



# Investigating the Problem of Cryptocurrency Price Prediction: A Deep Learning Approach

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**Abstract.** In last decade, cryptocurrency has emerged in financial area as a key factor in businesses and financial market opportunities. Accurate predictions can assist cryptocurrency investors towards right investing decisions and lead to potential increased profits. Additionally, they can also support policy makers and financial researchers in studying cryptocurrency markets behavior. Nevertheless, cryptocurrency price prediction is considered a very challenging task, due to its chaotic and very complex nature. In this study we evaluate some of the most successful and widely used deep learning algorithms forecasting cryptocurrency prices. The results obtained, provide significant evidence that deep learning models are not able to solve this problem efficiently and effectively. Conducting detailed experimentation and results analysis, we conclude that it is essential to invent and incorporate new techniques, strategies and alternative approaches such as: more sophisticated prediction algorithms, advanced ensemble methods, feature engineering techniques and other validation metrics.

**Keywords:** Deep learning · CNN · LSTM · BiLSTM ·  
Cryptocurrency price prediction · Time series

## 1 Introduction

Cryptocurrency is a new type of digital currency which utilizes blockchain technology and cryptographic functions to gain transparency, decentralization and immutability [12]. Bitcoin (BTC) is considered the first and the most popular cryptocurrency, which was invented by an anonymous group or person in 2009. Since then, 4000 alternative cryptocurrencies like Ethereum (ETH) and Ripple (XRP) were created proving that the cryptocurrency market has emerged in

financial area. BTC, ETH and XRP are the most popular cryptocurrencies, since they almost hold the 79.5% of the global cryptocurrency market capitalization.

Cryptocurrency price prediction can provide a lending hand to cryptocurrency investors for making proper investment decisions in order to acquire higher profits while it can also support policy decision-making and financial researchers for studying cryptocurrency markets behavior. Cryptocurrency price prediction can be considered as a common type of time series problems, like the stock price prediction. Traditional time series methods such as the well-known AutoRegressive Integrated Moving Average (ARIMA) model, have been applied for cryptocurrencies price and movement prediction [13]. However, these models are not able to capture non-linear patterns of very complicated prediction problems in contrast to Deep Learning algorithms which achieve greater performance on forecasting time series problems [17].

Deep Learning (DL) refers to powerful machine learning algorithms which specialize in solving nonlinear and complex problems exploiting most of the times big amounts of data in order to become efficient predictor models. The accurate cryptocurrency price prediction is by nature a significantly challenging and complex problem since its values have very big fluctuations over time following an almost chaotic and unpredictable behavior. Therefore, deep learning techniques may constitute the proper methodology to solve this problem.

Recent research efforts have adopted deep learning techniques for predicting cryptocurrency price. Ji et al. [8] conducted a comparison of state-of-the-art deep neural networks such as Long Short-Term Memory (LSTM), Deep Neural Networks (DNNs), deep residual network and their combinations for predicting Bitcoin price. Their results demonstrated slightly better accuracy of LSTM compared to other models for regression problem while DNNs outperformed all models on price movement prediction. Shintate and Pichl [16] developed a trend prediction classification framework for predicting non-stationary cryptocurrency time series utilizing deep learning. Their results revealed that their proposed model outperformed LSTM baseline model while the profitability analysis showed that simple buy-and-hold strategy was superior to their model and thus it cannot yet be used for algorithmic trading. Their results showed that LSTM was superior to the generalized regression neural architecture concluding that deep learning is a very efficient method in predicting the inherent chaotic dynamics of cryptocurrency prices. Amjad and Shah [3] used live streaming Bitcoin data for predicting price changes (increase, decrease or no-change), building a model based on the most confident predictions, in order to perform profitable trades. The classification algorithms which they used were Random Forest, Logistic Regression and Linear Discriminant Analysis. Their results seem to be very impressive since they achieved a high prediction accuracy ( $>60\text{--}70\%$ ) and about  $5.33x$  average return on investments on a test set.

In this work, we evaluate the performance of advanced deep learning algorithms for predicting the price and movement of the three most popular cryptocurrencies (BTC, ETH and XRP). The main contribution of this research lies in investigating three major questions: i) *Can deep learning efficiently predict*

*cryptocurrency prices?* ii) *Are cryptocurrency prices a random walk process?* iii) *Is there a proper validation method of cryptocurrency price prediction models?*

Furthermore, it also lies in the recommendation for new algorithms and alternative approaches for the cryptocurrency prediction problem.

The remainder of this research is organized as follows: Sect. 2 performs a brief introduction to the advanced deep learning models utilized in our experiments. Section 3 presents our research methodology and experimental results. Section 4 discusses and answers the three research questions, while Sect. 5 presents our suggestions on possible alternative solutions for the cryptocurrency prediction problem. Finally, Sect. 6 presents our concluding remarks.

## 2 Brief Description of Advanced Deep Learning Models

Deep learning algorithms constitute one of the most powerful machine learning algorithms categories which have been successfully applied on a multitude of commercial applications. Long Short Term Memory and Convolutional Neural Networks are probably the most popular, successful and widely used deep learning techniques.

Long Short-Term Memory (LSTM) [6] constitute a special type of deep neural networks, which are able to learn long-term dependencies by utilizing feedback connections in order to “remember” past network cell states. These networks have become very popular since they have been successfully applied on a wide range of applications and have shown remarkable performance on time series forecasting [5]. More specifically, LSTM networks are composed by a memory cell, an input, output and forget gate. The input gate controls the new stored information into the memory cell, while the forget gate controls the information which must be vanished. Finally, the output gate controls the final output information value which is given after a delay into the forget, input gate utilizing a feedback connection loop. In this way, LSTM is able to create a controlled information flow filtering unnecessary information and thus achieving to learn long term dependencies.

Bidirectional Long Short-Term Memory (BiLSTM) [15] are a special type of recurrent neural networks which connect two LSTM layers of converse directions to the same output, in order to remember past and future network cell states. The principle idea is that each training sequence is presented forwards and backwards into two separate LSTM layers aiming in accessing both past and future contexts for a given time. More specifically, the first hidden layer possesses recurrent connections from the past time steps; while in the second one, the recurrent connections are reversed, transferring activation backwards along the sequence.

Convolutional Neural Networks (CNN) [2] constitute another type of deep neural networks which utilize convolution and pooling layers in order to filter the raw input data and extract valuable features, which will feed a fully connected layer in order to produce the final output. More specifically, they apply convolution operations in the input data and in order to produce new more useful features. The convolutional layers are usually followed by a pooling layer

which extracts values from the convolved features producing a lower dimension instance. In fact, a pooling layer produces new features which can be considered as summarized versions of the convolved features produced by the convolutional layer. This implies that pooling operations can significantly assist the network to be more robust since small changes of the inputs, which are usually detected by the convolutional layers, will become approximately invariant.

### 3 Experimental Methodology

In this work, we evaluate the performance of advanced DL models for predicting the price of BTC, ETH and XRP. The evaluated DL models are constituted by CNN, LSTM, BiLSTM and dense layers. Table 1 depicts our DL models for the best identified topologies. We have to mention that exhaustive and thorough experiments were performed in order to identify the DL topologies which incur the best performance results.

**Table 1.** Best identified topologies for our deep learning models

| Model                   | Description   |
|-------------------------|---|
| LSTM <sub>1</sub>       | LSTM layer with 50 units  |
| LSTM <sub>2</sub>       | Two LSTM layers with 30 and 15 units, respectively  |
| BiLSTM <sub>1</sub>     | BiLSTM layer with 60 units  |
| BiLSTM <sub>2</sub>     | Two BiLSTM layers with 40 and 20 units, respectively  |
| CNN-LSTM <sub>1</sub>   | Convolutional layer with 64 of filters of size (2, )<br>Convolutional layer with 128 of filters of size (2, )<br>Max pooling layer with size (2, )<br>LSTM layer with 100 units                                 |
| CNN-LSTM <sub>2</sub>   | Convolutional layer with 64 of filters of size (2, )<br>Convolutional layer with 128 of filters of size (2, )<br>Max pooling layer with size (2, )<br>LSTM layer with 70 units<br>Dense layer with 16 neurons   |
| CNN-BiLSTM <sub>1</sub> | Convolutional layer with 64 of filters of size (2, )<br>Convolutional layer with 128 of filters of size (2, )<br>Max pooling layer with size (2, )<br>LSTM layer with 100 units                                 |
| CNN-BiLSTM <sub>2</sub> | Convolutional layer with 64 of filters of size (2, )<br>Convolutional layer with 128 of filters of size (2, )<br>Max pooling layer with size (2, )<br>BiLSTM layer with 70 units<br>Dense layer with 16 neurons |

We recall that the basic idea of utilizing LSTM and BiLSTM on cryptocurrency price prediction problems, is that they might be able to capture useful long or short sequence pattern dependencies, due to their special architecture design, assisting on prediction performance, while the convolutional layers of a CNN model might filter out the noise of the raw input data and extract valuable features producing a less complicated dataset which would be more useful for the final prediction model [9]. Therefore, we expect that a noticeable performance increase will be achieved by the incorporation of these advanced models comparing to classic machine learning algorithms.

Additionally, the performance of the DL models was compared against that of traditional state-of-the-art ML models: Support Vector Regressor (SVR) [4], 3-Nearest Neighbors (3NN) [1] and Decision Tree Regressor (DTR) [10]. The implementation code was written in Python 3.4 while for all deep learning models we utilized Keras library and Theano as back-end while Scikit-learn library was used for the machine learning models.

For evaluating the regression performance of forecasting models the most common validation metrics are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Since the cryptocurrency price prediction problem can be considered a regression problem, in our experiments we utilized these two evaluation metrics. Nevertheless, we included only the RMSE score in this study, since the MAE score had almost the same behavior with RMSE. Moreover, by comparing the predicted prices of our models, with the real ones, we managed to compute the classification accuracy of price movement direction prediction (if the price will increase or decrease). Therefore, we utilized two additional performance metrics: Accuracy (Acc) and  $F_1$ -score ( $F_1$ ).

### 3.1 Dataset

For the purpose of this research, we utilized data from Jan-2018 to Aug-2019, concerning the hourly prices in USD and were divided into training set consisting of data from Jan-2018 to Feb-2019 (10176 values) and testing set from Mar-2019 to Aug-2019 (4416 values). This data were taken from [www.kraken.com](http://www.kraken.com) website, which is a trading platform for cryptocurrency exchanges. Also, we utilized four forecasting horizons  $F$  (number of past prices taken into consideration), i.e., 4, 9, 12 and 16 h, while in this study we present only the 4 and 9 h horizon results, since for larger horizon values it was identified a decrease in performance. An extended report which includes all experimental results can be found in [14].

### 3.2 Experimental Results

Tables 2 and 3 present the experimental results of our DL models ML models. CNN-LSTM and CNN-BiLSTM models exhibited the best overall performance among all prediction models. In particular, the CNN-LSTM exhibited the highest RMSE performance for all datasets for every forecasting horizon comparing to other DL models, while the CNN-BiLSTM exhibited the best Acc and  $F_1$  score in most cases. Nevertheless, the performance variations for all DL models seem

to be minimal. The 3NN model reported the highest RMSE performance for forecasting horizon 4 among all the ML models on BTC and ETH datasets, while the DTR exhibited the highest RMSE on XRP. For forecasting horizon 9 the DTR outperformed all ML models for all dataset, regarding to RMSE score. Furthermore, the 3NN model managed to achieve the best overall performance in Acc score almost in all cases. In summary, advanced DL models seem to slightly outperform ML models while they did not manage to achieve a noticeable performance increase comparing to our ML models.

**Table 2.** Performance of DL and ML forecasting models for  $F = 4$

| Model                   | BTC    |        |       | ETH    |        |       | XRP    |        |       |
|-------------------------|--------|--------|-------|--------|--------|-------|--------|--------|-------|
|                         | RMSE   | Acc    | $F_1$ | RMSE   | Acc    | $F_1$ | RMSE   | Acc    | $F_1$ |
| SVR                     | 0.0209 | 50.80% | 0.484 | 0.0163 | 49.14% | 0.482 | 0.0370 | 47.67% | 0.644 |
| 3NN                     | 0.0161 | 49.51% | 0.469 | 0.0149 | 51.56% | 0.481 | 0.0115 | 52.33% | 0.492 |
| DTR                     | 0.0170 | 49.22% | 0.465 | 0.0199 | 50.11% | 0.467 | 0.0157 | 50.14% | 0.504 |
| LSTM <sub>1</sub>       | 0.0138 | 52.86% | 0.524 | 0.0130 | 53.59% | 0.531 | 0.0106 | 53.40% | 0.509 |
| LSTM <sub>2</sub>       | 0.0144 | 53.63% | 0.522 | 0.0165 | 52.68% | 0.501 | 0.0116 | 53.13% | 0.514 |
| BiLSTM <sub>1</sub>     | 0.0142 | 52.05% | 0.508 | 0.0130 | 53.89% | 0.538 | 0.0114 | 53.21% | 0.519 |
| BiLSTM <sub>2</sub>     | 0.0132 | 52.56% | 0.519 | 0.0134 | 53.30% | 0.502 | 0.0118 | 52.75% | 0.518 |
| CNN-LSTM <sub>1</sub>   | 0.0109 | 53.21% | 0.530 | 0.0106 | 53.77% | 0.533 | 0.0097 | 52.42% | 0.472 |
| CNN-LSTM <sub>2</sub>   | 0.0099 | 52.50% | 0.502 | 0.0106 | 54.20% | 0.524 | 0.0097 | 53.03% | 0.436 |
| CNN-BiLSTM <sub>1</sub> | 0.0107 | 54.51% | 0.544 | 0.0121 | 53.91% | 0.524 | 0.0119 | 53.61% | 0.534 |
| CNN-BiLSTM <sub>2</sub> | 0.0101 | 55.43% | 0.548 | 0.0115 | 54.18% | 0.541 | 0.0117 | 53.46% | 0.506 |

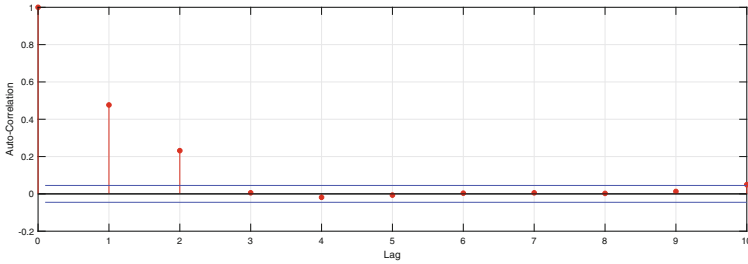
**Table 3.** Performance of DL and ML forecasting models for  $F = 9$

| Model                   | BTC    |        |       | ETH    |        |       | XRP    |        |       |
|-------------------------|--------|--------|-------|--------|--------|-------|--------|--------|-------|
|                         | RMSE   | Acc    | $F_1$ | RMSE   | Acc    | $F_1$ | RMSE   | Acc    | $F_1$ |
| SVR                     | 0.0192 | 52.57% | 0.546 | 0.0146 | 49.30% | 0.501 | 0.0292 | 47.92% | 0.457 |
| 3NN                     | 0.0197 | 51.57% | 0.484 | 0.0195 | 51.50% | 0.504 | 0.0132 | 54.35% | 0.485 |
| DTR                     | 0.0179 | 49.54% | 0.459 | 0.0228 | 49.64% | 0.465 | 0.0161 | 49.89% | 0.504 |
| LSTM <sub>1</sub>       | 0.0159 | 51.99% | 0.479 | 0.0158 | 53.06% | 0.500 | 0.0117 | 51.34% | 0.413 |
| LSTM <sub>2</sub>       | 0.0207 | 52.45% | 0.499 | 0.0208 | 52.75% | 0.527 | 0.0115 | 51.66% | 0.456 |
| BiLSTM <sub>1</sub>     | 0.0170 | 52.00% | 0.489 | 0.0165 | 53.31% | 0.512 | 0.0126 | 52.73% | 0.517 |
| BiLSTM <sub>2</sub>     | 0.0168 | 52.97% | 0.530 | 0.0166 | 53.80% | 0.527 | 0.0121 | 55.22% | 0.534 |
| CNN-LSTM <sub>1</sub>   | 0.0119 | 53.92% | 0.536 | 0.0130 | 53.92% | 0.530 | 0.0096 | 51.06% | 0.453 |
| CNN-LSTM <sub>2</sub>   | 0.0107 | 54.20% | 0.532 | 0.0124 | 54.45% | 0.537 | 0.0100 | 51.54% | 0.493 |
| CNN-BiLSTM <sub>1</sub> | 0.0149 | 53.44% | 0.533 | 0.0158 | 53.10% | 0.522 | 0.0148 | 54.01% | 0.540 |
| CNN-BiLSTM <sub>2</sub> | 0.0125 | 54.89% | 0.541 | 0.0152 | 53.95% | 0.533 | 0.0157 | 53.95% | 0.532 |

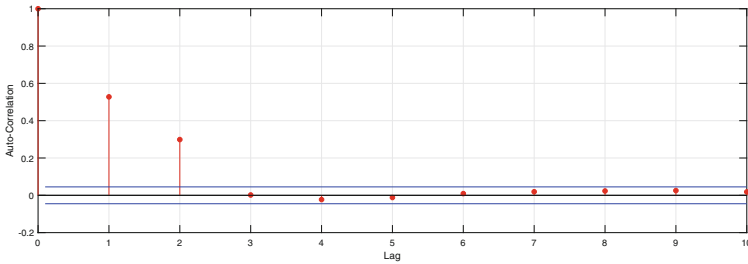
### 3.3 Forecasting Reliability Evaluation

In the sequel, we evaluate the forecasting reliability of the proposed prediction models, by performing a test of autocorrelation in the residuals [11]. This test examines the presence of autocorrelation between the residuals (differences between predicted and real values). In case autocorrelation exists, then the prediction model may be inefficient since it did not manage to capture all the possible information which lies into the data. To this end, we perform the autocorrelation test to the residuals in order to evaluate the reliability of CNN-BiLSTM for  $F = 4$ , CNN-LSTM for  $F = 4$  and CNN-BiLSTM for  $F = 9$  which presented the best overall performance for BTC, ETH and XRP, respectively.

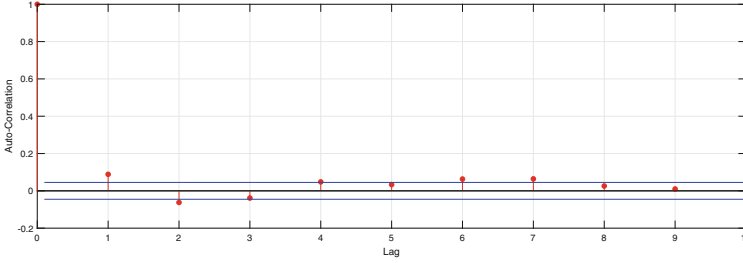
Figures 1, 2 and 3 present the Auto-Correlation Function (ACF) plot of the selected models for BTC, ETH and XRP, respectively. Notice that the confident limits (blue dashed line) are constructed assuming that the residuals follow a Gaussian probability distribution. Clearly, all present ACF plots reveal that some correlation coefficients were not within the confidence limits (dashed lines), violating the assumption of no auto-correlation in the errors. More specifically, the interpretation of Figs. 1 and 2 present that there are significant spikes at lags 1 and 2 while the interpretation of Fig. 3 show that there exist small spikes at lags 1, 2, 6, 7 and 10. Therefore, the presence of correlation indicates that the advanced DL models are unreliable for cryptocurrency price predictors since there exists some significant information left over which should be taken into account for obtaining better predictions.



**Fig. 1.** ACF plots on the residuals for BTC using CNN-BiLSTM for  $F = 4$  (Color figure online)



**Fig. 2.** ACF plots on the residuals for ETH dataset using CNN-LSTM for  $F = 4$  (Color figure online)



**Fig. 3.** ACF plots on the residuals for XRP dataset using CNN- BiLSTM for  $F = 9$  (Color figure online)

## 4 Discussion

Following our experiments, this section is dedicated in providing a thorough and sufficiently detailed discussion of our findings with regard to the predefined three research questions: *Can deep learning algorithms efficiently predict cryptocurrency prices? Are cryptocurrency prices a random walk process? Which is a proper validation method of cryptocurrency price prediction models?*

### 4.1 Can Deep Learning Efficiently Predict Cryptocurrency Prices?

Deep learning algorithms are considered to be the most powerful and the most effective methods in approximating extremely complex and non-linear classification and regression problems, therefore it was expected that a noticeable performance increase will be achieved by the incorporation of these models comparing to classic machine learning algorithms. Surprisingly, our results demonstrated that the utilized DL algorithms, slightly outperformed the other ML algorithms utilized in our experiments, whereas instead a noticeable performance increase was anticipated. So, it is paramount importance to investigate the reason why that happened. To this end, we summarize two possible reasons: The problem we are trying to solve is a random walk process or very close to it, thus any attempt for prediction might be of poor quality or the problem is just too complicated that even advanced deep learning methods cannot find any pattern that would lead to any reliable prediction. Thus, more sophisticated methodologies, techniques and innovative strategies are needed to be investigated.

When a time series prediction problem follows a random walk process or it is so complicated that most models face it as a random process, then the more efficient method to face it, is the employment of present values as the prediction values for the next state [11]. That is exactly what a persistence model does and maybe what most prediction models really do and possibly that's the reason why ML models used in our experiments achieve almost the same performance score compared to the deep learning models used in our experiments. In contrast, the deep learning models may attempt forecasting based on patterns that were traced and as a result are unable to achieve high performance because either those patterns are false or because there exist no such patterns at all, in the case that the cryptocurrency price prediction problem is a random walk process.



Nevertheless, as mentioned before, the DL models did not manage to achieve a noticeable performance score in our experiments, since their score was almost the same with the ML models. Thus, we conclude that these advanced DL models cannot efficiently predict cryptocurrency prices because the utilized datasets with the specific form which we “*fed*” them to our prediction models, probably follow almost a random walk process and thus not sufficient information lies on them in order to perform accurate and reliable future predictions.

## 4.2 Are Cryptocurrency Prices a Random Walk Process?

Towards the construction of a model which performs reliable and accurate predictions, firstly, we have to identify if the cryptocurrency price prediction problem is a random walk process. In a recent study, Stavroyiannis et al. [18] proved that Bitcoin prices follow a random walk process since their experiments revealed the presence of unit roots, for several time intervals from 1-min to 180-min, and thus reliable profitable trading opportunities may not be possible in Bitcoin markets. However, since this problem is highly affected by time evolution and external changes, these results maybe temporary and reverse in future.

However, there are numerous technical strategies that the majority of the professional traders utilize in order to make trading decisions in stock market and cryptocurrency investments. Most of them seem to be heuristic and empirical strategies which are based on various technical indicators and patterns such as the “*Engulfing Pattern*” and the “*Evening Star*”. A recent study utilized those technical indicators and trading patterns strategies in order to predict stock market and cryptocurrency prices [7]. Their results provide evidence that technical analysis strategies have strong predictive power and thus can be useful in cryptocurrencies markets like Bitcoin.

Therefore, we conclude that the cryptocurrency prices in general are not totally a random walk process but they may be close to it, which means that probably exist some actual patterns on historic data that could assist on forecasting attempts. In other words, we liken this problem as a “*huge sea of random walk points where small hidden islands (patterns) may exist in*”. As a result, more research is required for the discovery of alternative, innovative and more sophisticated methods such as the incorporation of new feature engineering strategies and the creation of new algorithmic and ensemble methods.

## 4.3 What is a Proper Validation Method of Cryptocurrency Price Prediction Models?

As mentioned above, the most common validation metrics for measuring the performance of most regression algorithms are MAE and RMSE. However, finding a proper validation metric for cryptocurrency price prediction models can be a very complicated and tricky task and cannot be considered an easy and straightforward process. The MAE and RMSE may constitute an incomplete way for validating cryptocurrency price prediction problems since a prediction model may have excellent MAE and RMSE performance but cannot properly

predict the cryptocurrency price direction move (classification problem). A cryptocurrency trader or investor may be more interested in the future price direction movement rather than knowing the exact future cryptocurrency price. Profitability analysis for algorithmic trading strategies reveal that classification prediction models were more effective than regression models [8].

Even if we utilize a third evaluation metric which will measure the performance accuracy of cryptocurrency price direction movement, that may still constitute an incomplete method for validating cryptocurrency prediction algorithms. Consider the following example: Suppose we wish to validate 2 cryptocurrency prediction models utilizing a test set of 100 questions, e.g. what is the future price direction movement on the next 100 time steps? The first model answers (predicts) all questions while it answers correctly 52 questions achieving an accuracy score of 52%. The second model answers only 5 from 100 questions but it cannot answer the other 95 questions, while these 5 answers are correct. So, the second model achieves a score of 5%. Thus, an important question is raised, “*which is the best model*”? A cryptocurrency trader or investor will probably choose the second model since it acts in a more reliable way and it would be more valuable for him to possess a model which performs accurate predictions on random times (specified by the model), rather than possessing a model which performs unreliable predictions on every moment (specified by the user).

Therefore, we conclude that finding a proper validation metric for cryptocurrency price prediction models is a very challenging task and thus alternative and new methods for evaluating cryptocurrency prediction models are essential.

## 5 Revisiting the Problem

One of the most significant steps in order to solve any problem, especially the really hard and challenging ones, lies in finding a proper strategy approach and securing the complete understanding of the problem we try to solve. A proper strategy approach should answer questions such as: should we have to predict prices, price movement direction, price trends, price spikes and so on. Next, should we apply data preprocessing and feature engineering strategies (e.g. which features should we use in order to efficiently train a prediction model?) Also, what is the best prediction model to apply (e.g. DNNs, other sophisticated prediction models, ensemble models and so on) and finally, which is a proper method to validate this model? All these issues, considered as discrete steps in the process, should be taken into serious consideration since each one of them can significantly contribute to any prediction attempt in order to efficiently approximate the problem.

These steps are not a straightforward process, since we should always have to consider its chaotic and extremely complicated nature with respect to its practical contribution after a possible solution. For example, it may be an easier task to solve and possibly more beneficial for the investment and trading world to predict if the price will just increase or decrease (classification problem for price direction movement prediction) rather than predicting the exact value of cryptocurrency price. Some strategy approaches examples are presented in brief below.

Instead of adopting a specific time interval, one could utilize various time intervals of higher and lower frequency historic datasets for predicting the prices on a specific future interval in order to utilize and exploit in a more efficient way all possible information that a historic dataset may contain. Another approach could be instead of predicting the price or the movement direction on one discrete future time value, to predict the average and movement direction price or peak price inside a future time window frame (this approach would be more similar to a trend prediction problem).

Pattern identification and recognition could be another approach. This approach would be more similar to a pattern detection framework in which the model would detect specific pattern areas in order to perform a prediction. More specifically, if we are able to identify the feature characteristics of possible useful patterns that a prediction model found, then we could filter out useless sequence inputs which have no predictive information and then utilize only the useful sequence inputs which will possibly assist on reliable and accurate predictions. In this case the prediction model will perform prediction operations only when the input sequence falls into the same category with the chosen patterns. This framework would be more similar to the way that a professional trader often acts, who performs investment decisions based on his/her personal chosen patterns and indicators recipes on technical analysis of historic price charts.

Finally, another approach could be the investigation of heuristic patterns and other financial indicators which professional traders and bankers utilize in their trading and financial technical analysis. It is essential to identify how these methods actually assist predictions and investment decisions in a more mathematic way (if they actually work) and maybe incorporate these techniques in a machine learning framework for developing co-operative prediction models. That could be an effective cryptocurrency prediction framework.

## 6 Conclusions

In this work, we evaluated advanced DL models for predicting cryptocurrency prices and also investigated three research question concerning this problem in a review and discussion approach. Our results revealed that the presented models are inefficient and unreliable cryptocurrency price predictors, probably due to the fact that this problem is a very complicated one, that even advanced deep learning techniques such as LSTM and CNNs are not able to solve efficiently. Also, based on our experimental results and investigation regarding to our research questions about cryptocurrency price problem, we conclude that cryptocurrency prices follow almost a random walk process while few hidden patterns may probably exist in, where an intelligent framework has to identify them in order for a prediction model to make accurate and reliable forecasts. Therefore, new sophisticated algorithmic methods, alternative approaches, new validation metrics should be explored.

Finally, since cryptocurrency datasets follow typical time-series patterns, one may logically conclude that the research questions posed in this work and our concluding remarks and proposals apply to all application domains in which the datasets demonstrate time-series behavior.

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