Application of AHP-GWO-SVM coupling model in landslide warning

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Abstract. In recent years, landslides have become more frequent under the influence of human damage. In order to reduce the loss, improve the accuracy of landslide prediction, we can analyze the data through Analytic Hierarchy Process (AHP) algorithm, then build a Support Vector Machine (SVM) model and optimize the SVM model by Gray Wolf Optimizer (GWO) algorithm. The experimental results show that the model established by GWO and SVM after the AHP method is accurate, and the predicted results are in good agreement with the actual results. Compared with single SVM, it has higher accuracy and better results, and is more suitable for multivariable complex nonlinear landslide warning.

1. Introduction
China's landforms and weather conditions are very complex, and it is one of the countries with frequent disasters. In order to reduce the losses of disaster, many scholars have proposed a variety of methods to predict landslides. More and more methods are used, such as the GM (1, 1) model [1] and BP neural network model et al. The prediction results of GM (1,1) in some cases are quite different from the actual situation [2]. BP neural network, there is no clear choice of hidden layer nodes [3]. Based on the above shortcomings, this paper uses the SVM algorithm.

However, the running accuracy of the SVM model is greatly affected by the artificially set parameters [4], so the gray wolf algorithm is introduced to optimize the parameters of the SVM. At the same time, the artificially set landslide classification label is not objective, and the objective classification label can be obtained through the AHP analytic algorithm.

2. Analytic hierarchy process

2.1. Principle of AHP
Analytic hierarchy process combines qualitative and quantitative analysis methods [5] to analyze and to obtain the decision attribute of the target. The core idea is to first judge the importance of different factors, assign values to each factor, then construct a judgment matrix, and finally get the weights of different factors after consistency test.

Analytic Hierarchy Process (AHP), based on in-depth study of the problem, divides the problem into three layers, namely, the top layer, the middle layer and the bottom layer [6]. The highest level is the goal to be addressed; The middle layer is the dividing factor and criterion; The bottom layer is an alternative to the middle layer.
Construct judgment matrix: fill in the corresponding position of judgment matrix with the corresponding values of different factors and the quantization table according to pair comparison, as shown in Table 1.

### Table 1. Pairwise comparison quantization table

| Standard value | Importance comparison       |
|----------------|-----------------------------|
| 1              | \( a_i \) is as important as \( a_j \) |
| 3              | \( a_i \) is slightly more important than \( a_j \) |
| 5              | \( a_i \) is significantly more important than \( a_j \) |
| 7              | \( a_i \) is more important than \( a_j \) |
| 9              | \( a_i \) is extremely important than \( a_j \) |
| 2, 4, 6, 8     | Median of the above judgment |

Reciprocal: \( a_{ij} = 1/a_{ji} \)

Definition: Maximum characteristic root of \( m \) order reciprocal matrix \( A \), only when \( \lambda = m \), \( A \) is the uniform matrix. If \( \lambda > m \), the judgment error will be larger. Consistency ratio is defined as follows:

\[
CR = \frac{CI}{RI}
\]

(1) \( CI \) is the consistency index and \( RI \) is the index of the constructed paired comparison matrix.

2.2. **The steps of AHP**

1. Establish the hierarchical structure model;
2. Construct judgment (paired comparison) matrix;
3. Consistency test.

3. **Grey wolf optimizer**

Gray wolf algorithm [7] is a population intelligent optimization algorithm proposed by Mirjalili et al., Griffith University, Australia, in 2014. Inspired by the gray Wolf's predation and predation activities, this algorithm is an optimized search method with strong convergence, few parameters and easy implementation.

3.1. **Principle of GWO**

Gray wolf are social canids whose survival strictly follows a social dominant relationship.

1. The first level of the hierarchy: the head wolf in the wolf pack is recorded as the \( \alpha \) wolf. It is mainly responsible for making decisions on activities such as predation, habitat, and rest time.
2. The second level of the hierarchy: \( \beta \) is subservient to the \( \alpha \) wolf and assists in decision-making. It is the best candidate for the \( \alpha \) wolf, and it has other levels of wolves at its disposal.
3. The third level of the hierarchy: \( \delta \) is subordinate to the and wolf, and dominates the rest.
4. The fourth level of the hierarchy: \( \omega \) wolf, the lowest level of wolf, whose role is to avoid problems within the pack.

3.2. **The genetic algorithm performs the steps**

1. Social class stratification: divide wolves according to their fitness from large to small.
2. Surround the prey, as shown in Formula 2:
\[ D = C \odot X_p(t) - X(t) \]
\[ X(t + 1) = X_p(t) - A \odot D \]  

Where, \( t \) is the number of iterations; \( \odot \) is represents hadamer product; \( A \) and \( C \) are collaborative coefficient vectors; \( X_p \) is the position vector of the prey; \( X(t) \) is the current position vector of the gray Wolf.

3. Hunting: the solution space characteristics of many problems are unknown, so the optimal solution cannot be determined. In order to search for the optimal solution, the best three gray wolves (\( \alpha, \beta, \delta \)) in the current population are kept for each iteration, and the optimal solution position is searched.

4. Attack prey.

5. Hunt for prey.

4. Support vector machine

Support Vector Machine (SVM) [8] is a widely used method to solve multivariable and nonlinear problems. Its essence is to use "kernel mapping" to solve the problem of linear inseparability in low-dimensional space.

4.1. Principle of SVM

Suppose \( (x_i, y_i) \) is the sample of the given training set, where \( x_i \) is the sample vector and \( y \) is the classification marker \( i = 1, 2, \ldots, n \), \( n \) is the number of samples, \( x \in \mathbb{R}^d \), \( y \in \{\pm 1\} \) To implement support vector machine, hyperplane should be defined as:

\[ w^T x + b = 0 \]  

\( X \) is the set of sample vectors \( X_i \); \( W \) and \( b \) are the vectors to be solved.

The construction of hyperplane is transformed into the optimization problem of objective function:

\[ \theta(w) = \min \frac{1}{2} ||w||^2 \]  

The interval from sample point to hyperplane must meet the condition of greater than or equal to 1. Therefore, the constraint condition of objective function is:

\[ y_i [(w^T x_i) + b] - 1 >= 0 \]  

To solve constraint, the Lagrange function is introduced, the problem is transformed into:

\[ \theta(w) = \min \frac{1}{2} ||w||^2 + C \sum_{i=1}^{d} \epsilon_i \]  

\[ s.t. \ y_i [(w^T x_i) + b] >= 1 - \epsilon_i \]  

Where, \( \epsilon \) is relaxation variable, indicating that some sample points do not meet the original requirements but can still be used; Penalty factor \( C \) characterizes the loss of giving up outliers.

5. Experiment Analysis

The experimental data comes from the Geotechnical Disaster Simulation Test Ground of China Jiliang University. The data is collected by sensors, and the data output is completed on the host computer, and the landslide warning model is completed through MATLAB software.

5.1. AHP divides the risk of data

Process the data obtained from the experiment, as shown in Table 2.
Table 2. Factor assignment table

| Evaluation factor                        | Factor assignment |
|------------------------------------------|-------------------|
| Change rate of surface displacement     | 1: >10, 0.5: 1–5, 0.1: <1 |
| Shallow water content (%)               | 1: >35, 0.5: 25–35, 0.1: <25 |
| Rate of change of deep water content    | 1: >0.1, 0.5: 0.05–0.1, 0.1: <0.05 |
| Rainfall                                 | 1: >40, 0.5: 20–40, 0.1: <20 |
| Stress change rate                      | 1: >1, 0.5: 0.5–1, 0.1: <0.5 |
| | Angle offset change | 1: >5, 0.5: 1–5, 0.1: <1 |

Then obtain the weight value according to the factor assignment, as shown in Table 3.

Table 3. Landslide factor weight table

|     | F1 | F2  | F3  | F4  | F5  | F6  | weight |
|-----|----|-----|-----|-----|-----|-----|--------|
| F1  | 1  | 7   | 6   | 8   | 3   | 3   | 0.43   |
| F2  | 1/7| 1   | 1/2 | 2   | 1/5 | 1/5 | 0.047  |
| F3  | 1/6| 2   | 1   | 3   | 1/4 | 1/4 | 0.071  |
| F4  | 1/8| 1/2 | 1/3 | 1   | 1/6 | 1/6 | 0.032  |
| F5  | 1/3| 5   | 4   | 6   | 1   | 1   | 0.20   |
| F6  | 1/3| 5   | 4   | 6   | 1   | 1   | 0.20   |

Calculate the risk according to the formula:

\[ R = \sum_{i=1}^{n} m_i q_i \]  \( (7) \)

In the formula, \( m_i \) is the evaluation factor value of different attributes, and \( q_i \) is the data weight. The calculated data danger degree is shown in Figure 1.

![Fig1. Risk diagram](image)

According to the landslide hazard degree and the observation landslide condition, the hazard degree is divided, and 0–0.2 is defined as low risk, 0.2–0.5 is moderate risk, and 0.5–1 is extreme risk.

5.2. GWO-SVM Model validation

Pass the obtained data into the GWO-SVM model for training, and analyze the obtained results. It is
found that the GWO-SVM model can better classify and predict the data, and the model execution speed is faster and the performance is better. And import different batches of experimental data, can be better classified. As shown in Figure 2.

![Figure 2. Result classification diagram](image)

Compared with the SVM model, the GWO-SVM model trained many times can maintain the accuracy of GWO-SVM above 95%, and can better classify the landslide data.

The analysis shows that the model prediction results are in good agreement with the actual results. The error between the predicted value and the true value is about 1 sample, and the model accuracy is high.

5.3. **Comparison between GWO algorithm and Genetic Algorithm (GA)**

The GWO-SVM model established in this paper is compared with the GA-SVM model after training. The accuracy obtained after 5 trainings is shown in Table 4.

| Training times | 1       | 2      | 3      | 4      | 5      |
|---------------|---------|--------|--------|--------|--------|
| GWO           | 97.59%  | 98.56% | 98.52% | 95.26% | 96.49% |
| GA            | 96.75%  | 94.25% | 95.21% | 93.56% | 95.24% |

The results show that although the accuracy of the GA algorithm is close to that of the GWO algorithm, the GA algorithm has poor stability and is not suitable for early warning models that require high stability.

GWO performs better both in terms of algorithm stability and local optimization problems. Because landslide warning requires a more stable model, the GWO algorithm is more suitable for the landslide simulation experiment in this paper.

6. **Conclusion**

1. The analytic hierarchy process solves the inaccuracy of artificially setting the degree of danger by relying only on surface displacement, and can quantitatively divide the risk of data.
2. The optimized SVM parameters of the GWO algorithm solve the problem of low data accuracy caused by artificially setting parameters in the model execution, and have better applications in nonlinear problems.
3. Compared with the GA algorithm, the GWO algorithm performs better on stability and local optimization problems.
4. The prediction results of the AHP-GWO-SVM model are highly consistent with the actual
results. It can be well applied to the multivariable landslide simulation experiment.

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