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Exploration of computer vision-based non-heritage cultural pattern recognition and reconstruction methods in cultural and creative design

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ABSTRACT

In order to optimize the design effect of cultural and creative products with non-heritage patterns, this paper uses image reconstruction algorithm and image recognition algorithm to process non-heritage problem patterns. By combining the processed non-heritage cultural patterns with consumer demand for cultural and creative products, non-heritage cultural pattern cultural and creative products are designed to meet market demand. On the basis of recursive network, we add multi-scale feature extraction module and attention feature fusion module, choose L_1 loss function to optimize the details of image reconstruction, and construct image super-resolution reconstruction algorithm based on multi-scale recursive attention feature fusion network. And the image feature extraction network containing MSA module is designed, which is the fine-grained image recognition network based on multi-scale attention. The non-heritage cultural pattern dataset is established, and in order to optimize the recognition rate of non-heritage patterns, the image reconstruction based on multi-scale recursive attention feature fusion network is carried out on the non-heritage cultural pattern data. In view of the creative design strategy of non-heritage culture, the evaluation indexes of non-heritage cultural and creative product design are obtained from the consumer research, and the implementation suggestions of non-heritage pattern cultural and creative product design are derived based on the ranking of the importance of the evaluation indexes. The multi-scale recursive attention feature fusion network proposed in this paper achieves 34.89dB and 90.52% indicator scores on the Set5 dataset. For the design of cultural and creative products with non-heritage patterns, consumers make more suggestions in terms of functional differentiation, having a response rate of 21.58%.

Keywords: feature extraction, attention feature, recurrent network, image reconstruction, image recognition

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1. Introduction

Non-heritage culture is a valuable treasure of the Chinese nation, the inheritance and embodiment of China's thousands of years of history and civilization, with rich historical connotations and historical origins. The inheritance of non-heritage culture is a vital cause, and it is of great significance to promote the excellent traditional culture of China, cultivate and carry forward the socialist core values and national spirit, develop socialist culture, build a strong socialist cultural country, and enhance the sense of identity and cultural pride [1-4]. As an important part of non-heritage, non-heritage cultural patterns have high historical value, cultural value and artistic value. In modern cultural and creative product design, non-heritage culture is used as the source of creation, and through innovative forms and concepts, non-heritage cultural traditions are given new life and value [5]. As a common non-heritage element in cultural and creative design, non-heritage cultural patterns are obtained from non-heritage such as embroidery, clothing, color painting, carving, bronze man, paper-cutting and so on. On the one hand, it promotes the non-heritage culture and improves the connotation and market value of the cultural and creative products, and on the other hand, it enriches the multi-dimensional design of the cultural and creative products in terms of modeling, material, and craftsmanship [6-8]. However, with the passage of time, due to the imperfect protection process and unsuitable environmental conditions, the non-heritage cultural patterns are gradually missing, and even face the risk of being lost [9]. The use of modern technology to identify and reconstruct non-heritage cultural patterns in a timely manner, to achieve sustainable protection and inheritance.

Computer vision is a technology in the field of artificial intelligence designed to allow computers to understand and interpret images, videos, and other visual data [10]. It is a complex and challenging field with important implications for many application areas, such as robotics, autonomous driving, medical analytics, security and surveillance, and military fields [11-14]. Computer vision is implemented by feeding images or videos into a computer system and utilizing algorithms and techniques that allow the computer to extract specific information and patterns from them, which can be used for applications such as target detection, image recognition, scene understanding, 3D reconstruction, etc [15-18]. This provides new possibilities and tools in the field of cultural and creative design. Therefore, computer vision is not a bad way to realize the recognition and reconstruction of non-heritage cultural patterns.

This paper explains the computer vision techniques and proposes the operational procedures of computer vision techniques. Describing the image super-resolution problem, an image super-resolution reconstruction algorithm, Multiscale Recursive Attention Feature Fusion Network (MSRAFFN), is designed based on recursive learning. The network contains three parts: shallow feature extraction module, multi-scale recursive attention feature fusion module and reconstruction module. In order to realize the recognition and classification of non-heritage patterns, the fine-grained image recognition network based on multi-scale attention (DD3-MSANet) is proposed. The non-heritage cultural pattern recognition dataset is established from multiple channels, the non-heritage cultural patterns after image reconstruction are processed, and a comparison method is used to analyze the data enhancement effect of the DD3-MSANet algorithm. Combined with the relevant strategies of creative design of non-heritage culture, the evaluation research of non-heritage pattern cultural and creative products is carried out based on consumer demand. Adjust the program of cultural and creative products according to the order of importance of non-heritage pattern cultural and creative product design.

2. Overview

In recent years, NRM culture has been spreading more and more widely due to the emphasis on intercultural exchanges and the development of tourism. However, most of the non-heritage cultural patterns have been damaged and lack a complete structure. However, with the application of artificial intelligence and other technologies, NRH cultural patterns have been recognized and reconstructed, realizing the digital protection and inheritance of NRH, and many of the patterns have been subsequently integrated into cultural and creative design works.Liu [19] constructed an image recognition model of ethnic NRH costumes, collected the costume patterns via a wireless network and composed a database, and then captured the features in the patterns under the convolutional neural network training to complete the recognition. Lei et al [20] used VGG (Visual Geometry Group) network to design an image recognition model for Wa and Yi ethnic costumes, the model was trained iteratively to improve the parameters of all parties, and finally obtained a high-performance model.Andrian et al [21] introduced data enhancement technology to optimize batik images, and constructed a training model supported by a convolutional neural network architecture, the combination of the two was used to optimize batik images. constructed the training model, and the combination of the two performed well in recognizing batik images.Pei et al [22] input the EfficientNet-B0 network model with the attribute of attention mechanism to the collected heritage images, and obtained the best model through iterative training, and improved the EfficientNet-B0 network model for recognizing and analyzing the heritage images.Zhao [23] used the deep learning to learn and feature extraction of paper-cutting patterns and regenerate local feature patterns to co-design paper-cutting patterns under network architecture design and perceptual loss function.Wang et al [24] designed a model for non-heritage design through computer-aided design modeling techniques, extracted non-heritage features and reconstructed the non-heritage culture with the assistance of reinforcement learning.Lei and Wei [25] created automatic and manual combination of Tang Sancai image recognition model, trained the model using transfer learning, and restored the integrity of its image by comparing the input object with the existent Tang Sancai image classification.

3. Cultural and creative design integrating non-heritage culture

Intangible cultural heritage refers to the various traditional cultural expressions, as well as objects and places associated with traditional cultural expressions, which have been handed down from generation to generation by peoples and are considered part of their cultural heritage.

3.1. Cultural Creative Design

Cultural creative design mainly refers to cultural creative product design. Cultural creative products are cultural products that can produce certain economic value based on culture by incorporating creative ideas and transforming them into innovative forms.

The concept of product is also expanding with the change of time, the product is definitely not only a tangible item, but also something that can be supplied to the market, be used and consumed by people, and satisfy people's certain needs. It contains both tangible goods and intangible services, organizations, concepts or their combination.

Culture is a relatively abstract form, with the help of material and at the same time outside the material, it can reflect the characteristics of humanities, geography, customs, lifestyle and cultural connotations.

Cultural and creative products is a creative transformation on the basis of material, so cultural and creative products have a high degree of originality creativity is based on the traditional reality, through the innovative transformation of people generated by the need to have innovative thinking, so cultural and creative products and innovative.

3.2. Creative Design Strategies for Non-Heritage Culture

1) Considering the Original Cultural Needs of Cultural Consumers. Embodying the original non-heritage cultural connotation is the most basic and core cultural consumption demand of cultural consumers in purchasing non-heritage cultural and creative products.

The excavation of non-heritage culture in current non-heritage cultural and creative products only stays at the level of surface form of non-heritage culture, and the design usually only involves the reference of non-heritage materials, colors and patterns, etc. However, the natural form is only the original form. However, the natural form is only a part of the original non-heritage connotation.

Original culture is only considered authentic if it meets the following three criteria:

(1) It retains its natural form, i.e., it is not artificially processed and untouched.

(2) It retains its natural ecology, i.e., it is not detached from the natural and humanistic environment in which it survives and develops.

(3) It retains a specific way of life and expression of emotions that is naturally transmitted and accompanied by folklore and folk customs.

Incorporate these three standards in the creative design of non-heritage culture, and form these three levels of excavation for non-heritage culture in order to form a complete understanding of the non-heritage “true”, so as to reflect the “true” in the creative design of non-heritage culture, and to meet the needs of cultural consumers for non-heritage culture. Creative design contains the real original non-heritage culture needs.

2) Considering the needs of cultural consumers for edutainment and entertainment. On the basis of retaining the authenticity of non-heritage culture, the textual description of non-heritage culture is integrated into the image story and matched with easy-to-understand textual annotations, which lowers the threshold for teenagers to obtain non-heritage cultural content, helps to enhance the interest of teenagers in feeling and learning non-heritage culture, and thus plays a role in meeting the needs of families to improve the comprehensive cultural quality of teenagers.

Teenagers' hands-on experience of non-heritage culture is an imitation of the objectively existing practices in history, which is closer to the process of non-heritage bearers' cognition of objective laws. They feel the non-heritage culture step by step in the hands-on experience, from cultivating learning interest to in-depth non-heritage culture learning, experiencing the process of “thinking to start interest stimulation-feeling experience-comprehending sublimation”.

3) Considering the trend and personality needs of cultural consumers. The new trend carrier enriches the performance of non-heritage personality. The fusion of trendy material carriers and non-heritage culture can enrich the expression of non-heritage, provide personalized experience for young people nowadays, and cultivate their interest in consuming non-heritage culture.

The expression form after the combination of new fashion material carrier and non-heritage culture has both personality and playability. After consumers experience similar cultural and creative products, they can not only satisfy their demand for consumption of emotional value and cultural connotation, but also extend the memory of related culture to their lives, which better meets the personalized cultural consumption demand of young groups.

Science and technology media to increase the innovative experience of non-heritage. On the one hand, the integration of non-heritage cultural creative design into the medium of science and technology brings the time distance between cultural consumers and non-heritage culture closer. On the other hand, the integration of creative design of non-heritage culture into the medium of science and technology brings the spatial distance between cultural consumers and non-heritage culture closer.

4. Recognition and reconstruction of non-heritage cultural patterns using computer vision

4.1. *Computer vision technology*

Computer vision is a technology that gives machines the ability to "see", and its main purpose is to analyze digital images or videos, extract useful information from them and process them. The realization process of computer vision technology can be divided into four main stages, the realization process of computer vision technology is shown in Figure 1.

STEP1, image acquisition stage. The visual data in the environment is acquired using cameras or other sensing devices and converted into a digital format that can be processed.

STEP2, Image Preprocessing Stage. Optimize the captured raw images using techniques such as denoising, contrast enhancement, edge detection, etc., to improve their quality for subsequent processing.

STEP3, Feature extraction stage. Extract key features in the image such as shape, color, texture, etc. to help the system identify the core elements of the scene.

STEP4, Pattern Recognition Phase. The extracted features are input into a classification algorithm or neural network to classify and recognize the scene or object based on a pre-trained model, resulting in a final decision. The stages of this process are closely linked to ensure that the system can extract high-quality and useful information from the image data.

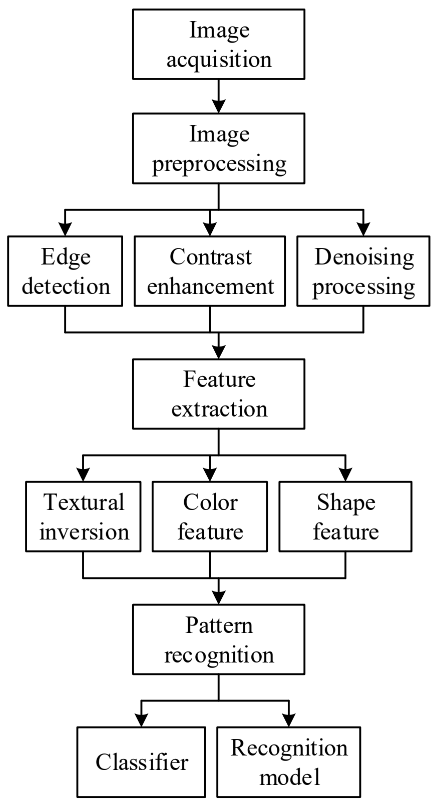


Fig. 1. Implementation process of computer visual technology

4.2. *Image reconstruction algorithm*

4.2.1. Overview of the image super-resolution problem. The purpose of image super-resolution reconstruction is to recover the corresponding HR image from the LR image [26]. The LR image is usually obtained by degrading the HR image. With I_x denoting the LR image and I_y denoting the HR image, the degradation process is shown in the following equation:

$$I_x = D(I_y;\delta) \tag{1}$$

where D is the degradation function and δ represents the relevant parameters in the degradation process, such as noise type and scaling factor. In reality, the degradation process information D and δ are unknown, and only known information is the low-resolution image I_x. The aim of the graphical super-resolution problem is to eliminate the degradation effect and recover a high-resolution or even a real scene image, i.e:

$$\hat{I}_y = F(I_x;\theta) \tag{2}$$

where θ is the parameter in the super-resolution model F, and $\hat{I}_y$ represents the reconstructed HR image.

In reality, the degradation process of non-heritage cultural patterns is unknown and complex, and there are many influencing factors, which makes it difficult to determine the exact image degradation process in practical problems. Therefore, most studies are based on a single downsampling as the degradation model, and the common downsampling operation is double cubic interpolation with anti-aliasing. There are also some studies that set the degradation model in the following form:

$$I_x = (I_y \otimes k)\downarrow_s + n_\varsigma \tag{3}$$

where $\downarrow_s$ denotes the downsampling operation with scaling factor s. $\otimes$ is the convolution operation between the HR image I_y and the convolution kernel operator k, and the variable n_ς denotes the additive Gaussian white noise with standard deviation. The degradation process of Eq. (3) is closer to the real scene than the single adoption of the downsampling degradation process and has been shown to be more effective for SR.

At this point, the SR problem can be understood as:

$$\hat{\theta} = \arg_\theta \min L(\hat{I}_y, I_y) + \lambda\varphi(\theta) \tag{4}$$

where $L(\hat{I}_x, I_x)$ is the loss function for the high resolution image $\hat{I}_y$ and the real image I_y. $\varphi(\theta)$ is the regularization term, λ is the trade-off parameter, and the loss function is the error in measuring the reconstructed image.

4.2.2. Multiscale Recursive Attention Feature Fusion Network MSRAFFN. In this chapter, the algorithm designs an image super-resolution reconstruction algorithm for non-heritage cultural patterns with recursive learning as the basic idea.

Recurrent network (RNN) improves the performance of super-resolution reconstruction by utilizing the same neural network module to process the feature information of the image, and the sharing of weight information can effectively reduce the number of parameters in the SISR method [27]. It can utilize both local features and global information in the image, making the reconstructed image clearer and more realistic.

The idea of the method designed in this paper comes from three image super-resolution reconstruction recurrent networks: the DRRN, DSRN and DRUDN.

1) MSRAFFN overall network structure. In order to effectively utilize the feature information extracted from the original image, this chapter investigates a MSRAFFN, which contains three parts: a shallow feature extraction module, a multi-scale recursive attention feature fusion module and a reconstruction module.

The shallow feature extraction module uses two 3×3 convolutional layers to capture the base feature information of the image, which can effectively reduce the training time of the super-resolution model and avoid excessive information loss for complex images. Mark the input LR image as I_{LR} and the extracted shallow features as F_0. i.e:

$$F_0 = H_{FEP}(I_{LR}) \tag{5}$$

where $H_{FEP}(\cdot)$ denotes the shallow feature extraction part.

The deep feature extraction module designed in this paper utilizes recursive learning, using several identical modules stacked by recursion. And residual learning is utilized in the backbone network to integrate the shallow features with the deep features by connecting them across layers. The effective use of layered features from the multiscale feature extraction module while retaining more detailed information helps to extract richer and more accurate feature information from low-resolution images for better reconstruction of high-resolution images. Namely:

$$F_{DF} = H_{MRA}(F0) \tag{6}$$

where F_{DF} is the deep features extracted from the whole network and H_{MRA} is the multi-scale recursive attention feature fusion module.

The reconstruction module generates the reconstructed image using ordinary convolution and anti-convolution operations, which are defined as shown in (7):

$$H_{SR} = H_{\pi}(F_{DF}) \tag{7}$$

where H_{SR} is the reconstructed image and H_{re} represents the reconstruction module.

2) Multi-scale feature extraction module. MSRAFFB is an important module of the multiscale feature extraction module of the designed algorithm, which is used to extract the deep feature information of the non-heritage cultural patterns. It is composed of two parts: the multi-scale feature extraction (MSFE) module and the attention feature fusion module, and local residual learning is introduced in the block across the internal layers to enhance the feature extraction of the network.

Through the design of multiple branches and interconnections between branches, the MSFE module is able to effectively capture and integrate the multi-scale information of the input features, thus enhancing the network's ability to represent features at different scales, as defined in the following equation:

$$F_{b-1}^{1} = f_{3\times3}(F_{b-1}) \tag{8}$$

$$F_{b-1}^{2} = f_{3\times3}(f_{1\times1}(concat(F_{b-1}, F_{b-1}^{c}))) \tag{9}$$

$$F_{b-1}^{c-1} = f_{3\times3}(f_{1\times1}(concat(F_{b-1}, F_{b-1}^{c-2}))) \tag{10}$$

$$F_{b-1}^{c} = f_{3\times3}(f_{1\times1}(concat(F_{b-1}, F_{b-1}^{c-1}))) \tag{11}$$

where f_{383} and $f_{1\times1}$ represent convolution kernels of size F_{b-1}^{c} and 1, respectively, and 3 represents the cth branch in the bth MSRAFFB.

3) Attention feature fusion module. The main function of the AFF module is to dynamically distribute the attention weights among multiple input features to enhance the focus on key features, thus capturing richer information.

First, the extracted output features from all branches of MSFE are downscaled as inputs to the AFF module using 1×1 convolution.

Then, the multi-scale features are adaptively fused through the SE attention mechanism to learn the correlation between the channels and adjust the weights of different channels so as to increase the representation of useful features.

Finally, the number of channels is recovered by 3×3 convolution as the input to the next recursive block.

The output F_b after attentional feature fusion can be expressed as:

$$F_b^* = f_{3\times3}(f_{SE}(f_{1\times1}(concat(F_{b-1}^1, F_{b-1}^2, \cdots, F_{b-1}^{c-1}, F_{b-1}^c)))) \tag{12}$$

$$F_b = F_{b-1}^* + F_{b-1} \tag{13}$$

4) Reconstruction module. The reconstruction module contains two 3×3 ordinary convolutional layers and one inverse convolutional layer, and the residual module is used to connect the images after bicubic interpolation and fuse them with the convolutional output to obtain the final reconstructed image of the non-heritage culture.

The first ordinary convolutional layer with 64 convolutional kernels is used to map the feature map to a super-resolution image. The inverse convolution is used to zoom the low-resolution image to the high-resolution level to realize the up-sampling of the image.

The last ordinary convolutional layer is used to recover the number of channels to generate an RGB three-channel image. In addition, this design has a simple structure that is easy to implement and train, as well as easy to converge during the training process.

5) Loss function. The L_1 loss function was chosen to be used in the design of the super-resolution network. This is because the L_1 loss function can effectively penalize the absolute error between the predicted value and the true value, thus making the network more concerned about the recovery of details in the NRM cultural images. If there are N training samples, the L_1 loss function is shown in Equation (14):

$$L_{loss} = \frac{1}{N}\sum_{i=1}^{N} \| F(X_i - Y_i) \|_1 \tag{14}$$

where, Y_i denotes the real high resolution image, X_i denotes the reconstructed NRM image, and $\| F(X_i - Y_i) \|_h$ denotes the loss of the average value of all pixels in the ith original image and the reconstructed NRM image.

4.3. *Algorithm for Recognizing Non-Heritage Cultural Patterns DD3-MSANet*

In this paper, we propose DD3-MSANet, a fine-grained image recognition network based on multi-scale attention.DD3-MSANet has a simple hierarchical structure, i.e., a four-stage sequence of decreasing spatial resolution of outputs, namely, $\frac{H}{4}\times\frac{W}{4}$, $\frac{H}{8}\times\frac{W}{8}$, $\frac{H}{16}\times\frac{W}{16}$, and $\frac{H}{32}\times\frac{W}{32}$. Here, H and W denote the height and the width of the input image. As the resolution decreases, the number of output channels increases in the order of 32, 64, 128 and 256.

For each stage, first, the NCS image is downsampled and the number of steps is used to control the downsampling rate. For each downsampling operation, the number of channels of the feature map is doubled and the size size is reduced by half. After downsampling, all other layers in each stage maintain the same output size, i.e., the spatial resolution and the number of channels remain unchanged. Next, the L-group batch normalization (BN), 1 × 1 convolution, GELU activation function, MSA, and convolutional feedforward network (CFF) are stacked sequentially to extract features. Where a layer normalization is applied at the end of each stage. Finally, the feature maps output from the fourth stage are used for classification in order to accomplish the task of NRM cultural image recognition.

4.3.1. MSA module. The following briefly summarizes the MSA module framework.

First, the original NRM feature map $A \in R^{H\times W\times C}$ is input into the deep convolution component to obtain the NRM feature map A_0, which acquires the local information of the image and reduces the parameters.

Second, the obtained feature map A_o is inputted into the parallel expansion convolution component with expansion rates of 1, 2, and A_1^1, A_1^2, A_1^3, which results in three multi-scale feature maps 4, and the three feature maps are simply stacked to obtain A_2. In order to highlight the important information of the three feature maps in terms of their spatial structure, the design introduces a 3D convolution component to obtain the fused attention map A_3.

Then, the fused feature map A_3 is passed through a 1×1 convolution to obtain the feature map F. To further extract the critical information, the dynamically fused features are passed through a SE attention to obtain the feature map F_1.

Finally, the output feature map is obtained by multiplying the feature map F_1 with the original feature map A. The computational procedure is shown in Eqs. (15) to (19):

$$A_2 = Stack_{1\le i\le 3}(A_1^i) \tag{15}$$

$$A_3 = 3DConv(A_2) \tag{16}$$

$$F = Conv_{1\times 1}(A_3) \tag{17}$$

$$F_1 = SE(F) \tag{18}$$

$$Output = F_1 \times A \tag{19}$$

In order to build a lightweight fine-grained image recognition model, deep convolution is introduced into the MSA module in this chapter. The deep convolution operation is performed on the input feature map $A \in R^{H\times W\times C}$ of the first convolutional operation block, and features are extracted using a 3×3 convolutional kernel for each channel separately. The feature map A_0^1, A_0^2, A_0^3 obtained through the 3 convolution kernels is then spliced to obtain the output feature map A_0. The computational procedure is shown in Equation (20):

$$A_0 = Concate(DWConv(A)) \tag{20}$$

In order to make the obtained features more flexible, three parallel expansion convolution branches are utilized in the MSA model, with expansion rates of 1, 2 and 4 respectively.The three parallel branches perform feature extraction on the feature map A_0 obtained through deep convolution respectively. Three parallel feature maps with different sensory fields are obtained through the three branches A_1^1, A_1^2, A_1^3. The computation process is shown in Eq. (21):

$$A_1^i = DWDConv(A_0)_{1\le i\le 3} \tag{21}$$

4.3.2. Weighted prediction units:

1) Spatial weights. The dynamic weight prediction process for fusing parallel branch expansion convolution feature maps is as follows:

First, the three parallel feature maps are simply stacked and considered as three frames applying 3D convolution. They are fused into one feature map, this operation is equivalent to doing spatial attention operation on the three feature maps to obtain feature map A_3.

In order to further enhance the features of the region of interest, the fused feature map A_3 is subjected to three operations: linear projection, average pooling and sigmoid to obtain the weight information. Multiply it with the fused feature maps to get the complete spatial attention map, which is shown by Eqs. (22) and (23):

$$Scale = Sigmoid(AvgPooling(LinearProj(A_2^{'}))) \tag{22}$$

$$A_3 = A_2^{'} \times Scale \tag{23}$$

2) Channel weights. To further highlight the region of interest, an SE attention is introduced. The feature weights between each channel are adaptively adjusted by means of feature recalibration, the input feature map is strengthened with channel features, and the input feature map F is compressed with spatial features by global average pooling. Then the feature map with channel attention is obtained by going through the fully connected layer to learn the channel features. The calculation process is shown in Eqs. (24) and (25):

$$S = F_{ex}(F_{sq}(F), W) = \sigma(W_2\sigma(W_1 GAP(F))) \tag{24}$$

$$F_1 = \mathrm{conv}(F)S \tag{25}$$

4.3.3. Classification module. The cross-entropy loss function L is the most commonly used loss function in image multicategorization problems. Its can speed up the convergence of the network, measure the degree of difference between two different probability distributions in the same random variable, and use it to increase the distance between subclasses. The smaller its loss value, the better the classification results. As shown in equation (26):

$$L_{cross}(G,P) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c}(g_{ij} \times \log(p_{ij})) \tag{26}$$

where G denotes the true label, P denotes the predicted value, N denotes the total number of samples, and C denotes the total number of categories.

5. Effectiveness of image identification and reconstruction of non-heritage cultures

5.1. Image reconstruction

The DIV2K dataset was used for training in the training phase. Subsequently, five widely recognized benchmark datasets, namely Set5, Set14, BSD100, Urban100 and Manga109, were used in the testing phase. Wherein, the Set5 dataset contains 5 images and the Set14 dataset contains 14 images.The BSD100 dataset contains a wide variety of images including specific subjects ranging from natural landscapes to botanical elements, individuals, and culinary items. The Urban100 dataset contains 100 cityscape images with different band details.The Manga109 dataset contains 109 manga drawn by a professional Japanese manga artist, which are usually used only for testing performance.

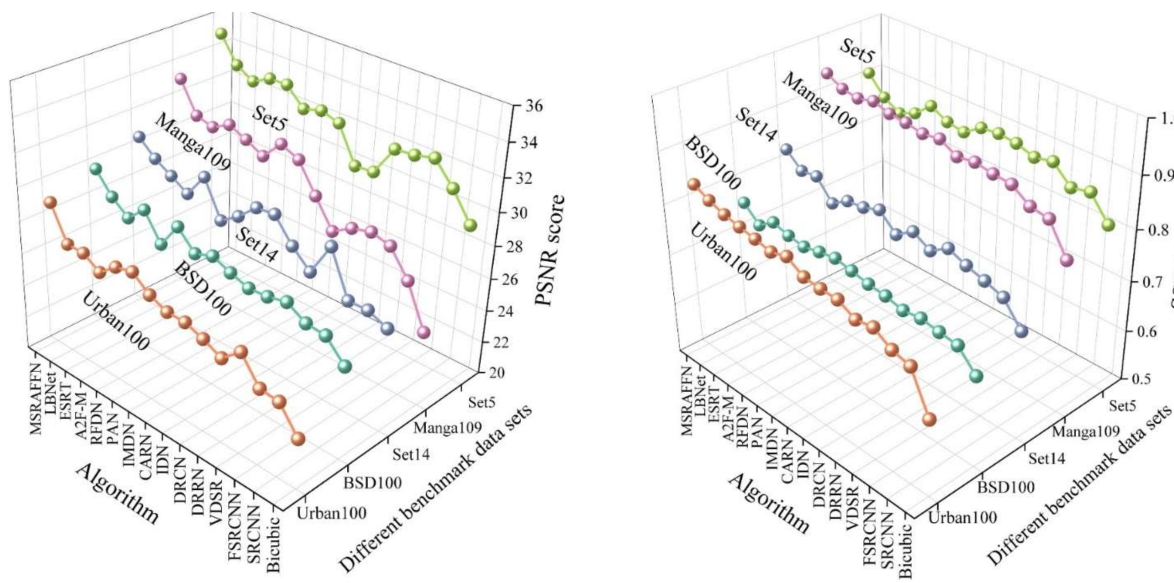
To evaluate the quality of SR images, two widely used metrics, peak signal-to-noise ratio (PSNR) and structural similarity (SSIM), were calculated on the Y channel of the YCb Cr color space. In addition, Multi-Adds and Parameters were used to evaluate the computational complexity of the model.

5.1.1. Experimental environment and parameter settings. To ensure that the proposed Multiscale Recursive Attention Feature Fusion Network (MSRAFFN) is adequately trained, the training data is randomly cropped into image blocks of size 48 × 48 during the training phase. The model was optimized using Adam's algorithm with the initial learning rate set to 3×10^{-5}. The training and testing process was performed within the Py Torch framework, which specifically includes CUDAToolkit 11.4, cu DNN 8.2.2, Python 3.8 and two NVIDIA 3090 Ti GPUs.

5.1.2. Objective evaluation. The proposed Multiscale Recursive Attention Feature Fusion Network (MSRAFFN) will be validated on five benchmark datasets, namely Set5, Set14, BSD100, Urban100 and Manga109.

It is also compared and analyzed with the current mainstream methods including Bicubic, SRCNN, FSRCNN, VDSR, DRRN, DRCN, IDN, CARN, IMDN, PAN, RFDN, A^2F-M, ESRT and LBNet.

The comparison results of the image reconstruction metrics on the benchmark dataset with $\times 4$ as the zoom scale are shown in Fig. 2, and Figs. (a) and (b) show the PSNR and SSIM scores, respectively. The average PSNR and SSIM of the proposed MSRAFFN on Set5, Set14, BSD100, Urban100, and Manga109 datasets are still the first place.The PSNR and SSIM scores of MSRAFFN on Set5 dataset are 34.89dB and 0.9052, respectively, which are the best scores for the five benchmark datasets.



(a) PSNR score (b) SSIM score

Fig. 2. Comparison results of image reconstruction index

5.1.3. Computational complexity analysis. In addition, the MSRAFFN proposed in this paper is compared with SRCNN, FSRCNN, VDSR, DRRN, DRCN, IDN, CARN, IMDN, PAN, RFDN, A^2F-M, ESRT, and LBNet in terms of number of parameters and computation.

The experiment was carried out on the Set5 dataset with $\times 4$ as the zoom scale, and the average PSNR corresponding to each method was also compared.The results of the comparison between the number of parameters and the computational effort on the Set5 dataset with $\times 4$ as the zoom scale are shown in Table 1, where the results of the comparison of the MSRAFFN with the other thirteen methods are listed.

The Params (K), Multi-Ads (G), and PSNR (dB) performance of the MSRAFFN algorithm in this paper on the Set5 dataset are 907K, 32.66G, and 31.25dB, respectively.

Table 1. The comparison of the parameters and calculations in the set5 data set

Method	Params (K)	Multi-Adds (G)	PSNR(dB)
SRCNN	63	56.32	30.57
FSRCNN	9	3.37	36.89
VDSR	647	654.05	32.22
DRRN	302	6365.69	36.47
DRCN	1823	18256.01	29.86
IDN	525	36.54	28.45
CARN	1563	90.26	33.87
IMDN	721	42.77	30.12
PAN	264	38.52	39.84

RFDN	563	27.15	35.21
A^2F-M	1023	60.38	36.11
ESRT	757	42.63	32.96
LBNet	713	51.82	36.75
MSRAFFN	907	32.66	31.25

The results of the visualization comparing the number of parameters to the computation on the Set5 dataset with $\times 4$ as the zoom scale are shown in Figure 3. The vertical axis of this figure represents the average PSNR, the horizontal axis represents the amount of computation, and the area of each circle in the figure represents the number of parameters of each model. The figure clearly reflects the differences in the number of parameters, the amount of computation and the PSNR score of each model.The PSNR score of the MSRAFFN algorithm is at around 32dB, which is consistent with the data in the table above. The figure illustrates that MSRAFFN strikes a good balance between performance and computational complexity of the model.

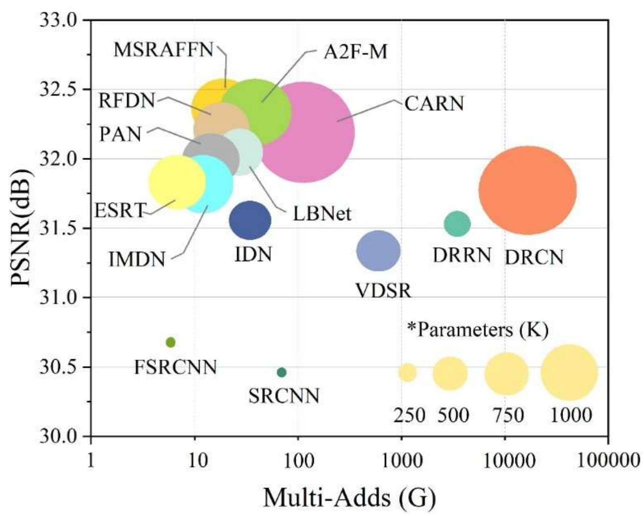


Fig. 3. The visual comparison of parameters and calculations in the data set

5.2. *Identification of cultural motifs of non-heritage*

5.2.1. Non-Heritage Cultural Pattern Recognition Dataset Construction. The non-heritage image dataset used in this paper comes from several sources to ensure the comprehensiveness and diversity of the images, and the data are mainly obtained through the following main ways:

1) Books. Books related to non-heritage patterns are scanned through scanners to digitize the rich pattern images.

2) Digital media and online platforms. With the emphasis on the inheritance of non-heritage cultural patterns, there are more and more related materials on the Internet. Make full use of the non-heritage cultural image resources already available on digital media and online platforms, from which a large number of high-quality images of non-heritage cultural patterns can be obtained. This includes art works, pattern design platforms, digitized exhibitions and illustrations in relevant research literature.

3) Existing Non-Heritage Cultural Patterns Resource Library. At present, certain achievements have been made in the collection of non-heritage cultural pattern related resources, thus providing basic support for the construction of non-heritage cultural pattern dataset in this paper. According to the existing non-heritage cultural pattern resource data for re-screening, organizing and classification.

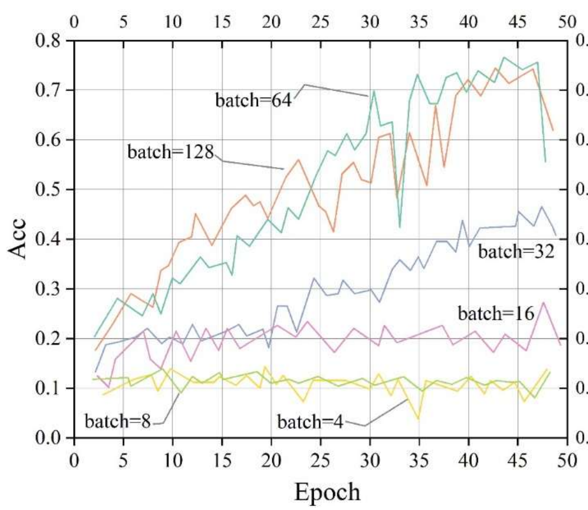
4) Field Photography. Visiting the non-heritage cultural bases for filming and taking materials, as well as interviewing the local non-heritage cultural inheritors to understand the non-heritage culture more deeply. This approach can collect the most authentic non-heritage culture image data, which provides a guarantee for the completeness and timeliness of the dataset.

After collecting a large amount of relevant data, the non-heritage cultural pattern data will be screened and organized. Considering the diversity and richness of non-heritage cultural patterns as well as the quality of the images, the richness and comprehensiveness of the patterns are ensured as much as possible in the screening process. Meanwhile, the help and advice of non-heritage cultural experts were also sought during the data screening process, and in-depth insights about non-heritage cultural motifs were obtained, thus helping to ensure the cultural accuracy of the selected data.

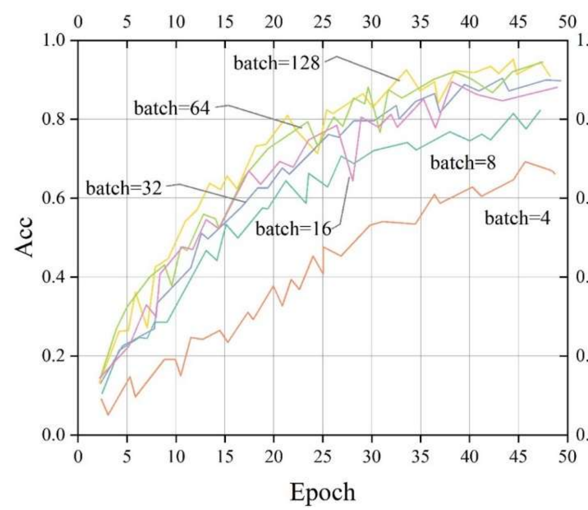
5.2.2. Hyperparameter Selection Experiments. The fine-grained image recognition network model based on multi-scale attention (DD3-MSANet) constructed in this paper is affected by the initial learning rate and batch size when performing training, and different learning rates and batch sizes will search for the global optimal solution at different paces. The learning rate is the step size of the model's gradient descent, which determines how fast or slow the search for the global optimal solution is. The batch size is the number of samples each time the model is trained and determines the direction in which the model seeks the optimal solution. Therefore, selecting the appropriate learning rate and batch size has a great impact on the experimental results.

In this paper, the learning rate is 0.1, 0.01, 0.001, and the batch size is 4, 8, 16, 32, 64, 128. Different learning rates and batch sizes are combined in the experiments, and the changes in the accuracy of the experimental results are observed to determine the optimal combination. The results of the hyperparametric experiments are shown in Fig. 4, and Figs. (a)~(c) show the experimental results of different batch sizes at learning rates of 0.1, 0.01, 0.001, and states, respectively.

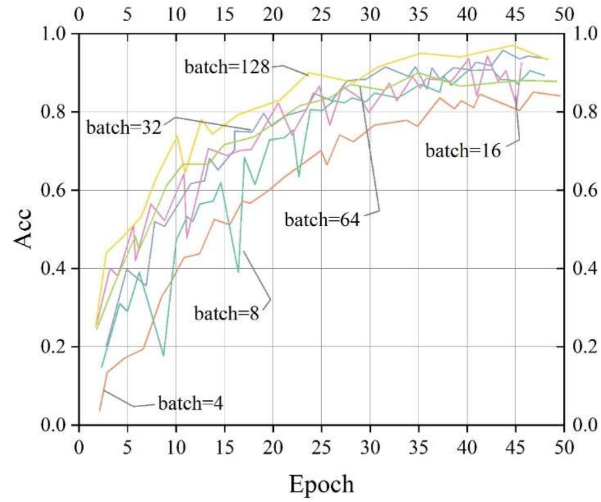
When the learning rate is 0.1, the accuracy fluctuation is relatively large no matter which batchsize. When the learning rate gradually decreases the accuracy rate as a whole becomes more stable when it increases, for comprehensive consideration, this paper selects an initial learning rate of 0.001 and a batch size of 64.



(a) Learning rate = 0.1



(b) Learning rate = 0.01



(c) Learning rate = 0.001

Fig. 4. Superparametric experiment results

5.2.3. Data Enhancement Comparison Experiment. The homemade non-heritage cultural pattern dataset used in this paper is considered a small sample dataset compared to the hundreds of thousands or millions of image data required by the deep learning model, which is prone to the problem of model overfitting. In order to mitigate the effect of small samples, enhance the performance of the model and improve the recognition accuracy. In this chapter, data enhancement comparison experiments are conducted.

In this chapter, the data in the dataset is subjected to image reconstruction using the proposed multi-scale recursive attention feature fusion network before training for image recognition. Then random cropping and rotation is performed to achieve data enhancement of the dataset. Comparison experiments between the data-enhanced dataset and the data without data enhancement are conducted to verify the effectiveness of data enhancement and to prove that the generalization ability of the model can be improved after data enhancement while avoiding the overfitting phenomenon.

Random cropping is to randomly crop a certain size of the image from the image, and if the random exceeds the size of the image, it will be filled to the required size. Rotation is to change the original image by rotating the image according to a certain rotation angle. Super-resolution image reconstruction is to reconstruct a low-resolution image into a high-resolution image, according to this technique, the lower-resolution images in the dataset can be processed clearly, so as to generate new sample images to expand the image dataset.

The results of the data enhancement comparison experiments are shown in Figure 5. It can be seen that the performance of the Resnet50 neural network is degraded after data enhancement, and the accuracy is improved after the introduction of the attention modules SE attention and CBAM attention. The DD3-MSANet algorithm proposed in this paper improves the accuracy, precision, recall, and specificity by 13.81%, 13.16%, 11%, and 3.34%, respectively, on the basis of Resnet50 neural network.

The fine-grained image recognition network based on multi-scale attention (DD3-MSANet) proposed in this chapter is trained on the data-enhanced dataset, and the accuracy is obviously improved, which proves that the model can effectively improve the recognition accuracy of the model by using the data-enhanced processed dataset.

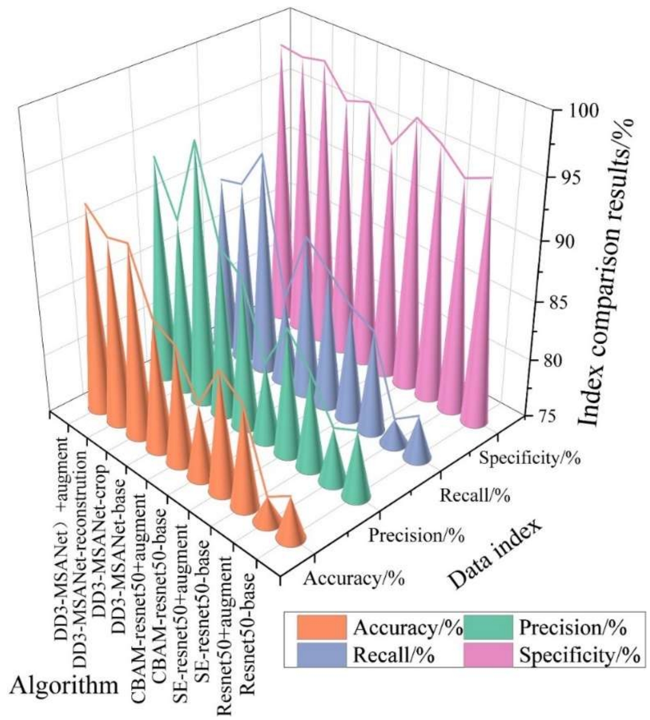


Fig. 5. Data enhancement comparison results

6. Design and scoring of cultural and creative products containing non-heritage cultural motifs

6.1. Evaluation Indicators for Cultural and Creative Products with Non-Heritage Cultural Motifs

In order to more accurately understand the evaluation indexes of the value of non-heritage cultural pattern product design, 12 people from each of the five fields of industry experts, non-heritage bearers, non-heritage enthusiasts, master's degree holders of different majors, and people of all ages were invited to participate in this research, with a total of 60 people. The research lasted 30 minutes and finally completed the preset content more successfully.

The evaluation indexes of non-heritage cultural pattern product design were obtained by collation, including the following colors, pattern motifs, appearance and shape, materials, fonts, layout, fluency, effectiveness, narrative, completion, real-time, security, adaptation to user cognition, content selection, presentation of cultural quantities suitable for the experience of non-heritage cultural connotations, and integration.

Interpretation of the connotation of evaluation indicators. The interpretation of the evaluation indexes of cultural and creative product designs containing non-heritage cultural patterns is shown in Table 2.

When users come into contact with non-heritage culture for the first time, the advantages and disadvantages of their sensory experience dimensions have an important impact on the experience. Aesthetics can attract users' attention through the design of visual elements, such as color, graphics, shape, etc. to show the unique charm of non-heritage culture, which can help users better understand non-heritage culture and enhance their visual experience. Attraction is a powerful motivation that inspires users to explore actively. Therefore, efforts should be made to create interesting visual effects, as well as to display NRL culture through interesting ways, so as to enhance users' loyalty.

Entertainment mainly refers to the fact that users will experience it with pleasurable emotions and feel amused. The user experience is enhanced by providing elements that are interesting and interactive. A good interactive experience needs to consider three aspects: ease of learning, functionality and fault tolerance. In terms of fault tolerance, the clarity of non-heritage cultural patterns and the smoothness of non-heritage cultural pattern design are emphasized.

The design of non-heritage cultural pattern cultural and creative products should satisfy the educativeness, avoidance and empathy in order to realize the good experience of users in terms of emotion. Educationality is the basic goal of letting users understand non-heritage culture, and good interaction design can convey cultural knowledge through various ways, trigger users' interest in non-heritage culture and form memories. The purpose of escapism is to let users get relaxed and happy feelings during the experience process and get psychological satisfaction. Empathy is mainly to stimulate the empathy of users during the experience.

Table 2. The evaluation index of the design of the design of non-legacy design

Design value	Evaluation index	Connotation
Artistic value	Aestheticism	The pattern is beautiful, the color meets the theme, easy to understand.
	Attractability	The content is unique, the rendering method is novel, and the multiple senses are mobilized.
	Entertainment	It presents non-cultural patterns and learning to non-legacy knowledge.
Technical value	Learnability	Easy to remember
	Functionality	Functional and functional function, easy to understand, and feature.
	Fault tolerance	The clarity of the non-heritage pattern and the fluency of the design.
Mental value	Education	It has depth and breadth and highlights.
	Evanescence	Visual and cohesive nature.
	Empathy	To arouse user's thinking, to arouse the response of the user, and to obtain psychological satisfaction.

6.2. Adjustment of non-heritage culture pattern cultural and creative product design strategy

The purpose of this section is to find out the importance ranking of each evaluation index of non-heritage cultural pattern cultural and creative product design by consumers, and adjust the non-heritage cultural pattern cultural and creative product design based on the indexes that consumers are concerned about. The importance ranking of non-heritage cultural pattern cultural and creative product design for consumers is shown in Figure 6.

The importance of the nine evaluation indicators sorted out above was ranked, and the scoring questionnaire was designed using a 5-level Likert scale, which was mainly used to score the importance of the evaluation indicators. It is divided into five levels: "very unimportant", "not important", "neutral", "important", and "very important", and is assigned a score of 1, 2, 3, 4, and 5 respectively.

Three hundred questionnaires were distributed, removing invalid questionnaires, totaling 292 valid data. Data analysis was performed. Aesthetic 69.62%, Functional 64.33%, Ease of learning 61% and Educational 60.64% ranked high in importance. The last rankings are fault tolerance 37.03% and avoidance 35.24%.

From this, it can be concluded that the design of cultural and creative products about non-heritage cultural patterns should be based on the overall aesthetics, and the inheritance of non-heritage cultural patterns should be combined with the functionality, so as to design the cultural and creative products that are easy to be understood by the public and help the spread of non-heritage culture.

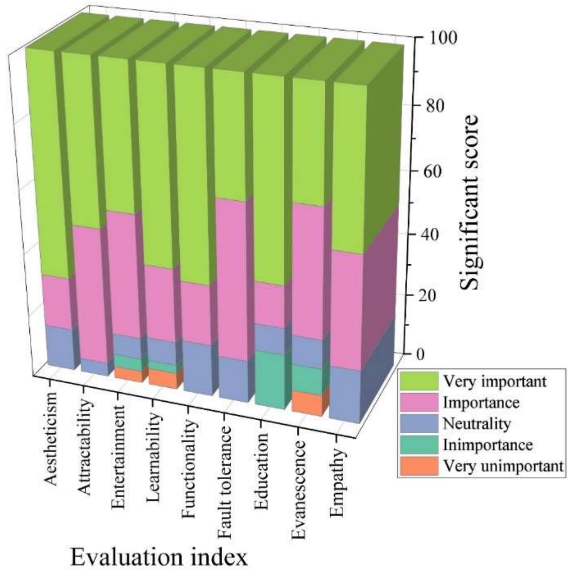


Fig. 6. The importance of the product design is sorted

6.3. Relevant Suggestions on the Design of Cultural and Creative Products with Non-Heritage Patterns

The relevant suggestions for the design of cultural and creative products with non-heritage motifs are shown in Figure 7, which involves relevant suggestions including enhancing the connotation of cultural elements, strengthening product recognition, increasing the application of beautiful symbols, combining tradition and modernity, functional differentiation, practical value, strengthening the overall aesthetics of the product, optimizing the overall shape of the product, and strengthening the uniqueness of the product. It can be seen that consumers put forward more suggestions on the functional design of non-heritage cultural pattern cultural and creative products, with a response rate of 21.58%.

In summary, it can be concluded that the relevant measures for the design of non-heritage pattern cultural and creative products.

1) Interpret the cultural connotation of non-heritage cultural and creative products in product shape, product function and product color. Through reorganization and processing into new symbol carriers, the products are endowed with the significance of non-heritage cultural inheritance. The non-heritage patterns are transformed into specific forms of product details in the process of product development. The details of the products are enriched, so that the cultural experience and concepts conveyed by the products are recognized by the audience, thus meeting the material and spiritual needs of the audience.

2) The modeling of non-heritage image symbols is created on the basis of the basic prototype according to the specific needs of the audience. In the context of mainstream design, these figurative and complex non-heritage image symbols sometimes cannot be directly attached to the cultural and creative products. At this time, designers need to redesign these non-heritage image symbols according to the actual needs. The specific image of the non-heritage pattern symbols can be deformed and simplified to add a sense of design to the symbols, but at the same time, the original characteristics of the symbols should not be lost. Different techniques can be used to exaggerate or implicitly deal with the modeling. Designers' secondary creation of image symbols can promote users' understanding of cultural and creative products and enhance the narrative of cultural and creative products.

3) Emphasize the overall aesthetics of the cultural and creative products, focusing on the use of non-heritage motifs in terms of shape, color and image.

4) For cultural and creative products with non-heritage patterns, by creating internal interaction with consumers in terms of functional experience, it can effectively enable consumers to make consumption decisions. At the instinctive level of emotional experience, consumers' visual experience

through cultural symbols at the material level can cultivate their aesthetic taste as well as artistic feelings. In the behavioral layer, through the integration of cultural elements and product functions, the interaction between consumers and products creates a sense of reality in the process of behavioral experience.

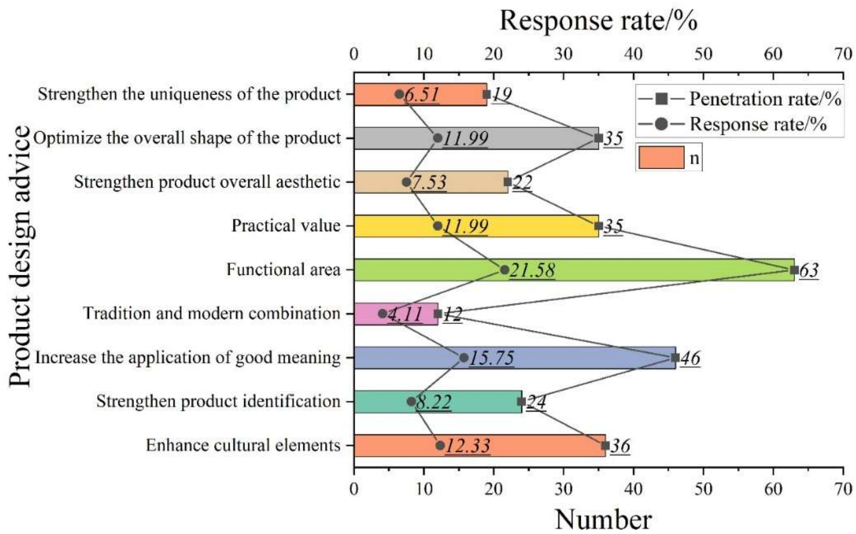


Fig. 7. Relevant Suggestions for design of non-legacy design

7. Conclusion

In this paper, image reconstruction technology based on multi-scale recursive attention feature fusion network and image recognition algorithm based on multi-scale attention mechanism are applied to process non-heritage cultural patterns. The processed non-heritage cultural patterns are combined with non-heritage cultural creative design strategies to investigate the consumer demand for cultural and creative products. According to the importance ranking of the evaluation indexes of the cultural and creative products of non-heritage patterns, the design scheme of the cultural and creative products of non-heritage cultural patterns is adjusted.

The initial learning rate of Multi-scale Recursive Attention Feature Fusion Network (MSRAFFN) is set to 3×10^{-5}, and the performance of MSRAFFN image reconstruction algorithm is examined using five benchmark datasets, namely, Set5, Set14, BSD100, Urban100, and Manga109.MSRAFFN algorithm achieves good results on the five benchmark datasets, and the performance of the algorithm on Set5 dataset is more excellent, and the Params and Multi-Adds indices of the algorithm are 907K and 32.66G respectively. The performance of MSRAFFN algorithm on Set5 dataset is better, the Params and Multi-Adds index of MSRAFFN algorithm on Set5 dataset are 907K and 32.66G respectively, and the computational complexity of the algorithm is less than that of other comparative algorithms, which is advantageous for computational operation. Establish the non-heritage cultural pattern recognition dataset, select the initial learning rate of 0.001 and the batch size of 64, and obtain the stable recognition rate of the DD3-MSANet model for non-heritage cultural patterns.

Investigating consumers' demand for non-heritage cultural and creative product design, nine evaluation indexes in three dimensions of artistic value, technical value and spiritual value are summarized, in which consumers are more concerned about the aesthetic, functional, easy-to-learn and educational aspects of non-heritage pattern cultural and creative products. Thus, the cultural and creative products designed by non-heritage cultural patterns need to emphasize the aspects of product shape, color, function and value communication.

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