J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 8979--8992

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Random Forest-based Pattern Recognition Method for Conservation of Cultural Heritage of Mural Paintings in Tomb Chambers

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ABSTRACT

The development of digital technology has made the use of machine learning algorithms to protect cultural heritage has become a trend. In this paper, based on the random forest algorithm, the conservation model of tomb mural cultural heritage is recognized. The mural paintings in the tomb of Prince Zhanghuai are used as the data source to construct the tomb mural painting dataset, and the images in the dataset are processed, augmented and labeled. The features such as color, texture and shape in the mural images are extracted as one of the input information of the cultural heritage protection model of the tomb murals. Based on the random forest algorithm, a pattern recognition model for the protection of cultural heritage of tomb frescoes is constructed, and the feature vectors obtained from the feature extraction are used to calculate the split points of the decision tree. The classification results of multiple decision trees are weighted and averaged to obtain the final recognition results. The recognition accuracies of this paper's model on the training set, test set and validation set are 99.45%, 95.46% and 92.58%, respectively. This is a significant improvement over other existing algorithms. Meanwhile, the algorithm consumes significantly less time than the ResNet18 deep residual network model before and after data enhancement, and is able to efficiently accomplish the task of recognizing the protection of cultural heritage of tomb chamber murals.

Keywords: random forest, feature extraction, feature vector, decision tree, pattern recognition

1. Introduction

In the long course of history, China has gone through dynastic changes, economic ups and downs and cultural prosperity, leaving behind a rich and unique cultural heritage and historical events. Among them, cultural relics have witnessed the history and culture of different eras and, as symbols of the country's culture, reflect the country's history and cultural heritage [1-3]. As one of the important

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Received 25 February 2024; Revised 05 April 2024; Accepted 15 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-499

cultural relics in China, mural paintings, which have lasted for thousands of years, are rich in content and have a wide range of themes, record the social and public sentiments, spirituality, political changes, and economic development of different historical periods, and are an important material for the study of ancient Chinese history [4-6].

Chinese murals contain three types: architectural murals, cave murals, and tomb murals, and tomb murals, as the only underground artifacts among them, are paintings found inside the burial chambers of ancient burial sites [7]. They usually depict aspects of the tomb owner's life, beliefs, family and social status [8]. These murals usually use bright colors and fine lines to represent the figures and scenes on the mural. The details and colors of the murals are usually coordinated with the artistic style of the time. In some cases, murals may also include text or pictographic symbols to provide additional information. The themes of burial chamber murals vary depending on the era, region, and culture, but common themes include mythological stories, religious scenes, agriculture, hunting, and domestic life [9-12]. In addition, some burial chamber murals may include depictions of death and the afterlife, as well as imagery of the tomb owner's role in the afterlife [13].

Cultural relics and cultural heritage are the precious wealth of the Chinese nation, they contain the essence of history, are the eternal spiritual pillar of the Chinese nation, and are irreplaceable and valuable assets. Tomb murals are a kind of precious historical and cultural heritage, which record the lifestyle of the tomb owners and have high historical and cultural value, therefore, it is especially important to protect and pass on these murals [14-16]. Cultural relics protection includes preventive protection and salvage protection. The rapid development of national economic development is accompanied by a large number of urban infrastructure, and the frequent excavation of valuable cultural relics has made "salvage protection" the main strategy of cultural relics protection in China. For cultural relics that do not have on-site protection conditions, in order to prevent their further deterioration, they need to be excavated and relocated for protection [17-18]. Taking the mural paintings in the tombs as an example, due to factors such as the collapse of the tomb passage, flood erosion and destruction by tomb robbers, it has become a better conservation measure to uncover and relocate the mural paintings to an off-site preservation site. Before the mural paintings in the tomb chamber were uncovered, the environment of the tomb chamber in which they were located was relatively stable, while after the uncovering, the storage environment changed considerably compared with the tomb chamber, which inevitably led to a series of lesion problems for the murals [19-20]. The large number of mural paintings in the tombs, the large demand for restoration, the heavy task, and the difficulty of the actual restoration, making most of the mural paintings from the excavation to meet with the majority of tourists in a long cycle. Another major factor contributing to this state of affairs is the loss of cultural relic restoration practitioners. Digital information processing tools offer a wealth of new opportunities for collecting, analyzing, reconstructing and disseminating the content of cultural heritage. The issue of research-focused applications of digital information processing technologies in cultural heritage conservation will be a hot topic in the field of heritage conservation worldwide [21-22].

In this paper, we use Xena P2 camera and Xena e Motion75LV viewfinder digital camera to collect image data from the murals in the tomb of Prince Zhanghuai, and screen texture-rich murals based on texture details and other features as the dataset for this paper. The content-adaptive Criminisi algorithm and the improved sample-filling restoration model are used for mold removal and crack restoration of the murals to reduce the extra noise in the murals and improve the image quality in the dataset. Aiming at the problem of too few images in the dataset, this paper adopts six methods, such as horizontal flipping and 90-degree rotation, to expand the tomb mural painting dataset and add the label of cultural heritage protection model to get the final dataset used for model training and experiments. By choosing the color null conceptual model and color quantization method, this paper performs color feature extraction on the tomb mural images. Combined with the texture features extracted under the grayscale covariance matrix and local binary mode methods, it constitutes the main image feature information for cultural heritage protection pattern recognition in this paper. The extracted mural image features are input to the random forest algorithm, which randomly selects some of the features at each node of a single decision tree to generate a binary tree by recursively splitting the tree from top to bottom, and realizes the task of recognizing the cultural heritage protection patterns of the tomb murals according to the common voting results of the recognition data of each decision tree. The proposed method is analyzed experimentally based on the constructed data set of tomb murals, and the experimental results are compared with the recognition results of the ResNet deep residual network model, which highlights the good performance of this paper's model in the recognition of cultural heritage protection patterns of tomb murals.

2. Data acquisition and processing

2.1. Data acquisition

The tomb of Prince Zhanghuai was discovered in the 1980s on the high ground north of Yangjiawa Village, Qianling Township, about 5 kilometers southeast of Qianling Mausoleum, Xianyang City, Shaanxi Province, and the mural paintings in the tomb were found to be more than 70 in total, of which the dataset used for this paper is the “Polo Map”. The whole “polo picture” painted during the Tang Dynasty, a rolling hills in the forest, the Tang people on horseback to carry out polo sports scenes, but also China's earliest record of polo murals. The whole mural is 2.27 meters high and 6.84 meters wide, and the whole mural is digitized and collected in pieces by using the Swiss Xena P2 camera and Xena e Motion75LV digital camera. After laser ranging and high-definition acquisition by cultural relics experts, the total amount of data collected from the mural painting of “Polo Map” reaches more than 20G, and the individual chunks of the mural painting is about 2-5G, and the specific amount of data is shown in Table 1. In this paper, firstly, five Tang Dynasty tomb murals “Polo Map” are segmented using MATLAB, and saved as mural images with a size of 512 × 512 pixels, and then, according to the texture details, the mural paintings with a relatively single texture are deleted, and finally, 758 texture-rich murals are filtered as the dataset of this paper.

Table 1. High clear mural data acquisition situation

Numbering	B16-1	B16-2	B16-3	B16-4	B16-5
Block diagram	2215×1750	2230×1830	2250×1280	2030×1385	2090×2115
Lens extension	25	26	19	28	26
Data volume (GB)	4.38	5.13	2.08	4.57	4.96

2.2. Data processing

2.2.1. Image data restoration. The “Polo Picture” has been lying underground for more than 1,300 years, and has been exposed to humid environment and harsh conditions for a long time, and its wall will cause mold growth and cracks on the surface of the mural due to unavoidable reasons (e.g., air humidity, peeling off of the ground battlement layer, hollowing out, crispy alkali, etc.). In order to avoid these errors from adversely affecting the training of the pattern recognition model, data preprocessing of 758 murals of size 512 × 512 is required.

The mold areas present in 758 murals are pre-restored using the content-adaptive Criminisi modeling method. The Criminisi algorithm is based on the sample restoration method [23], where the confidence level $C(p)$ is set during the iteration process so that it decreases with the increase of the number of iterations while the overall data item $D(p)$ remains unchanged, resulting in the restoration process in which the priority $P(p)=C(p)\times D(p)$ will be getting smaller and smaller, and the ability of the samples to be matched and the matching error rate increases, resulting in the problem that the repair effect gets worse as we go further into the interior. In this paper, the priority of Criminisi algorithm is redefined to improve the effect of internal repair.

The priority redefinition is as follows:

$$P(p) = \alpha M(p) \times \beta D(P) \tag{1}$$

$$M(p) = \chi C(p) + \psi \tag{2}$$

$$\chi = 1 - \frac{1}{t-1} \tag{3}$$

In the formula, χ represents the dynamic transfer operator, t represents the number of iterations, with the increase of the number of repair iterations, χ will gradually increase. The confidence level after $M(p)$ reset is updated by the dynamic operator χ, and ψ is a constant 0.8. α and β are the weights of $M(p)$ and $D(P)$, respectively, and after a large number of experiments, we get the best repair effect at $\alpha = 0.4$ and $\beta = 0.6$. From the above formula, it can be seen that with the increase in the number of iterative repair t, the dynamic operator χ is getting bigger and bigger, so as to remake the confidence $M(p)$, solve the problem of the priority $P(p)$ is getting smaller and smaller, and realize a more accurate matching mechanism.

Aiming at the cracked region of the mural, an improved sample-filling repair model is used to optimize the priority, sample size, and matching criterion to achieve the repair of the cracked region of the mural. The results of the mural crack repair are shown in Fig. 1, (a) and (b) represent the original mural and the repaired mural, respectively, and the white lines represent the cracks. From the results of image data processing, it can be found that different repair means are used for the mold as well as the cracked areas, and the pre-restored mural reduces the extra noise, improves the quality of the mural, and avoids the impact of the disease on the subsequent pattern recognition model.

(a) Original mural (b) Repaired mural

Fig. 1. The crack area repair effect of the mural

2.2.2. Broadening of data sets. Mural paintings of different periods are characterized by unique painting styles due to the influence of living customs, religious rituals and social systems. The Tang Dynasty tomb mural “Polo” has a simple and bright painting style, vivid overall atmosphere, and smooth and delicate lines, but according to the previous section, the number of existing Tang Dynasty tomb mural paintings is scarce, which is far from being able to meet the training requirements of the pattern recognition model. In this paper, only 758 frescoes dataset is used, which will cause the model's generalization ability to be low because the training set is too small, the analysis ability of the image is poor, and it is also easy to produce the problem of overfitting. Therefore, in order to solve this problem, in this paper, six traditional methods such as horizontal flip, 90-degree rotation, 180-degree rotation, 270-degree rotation, brightness increase, contrast increase, etc. are used for the mural images to augment the 758 512 × 512 mural dataset [24]. Through data augmentation, 10239 frescoes dataset is finally obtained in this paper. In order to follow the conventional dataset division method, the data are divided into training set, testing set and validation set in the ratio of 6:2:2. Among them, the training set includes 6143 images, while the test set and validation set each include 2048 images.

2.2.3. Protected Mode Label Addition. This paper focuses on the protection mode recognition of tomb mural painting cultural heritage, so after completing the augmentation and expansion of the tomb mural painting image dataset, the protection mode labels are added to the final 10239 tomb mural painting images. The cultural heritage protection modes selected in this paper mainly include five modes: in-situ protection, overall relocation, frame set, even brick uncovering and uncovering, and the following is a brief introduction of the five cultural heritage protection modes:

1) In-situ Protection. The in-situ conservation method is applicable to the mural paintings which have a better environment and a huge volume of their own. Through scientific planning and rational utilization, the original appearance and historical value of the murals are maintained to avoid damage and loss of information caused by relocation.

2) Overall relocation. The overall relocation mode is aimed at frescoes with small support volume, and relocates them to museums or other suitable preservation places for professional protection and display. This method is suitable for situations where effective conservation in situ is not possible.

3) Framing. The frame-sleeve mode is applicable to murals painted directly on the earth support body. By setting up a protective frame around the mural, it prevents the mural from erosion and perceived damage by the external environment, while facilitating daily maintenance and management.

4) Uncovering with bricks. The mode of removing the bricks is aimed at the murals with thin layers of ground battle and firmly connected with the supporting body. This mode combines the advantages of the uncovering protection mode, which can effectively protect the integrity of the mural paintings and reduce the damage to the cultural relics themselves.

5) Uncovering. Uncovering mode is mainly for the mural paintings that must contain mud layer in the structure. The mural is removed from its original position, professionally restored and protected, and then renewed and placed in a suitable environment to ensure its long-term preservation.

3. Key algorithmic studies

3.1. Image feature extraction algorithm

In order to realize the automatic recognition of conservation patterns, it is necessary to construct a feature set containing multiple features like. These features include the color, texture, shape and other visual features of the mural. By mentioning these features, rich input information can be provided for subsequent model training.

3.1.1. Color characteristics. Color is one of the simplest and most direct visual features in human senses, and has a very strong correlation with the things in the image. It is relative to the image as a whole for feature extraction, has a weak correlation with the image size and orientation, and has translation and rotation invariance. The color features of an image are usually extracted in two steps. First, select the color space model. Second, select the color quantization method.

From the perspective of color space model, the most common are RGB and HSV color space, RGB red, green and blue components from the perspective of human visual perception to express the color information of the image. While the HSV model three components from the perspective of image light and darkness to indicate the distribution of the image's chromaticity, color saturation, brightness, focusing on the expression of the color direction.

From the perspective of color quantization methods, the most commonly used methods to represent color features are color histogram, color correlation diagram, color set and color moment. Color histogram represents the proportion of different pixels in the whole picture, without considering the position of each pixel in the picture, and can be adapted to various different color spaces, such as RGB or HSV. The algorithmic process is to build a histogram to represent the feature information by dividing the whole color space into subspaces and by calculating the number of pixels in each subspace. The color correlation map considers the spatial correlation between different color pairs and describes the color features by calculating the relative distance. The color set is mainly applied to HSV color space, so it is necessary to first convert the image from RGB channel to HSV space for multiple subspaces, and then adopt a certain component of this color space to index on a number of image sub-regions, and finally generate a color index table to express the image information. The color moments take advantage of the fact that the distribution of colors is mostly concentrated in low-order matrices, and use statistics such as mean, variance and covariance for feature expression. The formulas for these three statistics in the ith channel of the image are expressed as follows:

$$E_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{4}$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - E_i\right)^2} \tag{5}$$

$$S_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - E_i\right)^3} \tag{6}$$

where the value of the jst pixel in the ind channel is denoted by P_{ij} and the total number of pixels in the image is noted as N.

3.1.2. Texture Characterization. Texture, defined from the point of view of human visual perception, is a feature that reflects homogeneity, as well as invariance to translation rotation, reflecting information about the spatial structure of the image. Gray scale covariance matrix feature measures and image local binary patterns are the two most common feature extraction methods [25-26]. Each of them will be described next.

Gray Level Co-occurrence Matrix: The computational process of GLCM is shown in Fig. 2. The left image size is 4 × 5 and the gray level size is 7, and then the frequency of occurrence of pixel pair (i, j) in the horizontal direction is counted to obtain the gray level covariance matrix $G(i, j)$ of the right side with the size of 7 × 7. This is a method to characterize the texture by calculating the joint probability density between two pixels. The four relevant statistics, corner second order moments, correlation, contrast and entropy of the matrix G are generally used as feature vectors for mural characterization.

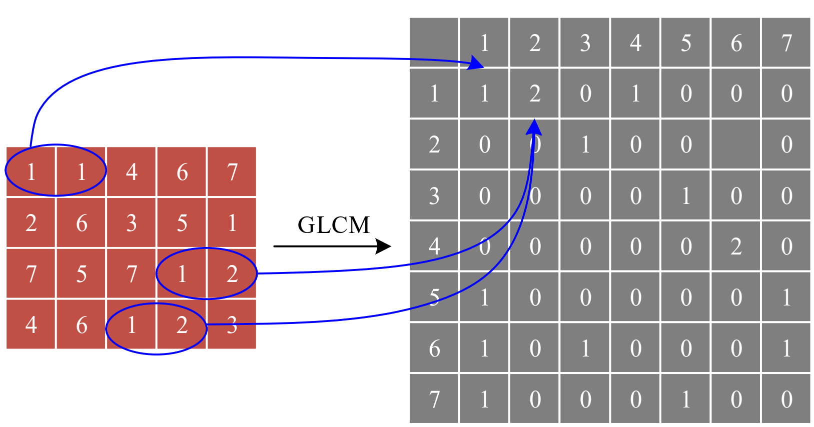


Fig. 2. GLCM of image

Local Binary Pattern: the computational process of LBP is shown in Fig. 3, where 8 or 16 surrounding pixels are used for texture feature extraction by drawing a clockwise circle. Taking the 8 pixels in Fig. 3 as an example, the values of the surrounding 8 pixels and the pixel at the center are compared, and if they are larger than the center value, the pixel value is set to 1, and vice versa, an 8-bit character sequence with only 0,1 encoding is obtained. Finally the LBP histogram is built by statistically creating a binary sequence of all the pixels to complete the representation of the image texture information.

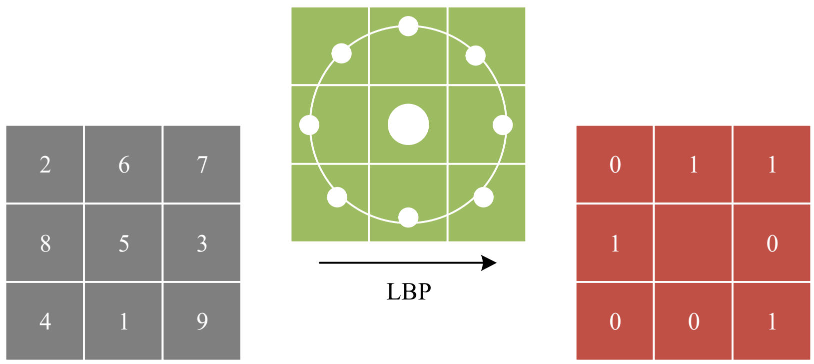


Fig. 3. GLCM of image(LBP)

For the murals, the pattern of the costumes and the pattern of the headdresses vary from one element to another. In terms of costumes, Buddha statues are unadorned, while Bodhisattvas are ornately decorated, often with precious stones and so on. In terms of headdress, for example, disciples have no hair ornaments, Buddhas usually have spiral bun hair, mortals usually have simple hair ornaments, and Bodhisattvas have more hair ornaments and more complex patterns. Therefore, texture features can be used to describe the information of mural images. Because of the consideration of the background noise problem of frescoes, this paper adopts the local binary mode, which is closely related to the information of the surrounding pixels, to express the fresco texture features.

3.1.3. Shape characteristics. Shape feature extraction requires transforming data-redundant raw image data into a simple representable sequence of shape features with invariance to color and texture variations. Commonly used algorithms include Fourier descriptors, chain codes and their associated techniques, and invariant moments. Shape can be understood in everyday life as the contour of a target or the area contained in the target contour. Depending on the understanding of shape features, there are two most commonly used extraction methods. The first is a shape feature that uses the contour boundary as the basis for information expression. The feature is the boundary information of the target, which can make the information inside the image region lose its value, resulting in misrepresentation of information about objects that are partially occluded or have discontinuous regions. Secondly, the shape feature that takes the region content understanding as the basis of information expression. This method not only focuses on the content information of the target region, but also needs the expression of the region boundary information to extract the shape features from a multifaceted design, but this will greatly increase the amount of computation.

For murals, shape is a concept that is difficult to quantify numerically. However, because the cultural heritage protection pattern recognition in this paper adopts the random forest algorithm, which extracts high-level abstract semantic features that can embody the overall shape of the mural including the shape of the mural, this paper adopts convolutional features to express the shape of the mural. In the protection pattern recognition, the two underlying features, color features and texture, are mainly used to express the underlying features of the frescoes.

3.2. Random Forest Algorithm

Random Forest is a machine learning algorithm that uses decision trees as recognizers [27], and introduces a random selection method for features on the basis of Bagging's random sampling of samples, so it has obvious advantages in dealing with data with high feature dimensions.

Random forest is essentially a collection of multiple decision trees, in the identification, first of all, in the initial sample randomly select a subset of samples after generating a decision tree, repeat the above process of random selection, and ultimately generate a number of decision trees, a number of decision trees together constitute a random forest, through the identification of a number of decision trees to vote on the results of the composite, and ultimately complete the training of the random forest on the original sample. The specific recognition process is as follows:

1) The original training sample set containing M sample is subjected to EMD processing and spectral energy ratio feature extraction to obtain the spectral energy ratio feature matrix A of the original training sample set, which can be expressed as follows:

$$A = \begin{bmatrix} \bar{E}_1(1) & \bar{E}_2(1) & \cdots & \bar{E}_N(1) \\ \vdots & \vdots & \ddots & \vdots \\ E_1(M-1) & E_2(M-1) & \cdots & E_N(M-1) \\ \bar{E}_1(M) & \bar{E}_2(M) & \cdots & \bar{E}_N(M) \end{bmatrix} \tag{7}$$

2) Randomly select a subset of data with a sample size of $S(S<M)$ from matrix A as the initial training set for a decision tree, where the subset of data has N feature attributes.

3) At each node of a single decision tree, $f(f<N)$ feature attributes are randomly selected from the N feature attributes, and the binary tree is generated by top-down recursive splitting, with the attribute selection criterion of node impurity G minimized. Node impurity G is denoted as:

$$G(i) = \sum_{w=1}^{W} p_w \cdot \left(1 - p_w\right) = 1 - \sum_{w=1}^{W} p_w^2 \tag{8}$$

where: $G(i)$ is the impurity of node i. p_w is the frequency of samples on node i belonging to class w (assuming the number of feature attributes of the sample is W).

4) Repeat the above process until N feature attributes are traversed. f remains constant during the growth of the decision tree, and eventually several decision trees are generated, which together form a random forest.

5) The final recognition result of the random forest for the sample data is determined by the recognition result of each decision tree by joint voting. The voting process can be expressed as:

$$C_p = \arg\max_C \left(\frac{1}{n_t} \sum_{i=1}^{n_t} I\left(\frac{n_{h_t,C}}{n_{h_t}} \right) \right) \tag{9}$$

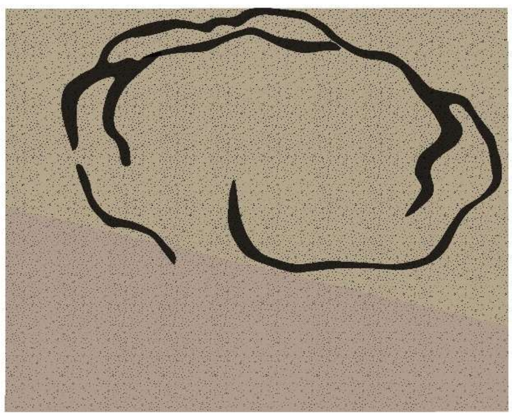
where: n_t is the number of decision trees. n_{hi} is the number of leaf nodes of decision tree h_i. $n_{hi,C}$ is the recognition result of the decision tree h_i for the prediction class sample C. $I\left(*\right)$ is the sex function.

4. Experimental results and analysis

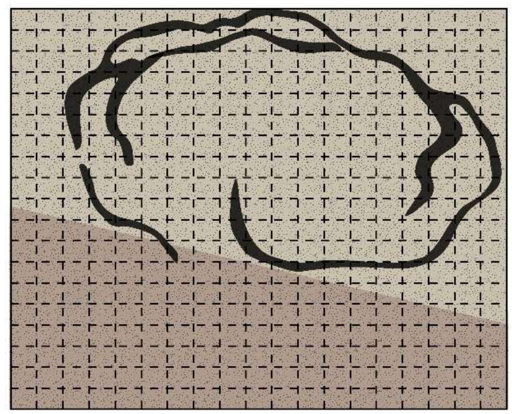
In order to verify the performance of the image feature extraction and random forest algorithm proposed in this paper on the recognition of cultural heritage protection modes of tomb murals, 10239 images of tomb murals under 5 classes of protection modes, which were preprocessed and labeled as described in the previous section, were selected for experiments. The training data and test data of each category in this paper are obtained by randomly slicing in the ratio of 6:4 respectively.

4.1. Feature extraction process

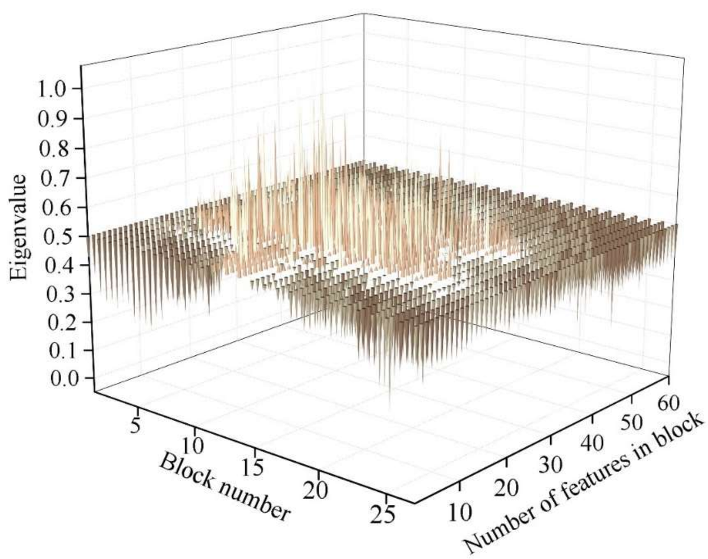
4.1.1. Color feature extraction. The HOG descriptor in HSV color space is determined by a detection window of size 20 pixels × 20 pixels, which is 1 pixel unit for each movement of the detection window in the horizontal and vertical directions again in the image. Meanwhile, the size of the block is defined as 16 pixels × 16 pixels, which is also 1 pixel unit for each movement of the detection window, and the size of the cell is defined as 1 pixel × 1 pixel. Here the statistics is the histogram of gradient in 3 directions within each cell. It is analyzed that a detection window has $((20-16)/1+1)\times((20-16)/1+1)=25$ Blocks, each Block includes 4 Cells, and a 3-dimensional vector is extracted from each Cell, so a $25\times4\times3=300$-dimensional HOG descriptor vector is in a detection window. Fig. 4 shows the original image, the number of Blocks and the number of features corresponding to the original image and the extracted HOG features in the in-situ protection class. After the above process, the dimension of HOG features is 300, and the dimension is in line with the model feature training annotation, which can realize the color feature extraction for tomb murals.



(a) Primary image



(b) HOG characteristics



(c) The number of blocks and features

Fig. 4. Color extraction process

4.1.2. Texture Feature Extraction. The four statistics of angular second order moments, correlation, contrast and entropy obtained from the grayscale covariance matrix are computed and they are used as features of the texture image. Here the values of the above four statistics corresponding to the directions at 0°, 45°, 90° and 135° are computed separately to obtain a 16-dimensional feature vector. Table 2 shows the GLCM feature values in the horizontal direction for each category of texture image, only one sample of texture image is listed for each category, and M1-M5 denote five cultural heritage preservation modes such as in situ preservation, respectively. The experimental comparison proves that extracting the GLCM feature values of the LBP image is better than extracting the GLCM feature values of the original image alone.The LBP image is a new image of the same size as the original image obtained by calculating the LBP value of the original image.

Table 2. GLCM eigenvalue

Category name	Angular moment	Correlation	Contrast ratio	Entropy
M1	0.023	4.531	75.892	4.073
M2	0.036	4.062	68.784	3.286
M3	0.022	4.284	41.239	4.154
M4	0.028	4.327	95.071	4.297
M5	0.027	4.299	88.492	4.212

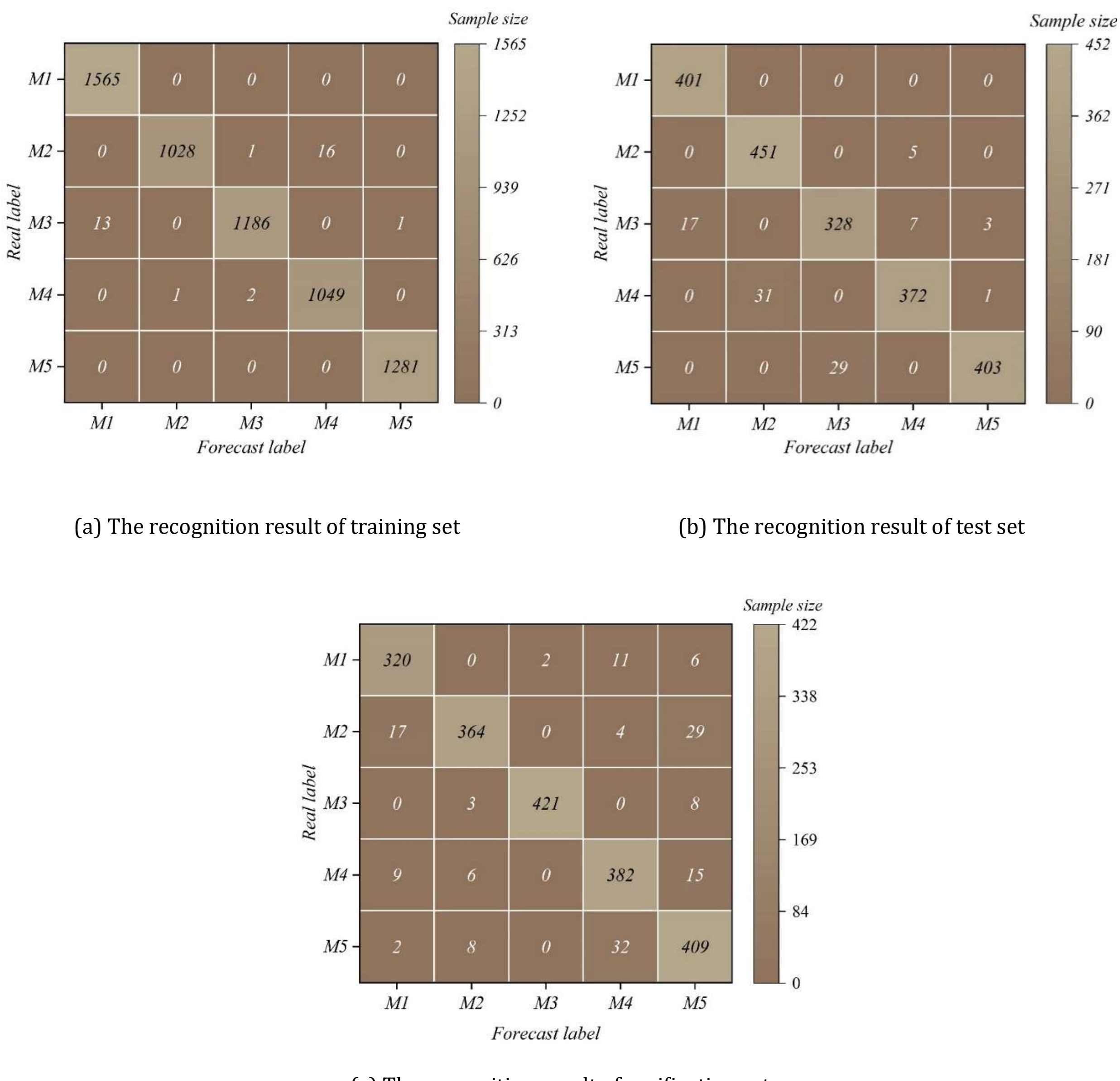
4.2. Identification of cultural heritage conservation models

4.2.1. Random Forest Algorithm Recognition Performance Analysis. In the experiment, the recognition model based on the random forest for the protection of cultural heritage patterns of tomb murals is used to separately count the recognition results before and after the data augmentation is implemented in the data set. At the same time, ResNet18 deep residual network is introduced for comparison, and the recognition accuracy of the two methods is shown in Table 3. As can be seen from the table, under the condition of not using data augmentation, the recognition accuracy of cultural heritage protection patterns using the two methods in the dataset has a small difference, while after data augmentation, the method in this paper improves 29.05%, 27.59%, 29.05% than the pattern recognition accuracy of the ResNet18 deep residual network in the training set, the test set, and the validation set, respectively. Therefore, the random forest recognition model in this paper is able to improve the accuracy of pattern recognition for cultural heritage protection of tomb murals compared with ResNet18 deep residual network, and the improvement effect is more significant. From the table, it can also be concluded that the data augmentation operation increases the recognition effect. In this paper, the recognition accuracy of the random forest model before and after the data augmentation operation is increased by 32.77%, 31.49% and 32.06% respectively. This is because the data augmentation operation enriches the picture information in the dataset on the basis of the original database, which enables the model to learn more comprehensively and improves the learning ability.

Table 3. Comparison of classification accuracy before and after data augmentation

Classification method	Data augmentation	Training set	Test set	Verification set
ResNet18	No	62.83%	61.49%	60.25%
	Yes	66.79%	65.48%	63.84%
Random forest	No	63.07%	61.58%	60.83%
	Yes	95.84%	93.07%	92.89%

The confusion matrix of the Random Forest-based model for cultural heritage protection of tomb murals under the training set, test set and validation set is shown in Fig. 5, (a)-(c) represent the pattern recognition results on the training set, test set and validation set, respectively, and M1-M5 represent the five cultural heritage protection patterns, such as in-situ protection. From the confusion matrix display, it can be concluded that in the training set, most of the cultural heritage protection patterns can be accurately recognized through the processing of this paper's model, and the recognition accuracy can reach more than 99%. However, the misrecognition of the overall relocation (M2) and framing (M3) modes is more serious, in which 16 images under the overall relocation mode (M2) are recognized as the brick uncovering mode (M4), and 13 framing modes (M3) are recognized as in situ preservation modes (M1). The overall false recognition rate is less than 1%, indicating that the random forest-based recognition model performs well on the training set. From Fig. 5(b) and (c), it can be seen that the model performs slightly worse on the test set than on the training set, and slightly worse on the validation set than on the test set. However, the accuracy of the model on the test set and validation set reaches 95.46% and 92.58% respectively, which are both higher than 90%. This fully demonstrates the effectiveness of the Random Forest-based model for pattern recognition of cultural heritage protection of tomb murals proposed in this paper.



(a) The recognition result of training set

(b) The recognition result of test set

(c) The recognition result of verification set

Fig. 5. Pattern recognition result

In order to better verify the advantages of the model in the recognition of cultural protection patterns of tomb murals, in addition to the comparison with ResNet deep residual network, based on the constructed tomb murals dataset, other existing centralized methods were compared, and the results are shown in Table 4. From the table, it can be seen that the recognition model based on random forest can better realize the recognition of cultural heritage protection patterns of tomb frescoes, no matter in the training set or test set and validation set. Compared with several existing methods, the recognition accuracy of this paper's method is improved by at least 12.88% in the training set, and by at least 12.24% and 11.50% in the test set and validation set, respectively. Therefore, the method proposed in this paper is significantly effective in the task of cultural heritage conservation pattern recognition of tomb murals.

Table 4. Recognition results of different algorithms

Classification method	Recognition accuracy		
	Training set	Test set	Verification set
Improved GhostNet	72.38%	70.26%	64.58%
ICNN	77.56%	74.39%	71.23%
DCDDF	82.39%	80.78%	79.24%
ResNet18	86.57%	83.22%	81.08%
Random forest	99.45%	95.46%	92.58%

4.2.2. Time-consuming analysis of data enrichment operations. Considering that data augmentation will increase the time of model learning, in this paper, the training time of ResNet t_1 and the training time of Random Forest model t_2 are recorded in the experiments, and the results of the consumed time before and after data augmentation are shown in Table 5. From the table, it can be seen that the overall time consumption of the random forest algorithm is much smaller than that of the ResNet algorithm. Before and after data augmentation, the growth rates of the two algorithms in time consumption are 94.09%, 79.74%, 70.40% and 28.41%, 30.06%, 40.99% respectively. It indicates that the model in this paper outperforms the ResNet algorithm in terms of recognition accuracy and time consumption of data augmentation operation, and is able to adequately perform the task of recognizing cultural heritage protection patterns of tomb murals.

Table 5. Comparison of time resource consumption before and after data augmentation

Data set	Training set		Test set		Verification set	
	t_1	t_2	t_1	t_2	t_1	t_2
Before	10.49s	2.71s	9.82s	1.63s	9.73s	1.61s
After	20.36s	3.48s	17.65s	2.12s	16.58s	2.27s

5. Conclusion

In this paper, the random forest model is used as the basis to construct a pattern recognition model for the protection of cultural heritage of tomb murals. The mural painting images collected from the tomb of Prince Zhanghuai are used to construct a dataset, and the pattern recognition model constructed in this paper is validated based on this dataset after data augmentation and label addition.

The recognition accuracy of the model in this paper is as high as 99.45% on the training set, although there are cases where the "overall relocation" mode is misidentified as the "brick removal" mode and the "frame" mode is misidentified as the "in-situ protection" mode, but the overall misidentification rate is less than 1%. And the model in this paper can also achieve a high recognition accuracy of 95.46% and 92.58% on the test set and validation set. It shows that the pattern recognition model for the protection of cultural heritage of tomb murals constructed based on the random forest algorithm in this paper has significant effectiveness. Meanwhile, compared with other existing models, the accuracy of this paper's model on the training set is 12.88% higher than that of the ResNet18 deep residual network model, which is the next best performer. The improvement of 12.24% and 11.50% on the test set and validation set, respectively, further highlights the competence of this paper's model for the task of pattern recognition of cultural heritage conservation of tomb murals.

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