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A Study on Analyzing Nonlinear Volatility and Risk Management in Securities Market by Image Recognition Algorithm in Digital Finance Era

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Abstract With the growth of the financial market, the securities market has become more important in the financial market, and it is conducive to the stability of the securities market to fully recognize the existence of risk and make preparations for risk prevention. The study proposes a generalized autoregressive conditional heteroskedasticity model based on particle swarm optimization algorithm for independent component analysis (PSO-ICA-GARCH), which is used for nonlinear volatility modeling of the securities market to generate a statistical image of securities market volatility. Then a multi-stage supervised bi-stream linear convolutional network (B-CNN)-based model is proposed for recognizing the images generated in the previous section to predict the rise and fall of the securities market. The results show that the PSO-ICA algorithm has higher separation accuracy compared to the ICA algorithm, and the four industries of agricultural services, environmental engineering, communication services, and logistics have significant positively correlated volatility spillovers to the electronics manufacturing industry, which verifies the existence of volatility spillovers among industries in the Chinese stock market. Using multi-supervised double convolutional neural network to analyze it to avoid the volatility of the stock market, the risk management of the stock market can be strengthened in this aspect.

Index Terms particle swarm optimization algorithm, independent component analysis, generalized autoregressive conditional heteroskedasticity, two-stream linear convolutional network, nonlinear volatility of securities market

I. Introduction

The securities market is the core of the digital financial system, and maintaining its stable operation is one of the key objectives of securities regulators. Classical capital market theory unfolds under the linear paradigm of Newtonian static mechanics, which holds that investors will respond to external information in a linear manner, and that market price fluctuations can be described by a series of linear equations containing stochastic error terms, rejecting nonlinear responses, and consequently concluding that the market system itself operates within a linear stability zone [1]-[4]. However, the complexity of the real securities market and the variability of investor behavior determine that the securities market is often in an unbalanced state of volatility [5]. The history of the development of the securities market also proves that there are periodic mutation points in the operation of the market, and without warning, crises can suddenly erupt and quickly spread to the whole market.

Contrary to the classical theory, the nonlinear system theory represented by the chaos theory assumes that the economic relationship is nonlinear, and believes that the irregular rise and fall of the market volatility is not the result of external random shocks, but is caused by the complex mechanism of the system's internal action, and the complexity and diversity of the system's internal complexity and diversity will lead to the phenomenon of chaos and fractal [6]-[9]. The widespread asymmetric supply and demand, irregular economic cycle fluctuations, information asymmetry, limited rationality of investor behavior and many other elements in the securities market determine the complexity of the operation of the securities market, and only the use of nonlinear system models can portray the market evolution process more scientifically [10], [11]. As an emerging market, the imperfect system of China's securities market, the irrational structure of market participants, and the misalignment of investment concepts pose a potential threat to the stability of the market.

A large number of scholars have made useful explorations to explain the nonlinear and chaotic phenomena of the market with the help of intelligent models.So, M. K. et al. applied the time-varying copula model to the analysis of volatility and dynamic dependence in the securities market with the help of statistical and computational methods of modeling, which is conducive to the further deepening of the understanding of the risk and uncertainty in the financial system [12]. Aloui, C. examined the value-at-risk prediction performance of two ARCH/GARCH type models in the securities market, in which the proposed FIAPARCH model provides good inspiration for risk quantification in the securities market by fully taking into account conditions such as the long-run dependence of return volatility [13]. Nilchi, M. and Farid, D. developed a typical stochastic volatility model (SNSV) with four skewed normal distributions to predict price volatility and price index risk in the securities market, which not only improves the transparency of the market, but also provides a reference for regulators to implement accurate risk management [14]. Singh, R. K. et al. used linear and nonlinear Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to assess the return volatility in the securities market to output valuable risk-return relationships for the stakeholders concerned to improve returns and reduce risks by optimizing the portfolios and making decisions [15]. Mittnik, S. et al. used the component gradient boosting technique to identify the relevant factors affecting the volatility of the securities market and consequently constructed a boosting-based market volatility forecasting model, which significantly improves the out-of-sample volatility forecasting performance in the short- and long-term, and provides data support for investment decision-making, risk management, and regulation [16]. Kim, H. Y. and Won, C. H. combined different GARCH models with long and short term memory (LSTM) models to form a hybrid model, which in turn predicts the price volatility of the securities market and provides good risk management for the development of related financial activities [17]. Fraz, T. R. et al. compared the prediction performance of machine learning models, GARCH series models and nonlinear region switching models for nonlinear fluctuations in the stock market and showed that LSTM models show more prominent advantages in predicting stock market fluctuations and can provide useful information for investment and risk management [18]. Considering the inherent randomness of securities market fluctuations under the nonlinear paradigm and the non-equilibrium normality in the operation process, image recognition algorithms can be combined to gain an in-depth understanding of individual market behaviors in order to uncover the essential laws of securities market fluctuations in the mutual influences and connections.

In this paper, we first collect and preprocess the data of the securities market, and then propose a particle swarm optimization algorithm based ICA-GARCH model for the shortcomings of the gradient descent algorithm in the generalized autoregressive conditional heteroskedasticity model for independent component analysis (ICA-GARCH) that is prone to fall into the local optimum and has a low convergence accuracy. Subsequently, several representative nonlinear fluctuation charts are drawn to initially classify the pictures according to the rise and fall during the output window time. The classified pictures form the input samples for this experiment, which in turn leads to the next stage of convolutional neural network learning training. Immediately after that, a multi-stage supervised bi-stream linear convolutional neural network model is proposed based on the bi-linear convolutional neural network model, which deepens the depth of the network using the residual module as well as the multi-stage learning, and improves the accuracy of the image recognition of the statistical map. Finally, the nonlinear volatility of the securities market and the effect of image recognition are analyzed respectively, exploring and proposing important methods to enhance the risk management of securities.

II. Data set preparation

II. A. Data sources and pre-processing

II. A. 1) Selection of data

The raw data for this experiment is the daily trading data of 1,000 stocks randomly selected from China's A-share market for a total of twenty years, with the time window from March 31, 2005 to March 31, 2023, and the daily trading data contains five dimensions: opening price, closing price, high price, low price, and trading volume. The daily trading data contains five dimensions: opening price, closing price, high price, low price, and volume of each stock.

II. A. 2) Pre-processing of data

This section includes two main parts, one is data cleaning, and the other is defining the technical indicators, and then initially categorizing the original data according to the technical indicators.

The first is data cleaning, which is mainly based on the following principles to eliminate and screen the raw data. One is to exclude the stock data of 20 years with insufficient trading data, and the other is to exclude the input images whose time span includes long holidays when drawing the images. The final number of stocks selected is 850.

Second, the classification rule is defined for the rise and fall of stocks. Let the closing price on day t be P_t, then the average closing stock price for the next five days is:

$$\overline{P}_5 = \frac{P_{t+1} + P_{t+2} + P_{t+3} + P_{t+4} + P_{t+5}}{5} \tag{1}$$

Where $\overline{P}_5$ represents the average closing stock price for the next five days since t, P_{t+1} represents the closing stock market price for the next 1 day since t, and so on.

Use the closing price of the last day of the input sample as a reference to define the stock's up/down classification rule, e.g., if the input sample time window is 60, the closing price of the 60th day will be used as a reference. Let the closing price of the last day of the input sample be S, then the classification rule is as follows:

$$\text{if}\begin{cases}\overline{P}_5 < S & label = 0\\ \overline{P}_5 \geq S & label = 1\end{cases} \tag{2}$$

In the above equation, label is the label assigned to the initial classification. If the average closing price $\overline{P}_5$ for the next five days is less than the closing price S of the last day of the input sample, then label 0 is assigned to the image, which represents that the overall situation of the stock is down in the next five days. If the average closing price of the next five days $\overline{P}_5$ is greater than or equal to the closing price of the last day of the input sample S, then the picture is given the label 1, which represents that the overall situation of the stock in the next five days is not falling (i.e., it contains both the no-go and go-up cases).

II. B.PSO-ICA Noise Reduction Model for Securities Market Data

II. B. 1) ICA noise reduction algorithm

ICA is a statistical signal processing technique that is able to obtain the higher order statistically independent non-Gaussian components of the implied features from the observed signal, denoting the observed signal by the vector $x = [x_1\ x_2\ \cdots\ x_m]^T$, where m denotes the input dimension. With $s = [s_1\ s_2\ \cdots\ s_m]^T$ denoting the unknown implicit features, whose components are assumed to be independent of each other, the principle of ICA is shown in Figure 1.

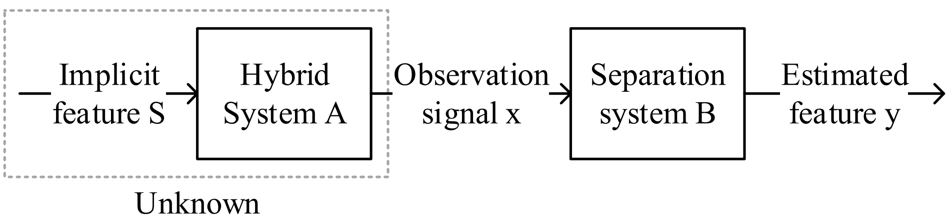


Figure 1: Schematic diagram of ICA principle

Assume that x has been centered and transformed by whitening through the matrix $V \in R^{m\times m}$:

$$z = Vx \tag{3}$$

So that the components of $z = [z_1\ z_2\ \cdots\ z_m]^T$ have unit variance and are uncorrelated. The solution of the whitening matrix v can be obtained by Principal Component Analysis PCA, $V = ED^{-1/2}E^T$, where E is the orthogonal matrix of the eigenvectors of $E\{xx^T\}$, and D is the diagonal matrix of the corresponding eigenvalues. In this way, the observed signal x is transformed into the whitened signal z. ICA is then used to find a separation coefficient matrix $W \in R^{m\times m}$, which linearly combines the z to make the components of y most independent.

$$y = W^T z \tag{4}$$

A variety of discriminant criteria have been proposed to measure the degree of independence between components, such as non-Gaussian type discriminant criterion, minimized mutual information discriminant criterion, great likelihood estimation criterion, etc. In this paper, we use a non-Gaussianity discriminant criterion based on negative entropy, a random variable with density $p_y(\eta)$, whose entropy is defined as:

$$a_1 = a_2 \tag{5}$$

$$H(y) = -\int p_y(\eta)\log p_y(\eta)d\eta \tag{6}$$

Entropy can be used as a measure of non-Gaussianity. Negative entropy is introduced in order to derive a more reasonable non-Gaussian type of metric:

$$J(y) = H(y_{Gauss}) - H(y) \tag{7}$$

where y_{Gauss} is a Gaussian random vector with the same correlation matrix as y.

In practice, the approximation of higher-order cumulants is generalized by considering only the scalar case:

$$J(y) \propto (E\{G(y)\} - E\{G(y_{Gauss})\})^2 \tag{8}$$

where $E\{\cdot\}$ denotes the expectation operation, and $G(\cdot)$ is an arbitrary non-quadratic function, and a better approximation of the negentropy can be obtained by choosing G, which is usually taken:

$$G_1(y) = -\exp(-y^2/2) \tag{9}$$

Or:

$$G_2(y) = \frac{1}{a_1}\log\cos a_1 y \tag{10}$$

The negative entropy approximation defined above is used as the objective function, and the fast immobile point algorithm based on Newton iteration is used to find out the corresponding W that satisfies the negative entropy maximization case.

II. B. 2) PSO algorithm

The PSO algorithm simulates the foraging behavior of a flock of birds, where the solution of each optimization problem is regarded as a "particle" in the search space, and each particle has its fitness value, which is determined by the actual problem to be optimized [19]. In addition, each particle has a velocity that determines its flight direction and distance, and then each particle searched in the space is used to track the position of the current optimal particle, i.e., the optimal solution to be found.

Let a population of N particles in a D-dimensional target search space, each particle $i(i = 1, 2, \cdots, N)$ has coordinates $z_i = (z_{i1}, z_{i2}, \cdots, z_{iD})$ in a D-dimensional space, and each particle's position is is a potential solution. Substituting z_i into an objective function, its fitness value is calculated and the solution is measured as such. Each particle will iteratively search the solution space, searching for new solutions by constantly adjusting its position. The velocity of particle i is the distance moved in each iteration $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, and the equation for updating the particle's velocity in a d-dimensional subspace:

$$v_{id} = \omega v_{id}(t) + \eta_1 r_1(p_{id} - z_{id}(t)) + \eta_2 r_2(p_{gd} - z_{id}(t)) \tag{11}$$

$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1) \tag{12}$$

where $v_{id}(t+1)$ is the velocity of the i th particle in the d th dimension in the $t+1$ th iteration, ω is the inertia weight, η is the acceleration constant, and r is a random number on the interval [0, 1], with an upper limit on the velocity of $|v_{id}| \le v_{\max}$. z_{id} is the coordinate position of i particles. p_{id} is the optimal solution searched by the particle itself, and p_{gd} is the optimal solution searched by the whole population, i.e., the global optimum. It can be seen that in each iteration of PSO, the particle updates itself by tracking these two optimal values.

In Eq. (11), $wv_{id}(t)$ is regarded as the speed of the last iteration; $\eta_1 r_1(p_{id} - z_{id}(t))$ can be regarded as the cognitive ability of the particle, which denotes the particle's self-learning; $\eta_2 r_2(p_{gd} - z_{id}(t))$ can be regarded as the social ability of the particle, which represents the collaboration between particles. Equation (11) is used to describe that the particle updates its velocity based on its last iteration velocity, its current position, and the distance between its own best experience and the group's best experience. Then the particle flies to the new position according to equation (12), then iterative learning is completed.

II. B. 3) PSO-ICA algorithm

Since traditional ICA algorithms mostly use gradient optimization, the algorithms have low accuracy, slow convergence and other shortcomings. In the application of noise reduction, it is easy to appear the phenomenon of incomplete noise reduction and long running time. PSO algorithm is used for optimization to achieve the improvement of noise reduction accuracy and operation efficiency.

The core of the ICA algorithm lies in the solution of the separation matrix W , which implements PSO-optimized ICA, i.e., using PSO to optimize the resolution of the separation matrix W . The basic steps of the PSO-ICA algorithm are as follows:

Step 1: Centering and whitening the observed signal x to obtain the matrices D and H , respectively.

Step 2: Initialize the particle swarm, randomly generate the initial position z_i and velocity v_i of particle i , and compute the fitness $F_i = -\exp(-y_{ij}^2/2)$ of each particle, where $y_i = z_i H$.

Step 3: Evaluate the best position of the particle $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD}) = z_i$ by the particle fitness, where $W_i = z_i$ and $z_i = (z_{i1}, z_{i2}, \cdots, z_{iD})$ is the separation matrix to be solved, $p_g = (p_1^g, p_2^g, \cdots, p_D^g) = \arg\max_i[-\exp(y_{ij}^2/2)]$ is the population optimal position.

Step 4: Update the position and velocity of each particle using equations (11) and (12).

Step 5: Orthogonalize the separation matrix.

$$W_i^{new} \leftarrow W_i^{new} / \| W_i^{new} \| \tag{13}$$

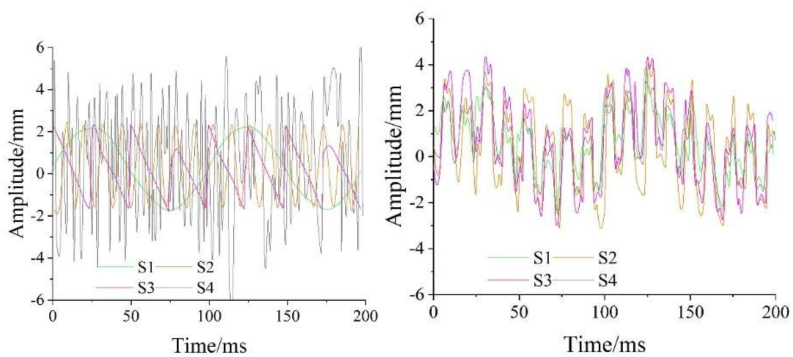
Step 6: Recalculate the particle fitness, update the particle and population optimal position, compare with the previous iteration, if optimal then keep the current value, turn to step 7, otherwise return to step 3.

Step 7: Update the population optimal position $p_g = \arg\max[-\exp(p_i x)]$, if $i < N$, let $i = i+1$, return to step 3, otherwise turn to step 8.

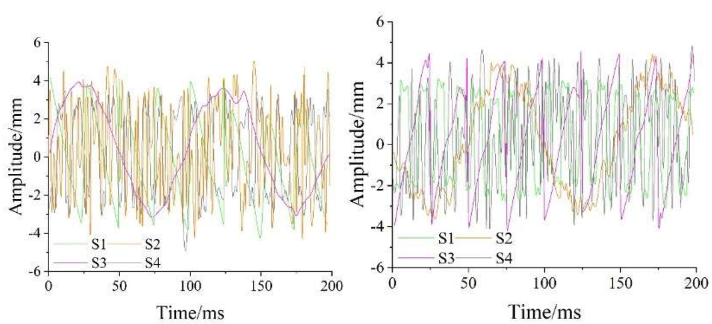
Step 8: The population optimal position p_g is the separation matrix W to be solved and the algorithm terminates.

II. B. 4) Experimental analysis

In the experiment, the sine signal S1, square wave signal S2, sawtooth signal S3, and random signal S4 with the number of signal points of 200 are selected as the detection signals respectively to test the effectiveness of PSO-ICA algorithm. Figure 2 shows the separation results of FastICA algorithm and PSO-ICA algorithm. The signal-to-noise ratio of the separation results is shown in Table 1, and Table 2 shows the correlation coefficients of the separation results of the two methods.



(a) Primary signal (b) Mixed signal



(c) The separation signal under FastICA (d) The separation signal under PSO-ICA

Figure 2: FastICA and PSO-ICA experiment results

Table 1: FastICA and PSO-ICA algorithm

Signal-to-noise ratio	Algorithm type	
	FastICA	PSO-ICA
S1	15.5723	15.0122
S2	11.1792	14.7857
S3	16.0322	16.1945
S4	6.6183	7.7349

Table 2: The correlation coefficient of the original signal and the separation signal

Primary signal		S1	S2	S3	S4
FastICA separation signal	y_3	0.9981	0.0458	0.0121	0.0137
	y_4	0	0.9884	0.0237	0.0118
	y_1	0	0.0025	0.9881	0.0135
	y_2	0.0388	0.0427	0.0333	0.9483
PSO-ICA separation signal	y_3	0.9919	0.1153	0.0568	0.0125
	y_4	0.1149	0.9924	0.0673	0.0028
	y_1	0.0652	0.0218	0.9943	0.0024
	y_2	0.0326	0.0021	0.0039	0.9581

II. C. Combined GARCH model for analyzing the volatility of stock markets

II. C. 1) GARCH model

As the financial market develops rapidly, scholars' research on financial data has gradually increased and deepened, and new volatility prediction models have emerged. Since the financial time series has heteroskedasticity, Engle proposed the ARCH model to analyze its heteroskedasticity, and the GARCH model can be used to portray the financial time series, and on the basis of the improvement of the ARCH model, Brollerslev proposed the GARCH model for the problem that there are too many parameters to be evaluated in the ARCH model, and the expression of the GARCH model is as follows. The expression of GARCH model is as follows:

$$Y_t = X_t \beta + \varepsilon_t \tag{14}$$

$$\varepsilon_t \mid \phi_{t-1} \sim N(0, h_t) \tag{15}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{16}$$

where $t = 1, 2, \cdots, T$, T denotes the number of samples, ε_t denotes the random variable, $N(0, h_t)$ denotes that the random variable obeys the normal distribution, X_i and Y_t denote explanatory and interpreted variables, respectively, and α_i, β_i denote the different influencing factors.The ARCH model is a special case of the GARCH model, i.e., the GARCH model is equal to the ARCH model when $p = 0$.

II. C. 2) PSO-ICA-GARCH models

According to the independent component analysis model, the source signal S is separated from the mixed signal X by the linear transformation matrix A. X is decomposed into mutually independent components $\{s_{i,j}\}$, where $i = 1, 2, , , N$, and these independent components are added as exogenous variables into the volatility equations of the GARCH model to obtain the ICA-GARCH model:

$$s_{it} = h_{i,t}{}^{1/2} \alpha_{i,t} \tag{17}$$

$$\alpha_{i,t} \sim i, i, d.(0,1) \tag{18}$$

$$h_{i,t} = \alpha_{i,0} + \sum_{u=1}^{p} \alpha_{i,u} s_{i,t-u}^2 + \sum_{v=1}^{q} \beta_{i,v} v_{i,t-u} \tag{19}$$

where s_i is the independent component at the moment of t and h_i is the variance at the moment of t. The above three equations (17), (18) and (19) form the ICA-GARCH model. In order to determine the smoothness of the established ICA-GARCH model, the volatility equations satisfy need to satisfy certain conditions: $\alpha_{i,u} \geq 0 (u = 1, 2, \cdots p)$, $\beta_{i,v} \geq 0 (v = 1, 2, \cdots q)$ and satisfy the condition $\sum_{u=1}^{p} \alpha_{i,u} + \sum_{v=1}^{q} \beta_{i,v} < 1$. t in $s_{1,t}^{m}, s_{2,t}^{m}, \cdots, s_{k-1,t}^{m}$ denotes the independent components obtained by extracting the residual series, from which it can be observed that the ICA-GARCH model can solve the problem of multiple covariance that exists in the stock data, and independent components can be obtained.

ICA-GARCH model is a good empirical analysis method of stock volatility. On the one hand, ICA-GARCH model can predict the stock market volatility, on the other hand, ICA-GARCH model can use the characteristics of independent component analysis to reduce the parameters to be estimated in the model, and to reduce the trouble of “dimensional catastrophe” brought by the high-dimensional characteristics of the financial data. ICA-GARCH model is able to characterize ICA-GARCH model can portray the impact of one market on another market, and can observe the volatility spillover effect of different markets, at the same time, it can also carry out the correlation test of the same market, compared with a single GARCH model, ICA-GARCH model is a superior volatility forecasting model.

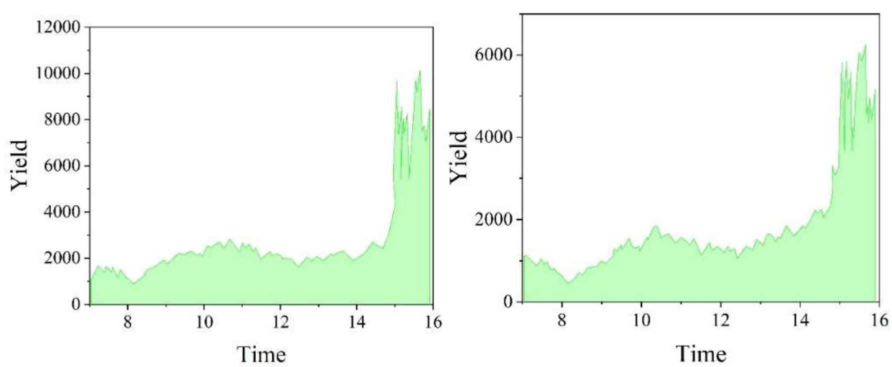
Similarly, the obtained independent component series are substituted as explanatory variables into the electronics manufacturing GARCH model for parameter estimation as well as t test, and the following results are obtained:

$$h_{dz,t} = 0.0798 h_{dz,t-1} - 0.0007010 \varepsilon_{dz,t-1}^{2} + 0.000105 a_t + \tau_t \tag{20}$$

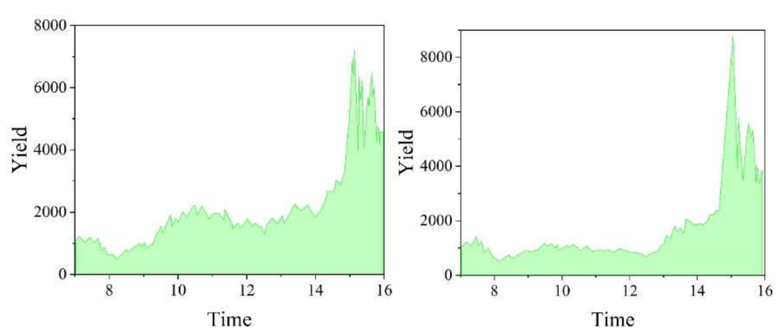
II. D. Image Generation of Nonlinear Volatility in Securities Markets

II. D. 1) Statistical analysis of data

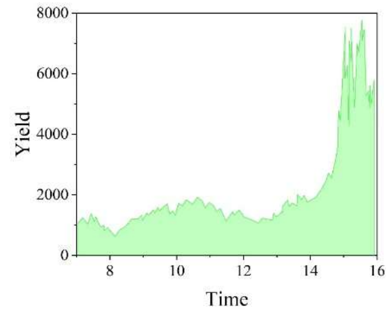
From the stock market software to obtain the above five industries 2080 original data as shown in Figure 3, taking into account the above five industries index data of the flying smoothness characteristics of the original index data to find its index return, that is, $rt = \ln y_t - \ln y_{t-1}$, and get the five sequences of 2079 return data, which is the correlation of the moment of t index of the industry is shown in Figure 4, and the descriptive statistics related to the data are shown in Table 3.



(a) Agricultural service (b) Electronic making

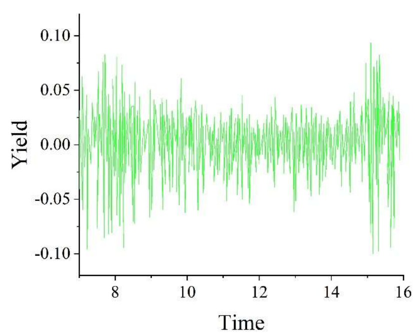


(c) Environmental engineering (d) Communication service

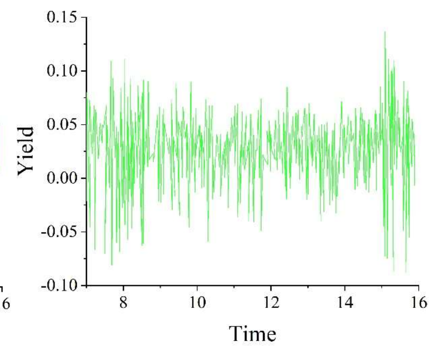


(e) Logistics

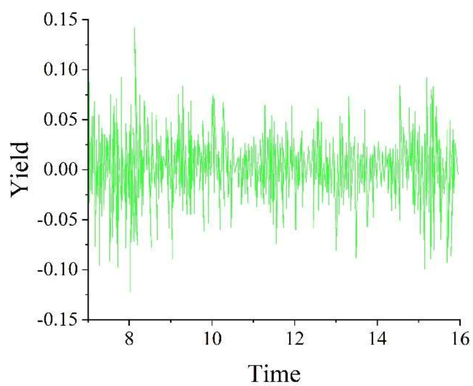
Figure 3: The trend of the relevant industry



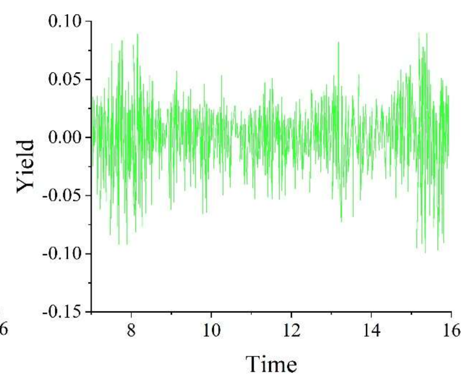
(a) Agricultural service



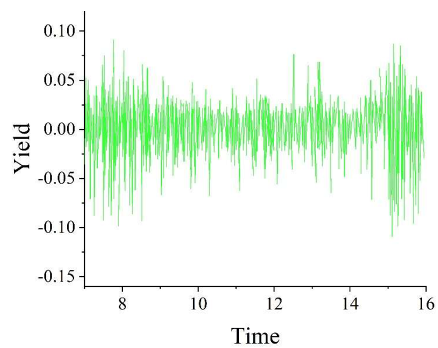
(b) Electronic making



(c) Environmental engineering



(d) Communication service



(e) Logistics

Figure 4: Index yields in related industries

Table 3: Descriptive statistics of yields

	Agricultural service(nf)	Electronic making(dz)	Environmental engineering(hg)	Communication service(tf)	Logistics(wl)
mean	0.00112	0.000857	0.000813	0.000714	0.000873
median	0.00293	0.00334	0.00245	0.00278	0.00329
Maximum value	0.0972	0.0958	0.1448	0.0967	0.0929
Minimum value	-0.1078	-0.148	-0.133	-0.1611	-0.124
Standard deviation	0.0255	0.0268	0.0288	0.0273	0.0269
Coefficient of bias	-0.593	-0.674	-0.448	-0.671	-0.636
Kurtosis coefficient	5.489	5.235	4.853	5.229	5.349
Jb statistics	637.278	585.856	365.475	583.572	614.129
Jb statistics Corresponding probability	0	0	0	0	0

II. D. 2) Analysis of volatility spillovers

Taking the electronics manufacturing industry as the object of study, a fast independent component analysis of the volatility series obtained by modeling the four industries, namely, agricultural services, environmental protection engineering, communication services, and logistics, through the GARCH model was conducted, and the following results were obtained:

$$B = (455.878, 471.755, 485.327, 516.876) \tag{21}$$

Based on the magnitude of the coefficients in the mixing vector obtained by the fast independent component algorithm, it can be seen that the obtained independent components represent the GARCH volatility series of the four industries of agricultural services, environmental engineering, communication services, and logistics, which are the joint volatility spillover indicators of these four industries. The obtained independent component data series is shown in Figure 5.

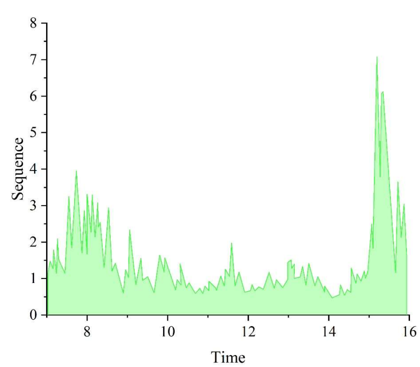


Figure 5: Independent component a_t data sequence

Similarly, the obtained independent component series are substituted as explanatory variables into the ICA-GARCH model of electronics manufacturing industry for parameter estimation as well as t-test, and the following results are obtained:

$$h_{dz,t} = 0.0811 h_{dz,t-1} - 0.0007121 \varepsilon_{dz,t-1}^{2} + 0.000108 a_t + \tau_t \tag{22}$$

where the data in parentheses are the t-test values that still correspond to the parameters. Because the sample size of the studied data is more than 2000, and the sample size is 45 and there is t(45)=1.683 at the 95% confidence level, and the parameter estimated t value of 23.574 is much greater than the zero cut-off value of 1.683, which indicates that the selected independent component series has a volatility spillover effect on the electronics manufacturing industry, that is, it indicates that the four industries of agricultural services, environmental protection engineering, communication services and logistics do have volatility spillover effects on the electronics manufacturing industry.

III. Classification of statistical images of market fluctuations in fine-grained securities

III. A. Bilinear Convolutional Neural Networks

B-CNN includes two VGG convolutional neural network models with a depth of five convolutional layers, an image is inputted into the two convolutional neural network models at the same time, the input image is denoted by i, all the images in the dataset are denoted by I, $i \in I$, the information of a certain spatial location in the image is denoted by 1, and all the location information in the image is denoted by L, $l \in L$, f_A and f_B denote the different features extracted from the same location of the input image by convolutional network A and convolutional network B respectively, which are the same in dimension, and then the features extracted from these two streams are fused by utilizing the outer-product operation with the following formula:

$$(l, i, f_A, f_B) = f_A(l,i)^T f_A(l,i) \tag{23}$$

By summing up all the positional features of the same graph as shown in the following equation:

$$\theta(i) = \sum_{l \partial L} f_A(l,i)^T f_B(l,i) \tag{24}$$

III. B. Multi-stage supervised bilinear convolutional networks

The bifurcated tree linear convolutional neural network model proposed in this paper increases the network model width compared to the bilinear convolutional neural network model, there is no increase in the depth of the model, the network parameters are shared among them, and the model is more robust compared to the four-stream linear convolutional model. Considering the superior feature extraction performance of the residual network model and the fact that network deepening can avoid the problem of gradient vanishing, this paper proposes a multi-stage supervised bilinear convolutional neural network structure on top of the bilinear convolutional network model B-CNN.

III. C. Network Training and Parameter Selection

III. C. 1) Network Training Algorithm

Gradient descent, small batch stochastic gradient descent, and stochastic gradient descent are commonly used training algorithms for network training. Gradient descent is an algorithm to find the global optimal solution, he needs to train all the sample data to update each weight. However, because of the need to train all the data of the data set at once, the computing time is greatly increased, the training speed and its slow, small sample data can be adapted to this gradient descent method.

III. C. 2) Initialization of weights

The purpose of weight initialization is to prevent the output loss gradient of the layer activation function from exploding r disappearing during forward (forward) propagation of the deep neural network. If either occurs, the loss gradient is too large or too small to effectively propagate backward, and even if it can propagate backward, the network takes longer to reach convergence. Matrix multiplication is the basic mathematical operation of neural networks. In a multilayer deep neural network, a forward propagation only requires performing successive matrix multiplications at each layer on the input and weight matrices for that layer.

III. C. 3) Neural Network Optimizer

The idea of SGD is to advance a certain distance in the direction of the gradient. To describe it in mathematical terms it can be written as the following equation:

$$W \leftarrow W - \eta \frac{\partial L}{\partial W} \tag{25}$$

In this case, W denotes the weights to be updated, $\partial L / \partial W$ denotes the gradient of the loss function with respect to W (this is a Jacobian matrix to be precise), η denotes the learning rate, and ← denotes that the right value is used to update the left value.The advantage of SGD is that it is simple and easy to implement. But its disadvantage is that it is inefficient because there are times when the direction of the gradient does not point in the direction of the minimum value. When the function is extended, the gradient points to the “valley”. This causes the value of the loss function to oscillate. When the gradient is pointing in the direction of the minimum, or saddle point, where the gradient is close to 0 in all dimensions, this makes the loss function change very slowly.

III. C. 4) Indicators for multiclassification problems

For binary classification problems, we have many evaluation metrics because there are only two types of classes, positive and negative, and often we only care about the accuracy and recall of the positive class. But for multiclassification problems, some of the evaluation criteria for biclassification are not so applicable. Recently, my internship involved multiclassification, and I spent a lot of time on model evaluation index selection, so I organized the commonly used multiclassification evaluation indexes for future use. One way is to transform the multiclassification problem into multiple 2vs2 problems for discussion, which is a more complicated step. There is also a directly defined multiclassification index.

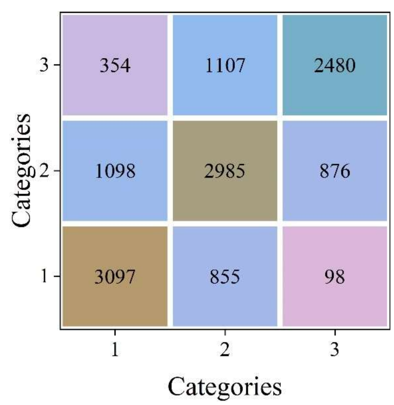
The evaluation metrics adopted in this paper are to transform the multiclassification into a 2vs2 problem discussion and calculate the accuracy rate of the training set and the test set. The structure of the data model as well as the parameter values are saved with the criterion of optimal accuracy. The save file is keras common save model file format HDF5 format.

IV. Image recognition-based volatility analysis and risk management

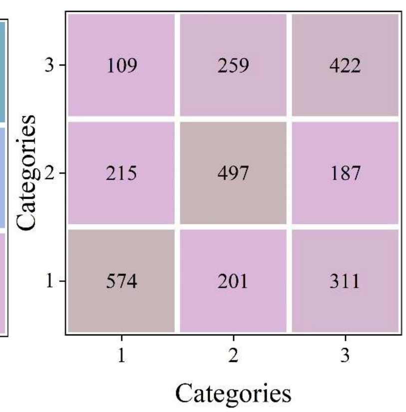
IV. A. Identification results and analysis

IV. A. 1) Image Recognition Analysis

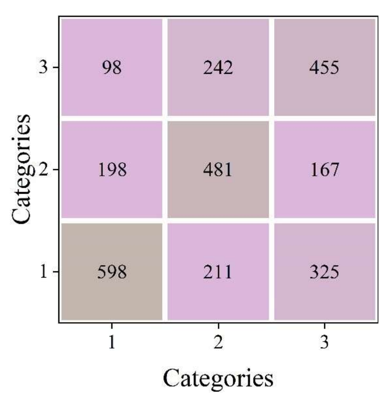
In pattern recognition analysis, confusion matrix is mainly used to represent the accuracy of pattern recognition. The process of image recognition in this paper the result of image processing is categorized into three categories i.e. up (1), unchanged (2) and down (3) and 70% of the data is used for training, 15% for testing and 15% for validation. The well made images are brought into the neural network toolbox of this paper for image pattern recognition. Figure 6 shows the pattern recognition confusion matrix for 18500 images, by observing we find that the training set results in the best image recognition rate up to 66.1% and for overall its recognition rate for the images is at 62.6%, although the validation and test sets are not as good as these two results but are above 50.0%.



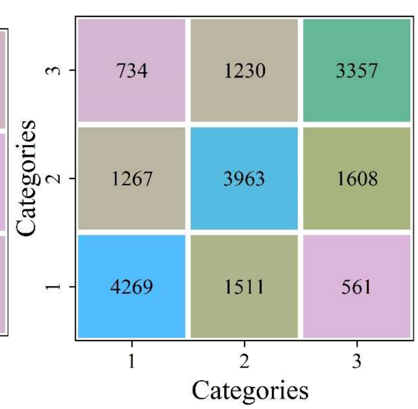
(a) Training Confusion Matrix



(b) Validation Confusion Matrix



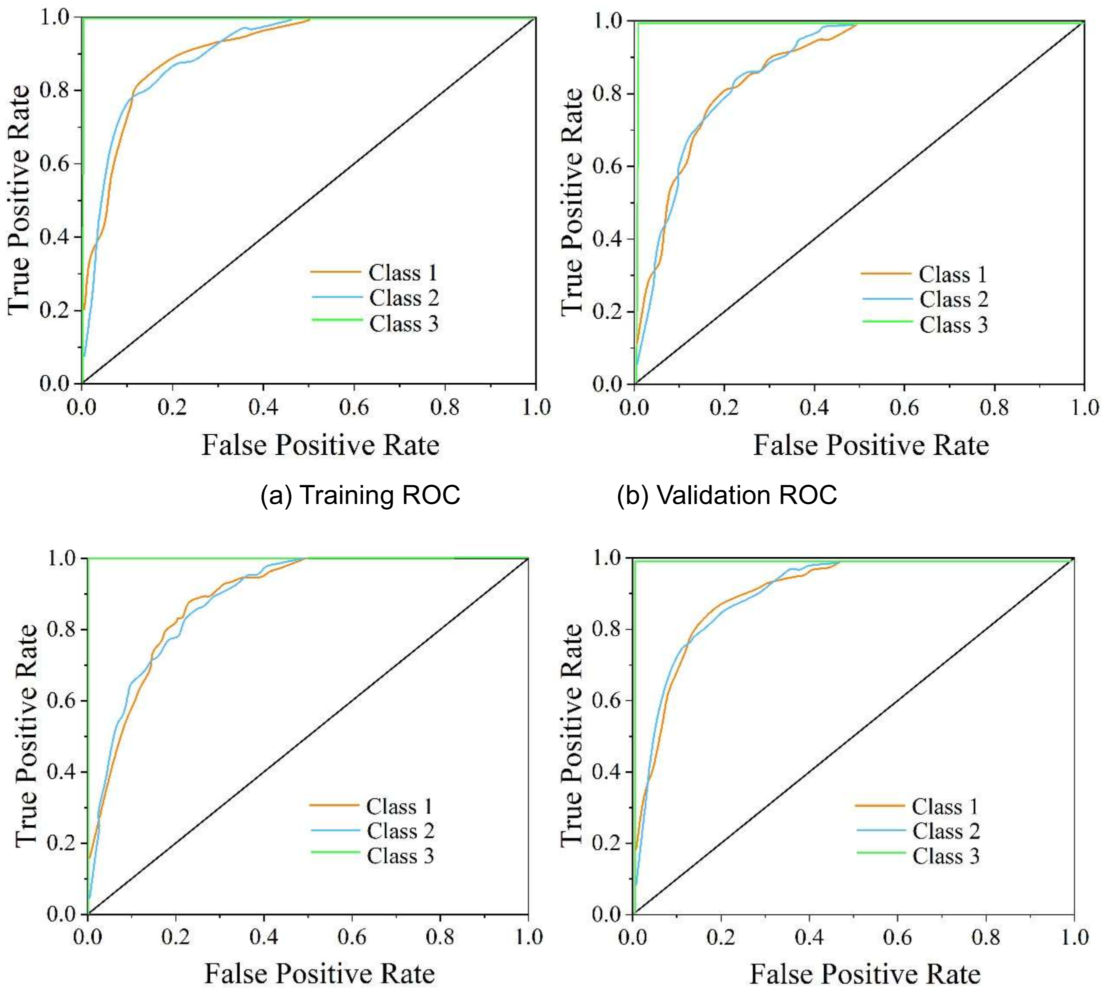
(c) Test Confusion Matrix



(d) All Confusion Matrix

Figure 6: Confusion matrix

Figure 7 shows the ROC curve of image pattern recognition, from the figure it can be seen that whether it is the training set, validation set, test set or overall, the ROC curve of the three types of division results are basically close to the ideal level, the model results are stable, and the training effect is better.



(a) Training ROC (b) Validation ROC

(c) Teat ROC (d) All ROC

Figure 7: ROC curve

IV. A. 2) Comparison of analytical results

A comparison of the model analysis results is shown in Table 4. From the table, we can conclude that whether it is the training set, validation set, test set or overall, the results of its image pattern recognition are better than the OHLC model, in addition, by observing and comparing the ROC curves of the two, we can also conclude that the results of the image pattern recognition are better than the results of the OHLC model recognition. This concludes that the image-based pattern recognition in this paper is better than the traditional direct use of stock prices to price options.

Table 4: OHLC is compared with image pattern recognition

	Training set	Verification set	Test set	Population
OHLC pattern recognition	35.8%	47.2%	35.8%	45.2%
Image pattern recognition	66.1%	53.8%	55.3%	62.6%

IV. B. Securities market risk management

(1) Suggestions for the improvement of relevant laws

The government can learn from the successful experience of foreign countries to formulate a series of laws that can be used in conjunction with the Securities Law to perform a combination of punches, such as the Securities Trading Law and the Securities Market Supervision Law, in order to make up for the gaps in the Securities Law, so as to achieve compliance with the law. At the same time, the government should increase law enforcement efforts, so that violations of the law will be punished.

(2) Suggestions for Government Management

On the basis of the development of a sound legal system, the government should also increase administrative supervision, the establishment of an authoritative securities regulatory system as the focus of work. Given that China's Securities Regulatory Commission (SFC) has the dual role of regulator and organizer of the securities market, the government should focus on strengthening the re-regulatory mechanism to ensure the efficiency and fairness of regulation.

(3) Suggestions for Improving the Securities Rating System

Securities ratings are generally performed by agencies specializing in securities ratings, and in order to ensure the objectivity and fairness of the rating results, the rating agencies are usually independent of the stock exchanges or securities issuers and other interested parties.

The significance of this behavior lies in the following: firstly, it provides high-quality investment choices for the majority of investors and is useful in guiding the investment direction of the securities market. The securities rating system fundamentally solves the phenomenon of information asymmetry in the securities market, reduces the uncertainty in the investment process, and helps to reduce the non-systematic risk in the investment process.

Secondly, using the securities rating as a restriction has well restrained the unhealthy operation of some enterprises, which is conducive to the smooth and efficient operation of the securities market. Enterprises with good reputation will undoubtedly become the first targets for investors to choose, and at the same time, some of the enterprises with unhealthy operation will be eliminated, which will not only help high-reputation enterprises to raise funds, but also help to contribute to a favorable market environment.

In order to get the most scientific and credible results, the review of listed companies should be accompanied by “follow-up” monitoring of the operation of the enterprises, and should preferably take into account every possible factor affecting the stable development of the company, such as whether the operation is in compliance, whether the financial statements are falsified, whether the internal control management is perfect, and whether the company's financial statements are in good condition. For example, operational compliance, financial statement falsification, internal control and management stability, and so on.

V. Conclusion

This paper combines the PSO-ICA algorithm with the GARCH model, proposes a particle swarm optimization algorithm based ICA-GARCH model, and uses the model to portray the volatility of the stock market. Using experiments to analyze the effect of the model, PSO-ICA algorithm has a higher separation accuracy compared to the traditional ICA algorithm, the separation of uncorrelated components and independent components for parameter estimation, parameter estimation t-value of 23.574 is much larger than the zero bound value of 1.683, electronics manufacturing, agricultural services, environmental engineering, communication services and logistics five industries have volatility spillover effects. Using the neural network processing method of this paper to identify the image, according to the ROC curve concluded that the image recognition model method of this paper on the stock risk identification will have a very good effect.

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