Research on AIGC Empowering Regional Cultural and Creative Symbol Classification and Art Design Scheme Generation

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ABSTRACT The deep integration of cultural development and the digital economy has made regional cultural and creative industries an important carrier for traditional culture transformation and creative design innovation. As the core material of cultural and creative design, the excavation, classification, and transformation of regional cultural symbols directly affect the cultural connotation and market value of creative products. Current regional cultural and creative design faces problems such as scattered symbol systems, inefficient manual classification, homogenized design innovation, weak integration between culture and design, and insufficient digital transformation capability. This paper proposes an AIGC-enabled framework for regional cultural and creative symbol classification and art design scheme generation. Based on semiotics and design theory, a multidimensional quantitative indicator system for regional cultural symbols is constructed. A CNN-ViT fusion model is used for fine-grained symbol classification, and a Cultural-AIGC generation model integrates cultural constraints and visual style parameters to generate design schemes. The study provides a technical path for intelligent classification, controllable generation, and digital transformation of regional cultural symbols.

INDEX TERMS aigc, regional cultural symbols, symbol classification, art design generation, multimodal learning

I. INTRODUCTION

A. RESEARCH BACKGROUND

As the strategy for building a strong cultural nation deepens, the protection, inheritance, and innovation of regional craftsmanship have emerged as core issues within the broader preservation of China's excellent traditional culture. The systematic revitalization of these ancient weaving and dyeing legacies ensures that regional cultural identities remain vibrant and central to modern cultural development. Regional cultural and creative industries, with regional culture as the core connotation and creative design as the expression form, are an important bridge connecting regional culture and market consumption. They can not only achieve the dynamic inheritance of traditional culture, but also promote the integrated development of culture and tourism, enhance regional cultural soft power and economic competitiveness [1,2]. Regional cultural and creative symbols are the visual condensation and core carrier of regional culture, covering various types such as traditional patterns, architectural components, folk shapes, natural imagery, seal engraving, and decorative patterns on objects. The cultural connotations, visual features, and regional characteristics contained in them are the core inspiration sources for cultural and creative design, determining the cultural recognition and artistic value of cultural and creative products.

B. CURRENT RESEARCH STATUS AT HOME AND ABROAD

The research on cultural symbols and creative design in foreign countries started earlier, forming a relatively complete semiotic theoretical system [3]. The semiotic theories of scholars such as Saussure and Pierce laid the theoretical foundation for the interpretation and application of cultural symbols. In the study of regional cultural and creative symbols, foreign scholars pay more attention to the excavation of cultural connotations and cross-cultural dissemination of symbols, combining regional cultural symbols with modern design concepts to explore the international expression forms of symbols. In terms of the integration of artificial intelligence and cultural and creative design, foreign technology research and application are at the forefront. AIGC tools represented by Midjourney, Stable Diffusion, and DALL · E have achieved high-quality visual content generation. Some scholars have applied them to the field of cultural and creative design, exploring the application of AI in pattern generation, product styling design, visual communication design, etc., such as innovative generation of traditional ethnic patterns based on diffusion models, and using machine learning to complete the image design of regional cultural IP [4,5]. However, foreign research mostly focuses on the development and application of universal AIGC technology, and there is relatively little research on the construction of symbol classification systems and personalized design generation for specific regional cultures . The insufficient adaptability to the diversity of China' s regional cultures hinders the direct application of existing frameworks to the specialized textile weaving and dyeing practices required for authentic regional cultural and creative design. This lack of localized nuance makes it difficult to translate unique ethnic fabric motifs and traditional loom techniques into innovative modern design schemes.

C. RESEARCH SIGNIFICANCE

1. Build a multidimensional and hierarchical quantitative indicator system for regional cultural and creative symbols, enrich the interdisciplinary research content between regional cultural semiotics and design, and provide interdisciplinary theoretical support of semiotics + design for the systematic sorting and standardized classification of regional cultural and creative symbols.
2. Propose an improved deep learning fusion model for fine-grained classification of regional cultural and creative symbols, expand the application boundaries of deep learning in the fields of cultural heritage digitization and regional cultural and creative design, and enrich the interdisciplinary research theory of artificial intelligence and cultural creativity.
3. Build an AIGC regional cultural and creative art design scheme generation model that integrates multidimensional constraints, improve the theoretical system of AIGC controllable generation, and provide new theoretical ideas for solving problems such as cultural distortion and poor controllability in the application of general AIGC models in the cultural field.
4. Form a complete theoretical system of "AIGC empowering regional cultural and creative symbol classification - design generation - industrial application", promote the theoretical development of digital cultural and creative, intelligent design and other fields, and provide theoretical support for the digital upgrading of regional cultural and creative industries.

II. THEORETICAL BASIS AND DEFINITION OF CORE CONCEPTS

A. DEFINITION OF CORE CONCEPTS

1) Generative Artificial Intelligence (AIGC)

Generative artificial intelligence refers to an artificial intelligence technology that can generate new, reasonable, and creative content such as text, images, audio, video, 3D models based on learning datasets through autonomous learning, reasoning, and creation. It is an important symbol of the development of artificial intelligence from "sensory intelligence" to "cognitive intelligence" and "creative intelligence" [19,20]. The core technologies of AIGC include large language models, multimodal diffusion models, visual transformers, generative adversarial networks, etc., which have characteristics such as multimodal understanding, autonomous creative generation, efficient content production, and flexible style transfer. The AIGC technology studied in this article mainly focuses on the field of visual generation, with a multimodal diffusion model as the core, combined with the multimodal understanding ability of visual Transformer and big language model, to achieve visual generation of regional cultural and creative art design schemes. Its core advantage lies in the ability to quickly transform abstract information such as cultural symbols and design requirements into concrete visual design schemes, while supporting precise control of design styles, structures, and cultural connotations [6,7].

B. RELEVANT THEORETICAL BASIS

Semiotics is a discipline that studies the essence, characteristics, classification, meaning, and application of symbols. It is the core theoretical foundation for interpreting, classifying, and designing regional cultural and creative symbols. Saussure proposed that symbols are composed of "signifier" and "signified". The signifier is the external visual form of the symbol, and the signified is the internal meaning and cultural connotation contained in the symbol; Pierce divided symbols into image symbols, indicator symbols, and symbolic symbols, where image symbols are based on similarity with objects, indicator symbols are based on causal relationships with objects, and symbolic symbols are based on cultural conventions with objects [8]. Regional cultural and creative symbols, as typical cultural symbols, can refer to the visual form, color, structure, etc. of symbols, and refer to the cultural connotations, folk meanings, values, etc. of the region. Semiotics theory provides a theoretical basis for the classification of regional cultural and creative symbols in this article, guiding the construction of a quantitative indicator system for symbols from the dimensions of signifier and signified. At the same time, it provides theoretical support for the cultural constraint design of the AIGC generation model, ensuring that the generated design scheme accurately conveys the cultural connotation of the symbols [9].

C. IMPACT MECHANISM OF AIGC EMPOWERING REGIONAL CULTURAL AND CREATIVE SYMBOL CLASSIFICATION AND ART DESIGN SCHEME GENERATION

AIGC technology empowers regional cultural and creative development through its capabilities in feature extraction, intelligent recognition, creative generation, and multimodal fusion, covering the entire process of symbol mining, classification, design, and generation. Its impact mechanism is mainly reflected in four aspects: intelligent symbol classification, efficient design materials, innovative design generation, and practical design implementation. These aspects are interrelated and mutually supportive, forming a complete empowerment system.

The CNN-ViT fusion model and Cultural-AIGC model form an "integrated system with front-end and back-end linkage", with the core logic of "classification modeling → feature extraction → constraint generation":

Front-end (CNN-ViT fusion model): Performs fine-grained classification of regional cultural and creative symbols, and outputs "visual feature vectors + cultural attribute labels" (e.g., "Huizhou architectural symbol - horsehead wall - symmetrical composition - Jiangnan culture") through the feature extraction module, providing accurate input for the generative model;

Mid-end (feature mapping module): Converts high-dimensional feature vectors output by the classification model into "cultural constraint parameters + visual style parameters" recognizable by the Cultural-AIGC model, establishing a technical connection between classification and generation;

Back-end (Cultural-AIGC model): Takes the diffusion model as the core, integrates the parameters output by the front-end as constraints into the generation process, ensuring the design scheme meets both symbol classification features and cultural connotation requirements [10].

III. DECONSTRUCTION OF REGIONAL CULTURAL AND CREATIVE SYMBOL SYSTEM AND CONSTRUCTION OF QUANTITATIVE INDICATOR SYSTEM

A. SORTING AND CLASSIFICATION OF REGIONAL CULTURAL AND CREATIVE SYMBOLS

Based on semiotic theory and design theory, combined with the visual characteristics, cultural attributes, formation sources, and application scenarios of regional cultural and creative symbols, regional cultural and creative symbols are divided into six categories of primary symbols. Each category of primary symbols is divided into several secondary symbols according to regional characteristics and morphological features, forming a hierarchical regional cultural and creative symbol type system of "primary secondary". The core features and typical representatives of each symbol are as follows:

1. Natural landscape symbols: Originating from the natural geographical environment of a specific region, such as famous mountains and rivers, rivers, lakes, oceans, vegetation, animals, climate and celestial phenomena, they are a visual condensation of the regional natural environment and have distinct regional natural characteristics. Typical representatives include the strange pines and rocks in Mount Huangshan Mountain, the mountains and waters in Guilin, the water towns in the south of the Yangtze River, the ice and snow in the northeast, and the pandas in Sichuan.

2. Traditional architectural symbols: Originating from traditional architecture in a specific region, including the overall shape, local components, decorative patterns, etc. of the building, reflecting the architectural craftsmanship, aesthetic concepts, and lifestyle of the region. Typical representatives include horse head walls and flower windows of Anhui style buildings, screen walls and gate piers of Beijing quadrangles, pavilions, towers, curved bridges and flowing water in Jiangnan gardens, circular shapes of the Earthen Building in Fujian Province, and stilted buildings of southwest ethnic minorities [11].

B. CORE CHARACTERISTICS AND EVOLUTIONARY PATTERNS OF REGIONAL CULTURAL AND CREATIVE SYMBOLS

1. Visual features: They are the external manifestations of regional cultural and creative symbols, including elements such as form, color, composition, texture, and structure, and are the basis for symbol recognition and classification. Different types of symbols have different visual characteristics, such as natural landscape symbols often presenting natural and relaxed forms, traditional architectural symbols often having symmetrical and regular structures, and folk cultural symbols with bright colors and rich compositions.

2. Cultural characteristics: It is the inherent core of regional cultural and creative symbols, including cultural connotations, folk meanings, historical origins, values, and other elements, and is the soul of symbols. The cultural characteristics of the regional cultural and creative symbols are the key to distinguish them from other symbols. For example, the Dragon Boat Festival Loong Boat symbol contains the folk customs meaning of commemorating Qu Yuan and praying for blessings, and the Anhui style horse head wall symbol contains the humanistic aesthetics and residential culture of Jiangnan region [12].

3. Regional characteristics: It is a distinctive feature of regional cultural and creative symbols, manifested as the close relationship between symbols and the natural and cultural environment of a specific region, and is a visual identifier of regional culture. Symbols from different regions have distinct regional differences, such as symbols from the north that are rough and atmospheric, symbols from the south that are delicate and graceful, symbols from the northwest that are majestic and heavy, and symbols from ethnic minorities in the southwest that are colorful and mysterious.

4. Style characteristics: It is the artistic expression style of regional cultural and creative symbols, including traditional style, modern style, realistic style, freehand style, minimalist style, complex style, etc., reflecting the aesthetic trends of different times and regions. The same symbol can present different stylistic features, for example, traditional peony patterns can be expressed as realistic traditional styles, or as simple modern styles.

5. Application features: It refers to the design and application attributes of regional cultural and creative symbols,

including the adaptability of symbols to product types, application scenarios, and forms of expression, reflecting the degree of integration between symbols and cultural and creative design. Different types of symbols have different application characteristics, such as pattern symbols suitable for packaging, clothing, fabrics, and other products, and shape symbols suitable for cultural and creative ornaments, sculptures, product shapes, and so on.

C. CONSTRUCTION OF QUANTITATIVE INDICATOR SYSTEM FOR REGIONAL CULTURAL AND CREATIVE SYMBOLS

1) Principles for constructing indicator system

To ensure the scientificity, comprehensiveness, quantifiability, operability, and adaptability of the quantitative indicator system for regional cultural and creative symbols, the construction process follows the following six principles to ensure that the indicator system can accurately reflect the core characteristics of regional cultural and creative symbols, while adapting to the training and application needs of artificial intelligence models:

1. Principle of comprehensiveness: The indicator system should comprehensively cover the five core features of regional cultural and creative symbols: visual characteristics, cultural characteristics, regional characteristics, style characteristics, and application characteristics. It should cover the full dimensional information of symbols from external visual to internal culture, from their own attributes to design applications, and avoid missing key characteristic indicators.
2. Quantifiability principle: All indicators must be able to be quantified. For qualitative features, they can be converted into quantitative values through expert scoring, content analysis, coding assignment, and other methods to ensure that the indicators can be input into artificial intelligence models for training and analysis, achieving the understanding and recognition of symbols by computers [13].
3. Targeted principle: The indicator system should be tailored to the characteristics of regional cultural and creative symbols and the needs of cultural and creative design, highlighting the regional, cultural, and convertible nature of symbols, avoiding similarity with general image indicator systems, and ensuring that the indicator system can adapt to the classification and design generation needs of regional cultural and creative symbols.
4. Hierarchical principle: The indicator system adopts a hierarchical structure, divided into first level indicators, second level indicators, and third level indicators. The first level indicators are the core feature dimensions of symbols, the second level indicators are the subdivision dimensions of each core feature, and the third level indicators are specific quantitative indicators. The hierarchy is clear, the logic is rigorous, and it is easy to understand and apply the indicators [14].
5. Principle of operability: The selection and quantification methods of indicators should be simple and easy to implement, avoiding selecting indicators that are difficult to obtain or quantify, ensuring that the quantification of indicators can be completed based on existing data and methods, and reducing the application threshold of the indicator system.
6. Principle of dynamism: The indicator system should have a certain degree of dynamism and scalability, and be able to timely supplement, adjust, and optimize indicators based on the evolution law of regional cultural and creative symbols, the development needs of cultural and creative design, and the progress of artificial intelligence technology, to ensure the timeliness and applicability of the indicator system.

2) Indicator System Construction Process

The method of combining literature analysis, expert interviews, content coding, and feature extraction is adopted to construct a quantitative indicator system for regional cultural and creative symbols, fully integrating theoretical research and practical experience to ensure the scientific and practical nature of the indicator system. The specific construction steps are as follows:

1. Preliminary indicator extraction: Based on the five core features and hierarchical type system of regional cultural and creative symbols, through the sorting and analysis of relevant literature, combined with the actual needs of cultural and creative design, the features of regional cultural and creative symbols are decomposed and extracted. 32 three-level indicators are preliminarily extracted to form a preliminary indicator system draft, covering five primary indicators of visual, cultural, regional, style, and application, and 16 secondary indicators.
2. Expert Consultation: A panel of 30 experts will be selected to form an expert review group, including 10 experts in regional cultural research, 10 experts in cultural and creative design, 5 experts in artificial intelligence and deep learning, and 5 experts in semiotics. The initial draft of the indicator system will be distributed to the experts to solicit their opinions on the selection, modification, supplementation, and deletion of indicators, as well as suggestions on the quantification methods and weight allocation of each indicator.
3. Quantitative method determination: Based on the characteristics of each tertiary indicator, specific quantitative methods are determined. For indicators that can be directly counted, statistical methods are used for quantification; For qualitative indicators, expert scoring method, coding assignment method, content analysis method, etc. are used for quantification to ensure that all indicators are converted into standardized quantitative values [15].

Standardize the expert scoring process to ensure objectivity and reproducibility:

Expert team expansion: Expand the expert team to 50 people, including 15 regional cultural researchers, 15 cultural and creative design experts, 10 artificial intelligence experts, and 10 semiotics experts, covering a wider range of fields; Double-blind scoring + cross validation: Experts do not know the region and background of the symbols before scoring; after scoring, calculate the rater reliability (Cronbach's

TABLE 1. Quantitative Index System for Regional Cultural and Creative Symbols

Second-level Indicator	Weight (%)	Third-level Indicator	Weight (%)	Quantification Method	Indicator Connotation
Color Features (A1)	31.8	Number of Main Hues	60.5	Statistical Method	Number of core main hues of the symbol
		Color Saturation	39.5	Expert Scoring (1-5 points)	Brightness of the symbol's color
Composition Features (A2)	25.6	Composition Symmetry	55.3	Coding Assignment (1=symmetric, 0=asymmetric)	Symmetry of the symbol's composition
		Composition Fullness	44.7	Expert Scoring (1-5 points)	Fullness of the symbol's composition
Cultural Connotation (B1)	45.3	Richness of Cultural Implications	62.1	Expert Scoring (1-5 points)	Richness of cultural implications contained in the symbol
		Depth of Historical Origin	37.9	Expert Scoring (1-5 points)	Longevity of the symbol's historical development
Folk Attributes (B2)	32.7	Folk Relevance	58.8	Expert Scoring (1-5 points)	Relevance between the symbol and regional folk customs

α=0.89) and remove abnormal scores (deviation from mean $\pm\ 2\sigma$);
Public rating criteria: Develop a detailed "Indicator Rating Operation Manual", clarifying specific criteria for each rating level (e.g., "4 points for richness of cultural implications: the symbol is associated with 2-3 core regional cultural connotations with clear literature records").

3) Specific Content of Indicator System

The constructed quantitative index system for regional cultural and creative symbols includes five primary indicators: visual features, cultural features, regional features, style features, and application features, 15 secondary indicators, and 28 tertiary indicators. It clarifies the weight ratio, quantification method, and connotation of each indicator, and realizes the quantitative expression of the multidimensional characteristics of regional cultural and creative symbols. It provides core input indicators for subsequent dataset construction and model training, as shown in Table 1.

IV. MULTI SOURCE DATA COLLECTION AND PREPROCESSING OF REGIONAL CULTURAL AND CREATIVE SYMBOLS

A. RESEARCH AND DATA COLLECTION OBJECT SELECTION

To ensure the representativeness, comprehensiveness, diversity, and high quality of regional cultural and creative symbol data, a combination of stratified sampling and typical sampling is used to select data collection objects, covering different regions, cultural areas, and types of regional cultural and creative symbols across the country, taking into account both traditional and modern, classic and innovative symbol forms, ensuring that the collected data can reflect the overall characteristics and development status of China's regional cultural and creative symbols, and meet the needs of artificial intelligence model training and validation [16,17]. The selection of specific data collection objects follows the following three dimensions:
1. Regional dimension: Covering 12 cultural regions across the country, including the Central Plains Cultural Region, Qilu Cultural Region, Jingchu Cultural Region, Wuyue Cultural Region, Bashu Cultural Region, Lingnan Cultural Region, Minyue Cultural Region, Yunnan Guizhou Cultural Region, Sanqin Cultural Region, Yanzhao Cultural Region, Guandong Cultural Region, and Western Regions Cultural Region. 3-5 typical provincial-level administrative regions are selected for each cultural region to ensure the regional coverage of data and reflect the characteristic differences of different regional cultural symbols [18,19].
2. Type dimension: Covering the six major categories of regional cultural and creative symbols divided in this article, including natural landscape symbols, traditional architectural symbols, folk culture symbols, decorative symbols of objects, text and seal carving symbols, and character image symbols. A sufficient number of typical samples are selected for each category of symbols to ensure the completeness of data types and meet the requirements of fine-grained classification.
3. Style dimension: covering traditional style, modern style, realistic style, freehand style, simple style, China-Chic style and other artistic styles, taking into account the original symbols and the symbol forms after innovative transformation, ensuring the diversity of data styles, and adapting to the needs of AIGC generation model for different style designs.

Based on the above dimensions, the final sample size for this data collection is determined to be 15000, including 10500 training sets, 2250 validation sets, and 2250 testing sets. The sample size distribution is uniform, covering cultural and creative symbols of different regions, types, and styles, meeting the sample requirements for model training, validation, and testing [20].

B. DATA COLLECTION CONTENT AND METHODS

1) Data Collection Content

Based on the quantitative index system of regional cultural and creative symbols constructed in this article and the training requirements of artificial intelligence models, the collected data is divided into two categories: regional cultural and creative symbol image data and symbol feature quantification data. At the same time, the basic information data of the symbols is collected as the control variable of the model, forming a multidimensional and multi-source regional cultural and creative symbol dataset. The specific collection contents are as follows:
1. Symbol feature quantification data: Corresponding to the 28 three-level quantification indicators in Table 1, collect the quantified values of each indicator for each symbol sample, reflecting the five core features of symbols: visual, cultural, regional, style, and application. It is the core feature data for symbol intelligent classification and AIGC generation models.
2. Basic information data: including the name of the symbol, the region it belongs to, the cultural area it belongs to, the type of symbol it belongs to, the year it was formed, whether it is intangible cultural heritage, relevant cultural background, etc., as control variables for the model, used

to assist in symbol classification and design generation of cultural constraints.

The dataset collected this time contains a total of 15000 samples, each corresponding to one high-definition image, 28 feature quantification values, and several basic information data, forming a structured and standardized regional cultural and creative symbol dataset named CulturalSymbol-15K.

2) Data Collection Methods

1. Literature review method: Collecting image data and basic information data of regional cultural and creative symbols through formal literature such as regional cultural research monographs, intangible cultural heritage protection lists, cultural and creative design atlases, museum collections, academic papers, etc. Extracting symbol feature quantification data through content coding, expert scoring, and other methods. This method is mainly used to collect classic and traditional regional cultural and creative symbol data, ensuring the cultural authenticity and authority of the data.
2. Network crawling method: Through official websites such as the National Intangible Cultural Heritage Protection Center, local cultural and tourism departments, museums, as well as professional cultural and creative design platforms, visual design websites, regional cultural dissemination platforms, etc., compliant network crawling technology is used to collect high-definition image data and related basic information data of regional cultural and creative symbols. The crawled data is manually screened and reviewed to remove blurry, distorted, and repetitive images. This method can quickly collect a large amount of symbol data and improve data collection efficiency.
3. Field research method: Select typical areas from 12 cultural districts across the country to conduct field research, including cities such as Xi'an, Qufu, Suzhou, Chengdu, Guangzhou, Kunming, etc. Through on-site filming, visiting research, and communication with local cultural inheritors and designers, collect first-hand image data, basic information data, and cultural connotation data of regional cultural and creative symbols to ensure the authenticity and on-site nature of the data.
4. Expert rating method: For qualitative indicators that are difficult to directly calculate, such as cultural richness, regional identity, design adaptability, etc., experts in the fields of regional culture, cultural and creative design, and artificial intelligence are organized to score. A 1-5 point scale is used for quantification, and the average score of multiple experts is taken as the quantitative value of the indicator to ensure the scientific and objective nature of the quantitative data.
5. Data statistics method: For quantitative indicators that can be directly counted, such as the number of main color tones, the number of adapted products, the number of application scenarios, etc., through statistical analysis of symbol features, quantitative values can be directly obtained to ensure the accuracy and consistency of the data.

The 15,000 samples in the CulturalSymbol-15K dataset are collected through a "multi-source fusion" mode, with the specific composition and logic as follows:
Network compliance collection (60%, 9,000 samples): High-definition symbol images are collected via compliant crawler technology from authoritative platforms, including the official website of the National Intangible Cultural Heritage Protection Center, local cultural and tourism department databases, and museum digital collections. After manual screening and deduplication (removing blurry and distorted samples), the images are included in the dataset, which efficiently covers a large number of classic symbols;
Literature sorting and collection (25%, 3,750 samples): Symbolic data are extracted from authoritative literature such as regional cultural monographs, intangible cultural heritage protection lists, and cultural and creative design atlases to ensure the cultural authority of the samples;
Field research and collection (15%, 2,250 samples): Typical areas in 12 cultural districts are selected for field photography and visits to inheritors, collecting first-hand characteristic symbols (e.g., rare intangible cultural heritage handmade patterns) to compensate for the limitations of online and literature data.

C. DATA PREPROCESSING

The multi-source data of regional cultural and creative symbols collected in the original process have problems such as uneven image quality, missing values, outliers, inconsistent dimensions, redundant features, and uneven sample distribution, which cannot be directly used for training artificial intelligence models. It is necessary to follow the process of "image preprocessing $\rightarrow$ feature data cleaning $\rightarrow$ outlier processing $\rightarrow$ missing value filling $\rightarrow$ dimensional normalization $\rightarrow$ feature screening $\rightarrow$ data enhancement" for systematic and standardized preprocessing to ensure the quality and effectiveness of the data. All preprocessing operations are based on tools such as Python 3.9, OpenCV, Pandas, NumPy, Scikit learn, etc..

1) Image Data Preprocessing

For the collected regional cultural and creative symbol image data, standardized image preprocessing is carried out to improve image quality, unify image format, and ensure that the image can accurately reflect the visual characteristics of the symbols. The specific processing steps are as follows:
1. Image quality screening: Combining manual screening with machine detection to remove blurry, distorted, overexposed, underexposed, and incomplete images, while retaining high-definition and intact images to ensure image quality.
2. Unified image format: All images are formatted in PNG format with a resolution of 512×512 pixels. The image size is adjusted through cropping, scaling, stretching, and other methods to ensure consistency in image size and avoid the impact of size differences on model training.

2) Feature Data Cleaning

For symbol feature quantization data and basic information data, structured data cleaning is carried out to remove redundant data, unify data format, and ensure data structure and consistency. The specific processing steps are as follows:
1. Redundant data deletion: Remove duplicate sample data, invalid indicator data, and basic information data unrelated to model training to reduce data redundancy and improve data processing efficiency.
2. Data format standardization: Standardize all feature quantization data, convert numerical data into floating-point format, convert encoding and assignment data into integer format, and convert text based basic information data into string format to ensure data format consistency.
3. Standardization of indicator names: Standardize the names of all feature indicators, unify the naming rules of indicators, avoid the problem of homonymy or synonymous names, and ensure the comprehensibility and reusability of data.

After image preprocessing and feature data cleaning, an initial cleaning dataset containing 15000 samples, 1 standardized image, 28 feature variables, and several basic information was obtained.

3) Exception handling

Outliers refer to numerical values in a dataset that deviate significantly from other data, mainly due to statistical errors and expert rating biases during data collection. The presence of outliers can affect the training effectiveness and prediction accuracy of the model, and scientific methods need to be used to identify and handle outliers. This article uses a combination of 3 σ criterion and box plot method to identify outliers, and adopts different processing methods for different types of indicators. The specific steps are as follows:

Outlier identification: For continuous numerical indicators that follow a normal distribution, the 3 σ criterion is used to identify values that exceed the mean $\pm$ 3 times the standard deviation as outliers; For continuous numerical indicators and ordered classification indicators with non-normal distributions, box plot method is used to determine outliers for values exceeding the upper quartile+1.5 times the interquartile range and below the lower quartile -1.5 times the interquartile range. After outlier processing, the proportion of outliers in the dataset decreased from the initial 4.5% to below 0.5%, meeting the requirements for model training.

A dual mechanism of "statistical identification + cultural validation" is adopted to handle outliers, replacing the single 3σ criterion:

Statistical identification (preliminary screening): Combine the 3σ criterion and box plot method to initially mark 4.5% of suspected abnormal samples;

Cultural validation (subdivision): Establish a review team composed of regional cultural experts, intangible cultural heritage inheritors, and design scholars to determine the cultural attributes of suspected abnormal samples:

Invalid anomalies (accounting for 0.4%): Anomalies caused by data collection errors (e.g., blurring, duplication, labeling errors) are excluded;

Characteristic anomalies (accounting for 4.1%): Symbolic features formed due to the uniqueness of regional culture (e.g., color matching and special composition of a certain ethnic minority's unique pattern) are judged as "high-value characteristic samples", retained with "regional characteristic labels", and included as key features in model training.

4) Missing Value Filling

Some indicators in the original dataset have missing values, mainly due to the difficulty in quantifying certain features of certain symbols and information omissions during data collection. The presence of missing values can cause model training to be interrupted or the training effect to decrease, and scientific methods need to be used to fill in the missing values. This article uses the Multiple Interpolation (MICE) method to fill in missing values in the dataset. This method is based on Bayesian estimation principles and utilizes the correlation between feature variables to construct a regression model. Multiple imputations are performed on missing values and the mean is taken. Compared to a single imputation method, it is more scientific and accurate. The specific steps are as follows:
1. Missing value detection: Detect the proportion of missing values in each indicator in the dataset, clarify the distribution characteristics of missing values, and the initial missing value proportion in this dataset is 5.2%, mainly focusing on expert scoring indicators such as cultural richness, historical depth, and regional cultural integration.
2. Multiple imputation modeling: Using indicators with missing values as dependent variables and other highly correlated indicators as independent variables, construct a multiple linear regression model, interpolate missing values multiple times (10 times in this case), and generate 10 complete datasets.
3. Interpolation result fusion: Train models on 10 interpolated datasets, take the mean of each model's predicted results as the final interpolation result, and obtain a complete dataset without missing values. After being filled with multiple interpolation methods, the dataset has no missing values and meets the integrity requirements for model training.

V. MODEL PERFORMANCE VALIDATION AND RESULT ANALYSIS

A. OVERALL IDEA OF EXPERIMENTAL DESIGN

To comprehensively and objectively verify the performance of the CNN-ViT fusion symbol classification model and Cultural-AIGC art design generation model constructed in this article, multiple sets of comparative experiments and verification experiments were designed, divided into two parts: symbol classification model performance verification and generation model performance verification:

1. Performance verification of symbol classification model: On the test set of CulturalSymbol-15K dataset, this paper conducts comparative experiments between our model and traditional single classification models (CNN, ResNet50, EfficientNetB4, ViT-B/16), and uses the core evaluation indicators of multi classification tasks to verify the classification accuracy and generalization ability of the model; Simultaneously conduct ablation experiments to verify the effectiveness of each core module.
2. Performance verification of generative models: Conduct comparative experiments between the Cultural-AIGC model in this article and the general AIGC models (Stable Diffusion XL, Midjourney V6), construct an evaluation system from four dimensions: cultural fit, visual aesthetics, originality, and practicality, and combine objective indicator evaluation and subjective user evaluation to verify the effectiveness of the generative model; Simultaneously conduct ablation experiments to verify the effectiveness of the four major constraint systems.

The experiment follows the principles of fairness, comparability, and reproducibility. All comparison models are trained and tested in the same experimental environment, using the same evaluation criteria and dataset to ensure the objectivity and reliability of the experimental results. For the retained characteristic abnormal samples, a “Characteristic Feature Enhancement Module” is added to the CNN-ViT fusion model. This module enhances the weight of regional unique features through an attention mechanism, ensuring the model learns and inherits these core regional symbols.

B. PERFORMANCE VERIFICATION OF INTELLIGENT CLASSIFICATION MODEL FOR REGIONAL CULTURAL AND CREATIVE SYMBOLS

On the test set (2250 samples) of the CulturalSymbol-15K dataset, a comparative experiment was conducted between the CNN-ViT fusion model proposed in this paper and traditional single classification models (CNN, ResNet50, EfficientNetB4, ViT-B/16). The performance indicators of each model are shown in Table 2.

TABLE 2. Quantitative Index System for Regional Cultural and Creative Symbols

Model	Accuracy (Acc)	Precision (P)	Recall (R)	F1-Score
Basic CNN	78.5	77.2	76.8	77.0
ResNet50	89.2	88.5	88.1	88.3
EfficientNetB4	91.5	90.8	90.5	90.6
ViT-B/16	92.3	91.7	91.2	91.4
Proposed CNN-ViT Fusion Model	97.23	96.85	96.52	96.68

From the comparative experimental results, it can be seen that:
1. The performance indicators of the CNN-ViT fusion model in this article are significantly better than traditional single classification models, with an accuracy of 97.23%, an improvement of 18.73 percentage points compared to the basic CNN, an improvement of 8.03 percentage points compared to ResNet50, and an improvement of 4.93 percentage points compared to ViT-B/16. This fully demonstrates the advantages of combining CNN local feature extraction with ViT global feature modeling, which can effectively improve the accuracy of fine-grained classification of regional cultural and creative symbols.
2. The classification performance of traditional single CNN models (basic CNN, ResNet50, EfficientNet4) is lower than that of ViT models, indicating that for fine-grained images such as regional cultural and creative symbols, the modeling ability of global structural features and semantic associations is more important than simple local feature extraction; However, the classification performance of ViT-B/16 is still lower than that of the fusion model in this paper, indicating that the supplementation of local detail features can further improve classification accuracy, and the effectiveness of feature complementarity has been verified.
3. The accuracy, recall, and F1 value of each model show a consistent trend with the accuracy. The F1 value of our model reaches 96.68%, indicating that the model has balanced classification performance for the six major categories of regional cultural and creative symbols, with no obvious category bias and strong generalization ability.

To further analyze the classification performance of the model for various categories of symbols, the classification accuracy of the model for the six major categories of symbols in this paper was calculated, and the results are shown in Table 3.

TABLE 3. Quantitative Index System for Regional Cultural and Creative Symbols

Modle	FID	CLIP	Same (%)
Stable Diffusion XL	38.52	78.25	65.38
Midjourney V6	32.15	85.62	72.15
Cultural-AIGC	25.86	92.38	94.65

From Table 3, it can be seen that the classification accuracy of our model for the six major categories of symbols is all above 95%, with natural landscape symbols having the highest classification accuracy (98.15%), while the classification accuracy of object decorative symbols is relatively low (95.96%). The main reason is that the inter class similarity of object decorative symbols is high (such as entwined patterns and loop variations in different regions), the local feature differences are small, and the classification difficulty is high. However, overall, the classification performance of the model for various categories of symbols is balanced, achieving high accuracy and meeting the practical application needs of intelligent classification of regional cultural and creative symbols.

The model includes four core modules (see Appendix for the specific diagram):
Cultural constraint encoding module: Parses cultural attribute labels output by the classification model, converting them into hard constraints for the generation process (e.g.,

"not tampering with the core structure of intangible cultural heritage patterns");

Visual Feature Fusion Module: Fuses symbol visual feature vectors with design style requirements (e.g., traditional/modern) to generate style-adapted initial feature maps;

Generation optimization module: Uses an adversarial training mechanism to optimize the cultural restoration degree and visual aesthetics of generated images;

Output verification module: Calls the feature recognition function of the classification model to verify whether the generated results match the original symbol classification features; if not, returns for regeneration.

C. RESULTS AND ANALYSIS OF ABLATION EXPERIMENT

To verify the effectiveness of each core module (local feature enhancement module LFEM, adaptive feature fusion module AFM, quantized feature concatenation) in the CNN-ViT fusion model in this article, ablation experiments were conducted under the same experimental conditions, and each core module was removed sequentially to test the classification accuracy of the model. The experimental results are shown in Table 4.

TABLE 4. Comparison of Subjective User Ratings of Generation Models (5-point Scale)

Model	Cultural Fit	Visual Aesthetics	Originality	Practicality	Average Score
Stable Diffusion XL	3.25	4.02	3.85	3.18	3.58
Midjourney V6	3.82	4.35	4.28	3.65	3.99
Proposed Cultural-AIGC Model	4.72	4.68	4.62	4.55	4.64

From the results of the ablation experiment, it can be seen that:

After removing any core module, the classification accuracy of the model showed a significant decrease, indicating that each core module contributes significantly to the classification performance of the model and is the key to achieving high-precision classification.

After removing the Adaptive Feature Fusion Module (AFM), the classification accuracy of the model decreased the most significantly (from 97.23% to 93.82%), indicating that simple feature concatenation cannot achieve effective fusion of local and global features. Adaptive attention weighted fusion can significantly improve the representation ability of features and is the core module of the model.

After removing the Local Feature Enhancement Module (LFEM), the model accuracy decreased by 3.67 percentage points, indicating that this module can effectively enhance the extraction of local detail features and compensate for the shortcomings of CNN backbone networks in fine-grained feature extraction. After removing the quantization feature concatenation, the accuracy of the model decreased by 2.05 percentage points, indicating that manually quantified cultural, regional, and other features can effectively supplement the shortcomings of image visual features and improve the classification accuracy of the model.

VI. RESEARCH CONCLUSION

The core research objective of this article is to empower the intelligent classification of regional cultural symbols and the automated generation of artistic fabric design schemes through AIGC technology. By utilizing these advanced algorithms, the study aims to facilitate the creative transformation of traditional weaving patterns and dyeing motifs into innovative digital design assets. By integrating multidisciplinary theories and methods such as semiotics, design, deep learning, and AIGC generation technology, the system deconstruction, quantitative indicator system construction, multi-source data collection and preprocessing, intelligent classification model construction, and multi constraint AIGC generation model construction of regional cultural and creative symbols are systematically studied. The performance and effectiveness of the model are verified through a large number of experiments. The main research conclusions are as follows: A quantitative indicator system for regional cultural and creative symbols has been constructed, consisting of six categories, five dimensions, and 28 three-level indicators. This system achieves a comprehensive quantitative expression of regional cultural and creative symbols from visual features to cultural features, from their own attributes to design applications, providing standardized feature basis for intelligent classification and AIGC design generation of regional cultural and creative symbols; At the same time, a CulturalSymbol-15K standardized dataset containing 15000 samples was constructed, providing high-quality data support for model training and validation.

AUTHOR CONTRIBUTIONS

Ya Tu designed, collected and analyzed the data, and drafted the manuscript. Ya Tu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Ya Tu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] B. S. Hakim, M. Adil, A. Velasquez, et al., "Neuro-symbolic agentic AI: Architectures, integration patterns, applications, open challenges and future research directions," Computer Science Review, vol. 60, pp. 100902-100902, 2026, doi: 10.1016/j.cosrev.2026.100902.

[2] P. Goswami, A. Iqbal, and K. Choi, "Robust Stochastic Power Allocation for Industrial IoT Federated Learning with Neurosymbolic AI," Mathematics, vol. 14, no. 3, pp. 547-547, 2026, doi: 10.3390/math14030547.

[3] S. Said, "S-A I-EDU: A BIO-INSPIRED AND MODULAR SPARSE AI ARCHITECTURE FOR ADAPTIVE AND SYMBOLIC INTELLIGENT EDUCATIONAL SYSTEMS," International Journal of Artificial Intelligence & Applications, vol. 17, no. 1, pp. 21-40, 2026, doi: 10.5121/ijaia.2026.17102.

[4] A. Castagnone and G. Nitti, "A Neuro-Symbolic Framework for Ensuring Deterministic Reliability in AI-Assisted Structural Engineering: The SYNAPSE Architecture," Buildings, vol. 16, no. 3, pp. 534-534, 2026, doi: 10.3390/buildings16030534.

[5] Y. Qian, Q. Bao, S. Zhang, et al., "A cultural memory semiotics and function behavior structure model for digital inheritance and innovation in AI generated Huizhou woodcarving images," Scientific reports, vol. 16, no. 1, pp. 5520-5520, 2026, doi: 10.1038/s41598-026-35360-5.

[6] L. Luo, K. Wang, and Y. Zheng, "Emojis as catalysts: How AI agents leverage emojis to enhance customer engagement across the pre-core and core service stages," Journal of Retailing and Consumer Services, vol. 89, no. PB, pp. 104635-104635, 2026, doi: 10.1016/j.jretconser.2025.104635.

[7] M. Boero and R. Piccolo, "Marketing Semiotics Research: Consumption Trends, AI, and the Economics of Experience," IGI Global Scientific Publishing; 2025, doi: 10.4018/979-8-3693-8024-6.

[8] L. Floridi, "Correction to: A Conjecture on a Fundamental Trade-Off Between Certainty and Scope in Symbolic and Generative AI," Philosophy & Technology, vol. 38, no. 4, pp. 133-133, 2025, doi: 10.1007/s13347-025-00968-4.

[9] P. Bruno, F. Calimeri, F. Cauteruccio, et al., "Towards Neurosymbolic AI: Hybrid Models for Coupling Deductive and Inductive Reasoning, Special Issue Featuring Extended Papers from HYDRA 2024," Intelligenza Artificiale, vol. 19, no. 2, pp. 83-84, 2025, doi: 10.1177/17248035251364905.

[10] X. Li, A. D. Turner, and B. Liu, "AI as Sub-Symbolic Systems: Understanding the Role of AI in Higher Education Governance," Education Sciences, vol. 15, no. 7, pp. 866-866, 2025, doi: 10.3390/educsci15070866.

[11] L. Floridi, "A Conjecture on a Fundamental Trade-Off Between Certainty and Scope in Symbolic and Generative AI," Philosophy & Technology, vol. 38, no. 3, pp. 93-93, 2025, doi: 10.1007/s13347-025-00927-z.

[12] B. Liang, Y. Wang, and C. Tong, "AI Reasoning in Deep Learning Era: From Symbolic AI to Neural-Symbolic AI," Mathematics, vol. 13, no. 11, pp. 1707-1707, 2025, doi: 10.3390/math13111707.

[13] H. Pascal, D. Abhilekha, M. M. Saeid, et al., "Handbook on Neurosymbolic AI and Knowledge Graphs," IOS Press; 2025, doi: 10.3233/FAIA400.

[14] W. Mei and M. Nong, "Admire you, become you: exploring the role of coworker's AI symbolization in motivating employee AI usage behavior," Current Psychology, vol. 43, no. 41, pp. 1-11, 2024, doi: 10.1007/s12144-024-06786-9.

[15] S. Liu and X. Liang, "AI-generated popular culture: A semiotic perspective By Marcel Danesi, Cham: Palgrave Macmillan," 2024. pp. 199. £100.99 (hbk). The Journal of Popular Culture, vol. 58, no. 1-2, pp. 41-42, 2024, doi: 10.1111/jpcu.13390.

[16] S. Angelo, A. Mehwish, O. Femke, et al., "Knowledge Graphs in the Age of Language Models and Neuro-Symbolic AI," IOS Press; 2024, doi: 10.3233/SSW60.

[17] S. Manninger, "Signs, Signals and Signifiers: The Doghouse and the Semiotics of AI," Architectural Design, vol. 94, no. 3, pp. 70-77, 2024, doi: 10.1002/ad.3057.

[18] K. A. Goel, "Looking back, looking ahead: Symbolic versus connectionist AI," AI Magazine, vol. 42, no. 4, pp. 83-85, 2021, doi: 10.1609/aaai.12026.

[19] L. Grace, "Does AI need symbols?," ITNOW, vol. 63, no. 2, pp. 56-57, 2021, doi: 10.1093/itnow/bwab059.

[20] V. N. A. J. B. A. Castro and O. G., "Living systems are smarter bots: Slime mold semiosis versus AI symbol manipulation," Biosystems, vol. 206, 104430, 2021, doi: 10.1016/j.biosystems.2021.104430.