Modeling and Analyzing the Impact of Mosaic Art on the Psychological Well-Being of Primary School Students

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Abstract: Contemporary children's mental health has emerged as a focal point of societal concern, particularly given that children are in the foundational stages of physical and psychological development. The exploration of children's mental health through expressive art therapies, including art therapy, has attracted widespread attention. First, we conduct mosaic art classes for 50 students at a primary school in Henan Province, China, collect students' works, and test the students' psychological status according to the mental health scale. Subsequently, we categorize the artworks into positive and negative types, combine them with various deep neural network models to classify the student works, and analyse the correlation between colors, brightness, and student psychological states in the works, aiming to provide a theoretical model for student mental health assessment. Finally, we found that the ResNet model achieved an accuracy of 76% in the artwork classification task. Brightness in student works cannot be a representative factor of psychological states, whereas the role of color (yellow, blue, green, brown) was particularly prominent. Through this study, we conclude that color in artistic expression has potential value for the mental health of primary school students, providing scientific evidence and theoretical support for contemporary children's mental health through expressive therapy.

1 INTRODUCTION

As the Chinese education system progressively shifts towards a focus on quality education, mental health issues among elementary school students have garnered widespread attention from various sectors of society. Children's psychological resilience and coping skills are relatively underdeveloped, and prolonged exposure to unregulated emotional states can result in adverse emotions such as aversion to learning, low self-esteem, anxiety, depression, and more severe psychological issues like personality disorders, potentially harming their future academic and personal lives (Zhang et al, 2022). Consequently, addressing children's mental health has become an imperative. Originating in Europe in the 1940s, art therapy employs visual arts as a form of psychological treatment, with expressive therapy serving as a crucial component. Research has demonstrated that expressive therapy effectively alleviates specific emotional states, overcomes communication barriers, and steers individuals towards positive changes (Hogan, 2001).

Mosaic art, a significant form of expressive therapy, utilizes materials like stones, shells, enamel, ceramics, and glass to create artworks. A distinctive feature of mosaic art is that it comprises many independent small pieces, yet visually forms a unified whole (Dunbabin, 1999; Hyatt, 2007). This design concept resembles the pixel concept in computing, facilitating the application of deep learning models in classifying mosaic works (Kim and Jeong, 2019). These models can distinguish not only the style of artworks but also classify them on an emotional level (Cetinic et al, 2019). This approach meets the need to analyze children's artworks and their psychological states. Currently, the analysis of artworks in expressive therapy primarily relies on questionnaire surveys and the clinical experience of therapists. We aim for computer models to provide a more objective assessment tool. In this study, we selected fifth-grade students from a primary school in Henan Province as

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the research subjects. We collected stress data from students through questionnaires and combined it with mosaic artworks created by the students themselves. We then utilized computer models such as ResNet, VGG, and AlexNet for data analysis to explore the potential impact of artistic expression on the mental health of elementary school students.

2 MATERIALS AND METHODS

2.1 Course Design

This study involved conducting a mosaic art course for 50 fifth-grade students at a primary school in Henan Province, China. Prior to the course, students completed the Psychological Health Diagnostic Test (MHT), which was developed according to the standards set by Professor Zhou Bucheng in 2009 and tailored specifically to the contemporary context of Chinese children (Zhang et al, 2022). The MHT comprises sections on learning anxiety and validity testing. The learning anxiety section contains 15 questions, whereas the validity testing section includes 10 questions. According to the guidance accompanying the scale, a score below 3 on the learning anxiety scale indicates good mental health, whereas a score above 7 suggests anxiety. Concerning the validity scale, which reflects the confidence level of student scores, a score of 7 acts as the threshold, with lower scores signifying higher confidence.

Students are required to independently create mosaic artworks following specific guidelines: They must use tiles to assemble a butterfly pattern on a circular base measuring 15.5 cm in diameter. The tiles, which may be triangular, square, or rectangular, should range from 1 to 3 cm in size and feature colors selected from blue, green, red, purple, or additional color palettes. Upon completion, the students' artworks are photographed and archived as 970x970 pixel images.

2.2 Samples and Preprocessing

2.2.1 Experimental Samples

Initially, after the class, 47 artworks and questionnaires are collected, and those artworks that do not comply with the specified requirements are excluded, resulting in 27 valid artworks. Subsequently, Python 3.11.5 was employed, along with the OpenCV and PIL libraries, to develop code for image analysis, including color classification and grayscale processing. Specifically, the edges of the figures were removed, and the color of each pixel was analyzed, with the resulting color proportions being reported. Finally, the data were subjected to inspection and color refinement by art professionals, who categorized the colors into ten types: yellow, blue, green, red, purple, brown, pink, black, white, and other.

2.2.2 Database Samples

The data are derived from a public dataset based on the International Affective Picture System (IAPS) images from 2010, where the emotional attributes of the samples encompass happiness, anger, awe, satisfaction, disgust, excitement, fear, sadness, among others. Emotions are categorized as either positive or negative, specifically excluding images with ambiguous emotional expressions such as "awe" (Machajdik and Hanbury, 2010). The dataset consists of 250 images depicting positive emotions and an equal number depicting negative emotions, divided into training and testing sets at a ratio of 4:1.

2.3 Model Methods

The deep learning models used in the experiment were ResNet, VGG, and AlexNet. Since ResNet showed the most effective performance in subsequent experiments, we focused on ResNet50, ResNet101, and ResNet152. These three models vary in their number of convolutional layers, specifically 50, 101, and 152 layers, respectively. The model is distinguished by a network depth of more than 100 layers and features a residual module, which enhances model accuracy by increasing depth. We utilized the model functions provided by Torchvision in PyTorch and employed the Cross Entropy Loss function. We compared various approaches in selecting the optimizer and learning rate, and ultimately chose the SGD optimizer, with the learning rate set at 0.005. The AlexNet model also utilizes the model functions provided in PyTorch. The AlexNet architecture comprises 5 convolutional layers, 3 fully connected layers, and dropout layers (Deng et al, 2009). The loss function, optimizer, and learning rate are the same as those used with ResNet. The VGG model improves on AlexNet by using multiple consecutive 3 × 3 convolutional kernels instead of AlexNet's larger ones, thereby better preserving the image's properties (Demir, 2020). The model includes 19 hidden layers, comprising 16 convolutional layers and 3 fully connected layers. PyTorch offers the VGG16 function for the 16-layer convolutional neural network. The selected loss function and optimizer are Cross Entropy Loss and SGD, respectively, with the learning rate set at 0.005. Furthermore, all three models ultimately output two-dimensional vectors to classify figures into positive and negative categories.

In the task of evaluating the importance of colors, we employed the Random Forest algorithm. The model was deployed in Python, utilizing the RandomForestClassifier function provided by scikit-learn to classify images based on color and ascertain the importance of various colors using features returned by the random forest.

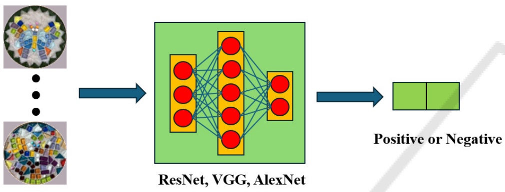

Figure 1: Model design. Student paintings are directly used as input for the model, outputting two-dimensional classification results.

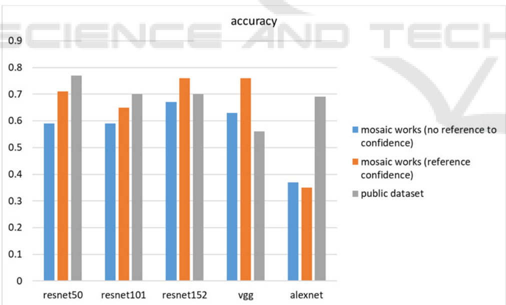

Figure 2: Accuracy of 5 models. Student works are divided based on their confidence score. The grey is the result of the public dataset. Student works are divided based on their confidence score. The works with high confidence are orange, and all works are blue.

3 RESULTS

3.1 Deep Learning Fitting Results

Initially, we utilized a public dataset of positive/negative images and applied deep learning models to train the dataset. The training set, consisting of 400 images, was divided into batches of 50 and trained 100 times. The predicted results for the test set are displayed in Figure 2. The ResNet model demonstrates strong performance on both the public dataset and in the classification of student artworks. Specifically, ResNet50 achieves the highest accuracy, reaching 77% on the test set and attaining over 70% accuracy in classifying student artworks. Conversely, AlexNet achieves an accuracy of 68% on the test set but does not meet the experimental expectations in classifying student artworks.

3.2 Grayscale Analysis Results

To ascertain whether image brightness serves as an indicator of psychological states, we converted the images to grayscale and retrained the models. Grayscale images reflect only brightness information and exclude color information. The results of the models retrained with grayscale images are displayed in Figure 3.

Grayscale images do not adequately fit the models, yielding a prediction accuracy on the test set of only about 60%. For the ResNet model, the highest accuracy achieved in classifying student artworks was only about 54%. Moreover, when considering confidence levels, ResNet101 and ResNet152 were unable to distinguish negative from student samples. Similarly, the predictive performance of the VGG model was poor, misclassifying all student artworks as positive samples. The AlexNet model's accuracy in classifying student data was less than 50%. Consequently, the parameter of image brightness may not be relevant to this study on psychological conditions. Further exploration is necessary to comprehend the reasons behind these results.

3.3 Color Analysis Results of Works

After eliminating the influence of image brightness, we explored the relationship between color and psychological states. In section 2.2.1, we employed a hybrid approach combining algorithmic and manual methods to categorize colors into ten categories: red, blue, green, yellow, purple, pink, brown, black, white, and others. Given that ResNet152 demonstrates the most robust predictive performance for student artworks (considering confidence levels), we integrated the color data analysis from the 27 student artworks with the ResNet152 predictions. The random forest algorithm was employed to perform nonlinear fitting of the data, with the importance of each color feature displayed in Figure 4. The analysis indicated that green, brown, yellow, and blue were the most significant colors, collectively accounting for 50% of the overall importance.

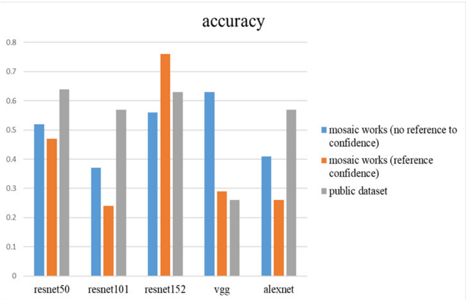

Figure 3: Classification results of grayscale model.

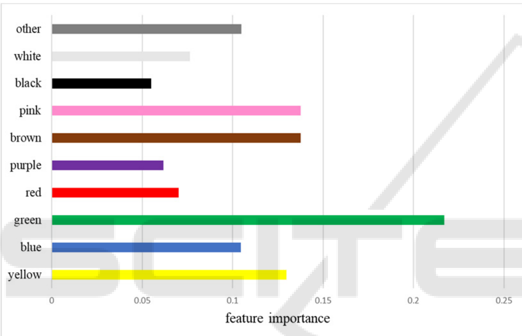

Figure 4: Random forest filters important colors in images.

Table 1: The significance of color representation.

Color	Positive significance	negative significance
Yellow	Bright and warm (Pastoureau, 2019), happy (Boyatzis and Varghese, 1994)	Hunger, frustration, anger (Gehred, 2020)
Blue	Positive, calm (Boyatzis and Varghese, 1994), wise, loyal (Gehred, 2020)	Impulsiveness, anxiety (Ran et al., 2017, Korkmaz et al., 2016), introverted sadness, depression, and cold (Güneş and Olguntürk, 2020)
Green	Relaxation, Comfort (Boyatzis and Varghese, 1994, Mammarella et al., 2016), Nature, Harmony (Gehred, 2020)	Symbolizing mystery, demons (Pastoureau, 2019), jealousy, envy, and misfortune (Güneş and Olguntürk, 2020)
Brown	Reliable, stable, friendly, comfortable, and safe (Gehred, 2020)	Negativeness (Güneş and Olguntürk, 2020, Madden et al., 2000), mourning (Gehred, 2020)

3.4 Retrospective Analysis of the Correlation Between Color and Psychology

Building on the analysis results from section 3.3, we further validated the psychological implications of yellow, blue, green, and brown through a comprehensive retrospective literature review. The findings of the literature review are presented in Table 1. The analysis reveals that most colors possess both positive and negative connotations, while warm and cool color tones do not exhibit clear tendencies towards positivity or negativity (Demir, 2020). Neutral colors display distinct emotional associations: white is typically linked with positivity, and black with negativity. Furthermore, warm and cool color palettes may exhibit emotional biases as the shades deepen or lighten (Hanada, 2018). Taking yellow as an example, although it evokes associations with warmth and brightness, some research suggests that it also symbolizes hunger (Eiseman, 1998). Additionally, the color green has dual positive and negative effects, with its negative connotations often tied to cultural customs, such as in Japanese culture where green is considered ominous, and in Christianity where it signifies demons.

Studies have reported associations between colors and depression-related psychological disorders; specifically, patients with depression exhibit a higher preference for blue and a reduced preference for yellow (Ran et al., 2017). The psychological significance of colors is dynamic; although brown is visually associated with the earth and connotes reliability, it can also evoke negative and mourning emotions in various contexts (Gehred, 2020). The retrospective analysis demonstrates that colors play a significant role in psychology, influenced by factors such as geographical location, upbringing environment, and the temporal characteristics of the subjects. Consequently, our study, which focuses on mosaic art, confirms that the colors of mosaic tiles can reflect the growth environments of elementary school students, with yellow, blue, green, and brown being particularly significant.

4 CONCLUSIONS

Psychological issues among primary and secondary school students are becoming increasingly prominent, necessitating the development of objective tools to assist schools and teachers in promptly identifying and addressing these issues. Traditional psychological surveys, characterized by their extensive number of questions, long update cycles, and rigid formats, are impractical as tools for daily and frequent monitoring. By employing expressive therapy within art therapy, psychological monitoring can be seamlessly integrated into art classes using computer models to analyze students' artworks. This approach significantly reduces the professional demands on teachers regarding psychology and can effectively detect changes in students' psychological states within a short period.

In this study, we conducted mosaic art classes for fifth-grade students at a primary school in Henan Province and utilized deep learning models to analyze the correlation between the students' artworks and their psychological states. The classification results from this study indicate that the discriminative models demonstrate robust performance and offer significant reference value. Furthermore, we discovered that yellow, blue, green, and brown play pivotal roles in the classification of artwork states, indirectly reflecting students' psychological states through their color classifications. However, a limitation of this study is the absence of long-term tracking data on students. As academic pressure increases, the nature of students' artworks may evolve. This study has preliminarily established significant correlations between mosaic colors and the psychological conditions of elementary school students. Additionally, this research contributes scientific evidence and theoretical support for the use of expressive therapy in contemporary children's mental health.

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