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Algorithm design for optimizing color analysis and teaching effect in oil paintings with AI technology support

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ABSTRACT

This paper discusses the application of AI color analysis technology in oil painting teaching, combined with experiments to verify its effect on improving teaching quality. Firstly, the core algorithm of AI color analysis technology is analyzed, and the implementation scheme of digital image sharpening preprocessing is proposed based on the RGB color model, and the edge and color information of the image is extracted based on the improved Canny operator. Improved GAN completes the reconstruction of the oil painting image, and the characteristic colors of the oil painting are extracted using the optimized K-means clustering algorithm. The oil painting images are selected for color feature analysis, and the color matching scheme is improved based on the color feature results to construct the color analysis process based on AI technology in oil painting teaching. Finally, students from art colleges were selected as the research subjects, and a control experiment was designed to investigate the effect of AI color analysis in teaching. The p-value of the five factors of the experimental group and the control group's post-test scores of creativity of modeling, application of color, color richness, emotional tendency of color and expression of the theme are all less than 0.05, and the average scores of the experimental group in these five aspects, 3.66, 3.74, 3.85, 3.77, 3.34, are all significantly larger than those of the control group, which indicates that the experimental group using AI color analysis to assist teaching has significantly widened the gap between the control group and the experimental group in terms of the use of color. It shows that the experimental group using AI color analysis to assist teaching has a significant gap with the control group in the use of color.

Keywords: oil painting teaching, color analysis, edge detection algorithm, GAN, K-means clustering, Canny operator

1. Introduction

With the continuous development of oil painting art in recent years, artists also pay more and more

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attention to their own expression of emotional concepts, so the status of color in oil painting and the means of realization are also more diversified [1]. The art of oil painting itself is a kind of art that uses color to shape the form, and it can be said that color is a means of realization in oil painting. In the continuous development of oil painting art, it has experienced three periods of exploration and research of nature, research of art psychology, and research of art means, and because of color, it can realize the tension of oil painting creation through the contrast between the purity and brightness of color and the color difference, not only expanding the painting field of oil painting, but also providing the maximum painting realizability for the art of oil painting [2-5]. Therefore, it can be said that color is a means of infectious force, through which the viewer and the painter can realize the docking of the mind. In addition, in oil painting, color is the carrier of the oil painting artist's emotional intention, this is because the elements in the color are very visual impact, is the artist can not be replaced by other symbols of a kind of emotional expression, which also presents a different oil painting style [6-8].

The artist Hegel once said that an artistic quality unique to the artist is the sensation of color, not only the embodiment of tonal conception, but also a pursuit of imaginative creativity [9]. It is because the artistic image portrayed in the work is recognized by the masses that there is a resonance between the artist's emotions and the viewer. The most important point is that color is the vitality and the first visual language of oil painting, the essence of oil painting shaping the form, and the key to the success of an oil painting, although the aesthetic concepts of each country are different, and there are differences in the cognition of color, but the language of color in the emotional and cultural connotations can be more than the national boundaries [10-12]. In the actual teaching of oil painting, the teaching content is single and the teaching form is solidified, the analysis and teaching of color exists subjective evaluation and experience teaching led by teachers, and the lack of quantitative analysis leads to a series of problems such as students' lack of solid skills in the use of color and lack of creative ability [13-15]. In order to improve the level of students' oil painting creation, it is of great significance to optimize the color teaching in oil painting education.

In this paper, the preprocessing of digital images is done by calculating the Laplace enhanced sharpening of component images. The edge detection algorithm with improved Canny operator is used to accurately identify and extract the color and structural feature data of the input image. Attention mechanism is added to the generator and Wasserstein distance is introduced to the discriminator to improve the difference degree of distribution distance. The k value is determined by observing the color information, and a specified number of colors are extracted using RGB mode. 185 oil painting images are selected to start the analysis, and the k-value is determined by preliminary counting of image colors. Deconstruct the proportion law of color matching through K-means clustering analysis and color extraction of oil painting sample colors. Explore the application of AI color analysis in oil painting creation, and identify the realization path of AI color analysis assisting oil painting teaching. Adopt the controlled experimental method for empirical investigation, and evaluate the students' oil painting works from three major dimensions. Collect the results of the pre- and post-test scores of the two groups of students to assess the feasibility of AI color analysis assisting oil painting teaching.

2. Color analysis algorithm based on AI technology

AI algorithms show great potential in the field of oil painting, this section aims to discuss the implementation process of oil painting color analysis using AI algorithms. It is divided into three parts: "image preprocessing-image reconstruction-color extraction", which extracts the colors of oil paintings on the basis of optimizing the quality of the original image, and provides an efficient and scalable technical framework for the digital analysis of oil paintings.

2.1. Image Preprocessing

Since the oil painting process focuses on showing the color of the image, it is necessary to implement sharpening on the digital image beforehand in order to make the color of the digital image more vivid. In this study, image sharpening is implemented by calculating the Laplacian of each component image, which is a differential operator that is structured as follows:

$$g(x,y) = f(x,y) + \nabla^2 f(x,y) \tag{1}$$

Eq. (1) where $f(x,y)$ and $g(x,y)$ represent the input image and the sharpened image, respectively, and the Laplace transform using Eq. (1) gives:

$$\nabla^2[c(x,y)] = \begin{bmatrix} \nabla^2 R(x,y) \\ \nabla^2 G(x,y) \\ \nabla^2 B(x,y) \end{bmatrix} \tag{2}$$

One of the more common sharpening operators used in image processing is substituted in Eq. (2):

$$\begin{aligned} \nabla^2 f = f(x+1,y) + f(x-1,y) \\ + f(x,y+1) + f(x,y-1) - 4(x,y) \end{aligned} \tag{3}$$

After the digital image has been sharpened and pre-processed, the color differences between different pixel clusters become clearer, giving a good foundation for the edge detection work required for image color block delineation.

2.2. *Improved GAN-based image reconstruction*

2.2.1. Edge detection algorithm with improved Canny operator. Edge detection algorithms based on traditional Canny operators can suffer from unsmooth edge connections and pseudo edges. To solve the above problems, an edge detection algorithm with improved Canny operator is used in the paper. Firstly, the traditional gradient operator is directionally expanded and a four-direction gradient operator is used for edge detection of the image. Secondly, the maximum inter-class variance method is also introduced to replace the traditional manual algorithm to determine the high and low thresholds, so as to reduce the appearance of pseudo edges. The specific algorithm implementation flow is shown in Figure 1.

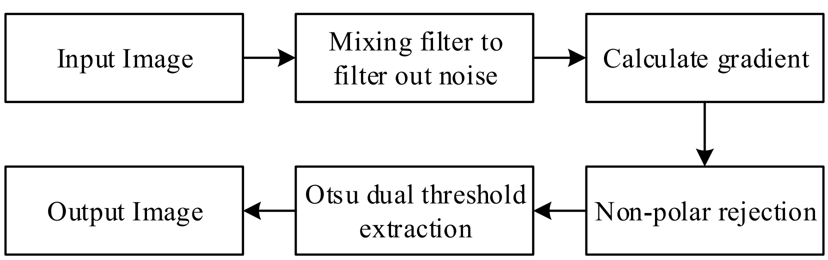


Fig. 1. Algorithm flow

In order to reduce the interference of noise information, the gradient template is also expanded in the paper, i.e., the gradient magnitude in four directions is calculated in eight neighborhoods of each pixel point. The Canny operator after the gradient direction expansion is performed has better noise reduction and edge connection localization ability.

Assuming that the size of the original image is $M \times N$ and the gray level of each pixel is a range $[0, L-1]$, the number of pixels with gray value i is counted as n_i, and the probability of a pixel having a gray value of size i can be determined as $p_i = n_i / (M \times N)$. Gray value t is chosen as the basis for classification, i.e., the gray level of a pixel in category C_0 is defined as $[0, t]$, and that of a pixel in category C_1 is defined as $[t+1, L-1]$. Using this as a basis, notation $P_0(t)$ denotes the likelihood of the occurrence of a pixel point in category C_0, and $P_1(t)$ denotes the likelihood of the occurrence of a pixel point in category C_1, both of which are calculated as follows:

$$P_0(t) = \sum_{i=0}^{t} p_i \tag{4}$$

$$P_1(t) = \sum_{i=l+1}^{t-1} p_i = 1 - P_0(t) \tag{5}$$

In addition, noting that the average gray levels of class C_0 pixel points and class C_1 pixel points are $u_0(t)$ and $u_1(t)$, respectively, we have:

$$u_0(t) = \sum_{i=0}^{t} \left(i \frac{p_i}{P_0(t)} \right) \tag{6}$$

$$u_1(t) = \sum_{i=i+1}^{t-1} \left(i \frac{p_i}{P_1(t)} \right) \tag{7}$$

Based on the above arithmetic relationship, the gray level interclass variance information of the original image signal can be obtained denoted as $\sigma(t)$, denoted as:

$$\sigma(t) = P_0(t) u_0^2(t) + P_1(t) u_1^2(t) \tag{8}$$

In summary, it can be seen that the threshold is optimized when $\sigma(t)$ is maximal, denoted as T_h, while the corresponding low threshold is denoted as $T_i = T_h / 2$.

2.2.2. Generating Adversarial Networks. Generative Adversarial Networks are unsupervised learning methods that generate virtual data through some mapping relation. The two main components of GAN include: generator and discriminator. The role of the generator is to generate false data through the mapping relationship, while the role of the discriminator is to determine the degree of similarity between the data and the real value. The network can be viewed as a confrontation and game between the two components, and ultimately generates data that is false to the truth.The infrastructure of the GAN network is shown in Fig. 2.

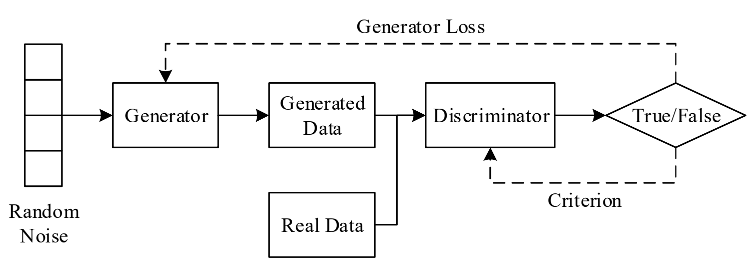


Fig. 2. The infrastructure of the GAN network

The objective of this time is to analyze and transform the input image information in different styles using an end-to-end approach. To better learn the style mapping relationship between the original image and the target image, a generator architecture based on the attention mechanism is designed. Since the attention mechanism refers to the overall characteristics of the image, it can give the model the ability to discriminate complex images.

The image data, which has been pre-processed, is fed into the multi-channel attention model. At the same time, the image color is extracted and sent to the color encoder, and finally the simulated reconstruction of the image is completed.

Traditional GAN in the state of the discriminator is optimized to the limit, the optimization goal of the generator is the combination of the minimum JS scatter and the minimum KL scatter of real and virtual data, which can be expressed as:

$$L_g = \mathrm{KL}\left(p_g \| p_{real}\right) - 2 \cdot \mathrm{JS}\left(p_{real} \| p_g\right) \tag{9}$$

where p_g denotes the virtual generated data distribution while p_{real} denotes the real data distribution. It can be seen that there is a conflict between the optimization of JS and KL scatter. When optimizing and adjusting the KL scatter, the generator only learns the local features, so the coverage is not comprehensive. This leads to a large difference in the distance between the KL and JS distributions, which in turn causes instability and even crashes in the training process.

As a result, the degree of difference in distribution distances is improved using the Wasserstein distance. Thus, the gradient of the function solution is smoother and the solution process is more stable.

The definition of Wasserstein distance is shown in equation (10):

$$W\left(p_{real}, p_g\right) = \inf_{\gamma S\left(p_{real}, p_g\right)} E(x, y)\gamma\left[\|x - y\|\right] \tag{10}$$

where inf is the maximum lower bound, $S\left(p_{real}, p_g\right)$ is the joint distribution of real and virtual data, $\gamma(x, y)$ characterizes the data (x, y) obeying the γ distribution, and E is the expectation. Finally, the loss function L is obtained as follows:

$$\min_G \max_D L(G, D) = E_{x-p_{real}}[D(x)] - E_{i-p_g}[D(\hat{x})] \tag{11}$$

2.3. *K-means clustering based color extraction*

2.3.1. Color extraction process. When extracting the characteristic colors of oil paintings, it is first necessary to analyze the source map of the oil painting and preprocess it to determine the value of k and then use the algorithm to extract the characteristic colors; then construct a color network model based on the adjacency and proportion of the extracted colors, use the model to guide the color matching, and generate a color matching scheme; finally, evaluate the scheme to validate the feasibility of the color feature extraction. The analysis process of oil painting color extraction is shown in Figure 3.

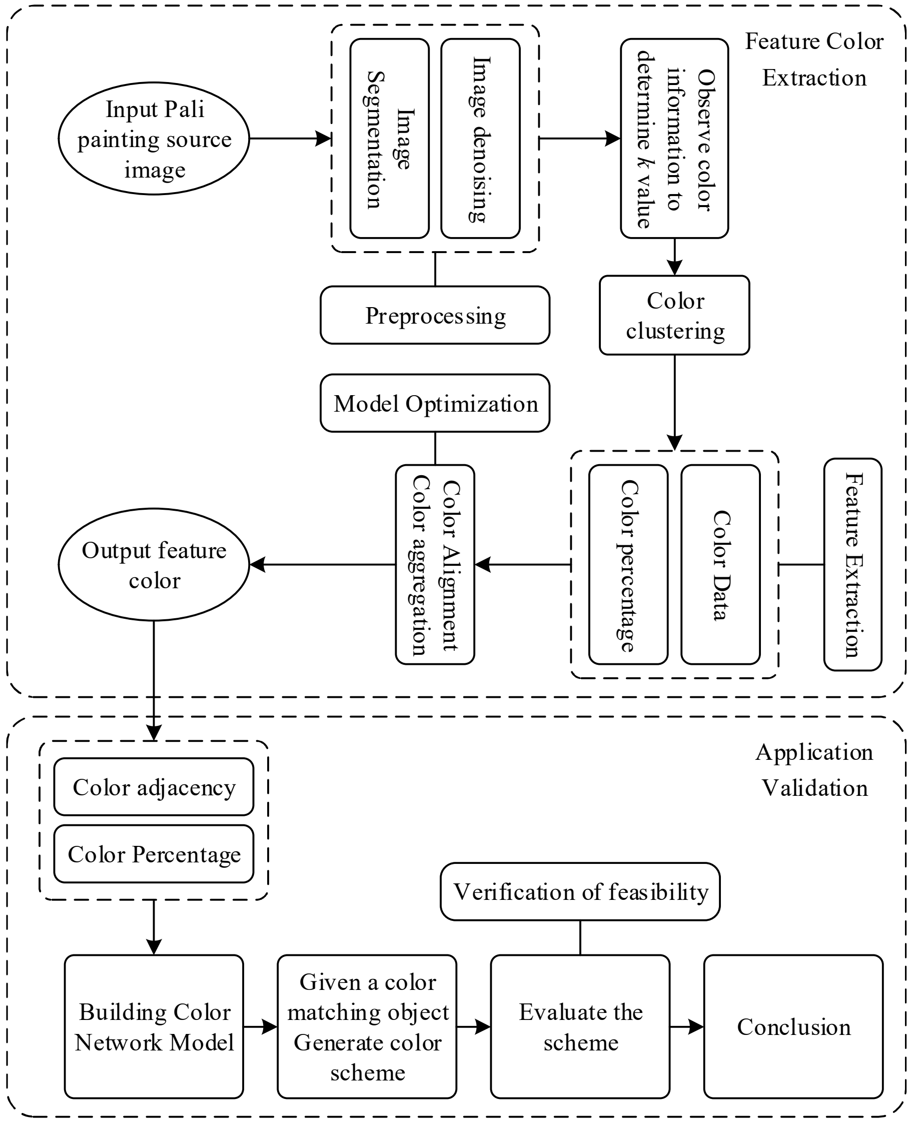


Fig. 3. Oil painting color extraction and analysis process

2.3.2. Principles of K-means clustering algorithm. K-means clustering is a distance-based clustering method, which has been widely used in color extraction of digital images, in which the value of the clustering target k needs to be given by human, k points are selected as the initial clustering centers among the pixels of the given image, the distance between the initial clustering centers and other pixels is calculated, and these points are assigned to the clustering centers with the closest distances, and then new clustering centers are calculated, and this process is repeated to meet the requirements set by the algorithm. This process is repeated continuously to complete the clustering after reaching the requirements set by the algorithm. The specific steps of K-means clustering algorithm in image color clustering process are as follows.

Given the clustering target k, k is the number of clustering centers;

Calculate the distance from the color value of each pixel to each cluster center one by one, and include the pixel in the nearest cluster center, the distance from each point to the cluster center D, see equation (12).

$$D=\sqrt{(r-r_i)-(g-g_i)-(b-b_i)^2} \tag{12}$$

Where: r, g, b are the color values of the cluster center, r_i, g_i, b_i are the color values of other pixels.

The average value of the color of all pixels in the clusters is assigned to the new clustering center, and this calculation process is repeated until the algorithm ends when the set criteria are met, and the final output value of the clustering center is the color value extracted by the target.

Each update of the clustering center is the completion of an iteration, the clustering center is constantly updated until it meets the set criteria, that is, to stop the iteration, usually use the mean square deviation as the basis for setting the standard, the mean square deviation α formula, see equation (13).

$$\alpha = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \mu\right)^2} \tag{13}$$

Where: n is the number of pixel points in the clustering; x_i is the pixel points in the clustering; and μ is the arithmetic mean of all the pixel points in the clustering. The clustering ends when the difference between the values calculated in the first and last two iterations is less than 1.

When clustering image colors, the way of selecting the initial clustering centers will have a certain impact on the color clustering process, in addition, the selection of color patterns will have an impact on the clustering results.

In the selection of the initial clustering center follow the principle of maximum - minimum, can make the clustering process faster and more accurate, the first initial clustering center can be any point on the image, select the first point and then calculate the distance between it and the other pixel points, and the point with the largest distance from the first point is the second initial clustering center, the next clustering center is the largest distance from the two points that have already been selected earlier, and follow this method until The next clustering center is the point with the largest distance from the previous two points, and so on until all the clustering centers are selected.

There are two general types of color modes: HSB mode (hue mode) and RGB mode (grayscale mode.) HSB mode has a greater generalization of colors, and there may be a situation where the number of objects in the clusters is zero, and the number of colors you end up with is less than the number of colors you set to extract. RGB mode selects the center of clustering in the image grayscale value 0~255, the computer vision image is displayed as RGB mode, there will be no clustering of zero, palindromic painting is rich in color, and some colors with small color difference need to be extracted. Therefore, RGB mode is used to extract the specified number of colors.

3. Research on the application effect of AI color analysis to assist teaching and learning

3.1. The realization path of AI color analysis to assist teaching and learning

AI color analysis can help students better master the use of color skills in practice and effectively assist oil painting teaching. This section proposes the whole process of color extraction and analysis, and specifically describes the realization path of AI color analysis to assist oil painting teaching. The research images come from the official website of an oil painting society, the public number of WeChat, and the actual shooting of photo materials in the painting exhibition held by the oil painting society totaling 206, the resolution does not meet the requirements, as well as unsuitable for color analysis of the picture to be deleted, a total of 185 pictures were selected for color characterization.

3.1.1. Color Extraction. Firstly, image preprocessing is carried out using sharpening technique based on RGB color model, after image preprocessing, image reconstruction technique is used to recover the details of the image to ensure that the color and brushstroke information of the oil paintings are recovered completely for more accurate analysis.

Referring to Web-safe colors in the color analysis induction, for each image 30,000 pixel points will be calculated and 256 colors will be counted, which can ensure that the colors are correctly displayed when extracted and applied. A single photo will be calculated to produce less than 256 colors in the color ratio map, and the feature color extraction of a single oil painting image is shown in Table 1. It can be seen that a total of 15 colors are obtained through the color ratio analysis, of which RGB (255,0,255) accounts for 45.29%, which is the highest percentage in the picture, indicating that the red color system dominates in this oil painting.

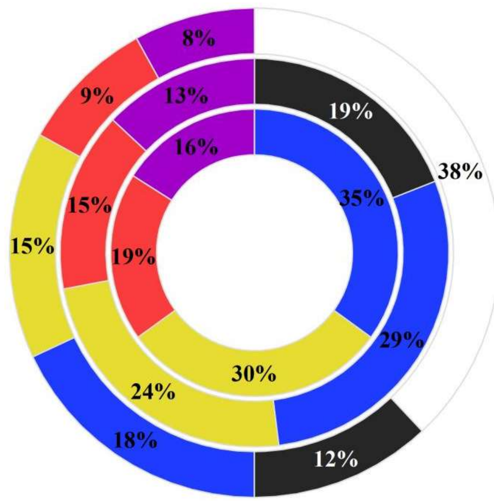
Table 1. Results of color extraction analysis of a single picture

Row	R-GRP	G-GRP	B-GRP	CNT	Percentage
1	255	0	255	13587/30000	45.29%
2	240	0	130	3497/30000	11.66%
3	250	60	60	2533/30000	8.44%
4	230	175	45	1348/30000	4.49%
5	230	220	50	1222/30000	4.07%
6	0	160	255	1203/30000	4.01%
7	30	60	255	1138/30000	3.79%
8	110	0	220	1086/30000	3.62%
9	160	0	200	987/30000	3.29%
10	128	128	128	959/30000	3.20%
11	177	56	43	926/30000	3.09%
12	206	189	55	625/30000	2.08%
13	45	117	168	478/30000	1.59%
14	255	255	255	216/30000	0.72%
15	37	38	38	195/30000	0.66%

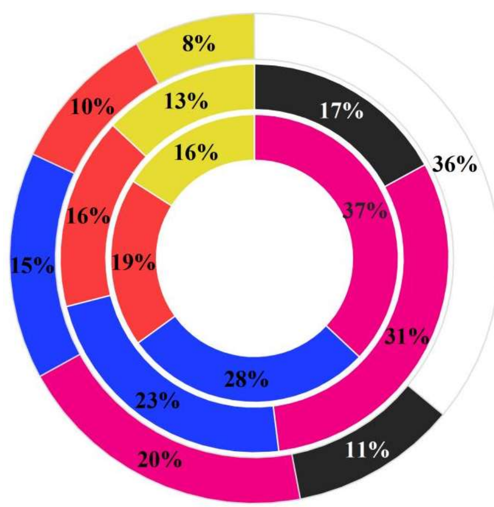
In the same principle, 185 pictures in the material library were imported in batch for calculation, and 219 colors were obtained through the color proportion analysis, of which 6 colors accounted for more than 2%, 33 colors accounted for more than 1%, and 25 colors accounted for more than 0.5%. Because of the large number of color extraction results, the color study was not representative, so the color information of the oil painting samples was observed, and the samples were divided into three types of color schemes for cluster analysis based on the results of the color percentage.

3.1.2. Color Analysis. The K-means clustering algorithm was used to analyze the color clustering of the classified oil painting images, and the color analysis data and color characteristics of the three classes after clustering are shown in Fig. 4 (a-c), which are, in order from the outside to the inside, the percentage of all the colors in the picture, the percentage of the colors after removing the blank parts, and the percentage of the colors after removing the blank and black outlined parts.

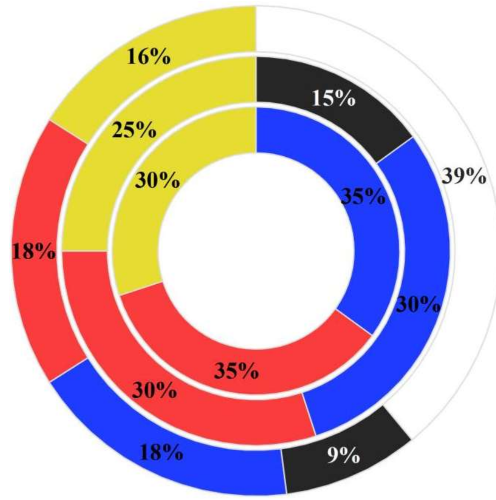
It can be seen that the most frequently occurring color scheme in all the samples is 146 copies of the A category. The average coloring area of all three types of oil paintings is about 60% of the total area of the picture, and the proportion of gray and black in each type is about 10%. 28 copies of Type B are made by replacing the purple with rosy red on the basis of Type A, and 11 copies of Type C are made by eliminating the purple. The color that accounts for the smallest proportion of the Type A paintings is purple, and the largest proportion of the paintings is blue, and the proportion of the red colors in the Type A and Type B paintings is almost the same, and the proportion of the magenta color is higher than that of the purple color, even though rosy red has replaced the purple color in Type B. The proportion of the magenta color in the Type B paintings is more than that of the purple color. However, the proportion of magenta is higher than that of purple, and it is the color with the highest proportion after removing black and white in Category B. From the analysis of hue composition, the three basic colors on the color ring of red, yellow and blue cannot be decomposed any more, which can produce strong color impact and show the strongest color atmosphere. The largest proportion of Class A oil painting samples are balanced with cool and warm colors. The cool colors in the picture are blue and purple, and the warm colors are yellow and red, with a 50/50 split between cool and warm in the percentage of the picture. According to tradition, oil painting includes four basic color classifications: hard colors, soft colors, yin colors, and yang colors. Hard colors refer to strong colors with little or no powder in the pigment, such as red, dark blue, dark green and black. On the contrary, soft colors are light colors that contain powder in the pigment, such as pink, powder blue, and so on. In sample oil paintings, the colors are balanced in terms of warmth and coolness, while soft colors are somewhat more predominant in B oil paintings compared to A oil paintings.



(a)Category A



(b)Category B



(c)Category C

Fig. 4. Color analysis results

All in all, the sample oil painting creates a unique colorful atmosphere through a simple yet bright color palette and a balanced use of warm and cool tones.

3.1.3. Application scenarios. Introducing color analysis based on AI technology as an introduction to teaching can provide students with intuitive color analysis reports. At the same time, design interactive teaching links, such as allowing students to adjust the color ratio of the painting based on the results of the color analysis, and observe the impact of color changes on the emotional expression of the painting.

The application is divided into two situations: the overall brightness of the picture is very high or very low, and the whole picture is in gray tones. Take the first one as an example, very high and very low is the opposite of brightness, it is easy to find the sense of difference in the picture. If you paint a very gray environment and add a lantern to it, the lantern needs to be in a brighter color to increase recognition. The brightness of the lantern will stand out from the grayness of the surroundings. The influence of the lantern also adds a sense of light to the surrounding things, giving a hint of mystery. The second kind of picture in the gray tone refers to the adjustment of the brightness of the subject, no matter how to adjust the difference is relatively small, the recognition will also be low. If the gray tone is applied in the creation, then the gap of the picture is small, and this time will usually apply a large area of gray to create a calm atmosphere, and ultimately achieve the harmony and serenity of the desired effect.

Students can upload their own oil paintings or selected classic oil paintings, the AI system will automatically conduct a color analysis and generate feedback reports, students based on the color results to improve the color scheme, thus improving students' understanding of the artistic expression of color.

3.2. Analysis of Teaching Effectiveness

3.2.1. Design of teaching experiments. In order to investigate the effect of AI color analysis-assisted teaching, students of an art college in C city were selected as the research object, and two classes were randomly selected, and through the teachers of the classes, it was learned that the oil painting creative ability and painting foundation of the students in the three classes were roughly close to each other. One of the classes was identified as the control group and the other as the experimental group, with 40 students in each group. The experimental group was taught with the aid of AI color analysis, while the control group was taught the same theme of conventional oil painting.

The students' oil paintings were evaluated in three dimensions: the shape of the line, the use of color, and the composition and idea. Each dimension includes three aspects: line modeling includes the use of lines and shapes, the grasp of structural features and the creativity of modeling; the use of color includes the use of color, the richness of color and the emotional tendency of color; and composition and conception includes the composition of the picture, the grasp of space and the expression of the theme. Each aspect can be divided into four grades according to specific criteria, with scores of 1, 2, 3 and 4 from low to high.

A three-month teaching experiment was conducted to observe and record the process of teaching activities in two classes, and to collect pre-test and post-test works. At the end of the teaching experiment, the oil paintings were scored, and the oil paintings under different teaching methods were analyzed from three dimensions.

3.2.2. Analysis of research findings. At the end of the experiment, the posttest data of the experimental group and the control group were subjected to independent samples t-test, aiming to explore whether and in what ways the oil painting expressiveness of the students in the experimental group and the control group produced significant differences at the end of the experiment, and the results of the independent samples t-test of the posttest data are shown in Table 2.

From the analysis of the data in Table 2, it can be seen that the p-values of 0.021, 0.009, 0.018, 0.016, and 0.032 for the five factors of creativity of modeling, application of color, richness of color, emotional tendency of color, and expression of theme are all less than 0.05 ($p<0.05$). The mean scores of 3.66, 3.74, 3.85, 3.77, and 3.34 of the experimental group in these five aspects were significantly larger than those of the control group, which indicated that at the end of the experiment, the experimental group's expressive power of painting was higher than that of the control group in the five aspects of creativity of shapes, application of colors, richness of colors, emotional tendency of colors, and expression of themes, and that there were significant differences between the two groups. The p-values of the four factors of the use of lines and shapes, grasping of structural features, picture composition and spatial grasping are all greater than 0.05 ($p>0.05$), and the mean values of the experimental group in terms of the use of lines and shapes and grasping of structural features are both significantly greater than those of the control group in terms of the use of lines and shapes and the grasping of structural features (2.67, 3.43), which means that the experimental group is significantly greater than the control group in terms of the use of lines and shapes, The mean values of 2.67 and 3.43 of the experimental group are significantly larger than those of the control group, indicating that the experimental group's expressive power in the use of lines and shapes and the grasp of structural features is higher than that of the control group, but there is no significant difference. The mean values of the two groups in terms of picture composition and spatial grasp are equal, indicating that the two groups are comparable in terms of composition and spatial grasp. It can be seen that the experimental group that adopts AI color analysis to assist teaching has a significant gap with the control group in the use of color.

Table 2. Post-test independent sample T-test of experimental group and control group

	Group	Number of cases	Mean value	Standard deviation	t	p
Use of lines and shapes	Control group	40	2.16	.697	-1.497	.062
	Experimental group	40	2.67	.583		
Grasp of structure	Control group	40	3.05	.636	-2.084	.051
	Experimental group	40	3.43	.601		
Creativity of modeling	Control group	40	2.18	.589	-2.135	.021
	Experimental group	40	3.66	.577		
Application of color	Control group	40	2.15	.604	-2.484	.009
	Experimental group	40	3.74	.518		
The richness of color	Control group	40	2.24	.629	-2.573	.018
	Experimental group	40	3.85	.501		
The emotional tendency of color	Control group	40	2.33	.736	-2.486	.016
	Experimental group	40	3.77	.537		
Picture composition	Control group	40	2.65	.728	.000	1.000
	Experimental group	40	2.65	.726		
Spatial grasp	Control group	40	2.89	.635	.000	1.000
	Experimental group	40	2.89	.573		
Thematic expression	Control group	40	2.82	.686	-2.189	.032
	Experimental group	40	3.34	.538		

In order to explore what changes occurred in the experimental group before and after the experiment, the pre-test and post-test data of the experimental group were subjected to a paired-sample t-test, and the results of the paired-sample t-test for the pre and post-test data are shown in Table 3.

From the data analysis in Table 3, it can be seen that the P values of the experimental group in seven aspects, including "use of lines and shapes", "grasp of structural features", "creativity of modeling", "use of color", "richness of color", "emotional tendency of color" and "theme expression", were all less than 0.05 ($P<0.05$), and the mean values of the post-test of these seven aspects were 2.67, 3.43, 3.66, 3.74, 3.85, 3.77, and 3.34, which were significantly greater than the mean of the pre-test, and the standard deviation of the post-test was also smaller than that of the pre-test. This indicates that after the end of the experimental activity, the expressiveness of the experimental group in seven aspects was significantly improved, which was significantly different from the pretest. The p-values of 0.265 and 0.277 of "picture composition" and "spatial grasp" were both greater than 0.05 ($p>0.05$), and the mean values of 2.65 and 2.89 in the post-test were greater than those in the pre-test, indicating that the experimental group had a certain improvement in "picture composition" and "spatial grasp", but there was no significant difference. After three weeks of teaching, the experimental group strengthened their ability in color, and made significant progress in theme expression, indicating that the use of AI color analysis to assist teaching is conducive to the improvement of students' overall oil painting expression.

Table 3. Paired sample T-test for the experimental group

	Group	Number of cases	Mean value	Standard deviation	t	p
Use of lines and shapes	Pretest	40	2.14	.587	-2.358	.019
	Post test	40	2.67	.583		
Grasp of structure	Pretest	40	2.94	.641	-2.326	.038
	Post test	40	3.43	.601		
Creativity of modeling	Pretest	40	2.12	.606	-2.535	.018
	Post test	40	3.66	.577		
Application of color	Pretest	40	2.11	.633	-2.435	.015
	Post test	40	3.74	.518		
The richness of color	Pretest	40	2.13	.598	-2.663	.009
	Post test	40	3.85	.501		
The emotional tendency of color	Pretest	40	2.25	.685	-2.521	.011
	Post test	40	3.77	.537		
Picture composition	Pretest	40	2.55	.719	-1.854	.265
	Post test	40	2.65	.726		
Spatial grasp	Pretest	40	2.76	.636	-1.689	.277
	Post test	40	2.89	.573		
Thematic expression	Pretest	40	2.71	.706	-2.748	.008
	Post test	40	3.34	.538		

4. Conclusion

This paper proposes a color analysis algorithm based on AI technology and introduces it into oil painting teaching to explore its practical application effect.

Comparing the post-test scores of the control group and the experimental group, the p-values of 0.021, 0.009, 0.018, 0.016, and 0.032 for the five factors of creativity of modeling, application of color, richness of color, emotional tendency of color, and expression of the theme are all less than 0.05 ($p<0.05$). The mean scores of 3.66, 3.74, 3.85, 3.77, and 3.34 for the experimental group in these five areas were significantly greater than those of the control group. The p-values of 0.062, 0.051, 1.000, 1.000 for the four factors of the use of lines and shapes, grasping of structural features, picture composition and spatial grasping are all greater than 0.05 ($p>0.05$), and the mean scores of the experimental group in the two aspects of the use of lines and shapes and grasping of structural features, 2.67 and 3.43, are all significantly greater than those of the control group. It can be seen that the experimental group that adopts AI color analysis to assist teaching pulls the gap significantly with the control group in the use of color.

The p-values of the experimental group in seven aspects, including "use of lines and shapes", "grasp of structural features", "creativity of modeling", "use of color", "richness of color", "emotional tendency of color" and "theme expression", were all less than 0.05 ($P<0.05$), and the mean values of these seven aspects were 2.67, 3.43, 3.66, 3.74, 3.85, 3.77 and 3.34, which were significantly greater than the mean of the pretest, and the standard deviation of the posttest was also smaller than that of the pretest. The p-values of 0.265 and 0.277 for "Picture Composition" and "Spatial Grasp" were both greater than 0.05 ($P>0.05$), and the mean values of 2.65 and 2.89 for the post-test were greater than those for the pre-test. After three weeks of teaching, the experimental group strengthened their ability in color, and made significant progress in theme expression, indicating that the use of AI color analysis to assist teaching is conducive to the improvement of students' overall oil painting expression.

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References

[1] Tian, W. (2022). Emotional information transmission of color in image oil painting. Journal of Intelligent Systems, 31(1), 428-439.

[2] Zhang, Y. (2017, June). Function and Manifestation of Decorative Color in Oil Painting Creation. In 2nd International Conference on Contemporary Education, Social Sciences and Humanities (ICCESSH 2017) (pp. 487-489). Atlantis Press.

[3] Dai, Y. (2018). Diversity of Color and Semantic Communication in Oil Painting. Archaeofauna, 27(5).

[4] Jingxian, C. (2022). Study on the development of Chinese oil painting color language under the fusion of Chinese and Western painting. Frontiers in Art Research, 4(1), 34-37.

[5] Yi, Z., & Si, S. (2020). Analysis of Flat Color Language in Chinese Contemporary Oil Painting Creation. CONVIVIUM, (39), 210-217.

[6] Zhang, J. (2021). COLOR EXPRESSIVENESS OF IMAGE OIL PAINTING BASED ON COLOR PSYCHOLOGY. Psychiatria Danubina, 33(suppl 5), 112-113.

[7] Yuan, Y., & Chu, Y. Y. (2024). Visual impact of colours in various painting media: oil paint, watercolour, pastel, and digital art. Journal of the International Colour Association, 37, 19-35.

[8] Zhang, L. (2020, September). Study on the Stylization of Color Language in Landscape Oil Painting. In 4th International Conference on Art Studies: Science, Experience, Education (ICASSEE 2020) (pp. 187-191). Atlantis Press.

[9] Chai, D. (2020). Daoism and Hegel on Painting the Invisible Spirit: To Color or Not?. Daoist Encounters with Phenomenology: Thinking Interculturally about Human Existence, 9-29.

[10] Shi, Y., & Tsetsegdelger, D. (2024). A Multidimensional Exploration of the Mechanism of Color Emotion Elicitation in Oil Painting under the Perspective of Psycho-Aesthetics. International Journal of Education and Social Development, 1(2), 20-23.

[11] Zhao, Y. (2022). Formation and Schema Analysis of Oil Painting Style Based on Texture and Color Texture Features under Few Shot. Computational Intelligence and Neuroscience, 2022(1), 4125833.

[12] Zhang, D. (2022). National cultural connotation and poetic charm of image oil painting under the background of color cognitive impairment. Psychiatria Danubina, 34(suppl 1), 756-757.

[13] Zhu, T. (2024). Analysis of Texture Construction Method of Picture Language in Oil Painting Teaching. Curriculum Learning and Exploration, 2(2).

[14] Wang, C. (2020, October). The Aestheticization of Oil Painting Teaching and the Construction of Multi-Dimensional Oil Painting Teaching System Based on Network Cloud Platform. In Journal of Physics: Conference Series (Vol. 1648, No. 2, p. 022018). IOP Publishing.

[15] Xia, T., Karanyathikul, A., & Kotchasit, S. (2023). Effect of Learning Management Using Interactive Teaching Mode on Students' Learning Achievement and Creative Ability of Chinese Contemporary Oil Painting. International Journal of Sociologies and Anthropologies Science Reviews, 3(5), 139-148.