Visual Narrative of Multi-Ethnic Pattern Symbols from the Perspective of the Chinese Nation's Community Consciousness: Intertextuality Between Southwest Ethnic Minority Brocade and Dunhuang Caisson Ceiling

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ABSTRACT With the increasing application of electromagnetic sensing, wireless imaging systems, and intelligent information transmission technologies in digital cultural heritage preservation, efficient cross-media analysis of visual symbols has become essential for reliable semantic understanding and knowledge dissemination. To address the insufficient analysis of cross-temporal and cross-spatial intertextuality between southwestern ethnic minority brocades and Dunhuang caisson ceilings, as well as the lack of quantitative symbol-sharing mechanisms and narrative reconstruction methods, this paper proposes a dual-channel feature extraction and association modeling framework. Mask R-CNN is first employed to extract pattern contours and generate cultural semantic annotations. A dual-branch neural network is then designed to quantify the color-texture characteristics of brocades and the geometric structures of caisson ceilings, while maximum mean discrepancy is adopted to align heterogeneous visual features in a unified latent space. Furthermore, cosine similarity and symbol co-occurrence analysis are combined to construct an intertextual association graph, and an LSTMbased sequence decoder reconstructs visual narrative paths to reveal spatiotemporal cultural transmission patterns. Experimental results show that the symbol sharing rate between Miao brocade and Dunhuang grid patterns reaches 0.92, while the cross-media sharing rate of sacro-symbolic motifs is 0.52, demonstrating significant intertextual relationships and cultural convergence. The proposed framework provides an effective computational paradigm for multi-ethnic visual narrative analysis and offers methodological support for intelligent information processing and electromagnetic-enabled digital heritage applications.

INDEX TERMS visual narrative, intertextuality analysis, dual-channel feature extraction, cross-media feature alignment, electromagnetic sensing

I. INTRODUCTION

THE integration and inheritance of multi-ethnic cultures are important driving forces for the development of Chinese civilization. As representatives of this cultural phenomenon, the southwestern ethnic minority brocade and the Dunhuang caisson ceiling have profound cultural symbolic significance [1,2]. The southwestern ethnic minority brocade integrates their regional characteristics and ethnic beliefs [3,4]. At the same time, the Dunhuang caisson ceiling is a representative of Dunhuang art and culture, embodying the historical traces of cultural exchanges along the Silk Road [5]. This intertextuality of patterns across time and space provides a unique entry point for exploring how community consciousness is constructed, disseminated, and internalized through visual symbols. In this study, the "Chinese Nation's Community Consciousness" is understood as the shared cultural identity and collective belonging that transcend regional differences, emphasizing both the preservation of ethnic diversity and the forging of a unified national identity. In existing cultural research, the intertextual relationship between the southwestern ethnic minority brocade and the Dunhuang caisson ceiling is often overlooked, and systematic cross-temporal and spatial analysis remains insufficient. More importantly, current studies rarely provide quantitative mechanisms to capture symbol sharing or reconstruct narrative paths that integrate the dimensions of space, time, and power. Most existing cultural symbol analyses focus on discussions of a single region or a single cultural context, making it difficult to fully reveal the interactions and connections between different cultural symbols [6]. In the process of integrating multi-ethnic cultures, effectively capturing and quantifying the patterns of symbol sharing between different regions, particularly to reveal cultural adaptation strategies and cultural memory reconstruction mechanisms during symbol migration, has become a significant challenge facing the current academic community. Some deep learning-based image recognition and analysis technologies have been applied to pattern symbol extraction and cultural semantic annotation. In particular, the application of instance segmentation technology in digitizing cultural heritage has made significant progress [7,8]. Cross-media feature vectorization and symbol co-occurrence analysis have become an effective means to connect different cultural symbols. The decoding of pattern arrangement by the sequence model not only reconstructs the visual narrative path but can also be regarded as an algorithmic reproduction and reconstruction process of "cultural memory." The limitation of existing methods is that they cannot fully solve the deep intertextual relationship between cultural symbols in the context of cross-time and space, especially the reconstruction of the narrative path of symbols and the cultural transmission mechanism is still insufficient, resulting in a gap in the understanding of the process of multi-ethnic cultural integration [9,10]. This paper proposes a framework based on dual-channel feature extraction and association modeling, which combines instance segmentation technology to extract and annotate the pattern symbols of the southwestern ethnic minority brocade and the Dunhuang caisson ceiling. Cross-media visual feature quantitative analysis is used to realize the spatial-temporal association of cultural symbols. Through the use of symbol co-occurrence and sequence analysis methods, the narrative path of symbols across different cultural backgrounds is reconstructed, revealing the interaction patterns between cultural symbols from various regions and eras. Combined with intertextuality analysis, this paper further establishes a symbol-sharing mechanism model, providing a new theoretical perspective and visual support for the internal formation logic of the Chinese cultural community.

II. RELATED WORK

Current research explores the role of ethnic attire in cultural identity and community building from multiple perspectives. Zhou, Yulan examined how ethnic clothing advances the consciousness of the Chinese national community, emphasizing its significance in facilitating intercultural exchange and heritage transmission [11]. Chen, Xindan analyzed festive attire culture among the Su Miao branch of the Miao ethnic group in Guangxi, investigating how the philosophical foundation "Round Heaven, Square Earth" influences garment forms and ornamentation [12]. Yuan, Nao assessed the aesthetic values and cultural connotations of Tujia ethnic clothing, revealing its intrinsic ties to marriage customs, agricultural festivals, and the Tusi chieftain system [13]. Chen, Guangfu developed cultural derivative products based on research into the historical evolution and cultural significance of Qiang ethnic attire in Maoxian, Sichuan, underscoring the integration of traditional Qiang cultural elements into contemporary product design [14]. Ezadpanah, Sima investigated temporality in textile artistry, exploring how time shapes creative processes, semantic meanings, and socio-cultural contextualization of artworks [15]. While existing studies offer in-depth insights into the preservation and innovation of diverse ethnic sartorial cultures, they have yet to fully incorporate modern technological approaches for transmedia and cross-temporal visual narrative analysis. In the field of textile cultural heritage, scholars pursue diverse innovative approaches. Beatriz E. Arias López employed narrative practices and textile-making as reflective research methodologies, presenting textile creation as a non-verbal expressive form that deepens understanding and communication of research content—though without addressing the deep intertextual mechanisms of historical patterns [16]. Wang, Peng examined preservation strategies for traditional Tujia brocade techniques [17]. Gao, Jie emphasized education's pivotal role in transmitting Nanjing cloud-pattern brocade (Yun Jin) craftsmanship [18]. While these studies enrich heritage theory, their intertextuality analyses remain confined to synchronic comparisons or linear historical narratives, particularly neglecting acculturation strategies in symbol migration. Digital technologies offer new paradigms for cultural heritage research. Odabasi, Sanem, through photographic observations in museums and exhibitions, posited that textiles function not merely as objects but as "actants" capable of evoking emotions and influencing lived experiences [19]. Current technological methods, despite progress in narrative construction, fall short of reconstructing visual narrative pathways.

III. ALGORITHM DESIGN

A. EXTRACTION AND ANNOTATION OF PATTERN SYMBOL

In this study, pattern symbol extraction and annotation primarily rely on instance segmentation technology. Images of decorative patterns from Southwest ethnic minority brocade and Dunhuang caisson ceiling undergo preprocessing, including noise removal and image enhancement, to improve accuracy in subsequent processing [20,21]. Image enhancement is achieved via contrast and brightness adjustments, along with edge detection algorithms to accentuate pattern contours. For pattern symbol extraction, the Mask R-CNN algorithm in deep learning is employed, with the procedure comprising the following steps: Data Annotation: Manual annotation is performed on selected sample images of Southwest ethnic minority brocade and Dunhuang caisson ceiling, delineating the contour regions of each pattern and assigning cultural-semantic labels. Model Training & Optimization: the Mask R-CNN framework, based on Convolutional Neural Networks (CNNs), is employed for training. In instance segmentation, Mask R-CNN generates pixel-level masks for each candidate region by adding a branch network, enabling high-precision object segmentation. The model is optimized through the standard classification, bounding-box regression, and mask prediction losses defined in the Mask R-CNN framework, while IoU is used as an evaluation metric during training and validation to monitor segmentation precision rather than as an additional optimization loss.

$$\mathrm{IoU} = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

In Formula (1), A and B represent the segmented result and ground truth annotation region, respectively. A higher IoU value indicates superior segmentation accuracy. Symbolic Contour Extraction: using the trained model, automated extraction of pattern contours is performed on brocade and caisson ceiling images. Mask R-CNN's classification network assigns cultural-semantic labels (e.g., "nature worship") to each pattern. Pattern Annotation: extracted pattern symbols are annotated based on their textural features, color attributes, and geometric morphology, contextualized with cultural background information to ensure each symbol carries explicit cultural semantics. The procedural workflow is illustrated in Figure 1.

B. CROSS-MEDIA FEATURE VECTORIZATION

In the cross-media feature vectorization phase, this study constructs a dual-path neural network to separately quantify the visual characteristics of brocade color-texture and caisson geometric structures [22,23]. This separation is necessary because brocade emphasizes complex color-texture distributions while caisson ceilings highlight geometric symmetry; a single unified extraction path tends to blur these heterogeneous features, leading to suboptimal alignment in the shared feature space. The dual-path framework employs a shared backbone based on a ResNet-50 architecture pretrained on ImageNet. The brocade branch retains the first four convolutional stages of the backbone with kernel sizes of 7×7 in the initial layer and 3×3 in subsequent layers. The spatial resolution is progressively reduced through stride-2 convolutions. The feature maps of the final stage are compressed into a 1024-dimensional vector through global average pooling. The caisson branch follows the same backbone configuration but introduces a geometry-focused refinement block after the final convolutional stage that preserves symmetry-related cues. To capture the complex color distributions and textural patterns in brocades, a multi-layer convolutional architecture extracts both low-level and high-level features. Following convolutional layers, fully-connected (FC) layers process these features, outputting a visual feature vector for brocade images. The vector representation for color-texture characteristics is formalized as:

$$V_{\text{color}} = f_{\text{color}}(I_{\text{jin}}) \tag{2}$$

In Formula (2), I_{jin} denotes the brocade image; f_{color} represents the trained convolutional network; V_{color} is the extracted color-texture feature vector. For extracting geometric features of caisson ceilings, convolutional neural networks (CNNs) are integrated with computational geometry methods. Given the strong symmetry and geometric regularity inherent in caisson patterns, convolutional layers capture geometric symmetry features from images. Convolutional layers incorporating morphological processing extract geometric shapes and symmetry descriptors, generating the feature vector formalized as:

$$V_{\text{geometry}} = f_{\text{geo}}(I_{\text{ceiling}}) \tag{3}$$

In Formula (3), I_{ceiling} denotes the caisson ceiling image; f_{geo} represents the trained convolutional network; V_{geometry} is the extracted geometric structure feature vector. The color-texture feature vectors of brocades and geometric structure feature vectors of caisson ceilings undergo unified feature space alignment. By applying a feature space mapping, vectors from both media are projected into a shared high-dimensional feature space. Within this space, Maximum Mean Discrepancy (MMD) is employed for alignment, ensuring high comparability of visual features across media. The feature alignment is formalized as the Maximum Mean Discrepancy (MMD):

$$L_{\text{MMD}}(X, Y) = \left\| \frac{1}{n}\sum_{i=1}^{n}\phi(x_i) - \frac{1}{m}\sum_{j=1}^{m}\phi(y_j) \right\|_{\mathcal{H}}^{2} \tag{4}$$

Among them, X and Y denote the feature sets of brocade and caisson respectively; $\phi(x_i)$ is the feature mapping induced by a kernel function; $\mathcal{H}$ is the corresponding reproducing kernel Hilbert space (RKHS). This formulation ensures that feature distributions across modalities are statistically aligned rather than relying on a simple mean difference. The kernel function used in this study adopts a Gaussian radial basis form. The bandwidth σ remains fixed throughout training to maintain stability in the feature alignment process, and its value is set to 1.2 based on the distributional scale of the extracted representations. The MMD module receives the output of the global average pooling layer in both branches, and the gradient of the kernel-based distance propagates through the mapping network to adjust the preceding convolutional parameters during training. The relevant steps are shown in Figure 2.

C. INTERTEXTUAL RELATIONSHIP MODELING

For intertextual correlation modeling, this study computes similarity between pattern symbols across regions and media, constructing a cross-regional pattern association graph based on symbol co-occurrence frequencies. Utilizing the previously extracted color-texture features of brocades and geometric structure features of caisson ceilings, the feature vector similarity between them is calculated. The similarity

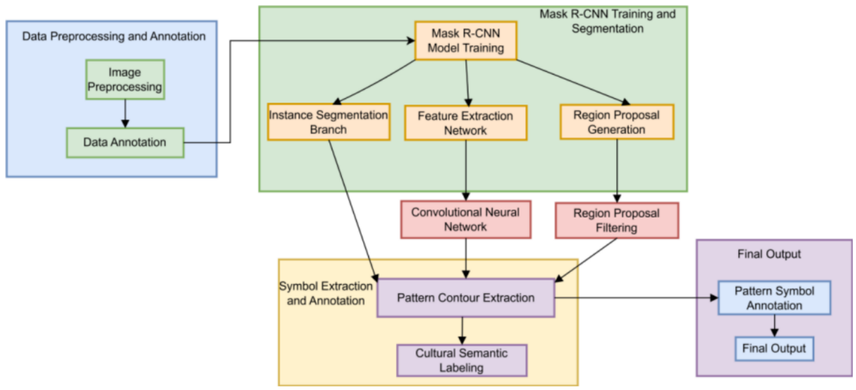

FIGURE 1. Extraction and Annotation of Multi-Ethnic Pattern Symbols

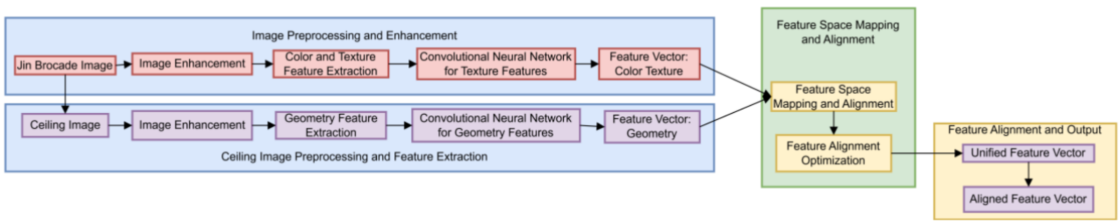

FIGURE 2. Image feature extraction and alignment

computation employs cosine similarity, formalized as follows:

$$S_{\cos}(V_1, V_2) = \frac{V_1 \cdot V_2}{\|V_1\|\|V_2\|} \tag{5}$$

In Formula (5), V_1 and V_2 represent the feature vectors of brocade and caisson ceiling, respectively, and $\|V\|$ denotes the L2-norm of the feature vectors. Symbol co-occurrence frequency analyzes the joint appearance of symbols across image samples. By counting the co-occurrence instances of brocade and caisson pattern symbols within the same image, a symbol co-occurrence matrix is generated. The co-occurrence frequency is calculated as:

$$F_{ij} = \frac{\sum_{k=1}^{N} \mathbf{1}\left(s_i^k \cap s_j^k\right)}{N} \tag{6}$$

In Formula (6), F_{ij} denotes the co-occurrence frequency of patterns s_i and s_j in image sample k; N is the total number of image samples; $\mathbf{1}(\cdot)$ represents the indicator function that takes the value 1 when patterns s_i and s_j appear together in the same image, and 0 otherwise. The symbolic units represented by s_i and s_j correspond to the full taxonomy of cultural-semantic pattern categories produced during the annotation procedure, and each unit retains its independent identity throughout the co-occurrence computation. The total number of categories remains constant across the dataset, and no resampling or redistribution is applied. The co-occurrence matrix is constructed from the original category frequencies without any balancing operations, allowing the symbol distribution captured during instance segmentation to remain intact and ensuring that the joint occurrences reflect the authentic cultural-semantic structure present in the data. The similarity threshold used for establishing connections in the association graph is fixed at 0.80, derived from the inflection point of the similarity distribution. Pairwise similarities above this value form edges whose weights follow the raw cosine score without normalization. The adjacency matrix is constructed through direct mapping of these weighted edges, and symbols falling below the threshold remain isolated from cross-regional links. Based on symbol similarity and co-occurrence frequency, a cross-regional pattern association graph is established. To profoundly unveil the cross-cultural connections between pattern pattern in Southwest ethnic minority brocades and Dunhuang caisson ceilings, this study employs a dual-path feature extraction framework and intertextual correlation model to quantitatively analyze the symbol co-occurrence frequencies of five representative ethnic brocades (Dong, Miao, Zhuang, Tujia, and Tibetan brocades) and three iconic Dunhuang caisson ceilings (lotus-pattern square caissons, Entwined Vine Motifs, and grid patterns). The results are depicted in Figure 3.

The co-occurrence counts shown in Figure 3 derive from the complete set of segmented pattern symbols contained in all annotated images, and the count for each pairing is obtained through direct accumulation of symbol pairs appearing within the same sample. No exclusion threshold is applied during this procedure, and each instance of joint appearance contributes one count to the matrix. The dataset used for computing these counts consists of 600 brocade samples and 80 caisson ceiling samples, and all extracted symbols are retained during the construction of the co-

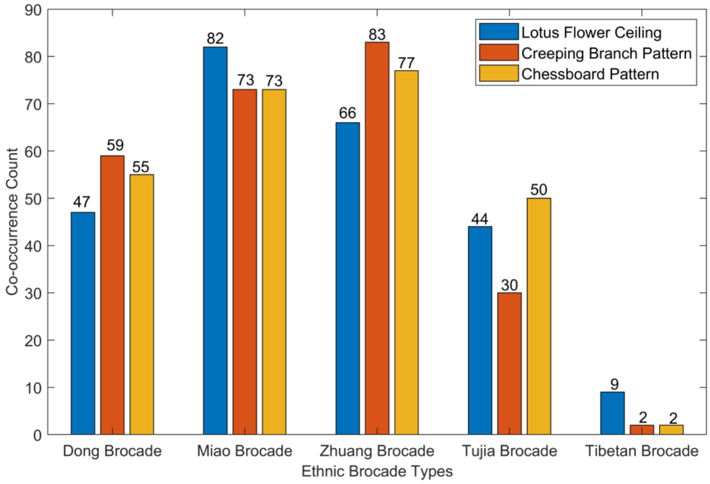

FIGURE 3. Co-occurrence Counts of Symbolic Patterns Across Ethnic Brocades and Dunhuang Caisson Designs

occurrence map to preserve the statistical integrity of the cross-regional associations. Figure 3 reveals differential co-occurrence frequencies between five ethnic brocades and three Dunhuang caisson ceilings. Zhuang brocade demonstrates the highest co-occurrence (83 instances) with interlaced vine scrolls, followed by Miao brocade paired with lotus-patterned square wells, while Tibetan brocade shows comparatively lower frequencies. Through the dual-path feature extraction model, Miao and Zhuang brocades exhibit closer affinity to Dunhuang pattern in both color-texture characteristics and geometric structures, forming robust intertextual relationships. In contrast, Tibetan brocade displays weaker co-occurrence due to feature dissimilarities, reflecting hierarchical disparities in symbolic sharing. High-co-occurrence pairings, exemplified by Zhuang brocade and interlaced vine scrolls, not only manifest formal convergence at the symbolic level but also epitomize profound cultural exchanges among ethnic groups.

D. ANALYSIS OF NARRATIVE STRUCTURE

During the narrative structure parsing phase, sequential models decode the spatiotemporal arrangement logic of patterns to reconstruct visual narrative pathways. To provide clarity regarding the construction of pattern symbol sequences, the spatial domain of each image is processed through a fixed ordering strategy based on a continuous scan from the upper-left region to the lower-right region. The spatial coordinates generated during instance segmentation determine the ordering index of each symbol, and this index is converted into a one-dimensional sequence without altering the relative positional relations. Images of different resolutions are normalized through a coordinate scaling procedure that maps all spatial positions into a unified reference grid while preserving the proportional distribution of symbol locations. Symbols located at identical scan positions after normalization are assigned consecutive sequence indices to avoid discontinuities. The LSTM model is trained using a learning rate of 1e-4, a hidden dimension of 256 units, a batch size of 32, and a sequence truncation length that matches the maximum number of symbols present in the normalized samples. This ensures that the narrative decoding remains stable and reproducible across varying spatial complexities. Extracted pattern symbols are sequentially tagged according to their spatial positions within images, generating sequential pattern arrangement data. To capture temporal dependencies among pattern symbols, Long Short-Term Memory (LSTM) networks are employed to learn spatial-temporal dependency structures between symbols, formalized as:

$$h_t = \mathrm{LSTM}(h_{t-1}, X_t) \tag{7}$$

In Formula (7), the hidden state at time t is written as h_t, the input vector at time t is written as X_t in bold type to emphasize its role as a feature representation, and the preceding hidden state is written as h_{t-1}. This formulation maintains consistency with the variable notation used throughout the narrative sequence analysis. Sequential inputs of pattern symbols, ordered by their spatial arrangement in images, are fed into the LSTM model, which learns inter-symbol dependencies to output a temporal feature representation. By decoding the LSTM output sequences, visual narrative pathways are constructed. Each pathway reflects culturally contextualized pattern deployment practices, with cross-mappings detailed in Table 1. The cultural narrative interpretations associated with the symbolic structures listed in Table 1 derive from established scholarship in ethnology, archaeology, and pattern studies, and the semantic associations have been drawn from historical descriptions of ritual symbolism, cosmological imagery, and the cultural logic embedded in textile production across the documented regions. These interpretations adhere to the explanatory frameworks recorded in classical ethnographic studies and contemporary analyses of southwestern ethnic textile traditions, together with the documented cosmological symbolism in Dunhuang pattern morphology [24,25]. The integration of these sources provides a stable basis for the narrative mappings and avoids subjective extrapolation during the construction of the visual narrative typology.

TABLE 1. Typology of Visual Narratives in Cultural Pattern and Mappings to Community Consciousness

Narrative Type	Typical Patterns and Structural Features	Community Consciousness Mapping
Radial Pattern	Dong brocade “Sunbeam pattern” (central radiating) / Dome “Lotus square well” (concentric layering)	Symbolizes the centripetal unity of the Chinese nation
Cyclical Progression	Miao brocade “Butterfly pattern” (two-way continuous) / Dome “Cicada wing pattern” (spiraling extension)	Metaphor for the continuous transmission of civilization
Hierarchical Symbolism	Zhuang brocade “Heaven, Earth, and Man Triad” (vertical layering) / Dome “Mount Sumeru” (cosmic hierarchy)	Reflects the “Harmony between Heaven and Man” concept
Grid Order Pattern	Tujia brocade “Chessboard pattern” (geometric partition) / Dome “Chessboard pattern” (well center division)	Reflects the Chinese concept of ritual and order

Table 1 delineates four visual narrative typologies and their corresponding ethnic pattern exemplars, reflecting the mapping between cultural traits of diverse ethnic groups and expressions of community consciousness. Each narrative type conveys core tenets of community consciousness, unity, intergenerational continuity, social stratification, and structural order, transforming patterns from mere decorative elements into a visual lexicon of cultural identity.

IV. EXPERIMENT AND VERIFICATION

A. EXPERIMENTAL DESIGN

During the experimental design phase, 120 brocade samples are systematically collected from each of five Southwest Chinese ethnic minorities (Dong, Miao, Zhuang, Tujia, and Tibetan), supplemented by 80 representative patterns selected from Dunhuang caisson art. During the data collection process, it is ensured that the pattern samples of each ethnic group are representative, covering a variety of traditional patterns, with clear textures and no serious damage. In the sample preprocessing stage, all images are optimized through image enhancement technology, including brightness, contrast adjustment, and denoising. The pattern areas in the image are automatically annotated through instance segmentation technology to ensure that the pattern outline of each sample is extracted, and cultural semantic labels are assigned to each symbol. The annotation process relies on artificial intelligence algorithms and combines manual correction to improve the accuracy and consistency of annotation. The image data is divided into 80% for training and 20% for testing. The training set is used to build feature extraction and pattern recognition models, while the test set is used to verify the model's generalization ability, avoid data overfitting, and ensure that the model can effectively identify pattern features in new samples. The entire experimental design process strictly controls data quality and processing standards, providing a solid foundation for subsequent pattern feature extraction, intertextuality analysis, and reconstruction of cultural symbol communication paths.

To ensure the transparency of quantitative evaluation, the computational formulations of the metrics used throughout the experiments are defined. Intra-Class Cohesion is derived from the mean pairwise Euclidean distance within each pattern category, written as the average of the distances among all feature vectors belonging to the same class. Inter-Class Separation is written as the mean Euclidean distance between samples of different classes across the feature space. Alignment Accuracy arises from the proportion of correctly aligned cross-media symbol pairs whose cosine similarity exceeds the predefined threshold of 0.80. Symbol Sharing Rate is written as the ratio between the number of cross-media symbol pairs with similarity above the same threshold and the total number of possible cross-media pairings. Narrative Theme Score is written as the normalized frequency of all symbols assigned to a given narrative theme within an image, obtained from the distribution of cultural-semantic labels generated during annotation. Density Value is derived from the spatial distribution of symbols in the spatiotemporal grid and written as the normalized count of symbol occurrences within each temporal–regional unit. These formulations provide the analytical foundation for all subsequent quantitative comparisons.

B. VALIDATION OF INTERTEXTUAL PATTERN SIMILARITY

Based on the calculation results of the intertextual association model, the symbol sharing rate between the brocade pattern symbol of the five major ethnic minorities in the southwest and the three typical caisson patterns in Dunhuang is sorted out. The calculation results quantify the proximity and symbol co-occurrence frequency of brocades of different ethnic groups and specific caisson patterns in the feature space, as shown in Figure 4.

Figure 4 reflects the degree of cultural convergence between ethnic brocades and Dunhuang caisson ceilings. Miao brocades exhibit high symbol sharing rates with lotus-patterned square wells (0.90) and grid pattern (0.92), indicating significant cultural-semantic affinity. Conversely, Tibetan brocades show minimal sharing with lotus pattern (0.01), underscoring distinct cultural identities. The high sharing rate of Miao brocade is related to the similarity of its cultural background, while the low sharing rate of Tibetan brocade indicates that its cultural symbol is relatively unique. This high sharing rate not only represents the consistency of visual symbols, but also reflects the mutual learning and emotional connection of multi-ethnic cultures under the community consciousness; while the low sharing rate shows that the community is not homogenized, but a diverse symbiosis. Importantly, the quantified symbol sharing rate provides not only a numerical comparison but also a cultural lens: high sharing rates suggest intensive symbolic interaction and mutual adaptation between ethnic groups and Dunhuang art, while lower rates reveal cultural distinctiveness and selective preservation. This quantitative perspective complements qualitative interpretation, allowing

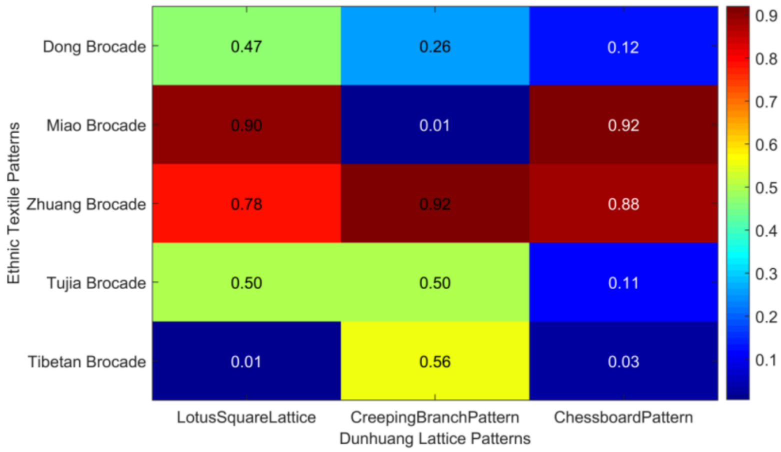

FIGURE 4. Heatmap of Symbol Sharing Rates Between Southwest Ethnic Minority Brocades and Dunhuang caisson ceilings Symbols

to trace patterns of cultural exchange with greater clarity and objectivity. To analyze the commonalities and differences of different pattern categories in cross-regional and cross-media communication, the symbol sharing rate data is classified and summarized according to the preset pattern types (plant patterns, geometric patterns, and sacro-symbolic motifs). The cross-media sharing rate discussed in the abstract refers specifically to the mean Southwest Brocade–Dunhuang Caisson shared rate within each pattern category reported in Table 2. The statistics cover the average sharing rate inside the Southwest Brocade, inside the Dunhuang caisson, and between the two. The data are shown in Table 2. The internal shared rate of Southwest Brocade and Dunhuang Caisson is written as the mean Symbol Sharing Rate computed within each region by calculating the cosine similarity among all intra-region symbol pairs and counting those exceeding the threshold of 0.80. The Cross-Media Shared Rate Standard Deviation is written as the standard deviation of Symbol Sharing Rates across all brocade–caisson pairings within each pattern category. The calculations use all 600 brocade samples and 80 caisson samples, and no subsampling is introduced during the aggregation process.

TABLE 2. Categorical Aggregation of Symbol Sharing Rates for Multi-Ethnic Pattern Symbols, with Cross-Media Values Representing the Mean Southwest Brocade–Dunhuang Caisson Shared Rate

Pattern Type	Southwest Brocade Internal Shared Rate (Mean)	Southwest Brocade & Dunhuang Caisson Shared Rate (Mean)	Dunhuang Caisson Internal Shared Rate (Mean)	Cross-Media Shared Rate Standard Deviation
Floral Patterns	0.82	0.71	0.93	0.08
Geometric Patterns	0.75	0.63	0.83	0.11
sacro-symbolic Motifs	0.68	0.52	0.87	0.15

Table 2 shows the sharing rates of different pattern types between Southwest Brocade and Dunhuang caisson, in which the cross-media column reports the mean shared rate across all brocade–caisson pairings and directly corresponds to the value cited in the abstract. Comparing the internal sharing rates of Southwest Brocade and Dunhuang caisson, the sharing rate of plant patterns is higher, 0.82 for Southwest Brocade and 0.93 for Dunhuang caisson, and the sharing rate between the two is 0.71, which shows that plant patterns have a strong consistency in cultural heritage and visual symbol with other patterns in these two regions. The data shows that in the process of cross-media communication of cultural symbols, the cultural context and usage scenarios of the symbols themselves have an important influence on their sharing rate. Especially when expressing the cultural characteristics of different historical periods and regions, the transmission and deformation of symbols are factors that cannot be ignored.

C. NARRATIVE THEME CONSISTENCY TEST

According to the cultural semantic labels assigned in the pattern symbol annotation stage, the sample patterns are classified into three preset narrative themes (cosmology, cultural heritage, philosophy, and nature worship). The assignment of narrative themes is produced through an expert annotation procedure independent from the Mask R-CNN classification stage. Three scholars specializing in ethnology, textile semiotics, and Dunhuang visual culture participated in the labeling process. The annotation guideline defines the narrative themes through stable cultural-semantic descriptors extracted from classical literature on symbolic cosmology, cultural lineage, philosophical imagery, and worship-related representations. Each expert independently reviewed all annotated symbols and assigned a theme label based on the semantic attributes produced during the instance segmentation stage. Consistency among annotators is assessed through Cohen's Kappa, and the resulting value of 0.87 confirms a high level of agreement. Disagreements are resolved through a consensus meeting, and the final theme distribution reflects the unified annotation outcomes. The proportion of symbols belonging to each narrative theme in the brocade samples of southwestern ethnic minorities and each type of Dunhuang caisson ceilings is counted. The values shown in Figure 5 derive from a two-step computation process. The LSTM model produces a hidden-state sequence for each image, and the final hidden state is passed through a fully connected transformation that maps the representation into three continuous outputs corresponding to the three narrative themes. These outputs are normalized through a softmax transformation to produce a probability distribution. The ground-truth theme labels originate from the expert annotation process described earlier, and the predicted probabilities are averaged across all images belonging to each ethnic group or caisson type. The final values displayed in Figure 5 represent the mean normalized theme distribution for each cultural group. The results are shown in Figure 5.

Figure 5 shows the distribution of narrative themes in the southwestern ethnic minority brocade and Dunhuang caisson ceiling. Taking the brocade data of the southwestern ethnic minorities as an example, the cosmology theme of the Tibetans is 0.87, showing a strong tendency towards cosmological themes, while the philosophy and nature worship of the Tujia people is 0.98, indicating that the brocade of this ethnic group pays more attention to the expression of nature worship. From the perspective of Dunhuang caisson, the cosmological distribution of the Lotus Square Well is 0.4, which is lower than the distribution of most ethnic brocades, indicating that the cosmological theme of the caisson is weak. The emphasis on cosmology and nature worship in brocades of various ethnic groups reflects the inheritance of the concept of symbiosis between heaven and earth, while the Dunhuang patterns strengthen cultural continuity through philosophical and natural themes. The two are intertextual and jointly construct the unity and diversity of the visual narrative of the Chinese nation.

D. FEATURE SPACE ALIGNMENT ACCURACY

Using the feature space mapping method, the color texture feature vectors of southwestern ethnic minority brocade and the geometric structure feature vectors of Dunhuang caisson ceiling are projected into a unified two-dimensional feature space. The 'pattern symmetry' dimension is derived from the geometric-refinement output of the caisson branch, where the rotational symmetry score is computed from the normalized eigenvalue dispersion of the feature covariance matrix after the final geometry-focused refinement block. The score is rescaled into the range 0.5–2.5 through min–max normalization applied across all samples to ensure comparability between brocade and caisson representations. The 'color and texture density' dimension originates from the activation histogram of the brocade branch after global average pooling. The texture-activation accumulation within the normalized spatial grid yields a density metric that reflects the concentration of high-frequency texture responses, which is also rescaled into the 0.8–2.8 range. These two values are not raw CNN outputs but standardized derivatives computed from the final-stage feature maps of both branches. The two dimensions of this space are defined as "pattern symmetry" and "color and texture density". All processed pattern sample points are placed in this space for observation. The distribution results are shown in Figure 6.

Figure 6 shows the distribution characteristics of multi-ethnic pattern symbol in the two-dimensional feature space of pattern symmetry and color and texture density. Tibetan brocade and lotus square well show a weak intersection in the symmetry 0.5-1.0 and density 1.8-2.3 areas, suggesting the cross-temporal and spatial echoes of religious symbols. This visual local overlap and separation is not only the result of algorithm analysis, but also vividly presents the diversity and inclusiveness of Chinese national culture in integration. To quantitatively evaluate the effect of feature space mapping, the concentration (within class) and separation (between classes) indicators of the distribution of sample points of different categories, as well as the feature alignment accuracy indicators, are calculated. These indicators are calculated for the sample distribution inside the Southwest Brocade, inside the Dunhuang caisson, and between the Southwest Brocade and the Dunhuang caisson. The data is shown in Table 3:

TABLE 3. Comparison of quantitative indicators of feature space alignment

Category Comparison	Intra-Class Cohesion	Inter-Class Separation	Alignment Accuracy	Intertextuality Annotation Count
Southwestern Brocade Internal	0.12	0.45	0.03	12
Dunhuang Caisson Ceiling Internal	0.15	0.58	0.04	8
Southwestern Brocade and Dunhuang Caisson Ceiling	0.18	1.2	0.12	20

The value reported as 'Intertextuality Annotation Count' represents the total number of cross-media symbol correspondences manually confirmed during expert validation. After the model produced all preliminary cross-media pairings with cosine similarity above the threshold, three annotators reviewed each suggested correspondence and recorded the instances in which a symbolic link was verified. The number listed in Table 3 corresponds to this manually validated count, rather than a raw model output. Table 3 shows the comparative data of the southwestern brocade and the Dunhuang caisson ceiling in different categories. In terms of intra-class aggregation, the internal clustering of the Dunhuang caisson (0.15) is higher than that of Southwest Brocade (0.12), and its intra-class aggregation is slightly higher, indicating that its pattern symbols are relatively dense. In terms of inter-class separation, there is a large difference between the Southwest Brocade and the Dunhuang caisson ceiling, and the inter-class separation between the two is as high as 1.2. To further evaluate the effectiveness of the proposed framework, it is compared with two baseline models: a shallow feature model based on low-level descriptors and a single-channel CNN. These two baseline models represent commonly used methods in cultural pattern analysis and general image comparison,

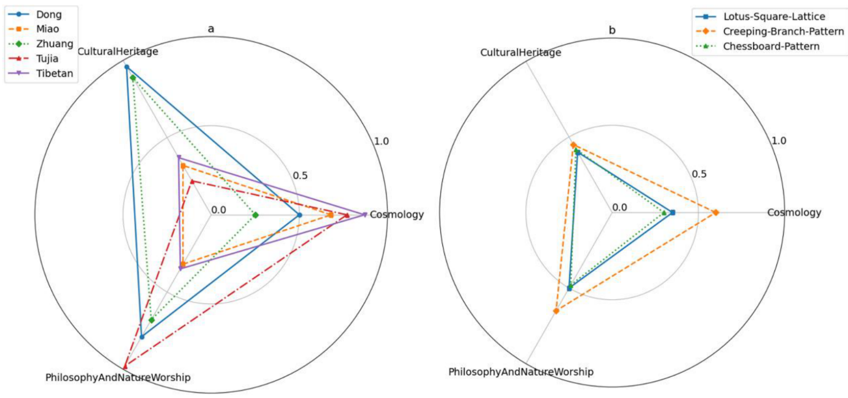

FIGURE 5. Comparative Distribution of Narrative Themes: Ethnic Brocades vs. Dunhuang Caisson Ceiling. (a) Narrative Theme Distribution in Southwest Chinese Ethnic Brocades, (b) Narrative Theme Distribution in Dunhuang Caisson Ceilings

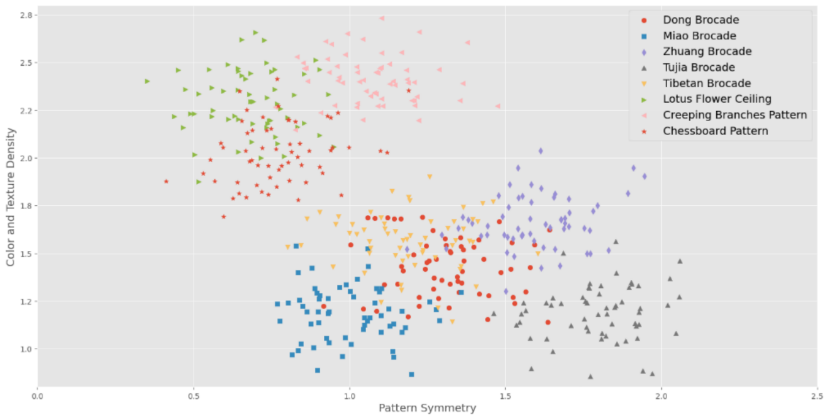

FIGURE 6. Feature space alignment and local overlap analysis of multi-ethnic pattern symbols

highlighting the advantages of the dual-channel design. The results are shown in Table 4.

TABLE 4. Performance comparison between models

Method	Inter-Class Separation	Alignment Accuracy	Interpretability
Shallow feature model	0.55	0.04	Low
Single-channel CNN	0.72	0.06	Medium
Proposed dual-channel model	1.2	0.12	High

As shown in Table 4, both baseline models show limited ability to distinguish and align heterogeneous cultural features. The shallow feature model achieves only very low inter-class separation and alignment accuracy, reflecting its inability to capture complex cross-media patterns. The single-channel CNN performs better but still performs poorly in aligning the texture-rich brocade with the geometric regularity of the caisson ceiling. In contrast, the proposed dual-channel model shows improvements in both separation accuracy (1.20) and alignment accuracy (0.12), while maintaining interpretability through an explicit mapping to cultural semantics. This comparison emphasizes the necessity of a dual-channel design for robust quantitative intertextual analysis.

E. RESTORATION OF THE COMMUNICATION PATH OF CULTURAL SYMBOLS

The temporal dimension used in the spatiotemporal grid is not derived from the visual data itself, since all images employed in this study are modern digital photographs. The temporal attribution is assigned through an external cultural-historical mapping procedure. Symbolic units extracted from brocades and caisson ceilings are matched against documented historical occurrences in classical ethnographic texts, archaeological catalogues, and Dunhuang pattern archives. Each symbolic category is associated with the earliest reliably recorded dynasty in which the motif appears in written sources. The temporal coordinate in the grid therefore reflects historically attested cultural presence rather than image metadata. This mapping enables the model to integrate cultural chronology even though the visual dataset consists of contemporary digitized images. To restore the dynamic propagation trajectory and driving mechanism of the southwestern ethnic minority brocade and Dunhuang caisson ceiling pattern in the long river of history, this study constructs a spatiotemporal grid analysis model, integrating the dual dimensions of time (Han, Tang, Song, Ming, and

Qing) and space (Yunnan Plateau, Guizhou Plateau, Sichuan Basin, Hexi Corridor, Gansu region). Figure 7 intuitively presents the calculation results based on this model:

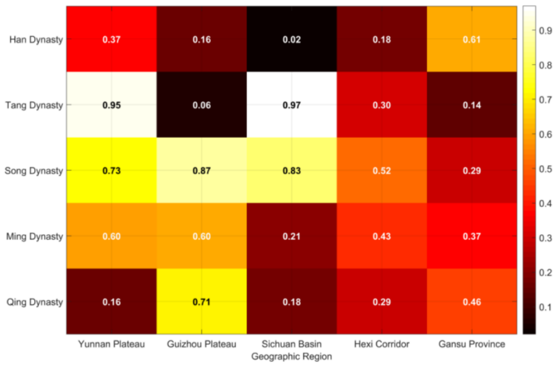

FIGURE 7. The spread of cultural symbols in time and region

Figure 7 restores the path of cultural symbol dissemination through the dual dimensions of time and space. In the Tang Dynasty, Yunnan (0.95) and Sichuan (0.97) are the cores, while Guizhou (0.06) forms a clear depression during the same period; in the Song Dynasty, there is regional dissemination, with Sichuan (0.83) and Guizhou (0.87) maintaining high levels; in the Qing Dynasty, there is a partial recovery in the southwest, with Guizhou (0.71) higher than Yunnan (0.16) and Gansu (0.46). This kind of spatiotemporal fluctuation reveals the triple driving mechanism of war, trade, and policy. The peak in the Tang Dynasty corresponds to close cultural exchanges, and the continued activity of the Sichuan Basin in the Song Dynasty reflects the deepening of the tea-horse trade. The intensity of cultural symbol penetration is quantified by density value.

V. CONCLUSION

This study establishes an intertemporal intertextuality analysis framework for multi-ethnic pattern symbols, empirically validating the intrinsic formation logic of the Chinese cultural community. The findings reveal that while southwestern ethnic minority brocade and Dunhuang caisson ceiling pattern belong to distinct regions and mediums, they demonstrate profound symbolic sharing and integration mechanisms within their visual narratives. This process substantiates the visual logic underpinning the pluralistic-yet-integrated pattern of Chinese civilization, where diverse ethnic cultures preserve regional identities while forging centripetal convergence through intertextual connections, ultimately crystallizing into the aesthetic expression of community consciousness. Nevertheless, this framework has certain limitations. The computational cost of deep models such as Mask R-CNN and LSTM remains non-negligible when processing large-scale datasets, which may constrain broader applications. In addition, potential biases in the training samples can affect the balance of intertextual analysis. Future research may extend this framework to other types of cultural artifacts and to more complex narrative structures, thereby enriching the cross-media reconstruction of cultural memory.

AUTHOR CONTRIBUTIONS

Conceptualization – Dapeng Li; methodology – Dapeng Li and Qin ZHANG; investigation – Dapeng Li; writing-original draft preparation – Dapeng Li and Qin ZHANG. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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