

Article

Cultural Perception of Tourism Heritage Landscapes via Multi-Label Deep Learning: A Study of Jingdezhen, the Porcelain Capital

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Abstract: In the face of rapid progress in heritage preservation and cultural tourism integration, landscape planning in historic cities is pivotal to showcasing regional identities and disseminating cultural value. However, the complexity of cultural characteristic identification and the imbalance in planning often restrict the progress of urban development. Additionally, existing studies predominantly rely on subjective methods and focus on a single cultural attribute, highlighting the urgent need for research on diversified cultural perception. Using Jingdezhen, a renowned historic cultural city, as an example, this study introduces a multi-label deep learning approach to examine cultural perceptions in tourism heritage landscapes. Leveraging social media big data and an optimized ResNet-50 model, a framework encompassing artifacts, production, folk, and living culture was constructed and integrated with ArcGIS spatial analysis and diversity indices. The results show: (1) The multi-label classification model achieves 92.35% accuracy, validating its potential; (2) Heritage landscapes exhibit a “material-dominated, intangible-weak” structure, with artifacts culture as the main component; (3) Cultural perception intensity is unevenly distributed, with core areas demonstrating higher recognition and diversity; (4) Diversity indices suggest that comprehensive venues display stronger cultural balance, whereas specialized ones reveal marked cultural singularity, indicating a need for improved integration across sites. This research expands the use of multi-label deep learning in tourism heritage studies and offers practical guidance for global heritage sites tackling mass tourism.



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Keywords: tourism heritage landscape; cultural tourism; heritage interpretation; multi-label classification; cultural diversity; spatial analysis; Jingdezhen historical center of porcelain

1. Introduction

According to data from the World Tourism Organization (UNWTO), cultural tourism is one of the significant drivers of global economic growth. The International Cultural Tourism Charter (2022) by ICOMOS states that cultural tourism contributes to the protection and sustainable development of cultural heritage [1]. In this context, China actively responds to international trends by approving the “Implementation Plan for Jingdezhen National Ceramic Culture Heritage Innovation Experimental Zone” [2], emphasizing cultural inheritance, tourism integration, and industrial revitalization.

As China’s first national-level cultural pilot zone and a world-renowned cultural tourism destination, Jingdezhen boasts a millennium of porcelain-making history and a rich ceramic cultural heritage. It is a city born of, prospered by, and renowned for porcelain. For centuries, Jingdezhen porcelain, traveling along the Maritime Silk Road,

spread exquisite Chinese porcelain-making techniques and profound ceramic culture across the globe, becoming a symbol of cultural exchange between China and the rest of the world. The value of Jingdezhen's porcelain production and industrial heritage lies in its historical, technological, and cultural significance. It is not only a showcase of craftsmanship and technology but also a crucial testament to socio-historical changes and cultural exchange, serving as a model for showcasing local characteristics and preserving cultural genes. With industrialization and the passage of time, many traditional porcelain production techniques have gradually disappeared, making the protection and inheritance of this historical heritage all the more crucial.

Since 2024, Jingdezhen has maintained integrated development of ceramic cultural protection and cultural tourism, using World Heritage application as an opportunity to protect core heritage sites such as ancient kilns and historic districts while establishing a comprehensive tourism pattern to create a world-class ceramic cultural tourism destination. However, with rapid urbanization and tourism development, discrepancies between local impressions and tourist expectations, as well as conflicts between tourism development and heritage authenticity preservation, have become increasingly prominent. The complexity of cultural heritage characteristics often limits viewers' understanding, hindering public communication. How to accurately perceive and evaluate the diverse characteristics of cultural heritage to achieve scientific protection and rational utilization of tourism resources has become an urgent issue requiring resolution.

Traditional cultural landscape perception studies primarily rely on questionnaires and interviews [3–5], with further exploration needed in objective quantitative evaluation. Moreover, although deep learning technology demonstrates significant potential in spatial research, existing studies mostly focus on single-feature perception, making it difficult to comprehensively reflect the multi-cultural attributes of landscapes.

Therefore, this study combines deep learning methods and social media big data to construct a multi-label identification model for Jingdezhen's tourism heritage landscape (Ceramic Cultural Heritage Landscape, CCHL) to identify and evaluate its cultural characteristics. This paper mainly focuses on the following questions:

1. How can deep learning techniques be applied to assess multi-label cultural perception in heritage landscapes?
2. What are the spatial patterns and characteristics of cultural perception in Jingdezhen's ceramic cultural heritage landscape?
3. How can the multi-label classification results provide a reference for heritage tourism planning and management?

By addressing these questions, this study not only innovatively expands the methods of cultural landscape analysis through the combination of artificial intelligence and spatial analysis but also helps to deepen the understanding of the diverse characteristics of cultural heritage landscapes; it also emphasizes the interdisciplinary integration of computer science, tourism research, and cultural heritage protection, providing scientific decision-making support for landscape planners and tourism industry managers.

2. Literature Review

2.1. Cultural Heritage and Landscape Tourism

In 1992, the World Heritage Committee officially incorporated "cultural landscapes" into the heritage category and defined it in the Convention Concerning the Protection of World Cultural and Natural Heritage as "cultural heritage representing the combined work of nature and humans", emphasizing that cultural landscapes reflect "the harmony and balance achieved between long-term human productive and living activities and nature" [6]. Since 1970, Western countries have continuously innovated cultural heritage

tourism models, promoting its development into a popular form of tourism. This form of tourism attracts visitors by transforming historical and cultural assets into commodities [7, 8], playing crucial roles in promoting cultural exchange, local economic development, and heritage preservation [9–11].

Numerous scholars have conducted in-depth research on cultural heritage tourism from various perspectives. Regarding visitor experience, Alahakoon and Udunuwara [12] explored how intangible cultural heritage enhances visitor impressions as a tourism experience through characteristics such as uniqueness and authenticity. Regarding cultural heritage preservation, Barnes [13] used economic logic and the Kuznets curve to understand the relationship between heritage tourism revenue, heritage preservation expenditure, and economic development. In terms of tourism development, Annadurai et al. [14] proposed a conceptual model discussing brand value, destination reputation, and tourist experience as key factors driving the development of heritage tourism.

In summary, cultural heritage tourism relies on the unique historical and cultural characteristics of destinations, such as historical architecture and religious beliefs, to attract tourists for sightseeing and experiences [9]. However, effectively capturing and interpreting the complexity of cultural heritage remains a key challenge, as it determines whether tourists can fully appreciate the profound cultural implications of heritage sites. Establishing a scientific cultural perception evaluation system and accurately identifying and quantifying the multidimensional characteristics of tourism heritage landscapes have become crucial issues that current research urgently needs to address.

2.2. Cultural Perception and Social Media

Cultural perception, as an individual's cognitive process of the cultural environment, is a complex psychological activity based on personal experience and cultural background. This concept encompasses not only the reception of sensory stimuli but also a deeper cultural understanding and interpretation [5,15]. Traditional research methods primarily rely on surveys and in-depth interviews, such as scholars' quantitative assessments of the cultural atmosphere of historical districts and empirical studies on the perceptual differences in cultural landscape genes [3,5]. However, these methods have inherent limitations in terms of sample representativeness and data comprehensiveness.

In recent years, the rapid development of social media platforms has opened new avenues for cultural perception research [16]. The vast amount of user-generated content (UGC) not only provides rich research materials but also offers real-time, multi-dimensional data support for observing and analyzing public cultural experiences [17]. Research has shown that through in-depth mining of social media data, it is possible to effectively capture people's perceptual patterns and emotional responses to spatial environments [18,19]. For example, scholars have used the BERT model to analyze tourists' online emotional experiences of cultural heritage [20] and applied NVivo 14 software to analyze online reviews on tourism websites, revealing multi-dimensional representations of rural landscapes, with significant results [21].

2.3. Deep Learning and Multi-Label Classification Methods

Deep learning techniques have made groundbreaking advances in recent years, particularly with significant achievements in the fields of computer vision and natural language processing. Since its introduction in 2006 [22], learning methods based on deep neural networks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [23], have become core technologies for solving complex pattern existing studies mostly focus on single-feature perception problems, with CNNs performing exceptionally in image classification [24].

In the field of spatial environment assessment, deep learning has shown great potential for application. Researchers have applied CNNs to image analysis of park systems [25] and cultural ecosystem service mapping of coastal landscapes [26]. However, traditional single-label classification methods are inadequate for addressing the identification needs of multidimensional cultural features in heritage landscape studies, leading to the growing application value of multi-label classification methods. Multi-label image classification technology can predict multiple class labels simultaneously, capturing rich semantic information [27], and has advantages in tasks such as semantic segmentation and scene parsing. It has been widely applied in fields such as human attributes, where existing studies mostly focus on single-feature perception [28], scene understanding [29], and mineral identification [30], but its application in cultural landscape heritage studies remains relatively limited.

In this context, Residual Neural Network (ResNet) offers new directions for multi-label classification tasks in cultural heritage. The ResNet proposed by He et al. [31] effectively addresses deep network training challenges through its residual learning framework, with residual connections mitigating the vanishing gradient problem and enabling deeper network training [24]. Compared to traditional convolutional neural networks, ResNet demonstrates superior performance in depth flexibility, training stability, and generalization capability [31,32]. Its modular design enables adaptation to various improvement requirements, giving ResNet advantages in handling complex label relationships and imbalanced categories in multi-label classification tasks [33].

3. Materials and Methods

This study combines computer science and landscape research to propose a deep learning-based multi-label cultural heritage landscape identification method, exploring the spatial distribution characteristics of cultural perception. First, a cultural identification system is established, creating multi-label datasets and optimizing the ResNet-50 model for CCHL classification. Combined with ArcGIS and diversity indicators, the visualization and quantitative analysis of tourism heritage spatial distribution and cultural perception are conducted (Figure 1).

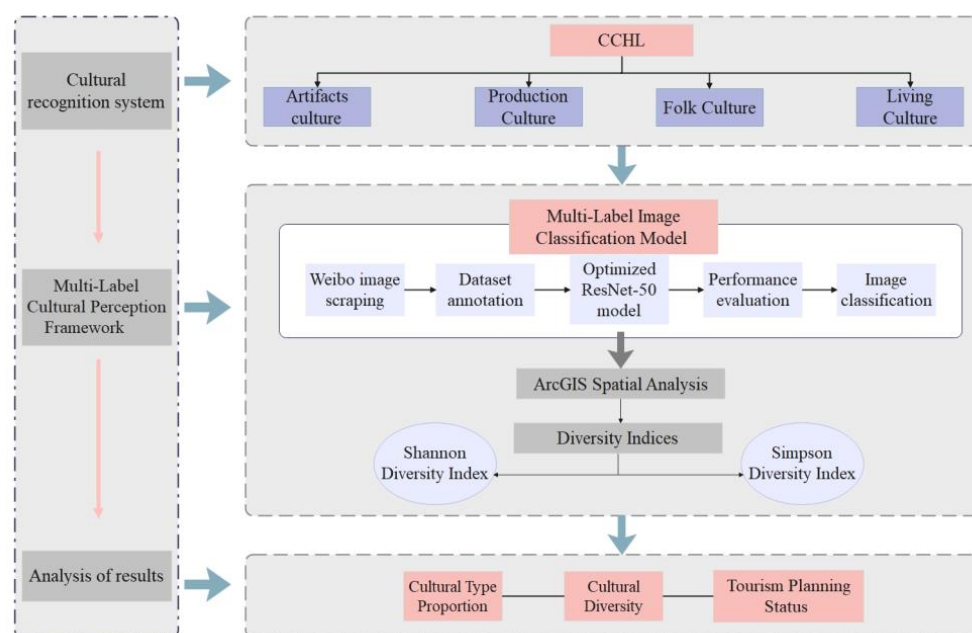


Figure 1. Research framework for multi-label cultural perception of CCHL.

3.1. Study Area

Jingdezhen, located in the northeastern part of Jiangxi Province, is one of China's first National Historical and Cultural Cities (Figure 2), renowned for its millennial porcelain-making history and unique kiln culture, which has become an important symbol of Chinese civilization's continuity. The old city district of Jingdezhen serves as the core area of ceramic culture, containing 160 ceramic industrial heritage sites, 108 historical alleyways, and numerous national and provincial-level cultural relic protection units. In recent years, Jingdezhen has trained 1899 intangible cultural heritage inheritors and has been acclaimed as the "World Ceramic Cultural Heritage Sample Zone" [34]. Following the implementation of the National Cultural Heritage Experimental Zone policy in 2019, the development of ceramic culture, related industries, and urban revitalization has been further promoted. From January to August 2024, the city received 41.6245 million domestic tourists, an increase of 18.97% year-on-year, with total tourism revenue reaching 47.868 billion yuan, up 13.76% year-on-year [35].

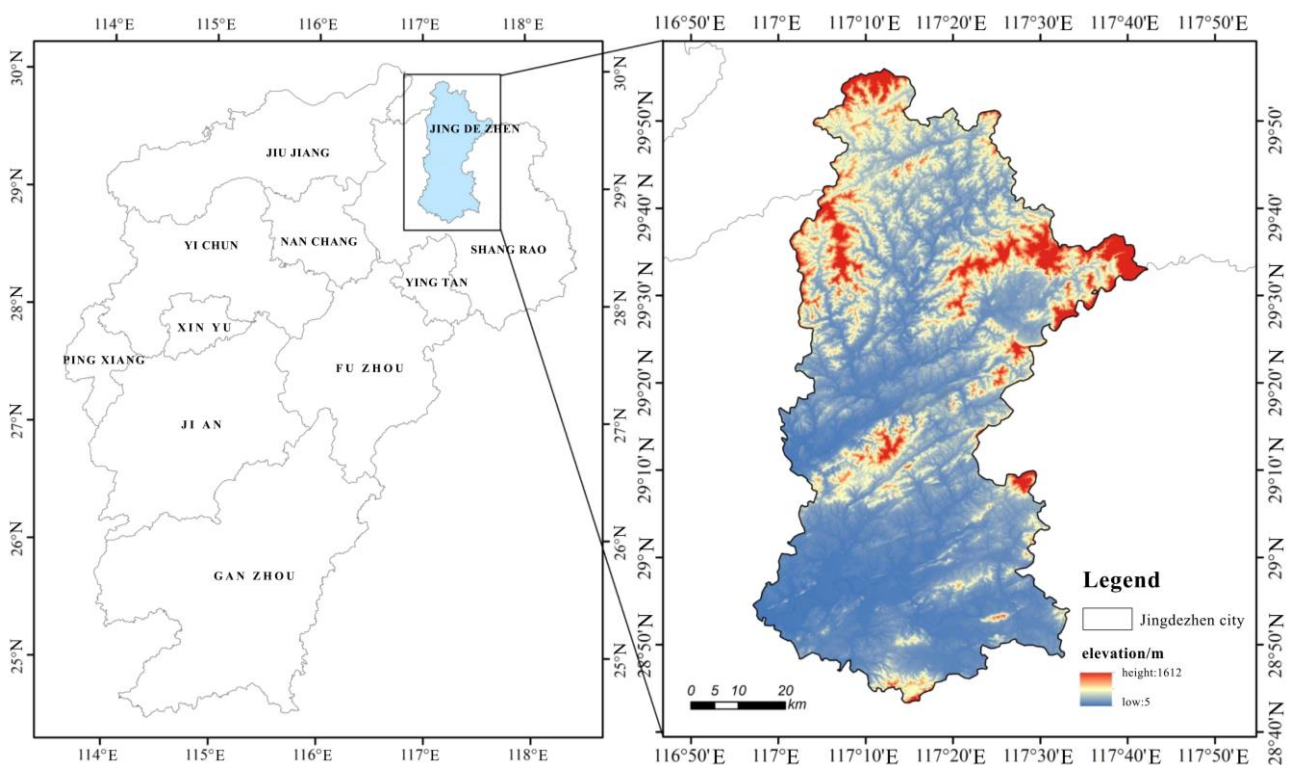


Figure 2. Overview of the Jingdezhen region.

Based on the research objectives, we combined real-time trending scenic spots in the Jingdezhen region from Weibo and organized expert discussions to select eleven CCHL sites, namely: the Ancient Kiln Folk Exhibition Area, Jingdezhen Imperial Kiln Museum, Sanbao International Ceramic Art Village, Sculpture Porcelain Factory, Taoxichuan Cultural and Creative District, Ceramic Art Street, Huang Kiln, China Ceramic Museum, Yuyao Alley, Bingding Chai Kiln, and Fuliang Xinping Porcelain Palace (Appendix A).

3.2. Data Sources

The research data is sourced from the social media platform Sina Weibo (<https://weibo.com/>). According to the "2020 Weibo User Trend Report," as of September 2020, there were 511 million monthly active Weibo users, with an average of 224 million active users every day [36]. With nearly 130 million users between the ages of 16 and 22, Weibo has 605 million monthly active users as of the third quarter of 2023, according to the "2023 Weibo Young

User Development Report” [37]. These statistics demonstrate Sina Weibo’s leading position among Chinese social media platforms. Data collection was conducted using the Sina Weibo API interface and web crawling tools in Python 3.12, with the date range selected from 2023 to June 2024. The data elements collected included user IDs, image paths, and check-in longitude and latitude information. A total of 167,000 check-in records and 35,644 images were obtained.

3.3. CCHL Identification System

Since the Song Dynasty, Jingdezhen has established a clear division of labor system in ceramic production, encompassing all aspects from raw material extraction to product sales. With the establishment of the Imperial Kiln during the Qing Dynasty, private kilns rapidly developed, attracting numerous renowned craftsmen from the north and local residents to Jingdezhen. Craftsmen formed guilds based on geographical ties, gradually assuming dominant positions in the porcelain industry. The prosperity of the ceramic industry drove the expansion of Jingdezhen’s urban space. The urban structure centered around ceramic workshops and kiln sites, with residential and commercial areas interwoven, forming a unique ceramic cultural spatial system. Throughout over 1000 years of porcelain industry development, every corner of the city has been imprinted with “ceramic elements,” becoming Jingdezhen’s unique CCHL.

In order to accurately capture the diversity of CCHL, this study has developed a multi-dimensional and multi-category system for the identification of CCHL. Based on previous relevant studies [15,38–40] and deep learning classification standards, the CCHL is divided into four main categories: artifacts culture, production culture, folk culture, and living culture (Table 1).

Table 1. Cultural identification system for CCHL, containing the four cultural categories, categorical descriptions, and photographic examples.

Cultural Categories	Description	Specific Visual Perception Elements	Legend
Artifacts culture	The material culture of Jingdezhen ceramics represents a convergence of culture, art, and craftsmanship	Ceramic vessels, porcelain shards, ceramic ornamental features, and related ceramic elements	
Production culture	The culture derived from ceramic production processes represents the craftsman spirit of ceramic producers	Ceramic production scenes, blanks, saggars, kilns, chimneys, etc.	
Folk culture	Local traditional memories are displayed through historical spaces	Folk architecture (doorways, eaves), alleyways, historical figure statues, etc.	

Table 1. *Cont.*

Cultural Categories	Description	Specific Visual Perception Elements	Legend
Living culture	Modern urban living culture reflects Jingdezhen's innovation and development	Modern buildings, museums, creative markets, artistic activities, etc.	

Specifically, artifacts culture refers to the cultural expressions centered around ceramic objects; production culture focuses on the cultural characteristics generated during the ceramic production process; folk culture primarily reflects the continuity of local historical memory and traditional customs, such as traditional dwellings, folk activities, and historical memories; and living culture focuses on the innovation and integration of traditional ceramic culture in modern cities. This classification system not only encompasses the material attributes of CCHL but also includes their intangible cultural characteristics, thus providing a comprehensive reflection of both the connotations and extensions of ceramic culture.

3.4. Multi-Label Cultural Perception Model

3.4.1. Optimized ResNet-50 Model

ResNet-50 is a deep neural network consisting of 50 layers. As shown in Figure 3 [41], the network contains five major stages (Stage 0 to Stage 4). Stage 0, serving as the initial processing stage, has a relatively simple structure, while the subsequent four stages are composed of bottleneck (BTNK) residual blocks. These residual blocks train the deep neural network by learning residual functions, eliminating the need for pre-trained models. Specifically, the first stage contains three residual blocks, while the subsequent three stages contain four, six, and three residual blocks, respectively.

In Stage 0, the input image shape is (3 224 224), representing the number of channels (C), height (H), and width (W). This stage includes two key operations: the first layer performs 7×7 convolution (CONV) with stride 2, outputting 64 channels, followed by batch normalization (BN) and ReLU activation; the second layer is a 3×3 max pooling (MAXPOOL) operation with stride 2. After these operations, the output feature map shape becomes (64 56 56).

ResNet-50 contains two different residual block structures: Residual Block 1 and Residual Block 2. Residual Block 2 is characterized by equal input and output channels, allowing direct identity mapping, while Residual Block 1 handles cases with different input and output channels, requiring additional convolution layers for dimension matching. The key innovation of residual blocks lies in introducing identity mapping, enabling the network to learn residual functions, and effectively alleviating the vanishing gradient problem in deep networks.

In the subsequent four stages, the network progressively deepens, and the number of feature channels gradually increases. Each stage contains a specific number of residual blocks, adjusting the spatial dimensions of feature maps through downsampling operations to enhance the network's ability to capture complex features.

Based on the characteristics of CCHL, this study implemented three improvements to the traditional ResNet-50 model (as shown in Figure 4). The CCHL possesses multi-scale and multi-level characteristics. Traditional single-feature extraction methods struggle to

comprehensively capture these characteristics. For instance, ceramic artifact patterns require fine-grained local feature extraction, while architectural layouts demand more global semantic information. Different types of cultural elements (such as artifacts and production scenes) vary in their importance and spatial distribution within images. Therefore, we introduced three enhancements to the standard ResNet-50 architecture, with the structural diagram shown below.

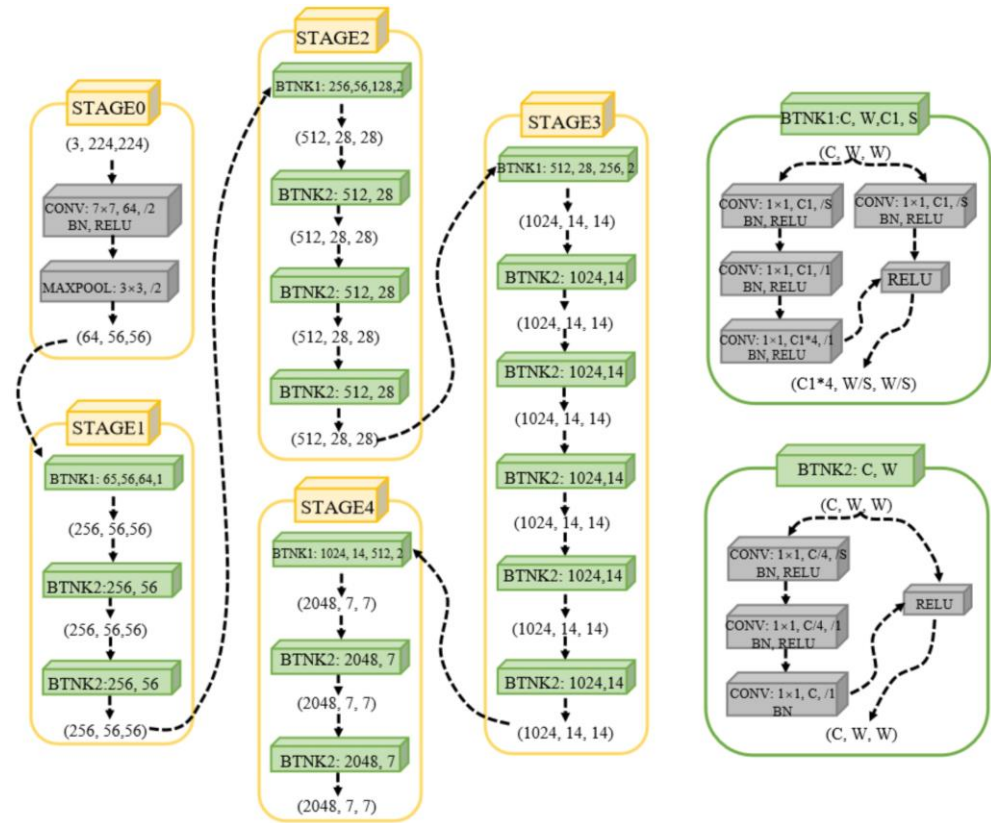


Figure 3. ResNet50 architecture: detailed structure of ResNet50 stages and residual blocks.

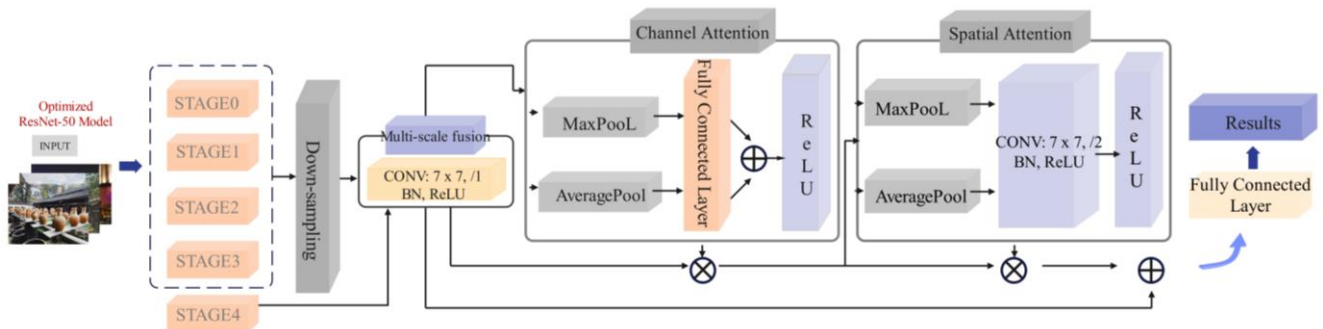


Figure 4. Enhanced ResNet-50 architecture. In the diagram, the circular symbols represent addition and multiplication.

- (1) **Multi-information Feature Fusion:** In the ResNet architecture, low-level features retain detailed information, while high-level features contain semantic information. Based on the residual learning framework proposed by He et al. [31], this study designed a bottom-up multi-information feature fusion strategy. Specifically, multi-layer features from STAGE 0–3 are downsampled to match STAGE 4 dimensions, then concatenated spatially and fused through 7×7 convolution. This approach integrates

local details and global semantic information, enhancing the model's multi-label prediction capability for CCHL, showing good performance in related studies [42].

- (2) Channel Attention Module: This study introduces channel and spatial attention modules [33,43] for more effective feature utilization. In the channel dimension, fused features undergo both max-pooling and average-pooling operations, followed by processing through fully connected layers, addition, and sigmoid activation, which is then multiplied with the original input features to generate channel attention features. This module helps the model focus on more meaningful features.
- (3) Spatial Attention Module: This study also introduces a spatial attention module to guide the model's focus on features in specific regions. This mechanism has been proven effective in the research by Woo et al. [44]. Its structure is similar to the channel attention module, with the difference being that pooling operations occur in the feature channel dimension.

Based on the optimized model, the final stage employs a global average pooling layer to compute spatial averages of feature maps, which are input to fully connected layers to generate N-length vectors. After sigmoid activation, prediction scores range from 0–1, with categories scoring above 0.5 considered as multi-labels for the input image.

3.4.2. Model Training

(1) Dataset Construction

From a collection of 35,644 Weibo images, 5000 high-quality images were selected through image quality screening and subject clarity evaluation to construct a dataset encompassing Jingdezhen's ceramic craftsmanship cultural landscapes and related elements, ensuring source authenticity and diversity. The dataset annotation was completed by three ceramic artists, each possessing over 10 years of industry experience, familiarity with local landscapes, and a minimum educational qualification of a bachelor's degree. The annotation process utilized the LabelImg tool, labeling cultural elements with corresponding tags and saving them in YOLO format (Figure 5).

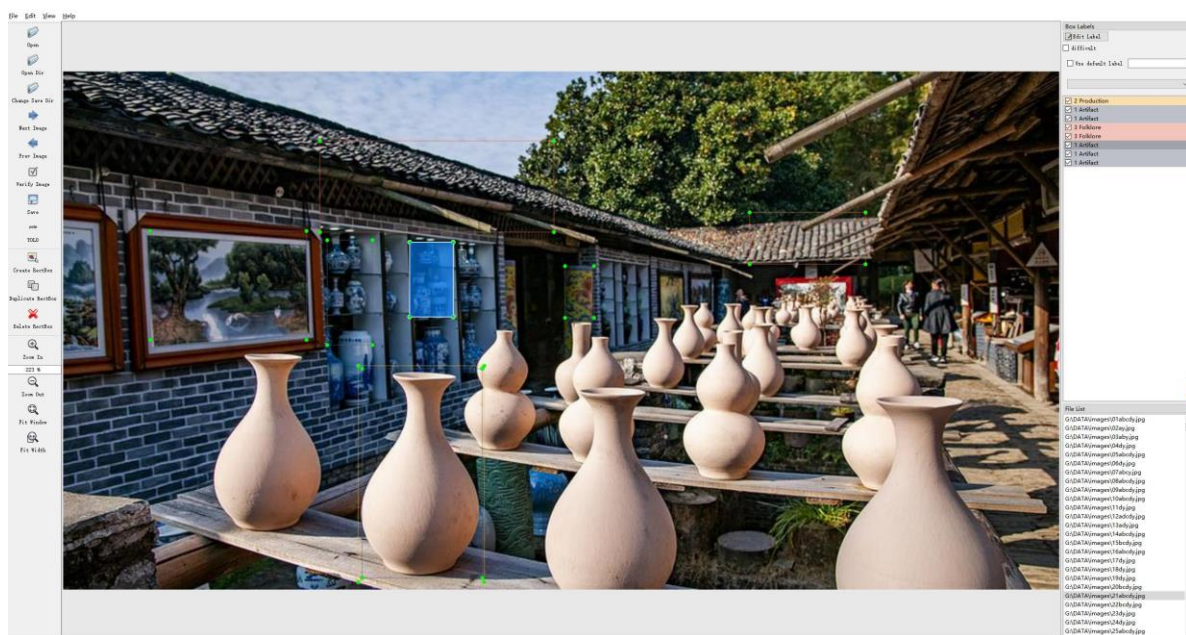


Figure 5. The interface of dataset annotation using the labellmg program.

To ensure annotation consistency, each expert completed the annotations independently, with consistency verified through random sample scoring (1–5), achieving

a Krippendorff's alpha coefficient of 0.84, indicating high inter-annotator agreement. Figure 6 shows an average consensus score of 3.72 for 20 images, reflecting consistency in cultural feature perception, while some images exhibited subjective disagreements, with low-consistency samples being revised through expert discussion. Following annotation completion, the dataset was divided into a 9:1 ratio, with 90% allocated for model training and 10% for testing, ensuring balanced data distribution.

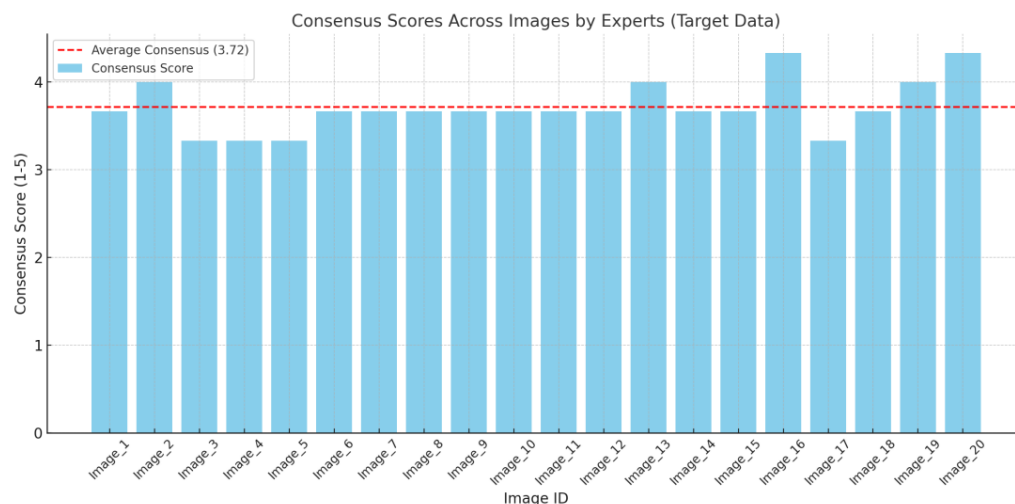


Figure 6. Expert sampling evaluation of venue images. The bar graph displays consensus scores for each image, with the overall mean consensus score (3.72) indicated by a red dashed line.

(2) Image Preprocessing and Data Augmentation

Images require preprocessing before input into the ResNet-50 model. First, images are resized to 224×224 pixels using bilinear interpolation to ensure model input compatibility while preserving original information. Data cleaning is conducted in two phases: The first phase employs a pre-trained EfficientNet-B0 model to automatically filter out irrelevant images using a 0.6 confidence threshold; the second phase involves verification by three ceramic experts who retain relevant images and remove irrelevant ones, with final quality assurance done through majority voting.

To enhance training stability, cleaned images are normalized using PyTorch 1.9.0 standard means [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225], with pixel values adjusted to the $[-1, 1]$ range. Additionally, data augmentation is performed using the torchvision.transforms module, including random flips, rotation (-10° to $+10^\circ$), cropping (80–100%), adjustments to brightness, contrast, saturation, and hue (80–120%), plus the addition of Gaussian and salt-and-pepper noise (0.01 each). Each augmentation operation has an independent probability of 0.3, expanding the dataset to triple its original size. These strategies improve the model's adaptability across various scenes and lighting conditions, enhancing the effectiveness of multi-label classification tasks.

(3) Model Training

Model training aims to continuously adjust parameters through optimization algorithms to improve prediction accuracy on unknown data. The training data is divided into training and validation sets, with the former used for updating model parameters and the latter for evaluating model performance. All images in both training and validation sets are annotated by experts, and the model generates predictions based on input data.

When predictions deviate from true values, the resulting errors are corrected through optimization algorithms (such as Stochastic Gradient Descent, SGD), allowing parameters

to gradually converge toward optimal solutions. The degree of inconsistency between predicted and true values is measured using the cross-entropy loss function:

$$C = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C [y_{i,j} \log(p_{i,j}) + (1 - y_{i,j}) \log(1 - p_{i,j})] \quad (1)$$

Here, N denotes the number of training samples, C represents the number of categories, $Y_{i,j}$ indicates the ground truth label of the i -th sample for the j -th category (1 indicates belonging to the category, 0 indicates not belonging), and $P_{i,j}$ represents the predicted probability of the model for the j -th category on the i -th sample (the output of the final sigmoid function).

The selection of hyperparameters has a significant impact on model performance. To determine the optimal hyperparameter combination, systematic experiments were conducted on key hyperparameters including learning rate, batch size, and optimizer (Figure 7).

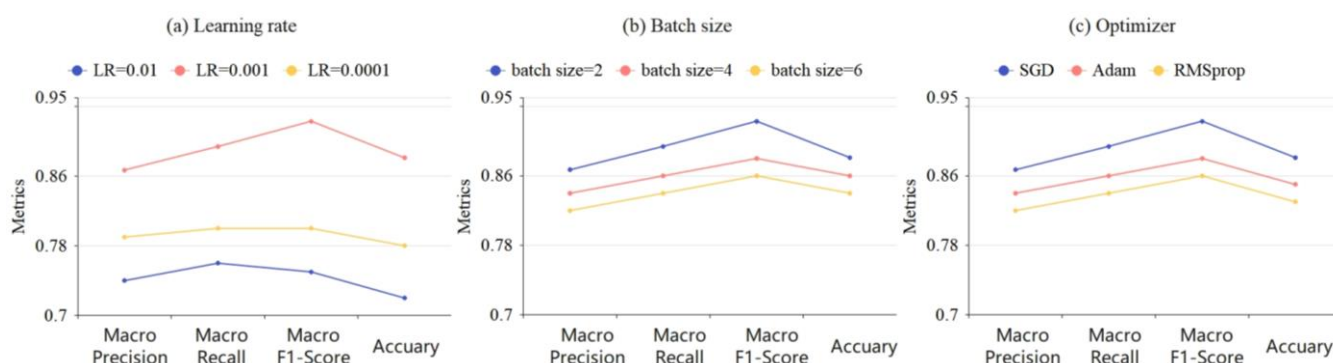


Figure 7. Model performance results for different hyperparameters.

The learning rate test results (Figure 7a) indicate that when the initial learning rate is 0.001, the model achieves optimal performance across all evaluation metrics (Macro F1 Score = 0.923, Macro Recall = 0.894, Macro Precision = 0.867, Accuracy = 0.881). A larger learning rate (0.01) significantly degrades performance (all metrics below 0.76), while a smaller learning rate (0.0001), though better than 0.01, still underperforms compared to 0.001, indicating the crucial importance of appropriate learning rate selection for model training. In the batch size experiments (Figure 7b), a batch size of 2 demonstrates optimal performance, achieving the same performance level as the 0.001 learning rate (Macro F1 Score = 0.923, Accuracy = 0.881). As batch size increases (e.g., 4 and 6), model performance notably deteriorates, possibly due to larger batches weakening the model's ability to learn detailed features. The optimizer study (Figure 7c) shows that the SGD optimizer outperforms Adam and RMSprop across all metrics, demonstrating better performance stability and validating its advantages in related research. Based on comprehensive experimental results, the final hyperparameter configuration of learning rate 0.001, batch size = 2, and SGD optimizer was selected, achieving optimal convergence and generalization performance that meets model performance requirements.

3.4.3. Model Performance Evaluation

(1) Model Evaluation Metrics

The evaluation criteria for models vary depending on the prediction problem, such as binary classification, multi-class prediction, and multi-label prediction, each requiring different assessment standards. Multi-label prediction models typically employ Macro Precision, Macro Recall, Accuracy, and Macro F1 Score to evaluate model accuracy [45,46]. The specific calculation formulas are as follows:

Accuracy: This refers to the proportion of correctly predicted labels. For multi-label classification, it is often considered a stricter metric since it requires all labels for each instance to be predicted correctly:

$$Accuracy = \frac{TN + TP}{TP + FP + TN + FN} \quad (2)$$

In the evaluation metrics, *TP* (True Positives) represents the number of samples correctly classified as positive, *TN* (True Negatives) represents the number of samples correctly classified as negative, *FP* (False Positives) represents the number of samples incorrectly classified as positive, and *FN* (False Negatives) represents the number of samples incorrectly classified as negative.

Macro Precision refers to the average precision across all classes, indicating the proportion of true positives among all instances predicted as positive by the model:

$$Macro\ Precision = \frac{1}{C} \sum_{i=1}^C Precision_i \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

Here, *i* represents the *i*-th category, ranging from 1 to *C* (where *C* is the total number of categories). In this formula, the Precision value is calculated for each category, then all Precision values are summed and divided by the total number of categories *C* to obtain the macro average precision. This reflects the model's average performance across all categories, independent of the sample size in each category.

Macro Recall: The average recall across all categories represents the proportion of true positive instances that the model can correctly identify:

$$Macro\ Recall = \frac{1}{C} \sum_{i=1}^C Recall_i \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

Macro F1 Score, which represents the harmonic mean between precision and recall, facilitates equilibrium between these metrics for thorough model performance assessment:

$$Macro\ F1 = \frac{1}{C} \sum_{i=1}^C F1_i \quad (7)$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad (8)$$

The dataset was randomly split into training and validation sets at a 9:1 ratio, specifically comprising 4500 images in the training set and 500 images in the validation set. After implementing the aforementioned parameter optimizations, the model's performance on the validation set is shown in Table 2. The optimized model demonstrated improved performance across all evaluation metrics and exhibited enhanced perception capabilities when processing complex scenarios containing multiple cultural labels, as illustrated in Figure 8.

Table 2. Model performance evaluation using four metrics after data preprocessing and model training.

Model	Macro Precision	Macro Recall	Macro F1 Score	Accuracy
Baseline ResNet-50 model	0.821	0.845	0.873	0.832
Optimized ResNet-50 model	0.867	0.893	0.923	0.880

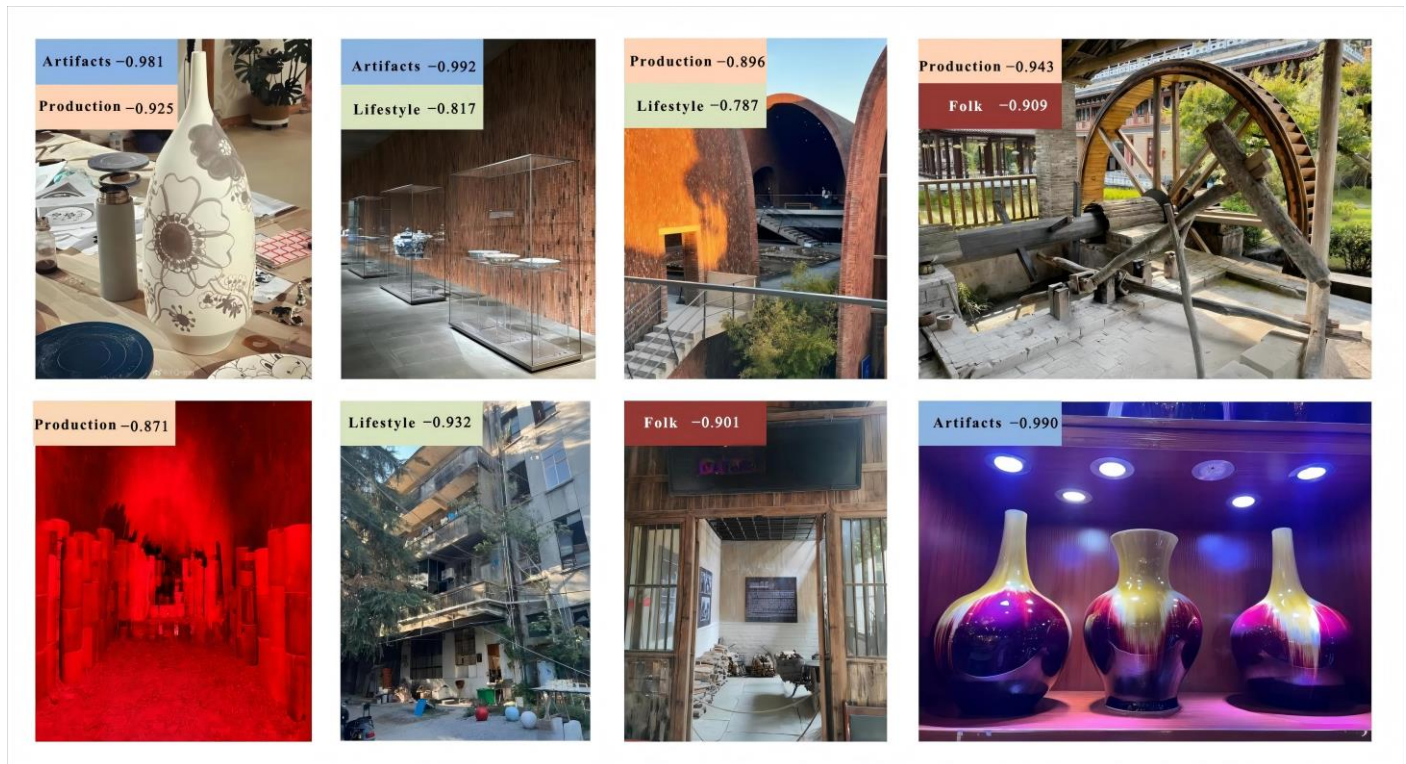


Figure 8. Several results from multi-label classification using the ResNet-50 model demonstrate high prediction accuracy for CCHL.

3.5. ArcGIS Spatial Analysis

In spatial analysis, cluster analysis is a commonly used technique that focuses on grouping data points based on specific similarity characteristics. The purpose of this technique is to partition data points into natural groups, where points within each group exhibit high similarity, while points between different groups are relatively distinct [47]. Similarity assessment typically relies on a series of predefined attributes or dimensions, which may involve spatial, temporal, or other relevant characteristics. In this study, we utilized the clustering analysis functionality of ArcGIS Pro 3.4.2 software to conduct a spatial analysis of CCHL regions with similar characteristics based on multi-label classification results. This method facilitates an in-depth exploration of the underlying factors behind the cultural composition of eleven CCHL in Jingdezhen, thereby providing scientific evidence for the preservation and sustainable development of CCHL.

3.6. Quantification of Cultural Diversity

Cultural diversity is a core element in evaluating cultural landscape quality and sustainable development. The distribution and balance of different cultural types directly affect landscape attractiveness, cultural preservation effectiveness, and the scientific validity of development planning [48]. Landscape diversity quantification commonly employs the Shannon Diversity Index (SHDI) or Simpson Diversity Index (SIDI) for quantitative assessment [49–52]. Therefore, in accordance with the research objectives, we calculated the Shannon Diversity Index and Simpson Index based on multi-label classification results from the ResNet-50 model and visualized the spatial distribution characteristics of cultural diversity using ArcGIS. The formula for Shannon Diversity Index is:

$$H = -\sum_{i=1}^n p_i \ln(p_i) \quad (9)$$

where n represents the total number of cultural types and p_i denotes the proportion of the i -th cultural type within a given landscape. The multi-label data identified by the ResNet-50 model undergoes normalization to obtain proportional data for each cultural type across landscapes, which is then applied to the formula. The Shannon Index results reflect the overall richness and complexity of cultural types within the study area, identifying both core regions of high cultural diversity and areas of lower diversity.

Subsequently, the Simpson Index is employed to quantify the cultural evenness of various landscapes. The Simpson Index formula is:

$$D = 1 - \sum_{i=1}^n p_i^2 \quad (10)$$

Based on the deep learning classification results, the relative proportions of different cultural types within each landscape are calculated to derive the Simpson Index through the formula. Compared to the Shannon Index, the Simpson Index demonstrates greater sensitivity in detecting imbalances in cultural dominance or the distribution of rare cultural elements. Through quantitative analysis using the Simpson Index, cultural type imbalances or cultural homogenization issues in different CCHL can be revealed, providing guidance for optimizing cultural distribution.

4. Results and Discussion

4.1. Proportions and Differences of Cultural Types in CCHL

Classification and identification of 35,644 Weibo images were conducted using the ResNet-50 model. Table 3 presents the number of cultural perception types within each CCHL site. The overall cultural distribution is shown in Figure 9, with a total of 31,958 images across all cultural categories. The distribution consists of 17,127 images (53.6%) of artifacts culture perception, 4451 images (14.0%) of production culture, 4745 images (14.9%) of folk culture, and 5653 images (17.7%) of living culture perception. This indicates the relative dominance of artifact culture within the overall CCHL.

Table 3. Statistical analysis of cultural perception quantities in eleven CCHL sites in Jingdezhen.

Cultural Type Region	Artifacts Culture	Production Culture	Folk Culture	Living Culture	Total Cultural Volume
Ancient Kiln Folk Exhibition Area	860	444	929	85	1936
Jingdezhen Imperial Kiln Museum	3570	1360	1754	3352	9485
Sanbao International Ceramic Art Village	2271	507	774	177	3697
Sculpture Porcelain Factory	1874	399	143	60	2407
Taoxichuan Cultural and Creative District	4459	1063	565	1569	7385
Ceramic Art Street	616	96	110	72	856
Huang Kiln	190	54	66	6	282
China Ceramic Museum	2359	120	162	154	2732
Yuyao Alley	292	84	110	105	559
Bingding Chai Kiln	180	302	33	36	747
Fuliang Xinping Porcelain Palace	456	22	99	19	542

The predominance of artifacts culture in the results aligns with Jingdezhen's long-standing history as a global center for ceramic production. Artifacts culture, represented by ceramic crafts and decorative items, remains the most visually and culturally appealing aspect of the landscape, reflecting its deep-rooted historical and artistic significance. This finding corresponds with research emphasizing the role of material heritage in shaping cultural identity and heritage tourism [53].

Meanwhile, the relatively low presence of folk culture and production culture suggests room for improvement in cultural diversity and representation in these areas. Folk culture,

encompassing traditional ceremonies, architectural styles, and local customs, presents opportunities for further promotion of cultural landscapes due to its potential for deepening cultural engagement and narrative [54]. However, our findings diverge from existing research. In Li et al.'s [55] study, tourists showed the greatest interest and appreciation for intangible cultural heritage, particularly folklore and craftsmanship, which can guide tourism development. In our study, the underrepresentation of production culture may indicate limited public awareness of or access to active ceramic production sites. As scholars suggest, this situation can be mitigated through cultural activities and enhanced interactive experiences [56,57].

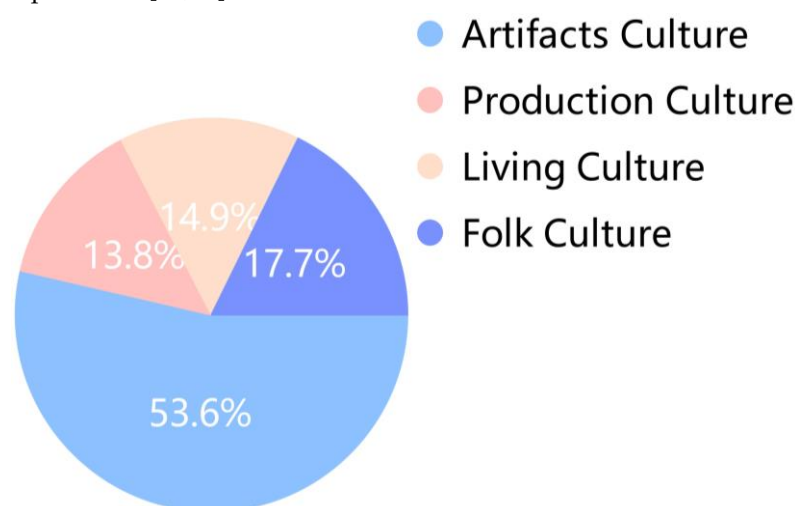


Figure 9. The percentage distribution of four types of cultural patterns in CCHL.

Furthermore, previous research [15] has employed a five-level classification of cultural perception at a place level; therefore, this study adopts the same classification standard (low, low-medium, medium, medium-high, and high). Cultural perception visualization was conducted through ArGIS, as shown in Figure 10, revealing significant spatial variations in cultural perception across different CCHL spaces. The results emphasized the heterogeneous distribution of cultural perception within CCHL. As tourist hotspots, Taoxichuan, Imperial Kiln Museum, and China Ceramic Museum exhibited notably higher levels of cultural cognition. This aligns with the findings of Paül i Agustí et al. [58] in their Barcelona case study. Images posted on Instagram predominantly feature central urban areas, confirming Jamhawi et al.'s [59] research that spatial configuration, such as accessibility and tourist site location, influences visitor behavior. The concentration of cultural awareness in urban core areas emphasizes the necessity for balanced development strategies to enhance the appeal of peripheral attractions. These attractions successfully integrate traditional and modern cultural elements, becoming must-visit destinations for both local and international tourists. For instance, Taoxichuan combines industrial heritage with cultural innovation, significantly enhancing its cultural prominence through creative industries and public activities, becoming a cultural tourism destination for both Chinese and international artists [60].

In order to examine the spatial variations in ceramic cultural type perception among different cultural landscapes, we utilized ArcGIS Pro 3.4.2 for natural breaks (Jenks) to perform quantitative analysis on cultural type distribution within eleven CCHL areas. The break values for the natural classification are low (316), medium-low (894), medium (2795), medium-high (3729), and high (10,036). The study focuses on the spatial distribution characteristics of four major cultural types (artifacts culture, production culture, folk culture, and living culture), examining both their absolute quantities and relative proportions. Through a five-level classification system, the study established a dual-dimensional assessment

framework: (a) absolute quantity distribution of each cultural element type and (b) relative proportion of each cultural element type to the total cultural volume in the region (as shown in Figure 11). Numbers 1, 2, 3, and 4 represent artifacts culture, production culture, folk culture, and living culture, respectively. In the chart displayed, columns a and b represent the absolute quantities and relative quantity characteristics of cultural perception, respectively. Denoted as (b3), it depicts the relative quantity distribution of cultural perception across eleven landscapes in the context of production culture.

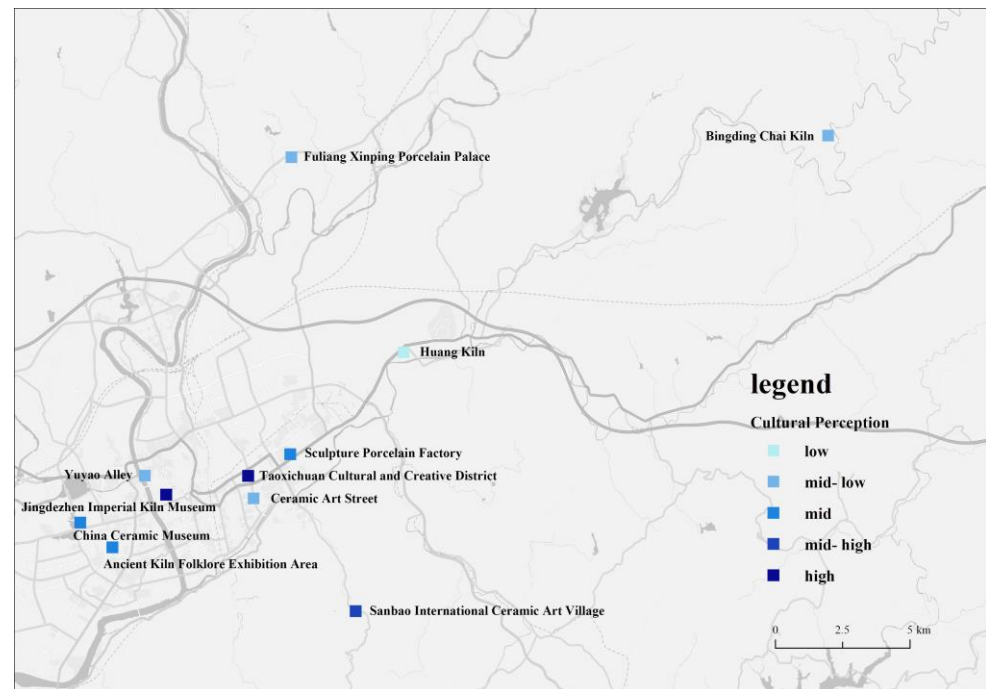


Figure 10. Cultural perception results of eleven CCHL in Jingdezhen.

As shown in Figure 11, in the absolute quantity category of group A, the cultural perception of Jingdezhen Imperial Kiln Museum and Taoxichuan Cultural Street is significantly higher than in other areas. This indicates that both locations have gained widespread recognition in their CCHL construction, leading to numerous visitors uploading related photos to Weibo, resulting in a richer cultural perception compared to other locations. The Jingdezhen Imperial Kiln Museum and Taoxichuan Cultural Street have made substantial efforts in cultural promotion and ceramic culture dissemination through various cultural publicity and artistic activities, achieving satisfactory results that align with actual circumstances. In areas with weaker cultural perception, such as Bingding Cha Kiln and Huang Kiln, due to their distance from the city center or lower level of cultural development, the absolute quantity of cultural perception tends to remain at a relatively low level. The results are consistent with other studies, indicating that cultural heritage often dominates cultural participation due to better infrastructure and transportation accessibility [61,62].

Moreover, the high cultural recognition of central area sites leads to what Pechlaner and Olbrich [63] term as center-periphery “tension,” where tourists focus on central attractions, potentially overlooking local narratives of peripheral locations.

From the perspective of relative cultural perception quantities (column b), the Ancient Kiln Folk Exhibition Area shows clear advantages over other areas in terms of artifact culture, production culture, and folk culture (b1–b3). This indicates that the Ancient Kiln Folk Exhibition Area, as a ceramic culture exhibition venue, contains rich ceramic cultural elements such as ancient kiln sites, folk residences, and craft heritage, all of which create a strong ceramic cultural atmosphere. However, data from group a shows that the

Ancient Kiln Folk Custom Exhibition Area does not exceed the Imperial Kiln Museum and Taoxichuan in terms of absolute cultural perception quantities, indicating that the area needs further enhancement in cultural perception. The results indicate that smaller, uniquely positioned cultural landscapes such as the Ancient Kiln Folk Custom Exhibition Area have the potential for achieving high engagement through targeted cultural programs. Similar strategies have been adopted in heritage cities including Kyoto and Venice, where surrounding cultural heritage spaces have been revitalized through community-driven initiatives and digital promotion [64,65].

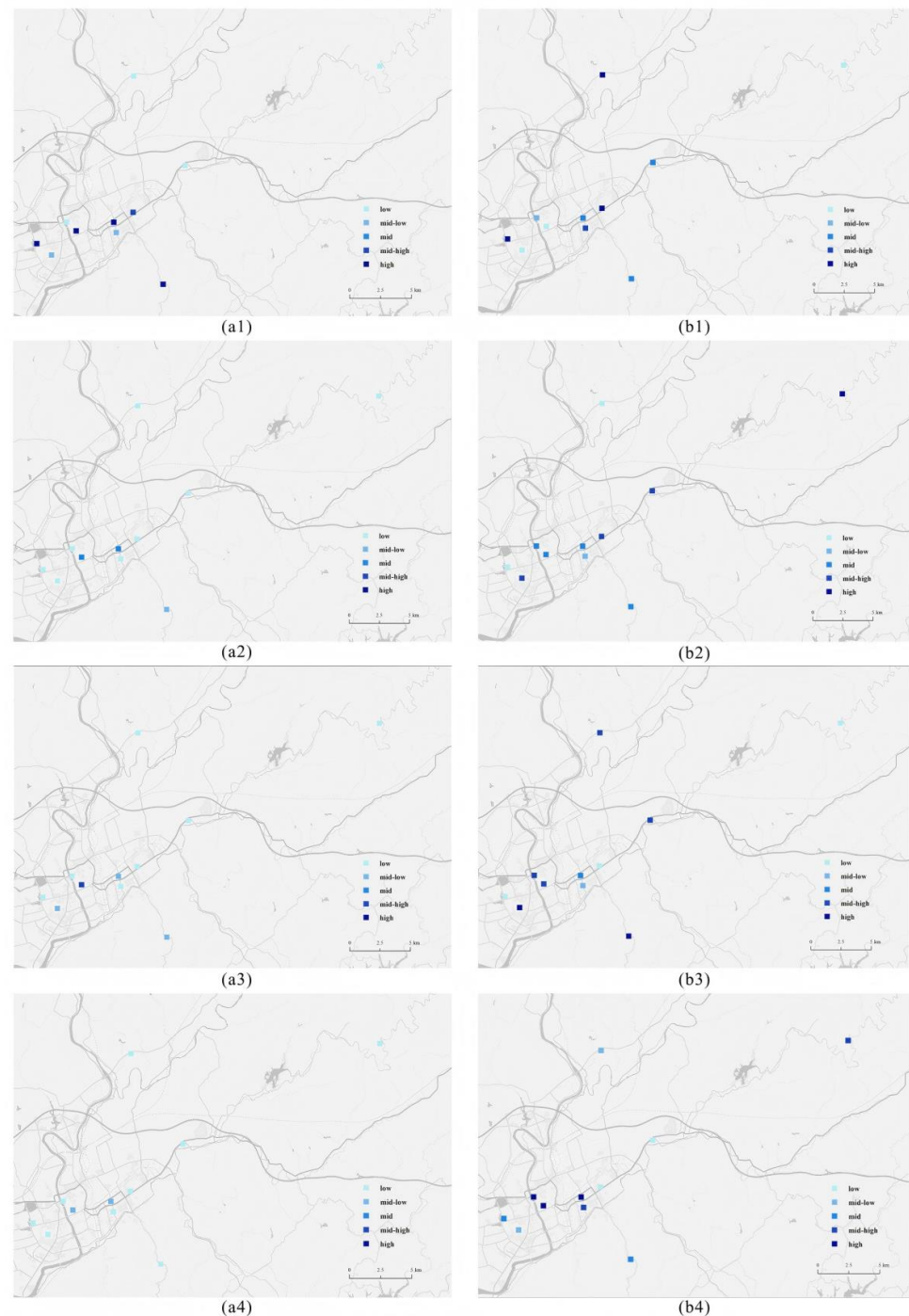


Figure 11. Absolute and relative quantities of cultural perception in different CCHL. a1–a4 represent the absolute number of four cultures (artifacts culture, production culture, folk culture, and living culture), and b1–b4 represent the relative number of four cultures.

4.2. Quantification of Cultural Diversity in CCHL

Following the analysis of the quantity of cultural types in CCHL and the landscape differences between each cultural type, this section investigates cultural diversity and cultural combinations. Using the ResNet-50 model for data classification, instances where two or more cultural types appear simultaneously are defined as multi-label, with classification results shown in Table 4.

Table 4. Results after multi-label classification of ResNet-50. For instance, among the images from the Jingdezhen Imperial Kiln Museum, 1399 images contain two cultural labels, 28 images have three cultural labels, and 904 images possess four labels.

Region	Cultural Type	Two Cultures	Three Cultures	Four Cultures
	Ancient Kiln Folk Exhibition Area	476	28	150
	Jingdezhen Imperial Kiln Museum	1399	28	904
	Sanbao International Ceramic Art Village	509	6	489
	Sculpture Porcelain Factory	247	1	180
	Taoxichuan Cultural and Creative District	1082	10	831
	Ceramic Art Street	109	1	73
	Huang Kiln	41	0	7
	China Ceramic Museum	161	1	100
	Yuyao Alley	94	1	64
	Bingding Chai Kiln	42	4	246
	Fuliang Xinping Porcelain Palace	80	1	28

Research results indicate that cultural diversity is a common characteristic of CCHL in Jingdezhen. As shown in the table, except for a few landscapes (such as the Huang Kiln), most landscapes contain more than two cultural types simultaneously, reflecting the spatial aggregation and fusion of different cultural elements. This diversity likely stems from Jingdezhen's rich historical and cultural foundation as the "Millennium Porcelain Capital," where ceramic cultures from different periods have left their distinct imprints, forming unique cultural landscapes. Further analysis reveals significant variations in cultural diversity among different landscapes, with the Imperial Kiln Museum, Sanbao International Ceramic Art Village, and Taoxichuan Cultural Creative District showing the highest numbers across four cultural labels, reaching 904, 489, and 831 respectively, indicating their high degree of cultural integration and frequent intersection of different cultural types. In contrast, the Huang Kiln, Ceramic Art Street, and Yuyao Alley show relatively lower numbers across the four cultural types, indicating less cultural richness compared to the aforementioned locations.

Through diversity index calculations based on multi-model, multi-label cultural perception classification results, we obtained SHDI (Shannon's Diversity Index) and SIDI (Simpson's Diversity Index) indices for eleven locations (Table 5) and we employed the equal interval method to divide the indicators into five classes, resulting in the spatial visualization shown in Figure 12.

Table 5. Results of the classification of eleven cultural landscapes by ResNet-50 combined with the diversity index.

Location	Shannon's Diversity Index	Simpson's Diversity Index
Ancient Kiln Folk Exhibition Area	0.88	0.76
Jingdezhen Imperial Kiln Museum	0.74	0.82
Sanbao International Ceramic Art Village	0.78	0.80
Sculpture Porcelain Factory	0.59	0.89

Table 5. Cont.

Location	Shannon's Diversity Index	Simpson's Diversity Index
Taoxichuan Cultural and Creative District	0.76	0.83
Ceramic Art Street	0.67	0.85
Huang Kiln	0.53	0.88
China Ceramic Museum	0.38	0.95
Yuyao Alley	0.80	0.79
Bingding Chai Kiln	0.86	0.75
Fuliang Xinping Porcelain Palace	0.63	0.86



Figure 12. Shannon diversity index and Simpson index distribution of the CCHL.

The results indicate that regarding cultural diversity differences, the Ancient Kiln Folk Custom Exhibition Area and Bingding Cha Kiln exhibit the highest SHDI values (0.88 and 0.86, respectively), reflecting their balanced and diverse cultural manifestations, including artifacts, production, folk customs, and modern living culture. This phenomenon is validated in Su and Ismail's study [66], which shows that open, highly interactive traditional craft exhibition spaces can accommodate more cultural elements, thereby achieving greater cultural diversity. Conversely, the China Ceramic Museum and Huang Kiln exhibit the lowest SHDI values (0.38 and 0.53, respectively), indicating cultural homogeneity under single-theme dominance (e.g., artifact culture in the museum and production culture in Huang Kiln).

In terms of specific cultural type dominance, cultural landscapes with higher SIDI values, such as the China Ceramic Museum (0.95) and Jingdezhen Sculpture Porcelain Factory (0.89), are characterized by an intense focus on specific cultural elements, which limits

overall cultural diversity. Conversely, sites with lower SIDI values, such as the Ancient Kiln Folk Custom Exhibition Area (0.76), exhibit a more uniform distribution of cultural elements, reducing the dominance of any single cultural type. Notably, the China Ceramic Museum demonstrates the lowest SHDI (0.38) while maintaining the highest SIDI (0.95), indicating that specialized museums typically exhibit a “deep focus” characteristic, wherein cultural types are concentrated yet display high equilibrium among various categories.

In peripheral areas such as the Bingding Chai Kiln, a high SHDI value is observed, indicating a broader integration of diverse cultural narratives. The name “Bingding” derives from the concepts of Bing fire, representing the radiant energy of the sun, and Ding fire, symbolizing the gentle serenity of moonlight. As a fusion of traditional craftsmanship and modern architectural aesthetics, it embodies a blend of the ancient and contemporary. Here, activities range from the firing of ceramics to fashion shows by renowned brands. As Belfanti [67] notes, fashion brands have long utilized cultural heritage as a strategic asset for brand identity, a strategy that not only preserves cultural heritage but also attracts younger generations who value both tradition and modernity. This illustrates how the integration of diverse cultural elements can create dynamic and inclusive heritage narratives. Furthermore, the high cultural diversity of peripheral landscapes suggests their potential as pivotal nodes for cultural innovation and integration.

Additionally, locations marked with multiple cultural labels exhibited notably higher SHDI values, suggesting increased cultural complexity. For instance, the Ancient Kiln Folk Custom Exhibition Area recorded 150 instances of four-label combinations, highlighting its role as a cultural hotspot. This exemplar of integrated multicultural themes has made it a primary destination for cultural tourism. They reflect a balance between historical traditions and modern interpretations of ceramic culture. The results emphasize the importance of multi-label cultural classification in capturing the complexity of cultural heritage landscapes. The findings reveal that locations with greater multi-label representation exhibit enhanced cultural diversity and visitor appeal, confirming the merit of incorporating diverse cultural viewpoints to enrich tourist experiences [68].

4.3. Current Status of CCHL Tourism Planning

Based on the multi-label cultural perception characteristics and spatial distribution patterns of CCHL, this study proposes three cultural tourism strategies: “cultural experience optimization,” “spatially equitable coordinated development,” and “technology-enabled innovation,” providing theoretical reference and practical paradigms for tourism development in global cultural heritage sites.

Cultural Experience Optimization: Addressing the cultural structural imbalance revealed by the research, characterized by “material dominance and intangible weakness” (material culture accounts for 53.6%, while production and folk cultures combined comprise less than 30%), it is necessary to optimize the cultural presentation logic to enhance visitor experience and immersion. For example, in areas with weak production culture, develop comprehensive experiential programs for intangible heritage craftsmanship, incorporating virtual reality and mobile app check-ins to transform visitors from passive observers into “porcelain craftsmen.” Alternatively, in high-traffic tourist areas, recreate scenes such as kiln workers worshipping the Kiln God based on local folklore like “Tongbin the Kiln God” using light and shadow technology, supplemented by oral history tours from local residents, creating a three-dimensional cultural perception model of “ritual performance–storytelling–spatial exploration.” For cultural living zones such as Taoxichuan, regularly implement “artist-in-residence programs” to encourage collaborative ceramic art creation between visitors and artists, enhancing cultural DNA expression in commercial spaces.

Spatial Equity and Coordinated Development: The spatial distribution of Jingdezhen's CCHL shows high perception and diversity in core areas (Imperial Kiln Museum, Taoxichuan), while peripheral areas (Huang Kiln, Bingding Chai Kiln) need increased visibility. To address this issue, a comprehensive heritage network needs to be established. For instance, differentiated thematic routes can be designed: establishing the Imperial Kiln Factory as the "Imperial Authority" core node, connecting with the Sanbao Village folk kiln creative cluster to form an "official-folk kiln" dialogue path, and using Taoxichuan as an "industrial heritage" hub, extending to the firewood kiln workshop in Bingding to create an industrial heritage revitalization axis. Furthermore, a cultural heritage alliance can be established to coordinate thematic planning between heritage sites (such as integrating the cultural heritage of the Ancient Kiln Folk Exhibition Area with modern art from the Sanbao International Creative Community).

Technology-Enabled Tourism Innovation: The success of the ResNet-50 model (92.35% accuracy) demonstrates the potential of artificial intelligence and media big data in enhancing cultural interpretation. Management planners can implement dynamic digital marketing: utilizing multi-label classification results to customize social media campaigns (e.g., highlighting the synergy of folk art, artifacts, and living culture in Sanbao Ceramic Village for young audiences) or develop virtual cultural heritage databases, collecting cultural DNA data such as ceramic patterns and production techniques to promote global academic and cultural tourism.

In conclusion, the sustainable development of CCHL requires striking a balance between maintaining traditional characteristics and promoting diversity. Quantitative analysis indicates that successful cultural landscapes can enhance cultural diversity through diverse presentations and interactive forms, providing valuable reference for cultural heritage tourism planning and management.

4.4. Theoretical Contributions and Practical Significance to Tourism Heritage Landscape Planning

(1) Theoretical Contributions:

The study establishes an innovative methodological framework incorporating an optimized ResNet-50 model, spatial analysis, and diversity indices, creating an integrated framework that bridges computer science and geographical sciences, expanding interdisciplinary research in cultural heritage tourism and addressing limitations of traditional qualitative studies.

Through innovative multi-label classification techniques, the study transcends the limitations of single-label classification, revealing multicultural coexistence within geographical regions and providing comprehensive insights into cultural heterogeneity research.

Furthermore, the study expands the case perspective of tourism heritage landscapes, with CCHL encompassing both tangible and intangible heritage of profound historical value. As China's sole cultural inheritance and innovation experimental zone, the research findings provide a model for cultural diversity exploration, cultural tourism integration, and heritage preservation.

(2) Practical Significance:

The research findings provide a scientific basis for cultural heritage landscape protection and management. Through precise identification and quantification of cultural characteristics using deep learning models, managers can better understand heritage landscape cultural distribution, develop more targeted cultural tourism protection strategies, and enhance the scientific nature of heritage tourism planning. The research also facilitates cultural tourism industry development. Based on cultural characteristic data derived from model analysis, tourism departments can optimize scenic area planning, design more

attractive tourist routes, and promote digital upgrades of smart guidance and cultural interpretation to enhance visitor experience.

Finally, the research methodology has the potential for wider application. The developed deep learning model and cultural perception system can be adapted for other cultural heritage sites, providing references for digital preservation and management and promoting technological innovation and digital development in heritage tourism.

4.5. Limitations

However, this study has several limitations. First, the research data was solely collected from the Sina Weibo platform, where users are predominantly young people whose cultural perceptions and photography preferences may differ from the general population, suggesting that future research should include studies of other age groups. Second, due to the complexity of multi-label classification, the study only utilized four categories of labels; future research could consider developing more sophisticated cultural label datasets to better reflect the complex reality of actual locations. While this study examines cultural diversity through user-generated data, it does not directly analyze tourist engagement, such as motivation, satisfaction, or emotional connection with attractions. Future research could consider using behavioral or physiological experiments, such as questionnaires, EEG, and eye-tracking, to more deeply reveal the interactions between landscapes and viewers. Additionally, while efforts were made to ensure consistency, the data annotation process relied on three ceramic artists as expert annotators, introducing potential subjective bias. Future research could incorporate a more diverse set of annotators with varied professional backgrounds (e.g., cultural heritage experts, tourists, local residents) to capture a broader range of cultural perceptions.

5. Conclusions

This study conducted a survey on the cultural perception of eleven typical CCHL in Jingdezhen, utilizing the optimized ResNet-50 deep learning model combined with social media big data analysis and ArcGIS spatial analysis. Through establishing a CCHL identification system, a multi-label image classification model based on CCHL categorization was developed, achieving an accuracy rate of 92.35%. The research findings indicate:

- (1) The potential application of the ResNet-50 deep learning image classification model in the field of cultural landscapes. The integration of big data technology enhanced the universality and representativeness of research samples, thereby improving classification efficiency. Furthermore, the application of multi-label technology better met the cultural complexity requirements of cultural landscapes.
- (2) Regarding the distribution of cultural types, artifacts culture (53.6%) and production culture (14.0%) constitute the dominant cultural elements of CCHL, reflecting Jingdezhen's cultural characteristics centered on artifact display and ceramic craftsmanship. The relatively low proportions of folk culture (14.9%) and living culture (17.7%) indicate room for improvement in cultural presentation and dissemination within these two dimensions.
- (3) In terms of spatial distribution, there are significant differences in the distribution of cultural types across different landscape sites, revealing distinct core-periphery differentiation characteristics. Core areas such as the Imperial Kiln Museum and Taoxichuan Cultural and Creative District show high cultural perception and diversity, while peripheral areas demonstrate relatively lower cultural perception and richness. This suggests that landscape planning and design should place greater emphasis on cultural exploration and presentation in peripheral areas to promote balanced regional cultural development. These cultural distribution characteristics

provide a foundation for developing differentiated heritage conservation and tourism development strategies.

- (4) Based on diversity index analysis, the Ancient Kiln Folk Custom Expo Area and Bingding Chai Kiln showed the highest SHDI (0.88 and 0.86, respectively), demonstrating good cultural equilibrium. Some specialized venues such as the China Ceramics Museum show lower SHDI (0.38) but higher SIDI (0.95), reflecting their specialization in specific cultural types. This diversity provides visitors with varied cultural experiences while suggesting the need to strengthen cultural connections and integration between different venues. These differences provide evidence for developing targeted management strategies: for high SHDI areas, it is recommended to strengthen cultural characteristics through in-depth experience programs; for high SIDI areas, digital technology applications are needed to balance professionalism and accessibility.

In conclusion, this study demonstrates the application of artificial intelligence in cultural landscape preservation and development: using computer vision perception technology and social media images to classify diverse cultural features in cultural landscapes, cultural diversity and spatial distribution characteristics can be evaluated, facilitating people’s capture and understanding of complex scene cultures and effectively improving management decisions for cultural heritage protection and cultural dissemination efficiency.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Introduction to the eleven ceramic cultural landscapes.

Region	Scene	Description
Ancient Kiln Folk Exhibition Area		China’s only national-level tourist attraction and intangible cultural heritage revitalization base themed on ceramic culture, encompassing ancient kiln sites from the Song, Ming, and Qing dynasties

Table A1. Cont.

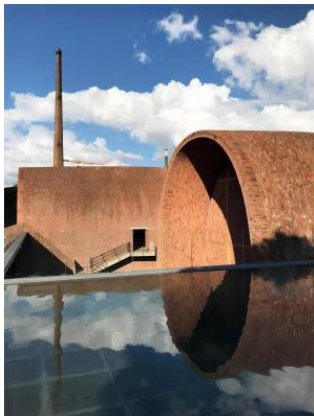
Region	Scene	Description
Jingdezhen Imperial Kiln Museum		As a globally unique imperial ceramic kiln site, this museum showcases ceramics from various historical periods and is situated within the city's historic district
Sanbao International Ceramic Art Village		The modern artistic community and tourist destination serves as an invaluable cultural platform for ceramic cultural exchange between the East and West
Sculpture Porcelain Factory		The youth art market, transformed from a traditional industrial porcelain factory, has attracted numerous artists and creators
Taoxichuan Cultural and Creative District		A cultural creative district centered on the original Cosmos Porcelain Factory, integrating tradition, fashion, art, and technology through structural renovation and revitalization while preserving ceramic industrial heritage

Table A1. Cont.

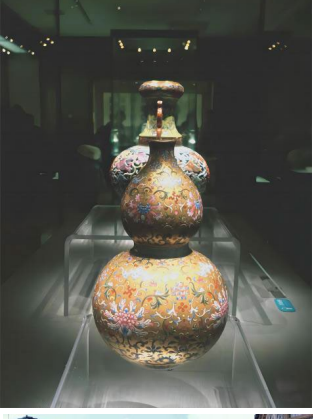
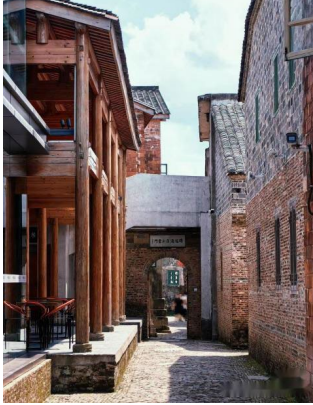
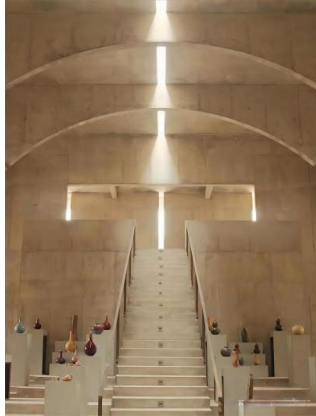
Region	Scene	Description
Ceramic Art Street		A culturally rich commercial street in Jingdezhen, the millennium-old porcelain capital, featuring ceramic products
Huang Kiln		National Demonstration and Research Base for Intangible Cultural Heritage (Handmade Porcelain)
China Ceramic Museum		The first specialized ceramics museum established after the founding of New China, housing a rich collection of historical artifacts and masterpieces produced in Jingdezhen from the Neolithic period through various historical epochs
Yuyao Alley		Historical districts: embodiments of urban memory and local culture

Table A1. Cont.

Region	Scene	Description
Bingding Chai Kiln		Traditional firewood kiln architecture incorporating modern architectural aesthetics has emerged as a popular tourist destination
Fuliang Xinping Porcelain Palace		A building adorned with tens of thousands of ceramic pieces located on elevated terrain in Xinping Village, Fujian County, Jingdezhen City, has attracted significant tourist attention

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