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Deep learning-driven digitization of traditional crafts and cultural and creative design innovation

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Abstract As part of human cultural heritage, traditional handicrafts carry rich historical and cultural values. Based on deep learning and super-resolution technology, this paper discusses the digitization of traditional handicraft elements and cultural and creative product design methods. First, the convolutional neural network in deep learning is applied for the super-resolution reconstruction of handicraft images, which enhances the detail presentation of handicrafts by improving the image resolution. Second, the combination of 3D modeling and virtual reality technology is used to inject new vitality into the design of traditional handicrafts, so that they can be innovated and inherited in modern cultural and creative design. The experimental results show that the designed digital handicraft products have high scores in terms of "ease of learning", "creativity", "improving skills" and "promoting participation", among which the score of "ease of learning" is 15 points and the score of "improving skills" is 10 points. Studies have shown that the combination of deep learning and digital technology can effectively promote the innovative design of traditional handicrafts, enhance their market competitiveness, and promote the modern inheritance of cultural heritage.

Index Terms Deep learning, super resolution, traditional handicrafts, cultural and creative products, digitalization, innovative design

I. Introduction

Traditional handicraft is the traditional culture of the Chinese nation inherited and carried forward by craftsmen with the technique of living inheritance, which has distinctive ethnicity, strong regional characteristics and is the soul of culture [1], [2]. As the carrier of China's long history and splendid culture, traditional handicraft carries the wisdom and emotion of the Chinese nation, which unites the spirit of craftsmanship, the spirit of creation, the courage to break through and innovate in the trend of the times, and has a very high cultural value and heritage status [3]-[5]. However, with the change of the times and the development of modernization, many traditional handicrafts are losing their due value and status [6]. Therefore, in the context of the era of digitalization applications and the growing demand for cultural and creative products, the protection and inheritance of traditional handicrafts has become an important task for the development of contemporary Chinese culture [7], [8].

Digital technology provides a new means for the protection of traditional handicrafts. By digitizing the elements of traditional handicrafts, not only can some archival materials of traditional handicrafts, such as pre-manuscripts, photographs, and images of the production process, be preserved in physical media, such as CD-ROMs and digital disks, through digitalization, which is conducive to the dissemination of traditional handicrafts [9]-[12]. The cultural and creative design, on the other hand, is another important way to inherit and protect traditional handicrafts. By skillfully applying traditional handicraft elements to the cultural and creative design, it can bring consumers a stronger cultural experience and feeling [13]-[15]. At the same time, the cultural and creative products can not only transmit local culture, but also carry out cross-regional, cross-cultural and cross-national cultural exchanges and dissemination, through which the effect and strength of the exchange and dissemination of traditional handicraft culture can be enhanced [16]-[18].

This study explores for the digital reconstruction of traditional handicrafts by combining deep learning with super-resolution technology. In terms of image processing, Convolutional Neural Network (CNN) is used to improve the quality of low-resolution images so as to enhance the detail representation of handicrafts. In addition, 3D modeling and virtual reality technologies are combined with modern design concepts to promote the innovative application of traditional elements in cultural and creative products. The study further evaluates the market performance and user feedback of the cultural and creative products designed based on these technologies, verifying their potential to enhance cultural heritage and increase the added value of the products.

II. Deep learning-based product design for traditional handicrafts

II. A. Traditional Handicraft Product Design Methods

II. A. 1) Adherence to the traditional division of labor between materials and processes

One of the characteristics of traditional handicraft production is the integration of the production process, the craftsman from the design conception to the production of molding to grasp the full range of artifacts production, with small-scale workshop or family production as the basic unit [19]. Modern design, on the other hand, corresponds to the industrialized production method, and the division of labor is more refined and clear. However, crafts and division of labor are not completely opposed to each other, and the mode of division of labor has also appeared in traditional handicrafts from a very early stage.

Therefore, in a certain scale of industrialized production of traditional handicraft products, under the condition of adhering to the use of traditional materials and techniques, the division of labor is appropriately adopted, so that different people can focus on different production steps, which not only adheres to the “authenticity” of traditional products, but also improves the efficiency of the work and enhances the quality of the products.

II. A. 2) Process improvement and innovation based on traditional materials

Craftsmanship is the means of treating materials. Traditional craftsmanship varies according to the industry and often has a long history of accumulation and improvement over time, and it is important for craftspeople to follow and hone traditional craftsmanship techniques, to the point where it is worth spending a lifetime polishing them.

II. A. 3) Adherence to traditional craftsmanship and exploration of new materials

"Redesign" is the second transformation of the traditional material form of products, is the aforementioned handicraft in the "people", "technology" and "instrument" value ontology of the "utensils" of the redesign, in the traditional handicrafts, the selection of raw materials is very important, the materials through the processing of technology, with different characteristics from natural objects, "turning materials into tools", so that the material materials have the function of use.

II. A. 4) Innovative product design based on authenticity

The definition of "authenticity" based on traditional handicrafts is "to make it possible to understand the nature, character, meaning and history of cultural heritage, all material, literal, oral and pictorial sources," including "form and design, materials and textures, use and function, tradition and technology, location and environment, spirit and emotion, and other internal and external factors."

II. B. Deep learning and super-resolution based techniques

The introduction of deep learning oversampling technology provides a new support for the interaction design process in the digital revitalization of traditional handicrafts, and can play a positive role in promoting the design strategy, design creation method and other levels [20], [21]. Consideration of the introduction of technology focuses primarily on the importance of innovation, this chapter will deeply analyze the algorithmic logic and underlying structure of deep learning supersampling technology, and analyze and study the feasibility of combining deep learning supersampling technology with the feasibility analysis of the traditional handicrafts living inheritance and innovative design process, as well as the bottlenecks and obstacles to the selection of the key points.

II. B. 1) Deep Learning Basic Theory

(1) Overview of neural networks

Deep learning is a machine learning method that relies on artificial neural networks, especially deep neural networks, with powerful pattern recognition capabilities. A neural network is a computational model consisting of multiple layers of neurons, the design of which is inspired by biological neural networks, simulating their structure and function.

First, a neuron receives inputs from the previous layer, which are weighted by connection weights and summed with bias terms. By adjusting these weights, the neuron is able to learn the importance of different inputs for feature learning and pattern recognition. Next, a nonlinear transformation is applied to the weighted summation result, i.e., an activation function, to obtain the output of the neuron. Commonly used activation functions include Sigmoid, ReLU, and Tanh, which introduce a nonlinear mapping and improve the expressive power of the neural network. Finally, the output is passed to the next layer of neurons as input.

(2) Convolutional Neural Network

The computational process of the convolution operation is shown in Fig. 1. Among other things, the input to the convolution kernel is a two-dimensional or three-dimensional data tensor, usually denoted as an input feature map. For example, in image processing, the input feature map can be a two-dimensional image or a three-dimensional tensor containing multiple channels (e.g., three channels for an RGB image). The output of the convolution kernel is a feature map, and the size of the output depends on parameters such as the size of the input features, the size of the convolution kernel, the step size, and the padding.The size of the convolution kernel refers to the dimensions of the convolution kernel, i.e., the height and the width of the convolution kernel. Step size refers to the step size of the convolution kernel sliding on the input data, which determines the size of the output feature map. Padding is the addition of extra values (usually zero-values) around the boundaries of the input data to expand the size of the input data, which resizes the output feature map while helping to process the boundary features. Specifically, for a feature map with input size $H \times W$ (H is the height and W is the width), convolution kernel size $K_H \times K_W$, step size S, and padding P, the length and width of the output feature maps (O_H and O_W) are shown in Eq. (1):

$$
\begin{aligned}
O_H &= \frac{H - K_H + 2P}{S} + 1 \\
O_W &= \frac{W - K_W + 2P}{S} + 1
\end{aligned}
\tag{1}
$$

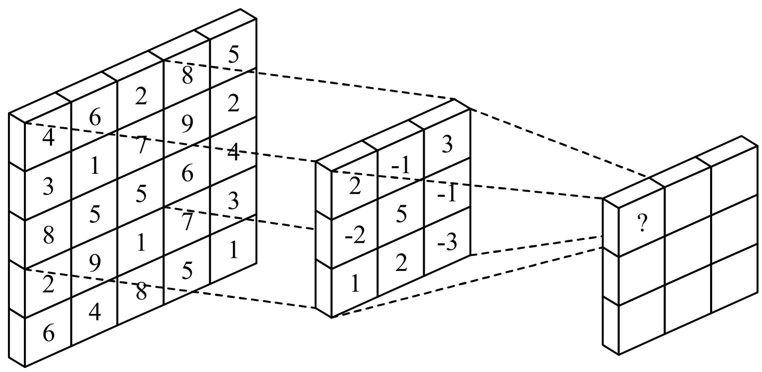

Figure 1: The operation process of convolution

II. B. 2) Image super-resolution reconstruction

Despite the continuous progress of modern image acquisition technology and the significant improvement of image resolution and clarity, the limitations of the performance of hardware acquisition devices and the shooting environment (e.g., lighting, focus, stability) still lead to the reduction of resolution or blurring of the captured images, a situation that has an important impact on the subsequent image processing and applications.

The super-resolution degradation model simulates the process of generating low-resolution images, including downsampling, blurring, and noise of images. The downsampling operation refers to the reduction of a high-resolution image to a low-resolution version, which can simulate the loss of pixels or the limitations of the camera sensor, the blurring operation simulates the blurring or distortion that the image suffers from the sensor or the transmission process, and the noise operation simulates the various disturbances and random fluctuations that are introduced into the image in the process of acquisition, transmission, or processing, and these noises can come from the environmental lighting variations, the electronic devices' signal interference, sensor errors, or approximation errors in image processing algorithms, etc. Digital images are captured from the real world as discrete pixel points, which is actually a degradation process from high-resolution images (HR) to low-resolution images (LR). This degradation process is shown in equation (2):

$$I_{LR} = \mathrm{D}(I_{HR}; \delta) \tag{2}$$

where I_{HR} represents the high resolution image, δ represents the hyperparameters of the degradation process, D represents the degradation mapping function, and I_{LR} represents the generated low-resolution image, and the degradation process usually includes downsampling, blurring, noise, etc., and the image super-resolution reconstruction is shown in Eq. (3):

$$I_{HR} = \mathrm{F}\ (I_{LR}; \theta) \tag{3}$$

where θ represents the hyperparameters of the reconstruction model and F represents the reconstruction model, the super-resolution of the image is actually the inverse of the degradation process. Super-resolution is a typical discomfort problem, i.e., the same low-resolution image can be generated by different high-resolution images.

II. C.Neural network based oversampling algorithm

II. C. 1) Multi-module convolutional neural networks

The whole multi-module oversampling convolutional neural network consists of three main modules: feature extraction module, feature reweighting module and image reconstruction module. In addition to this, there are two upsampling operations and an alignment operation used to achieve temporal reprojection, and the convolutional box size of all networks is 3*3. The network uses the first 4 frames of the history mixed with the current frames for weighting to get the final result, and it will transfer the input RGB image to the YCbCr color space before feeding it into the network, and then the final result will be transferred back to RGB from the YCbCr color space.

(1) Feature Extraction

The feature extraction module is based on a simple ResBlock residual basis structure, which utilizes jump connections to skip one or more layers, and passes the information from the shallow layer directly to the deep network, which helps to learn the constant mapping in the deep network. By introducing residual connections, the deep network is able to learn the feature representation of the data more efficiently, which improves the performance and generalization of the network. The feature extraction module consists of a three-layer convolutional neural network, the input of this network is the color and depth of each frame, and after three layers of convolution and ReLu activation function, the 8-channel features are learned, and then they are jump-connected to the input color and depth, and finally the 12-channel features are output.

(2) Temporal mapping

In order to reduce the required sensory field and thus the complexity of reconstructing the network, it is necessary to use the rendered motion vectors to project the learned features from the previous frames to the current frame through a temporal remapping operation, so that the neighboring frames are aligned with the target frame. This temporal remapping operation is also commonly referred to as warp and is widely used in video super-resolution methods. In order to obtain information about the motion of an object between neighboring frames, video super-resolution methods usually use optical flow estimated by various methods, while the rendering domain can use motion vectors computed accurately in modern renderers. Each element of the motion vector represents the offset in screen space between the pixel's current position and its position in the previous frame.

Next vector mapping is performed, the idea of backward warping is to align the previous frame image with the current frame image with the help of motion vectors and the process can be represented by equation (4).

$$F_W^{t-i} = f_W\left(F_H^{t-i}, M_H^t + \sum_{k=0}^{i} M_H^{t-k}\right) \tag{4}$$

where, f_W denotes the backward warp operation, F_H^{t-i} is the feature of the previous i th frame after zero up-sampling, M_H^t is the motion vector of the current frame after bilinear up-sampling, and $\sum_{k=0}^{i} M_H^{t-k}$ denotes the accumulation of the later frames into the current frame for the previous i th frame. running vectors, since the motion vectors are only defined for two neighboring frames, in order to use more history frames for warping, the motion vectors need to be accrued.

(3) Feature weighting

It was pointed out in the study of temporal backsampling that sudden light changes or shifts in occlusion relations may cause some pixels to be ineffectively reused. If such history samples are used directly without validation, serious artifacts will be generated. In fact, the rendered motion vectors do not fully accurately reflect the dynamic occlusion relations and shading changes between neighboring frames. Even the aligned history frames may still contain some invalid pixels that do not match the current frame. If these invalid pixels are not removed, the result after oversampling will also show serious ghosting. Therefore, the introduction of the feature reweighting module can reduce the effect of these invalid pixels.

(4) Reconstruction

The final reconstruction network uses the U-net architecture, which was first proposed to be applied in the field of medical image segmentation. The U-net structure is very similar to the traditional structure of Auto-Encoder, and its unique forward pass structure allows the network to acquire a lot of spatial information, so it is also used in image synthesis, reconstruction and other aspects of the work.

(5) Color space

Based on the fact that the human eye is insensitive to color but more sensitive to luminance, in super-resolution tasks, it is usually necessary to convert the RGB color space to the YCbCr color space to distinguish luminance from chroma, and then send it to the neural network, and then the final result obtained is transferred back to the RGB color space.

YCbCr color space, Y that the brightness of the color, can also be called gray scale, Cb that the blue concentration offset that is the blue part of the RGB and RGB luminance value of the difference between Cr that the red concentration offset that is the red part of the RGB and the RGB luminance value of the difference between. The conversion formula is given by equation (5), and delta is generally taken as 0.5:

$$\begin{cases} Y = 0.299 * r + 0.587 * g + 0.114 * b \\ Cb = (b - Y) * 0.564 + delta \\ Cr = (r - Y) * 0.713 + delta \end{cases}$$
$$\begin{cases} r = Y + 1.403 * (Cr - delta) \\ g = Y - 0.714 * (Cr - delta) - 0.344 * (Cb - delta) \\ b = Y + 1.773 * (Cb - delta) \end{cases} \tag{5}$$

II. C. 2) Loss function

A combined loss function is used to train the network and the training loss function is given by Eq. (6), which takes into account the oversampling results and the perceptual loss:

$$\begin{aligned} Loss &= L_s + L_p \\ L_s &= 1 - SSIM(I_H - I_T) \\ L_p &= w \cdot MSE(\Phi(I_H), \Phi(I_T)) \end{aligned} \tag{6}$$

where, I_H and I_T are the oversampled reconstructed image and the reference image, respectively, $SSIM$ is the structural similarity index with a window size of $9*9$, $\Phi(\cdot)$ is the pre-trained VGG-16 network used to compute the perceptual loss between reconstructed and reference images, and w is taken as 0.1.

III. Cultural and creative product design for traditional handicrafts

III. A. Design principles

III. A. 1) Maintenance of core skills in traditional crafts

Maintaining the core skills of traditional handicrafts is the primary principle in the design of cultural and creative products. This requires designers to have an in-depth understanding of the uniqueness and essence of each traditional handicraft to ensure that their traditional values are not lost in the design process. Traditional handicrafts often carry rich historical and cultural information, such as the delicate needlework of embroidery, the firing techniques of ceramics, and the fine carvings of wood carvings, etc., and their core skills are the soul of cultural and creative products. Therefore, designers should not simply copy or mechanically produce traditional handicrafts, but should take traditional handicrafts as the core elements of design, and refine and sublimate them with the help of modern design techniques, so as to ensure that each product designed can be a masterpiece that integrates traditional skills with modern aesthetics.

III. A. 2) Focus on the combination of product functionality and culture

Cultural and creative products should not only be ornamental, but also focus on practicality, and should realize the harmonious unity of functionality and culture. In order to do this, designers can skillfully integrate traditional handicrafts into the functional design of the products, so that the products can meet people's daily use while also conveying a deep cultural heritage. For example, applying traditional paper-cutting art to modern home decoration can not only preserve the beauty of traditional paper-cutting art, but also give the decorations cultural symbolism and practical value, the combination of the two will not only enhance the market competitiveness of the product, but also allow consumers to feel the charm of traditional culture in the process of using the product.

III. B. Application of digital technology in the design of handicraft cultural and creative products

As a bridge between modern technology and traditional culture, the essence of digital modeling technology lies in the use of advanced 3D scanning equipment and sophisticated modeling software to capture and reproduce every delicate form and unique texture of traditional handicrafts with unprecedented precision. This process is not only a simple data collection, but also a journey of skill inheritance and innovation across time and space. High-precision 3D scanning technology, like a meticulous craftsman, is able to penetrate into every tiny corner of the handicrafts, whether it is the complicated carving patterns, or the delicate texture of the material, it can be accurately transformed into 3D digital models, so that the beauty of the tradition can be eternally framed in the digital world.

In traditional cultural and creative product design, digital modeling technology can deconstruct, reorganize and recreate traditional elements with unprecedented freedom, realizing the refinement and personalization of product design. With the help of this technology, designers can easily adjust the proportions, curves, and even the smallest decorative details of the products, ensuring that each cultural and creative product can maintain the traditional flavor while incorporating modern aesthetics and practical functions, greatly enhancing the aesthetics and practicality of the product. This flexibility and efficiency in design not only stimulates the infinite creative vitality of the cultural and creative industries, but also provides strong technical support for the modern transformation of traditional culture.

In addition, digital modeling technology also gives traditional cultural and creative products an unprecedented way of display and marketing. Designers are able to transform digital models into vivid virtual display scenes, so that consumers can appreciate every detail of the products in an all-round and multi-angle way without having to be present in person. This immersive experience not only greatly enhances consumers' sense of participation and desire to buy, but also effectively reduces the high cost and time cost required for physical display, and lowers the market risk. At the same time, through the wide dissemination of the digital platform, the beauty of the fusion of traditional culture and modern design can cross the geographical limitations, reach a wider audience, and open up a new path for the inheritance and development of traditional culture.

IV. Analysis of the effects of traditional handicraft elements and cultural and creative product design

IV. A. User needs and satisfaction factor

IV. A. 1) Calculations

The 240 valid questionnaires were analyzed using the Better-Worse coefficient analysis, which is a measure of the impact of a user need in increasing satisfaction or decreasing dissatisfaction. When categorizing the attributes of user requirements, their specific impact can be assessed by calculating the Better-Worse coefficient, which represents the degree of increase in user satisfaction when a design requirement is met, while Worse reflects the degree of decrease in user satisfaction when a design requirement is not met. The formula for this indicator is as follows:

$$Better(SI) = (A+O)/(A+O+M+I) \tag{7}$$

$$Worse(DSI) = (-1)(O+M)/(A+O+M+I) \tag{8}$$

After screening and excluding the suspicious samples, the percentage analysis was carried out according to the attribute categorization of user demand attributes, and the corresponding Better-Worse coefficient value was calculated using the formula of Better-Worse coefficient, so as to clarify the importance of each user demand, and arrive at the categorization of each user demand attribute of the Miao silver ornaments forging technology virtual reality experience platform and satisfaction coefficients, as shown in Table 1. Among them, the introduction of the inheritor, related news and exchange community are undifferentiated demands, and the SI and DSI indexes are (0.4644,0.288), (0.4832,0.2861) and (0.4686,0.2929) respectively, and the shopping mall is an inverse demand, and the values of its SI and DSI are 0.6365 and 0.4528 respectively, which should be avoided as far as possible in the design, and therefore, the shopping mall is an inverse demand. Therefore, it should be eliminated from the overall requirements. Finally, the necessary requirements are: real modeling, immersive participation, clear goals, and skill protection; the expected requirements are: color reproduction, smooth animation, simple operation, streamlined steps, and reasonable difficulty: the attractive requirements are: comfortable environment, timely feedback, national characteristics, national spirit, and skill inheritance.

Table 1: Classification of user demand attributes and satisfaction coefficient

User demand	Attribute value					SI	DSI	Attribute
	M	O	A	I	R			
Modeling reality	0.3498	0.2969	0.1788	0.1088	0.0657	0.5092	0.6922	M
Color reduction	0.0159	0.6148	0.1985	0.1185	0.0523	0.8582	0.6655	O
animation	0.0248	0.6348	0.1498	0.1593	0.0313	0.8100	0.6809	O
immerse	0.3488	0.3088	0.1569	0.1285	0.057	0.4938	0.6973	M
Environmental comfort	0.0248	0.3048	0.4958	0.1168	0.0578	0.8497	0.3498	A
Simple operation	0.0248	0.6185	0.1785	0.1358	0.0424	0.8323	0.6718	O
Step down	0.0185	0.6058	0.1564	0.1769	0.0424	0.7959	0.6519	O
Clear target	0.3548	0.2948	0.1765	0.1596	0.0143	0.4781	0.6590	M
Timely feedback	0.0248	0.3248	0.4748	0.1752	0.0004	0.7999	0.3497	A

Reasonable difficulty	0.0248	0.5963	0.1723	0.1522	0.0544	0.8128	0.6568	O
National characteristics	0.0185	0.3187	0.5015	0.1155	0.0458	0.8596	0.3534	A
National spirit	0.0108	0.3024	0.4866	0.1458	0.0544	0.8344	0.3312	A
Skill protection	0.3548	0.3089	0.1785	0.1248	0.033	0.5040	0.6863	M
craftsmanship	0.0105	0.3125	0.5036	0.1196	0.0538	0.8625	0.3414	A
Introduction of inheritage	0.0168	0.2588	0.1857	0.4958	0.0429	0.4644	0.288	I
Relevant news	0.0185	0.2548	0.2068	0.4752	0.0447	0.4832	0.2861	I
Shopping mall	0.0185	0.2036	0.1086	0.1598	0.5095	0.6365	0.4528	R
Communication community	0	0.2748	0.1648	0.4985	0.0619	0.4686	0.2929	I

Note: M represents essential requirements; 0 represents expected requirements; A represents charm requirements; 1 represents undifferentiated requirements. R is the reverse demand; Q is a suspicious result.

IV. A. 2) Product evaluation

Overall, this model of combining digital products and traditional physical experiences achieved some results. The experimenters calculated the overall performance of this traditional handmade element experience based on the 10 dimensions corresponding to the assessment questions in the scale, as shown in Figure 2. Among them, each dimension is calculated based on the total score, and it can be seen from the data that this digital handicraft experience performed well in terms of "ease of learning", "creativity", "improving skills", and "promoting participation", with scores of 15, 10, 10, and 10 points, respectively.

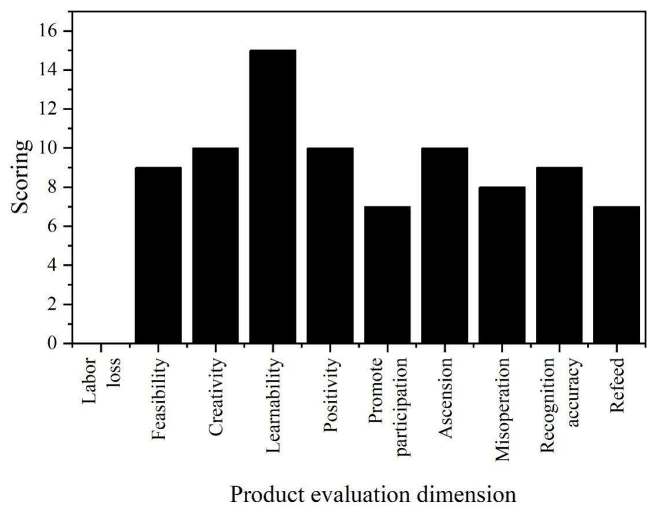

Figure 2: Product evaluation of the top 10 dimensions

IV. B. Verification of the effect of product use

(1) Users

After the participants completed the operation of each task as required, they then focused on the evaluation of the operability and aesthetics of the traditional handicrafts, using a 5-point Likert scale (1 means extremely dissatisfied, 5 means very satisfied), and the mean is now obtained, and Fig. 3 shows the statistics of the satisfaction of the operation of the traditional handicrafts tasks. Most of the users had good ratings for both operability and aesthetics, with the mean of 10 participants rating operability and aesthetics at 4.2 and 3.9 points respectively. While participant 7 was further asked about the reason for giving a score of 2 for aesthetics, he stated that the overall style was not very much in line with his aesthetics. Participant 8, on the other hand, thought that the digital display model of traditional handicrafts needed to be strengthened in terms of finish and that the details of the scene should be further increased.

A focus group of 10 participants was formed (remote video) and asked to point out the strengths and weaknesses of the model and directions for improvement. Most of the participants were positive about the positioning and implementation of the model, and expressed their expectations for immersive videos, interactive videos, zoomed displays of exhibits, and customization of traditional handicrafts. As for some icons in the interface, they hoped that the ideology should be clearer.

Six creative product designers were invited to design creative products based on the method in the article, and 10 audiences were invited to comment on the design.

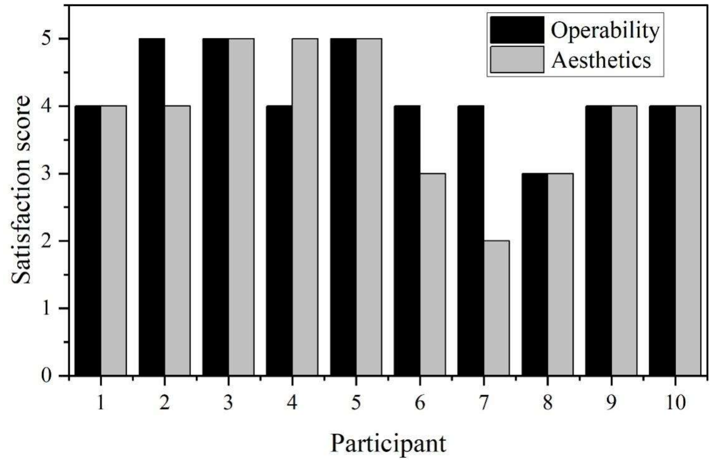

Figure 3: Statistics on the operation satisfaction of traditional handicraft tasks

Table 2 shows the statistics of audience satisfaction. The audience highly recognized the style of the cultural and creative products designed by the Wenwen method, and the probability of purchasing them was high. The proportions of the design style, purchase probability and favoritism of the designed cultural and creative products, which were recognized as excellent, were 6%, 15% and 20% respectively.

Table 2: Audience satisfaction statistics

Survey content	Design style	Purchase probability	Degree of affection
Excellence	6	15	20
Good	8	6	2
Medium	5	2	2
Better	2	1	0
Worse	1	0	1

(2) Designer satisfaction

Table 3 shows the statistics of designers' satisfaction,the designers made high evaluation on the ease of use,generalizability and practicality of the model in the paper,the higher ease of use indicates that the method is simple in procedure and easy to start,the highest generalizability given by the designers is 94.2488%,and the lowest reaches 88.7958%,which is a promising prospect for the market application. The utility of the model basically focuses on more than 90%, only one designer gives 88.5485% evaluation result, which indicates that the model has less redundant procedures and is committed to mining precise cultural association features.

Table 3: Designer satisfaction statistics

Designer number	Ease of use	Extensibility	Practicability	Response delay
1	95.5485	93.6452	92.1585	3.1525
2	92.6487	89.1258	93.6485	2.9854
3	95.8696	92.6425	94.5485	3.2485
4	96.4285	88.7958	92.8485	2.8485
5	96.4324	91.8485	92.4698	2.6485
6	97.1868	94.2488	88.5485	2.9485

V. Conclusion

The digital design method for traditional handicrafts combining deep learning and super-resolution technology in this study has significant advantages. The super-resolution reconstruction of traditional handicrafts improves the presentation of image details and enhances the user's immersion experience. In the user satisfaction survey, the designed cultural and creative products scored 15 points for “ease of learning” and 10 points for “creativity”, reflecting the practicality and innovation of the method in product design. In addition, the products designed based on this method gained high recognition in the market, and the design style was loved by consumers, with a purchase probability of 15%. These results show that combining digital technology and traditional handicrafts can not only enhance the cultural value and market competitiveness of products, but also provide effective support for the innovation and inheritance of traditional crafts.

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