A Comparative Study of Cryptocurrency Price Prediction

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Abstract

Finding an accurate, stable and effective model to predict the future price of cryptocurrencies has become a task increasingly favored by scholars. In this paper I studies and compares the performance of five various machine learning models in price prediction such as the long short-term memory(LSTM) model, the gated recurrent unit (GRU) model, the bidirectional long-short term memory(Bi-LSTM) model, the LSTM and Time2Vec combination model, the XGBoost model for Bitcoin and Ethereum price prediction. Experiment results shows that LSTM+T2V model substantially outperforms other models, no matter the prediction accuracy or the training speed. The prediction error and the time spent are respectively reduced by 40% and 90% compared with the double-layer lstm. Since minute-by-minute data was used in this experiment, taking into account the time window, XGBoost and Time2Vec are potentially available models, especially the latter.

Keywords: *Cryptocurrency; Price Prediction; Bitcoin; Time Series; Time2Vec*

1 Introduction

Over the past 13 years, cryptocurrencies have evolved from a niche technological proposal for peer-to-peer payments to a financial asset class traded by millions of users around the world. Forgery and falsification may be prevented using decentralized ledgers with blockchain technology in cryptocurrencies, which has received much interest[1]. Overall the galloping development of the crypto market led to a market capitalization of US$808 billion as of August 2021[2]. However, comparing those some stable financial assets such as stock indexes, gold, the cryptocurrency price has an unusual high volatility. In May 2021, the price of Bitcoin-currently the biggest cryptocurrency in terms of market capitalization-dropped more than 30% from around$58,000 to approximately $36,000 within a week. On May 8, 2022, there was a run on a stablecoin named TerralUSD that wiped out TerraUSD's market capitalization of over $18 billion[3]. Furthermore, each cryptocurrency has its own characteristics (i.e. value deviations, transaction speed, usages, ecosystem)[4].

Owning to the Independence of cryptocurrencies, forecasting their process becomes a big challenge. Price movement is an important factor that determine the value of each cryptocurrency. With the rapid flow of information and availability of high-frequency price movement data in crypto market, machine learning technologies are considered as a potentially better alternative applied to do price prediction, which is a critical step in financial decision-making related to portfolio optimization, risk evaluation, and trading, with the help of past data[5]. Besides, instant knowledge of price movements can lead to higher profits and lower investment risks for investors[6]. The available machine learning methodologies for time series forecasting including moving average, auto regression, neural networks, boosted tree models, etc.

In this paper, I compared the performance of various machine learning models, suitable to deal with time series, in cryptocurrency price prediction. In particular, I did a wide search on the key parameters and compared their forecasting performance under different settings. For comprehensiveness of comparison, i applied the models in two cryptocurrencies-Bitcoin(BTC) and Ethereum(ETH). The fundamental goal of this research is to provide a trustworthy reference for the performance of machine learning models (i.e. LSTM, BiLSTM, T2V, GRU, XGBoost, FBProphet, ARIMA), based on previous cryptocurrency prices that investors can trust.

1.1 Contributions

Following are the research contributions of this paper.

- I made finer adjustments to the models. For the different volatility in different periods, 5-fold time series cross validation was used to ensure that the models are applicable to the whole period. Furthermore, Optuna[7], an automatic hyperparameter optimization framework, was introduced to obtain the best parameters in the models.
- In contrast to most similar research using daily data, I used high frequency minute by minute data, which makes the application of deep learning models more meaningful.
- The comparison in this report is more comprehensive, spans tradition machine learning models and deep learning models. As far as known, it's the first paper to use time2vec for cryptocurrency price comparison.

1.2 Organization

Rest of the paper is organized as follows. Section 2 discusses the previous work that has been done to predict cryptocurrency prices. Section 3 explains the concepts of models I used. In section 4, I presents the schema of the prediction process, from data preparation to model construction. Section 5 discusses the experimental result and the models' performance for predicting cryptocurrency prices and finally, section 6 concludes the paper.

2 Literature Review

A substantial amount of research has been carried in the prediction of prices of equity and other market assets over the past decades, but due to the newfangledness, there is not many research done on the price prediction of cryptocurrencies. Nonetheless, the number of researches related to the prices of cryptocurrencies has year-on-year growth. In this section, I briefly present previous works in this field.

Some studies adapted traditional machine learning models. To forecast Bitcoins price, for instance, Madan et al. [8], applied generalized linear models (GLM), random forest, and support vector machine on Blockchain data; Jang and Lee [9] used a Bayesian neural network. Garlapati et al.[10] used Facebook Prophet and Arima models to analyze the future value of stock markets and how it varies from previous stock markets. Yamak et al. [11] compared three different machine learning models in making the Bitcoin's price forecast, Arima was shown to have better results. Jay et al.[12] proposed the approach based on the random walk theory and induced layer-wise randomness to simulate market volatility. Iqbal et al. applied ARIMA, FBProphet, XGBoost for predicting the ups and downs in the price of Bitcoin, ARIMA was considered as the best model in their research.

Furthermore, Some deep learning models for time series forecasting has caused the extensive concern in this field. Ji et al.[13] studied and compared LSTM ,CNN and a deep residual network for Bitcoin price prediction, it showed LSTM-based prediction models slightly outperforms others for price prediction. Li et al.[14] proposed a hybrid neural network model based on CNN and LSTM, aiming at forecasting the price of Bitcoin. Patel et al.[15] presented a LSTM and GRU-based hybrid cryptocurrency prediction scheme focusing on Litecoin and Menero. Wang et al. [16] compared CNN-BiLSTM with MLP, RNN, CNN-LSTM, and it indicated that the MAE, RMSE are all optimal. Tian et al.[17] presented a LSTM and LightGBM hybrid, named as LSTM-BO-LightGBM, to solve the problem of stock price fluctuation prediction.

3 Models overview

In this section, I have shown the models which has been used to predict the cryptocurrency price. Considering the high correlation between the prices, I only used the closing price to make the forecast. Each model has been tuned with time series 5-fold cross validation to ensure that it is sufficiently general.

3.1 LSTM

Long Short-Term Memory(LSTM) is a variant of Recurrent Neural Network(RNN) which can learn long term dependencies. For many learning tasks involving time series data, although RNN model can be used to predict, it suffers from the vanishing gradient problem with numerous layers. However, LSTM has an architecture with gates that govern the flow of information between cells, including Input Gate, Output Gate and Forget Gate. Fig 1 shows the basic unit of LSTM. This structure enables LSTM to regulate the flow of information into and out of the cell, which provides "highway" for the gradient to flow backward through time freely, thereby making it more resistant to the vanishing gradient problem. This made LSTM emerge as an effective and scalable approach for time series data prediction tasks.

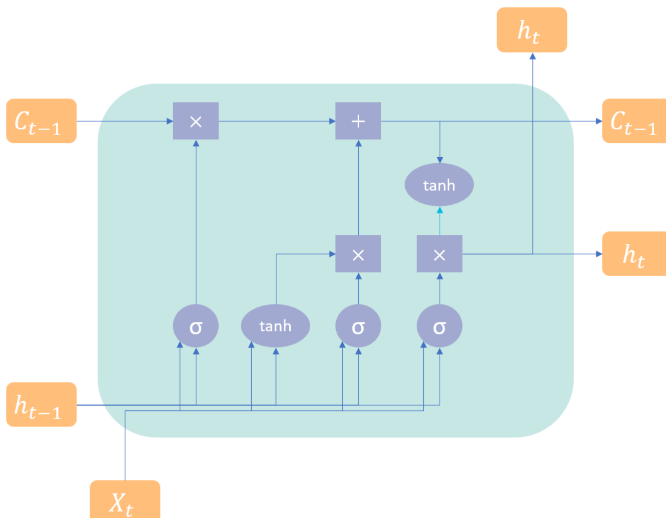

Figure 1: the basic unit of a LSTM cell

3.2 Bi-LSTM

Bidirectional long-short term memory(BiLSTM) are a special type of recurrent neural network which connect two LSTM layers of converse directions to the same output [18]. BiLSTM predicts the sequence of each element using a finite sequence based on the information in the past and future [19]. In time series prediction, the forward and backward information law of time series data should be fully considered, which can effectively improve the prediction accuracy, compared with the standard LSTM, BiLSTM considers the changing laws of the data before and after data transmission and can make more complete and detailed decisions[16]. BiLSTM consists of forward and backward calculation, Fig 2 shows the structure diagram of BiLSTM.

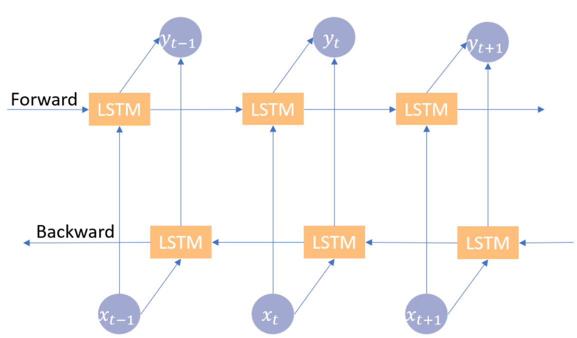

Figure 2: the structure diagram of BiLSTM

3.3 GRU

Gated recurrent network(GRU) is another variant of RNN that solves the vanishing gradient problem [15]. It has demonstrated the effectiveness in a variety of applications requiring sequential or temporal data[19]. GRU is similar to LSTM but has fewer gates, including an update gate and a reset gate, which is evident from Fig 3. GRU uses update gate and reset gate for vanishing gradient problem and also decide what will be the output.

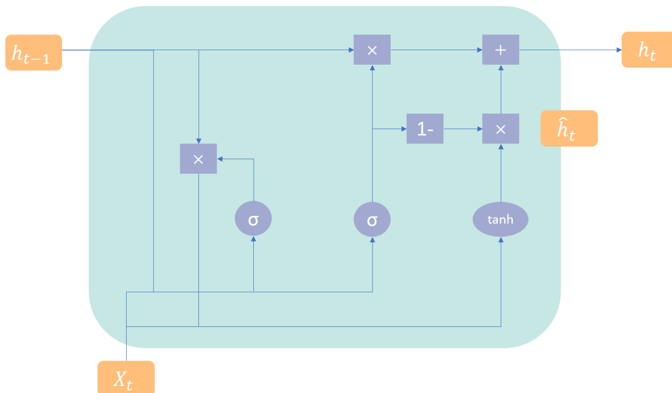

Figure 3: the basic unit of a GRU cell

Following Eqs. summarize a GRU.

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$
$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$
$$\hat{h}_t = \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{3}$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \hat{h}_t \tag{4}$$

where x_t is the input vector, h_t is the output vector, $\hat{h}_t$ is the candidate activation vector, z_t is the update gate vector, r_t is the reset gate vector, $W, U and b$ are parameter matrices and vector.

3.4 Time2Vec

Time2Vec is an approach to consume time information by providing a model-agnostic vector representation. It can be easily combined with many methods or architectures. The embedding of Time2vec with sequence model is shown in Fig 4. Time2Vec identifies three important properties to design a representation of time: 1-capturing both periodic and non-periodic patterns, 2-being invariant to time scaling, and 3-being simple enough so it can be combined with many models. For a given scalar notion of time τ, Time2Vec of τ, denoted as $\mathbf{t2v}(\tau)$, is a vector of size k+1 defined as follows:

$$\mathbf{t2v}(\tau)[i] = \begin{cases} w_i\tau \ + \ \varphi_i, & \text{if } i = 0. \\ \mathcal{F}(w_i\tau \ + \ \varphi_i), & \text{if } i \leq 0 \leq k. \end{cases} \tag{5}$$

where $\mathbf{t2v}(\tau)[i]$ is the i^{th} element of $\mathbf{t2v}(\tau)$, $\mathcal{F}$ is a periodic activation function, and φ_is are learnable parameters.

3.5 ARIMA

ARIMA model is a procedure of forecasting future values of time series by using historical data generate forecasting value of variables[20]. It consists of two main parts. The formula of ARIMA for time series forecasting is supposed to be a linear combination of past values and past errors, expressed as follows

$$y_t = \theta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q}, \tag{6}$$

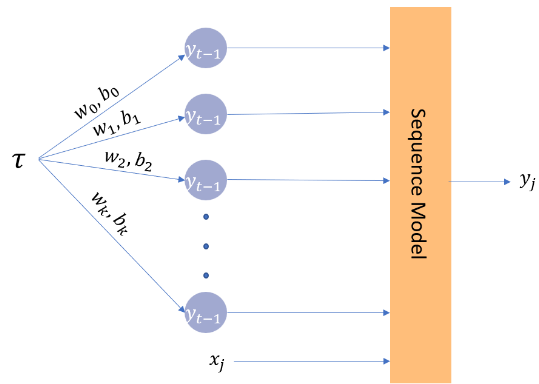

Figure 4: The embedding of Time2Vec

where y_t is the actual value and ε_t is the random error at time t, φ_i and θ_j are the coefficients, p and q are integers that are often referred to as autoregressive and moving average polynomials. The steps in building ARIMA forecasting model consist of *model identification*, *parameter estimation* and *diagnostic checking*[21]. (This model is used with daily data)

3.6 FBProphet

Prophet is an additivity (GAM) model that Facebook has open sourced, mainly for time series data, it is based on the curve fitting technique in the Bayesian model. Prophets has excellent processing ability for predicting highly seasonal data with long-term non-stationary rends or for missing data[22]. Facebook Prophet performs well in long-term stock prediction such as monthly and yearly[23]. It can smoothly deal with missing or outlier data, variation in trends, so it is regarded as an easily usable and interpretable model in time series forecasting problems. (This model is used with daily data)

4 The proposed schema

The prediction process starts from acquiring the price dataset for BTC and ETH. Then I trained models, predicted the close price and lastly compared the performance of the models using RMSE, MAE. Fig.1 presents the system architecture of the proposed system.

4.1 Data Description

The analyzed dataset was collected from two popular certified kaggle dataset[24][25]. They provide BTC and ETH price data. The recorded prices in the dataset were collected on a minute basis from 29 April 2019 to 29 April 2022. In this research, I used time-series data with 1578239 records respectively. Table 1 illustrates the dataset specification and Figure 5 shows sample data from Bitcoin dataset.The plot of log of prices(in USD) vs. date can be seen in Figure 9.

Variable Name	Variable Description	Data type
Date	Date of Observation	Datetime
Open	Initial price over 1-min interval	Number
High	Highest price over 1-min interval	Number
Low	Lowest price over 1-min interval	Number
Close	Final price over 1-min interval	Number
Volume	Volume of the currency transacted over 1-min interval	Number

Table 1: Dataset Specification

	Unix Timestamp	Date	Symbol	Open	High	Low	Close	Volume
0	1417411980	2014-12-01 05:33:00+00:00	BTC-USD	300.0	300.0	300.0	300.0	0.010000
1	1417412400	2014-12-01 05:40:00+00:00	BTC-USD	300.0	300.0	300.0	300.0	0.010000
2	1417415040	2014-12-01 06:24:00+00:00	BTC-USD	370.0	370.0	370.0	370.0	0.010000
3	1417416600	2014-12-01 06:50:00+00:00	BTC-USD	370.0	370.0	370.0	370.0	0.026556
4	1417498140	2014-12-02 05:29:00+00:00	BTC-USD	377.0	377.0	377.0	377.0	0.010000

Figure 5: Sample data from Bitcoin dataset

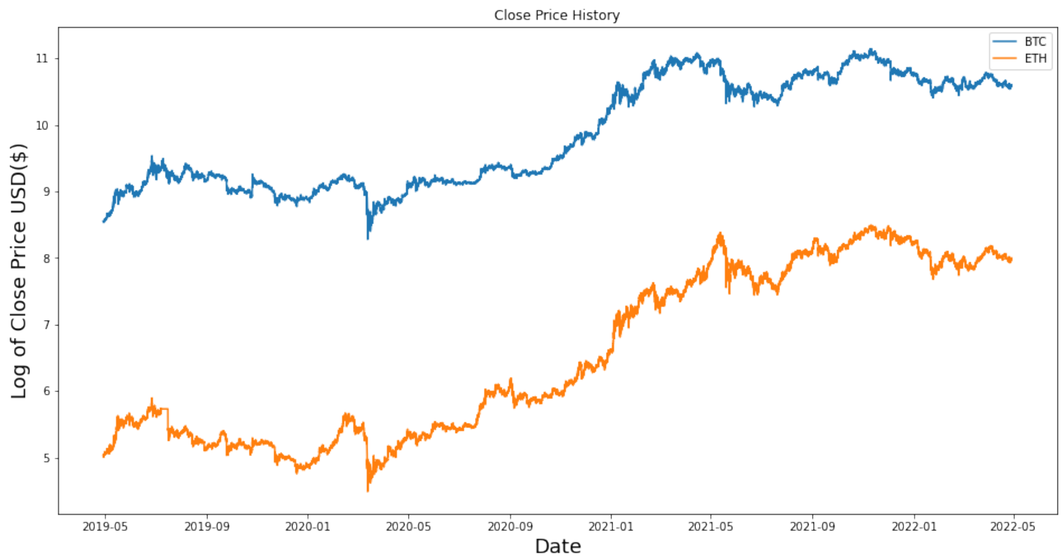

Figure 6: log of BTC and ETH prices(in USD) vs. date

4.2 Exploratory Data Analysis

First, I investigated the correlation values in the BTC data which can be used to review the data independence between various variables, Figure 7 is a heatmap reveals how much variable is correlated to every individual variable. It shows that all variables have either prefect positive linear correlation or no linear correlation with close price, that means the close price can be retained for the prediction task.

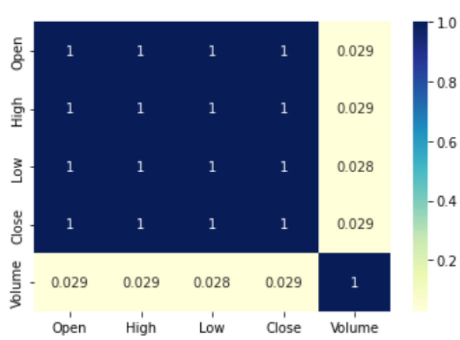

Figure 7: correlation heatmap of BTC raw data

Secondly, I applied moving average to take the average of close price history with some time frame. In real world finance data, the price does increase/decrease for some unexpected reasons, to get the figure that can represent the average price, I used moving average to smooth out price history by filtering out the noise from random-price fluctuations. It can help identify trend direction and determine support and resistant levels.

The exponential moving average of BTC price is shown in figure 8. Comparing to simple moving average, exponential moving average applies more weighting to the most recent prices. In the windows size of 30 and 100, the price from May 2020 to May 2021 is significantly above the moving average line, the BTC price is considered up. However, the relative position of the moving average line to the actual price during May 2021 and April 2022 was constantly fluctuating, which means there is not a stable up/down trend.

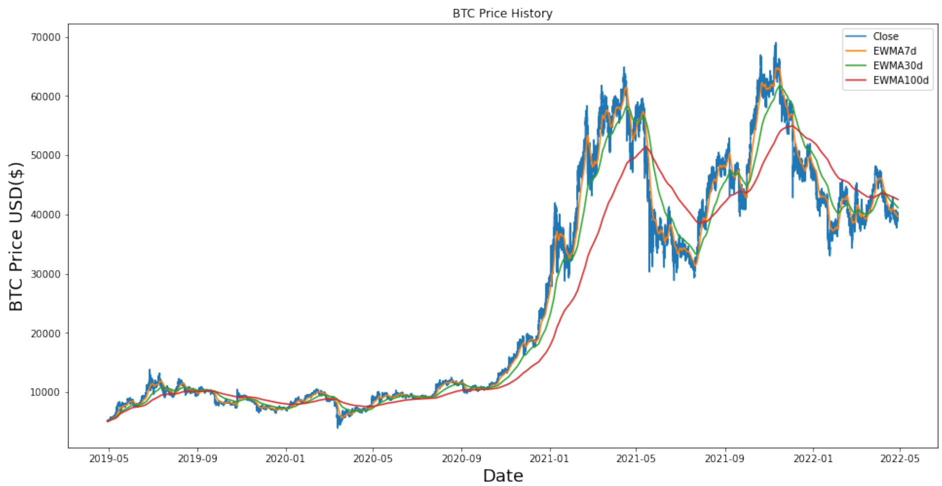

Figure 8: BTC moving average close price in different window sizes vs. date

Lastly, for higher volatility of crypto market compared with stock market, I also applied the log return of BTC price to identify the volatility and determine available models. Figure 8 shows the log return of BTC price over 10 minuetes from September 2020 to April 2022. It shows that Large price rises and falls usually occur at the same time range, and the largest increase is 10.8% and the largest fall is -13.82%.

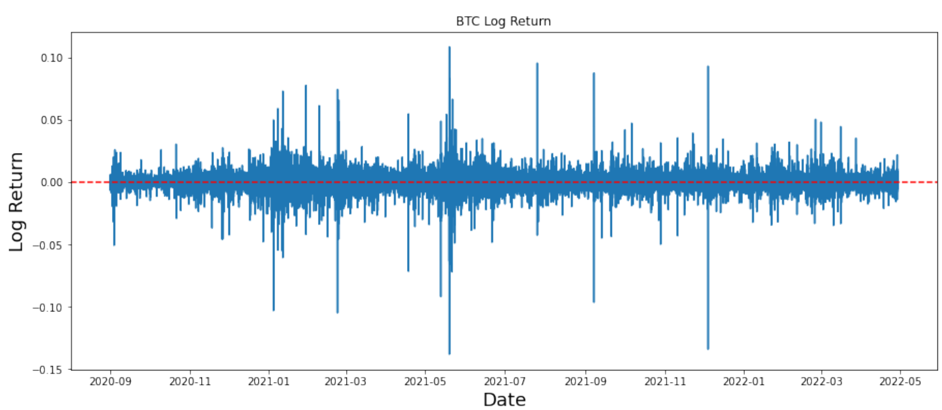

Figure 9: log return of BTC price over 10 min vs. date

4.3 Data Prepossessing

The datasets are min-max normalized to range 0 to 1 in the neural network models, i.e., LSTM, Bi-LSTM and GRU, the calculation formula is:

$$x_{scaled} = \frac{x - min(x)}{max(x) - min(x)}, \tag{7}$$

And in other models I used the unnormalized datasets. In train/test split step, 5-fold time series cross validation was applied, unlike standard cross validation methods, successive training sets are supersets of those that come before them. It avoids the testing set occurring before the training data, and the gap in the training series. In this research, the test size was set as $\frac{\#ofsamples}{\#offolds+1}$. The train/test split process of 5-fold time series split is shown in figure 10. For those missing values in the datasets, I used forward fill(ffill) method to fill them, it would propagate last valid observation forward.

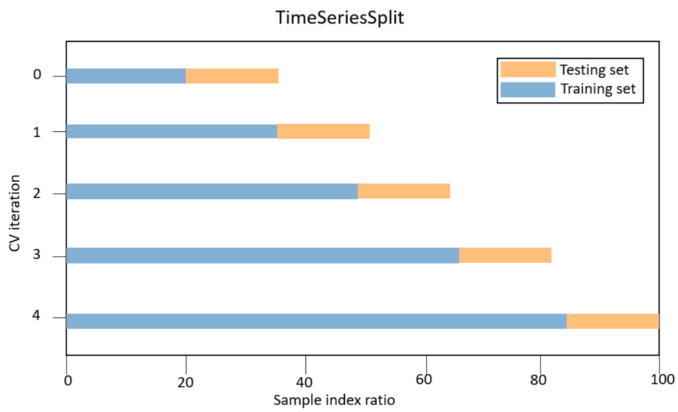

Figure 10: 5-fold time series split

4.4 Model Design

In the experiment, LSTM, Bi-LSTM, LSTM+T2V, GRU, XGBoost, ARIMA, FBProphet are used to compare. The last two models are only used to predict daily prices due to lack of GPU version. In all remain neural network models, I set the $batchsize = 256, epoch = 50$, and the window size was set as 10, which means I trained the model with the previous data of the past 10 minutes to forecast the price of the 11th minute. In the tuning process, I used Optuna to optimize some parameters(number of layers, number of units, dropout rate, learning rate, etc.). Instead of usual grid search or Bayesian search in parameters tuning, Optuna uses TPE Estimator which is an iterative process that uses history of evaluated hyperparameters to create probabilistic model. Table 2 and 3 shows the model parameters used by neural networks to forecast the close price of BTC and ETH separately. Except for the neural network models, the parameters of XGBoost model for predicting BTC is: $n\_estimators : 600, max\_depth : 10, min\_child\_weight : 1, gamma : 1, reg\_lambda : 0.1$, and for ETH it is: $n\_estimators : 500, max\_depth : 8, min\_child\_weight : 5, gamma : 0.4, reg\_lambda : 3$.

Model	Learning Rate	Type of Layers	Number of Layers	Number of units	Dropout Rate
LSTM	0.0001	LSTM	1	50	0
		LSTM	1	20	0.1
Bi-LSTM	0.001	Bi-LSTM	1	20	0.05
		Bi-LSTM	1	50	0.05
T2V+LSTM	0.001	T2V	1	64	
		LSTM	1	50	0.05
GRU	0.001	GRU	2	50	0
		GRU	1	50	0.05

Table 2: Parameters in DL models for BTC

Model	Learning Rate	Type of Layers	Number of Layers	Number of units	Dropout Rate
LSTM	0.0001	LSTM	1	50	0
		LSTM	1	30	0
Bi-LSTM	0.0004	Bi-LSTM	2	30	0.05
		Bi-LSTM	1	50	0.1
T2V+LSTM	0.001	T2V	1	128	0
		LSTM	1	50	0
GRU	0.001	GRU	1	50	0
		GRU	1	50	0.05

Table 3: Parameters in DL models for ETH

4.5 Evaluation Metrics

The trained models are evaluated on the basis of the following metrics, root-mean-square error(RMSE), mean absolute error(MAE) are used to evaluate the preformance of the models. MAE and RMSE measure the degree of deviation of the predicted value from the true value. Generally, the smaller the MAE and RMSE, the higher the accuracy of the prediction. The greater difference between them, the greater the variance in the individual errors in the sample, while if they are the same, then all the errors are of the same magnitude. The formulations for the same are presented below,

$$RMSE = \sqrt{\frac{1}{n}\sum_{n}^{i=1}(y^{(i)} - \hat{y}^{(i)})^2}, \tag{8}$$

$$MAE = \frac{1}{n}\sum_{n}^{i=1}\left|y^{(i)} - \hat{y}^{(i)}\right|, \tag{9}$$

y is the predicted true value and $\hat{y}$ is the predicted value.

5 Performance Evaluation and Discussion

All experiments were conducted on a workstation equipped with an AMD Ryzen 9 5900HS CPU, 16 GB of main memory, and an NVIDIA GeForce RTX 3060 GPU with 12 GB memory. The host operating system was the Windows 11 and all prediction models were implemented using Python 3 and the Keras 2.9.0 deep learning library[26]. For every deep learning-based prediction model, the number of epochs was 50 and the batch size was set to 256. All measurements were averaged over 5 sample runs.

In table 4 shows the comparison between the Bitcoin and Ethereum price predicted by different models and the true price, respectively. It can be seen that T2V+LSTM performs best in not only prediction accuracy but also time complexity. Adding time2vec, the prediction error of lstm in BTC price is reduced by 42% and 44% from mae and rmse, respectively. What is more noteworthy is that the introduction of time2vec reduces the number of lstm layers required, which leads to 90% reduction in training time. While LSTM performs the best in terms of RMSE when predicting the price of ETH, a crypto currency having relatively small value. The results of Bi-LSTM and XGBoost are far worse than other models.

6 Conclusion

As previously presented, this paper uses machine learning technology to predict the price of Bitcoin. Different from traditional research, this research applied time2vec, embedded it into lstm, and compared it with some common models. It was discovered that time2vec has great benefits in helping other

Model	Currency	MAE	RMSE	Training Time
LSTM	BTC	438.02	336.95	46m 50s
	ETH	16.84	**10.86**	45m 50s
Bi-LSTM	BTC	3264.71	1587.54	1h 19m 17s
	ETH	261.02	271.40	2h 8m 31s
T2V+LSTM	BTC	**257.46**	**190.61**	32m 20s
	ETH	**9.98**	22.98	**5m 4s**
GRU	BTC	577.04	523.02	1h 4m 56s
	ETH	54.09	50.85	37m 56s
XGBoost	BTC	3450.01	2342.52	**12m 27s**
	ETH	338.24	264.34	5m 14s

Table 4: Results of neural network models for 10-min prediction window

models improve in crypto currency price prediction. Some models take time over ten minutes to train, such as Bi-LSTM, GRU, they might not be suitable for high-frequency prediction, but the LSTM+T2V model for ETH satisfies the time limitation. In addition, the scale of our data is much larger than previous studies. And with Optuna, the performance of each model was further improved. Besides, in previous researches, Bi-LSTM mostly performed well, but in this research, under the background of using high-frequency large-scale data, the performance of bi-lstm dropped sharply.

There are still some details to be improved in this paper, which need to be further studied. The future work can be divided into

1. Except for the price history, It can be can be looked into more factors that influence cryptocurrency prices, e.g. macroeconomic variables, investor's attention. Especially, some natural language processing and sentiment analysis might bring some boost.

2. Some models applied on time series data should be further included for comparison, but the operating efficiency of the model and whether it can be trained using GPU need to be cared.

References

[1] S. Corbet, B. Lucey, A. Urquhart, and L. Yarovaya, "Cryptocurrencies as a financial asset: A systematic analysis," *International Review of Financial Analysis*, vol. 62, pp. 182–199, 2019.

[2] Coinmarketcap, *Cryptocurrency market capitalizations — coinmarketcap*, 2022. [Online]. Available: https://coinmarketcap.com/.

[3] S. R. Kim, "How the cryptocurrency market is connected to the financial market," *Available at SSRN 4106815*, 2022.

[4] M. A. Ammer and T. H. Aldhyani, "Deep learning algorithm to predict cryptocurrency fluctuation prices: Increasing investment awareness," *Electronics*, vol. 11, no. 15, p. 2349, 2022.

[5] D. Kumar and S. Rath, "Predicting the trends of price for ethereum using deep learning techniques," in *Artificial Intelligence and Evolutionary Computations in Engineering Systems*, Springer, 2020, pp. 103–114.

[6] A. A. Oyedele, A. O. Ajayi, L. O. Oyedelec, S. A. Bello, and K. O. Jimoh, "Performance evaluation of deep learning and boosted trees for cryptocurrency closing price prediction," *Expert Systems with Applications*, p. 119 233, 2022.

[7] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2019.

[8] I. Madan, S. Saluja, and A. Zhao, "Automated bitcoin trading via machine learning algorithms," *URL: http://cs229. stanford. edu/proj2014/Isaac% 20Madan*, vol. 20, 2015.

[9] H. Jang and J. Lee, "An empirical study on modeling and prediction of bitcoin prices with bayesian neural networks based on blockchain information," *Ieee Access*, vol. 6, pp. 5427–5437, 2017.

[10] A. Garlapati, D. R. Krishna, K. Garlapati, U. Rahul, G. Narayanan, *et al.*, "Stock price prediction using facebook prophet and arima models," in *2021 6th International Conference for Convergence in Technology (I2CT)*, IEEE, 2021, pp. 1–7.

[11] P. T. Yamak, L. Yujian, and P. K. Gadosey, "A comparison between arima, lstm, and gru for time series forecasting," in *Proceedings of the 2019 2nd International Conference on Algorithms, Computing and Artificial Intelligence*, 2019, pp. 49–55.

[12] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, "Stochastic neural networks for cryptocurrency price prediction," *Ieee access*, vol. 8, pp. 82 804–82 818, 2020.

[13] S. Ji, J. Kim, and H. Im, "A comparative study of bitcoin price prediction using deep learning," *Mathematics*, vol. 7, no. 10, p. 898, 2019.

[14] Y. Li and W. Dai, "Bitcoin price forecasting method based on cnn-lstm hybrid neural network model," *The journal of engineering*, vol. 2020, no. 13, pp. 344–347, 2020.

[15] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar, "A deep learning-based cryptocurrency price prediction scheme for financial institutions," *Journal of information security and applications*, vol. 55, p. 102 583, 2020.

[16] H. Wang, J. Wang, L. Cao, Y. Li, Q. Sun, and J. Wang, "A stock closing price prediction model based on cnn-bislstm," *Complexity*, vol. 2021, 2021.

[17] L. Tian, L. Feng, L. Yang, and Y. Guo, "Stock price prediction based on lstm and lightgbm hybrid model," *The Journal of Supercomputing*, vol. 78, no. 9, pp. 11 768–11 793, 2022.

[18] E. Pintelas, I. E. Livieris, S. Stavroyiannis, T. Kotsilieris, and P. Pintelas, "Investigating the problem of cryptocurrency price prediction: A deep learning approach," in *Artificial Intelligence Applications and Innovations*, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., Cham: Springer International Publishing, 2020, pp. 99–110.

[19] M. J. Hamayel and A. Y. Owda, "A novel cryptocurrency price prediction model using gru, lstm and bi-lstm machine learning algorithms," *AI*, vol. 2, no. 4, pp. 477–496, 2021, ISSN: 2673-2688. DOI: 10.3390/ai2040030. [Online]. Available: https://www.mdpi.com/2673-2688/2/4/30.

[20] M. Khashei and Z. Hajirahimi, "A comparative study of series arima/mlp hybrid models for stock price forecasting," *Communications in Statistics-Simulation and Computation*, vol. 48, no. 9, pp. 2625–2640, 2019.

[21] P.-F. Pai and C.-S. Lin, "A hybrid arima and support vector machines model in stock price forecasting," *Omega*, vol. 33, no. 6, pp. 497–505, 2005.

[22] W.-X. Fang, P.-C. Lan, W.-R. Lin, H.-C. Chang, H.-Y. Chang, and Y.-H. Wang, "Combine facebook prophet and lstm with bpnn forecasting financial markets: The morgan taiwan index," in *2019 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, IEEE, 2019, pp. 1–2.

[23] B. K. Jha and S. Pande, "Time series forecasting model for supermarket sales using fb-prophet," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, IEEE, 2021, pp. 547–554.

[24] Zielak, *Bitcoin historical data*, Apr. 2021. [Online]. Available: https://www.kaggle.com/datasets/mczielinski/bitcoin-historical-data.

[25] P. Kottarathil, *Ethereum historical dataset*, Apr. 2020. [Online]. Available: https://www.kaggle.com/datasets/prasoonkottarathil/ethereum-historical-dataset?select=ETH_1min.csv.

[26] K. Team, *Simple. flexible. powerful.* [Online]. Available: https://keras.io/.