Prediction of Shanghai Stock Exchange Composite Index Based on a Deep Convolutional Fuzzy System

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Abstract: Artificial intelligence has brought new ideas to the field of programmatic transactions in financial sector. Compared to factor analysis with historical data, models of artificial intelligence are more comprehensive and accurate. A deep convolutional fuzzy system with fast training algorithm is an effective model that can be used to predict the index of stock market. This model is a multi-layered structure containing many levels of fuzzy systems. Due to its high efficiency and accuracy, the system with fast training algorithm was quite successful in predicting Shanghai Stock Exchange (SSE) Composite Index. Past daily returns of stocks are also used in the strategy. Annualized rate of return, maximum drawdown rate, Sharpe ratio and information ratio are used to evaluate the application of this model. The deep convolutional fuzzy system with the training algorithm can predict not only the cost of stock and the index of both domestic and foreign stock, but also the index of digital currency such as bitcoin.

1. Introduction

China's stock market has developed over 30 years, and Shanghai Stock Exchange (SSE) Composite Index reflects the overall trend of the Shanghai stock exchange market. It is also of vital reference value for China's economic trends. The stock index forecasting methods and related forecasting technologies have been deeply researched and discussed by the majority of scholars. Scholars have tried to use various methods and methods to study and analyse the laws of stock market operation. Certain specific laws are found in the volatile stock market, and these laws are used to predict the future development trend of the stock market.

Quantitative research is frequently used for financial investment, which includes stock selection and index prediction. People usually use mathematical or statistical methods to determine whether to buy or sell stocks. The most common quantitative stock selection is to help people use mathematical tools to determine whether the stock of a company is worth holding through quantitative methods, and choose a portfolio that can exceed the market. Securities price data is a multi-dimensional time series, which is highly non-linear and time-varying. It is difficult to describe with analytical methods or exact mathematical models. Classic quantitative stock selection methods usually include multi-factor stock selection, style rotation stock selection, industry rotation stock selection, and capital flow stock selection.

The integration of the financial sector into artificial intelligence is more common and in-depth, and great progress has been made. In recent years, artificial intelligence has brought new ideas to the field of programmatic transactions in financial sector. Artificial intelligence constantly innovates and combines various fields to promote development of each other. The artificial intelligence method does not require any assumptions about the nature of the data distribution and can be effectively processed. This type of data is very suitable for securities price modeling and

forecasting.

In stock market, artificial intelligence is of great significance to help investors select stock more conveniently and systematically. The prospect of people using artificial intelligence to select stocks should not be ignored or underestimated. It is worthy of scientific and in-depth research. However, benefits and risks coexist in the stock market. For stockholders, stock selection has always been the most important and arduous part. In the stock market, there are many factors affecting stockholders' choice and prone to change, which is an unfavourable factor for stockholders. Therefore, the intervention of artificial intelligence helps people choose stocks more conveniently and efficiently.

In this paper, we will construct a deep convolutional fuzzy system (DCFS) and discuss the effects of the prediction of SSE Composite Index. This research focuses on the application of convolutional neural networks to help people choose their investment portfolios, confirm the feasibility of artificial intelligence, and develop a more scientific and reasonable systematic stock predication strategy. A multi-level DCFS model is put forward to construct trading strategy with SSE Composite Index and stock data. Section 2 presents previous work about application artificial intelligence in stock index prediction. In section 3, we analyse the historical data of SSE Composite Index from 2008 to 2020. Section 4 shows how the deep convolutional fuzzy system work to predict the stock index. In section 5, we present the performance of the deep convolutional fuzzy system and effects of different parameters on index prediction. Eventually, the conclusion is given in section 6.

2. Related Work

Many scholars have tried to conduct in-depth research on the strategies of artificial intelligence to help stock selection and put them into the stock market for prediction. However, the results of the experiment are quite different from expectations, with specificity and instability. At present, people mainly use statistical regression forecasting methods and time series forecasting methods to predict the stock market, including ARIMA model, ARFIMA, ARCH/G ARCH model, etc. Wang et al. incorporated the Markov chain concept into fuzzy stochastic prediction of stock indexes [1]. After three months' observation, the model performed quite well in stock prediction. Wichai et al. introduced the fuzzy quantitative analysis method for Stock selection into portfolio. Yang et al. used AHP method to help people make their stock select decision [8]. A practical case study is given to show that AHP is a useful and effective method in stock selection. Yee et al. summarized and analysed the basic measures of stock selection [9]. Kaur et al. examined the relevance of Graham's criteria in Indian stock market and used rule induction to make stock-selection [10]. Regression analysis demonstrates that not all the criteria are applicable to present economic environment and the method has limitations in the Indian stock market.

Intelligent forecasting methods are widely used in stock market forecasts and quickly occupy a dominant position. Among them, the BP neural network and other methods are the most representative. The neural network is quickly applied to stock market forecasts due to its superior forecasting performance. Artificial neural network models were used in stock market index prediction [2], which were proved to be useful and productive. Around the same time, Jacek et al. created a Neuro-genetic system for stock index prediction [3]. This system can be effectively applied to both upward and downward trends. Also, combining nonlinear independent component analysis and neural network were developed for the prediction of Asian stock market indexes [4]. The proposed forecasting model makes the prediction of stock index more precise. In 2017, Yang Bing started to use deep neural network ensemble [5], which is an effective tool to predict SSE Composite Index. Sharma found Combining of random forest estimates using LSboost for stock market index prediction [6], the accuracy has been improved to a large extent. Models based on the fuzzy quantitative analysis were designed to make stocks selection and investment portfolio [7]. The result showed fuzzy analytic hierarchy process (FAHP) and technique for order preference by similarity to ideal solution method (TOPSIS). Then, the overall weight for each stock was then derived from both of these weights and used for selecting a stock into the portfolio. Feng et al. introduced a hybrid stock selection model using genetic algorithms and supported vector regression

[11]. This method can provide reliable rankings of stocks and help people select stocks in the market. Wang et al. introduced a stock selection strategy using fuzzy neural networks [12]. The result showed that neural networks are useful in constructing an adaptive system which can learn from historical data, but unable to process ambiguous rules or probabilistic data sets.

Because deep learning can reach hundreds of thousands of layers in network depth, and most of its parameters are in the order of millions or even hundreds of millions, it can solve and model complex nonlinear optimization problems, so it has a high degree of index prediction in recent years. As a result, it is the research focus of academia and industry. In 2015, Rather, Agarwa and Sast combined autoregressive moving average mode (ARIMA), exponential smoothing model and recurrent neural network (RNN) to form a hybrid model for stock price forecasting, and obtained better results than using neural networks alone [3]. A state frequency memory recurrent network was proposed in 2017, which can discover and simulate the pattern of stock prices at multiple frequencies, and verified that the model performs better than the traditional LSTM model [4]. In addition, some scholars refer to the successful experience in the field of image recognition, using a one-dimensional convolutional neural network to extract local features in the time dimension and establish a mapping with the stock price, which also achieved similar effects [8]. The above successful experience proves that it is possible to predict the future stock price trend through the powerful nonlinear representation ability of the deep learning model and serve as an investment reference for quantitative trading.

In conclusion, the introduction of artificial intelligence methods can improve the ability to solve these problems and develop models with stronger generalization capabilities, which is of important reference significance for stock investment.

3. Data research

The Shanghai Stock Exchange Composite Index refers to using all the stocks listed on the Shanghai Stock Exchange as a template, through the collection and processing of a large amount of data, to achieve and reflect the real-time response to the stock market the stock trend of this part of the company. Its main function is to serve as an important basis for investors to measure and select stocks. SSE Composite Index, different from other index, covers a number of large enterprises in China. SSE Composite Index can roughly reflect the changes in current situation of the entire Chinese stock market. The difference between the index and other indexes is that it covers a large number of large enterprises, such as the Bank of China. In other words, the SSE Composite Index can roughly reflect changes in the current market situation.

Moreover, the Shanghai Stock Index plays an extremely important role in reflecting the overall economic situation in China, shown in Figure 2. For example, when a global economic crisis occurs in 2008, China is no exception. The effect of the crisis on China can be reflected in the sharp decline of the Shanghai Stock Index. On September 9, 2008, when the economic crisis broke out, the closing price at that time was 2147.58 yuan, and by December 31, 2008, the closing price had fallen to 1820.81 yuan. This happened because China's import and export at that time was one of the most important points. The economic growth rate in the first quarter of 2009 fell to 6.6%, and then the growth rate showed a negative value, which led to economic depression at that time. In light of this reality, China invested 4 trillion yuan to boost the economy, and meanwhile adopted various loose economic policies so that the negative economic impact could be reduced. This has not severely hit the growth rate of economy in China, and the rapid increase and decrease are clearly reflected in the Shanghai Stock Index.

Figure 1 also shows several past daily returns of stocks from 2008 to 2020 are used in the strategy, such as China Shenhua (601088) and Industrial and Commercial Bank of China (601398). Their correlation between index and stocks is high, as shown in Figure 2. This indicates that information of past stocks proves a chance to help predict SSE Composite Index.

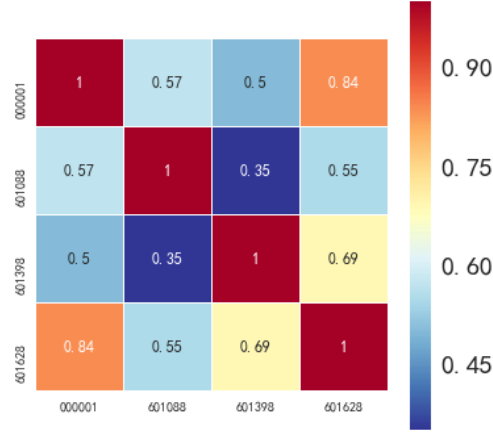Figure 1. Historical change of SSE Composite Index and stocks

Figure 2. Correlation between SSE Composite Index and stocks

4. Methodology

4.1 A deep convolutional fuzzy system

A deep convolutional fuzzy system (DCFS) is a multi-layered structure [13], as shown in Figure 4. There are n^l fuzzy systems FS_i^l (i=1, 2, …, n^l) in each level l (l=1, 2, …, L-1). The initial input vectors to the DCFS are denoted as x_1^0, x_2^0, …, x_n^0, and outputs of each level are x_i^l, which are inputs to the next level (l+1). The top level (L) of DCFS consists only one fuzzy system FS^L with n^{L-1} outputs from the previous level (L-1), forming the finial output x^L.

There is a moving window in each level selecting and forming input sets $(I_1^l, I_2^l, …, I_{n^l}^l)$ before which entering the fuzzy system. The length of the moving window is a constant m, which moves one variable every time beginning from x_1^{l-1} to $x_{n^{l-1}}^{l-1}$. Input sets are shown as follows:

$$I_1^l = \{x_1^{l-1}, …, x_m^{l-1}\})$$
$$I_2^l = (x_2^{l-1}, …, x_{m+1}^{l-1})$$
$$I_i^l = (x_i^{l-1}, …, x_{m+i-l}^{l-1})$$
$$I_{n^{l-1}-m+1}^l = (x_{n^{l-1}-m+1}^{l-1}, …, x_{n^{l-1}}^{l-1})$$

For the one-variable-at-a-time moving scheme

$$n^l = n^{l-1} - m + 1$$

with n^0=n, we can derive

$$n^l = n - l(m - 1)$$

Other moving schemes can also be applied to prevent a large number of fuzzy systems and

enhance efficiency of them when building DCFS. For instance, more than one variable can be moved at a time to replace input variables, such as moving window m variables every time for all fuzzy systems. Then, input variables can be covered. Also, window size m can vary for different fuzzy systems to improve the flexibility of the DCFS.
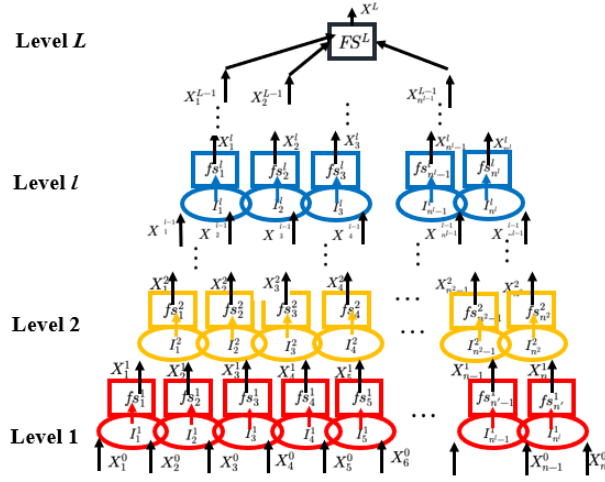

Figure 3. The Framework of a deep convolutional fuzzy system

The convolution system $FS_i^l (i = 1,2, \ldots, n^l, l = 1,2, \ldots, L-1)$ is a standard fuzzy convolution system. For the convolution system shown in Figure 3, input variables are $X_i^{l-1}, \ldots, X_{m+i-1}^{l-1} \in I_i^l$. And $A^1, A^2, \ldots, A^q$ have the same distance. Endpoints $min\, x_j$ and $max\, x_j$ are based on the training data (details will be given in the following part we will explain). Convolution system FS_i^l are defeined as:

$$(x_i^{l\text{-}1}, \ldots, x_{m+j\text{-}i}^{l\text{-}1}) \to x_i^l:$$

$$X_i^l = FS(x_j^{l-1}, \ldots, x_{m=i-1}^{l-1})$$

$$= \frac{\sum_{j1=1}^{q} \cdots \sum_{jm=1}^{q} c^{j1\cdots jm} A^{j1}(x_i^{l-1}) \cdots A^{jm}(x_{m+j-1}^{l-1})}{\sum_{j1=1}^{q} \cdots \sum_{jm=1}^{q} A^{j1}(x_j^{l-1}) \cdots A^{jm}(x_{m=j-1}^{l-1})}$$

$$= \sum_{j1=1}^{q} \cdots \sum_{jm=1}^{q} c^{j1-jm} A^{j1}(x_i^{l-1}) \cdots A^{jm}(x_{m+j-1}^{l-1})$$

where $i=1,2,\cdots,n^l$ and $l=1, 2,\cdots, L$-1. The member function, A^j is as shown in Figure 4, parameter $C^{j1\cdots jm}$ is designed using the fast training algorithm [14,15]. Top-level convolution system FS^L is the same form as previous formula.
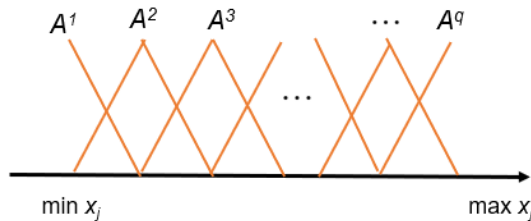

Figure 4. The Definition of membership functions

4.2 Multi-level DCFS with historical information of stocks

Now we are going to use the Multi-level DCFS with historical information of stocks to predict the SSE Composite Index return, as shown in Figure 5. k past daily returns of stocks work as the inputs to pass though the k DCFS to produce k weak estimators. Then, these k weak estimators

become the inputs of the last level (Level L+1) fuzzy system to produce the final prediction. The final prediction can present great accuracy, annualized rate of return and maximum drawdown rate because of more useful input information for prediction. The structure of the multi-level DCFS is based on previous system in section 4.1.

The deep convolutional fuzzy system and its fast learning algorithm overcome the shortcomings of the slow calculation speed of deep learning. Because the fast training algorithm only needs data once, without loop iteration, the amount of calculation is very small. A dozen layers of deep fuzzy systems are very constructive. On the other hand, the deep convolutional fuzzy system is composed of simple fuzzy subsystems in series, which is very interpretable.
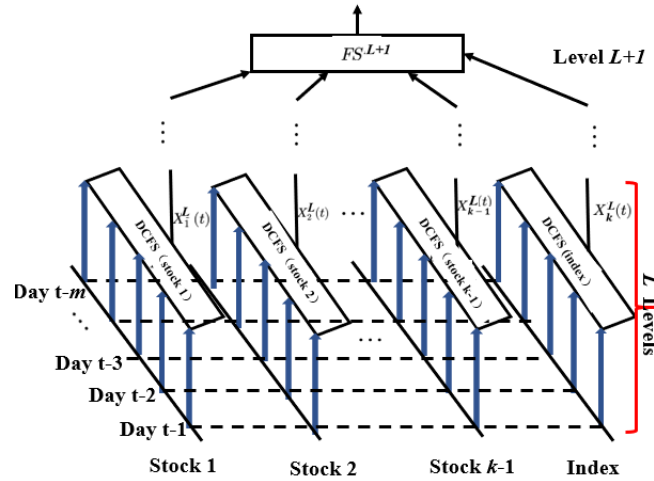

Figure 5. The framework of multi-level DCFS with m past daily returns of stocks

4.3 Trading Strategy

The multi-level DCFS we built can predict the value of stock indexes. When the forecast result shows that the stock index is rising, we can make long stock indexes; when the forecast result shows that the stock index is falling, we can short the stock index. We know that most of China's stock indexes cannot be shorted, but considering that most of the stock indexes in other countries in the world can be shorted, and in order to analyse the accuracy of the model's forecasting rise and fall, we then analyse the situation where the stock index can be shorted. The situation where the stock index cannot be shorted will be analysed in the discussion section. Assuming that the index can be shorted, it can be predicted by the formula:$ValueIndex(t)$, the value of the fund at day t is calculated for the value of the fund from the previous day $ValueIndex(t-1)$. And the amplitude $r(t)$ at day t is calculated, the formula is,

$$ValueIndex(t) = ValueIndex(t-1) \ [1 + r(t)]$$

Through this formula, we can get the value of this fund based on at day t, which is ValueIndex(t). Therefore, in the case of short selling, our correct prediction of the rise and fall of the stock price will be the only indicator of profitability. We will use this strategy to obtain the value of the fund on day t as ValueDCFS(*t*), which is similar to the previous calculation of the real fund value, except that the real value of the rise and fall is replaced by the predicted value of the fund, which can be obtained by the following formula

$$ValueDCFS（t）= ValueDCFS(t-1) \ [1 + I(t)r(t)]$$

Among them, *r(t)* represents the rise and fall of the index on day *t*, and I(*t*) represents the view on the trend of the next day from the previous day. If the prediction is correct, it is +1, and if the prediction is wrong, it is -1. It can be seen from the above formula that as long as the prediction is correct, no matter whether the stock market is going down or going up, you can profit by this model.

4.4 Strategy Evaluation

In this section we used alpha, annualized rate of return, Sharpe ratio and information ratio, maximum drawdown rate to evaluate our strategy [16-19].

Alpha is a common indicator for evaluating strategic results in quantitative investment. Alpha is non-systematic risk, which means the price of a single stock is closely related to the operating performance and major events of the listed company. Changes in the company's business management, financial status, market sales, major investments. This kind of risk mainly affects a certain kind of securities and has no direct connection with other securities in the market. This is shown as the following equation:

$$Alpha = \alpha = R_f - [R_f + \beta_p(R_m - R_f)]$$

where R_p is strategic annualized rate of return, R_m is benchmark annualized rate of return, R_f is risk-free interest rate (default is 0.04), and β_p is strategy beta. When α> 0, the strategy obtains excess returns relative to the risk; α = 0, the strategy obtains appropriate returns relative to the risk; α <0, the strategy receives less returns relative to the risk.

Sharpe Ratio is a standardized indicator for fund performance evaluation. The study of Sharpe ratio in modern investment theory shows that the magnitude of risk plays a fundamental role in determining portfolio performance. The risk-adjusted rate of return is a comprehensive indicator that can simultaneously consider both benefits and risks, in order to eliminate the adverse effects of risk factors on performance evaluation. The Sharpe ratio is one of the three classic indicators that can comprehensively consider returns and risks. The formula is shown as follows:

$$SharpeRatio = \frac{Rp - Rf}{\sigma p},$$

where R_p is annualized return on strategy, R_f is risk-free interest rate, σp is strategic return volatility. For each unit of total risk, how much excess reward will be generated, and the strategy's benefits and risks can be considered at the same time.

Information ratio indicates how much excess return will be obtained for each unit of downside risk, as shown in following equation:

$$InformationRatio = \frac{R_p - R_m}{\sigma_p}$$

where R_m is index annualized return. The larger the information ratio, the higher the excess return of the strategy unit tracking error. Therefore, the strategy with a larger information ratio performs better than the benchmark with a lower information ratio. A reasonable investment goal should be to pursue a high information ratio as much as possible while taking moderate risks.

Maximum drawdown rate refers to the maximum value of the return rate retracement range when the net value of the product reaches the lowest point after any historical point in the selected period is pushed back. The maximum draw down is used to describe the worst possible situation after buying a product. The maximum draw down is an important risk indicator. For hedge funds and quantitative strategy trading, this indicator is more important than volatility.

5. Results

Now we are going to use the multi-level DCFS to predict the SSE Composite Index return. Prices of index and stocks from June 1, 2008 to June 1, 2018 are used to train the model and predict the index prices from June 1, 2018 to June 24, 2020 (500 days). Two-level DCFS are construct with past stock information. Five past daily returns of stocks (600028, 601088, 601398, 603221 and 601628) in SSE Composite Index as the inputs to pass though the five DCFS to produce five weak estimators. Then, these five weak estimators become the inputs of the last level fuzzy system to produce the final prediction. The final prediction has shown great accuracy, with 34.2% annualized rate of return as well as 19.2% maximum drawdown rate, as shown in Figure 6. DCFS strategy

almost overperforms SSE Composite Index return from June 1, 2018 to June 24, 2020.
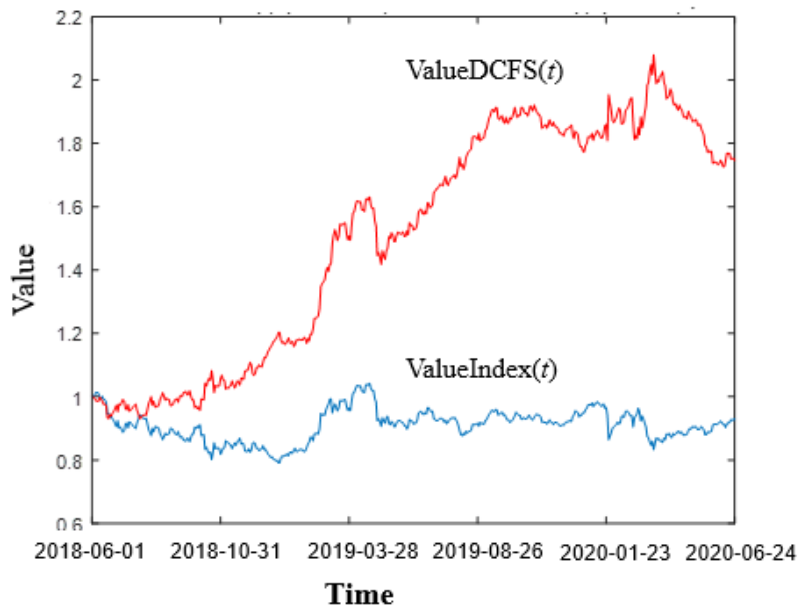

Figure 6. Value of DCFS strategy and SSE Composite Index

Table 1. Statistical analysis of DCFS strategy and SSE Composite Index from June 1, 2018 to June 24, 2020

	DCFS strategy	SSE
Alpha	23.1%	
annualized returns	34.2%	-4.1%
maximum drawdown rate	19.2%	11.0%
Sharpe ratio	3.4	-1.4
Information ratio	3.5	-1.2

Table 1 represents DCFS with the training algorithm is an effective model which can be used to predict SSE Composite Index. The annualized returns of DCFS strategy was 34.2%, which exceeded the direct purchase and holding of the SSE Composite Index with the annualized returns of -4.1%. But the performance of risk control of DCFS strategy was not better than that of the benchmark strategy (maximum drawdown rate: 19.2% vs. 11.0%). Sharpe ratio and information ratio of DCFS strategy were 3.4 and 3.5 respectively. It proves that the strategy we proposed is effective. Then we analysed effects of different parameters in DCFS on the performance.

6. Conclusion

In this study, we used convolutional neural networks and fuzzy system to develop a scientific and reasonable systematic index prediction strategy of SSE Composite Index and proved the feasibility of artificial intelligence. A deep convolutional fuzzy system (DCFS) is a multi-layered structure containing many levels of fuzzy systems. Input variables of DCFS are of high dimension, and have to pass through a moving window. This system selects and constitutes returns of stocks as input sets before entering the fuzzy system in each level. This model produces one final output, which is a scalar. Due to the model's high efficiency and accuracy, we applied DCFS to predict SSE Composite Index and constructed a trading strategy.

Five past daily returns of SSE Composite Index are applied, which are 605001, 600540, 603329, 603385 and 60322, into our research; and we used annualized returns, maximum drawdown rate, Sharpe ratio, and information ratio respectively to evaluate the results we got back from the five daily returns. Furthermore, the deep convolutional fuzzy system with the training algorithm can

predict not only the price of stock and index, but also the price of digital currency such as bitcoin. However, there is still room of improvement for our strategy. The choice of daily returns used to test the performance of the strategy can be improved. We may choose the kinds of stock which influence SSE more, such as the stock of banks, petroleum or machinery firms. In addition to this improvement, if we increase the number of transactions every day, we may receive higher revenue. These all might be useful to make the strategy more accurate.

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