Prediction, Monitoring, and Management of the Classified Training Quality of English Majors Based on Support Vector Machine

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Abstract—To attain higher teaching quality, adopting both quantitative and qualitative methods to discuss the mechanism of how active learning attitude influences the classified training quality of English majors is of practical meaning. However, few existing studies have concerned about this research topic, so to fill in this research blank, this paper aims to study the prediction, monitoring, and management of the classified training quality of English major students. At first, this paper analyzed the classified training of English majors, and introduced the factors of the cultivation of active learning attitude in English majors and the typical manifestations of English majors with an active learning attitude. Then, this paper used the comprehensive improvement level of each evaluation index to measure the classified training quality, and combined the Grey Wolf Optimizer (GWO) with the Support Vector Machine (SVM) to propose a model for predicting the classified training quality of English majors, which laid a basis for further quality monitoring and management. At last, the experimental results verified the effectiveness of using the constructed model to predict the classified training quality of English majors, and gave a few suggestions for monitoring and managing the classified training of English majors.

Keywords—support vector machine (SVM), English major, classified training, teaching quality monitoring

1 Introduction

The active learning attitude has been generally regarded as one of the decisive factors that determine the success of language learning of learners [1–4]. Active learning attitude is a kind of unobservable tendency of learning psychology, no doubt, the absence of an active learning attitude can have a negative influence on the English learning effect of learners. By analyzing the connotations, influencing factors, and cultivation principles of the active learning attitude, we can know that there're obvious differences in the learning attitude of English majors of different genders and with different learning experiences [5–9]. To attain higher teaching quality, adopting both quantitative and qualitative methods to discuss the mechanism of how active learning attitude influences the classified training quality of English majors is of practical meaning [10–18].

Shi et al. [19] argued that with the adjustment of military scale structure and the expansion of the enrollment scale of military masters, new requirements have been put forward for the cultivation of talents, especially the high-level applied-type talents, thus we must cultivate talents of different specifications, types, and levels; the authors systematically studied the classification criteria, training schemes, and graduation criteria of the classified training mode of masters in precision optical engineering, and the feasibility and implementation of the classified training of military masters. The research results showed that the quality of graduate training can be effectively improved by the classified training mode of "academic-type" and "applied-type" talents. The classified training mode is in line with the reform and development trend of military academies, it can not only meet the diversified demands of modern wars for military talents, but also provide references for the cultivation of high-level and creative military talents. Li et al. [20] proposed an innovative idea based on the personalized teaching and classified training; through the transformation of teaching concepts, integration of teaching contents, optimization of teaching methods, and reform of evaluation forms, teachers can leave more time for students to think, learn, and practice independently. In this way, objectives of talents cultivation and needs of students could be combined perfectly, fully reflecting the cultivation of innovative awareness and practical ability. Scholar Wei [21] investigated the different grades of private higher vocational education, analyzed the participation of students in teaching, and compared the influence of classified talent training on the students; then the author discussed and analyzed the results, and proposed a few strategies for improving the classified talent training mode in private higher vocational schools, thereby providing guarantees for the teaching reform of these schools. Ma et al. [22] believe that providing high quality and individualized service of training is the core target of distance education system, they proposed a new method that merges the quantified values of RFM (New, Frequency, and Number) model with the Naïve Bayesian algorithm to classify learners and offers more supports for decision makers, and their experimental results proved the validity and accuracy of the algorithm. Asish et al. [14] think that educational VR can help students by being more engaging or improving retention compared to traditional learning methods, however, in a VR environment, students may get distracted due to stress, mind-wandering, unwanted noise, and external alerts, etc., so they developed an educational VR environment and trained three deep learning models (CNN, LSTM, and CNN-LSTM) to measure students' distraction level from gaze data, using both supervised and unsupervised learning methods. Compared with unsupervised learning methods, the supervised learning methods have better test accuracy.

Classified training is a brand new concept and research direction that hasn't been formally accepted by world field scholars yet. Active learning attitude is an overall manifestation of students' comprehensive ability, it varies according to disciplines and specific course contents. After carefully reviewing relevant literatures, it's found that few scholars have concerned about the active learning attitude as an influencing factor of the classified training quality of English majors, so to fill in this research blank, this paper aims to study the prediction, monitoring, and management of the classified training quality of English major students. In the second chapter, this paper analyzed the classified training of English majors, and introduced the factors of the cultivation of active learning attitude in English majors and the typical manifestations of English majors with an active learning attitude. In the third chapter, this paper used the comprehensive improvement level of each evaluation index to measure the classified training quality, and combined GWO with SVM to propose a model for predicting the classified training quality of English majors, which laid a basis for further quality monitoring and management. At last, the experimental results verified the effectiveness of using the constructed model to predict the classified training quality of English majors, and gave a few suggestions for monitoring and managing the classified training of English majors.

2 The classified training of English majors

Table 1. Manifestations of active learning attitude

Rank	Project	Frequency	Proportion
1	Be more diligent in self-disciplined English learning	25	23.5
2	Inspire internal interest in learning	26	24.52
3	Higher learning concentration	12	11.32
4	Be prepared for English learning in terms of emotions and actions	8	7.54
5	Set goals and work hard	9	8.49
6	Change attitudes towards English and English teachers	5	4.71
7	Find a practice environment close to real scenarios	3	2.83
8	Build confidence during simple exercises	7	6.60
9	Understand the importance of English learning	4	3.77
10	Image oneself with mature English ability	7	6.60
	Total	106	100

Table 2. Factors of the cultivation of active learning attitude

Rank	Project	Occurrence Rate	Percent
1	Have the consciousness to compete with classmates	35	32.4
2	The teaching ability, encouragement, and influence of teachers	13	12.03
3	Enhance learning motivation through exams	11	10.18
4	Change of positive emotions of learning	15	13.88
5	Create real English communication scenarios	8	7.41
6	Improve listening, reading, and writing skills	3	2.77
7	Interact with foreigners	7	6.48
8	Encouraged by families and friends	4	3.70
9	Get positive English learning effect	8	7.41
10	Actively use English in daily communications	3	2.77
11	Gain experience from applying English in practice	1	0.92
	Total	108	100

Table 1 lists the typical manifestations of English majors with an active learning attitude. English majors with an active learning attitude are more diligent in self-disciplined English learning, they can trigger their own internal learning interest for English via reading or watching English movies, and they are more concentrated during the class or the self-learning process. These students have already prepared themselves for English learning, and they have formulated reasonable and achievable goals and would work hard for them. At the same time, these students generally hold a positive attitude towards English and English teachers, they have found a practice environment close to real scenarios and established a confidence in English learning during simple exercises. They think learning English is very important and they are eager to see their English ability grow up.

Table 2 gives factors of the cultivation of active learning attitude. As can be seen from the table, cultivating a competitive consciousness in English major students enable them to have the active learning attitude to not fall behind others; moreover, other factors of the cultivation of active learning attitude also include that the teachers may change their teaching methods, give encouragement in a timely manner, properly arrange exams to trigger learning motivation in students; also, the change in positive emotions during learning process is also a factor as well. Teachers can create real English communication scenarios for students, teach them listening, reading, and writing skills, arrange them to interact with foreigners, families, and friends to get encouragement from them, give positive evaluation on their English learning effect, encourage them to actively use English in daily communication and gain experience from practice. Through these measures, we can effectively cultivate students to have an active learning attitude.

3 About the classified training quality prediction model for English majors

The previous chapter introduced the factors of the cultivation of active learning attitude of English majors and the typical manifestations of students with an active learning attitude. All indexes listed in Table 1 and Table 2 are reference indexes for the classified training of English majors in this paper, and the comprehensive improvement level of each evaluation index is used to measure the classified training quality. In the management of the classified training quality of English majors, the monitoring of the comprehensive improvement level of each reference index is especially important. Next, this paper combined GWO with SVM to propose the model for predicting the classified training quality of English majors, in the hopes of laying a basis for further quality monitoring and management.

3.1 The improved GWO

In the GWO, wolves in a wolf pack are divided into four grades: σ, ε, ξ, and θ. σ represents the head wolf in charge of decision-making and command in the wolf pack; ε represents the first-grade assistant wolves in the wolf pack that are second only to the head wolf; ξ represents the second-grade wolves in the wolf pack that are in charge of executing various commands; θ represents the bottom-grade wolves in the wolf pack in charge of various complicated tasks. Figure 1 gives a schematic view of the position updates of different-type wolf individuals. In the GWO, when the wolf pack spots a prey, the head wolf makes a hunting decision and gives the command, the other wolves of different grades in the pack would quickly respond to the hunting command of the head wolf, and carry out actions after careful decision-making and deployment. The chasing and encircling actions of the wolf pack during the hunting process can be modelled as follows: assuming there're two points in a m-dimensional space, x represents a variable decreasing linearly from 2 to 0, then there are:

$$E = \left| D \bullet A_Z(o) - X(o) \right| \tag{1}$$

$$A(o+1) = A_Z(o+1) - X \bullet E \tag{2}$$

$$X = 2x \bullet s_1 - x \tag{3}$$

$$D = 2 \bullet s_2 \tag{4}$$

The above formulas are applicable in any dimension.

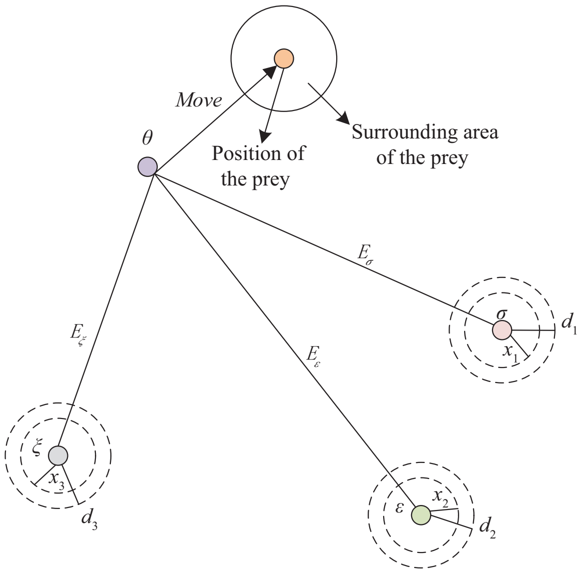


Fig. 1. Position updates of wolf individuals

Based on the above modeling, wolves in the wolf pack can locate the prey. In order to improve the cooperative hunting ability of the wolves, we'll need to find the optimal solution σ of the output results of the algorithm according to the grades in the wolf pack. Because the global optimality of the algorithm optimization is unknown, the premise of attaining the optimal solution is that wolves of σ, ε, and ξ grades can accurately locate the prey, at this time, the positions of θ are relatively flexible, and can be solved by the following formulas:

$$\begin{cases} E_\sigma = \left| D_1 \bullet A_\sigma - A \right|, A_3 = A_\sigma - X_3 \bullet E_\sigma \\ E_\varepsilon = \left| D_2 \bullet A_\varepsilon - A \right|, A_3 = A_\varepsilon - X_3 \bullet E_\varepsilon \\ E_\xi = \left| D_3 \bullet A_\xi - A \right|, A_3 = A_\xi - X_3 \bullet E_\xi \end{cases} \tag{5}$$

$$A(o+1)=\frac{A_1+A_2+A_3}{3} \tag{6}$$

To overcome the too-early maturity and poor robustness problems of the GWO, this paper improved it. The improved GWO can effectively reduce the number of iterations and attain ideal robustness at the same time. The specific improvements have a few aspects including the mutation operation, crossover operation, and selection operation, etc. In terms of the mutation operation, assuming: a wolf pack is initiated in the search space E, define the movement range of the wolf individual is within $[K, V]$; a_{z1}, a_{z2}, and a_{z3} represent the parameter vectors, then there are:

$$a_{ij}(0)=a_{ij}^{K}+rand(0,1)(a_{ij}^{V}-a_{ij}^{K}) \tag{7}$$

$$f_{ij}(h)=a_{z1}+G(a_{z2}-a_{z3}) \tag{8}$$

Assuming: DS represents the probability of crossover, then for the crossover operation, there is:

$$u_{ij}=\begin{cases} f_{ij}(h), rand(0,1)\le DS \text{ or } j=rand(1,m) \\ a_{ij}(h), rand(0,1)>DS \text{ or } j\ne rand(1,m) \end{cases} \tag{9}$$

At last, the comparison vectors of the evaluation function $vi(g+1)u_i(h+1)$ and $x_i(g)a_i(h)$ were introduced into the selection operation, and there is:

$$a_i(h+1)=\begin{cases} u_i(h+1), g\left[u_i(h+1)\right]<g\left[a_i(h)\right] \\ a_i(h), g\left[u_i(h+1)\right]>g\left[a_i(h)\right] \end{cases} \tag{10}$$

Figure 2 shows the flow of the improved GWO.

3.2 The combined algorithm and execution process

SVM is usually used to solve nonlinear regression problems, the method is quite practical and can be used in high dimensional cases, and the operation is not complicated. The nonlinear transformation process in SVM needs to use the inner product function. In this paper, the RBF kernel function with wide convergence domain and stable performance was adopted, assuming β is the width of kernel function, then there is:

$$GS(a,a_i)=exp\left\{-\frac{\left|a-a_j\right|^2}{2\beta^2}\right\} \tag{11}$$

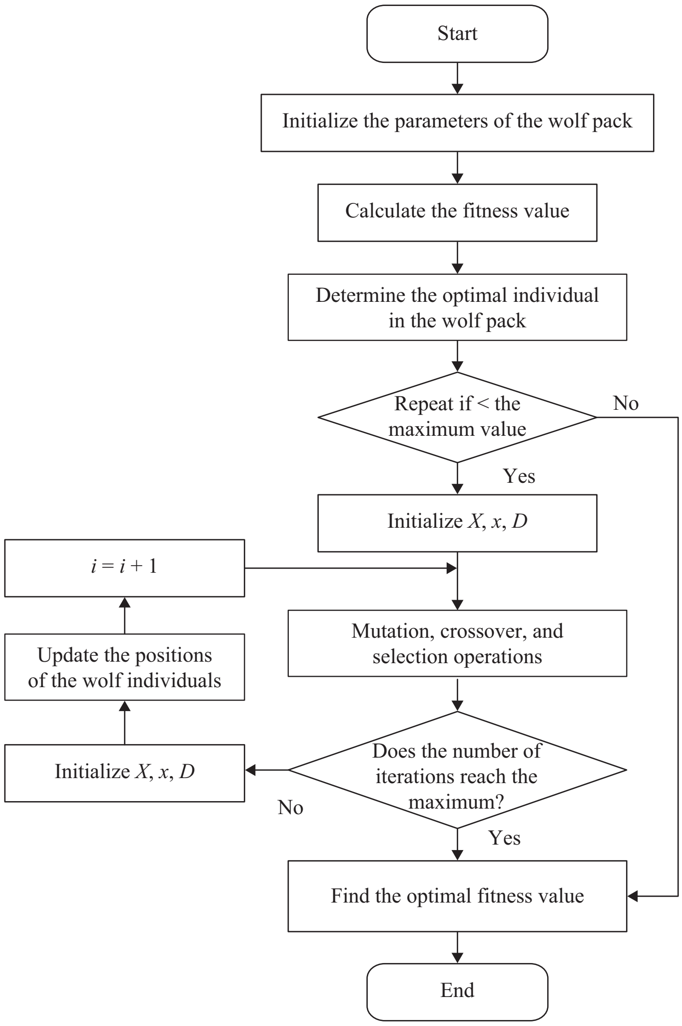


Fig. 2. Flow of the improved GWO

In view of the limitations of SVM and for the purposes of faster learning speed and easier implementation form, this paper introduced the linear regression function of Least Square SVM (LSSVM) to solve the problem, the following formula gives the corresponding relationship:

$$b = \theta\psi(a) + \rho \tag{12}$$

Assuming: φ represents the penalty factor; ρ represents the threshold, then according to the principle of minimized structural risk, the optimal value could be solved based on the following formula:

$$min_{\theta,\rho,p} SQ(\theta, p) = \frac{1}{2}\theta^T\theta + \frac{1}{2}\phi\sum_{L=1}^{M} p_l^2 \tag{13}$$

$$b_l = \theta^T\psi(a_l) + \rho + p_l, l = 1, ..., M \tag{14}$$

When solving the optimal value, the multiplier σ needs to be introduced to construct the Lagrangian function, and it satisfies $\sigma_i \geq 0$, at this time, the optimal value could be solved based on the following formula:

$$DG(\theta,\rho,p,\sigma) = SQ(\theta,p) - \sum_{l=1}^{M}\sigma_L\{\theta^T\psi(a_l) - \rho + p_l - b_l\} \tag{15}$$

After the transformation, there is:

$$\begin{cases} \frac{\partial DG}{\partial\theta} = 0 \to \theta = \sum_{l=1}^{M}\sigma_l\psi(a_l) \\ \frac{\partial DG}{\partial\rho} = 0 \to \sum_{l=1}^{M}\sigma_l = 0 \\ \frac{\partial DG}{\partial p_l} = 0 \to \sigma_l = \phi p_l, l = 1, ..., M \\ \frac{\partial DG}{\partial\sigma_l} = 0 \to \theta^T\psi(a_l) + \rho + p - b_l = 0, l = 1, ..., M \end{cases} \tag{16}$$

By eliminating θ and p_l and introducing the kernel function, there is:

$$HE(a_n, a_m) = \psi(a_n)^T\psi(a_m), n, m = 1, ..., M \tag{17}$$

Assuming: O represents the unit matrix, then there are $1^O = [1...1]_o$, $x = [x_1 \ldots x_M]O$, and the formula below gives the expression of the attained matrix:

$$\begin{bmatrix} 01^T \\ 1\Phi + \phi^{-1}I \end{bmatrix}\begin{bmatrix} y \\ x \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix} \tag{18}$$

This paper chose to take the *RBF* kernel function as the kernel function of the SVM, then the prediction model corresponding to the LSSVM is:

$$b(a) = \sum_{l=1}^{M}\sigma_l HE(a, a_l) + \rho \tag{19}$$

The specific execution steps of the prediction model are:

STEP1: Initialize the English major student classified training quality parameters of the LSSVM.

STEP2: Initialize the GWO and calculate the objective values of the English major student classified training quality parameters.

STEP3: Calculate the values of x, X, and C, and then calculate the distances between wolf individuals in the wolf pack and the optimal wolf individual, and constantly update the positions of all wolf individuals.

STEP4: Combine with the previous section to execute mutation, crossover, and selectin operations on the current wolf pack, and further determine the objective function values of the wolf individuals.

STEP5: Update the position of the optimal wolf individual.

STEP6: Verify the preset values of the English major student classified training quality parameters, if the output result reaches the preset value, then the algorithm stops iterating and outputs the prediction value of the English major student classified training quality; if the output result doesn't reach the preset value, then the algorithm continues to calculate iteratively.

Figure 3 shows the flow of the combined algorithm.

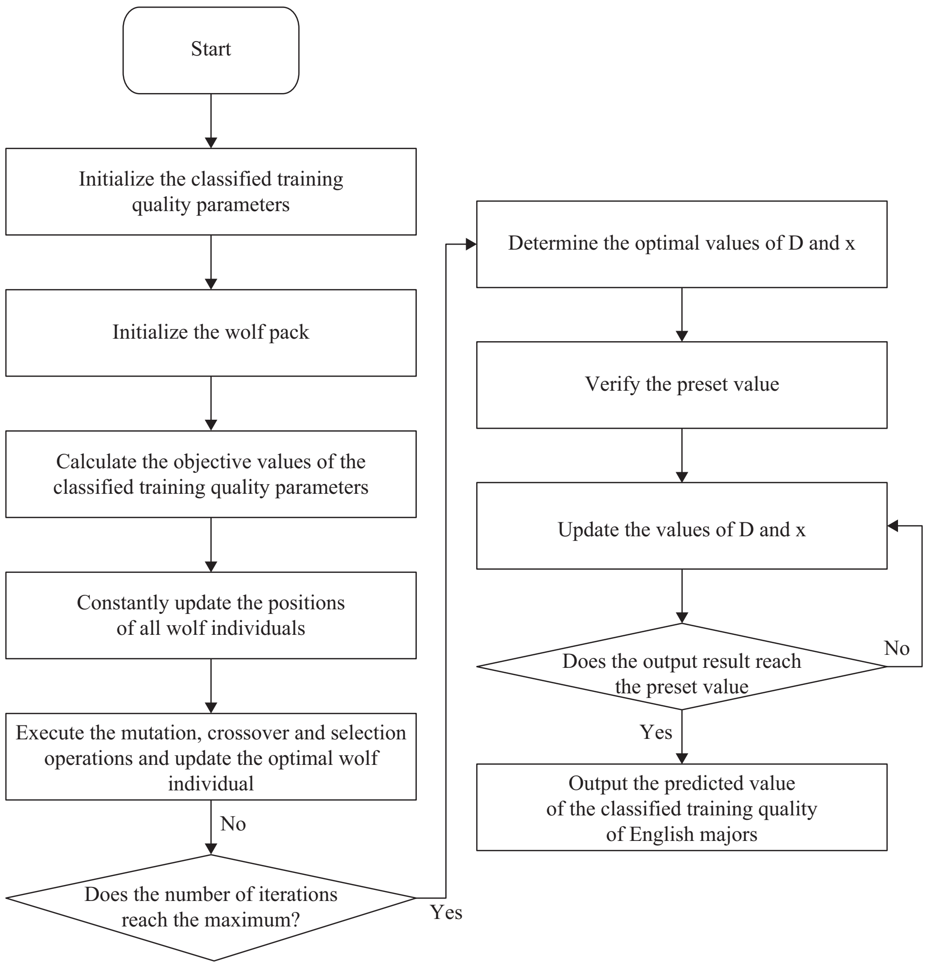
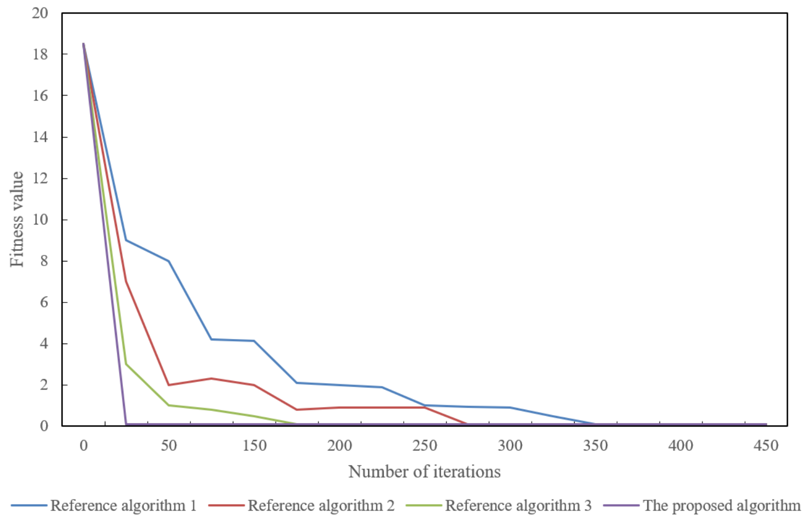


Fig. 3. Flow of the combined algorithm

4 Experimental results and analysis



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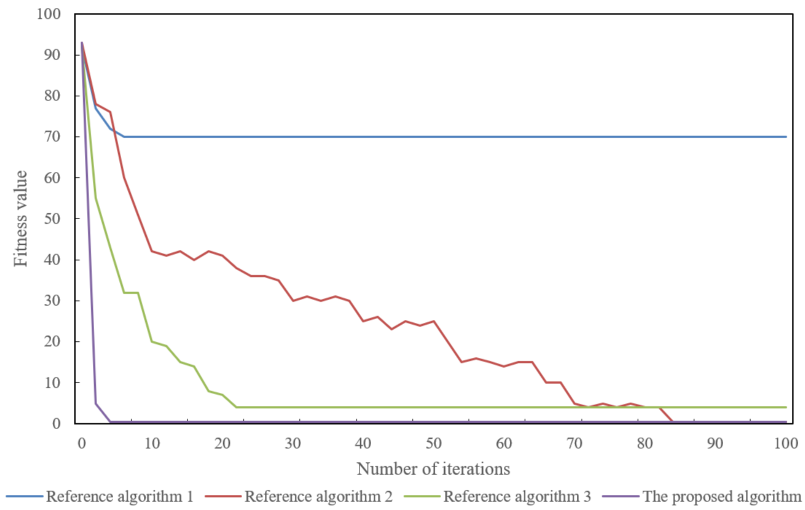

2)

Fig. 4. Convergence curves of different datasets

Figure 4 shows the convergence curves of different datasets. In the comparative experiment, the reference algorithms include the conventional SVM (reference algorithm 1), the SVM optimized by GWO (reference algorithm 2), the SVM optimized by improved GWO (reference algorithm 3), and the proposed algorithm. According to the figure, the convergence speed of the proposed algorithm was faster than that of the other three algorithms. For the proposed algorithm, although it had different convergence curves on different datasets, their search speeds were fast due to the structural advantages of the algorithm. This is because in the proposed algorithm, the head wolf spots the prey faster, and it takes the wolf pack a shorter time to search in the optimal area, and speed for attaining the optimal solution is higher.

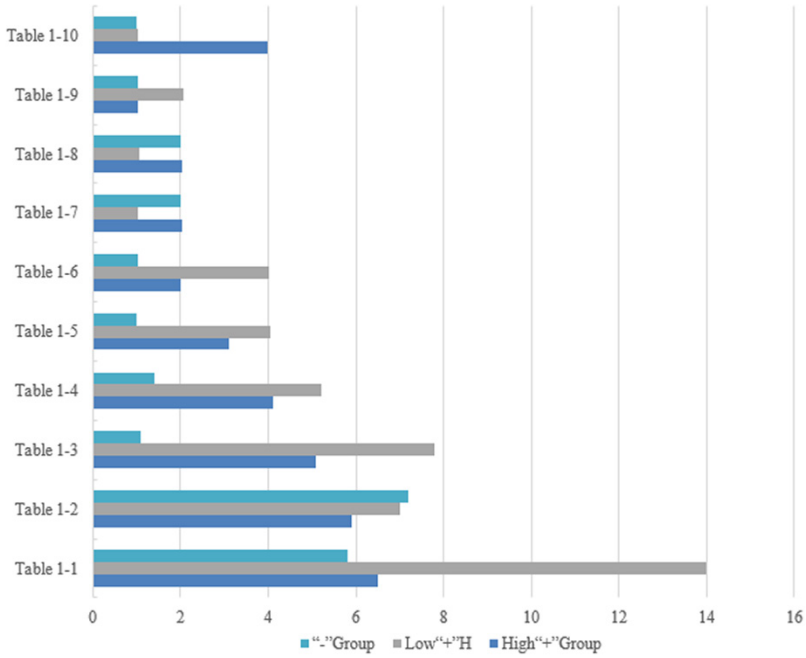

Fig. 5. Comparison of the performance indexes of active learning attitude

In this paper, the evaluation of the classified training quality of English majors was measured by the changes in the comprehensive improvement level of each reference index. Figure 5 compares the performance indexes of active learning attitude. As can be seen in the figure, the comprehensive improvement levels of the reference indexes were divided into three groups: the high "+" group, the low "+" group, and the "–" group, and there're obvious differences in the three groups in terms of the number and distribution of the performance indexes of active learning attitude. In the "+" groups, most samples tend to use the first three active learning attitude performance indexes: be more diligent in self-disciplined English learning (5.8% to 13.9%), inspire internal interest in learning (5.9% to 7.1%), and higher learning concentration (1.1% to 7.7%). This indicates that English majors who participated in the research paid more attention to the self-adjustment of active learning attitude in two aspects: the after-school self-adjustment and the in-class self-adjustment, which had effectively improved the classified training quality of English majors. By comparing the English majors in the "+" groups and the "–" group, it's found that, those in the "+" groups had made good preparations for English learning in terms of both emotions and actions. Although English majors in the "–" group paid attention to the after-school self-adjustment and emotion and action preparation, they generally ignored the in-class self-adjustment.

The large differences between the three groups indicated that, during the process of the classified training of English majors, students with similar active learning attitude and self-adjustment ability can get better synergistic learning effect by influencing each other.

To figure out whether there're differences in the performance indexes of active learning attitude between different types of majors, this paper made a comparison, and Figure 6 compares the performance indexes of active learning attitude of English majors and non-English majors. As can be seen from the figure, the two performance indexes of "be more diligent in self-disciplined English learning (7.4% and 18.4%)" and "inspire internal interest in learning (5.9% to 7.1%)" improved significantly. Compared with non-English major students, the English major students are more willing to get in touch with media that can trigger their internal learning interest, such as watching English movies or listening to English songs, so as to inspire their enthusiasm for English learning and cope with situations in which they may lack learning motivations. For students with similar active learning attitude in the learning groups, the implementation paths of their internal learning motivations are similar as well, they are less affected by students with different learning attitude, and their learning persistency is better.

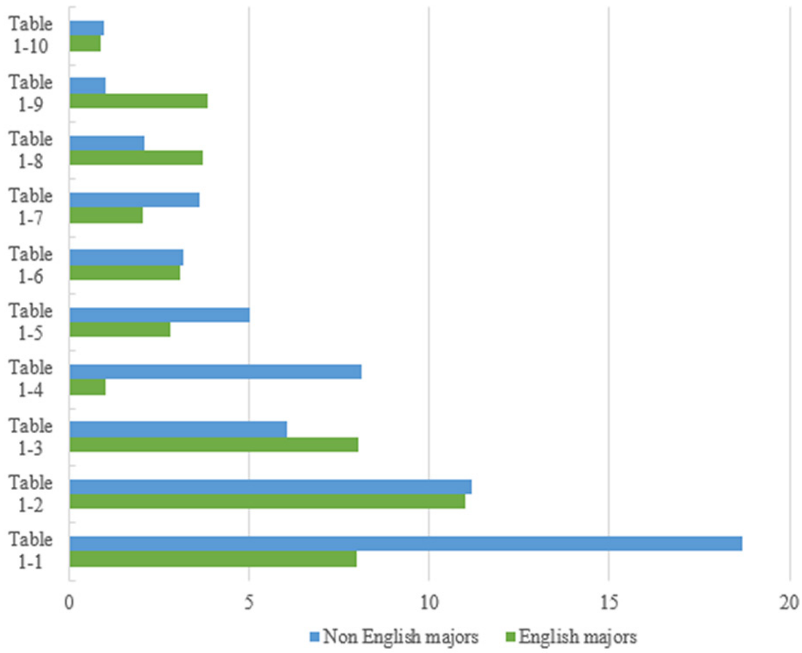

Fig. 6. Comparison of performance indexes of active learning attitude by major

To figure out whether there're differences in the indexes of the cultivation of active learning attitude between different learning groups, this paper also compared them, as shown in Figure 7, for the three groups of high "+", low "+", and "–", there're obvious differences in the number and distribution of the indexes.

For English majors in the high "+" groups and the "–" group, "have the consciousness to compete with classmates (10.8% and 20.5%)" and "the teaching ability, encouragement, and influence of teachers (4.9% and 6.4%)" are the main factors that play important roles in the cultivation of active learning attitude, and this indicated that the English majors in the three groups have a strong willingness to learn. Compared with students in the low "+" group, those in the high "+" group are more likely to get motivations and encouragements from English learning. Unlike the two "+" groups, English majors in the "–" group are prone to stimuli such as the exams or the emotional changes, thereby attaining an active learning attitude. Through the above analysis, the English learning requirements of English majors in different groups could be understood so as to get better improvement effect in terms of the classified training quality of English majors.

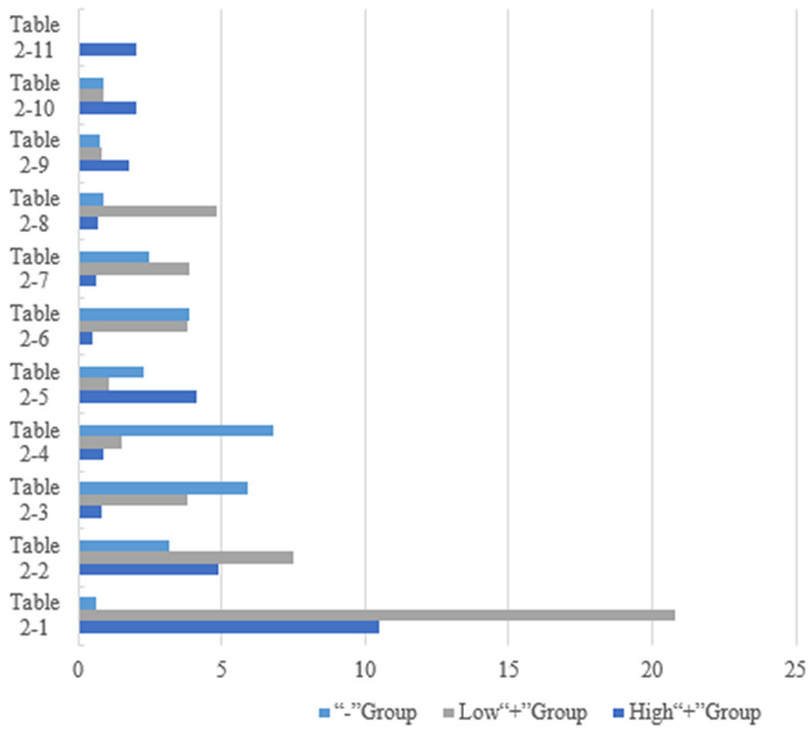

Fig. 7. Comparison of the indexes of the cultivation of active learning attitude

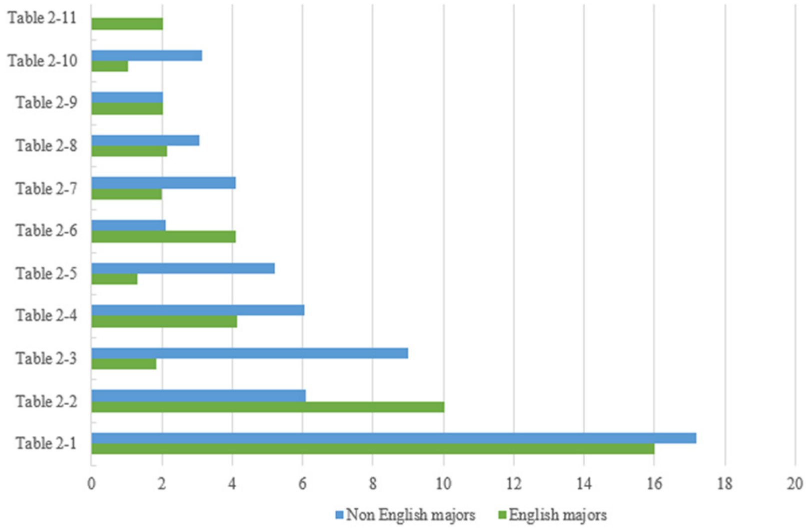

Fig. 8. Comparison the indexes of the cultivation of active learning attitude by major

To figure out whether there're differences in the indexes of the cultivation of active learning attitude between English majors and non-English majors, Figure 8 compares these indexes by major. As can be seen from the figure, there're significant differences in the number and distribution of these indexes between English majors and non-English majors. The English majors might re-gain an active learning attitude via the consciousness to compete with classmates (16.2%) or the influence of teachers' teaching ability and encouragement (8.7%). For English majors who can emerge themselves in an English atmosphere and learn from their peers with excellent English ability, such unintentional stimuli might be the reason for their good English learning achievement; while for non-English majors, they would pay more attention to the factors that can satisfy their English learning requirements, and this requires teachers to choose more suitable teaching methods for them when carrying out classified training.

5 Conclusion

This paper studied the prediction, monitoring, and management of the classified training quality of English major students. At first, this paper analyzed the classified training of English majors, and introduced the factors of the cultivation of active learning attitude in English majors and the typical manifestations of English majors with an active learning attitude. Then, this paper used the comprehensive improvement level of each evaluation index to measure the classified training quality, and combined the GWO with the SVM to propose a model for predicting the classified training quality of English majors, which laid a basis for further quality monitoring and management. Experimental results gave the convergence curves of different datasets, and verified that the convergence speed of the proposed algorithm was faster than that of the other three algorithms, and its prediction performance was better. After that, this paper compared the performance indexes of active learning attitude between English majors and non-English majors, and the results showed that, for students with similar active learning attitude in the learning groups, the implementation paths of their internal learning motivations are similar as well, they are less affected by students with different learning attitude, and their learning persistency is better. Moreover, this paper also compared the indexes of the cultivation of active learning attitude between English majors and non-English majors, and the results indicated that non-English majors generally pay more attention to the factors that can satisfy their English learning requirements, and this requires teachers to choose more suitable teaching methods for them when carrying out classified training.

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