A New Forecasting Framework for Bitcoin Price with LSTM

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***Abstract*—Long short-term memory (LSTM) networks are a state-of-the-art sequence learning in deep learning for time series forecasting. However, less study applied to financial time series forecasting especially in cryptocurrency prediction. Therefore, we propose a new forecasting framework with LSTM model to forecasting bitcoin daily price with two various LSTM models (conventional LSTM model and LSTM with AR(2) model). The performance of the proposed models are evaluated using daily bitcoin price data during 2018/1/1 to 2018/7/28 in total 208 records. The results confirmed the excellent forecasting accuracy of the proposed model with AR(2). The test mean squared error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) for bitcoin price prediction, respectively. The our proposed LSTM with AR(2) model outperformed than conventional LSTM model. The contribution of this study is providing a new forecasting framework for bitcoin price prediction can overcome and improve the problem of input variables selection in LSTM without strict assumptions of data assumption. The results revealed its possible applicability in various cryptocurrencies prediction, industry instances such as medical data or financial time-series data.**

Keywords—cryptocurrency prediction, Bitcoin, long short-term memory (LSTM)

I. INTRODUCTION

Bitcoin was launched in 2008 by an anonymous author under the name of Satoshi Nakamoto as a means of transacting among participants without the need for intermediaries. After that, cryptocurrency (or virtual currency) has become the main choice target for speculators and investors, and hope to benefit from the transaction. But, cryptocurrencies have the characteristics of skyrocketing and sudden fall, for the Bitcoin price between August 1, 2017 and July 31, 2018, from US$2,735.59 (August 1, 2017) to the highest price US$19,343.04 (up 607.09% , December 16, 2017), then fell to US$7,726.89 (down 60.05%, July 31, 2018); the coefficient of variance (CV) for the whole year was as high as 0.41458, and the Trade Weighted US Dollar Index for the same period (DTWEXM) is only 0.01750, S&P 500 is 0.04192, and the price of gold is 0.02526, indicating the high volatility of Bitcoin price. Therefore, cryptocurrency traders are very much looking forward to a method to accurately predict the price trend.

Regarding the study of cryptocurrency price fluctuations and forecasts, [1] divides the factors affecting cryptocurrency prices into internal and external factors. There are three external factors: cryptomarket: attractiveness (popularity), market trend, speculations, macro-financial: stock markets, exchange rate, gold price, interest rate, others, political: legalization (adaptation), restrictions (ban), others, external The factors are mainly: supply & demand: transaction cost (PoW / PoS), reward system, mining difficulty (Hash Rate), coins circulation, and forks (rule changes). Yhlas SOVBETOV (2018) [2] states that crypto market-related factors such as market beta, trading volume, and volatility appear to be significant determinant for all five cryptocurrencies (Bitcoin, Ethereum, Dash, Litecoin, and Monero) both in short- and long- Run and shows the high volatility of Bitcoin prices. The studies show that there are many factors influence the trend of cryptocurrency price, and it is difficult to grasp. To build a cryptocurrency price forecasting mechanism is important for potential investors and government agencies.

Cryptocurrency depends on a digital bookkeeping system called Blockchain. Blockchain systems offer ways to ensure privacy and security of the user data with the implementation of an access control mechanism[3]. A Blockchain is a decentralised linked data structure that is characterised by its inherent resistance to data modification, but it is deficient in search queries primarily due to its inferior data formatting. M Muzammal, et al.(2019)[4] showcase ChainSQL, an open-source system developed by integrating the Blockchain with the database, i.e. they present a Blockchain database application platform that has the decentralised, distributed and audibility features of the Blockchain and quick query processing and well-designed data structure of the distributed databases. The currency is built on a decentralized peer-to-peer network, with currency members creating currency and transaction management, without central authority control. All Bitcoin transactions are posted in blocks to an open ledger called a Blockchain for miners to use encryption certificates. This verification takes place in a no-trust system, without the need for the intermediary to pass funds from the sender to the receiver. The emergence of cryptocurrency and actual trading is actually a time series forecasting problem. Due to its special nature and high volatility, it is different from traditional financial markets, so it provides an interesting topic for price forecasting.

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Time series prediction is not a new phenomenon. Forecasting time series data is an important subject in economics, business, and finance. Traditional time series prediction methods, there are several techniques to effectively forecast the next lag of time series data such as univariate Autoregressive (AR), univariate Moving Average (MA), Simple Exponential Smoothing (SES), and more notably Autoregressive Integrated Moving Average (ARIMA) with its many variations [5] . This type of methodology is more suitable for a task such as forecasting sales where seasonal effects are present. With the recent advancement in computational power of computers and more importantly developing more advanced machine learning algorithms and approaches such as deep learning, new algorithms are developed for forecasting time series data. Due to the lack of seasonality in the cryptocurrencies market and its high volatility, these methods are not very effective for this task. The recurrent neural network (RNN) and the long short-term memory (LSTM) favor of artificial neural networks are favored over the traditional multilayer perceptron (MLP) due to the temporal nature of the more advanced algorithms [6] . ARIMA Time Series Model and the LSTM Deep Learning Algorithm have been compared to estimate the future price of Bitcoin [7] , and show approximately MAPE 11.86% with ARIMA and MAPE 1.40% with LSTM. The artificial neural network prediction is capable of approximate capture of the actual log return distribution; more sophisticated methods, such as recurrent neural networks and LSTM techniques from deep learning may be necessary for higher prediction accuracy [8]. Therefore, this study attempts to construct a framework to predict Bitcoin price with LSTM.

II. LITERATURE REVIEW

A. Cryptocurrencies

Cryptocurrencies are new economic and financial tools with special and innovative features. The most important thing is that they are not related assets, not issued by any government or central authority, nor bring interest or dividends. However, cryptocurrencies are becoming more and more popular, and many merchants accept payments, especially online payments. Bitcoin continues to grow in market share [9]. Because Bitcoin has its special nature, coupled with large volatility, these factors provide a new research topic, such as exploring whether cryptocurrency is a commodity or currency? Is the cryptocurrency market an efficient market?

Baur, Dirk G.et al.(2015) [10] proposed a paper to explore whether Bitcoin is an asset or currency, what is its current usage and what usage will most likely prevail in the future given its characteristics? If Bitcoin is mainly used as a currency for goods and services, it will compete with legal tenders such as the US dollar, thereby affecting its value and ultimately affecting monetary policy. On the other hand, if it is mainly used as an investment, it will compete with other assets, such as government bonds, stocks and commodities, and may affect the financial system and financial stability. Whether it is money or assets, the potential to influence the overall economy depends on the success of Bitcoin or similar alternatives compared to existing monetary and financial assets. Some research conclusions are as follows:(i)The definition of an asset in the IASB's Conceptual Framework is"a present economic resource controlled by the entity as a result of past events." "An economic resource is a right that has the potential to produce economic benefits." Entities will need to assess whether each cryptocurrency held qualifies as an asset. (ii)[11] estimate that approximately 70% of all Bitcoins are in dormant accounts. This shows that most people see Bitcoin as an asset. Bitcoin has many similarities with gold. Supply is not regulated by government or other organizations. Bitcoin has no nationality and should be a global currency. Both Bitcoin and gold derive value from the fact that they are scarce and costly to mine. They do not generate any form of cash flow. But Bitcoin also has the characteristics of fiat currency, so(iii) Dyhrberg (2015) [12] concluded that Bitcoin is a bit between assets and currency.

It is important to determine the cryptocurrency behavior under the effective market theory to ensure that no speculators or investors can take advantage of and ensure fair competition and market prospects. Some research conclusions are as follows: (i) [9] concluded that the Bitcoin market is highly efficient and that market prices immediately respond to new information. (ii) [13] used statistical tests to test Bitcoin data and concluded that Bitcoin returns were inefficient. (iii) [14] show that the market efficiency assumptions of the Bitcoin and Litecoin markets are inconsistent with the weak efficiency form because the unit root test shows that the Bitcoin model is stationary . (iv) Previous studies also found mixed results, and there are some indications that the Bitcoin market is inefficient [15, 16].

The high volatility of Bitcoin is well-documented [17, 18]. Some research conclusions are as follows: (i) Econometric methods, especially the GARCH model, were applied to Bitcoin volatility estimates by [19]. (ii) A sentiment analysis based on user reviews using a computational intelligence approach for Bitcoin volatility prediction is applied [20]. (iii) Wavelet coherence analysis was used to analyze the main drivers of Bitcoin prices, such as China's demand [21]. (iv) Prior study discussed the predictability of Bitcoin returns and volatility based on transaction volume, finding out that in the quantile range of 0.25 to 0.75, i.e., extreme events excluded, volume is an important predictor variable [22].

B. Bitcoin price prediction methods

Relatively few studies have thus far been conducted on estimation or prediction of Bitcoin prices. Papers using research methods other than LSTM are summarized as follows:(i) Shah et al. (2014) [23] implemented a latent source model as developed by [24] to predict the price of Bitcoin by the method of Bayesian regression. The model received an impressive 89 percent return in 50 days with a Sharpe ratio of 4.1. (ii) Pavel Ciaian et al.(2015) [25] evaluates Bitcoin price formation based on a linear model by considering related information that is categorized into several factors of market forces, attractiveness for investors, and global macro-financial factors. They assume that the first and second factors mentioned above significantly influence Bitcoin prices but with variation over time. The same researchers limit the number of regressors to facilitate linear model analysis. (iii) Greaves et al. (2015) [26] analyzed the Bitcoin Blockchain to predict the price of Bitcoin using SVM and ANN. The author reported price direction accuracy of 55 percent with regular ANN. (iv) Kim et. al. (2016) [20] used cryptocurrency web communities data to extract sentiment and predict price fluctuations. (v) Hegazy and Mumford (2016) [27] compute an exponentially smoothed Bitcoin price every eight minutes; using the first five left derivatives of this price as features in a decision-tree based algorithm, they predict the direction of the next change in Bitcoin price with 57.11% accuracy.(vi) Past study [28] presents a Multi-Layer Perceptron (MLP)-based

Non-Linear Autoregressive with Exogeneous Inputs (NARX) Bitcoin price forecasting model to demonstrated the ability of the model to predict Bitcoin price accurately while passing all model validation tests.

Papers using LSTM are summarized as follows:(i) To study the ability to make the short-term prediction of the exchange price fluctuations (measured with volatility) towards the US dollar for the Bitcoin market, the experiments are performed to evaluate a variety of statistical and machine learning approach [29]. (ii) Prior study predicts the Bitcoin pricing process using machine learning techniques, such as RNNs and LSTM, and compare results with those obtained using ARIMA models [6]. (iii) Karakoyun, et al. (2018) [7] compared the ARIMA time series model with the LSTM deep learning algorithm for Bitcoin price prediction. The conclusions show that approximately MAPE 11.86% with ARIMA and MAPE 1.40% with LSTM.

Since LSTM is used to predict cryptocurrency prices is still in development. Therefore, constructing a framework for predicting Bitcoin prices using LSTM is valuable and contributing.

III. Methodology

A. Research flow

Traditional approaches for time series prediction use parametric statistical models, such as autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and vector autoregression, to find the best estimates (Box, Jenkins, Reinsel, & Ljung, 2015) [30]. Virtanen and Yli-Olli (1987)[31] estimated Finnish stock market index using six explanatory variables, including lagged index and macroeconomic factors through ARIMA-based econometric modeling. Figure 1 presents the research framework of this study. We design three models in this study. In the stage I, there are two ways. The first way is to calculate the ACF and PACF directly for the bitcoin price without considering the limitation of the time series method, and find the number of periods of price lag by its graphical features. The second way is that we use the traditional time series method to perform ADF unit root test on the bitcoin price. If they do not conform to the null hypothesis, then we repeat the above steps based on the difference in the original price series. If the price series conform to the stationarity assumption, then we use the autocorrelation function (ACF) and partial autocorrelation function (PACF) figure type to assess AR(p), MA(q) or ARIMA(p, d, q) Model. (p: The number of lag observations included in the model, also called the lag order. d: The number of times that the raw observations are differenced, also called the degree of differencing. q: The size of the moving average window, also called the order of moving average).

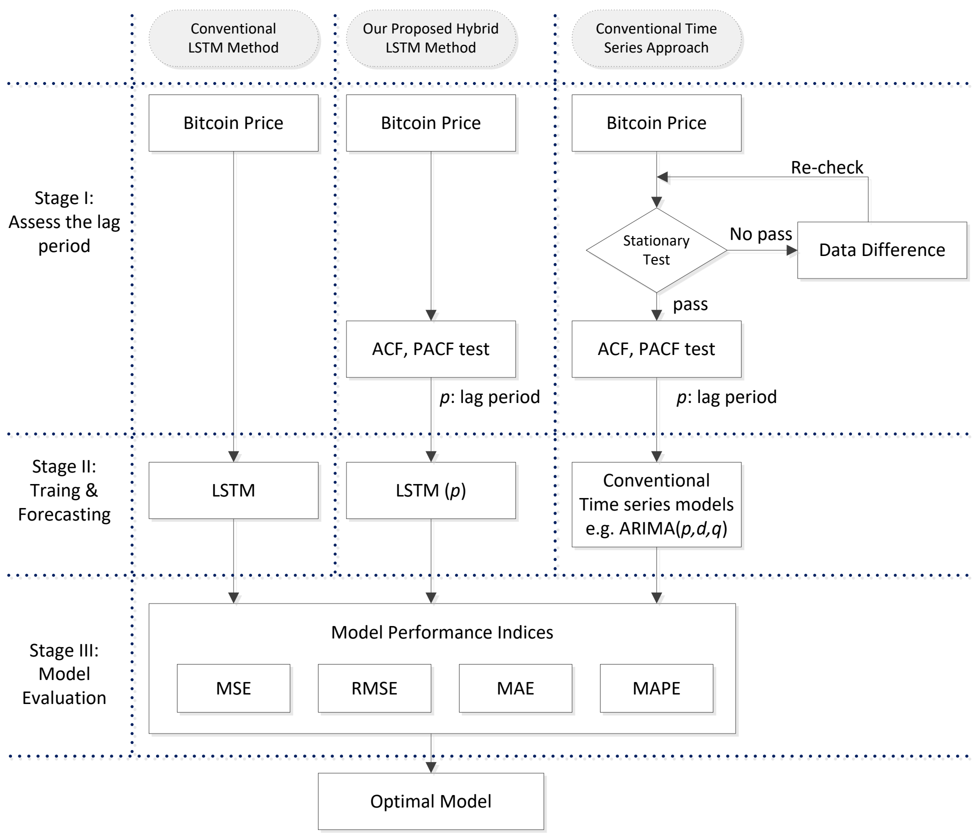

Fig. 1. Framework for bitcoin price prediction

The second stage is the demonstration of three models. The first model is conventional LSTM method that uses the original bitcoin closing price series and trade volumes directly for training and prediction with LSTM. The second model is our proposed hybrid LSTM method. The method first uses the ACF and PACF graphical features of the bitcoin price to find the p (price lag period) and q (moving averaging period), and the transaction volume as the predictive variables, and then use LSTM for training and prediction. The third model is the conventional time series method, which is based on the time series verification procedure described in stage 1, and is predicted by ARIMA or Transfer Function Method (TF). In the final stage, the prediction results of the three models are calculated respectively, such as MSE, RMSE, MAE and MAPE, to evaluate the three models, which have better predictive ability.

B. Augmented Dickey–Fuller (ADF) Test

In this section, the tests pertaining to the Bitcoin closing prices time series data are discussed. Further, this study uses the ARIMA(*p, d, q*) model to construct an empirical model.

If a time series is nonstationary, meaning it has unit roots, it must undergo difference in order to become stationary and be estimated and analyzed statistically. This study uses the augmented Dickey–Fuller (ADF) test to evaluate whether the Bitcoin closing prices time series data are stationary. The null hypothesis of the ADF test has a unit root; thus, the results of the test reject the null hypothesis, thereby confirming that the data are stationary. The three forms of the ADF test are as follows:

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \quad (1)$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \quad (2)$$

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \quad (3)$$

Eq. (1) has both an intercept item and a time trend item. (2) has an intercept item, but no time trend item. (3) has neither an intercept item nor a time trend item. p indicates that the residual item conforms to the optimal lag length with no sequence connections and is selected based on the minimum value of the Akaike information criterion (AIC) or Schwarz criterion (SC). The null hypothesis of these three models is $H_0 : \gamma = 0$. If the test result γ is not significantly different from 0, this variable is not a stationary time series. Then we use the ACF and PACF figure type to assess AR(p), MA(q) or ARIMA(p, d, q) Model.

C. Long short-term memory network (LSTM)

The LSTM networks are composed of an input layer, one or more hidden layers, and an output layer. The structure of LSTM memory cell is illustrated in Fig. 2 [32-34]. Each of the memory cell in LSTM network has three types of gates—the forget gate, the input gate, and the output gate to maintain and adjust its cell state S_t. 1. The forget gate f_t defines which information is deleted from the memory (cell state). 2. The input gate i_t specifies which information is added to the memory (cell state). 3.The output gate O_t specifies which information from the memory (cell state) to be used as output information [34]. At every time step *t*, LSTM decide what information will remove from the cell state through the decision by a transformation function (*sigmoid* or *tanh*) in the forget gate layer. The input $\boldsymbol{x}_t$ and its output h_{t-1} of the memory cells at the previous time step *t-1* and then outputs a number between 0 and 1 for each number in the cell state C_{t-1}. The number 1 denotes "completely keep this" while a 0 denotes "complete get rid of this" [33, 34].

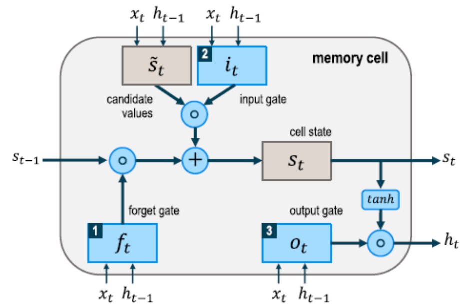

Fig. 2. Structure of LSTM [32-34]

1. The forget gate f_t defines which information is deleted from the memory (cell state).
2. The input gate i_t specifies which information is added to the memory (cell state).
3. The output gate O_t specifies which information from the memory (cell state) to be used as output information.

D. Performance evaluation indicators

This study uses the mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE) to evaluate the different performance indicators and develop a precise evaluation equation:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(Bit_t - Bit_t')^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Bit_t - Bit_t')^2} \quad (5)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|Bit_t - Bit_t'| \quad (6)$$

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{Bit_t - Bit_t'}{Bit_t}\right| \quad (7)$$

where Bit_t is the actual price of the Bitcoin, Bit_t' is the predicted price of the Bitcoin, and T is the predictive period number.

IV. Data Analysis

This study collected bitcoin daily price and transaction volume data from 2018/1/1 to 2018/7/28 on investing.com. The empirical data has total 209 data. Figure 3 shows that the bitcoin closing price reached a record high at 2018/01/06. A bitcoin value was as high as \$17,172.3, but then continued to fall sharply. It fell to 5,883.5 at 6/28 in the same year, and fell by 65.7% in about half a year. In addition, the figure 4 also shows that the volatility of bitcoin prices change rate is very large.

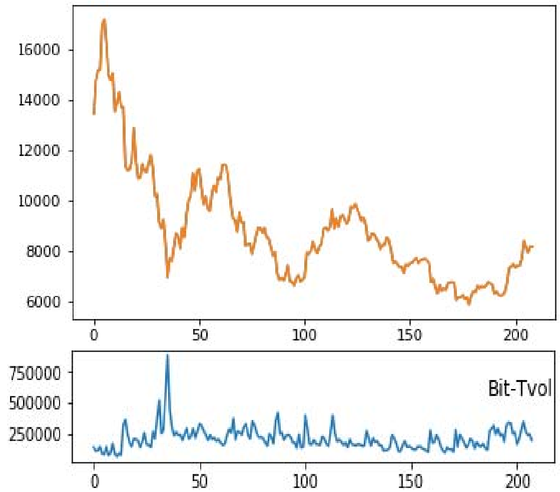

Fig 3. Trend of bitcoin price and trade volume in this study

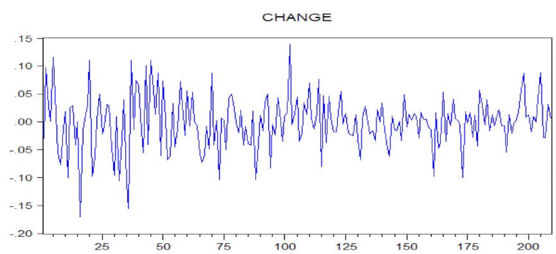

Fig 4. Bitcoin price change rate in 2018/1/1-2018/7/28

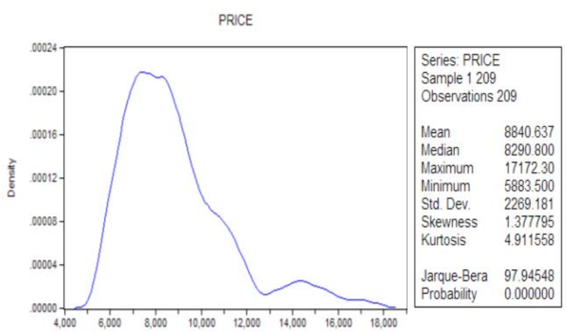

Fig 5. Kernel density curve of Bitcoin price

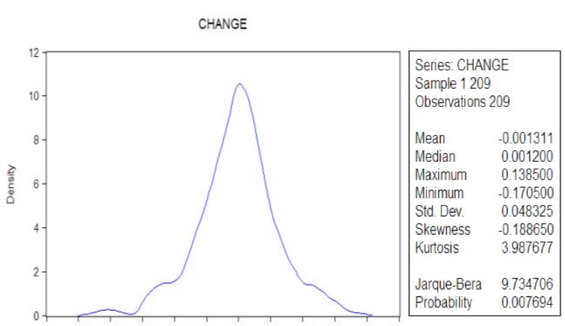

Fig 6. Kernel density curve of Bitcoin price change rate

As shown in Figure 5, the mean closing price of Bitcoin is \$8840.64, the standard deviation is \$2269.18, and the skewness and kurtosis are 1.378 and 4.912, respectively. The observed sequence data distribution shows a high kurtosis and a right-skewness pattern. In Figure 6 shown the mean value of the price change rate is close to 0, the standard deviation is 0.048, and the skewness and kurtosis are -0.189 and 3.988, respectively. There is also a high kurtosis, and both Jarqe-Bera tests are significant, indicating that they are not normal distribution. These characteristics are the same as most financial products.

A. Unit root test

This study employs the frequently used ADF method to conduct the unit root test. The original data of Bitcoin close price sequence do not reject the null hypothesis, implying that Bitcoin close price sequence has unit roots and nonstationary (t-statistic: -2.209, p-value: 0.204). Thus, after Bitcoin price difference (Fig. 7), we use the ADF test to evaluate the data. The test results reject the null hypothesis after Bitcoin price difference and show that the data are stationary (t-statistic: -14.999, p-value: 0.000**** at 1% significant level).

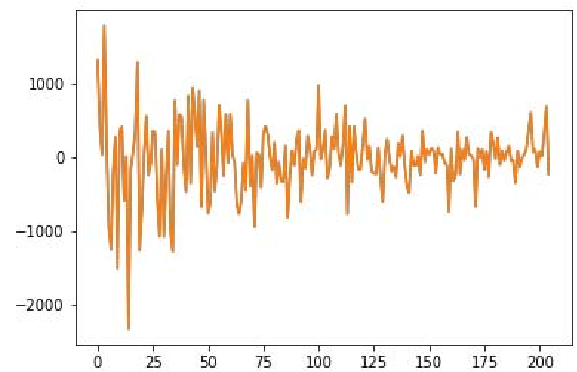

Fig. 7. Bitcoin price (Difference)

B. ACF & PACF

The ACF and PACF of the raw bitcoin closing price are shown in Fig. 8(A) and 8(B). The ACF graph shows a tail-off pattern, and the PACF graph finds that both lag 1 and lag 2 are significant. This result can be It is obvious that the raw series of the bitcoin closing price is AR(2) model. However, according to the conventional time series method, after the ADF test result in the previous section, the raw closing price of Bitcoin has a unit root, which is a non-stationary series. The ACF and PACF of the bitcoin closing price difference (d=1) are shown in Fig. 9(A) and 9(B). Both graphs show no significant lag period, and the series after the closing price difference cannot evaluate the number of periods of p and q, that is, the ARIMA(p, d, q) model cannot be formed. This result shows that the conventional time series method has some limitations for prediction.

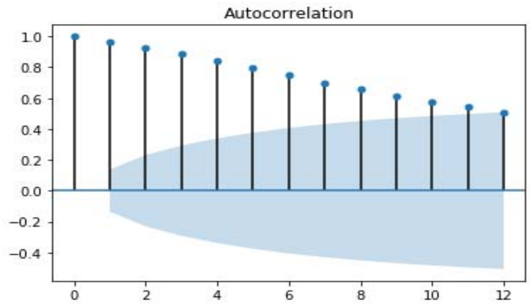

Fig 8 (A). The ACF of Bitcoin Price

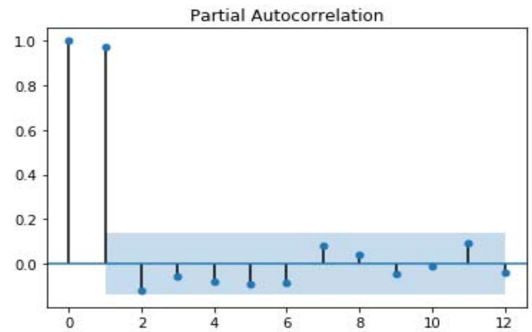

Fig 8 (B). The PACF of Bitcoin Price

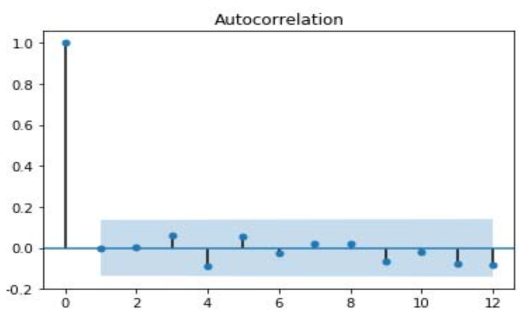

Fig 9 (A). The ACF of Bitcoin Price Difference(d=1)

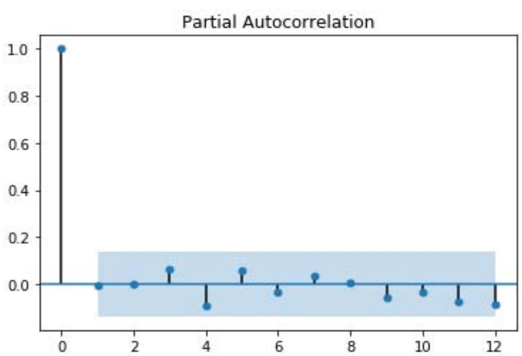

Fig 9 (B). The PACF of Bitcoin Price Difference(d=1)

C. *The results of each model prediction*

Since the series after the bitcoin price difference cannot establish the predicted model (model 3) through the conventional time series method, only the prediction results of model 1 and model 2 will be discussed later. The prediction model 1 and model 2 using LSTM in this study are Equation (8) and Equation (9), respectively.

LSTM

Model 1:

$$Bitcoin\ close\ price_t = \beta_0 + \beta_1 \times Bitcoin\ close\ price_{t-1} + \beta_2 \times Bitcoin\ volume_{t-1} + \varepsilon_t \quad (8)$$

Model 2 (AR(2) model)

$$Bitcoin\ close\ price_t = \beta_0 + \beta_1 \times Bitcoin\ close\ price_{t-1} + \beta_2 \times Bitcoin\ close\ price_{t-2} + \beta_3 \times Bitcoin\ volume_{t-1} + \varepsilon_t \quad (9)$$

D. *LSTM model setting*

We set LSTM model has 1000 neurons, 1 dense layer with linear activation function, and loss function is mean absolute error with 'adam' optimizer algorithm. This study used 66% samples (138 records) to train our LSTM model and then validated on 34% samples (71 records) in total 209 samples (under 300 epches and 72 batch size).

E. *The results of prediction*

The results of Model 1 and Model 2 for predicting the closing price of the 71 days Bitcoin are shown in Fig. 10(A) and 10(B), respectively. It can be seen from the two figures that the predicted values of the two models are close to the actual values, and the trend direction of the changes are also highly consistent. The diagnostic line plot based on loss function history of two LSTM models in training and testing are shown in Fig. 11(A) and 11(B). The results showed the train and validation loss meeting and revealed a good fit for our LSTM model. Based on loss function history of model, the forecasting error remain a stable status after 100 epches.

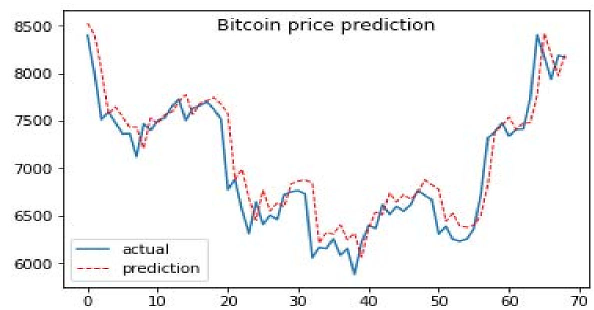

Fig. 10(A). Model 1 prediction result

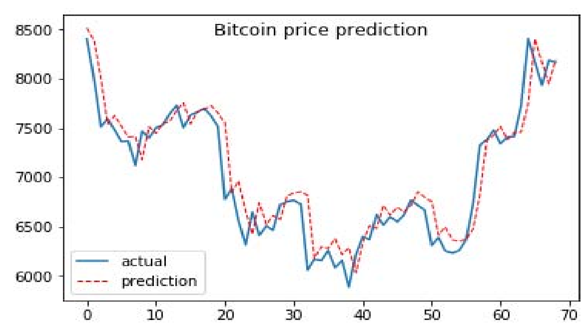

Fig. 10(B). Model 2 prediction result

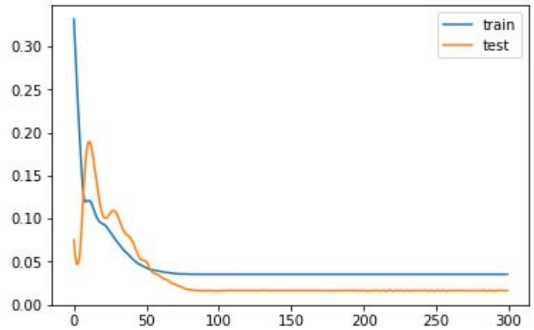

Fig. 11(A). loss function history of Model 1 in train & test

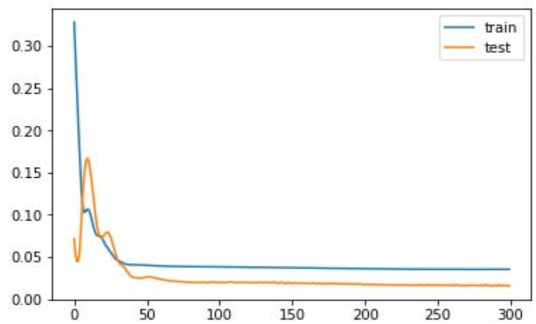

Fig. 11(B). loss function history of Model 2 in train & test

Table 1 shows that the two models prediction results respectively calculate MSE, RMSE, MAE, and MAPE evaluation indicators. The four evaluation index values of model 2 are smaller than the values of model 1. It also proves that our proposed hybrid LSTM method has better predictive power than conventional LSTM.

TABLE 1. EVALUATION OF LSTM MODEL FOR BITCOIN PREDICTION

	MSE	*RMSE*	*MAE*	*MAPE*
Model 1	65744.33	256.41	186.12	2.701
Model 2	61170.21	247.33	176.37	2.553
Prediction error	↓ 4574.12	↓ 9.08	↓ 9.75	↓ 0.15

V. Conclusion

The major contribution of this study described as below. First, our proposed LSTM forecasting framework can overcome and improve the problem of input variables selection in LSTM. The selection of input variables into conventional LSTM forecasting model need researchers' domain knowledge and trial-and-error to determine the optimal selection of input variables. Our proposed approach and help researcher determine optimal input variables for building LSTM time series forecasting model without trial-and-error process. Second, our framework based on LSTM model with time series techniques can build an efficient time series prediction model without strict assumptions of data distribution.

Traditional time series methods are often used to explore many topics of financial products, including ARIMA, autoregressive conditional heteroskedasticity (ARCH) model, generalized autoregressive conditional heteroskedasticity (GARCH) model-family, etc. to predict the price of financial products (rate of return). ARCH model or GARCH model-family to explore volatility asymmetry and clustering, but this type of method is subject to the limitations of many statistical assumptions. In the recent rapid development of AI methods, the LSTM network is the most advanced sequence learning in time series prediction deep learning. However, less research has been applied to financial time series prediction in cryptocurrency prediction.

In our study, the bitcoin price during the sample period is a non-stationary time series, and the difference sequence cannot verify the specific type. Therefore, the appropriate ARIMA model cannot be found. We propose a new forecasting framework with LSTM model to forecasting bitcoin daily price with two various LSTM models (conventional LSTM model and LSTM with AR(2) model). The predicted values of the two models are close to the actual values, and the trend direction of the changes are also highly consistent. The two models prediction results respectively calculate MSE, RMSE, MAE, and MAPE evaluation indicators. The four evaluation index values of model 2 are smaller than the values of model 1. The results confirmed the excellent forecasting accuracy of the proposed model with AR(2). The contribution of this study is providing a new forecasting framework for bitcoin price prediction, and its applicability in various cryptocurrency prediction, industry instances such as medical data or financial time-series data.

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