

Research Article

Machine Learning-Based Classification and Evaluation of Regional Ethnic Traditional Sports Tourism Resources

Cuihan Li  and Shaojun Lyu

College of P.E. and Sports, Beijing Normal University, Beijing 100875, China

Correspondence should be addressed to Cuihan Li; 11132020301@bnu.edu.cn

Received 24 June 2022; Revised 21 July 2022; Accepted 28 July 2022; Published 21 August 2022

Academic Editor: R. Mo

Copyright © 2022 Cuihan Li and Shaojun Lyu. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Traditional sports in ethnic minority regions are a valuable cultural heritage. Regional ethnic traditional sports are not only a sports business but also a tourism resource. The construction of a reasonable regional sports tourism resource classification model is fundamental to the development of sports tourism resources. However, the existing sports tourism resources classification is mostly constructed manually based on the national standard tourism resources classification system. The efficiency and accuracy of the traditional manual classification are poor and cannot reflect the characteristics of regional ethnic traditional sports tourism. In order to solve the above problems, a machine learning-based classification method for regional ethnic traditional sports tourism resources is proposed. Firstly, the relevant concepts and characteristics of traditional sports tourism resources are introduced. Then, taking the development of traditional sports of ethnic minorities in Yunnan Province as the research object, SWOT analysis, literature, interview, questionnaire, and mathematical statistics are used to investigate and analyse the overall status of the development of regional ethnic traditional sports. Secondly, a classification evaluation method based on an optimised back-propagation (BP) neural network is proposed. Finally, the optimised BP neural network model is applied to the classification of traditional sports tourism resources. The experimental results show that the optimised BP model performs well in the classification of traditional sports tourism resources, verifying its effectiveness.

1. Introduction

Traditional sports in China's 55 ethnic minority regions are a valuable cultural heritage. Nowadays, with the rapid development of rural tourism, it is important to analyse and study traditional sports from the perspective of tourism resources to promote the development of regional ethnic traditional sports. China is rich in ethnic cultures and characteristic landscapes. Intangible cultural heritage has been well protected in China and has become an important tourism resource. However, the traditional sports of ethnic minorities contain rich ethnic cultural connotations and are also an important tourism resource.

For an ethnic minority, regional ethnic traditional sports contain not only the exercise of labour skills and combat skills, but also many elements of ethnic minority culture, art and religion. Traditional ethnic minority sports have a history of several hundred or even thousands of years. In

recent years, the construction of rural tourism in China has been developing at a rapid pace. According to statistics, more than 85,000 villages with tourism as a development component have been built in China. Traditional sports of ethnic minorities have received great attention as an important tourism resource in cultural and ecological villages.

Sports tourism originated in the UK and has been widely concerned with the vigorous development of sports [1–5]. The global sports tourism industry is growing at a rapid rate of 14% per year and is expected to reach the USA \$412.7 billion by 2022, with nearly USA \$180 billion in the Asia-Pacific region. In China, there is a growing demand for diversified sports and tourism and leisure. Sports tourism has become an important embodiment of a healthy lifestyle [6, 7]. In recent years, China has issued a series of important documents and policies to actively promote the development of the sports tourism industry. It is expected that by 2022, the total number of sports tourism visits will reach 1 billion, accounting for 15%

of the total number of tourism visits. The total consumption scale of sports tourism exceeds 1 trillion yuan.

As the sports tourism industry continues to develop, with the resulting growing economic and social impact, academic research related to sports tourism is gradually gaining attention [8–11]. At present, research topics on sports tourism show a diversified trend, including sports tourism characteristics and types, the economic impact of sports tourism, the characteristics of sports tourists and sports tourism destination planning. As the material basis of sports tourism activities, the importance of sports tourism resources is indisputable, and it concerns the development of the entire sports tourism industry. Most studies have mainly focused on areas such as the characteristics of sports tourism and the development of products, while insufficient attention has been paid to sports tourism resources [12–14]. In practice, the inaccuracy of resource classification has caused the problem of low efficiency in the actual use of sports tourism resources, limiting the development of sports tourism products and making the structure of sports tourism products single, thus hindering the development of sports tourism.

The rational classification of sports tourism resources is an important condition for the study of sports tourism resources. However, most of the existing research focuses on the development and evaluation of sports tourism resources, so there is a lack of specific research on the classification of sports tourism resources. The classification of sports tourism resources has not yet formed a unified standard. Compared to traditional tourism resources that focus on enjoyment, regional ethnic traditional sports tourism resources place more emphasis on the participatory and experiential aspects of the activities. The existing national standard tourism resource classification system does not reflect the characteristics of sports tourism resources, and therefore cannot be applied to the task of classifying regional ethnic traditional sports tourism resources. Therefore, it is necessary to establish a regional ethnic traditional sports tourism resources classification method with unique sports characteristics.

The classification of regional ethnic sports tourism resources facilitates census statistics and helps to capture the quality of the region’s distinctive sports tourism resources. The tourism industry has a long history of development compared to the new sports tourism industry. Research on tourism is also relatively well developed. The dichotomous approach is the most widely used in the classification of tourism resources [15–17]. The dichotomous approach classifies tourism resources into two broad categories, natural and artificial, based on the different attributes of the resources. Although sport tourism resources are a subset of tourism resources, they are somewhat different from traditional tourism resources that focus on landscape. There is no uniform standard for the classification of sports tourism resources. A few common approaches to classifying sports tourism resources are shown in Table 1. Most existing sports tourism resource classifications are manually constructed based on the national standard tourism resource classification system. The efficiency and accuracy of the traditional manual classification is poor and does not reflect the characteristics of regional ethnic traditional sports tourism.

TABLE 1: Methodology for classifying sports tourism resources.

Basis of classification	Type	
Properties	Natural resources	Human culture resources
Purpose	Participatory	Ornamental
Space	Land	Water/air
Function	Leisure	Stimulation

As a fundamental artificial intelligence technique, machine learning algorithms have been widely used in various fields, especially for classification tasks of complex data. Currently, the main machine learning algorithms include multivariate discriminant analysis, logistic regression, decision tree classification, neural networks, genetic algorithms, support vector machines and cluster analysis, among others [18–21]. Srihadi et al. [22] proposed a method for classifying tourism markets based on cluster analysis. The method reveals the behavioural models of four categories of foreign tourists by clustering and analysing the differences in tourists’ lifestyles. At this stage, as the research on artificial intelligence continues to advance, neural networks are developing very rapidly. Neural networks can operate intelligently by mimicking neurons in the human brain. This method is usually used to find the optimal solution, and we usually call it a network that can be fed back. Qin et al. [23] proposed a recursive neural network-based method for classifying tourism resources. Afzaal et al. [24] proposed a machine learning-based method for classifying the sentiment of tourism reviews. It can be seen that machine learning techniques have been used in many applications in the traditional tourism industry. However, after extensive investigation, it was found that no research has been conducted to apply machine learning techniques to the field of sports tourism resource classification.

In summary, the classification of regional ethnic traditional sports tourism resources is a complex issue. The efficiency and accuracy of traditional manual classification are poor and cannot reflect the characteristics of regional ethnic traditional sports tourism. Therefore, this study proposes a machine learning-based method for classifying regional ethnic traditional sports tourism resources. The aim of the research is to use the strong learning and self-adaptive ability of BP neural networks to improve the accuracy and efficiency of the classification of regional ethnic traditional sports tourism resources.

The main innovations and contributions of this study include:

- (1) Taking the development of traditional sports of ethnic minorities in Yunnan Province as the research object, the SWOT analysis, literature, interview, questionnaire, and mathematical and statistical methods were used to investigate and analyse the overall status of the development of traditional ethnic sports in the region.
- (2) Based on the analysis of classification principles, a Quantum Genetic Algorithm BP (QGA-BP) neural network model was proposed by introducing a

probabilistic evolutionary mechanism and applied to the classification of regional ethnic traditional sports tourism resources.

The rest of the study is organized as follows: In Section 2, the research objects and methods are studied in detail, while Section 3 provides the classification method of sports tourism resources based on the QGA-BP neural network model. Finally, the study is concluded in Section 5.

2. Research Subjects and Methods

2.1. Research Objects. This study is based on traditional sports of ethnic minorities in Yunnan Province, China, and surveys and interviews were conducted with local villagers and tourists between May 2018 and October 2019. This study takes sports tourism resources as the research object and completes the task of classifying regional ethnic traditional sports tourism resources based on the principles of classification.

2.2. Research Methodology. The aim of the study was to collect literature on traditional ethnic sports according to the purpose and content of the study, summarise the concepts related to sport tourism resources by analysing the valid information in the literature and establish a classification of ethnic traditional sports tourism resources by combining the existing research results.

Based on expert interviews, the questionnaire was designed according to the principles of the social survey method. For traditional sports in ethnic minority areas, we designed two levels of research questionnaires. The sample distribution of the questionnaire is shown in Table 2. The questionnaires were targeted at local villagers and tourists. A total of 350 questionnaires were distributed, of which 150 were distributed to villagers (Questionnaire A) and 146 were returned, accounting for 97.33%. 200 questionnaires were distributed to tourists (Questionnaire B) and 197 were returned (98.00%).

A split-half reliability test was conducted on the villagers' questionnaire and the tourists' questionnaire, and the correlation coefficients $r_1 = 0.87$ and $r_2 = 0.85$ were obtained. Both exceeded 0.85, indicating good reliability and that the questionnaire met the survey requirements. The calibration process for the split-half reliability test used the Spearman-Brown formula [25–27]:

$$r_{SB} = \frac{2r_{hh}}{1 + r_{hh}}, \quad (1)$$

where r_{SB} indicates the reliability indicator of the whole test after correction and r_{hh} indicates the split-half reliability.

SWOT analysis was introduced by Steiner, an American management professor, in the early 1980s and is one of the common methods of competitive intelligence analysis [28–30]. Through investigation and analysis, the SWOT analysis method can derive Strengths, Weaknesses,

TABLE 2: Distribution of samples.

Object	Number	Number of recoveries	Effective number	Efficient (%)
Villagers	150	146	146	97.33
Tourists	200	197	196	98.00
Total	350	393	342	97.71

Opportunities, and Threats that are closely related to the object of study, and arrange them in a matrix in a certain order, as shown in Figure 1.

Then, using the idea of system analysis, the various factors are matched with each other and a series of corresponding conclusions are drawn through the analysis. The SWOT analysis method consists of the following steps: analysing environmental factors, constructing a SWOT matrix and formulating action strategies. External environmental factors include opportunity factors and threat factors, which are objective factors. Internal environmental factors include strengths and weaknesses, which are subjective factors. The factors are ranked according to their degree of influence and a SWOT matrix is constructed.

In the mathematical and statistical process, SPSS 19.0 statistical software was used to conduct relevant statistics and analysis of the returned questionnaires. The rationale framework for the classification of regional ethnic traditional sports tourism resources is shown in Figure 2.

3. Classification of Sports Tourism Resources Based on QGA-BP Neural Network Model

3.1. Principles of Classification. Sport tourism resources are a resource system consisting of various types of individual resources within a certain area, containing multiple single elements or individual resources, making the types of sport tourism resources more complex. It is important to have a full understanding of the various types of resources as a whole in order to maximise the range of sport tourism resources and thus ensure that the classification system encompasses all categories of sport tourism resources. When classifying sports tourism resources, it is important to ensure that resources in the same category meet the same classification criteria. In classifying, we accurately capture the characteristics of each type of resource so that resources with the same attributes are grouped together.

3.2. Analysis of Classification Indicators. This study uses two levels to build a classification system for sports tourism resources. The first level contains 2 types. Based on the meaning and characteristics of sports tourism resources, they are divided into two broad categories: participative and ornamental. The second level contains 6 categories. Based on the spatial distribution of the resources, the participative sports tourism resources are classified into the categories of geography, water, competition and leisure. Based on the classification of sports tourism, the spectator

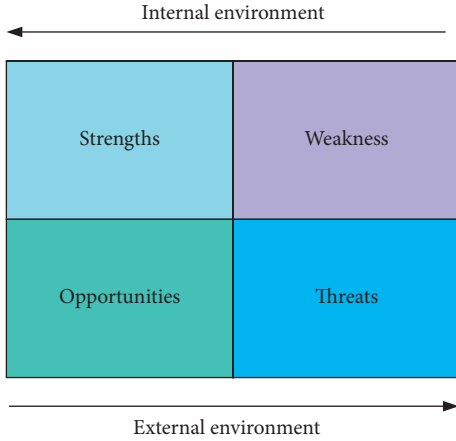


FIGURE 1: Traditional matrix for SWOT analysis.

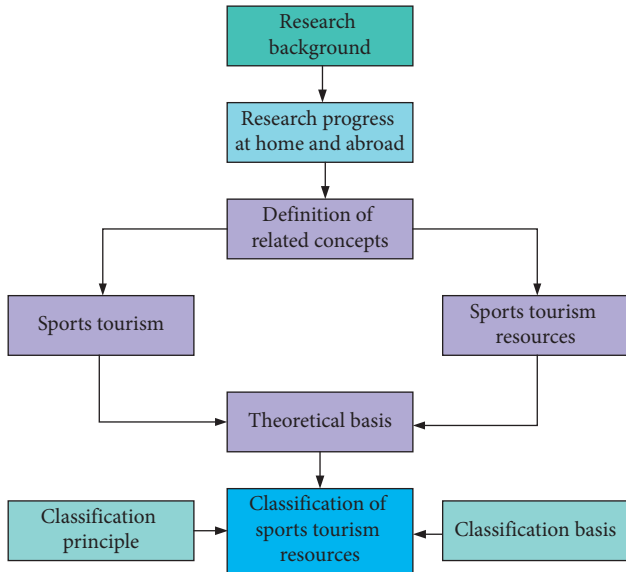


FIGURE 2: Rationale framework for the classification of tourism resources.

sports tourism resources are divided into performance and event categories.

3.3. Quantum Genetic Algorithm QGA. Genetic Algorithm (GA) is a randomised search algorithm [31–33] that seeks optimal solutions by simulating the behaviour of a population of organisms. GA is often used to optimise the weights and thresholds of neural networks. However, in practice, like similar heuristic search algorithms, GA suffers from long search time and low solution accuracy.

QGA is a new optimisation algorithm based on the GA algorithm [34]. Unlike the GA algorithm, QGA introduces the concept of quantum computing. First, the quantum state is considered as a primitive block of information. Then, the quantum states are superimposed. The problem of uncertain polynomial complexity is well solved by the quantum

juxtaposition calculation method. QGA performs the following procedure [35].

Step 1: initialize the quantum population $Q(t_0)$.

Step 2: using quantum collapse operation to deal with population problems. Then, record each solution after the corresponding measurement.

Step 3: a fitness function is used to complete the evolution of the population.

Step 4: if the stop condition is satisfied, the iteration can be exited immediately. Otherwise, the next step will be performed.

Step 5: record each solution of the population $Q(t_0)$ after the iteration.

Step 6: analyse each solution using a fitness function and update the population size using a quantum rotation gate.

Step 7: continue with the iterative process and return to Step 4.

When measuring all individuals in the initial population and selecting the output value according to the probability amplitude of qubits, the quantum state of the QGA is irreversible and therefore the quantum bit encoding reduces the generation of computational errors. In addition, the optimisation of the quantum circuit reduces the negative effects of noise.

3.3.1. Quantum Bit Coding. Each gene in the encoding pattern of quantum bits has n parameters.

$$q_j^t = \left[\begin{array}{c} \alpha_{11}^t | \alpha_{12}^t | \dots | \alpha_{1k}^t | \alpha_{21}^t | \alpha_{22}^t | \dots | \alpha_{2k}^t | \alpha_{n1}^t | \alpha_{n2}^t | \dots | \alpha_{nk}^t \\ \beta_{11}^t | \beta_{12}^t | \dots | \beta_{1k}^t | \beta_{21}^t | \beta_{22}^t | \dots | \beta_{2k}^t | \beta_{n1}^t | \beta_{n2}^t | \dots | \beta_{nk}^t \end{array} \right], \quad (2)$$

where q_j^t denotes the chromosome of individual j in generation t , k denotes the number of quantum bits in a single gene, and n denotes the total number of chromosomes. All quantum bits code $(\alpha, \beta)^T$ of a population individual is initialized to $(1/\sqrt{2}, 1/\sqrt{2})$ such that each chromosome is expressed with equal probability:

$$\varphi_{q_i^t} = \sum_{k=1}^{2^m} \frac{1}{\sqrt{2^m}} |S_k\rangle, \quad (3)$$

where $|S_k\rangle$ is the quantum rotation gate at different quantum bits in a single gene and x_i has a value of 0 or 1.

3.3.2. Quantum Revolving Doors. The adjustment of the quantum revolving door operates is shown as follows [36]:

$$U(\theta_i) = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix}. \quad (4)$$

The update process is shown as follows:

$$\begin{bmatrix} \alpha'_i \\ \beta'_i \end{bmatrix} = U(\theta_i) \times \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}, \quad (5)$$

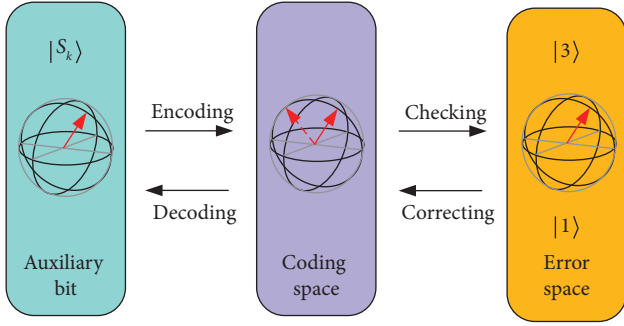


FIGURE 3: Quantum manipulation methods.

where $(\alpha_i, \beta_i)^T$ is the probability amplitude, $(\alpha'_i, \beta'_i)^T$ is the adjusted probability amplitude, and θ_i is the rotation angle. The quantum manipulation method is shown in Figure 3.

3.4. Optimising BP Neural Networks by QGA. Traditional BP neural networks have the disadvantages of slow convergence and falling into local optima. In order to overcome these problems, this study implements sports tourism resource classification through QGA-BP neural networks. Firstly, we optimise the BP network by QGA and set its weights and thresholds. Secondly, in order to make the output value of the optimised BP network model as small as possible close to the solution of the objective function, we search for a better search domain in a specific solution space. The QGA-BP algorithm operates as follows:

Step 1: initialize the population to $Q(t_0) = \{q_1^t, q_2^t, q_3^t, \dots, q_n^t\}$.

Step 2: use the operation of quantum collapse for the initial population. Denote the record of measurements as $P(t_0) = \{p_1^t, p_2^t, p_3^t, \dots, p_n^t\}$, p_i^t denoting the t th measurement for the t th generation of individuals.

Step 3: set the fitness function to $f = 1/E$. $E = \sum_{i=1}^n e_i^2$ is the sum of squares of the errors.

Step 4: keep a record of the fitness value and the best one for each individual in $Q(t_0)$.

Step 5: update the individuals by dynamically adjusting the strategy if the iteration stopping condition is not met.

Step 6: continue with the iterative process, and then jump to Step 2.

3.5. Classification of Sports Tourism Resources. As shown in Figure 4, the sports tourism resource classification method in this study is divided into two modules. The first part is the data pre-processing module, which is responsible for normalising the collected sports tourism resources data. The second part is the QGA-BP module. This module firstly inputs the pre-processed data into the input layer of the neural network and obtains the data features through convolutional processing. The data features are then compared with the desired value. If they do not match the desired result, the output layer will output 0. Otherwise, the network model will continue to be trained until the output layer outputs a result of 1.

4. Experimental Results and Analysis

4.1. Model Setup. A Sigmoid function is used for the transfer function of the QGA-BP neural network model. Meanwhile, the negative gradient function was used for the training function. The data samples we used originated from minority regions in Yunnan Province. Firstly, the dataset was divided equally into 100 groups, each group containing 50 pieces of data. Then, the dataset was treated as a non-linear function. The number of hidden layer neurons in the QGA-BP neural network model was determined by an empirical formula:

$$M = \sqrt{I + O} + a, \quad (6)$$

where a is a constant between 1 and 10. After 200 training sessions, the target error of the three-layer structure of the neural network is 10^{-10} . The length of the chromosomes of the QGA is $5 \times 10 + 10 \times 2 + 10 + 2 = 82$, i.e. 82 variable parameters. The bit number for each variable parameter of the QGA is 20, and the range is $[-1, 1]$. The total number of populations of the QGA is 20.

4.2. Model Performance Validation. The simulation was completed in a laptop computer with a central processor of Intel(R) i5-9300H CPU@2.40 GHz 2.40 GHz and a graphics card of NVIDIA GeForce GTX 1050. The simulation software is MATLAB 2019b. After 1000 iterations, the output results of the two models are shown in Figures 5 and 6 respectively.

The experimental results show that the QGA-BP model has the advantages of fast convergence and being less likely to fall into a local optimum solution. After 4 s of time, the fitness value of the individuals gradually increased. After 6 s, the individual fitness values continue to be optimised. After 9 s, the fitness value of the individual basically stabilises. It can be seen that the optimal fitness value of the QGA-BP model is significantly better than that of the traditional GA-BP model, and is more suitable for application in the classification of sports tourism resources.

The root mean square errors of the two models over 16 iterations are shown in Figures 7 and 8, respectively.

We can see that the training errors of both models show a linear decline from the beginning, but the decline is faster for QGA-BP. When the number of iterations was 15, the training error was consistent with the target error. This is because the GA-BP neural network model fluctuates greatly in the training process, so it cannot reach the required accuracy quickly.

4.3. Practical Case Studies. The GA-BP model and QGA-BP model were used to classify 30 sets of samples in the test dataset respectively. The classification errors of the traditional sports tourism resources with 10 sets of sample data are shown in Table 3.

Overall, the QGA-BP model was able to achieve the predicted results when applied to the traditional sports tourism resource classification, overcoming the problem of

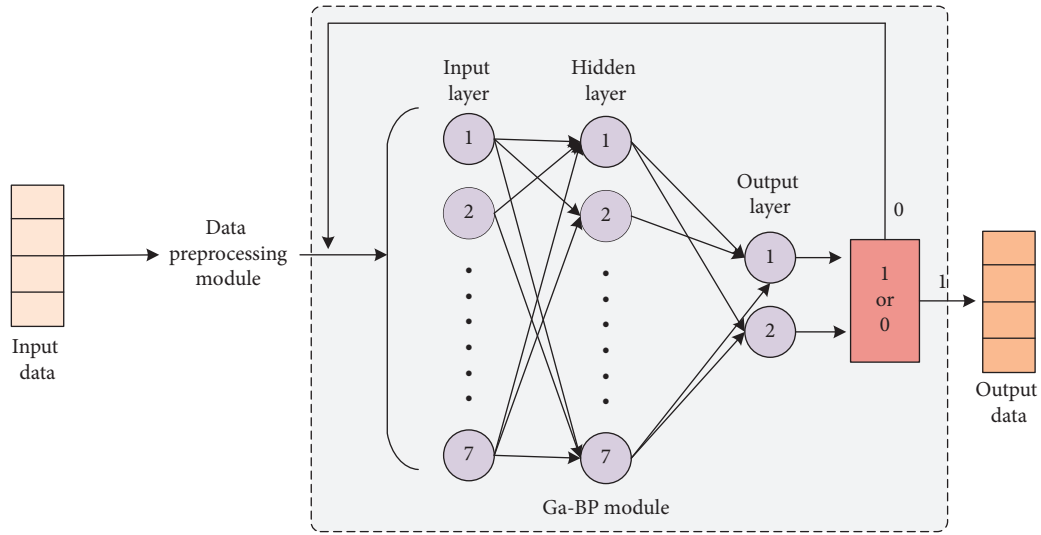


FIGURE 4: Traditional sports tourism resource classification based on QGA-BP neural network.

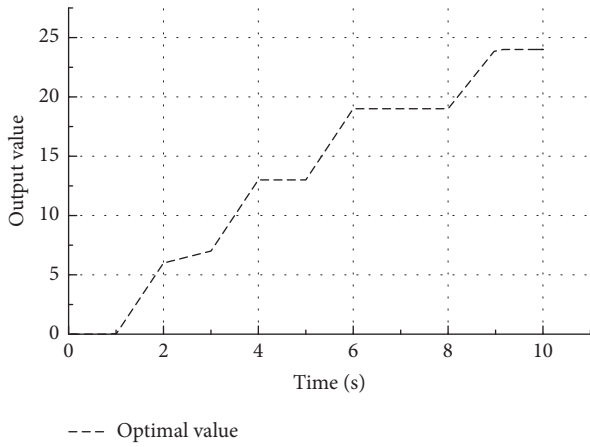


FIGURE 5: Output values of the QGA-BP neural network model.



FIGURE 7: Root mean square error of QGA-BP.

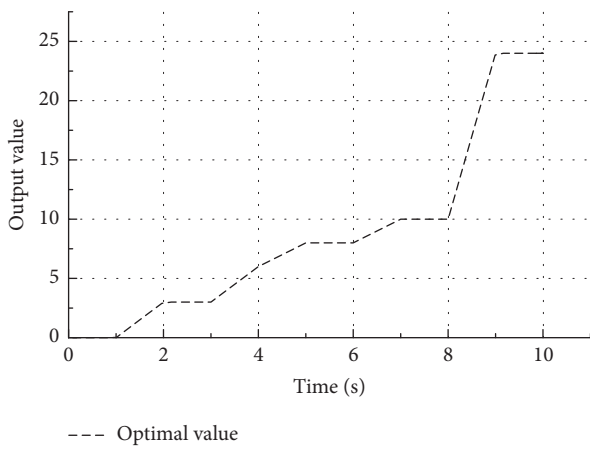


FIGURE 6: Output values of the GA-BP neural network model.



FIGURE 8: Root mean square error of GA-BP.

TABLE 3: Classification errors of traditional sports tourism resources.

Data	GA-BP	QGA-BP
Group 1	0.38273833	0.23973934
Group 2	0.38497236	0.2382949
Group 3	0.98736224	0.87469329
Group 4	0.82923224	0.57392474
Group 5	0.84739427	0.7329424
Group 6	0.04874424	0.0328294
Group 7	0.49482922	0.3928329
Group 8	0.12334422	0.0928372
Group 9	0.22455993	0.1039482
Group 10	0.39283244	0.2828492

TABLE 4: Classification of traditional ethnic sports tourism resources in Yunnan province.

Main category	Subcategory	Test sample of sports tourism resources	Number
Participative	Geography	Group 1, group 5, group 7	3
	Water	Group 6, group 8	2
	Competition	Group 2, group 3, group 4, group 10, group 11, group 12, group 14, group 15, group 16, group 20, group 22, group 23, group 25	13
	Leisure	Group 26, group 27, group 28, group 30	4
Ornamental	Performance	Group 9, group 13, group 17, group 18, group 21	5
	Event	Group 19, group 24, group 29	3

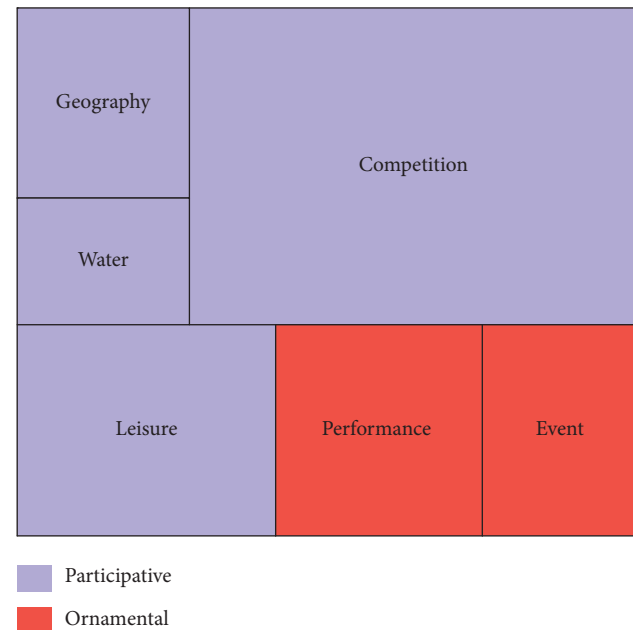


FIGURE 9: Tree diagram of classification results.

TABLE 5: Effect of the number of neurons in the hidden layer on the network model.

Number of neurons in the hidden layer	Classification errors
120	0.48736224
240	0.19036288
480	0.05672872
600	0.09726538
1024	0.12937344

the GA-BP model where large fluctuations in training error can occur.

The representative minority traditional sports tourism resources in Yunnan Province were collected and the collected resources were classified according to the proposed sports tourism resource classification method, and the statistical results are shown in Table 4 and Figure 9.

4.4. Neuronal Ablation Experiments. Because there are a large number of neurons in the hidden layer, a reasonable design of the number of neurons can not only reduce the amount of computation, but also help to improve the accuracy of sports tourism resource classification. Therefore, a large number of ablation experiments were done for how to set the number of neurons, and the experimental results are shown in Table 5.

In order to investigate the effect of the number of neurons per layer on the QGA-BP model, different numbers of neurons were chosen: 120, 240, 480, 600 and 1024. The results showed that when the number of neural units was too small, the network did not have enough fitting ability, which led to too large a classification error. As the number of hidden layers continues to increase, the classification error gradually decreases. However, an increase in the number of neurons leads to an increase in the time required for training. Therefore, in the QGA-BP neural network, we set the number of units per layer to 480.

5. Conclusion

This study uses QGA to optimise the BP network and applies it to the classification of traditional sports tourism resources. Taking the development of traditional sports of ethnic minorities in Yunnan Province as the research object, the SWOT analysis method, literature method, interview method, questionnaire method and mathematical statistics method are used to investigate and analyse the overall status of the development of regional ethnic traditional sports. The validity of the proposed QGA-BP model was verified through the sports tourism data obtained from the minority regions in Yunnan Province. The QGA-BP model effectively improves the accuracy of the classification of traditional sports tourism resources. Subsequent attempts will be made to apply the QGA-BP model to areas such as corporate finance and disaster risk assessment, so as to further verify its applicability and robustness.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

Acknowledgments

The study was supported by “the National Social Science Fund of China, China (Grant no. 2020CTY002)” and “Fundamental Research Funds for the Central Universities, China (Grant no. 2020NTSS08).”

References

- [1] L. E. Pedauga, A. Pardo-Fanjul, J. C. Redondo, and J. M. Izquierdo, “Assessing the economic contribution of sports tourism events: a regional social accounting matrix analysis approach,” *Tourism Economics*, vol. 28, no. 3, pp. 599–620, 2022.
- [2] C. C. Yang, C. C. Shen, Y. S. Lin, H. W. Lo, and J. Z. Wu, “Sustainable sports tourism performance assessment using grey-based hybrid model,” *Sustainability*, vol. 13, no. 8, p. 4214, 2021.
- [3] R. W. Pouder, J. D. Clark, and G. G. Fenich, “An exploratory study of how destination marketing organizations pursue the sports tourism market,” *Journal of Destination Marketing & Management*, vol. 9, pp. 184–193, 2018.
- [4] Y. Chen and Y. Chi, “Harnessing structures in big data via guaranteed low-rank matrix estimation: recent theory and fast algorithms via convex and nonconvex optimization,” *IEEE Signal Processing Magazine*, vol. 35, no. 4, pp. 14–31, 2018.
- [5] G. R. Burmester, “Rheumatology 4.0: big data, wearables and diagnosis by computer,” *Annals of the Rheumatic Diseases*, vol. 77, no. 7, pp. 963–965, 2018.
- [6] E. Koc, “Risk and safety management in the leisure, events, tourism and sports industries,” *Tourism Management*, vol. 54, pp. 296–297, 2016.
- [7] Y. Zhu and X. Liu, “Big data visualization of the quantification of influencing factors and key monitoring indicators in the refined oil products market based on fuzzy mathematics,” *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 4, pp. 6219–6229, 2021.
- [8] X. -L. Meng, “Statistical paradises and paradoxes in big data (I): law of large populations, big data paradox, and the 2016 US presidential election,” *Annals of Applied Statistics*, vol. 12, no. 2, pp. 685–726, 2018.
- [9] G. Tsekouropoulos, O. Gkouna, D. Theocharis, and A. Gounas, “Innovative sustainable tourism development and entrepreneurship through sports events,” *Sustainability*, vol. 14, no. 8, Article ID 4379, 2022.
- [10] S. Shin, W. Chiu, and H. W. Lee, “For a better campus sporting experience: scale development and validation of the collegiate sportscape scale,” *Journal of Hospitality, Leisure, Sports and Tourism Education*, vol. 22, pp. 22–30, 2018.
- [11] J. J. Yang, H. W. Lo, C. S. Chao, C. C. Shen, and C. C. Yang, “Establishing a sustainable sports tourism evaluation framework with a hybrid multi-criteria decision-making model to explore potential sports tourism attractions in taiwan,” *Sustainability*, vol. 12, no. 4, Article ID 1673, 2020.
- [12] E. Vayena and A. Blasimme, “Health research with big data: time for systemic oversight,” *Journal of Law Medicine & Ethics*, vol. 46, no. 1, pp. 119–129, 2018.
- [13] S. Nadal, O. Romero, A. Abelló, P. Vassiliadis, and S. Vansummeren, “An integration-oriented ontology to govern evolution in Big Data ecosystems,” *Information Systems*, vol. 79, no. 9, pp. 3–19, 2019.
- [14] Y. Cao, H. Song, O. Kaiwartya et al., “Mobile edge computing for big-data-enabled electric vehicle charging,” *IEEE Communications Magazine*, vol. 56, no. 3, pp. 150–156, 2018.
- [15] L. Laing, M. Piekarz, I. Jenkins, and P. Mills, “Risk and safety management in the leisure, events, tourism and sports industries,” *Sport Management Review*, vol. 22, no. 2, pp. 288–289, 2019.
- [16] P. Cichosz, “Unsupervised modeling anomaly detection in discussion forums posts using global vectors for text representation,” *Natural Language Engineering*, vol. 26, no. 5, pp. 551–578, 2020.
- [17] Y. Bao, Z. Tang, H. Li, and Y. Zhang, “Computer vision and deep learning-based data anomaly detection method for structural health monitoring,” *Structural Health Monitoring*, vol. 18, no. 2, pp. 401–421, 2019.
- [18] L. Shi, Y. Zhu, Y. Zhang, and Z. Su, “Fault diagnosis of signal equipment on the lanzhou-xinjiang high-speed railway using machine learning for natural language processing,” *Complexity*, vol. 2021, no. 8, Article ID 9126745, 13 pages, 2021.
- [19] S. Talukdar, M. W. Naikoo, J. Mallick et al., “Coupling geographic information system integrated fuzzy logic-analytical hierarchy process with global and machine learning based sensitivity analysis for agricultural suitability mapping,” *Agricultural Systems*, vol. 196, pp. 103343–103351, 2022.
- [20] V. Landa, Y. Shapira, M. David et al., “Accurate classification of fresh and charred grape seeds to the varietal level, using machine learning based classification method,” *Scientific Reports*, vol. 11, no. 1, pp. 13577–13615, 2021.
- [21] M. Tamal, M. Alshammari, M. Alabdullah, R. Hourani, H. A. Alola, and T. M. Hegazi, “An integrated framework with machine learning and radiomics for accurate and rapid early diagnosis of COVID-19 from Chest X-ray,” *Expert Systems with Applications*, vol. 180, Article ID 115152, 2021.
- [22] T. F. Srihadi, S. D. Hartoyo, D. Sukandar, and A. W. Soehadi, “Segmentation of the tourism market for Jakarta: classification of foreign visitors’ lifestyle typologies,” *Tourism Management Perspectives*, vol. 19, pp. 32–39, 2016.
- [23] Q. Li, S. Li, J. Hu, S. Zhang, and J. Hu, “Tourism review sentiment classification using a bidirectional recurrent neural network with an attention mechanism and topic-enriched word vectors,” *Sustainability*, vol. 10, no. 9, Article ID 3313, 2018.
- [24] M. Afzaal, M. Usman, and A. Fong, “Tourism mobile app with aspect-based sentiment classification framework for tourist reviews,” *IEEE Transactions on Consumer Electronics*, vol. 65, no. 2, pp. 233–242, 2019.
- [25] I. Van Heerden and A. Bas, “Viewpoint: AI as author - bridging the gap between machine learning and literary theory,” *Journal of Artificial Intelligence Research*, vol. 71, pp. 175–189, 2021.
- [26] B. D. M. Lopes, L. C. B. Silva, I. M. Blanquet, P. Georgieva, and C. A. F. Marques, “Prediction of fish mortality based on a probabilistic anomaly detection approach for recirculating aquaculture system facilities,” *Review of Scientific Instruments*, vol. 92, no. 2, Article ID 025119, 2021.

- [27] J. Kadupitiya, F. Sun, G. C. Fox, and V. Jadhao, "Machine learning surrogates for molecular dynamics simulations of soft materials," *Journal of Computational Science*, vol. 42, Article ID 101107, 2020.
- [28] L. Silva, M. Coutinho, and C. Santos, "Hardware architecture proposal for TEDA algorithm to data streaming anomaly detection," *IEEE Access*, vol. 9, pp. 103141–103152, 2021.
- [29] K. S. Rallis, C. R. Hillyar, M. Sideris, and J. K. Davies, "T-cell-based immunotherapies for haematological cancers, Part A: a SWOT analysis of immune checkpoint inhibitors (ICIs) and bispecific T-cell engagers (BiTEs)," *Anticancer Research*, vol. 41, no. 3, pp. 1123–1141, 2021.
- [30] K. Almutairi, S. J. Hosseini Dehshiri, S. S. Hosseini Dehshiri, A. Mostafaepour, A. X. Hoa, and K. Techato, "Determination of optimal renewable energy growth strategies using SWOT analysis, hybrid MCDM methods, and game theory: a case study," *International Journal of Energy Research*, vol. 46, no. 5, pp. 6766–6789, 2022.
- [31] I. Apostol, M. Preda, C. Nila, and I. Bica, "IoT botnet anomaly detection using unsupervised deep learning," *Electronics*, vol. 10, no. 16, p. 1876, 2021.
- [32] S. Emiroglu and Y. Uyaroglu, "Genetic algorithm (GA)-based delay feedback control of chaotic behavior in the voltage mode controlled direct current (DC) drive system," *Zeitschrift für Naturforschung A*, vol. 76, no. 1, pp. 13–21, 2021.
- [33] A. Y. Prasad and B. Rayanki, "A generic algorithmic protocol approaches to improve network life time and energy efficient using combined genetic algorithm with simulated annealing in MANET," *International Journal of Intelligent Unmanned Systems*, vol. 8, no. 1, pp. 23–42, 2020.
- [34] L. Xu, S. Zhao, N. Li, Q. Gao, T. Wang, and W. Xue, "Application of QGA-BP for fault detection of liquid rocket engines," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 55, no. 5, pp. 2464–2472, 2019.
- [35] S. Klembt, "Light detection nears its quantum limit," *Nature*, vol. 597, no. 7877, pp. 483–484, 2021.
- [36] H. Bao and W. Wang, "Canonical bases arising from quantum symmetric pairs of Kac–Moody type," *Compositio Mathematica*, vol. 157, no. 7, pp. 1507–1537, 2021.