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Research Article

Safety Risk Evaluation of Tourism Management System Based on PSO-BP Neural Network

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With the recovery of the tourism industry and the development of the field of artificial intelligence, the application of intelligent neural network technology to management systems for safety risk assessment is the choice of the times and an urgent real need for relevant practitioners. In this study, the BP neural network algorithm is used as a tool for safety evaluation of the tourism management system. The three-layer structure of the BP neural network and the role of nodes in it are introduced, the weight values and thresholds of nodes in each of the three layers are calculated, and the particle swarm algorithm is added to optimize the model. In the practical stage, the tourism data of a place in Switzerland was selected as the training data. After 12,859 iterations, the model achieved the best calibration error of 0.126. After 300 iterations of learning, the BP algorithm optimized with the PSO algorithm has a faster convergence rate, which indicates that the performance of the optimized algorithm has improved significantly and has the global search capability that was not available before, which significantly outperforms the FastText and LSTM models. With the increase in the number of samples of tourism data, macroaccuracy always remains above 80%, so it proves that the optimization algorithm used in this study is an effective and reliable model.

1. Introduction

Inspired by the activity of human consciousness, scientists in the field of artificial intelligence have invented artificial neural networks, which are the most basic roots of artificial intelligence, the modern technological building of mankind [1]. Human consciousness is the product of constant transmission of information transmitters between neurons in its own physiological structure, and only by constant transmission and circulation can it think continuously. And humans constantly adjust and update the connection weights between neurons in order to perform better and faster thinking activities [2]. Human consciousness is nonlinear and generates new signals with increasing knowledge and experience, and these new signals cause new stimuli to the neural synapses, which in turn generate new thoughts [3]. Artificial neural networks operate on the same principles as the human mind activity, where data is passed, processed, handled, and distributed at various nodes. Like human consciousness, it adjusts to changes depending on the input signals and has the same adaptive and autonomous learning capabilities as humans [4]. Neural network nodes in computer technology are as important as human neurons, and the number of nodes and the way they are connected determine what kind of nonlinear mapping capabilities they have [5]. Human neurons are composed of cell bodies, nuclei, dendrites, axons, cell junctions, Schwann cells, and synapses, which also look quite complex. The neural network was first proposed by a medical person. Dendrites are used to receive incoming information. Axons transmit information through the nucleus, or the nucleus correspondingly generates a signal to the axons. Axons are used as outputs to connect with the dendrites of other neurons. Therefore, the links of dendrites → axons → dendrites → axons constitute a huge human neural network system. BP (back-propagation) neural networks are the first and currently more developed artificial intelligence network technology, which uses error back-propagation to train data [6].

With the rapid development of the domestic economy and the change of national consumption habits with the reform and opening up, tourism has blossomed throughout the country, and travel has become the first choice for many citizens' holiday projects. After years of being affected by the epidemic, we have entered the postepidemic era, and tourism is gradually recovering [7]. With the continuous development of Internet technology, tourism practitioners have changed their original management. The tourism-related information is managed through the tourism management system. However, while the network brings convenience to users, it will also bring certain risks to the security of the tourism management system. Therefore, it is of great significance to adopt a certain method to evaluate the security risk of the tourism management system. In recent years, a variety of neural networks have arisen and developed like a mushroom, but they have not yet been applied on a large scale in the field of tourism management. It has the advantages of nonlinear mapping and parallel processing, and through its own network structure, it learns the multidimensional and complex features of tourism safety data and automatically adjusts the large number of internal connection weights to fit the data features as much as possible. The self-organization, self-learning, super memory, and high fault tolerance of neural networks are suitable for dealing with the current multidimensional and high noise nonlinear data like safety evaluation data. As one of the pillar industries in many countries, tourism drives the local economic development at the same time also reveals many problems in management. First is the lack of relatively strict market regulation. Many travel agencies have emerged to take advantage of market loopholes and operate illegally without travel agency qualifications. For example, as a mass organization, the tourism association is directly under the leadership of the government and lacks the corresponding guidance and regulatory role. In view of different regions' different emphases on tourism, the settings of tourism associations in different regions are also different. The tourism associations in some regions are not perfect and lack corresponding management personnel. Their work is lax, and they cannot effectively supervise, manage, and coordinate the development of tourism. Second is the lack of a set of uniform norms for the safety evaluation of travel agencies and tourists. All major travel agencies and online travel websites use their own evaluation standards, making it impossible for safety-related information to be fluently exchanged and transmitted. Third, the credit indicator system for tourists is not perfect. The quality of tourists can only rely on individual self-consciousness, and the evaluation is too broad to do a credit assessment combined with a comprehensive evaluation of a particular person [8–10]. In conclusion, an effective security risk evaluation scheme for tourism management systems is needed to cope with the increasing number of tourists and the needs of travel agencies. The nonlinear mapping characteristics of neural networks are well suited for the safety risk assessment of management systems, because safety or not is an abstract concept that requires many relevant environmental and human factors to be characterized. Therefore, this study selects the BP neural network as technical support and uses desensitized open-source security database as the training material for the neural network [11]. And it is optimized and upgraded using the particle swarm optimization (PSO) algorithm to obtain the PSO-BP neural network algorithm with fast convergence, few parameters, and simple and easy implementation [12]. The safety impact factors of the training data are stored in the network nodes, and after thousands of cycles of computation, a model that can qualitatively and quantitatively evaluate the safety evaluation of tourism management systems is finally constructed. This model makes full use of the special capabilities of neural networks for nonlinear mapping, which can help those involved in the tourism industry to counteract potential as well as formed security risks and reduce the consumption of human resources [13]. Such a system using efficient computer algorithms for safety evaluation can automate the process and is a new direction and a general trend in tourism management.

2. BP Neural Network and PSO Algorithm

2.1. Overview of BP Algorithm. Artificial neural network (ANN) systems appeared after the 1940s. It is connected by many adjustable connection weights of neurons. It has the characteristics of large-scale parallel processing, distributed information storage, good self-organization, and self-learning ability and is more and more widely used in the fields of information processing, pattern recognition, intelligent control, and system modeling. The BP neural network contains two processes of forward propagation of the correct signal and backward propagation of the error signal. It can be trained several times using the backward propagation of the error in it and is a typical multilayer prefeedback network [14]. There is a gradient search technique in BP neural to find the minimum error mean square difference between the desired and actual output values using gradient descent to reach the optimal solution. To accomplish the above-described function, it is structured as shown in Figure 1.

It can be seen that it consists of three parts: input layer, implicit layer, and output layer. When the amount of data to be outputted is determined, the number of nodes in the input layer is also fixed. The implicit layer, which is in the middle, needs to be determined by actual experimental operation. The number of nodes in the output layer can be determined only after the implicit layer is determined and the results are calculated [15]. Once the number of nodes in all three layers is determined, the data can be trained, and the training process is the mapping of the output data to the input data after a number of nodes. When the actual output value is obtained for the first time, the error is compared with the desired output value [16]. When the error is large, the nodes in the neural network are spontaneously adjusted and changed after direction propagation, and the actual output value is calculated again for the second time. After this cycle of uncertainty until the mean square difference between the actual and desired output values is within an acceptable range, this is the training process that takes advantage of the adaptive nature of the neural network. This adaptive nature is the greatest advantage of BP neural networks compared to other methods and is one of the important objects of this study, relying on this feature to achieve

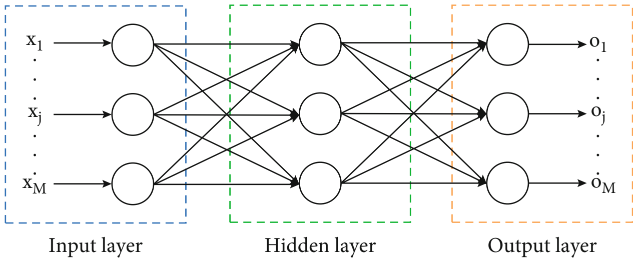

Figure 1: Basic structure of back-propagation neural network.

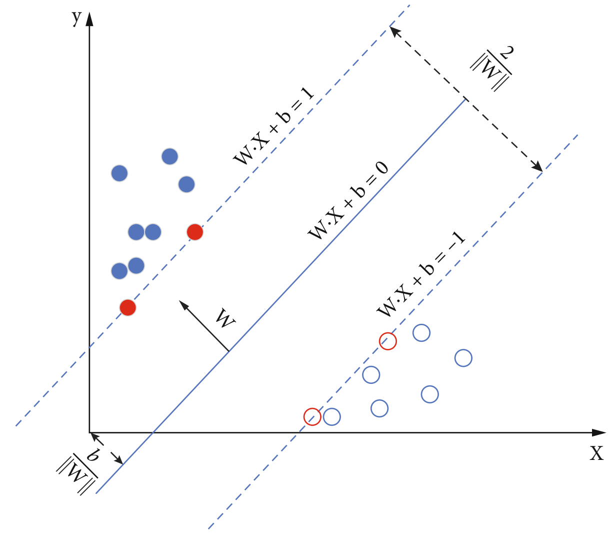

Figure 2: Schematic diagram of separating hyperplanes for back-propagation neural networks.

error minimization and obtain scientifically valid results of management system safety evaluation [17–21].

2.2. Specific Implementation of the Standard BP Algorithm. The BP neural network is a linear two-classifier whose main dominant intervals are recognizing high latitude models and solving small sample data and linear classification. Among them, having the largest interval in the feature space is the most important feature that distinguishes it from other perceptual machines. Although its classifier is linear, it can also be used as a nonlinear classifier because it includes kernel tricks. Its essence is to find the optimal solution of convex quadratic programming and to be able to accurately partition the training dataset [22]. Solving the optimal solution of the convex quadratic programming is described geometrically by finding the separating hyperplane with the largest geometric interval. It can also be represented by the following Figure 2.

For the BP network to have predictive and associative memory capabilities, the weight values of the implicit layer and the weight values of the implicit layer to the output layer need to be output in advance. Then, the threshold value of the implicit layer can be calculated using the following equation.

$$H_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - a_j\right), \tag{1}$$

where w_{ij} is the initially set weight value, $f(x)$ is the excitation function in the algorithm, and the a obtained by it is the requested threshold value of the hidden layer, and the next step is to calculate the threshold value of the output layer.

$$M_k = \sum_{j=1} H_j w_{jk} - b_k. \tag{2}$$

By using the threshold value a obtained from equation (1), not only the threshold value b of the output layer can be found but also the specific value of the output data M can be calculated. Combined with the expected output value Y, the difference between them is the prediction error, which is calculated using the following equation.

$$e_k = Y_k - M_k. \tag{3}$$

After getting the error value e, it will be found that its value is not within a reasonable range, so back-propagation is performed to correct the weight value and the threshold value, which will use the following formulas.

$$w'_{ij} = w_{ij} + \eta H_j(1 - H_j)x(i)\sum w_{jk}e_k, \tag{4}$$

$$y'_{jk} = w_{jk} + \eta H_j e_k, \tag{5}$$

$$a'_j = a_j + \eta H_j(1 - H_j)\sum w_{jk}e_k, \tag{6}$$

$$b'_k = b_k + e_k. \tag{7}$$

Equations ((4)), ((5)), and ((6)) used in η are the learning rates of the network algorithm; based on the premise that does not lead to system oscillation, the greater the learning rate, the faster the computation speed. Therefore, in the actual operation, it is necessary to select the best possible learning rate. After this cycle, the error is again judged to be in the acceptable range, and if not, the above steps are repeated with the new results.

The next step is to optimize the formula using derivatives. First, let the number of nodes in the input layer be n, the number of nodes in the hidden layer be l, and the number of nodes in the output layer be m. According to the relationship between the implicit layer and the output layer, we can know that the number of nodes in the implicit layer is in accordance with the following relationship: $l = 2n + 1$. Therefore, the value of the input of the i node in the implicit layer is calculated.

$$\text{net}_j = \sum_{i=1}^{n} w_{ij}x_i + \partial_j. \tag{8}$$

The corresponding implicit layer output then has the value

$$H_j = \varphi\left(\text{net}_j\right) = \varphi\left(\sum_{i=1}^{n} w_{ij}x_i + \partial_j\right). \tag{9}$$

Passing to the output layer corresponds to the k node, and continuing to use the formula, we get

$$\text{net}_k = \sum_{j=1}^{l} w_{jk}H_j + \beta_k = \sum_{j=1}^{l} w_{jk}\varphi\left(\sum_{i=1}^{n} w_{ij}x_i + \partial_j\right) + \beta_k. \tag{10}$$

In the process of feedback, the samples at each level follow the criterion function.

$$E_p = \frac{1}{2}\sum_{k=1}^{m}\left(T_k - O_k\right)^2. \tag{11}$$

The total variance criterion function for the sample is

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{m}\left(T_k^{\,p} - O_k^{\,p}\right)^2. \tag{12}$$

The weight value of the forward propagation from the input layer to the implicit layer can then be expressed as

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial \text{net}_k} = -\eta\frac{\partial E}{\partial \text{net}_j}\frac{\partial \text{net}_j}{\partial w_{ij}} = -\eta\frac{\partial E}{\partial H_j}\frac{\partial H_j}{\partial \text{net}_j}\frac{\partial \text{net}_j}{\partial w_{ij}}. \tag{13}$$

The corresponding forward propagation threshold equation is

$$\Delta a_j = -\eta\frac{\partial E}{\partial a_j} = -\eta\frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial \text{net}_j}\frac{\partial \text{net}_j}{\partial a_j}. \tag{14}$$

Similarly, the weight values and thresholds from the implicit layer to the output layer are expressed as

$$\Delta \beta_k = -\eta\frac{\partial E}{\partial \beta_k} = -\eta\frac{\partial E}{\partial O_k}\frac{\partial O_k}{\partial \text{net}_k}\frac{\partial \text{net}_k}{\partial \beta_k}. \tag{15}$$

From all the formulas above, it can be seen that the three-layer structure of the BP neural network is interrelated and influences each other, while the nodes in the same layer have no connection relationship.

2.3. BP Algorithm Correct Rate Validation. The number of nodes is chosen from 1000 to 8000 because the number of nodes is not too small to fully exploit the capability of the algorithm, and too many nodes are not too large to burden the server running the data. The three layers were learned by node transfer using the BP neural network and reinforced architecture neural network, and the correct rate was obtained; then, the BP neural network was optimized using PSO algorithm, and the third set of the correct rate was mixed. The average correct rate of each method is calculated every 12 times randomly by following this method 42 times, and the results are shown in Figure 3.

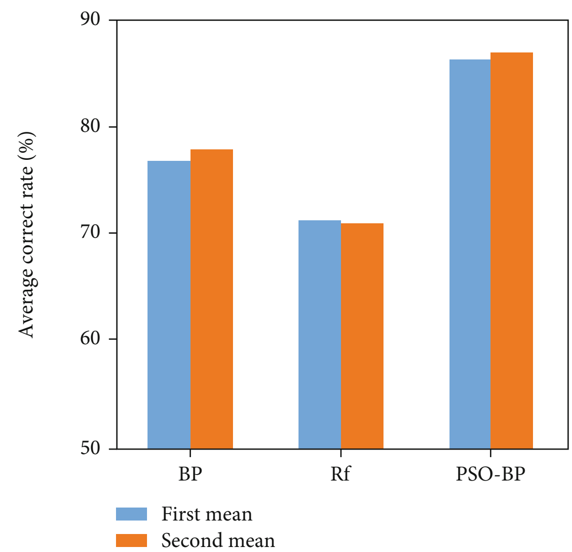

FIGURE 3: Comparison histogram of the accuracy rate of the classification results of the single algorithm and the hybrid algorithm.

As can be seen in Figure 3, the average correct rate obtained by performing multiple calculations is closer to the average correct rate of both the BP and Rf algorithms twice, indicating that the data has some reliability. If there is a large difference between the two calculations, it would indicate that a fundamental error has occurred and the code needs to be found and reworked to solve the problem. The average correct rate of the optimized neural network using the PSO algorithm is higher than the correct rates of both of the previous two, indicating that the hybrid algorithm model used in this study is scientifically valid and can be processed and calculated using real data.

3. Practical Application to Tourism Management Systems

3.1. Performance Testing of Neural Network Hybrid Models. In this study, the tourism management system of a location in Switzerland, a developed country in tourism, was chosen as the subject of the experiment. This database was first initialized using a text tool to eliminate indicators with a small impact on the security assessment. As a result, 10,000 samples remain in the initial database, of which 7,000 samples with good security assessment are set as positive samples, 2,000 samples with threatening security assessment are set as negative samples, and the remaining 1,000 samples are unknown samples or samples to be tested, which will be used for the actual validation.

Simulation experiments are used to test the performance of the PSO-BP neural network algorithm. Using the data from the tourism management system of a Swiss location mentioned in the previous paragraph as a training set, the

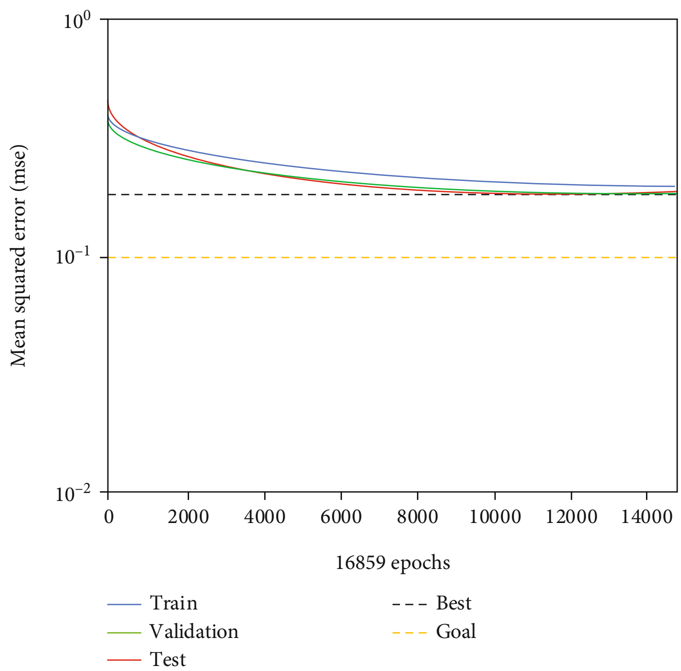

Figure 4: Neural network algorithm model performance test results.

algorithm model is made to perform optimally by an unlimited number of iterations. Finally, the best calibration error is obtained, and the smaller this value is, the better the performance of the model. The experimental results of the performance test in this study are shown in the following Figure 4.

In the results above, the blue curve is the error curve of the system training, the green curve represents the calibration error, and the red curve is the test error. The dotted line in the figure is the baseline, black is the best error target level baseline, and yellow represents the minimum error level baseline. After 12,859 iterations, the best calibration error achieved by the model is 0.126, and it can be seen that the curves in the figure are all smooth, so every point on the curve is derivable. Although there is still some gap between the performance of the model and the ideal minimum error line, it has reached the target baseline. And it should be stated that the rational minimum error value is an optimal ideal value that can be reached in theory, while it is impossible to be reached in practice because of the imperfection of the database, the limit of computer arithmetic power, and the upper limit of the algorithm itself, etc. It can only converge to this value infinitely. Therefore, it shows that the performance of the PSO-BP neural network model established in this study meets the expectations.

3.2. Comparison Test before and after PSO Algorithm Optimization. The BP neural network algorithm optimized by the PSO algorithm, i.e., the particle swarm algorithm, will have the advantages of compactness and efficiency. Particle swarm optimization (PSO) simulates the clustering behaviour of insects, herds, birds, and fish. These groups search for food in a cooperative way. Each member of the group constantly changes its search mode by learning its own experience and the experience of other members. Two test functions are used to test the algorithm before and after optimization to verify whether the optimization of the PSO algorithm is effective. As the number of neural network learning increases, the adaptability of the two algorithms before and after optimization to the test functions is observed, and the convergence of the corresponding algorithms is then analyzed Figure 5.

The test functions used in the above figure are the Schaffer function and Rosenbrock function, whose horizontal coordinates are the number of iterations and vertical coordinates are the corresponding fitness function values after each iteration, and the smaller the value of the vertical coordinates indicates the better performance of the algorithm. Because of the mathematical properties of the test function itself, the plotted curve must be monotonically decreasing. With nonstop machine learning, particles with better propagation performance will emerge, and using them as new node information propagation media will improve the quality and efficiency of the algorithm. The above figure clearly shows that after 300 iterations of learning, the BP algorithm optimized by the PSO algorithm has a faster convergence speed and a global search capability that was not available before. Moreover, the results of the unoptimized BP algorithm have larger errors and show the phenomenon of local prematureness. That is, after reaching only the local optimal solution in the figure, it no longer converges and the error will not be further reduced. This phenomenon does not occur after 300 iterations of optimization, which indicates that the performance of the optimized algorithm is substantially improved.

The performance of the hybrid PSO-BP neural network algorithm model is compared with that of the baseline, and the output results of the hybrid algorithm model are analyzed for the influencing factors. The performance of the

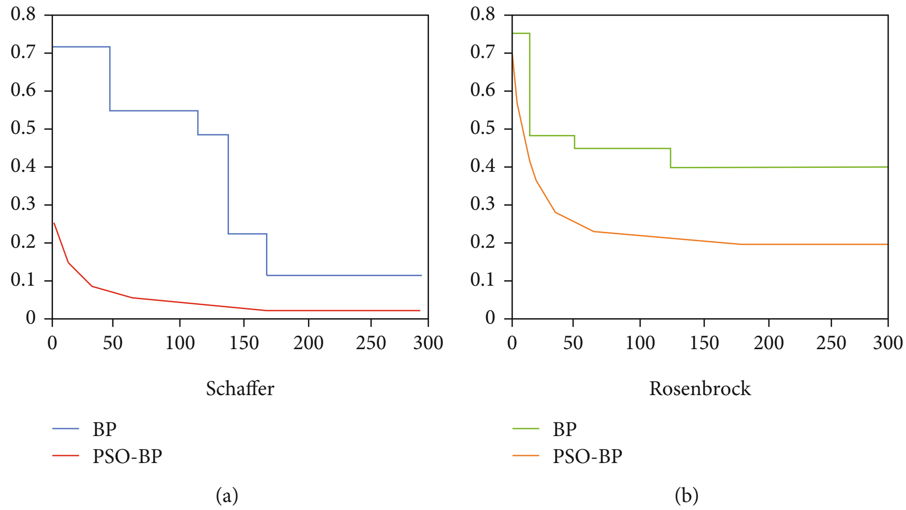

Figure 5: The performance comparison curve of the algorithm before and after optimization using the Schaffer test function (a) and the comparison curve of the Rosenbrock test function (b).

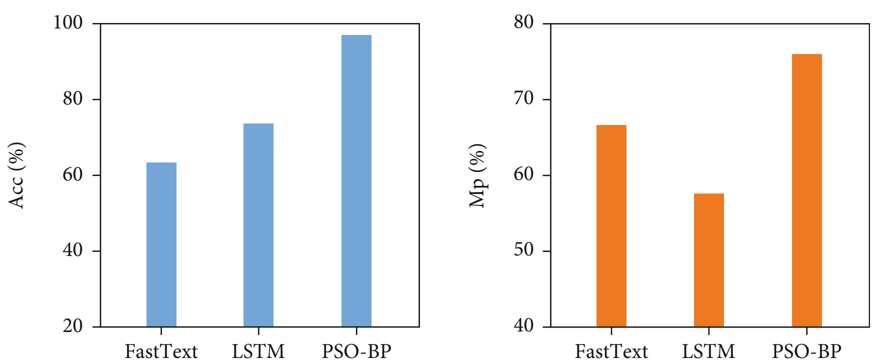

Figure 6: Comparison histogram of accuracy, macrorecall of hybrid model, and FastText and LSTM.

hybrid model was also evaluated using two classical metrics, accuracy and recall. Aiming at the problem that the BP algorithm is sensitive to the initial weight and threshold of the network and is easy to fall into local minima, the PSO algorithm is used to optimize the distribution of the initial weight and threshold of the BP neural network, and a good initial solution of the weight and threshold is obtained. For its efficiency in security assessment of the tourism management system, FastText and LSTM were selected for the study to perform comparative tests (Figure 6).

Figure 7 shows that the hybrid PSO-BP neural network algorithm model significantly outperforms the FastText and LSTM models in terms of accuracy and recall performance on the tourism management dataset of a Swiss location. Its accuracy in the final result obtained was 97.3%, while the FastText and LSTM algorithms could only reach 63.7% and 78.5% accuracies, respectively, when processing the same data, which obviously could not be accurately evaluated for safety. The optimized algorithm also showed similarly better data than the two compared algorithms in the recall test. These demonstrate the validity and reliability of the hybrid model established in this experiment.

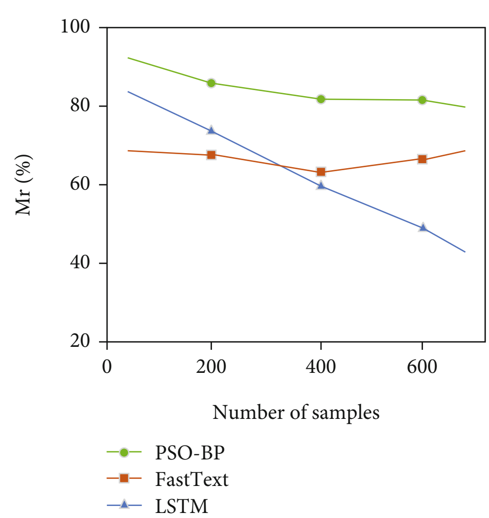

Figure 7: Discounted plot comparing macroaccuracy of hybrid models with FastText and LSTM.

The above figure shows the comparison of the macroaccuracy of the hybrid PSO-BP algorithm model with FastText and LSTM after the optimization of the particle swarm algorithm, and it is obvious that the macroaccuracy of the hybrid model is higher than that of FastText and LSTM when the number of samples is 200, 400, and 600. The LSTM algorithm model is only good at handling libraries with small amount of data, and as the number of samples increases, its macroaccuracy decreases fastest. In contrast, the PSO-BP hybrid algorithm model and the FastText algorithm model constructed in this study both maintain the stability of macroprecision in processing different sample sizes. Although, showing a trend of decreasing macroaccuracy as the number of samples of tourism data increases, it can be maintained above 80%, so it is a valid and reliable model.

4. Conclusion

The field of artificial intelligence, which has emerged and continued since the last century, has grown rapidly in the last decade or so with the support of humanoid neural networks. It has been used in various industries to a greater or lesser extent, but in the tourism industry, which has been severely affected by the epidemic, it has not received the attention it deserves and is not used on a large scale. Therefore, this study identifies this gap and chooses the earliest and currently most well-developed BP neural network algorithm as a tool for security assessment of management systems in the tourism industry. This study first introduces the importance of neural networks for artificial intelligence and describes the basic principle of human consciousness activity as the essence of BP neural networks. This is followed by an analysis of the opportunities and challenges facing the tourism industry in the postepidemic era. The significance and importance of this study is reflected by highlighting the analysis and listing of various chaotic aspects of safety issues in the tourism industry. It can replace manual auditing and save human resources to a great extent, making the cost of industry-related expenditures significantly lower. At the same time, it also improves the efficiency of security audits, and the very high correctness rate guarantees the safe operation of the management system.

After introducing the three-layer structure of the BP neural network and the role of nodes in it, the weight values and thresholds of nodes in each of the three layers are calculated. A particle swarm algorithm was added to optimize the model, and a more efficient and rapidly converging algorithm model was finally obtained. After the hybrid algorithm model was built, the data of a tourist resort in Switzerland was selected as the training data in this study. After screening, 10,000 samples were selected from the database, of which 7000 samples with good security assessment were set as positive samples, 2000 samples with more threatening security assessment were set as negative samples, and the remaining 1000 samples were the samples to be tested. After 12,859 iterations, the best calibration error achieved by the model is 0.126, and a smooth result curve is obtained, so that every point on the curve is derivable. Although the performance of the model does not reach the minimum error line, it has reached the target baseline, indicating that the performance of the PSO-BP neural network model established in this study meets the expectations. After 300 iterations of learning, the BP algorithm optimized using the PSO algorithm possesses a faster convergence rate. Moreover, the results of the unoptimized BP algorithm had larger errors and showed local prematureness. After reaching only the local optimal solution, it no longer converges and the error does not decrease further, while after optimization, 300 iterations did not appear to have this phenomenon, indicating that the performance of the optimized algorithm has improved substantially and has the global search capability that was not available before. The hybrid model of the PSO-BP neural network algorithm is significantly better than the FastText and LSTM models in terms of accuracy and recall performance, and both data prove the effectiveness and reliability of the hybrid model established in this experiment. As the number of samples of tourism data increased, macroaccuracy always remained above 80%, so it again proved that the optimization algorithm used in this study is an effective and reliable model. However, the tourism management security system is a large and complex collection of massive data, and this study was not able to add all the samples to the model for computing and iteration. It also suggests that using more servers with better performance for machine learning of neural networks will achieve more accurate results. Although optimized by the particle swarm algorithm, it did not reach the optimal target baseline when performance tests were conducted, proving that there is room for optimization and improvement in this algorithmic model. The travel management system should not only help its security risk evaluation through computer technology but also be able to resist hacking such as denial of service type attacks. The confidentiality of customer data information and prevention of account and password leakage are also the top priorities of system security. Moreover, the system is constantly updated, and new features added and old redundant code removed may cause unknown vulnerabilities, so the algorithm model constructed in this study should be updated accordingly with the system update. The purpose of introducing the PSO optimization algorithm in this study is to optimize the weight values of the data network, which is the same as the essence of most computer algorithms to solve the problem and find the optimal solution of several functions. Subsequent research can continue to delve into more optimal problem solving by introducing the relevant theoretical knowledge and formula theorems from topology and operation research. Finally, whether it is the prediction of the factors affecting the system safety or the risk assessment prediction of travel agencies and tourists, it only provides some scientific reference, and it needs to be treated with caution in practical application and reasonable application of the analysis results given by big data.

Data Availability

The figures used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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