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ANALYSING THE CLASSIFICATION OF ARTISTIC STYLES OF PAINTING IN ART TEACHING FROM THE PERSPECTIVE OF EMOTIONAL SEMANTICS

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Abstract. With the advancement of Internet information technology, a great number of art paintings have appeared on key small network platforms. These art paintings include not only a huge quantity of representational information, but also a large amount of semantic information; yet, there is currently a dearth of more systematic research on sentiment semantic analysis in painting art works. To provide basic support for study into the sentiment semantics of art paintings, we present a machine learning-based classification algorithm for painting art in art education from the standpoint of sentiment semantic analysis. To begin, we build machine learning models of different painting styles. Once machine learning is realized, we convert the color space into Lab color space and use the weighting function and the color values of the a and b channels to obtain the image's color entropy; to obtain the chunking entropy, we use the art image's chunking machine learning and the mean of the chunking machine learning; and to obtain the contour Entropy, we use the Contourlet transform to extract the image's contour information. With significant novelty and practical application value, this study presents a new direction for the study and practice of emotional level adaptive interaction in intelligent learning environments.

Key words: Sentiment semantic analysis, Machine learning, Deep learning, Painting classification

1. Introduction. Traditional culture is the spiritual source of a nation, and painting is one of the forms of expression of traditional cultural heritage[1]. Mankind's knowledge and understanding of the world, as well as his perception and emotion of real life, are expressed through the form of painting. From ancient times to the present, human civilization has progressed continuously and accumulated a huge amount of painting resources, such as Eastern landscape paintings, Western oil paintings, Dunhuang frescoes [2], and so on. These painting images are not only an effective carrier for passing down human civilization, but also an important force for human development and progress in the course of history[3]. In the current era of rapid social growth, smart mobile gadgets have been increasingly integrated into people's daily lives, and at the same time, digital painting images are gradually integrated into people's lives, and can be enjoyed anytime and anywhere through the Internet and electronic devices, which also makes it more convenient for researchers to explore them at a deeper level [4].

While research on computer cognitive science and artificial intelligence has reached a significant degree, it is still early in the development of machine cognitive aspects of emotion perception and expression [5]. Emotion is an essential element of human functioning and plays a crucial part in many human activities, including cognition, logic, planning, creation, and communication, as demonstrated by research in neurophysiology, brain science, and other fields [6]. The American study [7] is the first to propose allowing a computer to have emotions. The author made the argument that an intelligent machine can only be one that has emotions. According to study [8], since then, emotional computing research has drawn interest from nations all over the world in the field of information science. Affective computing aims to enable computers to perceive, comprehend, and communicate a wide range of emotional traits, among other things, with the ultimate goal of enabling computers to freely express and interact with one another just like people. The method of affective computing states that the gathering, analyzing, and modeling of emotional data, as well as the interpretation of emotional signals, are the principal areas of research [9]. The primary area of study in emotion computing is image emotion semantic recognition, and emotion computing will play a major role in experiments and research on artificial intelligence in the future [10].

The amount of image resources is currently increasing quickly, especially in the constantly updating Internet

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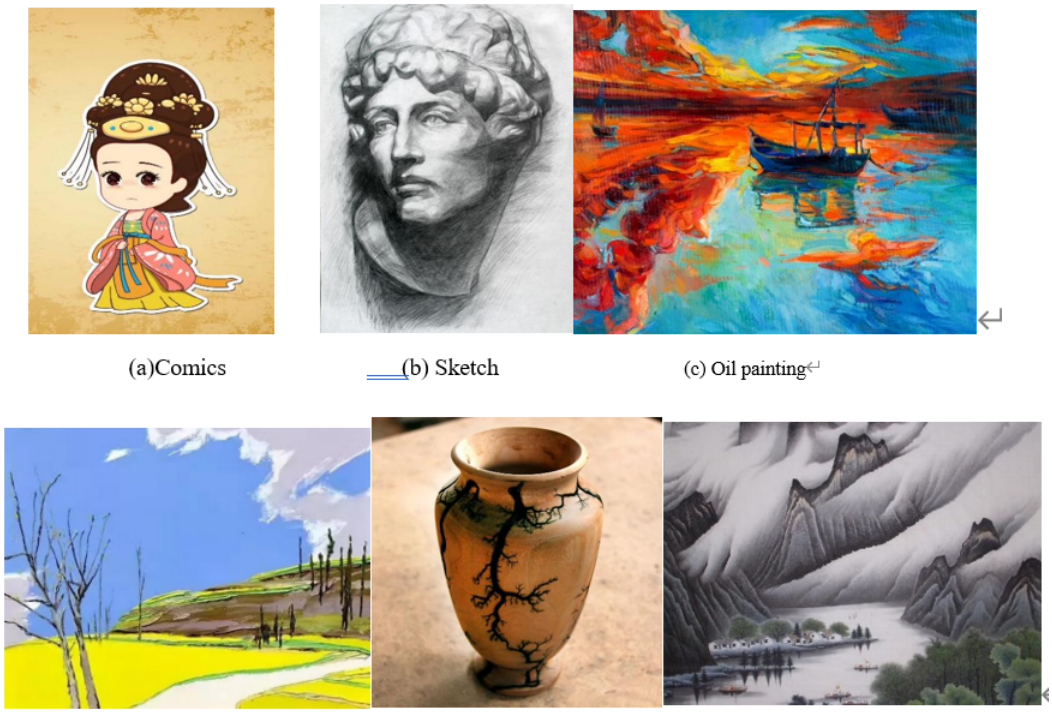

(a)Comics (b) Sketch (c) Oil painting

(d) Watercolor painting (e) Pyrography (f) Ink painting

Fig. 1.1: Example of style painting.

network, necessitating the efficient organization, administration, and application of these enormous image information resources. The majority of semantic-based research on the emotional semantics of images uses images from a variety of sources, such as landscape photographs, paintings, and life photographs in a variety of perplexing and complex categories. There is still a dearth of dedicated image resources in the field of image semantic research. The establishment of a comprehensive and applicable image material library for the analysis of the emotional semantics of images is a very necessary basic work. While the difficulty of experimental research may be lessened by the arbitrary selection of image resources, the accuracy of the experimental results for the study of the emotional semantics of images will be diminished.

Further systematic emotion semantic research on painting art works is now lacking. The thesis develops a semantic annotation system of painting emotion from the perspective of user cognition and based on the hierarchical semantic model of paintings, and offers an easy-to-use research platform for more scholars in the study of image emotion. The goals of this system are to establish a semantic dataset of Yunnan art paintings that has been annotated with standardised descriptions, and to provide basic support for the research on emotion semantics of art paintings.

2. Related work. Japan from the 1990s conducted research on perceptual engineering (kansei engineering), which is the combination of human emotions and engineering to design and manufacture goods [11]. In terms of market applications, the German multi-model shopping assistant EMBASSI, which mainly takes the psychology of shoppers and the demand for the goods environment in shopping malls as its research goal, establishes a convenient Internet e-commerce system [12], the multi-functional perception machine successfully developed and applied by the Harbin Institute of Technology [13], the research on robots with emotions based on artificial intelligence proposed by Tsinghua University, which is capable of controlling its own architecture [14], the research conducted by Beijing Jiaotong University to integrate multifunctional perceptual machines and emotional computing with each other [15], the research conducted by the University of Science and Technology of China on interactive perceptual image retrieval technology based on image content [16], and the research conducted by Zhejiang University to create a virtual character and emotional system in E-Teatrix [17].

In contrast, there is still a lot of room for growth and little research being done in the subject of picture emotional semantics, both domestically and internationally. Low-level visual characteristics like color, texture, and edge outlines can be directly used to extract emotional semantic information from an image, which will then naturally reflect the image's rich emotional content. As a result, low-level visual features and machine learning techniques (e.g., SVM, Adaboost, neural networks, fuzzy clustering, etc.) are used in the great majority of current image-based emotion semantic studies for emotion annotation and recognition as well as emotion-based image categorization and retrieval. A fuzzy similarity based emotion classification method for color photos was proposed by study [18], which used color as a key characteristic. Study [19] used an adaptive fuzzy system and neural network based approach to study and compare two emotion models based on color templates. An emotion prediction system developed by Study [20] uses visual characteristics to automatically identify particular emotions in textile imagery. According to the link between color and emotion, study [21] suggests an emotion retrieval model based on the semantic description of visual colors.

More methodical studies on the semantics of emotion for pictorial artworks are still lacking. Most of the work that has already been done only focuses on a small number of specific issues related to emotion computation (such as semantic-based painting retrieval, painting art style classification, etc.), or compares and identifies a particular painter or painters, a particular type of painting style, etc. A multi-resolution Hidden Markov (MHMM) technique was presented in study [22] to classify traditional Chinese black-and-white ink drawings. An approach based on SVM classifiers and low-level characteristics was reported in study [23] to divide traditional Chinese paintings into two style categories: writing and brushwork. Research [24] examined the brushstroke features of Van Gogh's paintings in an effort to pinpoint his original creations. Study [25] used an RBF neural network to automatically classify historical western artworks according to both local and global visual characteristics. Study [26]: Using clustering and vector quantization (VQ) based on MPEG-7 descriptors, high-level visual features are extracted to classify and retrieve semantic information from artworks of 18 Western European artists from 6 categories representing various stylistic periods. In order to conduct scientific research on the scientific understanding of visual art, the study [27] uses the Curvelet transform, information theory technology, and Sparse Code coding on the paintings of six painters: Xu Beihong, a representative of Chinese ink painting, and Van Gogh, a representative of Western painting. These techniques are used to extract the digital features of each school of painting and to summarize the statistical characteristics and the correspondence between painting styles. In a comparative study on the influence that artists have on one another, Research [28] first created a two-level painting classification model and then used knowledge discovery techniques to analyze the influence that artists have on one another. These works do not address sentiment analysis, even if they target paintings and concentrate on the connection between low-level characteristics and high-level semantics.

2.1. Emotion in color. It is widely recognized that color has the power to awaken emotions, and the symbolic nature of color can trigger associations, so that color is associated with certain emotions and feelings, and it can be said that color has emotionality. Although the emotions evoked by color can vary somewhat because of different cultural backgrounds, personal experiences and psychological factors, there are still many common feelings in the psychology of color under factors such as human physiological structure and the physical characteristics of color. In art, architecture, design and painting, the use of color is used to make the picture "pleasant, powerful, melancholic" and other emotions, which is a common daily experience [12].

In the study of image sentiment, [13]and others in Japan used a color vector composed of the average of the RGB components of the L row and column colors to establish a mapping between them to sentiment words, while [14] divided the image into 32 × 32 sub-blocks, calculated the average color intensity values of the image sub-blocks, and they composed a vector as the image color features. In these studies, basically, a simple extraction approach is taken for the color features and not much consideration is given to the connection between features and sentiment.

The approach of [15] is pioneering, and based on Itten's theory about the semantics expressed by colors and lines in art paintings, he integrates the lower-level image features with several rules, logical and relational operations into features with certain semantic descriptive ability, i.e., higher-level image expressive features, and then uses the expressive features for the derivation of image emotional semantics, so that the extracted features have a stronger ability to express emotion capability.

In general, color features are rarely used in current image retrieval systems to describe from the perspective of emotion, and emotion-based image color feature extraction must fully consider human feelings and psychology to construct appropriate color features, which is a further research trend for emotion-based image feature extraction.

2.2. Emotion in shapes and contours. Shapes also have their own aesthetic expression value, and certain shape features in images can stimulate people to produce perceptual awareness. For example, lines have rich expressive forms; vertical lines are clear and solemn, symbolizing dignity and eternity; horizontal lines are wide and still, indicating silence and stability; diagonal lines are vivid and energetic, with a sense of movement; circles and curves are soft, elegant, and rhythmic, in various shapes and forms.

Different shapes also convey different visual effects, and people often assign different shapes to different thoughts and emotions. For example, geometric shapes have a simple, simple, clear mechanical and indifferent sense; shape gives stability and solemnity; S shape gives change and liveliness; C shape causes centripetal flow, shape gives proper concentration; O shape gives a sense of roundness and relaxation; V shape produces instability; shape gives seriousness and silence; organic shape has a sense of liveliness and "human feelings and ignorance ".

Commonly used shape and contour features are boundary-based and region-based methods, and methods with better description are Fourier descriptors and invariant moment methods, which are invariant to translation, rotation, and expansion of the shape . In recent years there are some new methods such as finite element matching methods and wavelet transform description methods.

Emotion-based shape feature extraction should be relatively simple, its purpose is different from general shape feature extraction, and it does not require to identify the object type from the shape, so the requirements for shape are not strict, only need to judge the general line shape (straight line, curve, fold) or the basic area shape belongs to geometric shape (shape or V shape, etc.) or organic shape (O shape, S shape or natural shape, etc.). However, there are not many studies linking shape features with image emotion, and it is worthy of further in-depth exploration.

2.3. Emotion in texture. All images have surface texture, which is also called texture in design, and the material is different, the structure of the surface is different, and it gives different feelings. Smooth to give a sense of delicacy, soft to give a sense of warmth, rough to give a sense of old, hard to give a sense of strength, can produce different visual psychological effects, and people's emotions are closely linked.

Texture is an important and difficult to describe feature of an image, and there is still no accepted precise definition. An early typical representation of texture features is the symbiotic matrix approach based on traditional mathematical models. The so-called grayscale co-occurrence matrix $M(\lhd x, \lhd y)$ is mathematically represented as the joint frequency distribution of the simultaneous occurrence of two grayscale pairs in the image at positions $(\lhd x, \lhd y)$ apart, so that it can reflect the spatial dependence of the grayscale level texture. The drawback of the grayscale co-occurrence matrix method is that some of the texture properties it obtains (e.g., entropy) would have no corresponding visual content.

3. Methods. The goal of the picture feature extraction process, as seen in Fig. 3.1, is to recover objective underlying features like colour, texture, shape, etc. from the image, and the features are extracted mainly using computer vision and digital image processing techniques to obtain objective visual content features directly from the image, and the algorithms they correspond to are becoming increasingly mature. In the process of studying the emotional semantics of images, the feature extraction part of images is very heavy, and it is necessary to construct or select psychological and physiological models in combination with human physiological and psychological characteristics to find features, and to describe them using appropriate ways in order to play a positive role in the extraction of emotional semantics.

First, the edges were filtered and closed by morphological manipulation. Finally, the top six emotional semantic sub-images of the formed painting images in terms of density are used as the input features needed for classification. The flowchart of the emotion-semantic feature extraction method proposed in this chapter is shown in Fig. 3.2.

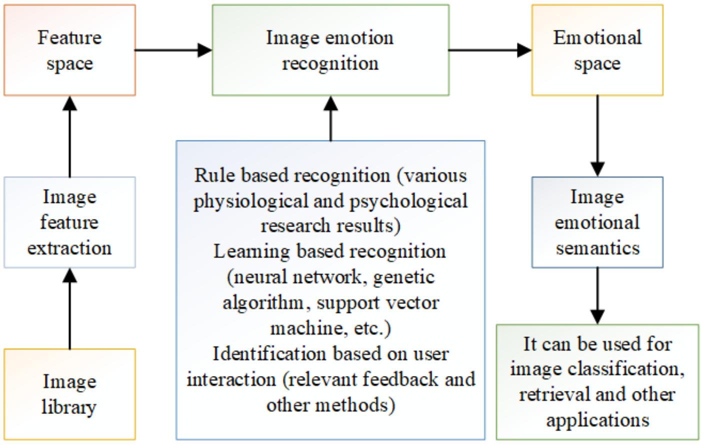

Fig. 3.1: Basic framework of emotion semantic extraction.

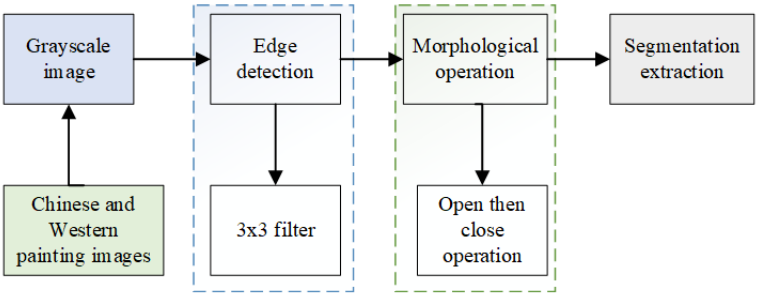

Fig. 3.2: Flowchart of extracting sentiment semantic features.

3.1. Methods of extracting sentiment semantic features in this paper.

3.1.1. Sobel operator edge detection method. Edge detection is one of the common methods for processing image edges. It is independent of the image content and acts mainly on the edges. Thus, in our model, we choose the edge as the first place if it contains the number of pixels between two thresholds (200 and 900).

Among them, the Sobel operator is an algorithm for edge detection based on the first-order gradient operation, which uses the convolution kernels G_X and G_Y to convolve in the X and Y directions of the image, respectively, in the process of extracting sentiment semantic features. The results computed from the convolution in X and Y directions are algebraically weighted and summed to obtain the edge results for the whole image. The convolution kernel G_X, G_Y is shown in Eq. 3.1:

$$G_X = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \quad G_Y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \tag{3.1}$$

The Sobel operator matrix has the following form:

$$G_x = f_x(x,y) = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad \mathrm{G}_y = f_y(x,y) = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{3.2}$$

The edge operation method, which is essentially a gradient change in the grey value of a pixel point, is carried out by the drawing image, and the edge location of a certain region is where the gradient change is

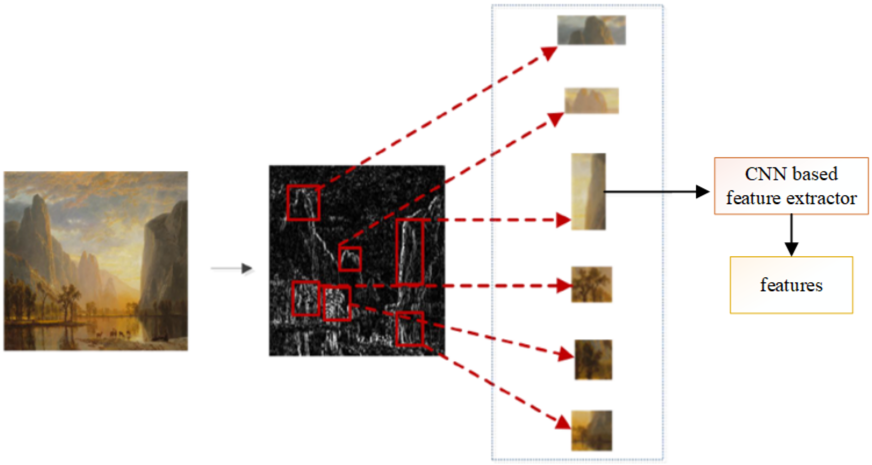

Fig. 3.3: Selection of emotional semantic sub-images.

located. The combined grey value represents the portion of the grey value that has changed in this instance. The following formula determines the point's grey value size.

$$G = \sqrt{G_x^2 + G_y^2} \tag{3.3}$$

In the process of extracting the emotional semantic features, the painting images are firstly converted into grayscale images, and the edge detection Sobel operator is used to perform the operation through a 3*3 filter.

3.1.2. Morphological operation. We have to select representative sentiment semantic features as the input for classification, because too sparse sentiment semantics will interfere with the classification results. The top six emotional semantic features with density extracted according to the above algorithm are used as the most representative emotional semantics of this painting image, and we call it selectable emotional semantics. As shown in Fig. 3.3, the process of extracting selectable sentiment semantics is shown.

Fig. 3.4 shows the block diagram of the system implementation.

3.2. Classification model based on sentiment semantic features. With the expansion of data set, CNN has been widely used in various fields of image processing, such as target recognition, classification and tracking. Therefore, based on the above mapping data set, we establish a convolution neural network classification model based on emotional semantic features.

3.2.1. CNN. This study uses morphological manipulation, segmentation, and extraction of the image after edge detection, and then uses the 64x64 image size as the CNN's input for learning and training. Fig. 3.5 depicts the architecture, and the structure is as follows:

1. Create six 60 × 60 mappings in the C1 layer in order to extract certain edge features from the original image pixels.
2. Each mapping in the S1 layer is lowered using a subsampling rate of 2, which aids in the extraction of important edge characteristics while lowering the model's parameters.
3. The second convolution layer in the C2 layer creates 12 mappings with a size of 26 x 26 in order to identify basic shape features from the edge features.
4. By creating fully connected layers, 2028 dimensional vectors are created in one layer of the S2 layer. In the output layer, 1014-dimensional features are finally obtained.

3.2.2. SVM. The essential idea of SVM is to transform the nonlinear problem in classification into a linear problem and finally get the optimal solution. SVMs maximize the distance between two types of images in a dataset and the hyperplane. Its diagram is shown in Fig. 3.6.

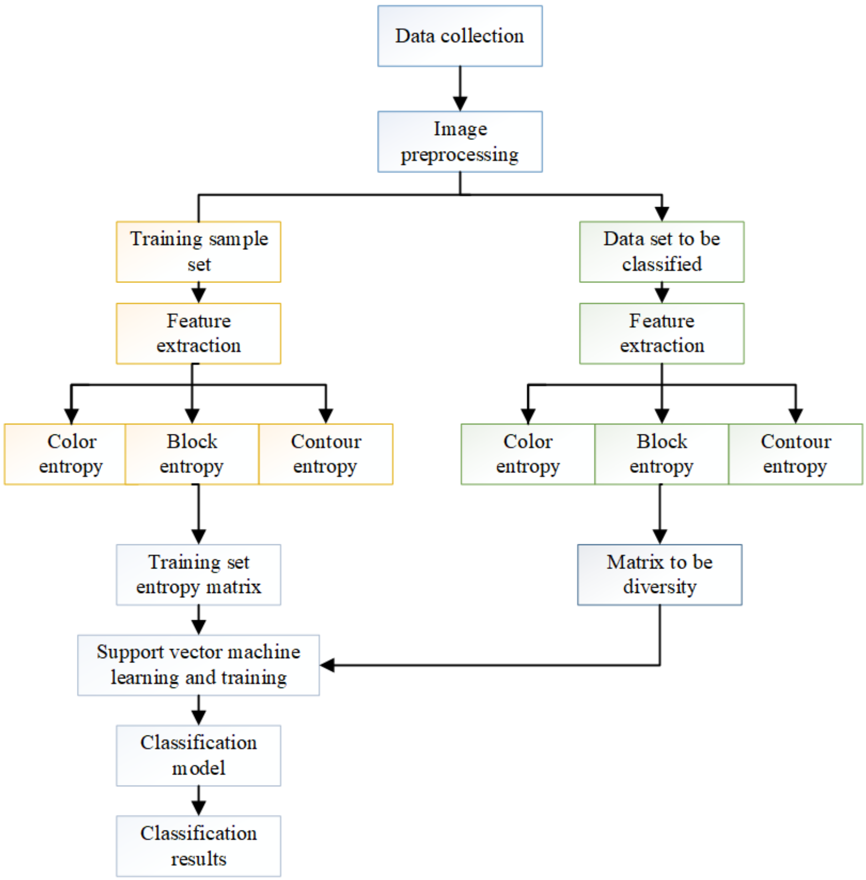

Fig. 3.4: Diagram of system implementation.

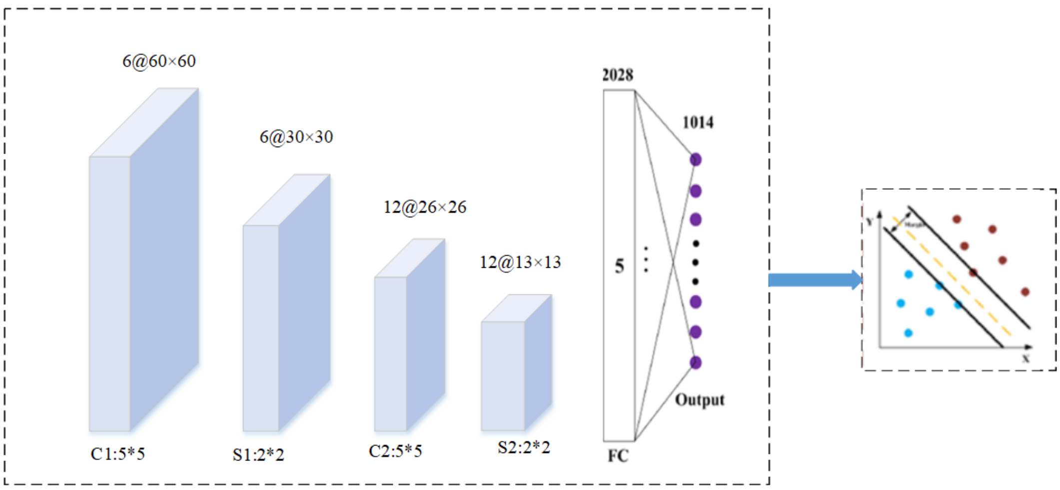

Fig. 3.5: CNN model.

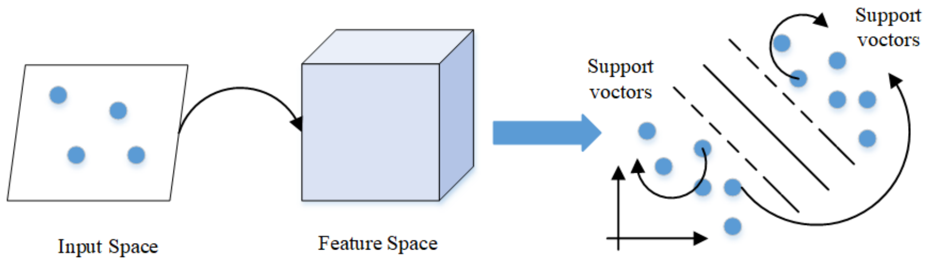

Fig. 3.6: SVM model.

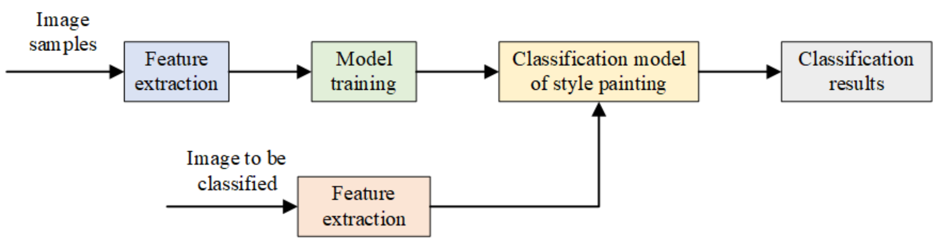

Fig. 4.1: Flow chart of the experiment.

For the test painting images, it is assumed that their affective semantic features are described as x, which is classified as a positive sample if $f(x) = 1$ and a negative sample if the opposite is true. In the algorithm of SVM for classification, we used generic values as parameters. The final decision of whether the test image belongs to good painting image or bad painting image is made by SVM.

4. Experiments. The experimental flow is shown in Fig. 4.1.

Step 1: To extract colour, block, and contour entropies, respectively, 100 paintings are randomly exhibited as simulation samples from seven genres, such as painting and sketching.

Step 2: The entropy is combined with [mxn] (m to show the training samples, and N to provide the sample attributes), and the associated tag set is established.

Step 3: Utilising the characteristic matrix as the training kit, choose the radial basis function kernel function, train the training kit repeatedly using libsvm, and obtain pattern classification for art instruction.

Step 4: Seven image styles such as patterns and patterns are selected as test samples, and the recognizable vectors of the images are obtained according to steps 1 and 2. The recognizable vectors are input into step 3 after the classifier is well trained for recognition, and the accuracy and results of the recognition are obtained.

Step 5: To retrieve the sorting results, set any label on the image to be recognised and enter it into the style to draw the classifier.

4.1. Accuracy and completeness. All experiments in this paper were conducted in Windows 7, 32-bit operating system, based on 2.3 GHz AMD Turion II CPU, 4 G memory, and programmed in Matlab2016. In this paper, experiments are conducted for seven different painting arts in art teaching: cartooning, drawing, oil painting, watercolor painting, branding, ink painting, and mural painting, and the proposed method is mainly validated by accuracy and completeness. One hundred paintings of each style were chosen at random from the remaining dataset to create the test set, while the other hundred paintings of each style comprised the experimental training set. Fig. 4.2 displays the outcomes.

Table 4.1 shows the accuracy of the classification. The findings of the experiment indicate that the categorization accuracy of oil, mural, and watercolor paintings is quite high, whereas that of cartoon and ink paintings

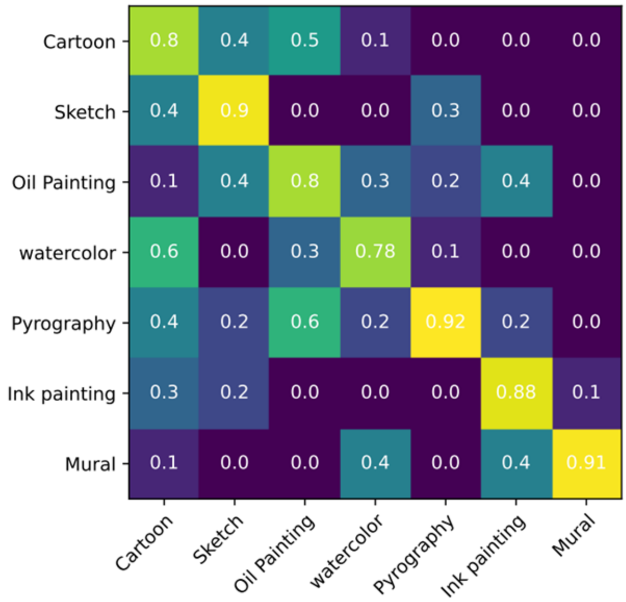

Fig. 4.2: The accuracy of different paintings.

Table 4.1: Rate of classification accuracy.

Painting animal species	Quantity of results for classification	Quantity of accurate categorizations	Accurate classification (%)
Cartoon	48	40	83.32
Sketch	50	44	88.00
Oil Painting	50	48	92.14
Painting in water colors	48	45	93.63
Pyrography	51	45	88.47
Chinese brush painting	55	44	79.62
Mural	46	46	95.75

is relatively poor. 309 of the 350 test photos that were selected had an average classification accuracy of 88.28%, meaning that they were accurately classified. Because cartoons and oil paintings have a particular style that is simpler to recognize than other types, the recognition accuracy is good. It is very difficult to identify and classify style paintings.

Table 4.2 shows the completion rates. Because branding and oil painting have such high recognition accuracy, their completion rates are comparatively high, often exceeding 90%, and they are not easily misidentified as other paintings, so the completion rates are high. The search rate of cartoons is relatively low, only 80%, because the recognition accuracy of cartoons is low, and they are easily classified as other types of paintings, so the search rate is low. The categorization accuracy has an impact on the search completion rate, and increasing the accuracy rate helps to increase the search completion rate.

4.2. Comparative analysis. The system finally achieves the classification of 5 types of paintings with different art styles by setting multiple classes of SVM classifiers and classifying them layer by layer, and each class of SVM classifiers adopts the specified image features to achieve their respective classification functions (see Fig. 4.3).

Fig. 4.4 shows the multiclass binomial tree classification system in the literature[7], which uses a 3-layer

Table 4.2: Classification rate.

Painting animal species	Quantity of results for classification	Quantity of accurate categorizations	Accurate classification (%)
Cartoon	40	10	82
Sketch	45	5	86
Oil Painting	46	4	95
Painting in water colors	44	5	87
Pyrography	45	5	91
Chinese brush painting	44	8	88
Mural	45	4	92

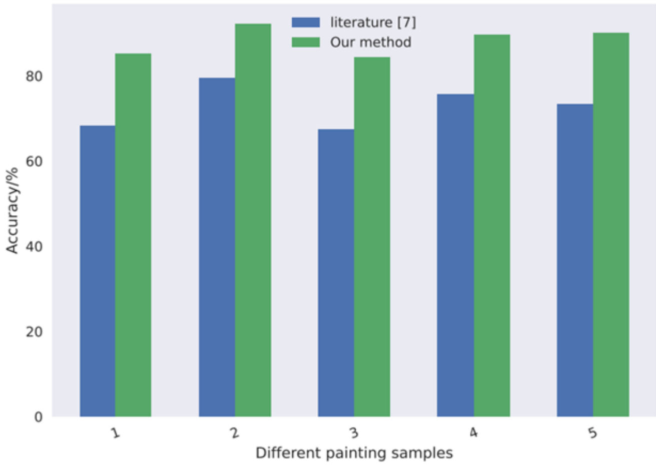

Fig. 4.3: The accuracy of painting samples.

4-class SVM classifier to progressively achieve classification of 5 classes of art style paintings, and each classifier uses different features to achieve classification of the specified style paintings from top to bottom layer by layer, and its overall classification accuracy is 85.56%. The classification accuracy of the algorithm in this paper for art painting styles is 88.28%, and the accuracy is improved. In addition, both the literature[7] and this paper use SVM classifier for classification, including 2 processes of training and classification. The literature [12] uses a hierarchical approach to perform at least three time-consuming SVM calculations on samples. The SVM is then used to train and classify the data set once, which speeds up the computational process when there are a lot of samples, improving the efficiency of the classification calculation.

We examined the teachers' level of satisfaction with the system after verifying the algorithm's accuracy. The particular outcomes are displayed in Fig. 4.5. As can be shown, the great majority of educators support the use of the algorithm, with 44% of educators between the ages of 35 and 39 being the largest group.

5. Conclusion. In this work, we suggest a painting-related machine learning-based categorization method for art education. The algorithm takes seven kinds of representative painting art in art teaching: cartoons, drawings, oil paintings, watercolor paintings, branding paintings, ink paintings and murals as objects, and uses neural networks and machine learning algorithms to train, test and classify different painting art in art teaching. The establishment of image semantic emotion model and accurate image semantic description standard model is a very challenging topic, in which the mapping relationship between the layers of image semantics, the normalisation of image emotion semantic feature description and the integration of theories from other related disciplines are important research directions, and the next research work includes the following:

1. Wearable devices based on psychological experiments can be added to the construction of the emotional

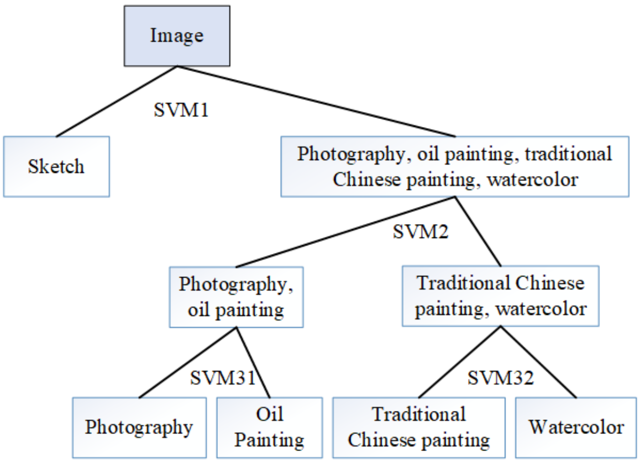

Fig. 4.4: SVM multiclass binomial tree classification for different art style classification.

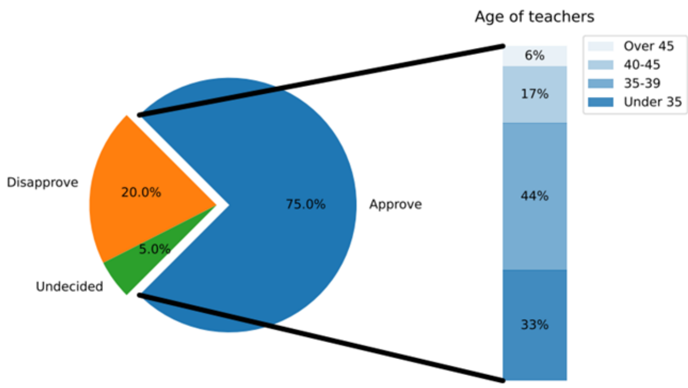

Fig. 4.5: Teachers' satisfaction with the method.

space model, such as human heart rate, visual attention area and brain waves and other physiological data.

2. Based on the visual human-computer interaction annotation to obtain the emotional semantics of the paintings, and find a better solution to solve the problem of semantic gap between the bottom visual features of the image to the higher level emotional semantics.

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

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