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Research Article

Deep LSTM Network for Word-of-Mouth Management of Rural Tourism

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With the development of tourism, rural tourism as an industry with great development potential is gradually attracting urban consumers. Considering the differences between different types of rural tourism, I refine it at the visitor level to balance the differences in visitor groups of different types of rural tourism. I propose an improved LSTM framework for rural tourism theme feature extraction. I chose a deep neural network approach to decompose the diverse rural tourism word of mouth into different tourism themes. Then, through tourist feedback data preprocessing, destination theme detection, rural tourism type classification, and word-of-mouth management prediction network, I finally achieve an accurate grasp of rural tourism word-of-mouth features and develop corresponding tourism management strategies. To test the performance of our method, I established different types of rural tourism databases through field surveys for experimental validation. The experimental results show that our method achieves over 90% accuracy in review sentiment detection.

1. Introduction

With the dramatic expansion of the urban economy, urban space is constantly being compressed, and people's recreational space and park areas are decreasing. Along with the industrial development, the air quality within the city is decreasing, and more and more people are planning to travel to the countryside. Every holiday season, most people who work in the city choose to leave the city and travel to a distinctive countryside or town to experience the beauty, food, and culture of the countryside. Villages in different regions have different characteristics. Villages in coastal cities are themed around fishing villages, creating an all-around atmosphere of fishermen's life and allowing visitors to experience the fun of fishing. The villages in the inner mountainous areas are themed around hunting, with livestock kept in captivity in the mountain forests for visitors to simulate hunting, in addition to creating a paradise atmosphere for visitors to enjoy the tranquility of the countryside away from the hustle and bustle of the city [1, 2]. The countryside in the inland plains is dominated by herdsmen, creating original herdsmen's life projects to attract tourists to experience the details of herdsmen's life and make tourists have a different experience with the grassland culture being the cultural background. I cannot deny the siphon effect of big cities and tourist attractions. But, with the development of tourism, the demand for rural tourism has gradually increased. Different regions of rural tourism with a characteristic cultural background need to have a reasonable management model. From the deep level of the local cultural background, a reasonable strategic plan for rural tourism is formulated, together with computer-aided technology, to form a closed-loop system for rural tourism management [3–5].

To allow tourists to intuitively understand the cultural context of rural tourism, a weighting model with historical and cultural and landscape features should be built during the construction of tourism culture. In rural tourism destination selection, researchers in the literature [6] proposed five key points: destination image, life cycle, tourism experience, condition value, and destination quality. Of these, the destination image is the foundation of rural tourism, and a good destination image can add more appeal to the other key points and increase tourism expectations in the minds of tourists. Researchers in the literature [7] have again demonstrated in a large number of studies that destination image is a decisive influence in tourism postmanagement and marketing. The destination image requires to be as simple and dynamic as possible. It gives more functionality to tourism activities in the process of building tourism culture and enhances tourists' sense of game experience and activity participation. Some tourism experts point out that tourists' image of the destination generates tourism word-of-mouth benefits, and excellent tourism word of mouth can enhance the chances of tourists' choice of tourist destinations and improve the value attributes of tourist destinations in tourists' minds [8]. In addition, good tourism word of mouth can bring a huge economic effect to rural tourism from souvenirs to food series.

The image of a tourism destination is directly proportional to the tourism word of mouth, so the image enhancement of rural tourism destinations is a key task in tourism management. The image of rural tourism is designed to convey the content, culture, and sense of the experience of rural tourism to the tourists. The tourists' understanding of the image of rural tourism needs to be combined with the actual tourism experience [9, 10]. Visitors' opinions and comments on rural tourism are the most important part of rural tourism word of mouth. Researchers in the literature [11, 12] have attempted to develop a mapping model between tourists' tourism experiences and tourism concepts for judging the conceptual differences in images between tourist destinations. The experimental results proved that heterogeneity exists between tourism purposes in terms of tourism word-of-mouth measures. Researchers in the literature [13] found that rural destinations with the tourism objective of discovering culture and history were more advantageous in the image assessment of rural destinations across geographic regions and that these rural destinations achieved an automatic closed-loop flow in terms of supply and demand pressure, which greatly reduced tourism development costs. Researchers in the literature [14] found that computer vision-based presentation of multidimensionality of tourism destination images can form a new concept for tourists and enhance the attractiveness of tourism destinations to tourists in terms of tourist numbers, cultural tourism definition, and tourist emotional variables for tourism word-of-mouth construction.

To enhance the impact of rural tourism, rural tourism uses optimal scheduling algorithms that play an active role in the rational allocation of resources [15, 16]. Diversification of rural tourism models is the most efficient means of enhancing the competitiveness of rural tourism. With the assistance of tourism agencies, rural tourism has introduced diversified experiences such as farmhouses, traditional culture experience villages, fishing villages, hunting grounds, and cultural and creative product villages. To save the development cost of rural tourism, the literature [17] proposes the construction and sharing of rural facilitation infrastructure and proposes a rural tourism organization to develop various comfort resources to revitalize citizens' rural tourism. In addition, rural tourism cultural product development and event planning are also important management tools for rural tourism to enhance the attractiveness of rural tourism to tourists and increase the network reputation of rural tourism. Researchers in the literature [18, 19] point out in the data analysis of rural tourism and the establishment of rural basic amenities that rural tourism, while preserving the local characteristics of resources, should take the construction of tourism culture as the main. In the analysis of data on rural tourism and the establishment of rural infrastructure facilities, the researchers pointed out that rural tourism, while preserving local resources, should focus on the construction of tourism culture as the main task and optimize tourism facilities by scientific means to reduce the uneven distribution of tourism resources such as vehicle congestion and accommodation shortage during the peak season. Reasonable expansion of tourist destinations to neighboring villages under the reasonable scope of tourism support construction not only can ease the pressure of tourism but also can create more economic benefits. The use of computer means for simulation and optimization is considered in the rational allocation of tourism resources to enhance the stability and sustainability of rural tourism [20].

The remainder of this paper is laid out as follows. Section 2 describes research related to rural tourism. Section 3 details the principles and implementation process related to the improved LSTM rural tourism word-of-mouth prediction network. Section 4 presents the relevant experimental datasets and an analysis of the results. Finally, Section 5 reviews our findings and reveals some additional research.

2. Related Work

The construction of rural tourism word-of-mouth should be judged on tourists' real experiences and tangible emotions, and the literature [21–24] has proposed a method of rational, and emotions were conceptually fused using images, and a cognitive evaluation method was proposed, which focused on testing three aspects of tourists' virtual impressions, real perceptions, and cultural knowledge of the tourist destination. Under the experimental conditions set by the authors, tourists' feelings are linearly correlated with the perceptions and perceptions of tourist destination images. The attributes of tourism word of mouth consist of tourism resources, tourism facilities construction, and tourism package completeness of the tourist destination, which also determine the relative excellence of the destination. Researchers in the literature [25] argue that different tourism cultures should have different assessment rules; therefore, the authors classify tourism destinations into four categories: natural landscapes, historical landscapes, cultural landscapes, and artificial parks. There are independent tourism word-of-mouth assessment models for different tourism destination categories, which make the construction of tourism word of mouth more balanced, detailed, and complete.

Researchers in the literature [26] have attempted to extract personal assessment opinions of tourist destinations from a list of representative attributes, using interval vectors with ordinal coding for automatic measurement of image cognitive components. In addition, researchers in the literature [27] used a multidimensional scale's array mapping model, which was able to effectively discriminate polar emotions in the reviews of tourist destinations, and the efficiency of this array mapping model was experimentally demonstrated. Researchers in the literature [28] proposed a dyadic analysis applying nominal scales, where the authors compare the heterogeneity between different tourist destinations to obtain the values of tourism word-of-mouth attributes. Researchers in the literature [29] used an open-ended question model in the data processing of tourist feedback, starting from adjective and noun suggestions of tourist responses, to develop a tourism word-of-mouth assessment in a preliminary model.

Many researchers have attributed the influences of tourism word of mouth to tourists' intuitive feelings and emotional reactions to the destination. Researchers have assessed strategic images through tourists' feelings and emotions, and there are some tourists' opinions that contain the real situation of the destination, some tourists' opinions that are filled with a lot of subjective factors, and some tourists' opinions that contain a lot of constructible suggestions. The current tourism word-of-mouth assessment model does not correctly classify the mixed tourist opinions [30]. Although sentiment and word of mouth are directly related, it would certainly be unfair to travel platforms if they cannot screen out malicious comments from tourists. Tourism word of mouth is an objective opinion and emotion conveyed by tourists after they have personally experienced a tourist attraction, and the emotional dimension of tourism destination image should be based on tourists' objective feelings. Some researchers have proposed a Russel-based structure of tourists' emotional perceptions, which is mainly developed with a two-dimensional structure of emotional variables and a bipolar structure. Based on this, subsequent studies have gradually subdivided tourist feedback emotions such as boredom, pleasure, relaxation, depression, and so on. All emotions were coded in the same dimension on an interval scale, and the method was experimentally shown to be efficient in distinguishing tourists' polar emotions.

Several researchers have computer-modeled tourist destination images covering both the perceptual part and the affective image part. The data were then summarized in terms of image images, where the perceptual part images consisted of tourist cognitive data and the affective images consisted of tourist emotional data. There is a fixed linear relationship between cognition, emotion, and the overall image of the tourist destination. The emotional component can directly affect the overall image of the tourist destination, and the cognitive component affects one-fifth of the overall image of the tourist destination, but the cognitive component and the emotional component can be transformed under certain conditions [31]. For example, tourists' reasons for choosing a tourist destination, tourists' characteristics, tourists' travel habits, tourists' sources of tourist information, and so on are all part of the cognitive component. Such a linear relationship has been transformed into a destination image assessment model in later studies and has been widely used in many studies.

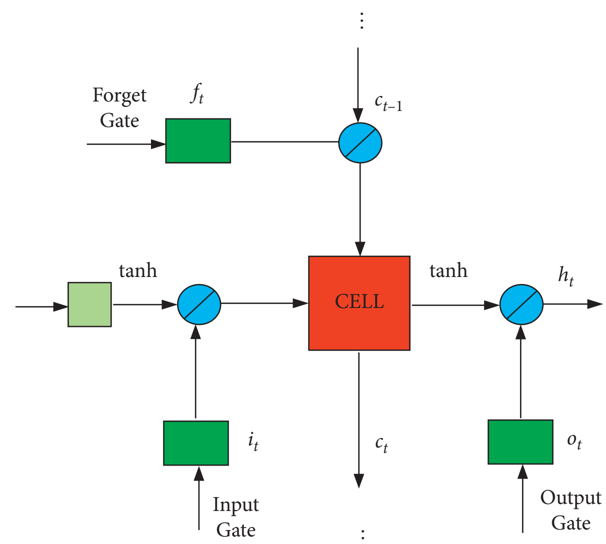

Figure 1: LSTM network.

3. Method

3.1. Travel Word-of-Mouth Feature Extraction Network. In the deep learning neural network model of traveler's word of mouth, I found that the long short-term memory network (LSTM) has extremely strong local perception ability in natural language processing, can learn traveler's word-of-mouth features with superhigh efficiency, and can store the relevant features in the short-term network to prevent the problem of information feature omission when learning new features subsequently. I found that some researchers also choose to use LSTM networks to parse tourist attraction text features and achieve good results. The structure of the LSTM network is shown in Figure 1. In this paper, I choose LSTM networks as the basic framework for rural tourism word-of-mouth feature extraction.

The semantic features of rural tourism word of mouth are input at the input side of the LSTM network, and all word-of-mouth semantic features form a feature sequence M before moving to the next stage with the following mathematical expressions:

$$M = [m_1, m_2, \ldots, m_t], \tag{1}$$

where t represents the length of the feature sequence M. Natural language processing was initially dominated by recurrent neural networks (RNN), and as natural language processing requirements became more stringent, RNNs were unable to provide complete features for global information due to the omission and loss of textual information due to the framework architecture. Therefore, the LSTM framework was formed based on the optimization of RNN, and the emergence of this method solves the problem of the sequential mapping of text features and also provides local features for global information continuously. The LSTM network has a total of four gates and one memory unit, which are an input gate i_t, forgetting gate f_t, output gate o_t, and a memory unit c_t for updating the hidden state h_t, as follows:

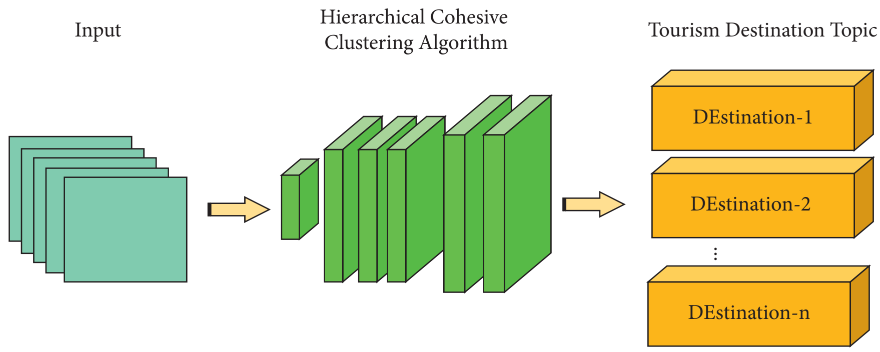

Figure 2: Tourism destination image topic detection network.

$$
\begin{aligned}
i_t &= \sigma\left(W_i x_t + V_i h_{t-1} + b_i\right),\\
f_t &= \sigma\left(W_f x_t + V_f h_{t-1} + b_f\right),\\
o_t &= \sigma\left(W_o x_t + V_o h_{t-1} + b_o\right),\\
c_t &= f_t \odot c_{t-1} + i_t \odot \tanh\left(W_c x_t + V_c h_{t-1} + b_c\right),\\
h_t &= o_t \odot \tanh\left(c_t\right),
\end{aligned} \tag{2}
$$

where $\odot$ is a function similar to a multiplicative operation, V denotes the matrix associated with the weights, and b denotes the learning vector. In the process of natural language text information processing, LSTM needs to be trained in advance on the forgetting gate side of the semantic elements to obtain deeper text features and implicit features. Forward and reverse bidirectional semantic training allows for travel word-of-mouth character features to be completed ahead of feature replication and stored in hidden memory cells in a tandem combination before being passed to the next layer.

3.2. Tourism Destination Topic Detection. Tourism destination image theme detection is a fusion between text features and sentiment features, and character features between lexemes, words, sentences, and paragraphs can be fully mentioned in the text feature detection phase. To map each character feature to the set of sentiment features, I use a tagging approach. In the data preprocessing phase, I reset all text data sets to be trained and classify all text features in layers with the support of professional linguists. I classify text at four levels: lexemes, words, sentences, and paragraphs, and at each level, I manually annotate using different sentiment tags. Manual annotation is a huge project, and to reduce the workload and improve efficiency, I use the word root dispersion method, where I encode the same word roots and their similar texts predefined to the computer, to achieve automatic annotation of text data. Finally, this is used as the textual theme of the tourism destination image.

In the stage of tourism destination image theme assignment, I adopt the rule of sameness, that is, different text units share the same; tourism theme, which will not affect their tourism theme labels in the subsequent text decomplication. In special cases, I also follow the specified coding units, such as the annotation of keywords, technical terms, and new vocabulary, and I redesign the annotation process according to the actual situation. The details of tourism destination image theme detection are shown in Figure 2. In our design, each lexeme, word, sentence, and paragraph have a unique label, but this does not affect sentence-to-lexeme disassembly either. The disassembled labels change only at the text level, but their labels correspond to the text level and do not affect the labels at their next level.

To ensure the requirements of rural tourism destination management, I finally chose the hierarchical intraclustering clustering algorithm through extensive experimental validation [32]. I first segmented the text for tourism topics and then filtered the tourism features of word positions by different thresholds. The text clustering similarity was then used to determine the degree of matching between character features and textual tourism features by setting a criterion line and then adjusting the similarity of the extreme data according to the criterion line. The clustering of lexical positions and words can be done at once, while the clustering of sentences and paragraphs requires two to three cycles to satisfy the clustering requirements. The literature [33] proposes two evaluation metrics to determine the effectiveness of text tourism topic clustering in the same context. The mean value of word-level similarity discriminates whether the character features at the word level satisfy the feature mapping condition. The mean value of the maximum similarity between graphemes determines whether the mapping between grapheme features and tourism theme features is within the specified threshold. The mathematical equation of the above evaluation index is expressed as follows:

$$
\operatorname{sim}\left(T_1, T_2\right) = \frac{1}{2}\left(\frac{\sum_{w\in\{T_1\}}\left(\operatorname{maxsim}\left(w, T_2\right) * idf\left(w\right)\right)}{\sum_{w\in\{T_1\}} idf\left(w\right)} + \frac{\sum_{w\in\{T_2\}}\left(\operatorname{maxsim}\left(w, T_1\right) * idf\left(w\right)\right)}{\sum_{w\in\{T_2\}} idf\left(w\right)}\right), \tag{3}
$$

where T_i represents a sentence and w represents a word contained in the sentence T_i. Considering that sentence- and paragraph-level clustering requires circular disambiguation and fairness of same-level clustering for bitwise N-dimensional character vectors, I additionally add cosine similarity as a weight.

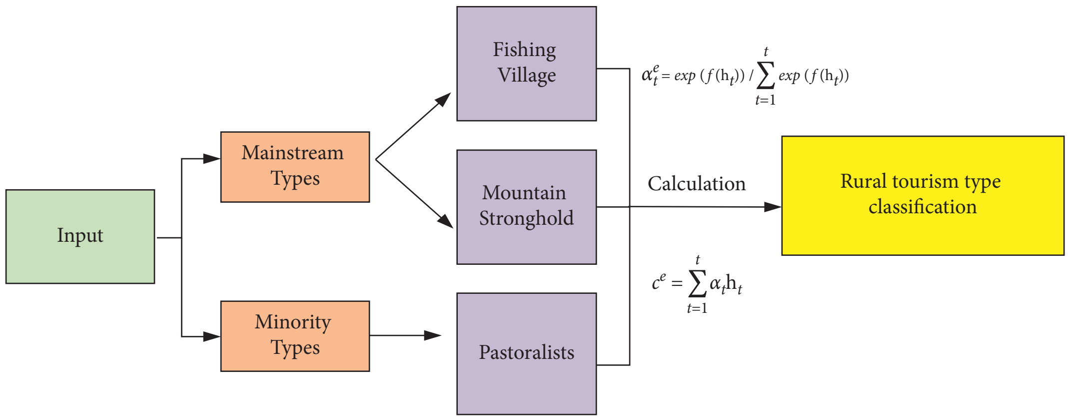

Figure 3: The rural tourism type classification network.

3.3. Rural Tourism Type Classification. Rural tourism type classification incorporates criteria of tourism themes and emotional characteristics of tourists. I need to classify the character hidden tourism theme features of lexemes, words, sentences, and paragraphs. Different character levels of hidden tourism theme features will have different responses. Considering the requirement of asynchronous homogeneity, I introduce an attention mechanism to monitor the abnormal states of different sequences and perform task control by classifier pointers so that the improved LSTM network can learn more character-level tourist sentiment features and improve the model's recognition accuracy of text sentiment features. Meanwhile, I add character sentiment tourism feature sharing in the improved LSTM network, and the weighted representation of the relevant feature sequences is $h_t = \sigma([\overrightarrow{h}_t, \overleftarrow{h}_t])$. Character sentiment features of different travel types correspond to different feature encoders, and I assume that the sequence of shared travel type features is $h_t = (h_1, h_2, \ldots, h_t)$, where t denotes the length of the sequence. I add an attention mechanism to the modified LSTM network to traverse the features α_t^e of the time sequence t. Each travel type corresponds to a weight h_t. The detailed mathematical expression is given below:

$$\alpha_t^e = \frac{\exp(f(h_t))}{\sum_{t=1}^{t}\exp(f(h_t))}, \tag{4}$$

where $f(h) = W^T h$, W represents the parameters that can be trained. c^e represents the weighted sum of the output sequences of the attention mechanism, and its weighting equation is as follows:

$$c^e = \sum_{t=1}^{t} \alpha_t h_t. \tag{5}$$

The travel type ordinary and hidden layers are interconnected, and the travel topic features are input to the next layer in the form of high-level semantic features c^e. The travel topic features are then classified. The rural tourism theme covers several categories of features, and to distinguish different tourism type features, I use a multimodal theme classifier. The rural tourism type classification network is shown in Figure 3. In this classifier, a total of 128 nodes are set in the fully connected layer based on the tourism features in the word element layer, and the activation function is chosen as ReLU for nonlinear activation. Before outputting to the next layer, I added a random deactivation layer to prevent the activation function from causing overfitting of the travel features. In the final output layer, I use softmax to activate the tourism theme features and then filter them according to the weights to get the text corresponding to the countryside tourism theme category.

3.4. Rural Tourism Word-of-Mouth Management Prediction Network. I developed the extraction of rural tourism word-of-mouth features via distributed vectors at the word position level using LSTM network processing in the initial stage. To complete the classification of multiple tourism theme features fed back by tourists, I manually constructed a rural tourism theme type database for detailed polar sentiment for each tourism category. Each character vector contains a set of tourism theme features, and all the character vectors are stacked to form a character vector matrix, and the matching of tourism theme features is obtained by mapping the unknown vectors to the categories in both directions. In the retrieval process, the index of tourism categories can be tracked in the projection layer by the rural tourism theme labels, and the tourism theme features are linked to the corresponding classification tables.

Considering that a large amount of tourist data is needed to support the pretraining of the rural tourism word-of-mouth prediction model. I pre-process tourist data from the restaurant, hotel, bar, and amusement park industries as data input for model pretraining. Considering the specificity of the embedding stage of tourism theme features, I split all tourism text features into characters for embedding, provided that such splitting does not affect the integrity of the text tourism type analysis. The detailed implementation network is shown in Figure 4. All the inputs are in the form of characters, starting from the left, and the thematic features of different tourism types are projected to the next layer through the bidirectional propagation and feedback of the network. The LSTM network can keep the number of features consistent in the process of text feature segmentation. I also used the CRFs method to ensure that the neighboring

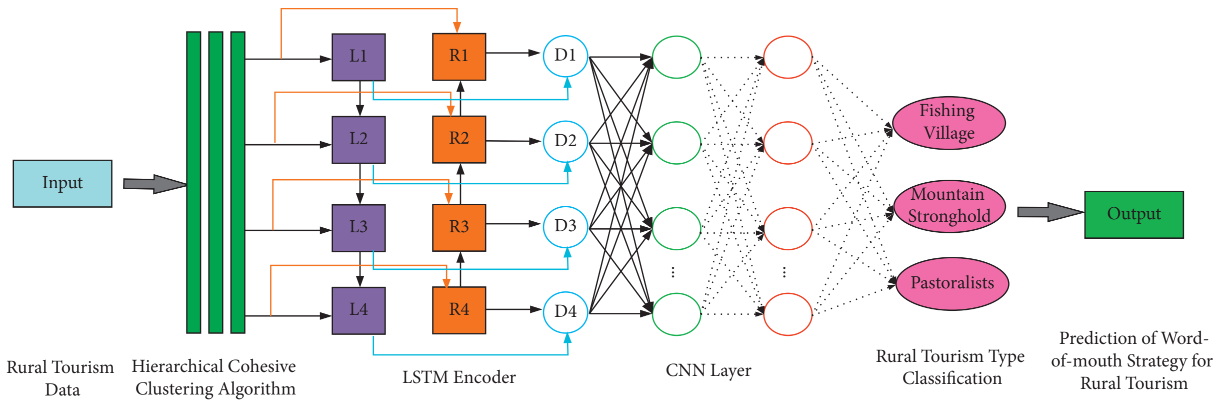

Figure 4: Rural tourism word-of-mouth management prediction network.

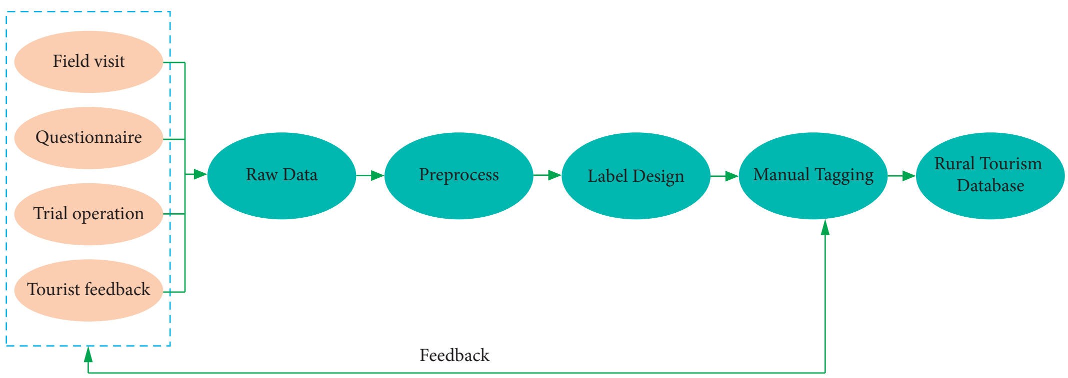

Figure 5: Rural tourism review data production process.

labels of each travel type do not affect the final predicted values. To refine the local information in long sentences, I added a CNN layer at the end to recursively feed the tour word-of-mouth features to ensure that the large-scale word-of-mouth features are fully controlled.

4. Experiment

4.1. Data Sets. Rural tourism is an emerging business in the tourism industry, with limited data on the same type of tourism industry, and there is no publicly available dataset on the Ib for rural tourism management. To validate the effectiveness of our method in rural tourism word-of-mouth management, I first collected feedback from rural tourism planning and trial operations in recent years on tourism websites and then visited some successful rural tourism cases in the field and recorded tourist satisfaction data of rural tourism. I used a splitting tool to preprocess each visitor's feedback data. Then I used the anomalous data detection system to screen out the anomalous data and obtained the preliminary polarity training set and test set by manual calibration. The data processing process is shown in Figure 5.

For different types of rural tourism, I categorized and outlined in the visitor feedback data so that rural tourism of the same type and scale is comparable, and rural tourism of different types and scales is only informative. For this purpose, I categorized different types of rural tourism data from field visits and finally obtained a homemade rural tourism dataset with details shown in Table 1. In the subsequent efficiency evaluation methods, I still use precision, recall, and *F*1 score to evaluate the effectiveness of rural tourism word-of-mouth prediction.

Table 1: The detail of data sets.

	Data sets classification		
	Fishing village	Pastoralists	Mountain stronghold
Train	4,932	3,966	4,261
Test	1,903	1,501	2,003
Total	6,835	5,467	6,264

Table 2: Accuracy of word-of-mouth prediction for different types of rural tourism.

	Fishing village (%)	Pastoralists (%)	Mountain stronghold (%)
RF	42	41	51
RNN	79	73	76
Ours	92	90	95

4.2. Experimental Results. To compare the efficiency of our approach in rural tourism word-of-mouth management, I

Table 3: Experimental reliability analysis results.

	Fishing village		Pastoralists		Mountain stronghold	
	Prediction	Actual	Prediction	Actual	Prediction	Actual
RF	0.94	0.88	0.91	0.85	0.96	0.88
RNN	0.95	0.91	0.92	0.88	0.95	0.90
Ours	0.94	0.93	0.94	0.93	0.95	0.95

Table 4: Comparison of prediction results of rural tourism word-of-mouth strategy.

	Fishing village			Pastoralists			Mountain stronghold		
	P	R	$F1$	P	R	$F1$	P	R	$F1$
RF	0.79	0.75	0.79	0.78	0.77	0.81	0.79	0.79	0.77
RNN	0.85	0.86	0.88	0.86	0.88	0.89	0.87	0.85	0.87
Ours	0.92	0.93	0.95	0.92	0.93	0.91	0.94	0.93	0.92

conducted experiments based on three major rural tourism categories. I selected the random forest method (RF) and recurrent neural network (RNN) as the comparison algorithms. Each model maintains an independent running process during the training process. For the training parameter set, I used the migration learning method to reduce the computational cost. The experimental results are shown in Table 2.

As shown in Table 2, the accuracy of word-of-mouth prediction for different types of rural tourism industry remains above 90% for all categories of our method. Compared with the random forest method, the prediction accuracy is improved by up to 50 percentage points. This is at most 19 percentage points higher than the recurrent neural network method. The random forest method does not perform well in word-of-mouth prediction of rural tourism in the fishing village category. The random forest method, as a traditional machine learning method, relies too much on the construction and labeling of manual tourism text databases and is slow in processing when facing a large amount of tourist data. For unfamiliar tourist feedback, it is easy to generate misleading problems. This also leads to the poor word-of-mouth management results of the random forest method in our experiments. From the data, I can find that the accuracy of word-of-mouth detection of pastoralists is generally lower than in other categories of rural tourism. This is because pastoralists deal with a small base of tourists, and it is difficult to incorporate more tourism word-of-mouth feature vectors at the data learning level. Since fishing village and mountain stronghold are more sought after by tourists, more tourism word-of-mouth factors can be analyzed, and then the activation function is used to highlight their features, which improves the word-of-mouth prediction accuracy. Therefore, the word-of-mouth prediction accuracy of pastoralists is lower overall. To verify the credibility of our experiments, I supplemented the credibility verification experiments, in which I mainly compared the word-of-mouth prediction results with the actual results. The experimental results are shown in Table 3.

From the reliability analysis experiments in the table above, it is clear that the random forest method has the largest difference between the predicted and actual values, with a difference of about 0.06. Our method has the highest reliability, with only a 0.01 difference between the predicted and actual values. This shows the superiority of our method. To verify the effectiveness of our method in more detail, I conducted a comprehensive validation in terms of three metrics: recall (R), $F1$ score, and precision (P). Based on our preliminary study, I found that different types of rural tourism have different impacts on their word-of-mouth predictions due to different levels of popularity among tourists. Therefore, in the next experiments, I will analyze the categorized feedback data of tourists. Based on our previous work on the refinement of rural tourism themes, I again conducted a refinement of visitor categories. The experimental results are shown in Table 4.

From the experimental results in the table above, it can be seen that our method performs better after visitor type refinement, as seen in the independent classification validation of different types of rural tourism. The experimental results are more objective and reliable and more responsive to the real feedback of the same type of tourists on rural tourism. From the accuracy and recall data, I can see that our method performs well. Our method can give word-of-mouth data management predictions for different types of rural tourism, and a weighted balance of this tourism theme features according to professional word-of-mouth evaluation agencies. Finally, rural tourism management strategies are developed based on the word-of-mouth prediction results. Such rural tourism word-of-mouth prediction results give tourists a detailed travel reference.

5. Conclusion

In this paper, I analyze the development and prospects of rural tourism and then discuss the links between rural tourism management and conventional tourism. Considering the differences between the different types of rural tourism, I refine them at the visitor level and balance the differences in the visitor base between the different types of rural tourism. Comparing various development factors of rural tourism, I propose an improved LSTM framework for rural tourism theme feature extraction. I discarded the traditional machine learning method and chose a deep neural network approach to decompose the diverse rural tourism word-of-mouth into different tourism themes for classification. Then, through visitor data preprocessing, destination theme detection, rural tourism type classification, and word-of-mouth management prediction network, I finally achieve an accurate grasp of rural tourism word-of-mouth features. To test the performance of our method, I built a database of different types of rural tourism through a field survey for experimental validation. The experimental results show that our method maintains over 90% accuracy in review sentiment detection, which is significantly better than other methods.

Since rural tourism is a new industry, the volume of data is too small. The performance of the deep neural network model is proportional to the amount of training data. The amount of data I have is far from sufficient for the later study. For the optimization of the network, I will consider using bidirectional recurrent neural networks to process the feature sequences of different types of rural tourism word-of-mouth to achieve better accuracy of word-of-mouth prediction.

Data Availability

The data set can be accessed upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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