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# Machine Learning Algorithm-Based Strategy for Identifying Housing Interior Design Styles and Optimizing Artistic Solutions

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**Abstract** Social progress has prompted people to gradually improve the quality of life, and the requirements for the living environment are also higher and higher, and the housing interior design with artistic style has attracted widespread attention. In this paper, HSV color model and GLCM algorithm are used to extract color features and texture features of housing interior design style images, and then combined with local sorting difference refinement algorithm to obtain local features of housing interior design style images. After obtaining the two features of housing interior design styles, a simple Bayesian classifier of machine learning algorithm is constructed to recognize and classify housing interior design styles. In order to enhance the accuracy of style identification and classification, an adaptive majority voting decision fusion algorithm is introduced to distribute the weights of the plain Bayesian classification results and output the optimal weights to improve the accuracy of housing interior design style identification and classification. The average accuracy of color features extracted by HSV color model is up to 91.05%, and the classification accuracy of LSDRP algorithm is 98.39% when local features are extracted. Compared with the TSVM model, the OA, AA and Ka indexes of this paper's method are improved by 20.79%, 29.03%, and 27.39%, respectively, when performing housing interior design style identification and classification. The use of machine learning algorithms can realize the accurate identification and classification of housing interior design styles, which provides a reference for improving the level of housing interior art atmosphere design.

**Index Terms** living environment, housing interior design, design style recognition, plain Bayes, LSDRP algorithm

## I. Introduction

In recent years, Artificial Intelligence (AI) and machine learning technologies have developed rapidly, and with the improvement of data availability and the enhancement of computational power, the landing projects of machine learning technologies have also grown. The characteristics of non-linear computation of machine learning models enable them to have more powerful computing power and model performance when facing complex mathematical problems [1]-[3]. In addition, neural network models represented by deep learning have a powerful fitting ability to approximate any complex mathematical function, and the dimension of neural networks can theoretically reach infinite dimensions [4]-[6]. In addition, the neural network contains many hidden layers, which in turn have many hidden nodes, thus making the neural network's expressive power very powerful, so that it can unsupervised learning of the characteristics of the data [7]-[9].

In housing interior design, deep reinforcement learning algorithms can be applied to multiple scenarios to effectively optimize design solutions and improve design efficiency. Machine learning techniques can be utilized to generate high-quality interior design images that can be used to provide design inspiration or for design solution presentation [10], [11]. It can also be used to classify and recognize industrial interior design images, such as identifying furniture types, colors, shapes, and other information, thus helping designers to better design interiors [12], [13]. Natural language processing can be applied to parse user needs and understand textual information related to interior design such as design requirements, budget constraints, etc. [14], [15]. Image processing techniques can be used to de-noise, enhance, and transform the interior design images to improve the visualization and quality of the design images [16], [17]. Artificial intelligence and machine learning technologies have a wide range of application prospects in housing interior design, which can help designers to complete design tasks more quickly, efficiently and accurately, and also provide better interior design experiences and services for ordinary users [18]-[20].

The article proposes an adaptive majority voting decision fusion algorithm, which can realize the effective fusion of global and local features for housing interior design style recognition, thus enhancing the recognition rate of housing interior design styles.

The combination of artistic style and housing interior design aims to emphasize the fusion of personalized and modern styles in order to achieve the purpose of combining design aesthetics and practicality. In this paper, the HSV color model and GLCM algorithm are used to extract the color and texture features of the interior design style, and the LSDRP algorithm is used to obtain the local features. Then, a simple Bayesian classifier is used to realize the effective classification of housing interior design styles. In addition, an adaptive majority voting decision fusion algorithm is proposed, which aims to assign the optimal weights to the classification results, so as to improve the performance of recognizing and classifying housing interior design styles. In view of the feasibility of the above methods, model validation is carried out with homemade datasets, and an optimization scheme for housing interior design art styles is proposed in combination with new Chinese decorative art styles.

## II. Theoretical foundations of relevant technologies

Times are changing, people's aesthetics are also changing all the time, interior design in the modernization of various elements to facilitate people's lives at the same time, but also let people feel the same boring. The combination of art style and housing interior design is an important means of innovative housing interior design, so that people feel the interior design of a new way of thinking, not just a certain style, but the perfect integration of modern interior design and art style. In the process of housing interior design that integrates artistic styles, it is necessary to combine machine learning algorithms to fully identify their specific styles in order to provide guidance for optimizing the artistic style of housing interior design. In order to provide a good livable environment to meet the diverse needs of people.

### *II. A. Image Style Recognition Classification*

#### II. A. 1) Semi-supervised image classification

For style recognition of housing interiors, its housing interior design style images belong to the category of semi-supervised images, while semi-supervised image classification utilizes a small amount of labeled data as well as a large amount of unlabeled data to classify the images. Given a dataset $D = D_l \cup D_u$, where $D_l = \{x_{l,i}, y_i\}_{i=1}^{N_l}$ is a collection of labeled data and $D_u = \{x_{u,i}\}_{i=1}^{N_u}$ is a collection of unlabeled data. $x_{l,i}$ and $y_i$ are the $i$ th labeled data and its corresponding labels respectively and $x_{u,i}$ is the $i$ th unlabeled data. $N_l$ as well as $N_u$ are the number of labeled data and the number of unlabeled data, respectively, and in general $N_l \ll N_u$. Typically, semi-supervised learning trains the model by minimizing the loss function below, i.e.,:

$$L = \lambda_l L_{sup} + \lambda_u L_{usp} \tag{1}$$

where $L_{sup}$ corresponds to the loss function used for training with labeled data, and $L_{usp}$ corresponds to the loss function used for training with unlabeled data, e.g., consistency regularization loss. $\lambda_l$ and $\lambda_u$ are the weights of the corresponding losses.

The steps of the consistency regularization method can be summarized as follows:

Step1 Randomly select batch data from the dataset, perturb the batch data, such as data enhancement and other operations, to get different views of the same data after different perturbations.

Step2 Input different views of the same data after perturbation into the model to get different predictions accordingly.

Step3 Train the model by minimizing the difference between the predictions of different perturbed views of the same data.

Step4 Repeat Step1 to Step3 until the model converges.

#### II. A. 2) Image style recognition process

Figure 1 shows the basic process of image style recognition and classification, which mainly includes four steps: data preprocessing, sample labeling, network training and classification, and classification results evaluation.

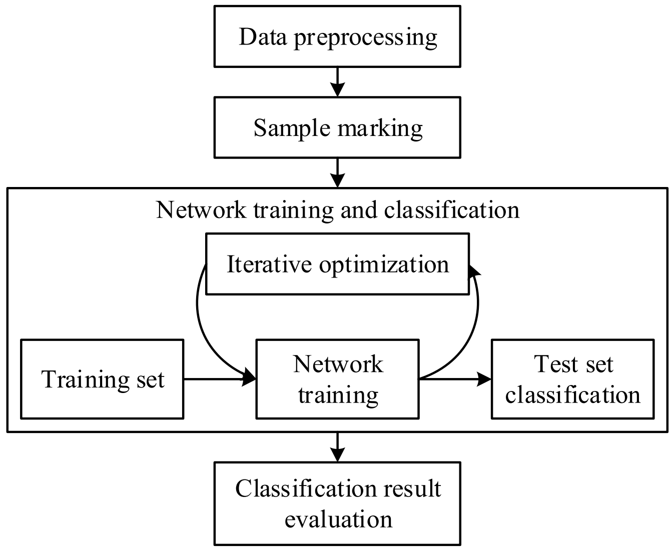


Figure 1: Image style recognition process

(1) Data Preprocessing

When shooting image data related to housing interior design, the camera is subjected to external changes in environmental factors, camera noise and other aspects of interference, resulting in a large amount of redundant information and noise filled with images of housing interior design. The data preprocessing operation improves the clarity and accuracy of the data through a series of steps, including normalization, noise reduction and so on.

(2) Sample labeling

Sample labeling involves labeling each pixel point on the spatial dimension of housing interior design image data, i.e., assigning pixels to the category to which they belong, e.g., furniture, decoration, etc. This process can be done manually by the researcher using a priori knowledge or by employing semi-supervised or unsupervised learning based labeling.

(3) Model Training and Classification

Model training and classification are the key steps in housing interior design image style recognition and classification. By feeding the training set into the constructed image style recognition and classification model, automatic learning of abstract and high-level features in the image is realized. Adaptive optimization of weights is achieved by defining a loss function and using an optimizer. This process usually involves multiple rounds of iterative optimization to ensure that the model fits and learns the complex features in housing interior design images well. After the model training is completed, a test set is fed into the model to obtain the predicted classification results for each pixel in the image.

(4) Evaluation of classification results

After predictive classification of housing interior design image style data by the model, the predictive classification map and the label information map need to be compared and analyzed to evaluate the performance of the model.

#### II. A. 3) Evaluation of style recognition classification

In order to quantitatively analyze the results of housing interior design style recognition classification, the classification results of the model need to be quantitatively evaluated. Whether it is machine learning or deep learning, the purpose of the identification and classification of housing interior design styles is to use the known information to categorize the unknown categories of interior design styles as reasonably as possible, and to assign the correct attribute labels to the pixels corresponding to the housing interior design styles.

The experimental evaluation criteria involved in this paper, i.e., Overall Accuracy (OA), Average Accuracy (AA), and Kappa Coefficient (Ka) are all computed by relying on the Confusion Matrix, and are used to evaluate and analyze the classification effect of the constructed model in the practical application of housing interior design style classification.

(1) OA indicates the proportion of the number of samples predicted to be correctly classified to all samples, and it evaluates the prediction accuracy of the overall samples. Then:

$$OA = \frac{\sum_{i=1}^{n} h_{i,i}}{\sum_{i=1,j=1}^{n} h_{i,j}} \tag{2}$$

(2) AA denotes the summed average of the number of samples in each category whose predictions are correctly classified as a proportion of all samples in this category, and it denotes the average accuracy of the predictions in each category. Then:

$$AA = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{h_{i,i}}{\sum_{j=1}^{n} h_{i,j}}\right) \tag{3}$$

(3) Ka denotes the consistency test between the prediction results and the true value of the label, taking the value of [-1,1], which is usually greater than zero, and its larger value indicates the stronger characterization ability of the model. Then:

$$Ka = \frac{OA - Pe}{1 - Pe} \tag{4}$$

$$Pe = \frac{\sum_{i=1}^{n}\left(\left(\sum_{j=1}^{n} h_{i,j}\right)\times\left(\sum_{j=1}^{n} h_{j,i}\right)\right)}{\left(\sum_{i=1,j=1}^{n,n} h_{i,j}\right)^2} \tag{5}$$

where $Pe$ denotes the desired precision, i.e., the sum of the products of the sum of the elements of row $i$ and the sum of the elements of column $i$ of the confusion matrix, divided by the square of the total number of all the samples, along with the statistics of the training and testing time of the model.

### *II. B.Global versus local features*

#### II. B. 1) Global feature extraction

For the identification and classification of housing interior design style, it is necessary to fully obtain the specific characteristics of housing interior design style image, mainly including color characteristics and texture characteristics, in order to assist researchers to better carry out the identification of housing interior design style, so as to provide reference for the optimization of housing interior design art style.

(1) Color features

Color characteristics depend on the color space selected, HSV color space can intuitively express the brightness, hue and vividness of the color, which is more in line with the characteristics of human visual perception. The images of housing interior design styles are usually constructed from common colors such as black, orange, blue, green, white, etc., and the pattern position of interior design styles is not fixed, and there is a phenomenon of incomplete patterns at the edges [21].

Color histogram describes the proportion of different colors in the whole image without focusing on the spatial location of each color, so it can be used as a color feature extraction method for housing interior design style images. A suitable color quantization scheme can reduce the computational complexity without losing too much color information. Based on the analysis of the color of housing interior design style images, too fine a color quantization method does not necessarily improve the ability to distinguish between housing interior design style images with different color combinations, but rather increases the computational complexity. Therefore, in the study of this paper, H is non-uniformly quantized into 8 parts based on the hue range of common colors used in housing interior design style images, and S and V are divided into black area, white area and colored area, i.e., quantized by H:S:V=8:3:3. I.e.:

$$H = \begin{bmatrix} 0H & \in & B16,20] \\ 1H & \in & [21,40] \\ 2H & \in & [41,75] \\ 3H & \in & [76,155] \\ 4H & \in & [56,190] \\ 5H & \in & [91,270] \\ 6H & \in & [271,290] \\ 7H & \in & [291,315] \end{bmatrix} \tag{6}$$

$$S = \begin{cases} 0S & \in & [0, & 0.2] \\ 1S & \in & [0.2, & 0.7] \\ 2S & \in & [0.7, & 1] \end{cases} \tag{7}$$

$$V = \begin{cases} 0V \in & [0, & 0.2] \\ 1V \in & [0.2, & 0.7] \\ 2V \in & [0.7, & 1] \end{cases} \tag{8}$$

A one-dimensional feature vector is obtained by combining the results of the quantization of the three color components, i.e:

$$F = Q_S \times Q_V \times H + Q_V \times S + V = 9H + 3S + V \tag{9}$$

where $Q_s, Q_v$ is the number of quantization levels of $S,V$ components respectively, $Q_s = 3, O_v = 3$ . $H,S,V$ maximum can be taken as 7, 2, 2 respectively, the value interval of $F$ is [0,71], and the dimension of the histogram after color quantization is 72 dimensions.

(2) Texture feature extraction

For texture features of housing interior design style images, this paper introduces the gray scale covariance matrix for extraction. Gray Level Coevolution Matrix (GLCM) is a statistically based method for image texture feature extraction [22]. It is defined as the statistical probability $P(m,n,D,r)$ of simultaneous occurrence with a pixel point with distance $D = \sqrt{\Delta} s^2 + \Delta w^2$ and gray level $n$ from a pixel point with gray level $m$ in image $(s,w)$, $x$ direction is the column of the image, $y$ direction is the row of the image, $f(s,w) = m$ is the value of the pixel at coordinate $(s,w)$, $f(s+\Delta s, w+\Delta w)$ is the value of the pixel at coordinate $(s+\Delta s, w+\Delta w)$, and mathematical expression of probability $P(m,n,D,r)$ is expressed as:

$$\begin{aligned} P(m,n,D,\gamma) &= \{(s,w),(s+\Delta s, w+\Delta w) \mid f(s,w) \\ &= m, f(s+\Delta s, w+\Delta w) = n; s,w = 0,1,2,\cdots M-1\} \end{aligned} \tag{10}$$

When GLCM is directly utilized for texture feature extraction of housing interior design style images, the extraction effect is not obvious due to the large dimension of GLCM. In order to make up for the shortcomings of large GLCM dimension and complex calculation, this paper introduces three quadratic GLCM feature statistics for texture feature extraction of housing interior design style images. The details are as follows:

Contrast is a measure of the distribution of the GLCM values and the changes in the image parts, the larger the value of the elements of the GLCM away from the diagonal, the greater the contrast and the better the result. Assuming that the normalized GLCM is $p(m,n)$ , the contrast can be expressed as:

$$CON = \sum_m \sum_n (m-n)^2 p(m,n) \tag{11}$$

The angular second order distance is used to describe the degree of uniformity of the GLCM distribution and the coarseness of the image texture.The closer the values of the elements in the GLCM are, the smaller the value of the angular second order distance is, which means that the texture is more detailed. If the difference between the element values in the GLCM is large, the angular second order distance value is large. If the normalized GLCM is $p(m,n)$ , then the contrast can be described as:

$$ASM = \sum_m \sum_n p(m,n)^2 \tag{12}$$

The inverse disparity reflects the magnitude of variation in the image texture; if the image has little variation between localities and is more uniform, the inverse disparity is larger. If the normalized GLCM is $p(m,n)$ , then the contrast can be formulated as:

$$IDM = \sum_m \sum_n \frac{p(m,n)}{1+(m+n)^2} \tag{13}$$

### II. B. 2) Local feature extraction

After fully obtaining the global features of the housing interior design style image, there are still some local features on the style image that will affect the accuracy of the image style recognition classification model for housing interior design style recognition. Therefore, it is necessary to extract the local features of housing interior design style images, considering the limitations of the traditional LBP algorithm in extracting local features, this paper proposes a local ranked difference refinement (LSDRP) algorithm to enhance the local feature extraction ability of housing interior design style images [23].The specific construction steps of the LSDRP descriptor are as follows:

Step1 Arrange the sampling points in the local neighborhood in descending order according to the pixel gray value to get the locally sorted neighborhood.

Step2 In the locally sorted neighborhood, binarize the adjacent sampling points and the center point, i.e., obtain the upper sorted binary sequence whose neighborhood value is greater than or equal to the center value and the lower sorted binary sequence whose neighborhood value is smaller than the center value. Then assign initial weights to the upper and lower binary sequences, so that the weight at the corresponding position of the upper binary sequence is $2^{p}$ and the weight at the corresponding position of the lower binary sequence is $2^{P-1-p}$.

Step3 Calculate the pixel grayscale difference between the center point and the adjacent sampling points in the locally sorted neighborhood, and normalize the grayscale difference so that its value is in [0,1], described as:

$$D_{p}=\frac{|g_{p}^{'}-g_{c}|}{255+g_{c}} \tag{14}$$

where $P$ is the number of local neighborhood sampling points; $g_{\varsigma}$ is the gray value of the pixel at the center point of the local neighborhood; $g_{p}^{'}$ is the gray value of the $p$ th sampling point within the sorted local neighborhood $(p=0,1,\cdots,P-1)$.

Step4 Update the initial weights at the corresponding positions in the upper sorted binary sequence and the lower sorted binary sequence using equation (14), described as:

$$W_{p}^{up}=(1+D_{p})2^{p} \tag{15}$$

$$W_{p}^{low}=(1+D_{p})2^{P-1-p} \tag{16}$$

Step5 Multiply the upper sorted binary sequence and the lower sorted binary sequence with the new weights $W_{p}^{up}$ and $W_{p}^{low}$ at the corresponding positions, respectively, and accumulate to obtain the localized sorted upper difference refinement pattern $LSDRP^{up}$ and the localized sorted lower difference refinement pattern $LSDRP^{low}$. For the localized centroid $(i,j)$ at a given position, its $LSDRP^{up}$ and $LSDRP^{low}$ descriptors are defined as:

$$LSDRP_{R,P}^{up}(i,j)=\sum_{p=0}^{P-1}z(g_{p}^{'}-g_{c})W_{p}^{up} \tag{17}$$

$$z(x)=\begin{cases}1, x\geq 0\\ 0, x<0\end{cases} \tag{18}$$

$$LSDRP_{R,P}^{low}(i,j)=\sum_{p=0}^{P-1}f(g_{p}^{'}-g_{c})W_{p}^{low} \tag{19}$$

$$f(x)=\begin{cases}0, x\geq 0\\ 1, x<0\end{cases} \tag{20}$$

Step6 For a texture image of size $M\times N$, construct the feature histograms of descriptors $LSDRP^{up}$ and $LSDRP^{low}$ respectively and cascade the histograms of $LSDRP^{up}$ and $LSDRP^{low}$, thus obtaining the LSDRP feature histogram representation of the image, described as:

$$H_{LSDRP}=[H_{LSDRP^{up}},H_{LSDRP^{low}}] \tag{21}$$

$$H_{LSDRP^{sp}}(k)=\sum_{i=1}^{M}\sum_{j=1}^{N}h(LSDRP_{R,P}^{sp}(i,j),k) \tag{22}$$

$$H_{LSDRP^{low}}(k)=\sum_{i=1}^{M}\sum_{j=1}^{N}h(LSDRP_{R,P}^{low}(i,j),k), 0\leq k\leq 2^{P}-1 \tag{23}$$

$$h(x,y)=\begin{cases}1, if\ x=y\\ 0, else\end{cases} \tag{24}$$

As can be seen from Eq. (14), the numerator part of $D_p$ contains the information about the magnitude of the difference in pixel grayscale between the centroid and the adjacent sampling points in the local neighborhood, and the denominator part contains the grayscale value of the centroid in that local neighborhood. In addition, the use of $W_p^{up}$ and $W_p^{low}$ to update the weights is to avoid the problem of a narrower distribution of feature histograms that would result from updating the weights directly using $D_p$.

## II. C. Machine Learning Classification Algorithms

### II. C. 1) Bayes' Theorem

Inside the Bayesian view, the production of a sample $x=(x_1,x_2.......x_n)$ is divided into 2 steps. The first step is to envision obtaining a sample $\theta'$ from the $(\theta)$, which is more abstract; the second step is to produce a sample $x=(x_1,x_2......x_n)$ from the overall distribution $P(x\mid\theta)$, which is more concrete, and the $x$ probability of this sample is to show a positive relationship with the joint density function, i.e., $P(x\mid\theta')=\prod_{i-1}^{n}P(x_i\mid\theta')$ [24].

This joint density function sets all the information with the sample messages together and is called the likelihood function, denoted $L(\theta')$. With the observations $x=(x_1,x_2......x_n)$ from the sample, the information $\theta$ from both the aggregate and the sample is in $L(\theta')$ what is known as the likelihood principle.

Because $\theta'$ is obtained by assumption, it remains unambiguous, it is calculated from the pre-test distribution $\pi(\theta)$ and one would like to take into account all the possibilities that $\theta$ may exist based on the pre-test data. The joint distribution of sample $x$ and parameter $\theta$ can be expressed as:

$$h(x,\theta)=p(x\mid\theta)\,\pi(\theta) \tag{25}$$

After obtaining the sample observations $x=(x_1,x_2.......x_n)$, one can make an inference according to $h(x,\theta)$ vs. $\theta$. $h(x,\theta)=\pi(\theta\mid x)m(x)$, where $m(x)$ is the edge density function of $x$, i.e:

$$m(x)=\int h(x,\theta)d\theta=\int p(x\mid\theta)\pi(\theta)d(\theta) \tag{26}$$

It has nothing to do with $\theta$, and $m(x)$ contains no information about $\theta$. So the speculation that can be made about $\theta$ should be the conditional distribution $\pi(\theta\mid x)$, which is given by:

$$\pi(\theta\mid x)=\frac{h(x,\theta)}{m(x)}=\frac{p(x\mid\theta)\pi(\theta)}{\int p(x\mid\theta)\pi(\theta)\mathrm{d}(\theta)} \tag{27}$$

### II. C. 2) Plain Bayesian Classifier

In order to realize the accurate identification and classification of housing interior design styles, after obtaining the global and local features of housing interior design styles, a plain Bayesian classifier is constructed from Bayes' theorem to realize the identification and classification of housing interior design styles.

A plain Bayesian classifier is a classification algorithm that introduces the assumption of conditional independence of attributes in a probabilistic framework. Let the sample dataset $D=\{x_1,x_2,\cdots,x_m\}$, each sample $x_i=(x_{i1},x_{i2},\cdots,x_{in})$ be a $n$-dimensional attribute vector with category labeling $y=\{c_1,c_2,\cdots,c_N\}$, i.e., $D$ can be classified into $N$ categories [25].

Based on Bayes' theorem, the posterior probability $P(c\mid x)$ can be expressed as:

$$P(c\mid x)=\frac{P(c)P(x\mid c)}{P(x)} \tag{28}$$

where $P(c)$ is the class prior probability, $P(x\mid c)$ is the class conditional probability of sample $x$ with respect to marker $c$, and $P(x)$ is the evidence factor.

Estimating the posterior probability $P(c\mid x)$ in Bayesian classifiers translates into estimating the prior probability $P(c)$ and the likelihood $P(x\mid c)$, $P(c)$ which can be estimated by the frequency of occurrence of each type of samples, but $P(x\mid c)$ is $x$ the joint probability on all attributes, which is difficult to estimate. So plain Bayes introduces the assumption of conditional independence of attributes and the above equation can be expressed as:

$$P(c\mid x)=\frac{P(c)}{P(x)}\prod_{i=1}^{n}P(x_i\mid c) \tag{29}$$

where $n$ is the number of attributes and $x_i$ is the value of $x$ on the $i$ th attribute.

Since $P(x)$ is the same for all categories, there is by Bayesian decision criterion:

$$h_{nb}(x)=\arg\max_{c\in y}P(c)\prod_{i=1}^{n}P(x_i\mid c) \tag{30}$$

This is the expression for the plain Bayesian classifier.

Let $D_c$ denote the set consisting of class $c$ samples in training set $D$, where $|D|$ denotes the total number of samples in the training set, and if there are sufficient independent identically distributed samples, the class prior probability can be estimated as

$$P(c)=\frac{|D_c|}{|D|} \tag{31}$$

For discrete attributes, let $D_c, x_i$ denote the set consisting of the samples in $D_c$ that take the value $x_i$ on the $i$ rd attribute, then the conditional probability $P(x_i \mid c)$ can be estimated as:

$$P(x_i \mid c)=\frac{|D_{c,x_i}|}{|D_c|} \tag{32}$$

Considering the probability density function for continuous attributes and assuming $p(x_i \mid c) \sim N(\mu_{c,j}, \sigma_{c,i}^2)$, where $\mu_{c,i}$ and $\sigma_{c,i}^2$ are the mean and variance, respectively, of the values taken by the samples of class $c$ on attribute $i$, we have:

$$p(x_i \mid c)=\frac{1}{\sqrt{2\pi}\sigma_{c,i}}\exp\left(-\frac{(x_i-\mu_{c,i})^2}{2\sigma_{c,i}^2}\right) \tag{33}$$

In the testing process, the information provided by other attributes may be "erased" by the values of the attributes that do not appear in the training set, and there will be problems in the discrimination, thus affecting the classification results, so the Laplace correction should be made in the estimation of the probability value. Let $N$ denote the number of possible classes in training set $D$, and $N_i$ denote the number of possible values of the $i$ th attribute, then the class a priori probability and conditional probability can be corrected as follows:

$$\hat{P}(c)=\frac{|D_c|+1}{|D|+N} \tag{34}$$

$$\hat{P}(x_i \mid c)=\frac{|D_{c,x_i}|+1}{|D_c|+N_i} \tag{35}$$

# III. Housing interior design style recognition model

The future of housing interior design will pay more attention to the balance between art and function. The full integration of artistic color theory and style can achieve the perfect combination of art and functionality in housing interior design. Through the use of diversified artistic colors and patterns, housing interior designers can not only achieve the visual aesthetics of housing interior design, but also create a practical space that meets the needs and lifestyles of the occupants. This combination will make interior design not only a kind of decoration, but also a way of life and expression.

## *III. A. Image data preprocessing*

### III. A. 1) Image normalization

(1) Housing Interior Design Style Image Collection

Data collection of housing interior design style images is the foundation of the whole research process. In order to construct a high-quality housing interior design style image dataset, this paper mainly uses crawler technology to collect different types of housing interior design style images on the Internet. Special attention is paid to housing interior design style images due to their age to fully realize the potential of the image style recognition model.

(2) Image cleaning

In the image cleaning stage, images that are too low quality or do not match the research objectives, such as overexposed or blurred images, are excluded, ensuring the quality of the dataset is crucial for model training.

(3) Resizing and normalization

The normalization process will ensure that the image data is within a uniform range of values, which helps to speed up the training of the model and improve its performance. All selected images were resized to a uniform resolution of 256*256 as a way to ensure the success rate of training the classification model for housing interior design style image recognition.

A total of 2468 housing interior design style images were collected, and 2247 housing interior design style images remained after data preprocessing, which were made into a HID dataset and divided into a training set and a test set according to the ratio of 7:3 for later research and analysis.

#### III. A. 2) Image noise removal

In order to improve the accuracy of the classification results of the subsequent housing interior design style image recognition, it is necessary to preprocess the housing interior design style image to reduce the noise interference and achieve the purpose of smoothing the image. In this paper, the noise reduction method of mean filtering is used to preprocess the image. First of all, the regularity and neighborhood correlation of pixel points with different gray values within the housing interior design style image are clarified. Since the noise has independence, when it is located in the image, it will stand out due to the absence of pixel points similar to it, which in turn determines the noise points and uses the weighted average within the image neighborhood to replace the noise. The mean filtering noise reduction expression is:

$$g(x,y)=\frac{1}{W}\sum_{(i,j)\in S_p}f(i,j) \tag{36}$$

where $g(x,y)$ is the pixel value corresponding to the image position $(x,y)$ after filtering and noise reduction processing, $W$ is the sum of all coefficients within the image template $S$ , $S_{xy}$ is the image center point, and $f(i,j)$ is the image to be preprocessed. The housing interior design style image is processed by the above equation to achieve the purpose of reducing image noise and smoothing the image.

The calculated new pixel values are traversed over the entire image to smooth the image edges and optimize the edge preservation effect, so that the housing interior design style image can be adapted to the subsequent recognition and classification requirements.

### *III. B. Style Recognition Classification Model*

#### III. B. 1) Adaptive decision-level fusion

Decision fusion algorithms for housing interior design style image classification mostly use a decision fusion strategy with uniform weight coefficients for all subclassifiers, so that each classifier in a multi-classifier system has the same vote length. For classifiers with different classification performance, using such a single decision rule will limit the classification performance of the algorithm. For example, for the traditional MV decision fusion strategy, when multiple categories receive the same number of votes, one of them is often randomly selected as the final result, and such a voting strategy is too general, which inevitably produces a certain degree of misclassification, thus reducing the accuracy of the final classification. Therefore, classifiers with strong separability and high accuracy should be given higher weights when voting. In view of this, this paper proposes an adaptive majority voting decision fusion method that assigns values to the weight coefficients in terms of classifier performance merits.

The decision fusion rule can be formulated as follows:

$$N(j)=\sum_{i=1}^{n}\lambda_i I(\omega_i=j) \tag{37}$$

$$\lambda_n=\frac{X_n-X_{\min}}{X_{\max}-X_{\min}} \tag{38}$$

where $I$ is the indicator function, $\omega$ is the class label of each class, $n$ represents the number of classifiers, and $N(j)$ represents the number of class $j$ . The weight coefficients of the sub-classifiers are evaluated by "cross-validation" $\lambda_n, X_n$ represents the classification accuracy of the validation set for the $n$ th classifier, $x_{\min}$ represents the minimum classification accuracy, and $X_{\max}$ represents the maximum classification accuracy.

In classifying housing interior design style images by adaptive majority voting decision fusion method, the number of subclassifiers should be determined, then the values of classification labels should be obtained based on the classification accuracy of all subclassifiers, and finally, the magnitude of the weight coefficients of individual classifiers should be determined by normalizing all classification labels.

The global class affiliation function of LOGP is estimated using the posterior probabilities of all classifiers. The improvement of the LOGP decision fusion rule can be expressed as:

$$C(w_j\mid x)=\prod_{i=1}^{n}p_i(w_i\mid x)^{\alpha_i}\Rightarrow\log C(w_j\mid x)=\prod_{i=1}^{n}\alpha_i\log p_i(w_j\mid x) \tag{39}$$

$$\alpha_i=\frac{\sum_{i=1}^{N}(A_i-\mu_i)^2}{N} \tag{40}$$

where $i = 1, 2, \cdots, n$, $n$ represent the number of classifiers and $C$ represents the number of possible classes. $w$ is the class label of each class. The same as the improved MV algorithm, the experiment is conducted by using "cross-validation", $\alpha_i$ is the weight of the $i$ th classifier, $A_i$ is the classification accuracy of the $i$ th validation set, $\mu$ is the average classification accuracy of the validation set, and $N$ represents the number of repetitions of the test for each classifier.

The classification accuracy of the test set of housing interior design style images was utilized to evaluate the performance of the classifiers, i.e., the consistency of the classification accuracy of the test set was used to determine the weighting coefficients of each group.

### III. B. 2) Style Recognition Process

Figure 2 shows the specific flow of the housing interior design style image recognition and classification model designed in this paper, which fuses global and local features through adaptive majority voting decision, and inputs them into the plain Bayesian classifier to obtain the final housing interior design style image recognition and classification results.

The specific process is as follows:

Step1 Image preprocessing. Normalization and noise reduction are performed on the image.

Step2 Feature extraction. Extract the color features of the image using the color histogram, extract the texture features of the image using the grayscale covariance matrix, and then extract the LSDRP features of the image. Among them, the color features and texture features are used as their global features, and the LSDRP features are used as the local features of the image.

Step3 Housing interior design style classification. The extracted color and texture features and LSDRP features are input into the plain Bayesian classifier for classification, and the classification results are obtained respectively.

Step4 Weight Determination. Adaptive majority voting decision fusion algorithm is utilized to measure the importance of features, i.e., as the weights for decision fusion.

Step5 Decision level fusion. The final housing interior design art style recognition classification results are obtained based on the weights.

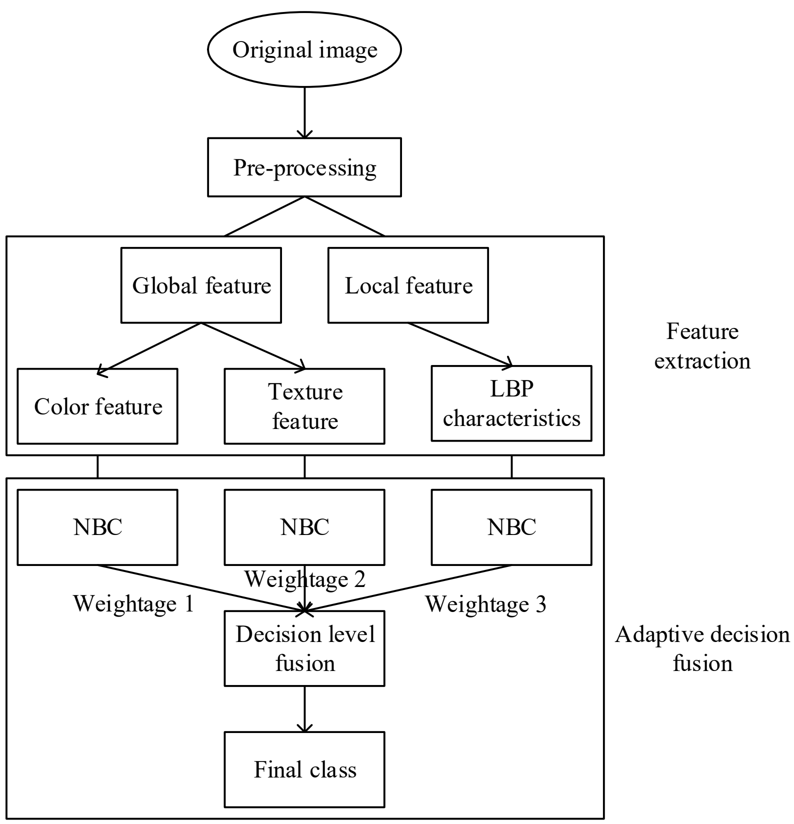


Figure 2: Design style image identification and classification

# IV. Identification and optimization of housing interior design styles

The purpose of combining art and housing interior design is to enhance the artistic aesthetics of the housing interior space environment, so that people can feel the mood of art in their daily lives. This chapter mainly focuses on the validation analysis of the style identification classification model of housing interior design, and based on the results of the analysis, it provides feasible solutions for the optimization of the artistic style of housing interior design, so as to provide guidance for the enhancement of the artistic aesthetics of housing interior design.

## *IV. A. Design style feature extraction validation*

### IV. A. 1) Color space comparison test

In order to HSV color model for housing interior design style image color extraction effectiveness, and relative to other single color features in housing interior design style image color expression integrity of the feasibility, as well as to assist in the realization of housing interior design style recognition classification advantage. In the HID data set established in the previous section, 10 housing interior design images are randomly selected as an example, Lab and RGB are chosen as the comparison color features, and the comparison results of different color spaces are obtained as shown in Figure 3.

The comparison data of the extraction results of the three different color features in 10 housing interior design images show that for each housing interior design image in the color space obtained from the HSV color model through the model extracted feature classification is the best, and its average accuracy reaches 91.05%, which is 1.19% and 0.49% higher than the results of the color feature extraction of Lab and RGB, respectively. This is due to the fact that in this paper, when using the HSV color model for color feature extraction of housing interior style images, the tonal range is non-uniformly quantized into eight different parts as a way to obtain a more complete color space. This indicates that each color space can be fully expressed by the HSV color model, and the combination of adaptive decision-level fusion algorithms can abstract such features and use them for the final decision of identifying and classifying housing interior design style images.

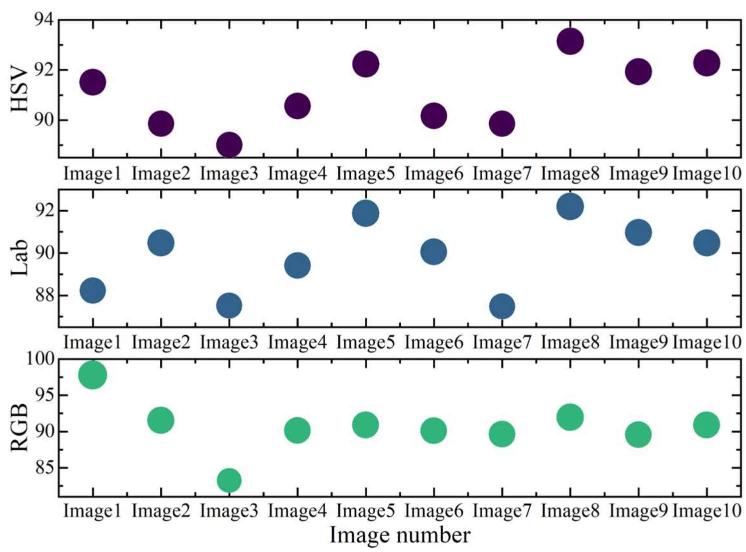


Figure 3: Color space comparison test

### IV. A. 2) LSDRP Validation of Effectiveness

In order to analyze the effectiveness of the LSDRP algorithm proposed in this paper in performing local feature extraction for housing interior design style images, in addition to the HID dataset collected and obtained in this paper, the UIUC dataset, the KTH-TIPS dataset, and the Outex-TC dataset were used as supplementary datasets to carry out the validation. In the experiments, eight commonly used different texture classification methods are selected for accuracy and runtime comparisons, including local binary pattern (LBP), non-uniform pattern of local binary pattern (uLBP), centrosymmetric local binary pattern (CS-LBP), complete local binary pattern CLBP), higher-order directional derivative local binary pattern (DLBP), multi-scale local binary pattern (MSLBP), PLBP, and SRIULBP. Table 1 shows the accuracies of the different algorithms on the four datasets, where the highest scores in each column are marked in bold font.

As can be seen from the table, compared with the eight compared algorithms, the LSDRP algorithm proposed in this paper achieves the highest accuracy on the UIUC, Outex-TC and HID datasets, and the accuracy on the KTH-

TIPS dataset is slightly lower than that of the latest PLBP by 1.62 percentage points. On the UIUC dataset, the classification accuracy of the LSDRP algorithm reaches 86.71%, which is 21.09 and 14.78 percentage points higher than MSLBP and PLBP, respectively, and 4.34 percentage points higher than CLBP. On the Outex-TC dataset, the classification accuracy of the LSDRP algorithm is 98.56%, which is 16.43 percentage points higher than SRIULBP and 2.82 and 1.25 percentage points higher than DLBP and PLBP, respectively. On the KTH-TIPS dataset, the classification accuracy of the LSDRP algorithm is 88.94%, which is 7.57 and 33.33 percentage points higher than MSLBP and SRIULBP respectively, and 1.62 percentage points lower than PLBP. The reason is that LSDRP does not consider the position information in the image compared to PLBP. On the homemade HID dataset, the classification accuracy of LSDRP algorithm reaches 98.39%, which is 5.13 and 1.65 percentage points higher than MSLBP and PLBP, respectively. Therefore, this set of experiments verifies the effectiveness of the LSDRP algorithm, indicating that considering more information about neighboring points and gradient changes can extract more effective texture information about housing interior design style images, which in turn improves the classification accuracy of housing interior design style.

Table 1: Accuracy rate on the four data sets (%)

| Algorithm | UIUC | KTH-TIPS2b | Outex-TC | HID |
|---|---|---|---|---|
| LBP | 60.26 | 78.43 | 90.45 | 88.95 |
| uLBP | 61.85 | 66.95 | 86.38 | 89.42 |
| CS-LBP | 41.48 | 53.37 | 92.64 | 71.64 |
| CLBP | 82.37 | 77.42 | 95.29 | 97.53 |
| DLBP | 48.64 | 76.86 | 95.74 | 90.17 |
| MSLBP | 65.62 | 81.37 | 97.67 | 93.26 |
| PLBP | 71.93 | **90.56** | 97.31 | 96.74 |
| SRIULBP | 38.56 | 55.61 | 82.13 | 78.48 |
| LSDRP | **86.71** | 88.94 | **98.56** | **98.39** |

Table 2 shows the results of comparing the computational time cost of different algorithms on the four datasets. The table shows that the LSDRP algorithm has a relatively short runtime. On the same dataset, the time used by the LSDRP algorithm for feature extraction is approximately the same as that used by the MSLBP, PLBP, and DLBP algorithms, but less than that used by the CLBP algorithm. The reason is that CLBP selects more reference points, which increases the computational and time costs and occupies the extraction time, and the LSDRP algorithm uses up to two reference points for the center point, so the time consumption is relatively less. However, the time consumption is relatively more compared to CS-LBP, LBP, and uLBP algorithms due to the fact that the extra descriptors increase the computation time of the gradient at the center point, thus consuming the extraction time. On different datasets, the Outex-TC dataset consumes the least time (203.28ms), the KTH-TIPS dataset consumes the second highest time, and the UIUC and HID datasets consume higher time. The reason for this is that the more pixel points in the image, the more points need to be computed, resulting in a longer average time for feature extraction. Overall, the LSDRP algorithm improves the algorithm's ability to extract local features from housing interior design style images with relatively low runtime consumption, thus achieving a high classification accuracy of housing interior design styles.

Table 2: Time cost on the four data sets (ms)

| Algorithm | UIUC | KTH-TIPS2b | Outex-TC | HID |
|---|---|---|---|---|
| LBP | 238.42 | 298.67 | 93.42 | 302.13 |
| uLBP | 265.11 | 324.08 | 124.78 | 367.28 |
| CS-LBP | 238.42 | 186.37 | 68.35 | 393.01 |
| CLBP | 526.53 | 636.87 | 312.17 | 627.39 |
| DLBP | 473.88 | 576.67 | 232.49 | 547.46 |
| MSLBP | 485.42 | 563.25 | 245.94 | 535.74 |
| PLBP | 493.95 | 480.93 | 260.66 | 563.27 |
| SRIULBP | 406.54 | 315.48 | 145.08 | 511.06 |
| LSDRP | 496.72 | 561.04 | 203.28 | 535.73 |

## IV. B. Interior Design Style Recognition Analysis

### IV. B. 1) Style Recognition Classification Validation

Taking the self-made HID dataset in this paper as an example, the designed adaptive decision fusion algorithm is utilized to carry out housing interior style image recognition classification experiments. When the HID dataset is labeled with categories, it is labeled with different categories according to European retro (classicism), European modern (modernism), Chinese retro (Ming and Qing styles), and Chinese modern (new Chinese decorative style). After dividing the dataset into training and test sets in the ratio of 7:3, the training set is used to train the interior design style recognition model, and the test set is utilized to test the accuracy of the method for housing interior design style recognition after the training is completed. Taking OA as the evaluation standard, the classification results of housing interior design style recognition are obtained as shown in Figure 4.

As can be seen from the figure, the classification OA values of the four different categories of housing interior design styles show a roughly increasing trend with the increase of training samples, which indicates that within a certain range, increasing the input samples can effectively improve the overall accuracy of the classification model for housing interior design style recognition. When the amount of training samples of housing interior design style images exceeds 500, the classification OA of housing interior design styles for all four categories exceeds 90% and floats around 90%. When the training sample size of housing interior design style images reaches 650, the OA values of European retro (classicism), European modern (modernism), Chinese retro (Ming and Qing styles), and Chinese modern (new Chinese decorative style) are 93.09%, 93.39%, 92.25%, and 91.66%, respectively. Overall, the adaptive majority voting decision fusion algorithm designed in this paper can effectively realize the feature fusion of housing interior design style images, and combined with the plain Bayesian classifier can realize the accurate classification and identification of housing interior design art styles, which can provide a reliable design basis for the optimization of the housing interior design art style scheme.

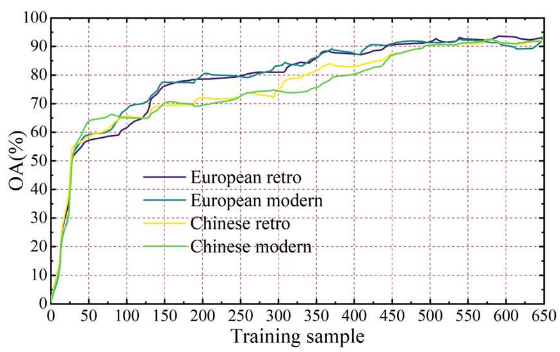


Figure 4: The design style of housing interior design is classified

### IV. B. 2) Comparison of model style identification

In order to assess the overall performance of the proposed method, three metrics were used in the experiments to compare with different methods, and the three metrics were the evaluation metrics OA, AA, and Ka proposed in the previous section. Where OA denotes the number of correctly categorized samples as a percentage of the total number of samples tested, AA denotes the number of correctly categorized samples in a single class as a percentage of the overall test samples within this class, and Ka is a metric to test whether the results predicted by the model remain consistent with the actual categorization results. A direct-push support vector machine (TSVM), domain adaptation network (DAN), domain adversarial neural network (DANN), unsupervised domain adaptation (UDA), class-level domain adaptation (CDA), confidence-learning-based domain adaptation (CLDA), and two-branch attentional adversarial domain adaptation (TAADA) are used as comparisons. By labeling European retro (classicism), European modern (modernism), Chinese retro (Ming and Qing styles), and Chinese modern (new Chinese decorative style) as Ⅰ, Ⅱ, Ⅲ, and Ⅳ, respectively, the results of the comparison of the different methods of style identification are shown in Table 3.

Among them, TSVM is a traditional direct-push domain adaptation method, which achieves domain adaptation simply by iteratively training a support vector machine using source domain samples with labels and target samples with pseudo-labels assigned by the classifier. Compared with this traditional method, the method in this paper improves 20.79%, 29.03%, and 27.39% on OA, AA, and Ka, respectively. For DAN and DANN methods, although they both consider edge alignment, they do not consider the discriminative performance of the classifiers on the target domain, whereas this paper's method mainly performs the decision fusion of global and local features through adaptive majority voting, so this paper's method is clearly superior to DAN and DANN. In terms of OA, UCLADA improved by 20.67% and 18.31% over DAN and DANN respectively. The UDA method achieves domain adaptation by combining confrontation and clustering, the CDA method considers class-level alignment as well as class-level confrontation, and CLDA uses a dual-classifier confrontation, all of which achieve good results in domain adaptation of housing interior design style images, but do not take into account the spatial information of the housing interior design style images themselves, and thus the results of this paper's method still superior to these methods. In terms of classification result OA, this paper's method improves 12.28%, 15.23, and 2.15% over UDA, CDA, and CLDA, respectively. For the TAADA method, which takes into account the spatial information of the housing interior design style images and performs domain alignment with dual classifier confrontation, but it still does not take into account the discriminative problem of the classifiers on the samples of the target domain, this paper's method improves the OA by 3.96% compared to TAADA. In addition, as can be seen from the table, this paper's method achieves optimal classification results on all three housing interior design styles, namely, European vintage (classicism), European modern (modernism), and Chinese modern (new Chinese decorative style).

Table 3: Different methods of style recognition comparison results (%)

| Model | Ⅰ | Ⅱ | Ⅲ | Ⅳ | OA | AA | Ka |
|---|---|---|---|---|---|---|---|
| TSVM | 70.18 | 33.51 | **99.99** | 23.15 | 76.03±0.05 | 72.45±2.21 | 71.42±3.06 |
| DAN | 77.24 | 68.06 | 98.27 | 73.05 | 76.62±1.43 | 78.06±1.18 | 72.23±1.63 |
| DANN | 80.75 | 73.48 | 98.21 | 86.62 | 78.15±4.06 | 80.79±2.21 | 74.38±4.34 |
| UDA | 72.06 | 66.49 | **99.99** | 25.43 | 82.35±0.51 | 77.65±0.57 | 78.38±0.55 |
| CDA | 87.06 | 78.42 | 99.95 | 61.48 | 80.24±1.04 | 81.16±1.83 | 76.86±1.25 |
| CLDA | 78.42 | 80.18 | 99.98 | 86.94 | 91.43±2.25 | 90.26±1.95 | 88.79±2.73 |
| TAADA | 74.57 | 72.65 | 99.91 | 95.67 | 88.94±2.83 | 88.06±3.32 | 86.36±3.43 |
| Ours | **99.48** | **86.07** | 98.93 | **96.49** | **92.46±0.75** | **93.48±0.61** | **90.98±0.79** |

**IV. B. 3) Analysis of model ablation experiments**

In order to analyze the effectiveness of each module in the housing interior design style recognition model proposed in this paper, this paper carries out ablation experiments to analyze the model. Taking the plain Bayesian classifier as the baseline model, Model A adds global features on the basis of the baseline model, Model B adds local features on the basis of Model A, and Model C adds adaptive majority voting decision fusion on the basis of Model B. Table 4 shows the results of the ablation experiments of the models.

As can be seen from the table, after combining the global and local features of the housing interior design style images, the classification results of housing interior design style recognition obtained by classifying through the plain Bayesian classifier and then combining with adaptive majority voting decision fusion get the optimal performance in all indicators. This indicates that in the model designed in this paper, the global feature module helps to help obtain the basic features of color and texture of housing interior design styles, and the local features can be mined for the in-depth features of housing interior design styles, which are then classified by using a plain Bayesian classifier for preliminary classification. An adaptive majority voting decision fusion algorithm is introduced to assign weights to the classification results, and then the result with the optimal weights is obtained as the result of recognizing and classifying housing interior design styles. After gradually adding various modules, the model's performance in recognizing and classifying housing interior design styles is significantly improved, which fully demonstrates the effectiveness of the model in recognizing housing interior design styles. Based on the results of housing interior style recognition, it can assist designers to better find inspiration for housing interior design, give more artistic atmosphere to interior design, and better satisfy people's pursuit of both art and life.

Table 4: The experimental results of the experiment

| Index | Model | Ⅰ | Ⅱ | Ⅲ | Ⅳ |
|---|---|---|---|---|---|
| OA (%) | Base | 90.15 | 89.58 | 88.72 | 87.42 |
| | Model A | 91.24 | 92.63 | 93.14 | 91.64 |
| | Model B | 92.38 | 94.75 | 95.06 | 95.83 |
| | Model C | **94.46** | **98.37** | **98.69** | **98.15** |
| AA (%) | Base | 89.75 | 90.25 | 91.03 | 88.26 |
| | Model A | 92.64 | 91.83 | 93.24 | 90.33 |
| | Model B | 94.07 | 93.76 | 96.58 | 92.64 |
| | Model C | **98.42** | **97.39** | **99.15** | **95.67** |
| Ka (%) | Base | 90.15 | 89.45 | 90.69 | 89.58 |

| | | | | | |
|---|---|---|---|---|---|
| | Model A | 92.67 | 92.06 | 92.24 | 92.35 |
| | Model B | 95.09 | 95.37 | 95.06 | 94.07 |
| | Model C | **97.58** | **97.72** | **98.83** | **97.54** |
| Time (min) | Base | 1.64 | 1.41 | 1.36 | 1.23 |
| | Model A | 1.59 | 1.37 | 1.63 | 1.38 |
| | Model B | 1.69 | 0.86 | 1.47 | 1.16 |
| | Model C | **0.95** | **0.74** | **0.86** | **0.81** |

## *IV. C. Interior design art style optimization*

The artistic expression of housing interior design is better to reflect the overall artistic sense in the decoration design to meet the artistic pursuit of the occupants. Interior design decoration style full of artistic style can inspire inspiration and cultivate artistic flavor. Specific to the process of interior design, spatial grasp of the space of the fine details of the treatment, to slightly larger space is preferred. Color tends to be quiet and solemn, high-end atmosphere of the tone, can reflect the side of the occupants of the quiet mind. Increase the amount of light on the light to achieve the fusion of color baking. Furnishings on the home furnishings as much as possible with ancient colors, full of ancient and traditional art. Based on the results of the identification of housing interior design style in the previous section, this section takes the new Chinese decorative art style of housing interior design as an example and proposes the optimization scheme of interior design art style.

### IV. C. 1) Focus on spatial hierarchy

Housing interior design of the new Chinese decorative style is both classical and modern temperament of the Oriental mood, it is to modern aesthetics and vision, to simplify the way to carry forward the precipitation of a thousand years of classical Chinese culture. It is subtle and introverted, and does not deliberately publicize the artifice, quietly interpret the ultimate oriental aesthetics of life, aptly showing the soul of the Chinese sentiment.

New Chinese interior design is very concerned about the sense of space levels, this traditional aesthetic concept in the “new Chinese” decorative style, and has been a new interpretation. New Chinese space layout draws on the traditional Chinese space design aesthetics, and pays great attention to the space level, pay attention to symmetry. Symmetry of architectural design, symmetry of furniture furnishings, symmetry of ornaments, etc., to balance the concept of yin and yang to reconcile the indoor ecology, the use of nature's decorative materials, releasing a strong natural flavor, but also to show the charm of traditional craftsmanship. New Chinese decoration style space layered, highlighting the sense of hierarchy, sense of jumping, the choice of Chinese objects partition space and rich space decoration. New Chinese style space hierarchy based on the number of residential users and the degree of privacy, the need to make the function of separation. Chinese traditional aesthetics in the new Chinese decorative style, eliminating excessive ornamentation, visual large areas of white, virtual and real, obvious and hidden, interacting with each other to form visual tension. If you need a separate functional space can be separated by a screen or a window pane, further showing the unique style of new Chinese furniture.

### IV. C. 2) Focus on color selection

The New Chinese Decorative Arts style of housing interior design emphasizes natural harmony and mostly uses soft, warm hues such as beige, ivory and pale yellow. At the same time, traditional Chinese red, blue, green and other bright colors are also commonly used to embellish and highlight design details. As a whole, the use of color should focus on harmony and unity, avoiding too strong or too monotonous color impact. New Chinese decorative arts style also focuses on the texture and quality of the selected materials. Commonly used materials include natural stone such as marble and granite, natural wood such as oak and walnut, and textiles such as silk and suede fabrics. In addition, metals such as iron and brass are also commonly used for decorative details. Therefore, in the selection of materials, in addition to considering the richness of the texture and grain of the material, designers should also consider the use of color and the overall interior design style coordination.

The use of color and material selection should also be based on the functional partition of the interior space. For example, the living room can use marble as a TV back wall, supplemented by wooden decorations to add texture. Dining room can be made of silk, suede fabric dining chairs, tablecloths, to show the elegant quality. Bedroom can be used in soft colors and comfortable textiles to create a warm and quiet interior atmosphere. In the selection of materials, designers must focus on the overall coordination, to ensure that the colors and materials echo each other, and thus create a sense of hierarchy and unique cultural charm of the interior space.

## V. Conclusion

The article proposes an adaptive majority voting decision fusion algorithm, which fuses global and local features of housing interior design style images, and carries out the identification and classification of design styles through a simple Bayesian classifier. A validation analysis is carried out for the effectiveness of the method, and an optimization scheme for the artistic style of housing interior design is proposed as an example of the new Chinese decorative style.

(1) For different types of housing interior design style images, the average accuracy of color feature extraction using the HSV color model can reach 91.05%, which is 1.19% and 0.49% higher than the results of Lab and RGB color feature extraction. The classification accuracy of the LSDRP algorithm reaches 98.39% when performing local feature extraction of housing interior design style images. This indicates that the feature extraction method and machine learning classifier proposed in this paper have better style classification performance and can meet the housing interior design style classification requirements.

(2) When the training sample size of housing interior design style images exceeds 500, the OA of housing interior design style classification for different categories exceeds 90%. Compared with the TSVM model, the method in this paper improves 20.79%, 29.03%, and 27.39% in OA, AA, and Ka, respectively. It is clear from the ablation experiment that the adaptive majority voting decision fusion method helps to improve the housing interior design style recognition and classification effect.

(3) The artistic optimization of housing interior design style needs to make full use of spatial changes, pay attention to the application of color and materials, in order to create a housing interior design style with an artistic atmosphere for people, and better realize the synergistic development of art and life.

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