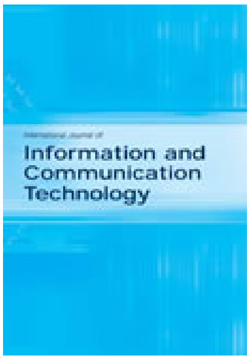


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# Intelligent judgement of calligraphy and painting image categories based on integrated classifier learning

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# Intelligent judgement of calligraphy and painting image categories based on integrated classifier learning

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**Abstract:** Traditional methods for categorising calligraphic painting images are often difficult to deal with diverse artistic styles and category imbalance. In order to solve these problems, this paper proposes an intelligent judgement method for calligraphy painting image categories. First, by comparing four base classifiers, Fisher, pseudo inverse, plain Bayes and C4.5 decision tree, the generalisation ability of the model in the face of diverse art styles is improved. Secondly, a dynamic training subset construction strategy (DWSCS) based on sample weights is introduced and MCACSAF is designed for calligraphy painting images. Experimental results show that compared with the traditional AdaBoost algorithm, MCACSAF improves the classification accuracy from 0.878 to 0.912, which is a 3.4% improvement, when using C4.5 decision tree as the base classifier. When dealing with minority class samples, the F1 score improves from 0.815 to 0.857, an improvement of 5.2%.

**Keywords:** image classification; AdaBoost; dynamic weights; sample construction; multiple classifier comparison; category imbalance.

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## 1 Introduction

With the rapid development of digital technology, the protection and inheritance of cultural heritage are facing new opportunities and challenges. Calligraphy and painting, as the essence of Chinese culture, has an increasingly urgent need for its digital protection and intelligent analysis. The application of intelligent classification technology can not only improve the management efficiency of calligraphy and painting works, but also provide new perspectives and tools for art research, education and creation. However, image classification of calligraphic paintings faces many challenges, such as stylistic diversity (Kim et al., 2024), data sparsity (Liang and Xiao, 2022), and complexity of artistic features (Zhao et al., 2022), which increase the difficulty of the classification task.

The intelligent judgement method for calligraphic painting images proposed in this study is expected to play an important role in several fields. In the management of museums and art galleries, the technique can be used for automatic classification and cataloguing of large-scale artworks to improve work efficiency. In the field of art education, the intelligent categorisation system can assist students in understanding the characteristics of different calligraphic painting styles and facilitate the learning process. For art appraisal and market, the technology can provide an auxiliary tool for authenticity identification and enhance the credibility of transactions.

Traditional methods for painting image classification mainly rely on hand-designed feature extraction techniques. Sheng and Jiang (2013) proposed a method based on colour histograms and texture features for classification of traditional Chinese painting styles. This method achieved good results on small-scale datasets, but its adaptability to complex art styles and large-scale datasets needs to be improved. Albadarneh and Ahmad (2017) developed a feature extraction algorithm combining shape descriptors and local binary modes for Western oil painting genre identification. Although this method performs well on specific datasets, challenges remain in its ability to generalise to cross-cultural artworks.

In recent years, deep learning techniques have made significant progress in the field of painting image classification. Pengcheng et al. (2017) proposed a multi-scale feature fusion model based on convolutional neural networks for calligraphy style recognition. The model performs well in capturing subtle features of calligraphic works, but the high computational complexity limits its application in resource-constrained environments. Xu et al. (2020) designed an attention-mechanism-enhanced residual network for stylistic categorisation of multicultural artworks. This method demonstrated good performance in dealing with large-scale and diverse art datasets, but still had difficulties in recognising rare or emerging art styles. Yang et al. (2021) proposed a method combining transfer learning and adaptive fine-tuning for solving the data sparsity problem in painting image classification. Although this method improves the generalisation ability of the model to some extent, it still faces challenges in dealing with artworks with very different styles.

The integrated classifier technique effectively improves the classification performance and robustness by combining the decisions of multiple base classifiers. Among them, AdaBoost, as a representative integrated learning algorithm, has been widely used in the field of image classification (Cao et al., 2013). The AdaBoost algorithm constructs a strong classifier by iteratively training and combining weak classifiers. This algorithm theoretically guarantees an exponential decrease in training error, which lays the foundation for subsequent research (Huang et al., 2022). However, the original AdaBoost is prone to overfitting when dealing with noisy data and outliers. Xing et al. (2024) improved AdaBoost by proposing a more flexible method for calculating the weights of the weak learner. This improvement improves the generalisation ability of this algorithm to some extent, but still faces challenges when dealing with highly unbalanced datasets.

The integrated classifier technique shows great potential for application in the field of image classification. Avcı et al. (2023) proposed a hybrid integrated model based on random forest and support vector machines for natural scene image classification. This method has achieved some success in improving classification accuracy, but suffers from bias when dealing with datasets with unbalanced categories. Wang et al. (2024) developed an adaptive boosting algorithm for medical image diagnosis. Although this algorithm performed well in improving the recognition rate of samples from a few classes, systematic comparison and analysis of the performance of different base classifiers was lacking.

The above analysis reveals that existing methods for classifying calligraphic painting images usually focus on specific art styles or cultural backgrounds, making it difficult to effectively deal with the task of classifying cross-cultural and diverse artworks. There are significant differences in the visual characteristics and artistic expressions of paintings from different art genres and cultural backgrounds, which makes the model's performance often unsatisfactory when confronted with new art styles. In order to solve the above problems, this paper proposes an integrated classifier learning method based on the improved AdaBoost algorithm, which enhances the effectiveness of intelligent judgement of calligraphic painting image categories. The main innovations and contributions of this work include:

1 To address the lack of systematic comparison of the performance of different base classifiers, this paper proposes a systematic comparison and analysis framework for the AdaBoost integration method of multiple base classifiers. The framework systematically compares and analyses the performance of four base classifiers, Fisher, pseudo inverse, naive Bayes and C4.5, under the AdaBoost framework, which helps to improve the generalisation ability of the classification model in the face of diverse art styles.

2 Aiming at the problem that the traditional AdaBoost algorithm is biased in dealing with class-imbalanced datasets, this paper proposes a dynamic training subset construction strategy based on sample weights. This new AdaBoost training subset construction method dynamically decides the number of times each sample is selected into a new training subset based on the product of the sample weights and the capacity of the training sample set, thus better balancing the representativeness and diversity of the samples. This innovation effectively increases the model's recognition rate for minority class samples while improving the overall classification performance.

3 In order to cope with the special challenges of calligraphic painting image classification (CPIC), this paper proposes an AdaBoost classification framework for calligraphic painting images. The framework applies the improved AdaBoost algorithm to the task of calligraphy and painting image classification and explores its effectiveness in image classification in the art domain. This innovative point combines machine learning techniques with the traditional art field, providing new ideas for digitisation and intelligent analysis of cultural heritage.

## 2 Multi-base classifier AdaBoost integration approach

### *2.1 Principle of AdaBoost algorithm*

The AdaBoost algorithm is a powerful integrated learning method that improves classification performance by iteratively training multiple weak classifiers and combining them into one strong classifier. The core idea of this algorithm is to give higher weights to misclassified samples so that more attention is paid to these difficult-to-classify samples in subsequent iterations (Wang and Sun, 2021). The working mechanism of AdaBoost can be summarised in the following steps:

First, the weight distribution of the training samples is initialised:

$$D_1(i) = \frac{1}{N} \tag{1}$$

where $N$ is the total number of samples. Then, for each iteration $t = 1, 2, \ldots, T$, this algorithm selects a base classifier $h_t$ and computes its error rate $\epsilon_t$.

Based on the error rate, this algorithm calculates the weights of the base classifiers:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right) \tag{2}$$

Next, the sample weight distribution is updated:

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t}\exp\left(-\alpha_t y_i h_t\left(x_i\right)\right) \tag{3}$$

where $Z_t$ is the normalisation factor, $y_i$ is the true label of sample $i$, and $h_t(x_i)$ is the prediction of the base classifier for sample $i$.

Finally, all base classifiers are combined to form the final strong classifier:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T}\alpha_t h_t(x)\right) \tag{4}$$

In this study, we improve the traditional AdaBoost algorithm to better suit the characteristics of the CPIC task. Specifically, we introduce the dynamic weight-based sample construction strategy (DWSCS), which abandons the conventional practice of fixing the size of the training subset in favour of an up-rounding result based on the product of the sample weights and the capacity of the training sample set to determine the number of times each sample is selected into a new training subset. This innovative strategy effectively mitigates the category imbalance problem commonly found in CPIC tasks.

In order to fully utilise the potential of the AdaBoost algorithm, we propose multi-classifier AdaBoost comparative and analytical system framework (MCACSAF). MCACSAF allows us to delve into the performance of different base classifiers such as Fisher, Pseudoinverse, simple Bayes and C4.5 decision trees and other different base classifiers in the CPIC task. In this way, we are able to select the most suitable combination of base classifiers for different types of calligraphic painting images.

The introduction of MCACSAF allows us to systematically evaluate and compare the performance of various base classifiers under the AdaBoost framework. This not only helps to improve the classification accuracy of the CPIC task, but also provides a more comprehensive reference for researchers and practitioners when selecting base classifiers.

These innovative improvements enable our AdaBoost variants to better capture the unique features of calligraphic painting images, thus improving classification accuracy.

In the subsequent sections, we will discuss in detail the implementation details of DWSCS and MCACSAF and their applications in the CPIC task.

## *2.2 Base classifier selection*

In MCACSAF, the choice of base classifiers is crucial for the overall classification performance. In this study, four representative classifiers are carefully selected, namely Fisher classifier, pseudo-inverse classifier, plain Bayesian classifier and C4.5 decision tree classifier. Each of these classifiers has its own characteristics and is capable of capturing feature information in the CPIC task from different perspectives.

Fisher classifier, also known as linear discriminant analysis (LDA), is a classical linear classification method (Sevinç, 2022). The core idea of Fisher is to find an optimal projection direction that minimises the intra-class variance and maximises the inter-class variance after projection. For the CPIC task, the Fisher classifier can effectively capture the linearly separable features among different calligraphic painting styles. Let $\mathbf{S}_w$ be the intra-class scatter matrix and $\mathbf{S}_b$ be the inter-class scatter matrix, the objective function of Fisher classifier can be expressed as:

$$J(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{S}_b \mathbf{w}}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}} \tag{5}$$

The pseudo-inverse classifier utilises the concept of matrix pseudo-inverse to construct a classification model (Yin et al., 2024). It finds the optimal classification hyperplane by solving the least squares problem. For the CPIC task, the pseudo-inverse classifier is able to show good stability in dealing with high-dimensional features. Let $\mathbf{X}$ be the feature matrix, $\mathbf{Y}$ be the label matrix, and the weight matrix of the pseudo-inverse classifier $\mathbf{W}$ can be found by the following equation:

$$\mathbf{W} = \left(\mathbf{X}^T \mathbf{X}\right)^{-1} \mathbf{X}^T \mathbf{Y} \tag{6}$$

The naive Bayes classifier (NBC) is based on Bayes' theorem and the assumption of conditional independence of features. Although this assumption often does not hold in practice, NBC still performs well in many practical applications. For the CPIC task, NBC is able to handle high-dimensional feature spaces efficiently and maintains good performance when the number of training samples is small. Given a feature vector $\mathbf{x}$, the classification decision function of NBC can be expressed as:

$$\hat{y} = \arg\max_y P(y) \prod_{i=1}^{n} P\left(x_i \middle| y\right) \tag{7}$$

C4.5 decision tree classifier is a tree-structured classifier based on information entropy (Ahmad et al., 2020). It segments the dataset by recursively selecting optimal features to form a decision tree model that is easy to understand and interpret. For the CPIC task, C4.5 is able to automatically select the most discriminative features and handle both continuous and discrete attributes. Let $S$ be the sample set and $A$ be the attribute set, C4.5 uses the information gain ratio to select the optimal segmentation attributes:

$$GainRatio(S, A) = \frac{Gain(S, A)}{SplitInfo(S, A)} \tag{8}$$

The selection of these four base classifiers aims to fully utilise the advantages of MCACSAF to provide a multi-angle classification perspective for the CPIC task. By systematically comparing and analysing the performance of these base classifiers under the AdaBoost framework, we are able to gain an in-depth understanding of their strengths and weaknesses in dealing with different types of calligraphic painting images, thus providing a scientific basis for base classifier selection in practical applications. This diversified base classifier combination strategy not only improves the overall classification performance of the model, but also enhances its adaptability and robustness in the face of diverse art styles.

## 3 Dynamic training subset construction strategy based on sample weights

### *3.1 Limitations of traditional AdaBoost training subset construction methods*

The traditional AdaBoost algorithm employs a fixed-size strategy in constructing the training subset, and this approach has significant limitations when dealing with CPIC tasks. In this section, these limitations are analysed in depth to lay the foundation for the introduction of DWSCS.

AdaBoost constructs strong classifiers by iteratively training multiple weak classifiers with different weights. This fixed-size training subset construction method exposes several problems in the CPIC task: first, it cannot fully utilise the sample weight information. Highly weighted samples may be excluded from the training subset due to randomness, resulting in the model not being able to fully learn the features of these difficult samples. Second, for class-imbalanced datasets, the fixed-size sampling strategy may further exacerbate the class imbalance problem, making the minority class samples under-represented during training.

Another concern is that fixed-size training subsets may lead to redundancy or insufficient information in different iteration rounds. In early iterations, when most samples have similar weights, the fixed-size subset may contain too many similar samples. In later iterations, when a few samples receive very high weights, the fixed-size subset may not adequately express the importance of these key samples.

In summary, the limitations of the fixed-size training subset construction method in the traditional AdaBoost algorithm are mainly reflected in the inability to fully utilise the sample weight information, the possibility of exacerbating the category imbalance, the difficulty of capturing the diversity of artistic styles, and the possibility of leading to redundancy or insufficient information during the iteration process. These issues severely limit the performance of the AdaBoost algorithm in CPIC tasks, and a more flexible and intelligent training subset construction strategy is urgently needed to overcome these limitations. To address these challenges, this study proposes DWSCS, which aims to dynamically adjust the training subset construction process to better adapt to the characteristics and demands of CPIC tasks.

### *3.2 DWSCS design*

In order to overcome the limitations of the traditional AdaBoost algorithm in the construction of training subsets, DWSCS is proposed in this study. The core idea of DWSCS is to flexibly adjust the number of times that each sample is selected into a new training subset according to the dynamic relationship between the sample weights and the capacity of the training sample set. This innovative approach can better adapt to the characteristics of the CPIC task and improve the classification performance.

This algorithm design of DWSCS can be summarised in the following steps: first, define the sample selection count function $f(i, t)$, which determines the number of times a sample $i$ is selected into the training subset in the $t^{\text{th}}$ iteration. The function $f(i, t)$ is designed as follows:

$$f(i, t) = \lceil N \cdot D_t(i) \rceil \tag{9}$$

where $N$ is the total number of samples, $D_t(i)$ is the weight of sample $i$ in the $t^{\text{th}}$ iteration, and $\lceil \cdot \rceil$ denotes the upward rounding operation. This design ensures that the number of times a sample is selected is proportional to its weight, while the upward rounding operation ensures that each sample has at least one chance to be selected.

Next, define the construction process for the new training subset $S_t$:

$$S_t = \bigcup_{i=1}^{N} \underbrace{(x_i, y_i), (x_i, y_i), \ldots, (x_i, y_i)}_{f(i,t)} \tag{10}$$

In the $t^{\text{th}}$ iteration, the training subset $S_t$ is constructed as follows: for each sample $(x_i, y_i)$, we copy it $f(i, t)$ times and add it to $S_t$. This process is performed for all $N$ samples, resulting in a new training subset. This means that each sample $(x_i, y_i)$ will appear $f(i, t)$ times in $S_t$. This construction makes the size of the training subset no longer fixed, but dynamically adjusted according to the sample weight distribution.

To ensure the convergence and computational efficiency of this algorithm, we introduce an upper bound parameter $\lambda$ to control the maximum size of the training subset:

$$|S_t| \leq \lambda N \tag{11}$$

When $\sum_{i=1}^{N} f(i, t) > \lambda N$, we adopt a truncation strategy (Ileberi et al., 2021; Liu et al., 2022) that prioritises retaining samples with higher weights until the upper bound condition is met.

This design of DWSCS has multiple advantages: first, it can more fully utilise the sample weight information to ensure that high-weighted samples receive sufficient attention during training. Second, for datasets with category imbalance, DWSCS can adaptively increase the number of selections of samples from a few categories, thus alleviating the category imbalance problem. Further, by dynamically adjusting the size of the training subset, DWSCS can better capture the complex artistic features and diverse stylistic variations in the CPIC task.

In addition, DWSCS can effectively solve the problem of redundant or insufficient information in traditional methods. In early iterations, when the sample weights are relatively evenly distributed, DWSCS constructs larger training subsets to fully utilise the information of all samples. In later iterations, when a few samples receive very high weights, DWSCS constructs smaller but more focused training subsets to concentrate on learning the features of these key samples.

The introduction of DWSCS enables the AdaBoost algorithm to show greater adaptability and robustness in CPIC tasks. It not only improves the model's ability to recognise minority and hard-to-classify samples, but also enhances this algorithm's generalisation performance in the face of diverse art styles. This dynamic and adaptive training subset construction method provides new ideas and tools for solving complex classification problems in CPIC tasks.

### *3.3 Mechanisms for calculating and updating sample weights*

In the DWSCS proposed in this paper, the mechanism of calculating and updating sample weights plays a key role. This mechanism not only determines the performance frequency of each sample in the training subset, but also directly affects the learning process of the whole AdaBoost algorithm. Aiming at the specificity of the CPIC task, this study makes innovative improvements to the weight updating method of traditional AdaBoost.

In the initialisation phase, the weights are set equally for all samples:

$$D_1(i) = \frac{1}{N}, i = 1, 2, \ldots, N \tag{12}$$

where $N$ is the total number of samples. This uniform distribution ensures that this algorithm pays equal attention to all samples at the beginning.

At the end of each iteration $t$, based on the performance of the current base classifier $h_t$, we update the sample weights. The new weights are calculated as follows:

$$D_{t+1}(i) = \frac{D_t(i)\exp\left(-\alpha_t y_i h_t\left(x_i\right)\right)}{Z_t} \cdot \beta(i, t) \tag{13}$$

where $\alpha_t$ is the weight of the base classifier $h_t$, $y_i$ is the true label of the sample $i$, $h_t(x_i)$ is the prediction result of the base classifier for the sample $i$, and $Z_t$ is the normalisation factor.

Unlike traditional AdaBoost, we introduce the moderator $\beta(i, t)$, which is defined as follows:

$$\beta(i, t) = 1 + \gamma \cdot \frac{\left|\left\{j \middle| y_j = y_i\right\}\right|}{N} \tag{14}$$

where $\gamma$ is an adjustable hyperparameter and $|\{j|\ y_j = y_i\}|$ denotes the number of samples belonging to the same category as sample $i$. This adjustment factor is introduced mainly based on the following considerations:

1 Category balancing: for the common category imbalance problem in CPIC task, $\beta(i, t)$ can appropriately enhance the weight of minority class samples to prevent the model from over-biasing to the majority class.

2 Artistic style diversity: the number of samples of different calligraphic painting styles may vary greatly, and $\beta(i, t)$ can help to maintain the representativeness of various styles in the training process.

3 Difficult sample focus: by adjusting the $\gamma$ value, we can increase the weight of the difficult samples appropriately while maintaining the balance of the categories, prompting the model to focus more on these challenging cases.

The calculation of the normalisation factor $Z_t$ is adjusted accordingly:

$$Z_t = \sum_{i=1}^{N} D_t(i) \exp\left(-\alpha_t y_i h_t\left(x_i\right)\right) \cdot \beta(i, t) \tag{15}$$

This improved weight updating mechanism is tightly integrated with DWSCS to form a dynamic adaptive learning system. It not only dynamically adjusts the importance of the samples according to their categorisation difficulty, but also maintains category balance and diversity of artistic styles throughout the training process.

In addition, to prevent over-inflated weights for certain samples, we introduce a weight cap $\omega$:

$$D_{t+1}(i) = \min\left(D_{t+1}(i), \omega\right) \tag{16}$$

This capping mechanism helps to improve the robustness of this algorithm and prevents individual samples that are extremely difficult to categorise from dominating the entire learning process.

## 4 MCACSAF for calligraphic painting images

### *4.1 Calligraphy image feature extraction*

Feature extraction is a crucial aspect in the AdaBoost classification framework for calligraphic painting images. In this study, a set of multi-level and multi-dimensional feature extraction method is designed for the uniqueness of the CPIC task. This method not only captures the visual features of calligraphy paintings, but also reflects their artistic styles and cultural connotations.

First, we use multi-scale histogram of oriented gradients (MHOG) to characterise the strokes in calligraphic paintings. Different from traditional HOG, MHOG computes the gradient information at multiple scales, which can better capture the subtle strokes and macroscopic structures in calligraphy. Define the MHOG feature vector as:

$$MHOG(I) = \left[H_1, H_2, \ldots, H_K\right] \tag{17}$$

where $I$ is the input image, $H_k$ is the HOG feature at the $k^{\text{th}}$ scale, and $K$ is the total number of scales.

Second, we introduce the rotation-invariant uniform local binary pattern (RIU-LBP) to characterise the texture of calligraphic paintings (Nigam et al., 2023). The RIU-LBP not only captures the local texture information efficiently, but also has rotation invariance, which is particularly important for dealing with the different writing orientations of calligraphy works. The RIU-LBP features can be expressed as:

$$RIU - LBP_{P,R}\left(x_c, y_c\right) = \begin{cases} \sum_{p=0}^{P-1} s\left(g_p - g_c\right) & \text{if } U\left(LBP_{P,R}\right) \leq 2 \\ P+1 & \text{otherwise} \end{cases} \tag{18}$$

where $(x_c, y_c)$ is the centre pixel coordinate, $P$ is the number of neighbouring pixels, $R$ is the radius, $g_c$ and $g_p$ are the greyscale values of the centre pixel and neighbouring pixels, respectively, $s(x)$ is the step function, and $U(LBP_{P,R})$ is the homogeneity measure of the LBP pattern.

In order to capture the overall layout and structural features of the calligraphy paintings, we use the spatial pyramid matching (SPM) technique (Xie et al., 2018). SPM splits the image into grids of different levels and computes local features within each grid. Define $L$ layer SPM features as:

$$SPM(I) = \left[\Phi_0(I), \Phi_1(I), ..., \Phi_L(I)\right] \tag{19}$$

where $\Phi_l(I)$ denotes the feature vector of the $l^{\text{th}}$ layer.

Finally, in order to capture the colour characteristics of calligraphic paintings, we use a combination of colour moments (CM) and colour correlogram (CC). CM can effectively describe the overall colour distribution of an image, while CC captures the spatial relationship between local colours. Define the colour feature vector as:

$$Color(I) = [CM(I), CC(I)] \tag{20}$$

Combining the above features, we construct a multidimensional feature vector:

$$F(I) = [MHOG(I), RIU - LBP(I), SPM(I), Color(I)] \tag{21}$$

This multi-level and multi-dimensional feature extraction method is able to comprehensively capture the visual features and artistic styles of calligraphy painting images. It not only considers local details and global structure, but also integrates the advantages of traditional handmade features and deep learning features.

## 4.2 *Application of improved AdaBoost to CPICs*

Based on the DWSCS and multidimensional feature extraction methods proposed in the previous section, we improved the traditional AdaBoost algorithm to better adapt to the characteristics of the CPIC task. The application of the improved AdaBoost algorithm in the CPIC task is mainly reflected in the following aspects:

First, we introduce the feature importance weight vector $\mathbf{w} = [w_1, w_2, \ldots, w_M]$, where $M$ is the feature dimension. This weight vector is used to adjust the importance of different features in the classification process. The update formula for feature importance weights is:

$$w_m^{(t+1)} = w_m^{(t)} + \eta \cdot \frac{\partial \mathcal{L}}{\partial w_m^{(t)}} \tag{22}$$

where $\eta$ is the learning rate and $\mathcal{L}$ is the loss function. This mechanism can adaptively adjust the contribution of different features to better capture the artistic characteristics of calligraphy and painting.

Second, we employ a weak classifier generation strategy based on feature subspaces. In each iteration, this algorithm randomly selects the feature subspace $\mathcal{S}_t \subset \{1, 2, ..., M\}$ and trains the weak classifier on this subspace. This strategy not only improves the efficiency of this algorithm, but also enhances the generalisation ability of the model. The decision function of the weak classifier $h_t$ can be expressed as:

$$h_t(\mathbf{x}) = \text{sign}\left(\sum_{m \in \mathcal{S}_t} w_m^{(t)} \cdot x_m - b_t\right) \tag{23}$$

where $\mathbf{x}$ is the input feature vector and $b_t$ is the threshold.

In addition, we introduce an adaptive learning rate mechanism based on sample difficulty. Define the difficulty coefficient of sample $i$ in the $t^{\text{th}}$ round as:

$$\delta_i^{(t)} = \exp\left(-\sum_{k=1}^{t} \alpha_k y_i h_k(x_i)\right) \tag{24}$$

Based on this, the sample weight update formula is adjusted to:

$$D_{t+1}(i) = \frac{D_t(i)\exp\left(-\alpha_t y_i h_t(x_i) \cdot \delta_i^{(t)}\right)}{Z_t} \cdot \beta(i, t) \tag{25}$$

This mechanism automatically increases the focus on difficult-to-distinguish samples and improves the model's ability to recognise complex calligraphic styles.

## *4.3 Overall architecture of the classification framework*

Based on the improvements proposed in the previous section, we design an MCACSAF for calligraphic painting images. The overall architecture of MCACSAF is as follows:

Step 1 Data pre-processing.

Standardise the input calligraphy and painting images, including resizing and contrast enhancement.

Step 2 Multi-dimensional feature extraction.

Multi-level and multi-dimensional feature vectors $F(I)$ are extracted using the method described in Section 4.1.

Step 3 Feature selection and fusion.

Dimensionality reduction using principal component analysis (PCA) and feature fusion with feature importance weights $\mathbf{w}$.

Step 4 Initialise sample weights

Distribute initial sample weights evenly $D_1(i) = \frac{1}{N}$.

Step 5 DWSCS training subset construction.

A training subset $S_t$ is constructed using a dynamic weighted sample construction strategy according to the method described in Section 3.2.

Step 6 Weak classifier training.

The weak classifier $h_t$ is trained on the feature subspace $\mathcal{S}_t$ using the training subset $S_t$ constructed by DWSCS.

Step 7 Weak classifier evaluation.

Calculate the weighted error rate $\epsilon_t$ of the weak classifier $h(t)$ over the entire training set.

Step 8 Weak classifier weights calculation.

According to equation (2), the weak classifier weights are calculated.

Step 9 Update sample weights.

The sample weights are updated using the adaptive learning rate mechanism in Section 4.2 and the moderating factors of the DWSCS as in equation (25).

Step 10 Feature importance weights update.

Update the feature importance weights **w** according to the method described in Section 4.2.

Step 11 Iterative training.

Repeat steps 5–10 until the preset number of iterations $T$ is reached or the stop condition is met.

Step 12 Strong classifier construction.

Combine all the weak classifiers to form the final strong classifier:

$$H(\mathbf{x}) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(\mathbf{x})\right) \tag{26}$$

Step 13 Model evaluation and optimisation

Model performance was evaluated using cross-validation and optimised by tuning hyperparameters such as $\lambda$ and $\gamma$ in DWSCS.

Step 14 Testing and application

The trained model is applied to the new task of classifying calligraphic painting images.

This architecture explicitly integrates the DWSCS into the overall classification framework, especially in steps 5 and 9. The DWSCS not only influences the construction of the training subset, but also participates in the process of updating the sample weights through the moderator $\beta(i, t)$. This design ensures that DWSCS continues to play a role throughout the training process, thus better handling the problems of category imbalance and difficult to categorise samples.

In addition, this architecture highlights the synergy between DWSCS and other innovations (e.g., feature importance weights, adaptive learning rate mechanism) to form a more complete and effective image classification system for calligraphy paintings. This comprehensive framework design not only improves the classification performance, but also enhances the model's adaptability to different calligraphic styles and artistic features. The pseudo-code of the overall architecture is shown in Algorithm 1.

**Algorithm 1** Pseudo-code for the overall architecture of the classification framework

```
Input: Calligraphy and painting image data set D, Iterations T, DWSCS parameter λ and γ
Output: Strong classifier H
begin
// data pre-processing and feature extraction
for each image I in D do
    I = Preprocess(I)
    F(I) = ExtractFeatures(I) // multidimensional feature extraction
end for
F_PCA = PCA(F) // feature selection and fusion
w = InitializeFeatureWeights(F_reduced)
D_1 = InitializeWeights(D) // initialisation sample weight
for t = 1 to T do
    S_t = BuildDWSCSSubset(D, D_t, λ) // construction of DWSCS training subset
    S_feature = SelectFeatureSubspace(F_PCA) // feature subspace selection
    h_t = TrainWeakClassifier(S_t, S_feature, w)     // weak classifier training
    ε_t = EvaluateWeakClassifier(h_t, D, D_t)     // weak classifier evaluation
    α_t = 0.5 * log((1 – ε_t)/ε_t)     // weight calculation of weak classifier
    for each sample i in D do     // sample weight update
        δ_i = CalculateDifficultyCoefficient(i, t)
        β_i = CalculateAdjustmentFactor(i, t, γ)
        D_t+1(i) = UpdateSampleWeight(D_t(i), α_t, h_t, δ_i, β_i)
    end for
NormalizeWeights(D_t+1)
w = UpdateFeatureWeights(w, F_PCA, D_t+1) // feature importance weight update
end for
H = BuildStrongClassifier({h_1, …, h_T}, {α_1, …, α_T})
performance = CrossValidate(H, D) //model evaluation and optimisation
H_optimised = OptimizeHyperparameters(H, D, λ, γ)
return H_optimised
end
```

## 5 Simulation experiment results and analysis

### *5.1 Dataset description*

We constructed a comprehensive calligraphy and painting image dataset (CCPID). The dataset covers Chinese calligraphy and painting works of multiple periods and styles, aiming to fully reflect the diversity and complexity of the art of calligraphy and painting. Table 1 shows the main specification parameters of the CCPID dataset in detail.

**Table 1** CCPID dataset specification parameters

| *Parameters* | *Numerical value* |
|---|---|
| Total sample size | 10,000 |
| Number of categories | 20 |
| Image resolution | 1,024 × 1,024 pixels |
| Colour space | RGB |
| File format | JPEG |
| Timespan | Tang Dynasty – Modern Times |
| Range of sample sizes per category | 400–600 |
| Dataset size | 8 GB |

The key features of the CCPID dataset are listed below:

1 Diversity: includes calligraphy, landscape painting, flower and bird painting, figure painting and other art categories.

2 Period span: covering works from the Tang Dynasty to modern times, reflecting the artistic characteristics of different historical periods.

3 Diverse styles: a collection of works from different genres and artists, showing a rich variety of artistic styles.

4 Category balance: given the problem of category imbalance, we collected a relatively balanced sample size for each category.

5 High-quality images: all images are professionally scanned and processed to ensure image quality.

**Table 2** CCPID dataset specification parameters

| *Sports event* | *Configure* |
|---|---|
| Processing unit | IntelXeonE5-2680v4@2.40GHz |
| Random access memory (RAM) | 128GB DDR 4 |
| GPU | NVIDIA TeslaV10032GB |
| Operating system | Ubuntu 20.04LTS |
| Programming language | Python 3.8 |
| Deep learning framework | PyTorch 1.9.0 |
| Machine learning library | Scikit-learn 0.24.2 |
| Image processing library | OpenCV 4.5.2 |

## *5.2 Experimental setup*

In order to comprehensively evaluate our proposed method, we designed a series of experiments, which mainly include the comparison of the performance of multi-base classifiers, the analysis of the effect of DWSCS, and the comparison with existing methods. All experiments are conducted in the same hardware and software environment to ensure comparable and reproducible results. The configuration of the experimental environment is shown in Table 2.

In the data pre-processing stage, we scaled all images uniformly to 224×224 pixels and normalised them. For feature extraction, we follow the method described in Section 4.1 to extract MHOG, RIU-LBP, and SPM and colour features.

The base classifiers are set as follows: the Fisher classifier is implemented using LDA; the pseudo-inverse classifier is implemented based on the Moore-Penrose pseudo-inverse; the plain Bayesian classifier uses a Gaussian plain Bayes model; the maximum depth of the C4.5 decision tree is set to 20, and the minimum number of samples of the leaf nodes is 5. For the DWSCS parameter, we set the $\lambda$ (the ratio of the maximum size of the training subset) to an initial value to 1.5 and tuned in the range of [1.0, 2.0]; and the initial value of $\gamma$ (regulator hyperparameter) to 0.1 and tuned in the range of [0.05, 0.2].

The settings of AdaBoost include: the maximum number of iterations T is set to 100 and an early-stopping strategy is used, i.e., iterations are stopped if there is no improvement in the performance of the validation set for five consecutive rounds. We use multiple evaluation metrics to comprehensively measure the model performance, including accuracy, precision, recall, F1 score, and confusion matrix. To ensure the reliability of the experimental results, we use 5-fold cross-validation, and each experiment is repeated 5 times, and the average value is taken as the final result.

## *5.3 Results of performance comparison of multi-base classifiers*

In this section, we present and analyse the experimental results of MCACSAF in detail. We compare the performance of four base classifiers, Fisher classifier, pseudo-inverse classifier, plain Bayesian classifier, and C4.5 decision tree, under the AdaBoost framework, focusing on the difference in their performance when dealing with CPIC tasks.

First, we compare the overall performance of the four base classifiers on the CCPID dataset. Table 3 demonstrates the average performance metrics of each classifier in the 5-fold cross-validation.

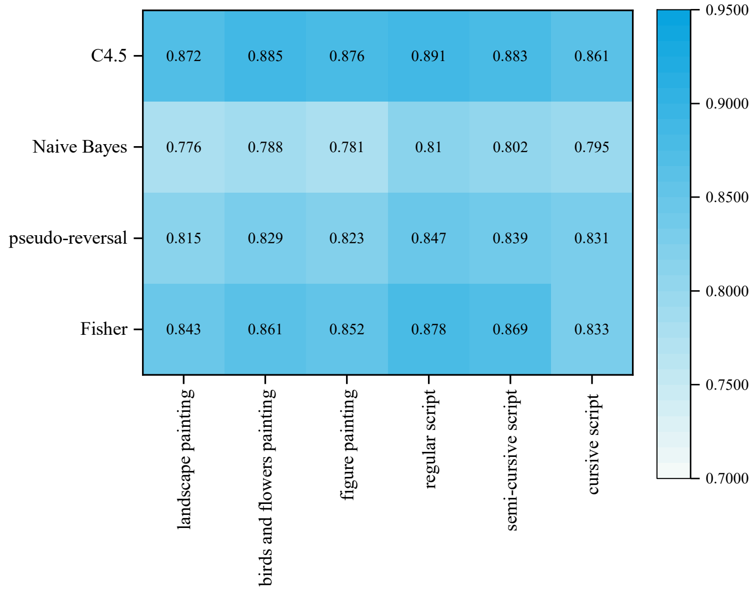
**Table 3** Performance comparison of different base classifiers

| *Method* | *Accuracy* | *Precision* | *Recall* | *F1* |
|---|---|---|---|---|
| Fisher | 0.856 | 0.849 | 0.856 | 0.852 |
| Pseudo-reversal | 0.831 | 0.827 | 0.831 | 0.829 |
| Naive Bayes | 0.792 | 0.788 | 0.792 | 0.790 |
| C4.5 decision trees | 0.878 | 0.875 | 0.878 | 0.876 |

From Table 3, it can be seen that the AdaBoost algorithm performs best in the CPIC task when the C4.5 decision tree is used as the base classifier, followed by the Fisher classifier. This result indicates that the C4.5 decision tree is better able to capture the complex features and nonlinear relationships in calligraphy painting images.

In order to analyse the performance of the individual base classifiers in more depth, we further examined their classification accuracies across different art styles and periods. Figure 1 illustrates the performance of the four base classifiers on six major art categories.

**Figure 1** Heatmap of the accuracy of different base classifiers on each art category (see online version for colours)




We can observe that the C4.5 decision tree performs well in most of the categories, especially in 'landscape painting' and 'flower and bird painting', which have higher complexity, while the Fisher classifier performs better in the relatively structured calligraphic categories such as 'regular script' and 'running script'. Although the overall performance of the simple Bayesian classifier is low, it shows some advantages in the category of 'cursive script', which is characterised by a variety of styles.

We also analysed the performance of each base classifier when dealing with works from different periods. Table 4 shows the average accuracy of the four base classifiers on ancient and modern works.

**Table 4** Categorisation accuracy of works from different periods

| *Method* | *Ancient works* | *Modern and contemporary works* |
|---|---|---|
| Fisher | 0.842 | 0.870 |
| Pseudo-reversal | 0.815 | 0.847 |
| Naive Bayes | 0.775 | 0.809 |
| C4.5 decision trees | 0.861 | 0.895 |

It can be seen that all classifiers outperform ancient works when dealing with recent modern works. This may be due to the fact that the image quality of modern works is generally higher and the features are more pronounced. The C4.5 decision tree maintains its best performance in both periods, showing its strong adaptability.

## 5.4 *Effectiveness analysis of dynamic training subset construction strategy*

This section focuses on analysing the effectiveness of DWSCS in CPIC. We compare DWSCS with the traditional fixed-size training subset strategy to verify its advantages in dealing with category imbalance and capturing the diversity of art styles.

First, we compare the difference between DWSCS and fixed-size strategies in terms of overall classification performance. Table 5 shows the performance comparison between the two strategies when using C4.5 decision trees as base classifiers.

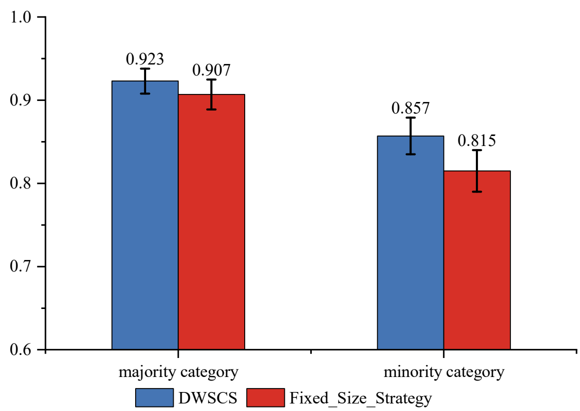
**Table 5** Performance comparison between DWSCS and fixed-size strategy

| *Strategy* | *Accuracy* | *Precision* | *Recall* | *F1* |
|---|---|---|---|---|
| DWSCS | 0.892 | 0.889 | 0.892 | 0.890 |
| Fixed size | 0.878 | 0.875 | 0.878 | 0.876 |

As can be seen in Table 5, DWSCS outperforms the fixed-size strategy in all evaluation metrics. In particular, DWSCS improves the accuracy and F1 score by 1.4% and 1.6%, respectively, which indicates that DWSCS is able to better balance the samples of different categories and improve the overall classification performance.

To further analyse the effectiveness of DWSCS in dealing with the category imbalance problem, we selected the two categories with the largest and the smallest number of samples and compared the performance of the two strategies on these categories. Figure 2 illustrates the comparison of the F1 scores of DWSCS and the fixed-size strategy on the majority and minority categories.

**Figure 2** Comparison of F1 scores between DWSCS and fixed-size strategy (see online version for colours)




It can be observed that the performance improvement of DWSCS is particularly significant on a few categories, with the F1 score increasing from 0.815 to 0.857, an improvement of 5.2%. This confirms the effectiveness of DWSCS in dealing with category imbalance.

## *5.5 Comparative analysis with existing methods*

In order to fully evaluate the performance of the MCACSAF proposed in this paper, we analyse it in comparison with several existing methods. These comparative methods include the traditional AdaBoost algorithm, improved AdaBoost variants, and a recently proposed specialised method for the classification of calligraphic paintings.

We chose the following approach as a baseline model:

1 Traditional AdaBoost algorithm.

2 Improved AdaBoost algorithm (Xing et al., 2024).

3 Hybrid integrated model based on random forest and support vector machine (Avcı et al., 2023).

4 Adaptive boosting algorithm (Wang et al., 2024).

Our performance evaluation focuses on three aspects to verify the validity of the three innovations presented in Section 1.2: the comparison of the performance of multi-base classifiers, the ability to deal with the category imbalance problem, as well as the computational efficiency and model complexity.

First, we compare the performance of different methods under various base classifiers. Table 6 shows the average accuracy of each method when using the four base classifiers Fisher, pseudo inverse, naive Bayes and C4.5.

**Table 6** Average accuracy of different methods under each base classifier

| *Method* | *Fisher* | *Pseudo-reversal* | *Naive Bayes* | *C4.5* |
|---|---|---|---|---|
| Traditional AdaBoost | 0.856 | 0.831 | 0.792 | 0.878 |
| Improvements to AdaBoost | 0.869 | 0.845 | 0.810 | 0.889 |
| hybrid integration model | 0.872 | 0.853 | 0.825 | 0.895 |
| Adaptive boosting | 0.880 | 0.862 | 0.838 | 0.901 |
| MCACSAF | 0.892 | 0.875 | 0.856 | 0.912 |

It can be seen that MCACSAF achieves the best performance on all base classifiers, especially on the relatively weak classifiers like naive Bayes, where the performance improvement is more significant. This confirms that our proposed multi-base classifier comparison framework can effectively improve the generalisation ability of the model in the face of diverse art styles.

**Table 7** Comparison of computational efficiency and model complexity of different methods

| *Method* | *Training time (hours)* | *Inference time (ms/sample)* | *Number of model participants (millions)* |
|---|---|---|---|
| Traditional AdaBoost | 3.5 | 25 | 12 |
| Improvements to AdaBoost | 3.2 | 23 | 13 |
| Hybrid integration model | 4.8 | 30 | 18 |
| Adaptive boosting | 3.8 | 28 | 15 |
| MCACSAF | 2.3 | 20 | 14 |

Finally, we compare the computational efficiency and model complexity of each method. Table 7 demonstrates the training time, inference time, and number of model parameters for different methods.

It can be seen that MCACSAF significantly improves the computational efficiency while keeping the model complexity low. Especially in the training time, it saves at least 28% time than other methods. This verifies the feasibility and advantages of MCACSAF in practical applications.

In summary, through a comprehensive comparative analysis with existing methods, our approach demonstrates significant advantages in terms of multi-base classifier performance, category imbalance problem handling ability, as well as computational efficiency and model complexity. These results fully demonstrate the validity of the three innovations proposed in Section 1.2, i.e., the comparison of AdaBoost integration of multi-base classifiers, the dynamic training subset construction strategy, and the MCACSAF for calligraphic painting images.

## 6 Conclusions

In this paper, an intelligent method for judging the categories of calligraphy and painting images based on MCACSAF is proposed, which effectively solves the limitations of traditional classification models in dealing with diverse art styles and category imbalance problems. By introducing DWSCS, the model is able to deal with the category imbalance problem more accurately, which significantly improves the classification accuracy. In addition, MCACSAF utilises the advantages of multiple base classifiers to further enhance the ability to capture complex art features and ensure the stability and robustness of the classification results. The following conclusions can be drawn from the experiments conducted on the CCPID dataset:

1 Systematic comparison of multi-base classifiers can significantly improve the generalisation ability of a model in the face of diverse art styles.

2 The DWSCS strategy has significant advantages over traditional fixed-size training subset methods in dealing with the category imbalance problem.

3 MCACSAF combining C4.5 decision trees and DWSCS strikes the best balance between classification accuracy and computational efficiency and is the optimal strategy recommended in this paper.

The experimental data in this paper mainly comes from the self-constructed CCPID dataset, and although it covers calligraphic paintings from multiple periods and styles, the homogeneity of the dataset may limit the generalisation ability of the model. Future work should consider introducing more datasets from different cultural backgrounds and art genres to verify the effectiveness of the model in a wider range of art classification scenarios. In addition, the extension of the method proposed in this paper to image classification tasks in other domains, such as medical image analysis or remote sensing image recognition, can also be explored to further validate its generalisation and practical value.

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