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Computer-Aided Design AND APPLICATIONS

Feature Extraction and Emotional Classification of Tourism Souvenirs Based on Deep Learning

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Abstract. Grasping the emotional needs of buyers of tourist souvenirs can guide the design of tourist souvenirs well and make them adapt to the development requirements of the times. The design of traditional tourist souvenirs often pays attention to the appearance of products, but lacks the attention to the interaction between tourists and souvenirs, which makes the products not vivid enough because of the lack of emotional communication with consumers. Focusing on the emotional interaction between tourist souvenirs and tourists, this article applies the graph convolution network (GCN) in DL to the optimization of computer-aided design (CAD) of tourist souvenirs, and optimizes the network structure by combining human perception of the emotional visualization results of images. Finally, the parameters of the network are fine-tuned to make it more suitable for the interactive design task of tourist souvenirs. It can be seen from the results that the accuracy of the emotion classification algorithm in this article has obvious advantages compared with the traditional back propagation neural network (BPNN) algorithm. Therefore, the emotional classification model based on DL and CAD is helpful to realize the emotional interaction design of tourist souvenirs.

Keywords: Deep Learning; CAD; Tourist Souvenirs; Feature Extraction; Emotional Classification
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1 INTRODUCTION

In recent years, the growth of social economy has brought about the vigorous growth of tourism, which will inevitably lead to the growth of tourism ancillary products, and tourist souvenirs are an important part of tourism ancillary products. The history and culture of various regions spread to all parts of the world through tourist souvenirs, which is a way for cultural exchange and development, so the design of tourist souvenirs has been given deeper connotation and higher requirements. Arun et al. [1] conducted exponential analysis of function calculation exploration in data information technology. It constructs an autoregressive model for predicting information processing. The use of autoregressive methods for tourism information extraction and analysis the needs and trends of the tourism market, thereby better planning tourism routes, promoting tourism products, and so on. At the same time, analyzing tourist behavior data and feedback information can also improve the quality and satisfaction of tourism services. The energy grid trading recognized by EAI refers to the trading of energy products through trading platforms recognized by the Energy Administration. This trading method can promote transparency and standardization of the energy market, improve the efficiency of energy commodity circulation, and thus provide support for the healthy development of the energy industry. By combining autoregressive methods with energy grid transactions recognized by EAI, data and trends in the energy market can be analyzed to predict the prices and demand of energy commodities, thereby providing more accurate and scientific basis for decision-making in the energy industry. At the same time, autoregressive methods can also be used to analyze and extract tourism information, providing more valuable references for market development and promotion in the energy industry. Emotion has become an important field of concern for tourism consumers. Adding emotional interaction to the process of obtaining, using and sharing souvenirs will help improve the commemorative value, cultural value and economic value of products. Chen [2] conducted a deep learning model for emotional recommendation of user comments. By learning emotional analysis from different data, it constructs denoising processing for emotional learning points. The experimental results indicate that user rating classification applications can effectively classify user ratings and identify their emotional tendencies. This application can be used for user rating analysis and recommendation systems in fields such as e-commerce and social media, helping enterprises better understand user needs and preferences, and improving the quality and satisfaction of products and services. Buying tourist souvenirs is an indispensable habitual behavior of tourists in the process of traveling, and tourism itself is also a process of releasing emotions, exchanging emotions and storing emotions, so the design of tourist commodities should consider people's emotional needs more. Word level contextual feature extraction is the extraction of emotional features by utilizing the contextual information of words. Huddar et al. [3] extracted features by calculating the similarity between words and surrounding text based on the textual information around words. In this process, attention mechanism is used to measure the importance of each word to the entire sentence or paragraph, in order to better extract emotional features. Secondly, cross modal fusion is the fusion of data from different modalities (such as text, images, and audio) to extract richer emotional information. This method can utilize the correlation between different modal data and combine different types of data to better understand emotions. They can extract richer emotional features, thereby improving the accuracy and reliability of emotion classification. The design of traditional tourist souvenirs often pays attention to the appearance of products, but lacks the attention to the interaction between tourists and souvenirs, which makes the products less vivid because of the lack of emotional communication with consumers. With the growth of intelligent, humanized and emotional product design in modern society, the design of tourist souvenirs should also take a step beyond tradition and connect with modern product design.

Emotional analysis refers to the systematic study, extraction and quantification of emotions in information. The basic theory of DL is neural network, which is a learning method that simulates the work of human brain neurons. At present, emotional analysis is often to analyze the emotion at sentence level, that is, to get the emotional polarity at sentence level, but it is often very important to get the emotion at word level. Obtaining word-level emotion can increase the interpretability of DL model and can be applied to other fields except emotion analysis. Different functional definitions, functional decomposition and working principles will produce completely different design ideas and methods, thus producing completely different solutions in the design of functional carriers. In this article, a model of feature extraction and emotion classification of tourist souvenir images based on GCN is constructed, and the network structure is optimized by combining human perception of the emotional visualization results of images, and the network is driven by human knowledge, focusing on learning more obvious features of emotional information;

Finally, the parameters of the network are fine-tuned to make it more suitable for the CAD task of tourist souvenirs.

Kanjanasupawan et al. [4] analyzed the information matching of recommended routes of tourism activities under the condition of deep learning. The prediction of tourist sequence patterns on tourism websites based on hybrid deep learning technology is an engineering application that can help tourism websites better understand tourist behavior patterns and needs, thereby providing better services and experiences. It integrates and compares multiple deep learning models. For example, integrating multiple CNN or RNN models, or fusing CNN and RNN models to improve the accuracy and reliability of predictions. Optimize the fused model by adding techniques such as dropout and compression to improve its generalization ability and robustness. The optimized model is applied to the prediction of tourist sequence patterns on tourism websites. By using hybrid deep learning technology to predict tourist sequence patterns on tourism websites, it is possible to better understand the needs and behavioral patterns of tourists, and provide more personalized and accurate services and recommendations. At the same time, it can also help tourism websites optimize page design, increase traffic and user satisfaction. Li et al. [5] extracted emotional responses from customer reviews through machine learning. The purpose is to convert customer text comments into quantifiable emotional indicators, in order to better understand customer attitudes and feelings towards the product. It uses Natural language processing technology and machine learning algorithm to score each comment emotionally, which can be classified into two categories (positive/negative) or multiple categories (positive/neutral/negative). Summarize and analyze the emotional scores of all comments to obtain the overall emotional response of customers to the product and the emotional distribution in different aspects. This method can help enterprises and attitudes towards products, thereby making product improvements and adjusting marketing strategies. At the same time, it can also provide support for personalized recommendations and customer service. Li [6] conducted a modal analysis of online comment optimization data for tourism products. It constructs a multimodal graphical content recognition and classification system for tourism products. In this system, different subsets of sentiment dictionaries for category analysis are used to construct predictive value for image content recognition. Utilize machine learning, deep learning, and other technologies to perform emotional analysis on the fused features and extract user emotional information. Associate emotional information with user travel behavior, tourist attractions, and other data to extract user online evaluation information. In the research of online evaluation and extraction of tourism emotions based on multimodal feature fusion, data quality has a significant impact on the accuracy and reliability of sentiment analysis, and it is necessary to ensure the quality and completeness of the data. Nowadays, people pay more and more attention to interaction and experience, because tourism is the process of interaction between tourists and nature and culture, so we should also let tourist souvenirs interact with tourists in order to understand the culture of tourist destinations more richly and comprehensively. The process of image emotion classification can be divided into three stages: image preprocessing stage, feature selection stage and feature learning stage. DL method is different from traditional machine learning method mainly in feature selection stage. Traditional machine learning methods usually need domain experts to participate in feature selection in order to extract image features accurately. However, because DL can automatically extract features, it has self-learning ability and reduces the participation of domain experts. The core idea of DL is that the data characteristics of network layer training are not obtained manually, but are obtained by network self-learning through training. This article studies the feature extraction and emotion classification methods of tourist souvenirs based on DL and CAD;

⊖ In this article, the emotional information of tourist souvenir images is obtained by using GCN model for integrated learning. This model can automatically analyze the user interaction experience of the input image without relying on the emotional knowledge summarized manually.

⊜ The model consists of image feature extractor and classifier, in which the feature extractor, as the underlying basic network, shares parameters in different tasks, while the classifier does not share the training parameters for specific tasks.

Firstly, this article introduces the significance of interactive design of tourist souvenirs, the classification of image emotion and the application requirements of CAD in tourist souvenir design. Then, combined with GCN, the feature extraction and emotion classification model of tourist souvenir images is constructed. Then, the performance of the model is tested to verify the effectiveness of the method.

2 RELATED WORK

Oh and Kim [7] conducted a survey and analysis of basic emotions under online machine learning. Through the survey on the target of core elements of restaurant Big data, it has constructed the core element experience of Semantic network. Emotion in online reviews of food restaurants, as it can help consumers understand the quality of the restaurant's dishes, service attitude, environmental conditions, etc., and thus decide whether to try or recommend to others. Semantic network analysis is a common method, which can analyze the semantic relationship in comments, extract key information, and then infer emotional tendencies. Paolanti et al. [8] preprocessed the collected data, including text cleaning. Using sentiment analysis technology to make emotional judgments on the preprocessed data and obtain the corresponding emotional values for each attraction. In this step, deep learning models (such as Recurrent neural network or Convolutional neural network) can be used to train the emotion classification model, so as to predict the emotion of text data. By analyzing the geographical location information of tourists, understand the flow of tourists and the correlation between scenic spots. In this step, a deep learning model (such as Autoencoder or Generative adversarial network) can be used to reduce the dimension of geographical location data or generate meaningful spatial features. Pelliccia et al. [9] analyzed the development of computer 3D factory software under digital models. By using 3D simulation software, there is no need to run real systems or real robot units, but testing and verification can be carried out in a real simulation environment. The advantage of this is that it can provide a highly realistic interactive experience, enabling employees to better understand and operate the device. In addition, 3D simulation software can also support the creation, management, and use of digital twins. Digital twins are virtual replicas of real systems that can be used for monitoring, optimization, and Preventive maintenance. 3D factory simulation software has high applicability, and can bring creative experience for innovative display forms in the industrial manufacturing field. The characteristic of this model is that it collects EEG signals through multiple channels and uses deep learning methods to fuse the signals, thereby improving the generalization ability and robustness of the model. In addition, the model also uses cross validation and early stop strategies to avoid overfitting and improve the model's generalization ability. In a word, the CNN-LSTM deep learning emotion recognition model based on Electroencephalography signal fusion is an effective emotion recognition method, which has broad application prospects, such as in the fields of medical treatment, psychotherapy, human-computer interaction, etc. This method uses Electroencephalography signal as input, extracts features in the signal through the fusion of CNN and LSTM networks, and classifies emotions. Ramzan and Dawn [10] analyzed the machine learning Analysis of algorithms under the emotional model. It constructs an accurate dataset classification for emotion model recognition. The Electroencephalography signal is convolved using CNN network to extract image features, and then the LSTM network is used to analyze the time series of the signal to extract dynamic features. Integrate CNN and LSTM networks to construct a deep learning model, Use emotion tags to train the model, for example, use the Cross entropy Loss function to measure the difference between the predicted results and the real results, and use the Backpropagation to update the model parameters. Ren et al. [11] conducted a client on comment platforms based on deep learning. By analyzing the content of photos posted by customers, we can understand their needs and preferences. This information can help hotel marketers develop marketing strategies that better meet customer needs, improve customer satisfaction and loyalty. This information can help hotel marketing personnel develop improvement measures to enhance the service quality and image of the hotel. By analyzing large-scale data on photo content, it is possible to identify which marketing strategies are more effective, such as promotional activities, advertising placement, etc. This information can help hotel marketers optimize marketing strategies, increase hotel revenue and market share. By comparing the content of photos posted by managers and customers, problems and deficiencies in customer experience can be identified, such as service attitude and hygiene conditions. This information can help hotel marketers develop improvement measures to enhance customer experience and loyalty. Based on deep learning, it is possible to conduct large-scale comparative analysis of hotel photo content posted by managers and clients on comment platforms. Firstly, it is necessary to collect a large amount of hotel photo data and preprocess it into a format suitable for deep learning models. This includes converting photos into digital matrices, scaling and enhancing images, data enhancement and Data cleansing. Then, Convolutional neural network (CNN) is used to extract the features of the photos for subsequent comparative analysis. CNN is a deep learning model suitable for processing image data, which can automatically learn image features and extract useful information. Next, we can use cosine similarity or Euclidean distance and other distance measurement methods to compare and analyze the extracted photo features. These methods can calculate the similarity or distance between two photos to determine their similarity.

Ruan et al. [12] conducted an emotional travel extension for deep learning, which constructed and analyzed language processing for cultural background diversity clustering based on emotional types. Through the analysis of the emotional dimension of the framework in Chinese texts, it determines the thematic differences in the emotional dimension. It uses sentiment analysis technology to make emotional judgments on the preprocessed data and obtain the corresponding emotional values for each attraction. Compare the emotional values of different scenic spots, analyze the emotional differences between them, and the reasons for these differences. The results indicate that exploring emotional is an effective research approach, which can help researchers understand the emotional differences of tourists towards different scenic spots and the reasons for these differences, providing guidance and support for the development and management of tourist attractions. Santamaria et al. [13] conducted an analysis of the architecture of a travel experience recommendation system based on user emotional states. It analyzes the application environment of physiological data and program label recognition through high-precision sensor recognition of emotion recognition resource database. Deep learning algorithms can process a large amount of data and extract useful features for emotion recognition and recommendation. By analyzing the wearable and behavioral data of tourists, deep learning algorithms can be used for emotion recognition, such as analyzing data such as the number of steps and heart rate of tourists, to determine whether their travel experience is positive or negative. A travel experience recommendation system based on wearable data and deep learning algorithms for emotion recognition can help tourists better understand their physical and emotional states, and provide them with more suitable travel experiences, thereby improving the quality and satisfaction of tourism. The tourism recommendation system based on emotion recognition. Scientific Metrology plays an important role in this field. Through the measurement and analysis of relevant research literature, we can reveal the research status, hot spots and trends in this field, and provide important support and guidance for the research of tourism recommendation systems. Santamaria et al. [14] extracted and collected feature data from emotional tourism sensors through scientific econometric analysis. Its introduction implements emotion collection for emotion recommendation recognition. Through collaborative network analysis, it is possible to reveal the main research teams and collaborative networks in a tourism recommendation system based on emotional recognition, as well as the connections and impacts between each team. Through Citation analysis, we can find out the main references and academic schools in the tourism recommendation system based on emotion recognition, as well as the relationship and impact between them.

Xia et al. [15] analyzed the development of text metadata information under the deep network recommendation model. Its data indicators based on the algorithm pooling layer validate the effectiveness of tourism recommendation analysis. In model construction, the algorithm pooling layer can be used to effectively extract and select features from text data. Which facilitates subsequent recommendation analysis. When constructing the tourism Knowledge graph, the attention mechanism can help the model focus on important information in the text, thus improving the recognition accuracy of entities and relationships. The attention mechanism can be achieved by calculating the weight of each word in the text, which can be learned through neural networks. By using the BERT BiLSTM CRF model, contextual information in text can be better captured, thereby improving the accuracy and recall rate of entity recognition. In addition, the model can automatically learn text features and use these features for classification and prediction, thereby improving the quality and accuracy of tourism knowledge maps. Attention mechanism is an important component of the BERT BiLSTM CRF model, which can help the model better focus on important information in text, thereby improving the accuracy of entity recognition. In the tourism knowledge graph, attention mechanism can help the model focus on some key information, such as the name, address, opening time, etc. of tourist attractions, thus more accurately identifying entities. So as to provide better services and products for the tourism industry. Xu et al. [16] constructed a data preprocessing system for tourism knowledge framework. Through the multi-dimensional analysis of the model of tourism information atlas management data resources, it constructs the Cosine similarity of model recognition entities. The results indicate that the model can effectively improve recognition efficiency. The emotional classification of Chinese tourism reviews based on ERNIE Gram+GCN is a method of emotional classification of tourism reviews using Natural language processing technology. Yang et al. [17] effectively extracted semantic information and emotional features from tourism reviews by combining the ERNIE Gram model and Graph Convolutional Network (GCN) technology. And classify it as positive, negative, or neutral emotions. First, we preprocess China tourism reviews, to extract key information in the reviews. Secondly, construct the ERNIE Gram model. Input the preprocessed comments into the ERNIE Gram model, which can automatically learn the semantic information and feature representation in the comments, providing a foundation for subsequent sentiment classification. Input the feature representations output by the ERNIE Gram model into the GCN network, which can perform graph convolution operations on the feature representations and further extract emotional features from comments. The current personalized data information recommendation for tourism faces problems such as low model recall and insufficient sparse layers of structured text information. Yu [18] conducted a semantic sentiment framework preference analysis for convolutional networks. By evaluating the cold start performance of the location dataset model for factor prediction, semantic sentiment interest points were obtained. Deep learning technology plays an important role. To conduct emotional analysis on tourism data, so as to predict tourists' emotional response to scenic spots and provide decision-making support for tourism enterprises. Through research in this field, tourism enterprises can be provided with more high-quality services and products, improving the competitiveness and sustainable development ability of the tourism industry.

3 IMAGE FEATURE EXTRACTION AND EMOTION CLASSIFICATION OF TOURIST SOUVENIRS

The design of tourist souvenirs is a re-creation of a culture. Any culture with vitality is all inclusive, and it needs to constantly absorb new nutritional elements to glow with new vitality. In today's tourism consumption, the characteristics of emotional and psychological satisfaction are becoming more and more obvious, and tourist souvenirs are the first to become one of the representatives of emotional consumer goods. As a tourist commodity, tourist souvenirs are the representatives of regional culture, humanistic feelings and national features of tourist destinations. Its essence is the materialized form of tourist destination culture. With the help of this materialized form of tourist souvenirs, the regional culture of tourist destinations can be better developed and disseminated, and it can gain sustained vitality. When consumers have consumption psychology, they are driven by consumption motivation to a certain extent, and motivation is transformed from human needs. Integrating emotional interactive design elements into the design of tourist souvenirs will make tourists have a closer interactive relationship with local tourism culture and make tourist souvenirs a link between people and the objective environment. If some simple and small modern designs

are also integrated into some traditional craft and cultural elements and combined with certain functionality, tourist souvenirs will not only be an ornament or a collection, but will really be integrated into people's daily life, providing people with better spiritual enjoyment in details.
The process of realizing deep emotional interaction between people and products is the most effective means to improve the intensity and time of corresponding sensory stimulation. If tourist souvenirs meet people's physiological and psychological needs, they will have acquisition behavior, deepen their understanding in the process of continuous use and appreciation, and finally be satisfied by sharing experiences with others. The contribution of different attributes of products to users' experience benefits is uneven, so it is not enough to guide managers to make decisions and support more in-depth data mining and analysis.

Tourist souvenirs not only meet the needs of material functions, but also meet the psychological expectations of tourists. According to the unique individual goals, the emotional demands in the design of tourist souvenirs are realized by giving souvenirs rich emotional representations. From the perspective of production principle, the emotional characteristics of images are multi-faceted characteristics from the feeling of physiological stimulation to advanced human emotions. Defining the influencing factors of image emotional characteristics is the premise of extraction. The model of emotional feature fusion and classification of souvenirs is shown in Figure 1.

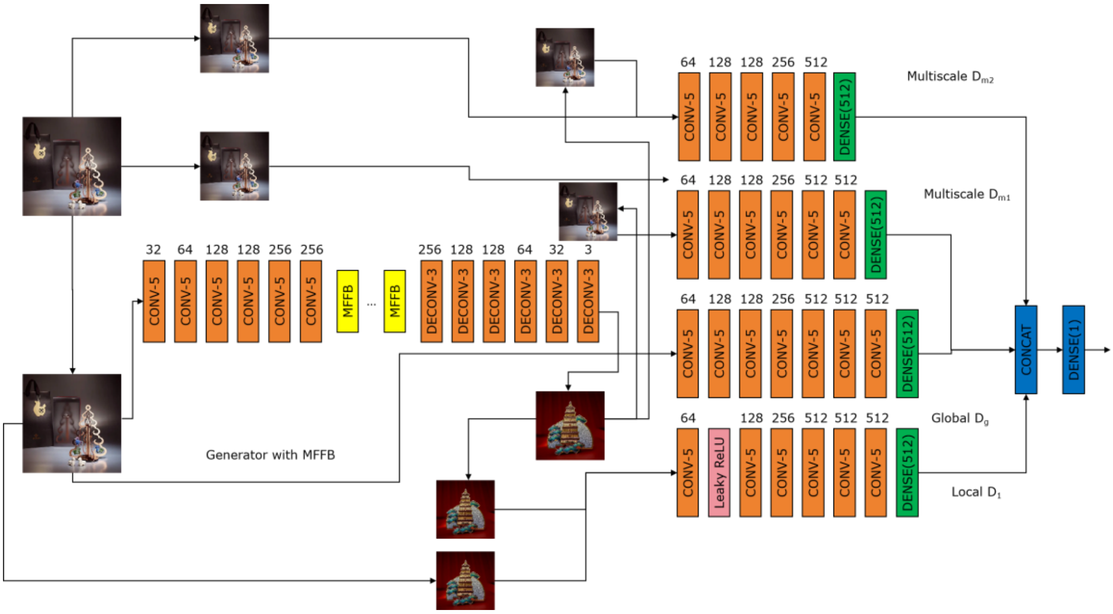

Figure 1: Souvenir emotional feature fusion and classification model.

In the design of tourist souvenirs, the elements that can stimulate people's emotions and have emotional interaction with consumers include visual elements, auditory elements, tactile elements and sensory elements. Emotional characteristics not only have the common characteristics of a certain group assessment in a certain period, but also have individual differences within the group. Assuming that the image size is $M \times N$, the gray level is $\{0,1,\cdots,L-1\}$, and the number of pixels in gray level i is n_i, the frequency of gray level i is:

$$p_i = \frac{n_i}{MN} \tag{1}$$

$$w_0 = \sum_{i=0}^{T} p_i,\ w_1 = 1 - w_0 \tag{2}$$

The average gray values of the two classes are:

$$\mu_0 = \frac{1}{w_0} \sum_{i=0}^{T} i p_i \tag{3}$$

$$\mu_1 = \frac{1}{w_1} \sum_{i=T+1}^{L-1} i p_i \tag{4}$$

Open operation is performed on image A through structural element B, which can be recorded as $A \cdot B$, and can be expressed as:

$$A \cdot B = (A \oplus B) \Theta B \tag{5}$$

The closing operation of tourist souvenir appearance image is that tourist souvenir appearance image A is firstly expanded by B, and then corroded by structural element B. Closing the image of commodity packaging can not only smooth the image of commodity packaging to a certain extent, but also connect the tiny broken parts and fill the tiny holes in the image of commodity packaging. The goal of activation maximization technology is to find the input that maximizes the activation response. If an input image can activate the features of a channel, the image contains the features represented by the channel. However, the number of qualified images is large, and the figure contains many features, so it is difficult to observe individual features just by listing them.

In the single-domain emotion classification model, it is very time-consuming and laborious to manually label the training samples in each field, and it may face the difficulty of insufficient comment data in this field, thus failing to provide enough training samples. Therefore, it is a solution to apply the emotion classification model trained in one field to other fields. Because the source domain and the target domain are not the same domain, the data distribution is different, and the feature space is different, the model trained in one domain is directly applied to other domains, and the classification effect is not very good. How to classify cross-domain emotions more effectively is a subject worth studying.

$$h_i^{(k)} = \rho\left(\sum_{j=1}^{q} A_{ij} W^{(k)} h_j^{(k-1)} + b^{(k)} \right) \tag{6}$$

$$P(i_j | k, \theta) = \frac{\exp(x_j(k,\theta))}{\sum_{1 \le i \le |X|} \exp(x_j(k,\theta))} \tag{7}$$

$$loss = -\sum_i \sum_j y_i^j \log \hat{y}_i^j + \lambda \|\theta\|^2 \tag{8}$$

Because neuron visualization can only represent the features in a few samples, visualization is of little significance. The channel visualization is more comprehensive, that is to say, neuron visualization is a local segment of channel visualization. For such subjective and abstract information as image emotion, it is more necessary to analyze the internal process and reasons of deep network feature extraction and judgment. Activation maximization technology generates visual images by maximizing the activation of a channel. This image can summarize some features learned by the corresponding convolution kernel from the data set to the greatest extent, while shielding the interference of other features. Aiming at tourist souvenirs, which only have the characteristics of 3D depth difference, this article uses CAD to reconstruct the souvenir surface in order to represent the depth information. The conceptual diagram of GCN is shown in Figure 2.

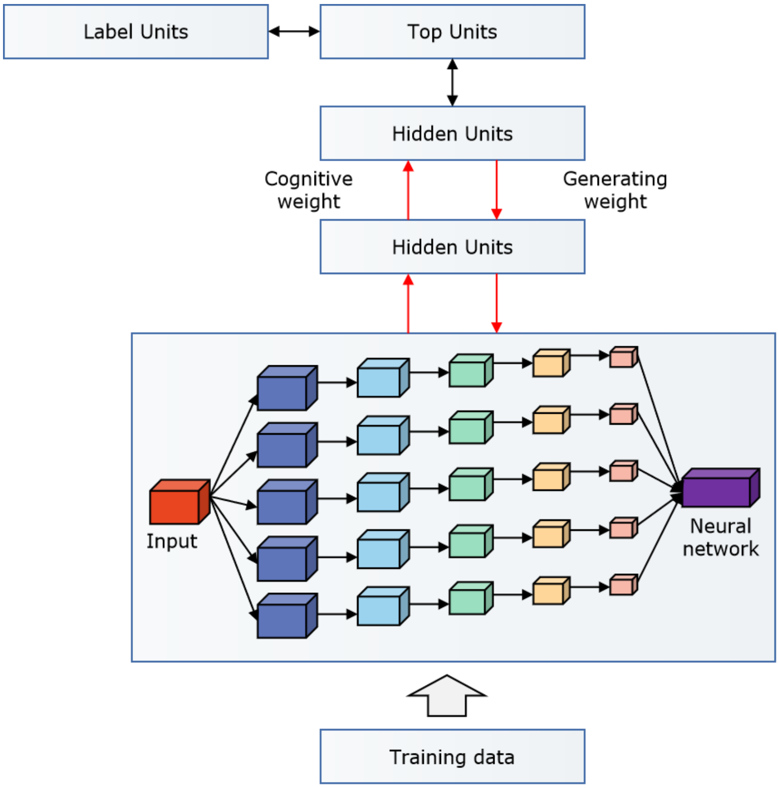

Figure 2: GCN concept map.

A neuron can do simple classification work, and a group of neurons can form a network, which can do more complex work. In which the hidden layer can include multi-layer nodes and is a nonlinear processing unit for feature extraction and feature transformation. Compared with the feedforward neural network, the neurons in the feedback neural network can not only receive the output of the neurons in the previous layer, but also take their own feedback signals as input. There are loops in the topology diagram. The state of feedback neural network will change with the change of time, which has the memory function and stronger computing power.

In the sample filtering module, an emotion dictionary is constructed by using tagged data in multiple fields, and emotional words with domain independence are extracted, and then sentences with the same emotional polarity as the document are filtered according to the emotional words, so as to obtain high-quality data sets. In the emotion classification module, firstly, two-way GCN is used to map the document to a distributed representation with fixed dimensions, which contains the grammatical and semantic information of the document, and then the document vectors of each domain are input into the multi-layer perceptron respectively to obtain the domain-specific feature representation, and finally the emotion classification is carried out.

Emotional value can be calculated by multiplying the emotional value of emotional units by negative and degree factors. Specifically, emotional value can be calculated by the following formula: emotional value=emotional value of emotional units × (1+Negative factors × Degree factor). Among them, the emotional value of the emotional unit can be -1, -0.5, 0.5 or 1, the negative factor can be -1 or 1, and the degree factor can be 0, 0.5, 1 or 2. For example, if the emotional value of the emotional unit is 1, the negative factor is -1, and the degree factor is 0.5, then the emotional value is: emotional value=1 × (1+(-1) × 0.5)=0.5. Therefore, when the emotional value of the emotional unit is 1, the negative degree is moderate.

$$v(u) = n * d * v(w) \tag{9}$$

$$v(t) = \sum_{U_i \in U} v(U_i) \tag{10}$$

Using the idea of transfer learning, the model parameters are transferred to CAD system, and then the model is trained by using the marked data in all fields. By using large-scale related data sets, it is ensured that the model can fully extract image information under the condition of insufficient data.

4 RESULT ANALYSIS AND DISCUSSION

The emotional classification model of tourist souvenir images constructed in this article consists of image feature extractor and classifier, in which the feature extractor, as the underlying basic network, shares parameters in different tasks, while the classifier trains parameters for specific tasks without sharing them.

Experimental environment: Windows 11 operating system, python 3.8 programming language, tensor flow2.0DL framework, NVIDIA GeForce GTX 1080Ti GPU acceleration, Intel (R) Core (TM) i7-8750h CPU @ 2.2ghz, and 16GB memory. The gray distribution of modeling area and background area is shown in Figure 3. This fact will further reduce the recognition accuracy of existing schemes.

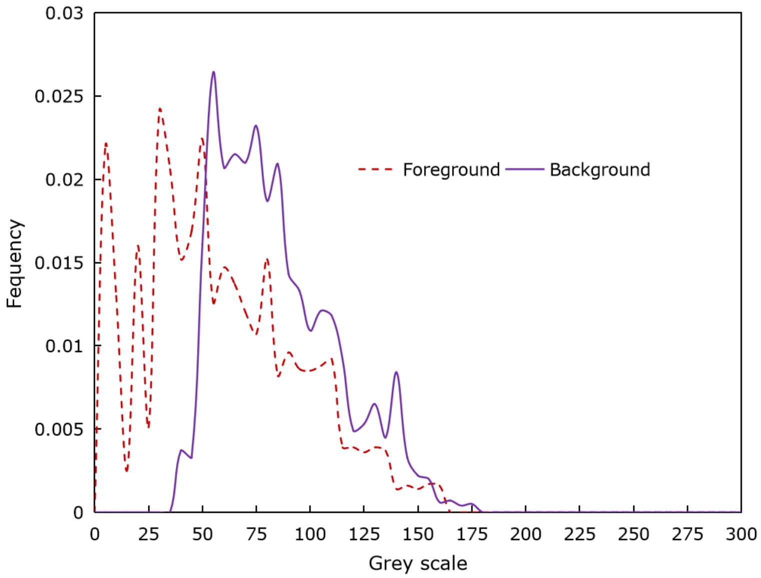

Figure 3: Gray distribution of modeling area and background area.

In order to verify the effectiveness of different algorithms, this article selects the classic outdoor scene 3D point cloud data set, tests the typical point cloud segmentation algorithm, and analyzes the effectiveness and applicability of the algorithm. For the comparison experiment of feature extraction and emotion classification of tourist souvenirs based on GCN and traditional methods, the emotion data with different regional distribution are discretized in intervals, as shown in Figure 4.

From the perspective of tourist souvenir design, the experience of behavior level determines the level of tourists' satisfaction through the association generated by tourists' actions and functions on tourist souvenirs, and the efficiency and effectiveness in the association process. If there is a lack of attention and understanding to tourists in the process of behavior experience, the design effect of tourist souvenirs will not be brought into play, which will give tourists negative emotions such as powerlessness and confusion. As shown in Figure 5, the running time comparison results of this algorithm and BPNN calculation are given.

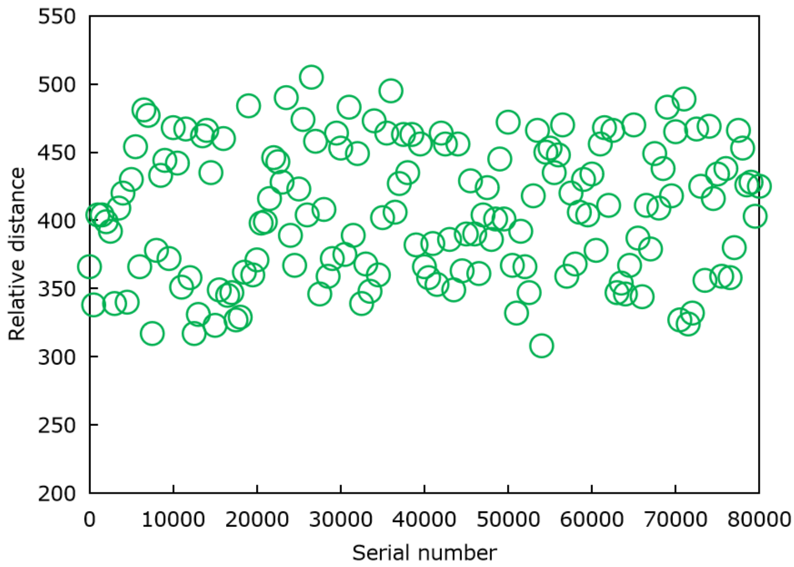

Figure 4: Interval discretization processing.

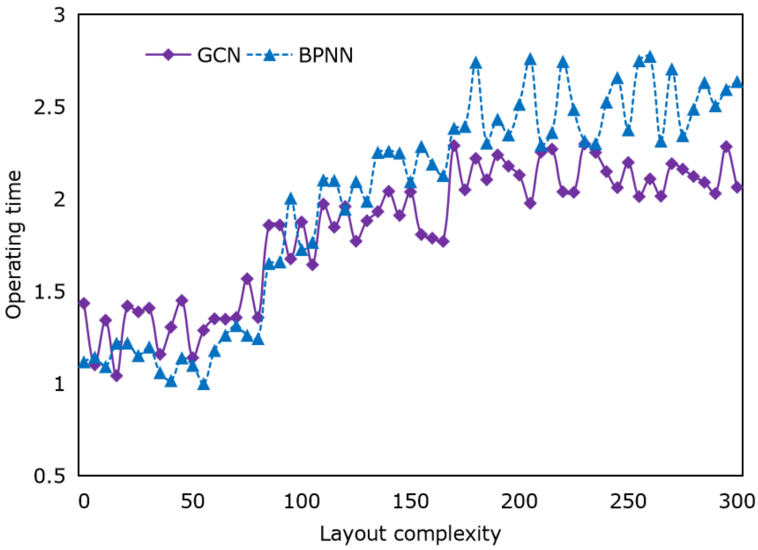

Figure 5: Calculation time comparison of algorithm.

When the complexity of souvenir features is increasing, the algorithm in this article shows high efficiency. Taking the whole vector as the input, the vector is used to represent features, and different dimensions in the vector record different attributes of the same feature. This processing method conforms to the expression habit of natural language and can extract more abundant image features to improve the accuracy of model classification.

The training samples are input into two kinds of image emotion classification models for learning, and then the test samples are input into two kinds of emotion classification models for testing. The result of sentiment classification test using BPNN is shown in Figure 6, while the result of sentiment classification test using GCN algorithm is shown in Figure 7.

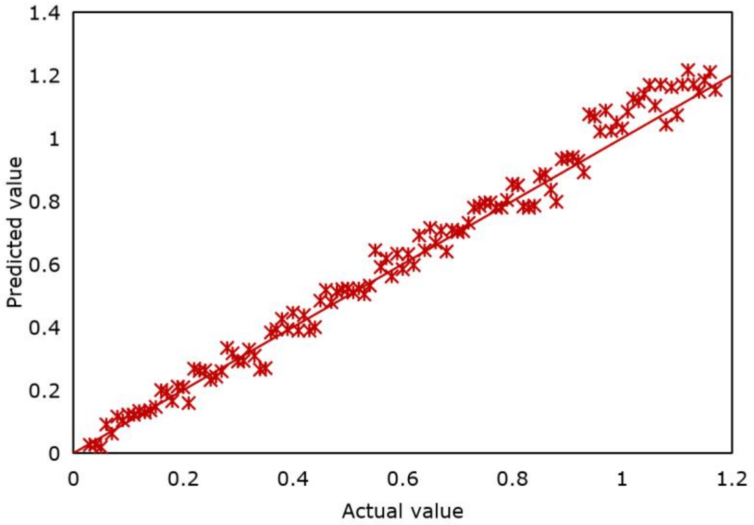

Figure 6: BPNN algorithm sentiment classification accuracy test.

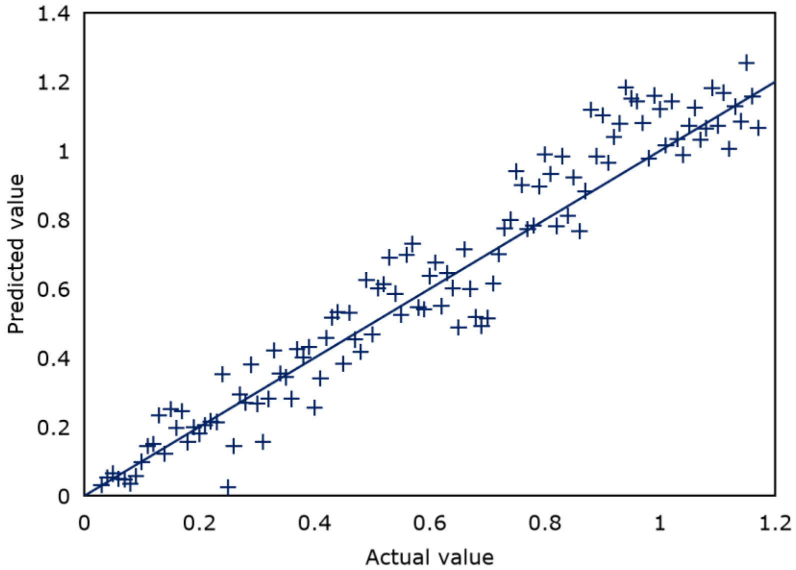

Figure 7: GCN algorithm emotion classification accuracy test.

As can be seen from Figure 6 and Figure 7, the accuracy of the emotion classification algorithm in this article has obvious advantages compared with the traditional BPNN algorithm, and the fitting degree is higher.

In the era of experience economy, entertainment and interaction are the regression embodiment of people's nature, and they are a way of leisure and entertainment that people are increasingly pursuing. Entertainment and interaction are not only one of the oldest experiences, but also a more advanced and universal experience today. The emotional demand of relaxing and entertaining in the travel experience leads tourists to pursue the experience that can produce pleasant atmosphere, so it also puts forward the demand of interesting and interactive design for tourist souvenirs.

5 CONCLUSIONS

It is an inevitable trend to develop tourist souvenirs that meet the psychological needs of tourists and integrate emotional interaction into the design in the future. Emotional analysis refers to the systematic study, extraction and quantification of emotions in information. In the cross-domain emotion classification, most researches are focused on difference between the source domain and the target domain. When the feature distribution between training and test data is quite different, the cross-domain method does not perform well. DL is a learning method that simulates the work of human brain neurons. In this article, the emotional information of tourist souvenir images is obtained by using GCN model for integrated learning. This model can automatically analyze the user interaction experience of the input image without relying on the emotional knowledge summarized manually. Compared with the BPNN algorithm, the accuracy of emotion classification algorithm in this article has obvious advantages, and the fitting degree between predicted value and actual value is higher. When the complexity of souvenir features is increasing, the algorithm shows high running efficiency. To improve the accuracy of cross-domain emotion classification, we may need to use new feature representation methods, try various combination methods or integration methods continuously, and also need to study technical means to solve feature differences and polarity differences. By fully extracting the feature representations shared, we can train a more stable classification model and obtain the best classification performance.

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