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Retraction

Retracted: Trend Prediction Model of Asian Stock Market Volatility Dynamic Relationship Based on Machine Learning

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] P. Lee, Z. Huang, and Y. Tang, "Trend Prediction Model of Asian Stock Market Volatility Dynamic Relationship Based on Machine Learning," *Security and Communication Networks*, vol. 2022, Article ID 5972698, 10 pages, 2022.

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Research Article

Trend Prediction Model of Asian Stock Market Volatility Dynamic Relationship Based on Machine Learning

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With the rapid development of the global economy and stock market, stock investment has become a common investment method. People's research on stock forecasting has never stopped. Accurately predicting the dynamic fluctuation of stocks can bring rich investment returns to investors while avoiding investment risks. Machine learning is a relatively important research field in artificial intelligence today, which is mainly used to study how to use machines to simulate human activities. In recent years, with the continuous development of the economy, machine learning under artificial intelligence has developed comprehensively in different fields, and it has been widely used in the field of the financial economy. Machine learning under artificial intelligence is currently widely used in stock market volatility dynamics and related research. This paper applied machine learning to the prediction of the dynamic relationship of Asian stock market volatility and established a model for predicting the dynamic relationship of stock market volatility under machine learning. By using statistical theory, linear support vector machines, generalizable bounds, and other algorithms, it provides the theoretical basis and feasibility analysis for the model. Through investigation and research, this paper found that compared with ordinary forecasting model methods, the stock volatility dynamic trend forecasting model based on machine learning has a relatively complete forecasting effect, and the accuracy of the machine learning forecasting model was up to 52%. The lowest was 39%, the average prediction accuracy was 46.5%, and the accuracy was improved by 16.8%. This showed that the introduction of machine learning prediction models in the dynamic prediction model of Asian stock volatility is relatively successful.

1. Introduction

With the progress of the times and the rapid development of science and technology, people's material life has been greatly enriched, people have more and more wealth, and many people have started stock investment. Stock investment is a well-known investment method nowadays. Stock investment can bring investment returns to investors, but it also has different degrees of investment risks. Since the establishment of the Asian stock market is later than that of the West, there are still many defects. The stock market often experiences sharp rises and falls, with large price fluctuations and unstable stock movements. The analysis and forecast of the Asian stock market is still full of complexity and uncertainty, and people's research on the trend forecast of the dynamic fluctuation relationship of the stock market has also become a top priority.

In order to make the research on the trend prediction model of the dynamic relationship between the fluctuations of the Asian stock market more scientific and rigorous, many researchers have devoted themselves to the study of the stock prediction model. Asaad studied the short-term and long-term price interdependence between Asia-Pacific stock markets before and after the Asian financial crisis [1]. Meza studied the stock market using daily data consisting of a value-weighted stock market index [2]. Salehi M used a unit root test, cointegration test, error correction model, and causality test to test the relationship between these markets [3]. Chu's findings showed that in the case of Asian stock markets, there is a fixed long-term relationship and a significant short-term causal relationship [4]. Sun believed that the long-term interdependence between stock markets has been strengthened since the crisis broke out [5]. Lee believed that there is a causal relationship between equity growth and emerging stocks, and there were opportunities for global portfolio diversification in Asian equity markets [6]. Jin found through investigation that although shocks to Asian stock markets have long-term effects on some of these markets, they still have short-term effects on other markets in Asian stock markets [7]. Zhang believed that the Asian stock market has a monthly effect. The monthly effect means that in a particular month of the year, the average stock return is higher or lower than the rest of the year [8]. The above-given research showed that researchers pay more attention to the forecast of volatility in Asian stock markets, but with the advent of the new era, other new problems have also emerged.

Machine learning belongs to a branch of artificial intelligence and is used in many fields. As an emerging technology, machine learning has been studied by many researchers. At present, humans have developed some intelligent robots, speech recognition, and machine learning. Whitfield believed that character recognition methods based on machine learning are of great significance to information technology [9]. Oterkus proposed an improved CRNN algorithm based on feature fusion, combining different moment features into a new feature vector. He then used the generalized K-L transform to compare the new feature dimension and remove redundant information [10]. Gupta R believed that stock market volatility forecasting was an important part of stock investing. Due to the highly nonlinear and noisy characteristics of stock market volatility, it is extremely difficult to predict stock market volatility [11]. Wei adopted the machine learning method to give a stock price index prediction model based on a support vector machine [12]. The whole process of Shen's stock index prediction based on machine learning included data acquisition, data preprocessing, eigenvector solution, and normalization [13]. Han believed that the Asian stock market is an unstable complex nonlinear system. There are many factors affecting stock market volatility, and research data are often difficult [14]. Machine learning has become an important method for forecasting research on Asian stock markets. Research on forecasting volatility trends in Asian stock markets required not only improvements in forecasting algorithms but also the impact of the features used for stock forecasting on forecasting.

This paper used machine learning to study the dynamic relationship trend prediction of Asian stock market volatility. Through research and investigation, it is found that the introduction of machine learning in the forecast of the trend model of the volatility dynamic relationship of the Asian stock market can improve the performance of the model, reduce the error rate, and improve the forecast accuracy.

2. Prediction Model of Dynamic Relationship of Asian Stock Market Volatility Based on Machine Learning

2.1. The Basic Meaning of Machine Learning. Artificial intelligence refers to neural networks and deep learning in machine learning [15]. The main goal of computer scientists is to put their interpretable shared knowledge and experience into a large database, which is then programmed into judgment rules that are often used in computer programs. This practice is called "knowledge engineering" and "expert system." However, these two types cannot input enough clear knowledge to the machine, and there is no way to accurately express their default knowledge and input it to the machine. Therefore, "expert system" and "knowledge engineering" died out after the 1980s [16]. It takes not only a lot of people but also a lot of time to write down all the experiences and rules of a field [17, 18]. The information processing speed of the computer is much faster than that of the human brain. The large amount of data generated in many scenarios can allow the computer to learn and simulate what would happen by itself. This is the popular machine learning nowadays. Today's machine learning can learn two categories of knowledge by itself: correlation between things expressed by probability and judgment rules expressed by a logic [19], as shown in Figure 1.

2.2. Five Schools of Machine Learning. Machine learning is generally divided into five schools, namely, the semiotic school, the analogy school, the Bayesian school, the evolutionary school, and the connection school [20].

The general semiotic school believes that there is a connection between things and a causal relationship, so new knowledge can be obtained through logical argumentation, and this new logical knowledge is generally represented by a decision tree. It is a tree structure for classifying things or things according to their properties [21]. Therefore, a simple learning decision tree can distinguish known data, and the result of known data are the closest, which belongs to the decision logic that the machine has figured out by itself.

The Bayesian school believes that there is a probability problem in the connection between cause and effect, so the Bayesian school collects a large amount of data and categorizes it statistically to improve the accuracy of judgment. So the Bayesian school of machine learning is that the machine pushes "inward" from the result to deduce the probability of the cause [22].

The analogy school depends on the common analogies in life. In the analogy school, the most basic algorithm is called the nearest neighbor method. The first thing is to define "similarity." Similarity can be statistical variables, continuous variables, and discrete variables. In short, only by determining the similarity can we determine whether a classification method is optimal. When doing similarity comparisons, machines can compare which features and attributes more accurately than humans, so as long as the machine grasps the features and attributes accurately, it would be more accurate than human judgment.

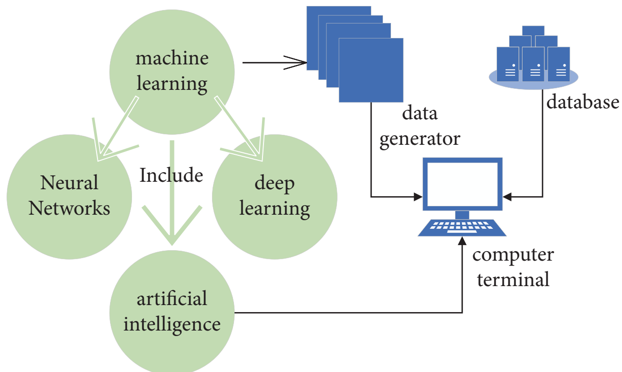

Figure 1: Machine learning basics.

The basic idea of the connection school is to imitate the working principle of neurons in the human brain, that is, artificial neural networks. The most popular theories in the connection school are neural networks and deep learning.

The last evolutionary school is a radical empiricist, who believes that all models are false. The basic idea of the evolution school is to imitate the evolution of nature, similar to the theory of biological evolution, but different from the theory of biological evolution, the algorithms of the evolution school are all "immortal." The final algorithm result is not even necessarily the same generation algorithm, as shown in Figure 2.

The symbolic, Bayesian, analogical, and connective schools of machine learning all have one thing in common: they build a predictive model based on events or outcomes that have already occurred. Then, it continuously adjusts retry parameters and existing data to predict new events [23].

2.3. The Relationship between the Four Concepts in AI. The most frequently heard terms in the information age are artificial intelligence, machine learning, deep learning, and neural networks [24]. Artificial intelligence includes another three and artificial intelligence can be divided into two parts: artificial learning and machine learning. Machine learning includes neural networks, which are subdivided into deep learning and shallow learning. When many neurons are formed into a multilayer network, it is called deep learning. The first layer is machine learning, the second layer is a neural network, and the outermost layer is artificial intelligence, generally expressed as artificial intelligence > machine learning > neural network > deep learning, as shown in Figure 3.

2.4. Prediction Model for the Volatility Trend of Asian Stocks. Since the emergence of stocks, stock forecasting has received extensive attention and active research in academia. How to accurately predict the direction of the stock market and bond market has become a difficult problem. There is no way to predict stock market volatility with 100% accuracy. However, by combining economic and statistical analysis, machine learning, and other methods, by analyzing historical stock transaction records and performance report analysis, a stock trend prediction model can be established to help investors make investment decisions. In the securities market, stocks follow the same direction as the stock market. The trend can reflect the direction of changes in stocks over a period of time, and whether the direction of the trend can be correctly judged is the key factor for the success of investment behavior. Advanced computer tools marked by sequence analysis methods were introduced into the field of stocks and became the forecasting models for the volatility trend of Asian stocks. From the regularity and continuity, it is possible to infer the changing laws of historical stocks and predict future data values, as shown in Figure 4.

3. Application of Linear Support Vector Algorithm in Machine Learning

In order to make the research on the prediction model of the dynamic relationship between the fluctuations of the Asian stock market more scientific and cautious, many researchers have used the algorithms in statistics and econometrics to study the time series of stock prices. Different from other time series, the study of financial time series is not the study of financial prices, but the study of stock market volatility and dynamic relationship trend prediction.

3.1. Statistical Learning Theory. Statistical learning theory is a machine learning theory that studies the machine learning theory of statistical estimation and prediction in the case of limited samples.

In the process of machine learning, due to the observation of the sample $(a_1, b_1), (a_2 b_2), \ldots, (a_i, b_i)$, the joint probability $F(a|b)$ cannot know the result, so that the expected risk $F(t)$ cannot be calculated. Therefore, in the traditional learning method, in order to evaluate the pros and cons of the algorithm, $F_{\text{emp}}(t)$ would be minimized, and the calculation formula is as follows:

$$\min_t F_{\text{emp}}(t) = \min_t \frac{1}{m} \sum_{i=1}^{m} L(b_i, f(a_i, t)). \tag{1}$$

As can be seen from the $F_{\text{emp}}(t)$ formula, the risk profile of existing observational trials cannot be scientifically demonstrated to reduce the risk in lieu of expectations.

3.2. Boundaries of Promotion. In machine learning, empirical value risk $F_{\text{emp}}(t)$ is not equivalent to expected value risk $F(t)$. It can be learned according to the empirical risk minimization criterion, and the general concept can be conceptualized and proved to describe the relationship between the potential risk $F_{\text{emp}}(t)$ and the expected risk $F(t)$, and the formula is as follows:

$$F(t) \leq F_{\text{emp}}(t) + \sqrt{\frac{m(1m2n/m + 1) - 1mR/4}{n}}. \tag{2}$$

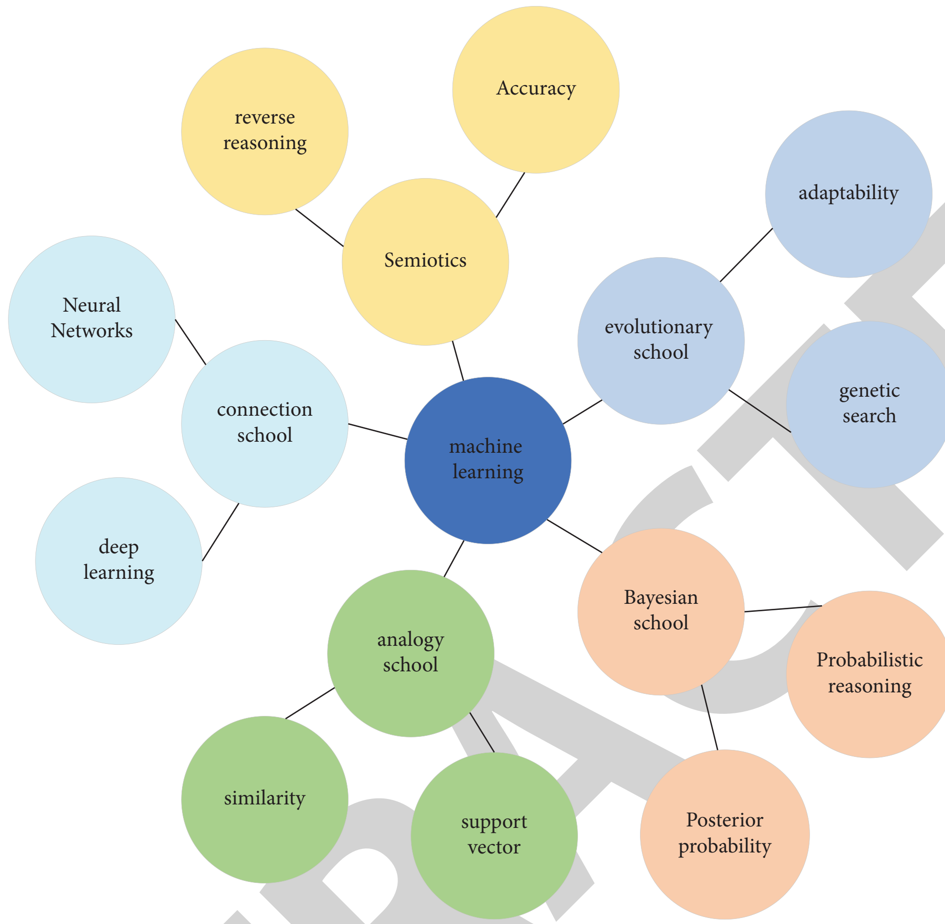

Figure 2: Five schools of machine learning.

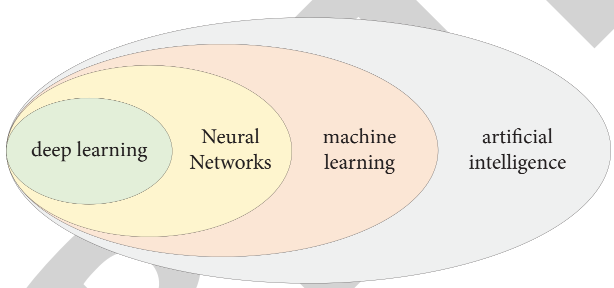

Figure 3: The relationship of four concepts in AI.

Among them, n is the number of samples, and m is the value of the learning function set, which is expressed as follows:

$$F(t) \leq F_{\text{emp}}(t) + H\left(\frac{m}{n}, R\right). \tag{3}$$

It can be seen that under the limited training sample set, the larger the $H(m/n, R)$ is, the larger the error between the expected risk and the empirical risk may be. Machine learning is to find the optimal learning function $f(a, t_0)$ in a set of learning activities $\{f(a,t)\}$ based on observation samples so that it takes at least the expected risk $F(t)$ of x and y when making predictions to check the observation results. The calculation formula is

$$F(t) = \int L(b, f[a,t])kF(a,b). \tag{4}$$

Machine learning is generally divided into pattern recognition problems, regression estimation problems, and probability estimation problems. The risk functions corresponding to these three problems generally have the following form.

Pattern recognition problem calculation formula:

$$L(b, f(a,t)) = \begin{cases} 0, & b = f(a,t) \\ 1, & b \neq f(a,t) \end{cases}, \tag{5}$$

Regression estimation problem calculation formula:

$$L(b, (a,t)) = (b - f(a,t))^2. \tag{6}$$

Probability estimation problem calculation formula:

$$L(\rho(a,t)) = -\ln \rho(a,t), \tag{7}$$

where $\rho(a,t)$ is the probability density.

3.3. Linear Support Vector Machine. Linear support vector machine has a strong classification ability for multi-dimensional linear separable data sets, and it can distinguish

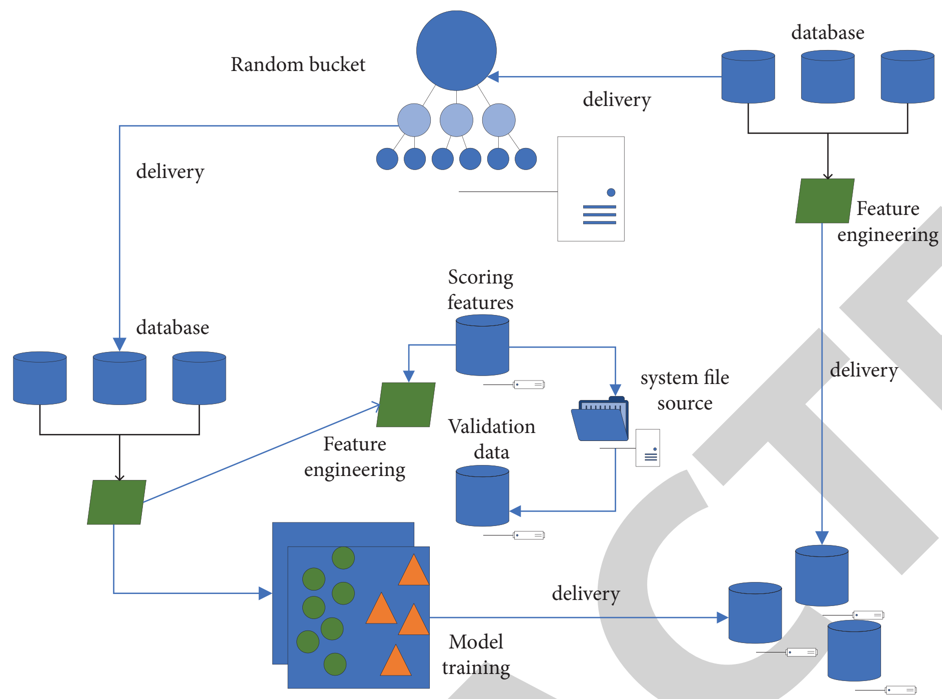

Figure 4: Prediction models for asian stock volatility trends.

samples of different categories by constructing a classification hyperplane.

Assuming that the linearly separable dataset is $W = \{(a,b),\ldots,(a_i,b_i),\ldots,(a_n,b_n)\}$, the classification hyperplane can be expressed as follows:

$$t^W a + y = 0. \tag{8}$$

In order to find the separation hyperplane that can separate the two types of samples as soon as possible, the following formula can be introduced.

$$\begin{aligned} t^W a_i + y &\geq 1, b_i = 1, \\ t^W a_i + y &\leq -1, b_i = -1. \end{aligned} \tag{9}$$

So such an original problem can be formulated as follows:

$$b_i \max\left(t^W + y\right) = 1, \quad i = 1,\ldots,n. \tag{10}$$

However, because the above formula is not easy to obtain the value of t, y, the formula is improved, and the improved formula is expressed as follows:

$$b_i \min\left(t^W a_i + y\right) = 1, \quad i = 1,\ldots,n. \tag{11}$$

After minimizing t^2 to get the formula, the Lagrange multiplier method is introduced into the function, and the formula is

$$L(t,y,\partial) = \frac{1}{2}\|t\|^2 - \sum_{i=1}^{n} \partial_i. \tag{12}$$

Among them, ∂_i is the Lagrangian multiplier corresponding to the th sample, and $\partial_i \geq 1$ is satisfied. In order to solve the convex optimization problem that occurs in the sample, it should first find the partial derivative formula, the calculation method is

$$\begin{aligned} \frac{\partial L(t,y)}{\partial y} &= \left(t - \sum_{i=1}^{n} \alpha_i b_i a_i\right) - 1, \\ \frac{\partial L(t,y)}{\partial y} &= \left(-\sum_{i=1}^{n} \alpha_i b_i a_i\right) + 1. \end{aligned} \tag{13}$$

Simplify $t = \sum_{i=1}^{n} b_i a_i \alpha_i$ into the formula to get the following equation:

$$L(t,y,\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} b_i a_i y_i^{\,T}. \tag{14}$$

Considering the constraint $\alpha_i \geq 0$, the above original problem is expressed by the dual formulas:

$$\begin{aligned} \min_{\alpha} \sum_{i=1}^{n} \beta_2 - \frac{1}{2}\sum_{i}^{n} b_i a_i &= 0, \\ \sum_{i=1}^{n} a_i b_i &= 0. \end{aligned} \tag{15}$$

Thus, the solution of the original problem is obtained as $t = \sum_{i=1}^{n} \alpha_i b_i a_i$.

Substituting t, y into $t^W a + y = 0$ yields the optimal hyperplane formula:

$$y = -\frac{1}{2} \min_{n,b_i=1} t^W a^n + \min t^W a^r. \tag{16}$$

After the optimal hyperplane is obtained, the discriminant function can be used to determine whether the sample belongs to the positive class or the negative class. The discriminant function is

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \beta_i b_i \langle a_i, a \rangle + y\right). \tag{17}$$

Support vector machines are suitable for high-dimensional small-sample classification problems. Entering the era of big data, the sample size for training datasets can be very large. In order to make full use of massive information to obtain a more accurate separation hyperplane for classification prediction, it is necessary to study the suspect samples that extract support vectors from massive samples. These suspect samples can be used to train the support vector machine, which greatly improves the training efficiency.

4. Experimental Part of Trend Prediction Model of Asian Stock Market Volatility Dynamic Relationship Based on Machine Learning

In the stock market, normal price fluctuations are conducive to the normal development of the stock market, but if the volatility is large, it will bring greater risks, which will adversely affect the stock market. Asian stock markets developed late. It is also in the process of development and change that the limitations of the development environment, the uniqueness of the model, and the uniqueness of the operating mechanism determine that the Asian stock market has a unique risk of price changes. Based on this, machine learning is introduced in the research on the trend prediction model of the volatility dynamic relationship of the Asian stock market, and machine learning and artificial intelligence are introduced into the Asian stock analysis model. Machine learning can continuously learn and improve based on continuously updated data during the application process, thereby improving trend forecasting models. In order to study whether the application of machine learning to the prediction model of the dynamic relationship between stock market fluctuations can improve the prediction accuracy, the seven-day stock trend of a certain Asian stock market is randomly selected as the research object. The ordinary prediction model and the machine learning prediction model are used respectively, which are referred to as the ordinary model and machine model for short. The two sets of forecasting models predict the same stock trend, so they are comparable.

4.1. Comparison of Prediction Model Performance and Recognition. Grasping the forecast of Asian stock market trends is a complex systematic project. Ordinary stock prediction models may be one-sided and cannot make complete and accurate predictions, but if too many indicators are used, it would lead to greater difficulties in operation. In this paper, machine learning is introduced into the stock market trend prediction model, and the performance of the operating model is enhanced through machine learning methods to help investors better grasp the volatility trend of the stock market. In order to get a clearer picture of which forecasting model performs better and is more recognized by investors, 100 stock professional researchers are now asked to rate the two forecasting models. At the same time, 100 people were randomly surveyed at the opening scene of a stock to investigate their recognition of the two prediction models, as shown in Figure 5.

It can be clearly seen from Figure 5 that Figure 5(a) is a comparison of the performance scores of the two groups of models, and Figure 5(b) is a comparison of the recognition scores of the two groups of models. The performance score of the machine model is higher than that of the ordinary model group. There are 89 people in the machine model group with a performance score of 100–60. In the general model group, only 70 people scored 100–60 points in the performance, and 30 people scored less than 60 points. In terms of recognition, there are only 8 people in the machine model group with a score below 60, and 20 people in the general group with a score below 60. This shows that the method of machine learning can indeed enhance the performance of the running model, and it can also be recognized by more people.

4.2. Comparison of Transaction Volume and Yield. In Asian equities, there is a causal relationship between volume and yield, and the higher the volume, the higher the yield. For investors alone, if they can accurately predict the trend of stocks and avoid risks, they can also improve their own returns. This article now compares the trading volume of different investors based on two different forecasting models in a certain week, as well as the one-week rate of return predicted by the two different forecasting models, as shown in Figure 6.

It can be clearly seen from Figure 6 that Figure 6(a) is the comparison of trading volume based on the two groups of models, and Figure 6(b) is the comparison of yields based on the two groups of models. The volume predicted by the machine-based model over the seven day period was higher than the volume predicted by the normal model. They believe that predictions based on machine models can more accurately predict the trend of stocks, thereby avoiding risks and achieving higher returns on investment. On the first day, the volume of the machine model was 790 higher than that of the regular model. The volume of the machine model on the second day was 1390 higher than that of the normal model; the volume of the machine model on the third day was 1638 higher than that of the normal model. The volume of the machine model on the fourth day was 856 higher than that of the normal model; the volume of the machine model on the fifth day was 896 higher than that of the normal model. On the sixth day, the trading volume of the machine model was 1110 higher than that of the ordinary model; on the seventh day, the trading volume of the machine model was 766 higher than that of the ordinary model. On the whole, investors believed in the prediction of the machine model. The machine learning-based stock returns are higher than the

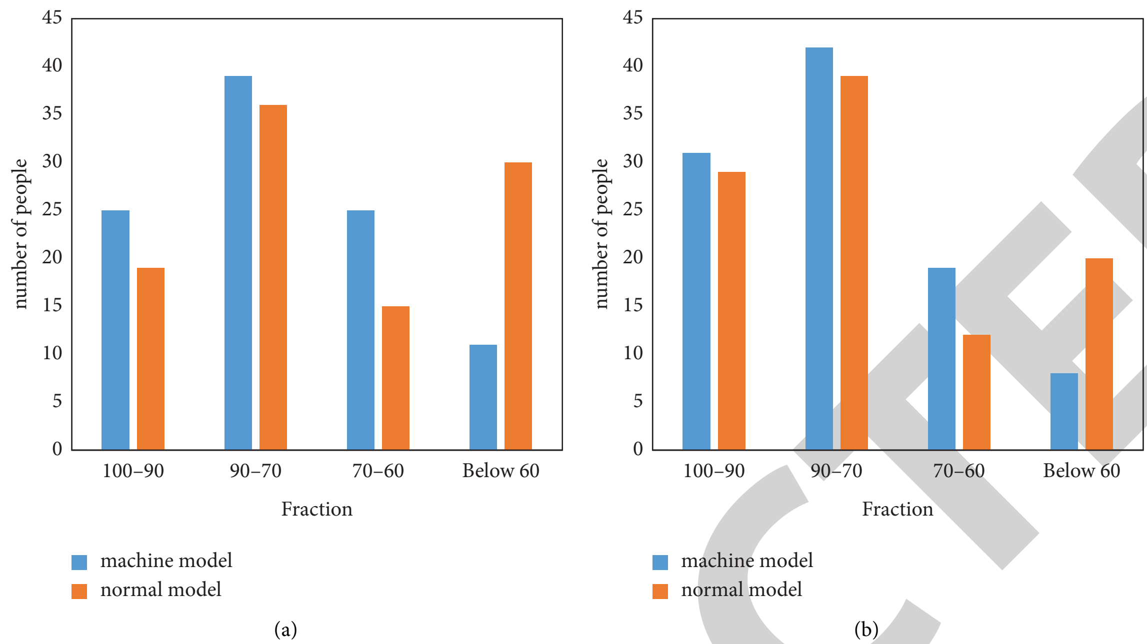

Figure 5: Comparison of performance and acceptance of two prediction models. (a) Predictive model performance comparison. (b) Predictive Model Approval Comparison.

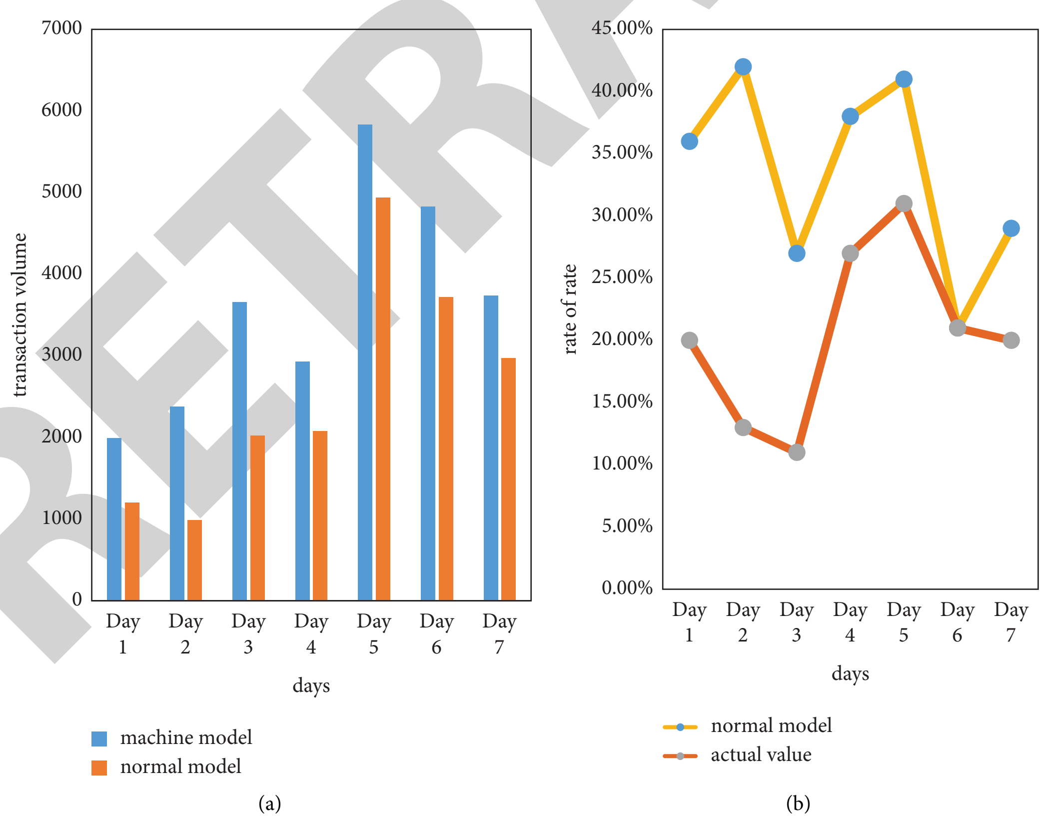

Figure 6: Comparison of transaction rates and yields between the two models. (a) Volume comparison of the two models (b) Comparing the returns of the two models.

Table 1: Comparison of the error rates of the two models.

	Machine model (%)	Normal model (%)	Actual value (%)
Day 1	3.2	4.6	3.0
Day 2	3.7	4.7	3.9
Day 3	4.2	4.6	4.0
Day 4	4.1	3.7	4.0
Day 5	6.3	6.8	6.1
Day 6	5.7	5.6	5.5
Day 7	4.6	4.1	4.7

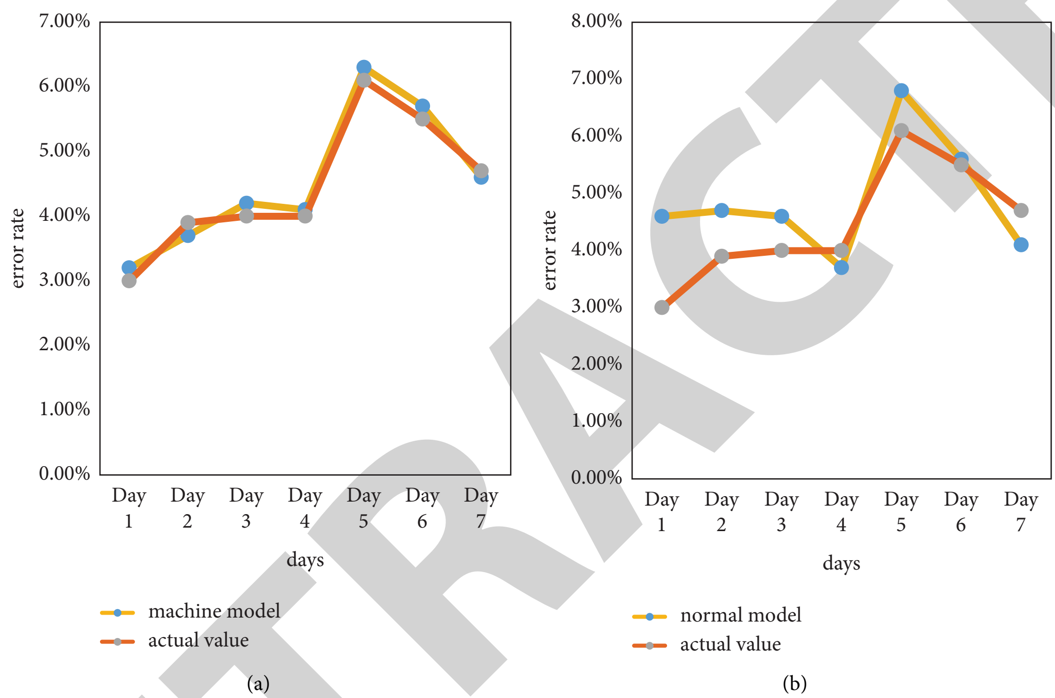

Figure 7: Comparison of the error rates of the two models. (a) Machine Model Group Error Rate. (b) Common model group error rate.

stock returns of the normal model over the same seven days. This shows that machine learning is more feasible in the dynamic relationship of Asian stock volatility based on machine learning.

4.3. Comparison of the Error Rates of the Two Groups of Models. The margin of error is also very important in forecasting Asian stock market movements. The smaller the error rate and the closer to the actual value, the more accurate the prediction. The current experiment randomly selects the stock situation of one week and uses two groups of models to predict the trend of the stock in seven days and compares it with the real situation. The results of the investigation are shown in Table 1.

In order to compare the error rates of the two groups of prediction models more intuitively, this paper plots the survey results in Figure 7, as shown in Figure 7.

Figure 7(a) is the error rate comparison based on the machine group model, and Figure 7(b) is the error rate comparison based on the common machine group. It can be clearly seen that the error rate of the machine model group is significantly smaller than that of the ordinary model group, and the predicted value of the machine model group is closer to the true value. On the first day, the error rate of the machine model group was 0.2%, and the error rate of the ordinary model group was 1.6%. On the second day, the error rate of the machine model group was 0.2%, and the error rate of the ordinary model group was 0.8%. On the third day, the error rate of the machine model group was 0.2%, and the error rate of the ordinary model group was 0.6%. On the fourth day, the error rate of the machine model group was 0.1%, and the error rate of the ordinary model group was 0.3%. The error rate of the machine model on the fifth day is 0.2%, and the error rate of the ordinary model is 0.7%. The error rate of the machine model on the sixth day is 0.2%, and the error rate of the ordinary model is 0.1%. The error rate of the machine model on the seventh day is 0.1%, and the error rate of the ordinary model is 0.6%. During these seven days, the error rate of the machine model group did not exceed 0.2%, and the error rate of the ordinary model group was unstable and larger. Therefore, in the dynamic

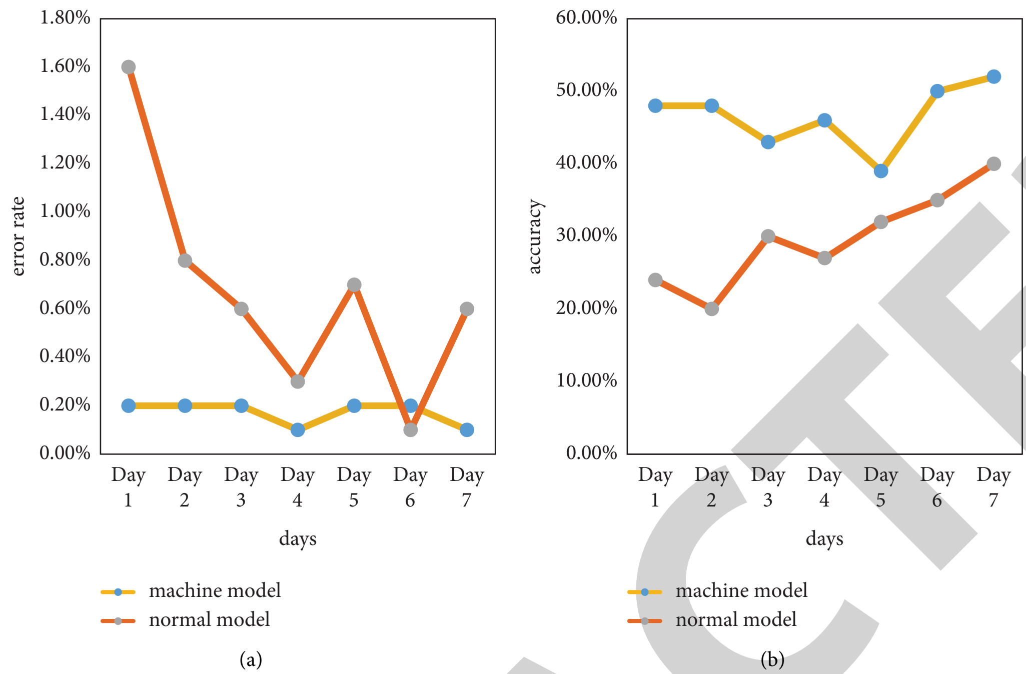

FIGURE 8: Comparison of the accuracy of the two models. (a) Comparison of the error rates of the two models. (b) Comparison of the accuracy of the two models.

model of Asian stock fluctuations, the introduction of machine learning prediction models can make up for the shortcomings of ordinary prediction models and reduce the error rate.

4.4. The Accuracy of the Two Groups of Models. Since there are many random factors in the Asian stock market, stock prices fluctuate wildly, and price changes cannot be predicted, so it is very important to accurately predict market trading trends. This has some guiding value for investors. Now, we would randomly select the stock forecast accuracy of a stock market for a week, as shown in Figure 8.

Figure 8(a) is a comparison of the error rates based on the two groups of models, and Figure 8(b) is a comparison of the accuracy rates based on the two groups of models. It can be clearly seen from Figure 8 that the accuracy of the machine learning prediction model is significantly higher than that of the ordinary group, and the prediction trend is more stable. The gap is smaller and more dependable. The error rate of the machine learning prediction model was up to 0.2%, and the highest error rate of the general group prediction model was 16%. The machine learning prediction model had the highest accuracy of 52% and the lowest of 39%, with an average prediction accuracy of 46.5%. The accuracy rate of the prediction model of the general group is the highest at 40%, the lowest is 20%, and the average prediction accuracy is 29.7%. The accuracy rate of the machine learning prediction model is 16.8% higher than that of the prediction model of the ordinary group. This shows that the introduction of machine learning prediction models in the dynamic prediction model of Asian stock volatility is relatively successful.

5. Conclusion

In order to make the research on the dynamic relationship trend of Asian stock market volatility more accurate, help investors to invest in stocks more accurately, and avoid risks at the same time, machine learning is introduced into the research on the dynamic relationship trend of Asian stock market volatility. The study found that the application of machine learning to forecasting Asian stock markets has been widely embraced by investors. Machine learning can mine important information from historical data and improve model prediction performance. It can improve the yield and transaction rate, reduce the forecast error rate, and improve the forecast accuracy rate. Therefore, applying machine learning to the prediction of the dynamic relationship between Asian stock market volatility can further promote the development of Asian stock markets.

Data Availability

This article does not cover data research. No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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