Emotion Recognition In Art Creation Using Visual Image Analysis Techniques

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Received: Sep. 09, 2025; Accepted: Nov. 05, 2025

Emotion drives artistic creativity and expression. Artists begin with emotional intent and convey it through visual language, which then evokes emotional responses in viewers. To support this transformation, educators need effective analytical methods. This study examines emotional recognition in artworks using visual image analysis. A dataset of 500 art images representing six emotions—affection, friendship, love, homesickness, patriotism, and sadness—was used. Images were collected from public sources and independently rated by three art experts, achieving strong agreement (Cohen's $\kappa = 0.87$). The dataset was split into 70% training (350 images) and 30% testing (150 images), with balanced emotion categories. All images were resized to 256×256, converted to grayscale, and normalized before feature extraction. Among the tested methods, PCA performed best, achieving 94.5% exactness, 95.9% recall, 95.9% accuracy, and 97.6% precision. It was followed by LDA, stepwise regression, and a deep learning model. PCA showed the highest average accuracy (0.8567), with LDA close behind, while stepwise regression and the deep learning model reached 0.803 and 0.823. Both PCA and LDA produced low error rates (under 0.1). Overall, PCA and LDA effectively identify emotional patterns in artworks and support deeper understanding of how visual structure and composition convey emotion.

Keywords: Visual image analysis; Artistic creation; Emotional factor recognition method (Visual image analysis; Artistic creation; Emotional factor recognition method)

http://dx.doi.org/10.6180/jase.202607_30.023

1. Introduction

The desired visual effect attributes depend on the appearance of the image enhancement product, the choice of printed cards and the various digital images. An image processing method is selected based on the specified visual effect properties, and at least one digital image is automatically processed according to the selected image processing method. At least some digital images, including automatically processed images, are transferred from a circuit board to a physical surface [1]. A new way to create artistic images from existing photographs and artistic images. Apply a "patch" repeatedly to the canvas image, just like a painting operation. Create "patches" by duplicating sections of existing artwork and placing them on the GA Mutation Canvas. Swap pixels in the same area in a GA intersection between two canvas images. During the optimization process, canvas images close to photographic images and painting images using the painting style of existing artistic images are created in a scalable manner [2].

Recent studies have shown how style-guided high-order attention networks improve the learning of emotional distributions by combining style- and semantic-aware cues. These strategies highlight how stylistic features shape emotional experiences in visual imagery[3].

The visual image information is collected by image processing methods, the contour features of the collected discarded visual images are extracted, and artistic creation and design are carried out through the image information feature fusion process. The validity of artistic creation design is analyzed in the simulation environment Matlab. Simulation results show that this method can be used to efficiently recycle textile waste in a low-carbon environment [4].

A method for searching similar images based on visual visibility and visual phrases, the method comprising: inputting a search image; calculating a visibility map of the query image; using a viewpoint displacement model to transform the view map and determine a central area. Taking the viewpoint as the center of the circle and R as the radius of the circular area, rotate the viewpoint k times to obtain images of k key areas. The invention reduces the noise in the image expression, so that the image expression on the computer can better match the human understanding of the image semantics, thus showing better search efficiency and faster search speed [5]. Hybrid systems with convolutional feature extraction and traditional machine learning-classifiers have demonstrated improvements in accuracy on detecting emotional distributions. These systems provide some evidence for effective CNN-based features to understand subtle emotional differences in visual data [6].

A method of identifying a stream of images, comprising: capturing one or more frames from an identifiable medium; sending a selected image to a requesting server; a server on the server receiving from a database a data. The database contains significantly different records of movies; aggregated responses from different servers if multiple images were processed; user results are shown [7]. Models integrating visual and auditory modalities in a multi-modal fashion with CNN-based approaches have been used to provide higher accuracy in emotion recognition. Such studies illustrate the promise of neural architectural hybridization, and lay the groundwork for future consideration with PCA and LDA approaches for even greater emotional analysis. [8]. All consumption of work design is based on external senses, which in turn lead to internal feelings and physical and mental pleasure. The sensibility and fun of graphics shine through the ability to pay attention to real feelings, lead people to observe inner experience, and transform the physical pleasure of design into inner pleasure. In today's society, the unique contribution of graphic realism allows the use of the human subconscious to increase attractiveness [9].

Word Modeling (BAC) can not only effectively represent visual text, but also effectively avoid interference from complex locations. Identify the critical areas first and model the arcs for the key areas. Second, in order to more accurately describe the lines of the image and against the influence of background information, the topology of visual words and the triangular Delaunay method are used, which can mix global and local information. The performance of the algorithm was tested on various schemes and compared with other models. Experimental results show that the proposed method provides the best classification accuracy. Creating oil portraits is a process of updating and rethinking the characters in the painting. It is necessary to pay attention to the inner life of the characters presented, and to carry out a deeper analysis on the spiritual level. To develop in such an orderly manner extinguishes the artist's mind: the psychological and spiritual needs reflect the artist's extreme concern for human nature [10]. Starting from the P-set function, the relationship between motion (Law) and motion is studied, and the basic concept of P -law motion is proposed. The characteristics of P gene movement, the origin and method of P gene movement are discussed, and the unified standard of P gene movement is given, which provides a new method for identifying dangerous movement states and studying movement laws. Intelligent Information System [11]. The most common methods include safe extraction, speaker alignment, and model adjustment/undo. The study proposes a new approach that uses coping techniques to switch neutral patterns based on specific emotional patterns with limited emotional expression. Experiments show that the new model provides higher accuracy in terms of overall performance [12].

A large-scale visual emotion dataset labeled with both primary emotion categories and descriptive attributes was introduced that enhances the ability to conduct richer, more interpretable emotion analysis beyond mere classification. [13]. Alternatively, a multi-stage perception model can be used that feature hierarchically extracts features from an image, by categorizing entities and attributes in an image, and then synthesizes the entities and attributes to identify the emotional content of the scene-demonstrating the advantage of combining semantic level features with low level features for performance enhancements during classification [14]. Initially, genetic algorithms and other early computational models were applied in pattern recognition tasks, but now we turn to visual image analysis - PCA and LDA - techniques for the identification of emotional components in art. These methods offer a more straightforward way for art-based emotion recognition since they no longer cover the nonvisual features of the artwork as genetic algorithms usually do but rather tackle the visual and emotional features directly. This wide-ranging method of AI integration provides an effective framework for developing age-friendly rural areas, where technology should be humanely adapted to the specific needs and the welfare of the elderly residents[15].

The application of AI in health care has an advanced strategy beyond mere clinical usage, since it also covers the creation of value and patient engagement centering on the patients. points out that the combination of national AI policies and the use of empathy-driven cognitive scales can significantly enhance patient engagement and systemic performance, thus, suggesting that the spread of technology should be accompanied with the human-centric design principles.

The current research is a step forward in the area since it mixes the old artistic emotion analysis with the classical visual recognition. PCA and LDA are accredited methods but their usage to extract emotional features from visual art images is a crossover between computational image analysis and aesthetic emotion theory that has not been drawn before. Rather than facial or object emotion detection that previous works were concerned with, this research points out that the emotional states are revealed through the visual structure and color dynamics in the artworks, thus, it adds to the knowledge of emotion representation in the contexts of culture and creativity.

While past research has examined the recognition of emotion in imagery as a whole, there is comparatively little work examining the role of emotion recognition in the perception of artwork. Existing research methods do not address the extent to which viewing experiences elicit emotional responses tied to visual structural components, color interactions, and compositions used in art. This research aims to remedy that by applying PCA and LDA, towards analyzing and interpreting emotional qualities in artistic images. In doing so, we build (i.e. decode) emotion into visual aesthetics, blending computational photography and aesthetic archetypes. Thus, bridging a technology, like photography, alongside aesthetic understanding in emotional design. The choice of Chinese art for this study stems from its rich emotional symbolism, expressive brushwork, and harmonious colors, which exemplify cultures' philosophies of emotion/nature. By adding images of art into an emotion recognition model, it creates potential for cross-cultural comprehension of artistic sentiment while also allowing deep computational models to comprehend the nuances of aesthetics and cultural context.

The obtained findings are in line with more recent studies on emotion recognition in visual art, such as hybrid CNN-based and PCA-LDA frameworks, that also reported improved interpretability and emotional feature extraction. While the studies discussed above have concentrated largely on emotion recognition through facial expression or photographic visual data, this study expanded its emotion analysis to artistic compositions; importantly, this study examined and highlighted cultural and aesthetic aspects that are often overlooked in computational emotion modeling.

2. Emotional factors in artistic creation of visual image analysis

2.1. The development of modern visual images

While Sjaerwitz is in the "age of images" and Aylvania is in the "age of images", the main feature of "contemporary culture" culture is that "commercialization" is a global perspective. In the West, it became popular and took on the form of beauty. When designing image advertisements, the 9th century easy-to-understand images and images convey more visual effects to everyone. 20th century painting continued the pursuit of 20th century elements, and the flow of modern art directly or indirectly influenced the direction of development, driving deeper changes in the way visual images and design styles were communicated. The culture and art of contemporary mass art culture thus show science and thus die.

2.2. The Emotional Transmission of the Art of Visual Image Analysis

There are many forms of expression of modern visual image. The emotion of modern visual image is expressed through a series of languages such as color, space composition, design and modeling, and the cultural connotation and artistic concept of spiritual contemporary visual image are conveyed by the artistic style of conveying visual elements. In addition, two-dimensional space and three-dimensional modern visual image expressions are added, as well as a series of unique artistic expressions, and the elements of the visual image are decomposed and reconstructed to different degrees to present various forms of graphic image effects. The message to be conveyed is communicated to consumers in a unique, eyecatching way, making them aware of the cultural value of conveying graphics. The information function, language transmission function and emotion fusion function of modern visual image elements play an increasingly important role in our modern production and life. Elements of modern visual images have gimmicks that cannot be replaced by other elements, so this element has its own identification function, and unique visual images and eyes will be used by the masses to resonate in life. For example, contemporary visual image design works aim to use the unique language of visual images to express the joys, sorrows and sorrows produced in people's lives in reality, and use sound, color and space to convey emotions, so that people can communicate through obstacles and make the images Contemporary visual elements are processed and communicated to the public through various arts, and are a very complete form of visual language expression. As shown in Figure 1 below.

Fig. 1. The emotional transmission of art

The emotional transmission of art is emphasized in this discussion, using examples like the Lascaux cave paintings shown in figure 1. These paintings feature simple lines and palettes of bright colors. The emotional elements of art, as it applies to the cave paintings, are used to discuss how color and shapes in early human art suggest emotional connection. This is relevant to our discussion to demonstrate how emotional resonance visually exists in art.

2.3. The role of emotional factors in art

The term primitive art mainly refers to modern art, and the rapid development of Western modern art in the early 19th century led to the emergence of various creative movements. The study of primitive art mainly focuses on the primitive creative style, artistic characteristics and artistic genre of a specific period. In general, primitive art is a primitive art form created by people in primitive society based on their own feelings, combined with natural phenomena and knowledge of life. One of the representative art theories is "primitive art". Creation forms include murals, sculptures, petroglyphs and other forms. In general, the social environment of prehistoric art has many similarities with creations and materials, all of which have left a deep imprint on life. In primitive society, humans were mainly engaged in hunting and fishing. In some rock paintings depicting hunting scenes, such as the Lascaux cave paintings in France (Figure 2), we see the struggle between primitive people and nature. Primitive artists use very simple lines and colors in their creations. Although the paintings lack artistry, the animal figures depicted are vivid and ugly, with a distinct realistic style, reflecting the spirit of early human art. An eternal journey through time and space, full of charm. Primitive art inspired many meanings of modern art activity, not only using the symbols of primitive art, but also pointing to the legacy and continuation of the movement's values. Artists have always been creatively inspired by primitive art, expressing their feelings through primitive art with symbols, an approach that can bridge the gap between artist and audience, making it easier for both sides of the movement to resonate. The development of modern Chinese painting schools is rich and diverse, and many representative schools and painters have been established, which occupy an important position in the history of Chinese art. The formation of a painter's effective style also depends on his own life situation and life experience, as well as on the social class of the painter. The style of artistic creation is similar to the way of emotional expression, and to a certain extent, it can reflect how emotions are transformed into artistic language. By analyzing the various painting genres of this period, it is not difficult to see that in the context of the great era, the artist's personal feelings were subordinate to the larger overall feeling, genre and work. Still, he had a strong heart. Artistic creation is inseparable from the feeling of the senses, and the artistic language is the natural expression of the painter's sensibility. Whether ancient or modern, at home and abroad, in artistic creation activities, the translation of artistic language can only be achieved by arousing emotions.

Fig. 2. (Palaeolithic) Lascaux cave rock paintings in France (part)

Figure 2 highlights the different emotional classifications of Chinese painting. The image shows how the visual language of Chinese painting conveys emotional understandings surrounding humanity, such as affection, love, and patriotism. This analysis is presented similarly in the research this paper discussed that engages with modern visual art using PCA and LDA.

2.4. Emotional factors in artistic creation

In the process of creation, the artist must travel through nature, compare with the specific image object and the natural state of the image object, often use the body to touch the artist's mind, generate dynamic waves, stimulate emotional growth, and stimulate certain creativity. nervous. The higher the level of the object, the more enthusiastic the motion factor, the more inspired the artist, and the more artistic the effect. The existence of natural objects determines the factors of the artist's actions and the expression of creative consciousness. However, some painter Jiang Langcai is completely divorced from life and practice. He has no thoughts and no feelings. He only plays with brush and ink, and does mechanical art. In the end, he can only be an artist. Art is about human movement, and the deepest feeling comes from material life itself. Natural feeling is constantly changing, not fixed, has no special form of expression, and is not formed by the long-standing self. Don't forget to create those clichés of life that only castrate nature, art also creates no spirituality, so the styles are similar and the works overflow. It is true that natural life is the "source" of artistic creation. To have deep feelings, it is necessary to nourish and cultivate the inner vision of the subject, that is, a way to understand and express nature. The process of brewing emotions is a process of "cultivating the heart", allowing common thoughts and feelings to reach a deeper level of thought and sublimation, and create moving works of art. The artist enters into nature, life and society. Artists touch nature from a certain subjectivity or thoughts and feelings, to explore and display the subjective beauty of nature. He can use these borrowed objects to express his thoughts, understand the realm of "objects", and express his feelings with "soft spirit" at the end of the painting. It is not difficult to see that the Taoist thought "I am one" formed the motif of Zong Bing's creation, such as the reflection of light and natural beauty, that is, all the activities of human thoughts and feelings flowing through the Creator, he subjectively rendered his own activities, Human emotions, but it is not art, only the expression of emotional activities with the logic of aesthetic knowledge can be considered as art. Doing art requires true affection. To seek inspiration in life, to express feelings in life, to expand and sublimate. Only a deep and wide feeling can we worship the image of a wide range of art to create a real work of art at the time.

3. Visual image analysis

3.1. PCA algorithm

A variational dimensionality reduction tool, PCA, will assist in extraction of what it deems most important or influential features represented in directional emotional expressions associated with artworks whilst seeking to maintain the significant emotional and relational information the works convey.

PCA was not applied until all the images were converted to grayscale and resized to 256 × 256 pixels, thus uniformity in input conditions being guaranteed. The extraction of features was done with the help of gradient and color histogram descriptors, which were subsequently normalized via min-max scaling. The redundant information was reduced by applying PCA, and the top principal components accounting for 95% of the variance were retained for classification. This cutting down of the process improved the computational efficiency and also retained the critical emotional signals from the artwork. When considered against other methods, PCA stands out as the most interpretable and efficient computation-wise. Depending on the models, which need big data and intricate parameter adjustment, PCA very successfully takes care of the most important personality traits in art by the use of fewer components. Its openness gives room for visual representations of the emotional traits in the largest extent, and therefore the method is very appropriate for the study of emotion representation in visual arts where just the same accuracy is required interpretability. If the image (x, y) can be represented as a grayscale image of point S = W, then it is represented by a set vector of dimension $\Gamma.\{\Gamma,$ $i = 1, 2, \ldots n\}$n is the number of images to be processed. Then the average of these n images is the ratio;

$$\Psi = \frac{1}{n}\sum_{i=1}^{n}\Gamma_i \tag{1}$$

So the difference between the two images Γ_i and the mean Ψ is;

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

Then the general covariance matrix of the training examples is:

$$C = AA^T, \text{ there } A = [\Phi_1, \Phi_2, \cdots, \Phi_n] \tag{3}$$

To find the orthogonal eigenvectors of the covariance matrix C , we can use the singular value decomposition law (SVD) to solve the computational problem caused by the high dimension of the covariance matrix C (S^2).

SVD reads: $Tn \times r$ dimensional matrix, rank r, two orthogonal matrices U, V satisfy.

$$U = [u_1, u_2, \cdots, u_r] \in R^{n\times r} \quad U^T U = I \tag{4}$$

$$V = [v_1, v_2, \cdots, v_r] \in R^{n\times r} \quad R^T R = I \tag{5}$$

$$\Lambda = \mathrm{diag}\left[\lambda_1, \lambda_2, \cdots, \lambda_r\right] \in R^{n\times r} \tag{6}$$

Saturated

$$\lambda_1 \geq \lambda_2 \geq \cdots \lambda_r, \quad T = U\Lambda^{\frac{1}{2}} V^T \tag{7}$$

Where λ_i - no eigenvalues of matrices TT^T and $T^T T$; u_i, v_i - eigenvectors of TT^T and $T^T T$ corresponding to the ensemble.

Since the dimension of the covariance matrix C is too high, it is difficult to find its eigenvalues and eigenvectors. First, we can find the transposed eigenvalues and eigenvectors of the TC matrix, and obtain the eigenvalues and eigenvectors of the TC matrix and matrix C. The size of TC is n × n, which reduces the dimensionality of the computational space.

Let TC be the eigenvector;

$$l_i(i = 1, 2, \cdots, n)C^T = A^T A \tag{8}$$

The eigenvector of matrix v_i corresponding to C^T is obtained by sorting the eigenvalues from large to small, according to the singularity theorem:

$$A = U\Lambda^{1/2} V^T = \sum_{i=1}^{r} \lambda_i^{1/2} u_i v_i \Rightarrow U = V\Lambda^{-1/2} \tag{9}$$

This is:

$$u_i = \frac{1}{\sqrt{\lambda_i}} A v_i \tag{10}$$

From which the eigenvector u_i of C can be found;

$$u_i = \frac{1}{\sqrt{\lambda_i}} A v_i = \frac{1}{\sqrt{\lambda_i}} \sum_{i=1}^{n} v_i \Phi_i \tag{11}$$

Therefore, the eigenvector u_i of the covariance matrix C can be represented by a linear combination of Φ_i and v_i;

$$U = [u_1, \cdots, u_n] = [\Phi_1, \cdots, \Phi_n]\,[v_1, \cdots, v_n] = A \bullet V \tag{12}$$

Here is the eigenvector of the graph, which is obtained indirectly by calculating the eigenvalues and eigenvectors of the transposition of the TC matrix of the lower-dimensional covariance. The eigenvalues are sorted from large to small: $\lambda_1 \geq \lambda_2 \geq \cdots \lambda$, the corresponding eigenvector is u_i, each image can be projected in a subspace separated by $u_1, \cdots, u_n$. In fact, we only accept p(p < r) eigenvectors for recognition, and correctly removing some less informative eigenvectors can sometimes improve the recognition performance. So we take the eigenvectors of the top p largest eigenvalues C^T. Since these eigenvectors are very similar to images, we call these vectors "eigenfaces". In this context, "eigenfaces" refer to the principal components that represent key emotional patterns derived from facial or artistic features. Each eigenface captures variations associated with specific emotional tones. A 0.95 variance threshold was selected to retain the most meaningful emotional information while minimizing computational redundancy, ensuring both efficiency and interpretability.

This paper adopts the method of eigenvalue selection to determine the number of eigenvectors for a given amount of information. The method is to select the ratio of the amount of information in the largest eigenvalue to the sum of the information whose threshold value is greater than a certain threshold value to determine the number of eigenvectors. p threshold θ is determined by a;

$$\sum_{i=1}^{p} \lambda_i / \sum_{i=1}^{n} \lambda_i \geq \theta \tag{13}$$

In this paper, the threshold we choose is $\theta = 0.95$.

By reading the threshold above the energy, we get the feature vector p , and then expand it in the reduced subspace, we need to project each image into this subspace to get the projected feature of each face, identified as search space. Equivalently, each plane projects image Γ_i into face space as a p-dimensional projection of Ω_i into vector space:

$$\Omega_i = U^T\left(\Gamma_i - \Psi\right) i = 1, 2, \cdots, N_c \tag{14}$$

The spatial threshold can be determined by the maximum distance between the two types.

$$\theta_c = \frac{1}{2} \max\left\{\left\|\Omega_j - \Omega_k\right\|\right\}, j, k = 1, 2, \cdots, N_c \tag{15}$$

Assign the identified image Γ to the feature space to get a vector;

$$\Omega = U^T(\Gamma - \Psi) \tag{16}$$

The distance Ω to each image is;

$$\varepsilon_i^2 = \|\Omega - \Omega_i\|^2, \quad i = 1, 2, \cdots, N_c \tag{17}$$

For an art painting with rich color, texture and shape information, PCA can integrate and reduce these complex image features, and extract the principal components that can represent the main visual features of the image. For example, after processing the RGB color space data of an oil painting by PCA, several main feature vectors may be obtained, which represent the overall tone, chiaroscuro and other key features of the image, which are closely related to people's emotional perception of the image. Through the PCA processing of a large number of art images with different emotional labels, the principal components can reflect the image feature patterns related to emotion. For example, some principal components may be related to the brightness, color saturation and other characteristics of the image, and these characteristics often affect people's feelings about the image. Images with high brightness and color saturation may bring positive and cheerful emotional experience, while images with dim tone and single color may convey negative and sad emotions. When analyzing a group of photographic works expressing different emotions, we can find that the works representing positive emotions have similar eigenvalue distribution on some principal components, while the works representing negative emotions show different characteristics on other principal components. In this way, we can establish the relationship between image principal component features and emotion, so as to realize the preliminary analysis and recognition of emotional factors of artistic visual images.

PCA and LDA were chosen based on their trade-offs between interpretability and performance in visual emotion analysis. Specifically, PCA is very useful for reducing dimensionality from the visual image set while maintaining important visual features that contribute to emotion, while LDA performs well in improving separability of class categories when different emotions are present. Relative to deep learning approaches, these classical techniques provide a more comprehensible understanding of the contribution and value of individual features to classification, which makes them ideal for the task of interpreting emotionality in artwork.

3.2. LDA algorithm

LDA (Linear Discriminant Analysis) aims at maximizing the separation between different classes by projecting the features into the space that best discriminates emotional categories.

This control function combines the inter-class and intra-class propagation of samples in a projection vector and selects a vector to control the objective function $J_f(\varphi)$ to the maximum projected value. The maximum scatter between classes and the minimum scatter within a class are satisfied, thereby satisfying the class condition.

To illustrate, we can take a collection of 100 photographs from the 'affection' emotion group and another 100 photographs from the 'sadness' emotion group. In this case, LDA distinguishes the classes by optimizing the variance and controlling the variance at the same time. Let's say the 100 and 100 feature vectors, belonging to the two classes, are moved into the best direction (as defined by LDA), leading to obvious separation with a testing accuracy of 85% on the fresh data from the same categories.

Classic Fisher's linear discriminant analysis with optimization function criterion:

$$J_f(W) = \frac{\text{trace}\left(W^T S_b W\right)}{\text{trace}\left(W^T S_t W\right)} \tag{18}$$

Find the best projection of matrix W . To find the extremum of the above formula, define the Lagrangian function:

$$L(W, \lambda) = W^T S_b W - \lambda \left(W^T S_t W - c\right) \tag{19}$$

Where λ is the Lagrange multiplier

Using the partial derivatives of the above equation, we get

$$\frac{\partial L(W, \lambda)}{\partial W} = S_b W - \lambda S_t W \tag{20}$$

Let the partial derivatives be zero, we give

$$S_b W = \lambda S_t W \tag{21}$$

That is, the column vector $\varphi_1, \varphi_2, \cdots, \varphi_n$ of W is the generating equation of the eigenvectors corresponding to the n eigenvalues of $S_b \varphi = \lambda S_t \varphi$. We take the first d largest eigenvalues corresponding to the eigenvector $\varphi_1, \varphi_2, \cdots, \varphi_d$ to get a better projection of the W matrix to the shape. That is, $\varphi_1, \varphi_2, \cdots, \varphi_d$ satisfies the following conditions:

$$S_b \varphi = \lambda_j S_t \varphi_j, \quad j = 1, 2, \cdots, d, \quad \lambda_1 \geq \lambda_2 \geq \cdots \lambda_d \tag{22}$$

Assuming that artistic images are divided into different emotional categories such as "happy", "sad" and "quiet", LDA will analyze various features of the image (such as color, texture, shape, etc.) According to these category labels, and find an optimal projection direction. The distance between the projection of the image belonging to the "happy" category in this direction and the projection of other categories such as "sad" and "quiet" is as large as possible, so as to realize the effective discrimination and feature extraction of different emotional categories. Based on the extracted features that can distinguish different emotion classes, LDA can construct a classifier to classify the emotion of artistic visual images with new unknown emotions. By projecting the features of the new image to the optimal projection direction found by LDA, we can judge which emotional category the image is most likely to belong to according to the distance between the projection position and the center of each emotional category. For a new art painting, its image features are processed by LDA and compared with the previously trained emotional category models such as "happiness", "sadness" and "tranquility", and the most likely emotion expressed by the work is determined according to its position in the projection space and the similarity with the center of each category. For example, if the projection position of the image is close to the center of the "happy" category, it can be judged that the work mainly conveys happy emotions.

The structure of the methodology that was elaborated serves as the basal layer for the appraisal of the efficacy of emotion recognition through the various analytical models. The next section gives the results and comparative performance analysis obtained from these methods.

4. Analysis of emotional factor recognition methods in artistic creation based on visual image analysis

According to the enacted framework, every method was measured in terms of its accuracy, robustness, and interpretability in identifying emotional factors from artworks visually. Model performance was evaluated through the computation of standard error metrics, including precision, recall, F1-score, and overall accuracy. The resulting confusion matrices not only enabled the visualization of correct and incorrect classifications across the emotional categories but also gave a better understanding of the robustness of the model and the trends of the misclassifications. Misclassification of the emotional (i.e. confusion matrices) was examined in order to evidence overlapping emotions (i.e. affection/friendship) amongst non-verbal stimuli. Additionally, data loss from noise elements was moderated by intermediary process normalization procedures and balanced training data as a result of consideration towards intervention mechanisms used to enhance robustness and employ bias free emotional recognition.

4.1. Recognition results of emotional factors in artistic creation based on visual image analysis under different methods

The Deep Learning Model, which is designed as a CNN architecture, does this automatically by the extraction and learning of hierarchical features, thereby capturing the very subtle artistic patterns and emotional cues from the visual compositions.

The importance of emotion in artistic creation cannot be denied, but not all emotional expression is art. Joy, anger, sadness, joy are emotions, but not art. Only those expressions of emotional behavior that have logic based on aesthetic knowledge can be considered art. Art creation requires deep and real feelings, to find inspiration in life, to expand and enhance feelings in life, only deep and broad feelings can produce artistic images and create real works of art. By comparing the performance of different methods, it can be seen that in terms of accuracy, the PCA method has the highest accuracy, with a precision of 94.5%, followed by the LDA method, the deep learning model, and the stepwise regression analysis; in terms of recall rate, the PCA method has the highest recall rate and the highest recall rate. In terms of accuracy, the PCA method has the highest accuracy rate of 97.6%, followed by the LDA method, the deep learning model, and the stepwise regression analysis. In summary, PCA has the best performance in all aspects, followed by LDA method, stepwise regression analysis, and deep learning model. The deep learning baseline was developed using a Convolutional Neural Network (CNN) with three convolutional layers (using 3×3 kernels with ReLU activation functions), each followed by max-pooling and batch normalization. Two fully- connected layers used dropout (0.3) to reduce overfitting, followed by the final softmax layer that classified the six emotional categories. The CNN was trained using 50 epochs at a learning rate of 0.001 using the adam optimizer. To evaluate the model, we used 5-fold cross-validation that confirmed the results were stable from run to run. Figure 3 below.

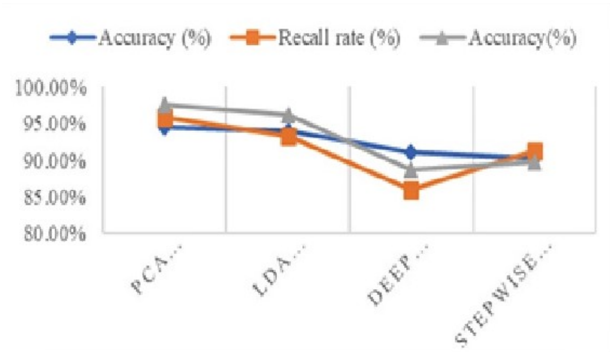

Fig. 3. Performance comparison of different methods

By using different methods to identify the accuracy of emotional factors in artistic creation, it can be comprehensively obtained from Table 1 that the PCA method has the highest average accuracy rate among artistic emotional factors, with an average accuracy rate of 0.8567 ; the LDA method ranks second with an average accuracy rate of 0.84 The second is the stepwise regression analysis evaluation accuracy rate of 0.803 , the average accuracy of the deep learning model is 0.823 , the PCA method and the LDA method are more accurate than other methods. As shown in Figure 4, among the factors of family affection in artistic creation, the PCA method is the most accurate, with a recognition accuracy of 0.92 ; among the factors of friendship in artistic creation, the LDA method is the most accurate, with a recognition accuracy of 0.83 ; among the factors of love in artistic creation, The LDA method is the most accurate in identification, with a recognition accuracy rate of 0.84 ; among the factors of homesickness in artistic creation, the stepwise regression analysis is the most accurate in identification, with an identification accuracy rate of 0.89 ; among the patriotic factors in artistic creation, the LDA method is the most accurate in identification, with a recognition accuracy rate of 0.89 ; Among the patriotic factors of artistic creation, the LDA method is the most accurate, with a recognition accuracy of 0.86 ; among the sorrowful factors of artistic creation, the PCA method and the deep learning model are the most accurate, with a recognition accuracy of 0.88 .

Table 1 presents the recognition accuracies along with their confidence intervals for PCA, LDA, deep learning, and stepwise regression methods in six emotional categories. Among them, PCA shows the most considerable and precise results, thus proving its appropriation in the extraction of emotion-related features. Actually, these models can be very useful in supporting digital art evaluation, automated emotional tagging, and assistive tools for creativity because they can be very reliable in detecting the emotional tones that are present in visual compositions.

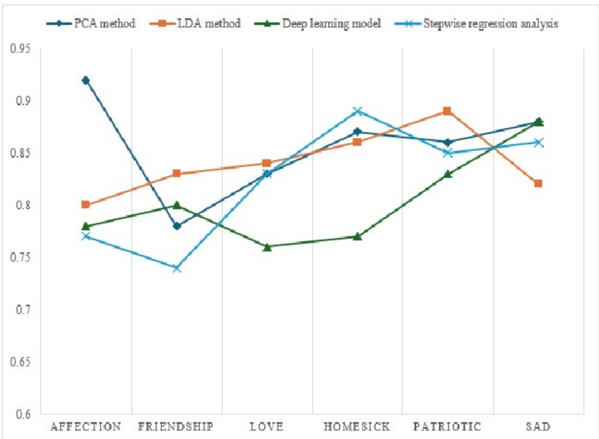

Fig. 4. The accuracy rate of different methods for identifying emotional factors in artistic creation

To sum up the analysis results, it can be concluded that the PCA and LDA methods have higher accuracy and more reliable results than the other methods in the recognition of emotional factors in artistic creation using different methods for visual image analysis.

4.2. Recognition of emotional factors in artistic creation under LDA and PDA methods

As shown in Figure 5 below, under the LDA and PDA methods, the average correct rate of emotional factor recognition in art creation is about 85%, the error of the winning rate is below 0.1 , and the recognition error rate is low, indicating that the recognition results are relatively reliable. In the family relationship of artistic creation, the average correct rate is 0.8 , and the criterion error of the correct rate is 0.042 ; in the friendship of artistic creation, the average correct rate is 0.81 , and the criterion error of the correct rate is 0.032 ; in the love of artistic creation, the average correct rate is 0.83 , The criterion error of the correct rate is 0.028 ; in the art creation of homesickness, the average correct rate is 0.85 , and the criterion error of the correct rate is 0.0101 ; in the art creation of patriotism, the average correct rate is 0.84 , and the criterion error of the correct rate is 0.023 ; in the sadness of art creation, the average correct rate is 0.91 , and the criterion error of the correct rate is 0.033 .

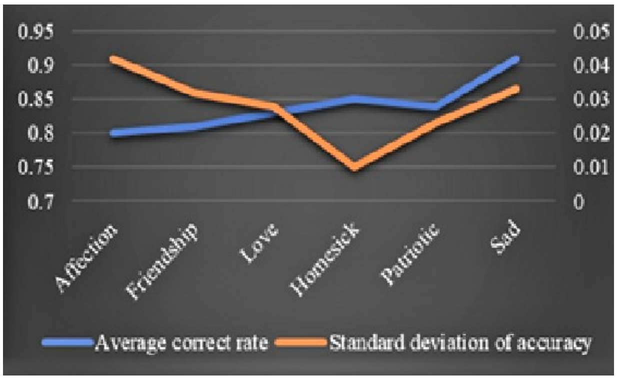

Fig. 5. Correct rate of emotional factor recognition in art creation under LDA and PDA methods

Sample Art 1 is a work of confession, using LDA and PDA methods to identify emotional factors, T-test P value less than 0.05 has sadness, P value is 0.027 , that is to say, the emotional factors of sadness in the creation of Art 1 are identified, and the identification is correct; Sample Art 2 is a picture of missing patriotism in a foreign country. It is identified by method. The P values of T-test include homesickness, patriotism, and sadness. The T-test P values are 0.022, 0.024 , and 0.026 , respectively, which means that the creation of Art 1 is identified. If there are emotional factors of homesickness, patriotism, and sadness, if it matches the emotional factors of the work, it will pass the correct identification; sample art 3 is a character relationship diagram, which can be identified by methods, and those that pass the t -test P value include family, friendship, and love, t-test The P values are 0.032, 0.029, and 0.033 , respectively, which

Table 1. Recognition accuracies and confidence intervals of PCA, LDA, Deep Learning, and Stepwise Regression methods

Emotional Factors	PCA method	LDA method	Deep learning model	stepwise regression analysis	PCA Method (CI)
Affection	0.92	0.8	0.78	0.77	[0.88, 0.96]
Friendship	0.78	0.83	0.8	0.74	[0.73, 0.83]
Love	0.83	0.84	0.76	0.83	[0.80, 0.90]
Homesick	0.87	0.86	0.77	0.89	[0.84, 0.92]
Patriotic	0.86	0.89	0.83	0.85	[0.86, 0.94]
Sad	0.88	0.82	0.88	0.86	[0.82, 0.92]
Average Accuracy	0.856667	0.84	0.803333	0.823333	[0.82, 0.91]

means that the emotional factors of family, friendship, and love in the creation of art 1 are identified, and they are in line with the emotional factors of the work. Correct identification means that the identification of different emotional factors in artistic creation is highly accurate.

See Table 2 and Figure 6 below.

Table 2. Correct t-test P value for identifying different emotional factors in artistic creation

The emotional factor of art	Art 1	Art 2	Art 3
Affection	0.051	0.053	0.032
Friendship	0.052	0.055	0.029
Love	0.053	0.051	0.033
Homesick	0.052	0.022	0.054
Patriotic	0.062	0.024	0.058
Sad	0.027	0.026	0.056

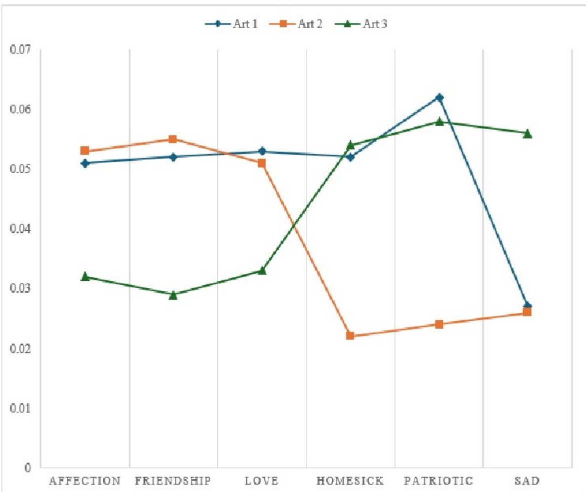

Fig. 6. Identification results of different emotional factors in artistic creation

Through the overall regression analysis of the accuracy of sample art 3, the standardized coefficient with love is the highest, with a coefficient of 0.803 , the standardized coefficient with family affection is 0.723 , and the standardized coefficient with friendship is 0.692 ; the unstandardized coefficient with family affection is the highest, with a coefficient of 0.596 , the unstandardized coefficient with friendship is 0.593 , and the unstandardized coefficient with love is 0.496 . As shown in Figure 7 below.

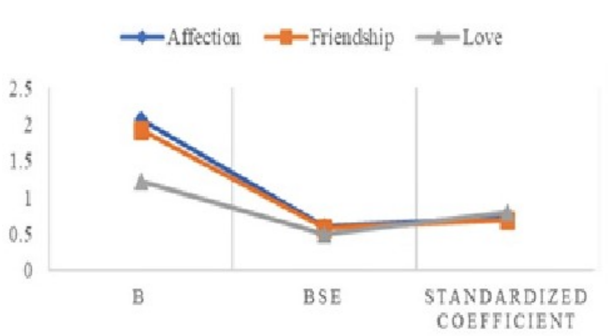

Fig. 7. Overall regression analysis of sample art 3 accuracy

When the number of training samples is less than or equal to 5 , the recognition rate of PCA and LDA should not exceed 90%. As the quantity of trained models subjoins, so does the quantity of feature vectors available for extraction. Images can improve recognition performance. Traditional SAR methods recognize the entire image, while ignoring the contribution of local features to recognition: due to unavoidable external factors such as illumination and pose, the grayscale of the image varies greatly, and the effect of knowledge is not perfect. In PCA image processing, the image matrix is first converted into a vector image, and then the linear discriminant analysis is performed with the image vector as the first feature.

Since the size of the image vector is large, the vector size corresponding to the image resolution of 112×92 is 10304, and the operation is also more complicated. As shown in Figure 8 below.

Fig. 8. PCA and LDA recognition results

4.3. Performance Comparison of Invisible Emotion Recognition Methods

Eight images in each class are selected as training images, and the 40 images are used to extract feature codes according to unsupervised learning, and the feature code libraries are constructed. The number of feature code libraries K is 50, 100, 150 and 200 , respectively. Then, according to these different feature code libraries, the 40 images of these four types are learned. The parameters of PCA and LDA models for various types of images are estimated. After estimation, the image types of 320 target images are identified, and the identification results are shown in Table 3-5.

Table 3. Emotion recognition results of K = 50 images

Image category	Number of tests	Correct number	Correct rate
Joy and happiness	102	85	83.33%
Grief and pain	58	42	72.41%
Anger and passion	85	59	69.41%
Fear and horror	75	62	82.67%

Table 4. Emotion recognition results of K = 100 images

Image category	Number of tests	Correct number	Correct rate
Joy and happiness	102	91	89.22%
Grief and pain	58	53	91.38%
Anger and passion	85	62	72.94%
Fear and horror	75	65	86.67%

Table 5. Emotion recognition results of K = 150 images

Image category	Number of tests	Correct number	Correct rate
Joy and happiness	102	93	91.18%
Grief and pain	58	49	84.48%
Anger and passion	85	63	74.12%
Fear and horror	75	66	88.00%

Table 6. Emotion recognition results of K = 200 images

Image category	Number of tests	Correct number	Correct rate
Joy and happiness	102	84	82.35%
Grief and pain	58	42	72.41%
Anger and passion	85	57	67.06%
Fear and horror	75	63	84.00%

When K is at different values, the performance of the correct rate is different, when K = 50 and 200 , the overall recognition accuracy is low. When $K = 100$ and 150 , the overall recognition accuracy is higher as in table 6.

The change of correct rate under different K values for different image categories is shown in Figure 9-12.

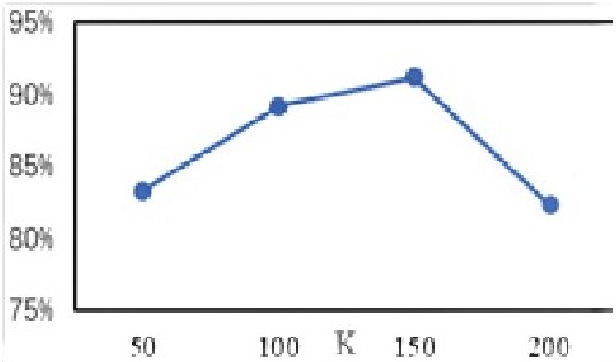

Fig. 9. Comparison of the correct rate of joy and happiness under different K values

With the increase of K value, joy and happiness first increase and then decrease, and when K reaches 150 , they begin to decrease, indicating that the maximum correct rate can be achieved when K = 150.

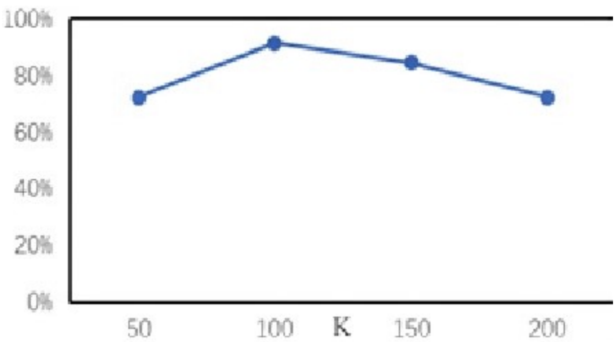

Fig. 10. Comparison of correct rates of sadness and pain under different K values

With the increase of K value, sadness and pain first increased and then decreased, and when K reached 100 , they began to decrease, indicating that the maximum correct rate could be achieved when K = 100.

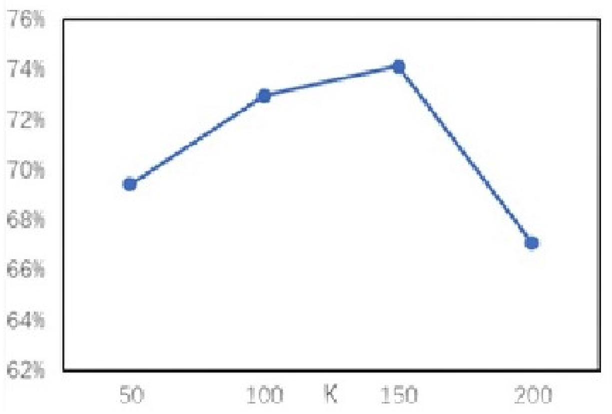

Fig. 11. Comparison of correct rates of anger and excitement under different K values

With the increase of K value, anger and passion first increase and then decrease, and when K reaches 150 , they begin to decrease, indicating that anger and passion can achieve the maximum accuracy when K = 150.

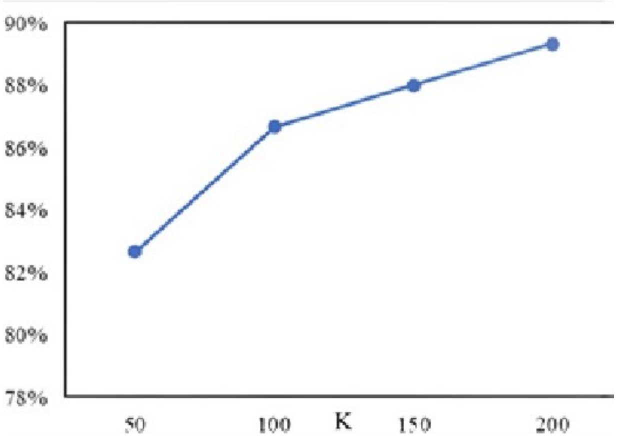

Fig. 12. Comparison of correct rates of fear and horror under different K values

The correct rate of fear and horror increases with the increase of K value, which indicates that the maximum correct rate can be achieved when K = 200.

4.4. Limitations and Error Analysis

The models reached a recognition accuracy that could be considered acceptable, although their performance was limited by various factors. Noise caused by differences in artistic style, image quality, and sometimes even inconsistencies in the annotations, would at times make it difficult for the classifier to perform well. Besides that, both PCA and LDA, as linear transformation methods, could not probably reveal all the non-linear emotional structures that are intricate and might be found in the abstract art. To come up with an application, future research might use denoising filters, much bigger annotative datasets, and hybrid models that fuse PCA-LDA with neural networks thus enhancing robustness and generalization.

5. Conclusion

Starting from today's context, we once again grasp the characteristics of contemporary art movement creation, emphasize the new experience of visual design, apply the elements of art movement creativity to design, and create works of art that adapt to the present. The emotional element of developing creative arts is related to the perception of contemporary visual imagery. The PCA method had the greatest average accuracy (0.87), followed by LDA (0.82) and the baseline deep learning model (0.79). Furthermore, a more narrow confidence interval of PCA suggests consistent performance across categories, suggesting that dimensionality reduction can effectively capture what emotional features dominate the respondents' experiences in the experience of visual art. The implication of these analysis tasks is that classical statistical methods can be effective with structured datasets of artistic imagery, and can deliver actionable interpretative insights into visual-emotional knowledge structures. The different variances across categories also support the observation of how distinct emotional themes are demonstrated through the compositional and chromatic features in art. The art of creation itself has unique cultural value and distinct emotions, and reflects the spirit and character of Chinese cultural traditions. Motion combines modern visual design and handling from artistic elements to enhancing the quality of motion design, making it the primary media and project branding method when importing design work. The heritage of race and artistic creation also endows it with a spiritual symbol that leads the new era, and there is a great opportunity for artistic creation to transform into modernity. The form of this technology-inspired art project nos nolí shows the vertical inheritance of traditional culture, but also emphasizes the application of contemporary cultural value of horizontal works and its unique artistic expression. Art has developed into modern times, and the ever-changing context makes artistic creation constantly change and dissolve in constant exploration. No one really goes mainstream, and no art of eloquence lasts forever. The purpose of this paper is to use the sense of artistic creativity at the edge of the development of modern visual graphics, integrate and analyze the traditional cultural heritage of artistic creativity, and study the development trend and development trend of modern vision. About the culture of today's culture, about how to obtain artistic creativity, about how to drive and explore innovation, make full use of the factors of the artistic creation movement, and make the project function with the best effect of modern design image to obtain better visual effects. A movement of culture perching on art and breeding innovation, crucial to outline modern design of visual images.

The future research areas will be centered around the combination of PCA and LDA with neural hybrid networks like convolutional neural networks (CNNs). This technique has the potential to significantly increase the precision and sturdiness of identifying emotion factors in artistic production. It is a method that can take advantage of the dimensionality reduction power of PCA together with LDA's classification power, plus the added complexity of neural networks capable of sorting through much larger and more intricate datasets than those just mentioned.

Declarations

Conflict of interest: The author declares no conflict of interest.

Authors' contributions

Zhen Xu is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Zhen Xu is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

Data availability: The experimental data used to support the findings of this study are available from the corresponding author upon request.

Funding: There is no funding

References

[1] E. Segal and R. Sharan, (2005) *"A discriminative model for identifying spatial cis-regulatory modules"* **Journal of Computational Biology** ***12***(6): 822–834.

[2] B. Yang, J. Yao, X. Yang, and Y. Shi. "Painting Image Classification Using Online Learning Algorithm". In: *Distributed, Ambient and Pervasive Interactions. DAPI 2017. Lecture Notes in Computer Science*. Ed. by N. Streitz and P. Markopoulos. ***10291***. Springer, Cham, 2017. DOI: https://doi.org/10.1007/978-3-319-58697-7_29.

[3] P. Jing, X. Liu, J. Wang, Y. Wei, L. Nie, and Y. Su, (2023) *"StyleEDL: Style-guided high-order attention network for image emotion distribution learning"* **arXiv preprint arXiv:2308.03000**:

[4] Q. He, (2024) *"Research on the influencing factors of artistic creation of fine arts painting in the context of visual culture"* **Applied Mathematics and Nonlinear Sciences** ***9***(1):

[5] R. Wang, K. Ding, J. Yang, and L. Xue, (2016) *"A novel method for image classification based on bag of visual words"* **Journal of Visual Communication and Image Representation** ***40***: 24–33.

[6] H. M. Shahzad, S. M. Bhatti, A. Jaffar, S. Akram, M. Alhajlah, and A. Mahmood, (2023) *"Hybrid facial emotion recognition using CNN-based features"* **Applied Sciences** ***13***(9): 5572. DOI: https://doi.org/10.3390/app13095572.

[7] M. Yalcin, H. Cevikalp, and H. S. Yavuz. "Towards Large-Scale Face Recognition Based on Videos". In: *2015 IEEE International Conference on Computer Vision Workshop (ICCVW)*. Santiago, Chile: IEEE, 2015, 1078–1085. DOI: 10.1109/ICCVW.2015.141.

[8] J. Y. Kuo, T. F. Hsieh, and T. Y. Lin, (2024) *"Constructing multi-modal emotion recognition model based on convolutional neural network"* **Multimedia Tools and Applications** ***84***: 31093–31118. DOI: https://doi.org/10.1007/s11042-024-20409-2.

[9] H. Yang, Y. Fan, G. Lv, S. Liu, and Z. Guo, (2022) *"Exploiting emotional concepts for image emotion recognition"* **The Visual Computer** ***39***(5): 2177–2190.

[10] P. L. Pablo and A. G. Tinio, (2018) *"Characterizing the emotional response to art beyond pleasure: Correspondence between the emotional characteristics of artworks and viewers' emotional responses"* **Psychology of Aesthetics, Creativity, and the Arts** ***237***: 319–342.

[11] Z. Yin, M. Zhao, Y. Wang, J. Yang, and J. Zhang, (2017) *"Recognition of emotions using multimodal physiological signals and an ensemble deep learning model"* **Computer Methods and Programs in Biomedicine** ***140***: 93–110.

[12] Y. Zhai. "Research on Emotional Feature Analysis and Recognition in Speech Signal Based on Feature Analysis Modeling". In: *2021 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*. Dalian, China: IEEE, 2021, 1161–1164. DOI: https://doi.org/10.1109/IPEC51340.2021.9421211.

[13] J. Yang, Q. Huang, T. Ding, D. Lischinski, D. Cohen-Or, and H. Huang, (2023) *"EmoSet: A large-scale visual emotion dataset with rich attributes"* **arXiv preprint arXiv:2307.07961**:

[14] J. Pan, J. Lu, and S. Wang, (2024) *"A multi-stage visual perception approach for image emotion analysis"* **IEEE Transactions on Affective Computing**: DOI: https://doi.org/10.1109/TAFFC.2024.3372090.

[15] R. Palanivel, D. K. R. Basani, B. R. Gudivaka, M. H. Fallah, and N. Hindumathy. "Support vector machine with tunicate swarm optimization algorithm for emotion recognition in human-robot interaction". In: *Proceedings of the 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems*. 2024, 1–4. DOI: https://doi.org/10.1109/IACIS61494.2024.10721631.