Prediction of Bitcoin Exchange Rate to American Dollar Using Artificial Neural Network Methods

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***Abstract* – Cryptocurrency trade is now a popular type of investment. Cryptocurrency market has been treated similar to foreign exchange and stock market. However, because of its volatility, there's a need for a prediction tool for investors to help them consider investment decisions for cryptocurrency trade. Nowadays, Artificial Neural Network (ANN) computing based tools are commonly used in stock and foreign exchange market predictions. There has been much research about ANN predictor on stocks and foreign exchange as case studies but none on cryptocurrency. Therefore, this research studied variety of ANN method to predict the market value of one of the most used cryptocurrency, Bitcoin. The ANN methods will be used to develop model to predict the close value of Bitcoin in the next day (next day prediction). This study compares four ANN methods, namely backpropagation neural network (BPNN), genetic algorithm neural network (GANN), genetic algorithm backpropagation neural network (GABPNN), and neuro-evolution of augmenting topologies (NEAT). The methods are evaluated based on accuracy and complexity. The result of the experiment showed that BPNN is the best method with MAPE 1.998 ± 0.038 % and training time 347 ± 63 seconds.**

Keywords – cryptocurrency; bitcoin; prediction; artificial neural network (ANN)

I. Introduction

The rapid growth of information technology has significantly affected many sectors including finance. Digitalization of financial products and process is not uncommon these days. Cryptocurrencies as one of digitalization in finance are becoming more and more popular [1].

One of the most popular cryptocurrencies in the world is Bitcoin. Bitcoin is a decentralized digital currency which appeared in 2009 [2]. Decentralized means that Bitcoin is not regulated by any party and applied as a form of peer to peer payment. Bitcoin supply is also limited, this is because of the nature of cryptocurrency itself. Other than that, Bitcoin is independent to other commodities in the world market.

The characteristics of Bitcoin have made Bitcoin demand to keep rising in the last few years. The rising demands have made Bitcoin exchange rate to American Dollar (USD) to reach an all time of $3000 USD on June 2017[1]. Even though it can have high value, the daily price fluctuations could reach 4.61%[2]. Therefore, it is important to be able to predict bitcoin value to ensure profitable investment.

Nowadays, Bitcoin is popularly used as an investment product in which people trade Bitcoin as they trade in foreign exchange or stock market [3]. There are online Bitcoin trading platforms where people can buy and sell Bitcoins [4]. With Bitcoin as an investment product, investors are still using the same basic principle in investment, that is "buy low, sell high". With this principle in their hands, investors don't blindly invest without calculating the risks. One of the common methods to calculate investment risks is market technical analysis.

Market technical analysis basically identifies the trend of the market in certain period by using historical market price [5]. To aid the analysis, candle graphs and market technical indicators are used. Even though market technical analysis is useful, it requires expert to interpret the technical indicators. Therefore, another method that employs automation is needed. Machine learning provides capability to produce prediction model that can estimate trend more accurately without expert knowledge. In stock and forex domain, Artificial Neural Network (ANN) is one of the popular machine learning methods used to predict future trends [6].

ANN based machines have been proven to be better than conventional prediction methods such as ARIMA [7]. There's already quite a few research that studied ANN based method to predict market value, especially stock and foreign exchange market [8] [7] [9] [10]. There are 4 methods that have been proven to be accurate enough for those case studies, namely backpropagation trained neural network (BPNN) [7], Genetic algorithm trained neural network (GANN) [9], hybrid method between backpropagation and genetic (GABPNN) [11], and neuroevolution of augmenting topologies (NEAT) [8].

Among those four methods, NEAT has the best accuracy to predict stock market value [8]. Meanwhile, GABPNN has better accuracy compared to BPNN and GANN [9]. However, GABPNN and NEAT were not yet compared to each other. BPNN has the least accurate performance compared to all methods [10]. Unfortunately, these studies were only using stock market and foreign exchange as the case study. There hasn't been any ANN based prediction study that used Bitcoin as a case study.

Machine learning methods is not the only factor that affects the performance of market value prediction. Features that are used to build the model are also a contributing factor. Czekalski, et. al [12] found that market technical indicators such as %R and EMA can be used as features to build the prediction model. All of the previous studies comparing the methods didn't select the best features; therefore, the models being compared might not show their best performance yet.

The purpose of this study is to find the best method among selected variant of ANN methods and the most optimal features to predict Bitcoin *close* value (Bitcoin exchange rate to American dollar) in the next day. Based on study literature,

[1] https://data.Bitcoinity.org

[2] https://www.satochi.co/all

there are 4 variants of ANN methods selected to be compared which are BPNN, GANN, GABPNN, and NEAT. The methods are compared based on its accuracy (represented by MAPE) and its complexity (represented by time required to build a model). To ensure the best performance for each method, the features and the topology were optimized first.

To answer the purpose of this study, the rest of this paper are structured as follows. Literature study are explained in the next section and then followed by the research methodology used. The result and the analysis section was then presented, followed by discussion section. Section six concludes the findings of this research.

II. LITERATURE STUDY

A. Cryptocurrency and Bitcoin

Cryptocurrencies are a group of digital money that's not regulated by any party (decentralized) and uses cryptographic functions as proof of work [2]. Proof of work is an economical term to measure whether a service is working and valid [13]. In this context, the service is the transaction itself. Solving a cryptographic function is the proof of work of a transaction in cryptocurrency [2].

One of the most and oldest cryptocurrency that has been circulating around the world is Bitcoin. Bitcoin originated from a peer to peer electronic payment scheme proposed by Satoshi Nakamoto [14]. For every transaction with Bitcoin, a process must be done to solve a hash function as proof of work [1]. This process is called mining [15].

Mining is done by an individual or group and they are rewarded by Bitcoins when they solve the hash function. This is one of few common ways to get Bitcoin. Another way is by buying Bitcoin directly from online Bitcoin exchange websites using fiat currency such as USD. The latter way is the main activity of Bitcoin trading. Bitcoin trading has been treated as an investment activity nowadays [4].

According to Briere [4], based on historical Bitcoin data from 2010 to 2013, Bitcoin investment return value has the average of 7.14% and could reach the maximum of 136.72% [4]. However, the return value could also reach the minimum of -41.78%. This high volatility matches the characteristic of high risk high return form of investment.

B. Market Technical Analysis

In making both long and short term investments, not all investors speculate blindly like gambling. There's a common method used to help investors take decision in investment, namely market technical analysis.

Market technical analysis is basically identifying and interpreting the trend in the market by analyzing historical market price data [16]. The interpretation of trend can be done by utilizing a few tools such as candle graphs and market technical indicators.

Candle graphs represents the market price in a period of time [17]. Each unit of time is represented in 4 values which form a bar. The first is *open*, which is the market price at the start of period. Second is *high*, which is the highest market price, and then followed by *low*, which is the lowest market price within the period. The last value is *close*, which is the market price at the end of period.

Another common tool used to interpret trend or even as a signal to buy or sell is market technical indicators. There are many indicators that can be used to help identify market trends [16]. Two of the common ones are Williams %R as a momentum indicator and Exponential Moving Averages (EMA) as a trend indicator [18].

Exponential moving average (EMA) is the average movement of market price in a period of time [18] while %R is an indicator that represent the strength of overbought or oversold market [18].

C. Market Value Prediction using Artificial Neural Network (ANN)

ANN based prediction machine is not uncommon to be used in stocks and foreign exchange sector. Artificial Neural Network is inspired from the neural network of human body which consists of nodes and connections between them. ANN also has nodes and connections, the nodes are categorized as three types which are input, hidden, and output nodes. These nodes are connected by lines. Each of these connection has weight that are used to calculate the value from one node to the other. Fig. 1 is an example of an ANN.

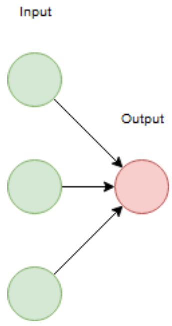

Fig. 1 Example structure of an ANN without hiden neurons

There are also many variants in ANN training methods. There have been a few studies concerning the performance of those methods, such as backpropagation, genetic algorithm, and neuro-evolution of augmenting topologies [7] [9] [10] [8].

One of the most basic training method in ANN and has been proven to be accurate enough is backpropagation [7]. Backpropagation Neural Network (BPNN) uses Multi-layered Feed Forward Network structure. The structure consists of input neurons, hidden neurons and output neurons. These neurons are connected by edges that has weights.

Backpropagation training consists of two steps [19]. The first one is propagating the input vector through the network until it is calculated in the output node. The second step is to backpropagate the calculated error from each node using gradient descent. The calculated error is used to calculate the new weight for each edge.

Another method used to optimize the training process is genetic algorithm. Genetic algorithm is an algorithm that is inspired from evolution theory [20]. The objects, in this case are the weights, are encoded into chromosomes. First, a population of these chromosomes is generated. Then, the fitness of these objects is calculated using fitness functions. Fitter chromosomes are better. After the chromosomes are ranked, they are mutated or crossed. The results of those operations are the new population. This process is iterated until the stated stopping condition or passed fitness threshold are achieved.

Genetic algorithm is also useful to optimize a BPNN. GA is utilized to optimize the initial weights of the BPNN. The initial weights need to be optimized because BPNN is vulnerable to minimum local result after training.

One of the latest and accurate training method is neuro-evolution of augmenting topologies or NEAT. NEAT also utilizes genetic algorithm to train the neural network. The main difference is that NEAT does not only train the weights but also the topology of the network itself.

D. Prediction Result Evaluation

Prediction result needs to be compared in order to determine which method is better. There are many types of error measurement for time series prediction. Some of them are Mean Absolute Percante Error (MAPE), Mean Standard Error (MSE), and Mean Absolute Deviation (MAD). In this study, MAPE is used because according to a study that compares accuracy method by Gentry, it is the best measurement suited for forecasting for example suited for stock prediction [21].Equation (1) is the formula to calculate MAPE.

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{A_i - P_i}{A_i} \right| \tag{1}$$

i = index of experiment
A = actual value
P = predicted value
n = experiment count

Accuracy is not the only aspect that is measured, time is also a factor that needed to be considered. Training time is also measured to ensure that the work needed to train the model is reasonable to the accuracy from the result. If the accuracy is high but the training time takes too long, it is not feasible to be applied in the real practice.

III. Research Methodology

To compare BPNN, GANN, GABPNN, and NEAT, this study used experimental approach to find the best training method for ANN in predicting next day close value of Bitcoin. MAPE is used to evaluate the accuracy and training time is used to evaluate the complexity aspect. For each method, the model generation was done 30 times to get the average of MAPE and training time. The repetition was conducted to ensure that the value of measurement was not coincidental.

The experiment process was based on the steps in Data Science Analysis [22] and Data Science Process [23]. The approach consists of 6 steps which are illustrated in Fig. 2.

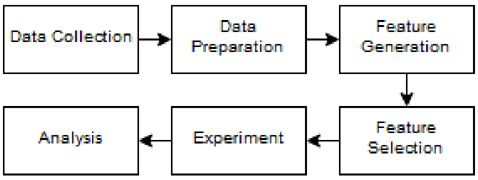

Fig. 2. Resarch methodology process

The data was collected from website that provide historical Bitcoin price from 2014 to early 2017. The data was then prepared so that it can be processed as input to the prediction machine by removing the time column. After it was processed, features were generated and then selected. After data is ready, the training and evaluation was conducted. The program used to execute the experiments was built with Java and Encog machine learning library [24]. The training and prediction for each method was executed 30 times.

Analysis was done by comparing the results from the experiment of each mothed. The average and standard deviation of MAPE and training time were calculated from the iterations for each method. Average and standard deviation were needed to determine the performance for each method and to find if there were any performance overlaps.

IV. Result & Analysis

The data were obtained from cryptocompare.com where they provide historical daily Bitcoin data from Kraken exchange platform. It was downloaded in csv format with the time period from 06/10/2013 to 02/04/2017 and the row count is 1278. There are 6 variables in the data, namely *date*, *open*, *high*, *low*, *close*, and *volume*. Fig. 3 is a snippet from the data.

time	open	high	low	close	volume
06/10/2013	238	238	122	122	0.1
07/10/2013	122	123.61	122	123.61	0.1
08/10/2013	123.61	124.19	123.61	124.18	3.99
09/10/2013	124.18	124.18	123.84	123.84	2.82
10/10/2013	123.84	125.86	123.84	125.86	2

Fig. 3. Snippet from the obtained data

The raw data was then prepared by removing the time variable and then adding next day closing price variable. After processing the raw data, market technical indicator features had to be generated first and then selected.

As discussed in the previous section, market technical indicators have been proven fit as features in ANN based market prediction. Such market technical indicators are %R and EMA. The periods that were used are 5 and 14 days for %R [24] [5] and 12 and 26 days for EMA [25] [11]. First, these features must be generated using the corresponding formula for each technical indicator and then added as variables in the data. Therefore, there were four additional features from market technical indicators that were generated, namely EMA 12, EMA 26, %R 5 and %R 14.

By generating the market technical indicators, there are rows where the indicators could not be calculated because of there was no prior data before that. The resolve this problem, the data was then cut. The remaining data start from 01/01/2014 and reduced from 1278 to 1219 rows. The data were then split into training and testing with proportion of 80% and 20% respectably. The data were also normalized to 0-1 or 1-1 depending on the activation function for each method. Fig. 4 is a snippet of the data with the generated market technical indicator features.

open	high	low	close	volume	will5	will14	ema12	ema26	next1
731.86	745.2	715.53	737.4	7.56	-26.0543	-29.2297	716.8664	796.3181	738.18
737.39	744.32	715	738.2	6.2	-25.4419	-28.9325	720.1454	792.0116	749
738.18	751	731.86	749	8.9	-23.1579	-5.6266	724.5846	788.8255	739.73
749	750	730	739.7	8.37	-53.3722	-7.99744	726.9147	785.1888	753.99
739.73	759.11	737.15	754	10.13	-11.6073	-6.71324	731.0801	782.8778	799.04

Fig. 4. Snippet from the data with the generated features.

To achieve the best performance, the total of 9 features (open, high, low, close, volume, ema 12, ema 26, %R 5, %R 14) need to be selected first for each method. To select the features, this study used *greedy forward selection* approach [26]. The feature selection only applies for the generated feature, that is the 4 market technical indicators. The selection was done by experimenting on each method for each possible feature combination. The best performing combination was the features that were used in the prediction experiment.

The variable resulted from the feature selections for both BPNN and GABPNN are: open, high, low, close, volume, and EMA 12. GANN and NEAT have the same features with BPNN and GABPNN except the period of the ema is 26 days (EMA 26).

After selecting the best features for each method, training and prediction was done 30 times and the result was processed. A single training was executed until overfit or reached epoch limit. Epoch limit for BPNN is 10000 while for the others is 10000. Each training and prediction yielded mean absolute percentage error (MAPE) and training time as the measurement. The average and standard deviation were calculated in order to analyze the result. Table I is the result of the experiments.

TABLE I. EXPERIMENT RESULT FOR EACH METHOD

Methods	MAPE (%)	Training Time (seconds)
BPNN	1.998 ± 0.038	347 ± 63
GANN	4.461 ± 0.49	467 ± 345
GABPNN	1.883 ± 0.066	1539 ± 558
NEAT	2.175 ± 0.096	470 ± 363

From Table I, it can be seen that GABPNN has the best accuracy with average MAPE 1.883%. The method with the worst accuracy is GANN with average MAPE 4.461%. All of the methods have no overlapping accuracy.

However, GABPNN has the longest training time which the difference compared to other methods is significant. This is a problem for GABPNN method, because in real practice training time have to scale well. Because of this problem, the next best candidate for the best method is BPNN. With the training time 300% faster and the accuracy only slightly less than GABPNN, BPNN is the best performing method for Bitcoin prediction.

V. DISCUSSION

There's a few differences of performance in accuracy between methods in this study case and the stock market case. In stock market case, GANN is better than BPNN [10]. On the contrary, in Bitcoin case, GANN is significantly outperformed by BPNN. This difference could be caused by the more volatile characteristic of Bitcoin compared to stock market so the genetic operations (mutation and crossover) is not suitable to train the prediction model.

Another difference is that BPNN is still better than NEAT in accuracy, while in stock market case NEAT is better than BPNN, GANN and GABPNN altogether. This also can be caused by the same problem as before, that genetic algorithm is not suitable for training prediction model for Bitcoin.

Other than the issues above, time is also important for Bitcoin prediction because the data can be streamed live from online resources. Therefore, faster training process is more beneficial to provide quick decision in Bitcoin volatile market. Evaluated by accuracy and training time, BPNN has the best performance for Bitcoin study case.

VI. CONCLUSION

Based on the results of the experiment, the best method for predicting next day close value of Bitcoin is BPNN. Even though GABPNN has the best accuracy with MAPE 1.883%, the training time is not feasible for real practice with much more data. BPNN was three time faster in average with the accuracy only slightly less than GABPNN. The MAPE difference between BPNN and GABPNN is only 0.115 % on average. With the high time difference, BPNN outperformed GABPNN in Bitcoin case study.

This study opens several possibilities for future study related to Bitcoin prediction. This study focused on four variants on ANN methods. Therefore, future study focused on other machine learning methods such as fuzzy logic based machine learning methods and or Support Vector Machines will enrich the analysis of best prediction method for Bitcoin. Regarding with the prediction target, this study only focuses on one-day prediction. In real practice, one-day prediction may not be enough for investors. The more days can be predicted, the more benefit investor can obtain by making long time investment decision.

In summary, this study contributed in the domain of investment and machine learning by comparing a variant of ANN methods in Bitcoin case study. There have been several studies on stock or investment prediction, but not yet on Bitcoin. In addition, this study also contributed by taking account on training time as the performance measurement.

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