



International Journal of Environment and Sustainable Development

ISSN online: 1478-7466 - ISSN print: 1474-6778

<https://www.inderscience.com/ijesd>

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DOI: [10.1504/IJESD.2023.10059215](https://doi.org/10.1504/IJESD.2023.10059215)

Article History:

Received:	18 May 2023
Last revised:	14 June 2023
Accepted:	31 July 2023
Published online:	02 December 2024

GA-IPSO-BSVM based sustainable development of ecological economic logistics data forecasting model

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Abstract: Considering the increasing accuracy of machine learning in detection and recognition tasks, this paper proposes a classification model, which consists of an improved genetic algorithm (GA), the improved particle swarm optimisation (IPSO) and balanced support vector machine (SVM) (namely GA-IPSO-BSVM), to increase the accuracy and to optimise the convergence of logistics data performance classification. Firstly, this paper embeds the elimination mechanism of GA to my model at the early stage of iterations to delete a lot of particles with low speed. Then, in the middle of the iteration, this paper improves the topology structure of particle relationship in PSO to avoid the algorithm trapping into local optimal solution. At the late stage of the iteration, this paper combines the excellent particles in all regions into the excellent particle population and iterates the population to obtain the global optimal solution.

Keywords: logistics data; ecological-economic belt; GA; particle swarm optimisation; PSO; support vector machine; SVM.

Reference to this paper should be made as follows: Sun, Y. (2025) 'GA-IPSO-BSVM based sustainable development of ecological economic logistics data forecasting model', *Int. J. Environment and Sustainable Development*, Vol. 24, No. 1, pp.22–34.

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1 Introduction

At present, with the development of social economy, large-scale environmental pollution occurs more and more, which makes the problem of environmental protection become more and more important. Therefore, the construction of ecological economic belt has been put on the agenda. For the development of green finance, it is necessary to put forward corresponding performance appraisal management methods to ensure the quality of development. In recent years, our logistics infrastructure system has a mature legal environment and a relatively systematic industry standard system about road, railway, aviation, waterway and other logistics lines. However, the ecological economic belt logistics infrastructure has not yet formed a complete system. In response to this demand, this paper have carried out a research on logistics intelligent performance classification

based on the combination of machine learning technology, which is of great significance to ensure the high-quality operation of the ecological economic belt.

With the continuous research of deep learning, CNN and RNN have been widely used in performance classification (Wang et al., 2019). However, most of these models focus on capturing the local and continuous information of performance and lack the interaction information of discontinuous and long-distance words. The performance classification model based on graphical convolutional networks (GCN) (Guo and Zhu, 2022) can deal with tasks with rich structural relationships and solve the problem of discontinuity between nodes to a certain extent. However, most of the previous models based on GCN simply fuse the neighbourhood information of different orders through the adjacency matrix to update the node representation, which cannot generate the word representation well. However, the model based on attention (Vaswani et al., 2017) usually uses Sigmoid function to generate a positive Attention score between 0 and 1 and cannot give negative weight to the performance with negative effect, so it ignores the influence of the performance with negative effect on the classification result. Therefore, in eco-economic logistics, the current classification model may face the following problems. First, there is often a category imbalance in the data, where instances in one category significantly outnumber others. This can lead to bias in model training and affect the accuracy of classification results. Secondly, the prediction of logistics performance involves the complex relationship between various factors, such as the volume of goods transported, delivery time, mode of transportation, weather conditions, etc. Classification models can be difficult to capture and model these complex relationships effectively, resulting in poor performance. Again, data is dynamic and subject to frequent changes. Patterns and relationships within the data may evolve over time, making a static classification model less effective. Models need to be able to learn and adapt from the latest data to maintain accurate predictions. Continuous model updating and retraining are necessary to adapt to the dynamic nature of logistics information. Finally, the explanatory nature of the classification model's predictions is crucial for decision-making. However, certain black-box models, such as deep neural networks, lack explanatory power and are difficult to understand and justify the reasons for their predictions. In logistics forecasting, models with transparent explanatory ability are very valuable.

To solve the problem, this paper propose a classification model, which consists of an improved genetic algorithm (GA), the improved particle swarm optimisation and balanced support vector machine (namely GA-IPSO-BSVM), to increase the accuracy and to optimise the convergence of logistics performance classification. By adopting GA at the early iteration, the particle relationships of PSO is optimised to cluster and select the excellent particles. Meanwhile, this paper combined GA and improved particle warm optimisation (IPSO) to optimise the hyperparameters of BSVM and this paper can achieve the results of the logistics performance. This paper will introduce the related work in Section 2, propose the method in Section 3 and conduct experiments in Section 4. Besides, the Section 5 is the conclusion. Main contributions are as follows:

- 1 This paper optimise the topology structure of particle relationship of PSO and combine K-means to prevent the model from local optimal solutions.
- 2 This paper fuse GA and IPSO to achieve the hyperparameters for BSVM, which can help model predict the logistics.

- 3 My GA-IPSO-BSVM achieves the best performance while comparing with other methods.

2 Related work

To solve the problem of logistics performance classification, a series of literature analysis algorithms exist to process high-dimensional information data of technology innovation performance, such as support vector machine (SVM) (Wang et al., 2022) and Naive Bayesian (Li et al., 2022a). Among them, SVM, as an efficient binary classification model, has been widely used to deal with various classification problems due to its ability to solve the accurate classification problem of a few of samples. Cai et al. (2019) establish a multi-parameter SVM model for prediction and verify the effectiveness of the model. Zhu et al. (2014) propose an SVM prediction model for online diagnosis. Chandra and Bedi (2021) summary the SVM and their application for classification. Tao et al. (2018) propose an improved intrusion detection method by GA and SVM and achieve the best performance, which can solve the problem the local optimal trapping. Deng et al. (2019) propose an improved intelligent diagnosis method by the boosted SVM, namely LS-SVM, which can search for the optimal solutions of global terms and classify the fault.

However, the performance of SVM is greatly affected by its key parameters, so parameter optimisation is needed. Jiao et al. (2018) propose a prediction model to optimise the parameters of SVM by using the improved Wolf pack algorithm. Huang (2019) combine the optimised weight of GM (1, 1) and SVM and verify the effectiveness of the model through a case study. Yang et al. (2015) propose an ant colony optimisation (ACO) to boost the SVM classification and verify the effectiveness of it. However, these optimisation algorithms still have some limitations in processing high-dimensional performance information data. For example, GWO global development ability is weak, exploration space is easy to repeat, computational resources are wasted and ACO has a long convergence process and is prone to be trapped in local optima. In addition, the classification methods based on SVM mentioned above are all established under the condition of perfect network data. However, there may be the phenomenon of uneven number of samples in the real network data crawling, which can lead to the large classification error problem of SVM.

3 GA-IPSO-BSVM

3.1 GA-IPSO

Particle swarm optimisation (PSO) is proposed in 1995, which is an evolutionary optimisation algorithm based on swarm intelligence (Marini and Walczak, 2015; Jain et al., 2022). By analysing the foraging habits of animal populations, such as birds, insects and fish, PSO considers each individual animal as a solution to the optimisation problem. Each particle has two attribute values of velocity and position. The optimal solution of the problem is found by the cooperation between individuals and the information sharing between populations, which is used to solve the optimisation problem, whose expression is shown as follows:

$$V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1^k (Pbest_{id}^k - X_{id}^k) + c_2 r_2^k (Gbest_{id}^k - X_{id}^k) \quad (1)$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \quad (2)$$

where this paper regard the particle position information as $X_i = (X_{i1}, X_{i2}, \dots, X_{id})^T$, $V_i = (V_{i1}, V_{i2}, \dots, V_{id})^T$ refers to the velocity information, V_{id}^k and X_{id}^k are the velocity and the position of the d^{th} dimension of the particle i in the k^{th} iteration, respectively and $Pbest_{id}^k$ and $Gbest_{id}^k$ are the individual and population historical optimal location of the particle i with the d^{th} dimension in the k^{th} iteration. In addition, ω refers to the inertia weight factor regulating the particle moving speed, c_1 and c_2 denote non-negative acceleration factors and r_1^k and r_2^k are random numbers of $(0, 1)$.

In the convergence process of PSO algorithm, there are a large number of clustered low-speed particles, which can neither accelerate the convergence of the algorithm nor explore new regions. As a result, the probability of particles falling into the local optimum is high and a large amount of resources are consumed in the iteration process, which reduces the convergence speed of the algorithm. In addition, PSO is a kind of algorithm model easily trapped in local optimum, which leads to the failure of the algorithm to achieve global optimum.

Based on the above two problems, this paper propose two improvement methods to optimise the rapid classification of logistics data in ecological-economic belt.

- 1 Introduce particle elimination mechanism. At the early stage of the training iteration, there are a lot of particles with low speed far from the optimal solution when the convergence trend appears. Besides, the exploration range of these particles is often far from the optimal solution range, which requires a large amount of computation and low yield. Therefore, this paper adopt the GA algorithm at the early stage of the iteration, which saves system resources and greatly accelerates the convergence speed.
- 2 Change the topological structure of particles. When the GA's iteration number is D , the formula can be presented as follow:

$$D = T_{\max} \left[\frac{1}{1 + e^{-n}} - 0.4 \right] \quad (3)$$

where $T_{\max}$ is the upper limit of particle iteration times and n refers to the number of particle dimensions sought. This paper will finish the iteration of GA algorithm at the D^{th} iteration. All particles are clustered by k-means and the number of categories is set as $2n$.

After the particle clustering is completed, this paper carries out the PSO algorithm via the clustering results and each particle is optimised in the current community. The initial particle population is composed of the optimal particles in each final region of the excellent group to start the PSO algorithm. Therefore, even if the particles in the existing community fall into the local optimum, the particles in other communities can still continue searching for the optimal solution, which can better ensure the global optimality of the understanding. After introducing the above two improvement mechanisms, this paper proposes the GA-IPSO model for PSO. Firstly, the GA algorithm is applied in the

early stage of particle iteration and the inert particles have been removed with poor fitness or edges during particle iteration. Secondly, this paper used the K-means clustering algorithm in the middle stage of iteration to partition the remaining particles and conduct PSO in each community until the particles converge. Finally, the optimal particles are managed into a new particle group at the late stage of the iteration to obtain the optimal solution.

3.2 *BSVM*

SVM algorithm's structure is simple, cost less training time and has good generalisation ability. In addition, it needs the less training sample whose precision is high. The basic idea of SVM classification can be expressed as follows: given two kinds of sample points, find the optimal linear hyperplane to separate the two types of sample points and maximise the classification hyperplane and distance of the distance between sample points of plane recently (Kurani et al., 2023; Chauhan et al., 2019; Ye et al., 2021).

Under the condition of linear separability, SVM can be formulated as follows:

For a given dataset:

$$\{x_i, y_i\}, i = 1, 2, \dots, N, y_i \in \{-1, 1\}, x_i \in R^n \quad (4)$$

The functions for classifying hyperplanes are:

$$w \times x + b = 0 \quad (5)$$

After normalisation, which is satisfied with follows:

$$\xi_i > 0, i = 1, 2, \dots, N$$

where x represents a input vector, ω denotes the weight vector and b refers to the classification threshold. After sorting, the problem of finding the hyperplane can be transformed into a solution problem:

$$y_i (w \times x_i + b = 0) = 1, i = 1, 2, 3, \dots, N \quad (7)$$

$$L = \min \frac{1}{2} |w|^2 \quad (8)$$

For the linear non-separable condition, the penalty factor C and the relaxation variable $\xi_i > 0$ are introduced where C is the penalty coefficients, which are mainly used to balance the relationship between the complexity of the support vector and the misclassification rate. Among them, too large of C will cause overfitting and too small of C will lead to poor generalisation ability of the model. If all samples are accurately classified, $\xi_i = 0$. In contrast,

$$f(x) = \text{sgn} \left(\sum_{i=1}^N \alpha_i \times y_i K(x_i \cdot x) + b \right).$$

In addition, for solving the convex optimisation problem above, the Lagrange multiplier method is introduced to transform it into the dual problem and the final optimisation classification function is:

$$f(x) = \text{sgn} \left(\sum_{i=1}^N \alpha_i^* y_i \phi(x_i) \phi(x) + b^* \right) \quad (9)$$

This paper replace the dot product operation in higher dimensional space with kernel function whose formula is as follow:

$$K(x_i \cdot x) = \phi(x_i) \phi(x) \quad (10)$$

So, the optimal classification function can be expressed as:

$$f(x) = \text{sgn} \left(\sum_{i=1}^N \alpha_i^* y_i K(x_i \cdot x) + b^* \right) \quad (11)$$

In SVM, kernel function is introduced to solve the problem of insufficient computing power caused by high data dimension and linear inseparability. The selection of general kernel functions is very important for solving the problem. The common kernel functions include linear kernel, multinomial kernel (poly), hyperbolic tangent kernel (Sigmoid), Gaussian radial basis kernel (RBF) and so on.

The stability of linear kernels and polynomial kernels in handling nonlinear data is inconsistent. When the data exhibits relatively linear separability, the performance tends to be better. However, for completely inseparable data, such as circular nonlinear data, the performance is notably poorer. In the case of linear datasets, both the linear kernel and polynomial kernel demonstrate satisfactory classification results, even in the presence of disturbance term interference. This indicates the superior efficacy of the polynomial kernel on linear datasets. Comparatively, hyperbolic tangent kernels outperform the two linear kernels on nonlinear data, albeit falling short of the effectiveness exhibited by Gaussian radial basis kernels. Hyperbolic tangent kernels exhibit weak performance on linear datasets and limited resistance to perturbation terms. Considering these factors, this paper opt for the Gaussian radial basis kernel function in SVM for the classification task involving data with an unknown positional distribution (Karimi et al., 2020; Zhou and Ding, 2020).

SVMs exhibit robustness and strong generalisation capabilities when dealing with high-dimensional data and nonlinear problems. There are two primary methods for implementing SVM: the direct solution method and the transformation method. The direct solution method is challenging to implement due to its high time complexity and limited computational performance when dealing with large amounts of data. Alternatively, the transformation method transforms multiple classification problems into multiple binary classification problems. In this paper, this paper followed the second method.

Common transformation methods include one-against-one (OAO), many-to-many, directed toroid graph, and binary tree approaches. Among these binary transformation methods, the number of binary classifiers trained varies depending on the chosen method, as it determines the number of binary trees constructed. A partial binary tree structure has been taken to achieve multi-layer classification. Initially, all samples are divided into the first class and the remaining classes. This process is repeated for the remaining categories until each category is individually separated into a leaf node. Through this approach, multi-layer classification is accomplished. Because the logistics performance data in ecological-economic belt is easy to obtain and the number of samples is not balanced,

this paper propose a nonlinear multi-classification balanced support vector machine (BSVM) to reduce the error problem caused by the imbalance of sample size.

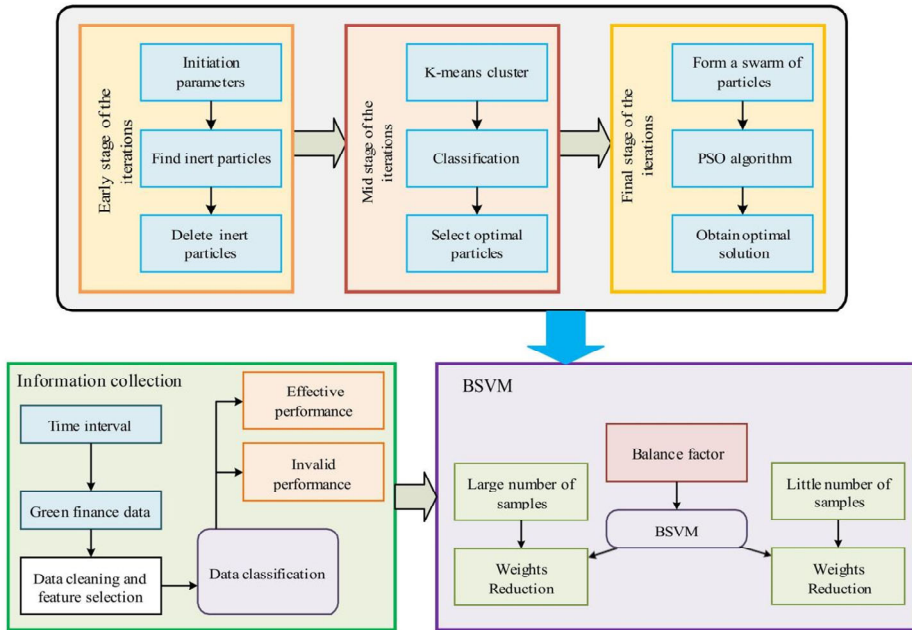
$$\begin{cases} \min \left(\frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^N \theta_{y_i} \zeta_i \right) \\ s.t. \begin{cases} y_i (\omega \cdot \phi(x_i) + b) \geq 1 - \zeta_i \\ \zeta \geq 0 \end{cases} \end{cases} \quad (12)$$

where θ_{y_i} is the equilibrium factor, the increase of value θ_{y_i} means that the weight of the category y_i increases and the probability of the sample being misclassified in y_i will decrease. Therefore, for a class with a relatively small number of samples, BSVM can increase its corresponding equilibrium factor θ_{y_i} and effectively reduce the error caused by sample number imbalance.

3.3 Structure of GA-IPSO-BSVM

In order to overcome the problem, which the hyperparameter selection of SVM algorithm is slow and is trapped into local optimum easily, this paper propose an improved GA-IPSO method for the hyperparameter optimisation of BSVM model by combining the fast convergence of PSO and the high reliability of SVM multidimensional extraction to achieve fast and accurate classification of microblog information.

Figure 1 Flow chart of GA-IPSO-BSVM (see online version for colours)



Current studies mostly focus on the dynamic change of the inertia weight in the PSO algorithm (Li et al., 2022b), but each calculation of the inertia weight requires a certain amount of system resources. Therefore, this paper proposes PSO based on the

introduction of GA and new topology to obtain better parameter optimisation effect. Furthermore, this paper proposed the nonlinear multi-classification equalisation SVM BSVM to reduce the error caused by sample size imbalance. The detailed implementation process is shown in Figure 1.

Through GA-IPSO-BSVM method, this paper can directly measure the innovation ability and innovation results of eco-economic logistics. By training the existing innovation performance data and using the model to predict and classify the future innovation performance, it is of great significance for the decision-making and resource allocation of eco-economic logistics, and can be adjusted and supported in advance. In addition, it also helps to understand and interpret the driving factors of innovation performance, and provides a basis for the formulation of ecological economic innovation strategies.

4 Experiments

4.1 Dataset

Due to the complexity of the performance information of logistics performance, the different time span of performance and information feedback, the randomness of performance owners and other features, the data may generate noise interference. In this paper, the information of ten different performance owners is collected every 12 hours. After data cleaning and feature screening, this paper can obtain the discrete 7-dimensional data and 3 binary data. Among them, the discrete 7-dimensional data can reflect the relevant information of the current logistics performance information more completely. Then, the proposed GA-IPSO-SVM algorithm can predict the output results of three categories, including effective performance, ineffective performance and pending performance. The settings of the model are presented in Table 1. Finally, the classification accuracy is obtained based on the output results of these three classifications.

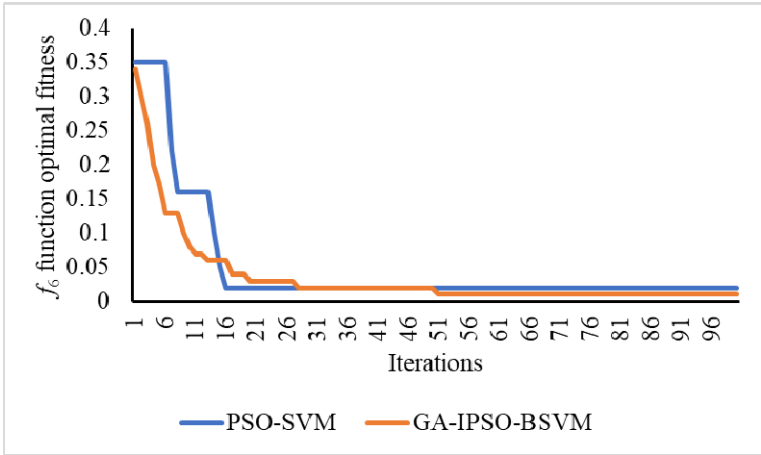
Table 1 Model parameters

<i>Parameters</i>	<i>Parameters</i>
CPU Information	R7-7600X
GPU Information	Rtx 3060Ti
Framework	Caffe
Epochs	20
Batch size	128
Initial learning rate	0.01

4.2 Results and comparison

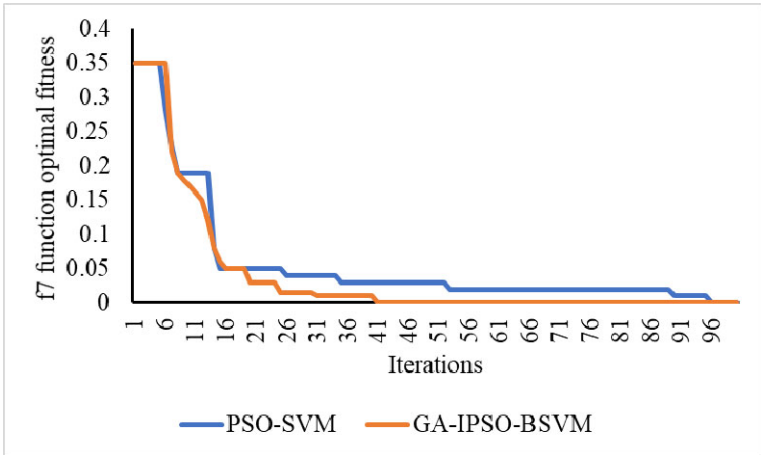
When solving n-dimensional problems, clustering is set at the number of iterations D and the number of K-means clustering categories is $Z = 4$. The GA-IPSO-BSVM algorithm is compared with the traditional PSO algorithm to verify the effectiveness of particle elimination mechanism and clustering partition mechanism introduced. This paper used Shaffer function of f6 and f7.

Figure 2 Optimisation effect comparison for f_6 (see online version for colours)



As can be seen from Figure 2, both algorithms find the same fitness position at the 20-th iteration with a fitness of 0.018. However, GA-IPSO-BSVM algorithm no longer fall into the local optimum at the 45-th particle convergence and find a better fitness position. The fitness is 0.007, while the unimproved PSO algorithm still falls into the local optimum until it reaches the maximum number of iterations.

Figure 3 Optimisation effect comparison for f_7 (see online version for colours)



As can be seen from Figure 3, both algorithms find the same position of fitness at the 83-rd iteration and the fitness is 0.01. However, the GA-IPSO-BSVM algorithm can find a position with higher fitness than the original algorithm at any of the same iterations after the 15th iteration, indicating that the convergence speed of GA-IPSO-BSVM algorithm is faster. According to the above results, the GA-IPSO-BSVM algorithm can effectively accelerate the convergence speed of particles, avoid falling into the local optimum and find the global optimal point more easily.

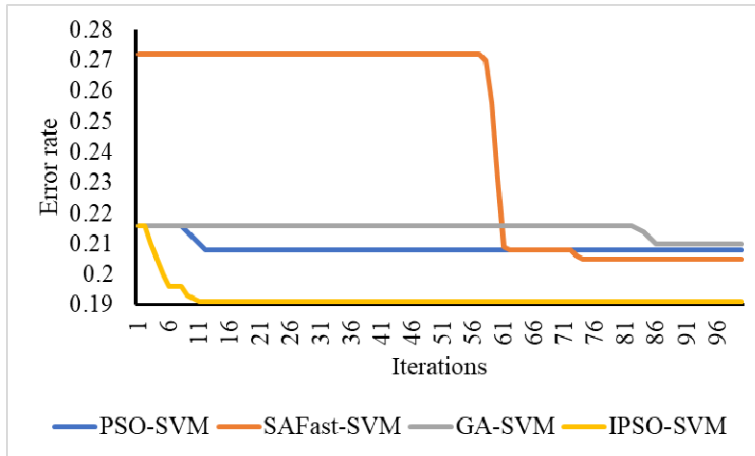
4.3 Results and comparison

In this paper, 16,000 pieces of data are managed into training and testing with the ratio of 4:1 to test the accuracy of recognition. Table 2 lists the classification accuracy of different kinds of performance and the number of samples. The kernel function of SVM is RBF kernel function. The IPSO optimisation parameters are set as follows: the initial population number of particles is 100, this paper set the maximum number of iterations to 1000, the inertia factor ω is set as 0.8 and the learning factor c_1 and c_2 are set as 0.5 and 0.7, respectively. Besides, this paper set the GA optimisation parameters as crossover probability 0.9 and mutation probability 1×10^{-7} .

Table 2 Classification results comparison

	<i>Effective performance</i>	<i>Ineffective performance</i>	<i>Pending performance</i>
Accuracy	90.13%	87.28%	83.07%
Numbers	6853	5283	2874

Figure 4 Comparison of the effects of various algorithms (see online version for colours)



As can be seen from the results of Figure 4, GA-IPSO-SVM used in this paper is higher in classification accuracy. In terms of convergence speed, GA-IPSO-BSVM has fewer iterations and the model used can find the global optimal SVM hyperparameter, which better overcomes the defect that PSO is prone to be trapped into the local optimal solution and can be quickly and effectively processed in the classification task of Logistics performance information. The root mean squared error (RMSE) and mean absolute percentage error (MAPE) of different models in different time periods are compared.

Table 3 compares the effect of BPNN (Bashir et al., 2022), CNN (Wei et al., 2022), SAFast-LSSVM (Liu, 2013) and GA-IPSO-BSVM on the classification of logistics performance data. It can be seen that, the error of GA-IPSO-BSVM is significantly lower than that of BPNN (18.63) and CNN (15.769) and slightly lower than that of SAFast-LSSVM (8.674) among the RMSE error measurement standards. It is the algorithm with the highest accuracy under RMSE standards. In MAPE error measure, the

error of GA-IPSO-SVM is significantly lower than 0.385 of BPNN and 0.294 of CNN and lower than 0.187 of SAFast-LSSVM. It is the algorithm with the highest accuracy under MAPE standard. The experimental results show that GA-IPSO-BSVM has better performance in the optimisation accuracy than the traditional algorithm (Han et al., 2022; O’Mahony et al., 2020).

Table 3 Comparison with other complete methods

	<i>RMSE</i>	<i>MAPE</i>
BPNN	18.63	0.385
CNN	15.77	0.294
SAFast-LSSVM	8.67	0.187
GA-IPSO-BSVM	5.76	0.124

5 Conclusions

This paper endeavors to tackle the classification task pertaining to logistics performance information by proposing a novel GA-IPSO-SVM approach, fortified with a multi-classification partial binary tree structure, which effectively classifies information using relevant data. The introduction of a particle elimination mechanism renders the model more efficient by saving considerable time during iterations, particularly by discarding redundant particles and expediting convergence. This facilitates fast optimisation to a significant degree. Moreover, the integration of a particle partitioning mechanism, grounded in a clustering algorithm, enhances the ability to overcome local optima, thereby endowing the particles with enhanced global exploration capabilities. Notably, the proposed algorithm outperforms traditional methods in terms of classification accuracy and overall effectiveness when applied to datasets. Leveraging modern information technology and advanced logistics techniques, this research assimilates logistics information and optimises enterprise resources, thereby streamlining logistics processes, reducing transportation costs, and bolstering operational benefits, while simultaneously elevating the quality of logistics services. Consequently, this approach fosters the high-quality development of the logistics industry within the ecological-economic belt. However, it is acknowledged that the current method’s limitations lie in its omission of several pertinent factors within the logistics process. Therefore, future work will concentrate on improving this aspect, endeavouring to incorporate diverse factors and comprehensively exploring their impact on logistics data to enhance innovation performance.

Disclaimer

This paper was not funded by any project or organisation.

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