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*Research Article*

# Innovative Research on the Construction of Learner's Emotional Cognitive Model in E-Learning by Big Data Analysis

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This article first addresses the problem that the unstructured data in the existing e-learning education data is difficult to effectively use and the problem that the coarser granularity of sentiment analysis results in traditional sentiment analysis methods and proposes multipolarized sentiment based on fine-grained sentiment analysis evaluation model. Then, an algorithm for behavior prediction and course recommendation based on emotional change trends is proposed, and the established multiple linear regression equation is solved with an improved algorithm. Finally, the method in this paper is verified by a comprehensive example with algorithm comparison analysis and cross-validation evaluation method. The research method proposed in this article provides new research ideas for evaluating and predicting the learning behavior of e-learners, which is conducive to timely discovering learners' dropout tendency and recommending relevant courses of interest to improve their graduation rate, so as to optimize the learning experience of learners, promote the development of personalized education and effective teaching of the e-learning teaching platform, and provide a certain reference value for accelerating the reform process of education informatization. In order to improve the speed of searching for parameters and the best parameters, this paper proposes a particle swarm algorithm (to improve the support vector machine parameters in a sense) and finds the best parameters which also achieved the goal from academic expression to academic performance.

## 1. Introduction

The e-learning teaching model has undoubtedly achieved great success in the reform of teaching methods, but the education model is also currently facing problems such as low student motivation, high registration rate, low graduation rate, and lack of learning experience [1], causing the development of this teaching model to gradually fall into a bottleneck period. Therefore, how to effectively analyze and evaluate students' learning behavior data so as to improve students' learning autonomy, optimize students' learning experience, and formulate personalized learning plans for them is a key issue for the e-learning teaching model to enhance educational competitiveness. However, although the existing learning behavior evaluation and prediction methods have optimized the operating mechanism of the e-learning teaching platform to a certain extent, there are still the following problems to be solved in practical applications: most of the educational data has the characteristics of large volume, fast growth, low value density, and various types, which brings great difficulties to the evaluation and prediction of students' learning behavior [2], which limits the evaluation and prediction of students' learning behavior to a certain extent. Most traditional e-learning behavior evaluation and prediction methods only use statistical analysis on structured data, and it is difficult to analyze a large amount of unstructured education data with subjective emotional characteristics and objective relevance. It is impossible to truly realize personalized education [3]; for the problems of low student enthusiasm, high registration rate, and low graduation rate that are commonly faced by the e-learning teaching model, it is difficult to find students' dropout tendency and the root cause of the problem in time [4] and to propose corresponding countermeasures to increase their graduation rate. It can be seen that the effective use of the educational data generated by the online course learning platform for automated modeling and analysis, real-time and accurate assessment and prediction of student learning behavior, then timely detection of students' dropout tendency, and taking corresponding intervention measures to improve e-learning teaching mode have extremely important application value in terms of teaching quality, promoting personalized teaching reform, and promoting the development of education informatization.

The key to constructing an emotional cognitive model is to identify different academic emotions. The key and difficult point of recognizing academic emotions is to establish the mapping relationship between the learner's facial expression feature parameters and the corresponding academic emotions. Although every learner has his/her own range of academic emotions, these academic emotions are all within a stable range. By analyzing these data, a personalized data model classification standard can be obtained. When constructing the emotional recognition model, firstly establish the avoidance model, the concentration model, and the pleasure model to realize the conversion from the collected facial expression feature values to these three models [4]. Then, the values converted into these three dimensions are mapped to the three-dimensional academic emotion space with reverse emotions, and finally a comprehensive emotion result is obtained through calculation. At present, there are not many studies on the conversion calculation from academic expressions to academic emotions in similar avoidance models, pleasure models, and concentration models in domestic and foreign research. The more typical methods are curve fitting method and neural network method [5]. The key to the research is to design a good classifier.

The basic idea of the curve fitting method is to obtain limited pairs of test data through experiments and use the obtained data to find an approximate function. First, it is necessary to capture and collect the facial expression feature values of the learner and then use the collected feature values to obtain a functional relationship through a certain method, so that these values are satisfied with this functional relationship. From a geometric point of view, a curve is determined such that all sample data values are distributed on or adjacent to it. This method requires a lot of experiments to ensure that the determined function or curve is accurate, so it has disadvantages such as a large amount of calculation [6].

The basic idea of the neural network method is to establish a neural network by determining the number of network layers, the number of nodes in each layer, and the transfer function. Then, part of the collected facial expression feature value data for network training is used, and finally the facial expression feature value that has not participated in the training for testing is used [7]. The problem of local minimization will cause large errors in recognition.

The advantage of using the improved support vector machine method is that, on the one hand, it overcomes the inability to distinguish complex nonlinearities in the above curve fitting method and, on the other hand, the support vector machine itself has good classification capabilities and does not exist in the neural network [8]. The main advantages of support vector machines are as follows: First, the required number of samples is small. Second, the problem of sample nonlinearity can be solved; the solution is to adjust loose variables and kernel functions. Third, due to the rigor of the theory, the extension ability of the model is increased.

Support vector machine technology has many areas that need to be improved. The biggest problem is the selection of parameters. Among the parameters of the support vector machine, the selection of penalty parameters and kernel function parameters has a greater impact on its performance. As to how to select the optimal parameters and parameters, a cross-validation method can be used, which can obtain a better accuracy of the test set data prediction and can effectively avoid the problems of overlearning and underlearning that the neural network will produce. However, if you want to find the parameters and best parameters in a larger range, it will greatly increase the search time. Therefore, in order to improve the speed of searching for parameters and the best parameters, this paper proposes a particle swarm algorithm (to improve the support vector machine parameters in a sense), to find parameters and the best parameters, so as to achieve the goal from academic expression to academic performance. The mapping of emotions offers another possibility.

## 2. Basic Concepts of E-Learning

Online learning (e-learning) refers to an online education service model that teaches learners or helps them learn [9]. E-learning education services in a broad sense include many forms, such as computer-assisted instruction (CAI), computer-assisted learning (CAL), computer-based education (CBE), and massive open online courses (MOOC). Through a comprehensive analysis of multiple forms of e-learning, it can be found that all forms of e-learning education services have two things in common, namely, learning and computers. The current theoretical research on e-learning education services mainly focuses on three aspects, namely, learners, technical support, and education services. Among them, theoretical research for learners refers to the exploration of a learner-centered personalized teaching model and reasonable learning effect evaluation methods [10]. Technical support theoretical research refers to the promotion of integrated content, support for communication, and collaborative tools. Various technologies are coordinated with each other to realize the direct or indirect interaction between learners and learners and between learners and teachers [11], so as to provide a feasible solution for improving learning effects. Theoretical research on educational services is aimed at integrating the educational activities corresponding to the teaching mode and teaching strategy and providing corresponding educational services according to the established teaching strategy.

*2.1. The Connotation of Learning Behavior of E-Learning.* The learning behavior of e-learning refers to the various learning-related behaviors or activities generated in the learning process of online courses [12], including explicit learning behaviors such as course learning, dropout behavior, and question-and-answer interaction. It also includes hidden learning behaviors such as curriculum understanding, mood swings, and changes in learning motivation [13]. The connotation of e-learning behavior is composed of three logical domain connotations, namely, behavioral science, information technology, and education theory.

Behavioral science explores the causal relationship of the learning behavior and the corresponding influencing factors. Information technology explores the quantitative representation, identification methods, and evaluation methods of learners' learning behavior in the network environment [14]. Education theory studies the influence of learners' individual behaviors on learning effects and analyzes the behavior characteristics of learning behaviors that positively affect learning effects.

*2.2. E-Learning's Behavior Characteristics.* E-learning is a new type of online learning mode. The subject of learning behavior is the learner, the learning path or means is computer-assisted learning, and the object is various learning activities related to online learning. In view of the fact that e-learners are mostly in a state of spontaneous learning and the e-learning education platform mainly provides open educational resources, it is difficult to implement educational intervention measures similar to the standardization of offline education models. Therefore, in the online learning process of e-learners, their learning behaviors mainly have the following characteristics: (1) Decentralized learning time: since most e-learning teaching models are not compulsory for education, a standardized education paradigm has not been formed; e-learners' learning behavior is also spontaneous, and the purpose of participating in course learning is mostly based on learning interest or assisting offline course learning, thus lacking a fixed learning plan. Therefore, the learning time of e-learners has the characteristics of heterogeneity, and the overall trend of course learning time is decentralized. (2) E-learning with random termination of courses: learners mostly use autonomous learning as the main form of learning in the learning process, and their learning behavior is easily affected by external factors; in addition, educational behavioral science research shows that [15] after the learning process is interrupted, less than 50% of the learners can continue the course. Therefore, the course learning of e-learners has the characteristics of random termination. (3) Curriculum assault learning: a domestic study [16] conducted a statistical analysis of learners who successfully completed an e-learning course and found that more than 75% of this type of learners completed it within 1-2 days, which reflects the concentration and surprise of course study behavior. Since the learning behavior of e-learners mainly has the above three characteristics, in the learning process, many learners often show learning states such as low participation and low learning input [17].

## 3. The Learner's Emotional Cognitive Model

Sentiment analysis (SA), also known as opinion mining (OM), refers to a method that uses Natural Language Processing (NLP), text data mining, and computer linguistics [18]. The purpose of sentiment analysis is to analyze the subject's bipolar or multipolar attitude towards topics or objective things, so as to discover potential problems and propose corresponding improvement measures. The objects of sentiment analysis can be divided into three types from low to high according to the text level, namely, word level, sentence level, and text level. Based on the research content of the subject, this section introduces and analyzes the key steps and specific processes of the current two mainstream sentiment analysis methods.

*3.1. Sentiment Analysis Method Based on Sentiment Dictionary.* The sentiment analysis method based on the sentiment dictionary is an unsupervised classification method, which is based on dictionary construction, text segmentation, and sentiment quantification and judges the user's sentiment tendency by calculating the sentiment score of the document through the sentiment scoring mechanism. The specific analysis process of this method includes three key steps.

*3.1.1. Dictionary Construction.* The sentiment analysis method based on sentiment dictionary is calculated based on the sentiment intensity value and sentiment strengthening and weakening values of sentiment words and degree adverbs. Therefore, it is necessary to construct a variety of dictionaries in the process of analysis, including sentiment dictionaries, degree adverb dictionaries, negative word dictionaries, and stop word dictionaries (also called noise words).

*3.1.2. Text Segmentation.* The purpose of text word segmentation is to split sentences into word sets, so as to facilitate the quantitative calculation of emotional intensity. Words in the English context are less coupled and easy to recognize. Word segmentation can be completed by searching and dividing spaces and punctuation. Unlike sentiment analysis in the English context, words such as emotional words and degree adverbs in the context are highly coupled and have coherence between each other, making it difficult to extract independent words. Two completely different semantics are presented; and domain migration means that the word segmentation effects of word segmentation dictionaries in different application fields are quite different. For example, when the word segmentation dictionary of restaurant reviews is used for word segmentation of movie reviews, its accuracy will be greatly reduce.

*3.1.3. Model Establishment.* Based on the above sentiment dictionary and word segmentation tools, a sentiment quantification model can be established to calculate the score of sentiment phrases. First, traverse all the word results in the corpus based on the word segmentation results, and delete the stop words; second, search for emotional words and negative words and mark their positions; finally, calculate the quantitative scores of each emotional phrase according to the modifier of the degree adverb, and count the scores of all emotional word groups to complete emotional analysis.

*3.2. Sentiment Analysis Method Based on Machine Learning.* The sentiment analysis method based on machine learning belongs to the supervised classification method, which judges the user's sentiment tendency through corpus construction and word vector training. According to the difference of implementation technology, it can be divided into two methods based on traditional machine learning and deep learning. The specific process of the method based on machine learning consists of three key steps [19].

*3.2.1. Corpus Construction.* Sentiment analysis methods based on machine learning are mainly based on the construction of stop word dictionaries, word embedding (WE) representation, and training of the corpus, to achieve emotional classification of text data. Therefore, it is necessary to construct a corpus in the analysis process, that is, a text dataset of positive and negative emotions.

*3.2.2. Acquisition of Feature Word Vector.* The term vector technology was first proposed by scholar Bengio in the Neural Probabilistic Language (NPL) model, which refers to a vector representation of words in a computer [19]. The acquisition of the feature word vector mainly relies on the conversion of the word vector, and its purpose is to train the emotional features obtained by the feature word vector through machine learning methods such as SVM, so as to realize the text emotion classification. At present, the commonly used basic word vector representation method is One-Hot Representation, which stores words in a sparse form and expresses them as a basic word vector.

*3.2.3. Word Vector Training.* According to the obtained feature word vector, combined with the training of the machine learning model on the feature word vector, sentiment analysis of the corpus can be realized. At present, the main word vector training models include traditional machine learning methods such as SVM, NB, and logistic regression, as well as Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) Network, and other deep learning methods. The processing flow of the sentiment analysis method based on machine learning is shown in Figure 1.

*3.3. Principles and Improvement Methods of Support Vector Machines.* The support vector machine is based on the dimensional theory and the principle of minimum structural risk [20–22].

*3.3.1. Linear Separable Problem.* SVM is developed from the optimal classification surface in the case of linear separability. The optimal classification surface requires that the two types of samples are completely separated and the classification interval is maximized to ensure that the true risk is minimized. The optimal classification surface problem for two-dimensional linear separable cases is shown in Figure 2.

Among them, $H$ is the classification line, and $H_1$ and $H_2$ are straight lines parallel to the classification line. They can be divided into two types of samples, and the distance to the classification line $H$ is the closest. The optimal classification surface problem of two linearly separable cases in two dimensions can also be equivalently expressed as follows.

Define the interval from a sample point to a hyperplane as

$$y_i = \frac{d_i}{(wx_i + b)}. \tag{1}$$

Normalize $w$ and $b$; then, the interval can be written as

$$d_i = \frac{|y_i (wx_i + b)|}{\|w\|}. \tag{2}$$

Since $\|w\|$ is equivalent to $(1/2)\|w\|^2$, the problem can be expressed as

$$\min \frac{1}{2}\|w\|^2. \tag{3}$$

*3.3.2. Linear Inseparable Problem.* To solve the problem of linear inseparability, it is necessary to transform the vector into a high-dimensional space. The mapping relationship obtained has a function called a kernel function, $G(w, x)$, which can accept vector input in low-dimensional space. After the value is calculated, the vector inner product value in the high-dimensional space is calculated. This vector inner product value is an important part of the kernel function obtained after transformation and is also the key to the SVM method. Different kernel functions have different effects on the performance. As long as the function meets the conditions, it can be used as a kernel function.

Research shows that when the prior knowledge of the process is lacking, the choice of radial basis kernel function can often provide satisfactory results for solving practical problems than other kernel functions, and the radial basis kernel function has better learning ability, so this article uses this kind of kernel function.

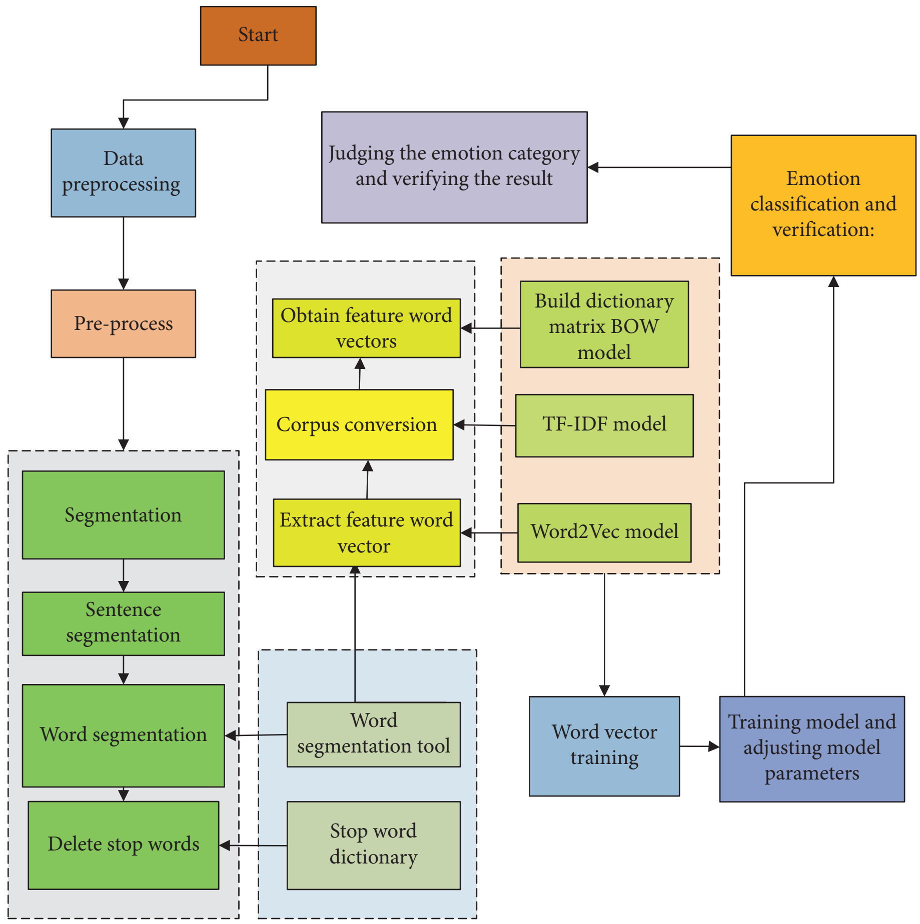


FIGURE 1: Flowchart of sentiment analysis based on machine learning.

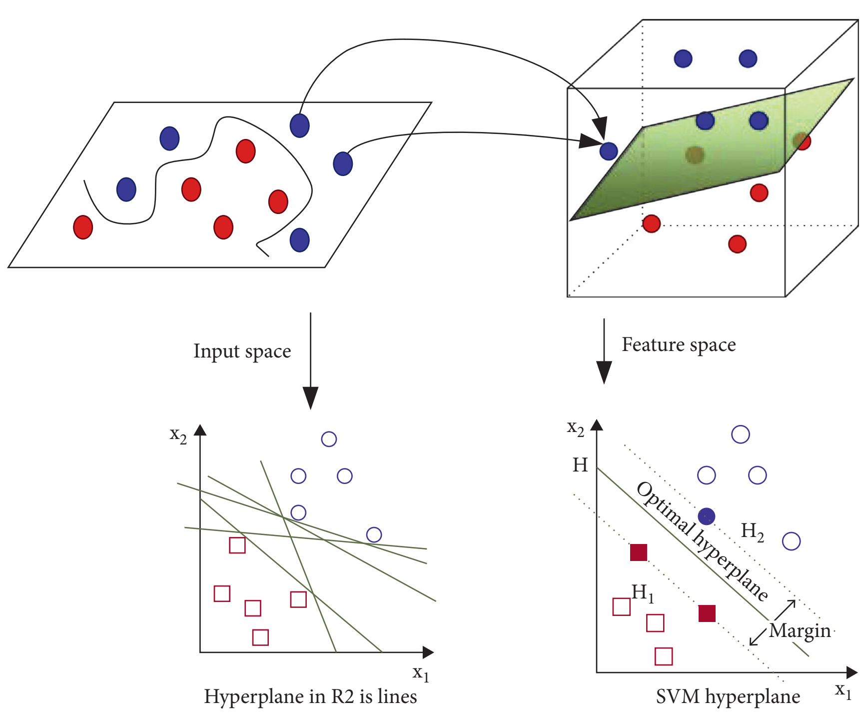


FIGURE 2: Two-dimensional optimal classification of two linearly separable cases.

Radial basis kernel function is expressed as follows:

$$\text{kernel}(x, y) = \exp\left(-\chi\|y - xi\|^2\right). \tag{4}$$

If the linear inseparability problem is still not solved after transforming the vector into a high-dimensional space, then a fault-tolerant slack variable *ksi* can be introduced. Therefore, the "loss" part is added to the objective function, and the penalty variable determines the importance of the loss caused by outliers. The original optimization problem becomes

$$\min \frac{1}{2}\|w\|^2 + \sum_{i=1}^{n} \varepsilon_i. \tag{5}$$

*3.4. Basic Principles of Particle Swarm Algorithm.* The particle swarm optimization (PSO) algorithm was first proposed. The most convenient way for birds to find food is to search the area where the bird closest to the food is. Each particle in the algorithm is a bird in the search space and, at the same time, a potential solution to the optimization problem. Each particle corresponds to a fitness value, and the fitness value is determined by the fitness function.

The direction and distance of the particles' movement are determined by the speed of the particles. The process of individual particle optimization in the entire solvable space is to adjust the speed of the particle based on the movement experience of the particle itself and other particles.

The algorithm flow of the PSO algorithm is as follows:

(1) Initialize the particle swarm; the parameters of initialization include the size of the swarm and the position and velocity of each particle.

(2) Calculate the fitness value $F$ of each particle.

(3) Update the individual position according to the individual extreme value $p_{\text{best}}$. The individual extreme value $p_{\text{best}}$ is the position with the best fitness among all the positions experienced by the individual. Compare the fitness value $F$ of the particle with the individual extreme value $p_{\text{best}}$. If $F_i > p_{\text{best}}(i)$, replace $p_{\text{best}}(i)$ with $F_{ii.}$

(4) Update the group position according to the group extreme value $g_{\text{best}}$. The population extremum refers to the position with the best fitness searched by all particles in the population. Compare the fitness value of the particle with the group extremum. If $F_i > g_{\text{best}}(i)$, use $F_i$ to replace $g_{\text{best}}(i)$.

(5) Through individual value and group value, update the particle velocity and position.

As a result, the particle swarm algorithm has strong global convergence ability in the early stage of iteration and strong local convergence ability in the later stage of iteration.

*3.5. Using Particle Swarm Algorithm to Optimize Support Vector Machine.* The method used in this paper is to take the training set as the original dataset and take the value of the parameter pair $(x, y)$ within a certain range. Use cross-validation to obtain the classification accuracy of each pair $(x, y)$, and select the pair with the highest accuracy as the best parameter. Using grid search on parameters and parameters for cross-validation, the essence of which is to arrange and combine parameters $c$ and $g$, select the pair with the highest accuracy, and train the selected parameter pair as the final parameter (see Figure 3).

However, a complete grid search will be very time-consuming, and if you want to find the best parameters $c$ and $g$ in a larger range, the search process will become more time-consuming. Therefore, this article uses SVM to optimize the parameters $c$ and $g$ in a sense to find the best parameters in a short time. The overall algorithm process of using PSO to optimize the parameter SVM is shown in Figure 3.

## 4. Experimental Verification and Analysis

*4.1. Experiment and Analysis of Graduation Probability Accuracy.* As one of the important branches of NLP, sentiment analysis is currently widely used in the network environment, deriving a variety of typical Internet applications, including marketing, public opinion supervision, and personalized education, with flexible information processing and deeper opinion understanding ability. In order to verify the accuracy of this method for predicting the graduation probability of e-learners, this paper uses the comparison calculation method of the artificial social network, artificial neural network (ANN), and the Bayesian neural network (BNN) based on the association rules of learning behavior and learning effect. The experimental dataset adopts the same experimental dataset of SVM model and PSO algorithm, and the ratio of training set samples to test set samples is 4 : 1. The specific experimental results are shown in Figure 4.

It can be seen from Figure 4 that the accuracy of the three prediction methods has been continuously improved with the increase of the number of training samples, while the average prediction accuracy (90.7%) of the support vector machine (PSO-SVM) optimized by the method, it has been higher than the other two methods (ANN: 83.1%, BNN: 71.2%), which proves the accuracy of this prediction method. On this basis, in order to further evaluate the generalization ability of this method, $K$-fold cross-validation (KCV) is further used to verify the prediction performance of this method, where $K$ is 5. In this paper, 2500 learners in the dataset are randomly arranged and divided into 5 equal parts, and they are marked with code numbers 1–5. The specific experimental results are shown in Figure 5.

It can be seen from Figure 5 that, with the continuous advancement of the course progress, the dimensions of the collected multipolar emotional change chain will continue to increase, and the learner's multipolar emotional characteristics that can be extracted by this method are also more comprehensive. The prediction accuracy of the method has been continuously improved; at the same time, by analyzing

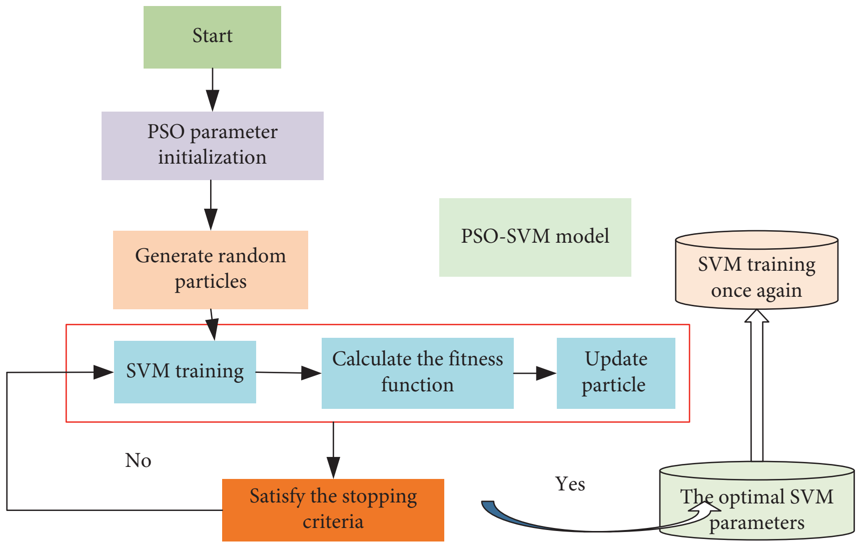


Figure 3: Flowchart of the algorithm using optimized parameters.

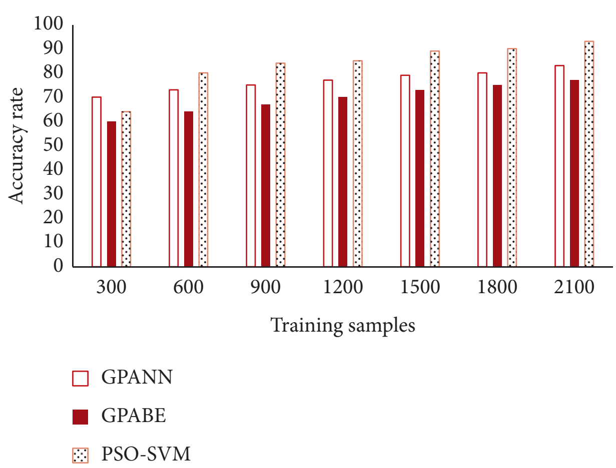


Figure 4: Comparison of the accuracy of graduation probability prediction.

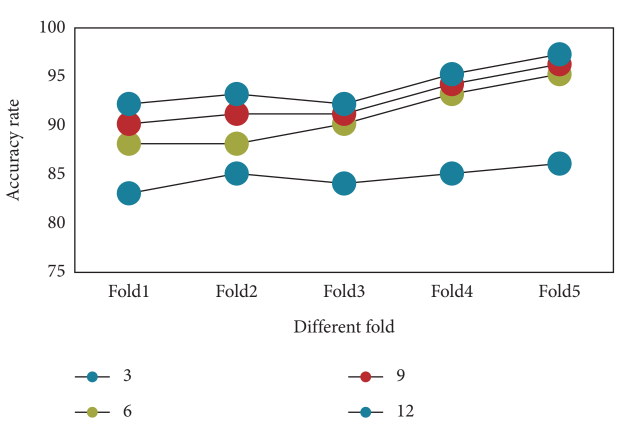


Figure 5: *K*-fold cross-validation diagram.

the change trend of the average prediction accuracy of the 5 test sets, it can be found that, with the progress of the course, the average prediction accuracy of the 5 test sets has a similar increasing trend. Finally, by analyzing the average prediction accuracy interval of the 5 test sets, it can be found that the highest accuracy rate of this method is 92.2%, and the lowest accuracy rate is more than 80%; that is, in the early stage of course learning, the dropout tendency of e-learners can be discovered in time, which further verifies the timeliness of the predictive ability of this method.

*4.2. Analysis of Learners' Emotional Orientation.* In order to deeply analyze the differences in the graduation rate and population distribution of learners with different emotional tendencies, the model proposed in this article is further used to evaluate the emotional tendencies of 2500 e-learners in the dataset. The number of anger, fear, trust, disgust, surprise, and expectation expressions of emotionally inclined learners; the proportion of the population; the number of graduated learners; and the average graduation rate are statistically analyzed, as shown in Table 1.

It can be seen from Figure 6 that the proportion of e-learners with "happiness" emotional tendencies is the highest, reaching 49.34%, and their number of graduates is also the highest, reaching 156. The proportion of the group of learners with "surprise" emotional orientation is also high, and the average graduation rate of learners with this type of emotional orientation is the highest; therefore, the corresponding educational programs to awaken learners' "surprise" and "happiness" emotions will play an important role in increasing the overall graduation rate of e-learners. From Figure 7, therefore, it is believed that the emotional tendencies of "expectation" and "trust" have similar effects on the probability of students' graduation. It is also basically the same, so it is believed that the emotional tendencies of "anger" and "sadness" have similar effects on the learners' graduation probability. The learners with "fear" emotional tendencies have the lowest average graduation rate, which is only 1.40%. Therefore, teaching intervention for this kind of learner population is particularly necessary. The proportion of learners with "disgust" emotional tendencies is the

Table 1: Analysis of learners' emotional orientation.

| Emotionally inclined | Learners population | Proportion (%) | Graduated learners | The average graduation rate (%) |
|---|---|---|---|---|
| Happiness | 1200 | 49.34 | 156 | 13.00 |
| Surprise | 540 | 22.20 | 76 | 14.07 |
| Expectation | 355 | 14.60 | 32 | 9.01 |
| Trust | 210 | 8.63 | 12 | 5.71 |
| Anger | 36 | 1.48 | 6 | 16.67 |
| Sadness | 42 | 1.73 | 7 | 16.67 |
| Fear | 34 | 1.40 | 4 | 11.76 |
| Disgust | 15 | 0.62 | 6 | 40.00 |

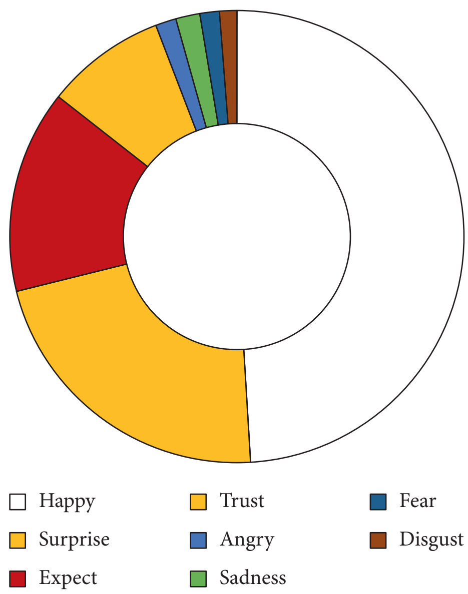


Figure 6: Results of learners' emotional orientation.

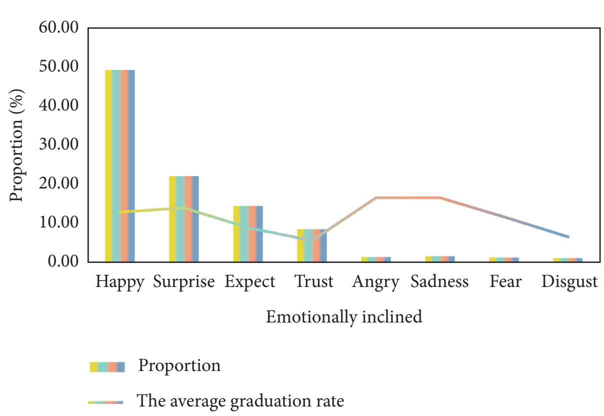


Figure 7: Analysis of learners' emotional orientation.

smallest, only 0.62%, and their average graduation rate is higher than those with "fear" emotional inclination. The analysis in this article reveals that the result is caused by insufficient sampling data. On the other hand, since the proportion of learners with "disgust" emotional inclination is the smallest, it can be considered that the learners have a high degree of acceptance. In summary, in order to further increase the graduation rate of e-learners, the e-learning platform should pay greater attention to learners with "happiness" and "surprise" emotional tendencies and in-depth analysis of the causes of these two emotional tendencies, so as to adopt certain teaching methods to induce the occurrence of these two learning emotions. At the same time, it is necessary to further analyze "expectation," "trust," "anger," and "sadness." On this basis, the e-learning platform can also regard the four negative emotional tendencies of learners, "anger," "sadness," "fear," and "disgust," as a kind of feedback on the course teaching content and teaching methods, so as to further optimize the course structure and teaching methods based on the teaching feedback, in order to improve the overall teaching quality of the e-learning platform and increase the graduation rate of e-learners from another perspective (see Figures 6 and 7).

## 5. Conclusion

The advantage of our method is that, on the one hand, it overcomes the inability to distinguish complex nonlinearities in the curve fitting method; on the other hand, the support vector machine itself has good classification capabilities and does not exist in the neural network without overlearning and underlearning problems. Firstly, based on the proposed PSO model and SVM algorithm, this paper elaborates the overall process of the e-learning behavior evaluation and prediction method based on sentiment analysis; secondly, based on the level analysis of the e-learner, an in-depth analysis of the e-learning behavior evaluation and prediction results is carried out, and two traditional e-learner graduation rate prediction methods are used to validate this method. The K-fold cross-validation method is used to verify the generalization performance of this method. Due to some shortcomings of the neural network, our method overcomes two deficiencies: one is that the neural network is easy to fall into local minimization, and the other is that its convergence speed is very slow. The real-time requirements of the system for emotion recognition are relatively high; if there is no real-time requirements, then the calculated results will lose meaning. The experimental results show that the method in this paper has high accuracy and generalization ability; on this basis, based on the proposed PSO model, SVM algorithm statistical analysis of the emotional tendency of e-learners, and constructive opinions on the e-learning platform based on the analysis results, to further improve the graduation rate of e-learners and e-learning, the core competitiveness of the platform provides a certain reference.

## Data Availability

The data used to support this study are included within the article.

## Conflicts of Interest

No conflicts of interest exist concerning this study.

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