Cnn-Based Intelligent Recognition and Digital Dissemination of Rural Cultural Symbols in Anhui, China

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Abstract

In rural areas, cultural communication is essential to human contact and societal development. As a crucial component of China's socialist building and revolutionary past, red culture has great significance and a broad impact. The study begins by outlining the significance of regional symbol identification and the context of its use in cultural heritage. Historic city landscape planning is essential to promoting regional identities and spreading cultural value in the face of rapid advancements in heritage preservation and cultural tourist integration. It has been difficult for scholars to define the link between the two, however. The rural cultural elements and dialect characteristics of various locations are reflected in several research on dialect maps in terms of spiritual civilization. In the context of material civilization, several academics have focused on the regional variability of changes in land use and behavior. The limits of the present conventional design approaches are also discussed, along with the need to introduce new technology to enhance them. Using the well-known historic Rural Cultural city of Anhui, China, as an example, this study introduces a multi-label deep learning approach to explore cultural perceptions in tourism heritage settings. (1) A framework including artifacts, production, traditional music and living culture was constructed utilizing social media big data and an enhanced ResNet-50 model, combining ArcGIS spatial analysis and diversity indexes. (2) The main component of heritage landscapes is artifact culture, which has a "material-dominated, intangible-weak" structure; (3) the intensity of rural cultural perception is unevenly distributed, with core areas demonstrating higher recognition and diversity; (4) diversity indices indicate that specialized locations reveal marked Rural Cultural singularity, while comprehensive venues present stronger Rural Cultural balance, suggesting a need for enhanced integration across locations. The multi-label classification model's accuracy of 92.35% was shown by the findings, confirming its potential. This work expands the application of multi-label deep learning in tourist heritage studies and offers helpful suggestions for international historic sites that cope with mass tourism.

Keywords: - Rural Cultural, Symbol Recognition, Human Interaction, Deep Learning, Landscape Planning, Tourism Heritage, Traditional Design, Anhui, China, ArcGIS Spatial Analysis, Classification Model, Disseminating.

I. INTRODUCTION

Cultural tourism is one of the main drivers of the worldwide economy's growth, according to the World Tourism Organization (UNWTO). ICOMOS's International Cultural Tourism Charter (2022) [1] states that cultural tourism promotes the conservation and sustainable development of cultural assets. China is actively addressing global trends in this region by creating the "Implementation Plan for Anhui, China National Ceramics Cultural Heritage Technology Experimental Zone," which emphasizes cultural inheritance, tourism integrating, and industry regeneration.

Cultural heritage inheritance and preservation have become more and more important as digital technology develops [2, 6]. However, it is difficult to satisfy the need for cultural knowledge in modern society since conventional methods of disseminating intangible cultural assets are limited by time and distance. Digital heritage distribution techniques must be used to improve the transfer of traditional intangible cultural assets [3].

The transmission and safeguarding of cultural heritage are now important global issues. Among the countries actively researching and establishing legal frameworks and management systems for digital heritage are the United States, Germany, China, and the United Kingdom. Notably, digital heritage preservation has entered a more comprehensive stage of international cooperation with the creation of the "China-Greece Digital Heritage Joint Laboratory," a partnership between both nations [4]. The interlacing of cultural affiliations inside cyberspace has enabled the digital expression of intangible cultural resources in this environment.

In addition to being a significant part of China's revolutionary past, it is also an essential part of modern Chinese culture, contributing significantly to its expansion in meaning and impact [5, 6]. The position of red culture in Chinese society is likewise changing and developing in tandem with the periods and social advancements. As a result of this integration, red culture's spiritual core is deeply woven into contemporary Chinese culture, making it an essential and crucial component of Chinese society [4, 5]. The Chinese government has stepped up its attempts to protect and promote red culture in recent years.

Red culture has been successfully spread across society and the general public via a variety of cultural building and tourist development methods [3, 4]. Red culture has been smoothly incorporated into many facets of China's social development at the same time, which has promoted both creative breakthroughs in Chinese society and the passing down of historical and cultural legacy.

As a result, Chinese society has come to rely heavily on red culture for confidence. Red culture has significant historical, political, and cultural qualities and is an essential component of China's revolutionary history and culture [3, 5]. However, issues including incomplete distribution, unequal information, and fragmented data have surfaced throughout the process of promoting and conserving red culture. In order for a wider audience to recognize red culture's remarkable legacy, it is crucial to solve these issues and guarantee its continuation [2].

Furthermore, the ways that red culture is disseminated are always changing, embracing creative and broad strategies. A broader audience may now access and learn about red culture thanks to the emergence of new media outlets like Internet live streaming and mobile apps, in addition to traditional techniques like book publication, TV plays, and movies [4, 6]. Red tourism, cultural events, and themed education are all ways that red culture is being incorporated into people's everyday lives at the same time [7].

More involvement in the creation and maintenance of red culture is guaranteed by these programs. In conclusion, study and transmission of red culture are very important because of its tremendous significance in China's revolutionary history and modern culture. It is imperative that red cultural study and preservation be strengthened going ahead [4] and that its dissemination be encouraged via a variety of channels in order to actively support the Chinese nation's great rejuvenation and restoration.

However, there are many intricate obstacles to overcome when using cutting-edge technology to preserve and share intangible cultural heritage [8]. The process of digitizing such artifacts is especially difficult because of its intrinsic variety and complex cultural components. A single technology solution is unable to properly capture the rich cultural character of intangible cultural assets, which often contains deep regional and historical traditions [8]. Furthermore, precisely preserving and replicating the dynamic qualities of intangible cultural material that depends on oral traditions and performances is a crucial difficulty.

Furthermore, the digital conservation of cross-border cultural assets is made more difficult by disparities in technology standards, restrictions in legislative frameworks, and the difficulties of international collaboration. To guarantee that technology successfully strikes a balance between preservation and protection, privacy protection and cultural sensitivity must be carefully taken into account throughout this process [8, 9] [9, 10]. For example, image processing techniques based on Convolutional Neural Networks (CNNs) show excellent identification skills when it comes to identifying characteristics in pictures of intangible cultural property.

However, these methods are unable to adequately convey the fluidity and intricacy inherent in dynamic cultural acts, like traditional theatre or dance. Intangible cultural assets may be disseminated via written forms thanks to language processing technology' superior text analysis and cultural background information extraction capabilities [9, 10]. However, they struggle to accurately understand non-standardized languages, dialects, and oral histories [11,12].

Digital research has replaced conventional academic research in the study of red culture due to the quick development of Internet technology [13]. This includes, among other things, using AI and machine learning to categorize and forecast red cultures and researching red culture retrieval using multimodal data.

Artificial intelligence techniques may enhance users' reading and learning experiences by providing more accurate recommendations for red cultural content based on users' preferences and interests [13]. These algorithms may also integrate multimodal data, such as red culture-related texts, films, and images, to build a robust red culture retrieval system [14]. This approach helps users become more aware of and informed about red culture by giving them quick access to information about it [15]. Thus, artificial intelligence is essential to the dissemination of red culture, and its use is expected to further accelerate its creation and maintenance.

For thousands of years, our Chinese nation's cultural ideals and talents have been displayed via intangible cultural heritage, a significant cultural emblem [16]. As times change, passing down intangible cultural assets may help promote national policies, satisfy the demands of social and economic growth, and strengthen the vitality and impact of traditional Chinese culture [17].

China has been actively looking for new methods to encourage the inheritance and conservation of intangible cultural assets in our nation, as network technology has advanced and the need for intangible cultural heritage inheritance has grown [18]. Diverse disciplines are continuously strengthening their integration of technology and knowledge, creating new avenues for the transmission of intangible cultural heritage materials and culture [18]. A new technique and instrument called "digital narrative" uses digital media to convey knowledge and extensively disseminate it via storytelling [19]. With a variety of application situations, it may include time, place, media, and affect narrative aspects and has the qualities of digitalization, storytelling, and interaction.

After a thorough examination of the state of research and current circumstances surrounding the inheritance of intangible cultural heritage, it was discovered that the strategy of cultural digitization and emerging technologies has created previously unheard-of development momentum and opportunities for the inheritance of intangible cultural heritage [19, 20]. It examines the opportunities and difficulties of inheriting intangible cultural heritage digital narrative in China from the macroenvironment, [21], technological environment, and new user needs based on an analysis of the concepts of digital narrative and intangible cultural heritage digital narrative.

We have extracted the spatiotemporal, medium, and impact parts of digital narrative in intangible cultural heritage inheritance by examining the elements of digital narrative in typical situations of intangible cultural heritage [22]. From the standpoint of digital storytelling, we have created a pathway for the inheritance of intangible cultural heritage that incorporates interactive media, spatiotemporal sceneries, and narrative experiences [22].

Creating a core discipline for the transmission of intangible cultural assets by combining research and practice [22, 23]. The inadequacies of single-discipline research may be compensated for by encouraging the preservation and inheritance of intangible cultural resources and offering direction and assistance for the development of allied fields.

Along with the current status of research on digital story and intangible cultural heritage inheritance, the basic concepts of digital narrative, tangible cultural heritage, and intangible cultural heritage were addressed online narrative [2]. Due to the development of digital technology, digital storytelling has become an inevitable trend in the preservation of intangible cultural assets. Digital technology not only affects the development of other industries but also positively impacts the inheritance of intangible cultural assets.

Digital information technology may be used to establish archives for intangible cultural heritage projects to bolster conservation efforts, enhance resource management techniques, and leverage digital information systems for inheritance. Digital technology, in particular, can optimize the ways in which intangible cultural heritage resources are stored by gathering a lot of traditional textual data, processing it, and creating a permanent database. This creates a strong basis for the inheritance of intangible cultural heritage.

To create a core field for the transmission of intangible cultural assets, research and practice must be integrated. It may compensate for the deficiencies in single-discipline research by fostering the preservation and inheritance of intangible cultural resources and offering direction and assistance for the development of adjacent fields [9]. The current status of research on digital narrative and intangible cultural heritage inheritance was also addressed, as were digital narrative, intangible cultural heritage, and digital narrative of intangible cultural heritage. As digital technology advances, digital storytelling has become an inevitable trend in the succession of intangible cultural assets [12].

Digital technology has a favourable impact on the inheritance of intangible cultural assets in addition to having an impact on the growth of other disciplines [13]. Intangible cultural heritage project archives may be created to enhance preservation efforts, digital information technology can be used to improve resource management techniques, and digital information systems can be used for inheritance [14]. In particular, by gathering a lot of traditional textual data, processing it, and creating a permanent database, digital technology can optimize the ways that intangible cultural heritage resources are stored, providing a strong basis for intangible cultural heritage inheritance [13].

Regional symbol identification technology based on deep learning opens up new avenues for intangible cultural heritage preservation and transmission. Nonetheless, it is worthwhile to consider the memory and silence problems that intangible cultural heritage regulations face in real-world implementations [18]. Effective analysis for regional symbol identification is provided by feature learning and classification capabilities that use deep learning approaches. Automatic identification and categorization of intangible cultural heritage materials in particular regions may be achieved by using deep learning models to train cultural relics, patterns, symbols, etc. [11]. This gives us a scientific foundation for the preservation and transfer of intangible cultural resources in addition to improving our comprehension and documentation of such programs [13].

1.1 The Idea Behind Regional Symbols and their Classification

Graphics, patterns, symbols, or texts having particular regional cultural implications and symbolic meanings are referred to as regional symbols [17], and they are significant elements of a particular region's distinct culture [19]. Regional symbols represent the way of life and aesthetic ideals of the local populace in addition to preserving the historical memory, folk traditions, and artistic style of the area. Regional symbols may be categorized into many categories based on several criteria, as Table 1 illustrates.

Table 1 Groupings of Regional Symbols.

Division standard	Geogtraphical symbol type	Illustration
Expression Form	Graphic symbol	For instance, the silhouettes of famous structures in a certain location.
	Pattern symbol	such are distinctive designs seen on carpets and national clothes.
	Letter symbol	For instance, the use of old Chinese characters and regional languages in writing.
Cultural connotation	Historical symbol	Like historical landmarks and spots from past occurrences.
	Folk symbol	For instance, traditional festivals and rituals include props and folk dances.
	Artistic symbol	In local operas, for instance, musical instruments and makeup.

1.2 Regional Symbols' Function in Cultural Transmission

Additionally, digital media may increase the inheritance industry's sales and advertising channels. It is simpler to draw in young people by advertising on digital media platforms like the internet. Some programs for study trips on intangible cultural assets have also been incorporated, which has helped to popularize artistic and cultural works [10]. The growth of the regional tourist sector has also been fuelled by intangible cultural assets. Being accepted by the general public encourages the development of high-tech in order to preserve and advance traditional culture, in addition to promoting the traditional culture of intangible cultural treasures.

1.3 DL's Potential Use in Regional Symbol Identification

Digital media provides a range of formats and locations for the digital narrative of intangible cultural heritage and enables the inheritance and promotion of intangible cultural property via digital means. In particular, multimedia techniques symbolize the empowering role of digital media in the digital narrative of intangible cultural assets & may be used for the dissemination and promotion of intangible cultural resources [13]. When many media—text, images, music, video, etc.—are integrated, the presentation of intangible heritage from cultures is increased.

Questionnaires and interviews are the mainstays of traditional cultural landscape perception research; objective quantitative assessment requires further investigation. Furthermore, despite the fact that deep learning technology shows great promise for spatial study, the majority of current studies concentrate on single-feature perception [16], which makes it challenging to accurately capture the multi-cultural qualities of landscapes.

Text data categorization and visual display are essential to the development of digital platforms. Researchers have carried out more thorough investigations on text categorization in addition to technical innovation [10].

Due to their intricacy and lack of resources, online social networks present difficulties with network language identification. They examined 27 Arabic automated detection system experiments and evaluated the efficacy of current approaches [11]. The findings showed that while automated solutions were available for numerous languages, Arabic research was still comparatively undeveloped.

The limitations of current study highlight the need of further dataset expansion and algorithm improvement [18]. Text categorization plays a crucial component in pattern recognition, especially when it comes to classification problems. According to their findings, a text classification feature selection approach based on often occurring and relevant characteristics may be used with association analysis to reduce redundant information and enhance the effectiveness of model building.

Using just 6% of the features, the test results demonstrated that this strategy obtained a high accuracy rate of 95.15% on a spam SMS dataset [7]. It illustrates how novel feature selection strategies may significantly enhance model performance in challenges involving pattern recognition. Creative feature selection strategies have the potential to greatly improve model efficiency and accuracy in text categorization problems.

Since the categorization and visual display of text data are fundamental components, accurate and effective feature selection methods have a direct influence on platform performance and user experience, serving as the cornerstone for intelligent and customized platform features. The research listed above provide digital platforms with useful technological references for handling and presenting massive amounts of text data [15]. In related studies on the development of digital platforms for dissemination.

Teaching art in the present day with multimodal perception systems [25]. The DenseNet-BC model, which is based on CNN rules, achieved a 96.15% accuracy rate in visual feature extraction and task recognition. Their findings increased the calibre and efficacy of art education and encouraged digital cultural transmission via a creative educational framework and multimedia interactive challenges, therefore optimizing art education.

DenseNet-BC, an integrated CNN architectural model, outperformed ResNets in terms of false positive rate for strong gravitational lens detection [16]. This provided an automated tracking and evaluation tool that was more reliable for identification and categorization.

Chromosome orientations in chromosome micro-images are automatically detected using a CNN classifier built on the DenseNet architecture. This new method improved the effectiveness and precision of image selection for detecting genetic anomalies and producing karyotypes. After being trained on 156,750 micro-images, the classifier shown remarkable potential for chromosomal imaging with an error rate of 1.46% [24,25].

In order to identify and assess the cultural features of Anhui, China's tourist heritage landscape (Ceramic Cultural Heritage Landscape, or CCHL), this research builds a multi-label identification model using deep learning techniques and social media big data.

II. LITERATURE REVIEW

Liu, E. (2020) [26] The main method of presenting the digitization of intangible cultural property is via the picture of national costumes, which also offers valuable materials for educational informatization. The effective retrieval of photographs of national costumes using contemporary information technology has emerged as a popular area of study. Ethnic clothes come in a wide variety of designs and vibrant hues, making it challenging to precisely characterize and extract visual elements. This study suggests an image recognition model of intangible cultural assets based on CNN and wireless networks in light of the aforementioned issues.

Liu, Z. (2025) [27] In order to promote the electronic safeguarding and distribution of Chinese intangible cultural assets, this research develops a framework for digital transmission. The platform integrates several state-of-the-art technologies, including the Densely Connected Convolutional Systems - Bottleneck and Compression model, a notable convolutional neural network, in addition to the latest natural language processing techniques, generative adversarial network algorithms, and neural shared filtering algorithms. The database has been validated using 224,055 publicly archived authentic data records, ensuring its effectiveness and reliability. The results demonstrate that the heteroscedasticity-robust standard error is 0.15, demonstrating the model's stability and predictive accuracy. The platform's accuracy levels in 5-fold and 10-fold cross-validation are 0.87 and 0.89, respectively.

Yu, H. (2024) [28] This study aims to optimize the evaluation and selection of ethnic tourism resources via the use of deep learning algorithms and Internet of Things (IoT) technology. Particular attention is paid to the recognition and feature extraction of Mongolian decorative patterns, providing new insights into the deep use of visual design and cultural history. This study enhances the existing DL method by combining the ResNet+Canny+Local Binary Pattern (LBP) extraction of features technology with an intelligent decision strategy to investigate the intelligent development of indigenous tourism resources. To achieve feature extraction and technology identification, IoT technologies are combined with convolutional neural networks (CNN), visual design, and the DL methodology.

Zhao, Y. (2023) [29] Cultural communication is essential to human interaction and societal development. Since red culture is central to China's socialist construction and revolutionary past, it is very significant and has a wide-ranging influence. However, in the digital era, effectively disseminating red culture and stimulating public interest and involvement has become a critical issue. In this study, we apply state-of-the-art deep learning technology to explore the use of multimodal data fusion to enhance the effectiveness and impact of red cultural communication. Specifically, we utilize BI-GRU and CNN to extract text and image features from user browsing data, respectively.

Yang, X. (2025) [30] The goods of culture and creativity are many, hard to create in large quantities, and insufficiently available. They may increase cultural and commercial worthwhile showcasing their unique features via multipurpose design. When creative and cultural consumers buy stationery, three situations often surface: contemplation, buying behavior, and purchasing inclination. Common problems with cultural and innovative products include limited mass production, undersupply, and the need to reconcile cultural and economic value.

Chen, J. (2022) [31] Tourist-generated photos are being produced at a never-before-seen pace, opening up new avenues for the analysis of photographs from tourist destinations. However, there is a dearth of study on how visitors interpret photographs from various angles and how to create unique marketing techniques that connect traveller's with locations. Here, we provide a unique marketing framework and quantitative analysis approach powered by photo big data—which includes pictures of tourist destinations—with the use of deep learning technology.

Khalid, F. (2020) [32] Many national languages use calligraphy as an artistic medium, and it is a vital component of their cultural legacy. Therefore, calligraphy art preservation and propagation are important. However, calligraphy fonts are difficult to identify because of their intricate structure and distinctive style. The need for calligraphy protection necessitates the establishment of a collection of integrated Artificial Intelligence (AI) calligraphy font recognition systems that combine several calligraphy font recognition techniques and databases.

Chowdary, V. (2020) [33] Agriculture is essential to every nation's economic development. It becomes difficult to meet the current population's food needs due to population growth, frequent fluctuations in the climate, and a lack of resources. Smart farming, another name for precision agriculture, has become a cutting-edge strategy to tackle today's issues with agricultural sustainability.

III. MATERIALS AND METHOD

The current investigation integrates landscape research and computational sciences to investigate the spatial distribution aspects of cultural perception, proposing a deep learning-based multi-label cultural heritage landscape recognition technique [36]. Initially, multi-label dataset are generated, a cultural identifying system is constructed, and the ResNet-50 model is tuned for CCHL classification [35]. Using ArcGIS and diversity indicators, the visualisation and quantitative analysis of tourism heritage's spatial distribution and cultural perception are conducted.

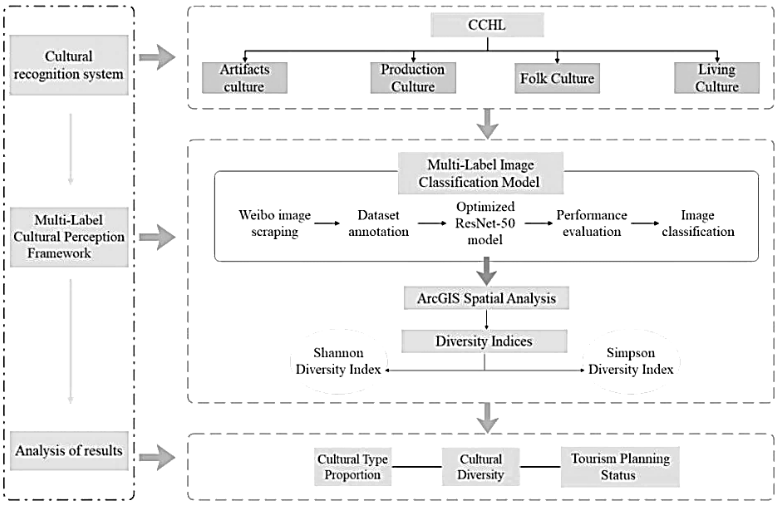

Fig. 1 Research structure for CCHL's multi-label cultural perception.

3.1 Study Area

One of the first National Historical and Cultural Cities in East China, it is situated in the inland province of Anhui Figure 2, [34]. It is renowned for its unique kiln culture and millennial porcelain-making history, which have developed into an important representation of the persistence of Chinese civilization [3].

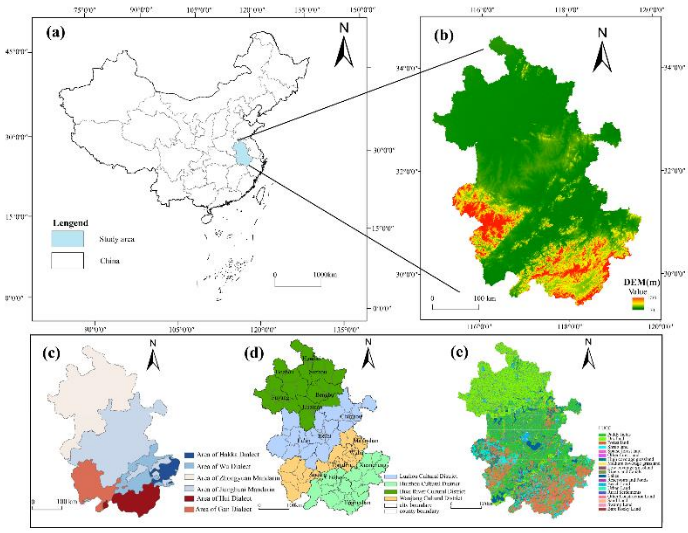

Fig. 2 An overview of the area of Anhui, China.

This study has developed a multi-dimensional and multi-category strategy for CCHL identification in order to better reflect the heterogeneity of CCHL [29, 34]. The CCHL is divided into four primary classifications: living culture, folk culture, producing culture, and artifacts culture, in line with deep learning classification standards and other relevant research [36] Table 2.

Table 2 A cultural identification system for CCHL that includes visual samples, categorization descriptions, and the four cultural categories.

Cultural Types	Description	Particular Aspects of Visual Perception	Ref.	Legend
Artifacts culture	Ceramics from Anhui, China, are a material culture that combines craftsmanship, art, and culture.	Porcelain shards, ceramic ornaments, ceramic vessels, and associated ceramic components	https://en.wikipedia.org/wiki/Main_Page	
Production culture	The culture that emerges from ceramic manufacturing methods embodies the artisans' mentality of ceramic manufacturers.	Production sceneries, chimneys, kilns, saggars, blanks, etc.	https://en.idei.club/	
Folk culture	Historical areas serve as a representation of local customary memories.	Alleyways, monuments of historical figures, folk architecture (eaves, doors), etc.	https://www.scmp.com/?module=masthead&pgtype=article	
Living culture	Anhui, China's creativity and progress are reflected in the culture of contemporary urban life.	Contemporary structures, museums, innovative marketplaces, artistic endeavours, etc.	https://www.foyerglobalhealth.com/	

Three enhancements were made to the conventional ResNet-50 model in this work based on the features of CCHL [37, 38]. The CCHL has both multi-level and multi-scale features. It is difficult for conventional single-feature extraction techniques to fully capture these traits. Architectural plans, for example, need more global semantic information, while ceramic artifact patterns require the extraction of fine-grained local features. The significance of various cultural components (such artifacts and manufacturing scenes) and their geographical distribution within pictures differ.

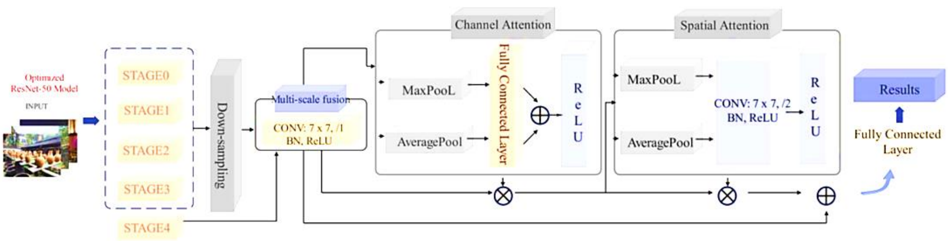

Fig. 3 ResNet-50 architecture has been improved. The diagram's round symbols stand for multiplication and addition.

In order to enable parameters to progressively converge toward optimum solutions, optimization methods (such Stochastic Gradient Descent, or SGD) are used to compensate for mistakes that arise when forecasts differ from actual values [39, 40]. The cross-entropy loss function is used to quantify the degree of discrepancy between expected and actual data.

$$C = -\frac{1}{N}\sum_{t=1}^{N}\sum_{f=1}^{C}\left[y_{1,l}\log\left(p_{1,l}\right) + \left(1-y_{1,l}\right)\log\left(1-p_{1,l}\right)\right] \ldots\ldots\ldots\ldots\ldots 1$$

Model assessment criteria differ depending on the prediction problem; for instance, binary classification, multi-class predictions, and multi-label prediction all need different evaluation standards. Typically, Macro Precision, Macro Recall, Accuracy, and Macro F1 Score are used to evaluate the accuracy of multi-label prediction models. These are the specific formulas for computation:

$$Accuracy = \frac{TN+TP}{TP+FP+TN+FN} \ldots\ldots\ldots 2$$

$$Macro\ Precision = \frac{1}{C}\sum_{t=1}^{C} Precision_1 \ldots\ldots\ldots\ldots\ldots 3$$

$$Precision = \frac{TP}{TP+FP} \ldots\ldots\ldots 4$$

$$Macro\ F1 = \frac{1}{C}\sum_{t=1}^{C} F_1 \ldots\ldots\ldots 5$$

$$F1 = \frac{2.Precision.Recall}{Precicsiom+Recall} \ldots\ldots\ldots 6$$

The dataset was randomly divided into two sets of training and validation images in a 9:1 ratio; the training set had 4500 pictures, while the validation set contained 500 shots. The performance of the model on the validation set after the implementation of the previously mentioned parameter modifications is shown in Table 3.

Table 3 Following data preparation and model training, four metrics are used to evaluate the model's performance.

Model	Macro Precision	Macro Recall	Macro F1 Score	Accuracy
Baseline ResNet-50 Model	0.489	0.249	0.219	0.964
Optimized resNet-50 Model	0.479	0.590	0.518	0.218

IV. RESULTS AND DISCUSSION

4.1 Cultural Types' Proportions and Disparities in CCHL

By employing the ResNet-50 model, 35,644 Weibo pictures were classified and identified. Each CCHL site's number of cultural perception categories is shown in Table 4. Fig. 4 displays the overall cultural distribution, which includes 31,958 photos from all cultural categories. In the distribution, there are 17,127 pictures (53.6%) that depict the perception of artifact culture, 4451 pictures (14.0%) that depict the perception of production culture, 4745 pictures (14.9%) that depict the perspective of folk culture, and 5653 views (17.7%) that depict the perception of living cultures. This shows the relative domination of artifact culture across the CCHL.

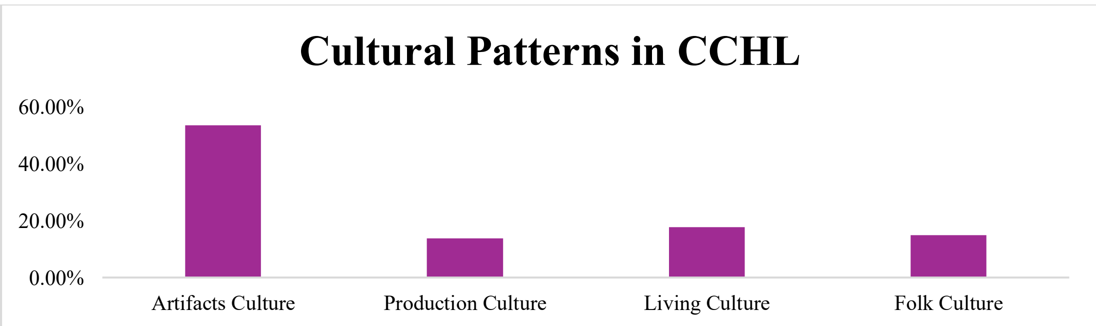

Fig. 4 The four categories of cultural patterns' percentage distribution in CCHL.

Table 4 Cultural perception amounts at eleven CCHL locations in Anhui, China, were statistically analyzed.

Cultural Type Region	Artifacts Culture	Production Culture	Folk Culture	Living Culture	Total Cultural Volume
Area for the Yuanquan Hui Culture Folk Museum	861	495	896	86	2338
ChengHuangMiao ZhanLanGuan	3549	1248	189	3296	8282
Huangshan Maofeng	2484	596	7495	189	10764
Anhui Hanshan Porcelain Co.	1496	354	142	59	2051
"Anhui Cultural and Creative District"	4821	1499	624	1488	8432
Huizhou architecture	621	218	152	95	1086
birthplace of Xuan paper	125	296	69	89	579
Huangmei Opera	2965	149	158	549	3821
Huizhou culture	235	89	149	1408	1881
Eight Great Cuisines of China	190	359	39	499	1087
Lantern Festival, Dragon Boat Festival,	479	26	98	149	752

Since Anhui has traditionally been a major ceramic manufacturing hub in China, the findings' preponderance of artifact culture is consistent with this reputation. Ceramic crafts and ornamental objects, which reflect the landscape's profound historical and artistic importance, continue to be the most aesthetically pleasing and culturally significant elements. The results of this study are consistent with studies that highlight how material heritage shapes cultural identity and legacy tourism.

Meanwhile, there may be space for development in terms of cultural variety and representation in these fields given the very low prevalence of production culture and folk culture. Folk culture, which includes local traditions, architectural styles, and traditional rituals [34, 41], offers chances to further promote cultural landscapes since it may enhance cultural involvement and storytelling.

4.2 CCHL's Cultural Diversity Quantification

This section examines cultural variety and cultural combinations after analyzing the number of cultural kinds in CCHL and the landscape variations among each type [42]. When two or more cultural categories emerge at the same time, the data is classified using the ResNet-50 model; the classification results are shown in Table 5 [43].

Table 5 Results of the ResNet-50 multi-label categorization process. Among the photographs from the Anhui, China Imperial Kiln Museum, for example, 1399 have two cultural labels, 28 have three, and 904 have four symbols.

Region Culture Type	Two Cultures	Three Cultures	Four Cultures
Area for the Yuanquan Hui Culture Folk Museum	489	29	120
ChengHuangMiao ZhanLanGuan	1498	22	987
Huangshan Maofeng	540	8	497
Anhui Hanshan Porcelain Co.	29	2	178
"Anhui Cultural and Creative District"	1089	11	894
Huizhou Architecture	149	2	77
Birthplace of Xuan Paper	46	0	9
Huangmei Opera	149	2	121
Huizhou culture	95	2	63
Eight Great Cuisines of China	43	3	298
Lantern Festival, Dragon Boat Festival,	89	1	22

Diversity index calculations based on multi-model, multi-label culture perceptions classification results were used to create SHDI (Shannon's Diversity Index) and SIDI (Simpson's Diversity Index) indexes for eleven locations [42] Table 6.

Table 6 Results from using the diversity index in conjunction with ResNet-50 to classify eleven cultural landscapes.

Location	Shannon's Diversity Index	Simpson's Diversity Index
Area for the Yuanquan Hui Culture Folk Museum	0.89	0.54
ChengHuangMiao ZhanLanGuan	0.49	0.94
Huangshan Maofeng	0.99	0.22
Anhui Hanshan Porcelain Co.	0.96	0.79
"Anhui Cultural and Creative District"	0.54	0.54
Huizhou Architecture	0.98	0.94
Birthplace of Xuan Paper	0.28	0.41
Huangmei Opera	0.97	0.21
Huizhou Culture	0.64	0.98
Eight Great Cuisines of China	0.32	0.87
Lantern Festival, Dragon Boat Festival,	0.77	0.49

4.3 CCHL Tourism Planning as of Right Now

This research proposes three tourisms for culture strategies: "technology-enabled creativity," "cultural experience optimizing," and "spatially equitable coordinated development" [43] based on the spatial distribution patterns and multi-label cultural perception features of CCHL. These tactics provide helpful models and theoretical frameworks for the development of tourism at places of worldwide historical importance.

The research identified a cultural structural imbalance characterized by "material dominance and intangible weaknesses" (material culture makes up 53.6%, [44], while manufacturing and folk cultures combined make up less than 30%). To address this imbalance, optimizing the cultural presentation logic is necessary to improve visitor experience and immersion. For example, in order to transform visitors from passive observers into "porcelain craftsmen," [44, 45] design comprehensive immersion initiatives for handicrafts of intangible cultural assets in areas with low production cultures. Virtual realities and mobile app check-ins are used in these programs.

V. THEORICAL ASSISTANCE AND PRACTICAL IMPORTANCE FOR THE DESIGN OF TOURISM HERITAGE LANDSCAPES

- **Theoretical Contributions:** Through the use of an optimized ResNet-50 model, spatial analysis, and diversity indices, the study creates a novel methodological structure that integrates computer science and geographical biological sciences in order to advance interdisciplinary research in cultural heritage tourism and address the limitations of traditional qualitative research [46].
- **Practical Significance:** The study's findings provide a strong scientific basis for cultural heritage landscape management and protection. By accurately identifying and quantifying cultural characteristics using deep learning models, managers can improve the scientific aspect of heritage tourism planning, develop more targeted cultural tourism protection approaches, and better understand the cultural distribution of heritage landscapes. Additionally, the research contributes to the expansion of the cultural tourism industry [46]. Tourism organizations should design more enticing travel routes, develop beautiful places more effectively, and promote digital upgrades of cultural interpretation and smart guidance based on model analysis data about cultural traits in order to enhance visitor experiences.

VI. CONCLUSION

This study evaluated the cultural viewpoint of eleven typical CCHL in Anhui, China, using the enhanced ResNet-50 deep learning model in combination with social media big data analysis and ArcGIS spatial analysis. By implementing a CCHL identification system, a multi-label image classification model based on CCHL categorization was developed, and it attained an accuracy rate of 92.35%.

The use of the ResNet-50 deep learning image classification model may be advantageous for cultural landscapes. Big data technology integration improved classification performance by making research samples more representative and universal. The spatial distribution of cultural types varies significantly between various landscape contexts, suggesting distinctive characteristics of core-periphery differentiation. While cultural perceptions and diversity are generally low in peripheral locales, they are high in central areas such as the Imperial Kiln Museum and Taoxichuan Cultural and Creative District.

According to the diversity index research, the Ancient Kiln Folk Custom Expo Area and Bingding Chai Kiln had the highest SHDIs (0.88 and 0.86, respectively), suggesting a sound cultural balance. Some specialized venues, such as the China Ceramics Museum, have a higher SIDI (0.95) but a lower SHDI (0.38), as a result of their focus on particular cultural types. This diversity allows visitors to have a range of cultural experiences, but it also emphasizes the need for better venue integration and connections between cultures.

In conclusion, this research shows how cultural landscapes may be developed and preserved via the application of artificial intelligence. Cultural diversity and spatial distribution characteristics can be evaluated by classifying different cultural features in cultural landscapes using computer vision perception technology and social media images. This makes it simpler for people to capture and understand complex scene cultures and greatly improves management decisions for the preservation of cultural heritage and the efficacy of cultural dissemination.

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