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Article

Research on an Evaluation Method for the Emotional Healing Effects of Abstract Color Field Art Based on Deep Convolutional Neural Networks

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Abstract: Based on the theoretical foundations of art therapy and color effects, this paper proposes an abstract color space art emotional healing effect evaluation method using a deep multi-task convolutional neural network model. The proposed model consists of a dual-stream deep residual network, which is used for color feature extraction and multi-task learning training, respectively, to predict emotional healing effects and overall scores. Using the training set of 8,500 images from the AADB dataset as the research object, the results show that the accuracy rates predicted by the proposed model are 87.40% and 83.24%, respectively. Therefore, deep convolutional neural network models can be applied to the assessment of emotional healing effects. The three feature factors—color harmony, color vividness, and balance elements—all exhibit positive therapeutic effects. The therapeutic evaluation results for the three different groups are ranked as follows: Group II > Group I > Group III.

Keywords: deep convolutional neural network model; emotional therapeutic effect; art therapy; multi-task learning training

1. Introduction

In modern society, people face various pressures and challenges, such as work-related stress, interpersonal relationship issues, and financial difficulties [1-2]. These issues often lead to feelings of depression, anxiety, and fatigue, and artistic activities are increasingly being recognized as an effective means of emotional healing [3-4].

Art-based emotional healing is a therapeutic method that enhances mental health and quality of life through participation in artistic activities. However, it is not simply about drawing, singing, or dancing; it has a deeper, more profound impact [5-7]. When people create artworks, such as paintings or sculptures, or appreciate artworks, such as music or theater, various reactions arise within them [8-9]. These reactions help people better understand their emotions and thoughts, find inner balance, alleviate stress and pain, and even promote the healing of psychological trauma [10-12]. Artistic emotional healing takes various forms. One is art therapy, where people express their inner emotions that are difficult to put into words through brushstrokes on canvas [13]. Some people may have many worries in their hearts but cannot express them verbally. When they pick up a brush, those worries are manifested on the canvas through colors and lines [14-15]. Another is music therapy, where different melodies and rhythms can evoke different emotional responses [16]. Soothing music can help people relax, while uplifting music may inspire inner resolve [17-18]. The third form is dance therapy, which involves releasing accumulated energy through bodily movement [19]. Accurate assessment of art-based emotional therapy enables therapists to understand its positive effects on individuals, which helps provide a basis for treatment, boost patient confidence, and promote the development of art therapy [20-22].

Literature [23] highlights the significant number of children suffering from severe psychological issues such as isolation, anxiety, and fear, and analyzes various art therapy methods to determine the role of art in recovery following traumatic experiences. Literature [24] explores the relationship between public art aesthetics and psychotherapy from a cognitive psychological perspective, proposing that public art aesthetics can enhance psychotherapy, aiming to provide insights and references for promoting holistic human development. Literature [25] points out that participating in artistic activities is an important way to improve personal health and well-being, contributing to public health, and introduces how the connection between art and health is widely recognized in the UK, becoming an important component of achieving social inclusion and “community renewal.” Literature [26] emphasizes the importance of combining artistic efforts with transformative learning, as both transcend cognitive responses to knowledge, and affirms this perspective. Literature [27] explores the impact of artistic emotional healing on students, revealing that students with marginalized identities, particularly those in border regions, are better able to recover emotionally.

Literature [28] addresses the widespread and socially recognized stereotype of machines being used for therapy, introduces the application of art in healthcare, and analyzes the impact of incorporating art interventions into healthcare as a potential solution. Literature [29] discusses the concept of art-based emotional healing, reviews the theoretical foundations of the healing properties of art spaces, and explores the healing potential of art spaces through sensory experiences and lighting atmospheres. Literature [30] outlines the application of artistic activities such as painting in the healing of mental patients, indicating that the current interest of artists in psychopathological art has enabled the organization of international exhibitions of mental patients' artistic works. Literature [31] introduces the application of creative expression in disease management and art therapy, which differs from traditional artistic expression in that the creative process emphasizes creative and expressive art therapy rather than the product. Literature [32] examines the intersection of trauma, artistic expression, and female resilience in Alice Walker's The Color Purple, and uses feminist theory and trauma theory to analyze the impact of artistic expression on female healing and resilience. Literature [33] studies the relationship between art and trauma and verifies the healing effect of art on trauma through the analysis of actual cases. Literature [34] analyzes the characteristics of Chu State bronze ware and explores aspects such as mechanical balance and artistic healing effects, emphasizing that analyzing the artistic healing effects of Chu State bronze ware can provide references for archaeology. The above studies affirm the positive impact of artistic activities on trauma and mental health issues. This therapeutic approach effectively improves treatment outcomes for patients and plays a significant role in enhancing overall well-being.

Addressing the limitations of traditional methods, which are relatively simple and superficial, this paper employs a deep multi-task convolutional neural network model grounded in psychological theory to assess emotional healing effects. The end-to-end dual-stream multi-task convolutional neural network model can be divided into two steps: one network is trained based on the prediction task to extract color features from images, while the other network extracts abstract color domains from images. These two are then fused and trained through multi-task learning to predict emotional healing effects. To validate the model's effectiveness, experiments were conducted on the AADB dataset.

2. Overview of Art Therapy and Color Effects

2.1. Art Therapy

The World Health Organization released a report in 2019 on the benefits of art for health, which fully affirmed the comprehensive healing effects of art on both physical and mental well-being. Abstract Color Field Art Therapy is rooted in the creative expression of artistic creation, providing participants with opportunities to express themselves and release emotions, thereby promoting improvements in mental health, enhancing participants' sense of well-being, and improving their quality of life. It represents a healing art language and methodology that emerges from the intersection of art and psychology. Under the guidance of a therapist, abstract color field art is used as a medium for healing, combined with traditional healing methods, enabling participants to engage purposefully in the process of artistic creation. Through sensory perception, exploration, and discovery of individual emotions and feelings, participants can discover themselves, release stress, relax their minds and bodies, and regulate themselves. Abstract color field art therapy is suitable for all age groups and does not require special artistic skills; everyone can participate [35].

The focus of abstract color field art therapy is on “healing,” which is a process of self-reflection and self-growth for participants. It approaches from a phenomenological perspective, using experience as a benchmark to articulate and analyze methodologies, thereby establishing the theoretical foundation of the discipline of art therapy. It primarily has the following characteristics: It accesses emotional and mood levels through artistic media and non-verbal forms, bypassing the left-brain-driven verbal judgment system to obtain more authentic information. It addresses higher-level human needs in Maslow's Hierarchy of Needs, specifically psychological needs such as aesthetic experiences and inner joy. It assists special populations, particularly those who struggle to express emotions verbally, benefiting individuals with limited vocabulary, impaired cognitive abilities, or language expression difficulties. It employs metaphors and symbols to help participants perceive, develop, transform, comprehend, and elevate their experiences. Through the experiential design of art therapy, participants imbue their own works with meaning, completing a journey of self-empowerment and gradually clarifying the process of constructing the meaning of life.

2.2. Color Effects

Color effects, also known as color psychological effects, refer to the subjective emotions such as joy, anger, sorrow, and happiness that people experience when perceiving the colors of the objective world. These effects arise when the brain establishes connections between current color environments and past experiences through thought processes, thereby triggering a series of special psychological reactions related to emotions and willpower. By leveraging color psychological effects, one can observe an individual's preferences for certain colors, thereby analyzing their personality traits and accurately assessing their psychological state. Additionally, color is a crucial element in artistic design, capable of setting the mood and expressing emotions. Designers can select appropriate colors based on the theme and purpose of a work to convey specific emotions, such as choosing bright or muted colors in a creation to consciously guide participants toward specific emotional responses.

3. Method for Evaluating the Therapeutic Effects of Emotions Based on Deep Convolutional Neural Networks

3.1. Convolutional Neural Networks

Convolutional neural networks (CNNs) are a type of neural network that uses convolution, a special linear operation method, and are also known as convolutional networks. They are currently a hot topic of research in multiple fields, including speech and image recognition, computer vision, and natural language processing [36].

CNNs were the first learning algorithms to successfully train multi-layer network structures. Through concepts such as sparse interaction and parameter sharing, CNNs have improved machine learning systems. In traditional neural network structures, every output unit interacts with every input unit. However, in deep convolutional networks, units in deeper layers may be indirectly connected to most inputs. That is, CNNs use sparse interactions to efficiently describe complex relationships among multiple variables, significantly reducing the amount of parameters that need to be trained and thereby greatly improving computational efficiency and performance. Additionally, CNNs feature a network structure with shared weight parameters, enabling the use of the same parameters across multiple functions within a single model. This characteristic aligns it more closely with the neural network mechanisms found in biology, significantly reducing the total number of weights and effectively lowering its complexity. CNNs are a type of multi-layer perceptron structure with properties of invariance to transformations such as translation, scaling, and rotation, making them highly effective for processing two-dimensional data. Image data can be directly input into the network without the need for complex manual feature extraction processes.

Typically, a convolutional network consists of three levels. The first level is the convolutional layer, which generates a set of linear activation responses through parallel computation of multiple convolutional filters. These responses are then processed in the second-level detection layer using nonlinear activation functions such as the Sigmoid function and the rectified linear unit (ReLU) function. The final level is the pooling layer, which adjusts the output of the layer.

When an image is input into a CNN network structure, the process of feature learning and training follows the data flow direction as described below. The input image is convolved with filters and bias terms to generate corresponding feature maps. The pixels in the feature maps are then summed, weighted, and added with bias terms, then passed through nonlinear activation functions and pooling functions to obtain feature maps. These maps undergo the same process again, i.e., convolution filtering, nonlinear functions, and pooling, to generate feature maps once more. Ultimately, these feature maps are input into the fully connected layer. The convolution layer is the feature extraction layer, and the nonlinear activation function is the feature mapping layer.

Image pixels are processed through layer-by-layer convolution to form low-level features of the image, such as edge features. By combining and integrating these low-level features, mid-level features of the image are formed, such as object shapes. Further abstraction and refinement gradually form high-level features, such as those that better represent semantic information or the intent of the object.

3.1.1. Classic Deep CNN Models

The development of deep CNNs has been a process of increasingly complex network structures. Among all network models, AlexNet is a historically significant model in the field of CNNs. It broke the record for image classification in the 2012 ILSVRC competition, establishing the position of deep learning in the field of computer vision. AlexNet first demonstrated the feasibility and effectiveness of complex CNN network structures and, based on GPU-accelerated computing, reduced the training time of deep CNNs to an acceptable range.

The AlexNet network model structure consists of eight layers, with the first five layers being convolutional layers and the last three layers being fully connected layers. Three of the convolutional layers are followed by max pooling layers, and the final fully connected layer is a Softmax layer. In CNNs, convolutional layers and fully connected layers have weight parameters that are obtained through network training. Therefore, AlexNet has eight layers of network parameters that need to be trained, with the total number of parameters in the network exceeding 60 million.

The main innovative technologies of the AlexNet deep CNN network model include the following aspects: First, the rectified linear unit (ReLU) is used as the activation function, replacing the commonly used Sigmoid function, which addresses the issue of gradient vanishing that occurs when the network has a large number of layers. Second, Dropout technology is used in the final few fully connected layers to prevent overfitting during model training, which involves randomly removing some neurons during the training process. Third, unlike the previous average pooling method, AlexNet introduces overlapping max pooling, which effectively addresses the blurring issues in average pooling. Additionally, the overlapping regions in the pooling output enrich the feature content. Furthermore, the Local Response Normalization (LRN) layer was introduced to amplify larger local neuron response values while suppressing smaller ones, thereby enhancing generalization capabilities. Additionally, the parallel computing architecture of GPUs was leveraged to significantly accelerate the training of deep networks.

3.1.2. CNN Loss Function

In machine learning algorithms, especially in supervised learning tasks, a loss function is typically used to evaluate the difference between the model's predicted value $f\left(x\right)$ and the true value Y, denoted as $L\left(Y, f\left(x\right)\right)$. The smaller the value of $L\left(Y, f\left(x\right)\right)$, the higher the robustness of the model. Additionally, to enhance the model's generalization ability on test data, a regularization term $\phi(w)$ is typically added to the function. The loss function is optimized using an optimization algorithm to obtain the optimal parameters w that minimize the objective function value, as expressed by the formula:

$$w^* = \arg\min_w \frac{1}{N}\sum_{i=1}^{N} L(y_i, f(x_i; w)) + \lambda\phi(w) \tag{1}$$

Among them, the coefficient λ is a hyperparameter, which can be $L1$, $L2$, or other forms of norm.

Common loss functions used in the Caffe computing framework include contrastive loss functions, hinge loss functions, information gain loss functions, polynomial logistic loss functions, sigmoid cross-entropy loss functions, and combinations of sigmoid and loss functions. For the one-to-one image classification application discussed in this paper, the appropriate loss function is the Sigmoid cross-entropy loss function. It uses the Sigmoid function to predict the target probability distribution. The computing framework divides the Sigmoid cross-entropy loss function into a Softmax classification layer and a cross-entropy calculation layer to enhance the stability of gradient calculations.

Among the optimization algorithms for solving parameters, the most commonly used is the optimization algorithm based on stochastic gradient descent. SGD is a special form of mini-batch gradient descent (MBGD), which adjusts model parameters based on the gradient value of a single sample during each iteration to solve the gradient. The weights w are updated using a linear combination of the negative gradient and the weight update value calculated in the previous iteration.

3.1.3. Mainstream Computing Frameworks

The ongoing surge in deep learning research has led to the emergence of various open-source deep network computing frameworks, including Caffe developed by the University of California, Berkeley; Torch7, Keras, and MXNet promoted by Facebook; TensorFlow by Google; Theano developed by the University of Montreal; and DeepLearning4J, among others. The Caffe framework is clear and efficient, featuring excellent convolutional models, and offers significant advantages in handling visual-type problems, making it one of the most widely used computational frameworks in the field of computer vision research. This paper will use the Caffe framework as the primary tool for implementing deep neural networks.

3.2. Methods for Assessing the Emotional Healing Effect

Based on photographic knowledge, the importance of specific abstract color domains largely depends on the image category. Therefore, even if the overall aesthetic performance is the same, the importance of different attributes in different images varies greatly. Inspired by this, this paper proposes an end-to-end dual-stream multi-task convolutional neural network model to predict the emotional healing effect and the overall abstract color domain score. The proposed evaluation model architecture consists of a dual-stream deep residual network. One stream is trained on image prediction tasks to extract color features from the image, while the other stream extracts the abstract color domain. These two features are then fused and trained through multi-task learning to predict emotional healing effects and overall scores. Based on this model design, the proposed method effectively utilizes image semantic information to optimize image predictions, thereby achieving excellent performance. The evaluation method framework is shown in Figure 1.

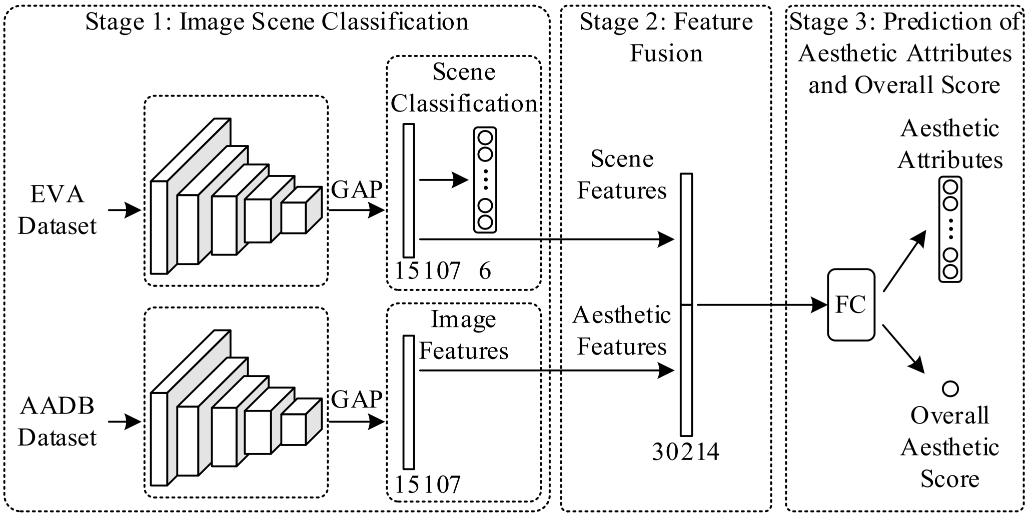

Figure 1. Aesthetic properties evaluation method block diagram.

The method steps of this paper are as follows:

1) Image classification. Due to the diversity, subjectivity, and ambiguity of aesthetic standards, the task of evaluating the aesthetic quality of images is highly challenging. Therefore, the dual-stream deep network is pre-trained using the large-scale visual recognition dataset ImageNet to accelerate model convergence. After pre-training, to utilize image information to assist in abstract color space prediction, the first branch network in the dual-stream model was first trained using the EVA dataset to predict image categories. The EVA dataset categorizes images into six classes: animals, architecture and urban landscapes, humans, natural landscapes, still lifes, and others. During training, the features of each layer of the residual network are globally average-pooled (GAP) and concatenated to obtain the image features. Compared to the traditional deep network method that only retains the features of the last layer, this method can simultaneously retain both low-level and high-level features in the deep network, which is beneficial for improving the performance of deep neural networks. Specifically, the features of each layer in the deep network are first globally average pooled. Let i denote the i th layer of the deep network, and let the feature F_i have dimensions $h_i \times w_i \times c_i$ After global average pooling, the feature size becomes $1 \times 1 \times c_i$. All features from all layers of the deep network are concatenated together, i.e.:

$$\phi(x) = \tilde{F}_1 \oplus \tilde{F}_2 \oplus \cdots \oplus \tilde{F}_N \tag{2}$$

In the equation, $\tilde{F}_i$ denotes the features after global average pooling, $\oplus$ denotes feature concatenation, and N denotes the total number of layers in the deep network.

Next, the overall features $\phi(x)$ of the image are input into the fully connected layer (FC) of the network, and then the probability of the image belonging to one of the six image categories is output through the softmax layer. Here, the cross-entropy loss function (CE) is used to measure the classification error, and the cross-entropy loss is calculated as:

$$L_{CE}(p,q) = -\sum_{i=1}^{N} p(x_i)\log(q(x_i)) \tag{3}$$

In the equation, N is the total number of samples, and $p(x_i)$ and $q(x_i)$ are the true probability distribution and predicted probability distribution of sample x_i, respectively.

2) Feature fusion. After training the image prediction branch network, it is necessary to extract the abstract color space of the image and fuse image features and aesthetic features for training. This paper uses the feature concatenation method to fuse the two types of features obtained from the dual-stream network. Feature concatenation involves concatenating two or more image feature maps in the channel or number dimension, and is often used to utilize the semantic information of feature maps at different scales to achieve better performance by increasing the number of channels. Compared to feature fusion methods such as element-wise dot product or addition/subtraction, feature concatenation has lower computational complexity and preserves more image information.

After training the prediction branch, the features from each layer of the branch network are globally average-pooled and concatenated along the channel dimension to obtain the image features. Similarly, the features from each layer of the aesthetic feature extraction branch are globally average-pooled and concatenated along the channel dimension to obtain the aesthetic features. Let $\phi_1(x)$ and $\phi_2(x)$ represent the image features and aesthetic features from the dual-stream deep network, respectively, with dimensions $1\times1\times c_1$ and $1\times1\times c_2$. Concatenate them along the channels to complete the feature concatenation:

$$\hat{\phi}(x) = \phi_1(x) \oplus \phi_2(x) \tag{4}$$

In the equation, $\hat{\phi}(x)$ represents the fused features, with a dimension of $1\times1\times(c_1+c_2)$, and $\oplus$ denotes the fusion of features through concatenation across channels. Next, the fused features are input into a fully connected layer and trained using multi-task learning to obtain predictions for the abstract color space and overall aesthetic score.

3) Abstract color space loss dynamic weighting. For each image abstract color space, its regression score needs to be obtained. This paper uses the mean squared error (MSE) loss function to measure the difference between the predicted value and the true value, calculated as follows:

$$L_{MSE}(\hat{y}_i, y_i) = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \tag{5}$$

In the formula, N is the total number of samples, $\hat{y}_i$ and y_i are the predicted values and actual values of the samples, respectively.

For multiple abstract color spaces, a fixed weight is assigned to each attribute loss, and then the loss function is set by weighted summation, which is calculated as follows:

$$L(f(x), y) = \sum_{i=1}^{N} w_i \times L_{MSE}(f_i(x), y_i) \tag{6}$$

In the equation, N is the number of abstract color spaces, w_i is the weight assigned to the i th attribute, and y_i represents the true score of the i th attribute. x denotes the image input to the model, $f_i(x)$ denotes the predicted value for the i th attribute, and $L_{\mathrm{MSE}}(f_i(x), y_i)$ denotes the mean squared error loss for the i th attribute.

The weight w_i values in the above loss function are always fixed and must be determined based on prior knowledge. To avoid improper weight settings affecting model performance, this paper adopts a dynamic weighting scheme for attribute loss, using a deep network to automatically learn the weights. The loss function is:

$$L(f(x), y) = \sum_{i=1}^{N} \hat{w}_i \times L_{MSE}(f_i(x), y_i) \tag{7}$$

In the formula, $\hat{w}_i$ is the weight corresponding to the i th abstract color space, which is a learnable parameter.

4. Results and Analysis

The fusion of abstract color field art therapy and color effects offers college students a unique means of emotional expression. Through the artistic creation process, one can utilize various abstract color field art elements such as different colors, patterns, and forms to project inner emotions and one's true self into the artwork. This non-verbal form of expression bypasses the linguistic judgment system, allowing emotions from the subconscious to flow naturally. During the painting process, individuals tend to choose colors that resonate with their current emotional state. High-saturation warm tones often reflect a positive and uplifting psychological state, while low-saturation cool tones may suggest negative or suppressed emotions. By analyzing the use of color in the creative process and the artwork, counseling teachers can more accurately assess students' psychological states and provide more targeted psychological support. Additionally, the creative process allows individuals to re-examine themselves, gaining a more comprehensive and objective understanding of their inner selves through the colors and forms expressed in their work. This process helps mobilize overlooked positive inner resources, leading to enhanced self-awareness and personal growth. This integrated approach breaks free from the limitations of traditional psychological counseling, which primarily relies on verbal communication, offering richer avenues for self-expression and self-awareness.

4.1. Method Performance Analysis

Different abstract color spaces have varying degrees of correlation with overall aesthetics in images of different categories. Obtain the emotional healing effects in each image. Select the “Predicted Value” option under the scoring function to obtain the predicted emotional healing effect values. By mapping the dataset fields to the corresponding fields of Image 1 and Image 2, you can obtain the predicted emotional healing effect values for Image 1 and Image 2, respectively, and use them as a comparison dataset with the corresponding actual emotional healing effect values for model validation analysis.

By abstracting the color space of different images, obtain the actual emotional healing effect values. Comparing the actual value dataset with the predicted value dataset can validate the effectiveness of the prediction model and calculate its accuracy rate. For Image 1, use the paired samples t-test to compare the predicted emotional healing effect values with the actual values. As shown in Table 1, there is no significant difference between the actual values and the predicted value sequences.

Table 1. Paired samples tests of scenario 1.

Pair difference							
Mean	SD	Standard error mean	Lower limit	Upper limit	t	freedom	Sig.
True value-Predictive value	-0.06457	0.8143	0.11272	-0.30784	0.17445	50	0.589

Further mean calculation results are shown in Table 2. The average value of the actual values is approximately 2.6459, and the average value of the predicted values is 3.0274. The difference between the average values of the actual and predicted values is not significant. Both indicate that the environmental resilience of Image 1 is at a “high” level, thereby validating the effectiveness of the deep convolutional neural network prediction model. For Image 2, the paired samples t-test method was also used to compare the predicted values and actual values of the emotional healing effect.

Table 2. Paired samples statistics of scenario 1.

	Mean	SD	Standard error mean
True value	2.6459	0.53896	0.07823
Predictive value	3.0274	0.29246	0.04267

The prediction results shown in Figure 2 are summarized in Table 3. There is no significant difference between the actual values and the predicted values. The mean values of the actual values and the predicted values are 2.4682 and 2.965, respectively, both of which are at a “moderately high” level, validating the effectiveness of the deep convolutional neural network prediction model.

Table 3. Paired samples statistics of scenario 2.

	Mean	SD	Standard error mean
True value	2.4682	0.5528	0.07861
Predictive value	2.965	0.5127	0.07486

By further comparing the actual values with the predicted values, we can calculate the accuracy of the model predictions for Image 1 and Image 2. The accuracy rates are 87.40% and 83.24%, respectively. This indicates that the accuracy of the deep convolutional neural network prediction model is within an acceptable range and can be applied in the assessment of emotional healing effects.

4.2. Evaluation Results of Therapeutic Effects

After 25 complete training runs on the 8,500 images in the AADB dataset training set, the model stabilized. Experimental results were measured using the Spearman correlation coefficient (SRCC) to characterize the consistency between predicted results and actual values.

The psychological state of participants after viewing colorful images was statistically analyzed. The experiment retained 30 valid questionnaires, with the following analysis:

1) A one-way analysis of variance (ANOVA) was conducted on different group sizes to validate the rationality of the grouping. The reliability and validity of the RS scale data were tested, with an alpha coefficient of 0.968 and a KMO value of 0.957, indicating good reliability and validity of the data. Descriptive statistical analysis was also performed.

2) Pearson correlation analysis was used to determine the correlation between pedestrian elements and the dimensions of the healing effect.

3) Perform hierarchical linear regression analysis on color harmony, color vividness, and balance elements to explore the explanatory power of color harmony and color vividness on street healing effects.

4) Factor analysis was performed on the independent variable indicators, with a KMO value of 0.740 and passing Bartlett's test, indicating the applicability of factor analysis. Three characteristic factors were extracted and combined with the healing effect for multiple linear regression analysis to determine the joint influence of color harmony, color vividness, and balance elements on the healing effect. The results of the analysis of variance are shown in Table 4, and the statistical analysis was performed using IBM SPSS Statistics 26. The classification of Group I (0–15 images), Group II (15–30 images), and Group III (30–50 images) was significant ($p < 0.01$), indicating that there were significant differences in the healing evaluations among the groups.

Table 4. Analysis of the variance of pedestrian Numbers.

Group variables (mean plus ± standard deviation)	I	II	III	F	P
Healing effect	3.82±0.28	3.95±0.29	3.45±0.15	8.669	0.003**

The results of the analysis of the mean and standard deviation of the therapeutic effects for each group are shown in Figure 2. The mean scores for the therapeutic effects, emotional, and physiological dimensions were close to 4 points, with the data distribution being concentrated and stable. However, the mean values for the cognitive and behavioral dimensions were lower, with data that was more dispersed and fluctuated significantly. This indicates that respondents' perceptions of the healing effects, emotional, and physiological dimensions across different street segments were consistent, with emotional and physiological healing experiences being the most easily triggered. Evaluations of the behavioral and cognitive dimensions showed significant differences, suggesting that people have certain preferences regarding emotional belonging and behavioral intentions in street contexts. The mean scores for all group sizes exceeded half of the scale's maximum score, indicating that color harmony, color vividness, and balanced elements all have positive healing effects. The healing effect values are ranked as follows: Group II > Group I > Group III, indicating that the healing effect is highest when exposed to a moderate number of abstract color field art images, followed by when there are fewer people, and lowest when there are more people.

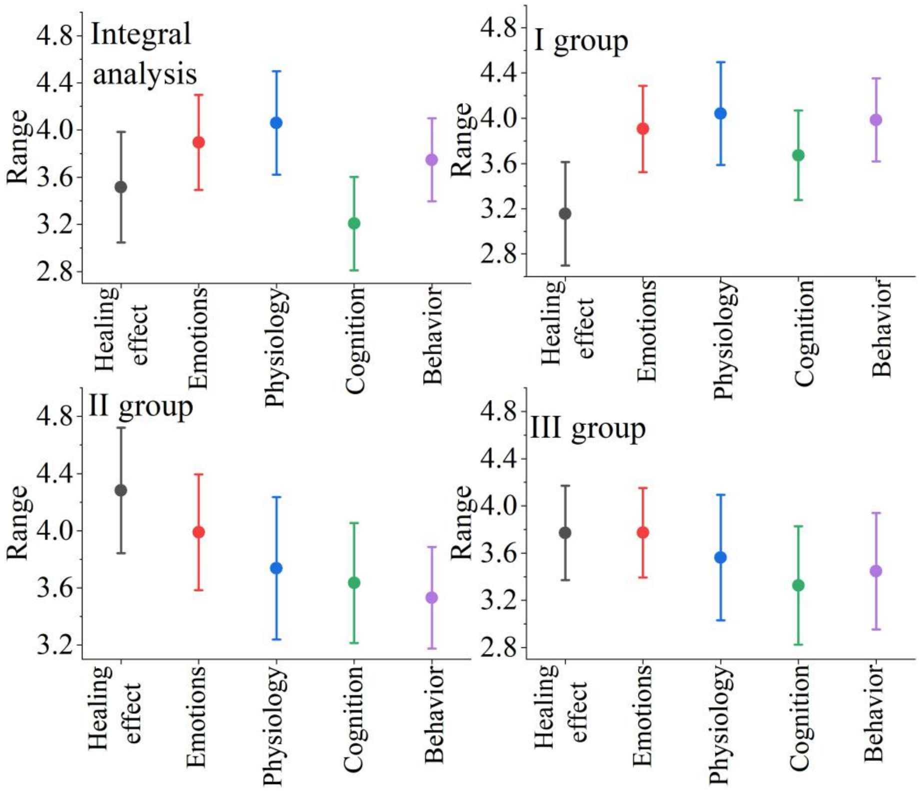

Figure 2. The mean and standard deviation analysis of each group therapy.

The distribution results of the therapeutic effects of each group are shown in Figure 3. Group I showed a large gap in physiological dimension scores, while Group III showed differences mainly affecting the behavioral dimension. Group II showed large fluctuations in scores across all dimensions, indicating that therapeutic effects vary depending on individual preferences.

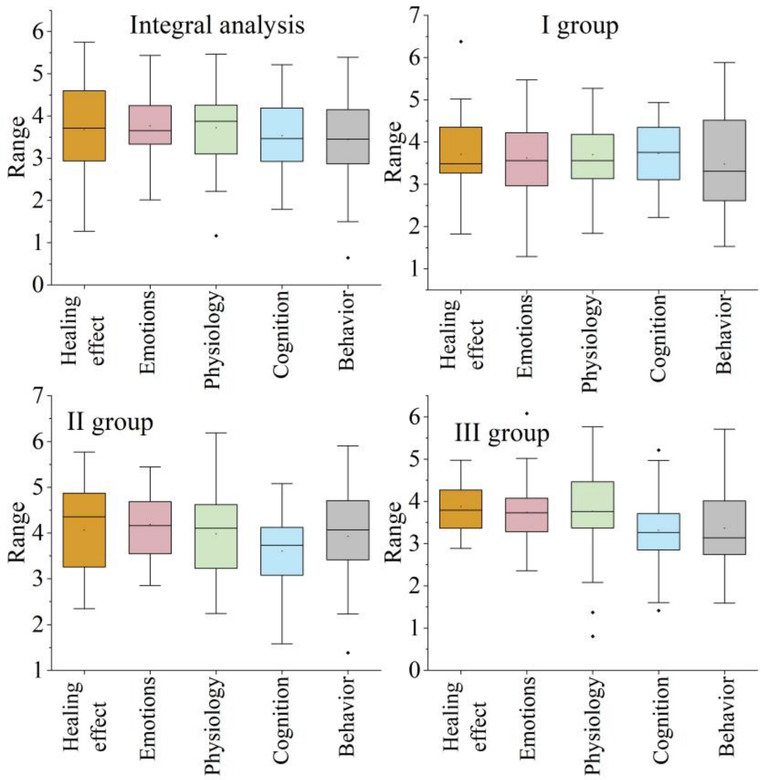

Figure 3. The data distribution of each group therapy effect.

The factor analysis of independent variables extracted three factors: color harmony, color vividness, and balance elements. Each element within each factor exhibits covariance. The results of linear regression indicate that the model fit R^2 is 0.527, demonstrating moderate explanatory power, as shown in Table 5. The *p*-value is significant at the 0.01 level, indicating that the independent variables collectively have a significant impact on the dependent variable. The *p*-values for each characteristic element were all less than 0.05, and their influence on the therapeutic effect was ranked as follows: color harmony (0.570) > color vividness (0.563) > balance elements (0.489).

Table 5. The tropic effect of the healing effect is the linear regression.

	Beta	t	p	VIF	Tolerance
Constant	-	72.205	0.001***	-	-
Color harmony	0.628	2.784	0.025*	1.557	0.570
Color intensity	-0.589	-2.684	0.026*	1.687	0.563
Equilibrium element	0.487	2.778	0.016*	1.015	0.489
R^2	0.527				
Adjust R^2	0.422				
F	F(3.18)=5.769,P=0.008**				
D-W value	2.268				

5. Conclusion

This paper primarily utilizes deep convolutional neural network models to evaluate the therapeutic effects of abstract color field art on emotions. Using the 8,500 images in the AADB dataset training set as the research object, we explore the explanatory power of color harmony and color vividness on the therapeutic effects of streetscapes. The results show that

(1) By comparing the predicted and actual values of the therapeutic effects, it was found that the model prediction accuracy rates for Image 1 and Image 2 were 87.40% and 83.24%, respectively.

(2) Among the three main factors of abstract color field art—color harmony, color vividness, and balance elements—the influence on therapeutic effects was ranked as follows: color harmony > color vividness > balance elements.

References

1. Byrne, K. A., Silasi-Mansat, C. D., & Worthy, D. A. (2015). Who chokes under pressure? The Big Five personality traits and decision-making under pressure. Personality and individual differences, 74, 22-28.
2. Galanopoulos Papavasileiou, I., Al Dhaheri, A., Al Mansoori, M., & Alqardaeai, S. (2024). Body, Loss, Memory and Healing: Three Emerging Emirati Women Artists. European Journal of Fine and Visual Arts, 2(3), 1.
3. Ettun, R., Schultz, M., & Bar-Sela, G. (2014). Transforming pain into beauty: on art, healing, and care for the spirit. Evidence-Based Complementary and Alternative Medicine, 2014(1), 789852.
4. Hammer, J. (2022). Healing. JOURNAL of ISLAMIC FAITH and PRACTICE, 101.
5. Farooq, H. (2023). Artistic Narratives of Resilience and Hope in Human History. Journal of Religion and Society, 1(2), 17-30.
6. Chen, L. (2023, November). A study on the positive effects of artificial intelligence intervention in the artistic healing of meditation. In IET Conference Proceedings CP868 (Vol. 2023, No. 45, pp. 149-150). Stevenage, UK: The Institution of Engineering and Technology.
7. Rezende, D., & Alice, T. (2019). Relational Art as a Healing Practice: The Participative Artistic Projects of the Platform Performers without Borders. EC Psychology and Psychiatry, 8, 180-188.
8. Sokmen, Y. C., & Watters, A. (2016). Emotion regulation with mindful arts activities using a personalized self-soothing kit. Occupational Therapy in Mental Health, 32(4), 345-369.
9. Sees, D., & Unrath, K. (2015). The Yellow Boat Project: How Art Heals, Connects, and Transforms. Canadian Review of Art Education: Research & Issues, 42(1).
10. Lin, D. R., Wang, Y. Y., & Chen, W. (2021). Research on improving the emotion and social relationship with elderly with dementia in expressive arts therapy. Turkish Journal of Computer and Mathematics Education, 12(11), 4055-4075.
11. Savytska, O., Shkrabiuk, V., Pedorenko, V., Sytnik, S., Naichuk, V., & Nazarevych, V. (2022). Art therapy as a means of psychological correction of emotional disorders. BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 13(4), 196-211.
12. Barfarazi, H., Pourghaznein, T., Mohajer, S., Mazlom, S. R., & Asgharinekah, S. M. (2018). Evaluating the effect of painting therapy on happiness in the elderly. Evidence Based Care, 8(3), 17-26.

13. Khodabakhshi Koolaee, A., Vazifehdar, R., & Bahari, F. (2016). Impact of painting therapy on aggression and anxiety of children with cancer. Caspian Journal of Pediatrics, 2(2), 135-141.
14. Khadar, M. G., Babapour, J., & Sabourimoghaddam, H. (2013). The effect of art therapy based on painting therapy in reducing symptoms of oppositional defiant disorder (ODD) in elementary school boys. Procedia-Social and Behavioral Sciences, 84, 1872-1878.
15. Wang, J., & Abdullah, A. B. (2024). A summary of expressive arts therapy and painting therapy. Creative Education, 15(2), 278-288.
16. Aalbers, S., Fusar-Poli, L., Freeman, R. E., Spreen, M., Ket, J. C., Vink, A. C., ... & Gold, C. (2017). Music therapy for depression. Cochrane database of systematic reviews, (11).
17. Yinger, O. S., & Gooding, L. (2014). Music therapy and music medicine for children and adolescents. Child and Adolescent Psychiatric Clinics, 23(3), 535-553.
18. Mofredj, A., Alaya, S., Tassaioust, K., Bahloul, H., & Mrabet, A. (2016). Music therapy, a review of the potential therapeutic benefits for the critically ill. Journal of critical care, 35, 195-199.
19. Saumaa, H. (2019). Dance therapeutics: Movement as a path toward healing. Alternative and Complementary Therapies, 25(5), 238-240.
20. Sumarsono, S., Handayaningrum, W., Sabri, I., & Suyandoko, W. (2025). Exploring Artistic Creativity: A Psychological Review. Journal of English Language and Education, 10(1), 25-30.
21. Haeyen, S. (2024). A theoretical exploration of polyvagal theory in creative arts and psychomotor therapies for emotion regulation in stress and trauma. Frontiers in Psychology, 15, 1382007.
22. Cui, X., Liu, X., & Xu, W. (2024). Evaluation of the Artistic Healing Effects of Digital Drawing and Paper Drawing Based on AHP and Paired T-Tests. In International Symposium on World Ecological Design (pp. 817-826). IOS Press.
23. Bair, L. E. (2022). Interacting With Art: Healing From the Inside Out. Journal of interdisciplinary studies, 34(1/2), 73-96.
24. Hu, R. (2023). Public art aesthetics and psychological healing. HTS Teologiese Studies/Theological Studies, 79(1), 8827.
25. Belfiore, E. (2016). The arts and healing: The power of an idea. Oxford textbook of creative arts, health, and wellbeing. International perspectives on practice, policy, and research, 11-17.
26. Bourgault, R., & Rosamond, C. (2024). Artistic research, healing, and transformation: Shared stories of resilience. Journal of Transformative Education, 22(1), 9-25.
27. Lou, H. C. (2023). Art resists. Art heals. Art is resilience: Utilizing creativity in postsecondary education. In Engaging images for research, pedagogy, and practice (pp. 197-212). Routledge.
28. Awtuch, A., & Gębczyńska-Janowicz, A. (2017, October). Art and healthcare-healing potential of artistic interventions in medical settings. In IOP Conference Series: Materials Science and Engineering (Vol. 245, No. 4, p. 042037). IOP Publishing.
29. Huang, Q. (2022). Research on the Healing Characteristics of Artistic Space. World Scientific Research Journal, 8(4), 463-466.
30. Ceaușu, F. (2018). HE HEALING POWER OF ART-THERAPY. Review of Artistic Education, (15+ 16), 203-211.
31. Uka, G. O., & Uka, O. E. (2022). Art therapy as a healing concept for the mentally challenged: Artistic approach. LWATI: A Journal of Contemporary Research, 19(4), 280-289.
32. Naseem, A., Komal, S. R., Iqbal, S., & Naz, A. (2025). Artistic Expression and Female Resilience: A Feminist and Trauma Theory Analysis of The Color Purple by Alice Walker. Journal of Political Stability Archive, 3(1), 421-435.
33. BARRETTE, C. (2014). TRAUMA: MOURNING AND HEALING PROCESSES THROUGH ARTISTIC PRACTICE CATHERINE BARRETTE. The Edges of Trauma: Explorations in Visual Art and Literature, 169.
34. Jin, S., & Zheng, G. (2023). Analysis of the Artistic Healing Effect and Installation Value of Bronzes Unearthed in the State of Chu. Mediterranean Archaeology and Archaeometry, 23(2), 231-240.
35. Suhui Qiu,Chao Ruan & Ying Wang. (2025). Anxiety relief in the post-pandemic era: a randomized trial on the integration of digital technology into dance art healing. Frontiers in Psychology,16,1545461-1545461.
36. Tingxin Zhou,Xiaodong Yu,Jian Zhang,Lin Shi & Hui Xu. (2025). Pressure pulsations intelligent prediction model for load rejection of pumped storage power station based on data augmentation and one-dimensional convolutional neural network. Energy,330,136915-136915.