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Intelligent Evaluation of Tourism Competitiveness Based on Improved Lenet-5 Network Model

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Abstract. *Mining and analysing tourism data through AI technology can reveal information on tourism market trends, tourists' preferences, market segmentation, etc., and help tourism practitioners make more scientific and precise decisions. At present, the research on tourism competitiveness evaluation based on artificial intelligence is still in the primary stage. Therefore, this work proposes an intelligent evaluation method of regional tourism competitiveness based on improved convolutional neural network. Firstly, the competitiveness theory is introduced into the field of regional tourism research, and the competitiveness evaluation index is constructed based on Porter's industrial competitiveness theory. Second, the LeNet-5 convolutional neural network model is improved in several aspects such as hidden layer, convolutional kernel and activation function in order to improve the recognition accuracy and solution speed of the LeNet-5 model. A smaller serial convolutional kernel is used to replace the convolutional kernel in the C3 layer of the Le Net-5 network. Replacing the Sigmoid activation function with the ReLU activation function. The S4 pooling layer of the LeNet-5 convolutional neural network is modified using Spatial Pyramid Pooling. Finally, Matlab 7.0 software is used to implement the regional tourism industry competitiveness evaluation model based on the improved LeNet-5. The experimental results show that the improved LeNet-5 network model performs well in the comprehensive competitiveness analysis of 20 provinces, which verifies its effectiveness.*
Keywords: Tourism competitiveness; LeNet-5; Convolutional neural network; Activation function; Spatial pyramid pooling

1. **Introduction.** In recent years, with the transformation and upgrading of the regional economy, many new regional tourism industries have emerged, which have greatly promoted the development of regional industries. The economic, social, ecological and cultural benefits of regional tourism industry have been increasing, and it has become an important part of national economic development [1,2]. Regional tourism is part of the service industry and is a feasible path to achieve regional revitalisation [3,4].In the first half of 2019, the total number of trips to regional tourism in China reached 1.51 billion, an increase of 10.2% year-on-year. The total revenue was 0.86 trillion yuan, an increase

of 11.7% year-on-year. By the end of June 2019, the total number of people employed in China's regional tourism was 8.86 million, an increase of 7.6% year-on-year.

Regional tourism industry is an organic combination of agriculture and tourism, which can reconfigure regional resources and at the same time broaden farmers' income channels [5,6]. In recent years, regional tourism has become a new focus of global tourism development. The study of regional tourism industry competitiveness has also received extensive attention from academics [7,8]. Tourism competitiveness is affected by a number of factors, including tourism resources, industrial chain, transport facilities, and cultural heritage. Traditional evaluation methods may not be able to fully consider these complex factors. The neural network model, however, can consider the association and weight of each factor at the same time, and assess the comprehensive performance of tourism competitiveness in a more comprehensive way.

Neural network models excel in handling large-scale data. In tourism competitiveness evaluation, various data indicators can be used, such as historical tourism data, economic indicators, and environmental data. Neural network models can effectively process and analyse these large-scale data to mine potential correlations and trends [9,10,11]. Neural network models can be used for forecasting and planning based on historical data. By assessing tourism competitiveness, it can provide reference and guidance for future tourism development. The model can predict the impact of different policies and development directions on tourism competitiveness based on historical data and trends, and provide a basis for decision makers to formulate development strategies [12,13].

In conclusion, the use of neural network models for tourism competitiveness evaluation can provide more accurate and comprehensive evaluation results, help decision makers make more scientific decisions, and provide reference and guidance for future tourism planning.

1.1. **Related Work.** In the traditional view, the primary influences on the competitiveness of the regional tourism industry [14,15] include government policies, economic structural factors and traditional culture, and the secondary influences [16] include institutional management and infrastructure.

Recently, Lacroix et al. [17] constructed a competitiveness evaluation model for the regional tourism industry using hierarchical analysis and concluded that the competitiveness of the regional tourism industry is affected by a combination of factors. Long et al. [18] analysed the main sources of the competitiveness of the tourism industry by using principal component analysis. Butnaru and Haller [19] used an explanatory-structural model to analyse the degree of influence and logical relationship of factors in the regional tourism industry. structural model to analyse the degree of influence and logical relationship of factors in regional tourism industry. Petrović et al. [20] integrated the competitiveness diamond model into the study of competitiveness enhancement of regional tourism industry, and concluded that the enhancement of competitiveness of regional tourism industry in the new era requires the integration of resources and the play of economies of scale.

Existing mainstream methods in the evaluation of competitiveness include [21,23]: principal component analysis, Analytic Network Process (ANP), fuzzy comprehensive evaluation, factor analysis, multiple judgement and packet structure analysis. Each evaluation method has its advantages and disadvantages. In the evaluation research of competitiveness, it is necessary to select suitable evaluation methods according to different objects in different industries [24,25]. Suitable evaluation methods are selected for different objects in different industries. With several contributing elements and a complicated, non-linear interaction between them, regional tourism is a complex, changeable system, therefore, there are certain shortcomings in applying the above methods to assess competitiveness, such as excessive subjectivity and difficult to clarify the boundaries. Artificial neural networks are a successful approach to solving complicated nonlinear systems [26,27]. Due to the characteristics of nonlinear mapping, self-learning and self-adaptation, artificial neural networks can approximate any continuous function according to arbitrary accuracy, and thus are widely used in the research fields of enterprise competitiveness, brand competitiveness, urban competitiveness, and so on.

Convolutional Neural Network (CNN) is a mathematical model that mimics the synapses of the brain and is a representative algorithm for artificial neural networks [28,29]. The LeNet-5 convolutional neural network, proposed by computer scientist Yann LeCun, is one of the earliest CNNs and has had a profound impact on the development of CNNs. A typical LeNet-5 network model consists of a seven-layer neural network structure with convolutional, pooling, fully connected, and output layers [30,31]. As a convolutional neural network, LeNet-5 has a broad application prospect. Various CNN models have been developed on the basis of LeNet-5, such as AlexNet, GoogLeNet, etc., all of which have gained wide recognition and applications.

1.2. **Motivation and contribution.** The purpose of this study is to determine the degree of influence of various key factors through the LeNet-5 network model, so as to construct a comprehensive evaluation system and evaluation model for the competitiveness of the regional tourism industry. There are relatively few studies on LeNet-5 in the field of tourism, so this paper chooses LeNet-5 to conduct a comprehensive evaluation study on the competitiveness of regional tourism. tourism competitiveness to conduct a comprehensive evaluation study. Using the evaluation model based on the improved LeNet-5, the competitiveness of regional tourism industry in Shaanxi Province is compared and analysed with other provinces. The results show that the regional tourism industry in Shaanxi Province has the advantages of abundant natural resources, sound soft service industry and perfect health care, while the shortcomings are the shortage of human resources, weak auxiliary industry, insufficient policy investment and limited potential demand.

The main innovations and contributions of this paper include:

(1) Introducing the competitiveness theory into the field of regional tourism research, and based on Porter's theory of industrial competitiveness, comprehensively screening out the variable indicators that have a significant impact on the competitiveness of the regional tourism industry, and constructing a comprehensive evaluation index system of regional tourism competitiveness.

(2) Based on the original LeNet-5 convolutional neural network model, several aspects such as hidden layer, convolution kernel and activation function are improved in order to improve the recognition accuracy and solution speed of the LeNet-5 model. Matlab 7.0 software is used to implement the regional tourism industry competitiveness evaluation model based on the improved LeNet-5, so as to reflect the comprehensive competitiveness of different regions more comprehensively and objectively.

2. **Relevant concepts.**

2.1. **Definition of regional tourism.** There is no uniform definition of the concept of regional tourism. By analysing the existing research results, this paper will define regional tourism as a special tourism activity.

This type of tourism activity is based on idyllic landscapes, folk traditions, farm life, agricultural production and handicrafts, and targets urban dwellers as a source of customers. The main feature of regional tourism is the difference between urban and rural areas. Regional tourism encompasses a wide range of aspects such as entertainment, leisure, holiday, convalescence, popular science and gastronomy. An industry is a form of organisation between a macroeconomic subject (the state) and a microeconomic subject (the enterprise or the individual). The competitiveness of an industry is the ability of an industrial entity to develop and occupy a market under certain trade conditions and thus gain more revenue than its competitors.

Regional tourism in the narrow sense refers to the tourism hospitality service industry in regional areas, which mainly covers regional accommodation, transport and entertainment, and retailing of local speciality products. In a broader sense, regional tourism includes other ancillary industries such as transport and logistics, tourist visas, security and health throughout the region.

2.2. **Principles of competitiveness evaluation.** There are many theories about industrial competitiveness, among which the "diamond model" proposed by Professor Michael Porter is widely circulated and has the highest degree of application, and is also the theoretical basis adopted in this paper.

Professor Michael Porter's "diamond model" includes four internal determinants and two external determinants. The four internal determinants are the company's strategic structure and peer competition, demand conditions, factors of production and related and supporting industries, and the two external forces are opportunities and government, as shown in Figure 1, where the combination and dynamics of these six factors determine the source, strength and future potential of industrial competitiveness.

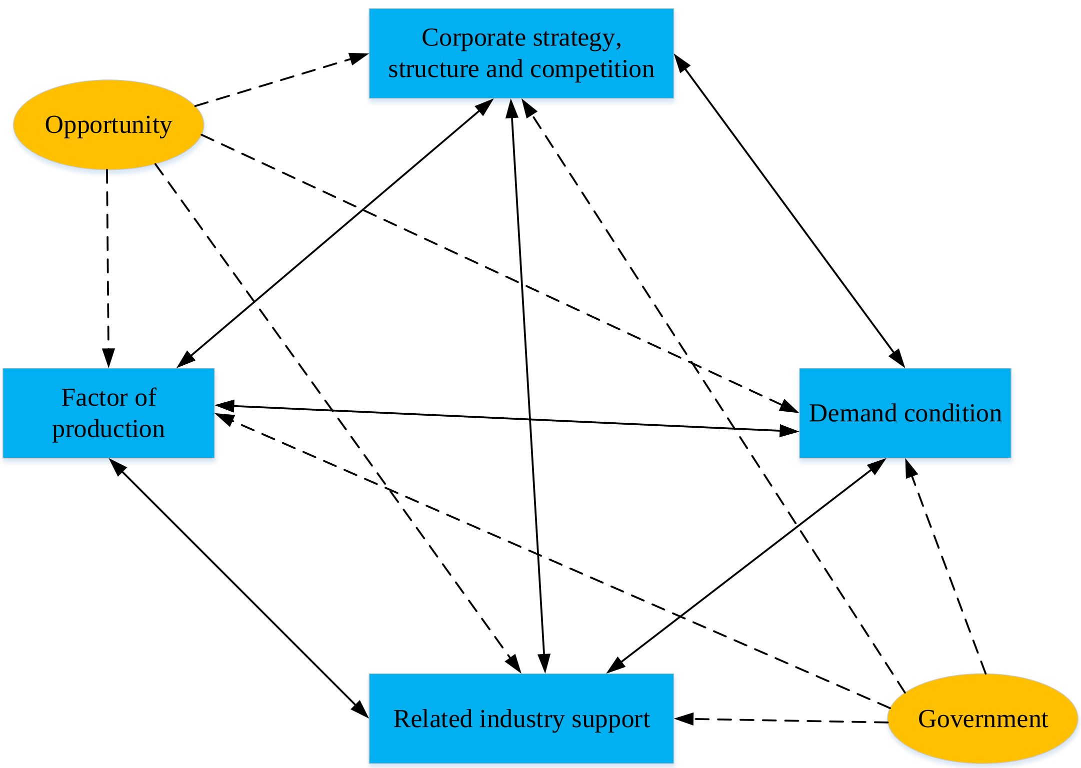

Figure 1. Porter's Diamond Model

Tourist destination life cycle theory was firstly put forward by Christaller, a German scholar, who observed that the development of European tourist destinations generally experienced three stages: discovery, growth and decline. Later, Canadian scholar R W Butler deepened and expanded this theory, and put forward the "six-stage theory" in

1980, believing that the development of tourist destinations should go through the exploration stage, participation stage, development stage, consolidation stage, stagnation stage and decline stage. As shown in Figure 2, tourist destinations show different characteristics and regulations in different life cycle stages. In the process of operation enterprises should focus on the ability to vary with the surrounding conditions, and at the same time constantly adjust their own internal organisational structure and corporate culture. The theory has a strong guiding significance for the transformation and upgrading of some age-old tourist places.

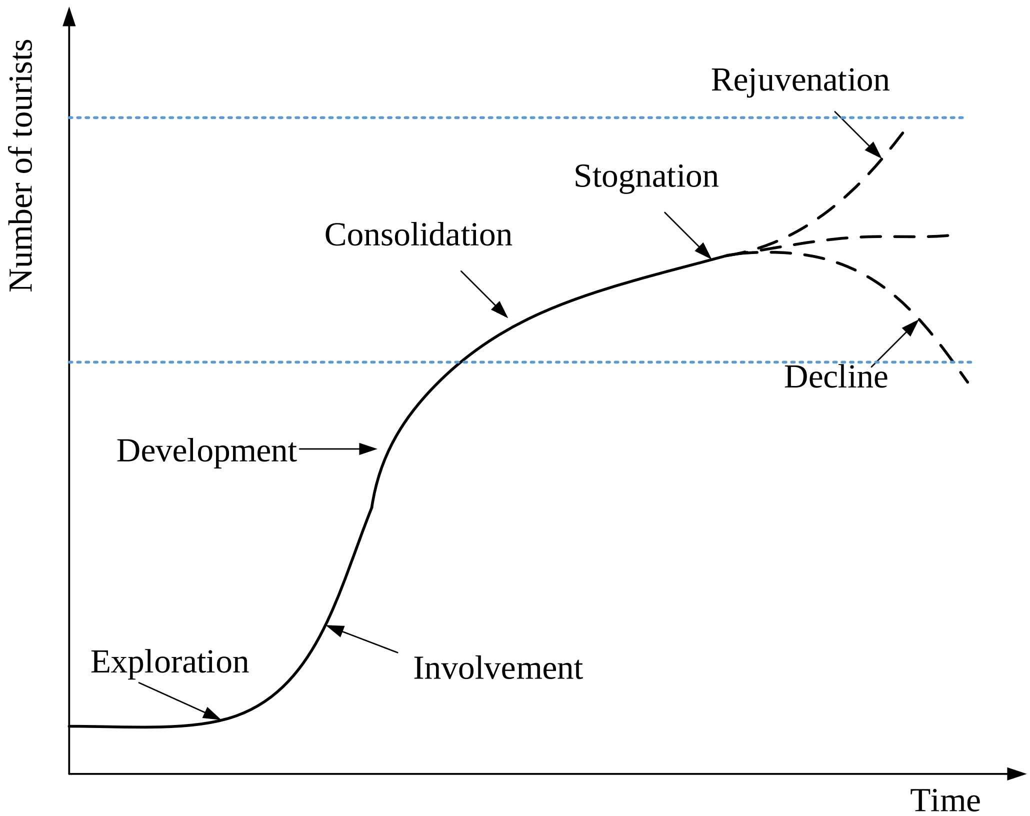

Figure 2. S-curve of Butler's life cycle theory of tourism

The IMD Regional Competitiveness Evaluation Model (IMD) is a model for assessing national competitiveness proposed in 1989 by the World Economic Forum and the International School of Management in Lausanne, Switzerland.IMD measures the ability of a country's wide range of firms to capture more wealth in the global marketplace. Each factor now includes five sub-factors.

As a relatively mature way of assessing comprehensive regional competitiveness, the IMD model requires the use of a large number of statistical data and questionnaires. However, the theory believes that the superposition of industrial competitiveness is national competitiveness, thus ignoring the two-way influence of industrial structure and organisational form on enterprises, and therefore cannot be directly applied in the evaluation of tourism competitiveness.

3. **Evaluation of indicators.**

3.1. **Principles of indicator construction.** In order to ensure that the evaluation of the competitiveness of the regional tourism industry is more accurate, objective and fair,

this paper, based on the Porter's diamond theory, follows certain principles and chooses the factor analysis method to collect data with typical representative indicators.

The competitiveness of the regional tourism industry is a comprehensive system involving a wide range of complex and varied contents, so on the premise of not exceeding the scope of the connotation, the regional tourism competitiveness indicator system must reflect as comprehensively as possible the influencing factors and their intrinsic correlation with each other. In the process of selecting evaluation indicators, the control samples selected should be comparable. At the same time, the selection of evaluation indicators should be feasible, that is to say, indicators with practical value should be selected.

3.2. **Description of indicator selection.** This work refers to the existing research results and combines the representativeness and feasibility to construct tourism competitiveness evaluation indicators, as shown in Table 1.

Table 1. Indicators for assessing tourism competitiveness

Level1 indicators	Secondary indicators	Tertiary indicators
Competitiveness of the regional tourism industry	Factor of production F1	Natural resources Z11 Human resources Z12
	Market demand F2	Existing size Z21 Potential demand Z22
	Ancillary industries F3	Catering & Accommodation Z31 Medical transport Z32
	Industrial Management F4	Infrastructure Z41
	Government Opportunities F5	Government investment Z51 Development Opportunities Z52

In terms of factors of production, there are two main components: natural resources (Z11) and human resources (Z12). In terms of market demand, it is mainly divided into two parts: existing scale (Z21) and potential demand (Z22). Considering the difficulty of data acquisition, the two parts of catering and accommodation (F31) and medical transport (F32) are mainly selected in the aspect of auxiliary industries. In order to adapt to the actual situation of regional tourism, this paper combines the government's role and opportunity analysis in Porter's diamond theory into one, and uses the amount of investment in fixed assets (X28) and the amount of financial loans (X29) to characterise the degree of government's financial support for regional tourism development.

4. Intelligent evaluation method based on improved LeNet-5 network.

4.1. **Selection of evaluation methods.** Existing mainstream methods in the evaluation of competitiveness include: principal component analysis, ANP, fuzzy comprehensive evaluation, factor analysis, multiple judgement and packet structure analysis. Each evaluation method has its advantages and disadvantages.

In competitiveness evaluation research, it is necessary to select suitable evaluation methods for different objects in different industries. It is important to choose an appropriate assessment technique for the industry and the desired outcome. To further complicate matters, the link between these elements is neither simple or linear, and regional tourism is in and of itself a complex and changeable system. Therefore, there are certain shortcomings in applying the above methods to assess competitiveness, such as excessive subjectivity and difficulty in defining the boundaries.

An efficient way to tackle complex nonlinear problems is to use artificial neural networks. Due to the characteristics of nonlinear mapping, self-learning and self-adaptation, artificial neural networks can approximate any continuous function according to any accuracy, so they are widely used in the research fields of enterprise competitiveness, brand competitiveness, urban competitiveness and so on. There are relatively few scholars who study artificial neural networks in the field of tourism, so the article decides to carry out a thorough analysis of regional tourist competitiveness studies using the LeNet-5 neural network. Matlab 7.0 software is used to implement the regional tourism industry competitiveness evaluation model based on improved LeNet-5.

4.2. **LeNet-5 convolutional neural network.** LeNet-5 model was proposed by Professor Yann LeCun in 1998 as a convolutional neural network base model. The model has a 7-layer structure and is capable of implementing functions such as convolution, pooling, and integrating information. The LeNet-5 model structure [32] is shown in Figure 3.

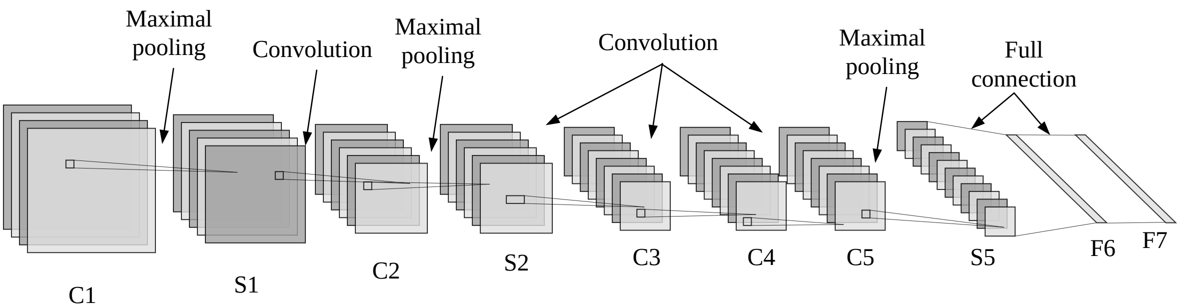

Figure 3. Structure of LeNet-5 convolutional neural network

Le Net-5 model structure in which C stands for convolutional layer, S stands for pooling layer and F stands for fully connected layer. each neuron on layer C1 is connected to a neighbourhood of the input. layer S2 is is is a pooling layer obtained by sampling from layer C1. layer C3 is connected as shown in Table 2. each neuron in layer F6 is connected to all the neurons in the previous layer.

Table 2. Connection method of C3 layer

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
0	×				×	×	×			×	×	×	×		×	×
1	×	×				×	×	×			×	×	×	×		×
2	×	×	×				×	×	×			×		×	×	×
3		×	×	×			×	×	×	×			×		×	×
4			×	×	×			×	×	×	×		×	×		×
5				×	×	×			×	×	×	×		×	×	×

Convolutional operations that enhance the original signal characteristics and reduce noise.

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} W_{ij}^l + b_j^l\right) \tag{1}$$

where l represents the layer, W represents the convolutional kernel weight parameter, M_j represents a selection of input features, and b represents the bias.

The aggregation of feature types is performed during the downsampling operation to reduce the spatial dimensions and thus mitigate the occurrence of overfitting. If the number of input features is n, the number of features after the downsampling layer may be less than or equal to n and the size of the output features will be smaller.

$$x_j^l = f\left(\text{down}\left(x_j^{l-1}\right) + b_j^l\right) \tag{2}$$

In the fully connected operation, a single neuron in the fully connected layer is connected to all neurons in the previous layer. The fully-connected layer integrates the class-distinctive local information from the convolutional and pooling layers and converts the feature information into a one-dimensional vector. Finally, the output of the fully connected layer is passed to the output layer.

4.3. **Improvement of LeNet-5.** In order to model the reduction of computation and training time, Le Net-5 convolutional neural network is improved in this paper. The structure of the improved Le Net-5 convolutional neural network model is shown in Figure 4.

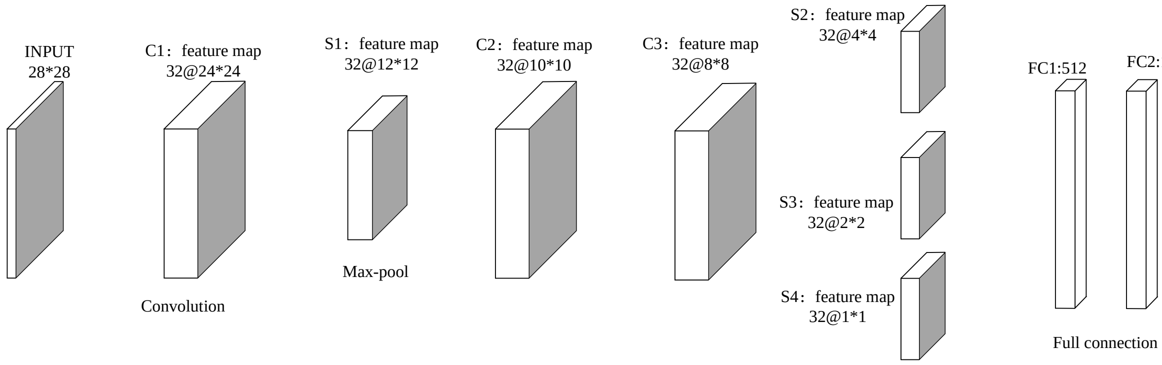

Figure 4. Structure of improved LeNet-5 convolutional neural networks

Firstly, a smaller serial convolutional kernel is used to replace the convolutional kernel at layer C3 in the Le Net-5 network. The 5*5 size convolutional kernel is replaced by two 3*3 size convolutional kernels. The computational complexity of different convolutional kernels is shown in Table 3.

Table 3. The number of parameters with different convolutional core size

	First 3*3 convolutional kernel	**Second 3*3 convolutional kernel**	**5*5 convolutional kernel**
Number of parameters	234	216	600

It can be seen that the number of parameters for convolutional computation using two 3*3 convolutional kernels is less compared to using one 5*5 convolutional kernel. At the same time, the number of network layers increases when a smaller convolution kernel is used instead of the original convolution kernel. The increase in the number of network layers helps to improve the accuracy of the model classification. Adding an activation function after the additional convolutional layers also improves the nonlinear capability of the model and facilitates the fitting of more complex functions.

The probability of a convolutional layer with respect to a single hidden neuron is:

$$P(v,h) = e^{-E(v,h)} \tag{3}$$

where $E(v,h)$ represents the energy function, consistent with the Bernoulli distribution.

$$E(v,h) = -\sum_{j=1}^{m} b_j v_j - \sum_{i=1}^{n} c_i h_i - \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} v_j h_i \tag{4}$$

The probabilistic solution considers only 1 neuron, then the probability of n hidden neurons acting on the convolutional layer can be expressed as:

$$P(v) = \sum_h P(v,h) = \sum_h e^{-E(v,h)} \tag{5}$$

The probability of m neurons in the convolutional layer acting on the hidden layer can be expressed as follow:

$$P(h) = \sum_v P(v,h) = \sum_v e^{-E(v,h)} \tag{6}$$

The probability that the i-th hidden neuron is triggered for m visible neurons can be expressed as follow:

$$P(h_i = 1|v) = \sigma\left(c_i + \sum_{j=1}^{m} w_{ij} v_j\right) \tag{7}$$

where w is the weight between the two layers, c and b denote the respective offsets. For n hidden neurons, the probability that the j-th visual unit is triggered can be expressed as follow:

$$P(v_j = 1|h) = \sigma\left(b_j + \sum_{i=1}^{n} w_{ji} v_i\right) \tag{8}$$

where $\sigma(\cdot)$ is the machine probability function.

$$\sigma(x) = sigmoid(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Then, the ReLU activation function is used to replace the Sigmoid activation function. In the same training environment, the ReLU activation function requires less training compared to the Sigmoid function.

For N input samples $v = \{v_0, v_1, \ldots, v_N\}$, and $v_0, v_1, \ldots, v_N$ obey independent distributions.

$$P(v) = \prod_{t=0}^{N} P(v_t) \tag{10}$$

The likelihood estimate for the sample set v can be expressed as:

$$L(\theta) = \prod_{t=0}^{N} P(v_t|\theta) \tag{11}$$

where $\theta = \{w, c, b\}$ is the energy parameter.

Solving for the maximum value of $L(\theta)$ translates into solving for the maximum value of $\ln L(\theta)$.

$$\hat{\theta} = \arg\max_\theta L(\theta) = \arg\max_\theta \sum_{t=0}^{N} \ln P(v_t|\theta) \tag{12}$$

$$\theta^* = \theta + \eta \frac{\partial \ln P(v)}{\partial \theta} \tag{13}$$

where η is the learning rate and $\eta > 0$.

For a single sample $v_0 = \{v_{01}, v_{02}, \ldots, v_{0m}\}$, the sample is solved logarithmically.

$$\ln P(v_0) = \ln \sum_h e^{-E(v_0,h)} - \ln \sum_{v,h} e^{-E(v,h)} \tag{14}$$

Apply the partial derivative to $\theta = \{w, c, b\}$.

$$\frac{\partial \ln P(v_0)}{\partial \theta} = -\sum_{h} P(h|v_0)\frac{\partial E(v_0, h)}{\partial \theta} + \sum_{v,h} P(v, h)\frac{\partial E(v, h)}{\partial \theta} \tag{15}$$

The conditional probabilities are shown as follow:

$$P(v, h) = P(h|v)P(v) \tag{16}$$

The partial derivatives of $\theta = \{w, c, b\}$ are obtained for each of the three parameters w, c, b.

$$\frac{\partial \ln P(v_0)}{\partial w_{ij}} = P(h_i = 1|v_0)v_{0j} - \sum_{v} P(v)P(h_i = 1|v)v_j \tag{17}$$

$$\frac{\partial \ln P(v_0)}{\partial b_j} = v_{0j} - \sum_{v} P(v)v_j \tag{18}$$

$$\frac{\partial \ln P(v_0)}{\partial c_i} = P(h_i = 1|v_0) - \sum_{v} P(v)P(h_i = 1|v) \tag{19}$$

Secondly, the S4 pooling layer of the LeNet-5 convolutional neural network is modified using the Spatial Pyramid Pooling (SPP) technique [33] to reduce the impact of the pooling operation on the feature values, as shown in Figure 5.

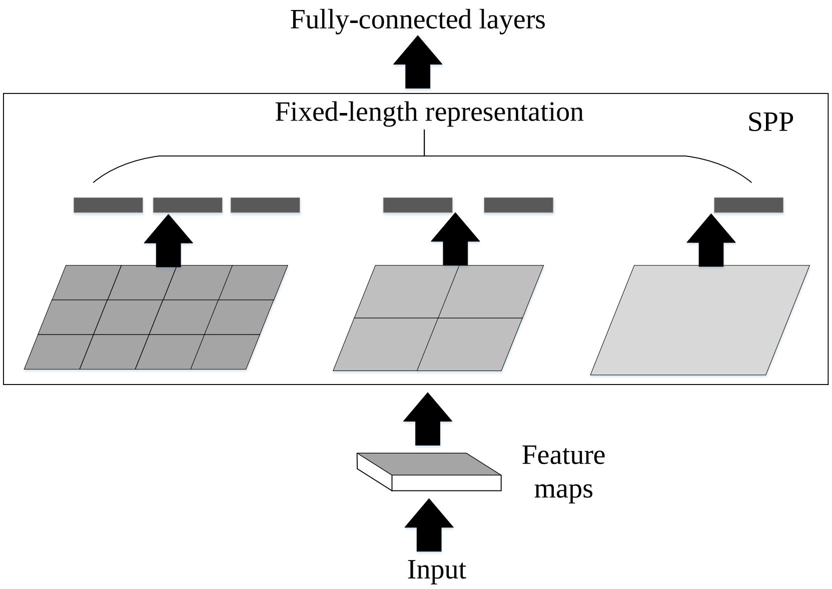

Figure 5. Technique of spatial pyramid pooling

The cubes represent the feature maps output from the convolutional layers. These feature maps are fed into the three pooling layers to get outputs of size 4*4, 2*2, 1*1. The outputs of the three pooling layers are spliced to obtain a 21-dimensional vector. The results of performance comparison of the model without SPP and with SPP are shown in Table 4. After using SPP technique, the error rate of single size trained and multi size trained network models decreased by 0.62% and 1.12% respectively.

Finally, a fully connected layer is used to replace the C5 layer of the LeNet-5 convolutional neural network. After the improvement, there are three convolutional layers before the C5 network layer. With no reduction in the convolutional layers, replacing the C5 layer with a fully connected layer further improves the stability and classification accuracy of the model.

Table 4. Performance of model using SPP technique

	Top-5 error(%)
no SPP	14.7
SPP single-size trained	14.14
SPP multi-size trained	13.64

5. Experimental results and analysis.

5.1. Experimental environment and data.
The experimental hardware is ThinkPad E580 laptop. The processor is Intel Core (TM) i5-8250U@1.60GHz 1.80Ghz, the graphics card is Intel UHD Graphics 620 Radeon 500 Series, and the RAM is 8.00GB. the operating system is 64-bit Windows 10, and the simulation software Matlab 7.0.

In this paper, a total of 20 provinces, including Shaanxi, Hubei, Henan, Anhui, Hunan, and Sichuan, were finally selected as the sample for online learning. The data sources are mainly based on official data, including statistical yearbooks and statistical bulletins (2020) released by national and provincial statistical bureaus. Before the training of LeNet-5 convolutional neural network model, all raw data shall be normalised. The normalised data of each indicator is obtained by projecting the data of each indicator to the values in the interval [0,1].

$$r_i = \frac{R_i - R_{\min}}{R_{\max} - R_{\min}} \tag{20}$$

5.2. Performance validation of improved LeNet-5.
The loss function is a cross-entropy loss function. The optimisation algorithm uses the momentum optimisation algorithm [34]. The learning rate is set to 0.005 and the momentum factor is set to 0.9. Table 5 shows the classification accuracies under different training batches. The accuracy of the model is optimal when the batch is 100.

Table 5. Classification of accuracy from different design of batch size

Batch size	**Accuracy**
25	0.9923
50	0.9921
100	0.9948
200	0.9928

It can be seen that different batch sizes have a significant effect on the results of the experiment. Increasing the batch is conducive to improving the memory utilisation. However, after the batch is enlarged to a certain extent, the descending direction of the gradient will no longer change, and the generalisation ability of the model will be reduced. The effect of blindly increasing the training batch is not the best choice.

Two convolutional layers with convolutional kernel size 3*3 are used instead of C3 layer and S4 maximum pooling layer is modified using SPP technique. ReLU is used as the activation function. After 30 rounds of training, the loss value and accuracy tend to converge. The loss value and accuracy curves of the model are shown in Figure 6 and Figure 7, respectively. At the end of training, the running result in the test set is 0.9948. when after 120 batches of training, the loss value reaches the lowest while the recognition accuracy reaches the highest.

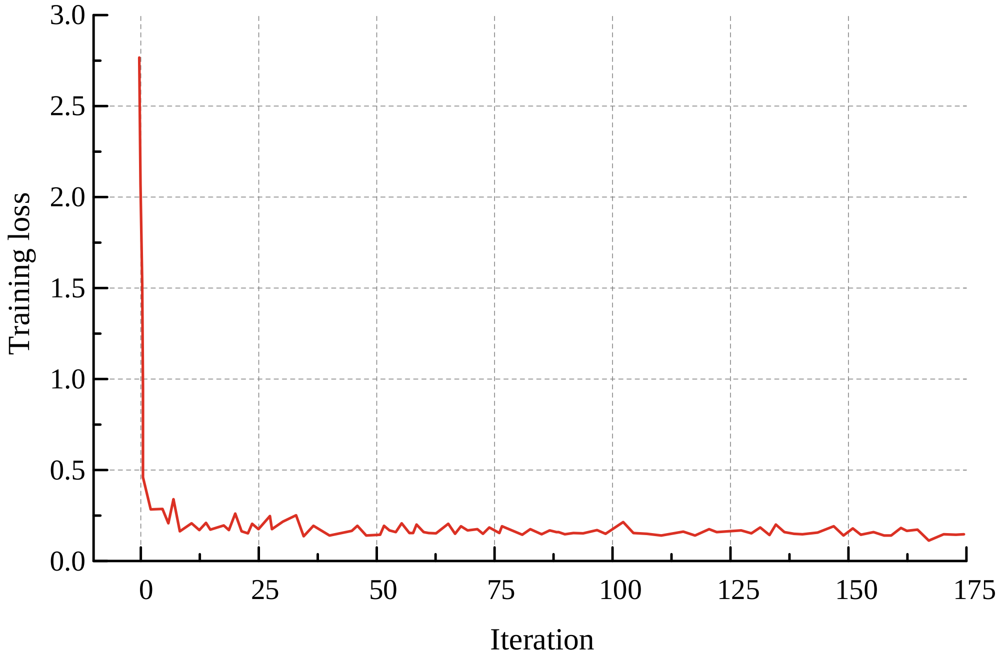

Figure 6. Changes of loss value from improved LeNet-5 model

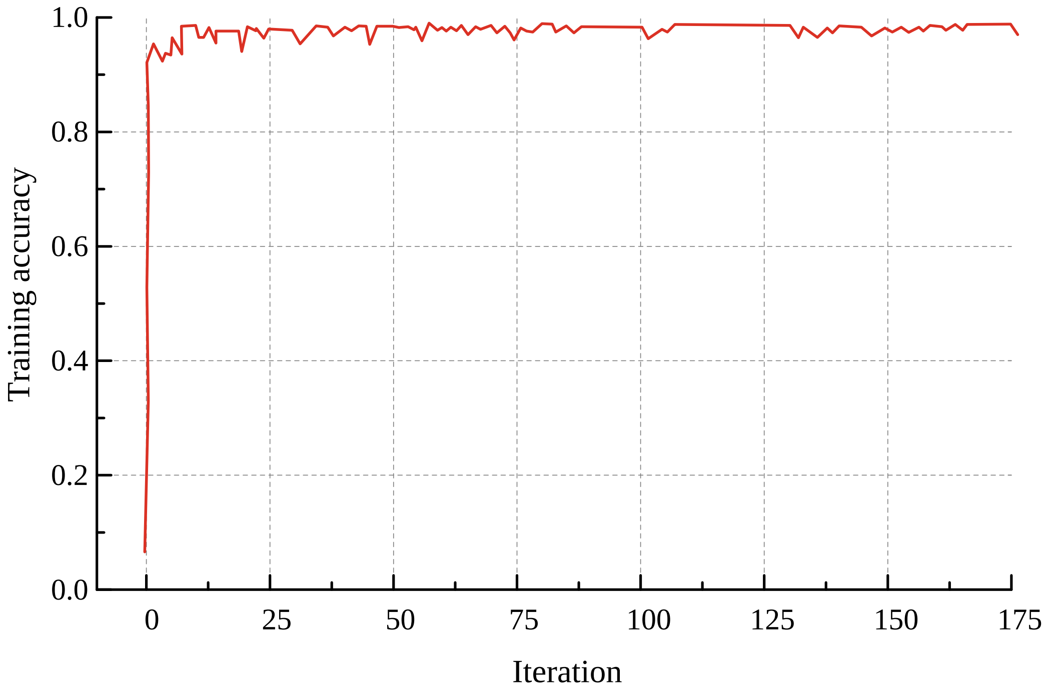

Figure 7. Changes of accuracy value from improved LeNet-5 model

Table 6 shows the performance of the different versions of the improved model. The designed improvement methods all yielded results that improved the accuracy of the model classification and achieved the purpose for which the model was designed.

Table 7 compares the amount of parameters in the modified LeNet-5 model to the original model, and it reveals that there are more parameters in the upgraded model. The next step should be to reduce the training settings.

Table 6. Classification accuracy from different improved models

Method	Accuracy
3*3 kernel no SSP Sigmoid	97.29 per cent
5*5 kernel no SSP Sigmoid	96.26 per cent
3*3 kernel SSP ReLU	98.48 per cent
5*5 kernel SSP ReLU	97.35 per cent

Table 7. Training parameters amount of the original model and improved model

Model	Training parameter scale
Improved LeNet-5	369000
Original LeNet-5	60,000

5.3. **Competitiveness analysis.** After obtaining the scores of the five secondary indicators F1, F2, F3, F4 and F5, we can calculate the score and ranking of the comprehensive competitiveness of each province.The variances of F1, F2, F3, F4 and F5 are 0.58, 0.36, 0.55, 0.36 and 0.50 in turn.Calculate the weight of the variances of the five secondary indicators in the total variance.The weights of the five secondary indicators are 0.25, 0.15, 0.23, 0.15 and 0.21 in turn. The weights are 0.25, 0.15, 0.23, 0.15, 0.21. Weighting is used to calculate the overall score of each province and rank them in order. The results of ranking the competitiveness of each province are shown in Table 8 for the first 10 examples.

Table 8. Competitive Sorting

No.	F1	F2	F3	F4	F5	Average value
1	1.13	0.78	1.31	0.67	1.39	0.79
2	1	0.66	1	0.66	0.87	0.7
3	0.99	0.61	0.81	0.5	0.64	0.65
4	0.89	0.6	0.68	0.49	0.6	0.56
5	0.89	0.49	0.64	0.45	0.56	0.54
6	0.39	0.46	0.53	0.42	0.5	0.45
7	0.35	0.41	0.4	0.4	0.43	0.35
8	0.28	0.39	0.29	0.39	0.39	0.29
9	0.24	0.09	0.24	0.3	0.25	0.21
10	0.23	0.08	0.08	0.26	0.1	0.02

It can be seen that in terms of comprehensive competitiveness, Shaanxi Province ranks first while Qinghai Province is at the bottom of the ranking. Figure 8 shows the comparison of the scores of Qinghai Province and Shaanxi Province in the five indicators of F1, F2, F3, F4 and F5. Shaanxi Province ranks first in the three indicators of production factors F1, auxiliary industries F3 and government opportunities F5. This indicates that Shaanxi Province has strong comprehensive strength and great potential for regional tourism industry development. Qinghai Province ranks first in the bottom two indicators of production factors F1 and government opportunities F5. This indicates that these two items seriously affect the ranking of Qinghai Province's comprehensive competitiveness, making its future development more difficult.

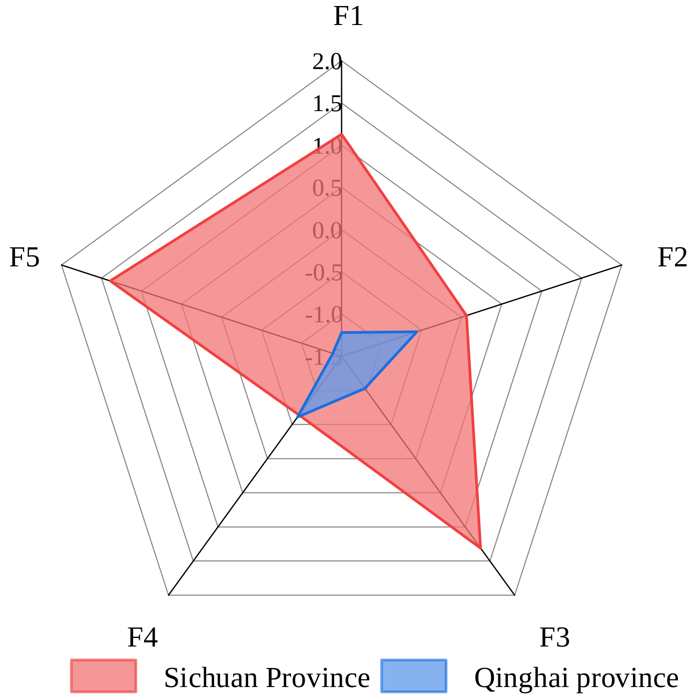

Figure 8. Competitiveness of Shaanxi Province versus Qinghai Province

6. **Conclusion.** In this paper, the LeNet-5 neural network model was chosen to study the competitiveness of the tourism industry for intelligent evaluation. Firstly, a smaller serial convolution kernel is used to replace the convolution kernel of C3 layer in Le Net-5 network. The 5*5 size convolutional kernel was replaced by two 3*3 size convolutional kernels. Then, replace the Sigmoid activation function with ReLU activation function. In the same training environment, the ReLU activation function requires less training compared to the Sigmoid function. The S4 pooling layer of LeNet-5 convolutional neural network is modified using, SPP technique to reduce the effect of pooling operation on the feature values. Matlab 7.0 software was used to implement the regional tourism industry competitiveness evaluation model based on improved LeNet-5. However, compared with the original model, the number of parameters of the improved LeNet-5 model is on the high side, and the hyperparameter optimisation problem of the model will be investigated in the following.

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