(IJACSA) International Journal of Advanced Computer Science and Applications,
Vol. 17, No. 7, 2026

Deep Learning-Based Image Recognition and Brand Identity Design for Intangible Cultural Heritage in Southern Sichuan

Zhihong Chen
Neijiang Normal University, Neijiang 641100, China

***Abstract*—The increasing emphasis on digital protection and creative transformation of intangible cultural heritage highlights the urgent need to apply artificial intelligence to accurately identify and brand rich cultural heritage resources in southern Sichuan. This study puts forward an image recognition and brand design model suitable for intangible cultural heritage in southern Sichuan. This model has obvious advantages in extracting key visual features such as texture, color, and shape, effectively coping with the challenges brought by complex texture and category imbalance in intangible cultural heritage images, and achieving stable and reliable recognition performance. The proposed model improves the overall accuracy, F1 score, and recognition rate of complex texture images, and the overall accuracy reaches 94.1%. Among them, the recognition accuracy of texture, color, and shape reached 92.8%, 95.2%, and 90.1%, respectively, which were better than the traditional models, and accurately captured the detailed features and visual style of intangible cultural heritage items. In the application of brand logo design, the evaluation results of user satisfaction show that the score is high in aesthetics, commercial value, and narrative quality, among which the average score of aesthetics is 3.92, which highlights the advantages of this model in visual language and artistic expression. This study has made a breakthrough in the high-precision and multi-dimensional feature extraction of image recognition of intangible cultural heritage in southern Sichuan Province, and provided an intelligent tool for the brand logo design of intangible cultural heritage. At the same time, the research promotes the integration of digital protection and creative transformation, which is of great value to cultural heritage inheritance, brand promotion, and creative industry application. The research results provide practical guidance for future model optimization, cross-regional intangible cultural heritage identification and multimodal design exploration.**

***Keywords*—Deep learning; southern Sichuan's intangible cultural heritage; image recognition; brand identity design**

I. Introduction

Southern Sichuan is rich in intangible cultural heritage, including projects with distinctive regional characteristics and cultural significance, such as Zigong Lantern Festival, Luzhou Oil Paper Umbrella, and Neijiang tanghua [1]. The core skills and cultural connotations of these intangible cultural heritages are usually embodied and passed down through physical image carriers, such as lantern patterns, umbrella design, and tanghua modeling [2]. However, the accelerated modernization process and the wide application of digital technology have brought two major challenges to the intangible cultural heritage in southern Sichuan: First, "live transmission" is facing the risk of interruption. Second, the progress of "digital protection" is lagging. Many intangible cultural heritage images still exist in traditional forms, such as paper files or physical collections, which are not conducive to efficient storage, retrieval, and sharing, and are also difficult to meet the needs of cultural communication and public participation in the new media era. Therefore, the vitality and influence of intangible cultural heritage are still limited [3–5].

Artificial intelligence (AI), especially deep learning, has shown excellent performance in image recognition. Its application in cultural heritage protection, such as cultural relics classification and traditional pattern extraction, has begun to appear [6]. However, at present, most studies only focus on individual categories of intangible cultural heritage and fail to systematically analyze the diverse cultural heritage images found in southern Sichuan [7]. In addition, traditional image recognition methods usually remain at the simple classification level. They rarely integrate recognition results with deeper cultural interpretation or the needs of branding and dissemination [8]. This separation between technology and culture limits the full potential of deep learning in intangible cultural heritage preservation. It also hinders the development of Southern Sichuan's intangible cultural heritage from "digital preservation" to "branded dissemination" [9].

This study takes Southern Sichuan's intangible cultural heritage images as the research object and attempts to establish an image recognition system based on deep learning and cultural interpretation. By optimizing the convolutional neural network (CNN) model, the system realizes high-precision recognition, feature extraction, and semantic analysis of images in different categories of Southern Sichuan's intangible cultural heritage. Based on the above recognition results, this study explores new ideas for brand identity design of Southern Sichuan's intangible cultural heritage. The cultural symbols contained in the intangible cultural heritage images displayed as the visual identity of the brand are integrated into contemporary people's needs in identification and expression. This study provides an effective and accurate method for digital protection of Southern Sichuan's intangible cultural heritage. This study bridges the gap in the application of deep learning in regional intangible cultural heritage image recognition. Simultaneously, it underpins the modernization of intangible cultural heritage branding and the market-oriented transformation of cultural value with theoretical justification and practical recommendations. These efforts contribute to sustaining the living transmission of Southern Sichuan's intangible cultural heritage and promoting its sustainable development in the new era.

To address the technical challenges of Southern Sichuan intangible cultural heritage image recognition, including multi-category classification, high visual complexity, and class imbalance, as well as the limited integration of image recognition results into brand communication, this study develops an integrated framework for Southern Sichuan intangible cultural heritage image recognition and brand identity design that combines deep learning with cultural interpretation. The study first reviews existing research on the application of deep learning in cultural heritage preservation and identifies current technical gaps and limitations in practical applications. Subsequently, this study proposes a CNN model based on multi-loss joint optimization and carries out high-precision image recognition and feature analysis of intangible cultural heritage in southern Sichuan from three visual dimensions: texture, color, and shape. On this basis, the study further discusses how to transform the identified cultural characteristics into brand visual elements that support contemporary brand identity design. Finally, the performance of the proposed framework in image recognition and the effect on brand identity design is evaluated through comparative experiments and customer satisfaction surveys. The research results provide a comprehensive solution that provides technical support and practical guidance for the digital protection and brand communication of intangible cultural heritage in southern Sichuan.

II. Related Work

With the deep integration of digital technology and intangible cultural heritage protection, deep learning has gradually become the core tool of intangible cultural heritage digitization research with its advantages in image feature extraction and pattern recognition [10]. As the carrier of folk culture in the southwest of China, the intangible cultural heritage in southern Sichuan combines regional characteristics and cultural values in the image. However, the systematic research on the application of deep learning in the image of intangible cultural heritage in southern Sichuan and its transformation into brand identity is still limited.

Yu et al. constructed the “AI for Dunhuang” dataset for the preservation of Dunhuang cultural heritage. The dataset included 10,000 mural images for automated restoration and 3,455 images for style transfer. By improving the U-Net network architecture, the precision of mural defect filling was optimized. Archaeologists evaluated the restoration quality as comparable to manual restoration [11]. Fernandes et al. focused on preventive conservation of artifacts by integrating the Mask Region-based CNN with infrared thermography for defect detection in Italian marquetry artifacts. By introducing an adaptive threshold segmentation module, their method improved the recognition of deep defects such as wood cracks and glue aging. However, they pointed out that existing models are often tailored to single materials or artifact types and lack general applicability to the diverse materials and forms of folk intangible cultural heritage images [12]. In addition, international research has mainly concentrated on “protection-oriented” applications, such as large-scale site restoration and artifact defect detection. Few studies have linked image recognition results to “application-oriented” needs, such as intangible cultural heritage brand communication and cultural product design. As a result, a complete “technology–culture–market” chain has not yet been established [13].

Domestic research has focused more on the digitization of local intangible cultural heritage, achieving progress in technology adaptation and regional practice. Qi et al. addressed the diverse needs of ancient Chinese character recognition by proposing the HUNet model, which integrated an attention mechanism. They constructed a multi-type dataset of ancient Chinese character recognition, including more than nine million samples of Oracle Bone Inscriptions, bamboo slips, and stone carvings. Their method has achieved an accuracy of 98.7% in many ancient character recognition tasks [14]. Sun et al. discussed the preservation of intangible cultural heritage from the perspective of digital protection. They developed an intelligent document recording system based on deep learning for the cultural heritage of the Li branch, and used the cultural pattern recognition model to automatically extract and realize the digital preservation of traditional cultural characteristics. This study provided technical support for the long-term preservation and intelligent management of intangible cultural heritage resources. The research showed that the combination of artificial intelligence and digital technology improved the efficiency of cultural document recording and improved the quality of digital preservation, which provided a new perspective for digital inheritance and innovative utilization of intangible cultural heritage [15]. Pan et al. studied the development of a digital twin of cultural heritage and proposed a method based on deep learning to automatically transform a semantic point cloud into a semantic building information model (BIM). This method can intelligently identify and semantically reconstruct the spatial structure and building components of cultural heritage buildings, thus improving the efficiency and accuracy of digital cultural heritage modeling. Although their research has expanded the application of deep learning in digital protection of cultural heritage, it mainly focuses on the three-dimensional modeling of architectural heritage and does not involve the image recognition of intangible cultural heritage, nor does it discuss its application in brand logo design and other cultural and creative fields [16].

In summary, although research on deep learning in the intangible cultural heritage field has achieved progress in technical accuracy and regional applications, three major gaps remain. First, international research has largely overlooked regional folk intangible cultural heritage such as that of Southern Sichuan, and its technical applications do not yet cover the full “image recognition–brand transformation” chain. Second, domestic studies have focused on local intangible cultural heritage, but dependence on single carriers limits accurate recognition of the multi-carrier intangible cultural heritage images of Southern Sichuan, while digital resources remain disconnected from brand design needs. Third, local branding practices for Southern Sichuan’s intangible cultural heritage lack technological support, relying on manual approaches that are inefficient and insufficiently standardized.

To address these gaps, this study examines multi-category intangible cultural heritage images from Southern Sichuan. By optimizing deep learning models, the study achieves high-precision recognition and cultural interpretation of multi-carrier images and links these results with brand identity design. The aim is to provide an integrated solution for both digital preservation and branded dissemination of regional intangible cultural heritage.

III. Deep Learning-Based Model for Southern Sichuan's Intangible Cultural Heritage Image Recognition and Brand Identity Design

A. Introduction to Deep Learning

Deep learning is a machine learning algorithm that simulates the operation mechanism of the human brain neural network. By constructing interconnected artificial neural networks, it can realize complex abstraction and learn from massive datasets [17]. In the deep network, the original input, such as an image, text, or audio, will undergo a series of nonlinear transformations and gradually generate more and more refined feature representations. The algorithm can directly mine related patterns from large-scale datasets without artificial feature design [18]. With the optimization algorithm of iteratively adjusting model parameters, deep learning realizes autonomous learning and continuous improvement, and can accurately predict and support scientific decision-making in complex environments [19]. In recent years, with the rapid growth of data and computing resources, deep learning has developed into the core research field of artificial intelligence, and has profoundly changed many industries [20].

Let the design matrix X be an m×n matrix, where the data are centered with mean zero, i.e., $E[x]=0$. If not, preprocessing subtracts the mean from all samples to achieve centralization. The unbiased sample covariance matrix corresponding to X is given as Eq. (1) presents the unbiased sample covariance matrix associated with X:

$$Var[x]=\frac{1}{m-1}X^TX \tag{1}$$

The variance Var[z] forms a diagonal matrix, obtained through the linear transformation $z=W^Tx$. The primary components of the design matrix X are defined via the eigenvectors of X^TX, represented in Eq. (2):

$$X^TX=W\wedge W^T \tag{2}$$

Letting W denote the right singular vector matrix obtained from the singular value decomposition (SVD) $X=U\Sigma W^T$, and treating W as the eigenvector basis, the original eigenvalue relation can be written as Eq. (3):

$$X^TX=\left(U\sum W^T\right)^TU\sum W^T=W\sum{}^2W^T \tag{3}$$

It follows that Var[z] is diagonal. When X undergoes principal component decomposition, its variance can be formulated as:

$$Var[x]=\frac{1}{m-1}X^TX \tag{4}$$

$$=\frac{1}{m-1}\left(U\sum W^T\right)^TU\sum W^T \tag{5}$$

$$=\frac{1}{m-1}W\sum{}^2W^T \tag{6}$$

Here, the relation $UTU=I$ holds, since by definition the matrix U is orthogonal under SVD. This demonstrates that the covariance matrix z possesses a diagonal form, as detailed below:

$$Var[z]=\frac{1}{m-1}Z^TZ \tag{7}$$

$$=\frac{1}{m-1}W^TX^TX^TW \tag{8}$$

$$=\frac{1}{m-1}W^TW\sum{}^2W^TW \tag{9}$$

The preceding analysis demonstrates that a linear projection of x onto z via W yields a diagonal covariance matrix (Σ^2), which implies mutual independence among the components of z.

The preceding analysis of the fundamental principles of deep learning and its feature learning mechanism shows that deep learning employs multi-layer neural network architectures to progressively abstract and efficiently represent data. Through parameter optimization, it continuously enhances the model's ability to learn from complex datasets [21]. The principles of feature dimensionality reduction and information extraction embodied in principal component analysis also provide an effective approach for representing high-dimensional data within deep learning models. In the context of the digital preservation and brand identity design of Southern Sichuan intangible cultural heritage, image datasets contain abundant cultural symbols and visual characteristics. Traditional image processing methods are often unable to effectively extract the underlying semantic information embedded in these complex visual features. Therefore, applying deep learning to Southern Sichuan intangible cultural heritage image recognition is essential for developing an intelligent recognition model with strong feature extraction and classification capabilities. Based on these considerations, this study develops a deep learning-based algorithm for Southern Sichuan intangible cultural heritage image recognition. A CNN is employed to extract image features, while a multi-loss joint optimization strategy is introduced to improve classification accuracy and feature discrimination. The proposed algorithm establishes a technical foundation for the automatic recognition of Southern Sichuan intangible cultural heritage images, cultural element analysis, and digital dissemination.

B. Deep Learning-Based Image Recognition Algorithm for Sichuan Southern Intangible Cultural Heritage

In order to realize the automatic recognition and application analysis of Sichuan southern intangible cultural heritage images, this research studies a recognition algorithm based on deep learning. The method is as follows: Firstly, use CNN to extract the local and global image features. The network output is transferred to class probabilities by the Softmax function.

Then, cross-entropy loss is used as a supervisory signal in the training process. Meanwhile, Focal Loss is introduced to solve the class imbalance problem. In addition, Triplet Loss and Center Loss are incorporated to enhance feature discrimination [22]. The model is optimized under a multi-loss framework, which ensures both high classification accuracy and strong feature separability [23].

The convolutional layer extracts local features from images as follows:

$$y_{i,j,k} = \sum_{u,v,c} W_{u,v,c,k} x_{i+u-1,j+v-1,c} + b_k \tag{10}$$

In Eq. (10), x denotes the input image, b_k represents the bias, W signifies the convolution kernel, and $y_{i,j,k}$ refers to the output feature map.

The Softmax function converts the network output into class probabilities:

$$p_{i,c} = \frac{\exp\left(z_{i,c}\right)}{\sum_j \exp\left(z_{i,j}\right)} \tag{11}$$

In Eq. (11), $z_{i,c}$ is the score of sample i in class c, and $p_{i,c}$ is the predicted probability.

Cross-entropy loss supervises classification training:

$$L_{FL} = -\frac{1}{N}\sum_i \left(1-p_{i,yi}\right)^{\gamma} \log p_{i,yi} \tag{12}$$

In Eq. (12), γ controls the weighting of difficult samples.

Triplet Loss enforces inter-class separability:

$$L_{tri} = \sum\left[\left\|f_a - f_p\right\|^2 - \left\|f_a - f_n\right\|^2 + \alpha\right] \tag{13}$$

In Eq. (13), f_a, f_p, and f_n are the features of the anchor, positive, and negative samples, respectively, and anchor α is a margin hyperparameter.

Center Loss strengthens intra-class compactness:

$$L_{cener} = \frac{1}{2N}\sum_{i=1}^{N}\left\|f\left(x_i\right) - c_{yi}\right\|^2 \tag{14}$$

In Eq. (14), $f\left(x_i\right)$ is the feature of sample i, and c_{yi} is the center of its class.

Finally, the comprehensive loss function jointly optimizes classification and metric learning objectives:

$$L = L_{CE} + \lambda_1 L_{tri} + \lambda_2 L_{cener} \tag{15}$$

In Eq. (15), λ_1 and λ_2 are the corresponding loss weights.

This multi-loss optimization strategy enables the proposed model to achieve both accurate classification and highly discriminative feature representations.

The quality monitoring of the Sichuan southern intangible cultural heritage image dataset is achieved through a multi-level verification and screening mechanism to ensure both reliability and usability. Processed intangible cultural heritage images are first organized and subjected to quality checks in terms of clarity, integrity, and format. Data that fail to meet requirements are either discarded or corrected. Qualified images then proceed to the classification stage, where the accuracy of category labeling is verified to maintain consistency and correctness. Once classification and labeling are complete, the system generates corresponding image package files. These files undergo an additional round of validity checks, and any defective data are returned for correction. Only verified image data proceed to the file generation stage, followed by a final review to ensure compliance with database storage standards. By implementing quality control in all stages from collection, classification, labeling to storage, this dataset provides a reliable basis for the subsequent image recognition and deep learning modeling of intangible cultural heritage [24]. Fig. 1 presents the procedure for monitoring the quality of the dataset.

The Sichuan southern intangible cultural heritage image recognition system is formed by three parts: computing platform, database platform, and integrated management system. The computing platform module includes the image acquisition module, image preprocessing module, feature extraction module, and classification module. These modules realize the whole process from raw image acquisition to feature categorization. The database platform module realizes data storage and retrieval. The module of the integrated management system includes an automatic labeling and statistical module, heritage category analysis module, cultural heritage recommendation module, and interactive display and education module. These functions can realize systematic annotation, category, cultural analysis, and public display [25].

The image recognition system for Sichuan's southern intangible cultural heritage realizes intelligent recognition on the computing platform, efficient management on the database platform, and the analytical and presentation functions on the integrated management system. These parts realize the whole closed loop from image acquisition to application and dissemination, as shown in Fig. 2. This system provides strong digital support for the protection, research, and communication of intangible cultural heritage.

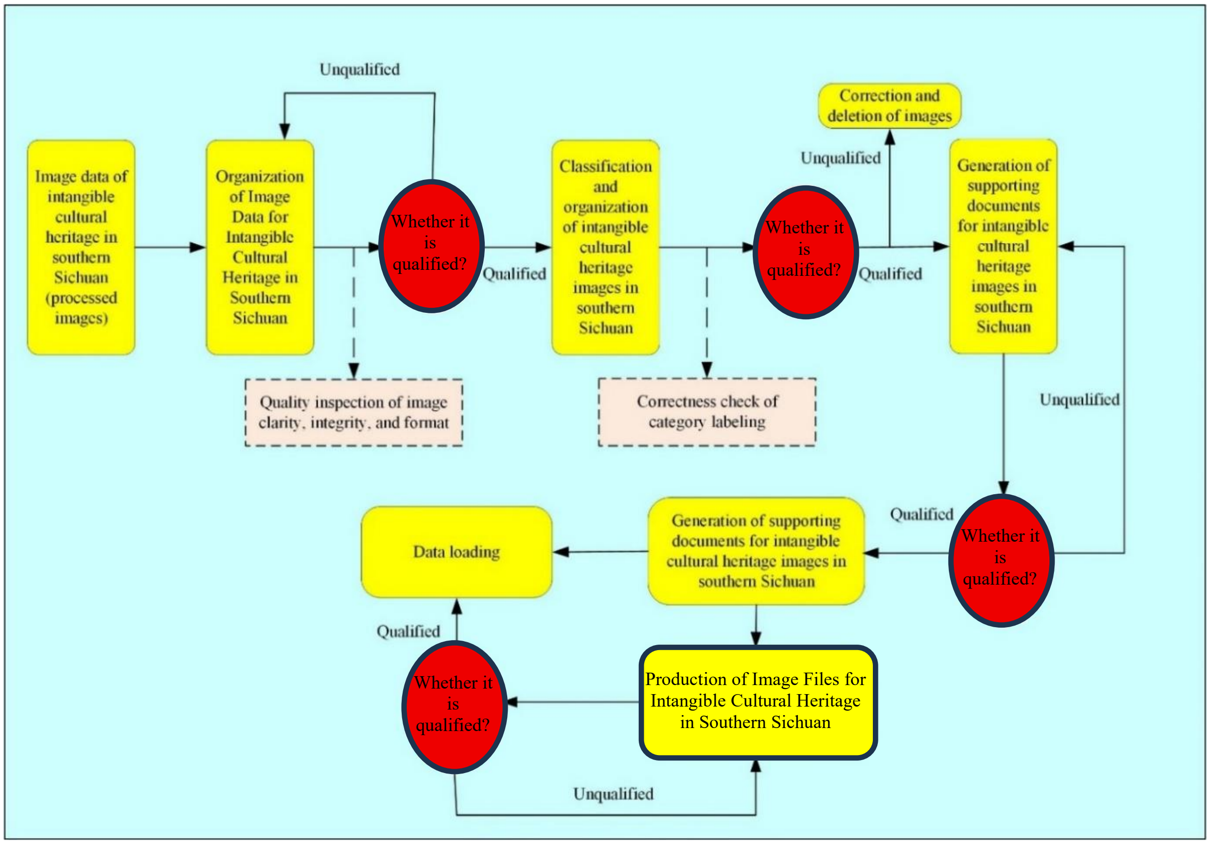

Fig. 1. Quality monitoring process of the Sichuan southern intangible cultural heritage image dataset.

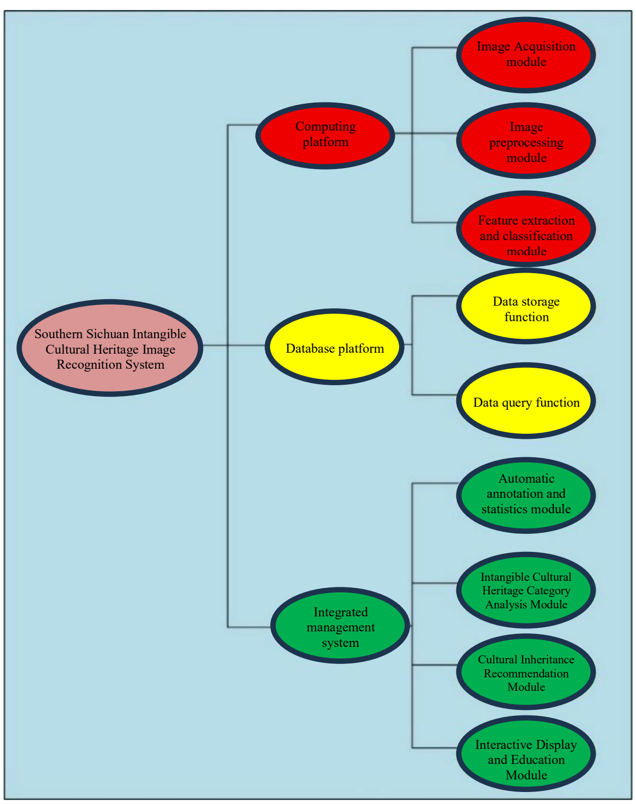

Fig. 2. System architecture of the Sichuan southern intangible cultural heritage image recognition framework.

C. Deep Learning-Based Brand Identity Design Model for Southern Sichuan's Intangible Cultural Heritage

The deep learning-based brand identity design model for Southern Sichuan's intangible cultural heritage primarily involves data collection, preprocessing, model training, and optimization. The system first gathers relevant intangible cultural heritage materials and evaluates whether they meet the quantity and quality requirements for modeling. If the data is insufficient, additional data will be collected and supplemented. Once sufficient data is obtained, pretreatment is carried out to standardize the material and ensure the consistency and usability of the input. Based on the preprocessed data, an appropriate deep learning model is selected as the basis to generate an initial model. In the process of model creation, training parameters are set, and the model is tested and verified. If the performance does not meet the requirements, adjust the parameters or modify the model architecture until the expected effect is achieved.

In the process of model optimization, the system will continuously adjust the training parameters and make many iterations to improve the generalization ability and generation quality of the model. When the preset accuracy and robustness requirements are met, the process will enter the stage of brand identity generation. In Fig. 3, the image generation module in the brand logo design model of intangible cultural heritage in southern Sichuan based on deep learning consists of four parts: cultural feature extraction, feature coding, visual element mapping, and generation model reasoning. Firstly, the trained deep learning model analyzes the intangible cultural heritage materials in southern Sichuan and extracts representative texture, color, shape, and cultural semantic features. These features are then encoded into computed feature vectors. Then, through the visual element mapping mechanism, the corresponding relationship between cultural characteristics and brand design elements is established. Specifically, texture features are mapped to brand logo graphics, color features correspond to the brand color matching system, shape features correspond to auxiliary graphics and layout style, and cultural semantic features are reflected in the expression of brand cultural identity. Based on these mapped features, the generation model will reorganize and optimize the design elements according to the user-defined design instructions and style parameters, and automatically generate multiple brand image schemes. Finally, the generated design is evaluated and comprehensively judged from the aspects of cultural consistency, visual beauty, and brand uniqueness. If the evaluation results do not satisfy the predefined criteria, the workflow returns to the parameter optimization stage for further refinement. Otherwise, the final brand identity design is generated. This closed-loop workflow—model optimization, feature extraction, visual element mapping, design generation, and result evaluation—transforms the cultural elements of Southern Sichuan intangible cultural heritage into brand visual symbols. As a result, it ensures cultural authenticity and design consistency while improving the automation and reproducibility of the brand identity design process. The workflow of the deep learning-based Southern Sichuan intangible cultural heritage brand identity design model is shown in Fig. 3.

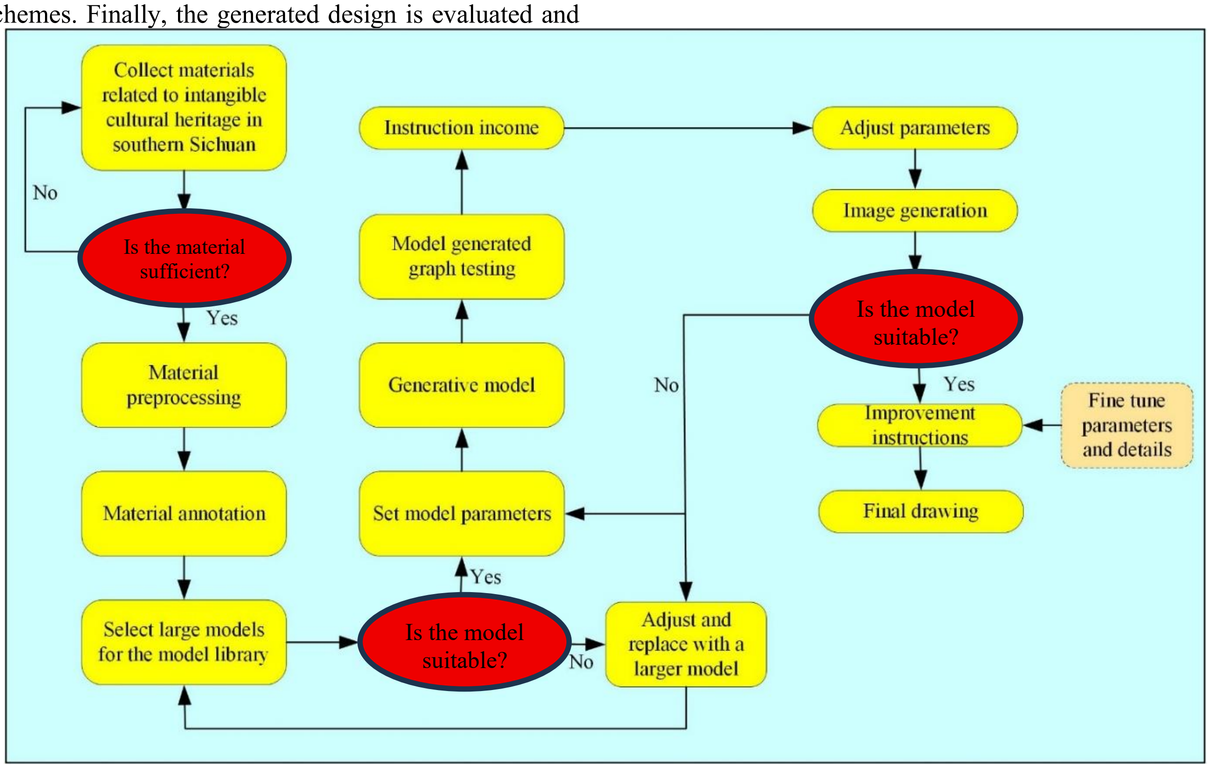

Fig. 3. Workflow of the deep learning-based brand identity design model for Southern Sichuan's intangible cultural heritage.

IV. Application of the Deep Learning-Based Model for Southern Sichuan's Intangible Cultural Heritage Image Recognition and Brand Identity Design

The construction of Southern Sichuan's intangible cultural heritage dataset is based on multi-channel systematic collection and organization. First, high-resolution images of typical intangible cultural heritage items, such as Shu brocade, Sichuan opera facial masks, bamboo weaving, embroidery, and ceramics, were captured through field surveys in southern Sichuan. This ensured the authenticity and completeness of textures, details, and colors. Second, the dataset integrates publicly available intangible cultural heritage resources from national and local cultural departments, including the Digital Museum of Chinese Intangible Cultural Heritage and the Sichuan Province intangible cultural heritage Information Management Platform. These resources supplement the historical documents and brand visual design materials that are difficult to collect in the field. In addition, brand image design images of enterprises and design institutions related to intangible cultural heritage, including signs, packaging, and posters, have been collected, and all images have been authorized by law or publicly licensed. In the process of database construction, all images are labeled according to the process type or brand design category, with category labels, texture features, colors, and style information attached. Using a standardized file structure, the dataset is divided into training, verification, and testing sets to support the training, verification, and testing of the model and ensure the repeatability of the experiment and scientific performance evaluation. This dataset captures rich process details and reflects the brand visual design style. It provides a high-quality foundation for the research of intangible cultural heritage image recognition and brand identity design based on deep learning.

This dataset contains images of eight representative categories of intangible cultural heritage in southern Sichuan: Zigong Lantern Festival, Luzhou Oil Paper Umbrella, Neijiang tanghua, Shu Embroidery, Sichuan Opera Mask, Bamboo Weaving, Embroidery and Ceramics. In order to improve the generalization ability of the proposed model, image acquisition covers various manifestations of each intangible cultural heritage category in different perspectives, lighting conditions, and craft styles. The dataset contains 8,080 images, which are randomly divided into a training set, a verification set, and a test set with the ratio of 7:1.5:1.5. The training set contains 5,656 images for model training and parameter optimization. The verification set contains 1,212 images, which are used for hyperparameter tuning and early stopping during training. The test set also contains 1,212 images, which are used to evaluate the final performance of the trained model. In order to ensure the fairness of model evaluation, the dataset is divided by stratified random sampling, so as to keep roughly the same category distribution in the training set, verification set, and test set, and minimize the possible deviation caused by category imbalance. Table 1 shows a summary of the number of images of each category and the division of corresponding training sets.

TABLE I. DISTRIBUTION OF IMAGE CATEGORIES AND DATASET PARTITION FOR THE SOUTHERN SICHUAN INTANGIBLE CULTURAL HERITAGE IMAGE DATASET

Intangible Cultural Heritage Category	Total Images	Training Set	Validation Set	Test Set
Zigong Lantern Festival	1,280	896	192	192
Luzhou Oil-Paper Umbrellas	1,150	805	173	172
Neijiang Sugar Painting	1,020	714	153	153
Shu Brocade	980	686	147	147
Sichuan Opera Facial Masks	1,350	945	203	202
Bamboo Weaving	890	623	134	133
Embroidery	760	532	114	114
Ceramics	650	455	96	99
Total	8,080	5,656	1,212	1,212

During the model training process, all hyperparameters are systematically configured. A ResNet-50 model pre-trained on the ImageNet dataset is adopted as the backbone feature extraction network. Parameter initialization based on the pre-trained weights is used to accelerate convergence and enhance the generalization capability of feature representations. The training process is conducted for 200 epochs with a batch size of 32. The Adam optimizer is employed for parameter updating, and the initial learning rate is set to 1×10^{-4}. A cosine annealing learning rate schedule is applied, gradually reducing the learning rate during training to a final value of 1×10^{-6}. To mitigate overfitting, a Dropout layer with a rate of 0.5 is added before the fully connected layer. In addition, an early stopping strategy is adopted, where training is terminated if the validation loss does not decrease for 15 consecutive epochs. The model finally converges at the 176th epoch. In the joint loss function, the weight of the classification loss λ_1 is set to 1.0, the weight of the triplet loss λ_2 is set to 0.1, and the weight of the center loss λ_3 is set to 0.01. All experiments are conducted on a deep learning workstation equipped with an NVIDIA RTX 3090 GPU (24 GB memory). The software environment is based on Ubuntu 20.04, the PyTorch 1.12 deep learning framework, and CUDA 11.6 acceleration libraries. Each training epoch takes approximately 3.2 minutes, and the total training time is about 9.5 hours.

To validate the effectiveness of the proposed deep learning model for Southern Sichuan intangible cultural heritage image recognition, comparative experiments are conducted against both traditional machine learning algorithms, namely Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), and mainstream deep learning architectures, including ResNet-50 and EfficientNet-B0. SVM and KNN are included to evaluate the performance improvement over conventional methods, while ResNet-50 and EfficientNet-B0 are used to assess the performance gap between the proposed model and state-of-the-art deep learning approaches, thereby providing a comprehensive evaluation of the model's technical contribution. Accuracy, F1-score, and recognition rate for complex-texture images were selected as evaluation metrics. They comprehensively reflect overall classification performance, the ability to handle class imbalance, and the capacity to capture detailed features in high-complexity images. Fig. 4 and 5 summarize the results obtained from the experiments.

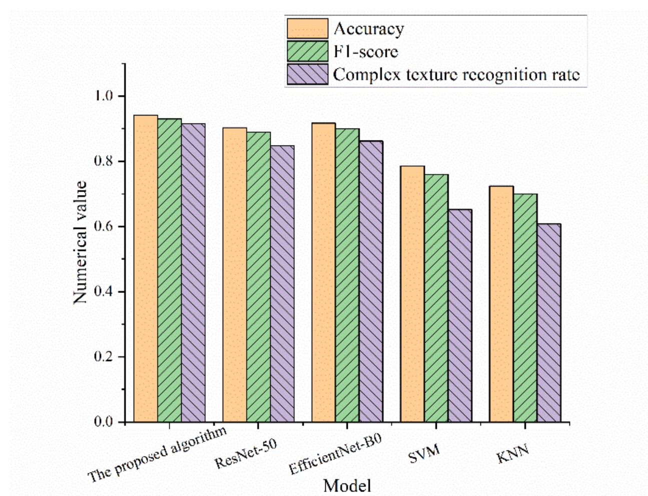

Fig. 4. Performance comparison of different models for Southern Sichuan's intangible cultural heritage image recognition.

As illustrated in Fig. 4, the proposed model significantly outperforms both traditional machine learning models and general deep learning models in terms of accuracy, F1-score, and recognition rate for complex-texture images. The overall accuracy reaches 94.1%, which is higher than SVM, KNN, ResNet-50, and EfficientNet-B0 by 15.6, 21.7, 3.8, and 2.4 percentage points, respectively. In terms of F1-score, the proposed model achieves 93.0%, surpassing ResNet-50 (89.0%) and EfficientNet-B0 (90.0%). For complex-texture image recognition, the model attains 91.5%, representing improvements of 6.8 and 5.3 percentage points over ResNet-50 (84.7%) and EfficientNet-B0 (86.2%), respectively. These results indicate that the proposed multi-loss joint optimization strategy more effectively captures fine-grained textures and complex patterns in intangible cultural heritage artifacts.

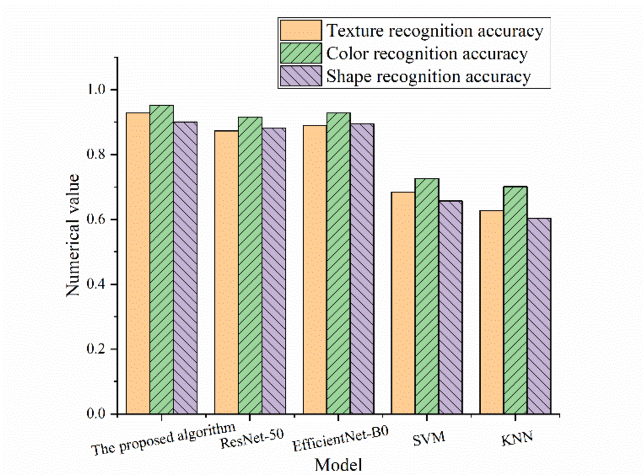

Fig. 5. Comparison of recognition performance across different image elements under various models.

As shown in Fig. 5, the proposed model achieves recognition accuracies of 92.8%, 95.2%, and 90.1% for texture, color, and shape, respectively, consistently outperforming SVM, KNN, ResNet-50, and EfficientNet-B0. In texture recognition, the proposed model improves performance by 5.5 and 3.9 percentage points compared with ResNet-50 (87.3%) and EfficientNet-B0 (88.9%), respectively, demonstrating the effectiveness of Triplet Loss and Center Loss in enhancing feature discriminability. For color recognition, all deep learning models perform relatively well. The proposed model achieves an accuracy of 95.2%, benefiting from both pre-trained feature extraction capabilities and the proposed joint optimization strategy, which further enhances fine-grained discriminative ability. For shape recognition, the proposed model reaches 90.1%, also showing steady improvements over ResNet-50 (88.2%) and EfficientNet-B0 (89.4%). Overall, the proposed model demonstrates clear advantages in multi-dimensional visual feature learning and exhibits strong applicability and technical advancement in Southern Sichuan intangible cultural heritage image recognition.

The performance satisfaction of the deep learning-based Southern Sichuan intangible cultural heritage brand identity design model was evaluated using a Likert scale survey. The survey targeted potential consumers of intangible cultural heritage products in Southern Sichuan. A total of 125 questionnaires were distributed, and 121 (62 males and 59 females) were effectively answered. Most of the respondents were between 18 and 35 years old, accounting for 77.12% of the sample. In terms of educational background, 26 respondents have an associate degree or below, 58 have a bachelor's degree, and 37 have completed graduate studies, indicating that the sample generally meets the representative requirements of this study. This study conforms to ethical standards and has been approved by the Ethics Committee of Neijiang Normal University. The written informed consent of the participants was obtained during the study. This study is conducted in accordance with the Helsinki Declaration.

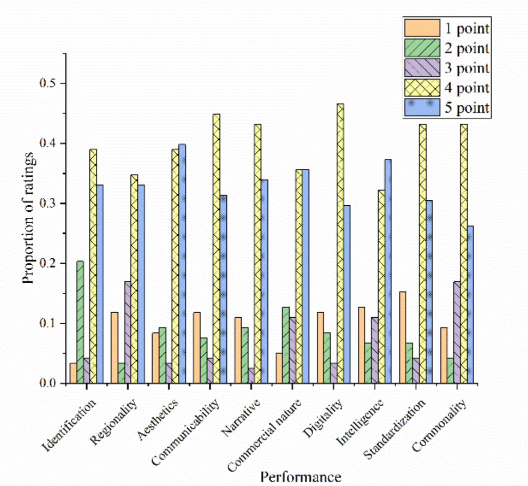

Fig. 6. User satisfaction with different performance aspects of the deep learning-based Southern Sichuan's intangible cultural heritage brand identity design model.

In Fig. 6, the aesthetic attraction scores the highest average score of 3.92, and 39.83% of the respondents give a perfect score of 5. This reflects the target users' high recognition of product visual language, formal aesthetics, and artistic expression. In contrast, the standardized dimension scored the lowest, only 3.67 points, and 15.25% of the respondents gave the lowest score of 1 point. This gap highlights the need for the design team to re-examine the compliance of design specifications, technical standards, and general design principles. The overall score of the intelligence dimension is in the middle, but the proportion of users getting full marks reaches 37.29%, indicating that users have positive expectations for technological innovation. On the contrary, the usability dimension has a low basic score (3.73 points) and has a limited full score (26.27%). It shows that the model needs further improvement in universality, accessibility, and public value creation.

V. Discussion

The experimental results show that the model based on deep learning for image recognition and brand design of intangible cultural heritage in southern Sichuan is consistently superior to SVM, KNN, ResNet-50, and EfficientNet-B0 in accuracy, F1 score, and recognition rate of complex texture images. The overall accuracy rate is 94.1%, which shows that the multi-loss joint optimization strategy effectively improves the fine-grained feature representation ability of intangible cultural heritage images and enhances the recognition performance of complex patterns, colors, and shapes. Compared with traditional machine learning methods, the deep learning model relies on hierarchical feature extraction and can learn higher-level semantic representations, so it is more suitable for complex cultural image recognition tasks. Based on the ResNet-50 backbone network, this study further integrates the ternary loss function and the central loss function to optimize the separability between categories and the compactness within categories, thus enhancing the performance of the model in capturing the subtle textures and complex visual features in the intangible cultural heritage images in southern Sichuan. The research results further confirm the importance of digital intelligence technology in the protection and dissemination of cultural heritage. Boboc et al. pointed out that emerging digital technologies such as augmented reality are changing the presentation and dissemination of cultural heritage, opening up a new path for the digital utilization of cultural heritage resources [26]. Similarly, Erturk emphasized that digital storage and management are the key guarantee for the long-term preservation and inheritance of intangible cultural heritage [27]. Different from these studies, which mainly focus on digital protection and dissemination of cultural heritage, this study applies deep learning technology to image recognition and brand logo design of intangible cultural heritage to realize automatic extraction of cultural characteristics and transform them into visual design elements. The generated brand image solution has received relatively high evaluation in both aesthetic and intelligent dimensions, indicating that deep learning can not only support the digital preservation of cultural heritage, but also transform cultural elements into modern brand visual language. However, there are still some limitations: the size of the dataset is still relatively limited, and the evaluation mainly depends on subjective user evaluation. Future research should expand the image dataset of intangible cultural heritage, incorporate multi-modal cultural semantic information, and explore more advanced visual models. These improvements are expected to enhance the generalization ability and practical application value of the model.

VI. Conclusion

The image recognition and brand design model of intangible cultural heritage in southern Sichuan based on deep learning shows significant advantages in recognition accuracy and multi-dimensional feature extraction. Experimental evaluation shows that the model is superior to the traditional method in key indexes such as accuracy, F1 score, and complex texture recognition, and the overall accuracy reaches 94.1%. This proves that deep learning can effectively extract and present the fine details contained in intangible cultural heritage items. Specifically, the model achieves 92.8% in texture recognition, 95.2% in color recognition, and 90.1% in shape recognition, which fully embodies its comprehensive learning ability and excellent performance in multi-dimensional visual features. The customer satisfaction survey further confirmed the actual value of the model. The high scores in aesthetics, commercial attraction, and narrative design show that the model performs well in identification tasks and contributes to brand communication and design innovation. These research results confirm the application value of deep learning in digital protection and creative transformation of intangible cultural heritage. In practice, the model provides intelligent support for digital archiving, brand design, and marketing. For researchers and cultural heritage practitioners, it can realize efficient and accurate classification and feature extraction. For designers, it is helpful to generate a brand image that embodies the cultural essence of intangible cultural heritage, thus improving artistic quality, communication effect, and market competitiveness. Finally, the model is helpful to promote the innovation and transformation of intangible cultural heritage from southern Sichuan to international communication in the context of modern consumption.

Although the experimental results are encouraging, there are still some limitations. First of all, the dataset is limited in scale and category coverage, which cannot fully show the diversity and complexity of intangible cultural heritage in southern Sichuan. In this study, only the representative intangible cultural heritage projects in southern Sichuan are selected for analysis, so the feature expression ability of this model in other types of intangible cultural heritage resources needs further verification. The scores of standardization and universality are relatively low, indicating that it may have challenges in cross-domain and cross-scenario applications. In addition, there are significant differences in cultural connotation, artistic style, and visual expression of intangible cultural heritage projects in different regions, so the portability and generalization performance of this model in the context of intangible cultural heritage in other regions still need further investigation. The survey of users' satisfaction shows that the intelligence and universal applicability still need to be improved. Future research should focus on improving the interpretability of the model, personalized design recommendations, and cross-platform adaptability. In addition, expanding multi-modal datasets, integrating generative artificial intelligence technology, and optimizing interactive user experience are worthy of promotion. At the same time, it is necessary to construct cross-regional and cross-category intangible cultural heritage datasets to systematically evaluate and optimize the applicability of the model in different cultural heritage protection and brand design scenarios. Such efforts will help explore its broader applicability in the field of intangible cultural heritage and promote the advancement of intangible cultural heritage image recognition and brand identity design toward higher levels of intelligence and inclusiveness.

References

[1] T. Zhang, Y. Yang, X. Fan, et al., “Corridors construction and development strategies for intangible cultural heritage: a study about the Yangtze River economic belt,” Sustainability, vol. 15, no. 18, pp. 13449, 2023.

[2] S. Qiu, P. Zhang, S. Li, et al., “Extraction and analysis algorithms for Sanxingdui cultural relics based on hyperspectral imaging,” Computers and Electrical Engineering, vol. 111, pp. 108982, 2023.

[3] D. Ma, P. Pu, J. Hao, et al., “Automatic extraction and classification of intangible cultural elements using reinforcement learning algorithm,” Computer-Aided Design and Applications, vol. 21, no. S23, pp. 51–68, 2024.

[4] R. Li and C. Wang, “Cultural and creative product design and image recognition based on deep learning,” Computational Intelligence and Neuroscience, vol. 2022, no. 1, pp. 7256584, 2022.

[5] J. Xie, “Innovative design of artificial intelligence in intangible cultural heritage,” Scientific Programming, vol. 2022, no. 1, pp. 6913046, 2022.

[6] K. Bobanewa and O. I. Olope, “Deep learning techniques for image recognition (machine learning),” Path of Science, vol. 10, no. 10, pp. 2029–2036, 2024.

[7] Y. Hou, S. Kenderdine, D. Picca, et al., “Digitizing intangible cultural heritage embodied: state of the art,” Journal on Computing and Cultural Heritage (JOCCH), vol. 15, no. 3, pp. 1–20, 2022.

[8] Z. Xu and D. Zou, “Big data analysis research on the deep integration of intangible cultural heritage inheritance and art design education in colleges and universities,” Mobile Information Systems, vol. 2022, no. 1, pp. 1172405, 2022.

[9] H. Sharma, “Applications of artificial intelligence and machine learning in the preservation and analysis of heritage structures: a comprehensive review,” Archives of Computational Methods in Engineering, vol. 33, no. 2, pp. 3001–3033, 2026.

[10] L. Qiu and M. Liu, “Innovative design of cultural souvenirs based on deep learning and CAD,” Computer-Aided Design & Applications, vol. 21, no. S14, pp. 237–251, 2024.

[11] T. Yu, C. Lin, S. Zhang, et al., “Artificial intelligence for Dunhuang cultural heritage protection: the project and the dataset,” International Journal of Computer Vision, vol. 130, no. 11, pp. 2646–2673, 2022.

[12] H. Fernandes, J. Summa, J. Daudre, et al., “Characterization of ancient marquetry using different non-destructive testing techniques,” Applied Sciences, vol. 11, no. 17, pp. 7979, 2021.

[13] J. Zhao, “Digital protection and inheritance path of intangible cultural heritage based on image processing algorithm,” Scalable Computing: Practice and Experience, vol. 25, no. 6, pp. 4720–4728, 2024.

[14] H. Qi, H. Yang, Z. Wang, et al., “AncientGlyphNet: an advanced deep learning framework for detecting ancient Chinese characters in complex scene,” Artificial Intelligence Review, vol. 58, no. 3, pp. 88, 2025.

[15] J. Sun, K. A. T. Khalid, and C. S. Kay, “Deep learning models for cultural pattern recognition: preserving intangible heritage of Li ethnic subgroups through intelligent documentation systems,” Future Technology, vol. 4, no. 3, pp. 119–137, 2025.

[16] X. Pan, Q. Lin, S. Ye, et al., “Deep learning based approaches from semantic point clouds to semantic BIM models for heritage digital twin,” Heritage Science, vol. 12, no. 1, pp. 65, 2024.

[17] Q. Qiu, “Identifying the role of intangible cultural heritage in distinguishing cities: a social media study of heritage, place, and sense in Guangzhou, China,” Journal of Destination Marketing & Management, vol. 27, pp. 100764, 2023.

[18] R. Archana and P. S. E. Jeevaraj, “Deep learning models for digital image processing: a review,” Artificial Intelligence Review, vol. 57, no. 1, pp. 11, 2024.

[19] B. Peng and M. Sirisuk, “Exploration of CAD and neural network integration in art design and cultural heritage protection,” Computer-Aided Design, vol. 21, no. 18, pp. 128–144, 2024.

[20] W. Xu, “Research on the communication opportunities of intangible cultural heritage under the background of big data and AI,” Journal of Artificial Intelligence Practice, vol. 6, no. 8, pp. 12–17, 2023.

[21] H. Cho, Y. Kim, E. Lee, et al., “Basic enhancement strategies when using Bayesian optimization for hyperparameter tuning of deep neural networks,” IEEE Access, vol. 8, pp. 52588–52608, 2020.

[22] J. Deng, “A brief analysis of the path of intangible cultural heritage inheritance and innovative development under digital technology,” Journal of Innovation and Development, vol. 3, no. 3, pp. 29–32, 2023.

[23] Y. Abgaz, R. Rocha Souza, J. Methuku, et al., “A methodology for semantic enrichment of cultural heritage images using artificial intelligence technologies,” Journal of Imaging, vol. 7, no. 8, pp. 121, 2021.

[24] M. Zhang, X. Guo, X. Guo, et al., “Consumer purchase intention of intangible cultural heritage products (ICHP): effects of cultural identity, consumer knowledge and manufacture type,” Asia Pacific Journal of Marketing and Logistics, vol. 35, no. 3, pp. 726–744, 2023.

[25] M. Dai, Y. Feng, R. Wang, et al., “Enhancing the digital inheritance and development of Chinese intangible cultural heritage paper-cutting through stable diffusion LoRA models,” Applied Sciences, vol. 14, no. 23, pp. 11032, 2024.

[26] R. G. Boboc, E. Băutu, F. Gîrbacia, et al., “Augmented reality in cultural heritage: an overview of the last decade of applications,” Applied Sciences, vol. 12, no. 19, pp. 9859, 2022.

[27] N. Erturk, “Preservation of digitized intangible cultural heritage in museum storage,” Milli Folklor, vol. 16, no. 128, pp. 100–110, 2020.