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Research on Art Classification Method Based on Decision Tree and Information Entropy

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Abstract. *With the progress of science and technology, many art paintings have been digitized, but, facing such a huge amount of data, how to use computers to effectively classify the huge amount of art style paintings is a very important topic. Traditional image classification algorithms do not consider the characteristics of painting art styles. Therefore, this paper suggests an art classification method on the ground of decision tree and information entropy. First of all, we extract the style features of the painting artwork, and achieve the colour entropy, chunk entropy and outline entropy of the picture, and connect them to shape into the information entropy of various painting styles. Then, the picture is decomposed into Lab color universe, and the color entropy is obtained through the channel color value; the block entropy is achieved through calculating the mean value of the information entropy of the block; and the outline entropy is obtained through the Contourlet transform. After taking out the information entropy of art style images, the decision tree is constructed to assign different k values to the samples, train the style painting recognition model, and then classify different art painting styles, and search the nearest-neighbor neighborhood oil painting information to enhance the classification precision through the K Nearest Neighbor (KNN) algorithm of the decision tree optimization; finally, the experimental outcome indicates that the method proposed in this article is with a high classification accuracy and efficiency, and it can be better applied in the field of art work classification field.*
Keywords: Art classification; information entropy; decision tree; k nearest neighbor algorithm; contourlet transformation

1. **Introduction.** The style of a work of art is a significant part of its meaning. For instance, a heavily painted portrait by Renoir, or a violent noir movie by Quentin. Famous artists often have their own unique styles of work, and understanding style is essential to the perception of art. In order to better understand works of art, researchers have

invested considerable effort in categorizing the style of works of art, e.g., by genre, movement, or period [1, 2]. However, it is hard to characterize the ideal processes involved in making selections for a special genre. As machine learning algorithms and image processing techniques growing, the field of computer vision has made significant progress in categorizing objects and scenes in images, and researchers have begun to try to automatically categorize the styles of artworks [3]. The purpose of this study is to improve the accuracy and efficiency of art classification by analyzing and extracting the attributes and characteristics of art and using decision tree algorithm to classify and predict it, so as to provide scientific basis for art appreciation and collection.

1.1. **Related Work.** Style includes each aspect of human's lives, and style categorization of oil paintings is a branch in the field of image recognition, recently, scholars have done a lot of research in this area. Jiang et al. [4] proposed the edge size histogram feature to identify the Chinese paintings from all the painting images, and categorized them into brushwork school and writing school. Gargano et al. [5] used machine learning techniques to extract color histograms to classify woodblock annual paintings into thematic styles, but the results were not good. In order to make up for the above shortcomings, Huang et al. [6] proposed color correlation map features based on the spatial correlation of colors. Kumar and Yildirim [7] proposed a 3D color histogram, which reduces the error of quantized edges. Chu and Wu [8] proposed an automatic classification system for painting image art style, using 3D color histogram to extract the main color features of paintings. Geng et al. [9] proposed a supervised learning-based classification algorithm for Chinese paintings, which classified Chinese paintings into gongbi school and freehand drawing school, but the classification efficiency is low. Kim et al. [10] proposed an oil painting style classification system based on color features to isolate misclassified images and correct the errors step by step. Huang et al. [11] combined sparse coding algorithm to extract features of images using information theory knowledge.

Subsequently, Bergamo and Torresani [12] classified image styles based on MC-bit features. Liao et al. [13] classified five types of stylized paintings by setting up multi-class Support Vector Machine (SVM) classifiers and classifying them layer by layer, and finally achieved classification of five types of stylized paintings. Zhang et al. [14] proposed an picture style categorization on the ground of deep correlativity characteristics. Wang et al. [15] classified oil paintings by orthogonal matching tracking and SVM to classify oil paintings, but the classification efficiency needs to be improved. Srinivasa et al. [16] offered a classification algorithm on the ground of chunked information entropy, which improves the accuracy of classification. Masquelin et al. [17] used wavelet three-layer decomposition, information entropy fusion algorithm to effectively classify the authenticity of Chinese paintings, but did not consider the internal characteristics of oil paintings, which lead to a low categorization accuracy. Noor et al. [18] offered a computer-aided categorization system for miniature portraits based on the brushstrokes, and realized a semi-automatic classification of the brushstrokes. Li et al. [19] synthesized edge detection, clustering and image segmentation to classify Van Gogh's works, but the classification accuracy is not high. Zhang et al. [20] used BP neural network and support vector machine to classify the works of different painters, but did not consider the internal characteristics of the artworks. Barat and Ducottet [21] proposed a K Nearest Neighbor (KNN) approach and used Euclidean distance to measure the similarity between the works to achieve the classification of different image styles. Chen and Yang [22] proposed a KNN-based classification method for art style oil paintings, but ignored the internal features of the paintings themselves, resulting in inefficient classification.

1.2. **Motivation and contribution.** Existing methods for classifying art paintings do not take into account the internal features of the image, which leads to the classification efficiency needs to be improved. Therefore, the research on the classification of paintings of different artistic styles still has problems such as the lack of high accuracy and the improvement of the generality of classification algorithms.

(1) To address the above problems, firstly, this article suggests an art classification method on the ground of decision tree and information entropy. On the basis of gray scale information entropy, three different calculation methods are proposed, namely, color entropy, chunk entropy and contour entropy. Among them, the color entropy reflects the color characteristics of the picture, the chunking entropy deliberates the spatial native dispersion characteristics of the picture, and the contour entropy reflects the edge and construction characteristics of the image.

(2) Secondly, the KNN algorithm of decision tree optimization is used to study and train the art style pictures to achieve the categorization method of art painting style; the entropy features of the painting style sample to be recognized are extracted, and the final classification results are obtained through KNN classification and recognition. The experimental outcome indicates that compared with the comparison algorithm, the designed algorithm has higher classification performance and efficiency.

2. Theoretical Analysis.

2.1. **Decision Tree.** Decision tree is a new inference algorithm that deals with modal uncertainty information present in the data when uncertainty knowledge is present in the system [23]. Assume that χ is a given finite set and $\chi = \{\alpha_1, \alpha_2, \ldots, \alpha_M\}$, $F(\chi)$ are sets consisting of all fuzzy subsets defined on χ. The fuzzy subset A is denoted as follows.

$$A = \frac{A(\alpha_1)}{\alpha_1} + \frac{A(\alpha_2)}{\alpha_2} + \cdots + \frac{A(\alpha_M)}{\alpha_M} \tag{1}$$

The potential in a set is used to measure the size of the set, and the potential of a subset A can be regarded as an extension of the potential in a clear set, as defined below.

$$M(A) = \sum_{i=1}^{M} A(\alpha_i) \tag{2}$$

The equation for the likelihood that a sample in node A in the decision tree belongs to a class C is defined as follows.

$$\beta_A^C = SIM(A, C) = \frac{M(A \cap C)}{M(A)} = \frac{\sum_{x\in\chi} \min(\eta_A(x), \eta_C(x))}{\sum_{x\in\chi} \eta_A(x)} \tag{3}$$

where χ is the finite set of all samples in node A, $M(A)$ denotes the sum of all affiliations of fuzzy set, $\eta_A(x)$ denotes the corresponding affiliation, and the degree of truth of node A is β_A, which is the maximum potentiality of each sample in the node belonging to each class.

For a non-leaf node X, the node has m attributes, denoted as $D^{(1)}, D^{(2)}, \ldots, D^{(m)}$, attribute $D^{(l)}$ has n_l semantic attribute values $S_1^{(l)}, S_2^{(l)}, \ldots, S_{n_l}^{(l)}$, and decision attribute $D^{(m+1)}$ has n values $S_1^{(m+1)}, S_2^{(m+1)}, \ldots, S_n^{(m+1)}$.

where $1 \le l \le m$. The relative frequency $p_{ij}^{(l)}$ on the non-leaf node X with respect to the j-th category is defined as follows.

$$p_{ij}^{(l)} = \frac{M(S_i^{(l)} \cap S_j^{(m+1)} \cap X)}{M(S_i^{(l)} \cap X)} \tag{4}$$

For each subset $S_i^{(l)}$ the categorical entropy is defined as follows.

$$FEntr_i^{(l)} = -\sum_{j=1}^{n} p_{ij}^{(l)} \log_2 p_{ij}^{(l)} \tag{5}$$

where $1 \leq l \leq m, 1 \leq i \leq n_l, 1 \leq j \leq n$.

2.2. **Information Entropy.** Shannon et al. suggested the idea of "information entropy" [24] in information theory, which describes the size of the amount of information, i.e., the uncertainty of the source. The more organized the signal distribution of a source is, the lower its uncertainty is, and the lower the information entropy is. Thus, information entropy reflects the complexity and distribution of the signal. The information entropy reflects the information probability distribution density, and the overall pixel distribution of the picture, which belongs to the global characteristics and is very suitable for the classification of style painting.

Assuming that there are m events $(X_1, X_2, X_3, \ldots, X_m)$ and the probability of the i-th event occurring is $P(X_i)$ $(i = 1, 2, 3, \ldots, m)$, the amount of information contained in the occurrence of event X_i is called self-information.

$$I(X_i) = \log \frac{1}{P(X_i)} \tag{6}$$

The mathematical mean value of self-information is the average amount of self-information, i.e., information entropy, expressed by the equation as follows.

$$H(X) = E\left[\log \frac{1}{P(X_i)}\right] = -\sum_{i=1}^{m} P(X_i) \log P(X_i) \tag{7}$$

The information entropy of a joint source of mutually independent sources X and Y is equal to the sum of their respective information entropies.

$$H(XY) = H(X) + H(Y) \tag{8}$$

Assuming that the probability distribution of X is $(p_1, p_2, \ldots, p_m)$ and the probability distribution of Y is $(q_1, q_2, \ldots, q_n)$, there are the following equations.

$$\begin{aligned} H(XY) &= H_{mn}(p_1q_1, p_1q_2, ..., p_1q_n, p_2q_1, ..., p_2q_n, ..., p_mq_1, ..., p_mq_n) \\ &= H_m(p_1, ..., p_m) + H_n(q_1, ..., q_n) \end{aligned} \tag{9}$$

Finally, the entropy function expression can be achieved as follows.

$$\begin{aligned} H(XY) &= -\sum_{j=1}^{n} q_j (\sum_{i=1}^{m} p_i \log p_i) - \sum_{i=1}^{m} p_i (\sum_{j=1}^{n} q_j \log q_j) \\ &= H_m(p_1, ..., p_m) + H_n(q_1, ..., q_n) \end{aligned} \tag{10}$$

3. **Optimization of image information entropy.** The message entropy of a picture often involves the information entropy of the gray scale of an image, i.e., the potentiality dispersion of the gray scale of an image [25]. In this paper, on the basis of obtaining the message entropy of grayscale picture, the information entropy is obtained by the color value, local grayscale value, and the value of Contourlet change constant of the picture, i.e., the color entropy, chunking entropy, and contour entropy of the image, which are used for the calculation of information entropy and the classification of art painting style in this article. The optimization process is implied in Figure 1.

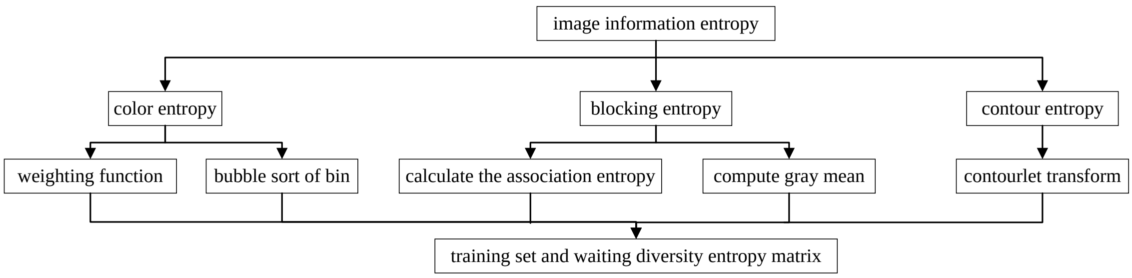

Figure 1. The optimization of image information entropy

3.1. **Image color entropy.** This article needs to transform the image into Lab color space and decompose the image into L component (grayscale), a component (chromaticity channel from red to green), and b component (chromaticity channel from yellow to blue). a channel and b channel deliberate the color message of the picture. The color entropy is calculated as below.

Initially, the information entropy of the a and b channels, respectively, represents the color domain dispersion features of the picture. Take the a channel as an example.

$$H_a = -\sum_{j=-128}^{127} P(j) \log_2 P(j) \tag{11}$$

Then, considering the symmetry of information entropy, two images with totally various colors may be with the equal message entropy. In order to avoid this situation, a weighting function is introduced here, let H denote a certain oil painting image, the histogram H is sorted from smallest to largest by bubble sort, and the number of times that the histogram element bin moves after the completion of the sorting is recorded as m. The weighting function $f(x)$ is defined as $f(x) = 1 + \frac{n_x}{n_z}$, where n_x denotes the number of times the bin of the canvas element has been moved, and n_z denotes the total number of bins of the histogram element. The color entropy of the image is expressed as $H(x) = f(x) \cdot H(x)$ after using the weighting function.

3.2. **Image chunking entropy.** In this article, we refer to the unit entropy in the literature [26], and propose the dispersion of message entropy of chunks to characterize the overall spatial distribution of images. The picture is allocated into $n \times n$ square blocks, and the message entropy is obtained for all blocks, and then the divergence of the message entropy of all the blocks of a picture is sought.

$$U = \frac{1}{m} \sum_{i=1}^{m} (H_i - H_m)^2 \tag{12}$$

where U denotes the message entropy variance, H_i denotes the message entropy of the chunks, and H_m denotes the average value of the message entropy of the bins.

After dividing the image into blocks, the joint entropy of the blocks is calculated by finding the mean gray value of each block, to exclude the effect of small divergence on the outcome, and then the mean gray values of the contiguous blocks are transformed into a distinct source, and the related space is as below.

$$\begin{bmatrix} X_1X_2 \\ P(x_1x_2) \end{bmatrix} = \begin{bmatrix} c_1c_{11}, c_1c_{12}, ..., c_1c_{18}, ..., c_mc_{m1}, ..., c_mc_{m8} \\ P(c_ic_{ij}) = P(c_i)P(c_{ij}|c_i) \end{bmatrix} \tag{13}$$

where $P(c_{ij}|c_i) = f(c_{ij})/q(c_i)$, $f(c_{ij})$ is the frequency of occurrence of blocks adjacent to c_i with gray mean value c_{ij} when the block gray mean value is c_i. $q(c_i)$ is the total amount of blocks adjacent to c_i. The chunk joint entropy is computed as follows.

$$H(X_1, X_2) = -\sum_{i=1}^{m}\sum_{j=1}^{8} P(c_{i,j}) \log P(c_{i,j}) \tag{14}$$

where m is $(n-2)^2$ (with n being the number of chunks in each row), c_i is the gray scale mean of the chunks, and c_{ij} is the gray scale mean of the adjacent chunks of c_i.

When the mean gray value distribution of each block of an image is more uniform, the closer the connection between the blocks is, the larger the corresponding conditional probability $P(c_{ij}|c_i)$ is, the larger $P(c_{i,j})$ is, and consequently the smaller $H(X_1, X_2)$ is.

3.3. **Image contour entropy.** The contour entropy method offered in this article is based on the contourlet change of image contour information entropy to represent the contour message of the image [27]. After a series of Contourlet transformations, the contour features are represented by Contourlet coefficients. For images with clear contour features, the contourlet coefficients change greatly, and the message dispersion is complicated, and the message entropy is higher according to the concept of information entropy; for images with unclear contour features, the contourlet coefficients change slowly, showing the information distribution is more uniform, so the message entropy is smaller. The average value of message entropy is computed for each direction coefficient of each LP layer, and the contourlet entropy of three levels is adopted to represent the contour features of the picture.

$$H_c = \begin{bmatrix} \text{Mean}[H_{11}, H_{12}, \dots, H_{12j}] \\ \text{Mean}[H_{21}, H_{22}, \dots, H_{22j}] \\ \text{Mean}[H_{31}, H_{32}, \dots, H_{32j}] \end{bmatrix} \tag{15}$$

where H_{12j} is the information entropy of the Contourlet transform of the i-layer LP decomposition and the j-layer DFB direction filtering in the i-layer 2^j-direction coefficient.

4. **Research on art classification method based on decision tree and information entropy.**

4.1. **Decision tree based optimization for k nearest neighbor classification.** After extracting the information entropy of art style images, it is essential to train and classify these images. Due to the large size of the data of different kinds of style paintings, the KNN algorithm, which has better results in the classification and recognition of large-scale data, is used in this paper for classification. Finding a suitable k value for the data is a difficult problem for KNN algorithm. The decision tree and KNN algorithm are combined to construct a decision tree to distribute various k values to the samples, train a style painting recognition model, and then classify different art painting styles, and optimize the KNN algorithm to search for oil paintings to enhance the categorization accuracy through the decision tree. The overall process is implied in Figure 2.

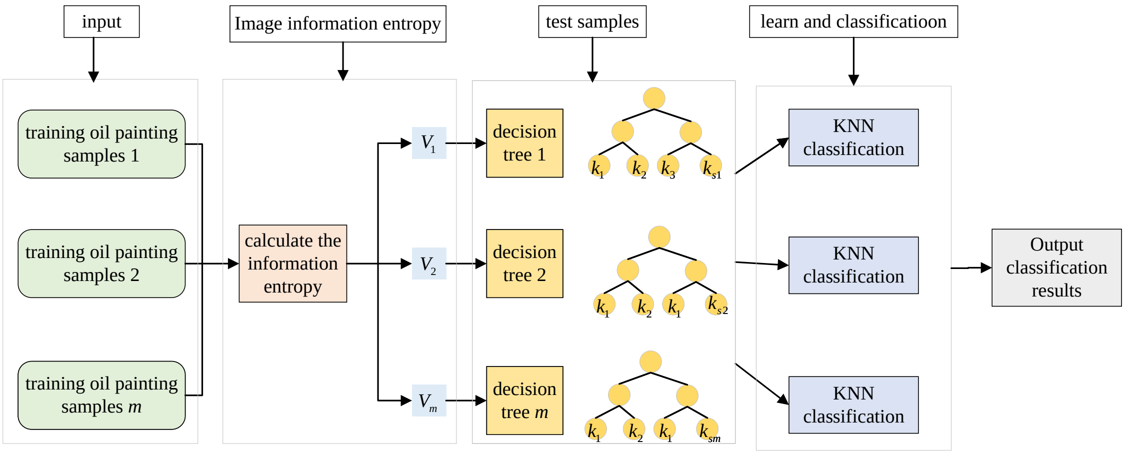

Figure 2. The whole process of decision tree based optimization for KNN algorithm

Define a set $X = [x_1, x_2, \ldots, x_m] \in \mathbb{R}^{d\times m}$ containing training samples of oil paintings of m styles, where the i-th training sample is defined as $x_i = [x_{i1}, x_{i2}, \ldots, x_{ic}]^T \in \mathbb{R}^c$, $(i = 1, 2, \ldots, m)$. The objective function is as follows.

$$\min_V \|XV - X\|_F^2 + \mu_1\|V\|_1 + \mu_2 \operatorname{Tr}(V^T X^T LXV) \tag{16}$$

where $V = [v_1, v_2, \ldots, v_m] \in \mathbb{R}^{m\times m}$ is the entropy matrix of the correlation information between the training samples, L is the Laplace matrix, and $\|V\|_1$ is the regularization term of the objective function.

In Equation (16), for the relationship between two sample points, if two sample points x_i and x_j are adjacent to each other, their corresponding new sample points A and B should also Locality Preserving Projections (LPP) preserve the relationship between sample points x_i and x_j as follows.

$$\sum_{i,j}(x_i' - x_j')^2 T_{ij} = \sum_{i,j}(V^T x_i^T - V^T x_j^T)^2 T_{ij} \tag{17}$$

where T_{ij} denotes the weight matrix, which represents the degree of correlation between sample points x_i and x_j. Specific calculation of weight matrix T_{ij} array is implied below.

$$S_{ij} = \begin{cases} \exp\left(-\frac{\|x_i - x_j\|_2^2}{2\sigma^2}\right), & x_j \in \text{the } k\text{-nearest neighbor of } x_i \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

Equation (17) is calculated by regularization principle as follows.

$$\frac{1}{2}\sum_{i,j}(x_i' - x_j')^2 T_{ij} = \sum_{i,j} V^T x_i^T T_{ij} x_i V - \sum_{i,j} V^T x_j^T T_{ij} x_j V \tag{19}$$

where x_i and x_j represent the reconstructed samples x_i and x_j.

Set $G_{ii} = \sum_j T_{ij}$, where G_{ii} denotes the metric importance of the i-th sample, and so there is the following equation.

$$\frac{1}{2}\sum_{i,j}(x'_i - x'_j)^2 T_{ij} = V^T X^T L X V \tag{20}$$

From the result of Equation (20), A can be obtained, and iteration is performed to find the optimal correlation matrix V^*.

$$V^* = \begin{bmatrix} v_{11} & \dots & v_{1m} \\ \vdots & \ddots & \vdots \\ v_{m1} & \dots & v_{mm} \end{bmatrix} \tag{21}$$

where $v_{ij}(i, j = 1, 2, \dots, m)$ is the correlation degree weight between training samples x_i and x_j.

The optimal k-value corresponding to the j-th training sample need to be calculated. According to the number of weights in each column of V^* to derive the size of the corresponding k-value for each sample, the optimal k-value corresponding to the j-th training sample is $k_j = \sum(v_{ij} + 1), i = 1, 2, \dots, m$.

Each k is computed from V^*. The amount of definite values in every column is needed to decide the optimal k_j. The training samples and their optimal k values are then used to establish a decision tree, which is used to discover a different optimal k for the new samples.

4.2. **Art classification method based on decision tree and information Entropy.** After constructing the decision tree, it is assumed that for a test sample $Y_s(s = 1, 2, \dots, n)$, k_s is obtained by KNN algorithm as its optimal k value. Then the nearest neighbor k_s set of Y_s is represented as $K_s = \{x_t, x_s, \dots, x_s\}$, and the nearest neighbor set k_s can be represented as $A_s = \{a_s, a_s, \dots, a_s\}$. The k value is obtained by the decision trees constructed under different images, and the corresponding subsets of the nearest neighbor training samples are searched.

The Dempster combination rule [28] is used to fuse the information entropy of each view.

$$\beta_s^w = [p_{s1}^w + 1, p_{s2}^w + 1, \dots, p_{sc}^w + 1] \tag{22}$$

where c is the amount of classes, $p_{si}^w \in [0, 1](i = 1, 2, \dots, c)$ is the proportion of samples with class i in K_s, $\beta_s^w = e_s^w + 1$. Whereas β_s^w is the distribution parameter of Y_s in the image w, and the intensity T_s^w with respect to β_s^w is defined as follows.

$$T_s^w = \sum \beta_s^w = \sum_{i=1}^{c}(p_{si}^w + 1) \tag{23}$$

The information entropy b_s^w of the s test sample in the w view is defined as follows.

$$b_s^w = \frac{e_s^w}{T_s^w} = e_s^w \left[\frac{p_{s1}^w}{T_s^w}, \frac{p_{s2}^w}{T_s^w}, \dots, \frac{p_{sc}^w}{T_s^w}\right] \tag{24}$$

where b_s^w represents the whole probability that Y_s is distributed to every classes in the image w, and $e_s^w = [p_{s1}^w, \dots, p_{sc}^w], w = 1, 2, \dots, \tau$ is the input color entropy.

Then, the uncertainty u_s^{w*} and $u_s^{w'}$ of the two views are calculated by the block entropy of the two views as $u_s^{w*} = S_s^{w*,w'}/T_s^{w*}, u_s^{w'} = T_s^{w*,w'}/T_s^{w'}$, where $S_s^{w*,w'} = \sum_{m,n} b_s^{w*}(n) b_s^{w'}(m)$.

Finally, the final joint entropy of the τ images is obtained.

$$e_s^{w_1+\dots+w_\tau} = b_s^{w_1 \oplus \dots \oplus w_\tau} S_t^{w_1+\dots+w_\tau} = [p_{s1}^{w_1+\dots+w_\tau}, p_{s2}^{w_1+\dots+w_\tau}, \dots, p_{sc}^{w_1+\dots+w_\tau}] \tag{22}$$

where $e_s^{w1,\ldots,w\tau}$ represents the joint entropy of all classes in τ images. Let $p_{sf} = \max_i p_{si}^{w1,\ldots,w\tau}$, f is the final oil painting classification result of the test sample Y_s under the joint entropy.

5. **Performance testing and analysis.**

5.1. **Classification accuracy analysis.** To train the model of this article, it adopts the large dataset Wikipainting [31], which contains more than 85,000 images and are mainly categorized into 25 styles labels, such as Abstract Art, Abstract Expressionism, and Baroque, etc. This article chooses 10 different art paintings (numbered 1,2,...,10) to form the "Selected-Wikipainting" dataset. The styles and the amount of works are indicated in Table 1. The classification performance metrics are Accuracy (Acc), Precision (Prec), Recall (Rec) and the reconciled mean of Prec and Rec F1. The comparison algorithms for the experiments are trained in Python v3.7. For ease of description, the literature [17] is denoted as WDFT, the literature [22] is denoted as ANMF, and the algorithm in this paper is denoted as RACM.

Table 1. Distribution of the number of works in different styles of art

No.	Art movement	Train	Test	No.	Art movement	Train	Test
1	demagoguery	135	56	6	supremacist	236	59
2	expressivism	117	62	7	impressionist	132	52
3	cubism	239	71	8	classicism	214	57
4	surrealism	137	63	9	renaissance	201	64
5	pop art	140	69	10	constitutivism	157	53

To prove that the KNN classification algorithm with image entropy features and decision tree optimization in this paper can effectively classify the style paintings, the experiments were conducted by using ten-fold cross-validation, where the dataset was divided into ten parts, and each time, nine of them were used as the training set, and the other one as the test set. The results of the classification experiments on the test set are indicated in Table 2 and Figure 3.

Table 2. Number of correctly categorized style drawings and their accuracy

No.	True classes' number	Acc	No.	True classes' number	Acc
1	53	94.64%	6	67	94.37%
2	58	93.55%	7	45	86.54%
3	51	86.44%	8	53	92.98%
4	55	87.33%	9	59	92.19%
5	63	91.37%	10	48	90.57%

From Table 2 and Figure 3, we can see that the classification accuracy of demagoguery, expressivism and supremacist is relatively high, while the classification accuracy of cubism and expressionist is relatively low. 552 out of the total 600 paintings in the style are correctly classified, with an overall average classification accuracy of 92%. Demagoguery and expressionism are characterized by distinctive oil painting styles and are easier to distinguish from other styles of paintings, so the recognition accuracy rate is high. On the other hand, cubism has a variety of painting styles. Different authors, different nationalities, and different contents will make the styles of the cartoons change in a million ways, and some cubisms are rich in color, while others are relatively monochromatic. Thus, the correct rate of cartoon recognition is very low, and the recognition of cubism is also one of the difficulties in the recognition of style paintings.

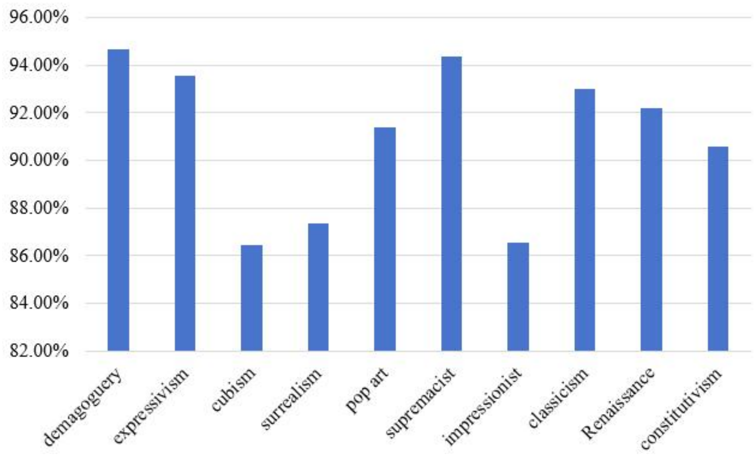

Figure 3. Accuracy of different styles of painting

Then, we compare their entropy features. The entropy features of three surrealisms misidentified as comics in the test sample are extracted and compared with the entropy features of ordinary comics, while the entropy features of one cubism misidentified as branding in the test sample are selected and compared with the entropy features of ordinary branding. The outcome is implied in Table 3.

Table 3. Misclassification surrealism and cubism image entropy

Information entropy	**Color entropy**		**Block entropy**		**Contour entropy**	
	a channel	**b channel**	**block entropy variance**	**block joint entropy**	**first entropy**	**second entropy**
surrealism1	4.1592	4.5961	4.3416	5.3154	3.5271	2.7641
surrealism2	4.3427	4.0631	3.9841	5.0269	3.1934	3.0983
surrealism3	3.9452	4.1934	4.0158	5.1227	2.9362	2.8462
cubism	3.7153	4.2739	4.1063	5.2139	2.9759	2.9517

From the comparison of the image entropy features of the misclassified surrealism and cubism above, it can be seen that the image entropy features of the cubism misclassified as surrealism and the surrealism misclassified as cubism are very close to those of the general surrealism and cubism, and the difference in entropy value is not more than 1. Similarly, ink painting and drawing are also misrecognized because the image entropy features of some data are close to each other. In this paper, by introducing a decision tree, we can distinguish the "mutually misrecognized pairs" better, and therefore, the RACM algorithm designed in this paper has a high correct classification rate.

5.2. **Comparative analysis of different art classification algorithms.** Table 4 indicates the accuracy, accuracy, recall and F1 values of the final test set using different types of models on the Wikipainting dataset. According to the analysis, RACM has improved in Acc, Prec, Rec and F1 compared with WDFT and ANMF classification methods. In Acc, 7.53% and 11.35% respectively, in Prec, 11.63% and 15.12% respectively, in Rec, 7.22% and 8.77% respectively, in F1, 9.44% and 12.01% respectively. This model performs better than WDFT method based on deep learning and ANMF method based on information theory in all four indexes. RACM uses decision tree to optimize classification efficiency on the basis of traditional KNN classification algorithm for oil painting. By increasing the internal feature entropy of the image, the overall features of the oil painting can be added on ground of improving the detailed features, and the art style can be described from the color entropy and contour entropy of the painter, so that more accurate classification results can be obtained.

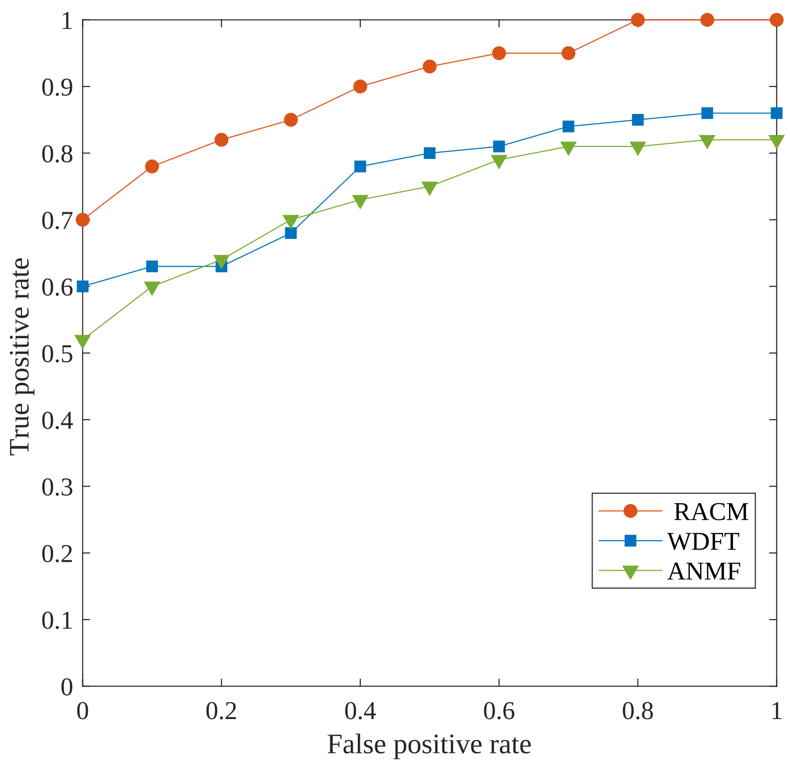

Figure 4. The ROC curve of different comparative art classification algorithms

Table 4. Comparison of different classification methods

Method	**Acc/%**	**Prec/%**	**Rec/%**	**F1/%**
WDFT	85.19	82.53	85.19	83.84
ANMF	81.37	79.04	83.64	81.27
RACM	92.72	94.16	92.41	93.28

Furthermore, the main statistical evaluation indexes used in this paper include ROC curve and AUC value, as shown in Figure 4, the ROC curve is drawn with the false-positive rate as the horizontal coordinate and the T-true-positive rate as the vertical coordinate. When the ROC curve is applied to the model evaluation, the smaller the horizontal coordinate and the bigger the vertical coordinate are, the higher the accuracy of the model is. In addition, the AUC value of each model can be calculated to compare the classification performance of various methods horizontally.

The AUC value of the RACM method is greater than 0.5, which indicates that the classification ability and stability of the algorithm designed in this article are stronger. The ANMF method has the smallest AUC value because it only uses the KNN algorithm to classify the oil painting images without optimizing the algorithm itself, which leads to inefficiency. The WDFT method does not take into account the information entropy features inside the oil painting, and applies the deep learning method to the classification of oil paintings only, resulting in poor classification effect. which leads to poor classification effect.

6. **Conclusion.** Aiming at the current art painting classification algorithms with low accuracy, this paper investigates an art classification algorithm based on decision tree and information entropy. Firstly, on the basis of gray scale information entropy, three different information entropy computation methods are proposed, namely color entropy, chunk entropy, and contour entropy, which serve as the basis for the computation of the information entropy of the image. Secondly, after the information entropy of art style images is obtained, the decision tree is combined with KNN algorithm to construct a decision tree to assign different k values to the samples, train a style painting recognition model, and then classify different art painting styles, and optimize the KNN algorithm to search for oil paintings in nearest-neighbor neighborhoods to improve the classification accuracy through the decision tree. Finally, the experimental outcome indicates that the designed method has good classification performance with accuracy, precision, recall and F1 values of 92.72%, 94.16%, 92.41% and 93.28%.

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