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Study on the Features of Public Space for Children's Emotional Healing Based on Facial Emotion Recognition Technology

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Abstract. This paper uses facial emotion recognition and machine learning techniques to explore the influence of spatial features of children's activity areas on children's emotions. Through the children's evaluation experiment on the emotional quality of public spaces, we obtained the facial expression pictures and the questionnaire data of the emotional self-assessment scale (SAM) when children used the public space. Then use MEGVII facial emotion recognition API to recognize children's facial expressions, and form a facial emotion feature variable dataset. Then, a public space emotional quality model was established using decision tree (DT), neural network (NN), and random forest (RF) classifiers. Finally, the model's performance was evaluated through the confusion matrix, and five groups of data reserved in the original dataset were used for external validation of the model. The results show that: 1) In the binary classification model, the classification accuracy of the emotional valence of the NN classifier was 94.44%, and the classification accuracy of arousal was 84.62%. These two results outperform the models built by the DT and RF classifiers. In the three-class model, the classification accuracy of the emotional valence of the DF classifier is 71.88%, and the accuracy of arousal is 84.62%. These two results outperformed the models built by NN and RF classifiers. 2) The analysis results of the correlation between spatial features and emotional quality showed that the width of the bordering tree, width-to-height-ratio of the bordering tree (w2/h2), the number of layers of the border, the continuity of the spatial border, the proportion of facilities, the color of the space, the number of types and pavement color types were usually correlated with the spatial emotional valence.

Keywords: children's activity area; emotional valence and arousal; facial emotion recognition; emotional quality classification model; spatial features.

1. Introduction

In recent years, primary and secondary school students' academic burden and psychological pressure are social issues that have been paid more attention to [1]. Continued stress affects students' learning, behavior, and physical and mental health [2]. Compared with drugs and psychotherapy, it is generally believed that public spaces with the natural environment as the main body have the best benefits for children's physical and mental health healing. However, few people have analyzed which spatial features are more conducive to children's physical and psychological health and emotional stress relief. This study established a model for evaluating the emotional quality of children's activity areas based on facial emotion recognition and machine learning technology by collecting children's facial expressions in the activity space and extracting relevant spatial features. The model can provide support to classify and optimize new spaces.

2. Related Studies

Previous studies have mainly used questionnaire surveys and data analysis methods for the relationship between the outdoor environment and children's physical and mental health. For example, Armstrong, N., & McManus, A. used a questionnaire to study the time changes in children's outdoor activities. The results showed that children's time outside the classroom decreased. In addition, children's physical activity levels in the school environment decreased [3].

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Pretty et al. also used questionnaires and surveys to study the effects of indoor activities and outdoor environments on mental health in 17 children. The results found that participating in green outdoor walking reduced children's anger and depression compared with indoor walking. At the same time, these activities also help increase children's vitality, especially the fun of collective participation in green fitness activities, as well as an opportunity to breathe fresh air, enjoy the scenery and appreciate wildlife, which is beneficial to children's physical and mental health [4]. Ole Johan Sando used video observation of 80 children to study how the characteristics of the outdoor environment affect children's health. The results show that play is related to health outcomes, and nature is positively related to children's well-being [5].

In addition, scholars have proposed the relationship between children's physical and mental health and public space environmental quality characteristics, such as space size, location, type, vegetation, normalized vegetation index, etc.[6] . Moreover, children's mental health may also be affected by the perception of green spaces, seasonal colors, plant arrangements, and the naturalness of plants also play an essential role in the quality of public spaces [7]. However, most of these studies only focus on the existence of attributes in public spaces, ignoring the quantitative analysis of the quality of public spaces[8].

Therefore, research on public space attributes mainly focuses on the psychological investigation and aesthetic preference analysis, and few studies use the emotional dimension to evaluate the quality of public space. Based on previous research, this study uses quantitative and qualitative research methods. It adopts the experimental approach combining facial emotion recognition technology and SAM emotion scale to quickly and effectively identify children's emotional information in public spaces and construct children's emotional statements.

3. Methods

3.1 Data Collection

3.1.1 Site selection

This paper takes the Central Living Park in 24 cities of Dalian and Xingye Park in Shahe City, Xingtai, as the research objects (Fig.1). The 24-city Central Living Park has relatively regular terrain, open space, and rich activity facilities. It is a "whole family" concept park integrating entertainment, sightseeing, leisure, and culture in Dalian; Xingtai Shahe City Xingye Park focuses on plant viewing. Function, the natural environment inside the park is prominent, the plant configuration is scattered, and it has a good viewing effect. The two parks are community parks with different main functions, each with its characteristics and typicality.

Fig. 1 Experimental Sites

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3.1.2 Experiments

We recruited twenty primary and secondary school students on site, ranging in age from 7 to 15, with an average age of 10.45 (Fig.2). We selected the paths of three typical public spaces in the two parks; each section is about 150-200 meters. Before the experiment, we introduced the purpose and content of the experiment to each child and their parents, and each parent signed the informed consent form.

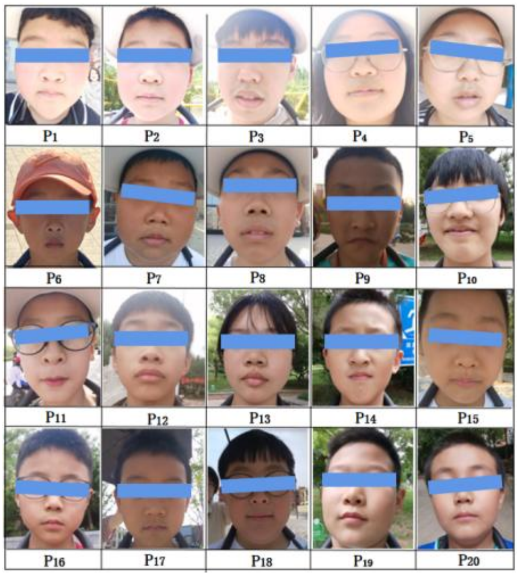

Fig. 2 Twenty experimental participants

Each participant then wore a portable selfie camera to take a photo of their face, set to take one every 5 seconds. Because children's behavior in the experiment was unstable, we also randomly captured pictures of the children's faces. Each participant walked along the prescribed path once. After the experiment, they filled out the SAM scale for this spatial emotion survey.

3.2 Data Analysis

3.2.1 Facial emotion recognition

First, we screened the face photos of the participants and removed the photos that were unclear, overexposed, or that the participants closed their eyes. Finally, we obtained 3419 valid photos.

We used the EGVII facial emotion recognition API to recognize facial emotions. At present, it can identify seven types of emotions and proportions: anger, disgust, fear, happiness, calmness, sadness, and surprise. Then, the SAM emotional scale questionnaires filled in by the participants were counted to obtain the values of each participant's emotional valence and arousal for each spatial path. Finally, the collected emotional valence, emotional arousal, and children's facial emotion data were classified as a dataset for binary, tertiary, and quintuple machine learning.

3.2.2 Spatial feature extraction

We summarized the characteristics of the spatial attributes of community parks in the relevant literature and eight spatial quality characteristics that may affect emotional responses. Then, according to the three paths in the selected two parks, we extracted the features of the public space from the scene. Finally, the correlation between 6 spatial features and spatial emotions was found based on the values of emotional valence and emotional arousal. Finally, we obtained the relationship between the quality of spatial features and the facial emotional score.

3.2.3 Spatial emotion classification model

Taking each participant's emotional valence and arousal to each space as the target variable and the participant's facial emotional data as the independent variable, a spatial emotion classification

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model was built using SPSS Modeler. The model uses Decision Tree (DT), Neural Network (NN), and Random Forest (RF) as classifiers, respectively, to establish the model data flow (Fig. 3).

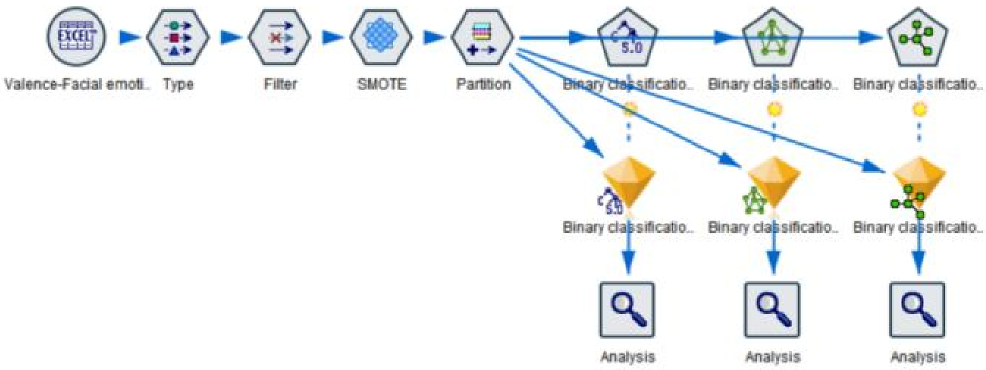

Fig. 3 Classification model flow of emotional valence and arousal

3.2.4 Evaluation of the model

We used the confusion matrix of the test set of the built model to evaluate the performance of the model. The indexes precision, recall, f1-score, AUC, and GINI were used in the binary classification model; The indexes precision, recall, f1-score, and kappa were used in the ternary classification and quinary classification models.

3.2.5 External validation of the model

First, we input the new data for verification into the established model, and the model output the emotion recognition result of the sample, and then we compared the identification results of each element in the output results with the results of the questionnaire and obtained the accuracy of the external verification model (Fig. 4).

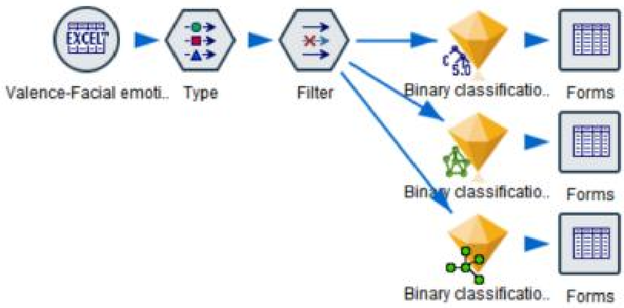

Fig. 4 External validation process of emotionalalence and arousal models

4. Results

4.1 Accuracy of the Models

We divided the data set into training set and validation set according to 7:3 and input it into the SPSS modeler data stream after specifying the type, filtering, and sample balance. After running, we get the binary, ternary, and quinary classification models established by DT, NN, and DF classifiers and their recognition accuracy (Table 1).

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Table 1 Accuracies of the binary, ternary, and quinary classification models

Valence-Category II				
		RF classifier	NN classifier	DF classifier
Recognition	Valence	1.00	0.94	0.83
Accuracy	Arousal	0.69	0.85	0.62
Valence-Category III				
		RF classifier	NN classifier	DF classifier
Recognition	Valence	0.72	0.66	0.72
Accuracy	Arousal	0.85	0.73	0.73
Valence-Category V				
		RF classifier	NN classifier	DF classifier
Recognition	Valence	0.72	0.64	0.64
Accuracy	Arousal	0.59	0.48	0.44

4.2 Evaluation Results of Multi-Classification Model Performance

We got the following results by combining the above comprehensive evaluation of the spatial emotion model's accuracy analysis, the model's internal verification analysis, and the model's external verification analysis. In the two-class model, the model established by the NN classifier is better than that built by the DT and RF classifiers. In the three-class model, the model created by the RF classifier is better than the model built by the NN and DT classifier; In the five-class model, the model produced by the RF classifier is better than the model built by the NN and DT classifiers (Table 2).

4.3 Correspondence Between Facial Emotions and Spatial Features

By calculating the average emotional valence of the 20 participants in the six spaces, we obtained the average ranking of the emotion values in the 20 spaces in the experiment. The 34 spatial features were refined to form the correlations between the seven spatial features and facial emotions.

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Table 2 Performance indexes of the binary, ternary and quinary classification models

Valence-Category II					
	Precision	Recall	F1-score	AUC	GINI
Decision tree	1.00	0.57	0.73	0.79	0.57
Neural network	1.00	0.86	0.92	1	1
Random forest	1.00	1.00	1.00	1	1
Arousal-Category II					
	Precision	Recall	F1-score	AUC	GINI
Decision tree	0.40	0.50	0.44	0.78	0.56
Neural network	0.75	0.75	0.75	0.72	0.44
Random forest	0.50	0.75	0.60	0.92	0.83
Valence-Category III					
	Precision	Recall	F1-score	Kappa	
Decision tree	0.70	0.71	0.71	0.57	
Neural network	0.60	0.60	0.60	0.47	
Random forest	0.65	0.65	0.65	0.57	
Arousal-Category III					
	Precision	Recall	F1-score	Kappa	
Decision tree	0.69	0.74	0.72	0.58	
Neural network	0.49	0.64	0.56	0.55	
Random forest	0.88	0.78	0.82	0.74	
Valence-Category V					
	Precision	Recall	F1-score	Kappa	
Decision tree	0.38	0.31	0.34	0.52	
Neural network	0.36	0.31	0.33	0.52	
Random forest	0.40	0.37	0.38	0.62	
Arousal-Category V					
	Precision	Recall	F1-score	Kappa	
Decision tree	0.45	0.54	0.49	0.31	
Neural network	0.44	0.57	0.50	0.36	
Random forest	0.56	0.65	0.60	0.49	

Therefore, we found that the width of the boundary tree, the width of the boundary tree, the height of the boundary tree (W2/H2), the number of layers of the boundary, the continuity of the spatial edge, facility ratio, number of space color types, and pavement color types have a positive impact on children's physical and mental health. In addition, environmental indexes may vary for different kinds of spaces. We do not attempt to define a complete set of indexes in this study.

5. Discussion

1) In the binary classification model, the accuracy of the decision tree classifier model (83.33%), the neural network classifier model (94.44%), and the random forest classifier model (100%) can meet the requirements of actual spatial emotional evaluation. The classification accuracy (61.54%) of the emotional arousal of the decision tree classifier model and the classification accuracy of the emotional arousal of the random forest classifier model (69.23%) are relatively lower. In the three-classification model, the classification accuracy of the emotional valence of the decision tree model (71.88%) and the classification accuracy of the emotional valence of the random forest model (71.88%) can meet the requirements of actual spatial emotional evaluation. The classification accuracy of emotional valence (65.62%) was relatively low. The classification accuracy of the emotional arousal of the neural network model (73.08%), the classification accuracy of the emotional arousal of the decision tree model (73.08%), and the classification accuracy of the emotional arousal of the random forest model (84.62%) were all accurate. It can meet the

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requirements of actual spatial emotion assessment. In the five-category model, the classification accuracy of all classifier models is relatively low, and none of them can meet the requirements of actual spatial emotion classification.

2) From the correlation analysis between emotional valence and spatial features, it can be found that the seven features positively impact children's physical and mental health. Furthermore, the research questions we sought to investigate only allow us to outline specific public space qualities that may lead to emotional responses assessment framework, and environmental indicators may vary for different places.

6. Conclusion

This paper explored the relationship between the environmental characteristics of public spaces and children's emotions. A classification model of children's spatial emotions was established through the evaluation experiment of public space emotional quality and facial emotion recognition. The results showed that the performance of the models established by binary and ternary classifiers could be applied to real projects and help designers design children's activity spaces in new spaces that are prone to positive emotions[, thereby promoting children's emotional health. Our findings can provide designers and managers with a basis for space transformation for built spaces.

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