

Retraction

Retracted: Improvement and Optimization of Feature Selection Algorithm in Swarm Intelligence Algorithm Based on Complexity

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

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.

References

- [1] B. Chen, H. Chen, and M. Li, "Improvement and Optimization of Feature Selection Algorithm in Swarm Intelligence Algorithm Based on Complexity," *Complexity*, vol. 2021, Article ID 9985185, 10 pages, 2021.

Research Article

Improvement and Optimization of Feature Selection Algorithm in Swarm Intelligence Algorithm Based on Complexity

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The swarm intelligence algorithm simulates the behavior of animal populations in nature and is a new type of intelligent solution that is different from traditional artificial intelligence. Feature selection is a very common data dimensionality reduction method, which requires us to select the feature subset with the best evaluation criteria from the original feature set. Feature selection, as an effective data processing method, has become a hot research topic in the fields of machine learning, pattern recognition, and data mining and has received extensive attention and attention. In order to verify the improvement effect of the feature selection algorithm based on the swarm intelligence algorithm on the data, this paper conducts experiments on six classes in the city's first middle school with similar conditions. First, count the current situation of the students in the class, then divide them into classes, use different algorithms to teach them, and count the changes of the students after a period of teaching. The experiment found that the performance of students under the feature selection algorithm is about 30% higher than other teaching methods, and the awareness of cooperation between students reaches 0.8. It solves the contradiction between popularization and improvement and solves the problems of polarization and transformation of underachievers. The individuality of the algorithm has been fully utilized and developed. The test results show that the improved algorithm has faster convergence speed and higher solution accuracy, and the feature selection algorithm based on swarm intelligence algorithm can effectively improve the efficiency of the algorithm.

1. Introduction

With people's widespread attention and a lot of research on feature selection algorithms, the filtering, encapsulation, and the hybrid model of the two in feature selection have been widely used in different fields. In recent years, encapsulation models based on swarm intelligence algorithms and hybrid filtering encapsulation models have gradually become research hotspots in feature selection algorithms. Feature selection algorithms are easy to implement, have fewer parameters, and have relatively low computational costs. The convergence effect is achieved quickly and is highly valued. Feature selection is the process of selecting a subset of the original features from the data set. It is usually necessary to find a subset that can represent the entire set without losing information. However, finding this subset is a notoriously

difficult problem, and the computational load may become tricky.

An important step in pattern recognition, machine learning, and data mining is feature selection. Although deep learning methods do not need to extract features in advance, deep learning methods obviously have a problem of poor interpretability. Feature selection has always been used in artificial intelligence and related fields. With the rapid development of information acquisition technology and storage technology, databases even need to store data with hundreds or even thousands of features in practical applications. A large number of features will seriously slow down the learning process of the entire algorithm when faced with a limited training data set. At the same time, the classifier will also face overfitting when learning, which is related to the impact of related redundant features on the classification results [1].

There have been many researches on intelligent algorithms at home and abroad. Kwak et al. [2] proposed a MIFS-U algorithm for the fact that the penalty factor of the evaluation function in the MIFS algorithm cannot clearly give the degree of redundancy growth; the same as the MIFS algorithm, the values of the parameters of the new MIFS-U algorithm will directly affect the size of the selected feature subset. In order to solve this problem, Novovicova [3] and others proposed an improved version of the algorithm, mMIFS-U, based on MIFS-U. The maximum feature mutual information is used as the redundancy measure between the two; in order to solve the influence of some uncertain information or wrong information caused by variability, Qu et al. [4] proposed using dependency to measure the dependency between features and degree and then proposed the DDC algorithm. The basic idea of the above algorithm is roughly the same, and the only difference is that the representation of the evaluation function is not the same. The continuous increase in the number of selected features will gradually reduce the uncertainty corresponding to the category, and the number of unidentifiable samples will gradually decrease. Therefore, considering the information interference that may be caused by the identified sample set, dynamic mutual information can be used as the evaluation indicator, and the identified sample information can be continuously deleted in the process of feature selection, so that the evaluation indicator is in the unidentifiable sample. There is less dynamic recognition on the top.

This paper simulates the process of teacher-to-student teaching and learning between students and the process of mutual learning between students and improves students' academic performance through the "teaching" of teachers and the mutual "learning" between students. It has the advantages of few parameters, simple ideas, being easy to understand, strong robustness, and so forth, combining the swarm intelligence algorithm into the feature selection teaching model; in this way, the classification accuracy and efficiency can reach the best results, and the convergence speed of the algorithm is further improved. At the same time, it also reduces the possibility of the algorithm falling into a local optimum and can ensure that the algorithm achieves an optimal solution.

2. Research Method of Feature Selection Algorithm

2.1. Feature Algorithm. In the face of these increasingly complex and computationally expensive data, the single use of data mining algorithms' optimization capabilities or the computing capabilities of high-performance computing tools can no longer meet the needs of data processing [5]. Researchers are thinking more about combining optimization algorithms with various computing tools, hoping to get faster and better data processing capabilities. Feature selection algorithm is a relatively new kind of swarm intelligence optimization algorithm, which has attracted the attention of many scholars and inspired their researches. Compared with other swarm intelligence optimization algorithms, the feature selection algorithm has the advantages of simpler operation, fewer parameters to be set and

adjusted, faster convergence speed, and so forth; it is also easier to implement, has fewer parameters and relatively low computational cost, and can be faster to achieve the convergence effect [6, 7].

The ACO (ant colony optimization) algorithm simulates the algorithm where ants start from the ant nest and distribute pheromone all the way to find food. Ants use their perception of pheromone concentration to find the shortest path to food [8]. When encountering obstacles, the ants quickly find a new path to the food through mutual cooperation. It is one of the feature selection algorithms.

Ants in nature can find food from the nest without any outside interference or help. As the environment changes, the path to find food also changes in real time, and the shortest path to food will be found again. When ants are looking for food, they will emit a kind of "pheromone" hormone substance [9, 10]. In the process of path selection, ants always move to a path with a high pheromone concentration. This forms a positive feedback mechanism, so that the concentration of path pheromone is proportional to the number of ants passing by. In this way, the shortest path between the ant nest and the food must be found. The process of ant colony algorithm is shown in Figure 1.

ACO algorithm solves the traveling salesman problem; and the parameters are defined as follows: m represents the number of ants; n represents the number of cities; d_{ij} represents the distance between city i and city j ; $b_i(t)$ represents the number of ants in city i at time t , and $m = \sum_{i=1}^n b_i(t)$ represents the ants in city (i, j) the pheromone left over; $\Delta\tau_{ij}^K$ represents the selection probability of ant K transferring from edge i to edge j , where j must be a city that has not been reached; α represents the pheromone heuristic factor; β represents the expected heuristic factor; ρ represents the pheromone volatilization coefficient. The specific expression is shown in the following formula:

$$P_{ij}^K(t) = \begin{cases} \tau_{ij}^\alpha(t) * \kappa_{ij}^\beta(t), & s \in \text{allowedk} \\ \tau_{is}^\alpha(t) * \kappa_{is}^\beta(t), & s \in \text{allowedk} \\ 0, & s \in \text{allowedk}. \end{cases} \quad (1)$$

Suppose that there are m ants traversing the set of distances in a cycle:

$$D = \left\{ D[k] \mid D[k] = \sum_{i,j \in C} d_{ij}[k], \quad k = 1, 2, \dots, n \right\}, \quad (2)$$

and then

$$d_{\min}(t) = \min\{D[1], D[2], \dots, D[m]\}. \quad (3)$$

In the above formula, $d_{\min}(t)$ represents the optimal one among the m paths found by m ants after the cycle is completed at time t . $d_{\text{avg}}(t)$ represents the average value of m paths found by m ants in this round. After the end of the period at time t , the global update operation of pheromone is performed on the path traversed by $d_{\min}(t) < d_{\min}(t-1)$ and $D[k] < d_{\text{avg}}(t)$, k according to the formula.

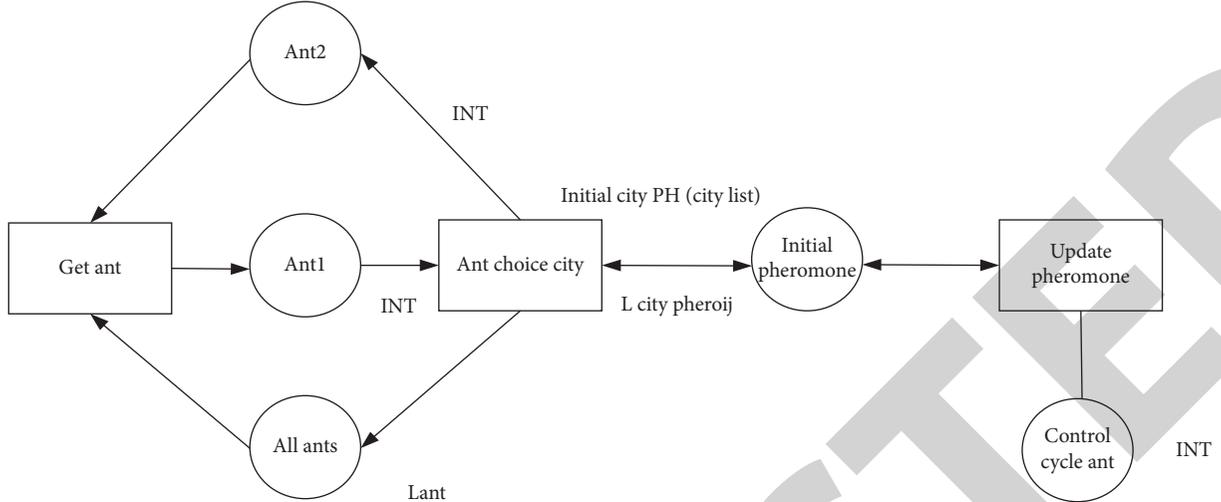


FIGURE 1: Basic ant colony algorithm framework diagram.

Pheromone will be left after the ants traverse all the cities in one round, but the concentration of pheromone will become less and less after volatilization over time. In the ACO algorithm, the pheromone on the path is updated at all times. The update formula of pheromone is as follows:

$$\tau_{ij}(t+1) = (1 - \gamma) * \tau_{ij}(t) + \gamma * \Delta\tau_{ij}(t, t+1). \quad (4)$$

The formula γ indicates that the pheromone volatilization coefficient is within (0–1); $\Delta\tau_{ij}(t, t+1)$ represents the pheromone left by the path of ants from i to j from t to $t+1$. The specific formula $\Delta\tau_{ij}(t, t+1)$ is as follows:

$$\Delta\tau_{ij}(t, t+1) = \sum_{k=1}^m \Delta\tau_{ij}^k(t, t+1). \quad (5)$$

In order to prevent the ants from traversing city i after traversing city j , a taboo table (Tab_{uk}) should be added to the ant colony algorithm to record the cities that the ants have walked in a period of time. After the ant traverses all the cities, the pheromone will be updated, and the data recorded in the taboo table will be used to calculate the total length of the path taken by the ant during the traversal [11]. When the current round of traversal is completed, the records (Tab_{uk}) in the table will be cleared, and a new round of traversal will be performed. The formula for calculating the ant week model is as follows:

$$\Delta\tau_{ij}(t, t+T) = \begin{cases} K, & k \in (i, j), \\ Ln, & \text{other.} \\ 0, & \end{cases} \quad (6)$$

In the formula, K is used to represent the total amount of pheromone emitted when the ant searches for the optimal path; Ln is used to record the total length of each city after ant k traverses one round. Through continuous traversal, artificially simulated ants will eventually find a path with the least cost to solve the problem.

2.2. Feature Selection Classification. Feature selection methods can be divided into filtering feature selection methods and encapsulated feature selection methods according to whether the classification results of the classifier are used as evaluation criteria. The filtering feature selection method does not use the classification result of the classifier as the evaluation criterion. Generally, different evaluation criteria are directly used to measure the correlation between the feature and the category. The method is fast, but the classification accuracy is low. The encapsulated feature selection method uses the classification result of the classifier as the evaluation criterion to evaluate the feature subset. This method has a high classification accuracy, but its computational complexity is large, and it is not suitable for large-scale data sets [12–14].

The feature selection problem is essentially a combinatorial optimization solution to solve a class of problems, and the main means to solve this type of problem is to combine in various ways, improve and optimize, and then search the complete solution space. The feature selection method refers to how to select outstanding features from all the features of the data set to form a nonempty feature subset as the optimal solution [15, 16]. The feature selection method is essentially a search process that is executed in the known solution space and tends to the optimal solution direction. The search process strategies included in this feature selection method are classified according to the core principles of search and can be divided into complete search, heuristic search, and metaheuristic search.

2.2.1. Full Search. From the perspective of the search process, the complete search can be divided into two types: exhaustive search and nonexhaustive search. Among them, the exhaustive method is a theoretically existing search strategy. It has been proved that the search problem of the optimal minimum feature subset is an NP problem. That is to say, if the search process of the feature selection algorithm does not use the exhaustive search process, then there is no

guarantee that the solution of the feature selection algorithm is the optimal solution [17]. Exhaustive search refers to searching the set of all nonempty feature subsets in turn by enumerating and searching the set of all nonempty feature subsets in accordance with the criteria established by the algorithm and selecting the best nonempty feature subsets as the solution to the problem based on the evaluation criteria established by the algorithm. For exhaustive search, it will bring about huge computational complexity and loss of computational resources, so it is difficult to quote. Breadth-first search is such an exhaustive search strategy, which traverses the solution space of the optimal nonempty feature subset by means of breadth-first traversal to obtain the optimal solution. There are many search strategies in the field of nonexhaustive search, such as branch-and-bound search by conditionally pruning redundant search branches, directed search, and optimal priority search based on several single features with higher evaluation to form an optimal feature subset queue. Wait.

2.2.2. Heuristic Search. Common methods of heuristic search include sequential search, which is also a way of greedy mountain climbing, including forward selection, backward selection [18], and two-way search. Because of forward selection and backward selection, each time a feature is added or removed, the selection cannot be changed in the subsequent steps, which results in a considerable arbitrariness in each selection. In order to avoid the adverse effects of single selection accumulation on the subsequent process, two improved heuristic search methods are proposed: sequence floating forward selection and sequence floating backward selection [19, 20]. In addition, the selection algorithm by adding L to R can also solve this problem. This algorithm usually has two forms. The initial state of the first is the same as the forward selection. The initial state is the empty set S , and, for each subsequent cycle when iterating, first add L features, and then remove R features. Second, the initial state is the same as the backward selection, which is the full set S . At the beginning of each iteration, R features are first subtracted, and then L features are added. But the values of L and R are a bottleneck of the algorithm.

2.2.3. Metaheuristic Search. The core idea of metaheuristic search is as follows: on the basis of the heuristic search algorithm "making rules for feature selection and cancellation," through the fusion of random methods and local search algorithm methods, the heuristic method is improved and perfected. The search process and search path of the feature selection method gradually approach the optimal solution or the suboptimal solution. In the actual process, it usually shows that the computer simulates the behavior of biological populations or ethnic groups in the natural environment.

In the classic field of statistical problems, scholars have begun to conduct in-depth research and discussion on feature selection algorithms since the 1960s; at the same time, feature selection algorithms are also one of the important research tasks in the field of machine learning [21]. From the 1990s to the present, research feature selection has

been a direction that many experts in the field of machine learning attach great importance to. The reasons are mainly divided into the three following aspects:

- (1) Irrelevant or redundant features have a great negative impact on the performance of many learning algorithms. Many learning algorithms will encounter the situation where the size of the training sample is increased sharply by the increase of redundant features or irrelevant features [22]. Therefore, selecting as few features as possible can not only reduce the computational complexity of the algorithm and improve the classification accuracy of the algorithm but also help to find a more concise and effective algorithm model.
- (2) The processing problems are faced by massive data. The so-called huge amount of data is reflected in the large number of samples on the one hand and the high feature dimension of the samples on the other hand.
- (3) When applied in various fields, the type of data that needs to be read or stored is constantly changing. Therefore, when performing feature selection algorithm experiments, new data storage types and reading processes need to be constantly considered [23].

2.3. The Principle of Feature Selection Algorithm Model. The hybrid filter package feature selection includes the combination of two models. In the first stage, the filter model part chooses to use the mutual information feature selection method to evaluate the strength of the connection between each different feature. At this stage, the features will be sorted according to their relevance to narrow the search range in the solution space of all possible feature subsets; this process will enable the second stage to search from the reduced solution space, greatly improving the efficiency of the algorithm [24]. The algorithm flow is shown in Figure 2.

The use of information theory is the main method to measure the information content of random variables. The core information metric is entropy $h(x)$, which measures the uncertainty of a discrete random variable x , defined as

$$h(x) = - \sum_{x \in K} p(x) \log p(x), \quad (7)$$

where K is the set of possible values of x , and when another y is known, conditional entropy is used to measure the residual uncertainty in the discrete random variable x . It is defined as follows:

$$h(x|y) = - \sum_{x \in K, y \in K} p(x, y) * \log(x|y). \quad (8)$$

If y completely determines x , then the conditional entropy is zero; then $h(x|y) = h(x)$, and then x and y are completely independent. I represents the mutual information that can be obtained under a given known situation, which is defined as

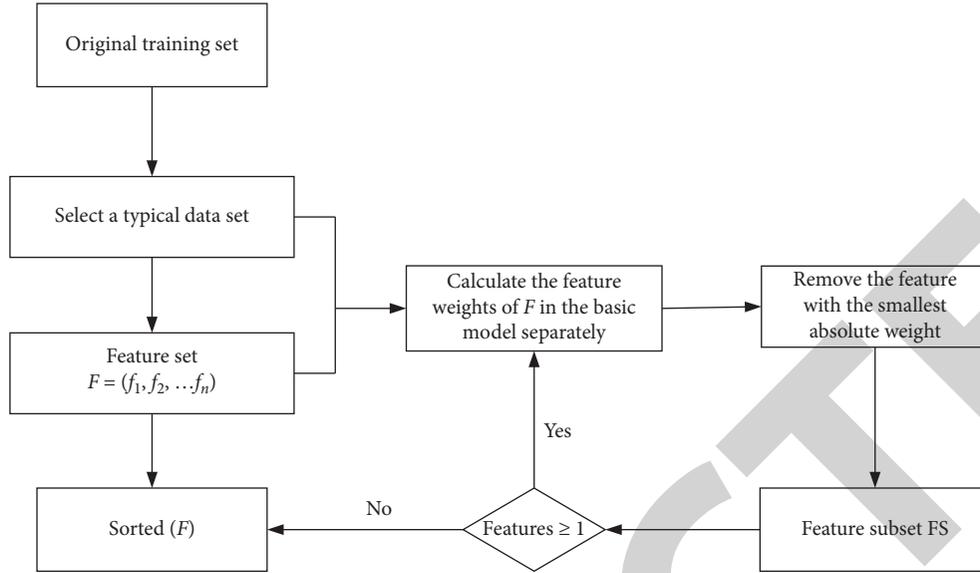


FIGURE 2: Feature selection algorithm flow.

$$I(x, y) = h(x) - h(x|y) = - \sum_{x \in \mathcal{X}, y \in \mathcal{Y}} p(x, y) * \log \frac{p(x, y)}{p(x)p(y)}. \quad (9)$$

If it is known that x does not provide additional information about y , that is, the two variables are independent, then I will be zero. Consider that the optimal feature subset should maximize its relevance:

$$T_0 = \arg \max_{s \in f} J(s), \quad x.t. |s| \leq t, \quad (10)$$

where t represents the upper limit of the number of selected features, f represents the feature set, s represents the set of selected features, and $J(s)$ represents the evaluation criterion. If it is independent and identically distributed, then $N \rightarrow \infty$, and, for a fixed m, t sum, the statistic $S(m, N, r, t)$ is always zero. After selecting the maximum and minimum radius, the error between the two can be defined as follows:

$$\Delta S(m, t) = \max(S(m, r, t)) - \min(S(m, r, t)). \quad (11)$$

According to the BDS statistical theory, the three equations can be calculated as follows:

$$\bar{S}(t) = \frac{1}{16} \sum_{m=2}^5 \sum_{i=1}^4 S(m, r_i, t),$$

$$\Delta \bar{S}(t) = \frac{1}{4} \sum_{m=2}^5 \Delta S(m, t), \quad (12)$$

$$S_{\text{cor}}(t) = \Delta \bar{S}(t) + |\bar{S}(t)|.$$

When $N=300$, $r = k * (\sigma/2)$, $\sigma = st d(x)$ (σ representing the standard deviation), the optimal delay time is the first minimum point that is calculated or found first. If the sum is fully considered, the length of the time window can be obtained when it is the global minimum.

If two or more standard samples are given, their characteristic values are all the same, and their corresponding categories are also the same, it means that the two or more samples are consistent; otherwise, it means that they are inconsistent. The consistency criterion is measured by the inconsistency rate. The inconsistency rate is not to find the separability of the categories but to maintain the discrimination ability of the original features and to find the smallest subset that has the same classification effect as the original data set. This method has the advantages of removing redundant effects, irrelevant feature subsets, and monotonic functions, as well as being fast. It can also find a feature subset with a small data scale. However, the algorithm is sensitive to noise data and is only suitable for discrete characteristic data.

3. Research Experiment of Feature Selection Algorithm

3.1. Subjects. We simulate the characteristic algorithm of a school in this city. The basic idea of the algorithm is to simulate the way in which students and teachers and students and their colleagues in the class learn from each other. The improvement of the learning level of each student in the class not only requires the “teaching” to be guided by the teacher but also requires the students to learn from each other’s strengths to promote the absorption of knowledge. If this idea of teaching and learning is transformed into a mathematical model of an algorithm, teachers and students are both individuals in the algorithm. Among them, the teacher is the individual with the best fitness value, and the student is the individual who needs to evolve. What each student learns in a certain course subject is equivalent to a decision variable for each student’s learning level.

TABLE 1: Mastery of male students.

	Creative thinking	Learning attitude	Learning ability	Basic ability	Athletic ability	Cultural lessons
Class 1	2.1	1.82	2.28	1.9	1.81	2.09
Class 2	2.07	1.93	2.4	2.18	2.19	2.17
Class 3	1.87	2.16	2.31	2.3	2.49	2.5
Class 4	2.03	2.06	2.23	2.24	2.16	2.27
Class 5	2.37	1.87	2.45	2.27	2.19	1.89
Class 6	2.03	2.08	2.09	2.38	1.99	2.02

3.2. Optimization Method. Teachers use “teaching” behavior to enable individual student X to learn from the optimal individual $X(t)$ in the population. If $X(t)$ is the global optimal solution of the function, the final global convergence of the algorithm can be guaranteed. Since the algorithm treats the optimal individual as a teacher every time, it has a strategy of preserving excellence. After the algorithm executes a sufficient number of iterations, the algorithm must be established; that is, it will converge to the global optimum. After that, through students’ learning various parameters, compare the differences between different algorithms, especially the difference between the ant colony algorithm and the algorithm based on swarm intelligence in this paper, and get the optimal solution.

3.3. Determination of the Evaluation Weight. The index weight is a numerical index indicating the importance and function of the index. In the indicator system of the evaluation plan, the weight of each indicator is different. Even if the indicator level is the same, the weight is different. Index weight is also called weight and is usually represented by a . It is a number greater than zero but less than 1, and the sum of the weights of all first-level indicators must be equal to 1, that is, satisfy conditions $0 < a < 1$ and $\sum a = 1$.

3.4. Statistics. The data analysis in this article uses SPSS 19.0, statistical test uses two-sided test, significance is defined as 0.05, and $p < 0.05$ is considered significant. The statistical results are displayed as mean \pm standard deviation ($x \pm SD$). When the test data complies with the normal distribution, the double t -test is used for the comparison within the group, and the independent sample P test is used for the comparison between the groups. If the regular distribution is not sufficient, two independent samples and two related samples will be used for inspection.

4. Research and Experimental Analysis of Feature Selection Algorithm

4.1. Student Status. We collect statistics on the current learning status of the students in the six classes of the city’s No. 1 Middle School and then use different algorithms for teaching and compare the changing trends between them, which can also prove the pros and cons of different algorithms. In order to facilitate the distinction, we classify the gender of the students. The current situation of male students is shown in Table 1.

From Figure 3, we can see that, before teaching, the male students do not have a deep grasp of various abilities, with an average value of about 2, which basically does not meet the requirements. In order to know whether the female students have met the requirements, we also made statistics on the mastery of the female students in these six classes, as shown in Table 2.

From Figure 4, we can see that the mastery level of female students is not much different from that of male students, and the average value is basically around 2, but the mastery levels of the two are different. Male students are better than female students in creative thinking. Female students have higher sports scores compared to male students.

4.2. Teaching of Different Algorithms. We divide these six classes into three groups and carry out 3 months of teaching according to different algorithm teaching. After the teaching is over, the relevant data of the students are counted. The male students’ postteaching data are shown in Table 3.

From Figure 5, we can see that, after teaching, male students have improved their skills. There is a big difference in the improvement range of each algorithm. The feature selection algorithm based on swarm intelligence algorithm has the best effect, which is 2 times higher than that before teaching and more than 50% higher than those in other teaching methods. In order to verify the correctness of the results, we also conducted statistics on the teaching data of female students, as shown in Table 4.

From Figure 6, we can confirm again that, after teaching, students have an excellent improvement effect on the mastery of learning skills, and the feature selection algorithm based on the intelligent swarm algorithm has the best effect, and students can be taught in accordance with their aptitude. Male students have improved more compared to female students in some aspects, but, overall, female students’ overall improvement after teaching is slightly greater than that of male students.

4.3. Survey of Teaching Perceptions. We have made statistics on the views of the students and teachers of these classes on the feature selection algorithm based on the swarm intelligence algorithm to understand their satisfaction with different algorithms. The statistics are shown in Table 5.

From Figure 7, we can see that, in the teaching based on feature selection algorithm, students and teachers are highly satisfied, and the total proportion of students who are dissatisfied towards teaching is about 10%. For the

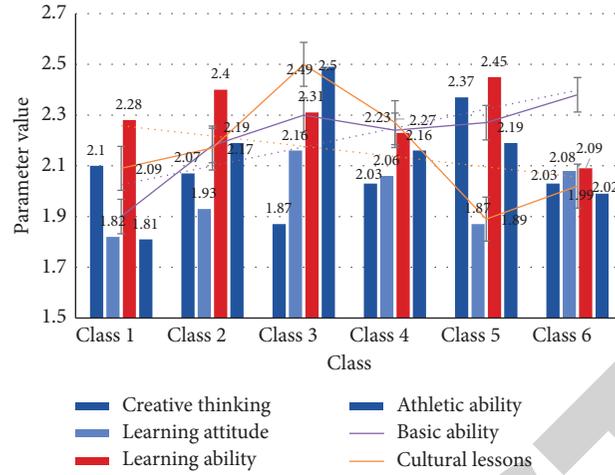


FIGURE 3: Boys' learning status.

TABLE 2: Art mastery of female students.

	Creative thinking	Learning attitude	Learning ability	Basic ability	Athletic ability	Cultural lessons
Class 1	2.36	2.11	2.18	2.34	2.1	1.95
Class 2	1.95	1.94	2.46	2.32	2.28	2
Class 3	2.26	2.09	2.39	2.46	2.15	1.85
Class 4	2.43	2.07	2.1	2.5	2.22	2.09
Class 5	2.11	2.09	1.98	2.28	2.43	2.26
Class 6	1.91	1.81	1.98	2.01	2.32	2.06

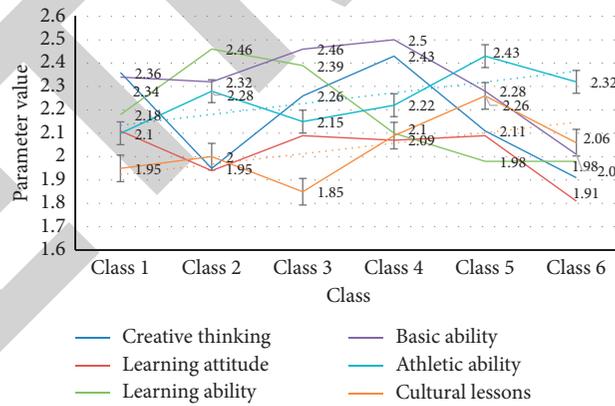


FIGURE 4: Female students' mastery.

TABLE 3: Male students after teaching.

	Creative thinking	Learning attitude	Learning ability	Basic ability	Athletic ability	Cultural lessons
Ant colony algorithm	2.91	3	2.74	2.39	2.57	2.82
Particle swarm optimization	3.13	3.02	3.46	3.43	3.59	3.55
Bee colony algorithm	4.2	3.81	4.03	3.91	3.82	4.23
Forest algorithm	4.78	4.95	4.94	4.99	4.77	4.7
Retrospective optimization	5.48	5.47	5.79	5.52	5.25	5.5
Feature selection algorithm	6.25	6.04	6.19	6.02	5.89	6.02

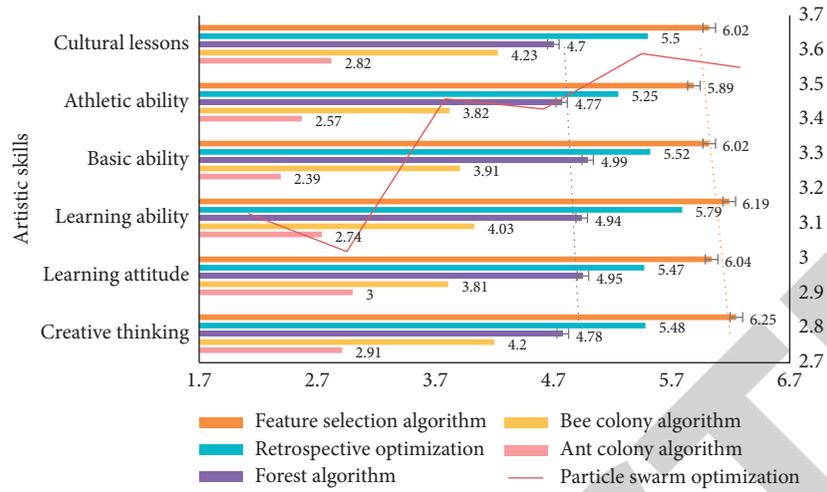


FIGURE 5: Changes of male students after teaching.

TABLE 4: Female students after algorithm teaching.

	Creative thinking	Learning attitude	Learning ability	Basic ability	Athletic ability	Cultural lessons
Ant colony algorithm	3.08	3.16	2.86	2.73	2.81	3.39
Particle swarm optimization	3.8	3.81	3.84	3.57	3.89	3.24
Bee colony algorithm	4.82	4.42	4.41	4.94	4.91	4.24
Forest algorithm	4.89	5.17	4.7	4.91	4.78	4.98
Retrospective optimization	6.14	6.22	5.7	6.13	5.77	5.89
Feature selection algorithm	6.55	6.82	6.62	6.3	6.85	6.42

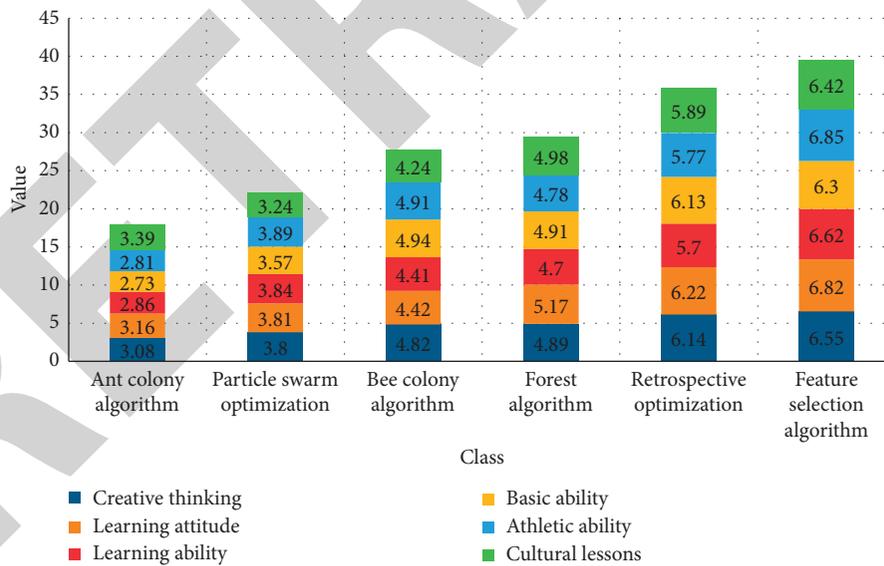


FIGURE 6: Female students after teaching.

TABLE 5: Attitudes towards multimedia teaching.

	Very dissatisfied	Not satisfied	General	Okay	Satisfied	Very satisfied
Class 1	2	4	12	14	17	19
Class 2	2	3	7	12	21	20
Class 3	3	5	13	12	20	24
Class 4	5	5	12	17	19	20
Class 5	1	6	8	11	22	21
Class 6	2	2	13	11	17	19

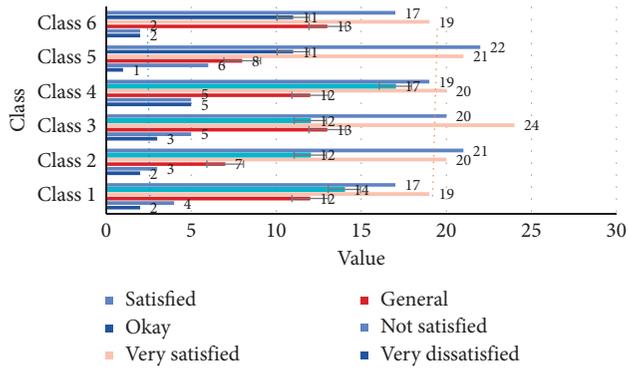


FIGURE 7: Multimedia teaching satisfaction.

TABLE 6: Traditional teaching satisfaction.

	Very dissatisfied	Not satisfied	General	Okay	Satisfied	Very satisfied
Class 1	6	5	22	14	6	7
Class 2	7	2	19	11	7	5
Class 3	9	7	25	15	9	10
Class 4	7	3	12	19	10	9
Class 5	4	6	18	19	11	7
Class 6	7	4	20	21	8	12

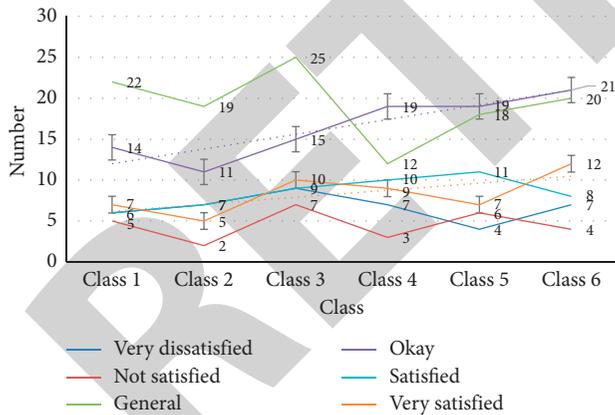


FIGURE 8: Traditional teaching satisfaction survey.

convenience of comparison, we also compare traditional teaching satisfaction, as shown in Table 6.

From Figure 8, we can see that the traditional teaching satisfaction is not high, which is far lower than the satisfaction of swarm intelligence algorithm teaching. Feature selection algorithm is a kind of swarm intelligence algorithm, which can effectively adopt different teaching methods according to different students, maximize the subjective initiative of students, and improve students' learning interest and learning ability. Feature selection algorithm teaching is a product born

of the development of modern computer network technology and multimedia technology to a certain extent, and it is extremely attractive to students.

5. Conclusion

Information in modern society is in a stage of rapid development. Not only has the amount of data faced by humans been increased dramatically, but also its forms have become more diversified. In order to meet the needs of society, it is necessary to design better feature selection algorithms. Through the selection of related features, the problem of dimensionality disaster can be properly handled, the generalization ability of the algorithm can be improved, and the intelligibility of the model can be improved. This article focuses on the in-depth research and discussion on the feature selection model and the binary version, but there are still some shortcomings. First of all, the theoretical knowledge research and algorithm structure research of feature selection algorithms can be further supplemented and perfected, and it is necessary to always pay attention to the existing theoretical support and the latest research results; the data set testing in this article does not fully cover all the reality. In order to achieve better experimental results, it is necessary to further increase the data set tests in practical applications. In future work, we need to pay attention to the difference between the improved algorithm and the original algorithm and the relationship between them. Only in this way can we more theoretically and substantively put forward innovative and important concepts based on the feature selection algorithm model.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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