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A Stock Trading Expert System Established by the CNN-GA-Based Collaborative System

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ABSTRACT

This article uses a new convolutional neural network framework, which has good performance for time series feature extraction and stock price prediction. This method is called the stock sequence array convolutional neural network, or SSACNN for short. SSACNN collects data on leading indicators including historical prices and their futures and options, and uses arrays as the input map of the CNN framework. In the financial market, every number has its logic behind it. Leading indicators such as futures and options can reflect changes in many markets, such as the industry's prosperity. Adding the data set of leading indicators can predict the trend of stock prices well. This study takes the stock markets of the United States and Taiwan as the research objects and uses historical data, futures, and options as data sets to predict the stock prices of these two markets, and then uses genetic algorithms to find trading signals, so as to get a stock trading system. The experimental results show that the stock trading system proposed in this research can help investors obtain certain returns.

KEYWORDS

Convolutional Neural Network, Genetic Algorithm, Leading Indicators, Trading Signals

INTRODUCTION

The financial market is a mechanism for determining the price of financial funds and trading financial assets. It is a market that enables the financing of securities and the trading of securities. The capital market is also called the "long-term financial market", which mainly includes the stock market, fund market, and bond market. Its volatility can reflect the degree of risk of assets. The fluctuation of stock prices plays a considerable role in the appropriate timing of buying and selling stocks (Kim, Kim, 2019). For investors, the true meaning of investing in the stock market is to obtain extraordinary returns by buying low and selling high, so the prediction of stock price fluctuations has become a

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special focus of private investors and investment companies (Samuelson, 1975). Due to a large amount of data in stocks, the low data correlation, and the many factors that affect stock prices, financial markets are full of uncertainty, which also makes predicting stock price fluctuations a significant problem for stock researchers. Initially, people had predicted the fluctuations of stock prices several times (Brooks, 1998; Keim & Stambaugh, 1986), but the results were unsatisfactory.

Investors are not completely rational. For example, people may have positive or negative emotions at certain moments (Hiew, Huang, Mou, Li, Wu, & Xu, 2019; Baker & Wurgler, 2006; Lee, Shleifer, & Thaler, 1991; Han, 2008; Chong, Cao, & Wong, 2014). Therefore, after this hypothesis was raised, there were both support and opposition, thus becoming one of the most controversial investment theories (Cowles, 1933; Borovkova & Tsiamas, 2019). Some researchers believe that if the trading signals (Bao, Yue, & Rao, 2017) of the stocks can be found, the stocks can be bought and sold at the appropriate time to obtain relatively high profits. Finding accurate stock trading signals is the key to obtaining huge returns. That is, in stock trading, when a buy signal appears, the stock is bought, and when a sell signal appears, the stock is sold. In other words, you should buy stocks at a lower price and sell stocks at a higher price if you want to obtain higher profits or income. Stock trading signals have always been the main research objects of investors and investment companies. Researchers have also tried many times to predict the best buying and selling signals, but because many factors affect stock prices, the prediction results are not satisfactory.

Support vector machines (SVM) is a binary classification model. Although it has not appeared for a long time, it has good classification performance in the field of machine learning. Huang et al. (Huang, Nakamori, & Wang, 2005) found in 2005 that SVM has better prediction results than traditional statistical methods. Nayak et al. (Nayak, Mishra, & Rath, 2015) proposed a hybrid model for the prediction of Indian stock indexes. This model mainly uses two machine learning algorithms, namely SVM and k-Nearest Neighbor (KNN). Studies have shown that the hybrid model they proposed has good scalability and predictability for high-dimensional data. Although the prediction results of SVM are significantly improved compared to other models (Cortes & Vapnik, 1995) and (Sheta, Ahmed, & Faris, 2015), it is still not satisfactory for stock prediction. The neural network model has received particular attention. Because neural network models can identify nonlinear relationships in data sets, many researchers have analyzed, and predicted stock price fluctuations based on various neural networks, and have also obtained relatively good results. For the stocks of the Tokyo Stock Exchange, Kimoto et al. (Kimoto, Asakawa, Yoda, & Takeoka, 1990) conducted a systematic study. They proposed a stock prediction system based on neural networks, and the system achieved relatively good profits in training. It stimulates the mechanism of the human brain to process data and can detect nonlinear relationships in the data. Oliveira et al. (De Oliveira, Nobre, & Zarate, 2013) used time series analysis, technical analysis, and financial theory to establish a neural network to predict the future price trend of stocks in the short term. This research shows that the proposed model has good performance.

Deep learning is based on traditional neural networks, including convolutional neural networks, recurrent neural networks, etc., and has good results in image recognition, text classification, machine translation and other fields. It forms the consistency of specific data and goals based on specific data, especially the rise of convolutional neural networks in deep learning research. At present, many researchers have applied convolutional neural networks to the prediction of the stock market (Gunduz, Yaslan, & Cataltepe, 2017; Siripurapu, 2014). Convolutional neural networks can consider possible correlations between stock markets as another possible source of information. Lu et al. (Lu, Li, Wang, & Qin, 2020) then proposed a framework consisting of CNN, Bidirectional Long Short-term Memory (BiLSTM) and Attention Mechanism (AM) for stock prediction. In addition, LSTM, MLP, and CNN use the S&P 500 index data set to predict the price of stocks (Di Persiob& Honchar, 2016). The results show that CNN is superior to LSTM and MLP. At present, in terms of sample feature extraction and financial time series, historical data volume, highest price, lowest price, opening price, and closing price are usually used for data prediction. In this study, in addition to using historical stock prices, a data set of leading indicators was also added. Leading indicators refer to statistical data of economic indicators that affect future economic development. Financial experts often use these leading indicators to analyze future economic growth and its impact on financial markets.

Yeoh et al. (Yeoh, Jhang, Kuo, & Chou, 2018) combine the technical indicator-moving average with the globe best-guide quantum-inspired tabu search algorithm to propose a new dynamic trading system. Among them, the moving average is used to find stock trading signals. The proposed method is then compared with the buy-and-hold strategy, and the experimental results show that this method significantly improves investment returns. This article mainly studies how to use deep learning algorithms and intelligent optimization algorithms to find the best trading signals. The framework extracts useful features from different data and then trains a predictive model based on these features. In this study, the output obtained by the predictive model is combined with the intelligent optimization algorithm to obtain a buying and selling signal. In stock trading, finding the best buying and selling signals is the key to gaining income. Wu et al. (Wu, Li, Srivastava, Tasi, & Lin, 2020) combined CNN with LSTM neural network to predict stock prices, and the system is named SSACNN. SSACNN integrates the collected data into the form of images and uses these images to train neural networks. Experimental results show that the developed SSACNN model has better performance. In this paper, we then apply the genetic algorithm to the SSACNN framework for finding the stock trading signals efficiently. The main contributions of this article are as follows:

- This study uses a two-dimensional tensor as the input of the SSACNN framework and divides the output into three categories: rising, falling and unchanged. In addition, two data sets, futures and options, have been conducted to show the performance of the designed model.
- In this research, the SSACNN framework and genetic algorithm are combined to present a novel stock trading system. This system can well find stock trading signals relatively so that investors can obtain a certain amount of profit/income.
- The experimental results show that the added datasets of leading indicators have a positive impact on stock trading. In addition, the performance of the proposed system is better than the classic Weighted Moving Average (WMA) strategy.

This article mainly includes the following parts. The second part introduces related work, including the background of stock research and various stock forecasting models. The third part introduces the methods used in this article. The fourth part mainly describes the framework proposed in this research. The fifth part gives the experimental results of this research and analyzes them based on the experimental results. Finally, a detailed summary and further planning of this research are made.

RELATED WORK

The prediction of stock prices is mainly the analysis of historical behaviours, such as people's historical emotions, historical market information, etc., and then useful features are extracted from them to train better predictive models. The value of stock prices is a time series. Revealing the development and changes of stock prices is an objective record of stock historical behaviour. In the early days of the stock market, a host of investors relied on their own experience to judge stock price movements, which seemed too subjective and lacked a scientific basis. In addition, stock prices are also affected by many other factors. For instance, Zheng et al. (Zheng, Jiang, & Long, 2019) studied the relationship between exchange rates and stock prices on the Hong Kong stock market. They built a model to analyze the correlation between Hong Kong company stocks, mainland company stocks and exchange rates. The experimental results show that the exchange rate is negatively correlated with the stocks of local companies in Hong Kong and positively correlated with the stocks of mainland companies. The price of stocks is also affected by external information and human emotions (Heston & Sinha, 2013). Many researchers have studied human emotions by analyzing the content on the forums or

Weibo, more accurately predict stock price volatility. As can be seen, the factors affecting stock price volatility than one, so we need some tools to analyze and predict stock.

Due to the volatility and high uncertainty of stock prices (Hagenau, Liebmann, & Neumann, 2013), traditional feature extraction methods mainly include statistical methods and technical analysis. Through the specific application of technical analysis, users assume that historical stock data should be correlated with future price trends (Taylor & Allen, 1992). Many technical indicators are defined by researchers to help people get income from investment. These technical indicators are generally mathematical expressions based on historical data. It can be seen that technical analysis is an analysis of post-event behaviour. It uses historical data to predict future trends and uses statistical methods, graphics, and data to explain related issues (Taylor & Allen, 1992). However, since the features extracted by the defined technical indicators are based on assumed patterns, using this method may make the information less accurate. Compared with technical analysis, statistical methods have better results. It mainly uses machine learning methods for feature extraction, establishes a mathematical probability model based on the data set, and uses the model to analyze and predict the data.

The predictions of machine learning and statistical methods are based on verified assumptions. Machine learning methods provide great help for learning the relationship between features and labels, overcome many limitations of traditional quantitative prediction methods, and avoid the influence of many human factors. With the rapid development of deep learning, neural networks are widely used in many fields. The principle of neural network learning is to use neural networks to extract features from data. In recent years, it has gradually been applied in the financial market. Selvin et al. (Selvin, Vinayakumar, Gopalakrishnan, Mennon, & Soman, 2017) used three deep learning architectures to learn the characteristics that exist in the data, predicted the prices of NSE listed companies, and compared the performance of these three deep learning architectures. The price of stocks changes with time, and the phenomenon of rising or falling occurs, so the data of stock prices is a typical time series. When we use the model to predict the price of stocks, the input of the model can be not only digital data but also image data. At this time, we thought that the CNN model could be used to predict the price of the stock. Research has proved that CNN is outstanding in image recognition, and its accuracy is higher than other models. Di Persio et al. (Di Persio & Honchar, 2016) proposed a model that uses wavelet and CNN methods to predict stock trends based on data from the past few days. Experimental results show that the proposed new method is superior to other models and superior to basic neural networks.

Intelligent optimization algorithms are used to find the optimal solution. In recent years, researchers have been more enthusiastic about using genetic algorithms to solve problems. In the financial market, many researchers also use genetic algorithms to find stock trading signals. Allen et al. (Allen & Karjalainen, 1999) used the genetic algorithm to learn a technical trading rule based on the daily prices of the S&P 500 index from 1928 to 1995. In this research, based on a series of technical indicators that generate buying and selling signals, a genetic algorithm is used to propose a trading strategy (Schoreels & Garibaldi, 2004). Hirabayashi et al. (Hirabayashi, Aranha, & Iba, 2009) proposed a genetic algorithm system to find suitable trading signals and automatically generate trading rules based on technical indicators. The focus of this system is not to predict the price of the transaction, but to find the right trading opportunity. Lin et al. (Lin, Cao, Wang, & Zhang, 2004) used genetic algorithms to set optimal values for the parameters of the problem and bought or sold stocks at the appropriate trading time.

METHODOLOGY

In the first part of this section, SSACNN neural network framework and a genetic algorithm will be introduced. This SSACNN framework has been proposed in our previous research. In the second part of this section, we will introduce the genetic algorithm used in this research. This algorithm is used to find the optimal solution of stock trading signals to maximize returns.

Advanced SSACNN Optimization Framework

The stock market has always been the focus of investors' attention. As the stock market is affected in many ways, finding trading signals for stocks is always a big problem. In the past, investors generally used trading strategies to obtain stock trading signals, which were generated by technical indicators or fundamentals (Chen, Lu, & Lin, 2019) and (Chou, Kuo, Chen, & Chao, 2014). CNN has been proven to have good image recognition capabilities, and many researchers have also used CNN for stock price prediction.

CNN includes a convolutional layer, pooling layer and fully connected layer. The convolution layer mainly extracts local features of the input data. The researcher defines a convolution kernel inside the convolution layer. Its shape is a square matrix that is used to extract a certain feature. The convolution kernel is multiplied by the corresponding bits of the digital input matrix and then added to obtain the output value of a convolution layer. The calculation process is shown in Formula 1 (Wu, Li, Srivastava, Tasi, & Lin, 2020).

$$V_{a,b}^{L} = i\left(\sum_{m=0}^{K-1}\sum_{n=0}^{K-1} w_{m,n} V_{a+m,b+n}^{L-1} + bias^{L-1}\right) \tag{1}$$

In Eq. 1, $V_{a,b}{}^{L}$ is the value of layer L at row a, column b, i is an activation function. $bias^{L-1}$ represents the bias of L-1. $w_{m,n}$ is the weight of convolution filter at row m, column n. The formula for calculating the output image size of the convolutional layer is shown in Formula 2 (Wu, Li, Srivastava, Tasi, & Lin, 2020).

$$w' = \frac{w + 2p - k}{s} + 1 \tag{2}$$

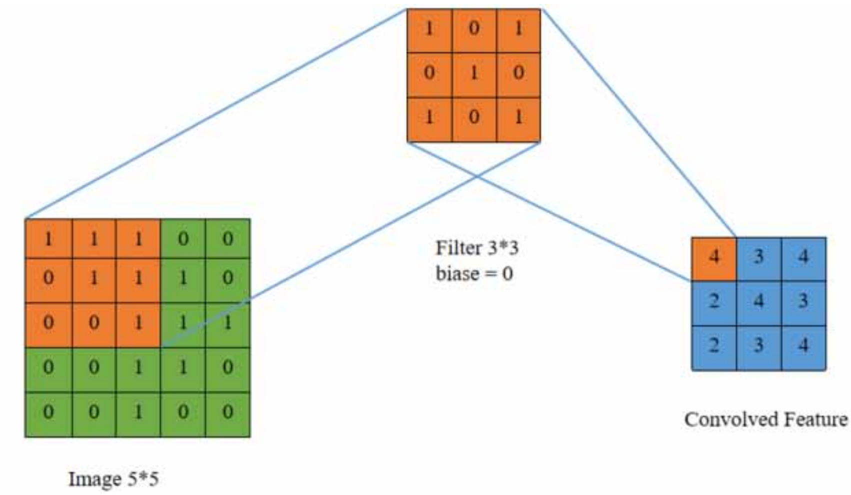
Among them, the size of the convolution kernel is k, the size of the input matrix is w, the number of zero-filling layers is p, and the step size is s. An example is shown below. The input layer L-1 is set as a 5*5 matrix and uses the 3*3 convolutional filter. The layer of input L is calculated by formula 1, which is set as 3*3. Figure 1 shows an example that defines a filter (3*3) to the input vector (5*5) for obtaining the vector of the next layer (3*3).

The higher the output value, the higher the degree of matching between the two. Because one convolution kernel recognizes one feature, and the input data may have multiple features, there may be numerous convolution kernels in one convolution layer to extract multiple features. Use the output of the obtained convolution layer as the input of the pooling layer. However, before entering the value into the pooling layer, an activation function is usually added to solve the nonlinear problem. At present, the activation function Relu (Rectified Linear Unit) is commonly used.

The pooling layer is mainly used to reduce the number of training parameters and reduce the dimension of the feature vector output by the convolution layer. The most common pooling layers are maximum pooling and mean pooling. In this article, we choose maximum pooling; that is, the maximum value in a specified area is selected to represent the entire area. The output value of the pooling layer is then expanded as the input of the fully connected layer to generate the final output.

After several times of convolution, excitation, and pooling, the model will learn a high-quality feature map, and then input the feature map to the fully connected layer to get the final output. The calculation process is shown in Formula 3 (Wu, Li, Srivastava, Tasi, & Lin, 2020).

Figure 1. A simple convolution process of convolutional neural network



$$V_a^b = i\left(\sum_K V_K^{b-1} w_{K,a}^{b-1} + bias^{b-1}\right) \tag{3}$$

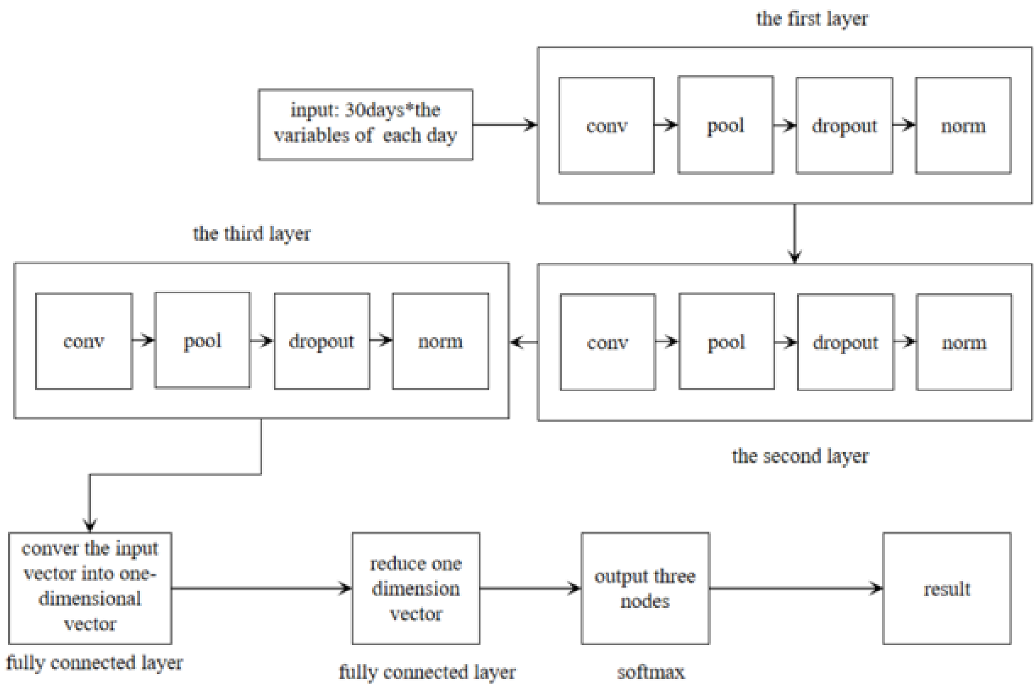
In this formula, V_a^b is the value of layer b in neuron a, i is an activation function, and $w_{K,a}^{b-1}$ is a weight that connects between neuron K from layer $b-1$ and neuron a from layer b. $bias^{b-1}$ represents the bias of $b-1$. In fact, before the fully connected layer, if the number of neurons is too large and the learning ability is strong, overfitting may occur. Therefore, a dropout operation is added to the convolutional neural network to randomly delete some neurons in the neural network to solve this problem. Dropout technology is to avoid the framework from learning too much data. In addition, operations such as local normalization and data enhancement can also be performed to increase robustness. The fully connected layer can be understood as a simple multi-class neural network, the final output is obtained through the softmax function, and the entire model is trained. The pseudo-code of this process is shown in Algorithm 1.

Algorithm 1. The proposed SSACNN framework and evaluation

Require: D is the data of training; K is the data of testing; z is the number of the maximum iteration as the terminal condition.
Ensure: the optimal weights w; evaluation result *accuracy*.
1: initialize the input data D to D^* ® D^* is an input array for the information generated by historical prices, futures and options and assume it consists of m input images.
2: labelling each individual in D^* and generate the label array D_r
3: generate the initial weights w randomly for the CNN network.
4: **for** each round 1 to z **do**
5: **for** each round $t = 1$ to m **do**
6: input D_t to the proposed CNN network and generate class label vector l
7: compare D_l^t and l to update w by Adam method(Kingma, & Ba, 2014)
8: **end for**
9: **end for**
10: evaluate *accuracy* using the optimal weights w for testing data K.
11: output w and *accuracy*.

In this study, the stock data for some time is converted into an image, and this image is used as the input of the CNN framework. The input here is 30-day stock data, and the generated "input image" is input to the convolutional layer, pooling layer, dropout layer, and norm layer. Then, loop this process three times. After a series of experiments, it is concluded that when the convolutional neural network is used for image recognition, the size of the convolution kernel is 3*3 and the size of the pooling layer is 2*2, the experimental effect obtained is the best it is good. Therefore, to achieve better results for this research, the size of the convolutional layer and pooling layer is set to 3*3 and 2*2, respectively. The CNN framework used for stock price prediction is shown in Figure 2.

Figure 2. A CNN framework for stock price prediction



The output of this framework is 3 nodes, representing three meanings. When the value of the first node is greater than a certain threshold, it means that there is a signal to buy the stock, and the buy operation will be executed at this time. When the value of the third node is greater than a certain threshold, it means that a sell signal for the stock appears, and the sell operation will be executed at this time. When other situations occur, neither buying nor selling is performed, but the operation of continuing to hold is performed. Therefore, to maximize revenue, two optimal thresholds need to be found. In this study, genetic algorithms are used to find the optimal threshold, which will be introduced in the next section.

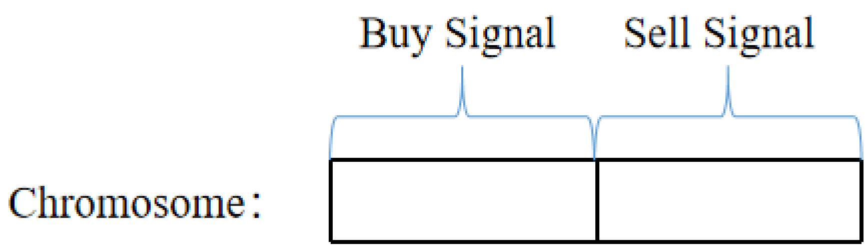
Genetic Algorithm

Darwin's theory of evolution is the root of the genetic algorithm. The genetic algorithm was first proposed by John Holland. This algorithm converts the process of solving actual problems into a process similar to biological evolution and finds the optimal solution by simulating biological evolution. In this section, the components of the method are described. The specific process is as follows.

Chromosome Representation

The main goal of this method is to find trading signals for stocks, namely buy signals and sell signals. Therefore, in this method, the chromosome is composed of two parts, as shown in Figure 3. The first part represents the threshold when the stock has a buy signal, and the second part represents the threshold when the stock has a sell signal.

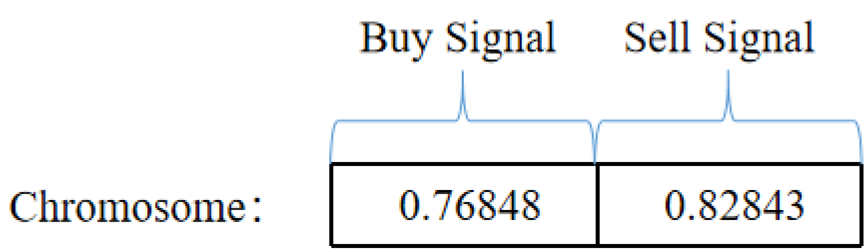
Figure 3. Representation of chromosome



Initial Population

It is very important to design a strategy for generating population initialization, which will affect the final profit. In this study, two floating-point numbers were randomly generated within a specific range as the threshold for the initial buying and selling signals. Next, use an example to explain in detail. Assume that the thresholds of two randomly generated buying and selling signals are 0.62461 and 0.85602 respectively, as shown in Figure 4.

Figure 4. An example of the threshold of randomly generated buying and selling signals



SSACNN is used to generate the values of 3 nodes, assuming the generated values are shown in Figure 5. It can be seen from Figure 6 that the value of the position of the first node on the first day is 0.72551, because 0.72551 > 0.62461, the stock is bought at this time. Then start to observe the third node of each day from the next day. It can be seen from Figure 5 that the value of the third node on the second day is 0.26545, which does not meet the condition of greater than 0.85602. Therefore, the stock will continue to be held on the second day and neither buy nor sell will be performed. The value of the third node on the third day is 0.93419, because 0.93419 > 0.85602, the stock is sold on the third day. After that, perform the buying and selling operations on the stocks following the above rules. In this research, the buying operation of stocks refers to buying with all funds, and the selling operation of stocks refers to selling all the stocks.

Figure 5. An example of the values of three nodes output by SSACNN

	Buy Signal		Sell Signal
1	0.85551		0.02341
2	0.14344		0.79545
3	0.17535		0.83419
……	……	……	……
……	0.71714		0.15575

Fitness Evaluation

The fitness function is used to evaluate the quality of chromosomes, that is, to evaluate whether the threshold value of the generated buying and selling signals is the optimal solution. In this method, the fitness function is the cumulative return over some time. As shown in Formula 4, Formula 5, Formula 6 (Yeoh, Jhang, Kuo, & Chou, 2018).

$$share_i = TotalAmount_i \,/\, BClose_i \tag{4}$$

$$balance_i = TotalAmount_i - share_i \times BClose_i \tag{5}$$

$$FinalAmount_i = balance_i + share_i \times SClose_i \tag{6}$$

Among them, formula 4 represents the share of the purchased stock, and formula 6 represents the final asset. $BClose_i$ and $SClose_i$ are respectively the buying price and selling price of the stock when the i-th trading signal appears.

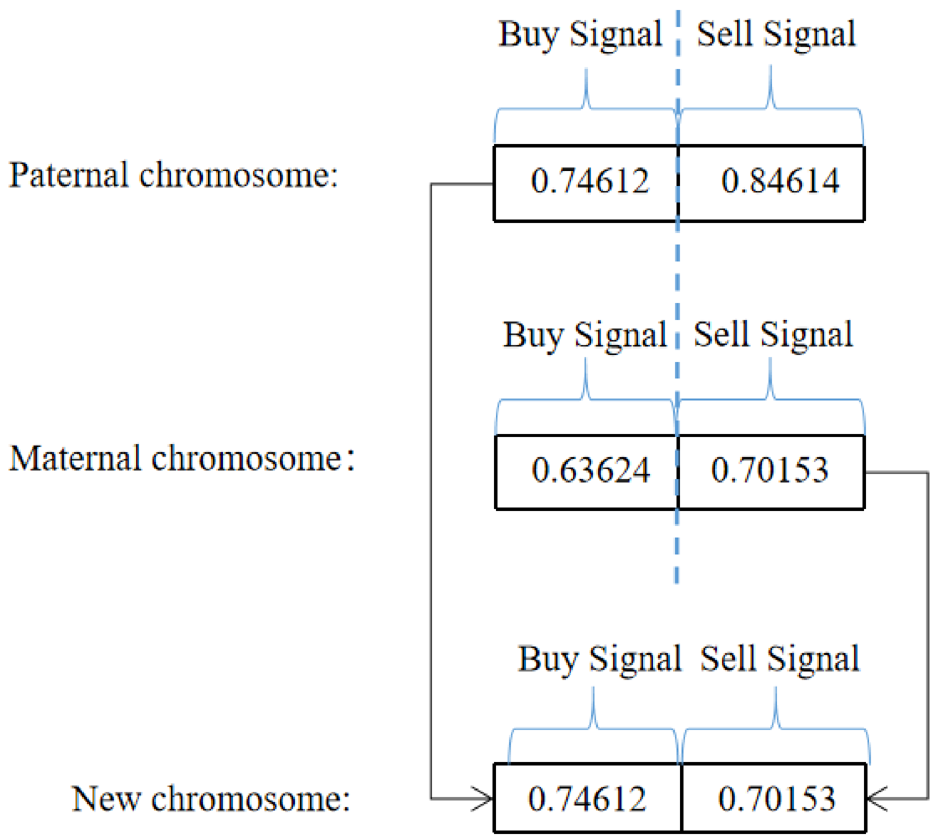
Population Selection

In each evolution, to retain good chromosomes, chromosomes need to be selected. The method of selecting chromosomes in the experiment is as follows. Randomly select chromosomes, with every two chromosomes as a group. Then compare the size of the result obtained by using each chromosome, and select the chromosome corresponding to the larger value of the result. That is, a chromosome will be selected in each group. For example, if there are 8 chromosomes in total, 4 chromosomes will be selected.

Crossover

The genetic algorithm performs crossover and mutation operations to generate new solutions. The crossover operation needs to find two chromosomes from the chromosomes of the previous generation, one as the father and one as the mother. Then the two chromosomes are cut and spliced together at a certain position to generate a new chromosome. Part of the new chromosome is the father's genes, and the remaining part is the mother's genes. The specific process is shown in Figure 6.

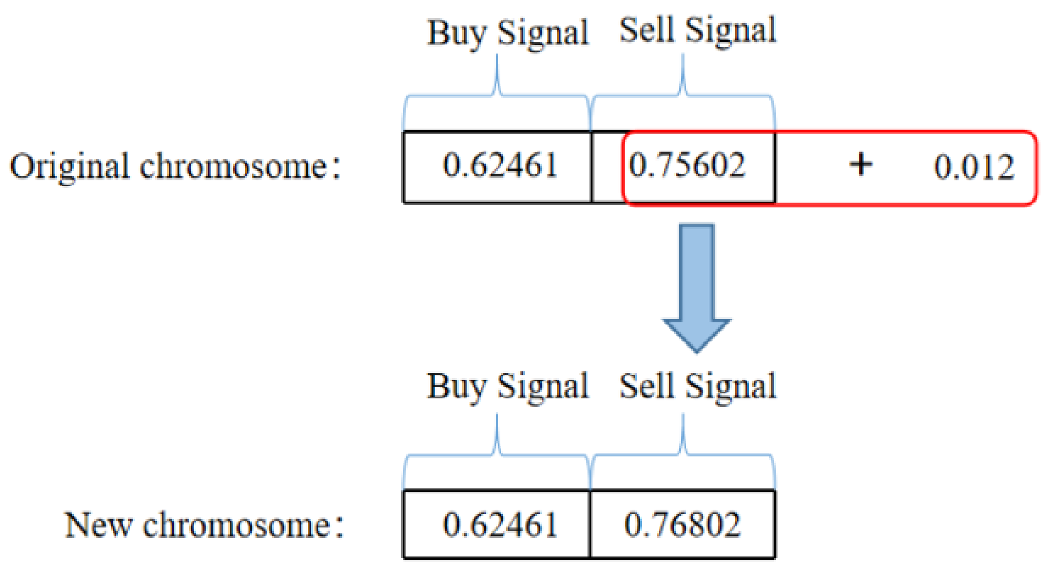
Figure 6. An example of chromosome crossover



Mutation

The crossover operation is only to operate on the original chromosomes, only to exchange their gene order. This can only guarantee a local optimal solution after multiple evolutions. To achieve the global optimal solution, a mutation operation is added. Introduce new genes into existing chromosomes by randomly modifying genes. The mutation process is shown in Figure 7.

Figure 7. An example of chromosome mutation



THE PROPOSED GA-BASED SSACNN FRAMEWORK FOR STOCK TRADING

Data Set

The data sets used in the experiment are historical data, futures and options. Because in financial markets, stock prices are affected not only by historical behaviour but also by leading indicators. Leading indicators can reflect the state of future economic development and are indicators that will change before economic growth or recession. Leading indicators are also called predictive indicators, which can provide predictive information for future economic conditions. Using this indicator, researchers can know the turning point of the economy in advance, to adopt appropriate trading strategies. For example, when the monetary authorities reduce the money supply, on the one hand, it shows the policy intentions of the authorities, implying the current trend of overheating in the economy. On the other hand, it will bring an increase in interest rates, which will increase the cost of enterprises and reduce profits, thereby reducing the attractiveness of investors. The increase in interest rates increases the opportunity cost of stock investment, which inevitably leads to a reduction in investment and a decline in stock prices. Therefore, this study focuses on the correlation between the two leading indicators of futures and options and the stock market and uses leading indicators to predict the trend of stock prices.

Futures trading, as a special trading method, has undergone two complex evolutionary processes from the beginning of spot trading to forward trading, and then from forward trading to futures trading. To put it simply, futures are not a spot, but a standardized contract. The purpose of futures trading is generally not to obtain physical objects at maturity, but to buy and sell futures contracts. Time, quantity, and quality are the three elements of this standardization, that is, a contract that delivers a fixed quantity and a certain quality of a certain quality at a specific time. Futures contracts are uniformly formulated by the futures exchange. The delivery period of futures is placed in the future. It can be one week, one month, or even one year later. The corresponding spot can be a financial instrument, such as bonds, foreign exchange. It can also be a commodity, such as soybeans or crude oil. An option is similar to futures and is also a contract. The option is generated based on futures. When the option is traded, the party who buys the option is called the buyer, the assignee of the right, and the party who sells the option is called the seller, the obligor who must perform the buyer's exercise of the right. The difference between futures and options is that option gives the buyer of the contract the right to buy or sell a predetermined number of commodities at the agreed price within the agreed period of the parties. It is a right to choose whether to execute or not in the future. In short, futures are one-way contracts and options are two-way contracts. For example, we bought an option from an Internet technology company for $50. In February 2020, the company gave us 1,000 stocks at an exercise price of $10 per share and an exercise date of February 2021. That said, in February 2021, we could buy 1,000 shares of the company for $10 a share. If the company's stock price reaches $15 per share when the exercise date is reached, then we choose to exercise our power to buy at $10 per share, which means that we have bought $15,000 stock with a market value of $10,000. And if the exercise date is reached, the company's stock price is $5 per share, at this time we will lose money if we exercise our power, so we choose to give up exercising our power. At this time, we will only lose $50 to buy this power.

Table 1. The historical prices of the five stocks

	$\mathbf{d}_{i1}$	d_{i2}	d_{i3}	d_{i4}	$d_{i.}$
CDA	266	266	260	262	...
CFO	118	118	115	115	...
DJO	260	264	259	264	...
DVO	264.5	246.5	243	246.5	...
IJO	3825	3880	3630	3635	...

Five important indicators of historical price are often used: the *opening price*, *lowest price*, *highest price*, *closing price* and *volume* for stock price analysis. The futures indicators use in our experiments include *opening price*, *highest value*, *lowest value, closing price* and *volume*. The indicators in the option include *volume, open interest, closing price* and *settlement price*. First, let's look at a dataset of five stocks in the Taiwan market. The five stocks are *CDA, CFO, DJO, DVO, IJO*. Table 1, Table 2, and Table 3 are the historical data, futures data, and options data of the five Taiwan stocks, respectively.

Table 2. Futures data of the five stocks

	$\mathbf{t}_{i1}$	t_{i2}	t_{i3}	t_{i4}	$t_{i.}$
CDA	262.5	265	265.5	262.5	...
CFO	117	117	117.5	117	...
DJO	163.5	262	263.5	258	...
DVO	246	244	246.5	243.5	...
IJO	3660	3815	3865	3635	...

Table 3. Options data of the five stocks

	$\mathbf{z}_{i1}$	z_{i2}	z_{i3}	z_{i4}	$z_{i.}$
CDA	5.2	70	7.3	11	...
CFO	3.25	20	0.51	15	...
DJO	14.85	1	0.27	1	...
DVO	3.4	2	6.85	2	...
IJO	297	0	30.1	0	...

The d_i, t_i, z_i are the various factors that affect the stock price. d_i represents the open, high, low, close or volatility attributes of the stock. t_i represents the current price, the opening price, the highest price, and the closing price of the futures. z_i represents the attributes of open interest and the settlement price of an option. Among them, options include the buy option and sell option. It is worth noting that the 10 call option and 10 put options with the contract price closest to the current stock price are selected as the data set of options.

Data Initialization

Before the experiment, input data needs to be further processed, that is, to standardize the data. Because the experiment may be affected by the size of the data and the results are not ideal. First, standardize the original data to make the range of all data consistent. The processed data conforms to the standard normal distribution and helps improve the accuracy of the prediction. As shown in Formula 7 (Wu, Li, Srivastava, Tasi, & Lin, 2020).

$$X^* = \frac{X - X_{mean}}{X_{max} - X_{min}} \tag{7}$$

where X_{mean} is the average of all data in 120 days, X_{min} is to select a minimum value within 120 days, and X_{max} is to select a maximum value within 120 days. Taking Taiwan's stock data as an example to standardize historical data, futures, and options. The normalized data of historical prices are shown in Table 4.

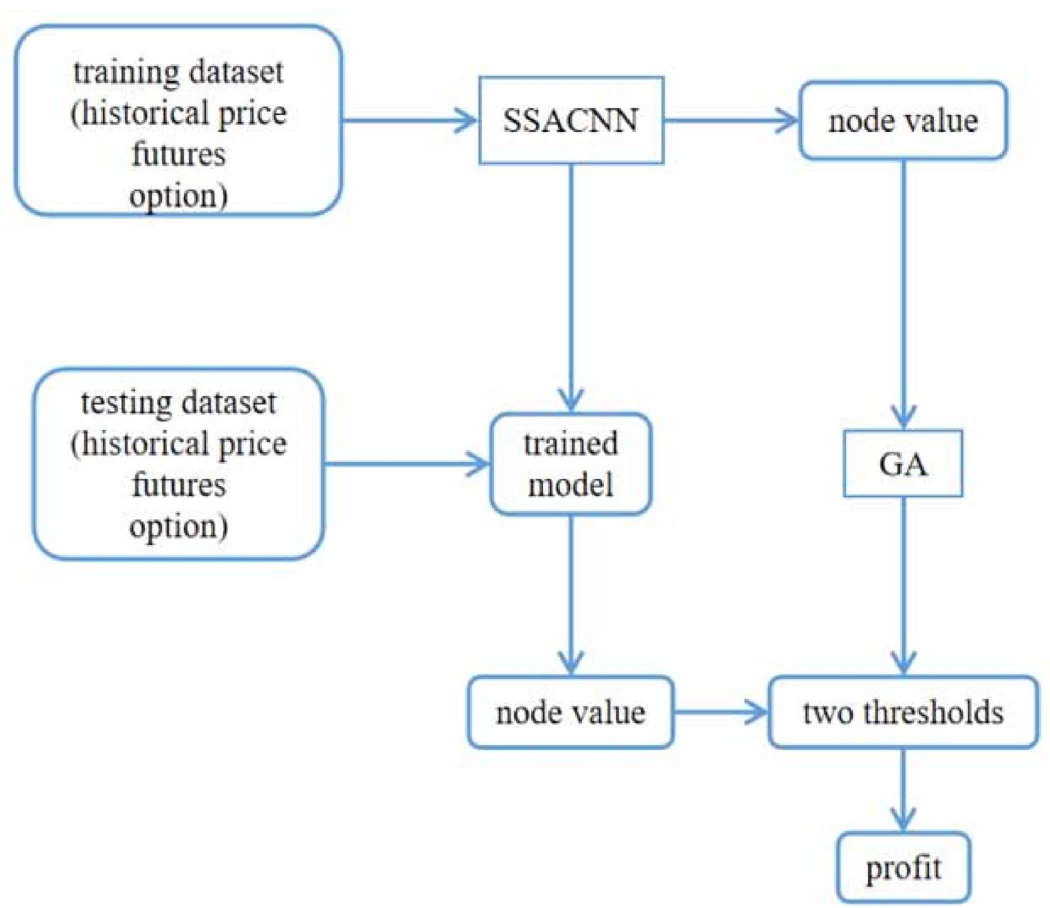
Table 4. The historical data of the five stocks after standardization

	$\mathbf{d}_{i1}$	d_{i2}	d_{i3}	d_{i4}	$d_{i.}$
CDA	1.42711759	1.36374702	1.28817718	1.29732091	...
CFO	4.4408209	4.2911262	3.92386591	3.58357233	...
DJO	3.48827139	3.75538658	3.65931874	3.92310615	...
DVO	0.136035	0.09801487	0.17144214	0.18939852	...
IJO	0.0073875	0.02757984	0.05991671	0.07369991	...

Proposed Stock Trading System

In this section, the proposed stock trading system will be introduced in detail. This system consists of the SSACNN framework and GA. To make the predicted stock price closer to the actual value, this research uses three data sets, including historical prices, futures and options. First of all, the three data sets are used as the input of the SSACNN framework. After convolution (as shown in Figure 1), pooling and other operations, the values of the three nodes are finally obtained. These three nodes represent three meanings: the first node represents a buy signal, the second node represents a hold signal, and the third node represents a sell signal. Here, only the first node and the third node are used. Because in this research, you only need to know the buy signal and sell signal of the stock. Next, use two nodes to find the optimal threshold of stock trading signals. The nodes are input into the genetic algorithm, and the thresholds of the two buying and selling signals can be obtained through operations such as crossover, mutation and iteration. Finally, the value of the node obtained through the test data set is compared with the threshold to obtain a more correct buying and selling point, and this rule is used to calculate the cumulative income over some time. The flow chart of this stock trading system is shown in Figure 8.

Figure 8. An example of a stock trading system

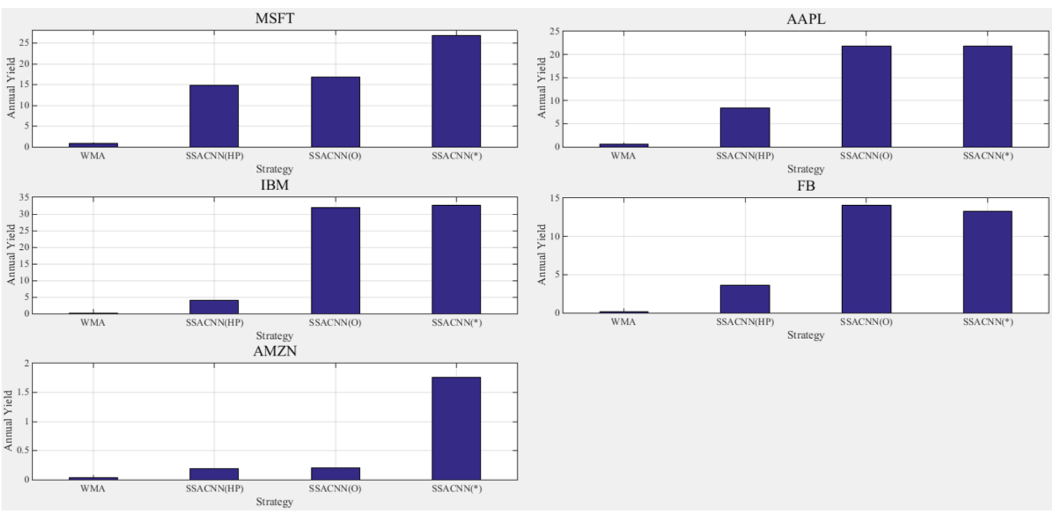


EXPERIMENTAL RESULTS

This experiment mainly uses leading indicators to study stock trading signals. For investors, finding accurate trading signals is crucial. Trading signals, that is, stock buy signals and sell signals. Because trading signals are not only affected by one factor, trading signals are difficult to accurately predict. In this study, a new SSACNN framework with leading indicators is used. Combining this framework with genetic algorithms can find a pair of trading signals. Using this trading signal for stock trading can get a certain amount of income. The data used in the experiment are the Taiwan stock market data from September 28, 2018, to October 30, 2019, and the US stock market data from September 28, 2018, to August 30, 2019.

In the experiment, a total of 10 stocks were used. Five of these stocks are from the US market (*Microsoft Corporation (MSFT), International Business Machines (IBM), Facebook, Inc. (FB), Amazon.com, Inc. (AMZN), Apple Inc. (AAPL)*), and the other five stocks are from China's Taiwan market (*MediaTek (DVO), Formosa Plastics (CFO), TSMC (CDA), Asustek (DJO) and Largan (IJO)*). Three data sets are composed of historical stock prices, futures and options. The data set is divided into two parts, one part is used for training and the other part is used for testing. This research compares the proposed stock trading system with Weighted Moving Average. The specific experimental process is shown below. First, we conduct a study on five stocks in the US stock market. The experimental results are shown in Figure 9.

Figure 9. In the US stock market, the annual yield based on each data set and trading strategy



Among them, the abscissa represents the data set, "HP" represents historical prices, "O" represents option, and "*" represents a data set combining historical prices and option. Because there is no leading indicator of futures in the US stock market, only two data sets, historical prices and options, are used. The ordinate represents the annual yield during the test period. The experiment compares the performance of our proposed stock trading system with Weighted Moving Average. In addition, the benefits obtained through the proposed trading system under different data sets are also compared. It can be seen from the experimental results that, in general, the performance of the stock trading system combined with SSACNN and GA is better than the Weighted Moving Average. It is worth noting that from the experimental results, it can be seen that the results obtained by the "O" and "*" data sets are much better than the results obtained by the "HP" data set. In other words, the result obtained by adding the leading indicator data set is better than the data set with only historical prices.

Then, study the five stocks in the Taiwan market of China. To evaluate this trading system more clearly, take the CFO as an example to show its trading signals in the experiment. According to the closing price, use the proposed trading system to find multiple sets of trading signals, as shown in Figure 10. A buy signal and a sell signal to help investors complete a transaction, as can be seen from Figure 10, there are a total of 7 transactions. The trading strategy in this experiment: a buy signal must be followed by a sell signal, but a sell signal must not be followed by a sell signal. Therefore, in Figure 10, the first red dot is a buy signal and the second red dot is a sell signal. It can be seen from Figure 10 that the trading signals found through the proposed trading system are effective. The annual rate of return is shown in Figure 11.

Figure 10. Trading signals found by the trading system on the test data set

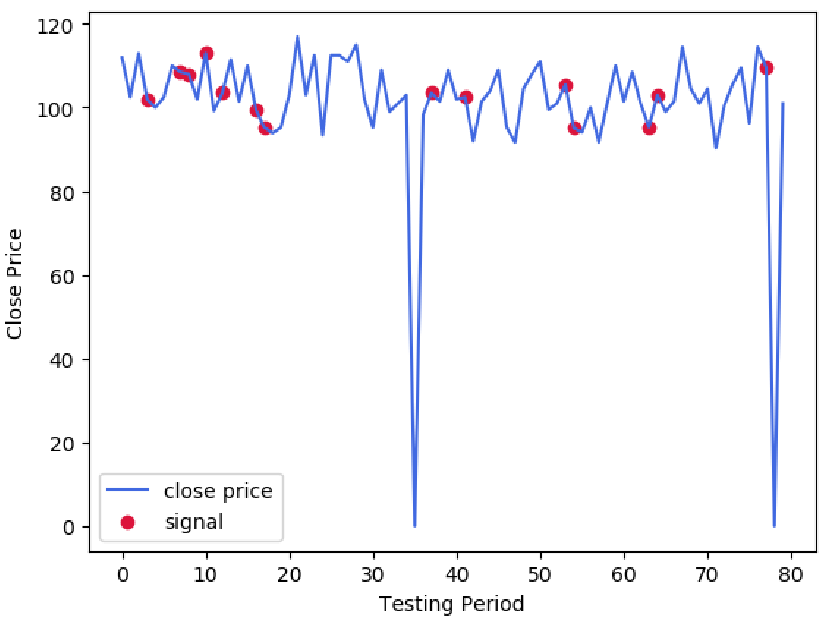
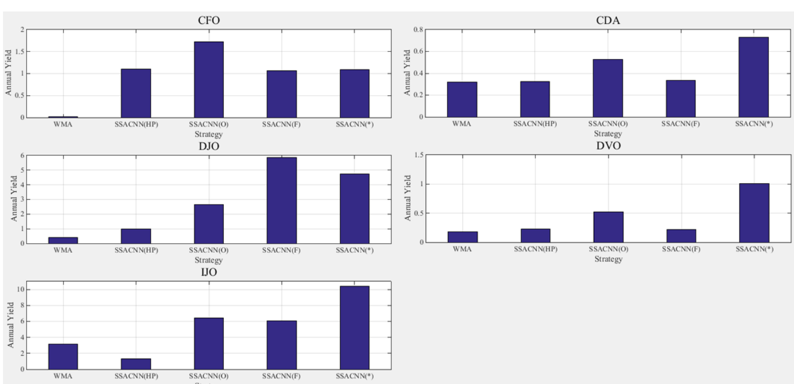


Figure 11. In the stock market in Taiwan, China, the annual yield based on each data set and trading strategy



In the experiment of five stocks in Taiwan, data sets such as historical prices (HP), futures (F), and options (O) were used. In addition, the three data sets are combined to form the fourth data set "*". The experiment is the same as the five stocks in the US market. The experimental results show that the results obtained by the proposed trading system under the "*" data set are far superior to Weighted Moving Average. The results obtained from the "O", "F" and "*" data sets are generally higher than the "HP" data sets. It can be seen that the leading indicators have had a positive impact on transactions in the stock market.

CONCLUSION

This article mainly proposes a stock trading system, which is composed of SSACNN architecture and GA. This research uses a new CNN architecture, SSACNN, which has been proposed in our previous research. This new framework has better performance for stock price prediction. In addition, genetic algorithms are used to find the optimal value of stock trading signals. In the input of the SSACNN architecture, to reduce useless information, this paper integrates the data into a matrix and then uses the matrix as input instead of inputting it into the model one by one. In other words, the input to the model in the paper is an image. In addition, the output of the model adopts a classification method to divide the stock price into three categories: +1, 0, -1, that is, the predicted stock price is no longer a specific value, but a category. The output of the SSACNN architecture is three nodes. In this study, only the first node and the third node are concerned, that is, only the buy signal and the sell signal are concerned. The experimental results show that the proposed stock trading system can help investors obtain certain returns within a period. Leading indicators can help researchers predict stock trends more effectively. This study only uses the two leading indicators of futures and options, and many factors affect the stock market, which requires further research. After that, we will further research and improve this stock trading system. Finally, the contribution of this research lies in the use of a new SSACNN architecture with leading indicators, and the combination of SSACNN and GA to form a stock trading system.

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CONFLICT OF INTEREST

We confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. We also confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

REFERENCES

Allen, F., & Karjalainen, R. (1999). Using genetic algorithms to find technical trading rules. *Journal of Financial Economics*, *51*(2), 245–271. doi:10.1016/S0304-405X(98)00052-X

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680. doi:10.1111/j.1540-6261.2006.00885.x

Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PLoS One*, *12*(7), 0180944. doi:10.1371/journal.pone.0180944 PMID:28708865

Borovkova, S., & Tsiamas, I. (2019). An ensemble of LSTM neural networks for high-frequency stock market classification. *Journal of Forecasting*, *38*(6), 600–619. doi:10.1002/for.2585

Brooks, C. (1998). Predicting stock index volatility: Can market volume help? *Journal of Forecasting*, *17*(1), 59–80. doi:10.1002/(SICI)1099-131X(199801)17:1<59::AID-FOR676>3.0.CO;2-H

Chen, C. H., Lu, C. Y., & Lin, C. B. (2019). An intelligence approach for group stock portfolio optimization with a trading mechanism. *Knowledge and Information Systems*, 1–30.

Chong, T. T., Cao, B., & Wong, W. (2014). A new principal-component approach to measure the investor sentiment. *IGEF Working Paper*, *24*, 1-19.

Chou, Y. H., Kuo, S. Y., Chen, C. Y., & Chao, H. C. (2014). A rule-based dynamic decision-making stock trading system based on a quantum-inspired tabu search algorithm. *IEEE Access: Practical Innovations, Open Solutions*, *2*, 883–893. doi:10.1109/ACCESS.2014.2352261

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297. doi:10.1007/BF00994018

Cowles, A. III. (1933). Can stock market forecasters forecast? *Econometrica*, *1*(3), 309–324. doi:10.2307/1907042

De Oliveira, F. A., Nobre, C. N., & Zarate, L. E. (2013). Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index—Case study of PETR4, Petrobras, Brazil. *Expert Systems with Applications*, *40*(18), 7596–7606. doi:10.1016/j.eswa.2013.06.071

Di Persio, L., & Honchar, O. (2016). Artificial neural networks architectures for stock price prediction: Comparisons and applications. *International Journal of Circuits*, *Systems and Signal Processing*, *10*, 403–413.

Gunduz, H., Yaslan, Y., & Cataltepe, Z. (2017). Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations. *Knowledge-Based Systems*, *137*, 138–148. doi:10.1016/j.knosys.2017.09.023

Hagenau, M., Liebmann, M., & Neumann, D. (2013). Automated news reading: Stock price prediction based on financial news using context-capturing features. *Decision Support Systems*, *55*(3), 685–697. doi:10.1016/j.dss.2013.02.006

Han, B. (2008). Investor sentiment and option prices. *Review of Financial Studies*, *21*(1), 387–414. doi:10.1093/rfs/hhm071

Heston, S., & Sinha, N. (2013). News versus Sentiment: Comparing Textual Processing Approaches for Predicting Stock Returns. SSRN *Electronic Journal*, 1-33. 10.2139/ssrn.2311310

Hiew, J. Z. G., Huang, X., Mou, H., Li, D., Wu, Q., & Xu, Y. (2019). *BERT-based Financial Sentiment Index and LSTM-based Stock Return Predictability.* arXiv preprint arXiv:1906.09024.

Hirabayashi, A., Aranha, C., & Iba, H. (2009). Optimization of the trading rule in foreign exchange using genetic algorithm. *The Annual Conference on Genetic and Evolutionary Computation*, 1529-1536. doi:10.1145/1569901.1570106

Huang, W., Nakamori, Y., & Wang, S. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, *32*(10), 2513–2522. doi:10.1016/j.cor.2004.03.016

Keim, D. B., & Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, *17*(2), 357–390. doi:10.1016/0304-405X(86)90070-X

Kim, T., & Kim, H. Y. (2019). Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data. *PLoS One*, *14*(2), 1–23. doi:10.1371/journal.pone.0212320 PMID:30768647

Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990). Stock market prediction system with modular neural networks. *International Joint Conference on Neural Networks*, *1*, 1-6. doi:10.1109/IJCNN.1990.137535

Kingma, D. P., & Ba, J. (2014). *Adam: A method for stochastic optimization.* arXiv preprint 576 arXiv:1412.6980.

Lee, C. M. C., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, *46*(1), 75–109. doi:10.1111/j.1540-6261.1991.tb03746.x

Lin, L., Cao, L. B., Wang, J. Q., & Zhang, C. Q. (2004). The applications of genetic algorithms in stock market data mining optimisation. *Management Information Systems*, *33*(8), 273–280.

Lu, W., Li, J., Wang, J., & Qin, L. (2020). A CNN-BiLSTM-AM method for stock price prediction. *Neural Computing & Applications*, *33*(10), 4741–4753. doi:10.1007/s00521-020-05532-z

Nayak, R. K., Mishra, D., & Rath, A. K. (2015). A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. *Applied Soft Computing*, *35*, 670–680. doi:10.1016/j.asoc.2015.06.040

Samuelson, P. A. (1975). Lifetime portfolio selection by dynamic stochastic programming. *Stochastic Optimization Models in Finance,* 517-524.

Schoreels, C., Logan, B., & Garibaldi, J. M. (2004). Agent based genetic algorithm employing financial technical analysis for making trading decisions using historical equity market data. *IEEE/WIC/ACM International Conference on Intelligent Agent Technology*, 1-4. doi:10.1109/IAT.2004.1342986

Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Mennon, V. K., & Soman, K. P. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. *The International Conference on Advances in Computing, Communications and Informatics*, 1643-1647. doi:10.1109/ICACCI.2017.8126078

Sheta, A. F., Ahmed, S. E. M., & Faris, H. (2015). A comparison between regression, artificial neural networks and support vector machines for predicting stock market index. *Soft Computing*, *4*(7), 55–63.

Siripurapu, A. (2014). Convolutional networks for stock trading. Stanford University Department of Computer Sciences.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, *11*(3), 304–314. doi:10.1016/0261-5606(92)90048-3

Wu, J. M. T., Li, Z. C., Herencsar, N., Vo, B., & Lin, J. C. W. (2021). A graph-based CNN-LSTM stock price prediction algorithm with leading indicators. *Multimedia Systems*, 1–20. doi:10.1007/s00530-021-00758-w

Wu, J. M. T., Li, Z. C., Srivastava, G., Tasi, M. H., & Lin, J. C. W. (2020). A Graph-based Convolutional Neural Network Stock Price Prediction with Leading Indicators. *Software, Practice & Experience*, *51*(3), 628–644. doi:10.1002/spe.2915

Yeoh, W., Jhang, Y., Kuo, S., & Chou, Y. (2018). Automatic Stock Trading System Combined with Short Selling Using Moving Average and GQTS Algorithm. *IEEE International Conference on Systems, Man, and Cybernetics*, 1570-1575. doi:10.1109/SMC.2018.00272

Zheng, L. Y., Jiang, Y. X., & Long, H. G. (2019). Exchange rates change, asset-denominated currency difference and stock price fluctuation. *Applied Economics*, *51*(60), 6517–6534. doi:10.1080/00036846.2019.1624920