural models	RMSE, MAE	Twitter data helps to predict price accurately	State-of-the-art tools are not used for the classification
[36]	2019	Relate the user data and network activity with economical theories for price prediction of *bitcoin* and *Etherium*	RMSE, MAE	Consideration of user data for prediction	LSTM is not explored
[37]	2020	Cryptocurrency price prediction using stochasticated neural network	MAPE, MAE, RMSE, MSE	The model decrypt the market volatility	Optimizing techniques are not used for hyper-parameters
[38]	2020	Blockchain financial products such as *Bitcoin*, price prediction using an Optimal Least Square SVM (OLS-SVM).	MSE, MAPE	OLS-SVM outperforms as compare to other algorithms such as BPNN, ANN, SVM.	Deep learning concept is not explored
[39]	2020	Data selection methodology is used to train Linear Regression model for *Bitcoin* price prediction.	Accuracy = 96.97%	Data selection methodology provide better portion of data for training which improves accuracy of the model.	Comparison of proposed model with other ML model has not done.
[40]	2020	Price prediction of *Bitcoin*, *Ripple*, and *Litecoin* using RNN model with Google Trend data	t-test p-test	The prediction with different RNN models shown that the difference between prediction accuracy is negligible.	GRU model gives better accuracy in prediction of cryptocurrency compared to RNN model
[41]	2021	Price prediction of cryptocurrency using neural networks and DL.	RMSE	Hybrid model of GRU and LSTM model performs better than current LSTM network.	Other parameters such as parent coin direction and social media data are not explored.
[42]	2021	Forecasting cryptocurrency prices within dropout weight constrained recurrent neural networks and calculate CCi30	RMSE MAE	Advance regularization techniques are used in this model	No use of higher frequency data
[43]	2021	*Bitcoin* and *Etherium* price prediction with the combination of LSTM and random walk model	MAE loss = 0.037	Gives the best balance practically and accuracy	The Window length is relatively large
[44]	2021	LSTM based sentimental analysis on social media data to predict cryptocurrency prices	LSTM sentimental analyzer precision = 87% recall = 92.5%	LSTM sentimental analyzer can achieve more precision and recall than traditional autoregressive approach	Close price prediction is not performed
Proposed Model	2021	Propose an LSTM-GRU based hybrid model with considering the inter-dependent feature of the parent coin-*Bitcoin* to forecast the accurate price of *Litecoin* and *Zcash*	MSE For *Litecoin*:- 1-day = 0.020381, 3-days = 0.021039, 7-days = 0.23374, 30-days = 0.26591 For *Zcash*:- 1-day = 0.004618, 3-days = 0.0048363, 7-days = 0.005243, 30-days = 0.010359	The advanced hybrid model with optimized hyper-parameter considering parent coin's direction that predicts the price of *Litecoin* and *Zcash* with minimal losses.	-

BiLSTM, and CNN, for predicting the price of *Bitcoin*, *Etherium*, and *Ripple*. Huang *et al.* [44] proposed an LSTM-based RNN model along with sentimental data collected from social media posts to predict the price of *Bitcoin*, *Etherium*, and *Ripple*. Jay *et al.* [37] proposed a model based on random walk theory and trained MLP and LSTM models for *Bitcoin*, *Ethereum*, and *Litecoin*. Patel *et al.* [73] proposed an LSTM and GRU-based hybrid technique to predict *Litecoin* and *Monero* prices, and Awoke *et al.* [74] used the same model to forecast the price of *Bitcoin*. Guo *et al.* [75] used a hybrid model of Multi-scale Residual CNN and LSTM to predict the closing price of *Bitcoin*.

A relative comparison of various existing approaches of crypto price prediction with the proposed scheme is mentioned in the Table 2. From Table 2, it is evident that the deep learning-based model gives better results compared to

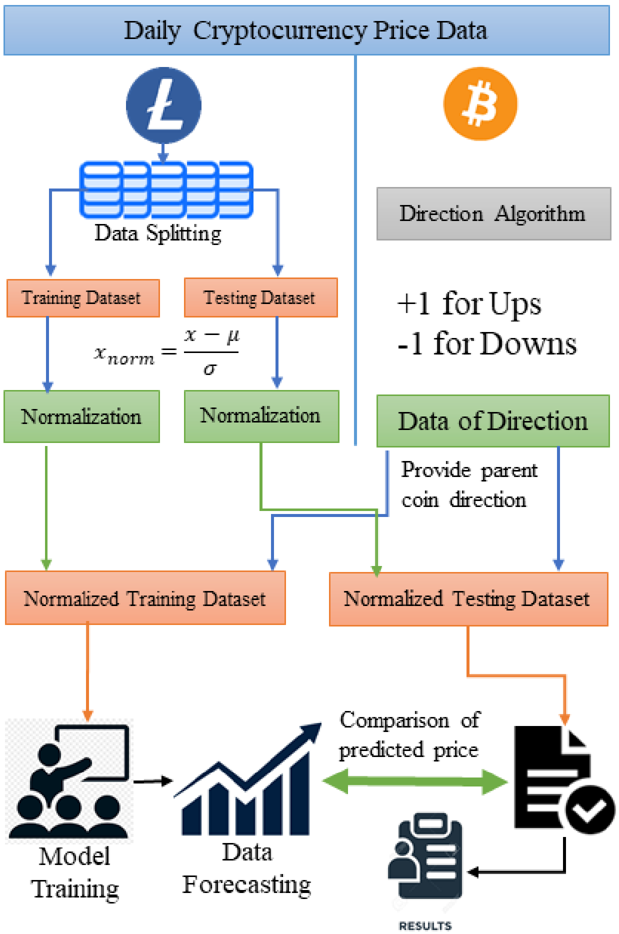

FIGURE 1. System model.

the classical machine learning-based models, and an MSE is considered for evaluation purposes. Another finding from the literature survey is that no one has used the direction of the parent's coin to predict the price of the dependent cryptocurrency.

III. SYSTEM MODEL AND PROBLEM FORMULATION

This section discusses the system model and problem formulation for improving the price prediction scheme for cryptocurrencies and also consider their inter-dependencies on the parent cryptocurrencies.

A. SYSTEM MODEL

Figure 1 shows the system model of the proposed scheme, which is used to predict the prices of *Litecoin* and *Zcash* and used *Bitcoin* as their parent currency considering inter-dependencies between them. In *Litecoin* model, first, the past data is collected, then split into two parts, i.e., testing and training data sets. After this, both sets are brought to the preprocessing stage. In the preprocessing stage, the data is normalized to remove outliers. We have used Z-score normalization to normalize the data to zero. In the end, we get the normalized data as output.

Meanwhile, in the parallel process, the daily data of the parent currency, namely *Bitcoin*, is passed through algorithm 1. The direction algorithm (Algorithm 1) uses two mathematical signs to describe the movement of parent currency. If it is going up, then the algorithm will mark it as $+1$, and in case of negative closing, -1 will be assigned. In this way, the data of direction for *Bitcoin* is created as an output.

In the next step, both the outputs (normalized training data of *Litecoin* and normalized testing data of *Litecoin*) are merged with the data of direction of *Bitcoin*. Then, the training dataset is used to train the proposed model, which is a hybrid model of LSTM and GRU. Moreover, the proposed model forecasts the price of *Litecoin* for the next day using training data. This forecasted price is compared with the actual price and finally, we get the predicted price for the next day. The price prediction is done in different window sizes of 1-day, 3-days, 7-days, and 30-days. This n-days price is passed to the proposed model to predict the price of $(n+1)$ day. In the similar way, the price of *Zcash* can be forecasted using the proposed system model.

B. PROBLEM FORMULATION

The proposed model considers the inter-dependencies between the currencies such as between *Litecoin-Bitcoin* and *Zcash-Bitcoin*. That is the reason why the direction of *Bitcoin* is taken into consideration for the price prediction. We have the past price data of all 3 crytocurrencies. ip_1 denotes the historical data of prices of *Litecoin* and *Zcash* and ip_2 represents the data of the direction of the parent currency, i.e., *Bitcoin*. Let us assume, the price of cryptocurrency at a specific instance be $p_1, p_2, p_3, p_4, \ldots\ldots, p_n$, where p_i denotes a price at specific time instance i, and $d_1, d_2, d_3, d_4, \ldots\ldots, d_n$ denotes the direction of the parent coin, where d_i denotes direction at a specific time instance i for the parent coin. Let the output vector be o. The motive is to calculate the output o using ip_1 and ip_2.

The input data is merged into tuples as (ip_1, ip_2) and the target is to forecast the value of o using the input tuple.

$$ip_1 = [p_{i-w+1}, p_{i-w+2}, p_{i-w+3}, \ldots, p_{i-1}, p_i] \tag{1}$$
$$ip_2 = [d_{i-w+1}, d_{i-w+2}, d_{i-w+3}, \ldots, d_{i-1}, d_i] \tag{2}$$
$$ip = [ip_1, ip_2] \tag{3}$$
$$o = [p_{i+1}] \tag{4}$$

The total length of the input window is w and as mentioned earlier, we have considered four different widow sizes, which are 1, 3, 7, and 30 days.

IV. THE PROPOSED SCHEME

In this section, we have described the proposed model to predict the price of *Litecoin* and *Zcash*. Figure 2 shows the entire flow of the proposed scheme, which uses an LSTM and GRU-based hybrid approach. LSTM and GRU are variants of RNN and the reason for using the LSTM-GRU hybrid model is that it can overcome the vanishing gradient problem faced by RNN. The model gives an output after processing

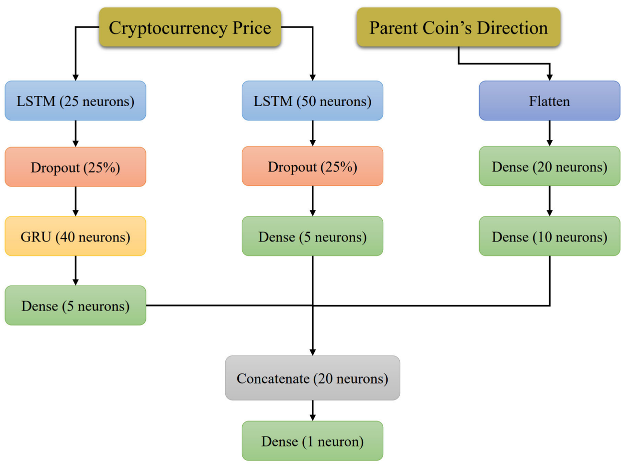

FIGURE 2. **Proposed model.**

Algorithm 1 Direction Algorithm

Input: $AP \in \{average\ price\ of\ parent\ cryptocurrency\}$
$OP \in \{opening\ price\ of\ parent\ cryptocurrency\}$
Output: $D \in \{direction\ of\ cryptocurrency\}$

procedure PROCESS_DATA(AP, OP)
  $data\_size \leftarrow count(AP)$ ▷ $data\_size$ is the number of data sample
  $D \leftarrow \emptyset$
  for $\alpha = 1 \ldots, data\_size$ **do**
    if $AP[\alpha] > OP[\alpha]$ **then**
      $D \rightarrow append(1)$
    else
      $D \rightarrow append(-1)$
    end if
  end for
  $\Re(D)$ ▷ $\Re$ returns the direction of parent coin D
end procedure

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two different inputs. The first input is the past data from previous inputs and outputs and the second input is the direction of the parent currency generated by the direction algorithm (Algorithm 1). The proposed model is tested for all the four window lengths, which generates significantly accurate results it terms of resemblance to the actual price.

$$price\_data = [p_1, p_2, p_3, \ldots, p_{k-1}, p_k] \tag{5}$$

$$direction\_data = [d_1, d_2, d_3, \ldots, d_{k-1}, d_k] \tag{6}$$

$$idp_1 = [[p_0, p_1, p_2, \ldots., p_{n-1}], [d_0, d_1, d_2, \ldots., d_{n-1}]] \tag{7}$$

$$odp_1 = [p_n] \tag{8}$$

$$idp_2 = [[p_1, p_2, p_3, \ldots., p_n], [d_1, d_2, d_3, \ldots., d_n]] \tag{9}$$

$$odp_2 = [p_{n+1}] \tag{10}$$

$$\ldots\ldots$$

$$idp_r = [[p_{r-1}, p_r, p_{r+1}, \ldots., p_{k-1}], [d_{r-1}, d_r, d_{r+1}, \ldots., d_{k-1}]] \tag{11}$$

$$odp_r = [p_k] \tag{12}$$

Here, price data and direction data is split into multiple input-output tuples and the input is the sequence of past observations. Eq. (5) shows the price data of *Litecoin*/*Zcash* and Eq. (6) shows the direction data of *Bitcoin*. *idp* represent the input data point and *odp* represent the output data point. n is the window length and k total number of data points. r is the possible data points available for model training based on window size. In tuple $([[p_0, p_1, p_2, \ldots., p_{n-1}], [d_0, d_1, d_2, \ldots., d_{n-1}]], p_n)$, the input value is $[[p_0, p_1, p_2, \ldots., p_{n-1}], [d_0, d_1, d_2, \ldots., d_{n-1}]]$, and p_n is the output value. In the same way, the next pair is $([[p_1, p_2, p_3, \ldots., p_n], [d_1, d_2, d_3, \ldots., d_n]], p_{n+1})$ with $[[p_1, p_2, p_3, \ldots., p_n], [d_1, d_2, d_3, \ldots., d_n]]$ as input value and p_{n+1} as output. In this manner, the entire dataset is prepared and is shown from eq. (7) to eq. (12).

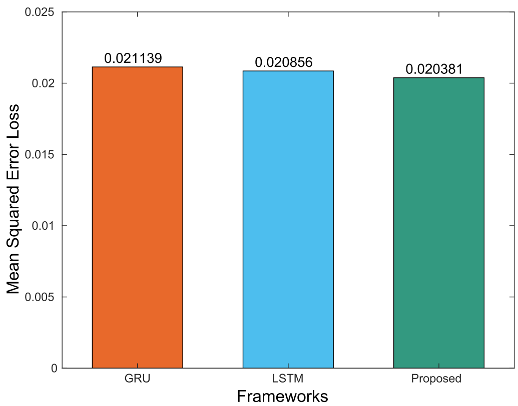
In the proposed model, we used two types of data. The first type is the cryptocurrency price dataset and the second one is the direction of the parent coin. Moreover, the data of cryptocurrency price is split into two LSTM networks. The first LSTM network has 25 neurons, which is followed by a dropout layer that has a 25% dropout rate to prevent the over-fitting problem. The dropout layer is followed by the GRU network with 40 neurons. Then, the output of the GRU network is passed to a dense layer with 5 neurons, which is the first output. Now, the second LSTM network that gets the input data has 50 neurons. This layer is followed by a dropout layer to avoid overfitting. The output of the dropout layer is given to a dense layer with 5 neurons, which is the second output. The data of the parent coin's direction is passed through a flatten layer before passing through a dense layer with 20 neurons. The output of the dense layer is again passed through a dense layer with 10 neurons creating the third output.

Now all three outputs are concatenated in a single output with 20 neurons. Then, the output is passed to a dense layer with a single neuron, which is the final output of the proposed model. The proposed model is trained for 50 epochs and after the training, the prices of *Litecoin* and *Zcash* are predicted. For forecasting, n observations are passed as an input and the next value is predicted using the given input. Here, n is the prediction window size, i.e., 1, 3, 7, and 30 days.

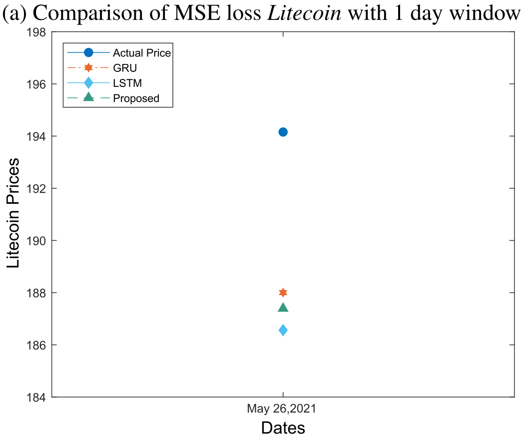
Algorithm 1 shows the process to determine direction of the parent coin. This algorithm takes the average price and the opening price of the parent currency as inputs and gives the direction of the parent coin as an output. The size of the data sample of the average price is stored in the variable named *data_size*, and an empty list is defined as D. A loop variable α runs from 1 to *data_size*. Inside the loop, a condition has been put that if the average price is greater than the opening price at an instance α, then $+1$ will be appended in the list D. If the condition is not satisfied, then -1 will be appended in the list. This loop is repeated for *data_size* times and after

TABLE 3. Performance parameters.

Parameters	Values
Programming Language	Python 3.8.0
Platform	Google Colab
Framework	TensorFlow
Total data Points	Litecoin 1,737 Zcash 1,671
Train data points	1,200
Test data points	Variable (window - based)
Window lengths	1, 3, 7, 30
Batch size	16
Epochs	50
Optimizer	Adam
Metrics	MSE



(a) Comparison of MSE loss *Litecoin* with 1 day window



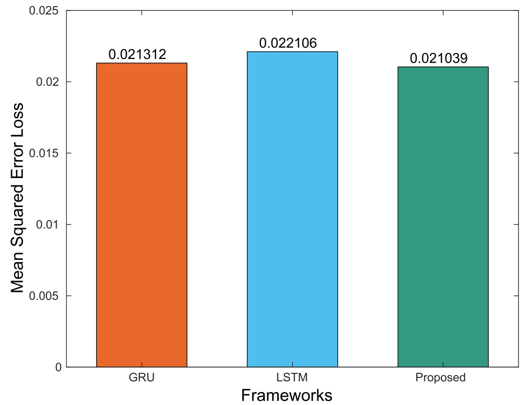
(b) Actual vs predicted *Litecoin* price for 1 day period

FIGURE 3. *Litecoin* data for 1 day window.

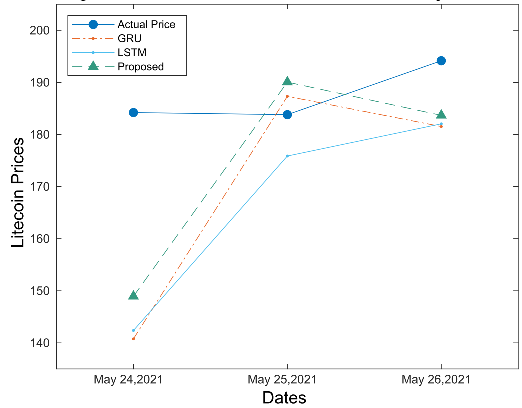
the termination, the algorithm returns the list D, which has either -1 or $+1$ in it. This direction of the parent coin is used by the proposed model to find the inter-dependent relation as discussed.

V. PERFORMANCE EVALUATION

This section discusses the performance evaluation of the proposed model and obtained results are also compared with LSTM and GRU models. We have implemented the proposed model with different window lengths i.e., 1-day, 3-days, 7-days, and 30-days. The DL models are trained using TensorFlow APIs over the python 3.8.0 platform. The proposed



(a) Comparison of MSE loss *Litecoin* with 3 day window



(b) Actual vs Predicted *Litecoin* price for 3 day period

FIGURE 4. *Litecoin* data for 3 day window.

model is trained for 50 epochs with Adam as optimizer with a batch size of 16.

Table 3 includes the information about various parameters and their values. This includes the programming language, number of training and testing data points, optimizer, and other parameters. Their precise value is included in the opposite column.

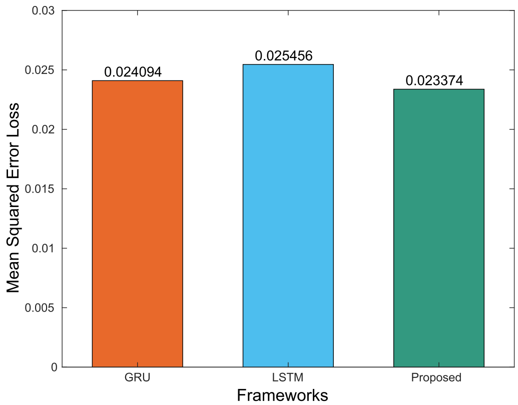
A. DATASET DESCRIPTION

The dataset used to carried out this research was collected from *Investing.com* [12]. It is a financial platform and news website and offers information about stocks, options, analysis, cryptocurrrencies, futures, and different commodities.

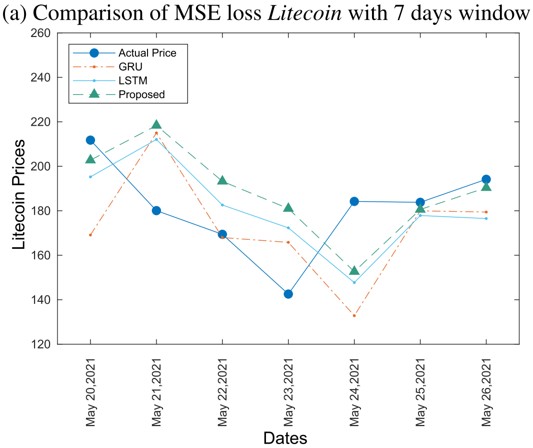
The data was collected for *Litecoin* and *Zcash* and has 5 features, which are as follows:

- *Price*: Average price of a particular currency for a day
- *Open*: Opening price of a particular currency for a day
- *High*: Highest price of a particular currency for a day
- *Low*: Lowest price of a particular currency for a day
- *Volume*: Volume traded of a particular currency for a day

We have used the average price as our main parameter because it provides both the trend and value of a currency. We have tested our hybrid proposed model by predicting prices of *Litecoin* and *Zcash* with four different window frames: 1 day, 3 days, 7 days, and 30 days. We have reserved

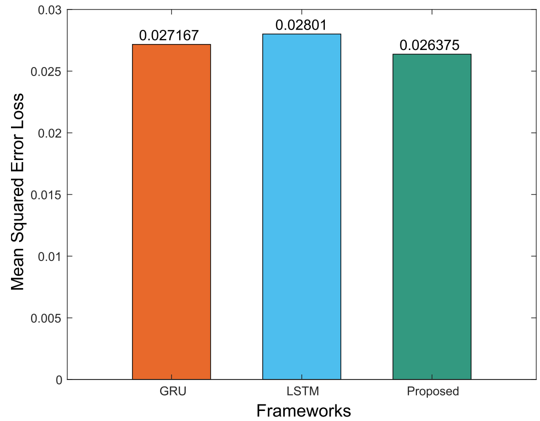


(a) Comparison of MSE loss *Litecoin* with 7 days window

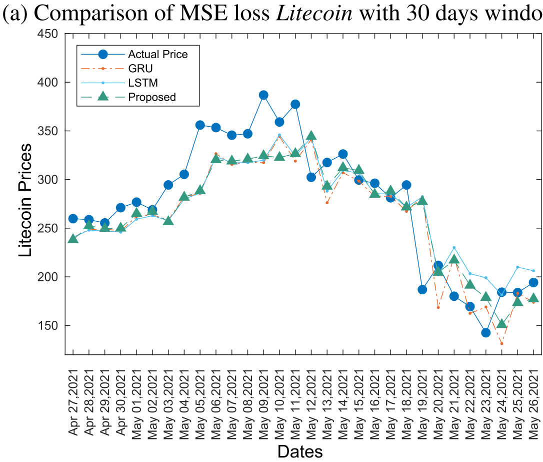


(b) Actual vs predicted *Litecoin* price for 7 days period

FIGURE 5. ***Litecoin* data for 7 days window.**



(a) Comparison of MSE loss *Litecoin* with 30 days window



(b) Actual vs predicted *Litecoin* price for 30 days period

FIGURE 6. ***Litecoin* data for 30 days window.**

1,200 datapoints of both currencies for training the proposed model, an.

- *Litecoin* contains 1737 datapoints from August 24^{th} 2016 to May 26^{th} 2021
  - *1 day*: Train dataset: 1,200, Test dataset: 536
  - *3 days*: Train dataset: 1,200, Test dataset: 534
  - *7 days*: Train dataset: 1,200, Test dataset: 530
  - *30 days*: Train dataset: 1,200, Test dataset: 507
- *Zcash* contains 1671 datapoints from October 29^{th} 2016 to May 26^{th}, 2021
  - *1 day*: Train dataset: 1,200, Test dataset: 470
  - *3 days*: Train dataset: 1,200, Test dataset: 468
  - *7 days*: Train dataset: 1,200, Test dataset: 464
  - *30 days*: Train dataset: 1,200, Test dataset: 441

B. DATA PREPROCESSING

The raw data values cannot be directly used for the proposed model because of outliers and variations. In the preprocessing stage, normalization is performed to remove noisy data in order to increase the accuracy. We have used the Z-score normalization method as follows:

$$Z = \frac{1}{\sigma}(x - \mu) \tag{13}$$

where mean of the sample data is denoted as μ and standard deviation is denoted as σ. Sample value that is same as the value of mean value will be normalized to 0. If sample value is less than the mean value then it will be negative number and if more than the mean value then it will be positive value after normalization. In this way, the normalized values will be closer to 0. This technique is very effective when raw data had a large standard deviation. After normalization, the data is converted into a suitable form and it is ready to be used as an input to the proposed model.

C. EVALUATION METRICS

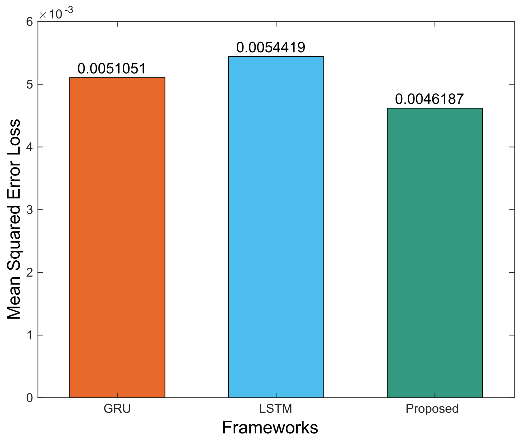
We have used MSE to evaluate the proposed model, which provides a quadratic loss function and also measures the uncertainty in forecasting as follows:

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(\hat{p}_i - p_i)^2 \tag{14}$$

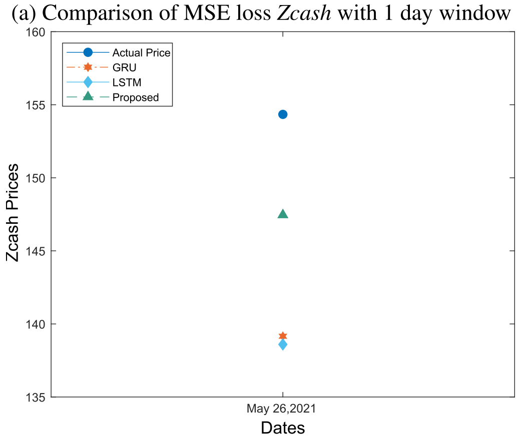
where $\hat{p}_i$ represents the predicted price, p_i represents the actual price, and N is total number of observations.

D. RESULTS AND DISCUSSIONS

The results obtained using the proposed model and its comparison with LSTM and GRU models are discussed in the following subsections.

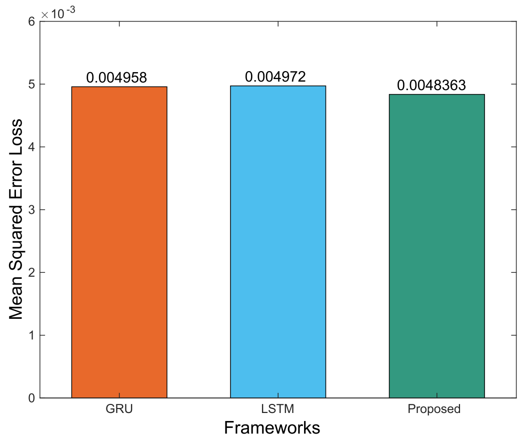


(a) Comparison of MSE loss *Zcash* with 1 day window

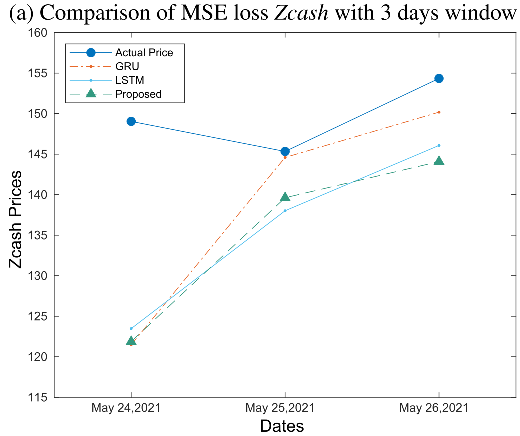


(b) Actual vs predicted *Zcash* price for 1 day period

FIGURE 7. ***Zcash* data for 1 day window.**



(a) Comparison of MSE loss *Zcash* with 3 days window



(b) Actual vs predicted *Zcash* price for 3 days period

FIGURE 8. ***Zcash* data for 3 days window.**

1) RESULTS FOR *LITECOIN*

For *Litecoin*, the price data is collected from August 24^{th} 2016 to May 26^{th} 2021, a total of 1,737 data points. These data points are converted to input format for 1-day, 3-days, 7-days, and 30-days window sizes. For all these different window sizes, the training data size is fixed to 1,200 data points, and the rest of the data points out of 1,737 are used for testing the model's performance. The MSE loss is calculated based on the prediction of testing data points, which are different and also related to particular window sizes. For example, 1,200 input pairs are used for training and 536 are used for testing for 1-day price prediction. The proposed model gives an MSE loss of 0.02038 for 1-day window size, whereas the standard LSTM and GRU models give an MSE loss of 0.02085 and 0.02113, respectively. FIGURE 3a shows the loss comparison for the 1-day prediction window. FIGURE 3b shows the time series graph for 1-day price prediction by different models and actual prices of *Litecoin*.

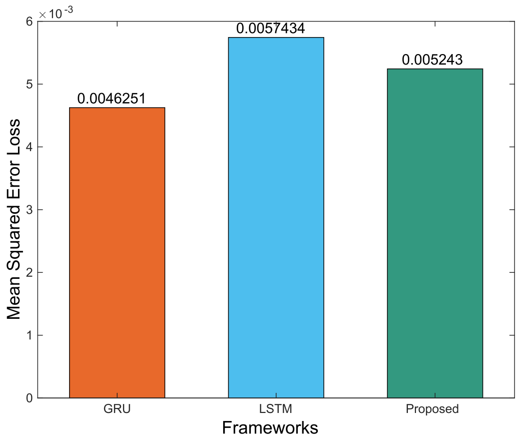
For the 3-days window size, the testing input pairs are 534, and the MSE loss of the proposed model is 0.02103. Standard GRU and LSTM have the MSE loss of 0.02210 and 0.02131, respectively. FIGURE 4a shows the MSE loss comparison of the proposed model, LSTM, and GRU, and FIGURE 4b illustrates the time series information for *Litecoin*.

The number of testing input pairs is 530 for 7-days window size. The proposed model gives the comparatively lower MSE loss of 0.02337 than the MSE loss of LSTM and GRU, which were 0.02545 and 0.02409, respectively. The bar chart, which compares the losses of three models, is described as FIGURE 5a, and FIGURE 5b displays the time series comparison.

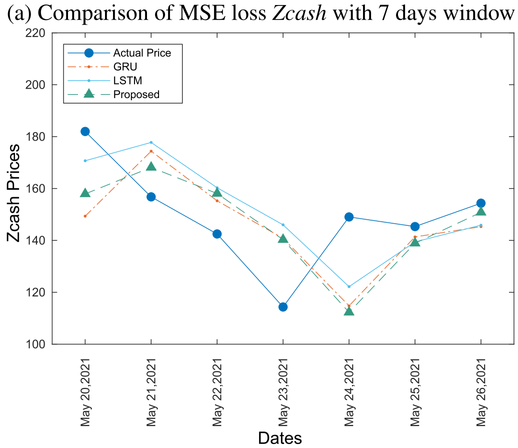
Similarly, testing input pairs and the MSE loss for 30-days are 507 and 0.026375, respectively. FIGURE 6a describes the comparison of losses of the proposed model with the losses of LSTM and GRU, which were 0.02800 and 0.02716. Moreover, FIGURE 6b shows the time-series comparison of all three models with the actual data from 27 April 2021 to May 26, 2021.

2) RESULTS FOR *ZCASH*

For *Zcash*, the price data is collected from October 29^{th} 2016, to May 26^{th} 2021, a total of 1,671 data points. These data points are converted to input format for 1-day, 3-days, 7-days, and 30-days window sizes. For all these different window sizes, the training data size is fixed to 1,200 data points, and the rest of the data points out of 1,671 are used for testing the model's performance. The MSE loss is calculated based on the prediction of testing data points, which are different and also related to particular window sizes.

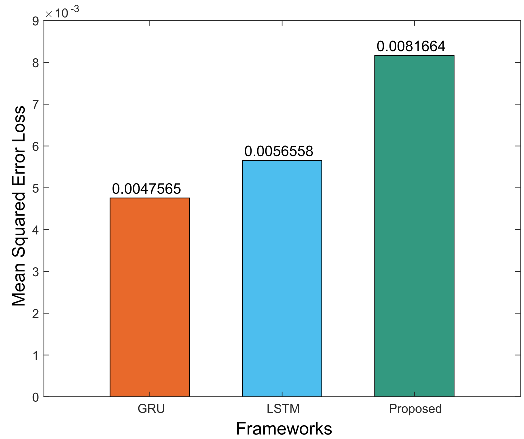


(a) Comparison of MSE loss *Zcash* with 7 days window

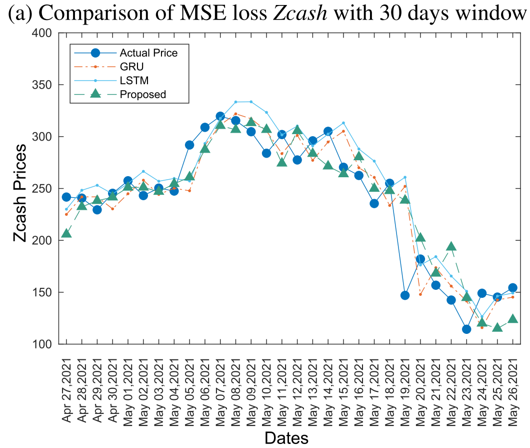


(b) Actual vs predicted *Zcash* price for 7 days period

FIGURE 9. ***Zcash* data for 7 days window.**



(a) Comparison of MSE loss *Zcash* with 30 days window



(b) Actual vs predicted *Zcash* price for 30 days period

FIGURE 10. ***Zcash* data for 30 days window.**

For example, 1,200 input pairs are used for training and 470 are used for testing for 1-day price prediction. The proposed model gives an MSE loss of 0.00461 for 1-day window size, whereas the standard LSTM and GRU models give an MSE loss of 0.00544 and 0.00510, respectively. FIGURE 7a shows the loss comparison for the 1-day prediction window. FIGURE 7b shows the time series graph for 1-day price prediction by different models and actual prices of *Zcash*.

For the 3-days window size, the testing input pairs are 468, and the MSE loss of the proposed model is 0.00483. Standard LSTM and GRU have an MSE loss of 0.00497 and 0.00495, respectively. FIGURE 8a shows the MSE loss comparison of the proposed model, LSTM, and GRU, and FIGURE 8b illustrates the time series information for *Litecoin*.

The number of testing input pairs is 464 for 7-days window size. The proposed model gives MSE loss of 0.00524, and the MSE loss of LSTM and GRU are 0.00574 and 0.00462, respectively. The bar chart, which compares the losses of three models, is described as FIGURE 9a, and FIGURE 9b displays the time series comparison.

Similarly, testing input pairs and the MSE loss for 30-days are 441 and 0.0081664, respectively. FIGURE 10a describes the comparison of losses of the proposed model with the losses of LSTM and GRU, which are 0.00565 and 0.00475.

TABLE 4. ***Litecoin* model-loss comparison.**

Model	MSE loss			
	1 day	3 days	7 days	30 days
GRU	0.02113	0.02131	0.02409	0.02716
LSTM	0.02085	0.02210	0.02545	0.02800
Proposed Model	**0.02038**	**0.02103**	**0.02337**	**0.02637**

TABLE 5. ***Zcash* model-loss comparison.**

Model	MSE loss			
	1 day	3 days	7 days	30 days
GRU	0.00510	0.00495	0.00462	0.00475
LSTM	0.00544	0.00497	0.00574	0.00565
Proposed Model	**0.00461**	**0.00483**	**0.00524**	**0.00816**

Moreover, FIGURE 10b shows the time-series comparison of all three models with the actual data from 27 April 2021 to May 26, 2021.

Table 4 shows the comparison of the losses for forecasting the price of *Litecoin*. The MSE losses of the proposed model for *Litecoin* for 1-day, 3-days, 7-days, and 30-days are 0.02038, 0.02103, 0.02337, and 0.02637, respectively. Table 4 provides the evidence that the proposed model performed well compared to the classical LSTM and GRU model for the window size of 1-day, 3-days, 7-days, and 30-days for *Litecoin*. The loss obtained using the proposed model is significantly good concerning the LSTM and GRU models.

Table 5 shows the comparison of the losses for forecasting the price of *Zcash*. The MSE losses of the proposed model for *Zcash* for 1-day, 3-days, 7-days, and 30-days are 0.00461, 0.00483, 0.00524, and 0.00816, respectively. Table 5 shows that the proposed model works well for the lower window size compared to the larger window size for *Zcash*. The proposed model shows the stochastic nature for a larger window size of 7-days and 30-days for *Zcash*.

VI. CONCLUSION

Forecasting cryptocurrency prices has been a difficult task for researchers as social and psychological factors affect the price of cryptocurrency. VARIMA, ARIMA, and GARCH are time series models that are often used to forecast and analyze the financial market. However, these techniques suffer from several weaknesses such as practicality, so the accuracy decreases with the nonuniform data. Many ML algorithms, such as SVM, random forest, and KNN, have been widely used by the researchers to predict the crypto prices. In recent times, DL algorithms have shown accurate results in the prediction of various financial markets. Neural networks have stepped up the whole scenario. In this paper, we proposed a hybrid model of GRU and LSTM with inter-dependent relation to the parent currency. The proposed model is used to predict the price of *Litecoin* and *Zcash* using the direction of *Bitcoin* with four window sizes. For *Litecoin* MSE losses of the proposed model for 1-day and 3-days are 0.02038 and 0.02103, respectively and for *Zcash* they are 0.00461 and 0.00483, respectively. For 7-days and 30-days, the proposed model predict the accurate prices for *Litecoin*. However, it followed stochastic nature for *Zcash*.

In the future, we will work on cryptocurrencies with more than one inter-dependency using the proposed model. Moreover, we will add sentimental factors, such as Twitter and Facebook posts and messages, to the proposed model to improve the accuracy of the prediction results. Traditional commodities such as gold and oil prices can also be considered to enhance the prediction results.

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