



Article Passenger Flow Prediction of Scenic Spots in Jilin Province Based on Convolutional Neural Network and Improved Quantile Regression Long Short-Term Memory Network

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Abstract: Passenger flow is an important benchmark for measuring tourism benefits, and accurate tourism passenger flow prediction is of great significance to the government and related tourism enterprises and can promote the sustainable development of China's tourism industry. For daily passenger flow time series data, a passenger flow forecasting method based on convolutional neural network (CNN) and improved quantile regression long short-term memory network (QRLSTM), denoted as CNN-IQRLSTM, is proposed with reconstructed correlation features and in the form of sliding windows as inputs. First, four discrete variables such as whether the day is a weekend and holiday are created by time; then, a sliding window of width 42 is used to pass the passenger flow data into the network sequentially; finally, the loss function of the sparse Laplacian improved QRLSTM is introduced for passenger flow prediction, and the point prediction and interval prediction results under different quartiles are obtained. The application of quantile regression captures the overall picture of the data, enhances the robustness, fit, predictive power and nonlinear processing capability of neural networks, and fills the gap between quantile regression and neural network methods in the field of passenger flow prediction. CNN can effectively handle complex input data, and the improved nonlinear QR model can provide passenger flow quantile prediction information. The method is applied to the tourism traffic prediction of four 5A scenic spots in Jilin Province, and the effectiveness of the method is verified. The results show that the method proposed in this paper fits best in point prediction and has higher prediction accuracy. The MAPE of the Changbai Mountain dataset was 0.07, the MAPE of the puppet palace museum dataset was 0.05, the fit of the Sculpture Park dataset reached 93%, and the fit of the net moon lake dataset was as high as 99%. Meanwhile, the interval prediction results show that the method has a larger interval coverage as well as a smaller interval average width, which improves the prediction efficiency. In 95% of the interval predictions, the interval coverage of Changbai Mountain data is 99% and the interval average width is 0.49. It is a good reference value for the management of different scenic spots.

Keywords: scenic passenger flow; quantile regression long short-term memory network; sparse Laplacian; grid constraints; convolutional neural network; interval prediction

1. Introduction

In this wonderful state of national harmony and domestic tranquility, not only do people have a certain economic base, but the face of cities has also changed like never before, making travel a necessary form of relaxation. In recent years, China has placed increased emphasis on tourism and has issued a string of relevant documents one after another in an effort to become a world power in tourism [1]. Jilin Province has made tourism a strategic choice and a decisive step in revitalizing its development, transformation, and upgrading. Over the past few years, ice and snow festivals such as the Changchun Ice and Snow Festival, the Jilin Fog Festival, the Chagan Lake Winter Fishing Festival, and the Changbai Mountain Powder Snow Festival have been held year after year, attracting visitors from all



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). directions and increasing the flow of visitors to Jilin's attractions. Therefore, having the correct passenger flow pattern can provide technical support to assist in decision making by setting reasonable ticket prices, setting up relevant tourism activities at attractions, and optimizing the configuration of attractions. This study uses the Jilin Province region as the research object to construct an accurate passenger flow prediction model using temporal features. A combination of quantile regression and machine learning is used for point prediction and interval prediction. The prediction results provide an important reference for scenic spots to implement development planning, maintenance and repair, and provide intelligent tourism services.

As early as the 1960s, some scholars began to study the prediction of tourism passenger flow and proposed many prediction models, such as time series models, artificial intelligence models, econometric models, and deep neural network models [2–6]. Many research results have been achieved in theory and practice. For example, Lim et al. [7] constructed a seasonal ARMA model for tourism flow forecasting to analyze the seasonality of passenger flows from Hong Kong, Malaysia, and Singapore to Australia to test and estimate the monthly seasonal patterns of international tourism time series. The model captures the distinct seasonal characteristics in tourism passenger flows. Niu et al. [8] established a railroad passenger flow prediction model based on time series analysis, combining long-term trend factors, seasonal factors, and weather factors. The passenger flow change pattern under different conditions was studied, and the railroad passenger flow was predicted for the next two weeks, and the corresponding vehicle configuration optimization and station docking scheme was proposed. If the influence of weather conditions on passenger flow is studied in depth, it will make the railway passenger flow prediction model more in line with the actual situation. Li [9] analyzed the prediction progress of scenic area passenger flow using big data analysis and used the ARIMA model and BP neural network to model scenic area passenger flow. Their prediction results were weighted, and the fitting and prediction accuracy of scenic passenger flow by big data analysis were improved compared with the classical model. Cui et al. [10] constructed a tourism passenger flow prediction model based on EMD-GRU with the Heihe valley scenic area as an example, and the prediction results showed that the prediction efficiency of the EMD-GRU model was higher compared with RNN and LSTM, and the prediction model could effectively improve the accuracy of the original data prediction model after using EMD denoising. However, more explanatory variables were not explored as the influencing factors of scenic traffic to construct the prediction model. Lu et al. [11] established a prediction method (GA-CNN-LSTM) combining CNN and LSTM and optimized by genetic algorithm (GA), which was more accurate than other intelligent algorithms in terms of MAPE and R predicting daily visitor flows more accurately than other intelligent algorithms. Although the GA-CNN-LSTM algorithm has higher accuracy in peak hours than other algorithms, the overall prediction accuracy for peak hours is still insufficient. Xu [12] designed a regression-analysis-based model for predicting cultural tourism flows in the Yangtze River Delta, with the competitiveness of flows as the core, and selected 28 indicators from four aspects: cultural tourism brand resources, cultural tourism support and protection, and urban tourism market income, to build an evaluation index system for the influencing factors of flows, and the designed model has a promising fit. Chen et al. [13] combined residual networks with fully connected networks to provide an enhanced Quad-ResNet model for predicting the regional tourist flow of rural tourism. This method can predict the regional passenger flow of rural tourism based on pedestrian location data, weather and holiday data to find hotspots of tourist attractions. However, since the regional passenger flow of rural tourism in this study was obtained from pedestrian data, there are still some aspects that need to be improved.

When we study regression models, we usually consider different loss functions [14]. The most commonly used one is the squared loss, i.e., the least squares estimate. However, it is sensitive to heavy-tailed distributions and outliers and is not robust. QR models [15] can not only handle heteroskedasticity and outliers but can also construct confidence intervals for parameters using empirical likelihood inference methods without the need to

estimate asymptotic variance. Zou et al. [16] first proposed a composite QR method by considering the losses of multiple quantile points simultaneously, which greatly extended the theoreticality and stability of the estimation results. In 2020, Rodrigues et al. [17] proposed a multi-output multi-quantile deep neural network structure based on convolutional long- and short-term memory layers, which can solve the embarrassing quantile crossover problem by approximating the quantile regression problem from a multi-task learning perspective using two large-scale datasets in transportation, while significantly outperforming existing quantile regression methods. Yu et al. [18] combined the advantages of hybrid neural networks and QR and proposed a spatio-temporal QR (SQR) algorithm for short-term nonparametric probabilistic prediction of regional wind power, and SQR enhanced the prediction effect with highly reliable performance. In the SQR-based forecasting process, all inputs are mapped directly to regional wind power, avoiding the cumulative errors caused by combining forecasts from individual wind farms.

At present, passenger flow forecasting methods are mainly divided into quantitative forecasting and qualitative forecasting. Qualitative forecasting is usually based on qualitative analysis combined with empirical judgment, and the forecasting accuracy is low. Quantitative forecasting is mainly based on mathematical methods to establish quantitative forecasting models. However, in the actual forecasting process, many methods only consider a single or a few factors affecting passenger flow, which lacks comprehensiveness and leads to bias in passenger flow forecasting. Algorithms such as random forest and support vector machine are widely used in passenger flow forecasting, but each algorithm has its drawbacks. Random forest tends to perform poorly when it encounters noisy data. Support vector machines also have the problem of slow computing speed. QR models can not only handle heteroskedasticity and outliers but can also construct confidence intervals for the parameters using empirical likelihood inference methods without estimating the asymptotic variance. The loss function of QR plays a crucial role in the prediction results, and this paper improves the loss function to fill the problem of low prediction accuracy. On the other hand, the application of QR can capture the overall situation of the data and enhance the robustness, fit, predictive power, and nonlinear processing ability of neural networks, which fills the gap between QR and neural network methods in the field of passenger flow prediction.

Scientific and reasonable prediction of tourist flow is an important guiding significance for the effective use of tourism resources and local economic development [19]. However, there is a lack of point prediction models with high accuracy, and there is less research on interval prediction of tourism passenger flow. In this paper, we take the tourist passenger flow of 5A scenic spots in Jilin Province as the research object, construct a deep network framework consisting of a convolutional layer, pooling layer, and improved QRLSTM, extend LSTM to QR, and compare it with the tree model, RNN, LSTM, GRU, and other models, and we can find that the proposed method significantly outperforms the baseline model. The results of the study contribute to the formation of a knowledge system for scenic area management, which can be used as a decision-making tool for tourism managers.

The main contributions of this paper can be summarized as follows.

- (1). This study extends the proposed sparse Laplacian quantile loss function to LSTM, adopts the network structure constraint as the penalty term of the objective function, and smoothens the deviation degree of the network weights in the iterative correction process according to the sparse Laplacian in order to improve the robustness of the prediction.
- (2). An IQRLSTM deep network framework model combined with CNN is proposed for point prediction and interval prediction for scenic tourist passenger flow data in Jilin Province, providing a reliable basis for uncertainty analysis of passenger flow.
- (3). Four relevant data features are added for the date attribute, combined with the sliding window extracted features as input data to obtain more information about the passenger flow, providing a new perspective and idea for the accurate prediction of tourism passenger flow.

(4). The CNN-IQRLSTM is critically evaluated on four scenic spot passenger flow datasets, and by comparing multiple tree models and neural network models, it is shown that the method in this paper significantly outperforms other baseline models.

The remainder of this paper is organized as follows: the material and methods of the paper are described in detail in Section 2. Section 3 of the paper presents the findings of the paper. Section 4 contains the discussion and conclusions of the paper.

2. Materials and Methods

2.1. Materials

The methods involved in this study are CNN, LSTM, and QR. The CNN model is one of the most popular and widely used models in the field of deep learning in recent years. The one-dimensional convolutional structure is simpler, with less weight input, and the complexity of data reconstruction and feature extraction is reduced, according to which the model extracts time-series features and deeply explores the connection between input data. LSTM is a kind of artificial neural network with the ability to be responsible for calculating the dependence between individual observations in the time series, and also has the inherent ability to quickly adapt to the sharp changes in the trend and has a high degree of fit to the passenger flow change trend. Compared with ordinary least squares estimation, QR estimation can more accurately describe the effect of the explanatory variables on the range of variation of the explained variables and the shape of the conditional distribution. It provides a more comprehensive characterization of the distribution, leading to a comprehensive analysis. Although LSTM is very good at processing time series data for predicting visitor flow, it cannot mine the effective information of data distribution. To solve this problem, a new model based on LSTM is built.

In this paper, daily historical data from August 2017 to December 2021 for four scenic spots, namely Changbai Mountain, the puppet palace museum, Sculpture Park, and net moon lake, were selected as the raw data, and all data were provided by the Jilin Provincial Tourism Information Center. Since the sample size of the dataset was not very large, this study initially divided the training and test sets into the ratios of 8:2 and 9:1, respectively, and the results showed that the prediction accuracy of dividing in the ratio of 8:2 was lower than that of dividing in the ratio of 9:1. Therefore, we decided to choose the ratio of 9:1. Figure 1 shows the time series of tourist passenger flow for the four scenic spots. Changbai Mountain is a tourist destination with the reputation of "sacred mountain, holy water, strange forest and immortal fruit", and is one of the 10 most famous mountains in China. The puppet palace museum of the False Manchus is a unique humanistic scenic spot that combines the False Manchus Palace, red tourism, cultural and leisure areas, and tourism and commercial services. Changchun World Sculpture Park is a famous practice base for sculpture research and teaching in China. Net moon lake is a natural landscape formed by 100 square kilometers of artificial forest surrounded by a pool of beautiful water and is famous at home and abroad for its strong tourism resources and superior ecological environment.

As the original data is time series data and contains less information, the general forecasting method is to use a sliding window forecast, for example, window 1 August 2017 to 11 September 2017 and the next window is 2 August 2017 to 12 September 2017, with the overall moving one unit to the right instead of one window. In this paper, the features of the data were expanded to include four discrete variables of the day of the week, week ordinal of the current month, whether it is a weekend, and whether it is a holiday, and then combined with the sliding window as the final feature to forecast the scenic passenger flow on a case-by-case basis, and Table 1 shows the partial input data of Changbai Mountain. Table 1 shows the passenger flow data for Changbai Mountain from 10 to 24 August 2017. The "Date" column indicates the date; the "Flow" column indicates the daily passenger flow. "Weekday" indicates the day of the week, ranging from 1 to 7, with 6 and 7 for Saturday and Sunday. "Week" indicates the week of the month, ranging from 1 to 5. "Weekend" indicates whether the day is a weekend, if yes, filled with



1, otherwise filled with 0; "Holiday" indicates whether the day is a holiday, if yes, filled with 1, otherwise filled with 0.

Figure 1. Time-series diagram of tourist passenger flow in four scenic spots.

Table 1. Partial input data of Changbai Mountain.

Date	Flow	Weekday	Week	Weekend	Holiday
10 August 2017	24,206	4	2	0	0
11 August 2017	24,169	5	2	0	0
12 August 2017	30,449	6	2	1	0
13 August 2017	28,578	7	2	1	0
14 August 2017	24,091	1	2	0	0
15 August 2017	22,634	2	3	0	0
16 August 2017	22,485	3	3	0	0
17 August 2017	23,082	4	3	0	0
18 August 2017	22,862	5	3	0	0
19 August 2017	26,855	6	3	1	0
20 August 2017	18,084	7	3	1	0
21 August 2017	20,733	1	3	0	0
22 August 2017	19,343	2	4	0	0
23 August 2017	18,161	3	4	0	0
24 August 2017	17,948	4	4	0	0

2.2. Methods

2.2.1. CNN Model

The CNN was proposed by LeCun [20]. The CNN uses local connectivity and weight sharing to extract features from the original data and build a dense and complete feature

vector. This study uses CNN to extract data features. The original data is processed at a higher level and more abstractly through convolutional and pooling layers to obtain the internal features in the data, to deeply mine the connections between the input data, and finally to pass the features into the LSTM network after processing. Figure 2 shows the structure of the CNN.



Figure 2. Schematic diagram of the CNN model structure.

Convolutional layer: convolutional operation is performed on passenger traffic data using convolutional layer to extract hidden features. In the deep learning process, the problem is solved by sharing the parameters of convolutional kernels using the weight sharing process of CNN. Here, each convolutional kernel has an acceptance domain for extracting local neurons from the previous layer. Additionally, the neurons between different layers are locally connected [21]. The feature mapping of the convolutional layer is obtained by computing the dot product of the feature mapping of the previous layer with the convolutional kernel, and then it is nonlinearized by the activation function as follows [21]:

$$C_j^l = f\left(\sum_{i \in N_i} I_i^{l-1} \otimes w_{i,j}^l + b_j^l\right)$$
(1)

where $f(\cdot)$ is the activation function. I_i^{l-1} denotes the feature mapping in layer l-1, \otimes is the convolution operation, N_i denotes the input set of the feature mapping, $w_{i,j}^l$ is the weight of feature mapping i in layer l-1 with respect to feature mapping j in layer l, b_j^l denotes the bias of feature mapping i in layer l-1 to feature mapping j in layer l, and C_j^l denotes feature mapping j in layer l.

Pooling layer: The effect of pooling is to downsample. The pooling layer can reduce the dimensionality of the kernel by preserving the significant features and increasing the perceptual field of the kernel. The pooling layer can reduce the dimensionality of the extracted feature information, which makes the feature map smaller, simplifies the computational complexity of the network, and avoids overfitting to a certain extent; on the other hand, feature compression is performed to extract the main features.

2.2.2. Long Short-Term Memory Network (LSTM)

LSTM is an improved model based on Recurrent Neural Network (RNN), which can be an effective solution to the emergent long-range dependency problem. LSTM cleverly preserves long and short-term memory through memory units and gating mechanisms, and its basic unit architecture is shown in Figure 3. LSTM units consist of forgetting gates, input gates and output gates. The forgetting gate controls the extent to which historical information is forgotten, the input gate controls the extent to which new information is accepted, and the output gate determines the final output [22].



Figure 3. Schematic diagram of the LSTM model structure.

Given the current input x_t , the implicit layer state h_{t-1} and the stored state C_{t-1} at the previous moment, the details are calculated as follows [23].

$$i_t = \sigma(W_i[x_t, h_{t-1}]^T + b_i)$$
⁽²⁾

$$f_t = \sigma(W_f[x_t, h_{t-1}]^T + b_f)$$
(3)

$$O_t = \sigma(W_o[x_t, h_{t-1}]^T + b_o)$$
(4)

$$\widetilde{C}_t = \tanh(W_C[x_t, h_{t-1}]^T + b_C)$$
(5)

$$C_t = C_{t-1}f_t + i_t \widetilde{C}_t \tag{6}$$

$$h_t = O_t \tanh(C_t) \tag{7}$$

where x_t is the input at the current moment; h_{t-1} is the output of the LSTM at the previous moment; f_t , i_t , O_t are the results of the forgetting gate, input gate, and output gate state operations, respectively; σ is the Sigmoid activation function; W_f , W_i , W_O are the forgetting gate, input gate, and output gate weight matrices, respectively; b_f , b_i , b_O are the forgetting gate, input gate, and output gate bias terms, respectively; C_t is the unit state of the input at the moment of t; W_C is the input unit state weight matrix; b_C is the input unit state bias item [23].

2.2.3. Quantile Regression (QR)

QR is a useful and popular alternative to mean regression, particularly for biased outcome data. In addition, quartiles at multiple quantile levels can provide information for capturing the distribution of the variable of interest. The advantages over mean reversion are as follows: first, the effect of the explanatory variables on the entire conditional distribution of the response variable can be carefully portrayed. Second, no distributional assumptions need to be made about the random perturbation terms of the model, enhancing the robustness of the model construction. Third, monotonic transformability is achieved for the response variable. Fourth, the parameter estimates are asymptotically good under large sample theory. For a random variable Y, the τ th quantile of Y is generally defined as Equation (8) [24].

$$Q_{Y}(\tau) = \inf\{y : \Pr(Y \le y) \ge \tau\}, \tau \in (0, 1)$$
(8)

where $Q_Y(\tau)$ is a function on τ that gives a complete description of the distribution of the random variable *Y*. Thus, given the covariates, the τ th conditional quantile of *Y* can be defined as Equation (9).

$$Q_{Y|X}(\tau) = \inf\{y : \Pr(Y \le y|X) \ge \tau\}, \tau \in (0,1)$$
(9)

The linear QR model is defined as follows:

$$Q_{Y}(\tau | X) = X^{T} \beta(\tau), \tau \in (0, 1)$$

$$(10)$$

where $\beta(\tau) = (\beta_1(\tau), \beta_2(\tau), \dots, \beta_n(\tau))^T$ is the quantile coefficient that depends on τ . The QR model can be used to estimate the regression coefficient $\beta(\tau)$. First, define Equation (11).

$$\rho_{\tau}(u) = u(\tau - I(u \le 0)) \\
= \begin{cases} u\tau & u > 0 \\ u(\tau - 1) & u \le 0 \end{cases}$$
(11)

where $I(\cdot)$ is the indicator function. The following QR model is developed:

$$\min\sum_{i=1}^{n} \rho_{\tau}(y_i - X_i^T \beta)$$
(12)

2.2.4. QRLSTM Model

Considering the temporal and non-linear nature of passenger forecasting, the LSTM is used as a conditional quantile function for passenger flow and by optimizing the objective function a little, the parameters of the QRLSTM model can be estimated [25].

$$L_{QRLSTM} = \min_{W(\tau_{i}), b(\tau_{i}) i=1}^{N} \rho_{\tau} (Y_{i} - f(X_{i}, W(\tau_{i}), b(\tau_{i})))$$

$$= \sum_{i|Y_{i} \ge f(X_{i}, W(\tau_{i}), b(\tau_{i})}^{N} \tau|Y_{i} - f(X_{i}, W(\tau_{i}), b(\tau_{i})| + \sum_{i|Y_{i} < f(X_{i}, W(\tau_{i}), b(\tau_{i})}^{N} (1 - \tau)|Y_{i} - f(X_{i}, W(\tau_{i}), b(\tau_{i})|$$
(13)

where L_{QRLSTM} is the loss function of the QRLSTM model at quantile τ_i ; Y_i is the actual value of the sample; N is the number of samples; $f(X_i, W(\tau_i), b(\tau_i))$ is the output value of the LSTM network; $W(\tau_i)$ is the weight matrix of the LSTM network; and $b(\tau_i)$ is the bias item of the LSTM network.

When an estimate $\hat{W}(\tau_i)$, $\hat{b}(\tau_i)$ of the best weight term is obtained, the conditional quartiles of the dependent variable can be treated using the following equation.

$$\hat{Q}_{Y}(\tau | X) = f(X, \hat{W}(\tau_i), \hat{b}(\tau_i))$$
(14)

where \hat{Q}_Y is the conditional quantile of Y at $\tau \in (0, 1)$.

2.2.5. Improved QRLSTM Model

Although LSTM models enhance the ability to adjust the feedback on the intrinsic features of the data compared to traditional machine learning, they are also inevitably affected by historical anomalous perturbations during the training process due to their inherent sensitivity, making the model less generalizable [26]. In this paper, the network structure constraint is used as the penalty term of the objective function to smooth the

deviation of the network weights during the iterative correction process according to the sparse Laplacian in order to improve the robustness of the prediction. According to the network structure theory, each feature is assumed to be a node, and if there is a relationship between every two nodes, it means that there is an edge between these two nodes, and the weights can be derived accordingly, and the larger the weight indicates the stronger the correlation between these two variables. In this paper, the Pearson correlation coefficient is used to construct a data matrix between features and between features and labels, denoted as $A = [a_{ij}]_{p \times p'}$ called the adjacency matrix. In a grid structure where orientation is not considered, the *A* matrix has symmetry and the element a_{ij} of it measures the degree of similarity between nodes *i* and *j*. The adjacency matrix is calculated as in Equation (15).

$$a_{ij} = |r_{ij}|[I(|r_{ij}| > r)][I(|r_{iy}| > r)][I(|r_{jy}| > r)]$$
(15)

where r_{ij} is the Pearson correlation coefficient between features *i* and *j*. r_{iy} is the Pearson correlation coefficient between features *i* and *y*. r_{jy} is the Pearson correlation coefficient between features *j* and *y*. *r* is the threshold value, determined according to the Fisher transformation and calculated as in Equation (16).

$$r = \frac{\exp(2c/\sqrt{n-3}) - 1}{\exp(2c/\sqrt{n-3}) + 1}$$
(16)

where *c* is the threshold value of $\sqrt{n-3f_{ij}}$. Establish the statistic $f_{ij} = 0.5 \log((1+r_{ij})/(1-r_{ij}))$. If the correlation between X_i and X_j is 0, $\sqrt{n-3}f_{ij}$ approximately obeys the standard normal distribution N(0, 1). The value of *c* is determined using hypothesis testing. The higher the value of *c*, the larger the threshold *r*, the higher the sparsity of the adjacency matrix, and vice versa the lower the sparsity. Similarly, the 0.95,0.975,0.995 quantile of the standard normal distribution can be taken, and in this paper the 0.995 quantile is taken to be 2.58.

The matrix is sparse since some elements of *A* can be taken to zero. The direction of the correlation is not taken into account and is applicable for both positive and negative correlations. In this study, a semi-positive definite matrix L = D - A is used to construct sparse Laplace smoothing (SLS) grid constraints as shown in Equation (17).

$$\beta_{\tau}^{T}L\beta_{\tau} = \sum_{1 \le i < j \le p} \left| a_{ij} \right| (\beta_{\tau,i} - s_{ij}\beta_{\tau,j})^{2}$$
(17)

where $s_{ij} = \operatorname{sgn}(r_{ij}), a_{ij} = a_{ji}, 1 \leq i, j \leq p$. Let L = D - A, D be diagonal matrices, $D = \operatorname{diag}(d_1, d_2, \dots, d_p), d_i = \sum_{j=1}^p |a_{ij}|$. Typically, a_{ij} is an edge and d_i is a degree, indicating the connectivity between nodes. The matrix L is associated with the weighted graph $\xi = (V, \varepsilon)$, the set of nodes $V = \{1, 2, \dots, p\}$, and the set of edges $\varepsilon = \{(i, j) : (i, j) \in V \times V\}$ [27,28]. As the correlation between X_i and X_j becomes stronger, the larger a_{ij} is, the more $\beta_{\tau,i} - s_{ij}\beta_{\tau,j}$ is compressed. In this paper, the grid constraint is extended to the QR loss function.

$$\underset{\beta}{\operatorname{argmin}}\sum_{i=1}^{n}\rho_{\tau}(y_{i}-Q_{y}(\tau|x))+\beta_{\tau}^{T}L\beta_{\tau}$$
(18)

Based on this, this study proposes a sparse Laplace quantile regression long short-term memory network model and applies the above loss function to the QRLSTM model to further improve the model training efficiency and prediction capability.

2.3. Algorithm Implementation

In this paper, GBDT, XGBoost, LSTM, and RNN models will be introduced as benchmark models to compare the predictive power of CNN-IQRLSTM models. Before performing validation, the hyperparameters of the basic models are first set. All models are trained on the training set, and to reduce the complexity of training and improve the training efficiency of the models, a normalization method is used to normalize all data to a value between (0, 1). Each method is iterated for 200 epochs to ensure convergence of the loss function when the training iterations are stopped and to achieve the best prediction results. Once the prediction is complete, the normalized data is inverted to obtain the true prediction.

The operating system used in this paper is Windows 10. The running software is Python version 3.8.8 and the running tool is Jupyter Notebook. Scikit-learn version is Sklearn 0.24.1. the processor is Intel(R) Core(TM) i7-10700 CPU @ 2.90 GHz 2.90 GHz and the RAM is 16.0 GB. All working environments have no costs and the software has no license fees.

Tourism has slowly become an important part of the local and national economy. How to manage scenic spots scientifically and efficiently is an urgent problem for scenic spot management. Passenger flow prediction is the premise of passenger flow management. Only on the premise of accurate prediction can scenic area management make reasonable allocation of scenic area resources and ensure sustainable development of scenic areas. Taking the famous 5A scenic spot in Jilin Province as an example, this study proposes a prediction method that extends LSTM into improved QR, effectively fuses the loss functions of CNN and IQRLSTM, fits the model to the training set with the best parameters, and evaluates it on the test set. The prediction results of the model proposed in this paper and different neural network methods are compared, and the performance of the model is evaluated comprehensively by quantitative analysis of the evaluation metrics of point prediction and interval prediction to find the best prediction model.

The general framework diagram of this paper is shown in Figure 4. This study was divided into three stages. The first stage includes data preprocessing. The left side of the first frame in Figure 4 shows the four datasets, and the right side shows some input data from the puppet palace museum, and we use the added data features and the features generated by the sliding window as model inputs. The second stage is model construction. The left side of the second frame in Figure 4 shows the improved quantile loss function, and the right side shows the flow of the CNN-IQRLSTM model. The third stage is model evaluation. The left side of the third frame of Figure 4 lists the comparison methods for point prediction and interval prediction, respectively, corresponding to the 5 plus 2 evaluation metrics on the right side.



Figure 4. Framework diagram of the proposed CNN-IQRLSTM model.

2.4. Evaluation Metric

2.4.1. Evaluation Metric of Point Prediction

When we evaluate the prediction model, the main measure is the difference between the predicted value \hat{y}_i and the observed value y_i . In this paper, five important metrics, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), and coefficient of determination (R^2), are used to evaluate the point prediction model. Meanwhile, three important indicators, interval coverage (PICP), interval width (WS), and coverage width criterion (MC), are used to evaluate the interval prediction model [29]. The specific formulae for MAE, RMSE, RMSE, SMAPE, and R^2 are shown below.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$
(19)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$
(20)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$
(21)

$$SMAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{(|\hat{y}_i| + |y_i|)/2}$$
(22)

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i=1}^{n} (y_{i} - \overline{y})^{2}}$$
(23)

where \overline{y} denotes the average of the actual values.

2.4.2. Evaluation Metric of Interval Prediction

The performance of interval prediction is usually evaluated using two metrics. The first one is called the prediction interval coverage probability (PICP) [30] and is expressed as Equation (24).

$$PICP = \frac{1}{n} \sum_{i=1}^{n} c_i \tag{24}$$

where *n* is the number of samples. c_i is the number of samples whose observations fall within the prediction interval (PI). If the actual observation of the *i*th sample falls within the prediction interval, then $c_i = 1$. Otherwise, $c_i = 0$.

Sharpness is measured by the width of PI and reflects the concentration of the predicted distribution. Its mathematical expression is Equation (25).

$$WS = \frac{1}{nR} \sum_{i=1}^{n} \left(U_i(x) - L_i(x) \right)$$
(25)

where *R* is the difference between the maximum and minimum values of the sample. $U_i(x)$ and $L_i(x)$ are the upper and lower interval boundaries of the *i*th sample, respectively.

The prediction interval was constructed to have a high PICP and a low WS, so the composite indicator of the interval prediction was defined as MC [29]. The smaller the MC, the more appropriate the prediction interval. MC is defined as Equation (26).

$$MC = \frac{WS}{PICP}$$
(26)

3. Results

In this study, the above methods are applied to multiple datasets to predict scenic passenger flow. To avoid the overfitting phenomenon, the dataset is divided into two parts: 90% of the data for model training and 10% for evaluating GBDT [31], XGBoost [32], LightGBM [33], RNN, LSTM, Gated Recurrent Unit (GRU) [34], Feedforward Neural Network (FNN) [35], QRGBDT, QRXGBoost, QRLightGBM, QRRNN, QRLSTM, QRGRU, QRFNN, CNN-LSTM, CNN-QRLSTM, and CNN-IQRLSTM models for prediction accuracy.

This study did not include the year 2022 for passenger flow forecasting, and as can be seen from the time series graphs of each scenic area, the passenger flow data is showing a certain periodicity. Therefore, the thesis framework is still applicable to the year 2022

today, and even to the forecast of passenger traffic in different regions. The processing of the dataset can still be undertaken in the same way as the current one. Meanwhile, existing model parameters can also be used.

3.1. Point Prediction Results Evaluation

The point prediction result evaluation is used to verify the prediction accuracy of CNN-IQRLSTM and to compare seven original tree models and neural network methods, as well as eight methods that incorporate QR. The point prediction evaluation metrics of the proposed method and the other seven methods on the four datasets are shown in Table 2. The point prediction evaluation metrics with QR methods are shown in Table 3. The best metrics in each dataset are highlighted in black font. Three results can be revealed from Tables 2 and 3 as follows.

Table 2. Comparison results of point prediction between the original tree model and the neural network method.

Scenic Spots	Metric	GBDT	XGBoost	LightGBM	RNN	LSTM	GRU	FNN	CNN-LSTM
	MAE	889.95	934.99	958.52	1224.88	1432.78	1454.47	1076.79	973.77
C1 1 '	RMSE	2034.23	1943.64	1963.18	2105.74	2608.47	2502.48	2114.24	2029.40
Changbai	MAPE	0.07	0.08	0.08	0.12	0.12	0.13	0.09	0.08
Mountain	SMAPE	7.43	8.04	7.89	12.52	12.60	12.32	9.32	8.25
	Rsquare	0.86	0.88	0.87	0.85	0.78	0.79	0.85	0.86
	MAE	152.28	164.87	156.04	270.05	355.66	326.05	318.31	221.47
The puppet	RMSE	218.33	237.84	230.12	385.64	573.94	480.37	425.60	316.54
palace	MAPE	0.06	0.07	0.06	0.11	0.14	0.13	0.13	0.09
museum	SMAPE	6.28	6.76	5.89	10.89	13.88	12.53	12.45	8.80
	Rsquare	0.95	0.94	0.95	0.85	0.67	0.77	0.82	0.09
	MAE	300.79	260.36	263.34	482.05	393.04	368.62	294.36	266.24
C 1 4	RMSE	443.91	358.09	364.12	624.44	486.56	512.22	392.87	362.43
Sculpture	MAPE	0.08	0.07	0.07	0.12	0.11	0.09	0.08	0.07
Park	SMAPE	7.80	7.02	7.02	13.19	10.68	9.61	7.99	7.21
	Rsquare	0.89	0.93	0.92	0.78	0.86	0.85	0.91	0.92
	MAE	668.21	688.44	785.90	1362.14	2337.98	2593.19	1461.58	727.35
Matura	RMSE	957.48	962.71	1094.55	1973.83	3289.31	4092.60	2092.17	942.36
Net moon	MAPE	0.07	0.07	0.07	0.13	0.21	0.22	0.14	0.08
аке	SMAPE	6.92	7.12	7.40	13.29	21.32	22.99	13.55	8.04
	Rsquare	0.97	0.97	0.96	0.87	0.63	0.43	0.85	0.97

Table 3. Comparison results of the point prediction with QR methods.

Scenic Spots	Metric	QRGBDT	QRXG Boost	QRLightGBM	QRRNN	QRLSTM	QRGRU	QRFNN	CNN- QRLSTM	CNN- IQRLSTM
Changbai Mountain	MAE RMSE MAPE SMAPE Rsquare	881.51 2179.63 0.07 6.80 0.84	859.14 2043.63 0.07 6.91 0.86	906.92 2206.63 0.07 6.96 0.84	1248.90 2285.87 0.11 11.00 0.83	1315.31 2800.54 0.10 11.02 0.74	1452.75 3481.84 0.10 11.18 0.60	1024.65 2103.18 0.09 8.99 0.85	879.72 2020.03 0.07 7.10 0.87	819.19 1913.09 0.07 6.68 0.88
The puppet palace museum	MAE RMSE MAPE SMAPE Rsquare	153.79 318.09 0.06 5.85 0.90	192.24 414.62 0.06 6.57 0.83	179.81 431.95 0.05 5.73 0.82	244.59 413.19 0.09 8.99 0.83	323.53 639.92 0.11 11.43 0.59	361.61 757.30 0.12 12.80 0.43	308.16 458.70 0.12 11.84 0.79	209.21 333.04 0.08 8.05 0.89	117.33 168.02 0.05 5.04 0.97
Sculpture Park	MAE RMSE MAPE SMAPE Rsquare	256.10 371.24 0.07 6.77 0.92	270.87 398.90 0.07 6.94 0.91	265.50 377.31 0.07 6.98 0.92	412.51 551.00 0.10 10.83 0.83	368.69 484.73 0.10 9.63 0.87	366.88 481.49 0.10 9.65 0.87	280.02 370.22 0.08 7.70 0.92	255.59 360.82 0.07 6.77 0.93	248.89 354.04 0.07 6.53 0.93
Net moon lake	MAE RMSE MAPE SMAPE Rsquare	757.20 1492.93 0.07 6.89 0.92	588.22 1065.44 0.05 5.38 0.96	809.90 1746.62 0.06 6.09 0.90	$1402.38 \\ 2680.74 \\ 0.11 \\ 11.65 \\ 0.75$	2545.55 4311.77 0.21 21.59 0.36	2543.18 4291.96 0.22 21.53 0.37	1297.89 1844.19 0.13 13.00 0.88	608.41 883.66 0.06 6.47 0.97	447.03 662.39 0.05 4.83 0.99

Note: boldface indicates the best result for each indicator.

(1) In the Changbai Mountain dataset in Table 2, the MAPEs of GBDT, XGBoost, LightGBM, RNN, LSTM, GRU, FNN, and CNN-LSTM are 0.07, 0.08, 0.08, 0.12, 0.12, 0.13, 0.09, and 0.08, respectively. Additionally, the MAPE of the CNN-IQRLSTM model proposed in this paper is 0.07. Although the MAPE is the same as the result of the GBDT method, the remaining four evaluation metrics show that the prediction accuracy of this paper's method is significantly higher than that of the seven methods, which has great superiority. Second, the original tree model shows better performance than the neural network method. The MAPE and R^2 of the tree model on the Changbai Mountain data and the Sculpture Park data were able to match the proposed model. The same conclusion can be obtained by comparing the point prediction evaluation metrics for the remaining three datasets.

(2) A further comparison of QRGBDT, QRXGBoost, QRLightGBM, QRRNN, QRLSTM, QRGRU, QRFNN, CNN-QRLSTM, and CNN-IQRLSTM was undertaken. The results of SMAPE in the net moon lake dataset are 6.89, 5.38, 6.09, 11.65, 21.59, 21.53, 13.00, 6.47, and 4.83, respectively. The results for R² were 0.92, 0.96, 0.90, 0.75, 0.36, 0.37, 0.88, 0.97, and 0.99, respectively. The results show that the prediction performance of the original four neural network methods is far inferior to the proposed method, especially the R^2 of QRRNN and QRGRU is only 0.36 and 0.37. The proposed method is optimal in all evaluation metrics of the four datasets. In particular, the R^2 of the method in the net moon lake data reached 0.99. In this study, the results of RMSE are as high as several hundreds or even thousands, the reason is that different attractions show different bases of passenger flow and tourist passenger flow itself is a larger dataset, especially attractions with characteristics that increase to tens of thousands of passengers per day. Therefore, the results of RMSE are reasonable. By comparing the point prediction metrics, CNN-IQRLSTM still has the highest prediction accuracy in the Changbai Mountain dataset, the puppet palace museum dataset, and the Sculpture Park dataset, which shows that the method is a competitive passenger flow prediction method in terms of prediction accuracy.

(3) Combined with Tables 2 and 3, the method with QR can achieve better forecasting performance. The conditional distribution of the dependent variable can be estimated using QR, which extends the existing passenger flow forecasting system for probabilistic forecasting. The method proposed in this study can handle complex problems with timeseries and nonlinear points capability. Additionally, the LSTM module incorporates dropout to reduce the probability of overfitting. Table 4 shows the comparison results of the point prediction difference between the method with QR and the method without QR. The values of MAE, RMSE, MAPE, and SMAPE are less than or equal to 0, which means that the method with QR performs better, otherwise the method in Table 2 performs better. The opposite is true for R^2 . A value greater than or equal to 0 means that the method with QR performs better, otherwise the method in Table 2 is better. MAE, MAPE, and SMAPE verify the conclusion in most of the methods. Although some negative values were obtained for R^2 , most of them differed within 10%. For the indicator RMSE, it measures the standard deviation of the residuals and is more influenced by outliers. We can see in the time series plot of the four datasets that the passenger flow is very high on one day, which may be one of the reasons for the increase in RMSE. Five methods showed excellent performance in the Sculpture Park data, while the rest of the dataset needs to be adjusted with better parameters to increase the model performance. In addition, Table 5 shows the comparison results of CNN-LSTM, CNN-QRLSTM, and CNN-IQRLSTM methods. The results show that the CNN-IQRLSTM method outperforms the CNN-LSTM method in all five metrics including RMSE. Except for the puppet palace museum dataset where the RMSE of the CNN-QRLSTM method is higher than the RMSE of the CNN-LSTM method, all the other metrics show that the CNN-QRLSTM method outperforms the CNN-LSTM, further validating the effectiveness of the QR method.

Scenic Spots	Metric	QRGBDT GBDT	QRXGBoost XGBoost	QRLightGBM LightGBM	QRRNN RNN	QRLSTM LSTM	QRGRU GRU	QRFNN FNN	CNN-LSTM CNN-QRLSTM
	MAE	-8.44	-75.85	-51.60	24.03	-117.47	-1.71	-52.13	-94.05
C 1 1 ·	RMSE	145.39	99.99	243.45	180.13	192.07	979.36	-11.06	-9.37
Changbai	MAPE	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01
Mountain	SMAPE	-0.62	-1.14	-0.93	-1.52	-1.58	-1.14	-0.33	-1.15
	Rsquare	-0.02	-0.01	-0.03	-0.03	-0.03	-0.19	0.00	0.00
	MAE	1.51	27.37	23.77	-25.45	-32.13	35.57	-10.15	-12.26
The puppet palace museum	RMSE	99.76	176.79	201.84	27.55	65.99	276.94	33.10	16.50
	MAPE	-0.01	0.00	0.00	-0.02	-0.03	-0.01	-0.01	-0.01
	SMAPE	-0.44	-0.19	-0.17	-1.90	-2.45	0.27	-0.61	-0.75
	Rsquare	-0.05	-0.11	-0.13	-0.02	-0.08	-0.34	-0.03	0.80
	MAE	-44.68	10.51	2.16	-69.54	-24.35	-1.74	-14.34	-10.65
C 1 (RMSE	-72.67	40.81	13.19	-73.44	-1.83	-30.73	-22.65	-1.62
Sculpture	MAPE	-0.01	0.00	0.00	-0.02	-0.01	0.00	-0.01	0.00
Park	SMAPE	-1.03	-0.08	-0.04	-2.36	-1.05	0.05	-0.29	-0.44
	Rsquare	0.03	-0.02	-0.01	0.05	0.00	0.02	0.01	0.00
	MAE	88.99	-100.22	24.00	40.24	207.56	-50.01	-163.69	-118.94
NT 4	RMSE	535.44	102.73	652.07	706.91	1022.46	199.36	-247.98	-58.70
Net moon	MAPE	0.00	-0.02	-0.01	-0.02	-0.01	-0.01	0.00	-0.02
аке	SMAPE	-0.03	-1.74	-1.32	-1.63	0.26	-1.47	-0.55	-1.57
	Rsquare	-0.04	-0.01	-0.06	-0.11	-0.27	-0.06	0.03	0.00

Table 4. Comparison results of point prediction differences with and without QR methods.

Table 5. Comparison results of CNN-LSTM, CNN-QRLSTM, and CNN-IQRLSTM.

Scenic Spots	Metric	CNN-LSTM	CNN-QRLSTM	CNN-IQRLSTM
	MAE	973.77	879.72	819.19
	RMSE	2029.4	2020.03	1913.09
Mountain	MAPE	0.08	0.07	0.07
	SMAPE	8.25	7.1	6.68
	Rsquare	0.86	0.87	0.88
	MAE	221.47	209.21	117.33
The nunnet	RMSE	316.54	333.04	168.02
nalace museum	MAPE	0.09	0.08	0.05
palace museum	SMAPE	8.8	8.05	5.04
	Rsquare	0.9	0.89	0.97
	MAE	266.24	255.59	248.89
	RMSE	362.43	360.82	354.04
Sculpture Park	MAPE	0.07	0.07	0.07
	SMAPE	7.21	6.77	6.53
	Rsquare	0.92	0.93	0.93
	MAE	727.35	608.41	447.03
	RMSE	942.36	883.66	662.39
Net moon lake	MAPE	0.08	0.06	0.05
	SMAPE	8.04	6.47	4.83
	Rsquare	0.97	0.97	0.99

Note: boldface indicates the best result for each indicator.

In conclusion, CNN-IQRLSTM can capture more distribution information without reducing the prediction accuracy. The same conclusion can be drawn from the comparison graph of point prediction results, as shown in Figure 5. The green line in the figure indicates the predicted value and the orange line indicates the true value. From the figure, it can be seen that the data of net moon lake has a high degree of fit, which basically satisfies the travel demand. However, the QRGBDT, QRXGBoost, QRLightGBM, QRRNN, QRLSTM, QRGRU, QRFNN, CNN-QRLSTM, and CNN-IQRLSTM algorithms are all inadequate in predicting the number of passengers during peak hours. The prediction of peak hour passenger numbers is generally low in Changbai Mountain data and the puppet palace museum data. The predicted values for the rest of the datasets also have the same oscillation trend as the true values, and the prediction models have a relatively excellent fit for both the trained and new samples. The comparison plots of the true and predicted values of

the other compared methods for the Changbai Mountain dataset are shown in Figure 6. A plot of the true versus predicted values for the other comparison methods for the puppet palace museum dataset is shown in Figure 7. Point prediction comparison plots for other comparison methods for the Sculpture Park and net moon lake datasets are shown in Appendices A and B. (a) plot of prediction curves for the GBDT, XGBoost, and LightGBM methods; (b) plot of prediction curves for the RNN, LSTM, and GRU methods; (c) plot of prediction curves for the FNN, CNN-LSTM, and CNN-QRLSTM methods; (d) plot of QRGBDT, QRXGBoost, and QRLightGBM methods prediction curves for the QRRNN, QRLSTM, QRGRU, and QRFNN methods; (e) plotted prediction curves for the QRRNN, QRLSTM, QRGRU, and QRFNN methods. The fluctuations of RNN, LSTM, GRU, and the methods with QR added are larger than the rest of the methods, but they are also in line with the general trend. The tree model approach is relatively smooth.



Figure 5. Comparison of the actual and predicted values of the four datasets. (**a**) Actual and predicted values of Changbai Mountain data; (**b**) actual and predicted values of the puppet palace museum data; (**c**) actual and predicted values of Sculpture Park data; (**d**) actual and predicted values of net moon lake data.



Figure 6. Cont.



Figure 6. Comparison of true and predicted values of other comparison methods for the Changbai Mountain dataset. (a) GBDT/XGBoost/LightGBM; (b) RNN/LSTM/GRU;
(c) FNN/CNN-LSTM/CNN-QRLSTM; (d) QRGBDT/QRXGBoost/QRLightGBM; (e) QR-RNN/QRLSTM/QRGRU/QRFNN.



Figure 7. Cont.



Figure 7. Comparison of true and predicted values of other comparison methods for the puppet palace museum dataset. (a) GBDT/XGBoost/LightGBM; (b) RNN/LSTM/GRU; (c) FNN/CNN-LSTM/CNN-QRLSTM; (d) QRGBDT/QRXGBoost/QRLightGBM; (e) QR-RNN/QRLSTM/QRGRU/QRFNN.

There may be the following reasons for the poor prediction results of peak data. For deep learning models, the more data in the training set, the better the effect. In this paper, due to the limited data obtained by objective conditions, the fitting effect of the model needs to be further improved. Secondly, the later period of the prediction data selection period may be affected by the new crown epidemic.

3.2. Interval Prediction Results Evaluation

The interval prediction results are evaluated to verify the interval coverage probability and the average width of the interval, and thus to determine whether the time interval is appropriate. In this study, 90% and 95% interval prediction results are provided, and Table 6 and Figure 8 show the different interval prediction evaluation metrics for each method on the four datasets. The best metrics are highlighted in black font for each dataset. Two results were analyzed from Table 6 and Figure 8 as follows.

Scenic Spots	Metric	QRGBDT	QRXGBoost	QRLightGBM	QRRNN	QRLSTM	QRGRU	QRFNN	CNN- QRLSTM	CNN- IQRLSTM
Changbai	PICP	0.92	0.93	0.94	0.80	0.83	0.91	0.86	0.97	0.98
Mountain	MC WS	0.41 0.45	0.43 0.46	0.47 0.50	0.40 0.50	0.56 0.67	0.50 0.55	0.48 0.55	0.39 0.41	0.37 0.38
The puppet palace museum	PICP WS MC	0.89 0.43 0.48	$0.95 \\ 0.42 \\ 0.44$	0.88 0.51 0.57	0.93 1.58 1.70	0.86 0.47 0.55	0.89 0.47 0.53	0.72 0.31 0.43	0.97 0.49 0.50	0.94 0.36 0.39
Sculpture Park	PICP WS MC	0.91 0.43 0.47	0.92 0.36 0.39	0.95 0.40 0.42	0.79 1.23 1.55	0.90 0.38 0.43	0.97 0.64 0.66	0.85 0.40 0.47	$0.95 \\ 0.43 \\ 0.46$	0.97 0.38 0.39
Net moon lake	PICP WS MC	0.87 0.50 0.58	0.91 0.60 0.66	0.87 0.53 0.61	0.88 0.63 0.71	0.90 1.06 1.18	0.89 1.31 1.47	0.58 0.31 0.53	0.92 0.56 0.61	0.93 0.32 0.34

Table 6. Comparison of 90% prediction interval results.

Note: boldface indicates the best result for each indicator.

(1) Taking Changbai Mountain data as an example, the PICP, WS, and MC of the CNN-IQRLSTM model are 0.98, 0.37, and 0.38, respectively. Compared with the CNN-QRLSTM model before improvement, the PICP, WS, and MC of the CNN-IQRLSTM model are improved by 1%, 2%, and 3%, respectively. Compared with the PICP of the QRRNN model, the improvement is 18%. Compared with the WS and MC of the QRLSTM model, the improvement is 19% and 29%, respectively. The scalability and practicality of the CNN-QRLSTM model does not perform optimally in all evaluation metrics, with PICP and WS just 3% and 5% lower. Similarly, the above conclusions can be obtained for the remaining two datasets.

Although the WS of the QRFNN method in the net moon lake data is the optimal result, the PICP is only 0.58, indicating that the smaller interval width leads to a lower interval coverage. From these tables, it can be concluded that the prediction results of QRRNN, QRLSTM, QRGRU, and QRFNN algorithms are more volatile than the amount of scenic tourist traffic, and there is a large gap between the predicted trends. By observing the comprehensive index MC, all four datasets perform optimally on the model proposed in this paper, which can better describe the changing characteristics of scenic passenger flow, and the comparison results validate the superiority of the scenic passenger flow prediction model combining QR and machine learning methods.



Figure 8. Performance results of different models for the 95% prediction interval.

(2) Figure 8 represents the 95% prediction interval performance histogram of different models, with indicator PICP in green, indicator WS in orange, and indicator MC in blue. Specific numerical results are shown in Appendix C. The coverage probability of the nine methods on the four datasets is close to 99% as seen in the figure, indicating that the interval prediction of the nine methods is reasonable. In the Changbai Mountain dataset, CNN-IQRLSTM has the highest PICP value of 0.9913, and the smallest WS and MC values of 0.4886 and 0.4929, respectively, which shows that the prediction ability of this model is significantly better than other models. The worst performer was the QRRNN model, which ranked last with the smallest PICP and highest WS and MC. The second-ranked model is CNN-QRLSTM without improvement, which indicates that the deep learning framework using CNN for feature filtering combined with LSTM prediction has important application value for scenic spots passenger flow. For the puppet palace museum dataset, the PICP, WS, and MC of CNN-IQRLSTM model are 0.9661, 0.408, and 0.4223, respectively. WS and MC perform best among all methods. The PICP of the QRLightGBM model is the best with 0.9813. As a witness of Changchun's history, the pseudo-Manchu architecture is an

artistic symbol that can be appreciated. Therefore, it is important to accurately forecast its patronage. In the Sculpture Park dataset, the PICP, WS, and MC of CNN-IQRLSTM model are 0.9914, 0.5187, and 0.5233, respectively. The PICP, WS, and MC of the CNN-QRLSTM model are 1, 0.5815, and 0.5815, respectively. Although the interval coverage of the CNN-QRLSTM model is 100%, its interval width is also 6.28% higher than that of the CNN-IQRLSTM model. Except for the QRRNN, QRLSTM, and QRGUR models, the rest of the MCs are between 0.5 and 0.6, reflecting the advantage of the tree model in this type of dataset. In the net moon lake dataset, the PICP, WS, and MC of the CNN-IQRLSTM model are 0.9915, 0.4841, and 0.4883, respectively. The PICP, WS, and MC of the QRFNN model are 0.6496, 0.4197, and 0.6461, respectively.

In summary, the 95% prediction interval will cover more true values than the 90% prediction interval, which makes it probable that our estimated interval will contain true values in the future actual prediction. It can greatly improve the accuracy of scenic spots' passenger flow prediction and achieve better prediction results regardless of whether in the peak tourist season or holidays. However, only to predict a larger interval has no practical significance, we need to make the prediction interval smaller under the condition of guaranteeing the accuracy rate, prompting the scenic spots management to make a reasonable allocation of scenic spots to ensure the sustainable development of scenic resources.

Figures 9 and 10 show plots of the 90% and 95% prediction interval results for the four datasets. The 90% prediction interval is composed of the quantile predicted by the 0.95 quantile and the quantile predicted by the 0.05 quantile. The 95% prediction interval is composed of the quantile predicted by the 0.975 quantile and the quantile predicted by the 0.025 quantile. The 90% prediction interval results for the GBDT, XGBoost, and LightGBM methods are shown in Figure 11. The 95% prediction interval results for GBDT, XGBoost, and LightGBM methods are plotted in Appendix D.



Figure 9. The 90% prediction intervals for four datasets. (**a**) PI of Changbai Mountain data; (**b**) PI of the puppet palace museum data; (**c**) PI of Sculpture Park data; (**d**) PI of net moon lake data.



Figure 10. The 95% prediction intervals for four datasets. (**a**) PI of Changbai Mountain data; (**b**) PI of the puppet palace museum data; (**c**) PI of Sculpture Park data; (**d**) PI of net moon lake data.

Figure 9 shows the 90% PIs, which were obtained through the proposed methodology from 17 July to 31 December 2021, with a forecast time resolution of daily. The actual tourist flow curves are also plotted in Figure 9. It can be seen that the PIs obtained using the proposed model can cover the actual tourist flow curve well, which visually illustrates the effectiveness of the proposed method for probabilistic forecasting of tourist flow in scenic areas. Figure 10 shows the 95% PIs, and it can be clearly seen that the 95% PIs are wider than the 90% PIs. The 95% over 90% PICP and WS for the four datasets improved by 0.0087, 0.1144, 0.0254, 0.0451, 0.0259, 0.1419, 0.0611, and 0.1653, respectively. Although the differences in the evaluation index results of different models are small, the superiority of the CNN-IQRLSTM model can still be seen, which further illustrates that the method proposed in this study is the best scenic tourist flow prediction model.

The training time of the neural network is shown in Table 7. It includes point prediction, 90% interval prediction, and 95% interval prediction. As seen in the results, the CNN-QRLSTM model and the CNN-IQRLSTM model show excellent performance. In the interval prediction, the training time of QRRNN, QRLSTM, and QRGRU is as much as tens of times that of the CNN-IQRLSTM model. In this study, we train all samples at once before updating the parameters and use the gradient descent method for calculation.

For the new dataset, after feature filling and sliding window processing, it can be directly input into the neural network for training. The results of parameters such as hidden layers, neurons, and epochs for different models are shown in Table 8. In the defined CNN-IQRLSTM network, first, all features pass through a 1D convolutional layer with a convolutional window of length 3 and a step size of 1. Second, they pass through a max-pooling layer with a window size of 2 and a step size of 1. Finally, after the LSTM layer, the loss function is set to quantile loss with grid constraints.



Figure 11. Plot of the 90% interval prediction results for GBDT, XGBoost, and LightGBM methods.

The accuracy of the prediction model for the four datasets before feature selection was low and the error was large. Therefore, we added data features considering the dimensionality of the dataset. We found a significant improvement in the accuracy after subjecting the data to the increased features. The simulation experiment results show that the model in this paper is a type of scenic area passenger flow average prediction model with high accuracy and excellent generality, which has wide application prospects.

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Scenic Spots	Metric	RNN	LSTM	GRU	CNN- LSTM	QRRNN	QRLSTM	QRGRU	CNN- QRLSTM	CNN- IQRLSTM
Changbai Mountain	Point prediction 90% PI 95% PI	143.00	235.00	208.00	58.50 	248.00 530.00 459.00	203.00 4679.00 2479.00	204.00 601.00 2776.00	65.08 45.57 45.57	92.00 42.00 52.40
The puppet palace museum	Point prediction 90% PI 95% PI	51.10	235.00	208.00	234.00	243.00 748.00 775.00	185.00 3638.00 3536.00	187.00 3119.00 3882.00	42.40 118.00 45.70	97.00 82.00 373.00
Sculpture Park	Point prediction 90% PI 95% PI	52.00	201.00	314.00	87.60	280.00 960.10 618.00	236.00 4860.80 4224.00	199.00 422.00 570.00	51.40 44.10 101.60	16.90 156.00 61.01
Net moon lake	Point prediction 90% PI 95% PI	42.60	168.00	153.00	275.00	227.00 883.00 767.00	227.00 4348.00 2920.00	202.00 816.00 2682.00	43.40 44.80 150.00	96.00 106 118.00

Table 7. Neural network training time (s).

Note: boldface indicates the best result for each indicator.

Table 8. Summary of parameters of neural networks.

Model	Parameter	Value
GBDT QRGBDT	Default parameters	
XGBoost QRXGBoost	Default parameters	
LightGBM QRLightGBM	Default parameters	
RNN QRRNN	Number of hidden layer nodes	32
LSTM QRLSTM	Epochs of training	100
GRU QRGRU	Number of hidden layers	1
	Number of hidden layer nodes	128
ENIN OPENINI	Activation function	sigmoid
This Quinn	Epochs of training	100
	Number of hidden layers	3
	Number of hidden layer nodes	128
CNIN I STM CNIN OPI STM	Activation function	elu
CNN IODI STM	Epochs of training	100
CININ-IQKL51M	Number of hidden layers	2
	Dropout	0.1

4. Discussion of the Proportion of Datasets

This section provides a detailed description of the division of the dataset. Since the sample size of the dataset was not very large, this study initially divided the training and test sets into ratios of 8:2 and 9:1, respectively. In the results for the Changbai Mountain data, it was shown that the prediction accuracy of dividing the data at a ratio of 8:2 was lower than the prediction accuracy of dividing the data at a ratio of 9:1. Therefore, it was decided to choose a ratio of 9:1 for data partitioning in this paper. Table 9 in the paper shows the point prediction results for dividing the data at 8:2 and dividing the data at 9:1. Regardless of which of the four indicators MAE, RMSE, MAPE, and SMAPE was used, the result was the lowest error in dividing the dataset by 9:1.

Table 9. Point prediction results for data divided by 8:2 and data divided by 9:1 for the Changbai Mountain dataset.

Proportions	Metric	QRGBDT	QRXG Boost	QRLightGBM	QRRNN	QRLSTM	QRGRU	QRFNN	CNN- QRLSTM	CNN- IQRLSTM
9:1	MAE	881.51	859.14	906.92	1248.9	1315.31	1452.75	1024.65	879.72	819.19
	RMSE	2179.63	2043.63	2206.63	2285.87	2800.54	3481.84	2103.18	2020.03	1913.09
	MAPE	0.07	0.07	0.07	0.11	0.1	0.1	0.09	0.07	0.07
	SMAPE	6.8	6.91	6.96	11	11.02	11.18	8.99	7.1	6.68
8:2	MAE	1114.43	1138.04	1210.61	1487.63	1619.96	1778.79	1442.06	1198.22	1190.85
	RMSE	2274.99	2186.64	2341.93	2468.29	3183.739	3183.92	2444.487	2255.28	2246.74
	MAPE	0.07	0.08	0.08	0.11	0.1045	0.12	0.1033	0.08	0.08
	SMAPE	7.57	7.8	8.09	11	11.2412	12.54	10.63	8.24	8.16

Note: boldface indicates the best result for each indicator.

Using 90% as a training set and 10% as a test set increases the risk of overfitting, but this is not absolute. Figure 12 in the paper shows the loss of the training and test sets for point prediction using the CNN-IQRLSTM method on the Changbai Mountain data, and the results show that no overfitting occurs using 90% of the data as the training set.



Figure 12. Training set and test set losses for point prediction of the Changbai Mountain dataset.

5. Discussion and Conclusions

With the continuous reform and opening up and the rapid development of the national economy, the economic ability and living standard of Chinese people have been improving. Nowadays, more and more Chinese people are focusing on better quality of life and higher level of spiritual pursuit [11]. Tourism around the world has not only changed the way information is disseminated but also profoundly influenced people's life, work, and entertainment, changing the way people receive information and their way of thinking, and people have higher requirements for information [36]. The modeling and prediction of scenic area passenger flow can help scenic area managers understand the changing dynamics of scenic area management. Therefore, scenic spots passenger flow prediction has become a hot issue in the field of economic research. With the booming development of tourism, how to bring good benefits to tourist attractions has become a topic worth thinking about. Choosing the appropriate method to process the type features plays an important role in improving the universality and prediction accuracy of the prediction model.

Accurate passenger flow prediction is essential to ensure the proper operation of scenic spots. However, a single model does not effectively capture the characteristics of the data. Daily tourist flow data has strong non-linear characteristics and needs to be accurately predicted. Accordingly, this study took Changbai Mountain, the puppet palace museum, the Sculpture Park, and the net moon lake as the research objects to realize the daily passenger flow prediction of scenic spots in Jilin Province. Aiming at the drawbacks of the current poor scenic spots passenger flow prediction and improving the scenic spots passenger flow prediction results, this paper constructed a deep network framework consisting of a convolutional layer, pooling layer, and improved QRLSTM to extend LSTM to QR. A sparse Laplacian smoothing grid constraint was proposed as a penalty term for quantile loss to improve the robustness of the prediction. Four relevant data features were added for the date attribute and combined with the sliding window extracted features as the input data to obtain more information about the passenger flow and provide a new perspective and idea for the accurate prediction of tourism passenger flow.

Unlike previous passenger flow forecasting, this paper creatively proposed a nonparametric probabilistic forecasting method for scenic tourist flow forecasting. The QR model was applied to the scenic tourist passenger flow prediction, and the CNN-IQRLSTM model was built on this basis to improve the prediction performance. Based on the actual data of four 5A scenic spots in Jilin Province, this paper used GBDT, XGBoost, LightGBM, RNN, LSTM, GRU, FNN, QRGBDT, QRXGBoost, QRLightGBM, QRRNN, QRLSTM, QRGRU, QRFNN, and CNN-QRLSTM as the benchmark to calculate 120 days before the passenger flow forecast and analyze MAE, RMSE, MAPE, SMAPE, PICP, WS, and MC, respectively, to verify the performance of the CNN-IQRLSTM model. The CNN-IQRLSTM model is the most accurate, reliable, and sharpest model among the 15 models, proving the potential of the method to be widely used in practice. The research framework in this paper is not proposed only for Jilin Province passenger flow and can be validated on cross-datasets. The method proposed in this study is applicable for any dataset framework. When applied to other domain datasets, we need to adjust the corresponding parameters to make the prediction accuracy ideal.

In the point prediction results, the methods with QR and without QR were compared separately. First, in the method without QR, the MAPE of the CNN-IQRLSTM model for Changbai Mountain data is 0.07. Although the MAPE is the same as the result of the GBDT method, the remaining four evaluation metrics show that the prediction accuracy of this paper's method is significantly higher than that of the seven methods, which is vastly superior. Secondly, the original tree model shows better performance than the neural network method. Secondly, among the methods with QR, CNN-IQRLSTM still has the highest prediction accuracy in the Changbai Mountain dataset, the puppet palace museum dataset, and the Sculpture Park dataset. Finally, methods with QR achieve better prediction performance, and MAE, MAPE, and SMAPE validate this conclusion in most methods. In the interval prediction results, by observing the composite index MC, all four datasets perform optimally on the model proposed in this paper, which can better characterize the change in scenic traffic, and the coverage probability of the nine methods on the four datasets is close to 99%. Meanwhile, the 95% prediction interval will cover more true values than the 90% prediction interval, and the 95% PI of the four datasets improve the PICP and WS by 0.0087, 0.1144, 0.0254, 0.0451, 0.0259, 0.1419, 0.0611, and 0.1653, respectively, compared with the 90% PI. In a subsequent study, we will try to use GPUs supporting Computational Unified Device Architecture (CUDA) to achieve accelerated training times. CUDA is a novel hardware and software architecture for issuing and administering computations on GPUs as data parallel computing devices on GPUs without mapping them to image APIs.

This study combined QR and neural network techniques to provide a new framework to enhance the analysis and prediction of tourist passenger flow in different scenic spots by fusing multidimensional features. Compared with previous methods, the advantages of the proposed CNN-IQRLSTM model are as follows. (1) Compared with the traditional QR model, the QR prediction model constructed based on CNN and LSTM can better capture the dynamic features of passenger flow changes and obtain higher prediction accuracy. (2) CNN-IQRLSTM can predict multiple quantile prediction results at the same time, and it is trained with appropriate parameters during the training process, which significantly improves the prediction efficiency while ensuring the prediction effect. (3) Compared with the CNN-QRLSTM model, the addition of grid constraints effectively avoids the crossover between quantile prediction values, and the sparse Laplacian smoothing grid constraint makes the prediction results more reasonable and significantly improves the reliability of point prediction and interval prediction. In summary, the method in this paper not only has high accuracy of point prediction, but also can obtain reasonable interval prediction results, which can provide more accurate and rich information for scientific decision-making of scenic spots managers.

Since the neural network will be affected by abnormal historical disturbance during the training process, the generalization of the model is reduced. In this paper, we adopted the network structure constraint as the penalty term of the objective function to improve the robustness of prediction by smoothing the deviation degree of network weights in the iterative correction process according to the sparse Laplacian. However, there are still some limitations. First, the validation dataset does not have a long enough period to study the effects of longer spatial and temporal factors, such as year, season, etc. Second, the effects of external factors, such as financial crisis, climate, etc., were not taken into account. Third, the dynamic spatial characteristics of passenger flow were not studied in this paper, and the rich spatio-temporal correlation and non-linear information would improve the validity of the prediction. Finally, the model running time is improved over some methods, but not significantly and substantially. In the future, we will further explore the influence of external and spatial features and investigate the application of CNN-IQRLSTM in more complex datasets. This study also intends to investigate the extension of composite quantile regression in deep learning models to flexibly exploit the properties of neural networks to explore nonlinear relationships between variables, and multiple regression quantile features can be exploited to improve estimation efficiency and predictive power. Finally, a framework of swarm intelligence optimization algorithms can be established for the parameter problems in neural networks to perform the optimization search process, aiming to develop a more effective and accurate and reliable prediction model. It has excellent prospects for tourism management research and application and can promote the healthy and sustainable development of the tourism industry.

The factors considered in this paper are not representative of all influencing factors and do not take into account unexpected events, financial crises, economic collapse, energy crises, or unknown causes. Therefore, if other influencing factors can be explored and analyzed, the forecasting model can be enhanced and the forecasting accuracy can be further improved. For potential anomalies, such as coronavirus, there are numerous impacts on the tourism industry. We can divide the passenger flow forecast for tourist attractions in Jilin province into pre- and post-epidemic, considering the actual situation of each attraction, as well as the availability of travel in each province. Next, future passenger flow can be further predicted based on the duration of the virus that has been predicted.

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Figure A1. Comparison of true and predicted values of other comparison methods for the Sculpture Park dataset. (a) GBDT/XGBoost/LightGBM; (b) RNN/LSTM/GRU; (c) FNN/CNN-LSTM/CNN-QRLSTM; (d) QRGBDT/QRXGBoost/QRLightGBM; (e) QRRNN/QRLSTM/QRGRU/QRFNN.



Appendix **B**

Appendix A



Figure A2. Comparison of true and predicted values of other comparison methods for the net moon lake dataset. (a) GBDT/XGBoost/LightGBM; (b) RNN/LSTM/GRU; (c) FNN/CNN-LSTM/CNN-QRLSTM; (d) QRGBDT/QRXGBoost/QRLightGBM; (e) QRRNN/QRLSTM/QRGRU/QRFNN.

Appendix C

Scenic Spots	Metric	QRGBDT	QRXGBoost	QRLightGBM	QRRNN	QRLSTM	QRGRU	QRFNN	CNN- QRLSTM	CNN- IQRLSTM
Changbai Mountain	PICP WS MC	0.95 0.70 0.74	0.95 1.15 1.21	0.96 0.78 0.82	0.87 2.72 3.13	0.97 0.81 0.84	0.93 0.82 0.88	0.88 0.62 0.71	0.98 0.58 0.59	0.99 0.49 0.49
The puppet palace museum	PICP WS MC	0.96 0.69 0.72	0.97 0.64 0.66	0.98 0.80 0.82	0.96 1.70 1.77	0.95 1.33 1.40	0.92 0.67 0.73	0.83 0.46 0.56	0.97 0.61 0.63	0.97 0.41 0.42
Sculpture Park	PICP WS MC	0.96 0.55 0.57	0.97 0.52 0.54	0.98 0.58 0.59	0.87 1.59 1.82	0.98 1.22 1.25	0.98 1.28 1.30	0.92 0.53 0.57	1.00 0.58 0.58	0.99 0.52 0.52
Net moon lake	PICP WS MC	0.91 0.71 0.78	0.93 1.00 1.07	0.96 0.76 0.79	0.95 2.74 2.89	0.96 1.42 1.49	0.97 1.68 1.74	0.65 0.42 0.65	0.94 0.56 0.60	0.99 0.48 0.49

Table A1. Comparison of 95% prediction interval results.

Note: boldface indicates the best result for each indicator.

Appendix D

GBDT - Changbai mountain XGBoost - Changbai mountain LightGBM - Changbai mountain 30,000 Observations 97.5% Predictions 30,000 30,000 2.5% Predictions 25,000 25,000 95% PI 25.000 Assenger flow 15,000 15,000 § 20,000 off 20,000 Lassenger fl 15,000 Passenger 15,000 10,000 10,000 10,000 5000 5000 5000 0 40 60 Day Inc 60 Day 100 40 60 Day 20 100 GBDT - The puppet palace museum LightGBM - The puppet palace museum XGBoost - The puppet palace museum 35,000 30,000 30,000 30,000 25,000 25,000 25,000 Assenger flow flow Passenger flow 20,000 Bassenger fl 15,000 15,000 10,000 10,000 10,000 5000 5000 5000 ⁶⁰ Day ⁶⁰ Day ⁶⁰ Day GBDT - Sculpture park XGBo ost - Sculpture parl LightGBM - Sculpture park 30,000 25,000 25,000 25,000 Agger flow Passenger flow 15,000 Agender flow 15,000 Passenger flow 20,000 15,000 10.000 10,000 10,000 5000 5000 5000 20 60 Day 60 Day 80 100 120 60 Day 120 40 40 LightGBM - Net moon lake GBDT - Net moon lake XGBoost - Net moon lake 40,000 30,000 30,000 35,000 25,000 30,000 25,000 Passenger flow 15,000 Passenger flow 12,000 lo≪ 25,000 Passenger 20,000 15,000 10,000 10,000 10,000 5000 5000 5000 60 Day 60 Day 120 100 120 60 Day 120 40 40

Figure A3. Plot of 90% interval prediction results for GBDT, XGBoost, and LightGBM methods.

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