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Research Article

E-Commerce Intelligent Logistics Data Based on Neural Network Model

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Not only e-commerce is developing rapidly, but also intelligent logistics technology is becoming more and more mature. In daily life, we can track the logistics information synchronously. On the smartphone app, the logistics information can be viewed at any time. However, the current processing algorithms are not enough for the exponentially increasing data volume and increasingly complex data types. This paper aims to analyze the massive data generated by e-commerce intelligent logistics. In this paper, a new classification algorithm is proposed, which is improved on the ordinary ladder classification algorithm, and artificial neural networks are added for automatic iterative update learning, which can automatically classify a large amount of data. The experimental results show that the classification error rate of the improved algorithm is less than 5%, and when the sample size is less than 30,000, the improved algorithm can significantly outperform the original algorithm.

1. Introduction

With the development of new technologies such as cloud computing, Internet of things, Internet of vehicles, and social networks, big data is characterized by scale, diversity, and high speed, and the data stream is often a high-speed real-time data stream. Therefore, it needs to be processed quickly and continuously in real time to reflect the real value of big data. Under the influence of big data (BD), the logistics industry has also entered the era of BD, which has continuously generated massive logistics data, especially the whole process of logistics. Compared with the logistics e-commerce data that is easier to process, the amount of data and information generated by the whole process of logistics is huge, and it is difficult for logistics companies to process these data in real time and accurately. However, big data technology has also brought spring to logistics enterprises. By establishing logistics big data centers, the information value behind logistics big data can be excavated, which will bring more profits to logistics enterprises.

Big data can be applied to market forecasting, forecasting the changes of market demand for products, and also to the location of logistics centers and the selection of distribution routes. As far as the current research is concerned, the discussion of intelligent logistics still stays at the construction of more complex logistics parks, and the purpose is to use artificial intelligence to replace manual labor and make logistics more intelligent and convenient. The most important application of BD in the logistics industry is logistics intelligent early warning. Because the logistics business has the characteristics of randomness and suddenness, the traditional intelligent early warning system cannot play an accurate early warning role. With the continuous accumulation of logistics data, traditional technology can no longer meet the processing of massive logistics data, and BD technology can effectively solve this problem. Therefore, it is necessary to conduct intelligent logistics data analysis at present.

In this paper, the research on logistics data mainly has the following two innovations: (1) the research on logistics data not only analyzes the distribution of logistics but also analyzes the circulation of logistics, logistics information data, cargo tracking data, etc., synchronously; and (2) for intelligent logistics data, a logistics data classification algorithm based on artificial neural network is proposed. The algorithm can classify the massive data generated by logistics.

The purpose of this paper is to analyze the massive data generated by e-commerce intelligent logistics and provide more efficient data processing algorithms for intelligent logistics. First of all, this paper summarizes and analyzes the current situation and research situation of intelligent logistics and proposes the necessity of this research. After that, after summarizing and analyzing the related research, compared with the traditional research, the algorithm proposed in this paper can analyze the data generated by intelligent logistics more comprehensively, and the algorithm is more targeted. After that, the algorithm of this paper is designed and analyzed in detail, and the computational framework of this algorithm is proposed. Finally, the proposed algorithm is applied to the data processing of intelligent logistics, and the algorithm in this paper is compared with the traditional algorithm, and the effectiveness of the algorithm in this paper is obtained.

2. Related Work

As a machine learning model with good performance, a neural network model has applications in many aspects, and there are many research projects on it. Eric and Chen explored the impact of dysfunction on hippocampal-cortical interactions through neural network simulation experiments. Their results suggest that increasing correlations between input patterns impair the storage capacity of cortical networks when hippocampal function is suboptimal for classification and reduced input overlap [1]. Kasap and van Opstal proposed a simple spiking neural network model that reproduces the spiking sequences of saccade-related cells in the middle and deep SC layers during saccades. Their model provides the basis for neuron algorithms for spatiotemporal transformations and biomimetic optimal controllers [2]. Funes et al. created nine neural models to predict the properties of extra virgin olive oil developed as a quality target and by-product. They analyzed various properties of olive oil through multiple models [3]. Kang et al. developed an artificial neural network (ANN) model to explore energy-saving technologies for air conditioners. Through experiments, it is found that the control algorithm embedded in the artificial neural network model can determine the most energy-saving control strategy [4]. In terms of intelligent logistics, more in-depth research has also been carried out at home and abroad. Kirch et al. created smart logistics zones for logistics and production processes by using techniques such as machine learning. Their experiment proves that the intelligent logistics created by machine learning technology can save more than 30% of the cost compared with the traditional logistics [5]. Humayun et al. proposed a layered framework, BCTLF, for intelligent logistics technology [6]. The study by Choi and Jung explores the trend of smart logistics and proposes the application of IoT in the Pyeongtaek port. They found through experiments that the cargo monitoring system is the most important in the intelligent logistics system [7]. Guan discussed smart cities and conducted research on smart logistics in Zhengzhou, China. Their research believed that the application of BD technology to build smart logistics is very meaningful [8]. It can be found that, although there are many in-depth studies on neural networks and intelligent logistics, the combination of the two is not particularly discussed. Especially in the analysis of logistics data, it is more about the planning of express routes and rarely involves other data mining.

3. E-Commerce Intelligent Logistics Data Analysis Method

3.1. E-Commerce and Intelligent Logistics. Modern logistics is a combination of mechanization, intelligence, and informatization [9]. To this end, modern logistics makes full use of Internet of things technology, cloud computing, radio frequency identification technology, all kinds of sensors, all kinds of intelligent terminals, intelligent logistics management platforms, and all kinds of advanced handling and packaging technologies to continuously improve the quality of logistics services and reduce logistics costs, so that logistics enterprises can obtain greater benefits in all stages of logistics [10, 11].

As shown in Figure 1, each stage of the logistics process needs to obtain logistics-related data in real time. For example, the secondary data generated in the data processing process, the data in the transaction process, the environmental data, the warehousing data, the inventory data, etc.; these data are huge and complex. The current sensing technology led by RFID technology has become the main way to obtain logistics data. The working principle of radio frequency identification (RFID) (as shown in Figure 2) is based on the electromagnetic theory. When the radio frequency tag with cargo information enters the applicable magnetic field area of the reader, the tag receives the signal from the reader, thereby generating an induced current, so that the reader obtains the cargo information on the tag in a noncontact manner. Compared with bar codes and magnetic cards, radio frequency tags have the advantages of large information storage, strong anti-interference ability, good confidentiality, wireless communication, and relatively low cost. Therefore, radio frequency identification technology has become one of the important technologies in the field of IoT perception and is widely used in warehousing technology and packaging technology in logistics technology [12, 13].

As shown in Figure 2, in the field of warehousing, radio frequency identification is widely used to obtain real-time massive logistics warehousing information. A warehouse is the distribution center of goods, which plays a role in adjusting and buffering goods. Efficient warehousing can greatly reduce costs and avoid shortage or backlog of goods. Many e-commerce companies now have their own smart warehouses, such as JD.com and Suning. These warehouses are affixed with corresponding RFID tags on the warehouse racks, on the inventory goods, and on the transported

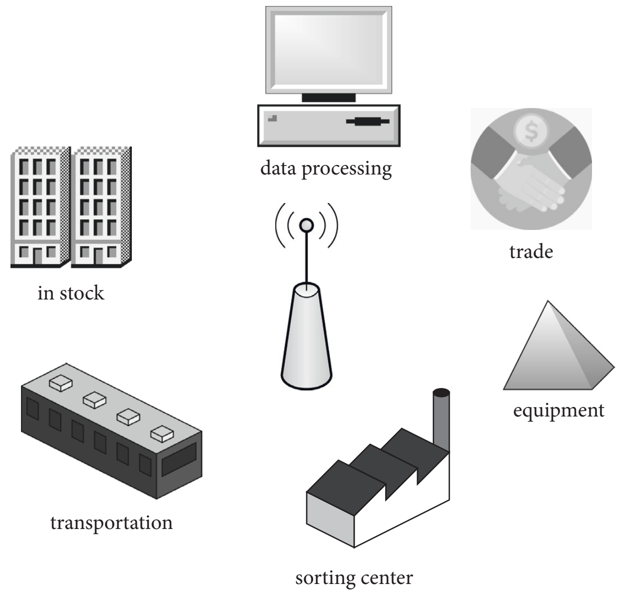

Figure 1: Logistics-related data processing.

forklifts to record the commodity information. At the same time, the entrance and exit of the warehouse will also be equipped with RFID readers to monitor all the goods entering and leaving the warehouse. After the warehouse management system collects cargo information, it completes cargo statistics and provides decision support for warehousing. In addition, RFID-based portable smart terminals are also used in warehousing, which makes warehouse management faster. The highly automated sorting system in the warehouse also uses RFID technology [14].

As shown in Table 1, traffic BD mainly includes four types of BD: people-based, vehicle-based, road-based, and environment-based. As the recording time increases, these records will form massive data, as shown in Table 1.

For the collected data, the main 6-point features are shown in Table 2.

3.2. Neural Network Model. In deep learning, neural networks have many excellent properties, so this paper processes intelligent logistics data based on neural network. This paper will introduce the neural network algorithm in detail and combine neural network and support vector machine to classify and process logistics big data.

3.2.1. Neuron Model. Artificial neural networks are a nonlinear and adaptive information processing system composed of a large number of interconnected processing units. It is put forward on the basis of the research results of modern neuroscience, trying to process information by simulating brain neural network processing and memorizing information. Artificial neurons, also named perceptrons, are mathematical functions defined as biological neuron models. The neuron is the basic unit of processing information in artificial neural networks. As shown in Figure 3, like brain neurons, artificial neurons receive one or more inputs (representing excitatory and inhibitory postsynaptic potentials of neural dendrites) and add them together to produce an output or activation (representing the action potentials a neuron transmits along its axons) [15, 16]. Usually, in the synaptic part of the neuron, there is an input weight value w_{kj} as the feature of strength, and the input x is multiplied by the synaptic weight w. Then, the weighted results of the input and the synapse are summed by an adder to achieve a linear combination of the input features [17, 18]. Finally, the activation function maps the input signal to a value within a certain range to limit the output amplitude of the neuron. From the point of view of the calculation process, the artificial neuron can be regarded as a weighted accumulator of the input and activate the activation function. Therefore, the formula of the perceptron is expressed as formula (1), where ϕ is the activation function.

$$y = \phi\left(\sum_{i=0}^{m} w_i x_i + b\right). \tag{1}$$

3.2.2. ReLU Activation Function. In artificial neural networks, activation functions play a very important role. The choice of activation function determines the classification ability of the neural network. When there is no activation function, the weights and biases are simply transformed linearly. Linear formulas are easy to implement, but their ability to solve complex problems is limited. A neural network without an activation function is basically just a linear regression model. Activation functions nonlinearly transform the input, allowing it to learn and perform more complex tasks such as language translation and image classification. At present, the widely used linear rectification function (ReLU) is used as the activation function. One of its biggest features is that it simplifies the calculation process, and it does not have the influence of other complex activation functions, such as exponential function. At the same time, the dispersion of activity reduces the overall calculation cost of neural networks. Its function formula is as follows:

$$f(x) = \max(0, x). \tag{2}$$

Sigmoid function and tanh function are commonly used activation functions. As shown in Figure 4, when $x < 0$, then $f(x) = 0$; and when $x \geq 0$, then $f(x) = x$. Therefore, the output value range of ReLU is $[0, +\infty]$, which is greatly different from the sigmoid function and the tanh function. And since complex floating-point budget operations are not required, the computation is extremely fast. At the same time, since ReLU is linear when it is a positive number, there is no saturated interval. So it avoids the vanishing gradient problem during model training.

3.2.3. Loss Function. In several fields such as machine learning and computational neuroscience, a loss function or cost function is a way of evaluating how a particular algorithm is modeling given data. It maps events of input space

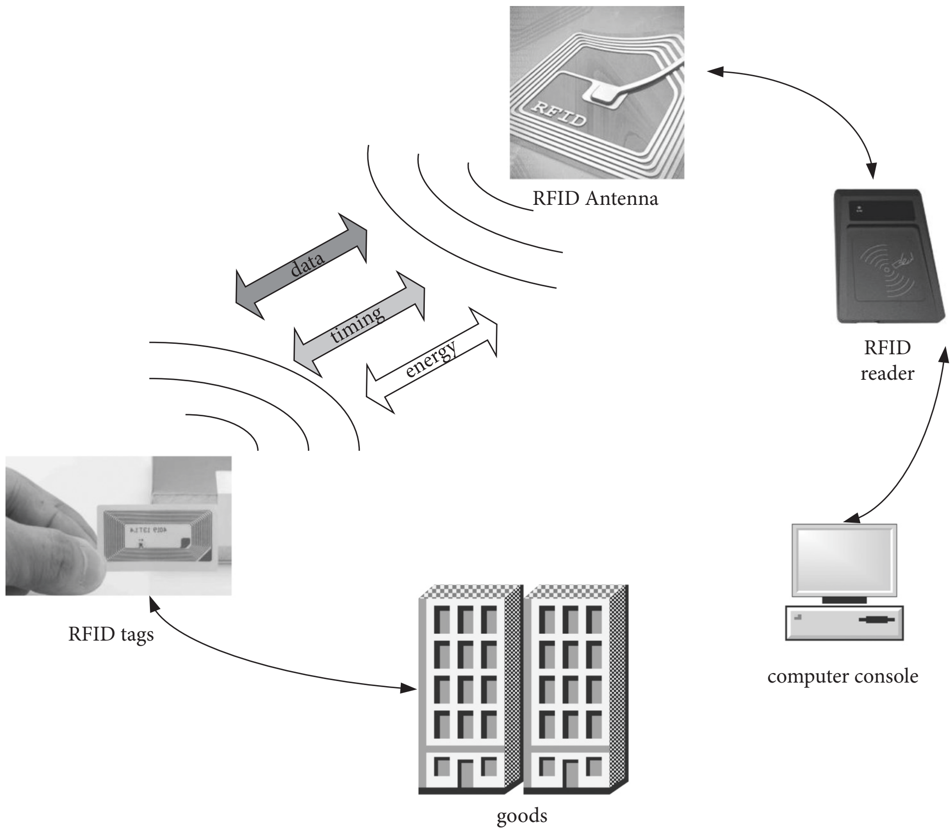

Figure 2: Working principle of RFID.

Table 1: Traffic BD classification.

Traffic BD	Feature
People-based traffic data	As the recording time continues to increase, so does the number of traffic
Vehicle-based traffic data	With the continuous increase of vehicles, traffic data has grown into massive data
Road-based traffic data	Real-time performance and conditions of roads change over time
Environment-based traffic data	Refers to the static data and dynamic data generated by the climatic environment and geographical environment

Table 2: Main characteristics of traffic flow.

1	Mesh features
2	Periodic
3	Randomness
4	Spatiotemporal correlation
5	Inherent convention
6	Velocity and density relationship properties

variables to evaluation functions on the output space of real numbers. The usual optimization problems such as machine learning and convex optimization are aimed at minimizing the loss function [19, 20]. The objective is the loss function or its negative value (in a specific domain, it is called reward function, profit function, utility function, fitness function, etc.), in which case it will be maximized.

In artificial neural networks, loss functions are often used for parameter estimation, and the event in question is some function of the difference between the estimated and true values of the data instance. In classification, it is a penalty for incorrect classification of samples.

Generally, in deep neural network classification tasks, softmax is the most commonly used classifier. It is a logistic binary regression classifier capable of classifying multiple classes. Therefore, the softmax logistic regression function formula is as follows:

$$h_\theta\left(x^i\right) = \begin{bmatrix} p\left(y^i = 1 \middle| x^i; \theta\right) \\ p\left(y^i = 2 \middle| x^i; \theta\right) \\ \vdots \\ p\left(y^i = k \middle| x^i; \theta\right) \end{bmatrix}. \tag{3}$$

It can also be expressed as follows:

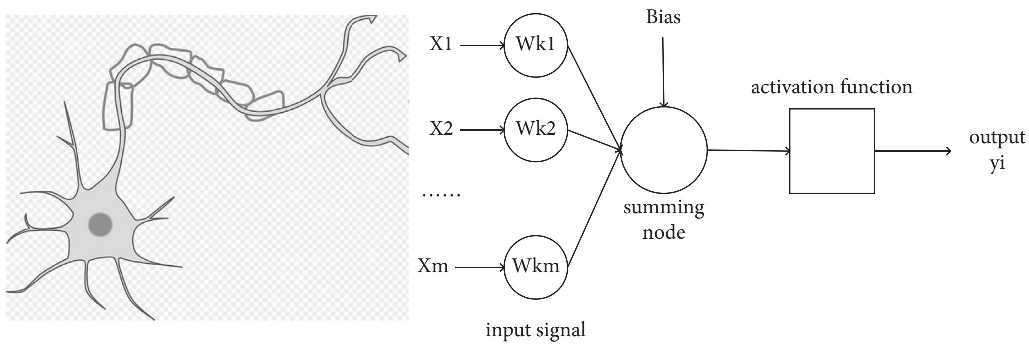

FIGURE 3: Biological and mathematical models of neurons.

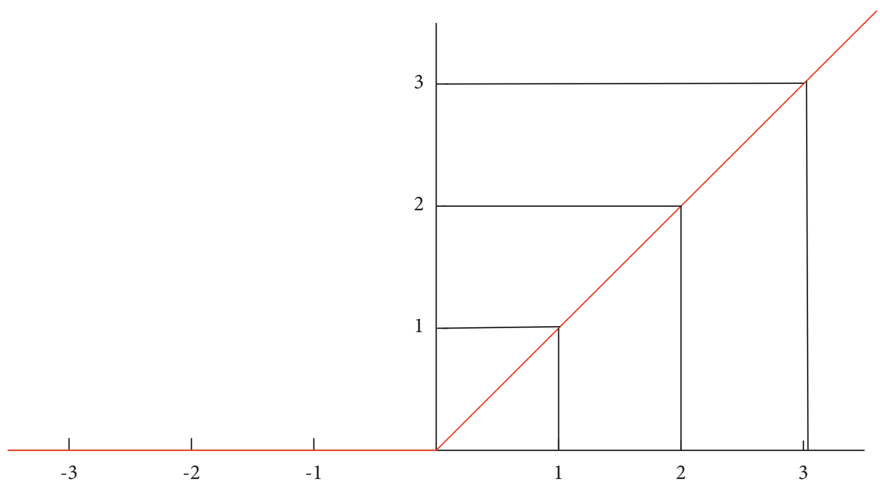

FIGURE 4: ReLU activation function.

$$h_\theta(x^i) = \frac{1}{\sum_{j=1}^{k} e^{\theta_i^T x^i}} \begin{bmatrix} e^{\theta_1^T x^i} \\ e^{\theta_2^T x^i} \\ \vdots \\ e^{\theta_k^T x^i} \end{bmatrix}, \quad (4)$$

where x is the output sample, θ represents the parameters to be trained, and $p(y = j \mid x)$ represents the predicted probability for each category j. Therefore, its loss function is obtained from the softmax regression function, as in formula (5), where m represents the number of sample categories.

$$J(\theta) = \frac{1}{m}\left[\sum_{i=1}^{m}\left(1 - y^{(i)}\right)\log\left(1 - h_0\left(x^{(i)}\right)\right) + y^{(i)} \log h_0\left(x^{(i)}\right)\right]. \quad (5)$$

3.2.4. Full Link Layer. The fully connected layer, which can also be viewed as a multilayer perceptron, can be viewed as a logistic regression classifier, which functions as a "distributed feature representation" mapped to the sample space. Firstly, the learned nonlinear transformation is used to transform the input, which projects the input data into a linearly separable space. As shown in the upper part of Figure 5, it is a multilayer perceptron, which includes a three-layer fully connected adjacency network. The fully connected layer is to fully connect the neurons of this layer with each neuron of the previous layer with weights, so the calculation of the fully connected layer is as follows:

$$y_i = f\left(\sum_{i=0}^{O}\sum_{j=0}^{I} w_{i,j} \times x_j + w_b\right). \quad (6)$$

In formula (6), y_i and x_j represent the output of the i-th neuron and the j-th input, respectively, and $w_{i,j}$ means that the i-th neuron is connected to the j-th input weight. In general, the fully connected layer contains a large number of weight connections, and usually only the weight parameters of the fully connected layer can reach more than 80% of the entire network model. At present, the convolution layer of the 1×1 convolution kernel with special structure can be set to realize the specific operation of full connection.

3.2.5. Convolutional Layer. Convolutional neural networks are inspired by the brain, and the study of the mammalian brain has proposed a new model of how mammals perceive the world visually. As shown in the lower part of Figure 5, the convolutional layer is a multilayer perceptron with a special structure for the recognition of two-dimensional data features.

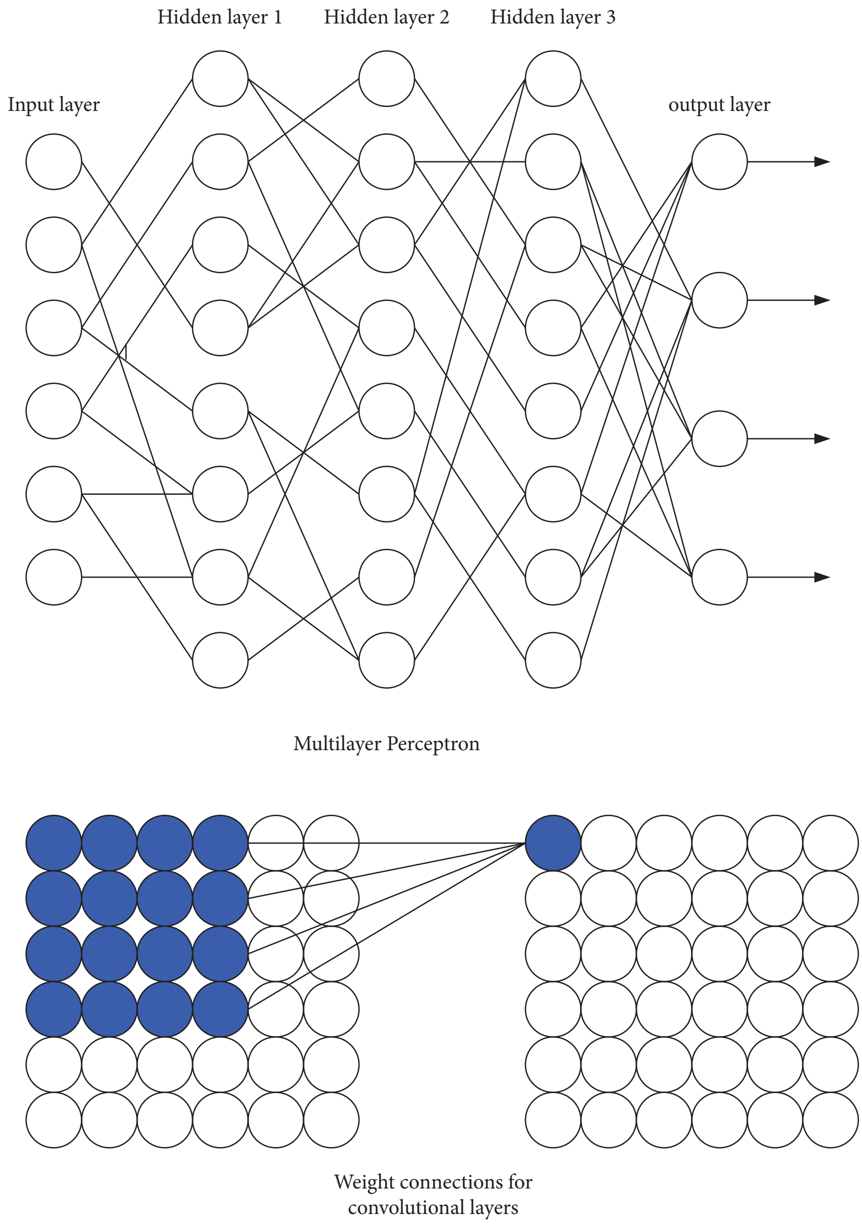

FIGURE 5: Convolutional layer and fully connected layer.

In each neuron in the convolutional layer, the neuron obtains the feature input from the local receptive field range of the upper layer, thus giving it the ability to extract local features. In the convolutional layer, each feature map is a two-dimensional plane, and individual neurons can share their synaptic weights to achieve weight sharing. The convolution calculation method is thus shown in formula (7), where O and F represent the dimensions of the output feature map and convolution kernel, respectively:

$$y_{i,j} = f\left(\sum_{i=0}^{O}\sum_{j=0}^{O}\sum_{m=0}^{F}\sum_{n=0}^{F} w_{m,n}x_{i+m,j+n} + w_b\right). \quad (7)$$

Therefore, each convolution calculation uses the shared weight convolution kernel of the output feature map to perform a weighted accumulation operation on the input local features. Therefore, the calculation process of the convolutional layer is essentially the same as that of the perceptron, except that it becomes the accumulator of the perceptron with shared weights.

4. Classification and Analysis of Logistics Data

Due to the rapid growth of logistics data, the traditional logistics software and hardware equipment is lagging behind, resulting in a slow processing speed of logistics data classification. The logistics industry and machine learning can be effectively combined, and the processing speed of logistics data can be effectively improved through machine learning-related algorithms. The support vector machine classification algorithm in machine learning takes into account the loss function, which is used to measure the

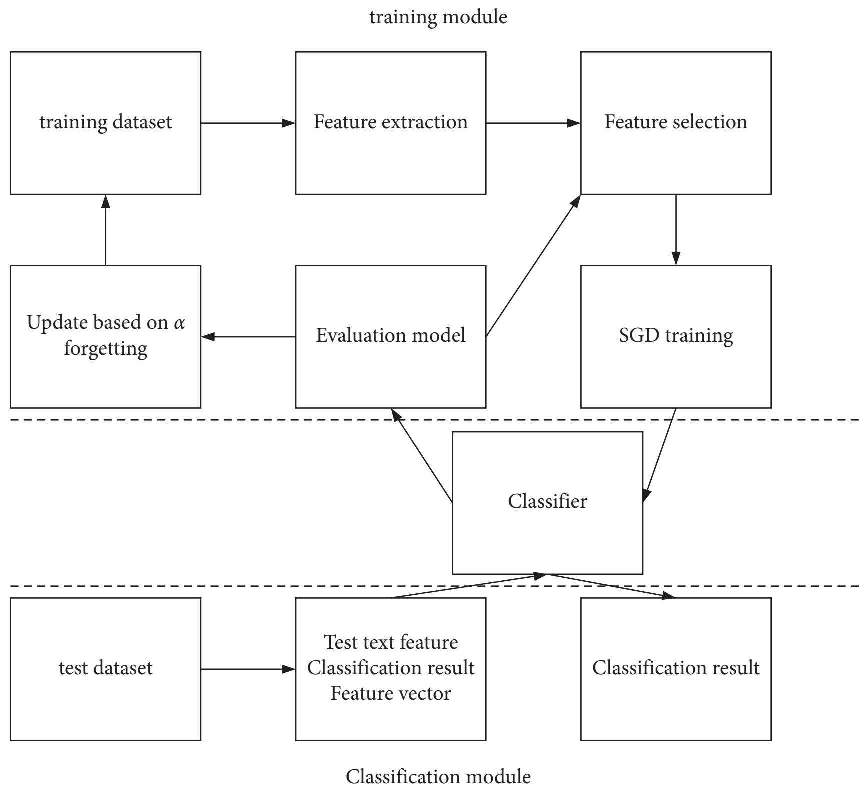

FIGURE 6: Model diagram of data classification scheme based on forgetting factor.

inconsistency between the predicted value and the true value. The smaller the loss function value, the better the robustness of the model. We hope to find a function that can minimize the loss function, but do not know the deeds distribution of the data, so when modeling data classification, we use empirical risk to measure the effect of the training set, that is, the ability to predict unknown examples.

The processing efficiency of traditional data classification algorithms is low, and the existing data classification algorithms are still lacking in the processing of massive logistics data. Some algorithms cannot satisfy incremental learning and cannot adapt to the classification of real-time data. Some algorithms are relatively complex. Although they improve the classification effect, they are prone to lag in data processing. In response to these urgent problems, many scholars have improved the classification algorithm in multiple directions and proposed many high-quality improved algorithms, among which the improvement of the SVM algorithm is relatively popular [21].

4.1. SVM Classification Algorithm Based on Stochastic Gradient Descent. Mass data classification is an important research branch in the field of data mining today. Faced with the classification of massive real-time data, many complicated factors need to be considered, such as how to reduce the complexity of classification model, how to avoid or reduce data redundancy, and how to improve data processing speed. For this reason, a large number of improved algorithms for data classification problems have emerged at home and abroad. Below we briefly summarize the improved algorithms for SVM. Broadly speaking, a support vector machine can be thought of as a linear classifier. The basic idea is to find an optimal classification surface from numerous multidimensional data.

4.1.1. Forgetting Factor. Forgetting factor can eliminate data saturation. When classifying data, we should pay attention to current real-time data and reduce the influence of historical data on classification results. The data classification algorithm with forgetting factor mechanism has fast convergence speed and strong tracking ability when training the classifier and has little fluctuation for random input.

The forgetting factor, that is, the weighting factor in the error measurement function, is introduced into the recursive least squares (RLS) algorithm, so that the weight of the recent input data is larger, while the weight of the historical input data is smaller. The specific operations are as follows:

Supposing the indicator function is as shown in formula:

$$J = (y_N - \Phi_N\widehat{\theta})^T W_N (y_N - \Phi_N\widehat{\theta}) = \Phi_N^T W_N \Phi_N. \tag{8}$$

Here, $W_N$is the weighted matrix, ρ is the forgetting factor, and $0 < \rho < 1$, and then there is the following formula:

$$J = \sum_{n=1}^{N} \rho^{N-n}\Phi^2(n). \tag{9}$$

Expanding into formula:

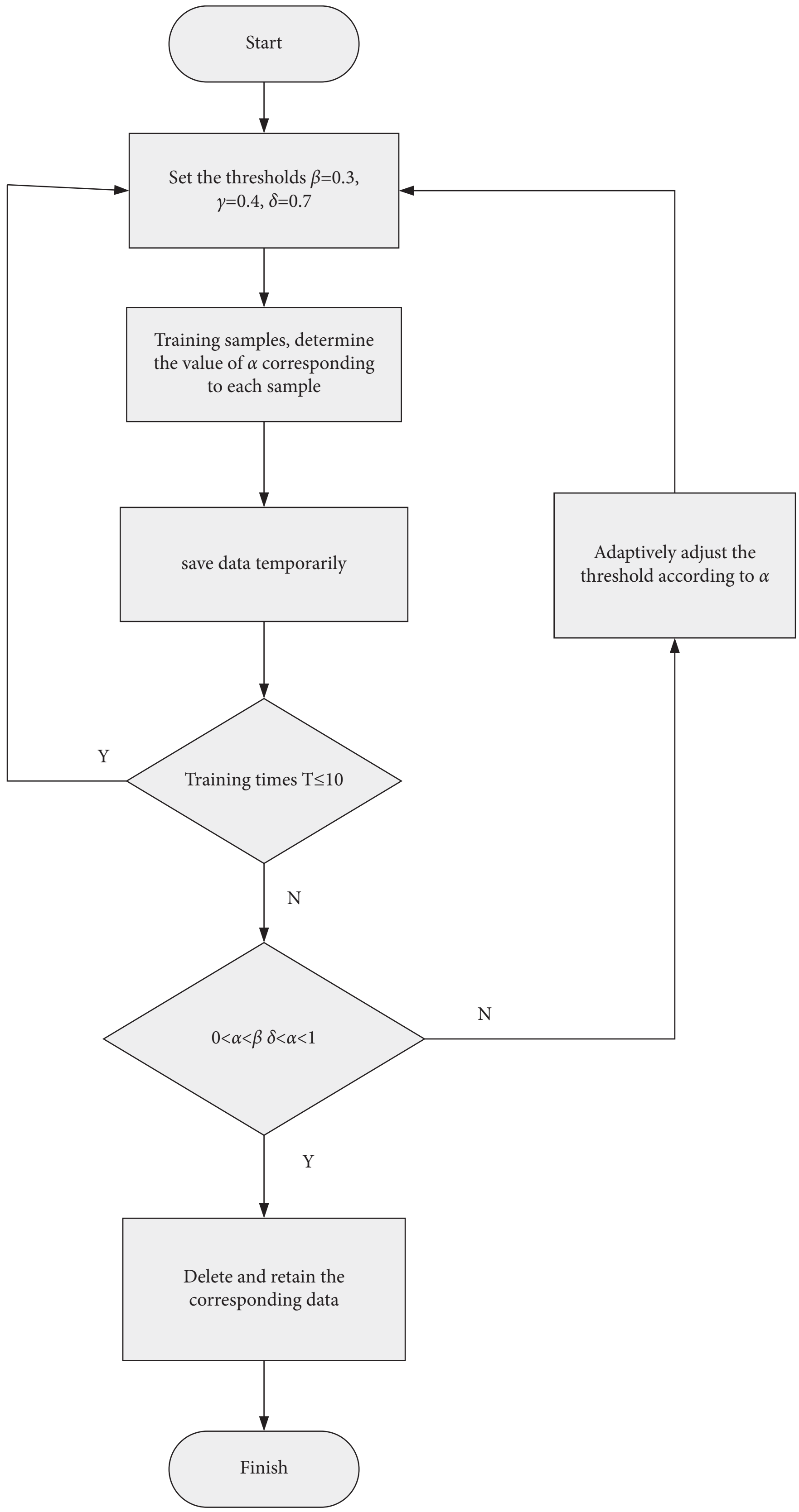

Figure 7: Algorithm flow chart.

Table 3: List of experiments.

Group	Purpose
First group	For the error rate of the algorithm in different situations
Second group	Contrasting error rate versus sample size
Third group	Compare the relationship between algorithm time and sample size

$$J(n) = \varphi^2(n) + \rho\varphi^2(n) + \rho^2\varphi^2(n-1) + \cdots + \rho^{n-1}\varphi^2. \quad (10)$$

Among them, φ^2 is the error. It can be seen from formula (10) that the new error coefficient is 1, and the error coefficients of the historical data are respectively the power exponential times of the forgetting factor. Formula (11) can be derived from the forgetting factor RLS formula:

$$\widehat{\theta}(N+1) = \widehat{\theta}(N) + K(N+1)\left[y(N+1) - \varphi^T(N+1)\right]. \quad (11)$$

Among them, $K(N+1)$and $P(N+1)$ are as in formulas (12) and (13):

$$K(N+1) = \frac{P(N)\varphi(N+1)}{\rho + \varphi^T(N+1)P(N)\varphi(N+1)}, \quad (12)$$

$$P(N+1) = \frac{1}{\rho}\left[1 - K(N+1)\varphi^T(N+1)\right]P(N). \quad (13)$$

By adding the forgetting factor idea, the support vector machine classification algorithm has the ability to choose and eliminate when processing logistics data, reduce data redundancy, and alleviate data redundancy. And potentially useful logistics information can be found, and the more massive logistics data updated in real time can be processed in a timely and effective manner.

4.1.2. Improved Algorithm Description. Aiming at the slow speed of SVM data classification, SGD is used to randomly select data samples to train data and speed up data convergence, and then the forgetting factor mechanism is used to reduce the redundancy of historical data, so as to discover potential classification and potential information in data. The self-adapting forgetting factor mechanism can flexibly adjust the forgetting factor α value for real-time data samples, so that the classifier can quickly adapt to new data. The overall scheme model of the improved algorithm is shown in Figure 6.

The relevant definitions involved in the above algorithm are as follows:

The objective function to be optimized to improve the algorithm is shown in formulas (14) and (15):

$$obj(w) = \frac{1}{2}\lambda w^2 + c\sum_{i=1}^{n} l(z_i, w), \quad (14)$$

$$s.t.\, y_i\left(w^T x_i + b\right) - 1 \geq 0, i = 1, 2, \cdots, n. \quad (15)$$

Here, w is a parameter, $1/2\lambda w^2$ is the regularization term with parameter λ, $l(z_{i,w})$ is a loss function, $\{z_1, z_2, \cdots, z_n\}$ is a

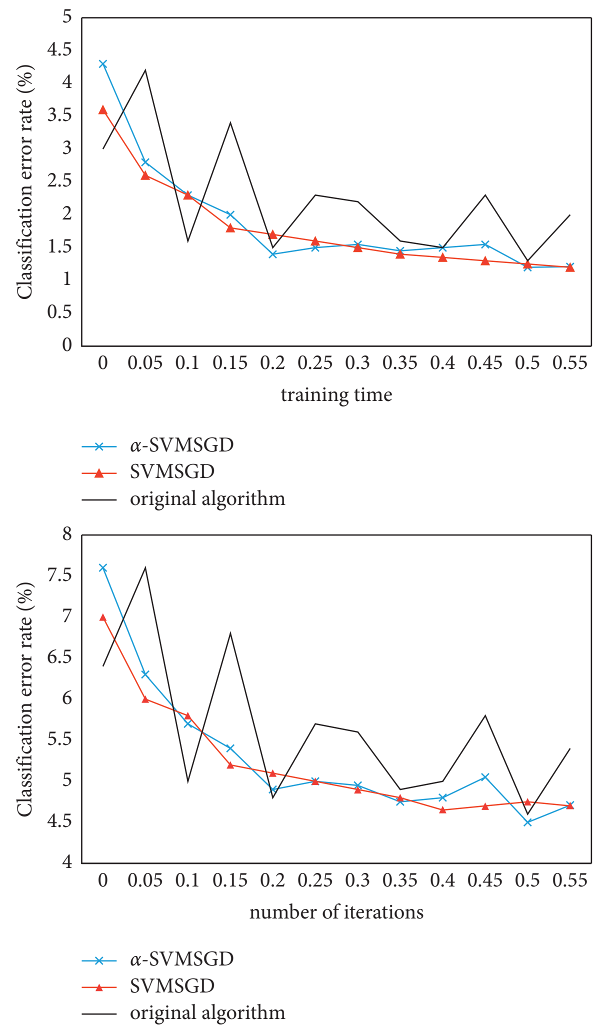

Figure 8: Classification error rate versus training time on different data sets.

training sample set, c is a penalty parameter, and $y \in (-1, 1)$ is a class label.

The loss function is shown in the following formula:

$$l(z, w) = \lambda w^2 + \max 0, 1 - yw^T f(x)\}. \quad (16)$$

Here, $f(x) \in R^d, y = \pm 1, \lambda > 0, f(x)$ projects the data samples into a d-dimensional space.

The function to update ω is shown in the following formula:

$$w_{t+1} = w_t - \gamma_t \begin{cases} \lambda w_t, y_t w^t f(x_t) > 1, \\ \lambda w_t - y_t f(x_t), otherwise. \end{cases} \quad (17)$$

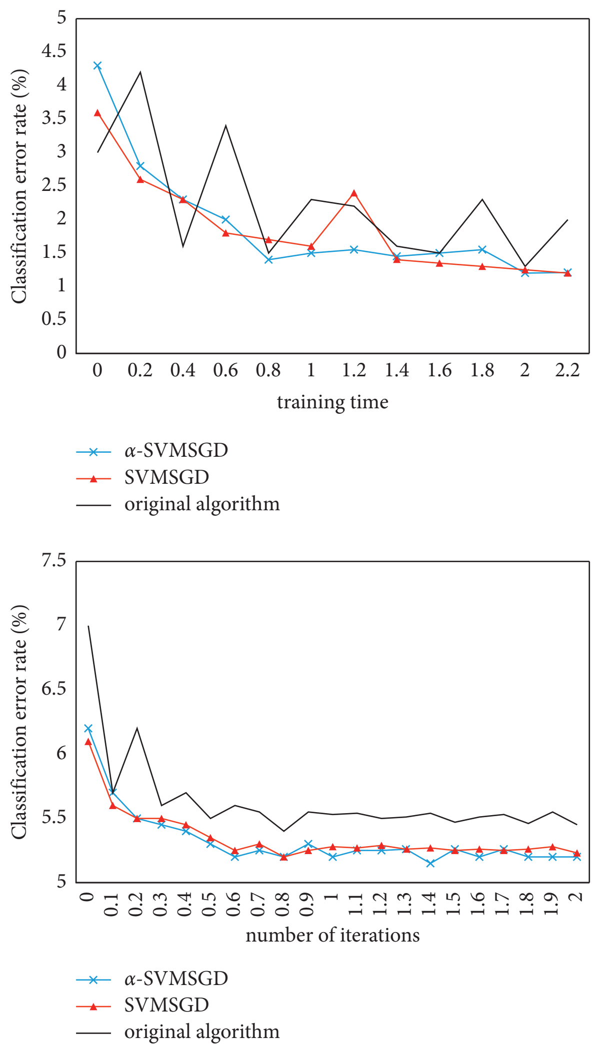

FIGURE 9: Classification error rate and number of cycles on different data sets.

Here, γ_t is the learning rate of step t.

According to the traditional Karush–Kuhn–Tucker (KKT) conditions, the optimal hyperplane satisfies the conditions, such as Equations (18) and (19):

$$w = \sum_i \alpha_i y_i H(x_i), \tag{18}$$

$$0 \le \alpha_i \le 1, \sum_i \alpha_i y_i = 0. \tag{19}$$

Here, $\alpha_i = r_i/T_i$ and r_i represents the number of SVs after the i-th data sample is trained by T; T_i represents the total number of test sets training; and a_i is the forgetting factor, which represents the ratio of the i-th sample SV after the data test set is trained for T times.

As can be seen from the flow chart in Figure 7, we first set three thresholds for the forgetting factor, $\beta = 0.3$, $\gamma = 0.4$, and $\delta = 0.7$. Then, according to the steps in the figure, the values of the thresholds β, γ, and δ are updated.

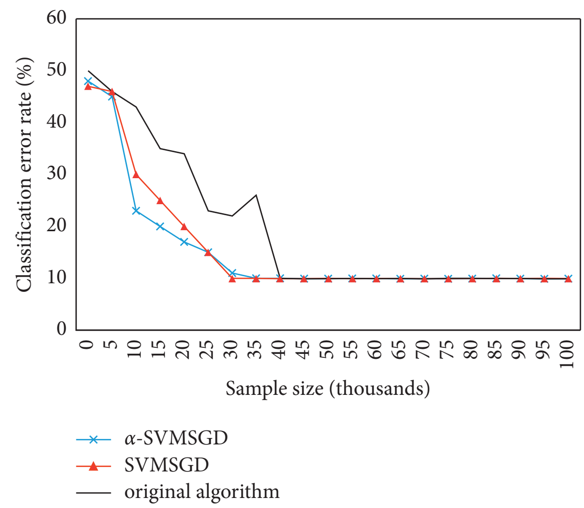

FIGURE 10: Classification error rate and sample size.

4.2. Algorithm Experiments and Results. The experimental simulation in this section uses C++ and applies two data sets: mnist9 and rcv1. The data set mnist9 contains more than 60,000 data samples, and the data set rcv1 contains more than 8,000 data samples. The value used in the simulation is 10ˆ−5. This part is simulated by three groups of experiments. The comparison of α-SVMSGD algorithm with the algorithms of LIBLINEAR (original algorithm) and SVMASGD shows the performance of the α-SVMSGD algorithm.

As shown in Table 3, the simulation experiments in this section are mainly divided into three groups. The simulation results are shown in Figures 8 and 9, and the experimental data is divided into the data set rcv1 and the data set mnist9. The second set of experiments compared error rates as a function of sample size. The third group of laboratories compared training time and sample size, and the simulation results are shown in Figure 10.

The upper part of Figure 8 is a comparison of the classification error rates of the data samples of the three algorithms, and the classification error rate gradually decreases. When the training time is less than 0.2, the fluctuations of SVMASGD and α-SVMSGD are relatively stable compared with the original algorithm, showing a downward trend all the time. As the training time increases, α-SVMSGD is even better than other algorithms.

As can be seen from the lower part of Figure 8, the classification error rates of all three classification algorithms decrease. Among them, the α-SVMSGD and SVMASGD algorithms still outperform the other two algorithms.

As shown in the lower part of Figure 9, we can find that the SVMASGD and α-SVMSGD algorithms are still more stable than the other two algorithms, especially when the number of cycles is less than 1.

From Figure 10, we can find that, with the continuous expansion of the training set size, the algorithms are almost the same.

It can also be seen from the training time shown in Figure 11 that the algorithm in this paper has a greater advantage under large samples. And the algorithm based on

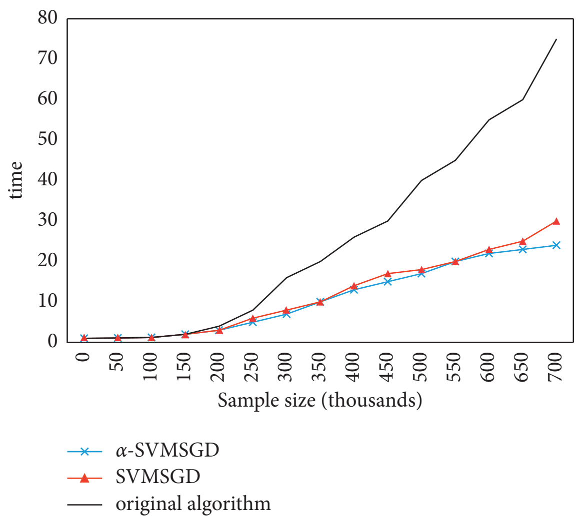

Figure 11: Training time and training data samples.

neural network optimization has greater advantages in large samples. Generally speaking, the larger the sample size, the more complex it is to process. The algorithms studied by many scholars are not very good in large samples.

5. Conclusions

Intelligent logistics is now more deeply embedded in people's lives, and the information generated by intelligent logistics is closer to people's lives, and the analysis of intelligent logistics data is becoming more and more important. In this paper, the background of e-commerce and smart logistics is first explained, and then the related research is also summarized. Then, the intelligent logistics is introduced in detail, the FRID technology is described, and then the artificial neural network of this paper is introduced in detail, which lays the groundwork for the classification of logistics data. Finally, the paper proposes an improved classification algorithm based on artificial neural network for intelligent logistics data, introduces the improved principle in detail, and analyzes the improved and unimproved algorithms. The improved algorithm in this paper has great advantages. But at the same time, this paper also has a certain room for improvement, such as the predictive analysis of logistics data to provide better services, etc., and hope to improve in future research. In the follow-up work, the artificial intelligence logistics park will be researched, hoping to summarize and analyze the complete intelligent logistics industry.

Data Availability

No data were used to support this study.

Conflicts of Interest

There are no potential conflicts of interest in this study.

Authors' Contributions

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