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Stock Trading Suggestion Strategy Based on Kelly Criterion and Stop Loss Strategy

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Abstract. In the financial markets, artificial intelligence technology is widely used for stock forecasting. The precision of forecast results and the timing of transactions are crucial. In this paper, ten stocks from the U.S. and Taiwan stock markets serve as the research objects, and the long short-term memory neural network (LSTM) is employed to analyze the stock price fluctuations. To optimize trading signals, using particle swarm optimization (PSO) with a faster convergence speed. Kelly Criterion is used to calculate the optimal investment ratio, and the stop-loss double threshold is chosen as the stop-loss strategy for stock trading. The experiment demonstrates that not only does the trading method proposed in this paper improve investors' returns, but it also reduces their risks.
Keywords: long short-term memory neural network, particle swarm optimization, kelly criterion, stop loss strategy, trading signals

1. **Introduction.** In recent years, emerging technologies represented by artificial intelligence have thrived. Artificial intelligence technology has powerful applicability. It can be applied to many fields, such as medicine [1], agriculture [2], communication [3], and finance [4]. In the financial field, many services, including investment, insurance, and prediction, are related to artificial intelligence technology. Prediction is the most exciting thing in the financial market. Many scholars and investors continue to study and develop different prediction methods [5, 6], especially for stock prediction. At first, people used many ways to predict stock price fluctuations. However, due to many factors affecting stock price fluctuations [7], the financial market is full of uncertainty. Furthermore, investors are often affected by their own emotions [8], making them unable to make rational

judgments, resulting in low prediction accuracy of stock price fluctuations, low returns for investors, or capital losses.

Scholars use various algorithms to predict stock price fluctuations. In 2013, Guo *et al.* [9] proposed a stock market trend prediction method based on support vector machine (SVM), which has better generalization performance than traditional methods in terms of hit rate. Fenghua *et al.* [10] used singular spectrum analysis (SSA) to decompose the stock price into noise with different economic characteristics in 2014 and then introduced SVM for price prediction. Compared with SVM without price characteristics, the prediction effect of the SSA-SVM combination will be better. Although the effect of SVM has been dramatically improved compared with traditional algorithms [11], it still cannot meet the needs of stock forecasting because it is difficult to implement large-scale training sets.

Deep learning has gradually attracted people's attention. Numerous artificial neural network (ANN) models have been evaluated in certain studies for statistical stock prediction models. ANN is additionally contrasted to various data mining categorization algorithms, and the results reveal that the artificial neural network model performs better [12, 13]. Singh *et al.* [14] used the (2D) 2PCA + deep neural network (DNN) method to prove that deep learning can improve the accuracy of stock market prediction. In addition, deep learning is also applied to other fields [15, 16]. Convolutional neural networks (CNN) were effective before recurrent neural networks (RNN) were developed [17]. Wu *et al.* [18] proposed a CNN-based stock sequence array convolution neural network (SSACNN) by combining leading indicators such as futures and options, which is superior to previous frameworks in the accuracy of stock price prediction. Because the inputs of CNN are independent of each other, it cannot consider the results of the last time. That is, there is no memory, so CNN still cannot meet people's requirements for stock prediction. Therefore, RNN was born [19]. RNN is a particular neural network based on previous experience and cognition. The input at the current time and the output of the hidden layer at the last time jointly participate in calculating the current hidden layer. In other words, the nodes between its hidden layers are connected, and the previous data can be transferred to the back, a divine network with a memory function.

At present, RNN is widely used in video processing [20], text analysis [21], machine translation [22], and other fields. Because the stock series is a time series, RNN has achieved good results in stock prediction. However, it has two apparent disadvantages [23]: First, RNN suffers with short-term memory and has trouble processing lengthy input sequences, and their learning ability is limited; In addition, there is the problem of gradient disappearance. Therefore, LSTM was born. It changes from RNN. Its essence is to introduce a definition of cell state. Unlike RNN, which simply considers the most recent state, LSTM calculates which states should be ignored and which ones should be maintained based on the cell state.

In addition, The choice of a trading strategy is crucial for stock trading [24]. Researchers [25] found that if investors can accurately find the timing of buying and selling stocks, they can accurately buy and sell stocks and obtain high returns. The time of buying and selling stocks is called a "buy and sell signal." When the buying signal appears, it means that the stock price will rise in the future. Investors can buy stocks before the stock price increases to buy at a low price. When the selling signal appears, it means that the stock price will fall in the future. Investors can sell stocks before the stock price falls to sell at a high price. Numerous attempts have been made by researchers to forecast the greatest stock trading signal, but the outcomes have not been adequate.

Wu *et al.* [26] used LSTM to predict the stock price and achieved good results. After that, based on using LSTM to predict the fluctuation of stock price, GA is used to find appropriate stock trading signals [27]. A very considerable cumulative income is obtained by buying stocks when the buy signal appears and selling them when the sell signal appears. Another aspect of stock trading is fund management [28]. In the previous research on stock trading, people usually use Kelly criterion to manage funds [29]. Chen *et al.* [30] added Kelly fund management based on LSTM and GA to determine the investment proportion and help investors maximize the growth rate of funds. Wu *et al.* [31] use the Kelly criterion to determine the investment ratio for each trade. Dai *et al.* [32, 33] applied the stop loss strategy to stock investments and proved that the stop loss rule increases the investment return of stocks with lottery characteristics, reduces losses, and allows investors to benefit from the sharp rise in prices. This paper compares the effects of different optimization algorithms, uses Kelly criterion for fund management, introduces the stop loss strategy, and compares the effects of stop loss single threshold and stop loss double threshold on reducing risk to improve the return on investment. The primary significance of this paper includes the following:

- This paper proposes a stock trading strategy based on the LSTMLI framework. It compares the optimization effects of PSO and GA algorithms on the stock trading threshold to find the appropriate trading opportunity and increase the income of investors.
- The research applies Kelly criterion to the stock trading strategy to guide investors in determining the proportion of the budget of buying stocks to maximize investors' returns.
- This paper introduces the stop loss strategy to the stock trading strategy, points out the problems of the stop loss single threshold, puts forward the stop loss double threshold, and verifies the excellent effect of the stop loss double threshold for investors to stop beating in time, reduce investors' risks, and increase investors' return.

The remainder of the paper is organized as follows. The second section is related work. The third section of the study mainly introduces the methodologies employed, such as the data set and data processing, LSTM based on leading indicators, PSO, and Kelly criterion. The fourth section is the experimental part, which compares the performance evaluations of stop loss single threshold and stop loss double threshold. The proposed stock trading strategy is compared with the previous methods; the comprehensive experimental results are provided in this section. The last section is a summary of the proposed method.

2. **Related Work.** With the continuous development of artificial intelligence technology, machine learning is widely used in various fields. In the financial field, machine learning is often used for financial time series prediction. LSTM is one of the most popular deep learning models [34]. Nelson *et al.* [35] transformed the historical data of chinese stock market into a 30 day sequence, and used LSTM to model and predict chinese stock return. Compared with the random prediction method, the prediction accuracy of this method has increased significantly, which proves the power of LSTM in chinese stock market prediction. Kim *et al.* [36] indicated a new hybrid LSTM model to predict stock price variations by combining the LSTM model with several generalized autoregressive conditional heteroscedasticity (GARCH) models. The experiment found that the hybrid model combining LSTM model with three generalized autoregressive conditional heteroscedasticity models has an average absolute error (MAE), mean square error (MSE), and heteroscedasticity adjusted MAE (hmae) and heteroscedasticity adjusted MSE (hmse) had the lowest prediction errors.

Based on the advantages of machine learning, Lu *et al.* [37] indicated a CNN-LSTM-based stock price prediction approach, in which CNN was utilized to successfully extract characteristics from data, and LSTM was used to forecast the stock price using the collected feature data. The model has the best prediction accuracy and can deliver dependable stock price predictions.

Population-based algorithms are a powerful optimization technology family that Population-based algorithms are a powerful optimization technology family that draws its inspiration from the group behavior of social animals. The candidate solution set for the optimization issue is described as a particle swarm in PSO. This particle swarm can move across the parameter space and construct a trajectory that is guided by its own and its neighbors' best performances [38]. Thakkar *et al.* [39] studied the behavior of the stock market and analyzed the advantages of PSO in stock price, stock trend, and stock optimization of portfolios. Zhang *et al.* [40] examined the short-term price trend of American stocks using three sample historical data sets of American stocks as the research subject, and predicted the stock price using a prediction model combining PSO with LSTM. The performance of the LSTM model optimized by PSO was significantly improved in finding the optimal network weight, the accuracy of prediction effect is higher. Wu *et al.* [41, 42] proposed two novel meta-heuristic optimization algorithms and proved experimentally that both meta-heuristic algorithms possessed very good optimization results and verified the accuracy in stock prediction. Silva *et al.* [43] added risk management on the basis of stock prediction using LSTM, and automatically traded according to historical data, technical analysis indicators, and risk management. Chen *et al.* [44] argue that investment and financial management have also become more flexible and diverse in the IoT environment. However, as the impact of IoT on the financial industry deepens, security issues are also exposed. Many researchers have studied some complete problems of IoT and proposed different solutions [45, 46]. The security problems brought by IoT also exist in areas such as healthcare, and many researchers have conducted studies on the security problems of IoT in healthcare and other areas [47, 48]. In general, although the Internet of Things brings us a lot of convenience, the security problems it brings should not be ignored.

3. **Methodology.** This section introduces the methodology used. The first section focuses on the dataset used in this paper and the data pre-processing process. The second section presents the input of the transaction framework. The third section introduces the SSACNN model [49], which was proposed in a previous study and is mainly used in this paper for comparison experiments. The fourth part introduces the LSTM, which is mainly used to predict the trend of stock price fluctuations. The fifth section introduces PSO, which is used to find the best stock trading signals. The last section introduces Kelly criterion, which is used to calculate the optimal investment ratio of stocks.

3.1. **Datasets and Preprocessing.**

3.1.1. *Datasets.* Leading indicators are indicators that can take the lead in changing before the economic situation has changed. They can reflect the future of economic development and provide effective information for the formulation of trading strategies, so as to reduce investors' risks and maximize their profits. Therefore, this paper uses historical prices, options and futures as the data set for the study. The stock data used in this paper are from Taiwan and the United States. Because there are no futures for U.S. stocks, historical prices and options are used as data for the study of U.S. stocks. Three sets of data are used for the study of Taiwan stocks: historical prices, options, and futures.

Historical price includes five indicators: opening price, highest price, lowest price, closing price, and trading volume. Options include trading volume, open position, closing price, and settlement price. Futures indicators include opening price, highest value, lowest value, closing price, and trading volume. In this section, five stocks in Taiwan are used as examples to introduce the data used in this paper. These five stocks are CDA, CFO, DJO, DVO, and IJO, respectively. As shown in Tables 1-3, there are some data of five stocks, among which p_i, u_i and z_i are various factors affecting the stock price. Where p_i represents the opening, high, low, closing or volatility attributes of a stock. u_i represents the current price, opening price, maximum price and closing price of futures. z_i represents the attributes of the open interest and settlement price of the option.

TABLE 1. Historical prices of the five stocks.

	p_{i1}	p_{i2}	p_{i3}	p_{i4}	p_{i5}
CDA	231	237	229	237	...
CFO	101.5	106	101	106	...
DJO	235.5	240	234.5	240	...
DVO	211	221.5	210.5	219	...
IJO	3275	3555	3205	3555	...

TABLE 2. Futures data of the five stocks.

	u_{i1}	u_{i2}	u_{i3}	u_{i4}	u_{i5}
CDA	236.5	231	237.5	231	...
CFO	105	105	105.5	101.5	...
DJO	240	236	240	235	...
DVO	219	212	221.5	212	...
IJO	3535	3275	353	3230	...

TABLE 3. Options data of the five stocks.

	z_{i1}	z_{i2}	z_{i3}	z_{i4}	z_{i5}
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	...

3.1.2. *Preprocessing.* In the experiment, the data is input into the LSTM framework in the form of a matrix. The width of the matrix is 30, representing 30 days of stock data. Table 4, shows the input matrix of historical price , where "open, high, ..." represents the attribute of the data and "1, 2, ..." represents the number of days.

TABLE 4. Example of input matrix.

	1	2	3	...	30
Open	224.79	227.95	227.25	...	205.55
High	225.84	229.42	230	...	206.01
Low	224.02	226.35	226.63	...	202.25
Close	225.74	227.26	229.28	...	204.47
Change	0.79	1.52	2.02	...	4.02

Considering that the inconsistent data size may have a certain impact on the experimental results, it is necessary to standardize the data before inputting it into the LSTM framework. The standardized data conforms to the standard normal distribution, so as to ensure the consistency of the data range and reduce the impact of other factors on the experimental results. The standardization process is as follows:

$$X^* = \frac{X - X_{mean}}{X_{max} - X_{min}}. \tag{1}$$

Where X_{mean} represents the average value of data, X_{max} means the maximum value of data, X_{min} represents the minimum value of data, and X^* indicates the standardized data.

3.2. **Stock Squence Array Convolutional Neural Networks.** CNN is widely used in image processing, video processing, natural language processing, and other fields. It has very good performance in image recognition, video classification, machine translation, etc. It includes data input layer, convolution calculation layer, relu excitation layer, pooling layer, and full connection layer. The data passes through the input layer into the CNN layer and feature extraction is performed in the convolutional layer. One or more square matrix convolution cores are defined in the convolution layer, which are multiplied and added with the corresponding position numbers of the input matrix to obtain the output of the convolution layer. The output of relu is mapped to the most commonly used excitation function. The pooling layer reduces the calculations in the network by reducing the spatial size of the representation, and compresses the data to reduce the occurrence of over fitting phenomena. Maximum pooling and average pooling are the most common ways of pooling layers. After repeated convolution, excitation, and pooling, finally, through the full connection structure, the features of the previous repeated training output are combined into a complete image to form the output of the whole convolution neural network.

This paper integrates the 30 day stock data into an image as the input of convolution neural network, and obtains the final stock data through multiple convolution, excitation, and pooling. In the field of image recognition, the most frequently used convolution kernel has a size of $3 * 3$ and the pooling layer size is $2 * 2$, which is obtained through a large number of experiments. Therefore, for better experimental results, the same size of convolution kernel and pooling size are also used in this paper.

3.3. **Long Short-Term Memory Neural Networks.** Memory of the past is important for predicting the future, so we need to choose useful information from the past and predict the future based on these information. RNN differs from a typical neural network in that it gives the network a "memory" function for the prior material in addition to taking into account the input from the previous time. It uses the timing feedback mechanism, so that the input to the RNN includes data from both the previous time and the current time. However, RNN has some disadvantages, such as the disappearance of gradient in the process of back propagation and the problem that it cannot be relied on for a long time. Therefore, on the basis of RNN, LSTM is proposed. It creatively uses the structure of "gate", including "input gate", "forgetting gate", and "output gate". Through these "gate" structures, the information flow can be adjusted. The internal structure of LSTM is shown in Fig. 1.

In this paper, there are three input data sets of LSTM, including historical prices, leading indicators, and their combinations. Leading indicators are a set of indicators used to forecast future economic conditions. They are used to forecast economic operations

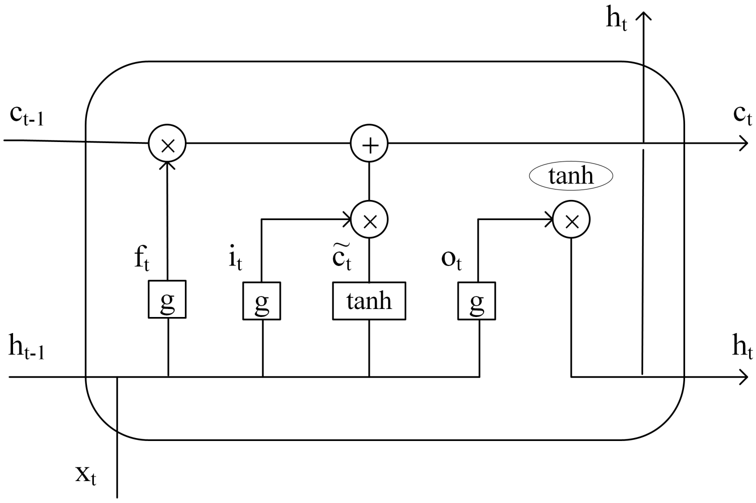

Figure 1. Schematic diagram of the internal structure of LSTM.

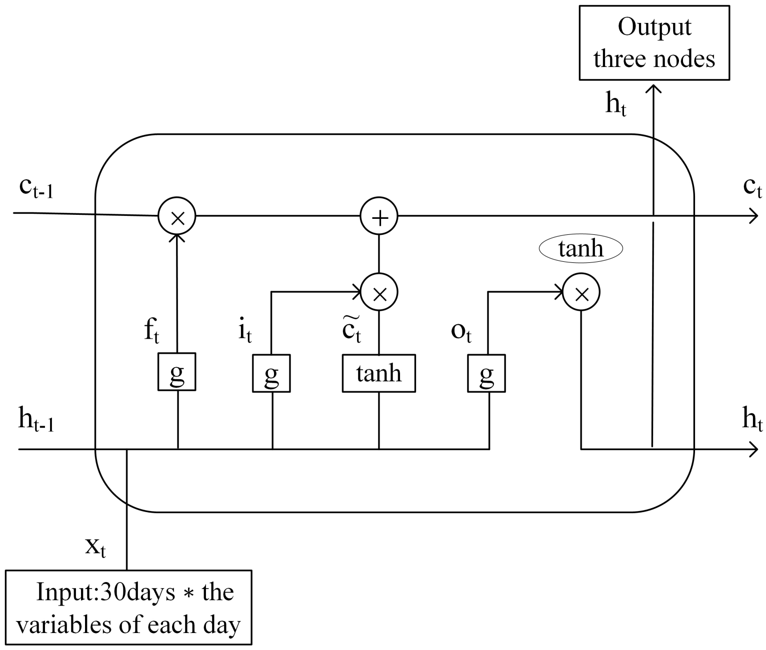

Figure 2. LSTMLI algorithm experiment flowchart.

and market trends at an early stage. This paper divides the data into two parts, which are used for training and testing, respectively. The study proposes a LSTM framework based on leading indicators, which is mainly used to classify stock prices, called LSTMLI, and its structure is shown in Fig. 2. After the model calculation, the 30-day matrix of inventory information will be transformed into an output of three nodes. According to investors' investment habits, a specific range of categories can be chosen, as shown in the Equation (2).

$$y_i = \begin{cases} 1 & \text{Change} > \text{Upper critical value} \\ 0 & \text{others} \\ -1 & \text{Change} < \text{Lower critical value} \end{cases} \tag{2}$$

When the fluctuation of the stock price is greater than the critical upper value of the classification range, it is classified as 1, which indicates that the stock price will rise the next day and that the rise was in line with investors' expectations. When the fluctuation of the stock price is less than the critical lower value of the classification range, it is classified as -1, indicating that the stock price will fall the next day and the fall is not in line with the investor's expectation. In addition, when the stock price is within the classification range, it is classified as 0, which means that the stock price fluctuation is small and investors will not perform trading operations.

3.4. **Particle Swarm Optimization.** The central issue in the stock trading process is trading signals. The correct trading signal can bring good returns to investors. Therefore, how to find the trading signal more accurately is very important for investors. PSO is an intelligent evolutionary algorithm that simulates social activities such as bird flight and foraging. It uses the information transmission between individual birds to find the global optimal location. The solution of each bird in space is the position of each bird in space. Each particle has two attributes: position and velocity, as shown in Equation (3):

$$\begin{aligned} S &= \{x_1, x_2, ..., x_n\}, \\ P_i &= \{P_{i1}, P_{i2}, ..., P_{in}\}, \\ V_i &= \{v_{i1}, v_{i2}, ..., v_{in}\}. \end{aligned} \tag{3}$$

Where S represents all n particles in the solution space, x_i means the i_{th} particle. P_i indicates the positions where the i_{th} particle moves, and v_i represents the speed when the i_{th} particle is in each position. In addition, the velocity and position of each particle are multidimensional, which depends on the dimension of solution space.

This paper uses PSO to iteratively optimize the values of the buy signal and sell signal to find the best trading threshold. A simple stock trading strategy only includes two dimensions: a buy signal and a sell signal. Therefore, in a simple stock trading strategy, the particles in the population only need to be set to two dimensions. As shown in Fig. 3.

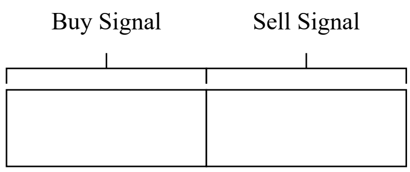

Figure 3. Representation of particles.

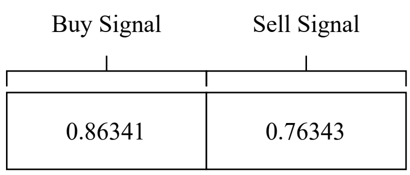

Figure 4. Examples of randomly generated trading signal thresholds.

3.4.1. *Initialize Particle Swarm.* First, each particle's position and speed must be initialized. Because the sum of the three node values obtained by the LSTM framework is 1, this paper initially sets the threshold of the buy signal and the sell signal as a random number between 0 and 1. As shown in Fig. 4.

A simple stock trading strategy will be introduced in detail. Suppose that the output result of the LSTM framework is as shown in Fig. 5. The first column on the left is the trading day, the second column is the buy signal of each day, and the fourth column is the sell signal of each day. The rightmost column represents the settlement price on the trading day. The value of the buy signal on the first trading day is 0.89346, which is obviously higher than the buying threshold of 0.86341, so the buy operation is performed on the first trading day. In the trading strategy set out in this paper, the buy operation and sell operation must appear in pairs. In other words, the buy operation must be followed by the sell operation, and the buy and sell operations are not allowed to be carried out simultaneously within one day. Therefore, after buying stocks on the first trading day, it is necessary to find the sell operation on the next trading day. The value of the sell signal on the second day is 0.65374, which is less than the sell threshold, so keep looking for a sell signal. The selling signal value on the third and fourth days is still less than the selling threshold, so continue to hold. The selling signal value on the fifth day is greater than the trading threshold, so sell on the fifth day. Similarly, continue to look for the next buying signal to carry out the buying operation, and repeat the operation until the end of the transaction.

	Buy Signal		Sell Signal	Day Price
1	0.89346		0.08792	100.143
2	0.20175		0.65374	93.237
3	0.90175		0.06753	94.278
4	0.20175		0.40128	95.823
5	0.16438		0.81938	101.375
......	......		......	......
......	0.34256		0.53218	99.923

FIGURE 5. Trading process of simple trading strategy.

3.4.2. *Fitness Evaluation.* The fitness function is used to evaluate the critical value of trading threshold. In this paper, the cumulative return over a period of time is taken as the fitness function, as shown in the Equation (4):

$$\begin{aligned} quantity_i &= \frac{Total\,fund_i}{BClose_i}, \\ balance_i &= Total\,fund_i - quantity_i * BClose_i, \\ Final\,fund_i &= balance_i + quantity_i * SClose_i. \end{aligned} \tag{4}$$

$BClose_i$ represents the closing price when buying stocks, $SClose_i$ means the closing price when selling stocks. The $Total\,fund$ represents all assets before each stock purchase, $quantity_i$ means the number of stocks purchased, $balance_i$ indicates the remaining funds after purchasing stocks, and the $Final\,fund$ means the final assets.

3.4.3. *Update particle velocity and position.* The velocity and position of particles will be updated after each iteration. The update of particle speed and position is shown in Equation (5):

$$\begin{aligned} v_{id}^{k} &= wv_{id}^{k-1} + c_1 r_1 (pbest_{id} - x_{id}^{k-1}) + c_2 r_2 (gbest_d - x_{id}^{k-1}), \\ x_{id}^{k} &= x_{id}^{k-1} + v_{id}^{k-1}. \end{aligned} \tag{5}$$

Where w represents the inertia factor, which is used to modify the particle swarm's capacity for both global and local optimization, c_1 is the individual learning factor, c_2 is the group learning factor, $pbest_{id}$ is the ideal value of the i_{th} particle's extreme value in the d dimension, and $gbest_{id}$ is the ideal value of the d dimension of the overall optimal solution. Particle updating involves four dimensions. The updated particles will be evaluated for fitness and judged whether they meet the requirements of iteration or fitness.

3.5. **Kelly Criterion.** For investors, "when to buy" and "how much to buy" are two key issues directly related to investment risk and return in the process of a stock trading. The formulation of trading strategy solves the problem of "when to buy and sell" to a certain extent, and "how much to buy" is still a problem worthy of study. Kelly criterion points out that in a repetitive gamble or repetitive investment with a positive expected return, the optimal proportion that should be bet in each period. Relying on this proportion, investors can effectively reduce risks and obtain more returns.

If in a gambling game, there are two results, winning and losing. Assuming that the gambler's principal is N_0 yuan, the winning net profit rate is b_1, the failed net loss rate is b_2, and the betting proportion of each game is f, of which $0\% < f < 100\%$. After T rounds, win W rounds and fail L rounds, that is, $W + L = T$, then the final total assets are:

$$N_T = N_0(1 + b_1 f)^W (1 - b_2 f)^L. \tag{6}$$

Divide both sides of the equation by N_0 and take the logarithm, and then divide by the total number of rounds T to obtain the following results:

$$\frac{1}{T} log(\frac{N_r}{N_0}) = \frac{W}{T} log(1 + b_1 f) + \frac{L}{T} log(1 - b_2 f). \tag{7}$$

Assuming that the probability of winning is p and the probability of failure is $1 - p$, where $p > 1 - p$, that is, the probability of winning is greater than 0.5, and the results of each game are independent of each other, the long-term expected return of the game is positive, so it is beneficial for us to play it. Consequently, if T goes to infinity, the game can be played an infinite number of times, we can get the following results:

$$\lim_{T\to\infty} \frac{1}{T} log(\frac{N_T}{N_0}) = Plog(1 + b_1 f) + (1 - p) log(1 - b_2 f). \tag{8}$$

Let the above formula take the derivative of f, and the betting ratio when taking the extreme value is the best, then there are the following results:

$$f = \frac{pb_1 - (1 - p)b_2}{b_1 b_2}. \tag{9}$$

In order to obtain the investment proportion of each transaction, that is, the f value of Kelly criterion, it needs to obtain the winning probability p, net profit b_1 and net loss

b_2 of the game. The steps for resolving the investment score f are demonstrated with an example. The profit and loss of each transaction can be determined using the particular trading technique, assuming 0.5 times of the total assets invested in each transaction. For example, with a principal of 1 yuan, there are 10 transactions, and the profit and income of each transaction are $+4, -2, -1, +5, -3, +2, +6, +3, -4$ and $+4$ respectively. Then calculate b_1 and b_2 respectively. Of these 10 transactions, 6 are profitable, and the profit amounts are $+4, +5, +2, +6, +3$ and $+2$. The other four losses were $-2, -1, -3$ and -2. Therefore, the winning rate P is $6/10 = 0.6$, b_1 is $(4+5+2+6+3+4)/6 = 4$, and the penalty is $-(2+1+3+2)/4 = -2$. The investment score f can be obtained by substituting each variable into Kelly criterion.

Algorithm 1 The process of searching for optimal indicators.

Input:

D: the data of training; K: the data of testing; N: maximum number of iterations for LSTM model training; Z: maximum number of iterations of PSO; $Adam$: an SGD algorithm.

Output:

buy threshold: bthreshold, sell threshold: sthreshold, stop loss range: slrange, trade ratio: trade.

Initial $i = 1$, $j = 1$, $p = 1$, $bthreshold \in (0,1)$, $sthreshold \in (0,1)$, $slrange \in (0,1)$, $ratio \in (0,1)$.
Initialize algorithm
$\{D_{x1}, D_{x2}, \ldots, D_{xm}\} \leftarrow$ standardize the data
$\{D_{y1}, D_{y2}, \ldots, D_{ym}\} \leftarrow$ generate true label value
while $i < N$ **do**
  while $t < m$ **do**
    $D_{pt} \leftarrow$ input D_{xt} to the proposed LSTM
    $n_i \leftarrow$ weightsUpdate($Adam$, D_p, D_y)
  end while
end while
$D_p \leftarrow \{D_{p1}, D_{p2}, \ldots, D_{pm}\}$
$D_q \leftarrow$ generate label vectors for the test set
while $p < Z$ **do**
  $fitness \leftarrow$ calculateFit(D_p, $bthreshold$, $sthreshold$, $slrange$, $ratio$)
  $(v_p, x_p) \leftarrow$ update the velocity and position of the particles
  ($bthreshold$, $sthreshold$, $slrange$) $\leftarrow$ update trading threshold, stop loss range and trade ratio
end while
Generate optimal buy threshold, sell threshold, stop loss range, trade ratio

3.6. **Find Optimal Indicators and Simulate Trades.** Optimal trading signal, stop loss range, and trade ratio are the core elements of the trading strategy proposed in this paper. In this section, the optimal search process of these indicators and the procedure of simulated trading will be introduced.

Algorithm 1 is the process of finding the optimal trading threshold, stop loss range and investment ratio, which requires the input of the following parameters: (1) D, the data of training; (2) K, the data of testing; (3) N, maximum number of iterations for LSTM model training; (4) Z, maximum number of iterations of PSO; (5) $Adam$, an SGD algorithm.

Algorithm 2 The process of simulating stock trading.

Input:

$Y = \{y_1,y_2,...,y_N\}$: predict label; $C = \{c_0,c_1,c_2,...,c_N\}$: closing price; R: fund ratio; S: stop loss range.

Output:

profit rate: rate.

1: Initial $init\_fund = 100000$, $fund = init\_fund$, $i = 1$, $quantity = 0$;
2: **while** $i<N$ **do**
3:   **if** y_i==1 **then**
4:     $quantity = fund \times c_{i-1}$;
5:     $fund = fund$ - $quantity \times c_{i-1}$;
6:     $j = i + 1$;
7:     **while** $j \times N$ **do**
8:       **if** y_j==-1 or (c_{i-1}-c_{j-1}) / $c_{j-1} \in S$ **then**
9:         $fund = fund + quantity \times c_{j-1}$;
10:         $quantity = 0$;
11:         $i = j$;
12:       **else**
13:         $j = j + 1$;
14:       **end if**
15:     **end while**
16:   **end if**
17:   $i = i + 1$;
18: **end while**
19: **if** $quantity \neq 0$ **then**
20:   $fund = fund + quantity \times C_N$
21: **end if**
22: $rate = (fund$ - $init\_fund)$ / $init\_fund$;

Since the features of the data represent different ranges and meanings, they need to be initialized (Line 3). Also, the true label values of the training set can be obtained (Line 4). Then the data from the training set is fed into the LSTM model for training, and the label vector of the training set is generated (Lines 5 to 10). After several iterations, the trained LSTM model is obtained, the data from the test set is input, and the label vector is generated for simulated trading (Line 12). Then PSO is used to obtain the fitness function values based on the label vectors, trading threshold, and stop loss range. The stop loss strategy is described in section 4.2. Finally, the population is assessed using the fitness function, and changes are made to the population's particle positions and velocities based on the evaluation's findings. Repeating this process until the termination condition is reached, the optimal trading threshold, stop loss range, and investment ratio are obtained (Lines 13 to 17).

Algorithm 2 is a pseudocode to simulate the trading process, which requires the input of the following parameters: (1) Y, the label to predict the rise or fall of the stock; (2) C, the closing price of the stock for each trading day; (3) R, the investment ratio for each trade; (4) S, the stop loss interval.

If the prediction label is 1, the stock is bought in proportion to the investment calculated by Kelly Criteria, and then the quantity of stocks purchased is calculated along with the amount of money remaining (Lines 3 to 6). After holding the stock, if the prediction label is -1, or if the stock price declines and the loss rate is within the stop loss range, sell all stocks (Lines 8 to 11). The buy-and-sell operations will be repeated until the end of the period (Line 18). If a certain quantity of stocks are still held at the end, they will be sold at the closing price of the last day, and the profit rate will be calculated (Line 22).

4. **Experiment.** This section will mainly introduce the selection of optimization algorithm in a simple stock trading strategy, then apply Kelly criterion to fund management on the basis of the simple stock trading strategy, and introduce the stop loss function to form a more complex stock trading strategy with fund management and stop loss function. This section will also analyze the selection of single threshold and double threshold in the stop loss strategy. Finally, the more complex stock trading strategies constructed are compared with other trading strategies studied in the past.

4.1. **Selection of Optimization Algorithm in Simple Trading Strategy.** In previous studies, GA is often used to optimize the transaction threshold, while PSO is widely used because of its simple principle, fewer parameters, and easier implementation. Both PSO and GA can be used to optimize the threshold and find the optimal solution to a specific problem. Both of them are solved in the solution space by simulating the foraging behavior of individuals in the population.

This section will take historical prices, futures, and options of 10 stocks in the United States and Taiwan as the research objects, use the LSTM model to predict the fluctuation of stock prices, and then use PSO and GA to optimize the trading thresholds, respectively, and simulate the stock trading process to obtain the annual return of stock trading.

Fig. 6 shows the optimization of stock trading thresholds using PSO and GA, respectively, and the comparison of annual returns from stock trading. Where (a) (b) (c)... represent different stocks, the abscissa represents different data sets of each stock, and the ordinate represents the difference level of annual return obtained by two different optimization algorithms. The smaller the value, the smaller the difference between the two annual rates of return. The calculation process for the difference rate is as Equation (10). The difference level of the annual yield of each data set trading threshold optimized by the two algorithms is measured by the size of 0% of the distance between each point on the broken line and the smoothness of the broken line. If the fold formed by the difference level of all data sets of a stock is less curved and the difference value tends to 0, it shows that PSO and GA have very similar optimization effects on all data sets of this stock. It can be seen that the bending range of the difference horizontal line of each blank is between -1% and 1%, and only the difference of individual data sets is about 2%, which indicates that the annual yield obtained by the transaction threshold optimized by the two algorithms have little difference.

$$\begin{aligned} Profit\,margin &= \frac{Total\,return - Total\,investment}{Total\,investment} * 100\%, \\ Difference\,level &= Profit\,margin_{PSO} - Profit\,margin_{GA}. \end{aligned} \tag{10}$$

Since the difference in optimization effect between PSO and GA is not significant, the faster optimization speed is chosen for the same level of production. Tables 5 and 6 shows the number of iterations when convergence is reached in the process of threshold optimization using PSO and GA under the same conditions. It can be seen that in all data sets, PSO can converge after fewer iterations, while GA needs more iterations to reach convergence. Therefore, this paper will use PSO for subsequent research.

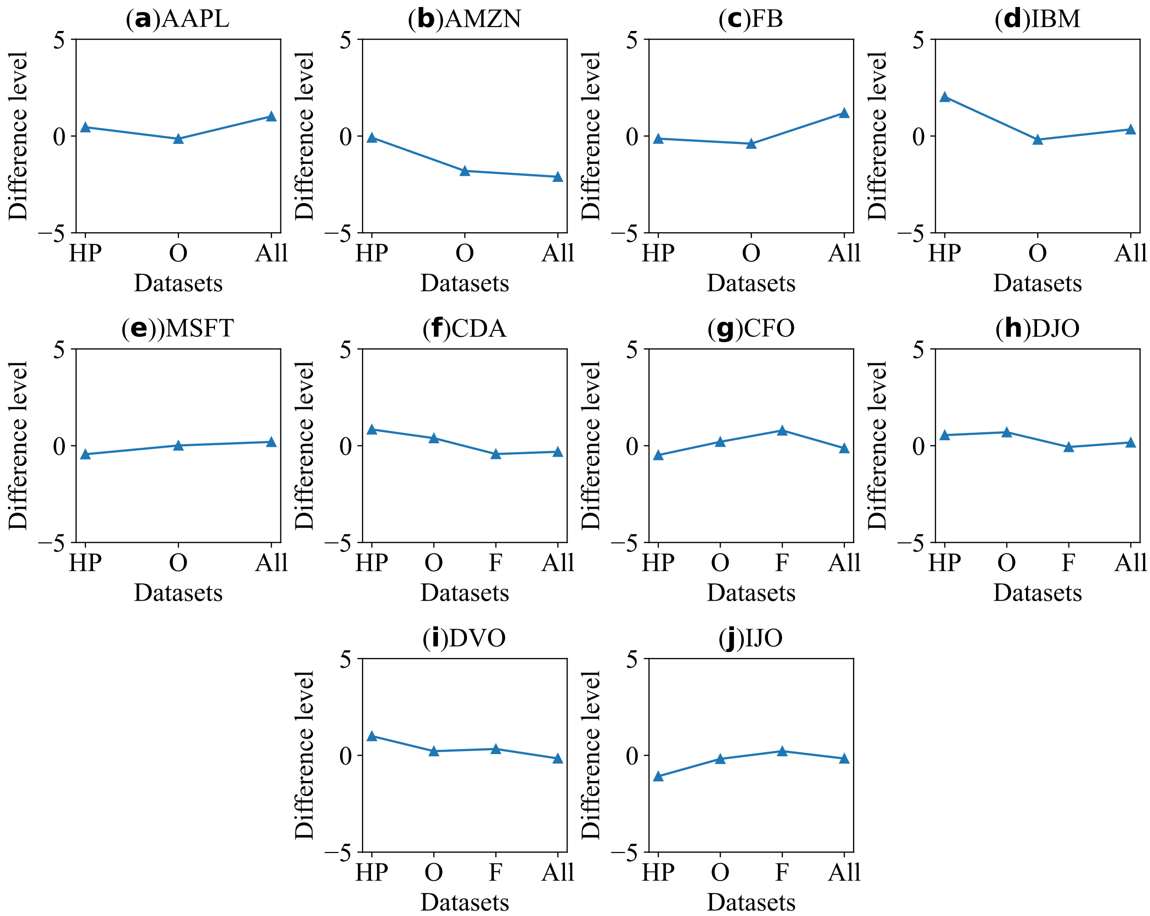

FIGURE 6. Comparison of yield after PSO and GA optimization thresholds.

TABLE 5. Comparison of iteration times when using PSO and GA convergence in American stocks.

Stock	HP		O		All	
	PSO	GA	PSO	GA	PSO	GA
AAPL	43	175	72	322	43	154
AMZN	23	142	28	160	45	175
FB	14	101	51	246	53	379
IBM	24	161	47	319	30	309
MSFT	28	80	29	115	52	117

4.2. **The Stop Loss Strategy.** For a complex stock trading strategy, reasonable trading time, appropriate capital investment and timely stop loss selling are three highly important components. In the above research, the choice of trading opportunity and the determination of capital investment ratio are discussed. This part will introduce the timely stop loss selling and introduce it into the stock trading strategy.

When the price of a stock held by an investor falls and the loss rate is within a set range, the stock will be sold in time to reduce the investor's losses. If it does not fall into this range, it will choose to continue to hold. In the past, the stop loss of stock trading often used a single value as the stop loss critical point, but this would be counterproductive, as shown in the Fig. 7.

TABLE 6. Comparison of iteration times when using PSO and GA convergence in American stocks.

Stock	HP		O		F		All	
	PSO	GA	PSO	GA	PSO	GA	PSO	GA
CDA	18	154	29	156	48	287	67	125
CFO	35	101	26	101	18	100	35	224
DJO	35	92	24	183	19	101	22	140
DVO	23	230	22	127	32	347	13	81
IJO	37	237	35	148	31	102	18	181

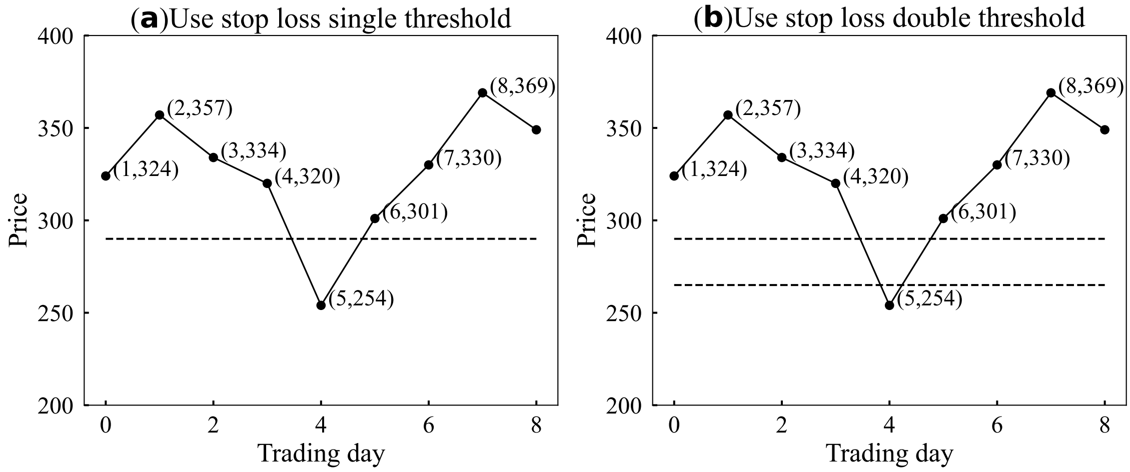

FIGURE 7. Income comparison between stop loss single value and stop loss range.

Fig. 7 (**a**) shows that the critical single value is used in the stop loss strategy. The abscissa represents the trading day, and the ordinate represents the trading price. If it buys and holds stocks before the third trading day, and the stock price will fall sharply on the fourth trading day. So in the stop loss strategy using the critical single value, the loss at this time will inevitably exceed the critical single value of the stop loss, so sell on the fourth trading day. Then it will inevitably cause great losses. Since the price on the third trading day was 320 and the price on the fourth trading day was 254, the loss rate was 20.635%. Equation (11) is the calculation process of stop loss rate.

$$Loss\,rate = \frac{Invested\,fund - Income\,fund}{Invested\,fund} * 100\%. \tag{11}$$

Fig. 7 (**b**) uses the critical range, that is, the critical upper limit and the critical lower limit are used to replace the critical single value. Only when the loss value is within this critical range can the stop loss strategy be triggered for stop loss selling. Therefore, in this case, when the stock price falls precipitously on the fourth trading day, as the loss value is not within the stop loss range, no selling will be carried out until the next selling signal appears, that is, selling will be carried out on the seventh trading day. Since the price on the third trading day was 320 and the price on the seventh trading day was 369, the yield was 15.3125%.

It can be seen that when the critical single value is used, the loss rate is 20.635%, while when the critical range is used, the return rate is 15.3125%. Therefore, the design of the critical range can effectively avoid serious losses in the situation of a critical single value, which is a very important point in the timely stop loss strategy. After the stop loss strategy is applied, the dimension of the population in PSO will be changed to 4 dimensions, which are: buy signal, sell signal, lower limit of stop loss, and upper limit of stop loss. The dimensions of individuals in the population and the trading thresholds and stop loss thresholds in the trading process are shown in Fig. 8 and Fig. 9.

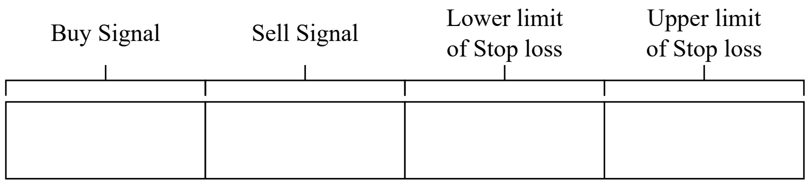

FIGURE 8. Particle representation after adding stop loss strategy.

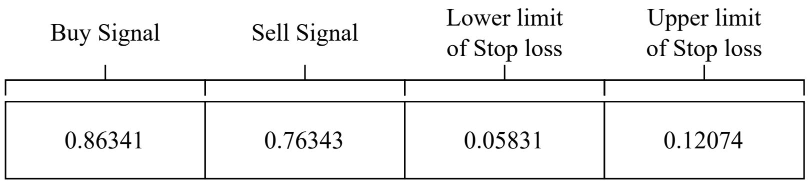

FIGURE 9. Examples of randomly generated trading signal thresholds and stop loss thresholds.

The specific trading process after applying the stop loss strategy is shown in the Fig. 10. Among them, the first column is the trading day, the second column is the buying threshold, the third column is the selling threshold, the fourth column is the lower limit of stop loss, the fifth column is the upper limit of stop loss, and the last column is the stock price on the trading day. The buying signal value on the first trading day was 0.89346. Obviously, it is greater than the buying threshold of 0.86341, so buy on the first trading day. The selling signal value on the second day was 0.65374, lower than the selling threshold. However, the trading price is 93.237, and the calculation shows that the loss rate is 6.896%, which is between 5.831% and 12.074% of the stop loss range. Therefore, although the selling threshold was not reached on the second trading day, the timely stop loss strategy was touched, so the selling operation was carried out. The purchase signal value on the third day is greater than the purchase threshold, so the purchase operation is performed. After the buy signal, it must correspond to the sell signal. The selling signal on the fourth day was lower than the selling threshold, and the loss rate was not within the timely stop loss range, so it was not sold. The selling signal value on the fifth day is greater than the trading threshold, so sell the stock.

In order to verify the advantages of the stop loss double threshold in the stock market, this section uses HP+O of five stocks in the United States and HP+O+F of five stocks in Taiwan as the research objects. Based on the use of LSTM for stock price fluctuation prediction, PSO for threshold optimization, and Kelly criterion for fund management, the comparison of stop loss single threshold and stop loss double threshold is carried out. As shown in the Fig. 11, it can be seen that the annual yield using the double threshold of stop loss is significantly higher than that using the single threshold of stop loss. This is because the single threshold of stop loss cannot avoid the stop loss selling when the stock price falls precipitously, and the double threshold of stop loss can well avoid this.

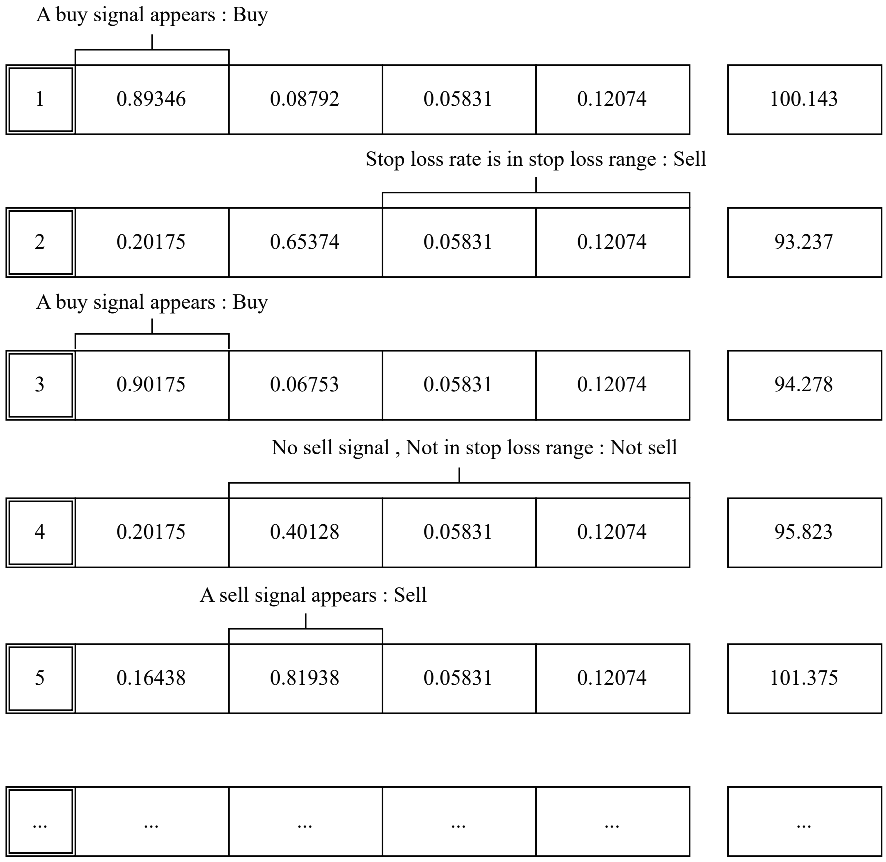

Figure 10. Specific trading process after adding the stop loss strategy.

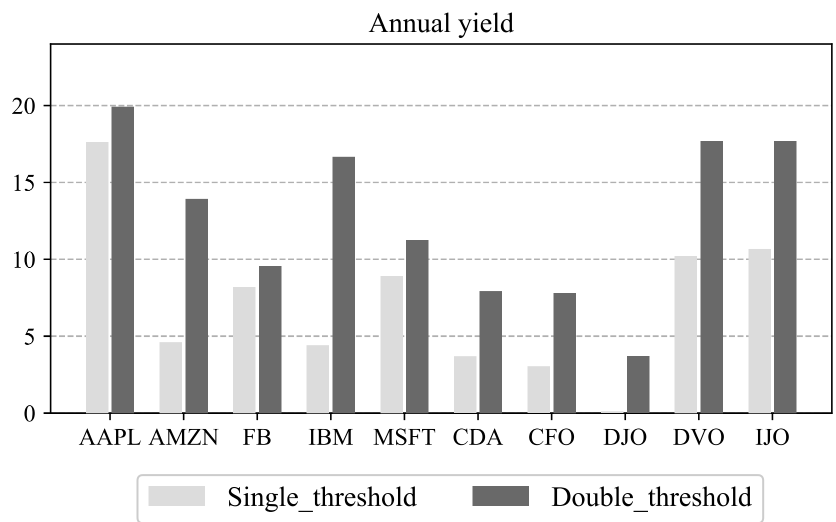

Figure 11. Comparison of annual yield between stop loss single threshold and stop loss double threshold.

The Fig. 12 shows the fluctuation of the IBM stock price, in which the yellow mark represents the buy signal, the red mark represents the sell signal, and two trading signals appear in pairs. It can be seen that after buying on the 24th trading day, the stock price fell, but due to the limit of the stop loss double threshold, stop loss selling was not carried out at this time, and the stock continued to hold until the 30th trading day. Similarly, after buying on the 88th trading day, the stock price also fell, and it was not until the 95th day that the stock was sold.

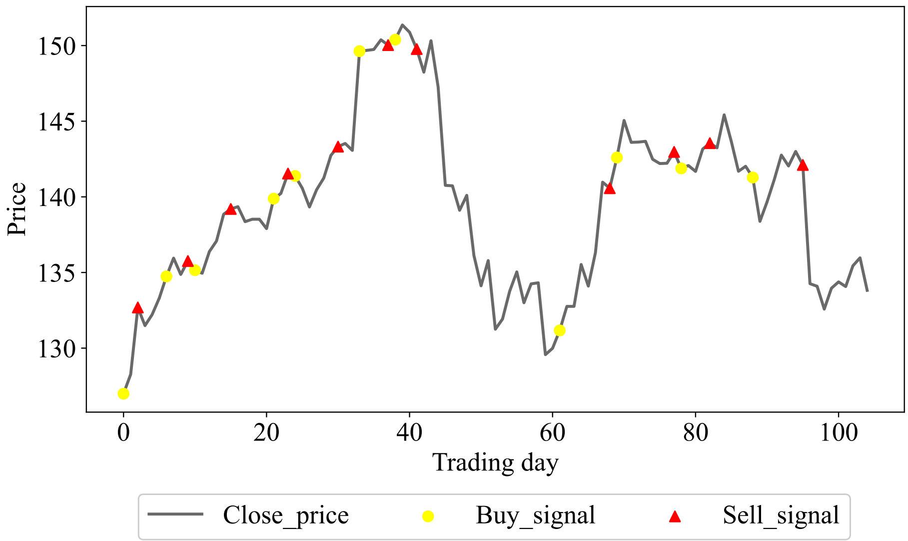

FIGURE 12. An example of when a buy or sell signal appears.

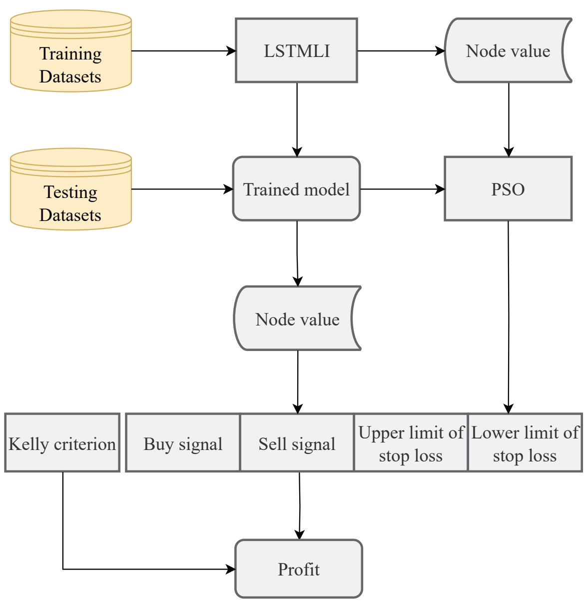

FIGURE 13. The flow chart of the stock trading strategy.

4.3. **Complete Stock Trading Strategy.**

4.3.1. *Trading Framework.* This section will introduce the proposed stock trading strategy in detail. The strategy includes LSTM, PSO, Kelly criterion and stop loss strategies, which mainly provide investors with accurate trading signals and help them to increase their income. As shown in Fig. 13: First, the data from the training set is fed into the LSTM framework in the form of a matrix for training the neural network model, and finally three node values are obtained, where the first node is the buy signal value, the second node is

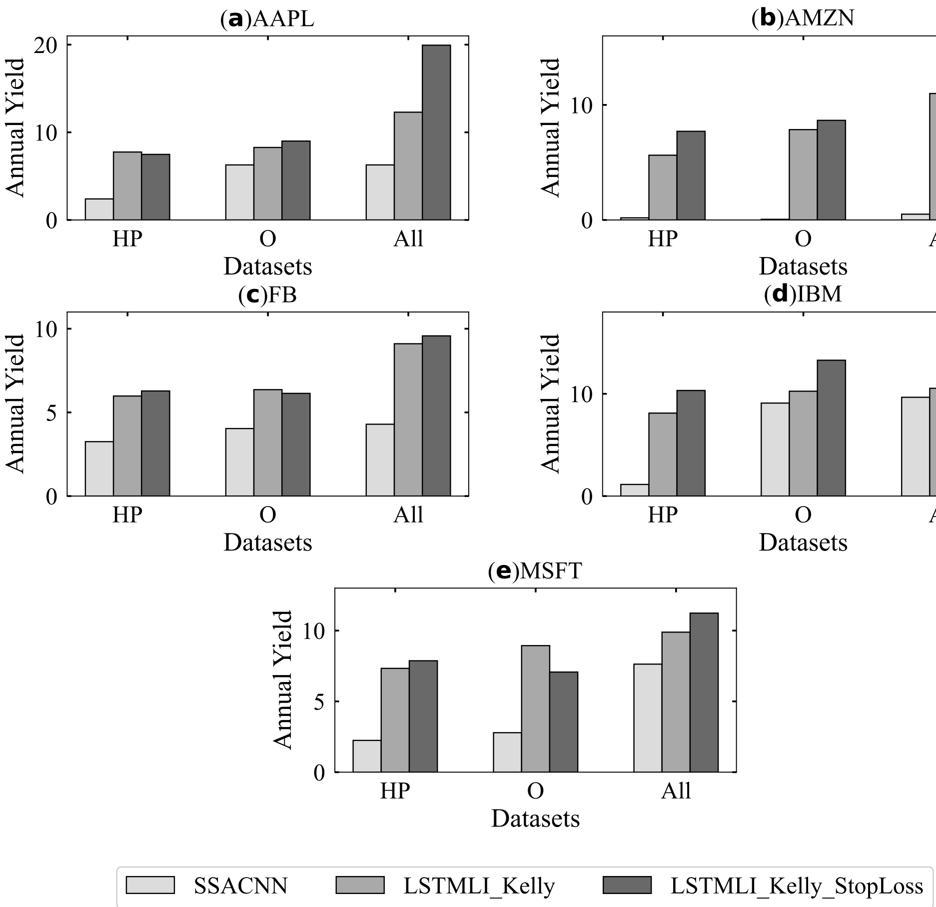

Figure 14. Using five American stocks as the data set, verify the effectiveness of the proposed stock trading model: the annual yield of (**a**) AAPL stock, (**b**) AMZN stock, (**c**) FB stock, (**d**) IBM stock, and (**e**) MSFT stock.

the hold signal value, and the third node is the sell signal value. And according to the nodes obtained from the training set, PSO is used for optimization to obtain the optimal stock buy threshold, sell threshold, stop loss lower limit, and stop loss upper limit. Then input the data of the test set into the trained neural network model to get the nodes of the test set. Compare the nodes obtained from the test set with the buy threshold, sell threshold, stop loss lower limit and stop loss upper limit to determine whether to buy and sell. When looking for a buy signal, you only need to compare it with the buy threshold. When looking for the sell signal, it not only needs to compare the test set node with the sell threshold but also needs to calculate the loss ratio on the trading day, and compare the loss ratio with the stop loss upper limit and stop loss lower limit, so as to determine whether a stop loss is needed. In addition, Kelly criterion is also introduced into this experiment to determine the appropriate investment proportion, so as to reduce the risk of investors. Trading threshold, upper limit of stop loss, lower limit of stop loss, and Kelly criterion jointly restrict the trading strategy, which greatly improves the performance of the trading strategy and improves the income of investors. The final income is located in the rounded rectangle.

4.3.2. *Comparison of Different Trading Strategies.* This paper compares the proposed stock trading strategy with two other stock trading models: the SSACNN model optimized

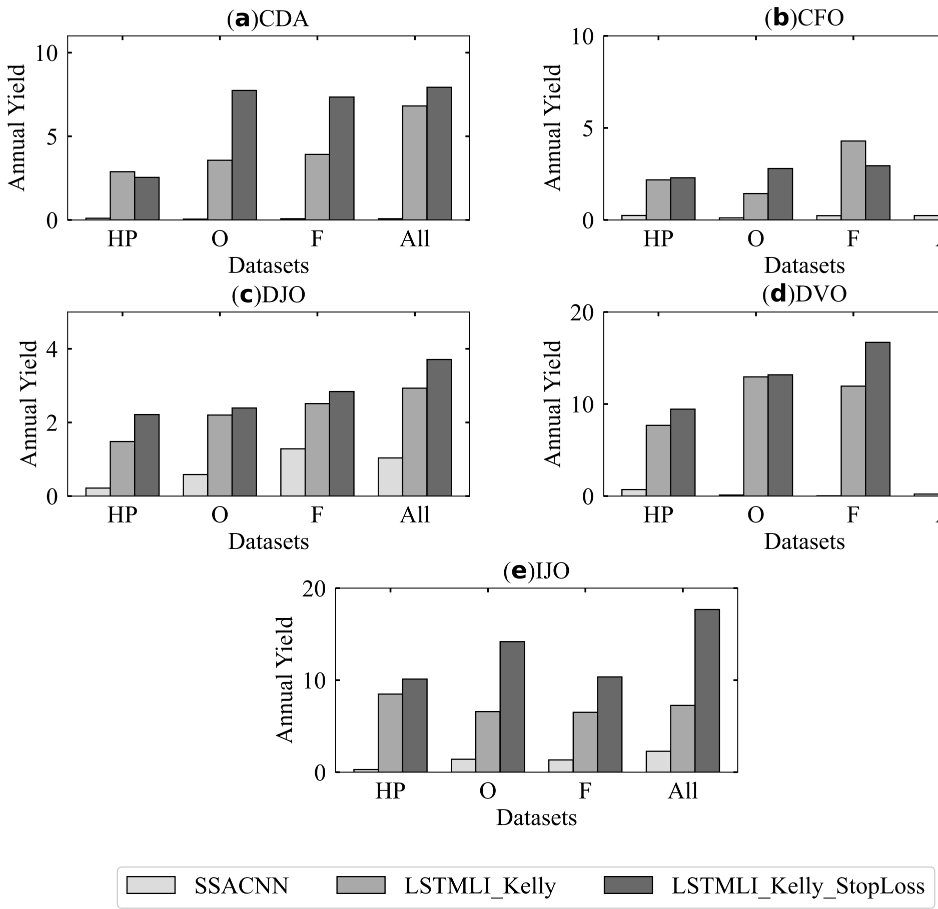

FIGURE 15. Using five Taiwan stocks as the data set, verify the effectiveness of the proposed stock trading model: the annual yield of (**a**) CDA stock, (**b**) CFO stock, (**c**) DJO stock, (**d**) DVO stock, and (**e**) IJO stock.

by GA and the LSTMLI model optimized by PSO. Both models do not include the stop loss strategy.

Use five U.S. stocks to mimic stock trading, and the results are presented in Fig. 14. The experiment data set is represented by the abscissa, "HP" represents the historical price data set, and "O" represents the option data set, "All" represents the combination of historical price and option data set, excluding futures. The ratio of profit to principal is represented by the ordinate. Experimental results show that the effect of our stock trading model is better than the other two models.The addition of leading indicators can have favorable effects on the prediction of stock price fluctuations. In addition, the addition of Kelly criterion and the stop loss double threshold can effectively reduce investors' losses and improve the final annual income level..

The experimental results of five stocks in Taiwan stock market are shown in Fig. 15. The abscissa represents the experimental data set, "HP" represents the data of historical price, "O" represents the data of option, "F" represents the data of futures, "All" represents the combination of historical price, options, and futures. The ratio of profit to principal is shown in the ordinate. The findings of the experiment demonstrate that the stock trading model using Kelly criterion for fund management and stop loss strategy has a higher ratio of return to principal than other models without Kelly criterion or stop loss strategy. In addition, the effect of using the combination of historical data, options, and futures as the research data set is better than using any other data set as the research data set.

5. **Conclusion.** Stock trading has always been characterized by "high risk and high return." The high risk of stock trading is often caused by the continuous decline of the stock price held by investors. From the perspective of the high risk of stock trading, this paper proposes a more complex stock trading strategy that takes LSTM as the prediction models and inputs the data into a LSTMLI architecture in the form of a matrix. This architecture adopts a classification method for stock price fluctuations, in other words, it classifies stock price fluctuations. That is, the price of stock fluctuations is converted from a specific value into three categories. This paper compares different optimization algorithms, selects PSO as the optimization algorithm of trading threshold and stop loss threshold, and applies Kelly criterion to the trading strategy to calculate the optimal investment proportion. In order to better reduce investors' losses, this paper introduces the stop loss strategy and compares the effects of stop loss single threshold and stop loss double threshold on reducing investors' losses. The introduction of a stop loss strategy can help investors sell at a time when the stock price continues to decline, so as to achieve the purpose of a stop loss in time. By comparing with the trading strategies in previous studies, it shows that the addition of Kelly criterion and the use of stop loss double thresholds can help investors reduce risks and increase returns.

Although a profitable stock trading strategy was developed in this work, there are several aspects that need to be further improved: First, the accuracy of stock price fluctuation trend prediction needs to be improved; Second, it is expected that other intelligent algorithms can obtain more accurate trading signals; Third, the addition of other trading strategies may improve the performance of the trading strategy.

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