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Intelligent Tourist Flow Prediction of Scenic Spots Based on Self-organized Migration Optimization Deep Learning

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Abstract. *At present, tourism has turned into a significant industry in the global economy, which has a huge pulling consequence on economic development. The forecasting of tourist flow in tourist attractions has become one of the hot and hard issues in tourism research. For the purpose of dealing with the issue that tourist flow of scenic spots is prone to load imbalance, which conduces to low prediction accuracy, this article suggests a scenic spot intelligent passenger flow prediction method on the ground of self-organized migration optimization deep learning. Firstly, to deal with the issue of negative transfer in self-organizing transfer learning algorithm, the data source domain is reconstructed by adopting the idea of minimizing the uppermost mean divergence. Then, on account of the optimized self-organized migration algorithm, wavelet analysis is introduced to establish a scenic spot intelligent tourist flow forecasting method on account of self-organized migration optimization and time-sharing distribution characteristics of passenger flow. By adopting the supervised learning method, the lowest speed descent method of forward transmission of deviation is adopted to gradually correct the weight to acquire intelligent forecasting of tourist flow. Finally, the experimental outcome indicates that Correlation Coefficient (R), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of scenic spot intelligent passenger flow prediction method suggested in this article on the ground of self-organizing migration optimization deep learning were 0.9604, 0.0371 and 0.0613, which were superior to the comparison model and had better prediction accuracy*
Keywords: Tourist flow; Self-organized migration; Deep learning; Neural network; Wavelet analysis

1. **Introduction.** Tourist flow prediction of scenic spots plays a significant part in the expression of tourism growth policies and tourism tactic provision of a country. It can effectively guide the resource allocation of the national tourism market, the future development direction of tourism, and help tourism enterprises to formulate effective strategic deployment [1,2,3]. Tourism forecasting plays a decisive role in the long-term development of scenic spots. Precise visitor flow prediction can effectively avoid the phenomenon of "overload" of visitor flow in scenic spots and realize the sustainable development of

scenic zone. Guide visitors to make healthy and reasonable travel plans, for the purpose of helping tourists get a better travel experience.

As the urbanization process accelerating, the visitor stream of scenic spots has increased rapidly, and the problems such as over-saturation of passenger flow density during peak hours have become increasingly prominent [4,5]. The time distribution tendency and spatial dispersion characteristics of visitor stream play a crucial role in the governance and resource arranging of scenic spots. The outcome of passenger stream sketch and forecasting are the foundation and foundation for scenic spot handlers to make decisions and offer visitant assistance.

1.1. **Related Work.** According to visitor stream forecasting, the relevant prediction of tourist attractions began in the 1960s. In terms of tourist flow prediction, scholars commonly use Artificial Neural Network (ANN) model and Support Vector Regression (SVR)model, Grey Model (GM). Automobile degenerating merged shifting average model and other forecasting models were used to predict passenger flow. Good experimental results have been obtained [6, 7, 8, 9, 10].

However, the above studies mostly predict the overall visitor stream in scenic zone without fully considering the spatial relationship among scenic spots in mountain scenic spots, and most of the studies are on account of the time series of tourist stream data prediction, and the spatial distribution characteristics of tourist stream in scenic zone and the spatio-temporal relationship of tourist stream in scenic zone have not been fully utilized. For the prediction problem of Spatiotemporal automobile degenerating and transferring average, Martin and Oeppen [11] first proposed the spatiotemporal automobile degenerating and shifting average model. Block et al. [12] presented a Spatiotemporal Integrated Forecasting Framework (STIFF). On this basis, Sun et al. [13] presented a Spatiotemporal bayesian network predictor to forecast traffic flow. Nourani and Kalantari [14] established an Integrated artificial neural network (ANN) model for spatiotemporal prediction of formal debared deposit at multiple stations in the Eel River Basin in northwestern California. Spatiotemporal support vector regression (STSVR) proposed by Yaseen et al. [15]. Dehghani et al. [16] constructed a Dynamic Linear Spatiotemporal Model (DLSTM) for predicting monthly traffic. The spatial-temporal multiple regression model constructed by Lwin et al. [17]. Khashei and Bijari [18] proposed a Spatiotemporal Deep Learning (STDL) model for predicting air quality. It has been proved by experiments that STANN has better prediction accuracy than STARIMA model [19] and can better process nonlinear spatiotemporal series data.

At the moment, the study on STANN almost concentrates on prediction and recognition. In terms of prediction, Nourani et al. [20] built a spatial-temporal neural network model for groundwater level prediction. Yu et al. [21] used the spatial cyclic convolutional network to forecast the short and medium semester traffic stream of the road network. Polson and Sokolov [22] proposed a deep learning model structure combining multi-layer nonlinear network and single-layer linear network, and applied it to short-term visitor stream forecasting. Zhao et al. [23] forecasted short-term visitor stream on account of BP-ANN. Li et al. [24] used LSTM and CNN to predict passenger flow. Zhang et al. [25] adopted LSTM network to forecast subway passenger flow. In the same year, Rahimipour et al. [26] adopted suitable neural network to forecast subway visitor stream, but its adaptability to data was poor.

Even though a prediction model combining various traditional algorithms has emerged, its application scope still lags behind that of deep learning methods. The prediction method of deep learning, on account of big data, can realize the analysis of data in high-dimensional space. Moreover, the structural variability of deep learning models is strong, so this kind of method has a wider application range and stronger data adaptability. Based on the above, this paper decides to use the deep learning method to forecast visitor stream of scenic zone. Based on the characteristics of visitor stream data of scenic zone, the self-organizing neural network model is adopted and the transfer learning algorithm is combined to achieve accurate prediction.

1.2. **Contribution.** From the above, it can be seen that tourist flow prediction of scenic spots plays a decisive role in the long-term development of scenic zone, and exact visitor stream prediction can effectively avoid the phenomenon of ”overload” of visitor stream in scenic zone and realize the sustainable development of scenic spots. In order to realize the exact forecasting of visitor stream of scenic zone, this article designs an intelligent visitor stream forecasting method based on self-organized migration optimization deep learning.

First, the method minimizes the MMD distance among the origin field and the object field data, filters the origin field data, and optimizes the self-organizing migration algorithm. Then, through the iterative deviation calculation of forward deviation transmission and reverse deviation transmission in the optimized self-organizing migration algorithm, the intelligent prediction of passenger flow is completed. Finally, the simulation outcome certifies that the prediction method designed in this article can excellently realize the accurate prediction of tourist flow in scenic spots.

2. Relevant theoretical analysis.

2.1. **Self-organizing neural networks.** Self-organizing Neural Network (SOM) retains the topological scheduling among samples as well as decreasing the property of the stimulant sport space [27], and its internal connections are indicated in Figure 1.

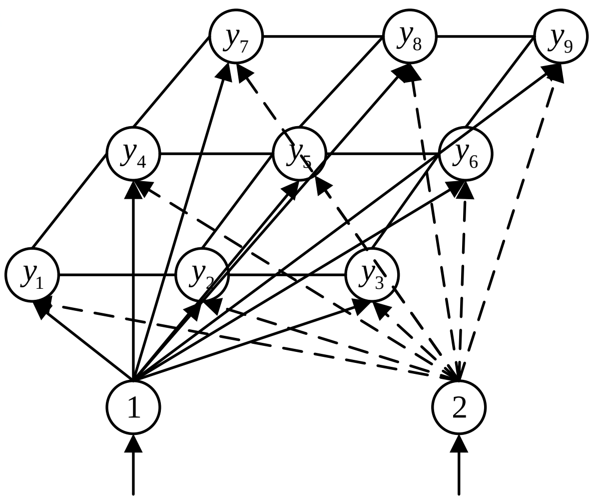

Figure 1. Self-organizing neural network structure

For d-dimensional data, when the output dimension of SOM network contains $N = n\times n$ neurons, the data of each dimension must correspond to a weight vector. In this case, the dimension of the weight vector is also d, and weight can be expressed as Equation (1).

$$H = \{h_j \mid h_j \in \mathbb{R}^c, j = 1, \cdots, N\} \tag{1}$$

SOM network is trained through several iterations, and each iteration includes two processes: competition and cooperation. To find the best matching unit through competition is Equation (2).

$$d = \arg\min_{j} \|\mathbf{y}(s) - h_j(s)\| \tag{2}$$

where $\mathbf{y}(s)$ represents the input of the s iteration. After the competition is completed, the weights of the neurons of the greatest mapping unit and the neighborhood are adjusted to realize the self-organization of the network as Equation (3).

$$h_j(s+1) = h_j(s) + w_{dj}(s)\left[\mathbf{y}(s) - h_j(s)\right] \tag{3}$$

where $w_{dj}(s)$ is used to define the updating mechanism for preserving topological relationships in the neuron neighborhood. The updating mechanism in this paper adopts Gaussian function, namely Equation (4).

$$w_b(s) = \beta(s)\exp\left[-\frac{\text{tpdist}(d,j)}{2\sigma^2}\right] \tag{4}$$

The SOM constantly adjusts the weight of each node connection during the training process to screen out more winning neurons. Through cooperation, the winning neurons are kept in contact with other neurons in the neighborhood, so as to ensure the topological stability of the network.

2.2. **Transfer learning.** Transfer learning is able to transfer knowledge adaptively from the origin field to the objected field, and reduce the distribution difference with the origin field data by means of local manifold self-learning in the objected field [28,29]. The steps are as follows:

(1) Target data k-means bunching. The classical k-means algorithm is used to obtain the clustering prototype, which is regarded as a pseudo-class core, and the distribution structure information of the target domain samples is obtained. The calculation formula is Equation (5).

$$\vartheta(Q, U, V_s) = \|QY_s - UV_s^T\|_2^2 \tag{5}$$

where: Q represents the projection matrix; U stands for target data cluster centroid; V_s stands for target pseudo-label matrix.

(2) Native manifold self-learning of objected data. The native manifold self-learning intrigue is inserted to adjustable study the homogeneity of data in terms of the native connection in the low-dimensional space projected by the target data.

$$\phi_j(Q, T) = \sum_{i,j=1}^{m_j} \|QY_{jj} - QY_{ij}\|_2^2 T_{ij} + \theta T_{ij}^2 \tag{6}$$

where T represents the target adjacency matrix; θ indicates the hyperparameter.

(3) Source domain data class centroid calculation. The clustering prototype based on target domain data is obtained through computing the imply of the sports of the same class of samples.

(4) Source domain data discrimination structure retention. In the source domain data, the specimen of the equal kind is as close as possible in the projection space, and samples of various kinds are as far away as possible, and the discriminant structure information of the source domain is retained.

$$\phi_l(Q) = \frac{1}{m_d}\sum_{d=1}^{D}\sum_{i=d}^{m_d} \|QY_{ij} - QY_{il}\|_2^2 \tag{7}$$

(5) Two domain course centroid mapping. The closest neighbor comb method is used to solve the class centroid problem, and the closest origin centroid is found for every

objected field bunch centroid, and the distance sum is minimized. The course centroid mapping of the two fields is expressed as Equation (8).

$$\Omega(Q,U) = \|QY_lE_t - U\|_2^2 \tag{8}$$

where E_t represents the constant matrix, which is adopted to calculate the origin field data's centroid in the projection space; Y stands for source domain data.

3. **Optimized self-organizing migration algorithm.** In Self-Organized Transfer Learning (SOMA), the dispersion deviation among origin field data and objected field data is large, so negative transfer may occur. SOMA is more about processing the objected field data, and does not filter the source field data, which may cause negative migration due to the large divergence among the origin field and the objected field data. If you are able to effectively eliminate bad data in the source domain, you can avoid negative migration or poor migration effect. Therefore, based on the idea of minimizing the Maximum Mean Discrepancy (MMD), this section reduces the distribution difference between the two domains by downplaying the MMD distance among the data in the origin field and the objected field, and then constructs a new source domain, as shown in Figure 2.

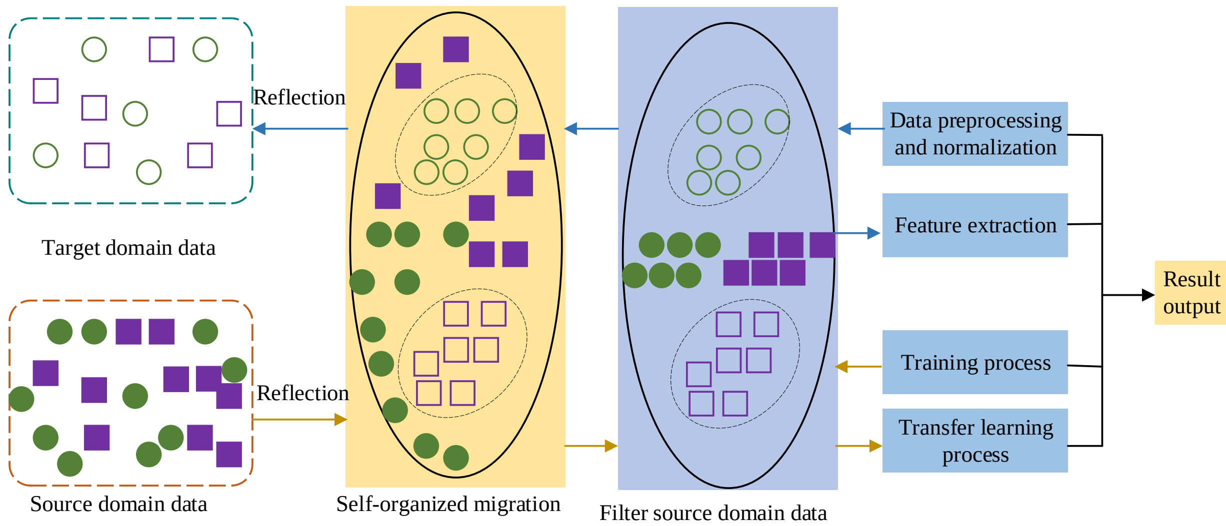

Figure 2. Optimized self-organizing migration algorithm framework

Suppose there is a set of L training samples $T' = \{(y_j, x_j)|j = 1, 2, \ldots, L; i = 1, 2, \ldots, K\}$, where the input to each training sample contains K high-dimensional attributes, and x_j is the label of the sample. For training sample T', the optimization process is as follows:

(1) Data preprocessing and normalization. Use the SMOTE method to increase the few classes in the dataset to construct a balanced dataset. After synthesizing A few class samples, we can get a new set $T = \{(y_j, x_j)|j = 1, 2, \ldots, M; i = 1, 2, \ldots, K\}$ containing M training samples, and use Equation (9) to normalize the data.

$$y_{ji} = \frac{y_{ji}^{\max} - y_{ji}}{y_{ji}^{\max} - y_{ji}^{\min}}, \quad j = 1, 2, \ldots, M, \quad i = 1, 2, \ldots, K. \tag{9}$$

where $y_{ji}^{\max} = \max\{y_{1i}, y_{2i}, \ldots, y_{Mi}\}$, $y_{ji}^{\min} = \min\{y_{1i}, y_{2i}, \ldots, y_{Mi}\}$, $j = 1, 2, \ldots, M$, $i = 1, 2, \ldots, K$. If $y_{ji}^{\max} = y_{ji}^{\min}$, then $y_{ji} = 1$.

(2) Feature extraction. According to the data characteristics of the origin field and the objected field, the input sample characteristics of the two domains are minimized. In the

infinite dimensional regenerated kernel Hilbert space, there are:

$$\min \left\| E_{q(y)}\left[\phi(Y_j)\right] - E_{q(x_j)}\left[\phi(Y_{ji})\right]\right\|^2 \tag{10}$$

where $\phi(\cdot)$ is the function that maps the original data to the regenerated Hilbert space; Y_j stands for origin field data; X_j stands for objected field data; MMD values represent the difference in the dispersion of data between origin field and objected field. With the help of kernel calculation, Equation (10) is rewritten as Equation (11).

$$\sum_{j=1}^{m_1}\phi(Y_j) - \sum_{j=1}^{n_2}\phi(Y_{s_i})_w^2 = \mathrm{tr}(LN) \tag{11}$$

The kernel matrix L is then decomposed into $(LL^{-\frac{1}{2}})(L^{-\frac{1}{2}}L)$, and the transition matrix B is used to reduce it to n-dimensional space.

(3) Training process. The data in the training sample is input into the SOM neural network for training, and the training is stopped until the uppermost amount of training times is obtained. After the training, the network completes the clustering of K attributes of the input sample Y by self-organizing. The nodes of the output layer become the excited neurons in this input mode, and the relation weights among the output neurons and the input neurons become the clustering center vector of the input data. The weight vector $H = (h_{ji}|j = 1, 2, \ldots, M;\ i = 1, 2, \ldots, Q)$ of excitatory neurons is extracted and normalized as input data $T'' = \{(h_{ji}, x_j)|j = 1, 2, \ldots, M;\ i = 1, 2, \ldots, Q\}$ of the integrated classifier.

(4) Transfer learning process. Let $B = L^{-1/2}\tilde{B}$, $\tilde{B} \in \mathbb{R}^{(m_1+m_2)\times r}$, then the objective function is Equation (12).

$$\min_{B^T} \mathrm{tr}(B^T LNL^T B) + \alpha \mathrm{tr}(B^T B) \tag{12}$$

where $W = I-(1/(m_1+m_2))\Pi$, I is the identity matrix and Π is the all-1 moment matrix; α represents the equilibrium parameter; $(B^T B)$ represents the complexity of matrix B. By introducing the Lagrange function, we obtain:

$$K_v = \mathrm{tr}(B^T(LNL^T + \alpha I)B) + \mathrm{tr}((I - B^T LWLB)\phi) \tag{13}$$

The new feature space is $B^T L$, and a new source domain sample is constructed based on it, and then the SOM method is used to calculate and get the final recognition result.

4. Intelligent tourist flow prediction of scenic spots based on self-organized migration optimization deep learning.

4.1. Forward bias transmission in SOM.

Due to the wide distribution range of visitor stream in scenic spots and the non-stationary distribution of tourist flow over time, the ancestral time series model is not fit for solving such problems. As a large-scale parallel distributed structure model with strong generalization ability, the self-organizing neural network can deal with complex and nonlinear problems. Therefore, this paper selects the self-organizing neural network model as the visitor stream prediction model of scenic spots, introduces wavelet analysis on the basis of the optimized self-organizing migration algorithm, and combines the time-sharing dispersion feature of visitor stream to establish the scenic spot intelligent visitor stream prediction model of self-organizing migration optimization with deep learning. Through the iterative deviation calculation of forward deviation transmission and reverse deviation transmission in SOMA algorithm. The intelligent prediction of visitor stream is completed, and the forecasting accuracy is high. The prediction process is shown in Figure 3. This method is explained in detail below.

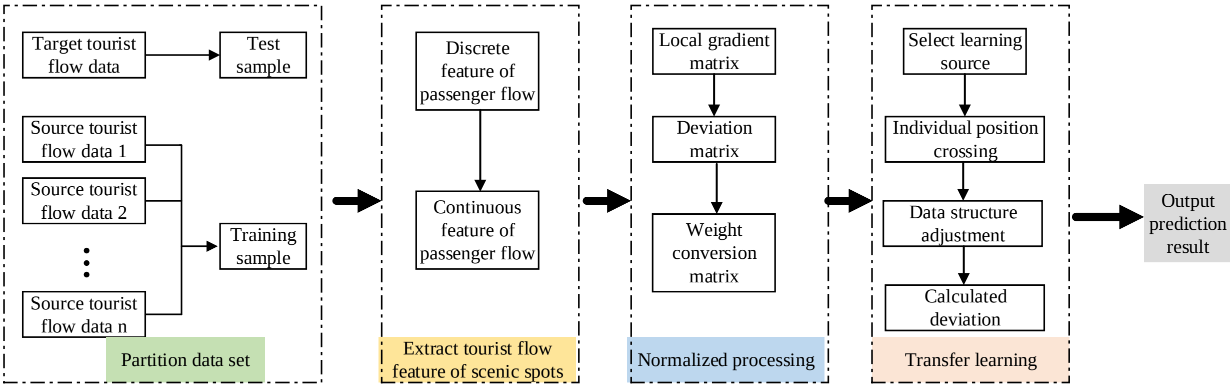

Figure 3. Forecasting process

Self-organizing neural network is an optimization neural network that replaces the hidden layer transmission function with wavelet function. Through supervised learning method, the weight is gradually corrected by using the lowest speed descent method of forward transmission of deviation, so as to achieve the training goal. Self-organizing neural network can deal with nonlinear and high dimensional problems well and has good generalization performance. The specific flow of forward propagation in AD hoc networks is shown in Figure 4.

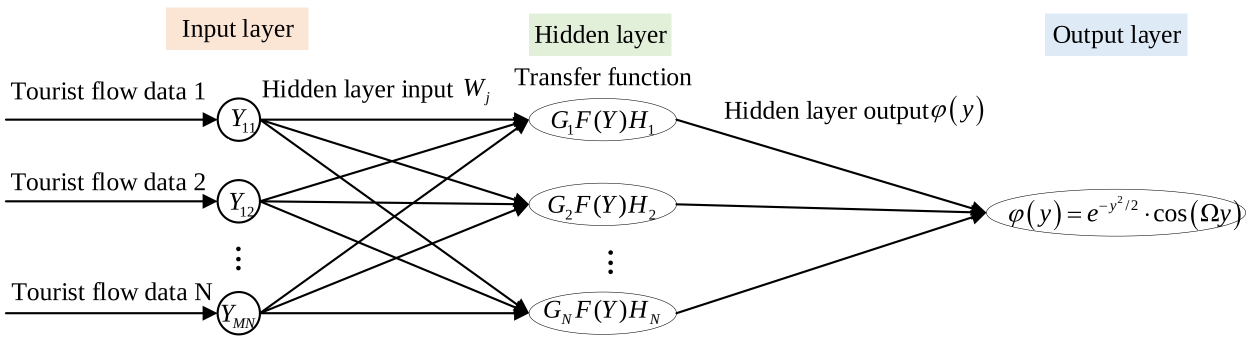

Figure 4. Forward propagation operation flow

Firstly, the stimulant of the obscured layer is calculated, and the influencing factors in each group of the training data are regarded as the row vector Y_i containing elements. An $M \times N$ input matrix $Y = [Y_{11}, Y_{12}, \dots, Y_{1N}]$ is established, and the relation weights between the obscured layer and the stimulant layer are arranged in the corresponding order to obtain the weight matrix h_i. The original value of the connection weight H_i is usually set randomly, and the original value h is generally set to a small non-zero random number. The input matrix F of the hidden layer is obtained by matrix calculation. In the matrix, the elements of the n-th column in the j-th row represent the value of the input data W_j in the n-th group, which is expressed as $F = H_i \cdot Y$.

Each element of the matrix F is introduced into the transfer function $f(x)$ to achieve the obscured layer output matrix $G = f(F)$. The transfer function of the hidden layer of SOM neural network is log-Sigmoid function, which is converted into Morlet function in this paper, as shown in Equation (14).

$$\varphi(y) = e^{-y^2/2} \cdot \cos(\Omega y) \tag{14}$$

The relation weights h_j between the output layer and the obscured layer are sorted respectively, and the weight matrix H_j is established. The output matrix X_i is obtained by matrix calculation, and its network output value is expressed as $X_i = H_i \times G$.

4.2. **Intelligent tourist flow prediction of scenic spots based on self-organized migration optimization deep learning.** Aiming at the complicated and uneven distribution of visitor stream in scenic spots, this article proposes an intelligent tourist stream forecasting method on account of SOMA optimization deep learning according to the SOMA optimization algorithm and forward bias transmission method. This method uses gradient descent to continuously transform the weight of each node in terms of the deviation between the network output value and the expected output value, so as to reduce the prediction deviation until the weight can accurately map the interrelationship of factors affecting tourist entry and exit of scenic spots.

(1) Divide the data set. All sample data of any passenger flow d are extracted from tourist data of scenic spots, and the sample data are divided based on the optimized SOM algorithm to form training sample Y and test sample X respectively.

(2) Extracting visitor stream characteristics of scenic spots. The travel times of each type of visitor stream and the travel time and weather in the travel records of each type of passenger flow have an important effect on the visitor stream attribute, so the passenger flow attribute A can be expressed as: $A_{ij} = (f_{i1}, \dots, f_{i1}, \dots, f_{ij})$ where f_{ij} represents the factors affecting tourist flow in scenic spots. For discrete attribute elements and continuous attribute elements that do not satisfy the conditional distribution independence, we use Equation (15) and Equation (16) respectively.

$$(f * v)(m) = \sum_{s=-\infty}^{+\infty} f(s)v(m-s) \tag{15}$$

$$(f * v)(m) = \int_{-\infty}^{+\infty} f(s)v(m-s)ds \tag{16}$$

(3) Normalization processing. The actual tourist flow value of scenic spots is established as an expected output matrix C, and its deviation matrix is obtained: $E = C - X$. Set a local gradient matrix ϕ_2, which has the same value as the deviation matrix E, where the m-th factor θ_m represents the local gradient value of the M-th data about the output layer node: $\phi_2 = E$. The weight conversion matrix ΔH_2 and the weight matrix H_2 ($H_2 = H + \Delta H_2$) from the output layer to the obscured layer can be derived by using the local gradient, and the specific analytic formula is Equation (17).

$$\Delta H_2 = \mu \times \phi_2 \times G^T \tag{17}$$

where μ represents the learning rate, which can automatically adjust the weight of the reverse deviation transmission number of the self-organizing neural network to ensure that the network can try to maximize convergence and the convergence rate is high.

Adopt the same method to adjust the weight matrix H_1 from the obscured layer to the input layer:

$$H_1 = H + \Delta H_1 = H + \mu \times \phi_1 \times Y^T \tag{18}$$

(4) Transfer learning process. Suppose that at some point, a group of data in the data set stagnates in evolution, and data S_j is selected as the source of transfer learning. The individual location of data S_j is crossed with all individual locations in the data set according to Equation (19). Migration is not a simple increase in information, but a readjustment of data structures after the migration of information.

$$y_{ij}^{b}(s+1) = 0.5 \cdot \left(y_{ij,\text{start}}^{b}(s)\right) + \left(y_{ij}^{b}(s) - y_{ij,\text{start}}^{b}(s)\right) \cdot t \cdot \Delta H_2 + y_{ij}^{'}(s) \tag{19}$$

(5) Output forecast results. After completing the above process, the reverse deviation transmission process terminates. The weight matrix H_1 and H_2 are combined with the forward bias transmission algorithm in the previous section to re-calculate the forward propagation process and obtain the bias matrix E, so as to obtain the analytical expression of the total deviation E_R in the network.

$$E_R = \sum_{i=1}^{m} e_m^2 \cdot \phi(H_1 + H_2) \tag{20}$$

If E_R is still in a downward trend, then recalculate the reverse deviation transmission process and forward propagation process, and terminate the iteration until the value of E_R is the minimum or no longer changes, complete the whole process of visitor stream prediction of scenic spots, and realize the accurate prediction of passenger flow.

5. **Performance testing and analysis.**

5.1. **Performance comparison.** For the purpose of verifying the performance of the prediction model designed in this article, the Huangshan Scenic area in China is choosed as the research object. The data adopted in this research include the passenger flow data of Huangshan scenic spot from September 1, 2017 to March 7, 2020. The models in literature [19, 30, 31] were used to conduct comparative experimental design, and the experimental comparison models were trained in MATLAB R2017b environment. For the convenience of description, reference [19] is denoted as SG-ANN, reference [30] as TF-LSTM, reference [31] as ADLA, and the algorithm in this paper is denoted as ST-SOM.

After analyzing the passenger flow of Huangshan scenic spot, it is found that the dispersion of visitor stream in ordinary days and holidays is different with time and space. Therefore, in the experiment of forecasting visitor stream in Huangshan Scenic spot, holiday passenger flow and non-holiday passenger flow are distinguished in the experimental data. The distribution of cable car passenger flow in Huangshan Scenic area can be divided into twelve groups according to the month. Combined with the prediction of monthly specific factors, the future tourist flow of scenic spots can be dynamically predicted. Table 1 shows the results of the real and predicted values predicted by the model designed in this paper in 2020.

As can be seen from Table 1, the passenger flow data of Huangshan scenic spot is closely related to holidays, and the passenger flow in May and October has an explosive growth. The passenger flow predicted by ST-SOM model in May and October is 648,437 and 615,643 respectively, which is different from the real value of 145 and 277 respectively, and almost consistent with the true passenger flow. Figure 5 displays the prediction effect of SG-ANN model, TF-LSTM model, ADLA model and ST-SOM model with the actual value on the tourist flow data set of Huangshan scenic spot.

From the forecast results in Figure 5, the tourist flow of scenic spots shows a certain volatility and a peak. When SG-ANN, TF-LSTM and ADLA models were used to forecast the visitor stream of Huangshan scenic spot, the fitting degree between the forecasted value and the actual value was low, especially for the forecast of the May Day and National Day holidays, and there was a big difference between them and the actual tourist flow. However, the ST-SOM model established in this paper based on SOM method had a better prediction effect. Comparing the predicted value and the actual tourist volume, it can be intuitively seen from the two line charts that the predicted value of ST-SOM model is closer to the actual tourist flow line and almost coincides, which indicates that

Table 1. ST-SOM model forecast for 2020

The year 2020	Actual data	Forecast data
January	119372	118736
February	186528	187042
March	367284	367345
April	253637	253562
May	648292	648437
June	457238	457091
July	548271	547453
August	583724	583542
September	385272	385076
October	615366	615643
November	287465	286904
December	183749	183075

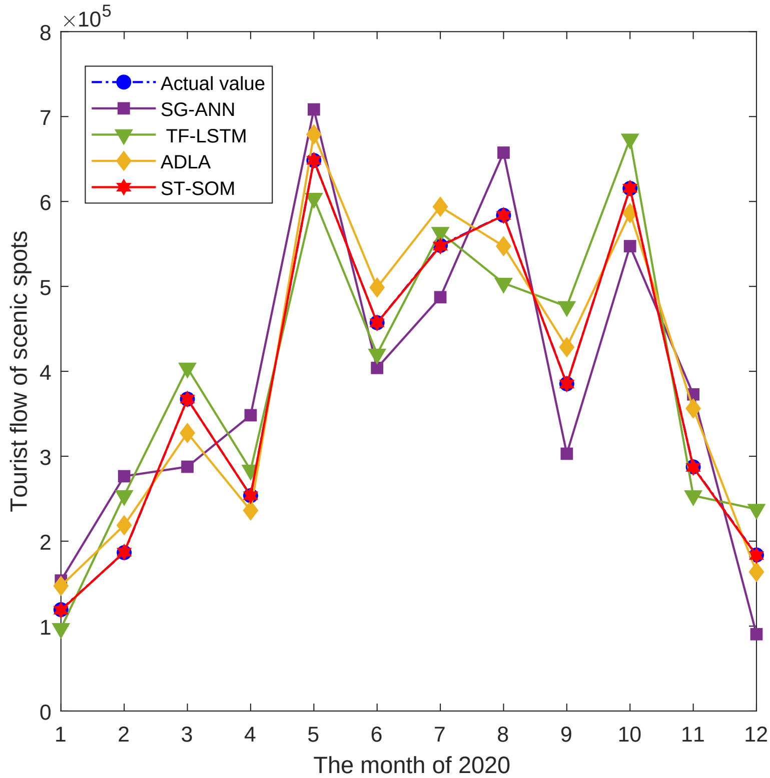

Figure 5. Comparison of forecast results of tourist flow of scenic spots in 2020

the prediction error is small. This model can effectively forecast the visitor stream of Huangshan scenic spot in advance and actually forecast the visitor stream of future scenic spots.

5.2. **Comparison of model methods and performance evaluation.** For the purpose of evaluating and compare the prediction accuracy of the models, SG-ANN model, TF-LSTM model, ADLA model and ST-SOM model were respectively used to train and forecast the visitor stream data of Huangshan scenic spot, and the forecasting outcome of these four models were compared. The experimental results are measured by Correlation coefficient (R), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) [32].

Table 2 shows the outcome of four model evaluation indicators, and draws a visual bar comparison chart for the results, as shown in Figure 6.

Table 2. Comparison of prediction accuracy

Model	R	MAE	RMSE
SG-ANN	0.8746	0.0974	0.1292
TF-LSTM	0.9162	0.0748	0.1741
ADLA	0.8479	0.1725	0.2775
ST-SOM	0.9604	0.0371	0.0613

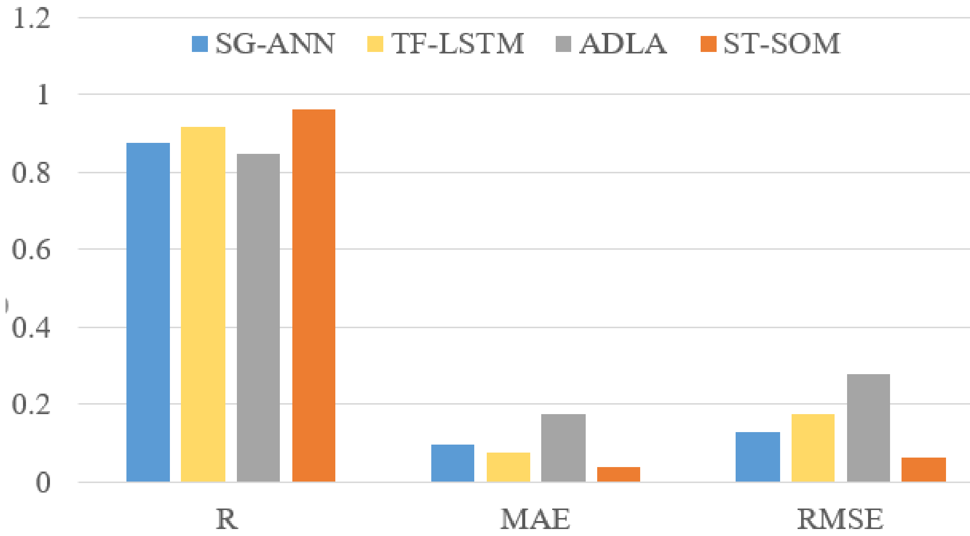

Figure 6. Performance comparison

As can be seen from Table 2 and Figure 6, in the experiment, the accuracy evaluation indexes of the ST-SOM model are significantly better than those of the SG-ANN model, TF-LSTM model and ADLA model. The RMSE of ST-SOM model was 0.0613, which decreased by 6.79%, 11.28% and 21.62% compared with SG-ANN model, TF-LSTM model and ADLA model, respectively. MAE is 0.0371, which is 6.03%, 3.77% and 13.54% lower than SG-ANN model, TF-LSTM model and ADLA model, respectively. In addition, in the prediction results, the MAE and RMSE values of the SG-ANN model, TF-LSTM model and ST-SOM model are significantly lower than those of the ADLA model, and the errors are all lower than 15%, which indicates that the neural network model is more fit for dealing with the prediction issue of multi-input and multi-output. Through comparing the correlation coefficient R, it can be seen that the R-value of ST-SOM model is 0.9604, which is 8.58%, 4.42% and 11.25% higher than that of SG-ANN model, TF-LSTM model and ADLA model, respectively. In addition, the R-value of the SG-ANN model is slightly lower than that of the TF-LSTM model, and the R-value of the ST-SOM model is higher than that of the SG-ANN model, TF-LSTM model and ADLA model, which indicates that after self-organized transfer learning, the R-value of the ST-SOM model is higher than that of the SG-ANN model, TF-LSTM model and ADLA model. The ST-SOM model, which introduced the deviation matrix of forward transmission and reverse transmission, is superior to the contrast model and has a better fitting effect for tourist flow in scenic spots. Therefore, it can be seen from the accuracy of the experimental outcome that the ST-SOM model contains more passenger flow transfer learning information and attribute feature information, which can excellently enhance the prediction precision of the model and make the ST-SOM model have better fitting effect and prediction accuracy.

6. **Conclusion.** Aiming at the issue of low accuracy of present tourist flow prediction methods, this article suggests an intelligent tourist flow prediction method based on self-organized migration optimization deep learning. The method first screens the origin field data, minimizes the MMD distance between the source domain and the target domain data, reduces the distribution difference between the two domains, and achieves the purpose of optimizing the self-organizing migration algorithm. Then, through the supervised learning method, based on the optimized self-organized migration algorithm, the wavelet function is introduced, and the minimum speed descent method of forward transmission of deviation is used to gradually correct the weight, so as to accurately map the interrelation of factors affecting tourist entry and exit of scenic spots, and realize the accurate prediction of tourist flow of scenic spots. Finally, the experimental outcome indicates that the method suggested in this article can excellently enhance the R, MAE and RMSE of tourist flow prediction methods. It can be well applied to scenic spot intelligent passenger flow forecasting.

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