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Improving the Cryptocurrency Price Prediction Performance Based on Reinforcement Learning

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ABSTRACT During recent developments, cryptocurrency has become a famous key factor in financial and business opportunities. However, the cryptocurrency investment is not visible regarding the market's inconsistent aspect and volatility of high prices. Due to the real-time prediction of prices, the previous approaches in price prediction doesn't contain enough information and solution for forecasting the price changes. Based on the mentioned problems in cryptocurrency price prediction, we proposed a machine learning-based approach to price prediction for a financial institution. The proposed system contains the blockchain framework for secure transaction environment and Reinforcement Learning algorithm for analysis and prediction of price. The main focus of this system is on Litecoin and Monero cryptocurrencies. The results show the presented system accurate the performance of price prediction higher than another state-of-art algorithm.

INDEX TERMS Cryptocurrency, price prediction, machine learning, reinforcement learning.

I. INTRODUCTION

Third party institution for financial environments in a system of the traditional economy operates the payment in different forms. These environments are intermediaries between the fund-changing parties and, in the same way, controlling the complete transactions records. This process is working fine for limited money transactions, and it contains a lack of transparency, feasibility, security, and trust. To overcome these issues, there is a need to clear the intermediary parties from the final transactions. e.g., allowing the transaction of funds to be directly between parties can cause changes in terms of economic works. Cryptocurrency has the ability of currency exchange between groups or in a single way [1]. The network-based transactions and exchanges use the algorithm cryptographic for securing the transactions. The cryptocurrency is directly related to the blockchain framework and be devised the blockchain properties such as transparency and decentralization. Still, in the traditional cryptocurrency system, the central authority can't be controlled. This procedure validates the consensus algorithm of blockchain to solve the trust problem between the network stakeholders.

The cryptocurrency price is one of the researchers' inquisitiveness in the entire world. The price changes are based on some factors like cost of the transaction, difficulty of mining, trends of markets, popularity, coins alternates, etc. [2]. The named factors give unstable price changes of a cryptocurrency over time and a difficult prediction process. Figure 1 presents the overview of cryptocurrency price prediction based on blockchain and machine learning techniques. The price data in cryptocurrency contains various categories: bitcoin, litecoin, ripple, monero, tether, and IOTA. In this process, we used two data sources as Litecoin and Monero. The machine learning section processes the data and slips it into a train and test set to prepare it for the blockchain network and feature extraction. The blockchain framework contains the transaction IDs, hash records, timestamps, and several blocks. The feature layer has reports related to cryptocurrency tokens, digital wallets, smart contracts, and distributed apps.

A. MOTIVATION

The main usage of cryptocurrency systems is for exchanging money. In the past years, cryptocurrency-based trading has become a pleasant topic [3]. This is the frequent idea of the professional stock market that it doesn't have a certain place for enterprise regarding the dependency and volatility of the social sentiments. Besides this, the price prediction effectiveness of the different cryptocurrencies gives the ability of complete power computing of the blockchain [4].

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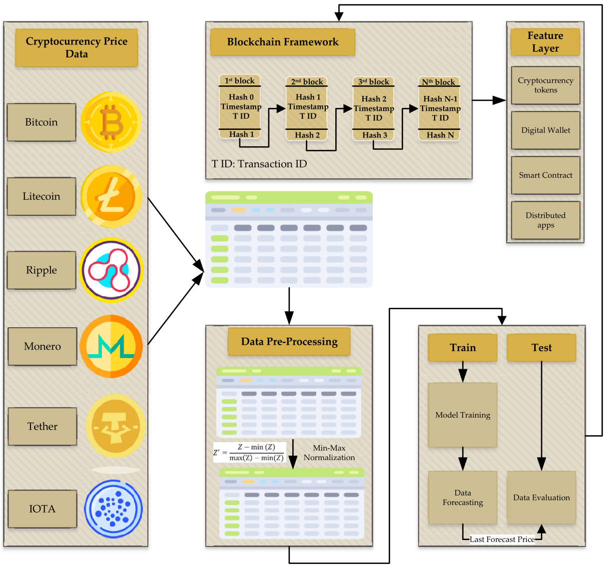

FIGURE 1. Overview of the cryptocurrency price prediction process.

The cryptocurrency value mainly affects many factors such as the past trend of prices, social sentiments, the volume of trades, and legislature. Motivated from the existing state-of-arts, we designed a model to predict the differences of cryptocurrency prices applying the Reinforcement Learning model. Similarly, the erratic fluctuation problem in the cryptocurrency price is addressed in this process.

The main contribution of this process is divided as:

- Applying Reinforcement Learning (RL) to present the prediction of Monero and Litecoin prices.
- Performance evaluation of the presented system using the evaluation matrices e.g., MAE, MSE, RMSE, MAPE.
- Using the blockchain framework to create a secure and transparent environment for price prediction.

The advantages of the presented system describes cryptocurrency characteristic which has the global access and it is easy to use for the medium type of transaction for storing wealth. Although, the different cryptocurrencies value is totally based on the social sentiments and trends of erratic market which has the less correlation with most of the financial assets. Based on this the traditional methods become ineffective for this process.

The rest organization of the paper is as follows. Section 2 presents the recent existing works regarding price detection. Section 3 presents the system model and definition of problem and formulation in cryptocurrency price prediction. Section 4 presents the prediction workflow and performance evaluation, and we conclude this process in the conclusion section.

II. RELATED WORK

A fundamental part of this section focus on the prediction and stability of the cryptocurrency price over decades. There are two main parts focused on in this research: cryptocurrency in blockchain and machine learning on the price prediction. We have explained the recent researches done in this area and the comparison of them.

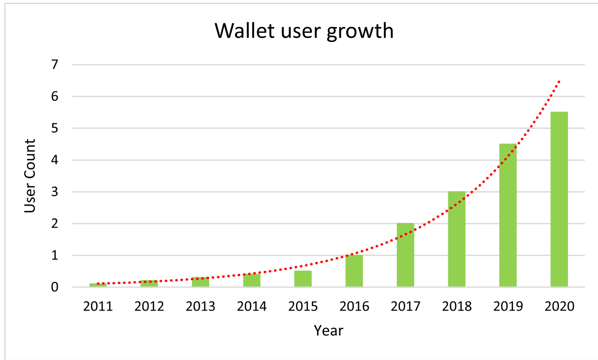

FIGURE 2. User wallet growth in years.

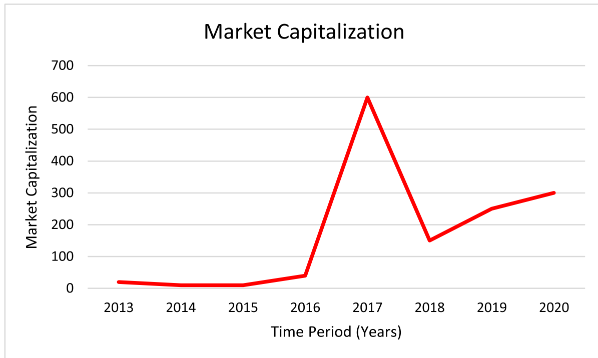

FIGURE 3. Cryptocurrency market capitalization.

A. CRYPTOCURRENCY IN BLOCKCHAIN

Blockchain technology applications go further in the peer-to-peer system of payment. This gives the trust, privacy, and security to the system based on a distributed ledger to make the Internet of Things applications applicable for the system distributed storage [5]. The advantage of this system is to be decentralized and fully secure of whole environment which only allows that the new blocks append. The blockchain applications ranges are at the head of many blockchain and cryptocurrencies. Cryptocurrency is connected to blockchain because of providing an inducement to the machine and electricity consumption for blockchain validation. Cryptocurrency is the recent and new digital currency type for using the blockchain to increase transparency, immutability, and decentralization [6]. Regarding the increase of the usage of blockchain the cryptocurrency usage also increases. This contains the inherent value to this network based on various factors. This process is the new currency type that saves the values and increases the level of understanding price changes based on the values.

Figure 2 shows the price difference of cryptocurrency coins during years. The market capitalization from 2017 increased

TABLE 1. Comparison of the related works on cryptocurrency price prediction.

Author	Summery	Technique	Cryptocurrency	Dataset
Marcell et al. (2019) [10]	Using the bitcoin transaction network for the price prediction movement.	Single layer neural network	Bitcoin	coindesk.com
Wirawan et al. (2019) [11]	Using ARIMA to predict the price of bitcoin	ARIMA	Bitcoin	-
Lahmiri et al. (2018) [12]	Using the Largest Lyapunov Exponent and Detrended Fluctuation Analysis	LSTM	Bitcoin, Ripple	-
Laura et al. (2018) [13]	XGBoost and LSTM for the ensemble regression tree	RNN, LSTM	1681 cryptocurrencies	coinmarketcap.com
Chen et al. (2020) [14]	Feature engineering using 4 classes	LDA, Logistic Regression, SVM, LSTM	Bitcoin	coinmarketcap.com
Smuts et al. (2019) [15]	Predicting the telegram and trends data	LSTM	Bitcoin, Ethereum	Google trend, Telegram, Market data aggregator
Mittal et al. (2019) [16]	Tweet sentiment and google trends to predict the bitcoin prices and improving the prediction based on Wikipedia and Facebook posts	RNN, LSTM, Regression	Bitcoin	Coindesk, Google trends, Twitter API
Jang et al. (2017) [17]	Capturing non-linear information of blockchain using Bayesian Neural Network	MLP	Bitcoin	Bitcoinchart.com, Blockchain.info
Sin et al. (2017) [18]	Next day dependency price based on Genetic Algorithm	MLP, Ensemble of neural networks	Bitcoin	Bitcoinity.org Blockchain.info
Saad et al. (2019) [19]	Analyzing the cryptocurrency market using the correlation analysis	Multivariate Regression	Bitcoin, Ethereum	Etherscan.io Blockchain.info

and summed to almost 19 billion USD. Regarding this amount, seven currencies and 97% of the market incorporated in 90% of the market capitalization. Figure 3 shows the market capitalization records based on year-wise and USD.

B. MACHINE LEARNING ON PRICE PREDICTION

Deep learning is a powerful machine learning algorithm for solving complex and nonlinear issues to exploit the huge number of data and good predictions. The price prediction with accurate results is a complex problem because the variation of values is a lot, but the deep learning approach overcomes this issue. Ji *et al.* [7] presented the comparison of Long Short Term Memory (LSTM) with Deep Neural Network (DNNs) and combined the results with the bitcoin price prediction. The presented result of their approach shows the acceptable accuracy of LSTM comparing with the other regression models. In this approach they tried to analyze the deep learning models in term of regression analysis which is immature to just for trading of bitcoin. Shintate *et al.* [8] presents the framework of trend classification and prediction for the non-stationary cryptocurrency time series data based on deep learning. The developed approach results show the LSTM model performance based on profitability analysis using the buy and hold strategy. The output results of this system show the LSTM generalized perfectly in the prediction of cryptocurrency prices. Peng *et al.* [9] proposed the Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) with Support Vector Machine (SVM) for Bitcoin and Ethereum price prediction. The analysis was based on the low and high frequency and similarly the prediction is evaluating based on Dielbold-Matiano test and confidence set of Hansen's Model. Table 1 presents the summery of recent related studies regarding cryptocurrency price prediction.

TABLE 2. List of acronyms used in this system.

Acronyms	Description
RL	Reinforcement Learning
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
LSTM	Long Short Term Memory
DNNs	Deep Neural Network
GARCH	Generalized Auto Regressive Conditional Heteroeskedasticity
SVM	Support Vector Machine

III. SYSTEM MODEL AND PROBLEM FORMULATION

Cryptocurrency price prediction contains three important data sources. The first one is a market statistic. The second one is network information of blockchain that contains the transaction count and fee, hash rate, etc. The last one is google trends and volume of tweets. Most of the research works use the mentioned data sources to apply to their model which is mostly regression models. The data collected from three sources were aggregated to the data loader. Data features become normalized, and in the next step, create the data stacks. Reinforcement learning process the input data for predicting the N days price. Figure 4 presents the price prediction process in detailed form.

Table 2 presents the list of acronyms which used in this work.

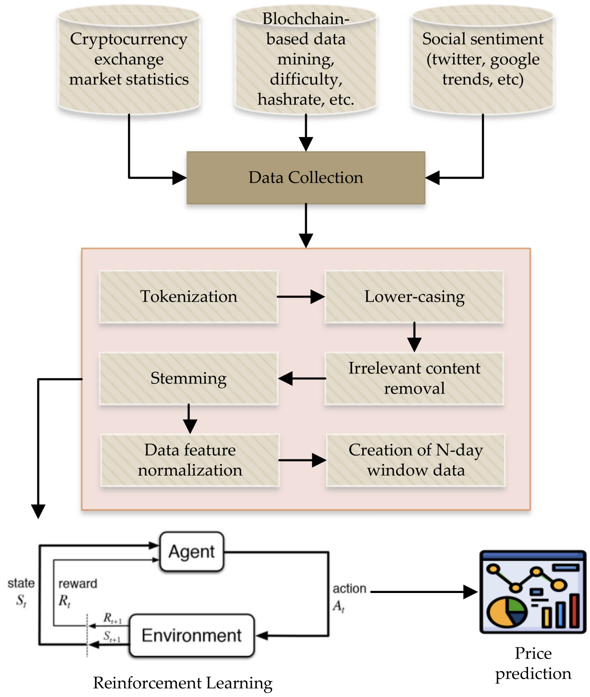

FIGURE 4. **Proposed cryptocurrency price prediction based on blockchain and reinforcement learning.**

A. DATA

In this process, Litecoin and Monero are considered as data sources of cryptocurrency price prediction. The training set for Litecoin contains the data from 2016-2020 with 1276 points of data records. The trained model is supposed to predict the next day's price. The training set Monero is from 2015 to 2020. The total number of records of data is 1276. The trained model predicts the next-day price records. The training set for Litecoin and Monero is 80% and the test set is 20% for processing and analyzing. Due to project rules the dataset is not available publicly.

1) TRANSACTIONS AND MARKET VOLUME

Regarding the days, the number of transactions performed. The share market is not part of the stock exchange because there is no timetable for opening and closing. The number of traded coins are records of a single day, and it's one of the features. The market volume is specified for the particular day, and it supposes to have the units of currency. The coins' quantity is the index of encompassing value.

2) MINING DIFFICULTY, MINING PROFITABILITY AND HASHRATE

Mining the single block coins required the mining difficulty. The transactions confirmation requires the specific hardware to get more hash for mining a block. Power consumption and hash rate have a trade-off in between. This process shows the profit of mining rate and difficulty. The minor useful income opposed the use of power-consuming resources and time. Increasing the number of minors decreases the reward of minors exponentially.

3) CONFIRMATION TIME AND CAPITALIZATION OF MARKET

Transaction confirmation between parties requires the average time and logging to the block table. The transaction logging needs around ten minutes to confirm the transaction, which is based on the activated users and their location for table block update. The cryptocurrency amount per day is based on USD.

4) GOOGLE TRENDS AND TWEETS

Increasing the volume of tweets cause more transaction from people. This process is not only the correlation it contains the feedback loop too. Tweet volume is not the end of correlation, and people tend to look for updated trending topics [20]. Google search spike also has speculation to be in relation with coins price that is an insignificant assumption.

B. REINFORCEMENT LEARNING-BASED PRICE PREDICTION

Reinforcement Learning (RL) is one of the useful machine learning frameworks for evaluating the reward selected from the action. RL is based on a model-based and model-free design which gives the learning-based structure to the system. Training the learning-based model can improve the designed system structure and improve the system performance with high accuracy. RL's key goal is to determine a policy for actions to take the various states and maximize the rewards in the future. In some cases, the RL algorithm performing this regarding the learning from reward to take the certain action and specify the policy for the valuable actions. In the process of price prediction, Figure 5 presents the prediction steps based on usage of the RL algorithm and the collected data regarding Litecoin and Monero. The raw data information contains four steps of pre-processing, feature engineering, transformation, and feature selection. We split the dataset and applied it into the RL procedure to train and test the price information. Table 3 gives the information related to extracted features from the price prediction system. In total, there are 13 extracted features with explanations and units.

C. EVALUATION METRICS

The trained price prediction model was evaluated based on various performance metrics such as Mean Absolute Error, Mean Absolute Percentage Error, Root Mean Square Error, and Mean Square Error. The formulation is divided as below:

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{m}\Sigma_{n=1}^{m}\frac{|x_n - \hat{x_n}|}{|x|} \tag{1}$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{m}\Sigma_{n=1}^{m}\frac{|x_n - \hat{x_n}|}{|x|} * 100 \tag{2}$$

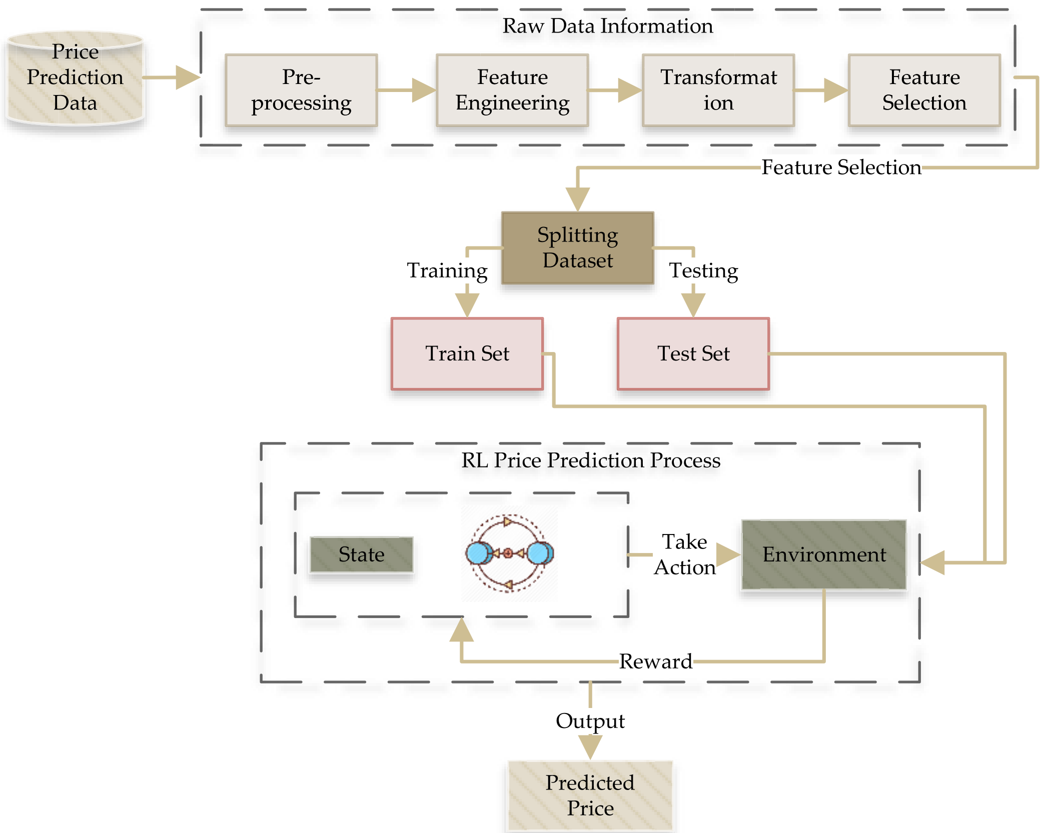

FIGURE 5. Price prediction process based on reinforcement learning.

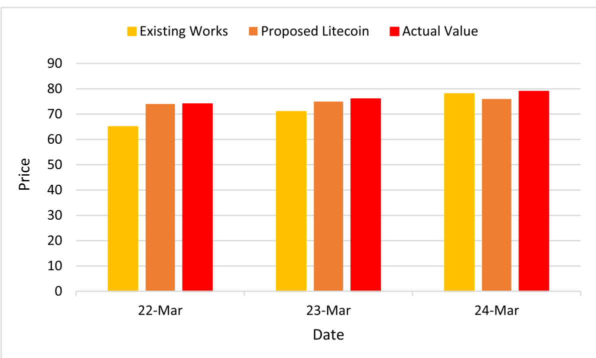

FIGURE 6. Prediction results of Litecoin in 3 days.

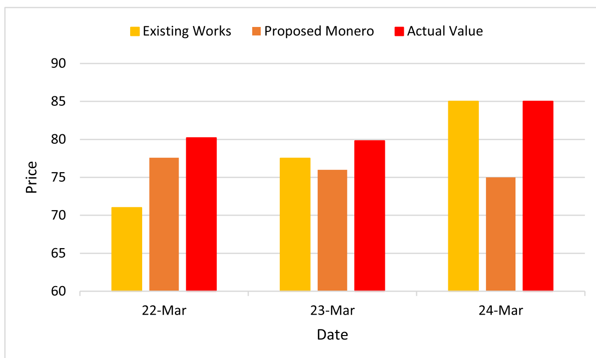

FIGURE 7. Prediction results of Monero in 3 days.

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{m}\Sigma_{n=1}^{m}(\frac{x_n - \hat{x_n}}{x})^2} \quad (3)$$

- Mean Square Error (MSE):

$$MSE = \frac{1}{m}\Sigma_{n=1}^{m}(x_n - \hat{x_n})^2 \quad (4)$$

IV. IMPLEMENTATION AND RESULTS

This section defines the implementation process and development area of the price prediction system in detail. Table 4 summarizes the components of machine learning and blockchain framework in this system. The operating system of the machine learning environment is windows 10. Browser is Internet Explorer, Firefox, and Chrome. The programming language for train and test the developed models are Python and IDE. The blockchain framework was designed based on the Ubuntu Linux 1804 LTS operating system and Node.js programming language. The CPU model is Intel(R) Core(TM) i7-8700 @3.20 GHz, and the docker engine version is 18.06.1-ce. Docker composer version is 1.13.0, and the IDE is Composer Playground. The memory usage in this system is 12GB.

TABLE 3. Description of extracted features in cryptocurrency price prediction system.

Features	Explanation	Unit
Timestamp	Time of data collection from stock market of cryptocurrency	The format of data is in dd/mm/yyyy
Open Price	Each day open price based on the timestamp	USD
High Price	Highest price per day records	USD
Low Price	Lowest price per day records	USD
Close Price	Final price of a day	USD
Currency Volume	Exchange rate price turnover	USD
Price Weight	Shared price average	USD
Size of Block	Average size of block in MB	Network and Property
Hash Rate	Estimated tera hashes in the performed network	Network and property
Trades per minute	Number of traded coins	Market and Trade
Transaction numbers	Per day transaction records	Market and Trade
Confirmed Transaction Records	Daily confirmed transaction records	Market and Trade
Estimated Value for Transactions	Transaction value total records in blockchain	Market and Trade

TABLE 4. Development environment.

Name	Components	Description
Machine Learning	Operating System	Windows 10
	Browser	IE, Firefox, Chrome
	Programming Language	Python, IDE
	ML Algorithm	Reinforcement Learning
Blockchain Network	Operating System	Ubuntu Linux 1804 LTS
	Programming Language	Node.js
	CPU	Intel(R) Core(TM) i7-8700 @3.20 GHz
	Docker Engine	V18.06.1-ce
	Docker Composer	V1.13.0
	IDE	Composer Playground
	Memory	12GB

A. PRICE PREDICTION DAILY ANALYSIS

Daily analysis of Litecoin and Monero presented in Figure 6 and 7. The trained data for Litecoin and Monero is from the 2016 to 2020 time period and contains 1276 points of data. The trained model is to predict the 3 days price from March 22 to 24. The price records are in USD.We have compared our proposed approach result with other existing works. The yellow color in the figure defines the existing works [21] related to this system. The orange color shows the proposed system results, and the red color presents the actual value results in this system during 3 days. The prediction is based on the information of cryptocurrency price for each day. The prediction is based on the step size and prediction window. The selected days are from March 22 to March 24 for both Litecoin and Monero.

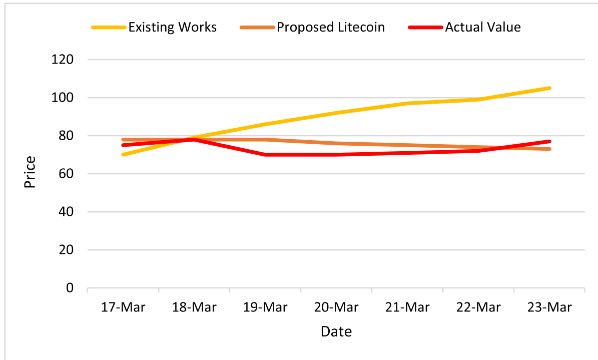

FIGURE 8. Prediction results of Litecoin in 7 days.

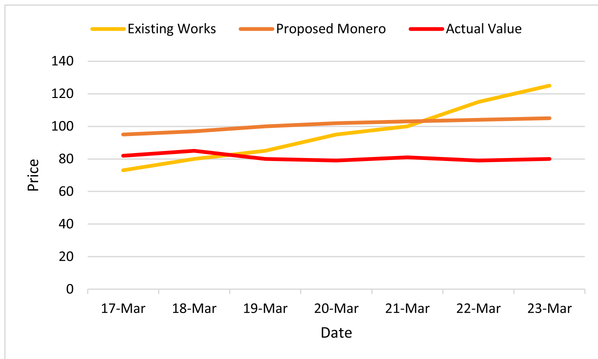

FIGURE 9. Prediction results of Monero in 7 days.

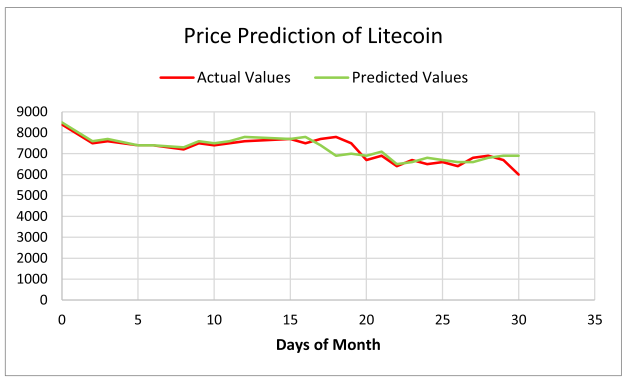

FIGURE 10. Prediction results of Litecoin in 30 days.

B. PRICE PREDICTION WEEKLY ANALYSIS

The weekly analysis results in this system are summarized in Figure 8 and 9 for Litecoin and Monero during one week and

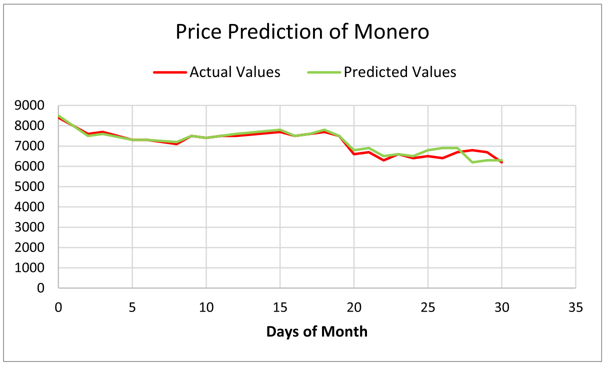

FIGURE 11. Prediction results of Monero in 30 days.

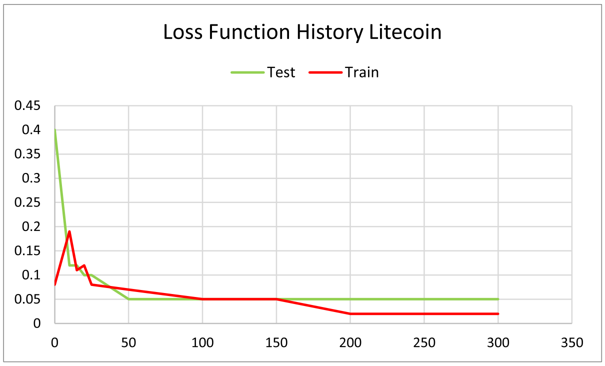

FIGURE 12. Loss function history based on train and test set of Litecoin.

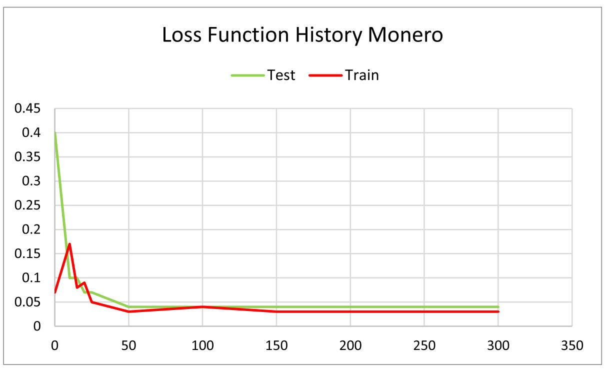

FIGURE 13. Loss function history based on train and test set of Monero.

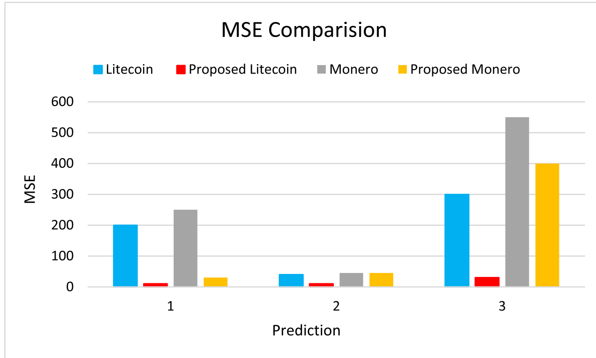

FIGURE 14. MSE comparison of the proposed approach.

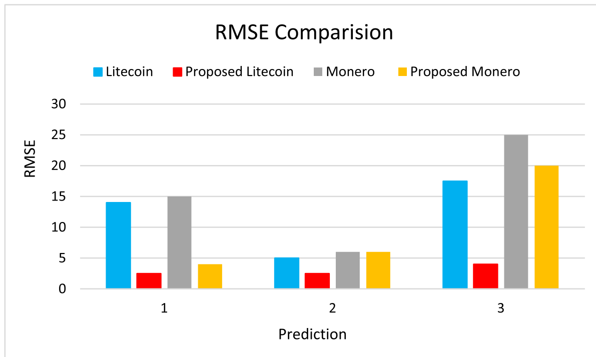

FIGURE 15. RMSE comparison of the proposed approach.

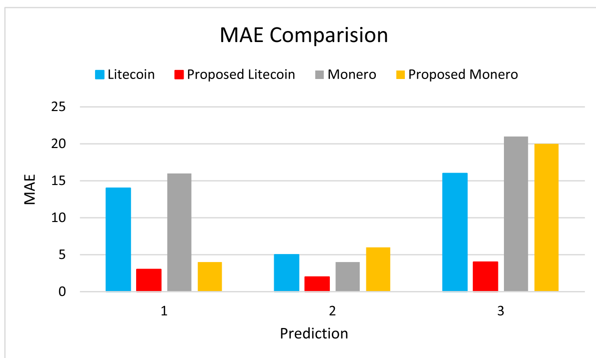

FIGURE 16. MAE comparison of the proposed approach.

seven days in the price of USD. The prediction is based on the step size and RMSE. The colors present the differences of the existing study, proposed Litecoin and Monero, and actual value. The yellow color shows the records of existing works. The orange color shows the records of the proposed Litecoin and Monero, and the red color shows the actual value in both of them.

C. PRICE PREDICTION MONTHLY ANALYSIS

The 30 days price prediction results of Litecoin and Monero are presented in Figure 10 and 11. It can be visible in both Figures the actual value and the predicted value are close together, and the direction of the trend is also highly stable.

Figure 12 and 13 show the function history in the training and testing set. The validation loss fits well with the presented model, and the history function remains stable.

Figure 14, 15, 16 and 17 shows the evaluation metrics results of the MSE, RMSE, MAE and MAPE. The results show the three days, seven days, and one month in a row. Number one is the records of 3 days, number 2 is the records of 7 days, and number 3 is the records of one month. Each day records are specified based on different colors. As shown in the Figures, the blue color represents the existing studied

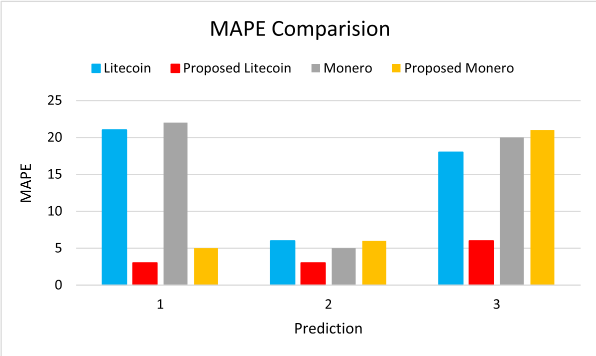

FIGURE 17. MAPE comparison of the proposed approach.

TABLE 5. Results of the 3 days price prediction.

Model	Coin Type	MSE	RMSE	MAE	MAPE
Normal	Litecoin	196.5063	14.0572	14.0572	22.5067
	Monero	232.0476	16.1076	16.1076	23.3272
Proposed	Litecoin	6.3949	3.3097	3.3097	4.0048
	Monero	11.8142	4.3826	4.3826	5.1838

TABLE 6. Results of the 7 days price prediction.

Model	Coin Type	MSE	RMSE	MAE	MAPE
Normal	Litecoin	28.2988	6.3255	5.3749	7.4219
	Monero	31.9216	6.6618	4.9481	6.5516
Proposed	Litecoin	5.2429	3.1438	2.6536	3.1692
	Monero	31.3669	6.6116	5.8589	7.3865

TABLE 7. Results of the 30 days price prediction.

Model	Coin Type	MSE	RMSE	MAE	MAPE
Normal	Litecoin	287.2785	17.9273	15.8082	16.9552
	Monero	524.8219	23.9958	20.7854	20.2365
Proposed	Litecoin	21.8329	5.6632	4.9246	5.9518
	Monero	410.9197	21.3548	20.6614	20.4594

Litecoin records during 3,7 and one month period, and the red color presents the trained records of Litecoin in the purposed approach. The gray color shows the existing studies Monero records, and the yellow color shows the purposed system trained Monero records.

Table 5, 6, 7 presents the price prediction performance evaluation in term of MSE, RMSE, MAE and MAPE. Table 5 shows the results due to three days. Table 6 shows the results of seven days and Table 7 shows the results of 30 days.

V. CONCLUSION

Cryptocurrency price prediction is a challenging area for researchers regarding the external and objective factors that affect price prediction, such as ARIMA, SARIMA, etc, which are normally used for financial schemes analysis. The mentioned are mostly used for time-series but contain lots of limitations regarding the assumptions. In the recent research topics, usage of neural networks contains acceptable results with many variants regarding the price prediction topic. In this paper, we defined the Reinforcement learning prediction approach integrated with blockchain framework for price prediction of Litecoin and Monero. The proposed scheme shows better performance comparing with other state-of-art in this area. In this system, we achieved to the higher accuracy comparing with the other systems in term of Litecoin and Monero which we earlier discuss in related work. The goal of this research is to achieve the better performance for the prediction of cryptocurrencies with less error rate.

VI. FUTURE WORK

In recent decade, cryptocurrency become a famous business environment which people all over the world try to be part of this network. Regarding this aspect, there are lots of problems to predict the daily and monthly price of this digital coins. Due to this problem, we used the reinforcement learning technique for the prediction of two selected Litecoin and Monero digital coins to overcome this issue. The plan for future research is, try to analyze and add more details to the proposed framework. Similarly, trying to analyze other digital coins and compare the results of the current system with other cryptocurrencies and determining the achieved results with the different environment.

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