Digital Protection and Display of Cantonese Embroidery Patterns Based on CAD and Human-Computer Interaction

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Abstract. In the digital preservation and display of Cantonese embroidery patterns, computer-human-computer interaction technology is particularly important. By utilizing computer-assisted human-machine interaction technology, this article presents a cutting-edge digital preservation and display of the image algorithm model for Xiangyun yarn patterns. The research method scanned high-resolution data by capturing the complex texture of auspicious cloud colours in Cantonese embroidery patterns. The use of image processing algorithms eliminates a series of noise generated during the process of capturing pattern tones and sharpens details. Following this, the refined image undergoes vectorization and precise modelling via CAD software, yielding an editable and scalable digital representation. Additionally, we've crafted an interactive exhibition system that immerses viewers in the cultural allure of Cantonese Embroidery through HCI. Experimental results demonstrate that our enhanced model outperforms the original AlexNet in embroidery classification, notably improving accuracy, recall, precision, and the F1 score. This underscores the significance of tailoring deep learning models to specific applications.

Keywords: Cantonese Embroidery; Xiangyun Gauze; CAD; Human-Computer Interaction; Digital Protection; Exhibition Platform
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1 INTRODUCTION

Cantonese Embroidery, the bright pearl of China's traditional embroidery technology, combines profound cultural heritage and unparalleled artistic value. Since the origin of the Tang Dynasty, after many dynasties' precipitation and polishing, Cantonese Embroidery is unique in the history of arts and crafts in China with its exquisite stitches, gorgeous colours, and unique pattern design [1]. As the soul of this art, the Cantonese Embroidery pattern bears the ingenuity and creative inspiration of countless craftsmen. These patterns are not only pleasing to the eye but also contain profound cultural connotations. From delicate flowers, birds, fish, and insects to magnificent landscapes, every detail tells the richness and profundity of Chinese culture. With the rapid development of modern technology and the rise of new media, embroidery patterns, a traditional art form, are facing unprecedented challenges in protection and inheritance. Especially its costume culture, as an indispensable part of embroidered patterns performance, also faces many difficulties. Digital protection shows great potential in the application of embroidered pattern costumes [2]. The digital inheritance method not only expands the dissemination channels of embroidery patterns but also enables more people to come into contact with and understand this traditional art form. In order to further protect and inherit this precious cultural heritage, some scholars have adopted 3D virtual visualization technology to successfully virtually restore 12 sets of traditional embroidered costumes. Based on virtual restoration, further digital protection and innovative design have been carried out on the embroidered pattern series costumes. Through comprehensive digital display, the audience can more intuitively feel the charm and charm of embroidered pattern costumes. It deeply analyzed the unique style and complex structure of embroidered pattern costumes, not only extracting their rich and colourful colours but also meticulously summarizing their unique pattern designs. Not only can precise copying and preservation of costumes be achieved, but also through virtual reality and other technological means, the audience can personally experience the feeling of wearing costumes [3]. The application of this technology not only provides a new digital display method for costumes but also opens up new avenues for their protection and inheritance. This immersive experience will undoubtedly greatly enhance the audience's interest and sense of identification with embroidery pattern culture. By digitizing and analyzing traditional costumes, designers can gain a deeper understanding of their structure and characteristics, thereby creating costumes that better meet modern aesthetic and dressing needs. This innovative design is not only the inheritance and development of traditional embroidery pattern culture, but also the innovation and breakthrough of traditional art forms. In addition, digital protection also helps promote innovative design of costumes.

In China, the digital protection of Cantonese embroidery patterns as an intangible cultural heritage has become a highly anticipated focus and challenge. At the same time, every detail in the pattern is sharpened to ensure that the digital results can truly restore the exquisite and unique Guangdong embroidery [4]. The use of image processing algorithms for meticulous preprocessing of scanned data aims to eliminate potential noise. In order to gain a deeper understanding of the current situation in this field, some scholars have conducted in-depth inspections of local intangible cultural heritage protection centres and used semi-structured interviews to explore the actual situation of digital protection of Guangdong embroidery pattern intangible cultural heritage sites. But at the same time, the composition is also very diverse. These intangible cultural heritage protection centres have abundant digital resources. The research method first starts by capturing the complex texture and colour tone of Xiangyun yarn in Cantonese embroidery, thanks to the precise ability of high-resolution scanners to capture the complex texture and colour tone of the yarn. In the face of this situation, it is necessary to further clarify the rights and responsibilities of these protection centres, ensuring that each institution can clarify its role and tasks in digital protection. After an in-depth analysis, it was found that the digital preservation system of Chinese Cantonese embroidery patterns and cultural heritage exhibits a clear structure. Such a platform can not only promote communication and cooperation among various protection centres but also provide the public with more opportunities to understand and learn about Cantonese embroidery culture [5]. At the same time, it is crucial to establish unified storage standards, which not only regulate the storage and management of resources but also improve their accessibility and shareability. However, the storage and management of these resources appear relatively chaotic. Although there is policy support, there are still shortcomings in actual management. By strengthening digital preservation management, we can ensure that these precious intangible cultural heritage are better inherited and protected, leaving more cultural wealth for future generations. However, the treasure of Cantonese embroidery is also facing challenges brought about by changes in times [6]. The fault of skill inheritance and the reduction of market demand all pose a threat to the survival and development of Cantonese Embroidery. Especially in the use and inheritance of ——Xiangyun Gauze, the traditional carrier of Cantonese Embroidery, difficulties were encountered. Xiangyun Gauze, as a traditional fabric of Cantonese Embroidry, has the characteristics of lightness, breathability, and flexibility, which complement the skills of Cantonese Embroidry and create countless classic works together. But nowadays, with the rise of modern textile materials, the production and application of Xiangyun

Gauze are gradually decreasing, which undoubtedly brings additional pressure to the inheritance of Cantonese Embroidery.

As a treasure of traditional Chinese handicrafts, the digital protection of Cantonese embroidery patterns is particularly important. Especially in the analysis of nuclear imaging raw data, fine digital restoration is carried out for artworks with Cantonese embroidery patterns. These differences are not only reflected in processing speed but also involve the accuracy of image restoration and the degree of detail preservation. Integrate these trained neural networks seamlessly into cloud-native web applications to achieve real-time analysis of XRF raw data [7]. The AIRES-CH (Artificial Intelligence) project for the digital restoration of Guangdong embroidery pattern cultural heritage is not only committed to promoting this protection work through cloud-native network applications but also combines computer vision technology [8]. The appearance design of Yue embroidery is one of the core links in Yue embroidery clothing design, which makes an important contribution to the overall beauty and sales of clothing. The overall style design method of clothing based on DCGAN also has the problem of blurred transfer effect. At present, the attribute generation effect of clothing local attribute design methods based on WGAN is poor. It mainly includes three aspects: clothing partial attribute design, Guangdong embroidery clothing partial decoration design, and clothing overall style design. The design method of Cantonese embroidery patterns in clothing partial decoration design heavily relies on designers and lacks end-to-end intelligent design solutions [9]. Traditional clothing pattern design heavily relies on designer experience and design inspiration, lacking intelligent generation solutions. At the same time, the perceptual loss function was used to optimize the attribute learning process, significantly improving the effectiveness of attribute generation. Based on the clothing dataset design experiment, it was verified that the algorithm proposed in this paper can generate and edit various local clothing attributes. In response to the problem of poor attribute editing performance caused by insufficient feature extraction network representation ability in the original WGAN algorithm, residual structure optimization is adopted to enhance feature extraction ability. Using a real-time style transfer network to intelligently generate new fashion patterns and seamlessly fit them onto stylish clothing, achieving the end-to-end intelligent design of local clothing patterns [10].

This study is devoted to opening up a new way for the digital protection and display of Cantonese Embroidery patterns and its traditional material, Xiangyun Gauze, through CAD and HCI technology. We hope that through these modern scientific and technological means, not only can the Cantonese Embroidery pattern be better preserved and spread, but also people's attention and interest in Xiangyun Gauze, a traditional material, can be aroused again. By employing scientific and meticulous research methods, along with cutting-edge technological applications, we aim to breathe new life into the preservation and advancement of Cantonese Embroidery and Xiangyun Gauze, ensuring these cultural gems continue to dazzle in modern times. The major contributions of the paper are below.

(a) Our study integrates CAD technology with deep learning (DL), introducing an enhanced AlexNet model to aid in the preservation of Cantonese Embroidery designs. Utilizing high-precision modelling and the intelligent recognition capabilities of deep neural networks, we've achieved meticulous digital recreations of these intricate patterns.

(b) We've crafted an interactive exhibition platform for Cantonese Embroidery designs, fostering engagement between the audience and these cultural treasures. This fusion of advanced technology and traditional artistry significantly elevates the audience's immersive experience.

(c) Our research bridges the gap between computer science, art design, and heritage preservation, forging an innovative interdisciplinary approach. This offers a fresh scientific and technological viewpoint for the digital conservation and exploration of intangible cultural heritage.

In the next chapter, we will first review the research status of the Cantonese Embroidery pattern and the application of CAD and HCI technology in cultural heritage protection. Then, it introduces the research methods and specific technical routes adopted in this study in detail, and then focuses on the digital protection and display process of Cantonese embroidery patterns and their effect evaluation. Finally, the research results are discussed and prospected, and possible improvement measures in the future are put forward.

2 LITERATURE REVIEW

With the rapid development of deep learning technology, research on style conversion has become a trend, such as converting modern photos into Chinese painting, sketching, or comic style. Ink is known for its unique brushstrokes and artistic conception, but often contains low-quality textures and blurred boundary features, which pose additional difficulties to the conversion process. As a generative model, GAN can create new images that are very similar to the original training data through its unique adversarial training process. To overcome these challenges, Lu et al. [11] combined the cyclic consistency GAN with the pix2pix framework and creatively introduced label functions to enhance boundary recognition and processing. This combination not only ensures the stability of the conversion process and the quality of the generated image but also makes the converted image more realistic while maintaining the spirit of ink and wash by introducing label functionality. Through user interaction, more people can participate in the appreciation and creation of Chinese paintings, experiencing the unique charm of this ancient art form. However, compared to the general image-to-image translation, converting Chinese ink paintings into realistic images presents higher challenges. This study not only provides new ideas and methods for the digital protection of patterns but also provides valuable experience for us to further explore the integration of traditional Chinese painting and modern technology. There is little research on transforming Chinese painting into realistic images and enriching painting content through user interaction. At the same time, this digital protection method has also opened up new paths for the inheritance and development of traditional culture.

In the field of Art and Painting Style Transformation (APST), deep generative models demonstrate their powerful application capabilities. To address these challenges, Trunfio et al. [12] proposed a unique stream-based architecture where two encoders and decoders share a reversible network layout. The experimental results are encouraging. Compared with existing models on the ChipPhi dataset, our method achieved a 5% increase in PSNR, a 6.2% increase in SSIM, and a 29.4% reduction in style error. This new APST flow model significantly reduces the uncertainty of the model through compact analysis and synthesis methods, thereby improving its generalization performance and convergence stability. In terms of generator design, Wang et al. [13] implemented a traffic network based on wavelet additive coupling (WAC) layers, which can effectively extract multi-scale content features and provide a more refined transformation foundation for pattern digital protection. During the training process, in order to enhance the generated salient details, we applied an adaptive stroke edge loss function not only at the global level but also at the local level. In addition, Wang et al. [14] also introduced a style checker, which further enhances global style consistency by minimizing the error between the reconstructed image and the original input image. In terms of maintaining reconstruction spatial details and model convergence efficiency, this is usually limited by the irreversible decoder methods in existing models. These competitive results fully validate that the APST Flow model significantly enhances its generalization ability while maintaining small content bias, thus achieving high-quality generation results.

When delving into the digital protection of China's intangible cultural heritage, we have to mention a key area - the digital protection of patterns. Zhou et al. [15] attach great importance to the digital protection of intangible cultural heritage. From the research results, it can be seen that the digital preservation system of Chinese cultural heritage presents a clear and diverse structure. Through detailed research on the activities of intangible cultural heritage protection centres in cities such as Nanyang, Kaifeng, Xianning, Chibi, Sanming, and Jingdezhen, I found that the current status of digital protection work not only has significant advantages but also exposes some problems. This field is not only an important component of China's cultural heritage protection but also faces a series of challenges and opportunities. However, the storage status of these digital resources appears somewhat chaotic, lacking unified standards and norms. These protection centres have abundant digital resources, including various exquisite patterns that can be permanently preserved and inherited through digital means. Firstly, the rights and responsibilities of these protection centres should be further clarified to ensure that they play a greater role in digital protection work. Using virtual reality technology, construct a virtual display space for patterns, allowing the audience to experience the charm of the patterns firsthand. However, in the actual operation process, we found that there are certain difficulties in implementing these policies, especially in the management of digital preservation. In terms of digital protection of patterns, Zidianakis et al. [16] drew on successful experiences in other fields, such as using advanced image processing techniques to perform high-precision scanning and restoration of patterns. At the same time, establish a shared platform to promote communication and cooperation among different protection centres, and jointly promote the progress of digital protection work. In response to the above issues, we believe it is necessary to start from multiple aspects and further strengthen the digital protection of intangible cultural heritage. Weak management and unclear responsibilities have to some extent hindered the further development of digital protection work. Secondly, a unified digital protection standard should be established to standardize the storage and management of digital resources. In addition, innovative redesign and development of patterns can be carried out by combining modern design concepts and market demands, promoting the digital protection of patterns and the integrated development of the cultural industry.

CAD technology, renowned for its precision modelling and measurement abilities, has gained widespread application in cultural heritage preservation. Numerous studies have attested to CAD's efficacy in restoring cultural artifacts, devising protection strategies, and creating virtual exhibitions.

3 METHODOLOGY

The acquired image data will be used as the basis for subsequent digital processing. After the acquisition is completed, enter the pretreatment stage. The main purpose of this stage is to remove the noise in the image, enhance the details of the pattern, and adjust the colour to restore the true features of the Cantonese Embroidery pattern.

During the implementation process, $\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}$ consists of four adjacent pixels, whereas p the point lands on one of these four points. Let the origin of the area be set at the upper left corner. If Δ_{col} represents the horizontal distance from the target pixel to this origin, then the formula to compute the colour value of R_1, R_2 in the x direction is given below:

$$\delta\ R_1 = Color\ M_{21} - Color\ M_{11} \cdot \Delta_{col} + Color\ M_{11} \cdot 256 \tag{1}$$

$$\delta\ R_2 = Color\ M_{22} - Color\ M_{12} \cdot \Delta_{col} + Color\ M_{12} \cdot 256 \tag{2}$$

In this context, $Color\ X$ represents the colour value corresponding to the point X, which is determined using the 24-bit true colour format for precise calculation.

To illustrate, let's consider the extraction of colour moments from the brightness component in a mixed-colour space. We transform a small section of the image into HSV, HIS, and YUV colour spaces. Then, we weigh and combine the respective first-order moments of these three components to derive the first-order moments $F_{MIX-L}\ \mu$ of the brightness component within the mixed colour space:

$$F_{MIX-L}\ \mu = \frac{W_{HSV} \times F_{HSV-V}\ \mu + W_{HIS} \times F_{HIS-I}\ \mu + W_{YUV} \times F_{YUV-Y}\ \mu}{W_{HSV} + W_{HIS} + W_{YUV}} \tag{3}$$

W_{HSV}, W_{HIS}, and W_{YUV} represent the weights assigned to the respective colour spaces.

Cantonese embroidery patterns show unique styles and aesthetic concepts in colour application. Different from some art forms that pursue the authenticity of colour, Cantonese Embroidery patterns pay more attention to the symbolic meaning and harmonious aesthetic feeling of colour. In Cantonese Embroidery, each colour may carry profound cultural connotations, and through clever colour matching, it conveys rich emotions and implications.

After preprocessing, high-precision modelling is carried out by using CAD software. Aiming at the problem that current clothing pattern design heavily relies on designer experience and design inspiration, and lacks intelligent generation, a clothing local pattern generation algorithm based on an improved style transfer network is proposed. Through experimental comparison, it is verified that the algorithm proposed in this paper has better performance in pattern generation than classical style transfer algorithms and real-time style transfer algorithms, and can successfully achieve local pattern generation design for clothing. Using real-time style transfer network to intelligently generate new fashion patterns, and then seamlessly fitting them onto stylishless clothing, achieving end-to-end intelligent design of local clothing patterns. The function of a generator is to generate images based on input noise. The discriminator, on the other hand, determines the probability that the input image is a true image based on its input. The generator continuously generates images that are close to the real image, while the discriminator continuously improves its ability to recognize true and false images. The two compete and work together to improve. The calculated true and false losses are fed back to the generator so that the weights of the generator can be updated and optimized. The discriminator also improves its discriminative ability during the training process, making it easier to identify false images generated by the generator. During training, the generator and discriminator alternate for training. When the discriminator is unable to distinguish the authenticity of the images generated by the generator, the training is completed. In this game process, the generator's ability to fit the original data increases, and the generated images become closer to the real data, ultimately making it difficult for the discriminator to distinguish its authenticity.

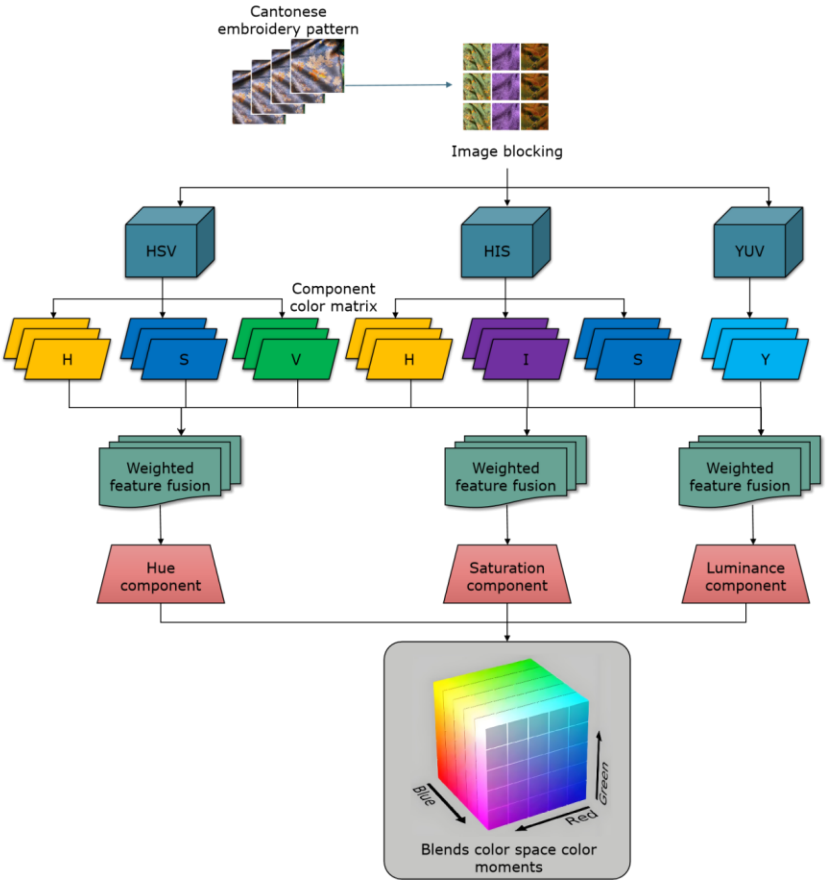

Figure 1: Color moments in mixed colour space.

Figure 1 shows the Color moments in mixed colour space. In Guangdong embroidery, each colour may carry a profound cultural connotation, and through clever colour matching, it conveys rich emotions and implications.

The colour contrast of Guangdong embroidery patterns is not only for visual beauty but also for highlighting the theme and details in the patterns. The use of this color makes the patterns of Guangdong embroidery more vivid visually. Furthermore, it also enables viewers to understand the cultural heritage and artistic value of Guangdong embroidery more deeply. Initially, the colour disparity of pixels in an image I is computed:

$$d\ I_i\ = \sum_{j \in N\ i} \left|I_i - I_j\right| \tag{4}$$

Here, $\left|I_i - I_j\right|$ denotes the absolute disparity between pixel i and its adjacent pixel j, while $N\ i$ signifies the pixel count in the proximity of pixel i.

The process of efficiently encoding natural images based on sparsity principles is termed sparse coding. Every image can be constructed through a linear combination of various basis functions contained within an over-complete dictionary. These necessary basis functions exhibit sparsity relative to the over-complete dictionary. Basis functions can be acquired through learning from natural images, and the acquired functions bear a resemblance to the receptive fields of simple cells.

The fundamental concept behind sparse coding involves identifying the minimal number of atoms from the learned over-complete dictionary that aligns closely with the signal being approximated. These atoms are then linearly combined to closely mimic the original signal. The mathematical representation of sparse coding is outlined below:

$$\min_x = \left\|x\right\|_0 \textit{subject to} \left\|y - D_x\right\|_2 \leq \varepsilon \tag{5}$$

Here, $\left\|x\right\|_0$ denotes the 0-norm, which counts the number of non-zero elements within the vector. y Stands for the input signal, D represents the over-complete dictionary, and x signifies the sparse coding coefficient. To achieve sparse coding of signals, it is imperative to construct a basis that is adequately dense within the signal space.

$$V = \frac{1}{n} \sum_{i=1}^{n}\ H_i - H_m\ ^2 \tag{6}$$

During colour prediction, the averaging effect may cause coloured images to lose saturation. Furthermore, if the set of viable colourings is non-convex, the true solution may fall outside of this set, yielding an uncertain outcome. Given the brightness input X, the CNN learning function mapping $\delta\ \cdot$ is utilized to determine the probability distribution of potential colours for each pixel.

$$\hat{Z} = \delta\ X \tag{7}$$

To enable a comparison between the predicted colour probability distribution $\hat{Z}$ and the real colour probability distribution Z, a function has been established to convert the true colour Y into the vector Z:

$$Z = H_{gt}^{-1}\ Y \tag{8}$$

This process adopts a soft-encoding method by identifying the nearest five neighbours of the true colour $Y_{h,w}$ in the output space of class 213 and using Gaussian weighting determined by their closeness $Y_{h,w}$.

The final layer of this study utilizes the softmax classification function, which is prevalent in multi-classification assignments. Within reinforcement learning, the softmax function frequently transforms specific values into activation probabilities. In this context, the softmax function evolves into one with temperature parameters:

$$\sigma_t(z)_j = \frac{\exp(z_j/T)}{\sum_{k=1}^{K}\exp(z_k/T)} \qquad for\ j = 1,2,\cdots,K \tag{9}$$

In this context, T represents the temperature parameter. When T nears positive infinity, the probabilities of activation for all activation values tend to equalize, implying minimal differences among them. On the contrary, when T is nearly zero, the disparities in activation probabilities among distinct activation values become more evident.

Shape features constitute highly intuitive characteristics, remaining unaffected by operations like image translation, rotation, or flipping, which don't alter colour features. Shape feature extraction can be categorized into two methods: one involves tracing the object's boundary to extract its contour, while the other focuses on extracting shape based on the region. Figure 2 illustrates the outcome of edge contour feature extraction from a Cantonese Embroidery image.

(a) Gambiered Guangdong gauze (b) Edge features

Figure 2: Edge feature extraction from Cantonese Embroidery image.

To define the style loss function, a Gram matrix is required:

$$l_{style}^{\phi,j}\left(\hat{y}, y\right) = \left\| G_j^{\phi}(\hat{y}) - G_j^{\phi}(y) \right\|_F^2 \tag{10}$$

F represents the Frobenius norm, also known as the F-norm, which is a matrix norm. $G_j^{\phi}(x)$ Denotes the Gram matrix associated with the activation value of image x in the j layer of model φ. $G_j^{\phi}(x)$ is defined as follows:

$$G_j^{\phi}(x)_{c,c'} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \varphi(x)_{h,w,c} \varphi_j(x)_{h,w,c'} \tag{11}$$

$G_j^{\phi}(x)_{c,c'}$ signifies the correlation between two channels c,c' in the feature map, expressed through the Gram matrix. Meanwhile, $\varphi_j(x)_{h,w,c'}$ designates the coordinate values of the height and width channels for the activation value (or feature map) of the j layer within the module φ, specifically at the h,w,c position.

The overall loss for the rapid style transfer network is defined in the following manner:

$$L_{total}(p,a,x) = \gamma_1 L_{content} + \gamma_2 L_{style} \tag{12}$$

To simplify computations during the coding process, the content loss function is frequently computed using just a single network layer. On the other hand, multiple network layers are involved in calculating the style loss function, which is then averaged out.

Upon completion of modelling, the model undergoes optimization to shrink the file size and enhance rendering efficiency. This optimization includes combining repeated lines, eliminating redundant nodes, and modifying line thicknesses. These actions are designed to streamline the model's structure without compromising the pattern's visual appeal.

The optimized model will be stored in a format supported by CAD software, such as DWG, DXF, etc. These formats have good compatibility and expansibility, which is convenient for subsequent editing and viewing in other software. Furthermore, version control technology is used to manage different versions of model files to ensure the integrity and traceability of data.

4 EXPERIMENT AND ANALYSIS

4.1 Experimental Environment

To validate the efficacy of the proposed digital preservation and exhibition method for Cantonese Embroidery patterns, a model training experiment was carried out on a 64-bit Windows 11 operating system. To ensure precise and efficient experimentation, we utilized a high-performance Intel I7-12700H processor and an NVIDIA GeForce RTX 3060 graphics card. For the software aspect, we employed the PyTorchDL framework, integrated with the PyCharm 2022.3 development environment, offering comprehensive support for model training.

During the training phase, we established these critical parameters: an iteration count of 300 to guarantee thorough data characteristic learning by the model; a batch size of 32 to strike a balance between training efficiency and memory consumption; the incorporation of MixUp technology (λ=0.2) and GridMask technology (P=0.65) to bolster the model's generalization capabilities; a learning rate of 0.001 for precise model parameter adjustments; and a Dropout rate of 0.5 to mitigate the risk of overfitting.

4.2 Analysis of Experimental Results

In this study, a DL model tailored for Cantonese Embroidery pattern classification is devised. To assess the model's efficacy, both the original and an enhanced version of the AlexNet network are utilized for classifying and training Cantonese Embroidery images within a designated experimental setting.

Throughout the training phase, detailed records are kept of how the accuracy and loss of both the training and validation sets evolve with each iteration. Figures 3 and 4 clearly illustrate that, as training progresses, the enhanced AlexNet model demonstrates remarkable proficiency in classifying Cantonese Embroidery designs. After approximately 90 generations, the model starts to converge steadily, ultimately achieving a remarkable 95.8% accuracy on the training set, with the loss value dipping below 0.01.

To gain a more comprehensive understanding of the model's performance, a comparison between the original AlexNet model and its improved counterpart was conducted on the validation set. By contrasting Figure 5 with Figure 6, it becomes evident that the enhanced model exhibits swifter convergence and attains stability more rapidly during the training process.

To precisely quantify the enhancement achieved by the model, a detailed comparison of recall, precision, accuracy, and F1 score between the two models was conducted at Epochs 100 and 200 (refer to Table 1). The findings reveal that the refined AlexNet model significantly outperforms the original model across all metrics. Notably, at Epoch 100, the accuracy of the enhanced model surpasses the original by 90.5%, and at Epoch 200, it improves by 86.7%. In general, the peak accuracy of the original model capped at 0.5538, whereas the refined model elevated it to 0.9511, marking a substantial increase of 71.7%.

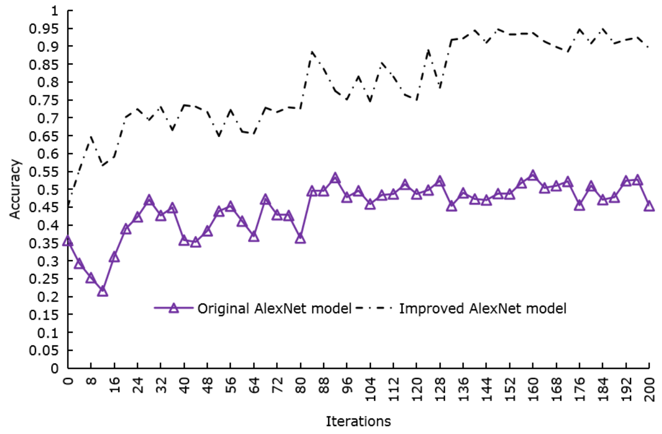

Figure 3: Accuracy of training set.

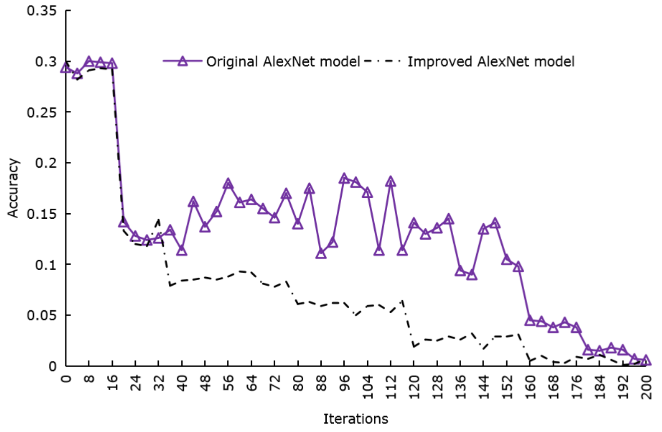

Figure 4: Loss value of training set.

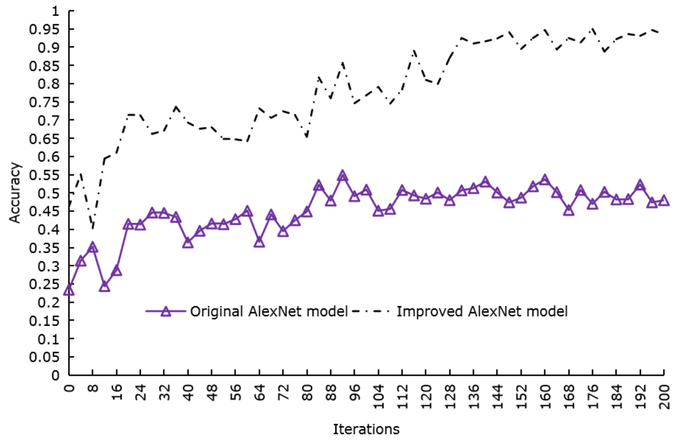

Figure 5: Verification set accuracy.

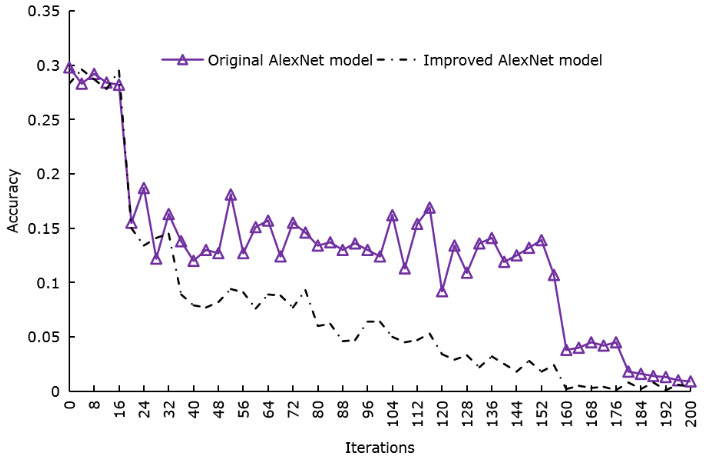

Figure 6: Verification set loss value.

Epoch	*Model*	*Recall*	*Precision*	*Accuracy*	*F1*
100	Original AlexNet	0.6017	0.6427	0.5001	0.6215
	Improved AlexNet	0.9499	0.9334	0.9523	0.9437
200	Original AlexNet	0.6252	0.6745	0.5538	0.6415
	Improved AlexNet	0.9612	0.9422	0.9511	0.9507
Highest value	Original AlexNet	0.6238	0.6710	0.5538	0.6429
	Improved AlexNet	0.9611	0.9401	0.9511	0.9544

Table 1: Comparison of indicators when EPOCH is 100 and 200.

In order to further intuitively show the improved effect of the model, the original AlexNet model is used to classify some Cantonese Embroidery patterns, and the results are shown in Figure 7. Obviously, because different kinds of Cantonese Embroidery patterns are similar in style and style, the original model is not ideal for identifying these subtle differences, which leads to a high error rate in classification results.

However, when using the improved AlexNet model for the same classification task (as shown in Figure 8), the model demonstrated excellent recognition ability and was able to accurately distinguish different types of Cantonese Embroidery patterns. This significant improvement fully demonstrates the practicality of the proposed model in the Cantonese Embroidery pattern classification task.

4.3 Discussion

This article delves into the digital protection methods for Cantonese Embroidery patterns, particularly by combining CAD technology and an improved AlexNet model to achieve high-precision protection and classification. Cantonese Embroidery, This treasure of traditional Chinese craftsmanship, with its unique artistic value and complex manufacturing techniques, makes digital protection particularly important. Cantonese Embroidery often uses Xiangyun Gauze as embroidery fabric, and the unique texture and texture of this material also pose certain challenges to digital reproduction.

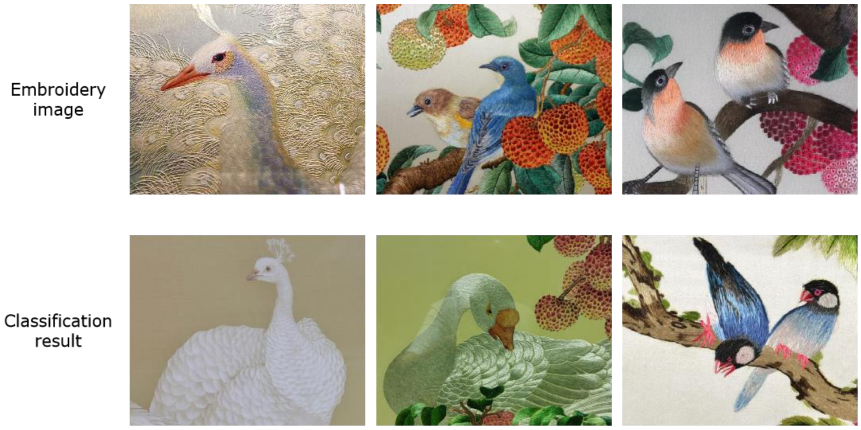

Figure 7: Classification results of the original AlexNet model.

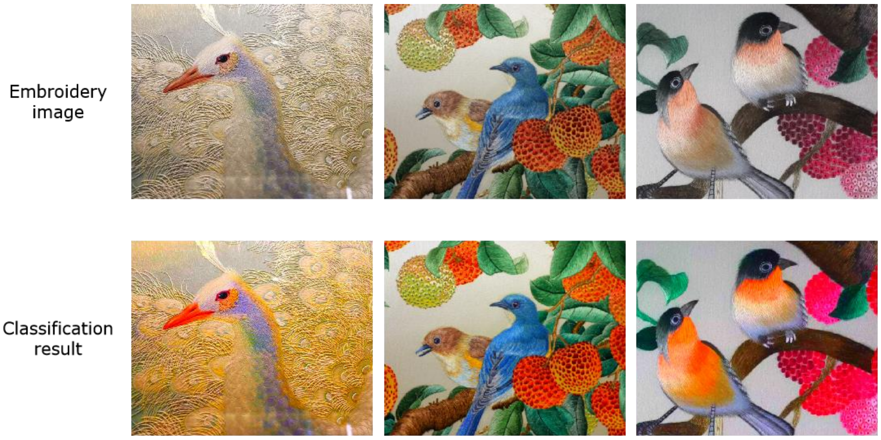

Figure 8: Classification results of improved AlexNet model.

By introducing CAD technology, high-precision modelling and reproduction of Cantonese Embroidery patterns have been successfully achieved. This not only ensures that the details of cultural heritage are fully preserved, but also provides strong technical support for subsequent material research, display methods, and innovative design.

It became evident that the enhanced model exhibited notable advancements in terms of accuracy, recall, precision, and F1 score. This underscores the significance of tailoring deep learning models to specific applications. Notably, when dealing with embroidery featuring comparable designs and aesthetics, the upgraded model exhibited superior recognition capabilities. This undoubtedly holds immense practical significance in distinguishing various types of Cantonese Embroideries, particularly those crafted using similar Xiangyun Gauze fabrics.

Nevertheless, this study bears some limitations. Despite the improved AlexNet model's commendable performance in classification tasks, its training and refinement still hinge on a substantial amount of high-quality data.

5 CONCLUSIONS

The application of HCI enhances the interaction between the audience and cultural heritage, enhancing public interest in traditional culture. During the experiment, the enhanced AlexNet model was utilized for embroidery classification, yielding remarkable outcomes that highlight the vast potential of deep learning in preserving cultural heritage. Furthermore, digital technology not only aids in the preservation of Cantonese Embroidery patterns but also offers fresh insights and approaches for exploring and applying traditional materials in Cantonese Embroidery, Xiangyun Gauze being a prime example. The unique texture and qualities of Xiangyun Gauze, a vital component of Cantonese Embroidery, have been precisely replicated in digital models, greatly aiding future material research and design innovation.

This research not only blazes a new trail for the continuation and advancement of Cantonese Embroidery but also serves as a valuable reference for the digital preservation of other forms of intangible cultural heritage. By embracing digital technology, we can better conserve, showcase, and share traditional cultures, enabling a wider audience to appreciate the distinctive allure of ICH.

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