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Review

A Review: How Deep Learning Technology Impacts the Evaluation of Traditional Village Landscapes

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Abstract: Recently, the deep learning technology has been adopted in the study of traditional village landscape. More precisely, it's usually used to explore the representation of cultural heritage and the diversity of heritage information. In this study, we comprehensively reviewed these deep learning-related literatures for the evaluation of traditional village landscapes. E.g., the landscape image recognition led by the pixel-level semantic segmentation algorithm and image feature extraction technology enable user-centred exploration and make cultural heritage digitally and visually accessible. By suggesting a analytic framework using the pixel-level semantic segmentation algorithm and extracting image features, we attempted to identify the physical attributes and spatial characteristics of traditional village landscapes and further simulate the value perception thinking of experts and the public. Besides, we analysed the impact factors and correlation mechanism of spatial attributes to provide a scientific basis and technical support for the protection and utilization of traditional villages.

Keywords: cross-disciplinary perspective; cognitive evaluation; deep learning; image recognition; traditional village landscape

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1. Introduction

In recent years, the use of computing and digital technology to record and assess cultural heritage has become a global trend in heritage conservation. UNESCO's Charter for the Preservation of Digital Heritage [1] and the Vancouver Declaration on Digitization and Conservation [2] have expanded the traditional understanding of cultural heritage to include digital representation as an object of conservation. Digital and computing technologies offer unprecedented perspective, detail, and precision in observing and recording cultural heritage, which has revolutionised the workflow of heritage documentation and provided opportunities to explore innovative approaches to conservation and management. Moreover, advances in the digital technology of computers have made the acquisition, recording, and manipulation of visual three-dimensional (3D) data and image recognition technically possible [3]. Other computing techniques, such as reverse engineering and computer graphics, are used to analyse, study, conserve, and visualise cultural heritage assets [4]. Under this context, cultural heritage, as a domain field in preserving urban and rural landscapes, benefits significantly from using these computing technologies as users and practitioners can experience and understand cultural artefacts in a new way.

In terms of integrating computing technologies with cultural heritage, the concept of cultural computing has been developed. It is used to collect, record, analyse, organize, mine, express, relate, disseminate and display the information/knowledge contained in cultural heritage-intelligent information technologies such as big data, artificial intelligence and virtual reality [5,6]. Moreover, cultural computing can integrate other digitisation methods and artificial intelligence, such as computational analysis, historical simulation, virtual simulation, and immersive experience. Such integration may bring new opportunities for understanding and preserving cultural heritage [4]. In recent years, the development of deep learning algorithms, image recognition and evaluation applications has provided experience and technical support for cultural heritage in urban and rural contexts [7]. Furthermore, digitisation and artificial intelligence could promote the construction of digital villages [8], and such methods also provide a new perspective and technical approach for studying the traditional village landscape.

Image recognition and deep learning technologies help interpret recognition and classification in multiple aspects of processing large-scale image dataset, including image aesthetics quality evaluation, urban and rural environment recognition, etc. [3,9,10]. Furthermore, image recognition based on deep learning technology provides technical support for the mining, cognition, protection, and utilisation of traditional village features [11,12].

This study used the Web of Science (WOS) Core Collection (i.e., SCI-EXPANDED, SSCI, A&HCI) to obtain literature information including titles, authors, abstracts, keywords, citations and references by literature search method. The CiteSpace was used to perform the data analysis. For this study, the time span for filtering these literatures was from 1950 to 2020. We searched the databases by using keywords: "deep learning", "machine learning", "traditional village landscape", "image recognition", "landscape evaluation", and a total of 238 papers were obtained, and by carefully checking the title and abstract of each paper, we removed these articles that were not closely relevant to the research of this paper, and finally 96 papers, which are closely related to the research and up-to-date ones, were selected.

The contributions in this article are summarized as:

(1) we investigate these literatures introducing the advancement of artificial intelligence and its application to the evaluation of traditional village landscape with artificial intelligence technology.

(2) we summarize the current advancements in this field, thereby revealing the main technical features of deep learning.

(3) we construct a cutting-edge analysis framework to analyse the characteristic interpretation and cognitive evaluation of traditional village landscapes based on deep learning.

The rest of this article is organized as follows: Section 2 introduces the methodologies for the evaluation of traditional village landscape; Section 3 details the insides of deep learning technology for landscape recognition and evaluation; Section 4 focuses on the evaluation of traditional village landscape based on deep learning; Section 5 concludes the study.

2. Methodologies for the Studies of Traditional Village Landscape

As sites of revitalised cultural heritage, traditional villages carry a considerable amount of historical memory, human ecology, architectural aesthetics, and social development [13]. However, the cultural heritage found in traditional village landscapes faces destruction due to globalization, modernisation, and urbanization, and its protection and utilisation have become an issue of great concern to all countries in the world [14]. Traditional villages are considered as heritage sites and offered legislative protection. The International Council of Antiquities and Heritage has issued documents, such as the "Tlaxcala Declaration on the Regeneration of Small Settlements" and "the Charter on Vernacular Architectural Heritage", to provide a theoretical basis and technical support for the protection and utilization of traditional villages [15,16].

Research on rural landscapes was initially based on subjective and empirical research on the results of rural construction, focusing on the shaping of the landscape and the establishment of a theoretical framework [17,18]. Later, it gradually began to emphasize data analysis, focusing on objective data research and paying attention to the evolution, characteristics, evaluation system, prediction model, and construction mode of the rural landscape style, historical humanities, and ecological environment [19,20]. At present, studies on rural landscapes mainly rely on modern communication techniques to carry out comprehensive multidisciplinary and multi-method research. Visualisation technologies based on 3D graphics and integrated interactive studies using various methods for landscape study are manifested and combined with multiple natural, artificial, and human aspects [21,22].

In China, research on rural landscapes mainly focuses on analysing landscape features, remediation planning, evaluation and optimisation, and protection and management. Firstly, in terms of village site selection, architectural texture, and street space, current research aims to analyse the composition, development, evolution, essential characteristics, typical features, and problems of landscape elements [5,23,24]. Secondly, to explore the mode, strategy, and path of rural landscape planning and renovation based on a multidisciplinary perspective, current studies focus on creating rural revitalisation strategies and countryside construction plans [12,25,26]. Thirdly, with respect to the triadic evaluation of ecology, morphology, and mentality, current research integrates resident perception, environmental ecology, and morphological aesthetics and applies new technological methods, such as databases [27–30]. Finally, it is necessary to analyse current predicaments, problems, and causal mechanisms; explore the modes, methods, strategies, and paths of rural landscape protection and management; and emphasise public participation [7,31].

These researchers have gradually expanded their research on rural landscape scenery to multiple fields and have carried out comprehensive explorations, obtaining rich results with image recognition and deep learning technology, especially in image aesthetic quality assessment and town scenery recognition. Furthermore, although deep learning technology and image recognition have not been widely applied in traditional village landscape protection, the relevant literature already provides empirical references and technical support. Therefore, with computer-aided analysis and mathematical models, the identification, evaluation, and construction of models will be an important part of the research on the protection and use of traditional village landscapes in China.

As shown in Table 1, the application contexts include the value research of traditional villages, cultural landscape characteristics, integrated protection and development, the evolution of village spatial forms, and landscape planning and design, the development of the village landscape, the improvement of the tourism environment, and the improvement of the overall landscape, etc. The mainstream research methods include landscape genetic methods [32], space syntax [3], landscape patterns [33], ArcGIS analysis methods [34], least resistance models [35], and landscape sensitivity analysis methods [36]. The methods used in foreign countries are more mature, and mainly include ASEB raster analyses of tourists' experiences [37], decision-making laboratory analysis methods [38], GIS analysis methods [39], etc.

Table 1. Comparison of the methods applied in landscape research.

Method	Application Contexts	Representative Literatures
Landscape genetic method	Traditional settlement zoning, feature recognition, tourism planning, and other fields.	Van Strien M J, 2012 [32]
Space syntax	Urban renewal, analysis of spatial structure changes, analysis of the city's diachronic changes, etc.	Bafna S, 2003 [3]
Landscape pattern	Conservation of ecosystem, land utilization, industry change, etc.	O'Neill R V, 1988 [33]; Wu J, 2004 [40]
ArcGIS analysis method	Users create, browse, use, and share smart map information online.	Jiménez-Perálvarez J D, 2009 [34]; Xiao Y, 2016 [41]
Least resistance model	Land ecological suitability evaluation, cost analysis, landscape protection, etc.	Hultman K E, 1979 [35]
Landscape sensitivity analysis method	Landscape planning and design, landscape protection and utilization, area division, etc.	Newham L T H, 2003 [36];

Table 1. *Cont.*

Method	Application Contexts	Representative Literatures
ASEB raster analysis method	Design of Beijing Longcheng Garden, tourism product development, etc.	Yang-lian LIU, 2013 [42]
Decision-making laboratory analysis method	Risk assessment of traditional architectural landscapes, application of efficiency curve, etc.	Seyed-Hosseini S M, 2006 [38]; Liu H C, 2015 [43]
GIS analysis method	Various types of spatial analysis, use of maps for tactical research and strategic decision making, etc.	Hayou S, 2019 [44]; Nantomah K, 2019 [45]; Lau M, 2018 [46], Nicolae A, 2018 [47]

3. Technical Details of Deep Learning Used for the Study of Traditional Village Landscape

The traditional village landscapes involving information technologies have been heavily studied in past decades, as shown in Table 2, we grouped these literatures (by searching http://scholar.google.com (accessed on 30 December 2020) with keywords: "traditional village landscape", "evaluation", "artificial intelligence", "deep learning") into three categories: (1) image recognition and evaluation based on deep learning, (2) application of image recognition in the field of urban and rural construction, (3) recognition, evaluation, and protection of rural landscapes.

Table 2. A list of these existing literatures by three categories.

Category	Research Topics	Representative Literatures
Image recognition and evaluation based on deep learning	Image object classification, image segmentation, image recognition, face beauty prediction, agricultural pest and disease recognition, plant species recognition, medical imaging diagnosis, migration learning algorithms, etc.	Simonyan K, 2014 [48]; Szegedy C, 2015 [49]; Wu R, 2015 [40]; Feng Q, 2017 [50]; Xue Z, 2018 [51]
Application of image recognition in the field of urban and rural construction	Street greening, architectural features, urban form, walkability status, urban image, urban skyline, urban style, building recognition, intelligent classification of landscape elements, landscape visual quality evaluation, etc.	Li X, 2017 [52]; Hu F, 2015 [14]; Yin L, 2016 [53]; Porzi L, 2015 [54]; Glaeser E L, 2018 [55]; Cheng L, 2017 [9]; Liu L, 2017 [56]
Recognition, evaluation, and protection of rural landscapes	Subjective and empirical, objective data-based research, and multiple comprehensive research; focus more on the analysis of style features, style renovation planning, style evaluation optimization, style protection and management, etc.	Hull IV R B, 1989 [18]; Falade J B, 1989 [17]; Giupponi C, 2006 [19]; Hietel E, 2007 [20]; Milder J C, 2014 [22]; Hart A K, 2014 [21]; Bo L, 2020 [5]; Yong L, 2019 [24]; Gui Y, 2018 [23]; Tie L, 2020 [26]

In recent years, image recognition using deep learning has seen several breakthroughs and has surpassed that of the human eye. Moreover, compared with traditional machine learning, intelligent recognition based on deep learning and large-scale image dataset greatly improves the accuracy [40,48,49,57]. This technology is used in many fields, such as in the prediction of facial beauty [58], the image feature extraction of agricultural diseases and insect pests [50], and the intelligent recognition of plant species from images [51,52]. These methods help analyse the composition and characteristics of urban physical environment elements. For example, by identifying the urban elements in an image and the social environmental attributes [53,54]. In terms of economic and political aspects, these methods could provide information for predicting the non-visual attributes of a city based on the characteristics of the physical environment and link household income data and housing price data to realise an intelligent evaluation of the economic environment [55]. In terms of visual aesthetic and experience, it is critical to utilise image recognition based on the characteristics of the physical environment to associate aesthetic theories with people's cognitive concepts and carry out an intelligent evaluation of urban style [9], visual quality [56].

In China, research on deep learning and its use in image recognition technology has gradually focused on the levels of streets and cities. At the street level, based on the large-scale street view images, deep learning has been used to identify and classify street space elements, measure the level of greening [59], openness [41], and walkability [60]. and it's also used for the evaluation of street space quality, dynamic change measurements, and the factors influencing discrimination [61]. At the city level, the deep learning has been used to carry out a cognitive evaluation of urban image structures and types [62]: (1) the extraction of urban development types and their evolutionary routines [63]; (2) an essential evaluation and quantification of urban colours [64] and (3) the identification and evaluation of urban textures and an analysis of their economic relevance [65]. The custom image discrimination model has also been used to recognise and evaluate the aesthetic characteristics of the city skyline [66] and the city style [67]. In addition, research has also been conducted on remote sensing images for township building recognition, the intelligent classification of landscape elements, and the quality evaluation of landscape visualization.

At present, deep learning-based image recognition and evaluation techniques mainly involve convolutional neural networks [68], pixel-level semantic segmentation [1], image feature extraction techniques [69], image recognition [42], image evaluation [70], migration learning algorithms, and many other methods. The keys for deep learning-based image recognition is: (1) to establish the most effective fit between the selected model and the image feature elements; (2) to integrate and translate traditional cognitive language and image feature information data; (3) to determine the most effective elements to characterise the image through a set of procedures (e.g., image segmentation, feature extraction). Firstly, image pre-processing, such as geometric correction, image mosaic, image cropping, is employed for different categories of image dataset to eliminate irrelevant information. These methods help enhance the detectability of relevant information and improve the reliability of image feature extraction to some extent. Secondly, due to the large amount of information carried by various types of images, it is necessary to select the appropriate techniques for feature extraction and image segmentation. Thirdly, algorithms such as Histogram of Oriented Gradient (HOG), Maximally Stable Extremal Regions (MSER), and Scale-invariant Feature Transform (SIFT) are used to extract features from images to obtain elements that can fully characterize the features. The feature detection layer of the convolutional neural network learns automatically from the training data, avoiding explicit feature extraction, which is more effective for image recognition. The following subsections will introduce the technical details.

3.1. Image Feature Extraction

Feature extraction is an essential stage of image processing. Each image has characteristics that distinguish it from other images, some of which are natural and intuitively perceptible, such as brightness, edges, texture, and colour, while others require transformation or processing to observe, such as histogram moments and principal components. In 1988, Harris et al. [71] proposed the Harris corner detection algorithm to obtain an image's corner points (as an image features) by judging the singular values in the image structure. In 1996, T. Ojala and others [72] proposed the Local Binary Pattern (LBP) algorithm, which generates a LBP value by comparing the local pixel value and the centre pixel value to extract the image texture. In 1999, David Lowe [73,74] proposed the SIFT algorithm, which was perfected and supplemented in 2004 [75]. The algorithm selects key feature points in different scaled spaces for description and generates image features. In 2001, Viola et al. [76] proposed the combination of the Haar feature extraction method and the AdaBoost classification algorithm to achieve face detection. In 2005, Dalal [77] proposed the HOG algorithm. This algorithm uses edge features for feature recognition combined with SVM classifiers to achieve pedestrian detection. In 2008, Bay et al. [78] proposed Speed-up Robust Features (SURF) as an improvement to the SIFT algorithm. It significantly reduces the program's running time and increases the algorithm's robustness. As shown in Table 3, these classical methods for feature extraction are compared.

Table 3. Comparison of image feature extraction techniques.

Model	Year	Authors	Achievement
Harris corner detection algorithm	1998	C. Harris et al. [71]	Obtains the corner points of an image by judging the singular values in the image structure to extract the image features.
Local binary pattern algorithm	1996	T. Ojala et al. [72]	Generates the LBP value by comparing the local pixel value and the centre pixel value and extracts the image texture.
Scale-invariant feature transform algorithm	1999	David Lowe [73,74]	Selects key feature points in different scaled spaces for description and generates image features.
The Haar feature extraction method	2001	Viola et al. [76]	Combined with the AdaBoost classification algorithm to achieve face detection.
Histogram of oriented gradient algorithm	2005	Dalal et al. [77]	Uses edge features for feature recognition combined with SVM classifiers to achieve pedestrian detection.
Speed-up robust features algorithm	2008	Bay et al. [78]	An improvement to the SIFT algorithm, greatly reduces the running time of the program and increases the robustness of the algorithm.

3.2. Deep Learning-Based Workflow of Image Recognition & Evaluation

Deep learning simulates the neural connectivity structure of the human brain, discovers hidden structures and relationships within image data, and characterizes and interprets the data [79]. Typical deep learning models include convolutional neural networks (CNNs) [2], recurrent neural network (RNNs) [10], generative adversarial networks (GANs) [6], and CNN is the most widely used [80]. The essence of a CNN is the realization of an input-to-output mapping relationship, where no precise mathematical expressions are required between the input and output. A CNN contains convolutional calculations and a feedforward neural network with a deep structure, which has the ability to characterize learning. It can automatically learn features from large-scale data and generalise the results to anonymous data of the same type. The CNN extracts the local and global characteristics of the image by constructing a reasonable network model. Moreover, the evaluation model can learn the shallow features that humans can perceive while extracting deep features and laws that are otherwise difficult to discover. Therefore, the objective cognitive score given by a deep learning algorithm based on a CNN is more in line with the subjective score of people. As shown in Table 4, the classic CNN models are: LeNet-5, AlexNet, ZF-Net, VGGNet, GoogLeNet, ResNet, and DenseNet.

The LeNet is the first CNN structure [81]. However, the first well-known network was AlexNet [82]. AlexNet won the 2012 ImageNet competition with an absolute advantage of 10.9% over the runner-up, and convolutional neural networks (CNN) and deep learning (DL) have regained widespread attention [83]. Compared to LeNet, AlexNet has a deeper network, which uses ReLU as the activation function and uses dropout in training [84]. In addition, it randomly ignores some neurons to avoid overfitting the model. VGGNet was proposed by the Visual Geometry Group (VGG) of Oxford University [18], and it won first place in the positioning task and second place in the classification task in the 2014 ImageNet competition [85]. GoogLeNet defeated VGG-Net on the 2014 ImageNet classification task to win the championship [86]. GoogLeNet is different as it does not simply rely on deepening the number of network structure layers to improve network performance. By extracting information at different scales through multiple convolutional kernels and fusing them to better represent the image [43]. ResNet was launched by He in 2016 [87], and it is characterized as very deep, with more than a hundred layers. The main idea of ResNet is the addition of a direct connection channel to the network; that is, the idea of a highway network [88].

Table 4. Comparison between CNN classic models.

Model	Year	Author	Achievement
LeNet-5	1994	LeCun Y et al. [81]	One of the earliest convolutional neural networks; promoted the development of deep learning.
AlexNet	2012	Krizhevsky A et al. [82]	Won the 2012 ImageNet competition with an absolute advantage of 10.9% over second place.
ZF-Net	2013	Matthew D. Zeiler et al. [83]	A network architecture with better performance than AlexNet; proposed a method of feature visualization to analyse and understand the network accordingly.
VGGNet	2014	Hull, R et al. [18]	Based on AlexNet; an attempt to build a network with more layers and greater depth.
GoogLeNet	2014	Szegedy C et al. [86]	Defeated VGG-Nets on the 2014 ImageNet classification task to win the championship.
ResNet	2015	Kaiming H et al. [87]	Beat all players on ISLVRC and COCO to win the championship.
DenseNet	2016	Gao H et al. [89]	The paper "Densely Connected Convolutional Networks" was selected as the best paper of CVPR 2017.

The image evaluation based on deep learning aims to use computers to simulate the perception and understanding of images and scenes by the human brain and automatically make objective evaluations about the "value" of the image content. The core idea is to use CNNs to learn a large number of sample images with labels to build a model and extract the hidden rules and mechanism of action. It usually consists of three steps: (1) image collection and pre-processing; (2) model training; and (3) evaluation applications. The first step is to use the extracted image features to train a regression model. This step aims to form a mapping relationship between the extracted features and the scoring values and then use this mapping relationship to make decisions, which can be implemented with mature feature parameters and algorithms, such as SVM, SVR, and random forest [90]. Secondly, to minimise the difference between predicted values and manual ratings, credibility weights are added based on the number of ratings of the image and the kurtosis of the rating distribution, the weight size is adjusted, and the weight calculation method is optimized. Third, to evaluate the score distribution prediction, one can choose algorithms such as LDSVR [91,92]. It can predict the multi-label distribution for any input instance, and overcomes the unobjective problems caused by using only a single point value. Finally, based on the individual scores of each characteristic factor, the overall cognitive score is increased to test and check the accuracy and objectivity of the evaluation. There are many evaluation indicators for image quality evaluation [93], e.g., PLCC, SROCC, KROCC, and RMSE.

Image recognition and evaluation extracts potential features, laws, and patterns from a considerable amount of labelled image dataset to realize the prediction and classification, which requires a large number of training samples. Currently, the datasets used to train image models include open-source label datasets and custom label training sets. The direct use of existing open-source image datasets brings greater limitations and errors, while the traditional method with manually labelling operation requires extensive labour and time-consuming. In order to overcome the problem of overfitting caused by too few labelled samples, small-sample deep learning techniques are proposed [8]. The typical technique is based on the transfer learning [94]. Its core idea is to establish a mapping relationship between the source dataset and the target dataset (e.g., SIFT Flow dataset, Pascal VOC dataset) with a large amount of rich annotation information using cross-domain migration algorithms.

4. Evaluation of Traditional Village Landscape Based on Deep Learning

As summarised in the previous sections, digital technology offers unprecedented perspective in observing and recording cultural landscape, and has revolutionised the workflow of landscape recording. To date, most digital cultural landscape projects have focused on technical challenges, such as methods and tools, to quickly obtain accurate and complete physical spatial information [4,95]. Such information includes the site selection pattern, spatial texture, streets and lanes, courtyards, and vernacular buildings. With it, the historical memory, wisdom of production and life, and crystallisation of the culture and art can be inherited [13,96]. However, the focus of digital landscape research is gradually expanding its attention to theoretical and ethical aspects [97]. Such elements include paying attention to integrating cultural, intangible, sensory, or experiential elements in the documentation of digital cultural landscape [11,98] and staying grounded in ethical principles that can inform and improve landscape documentation practices [98].

4.1. Interpretation of the Physical Characteristics of Traditional Village Landscape

Technologies enable the conceptual interpretation, connotation, and extension of traditional village landscapes, exploring the hierarchical structure and element types, from the macro site selection pattern and the meso-morphology to the microsite space, and summarising and analysing their influencing factors and formation mechanisms. To achieve such objectives, we suggest to adopt network data capture, drone aerial photography, departmental data collection, and other methods to obtain a considerable amount of image data reflecting the landscape of traditional villages. Then, the pixel-level semantic segmentation technology was adopted to build a deep learning model of the traditional village landscape style based on the image contents. Moreover, large-scale and refined style feature recognition can be used to analyse the spatial characteristics and physical representations of traditional village landscapes of different scales and types. Finally, these influencing factors and formation mechanism for protecting the traditional Chinese village landscape can be determined.

In terms of collecting image data for cognitive evaluation and deep learning processing, image recognition models can be used to identify, classify, statistically analyse, and compare various landscape elements. Furthermore, three levels of image recognition-morphology and fabric, streets and zones, and quarters and buildings-were organised by the measurable spatial features, visual patterns and appearances, and cultural characters from the image data to achieve a formal refinement quantitative description of these core features.

At the level of the morphology and fabric of the village landscape, image recognition measured two-dimensional plane attributes integrated with the data collected from unmanned aerial photography, satellite remote sensing, and GIS. The characteristics obtained at this level include the spatial distribution, size, shape, texture, and fractal dimension of traditional villages. Such characteristic elements could help summarise the spatial pattern and relationship of rhythm, form, contrast, change, etc. At the level of streets and zones, the various constituent elements and their three-dimensional spatial attributes, such as scale, quantity, shape, and volume, were identified. Digital methods, such as 360-degree panoramic photography and 3D landscape models, were manifested and processed with image recognition. Then, the characteristics of each element, such as the association and combination, proportional relationship, and influence mechanism, were deciphered for image recognition analysis. The last level was quarters and buildings. AR (augmented reality) and AV (augmented virtual) were employed to offer architectural details and texture information for specific buildings and small-scale places. Image data generated from the three levels were integrated with image recognition, processing representative characters and evaluations of the different types of traditional village landscape.

In addition to the image data collected at the research site, this study captured online image data from open-source database websites. Based on open-source database systems, such as traditional village databases and digital museums, rural tourism websites, forums, and other thematic websites, the Python language-based crawler technology was used to obtain a large amount of image data related to the traditional village cultural landscape space. The image data included social media images, Baidu Street View photos, satellite images, air-ground combination 360 panoramas, overall aerial views, characteristic node maps, and many other types. On-site image data collection of typical traditional villages was also employed. Standard samples of traditional villages were selected based on the principles of balanced distribution, comprehensive types, and strong representativeness.

Based on the collection and sorting of original image data, pixel-level semantic segmentation technology was applied to build an algorithm model based on the classic semantic segmentation convolutional neural network on the Caffe deep learning framework. The first step of processing the image data is to increase the effective information of model training and its generalisation performance through pre-processing and external assistance. It then applies a framework of deep learning techniques based on transfer learning algorithms across data domains. After that, the pixel-level semantic segmentation technology then explores the joint application of open-source image datasets and manually annotated image training sets, then builds a traditional village landscape recognition model based on deep learning. Finally, it summarises the matching algorithm model and its empirical parameters and structure between image attributes and features. Therefore, any complex image scene can be quickly decomposed and clustered under the model, enabling interpretation and quantitative analysis to be processed with image data. The analysis carries out the identification, classification, measurement, and quantification of traditional village landscape elements. It then analyses the spatial characteristics and physical properties of different scales and types through image pre-processing, feature extraction, semantic segmentation, and post-processing.

4.2. Cognitive Evaluation of Traditional Village Landscape

Evaluation Index of Traditional Village Landscapes

With regards to the regional characteristics and core attributes of traditional village landscapes, theoretical analysis and expert consultation based on image recognition and deep learning should be taken into consideration. In this way, we could determine the value system of conservation and utilisation based on image, associations, and symbols they evoked. Moreover, the combination of computing technologies and theoretical analysis could help overcome the shortcomings of traditional text questionnaires that “ignore the process” and integrate the ideas of “self-recall” and “self-experience”.

An essential prior to performing the intelligent cognitive evaluation of traditional village landscapes is to obtain a large number of high-quality image samples with score tags from different groups of people. A combination of online and offline large-scale public and small-scale expert samples was used to obtain a consensus accumulation of large-scale individual opinions from different groups of people, such as villagers, tourists, academics, designers, and government personnel. In addition, various methods, such as laboratory manual scoring, field questionnaire interview scoring, social media online scoring, and internet crowdsourcing platform scoring, were employed to collect and calibrate evaluation information. We obtained a cognitive evaluation of the traditional village landscape from people with diverse background attributes, including different regions, ages, educational backgrounds, and occupations. Then, the cognitive evaluation was used to construct a label image dataset with multi-dimensional value information, such as history, aesthetics, culture, usage, economy, and society, all of which were used to form training and testing samples for subsequent deep learning models. At the same time, based on the individual scoring of each feature factor, an overall cognitive evaluation of the image landscape features was added to check and verify its accuracy and objectivity, solving the quality and quantity problems of traditional village landscape image data at the source and ensuring the depth and breadth of subsequent processing.

Based on artificially labelled image sets and experts' cognitive and situational processes, tourists and villagers were simulated to construct an intelligent image evaluation model. To address the potential overfitting problem caused by insufficiently annotated samples, this study explored a framework of small-sample deep learning techniques based on internal data augmentation and cross-domain transfer learning. Of the annotated images, 75% were selected for model training, optimisation, and tuning, and the remaining 25% were used for validation and testing. In summary, the sample selection and deep analysis was used to build a deep learning model capable of simulating human recognition for value assessment, enabling the evaluation and measurement of traditional rural landscape images.

4.3. The Protection and Utilisation of Traditional Village Landscapes

4.3.1. Utilisation Countermeasures Based on Physical Characterization

Based on the superposition, clustering, and correlation of information, including human historical background, spatial characteristics and attributes, value perception, and evaluation, a GIS-based map of traditional village landscape features was constructed from an authentic perspective, linking relevant historical images, real-world photos, and critical features and evaluation information; providing real-time queries and dynamic updates; and building a digital display platform in combination with signage, tour route systems, etc.

According to the type and distribution of the traditional village landscapes and their characteristic attributes, a core protection zone, characteristic demonstration zone, characteristic experience zone, and coordinated integration zone were designated from the perspective of adaptability, and region-wide protection and development zoning, a co-ordination mechanism, and a digital management platform were established. Such platforms aim to explore the control and continuation of morphological patterns, the reproduction and implantation of characteristic places for protection, and the enhancement and creation of typical landmarks. Finally, we combined the character map and conservation and development zoning, then identified proposals and directions for maintaining, enhancing, restoring, and creating various landscape features. As such, we proposed response strategies and technical support for overall protection, relevance protection, authenticity protection, adaptive development, etc., highlighting the control and continuation of the pattern of landscape forms and the reproduction and implantation of characteristic places.

4.3.2. Utilisation Countermeasures Based on Cognitive Evaluation

Firstly, this study explored the conservation model and implementation path from "elite conservation" to "public conservation", from "government-led" to "people-initiated", and from "top-down" to "bottom-up". Secondly, it emphasised the transition from "absolute value quantification" to "subjective and objective compound value", which highlights village democracies' status and gives full play to the role of civil society organisations. Moreover, we adopted a multi-professional, multi-department, and multi-channel collaborative protection and utilisation mode. Thirdly, it respected the multi-dimensional perception and interpretation of the landscape features of traditional villages and the meaning and values they carry for the public and experts of different backgrounds and attributes. Finally, based on public perception and preference attributes, diversified media platforms, such as microblogging, WeChat, and television. They were selected to showcase the spatial characteristics and historical, cultural, and value attributes of traditional village landscapes; improve public awareness and education for all; and enhance public cultural self-awareness and cultural confidence.

4.3.3. Utilization Countermeasures Based on Multiple Appropriateness

Based on the spatial composition of cultural landscapes and the analysis of intelligent decision-making platforms, this study analysed the challenges, opportunities, and constraints faced by different villages in their future conservation and development by exploring conservation and development models and pathways that suit their characteristics and critical users. Moreover, it focused on liveable villages, highlighting the main position and actual needs of villagers, and building a bottom-up conservation and utilisation model to improve the living environment of villagers as the main body of construction and countermeasures. In relation to tourism, this study examined tourism expansion villages as emphasising the aesthetic values and tourism needs of tourists under the premise of conservation. Moreover, it highlights the improvement of facilities and tourism experience and promotes the sustainable conservation and use of village cultural landscape spaces through tourism development. Finally, in the construction and development of cultural heritage villages, it is necessary to fully consider the theoretical and cultural values of unique cultural landscape spaces and the policy support from the national and local governments when exploring appropriate modes and strategies of conservation and utilisation.

5. Conclusions

This study aims to provide the overview of the adoption of the artificial intelligence to the evaluation of traditional village landscapes. We investigated the state-of-the-art deep learning methods, and their applications in the field of traditional village landscape applied in recent years. We first introduce the basic concepts and history the studies of artificial intelligence and traditional village landscape. Then we analyse the core technical principles of artificial intelligence technology (e.g., deep learning), discuss the technical roles of deep learning help improve the study of traditional village landscape in different application contexts and processes. It reveals that the image recognition technology enabled by deep learning could significantly improve the efficiency of the study of traditional village landscape. We further suggest a cutting-edge analysis framework for applying deep learning technology into the evaluation of traditional village landscape, with which, the deep aggregation and knowledge output of multi-dimensional attribute information was achieved.

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