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Research Article

Application Effect of the Deep Neural Network PointNet in Ancient Architectural Carving in the Artificial Intelligence Environment

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ABSTRACT

This study aims to better study the application of the deep neural network PointNet in ancient architectural carving and improve its efficiency of protection and restoration. Firstly, in the environment of artificial intelligence (AI) technology, a point cloud semantic segmentation model based on the deep learning neural network (DLNN) is established. Secondly, the PointNet point cloud semantic segmentation neural network is designed. Finally, the point cloud semantic segmentation neural network and the DLNN-based point cloud semantic segmentation model are verified experimentally in indoor and outdoor environments. The results show that the loss rate of the point cloud semantic segmentation model based on DLNN is finally stable at 0.05, the overall accuracy is 88.7%, and the mean intersection of union is 73.7%. The accuracy of the designed network model is above 95%. In the outdoor scene test, when the learning rate is 0.03, the overall model stability is the highest, the object roughness error is only 0.01, and the error of contour segmentation recognition is 0.398. These research data prove the feasibility and effectiveness of applying DNN PointNet in ancient architectural carving in the AI environment. This provides a new idea and method for protecting and restoring ancient architectural carvings.

Keywords: Artificial intelligence; Deep neural network; PointNet; Ancient architectural carving; Point cloud semantic segmentation

1. INTRODUCTION

1.1 Research Background and Motivations

As an important part of Chinese traditional culture, ancient architectural carving carries rich historical and cultural connotations and is of great significance for the protection and inheritance of cultural heritage (Fazio, Lo Brutto, Gonizzi Barsanti & Malatesta, 2022; Łukaszewicz, 2020). However, due to the long age of ancient architectural carving and the erosion of the external environment, many carving works have been damaged to varying degrees (Scott, 2023; Solievich & Ravshanovna, 2021). Traditional carving protection methods usually require a lot of manpower and time, especially for complex and detailed carving works, and the restoration process is quite time-consuming (Tian, 2020; Zhang, Liu, Li, Yu & Li, 2019). Moreover, traditional restoration methods that rely heavily on manual craftsmanship require the training of experienced craftsmen, which is costly. At the same time, traditional restoration often relies on the experience and skills of craftsmen, and subjective factors may affect the repair effect (Nishizawa&Jing, 2021; Wallis, Hornblow, Smit, Gough, Wise&Bailey, 2021).

Faced with the above problems, artificial intelligence (AI) technology and deep neural network (DNN), as one of the core technologies of AI, have made remarkable progress in the field of image processing and pattern recognition (Zhu & Li, 2022; Ivashko, 2021; Bai, Jia, Chen, Gong, Cheng & Wang, 2021). As a point cloud processing network in deep learning (DL), PointNet is capable of feature extraction and classification of point cloud data, and has advantages in processing three-dimensional (3D) shape data (Dornelles, Gandolfi, Mercader-Moyano & Mosquera-Adell, 2020; Bienvenido-Huertas, León-Muñoz, Martín-del-Río & Rubio-Bellido, 2021).

Therefore, by utilizing PointNet's efficient feature extraction and classification capabilities, it may be possible to automate the detection, damage assessment, and generation of restoration schemes for ancient architectural carvings (Zhang, Zhi, Xu & Han, 2022; Liu, 2023). This will greatly improve the efficiency and accuracy of the protection of ancient architectural carving, reduce the manpower and cost required for traditional restoration, and decrease the interference of subjective factors, bringing vital innovations and breakthroughs for the protection of the cultural heritage of ancient architectural carvings (Liva, 2021; Payne, 2019; Loke, Pallav & Haldenwang, 2020).

1.2 Research Objectives

In the context of AI, this study aims to verify whether DNN PointNet is suitable for processing point cloud data for ancient architectural carving, and to identify its advantages and limitations in this field. PointNet's feature extraction and classification capabilities are utilized to automate the detection and classification of ancient architectural carvings, involving automatic identification and analysis of carving styles, elements, and damage. PointNet model is used to analyze the point cloud data of ancient architectural carving, to realize the quantitative assessment of the carving damage degree, including the geometric information of loss, the degree of damage, and the impact on the overall structure.

To achieve these goals, section 1 describes the background and objectives of the topic; Section 2 summarizes the relevant domestic and international research results; Section 3 is the design and establishment of the point cloud semantic segmentation model based on the deep learning neural network (DLNN) and PointNet-Pro point cloud semantic segmentation neural network. Section 4 is the experimental verification of the designed model. The superiority of the research method in this study is illustrated through the experimental verification of the indoor point cloud semantic segmentation neural network and outdoor granite carving of the DLNN-based point cloud semantic segmentation model. Section 5 is the summary of the whole experimental results and the prospect of future research direction. The research innovation lies in fully using PointNet's advantages in point cloud data processing, which brings new possibilities for the protection and inheritance of ancient architectural carving.

2. LITERATURE REVIEW

The application effect of DNN PointNet in ancient architectural carving in an AI environment has also attracted the attention of domestic and international researchers. Although there is relatively little specific research on ancient architectural carving, research results in related fields provide some inspiration and reference for this.

Li et al. proposed that in the field of cultural heritage protection, DL and computer vision technology had been applied to the scanning, modeling, and protection of ancient buildings (Li, Hou, Dong, Wang, Ji & Huo, 2021; Gangey, 2020). For example, Shivakumar et al. adopted DNN to carry out feature extraction and classification of 3D scanning data of cultural heritage, and realized the identification and style classification of ancient architectural elements. Point cloud data was a common form of data for ancient architectural carving (Shivakumar, Selvaraj & Dhassaih, 2021; Yang, Hou & Li, 2023). Zhao et al. believed that as a point cloud processing network, PointNet was widely used in object recognition, scene analysis, and other fields. Its feature extraction and classification capabilities on point cloud data supported the application of ancient architectural carving (Zhao & Fan, 2023; Georgiou, Liu, Chen & Lew, 2020).

Qin et al. paid attention to the overall digitalization framework and cultural heritage protection. They tried to combine DL technology with traditional protection methods to realize intelligent protection of cultural heritage (Qin & Gruen, 2021; Vaananen & Lehtola, 2019). Kim et al. focused on the digitalization and conservation of ancient buildings, including the digital reconstruction using 3D laser scanning technology (Kim & Lee, 2023; Liu, Cao, Kuang, Kobbelt & Hu, 2019). These studies laid the foundation for the digital application and data acquisition of ancient architectural carving. Zhang et al. tried to combine traditional craft with digital technology, and explored the application of traditional craft and AI technology in protecting ancient architectural carving (Zhang, Zhao, Chen & Lu, 2019; Xia, Yang & Chen, 2022).

These attempts offer a certain background and foundation for the application of DNN PointNet in ancient architectural carving. There has yet to be large-scale research on the application effect of PointNet in ancient architectural carving in foreign research status. However, the research results in related fields reveal that in the fields of cultural heritage protection, point cloud data processing, and the combination of traditional technology and digital technology, etc., some relevant studies have provided some reference and basis for the application effect of DNN PointNet in ancient architectural carving.

3. RESEARCH METHODOLOGY

3.1 The point cloud semantic segmentation model based on DLNN

In an AI environment, the DLNN-based point cloud semantic segmentation model is a model for processing 3D point cloud data to classify each point semantically (Lee, Park & Ryu, 2021; Xie, Tian & Zhu, 2020). The point cloud is a set of 3D coordinate points, usually used to represent the geometric shape of objects or scenes, with strong learning and generalization ability. Besides, it can perform efficient semantic segmentation tasks on large-scale point cloud data and generate important applications in various 3D scene understanding problems (Chen, Li, Fan & Wang, 2021; Mo, Wu, Yang, Liu & Liao, 2022). The structure is displayed in Figure 1:

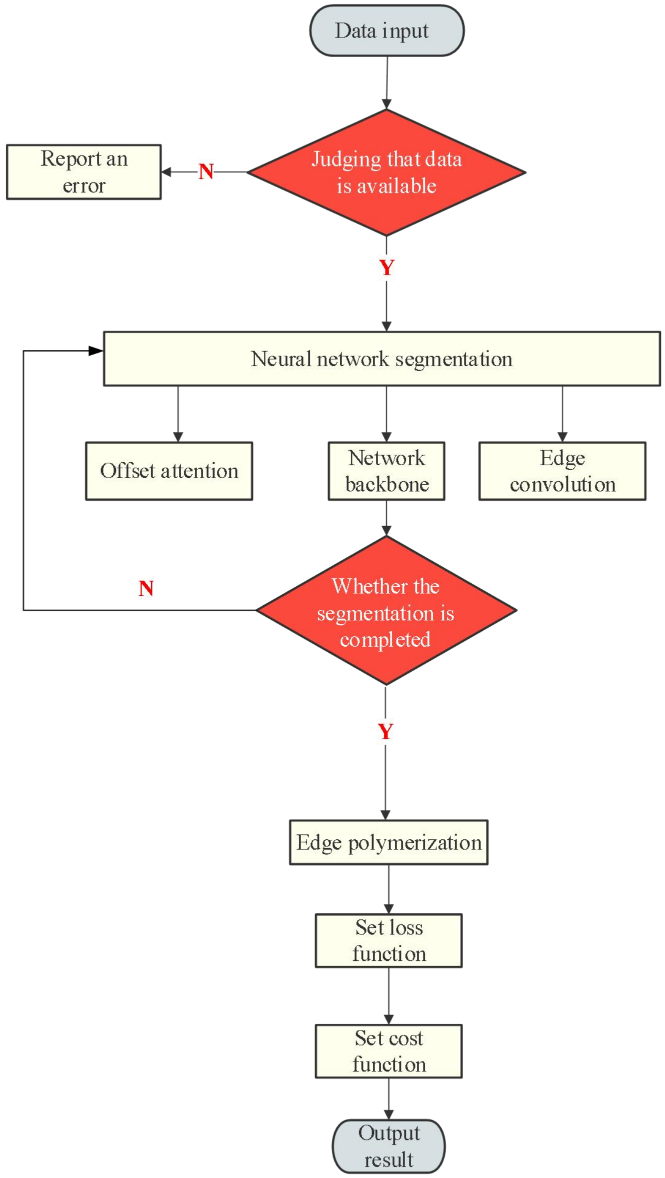


Figure. 1 Architecture diagram of DLNN

In Figure 1, the model first requires 3D point cloud data to generate the distance centroid offset of the test object after encoding and decoding. Then, in the second stage, the origin point cloud coordinate information is superimposed, and corresponding semantic labels are attached to each point (Poux & Billen, 2019; Imad, Doukhi & Lee, 2021). The specific design steps are as follows:

Step 1: Offset attention mechanism;

Object recognition is described as the centroids' prediction to achieve correct object recognition. The first stage adopts a three-layer feature extraction structure (similar to the PointNet++ classifier structure), while the second stage uses a complete four-layer structure (Kamari & Ham, 2021; Guo, Cai, Liu, Mu, Martin & Hu, 2021). After the first decoding is completed, the point coordinate offset is output, and all coordinates are translated according to the offset to obtain a new category point (Ma, Czerniawski & Leite, 2020; Yao, Guo, Hu & Cao, 2019).

Step 2: Establishment of the network backbone;

In 3D space, the continuous convolution operator weights are treated as a 3D local coordinate reference point function, and the function is continuous, as expressed in equation (1):

$$A(W,F)_{xyz} = \iiint_{(\rho_x,\rho_y,\rho_z)\in G} W(\rho_x,\rho_y,\rho_z)F(x+\rho_x,y+\rho_y,z+\rho_z)d\rho_x\rho_y\rho_z \tag{1}$$

W and F are continuous functions; (ρ_x,ρ_y,ρ_z) represent the relative coordinates of the midpoint (x,y,z) of the neighborhood G. The expression of the network backbone function is:

$$PA(S,W,F)_{xyz} = \sum_{(\rho_x,\rho_y,\rho_z)\in G} S(\rho_x,\rho_y,\rho_z)W(\rho_x,\rho_y,\rho_z)F(x+\rho_x, y+\rho_y, z+\rho_z) \tag{2}$$

S refers to the inverse density coefficient function, and the calculated output feature F^{out} can be written as equation (2):

$$F^{out} = \sum_{n=1}^{N}\sum_{c_{in}=1}^{C_{in}} S(N)W(n,c_{in})F^{in}(n,c_{in}) \tag{3}$$

N indicates the number of points in the neighbourhood; *n* means the local area index point; c_{in} stands for the input index; F^{in} represents the input feature. Equation (4) shows the output features after simplifying:

$$F^{out} = A_{1\times1}(H,(S\cdot F^{in})^T \otimes M) \tag{4}$$

H represents the last layer of weight; $A_{1\times1}$ indicates 1*1 two-dimensional convolution; M means the last layer input of the perceptron module.

Step 3: Creation of edge convolution module;

Assuming a point cloud formed by n points in the neighborhood, the output of edge convolution at the i-th point reads:

$$x_i^{'} = max_{j:(i,j)\epsilon\varepsilon}\, h_\theta(x_i,x_j) \tag{5}$$

x_i means the center point; $max_{j:(i,j)\epsilon\varepsilon}$ represents the largest block around the center point; *h* refers to the symmetric edge function; *max* refers to the maximum pooled aggregate function, as shown in equations (6), (7), (8), and (9):

$$x_{im}^{'} = \sum_{j:(i,j)\epsilon\varepsilon} \theta_m \cdot x_j \tag{6}$$

$$h_\theta(x_i,x_j) = h_\theta(x_i) \tag{7}$$

$$h_\theta(x_i,x_j) = \overline{h_\theta}(x_j - x_i) \tag{8}$$

$$h_\theta(x_i,x_j) = \overline{h_\theta}(x_i, x_j - x_i) \tag{9}$$

x_i can capture global shape structures; $x_j - x_i$ can capture adjacent local information. A shared multilayer perceptron is defined as:

$$E_{ijm}^{'} = RELU(\theta_m \cdot (x_j - x_i) + \varphi_m \cdot x_i) \tag{10}$$

Edge feature $E_{ijm}^{'}$ is aggregated as follows:

$$x_{im}^{'} = \max_{j:(i,j)\epsilon\varepsilon} E_{ijm}^{'} \tag{11}$$

$x_{im}^{'}$ is the result of the final aggregation.

3.2 PointNet point cloud semantic segmentation neural network

PointNet is a DLNN model for point cloud data processing, aiming to solve the problem of feature extraction and representation of point cloud data (consisting of a set of 3D coordinate points) in DL (Li, Shi, Li, Chen, Zhang, Xiang & Jin, 2022; Wang, He & Ma, 2019), as indicated in Figure 2:

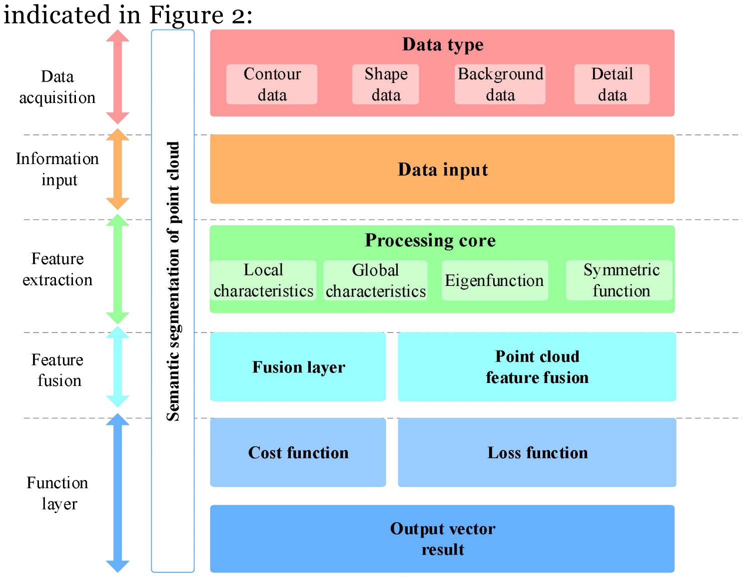


Figure. 2 PointNet neural network structure

Figure 2 signifies that the main feature is that unordered point cloud data can be processed directly without the need to convert it into a regular mesh structure such as voxels or triangular meshes beforehand. This makes PointNet ideal for working with point cloud data. Because the structure of point cloud data is very flexible and free, it is suitable for describing irregularly shaped objects and scenes (Malinverni, Pierdicca, Paolanti, Martini, Morbidoni, Matrone, & Lingua, 2019; Orlenko, Ivashko, Kuśnierz-Krupa, Kobylarczyk & Ivashko, 2021). The construction process is as follows:

Step 1: Construction of the input layer;

The PointNet network structure has two input layers, the first layer is used to input the point cloud, and the second layer is employed to extract the characteristics of the point cloud after it (Wen, Yang, Li, Peng & Chi, 2020; Cui, Chen, Chu, Chen, Tian, Li & Cao, 2021);

Step 2: Establishment of local and global feature extraction layers;

PointNet network structure extracts layer weight sharing, and uses the maximum symmetry function to approximate the arbitrary click definition function, as follows:

$$f(\{x_1, x_2, x_3, \cdots, x_n\}) = g(h(x_1), h(x_2), \cdots, h(x_n)) \tag{12}$$

f stands for the global feature function; g refers to the maximum symmetry function; h represents the feature extraction hierarchy named by layer.

Step 3: Local and global feature fusion

After multiple feature extractions, the PointNet model obtains multi-dimensional point features and a 1024-dimensional global feature, and fuses the global feature with the specified 64-dimensional point feature. As a result, each point gets new local and global features, and after segmentation, the output vector is obtained, which is used as the category prediction of each point (Lin, Vosselman, Cao & Yang, 2020; Balado, Martínez-Sánchez, Arias & Novo, 2019).

Step 4: Setting of the loss function L;

Equation (13) is as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i log p_i + (1 - y_i) log(1 - p_i)) \tag{13}$$

y_i indicates the true category of the x_i; p_i means the predicted class probability.

Step 5: Setting of the cost function WL;

As signified in equation (14):

$$WL = -\frac{1}{N}\sum_{i=1}^{N}(wr_n log p_n + (1 - y_n) log(1 - p_n)) \tag{14}$$

r_n refers to the true value at any point in the split label. The weight w is calculated as:

$$w = \frac{N - \sum_n p_n}{\sum_n p_n} \tag{15}$$

p_n represents the point cloud prediction probability value.

4. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

4.1 Datasets collection

(1) The DLNN-based point cloud semantic segmentation model

This study uses the S3DIS and ScanNet datasets as test data for the proposed model. The S3DIS dataset contains 271 rooms in 11 scenes. The ScanNet dataset consists of 2.5 million RGB-D images scanned over 1,513 scenes in 707 different Spaces.

(2) PointNet point cloud semantic segmentation neural network

This study employs the S3DIS dataset to test the designed network model. For the S3DIS dataset, a scene dataset is randomly sampled first, and 4096 points are collected simultaneously until all room points are acquired. This network model is applied to outdoor object recognition to verify the example of ancient architectural carving under the background of an AI environment.

4.2 Experimental environment

The experimental configuration of this study is exhibited in Table 1:

Table 1 The experimental configuration

Experimental configuration	Type (version)
Central Processing Unit (CPU)	I7-8700
Graphics card	12G
Memory	16G
Operating system	Ubuntu 16.04
CUDA	CUDA9.0
CUDNN	CUDNN7.0
DL framework	Tensorflow 1.21
Programming language	Python 3.5

In Table 1, the hardware configuration includes a CPU processor, video memory, graphics card, and memory for the research on the application of DNN PointNet in the process of ancient architectural carving in the context of the AI environment. The environment configuration involves the operating system, learning framework, programming language, and basic operating environment.

4.3 Parameters setting

(1) The point cloud semantic segmentation model based on DLNN

For the cloud semantic segmentation model test proposed in this study, the overall segmentation accuracy, the intersection of union (IoU), average class accuracy, and mean intersection of union (MIoU) are used to verify the proposed model's performance. The initial learning rate is set to 0.001, the decay rate is 0.0001, and the initial decay rate is 0.5. The loss function is cross-entropy, edge convolution N critical value IS 30, the processing step size is 9, the iteration number is 300, and the number of points within the block is 4096.

(2) PointNet point cloud semantic segmentation neural network

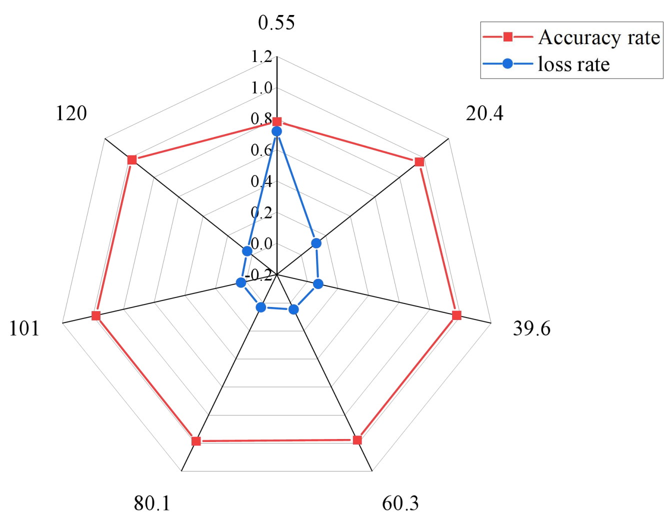
In the testing process of the PointNet point cloud semantic segmentation neural network, the initial learning rate of the indoor test is set to 0.001, the data input size is 16, the optimizer momentum is 0.8, the iteration batch is 50, the input information feature value is 9-dimension, and the number of point clouds is 4096. The indoor measurement range is 0.5-30m, the accuracy is 0.6mm, the viewing angle is 120-360 degrees, the resolution is 0.1mm, and the data acquisition rate is 1.2 million points/second. The learning rates of outdoor ancient architectural carving recognition segmentation are set to 0.02, 0.03, 0.04, and 0.05.

To ensure the superiority of the proposed method in this study, it was compared with PointNet Pro, KNN and VLAD combined Graph Convolution Network (KVGCN), PointASNL, and SegGCN models.

4.4 Experimental environment

(1) The DLNN-based point cloud semantic segmentation model

Figure 3 suggests the curve changes of accuracy and loss rate in the test process and the comparison of overall accuracy and MIoU between the proposed model and previous models:



(a)

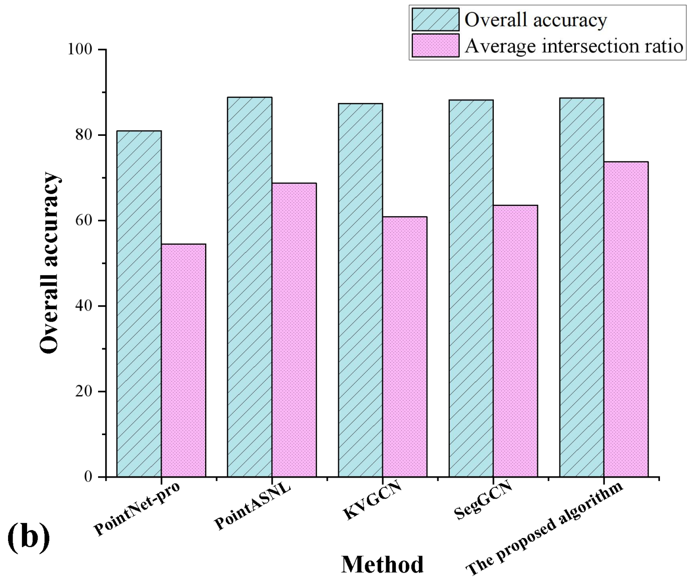


Figure. 3 ((a): Accuracy and loss rate curves during model testing; (b: The comparison of the overall accuracy and MIoU of the proposed model with previous models)

Figure 3 reveals that in the AI environment, the proposed model increases with the number of iterations, the segmentation accuracy keeps rising, the loss rate decreases, and the loss rate stabilizes at 0.05. The overall accuracy and MIoU of the proposed model are 88.7% and 73.7%, which is obviously superior to the comparison model. On this basis, the proposed segmentation model can better extract the local features of ancient architectural carving and achieve effective segmentation. The changes of IoU in each scenario of in the S3DIS dataset are denoted in Figure 4:

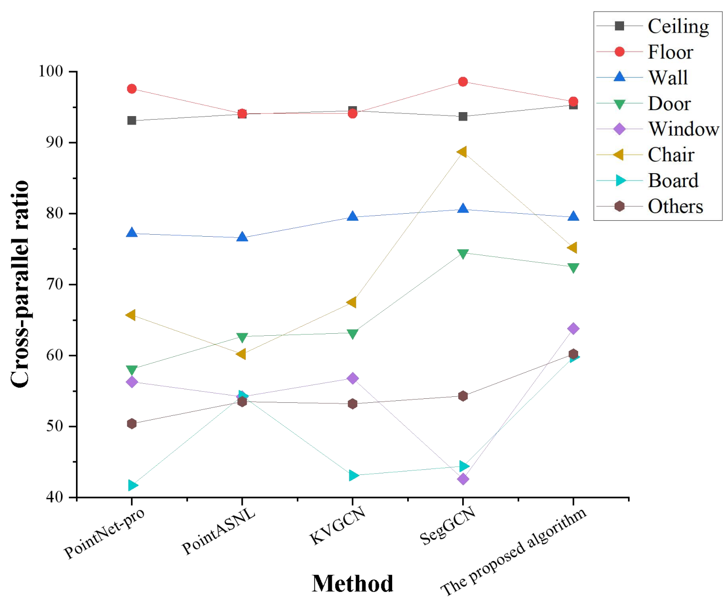


Figure. 4 The variations of IoU in each scenario of the S3DIS dataset

Figure 4 demonstrates that the IoU of the proposed model is 95.3% for the ceiling, 95.8% for the floor, 79.5% for the wall, 72.5% for the door, 75.2% for the chair, and 60.2% for the debris. The model performs well in segmenting ceilings, windows, and templates. Figure 5 plots the variation curve of accuracy and loss rate in the training process of the ScanNet dataset and the IoU of each scene on the dataset:

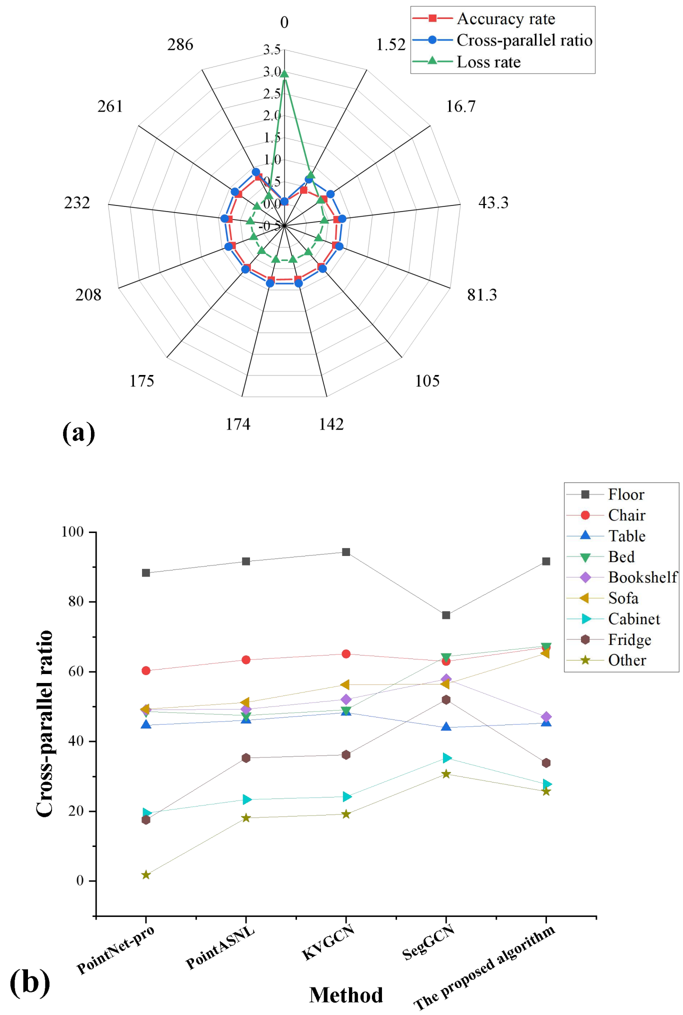


Figure. 5 The training situation of the ScanNet dataset ((a): The change curve of accuracy and loss rate in the training process; (b): The IoU for each scene on the dataset)

In Figure 5, the accuracy of the proposed model gradually stabilizes at 1 with the increase in the number of iterations, and the data loss rate fluctuates around 0.25. The segmentation of the floor, chair, bed, sofa, and other large objects is better than other algorithms, and the IoU can reach about 67%, while the IoU of the floor is 91.6%, indicating that in the AI environment, the proposed model is more effective. The model proposed here apparently exceeds other algorithms in data segmentation processing.

(2) PointNet point cloud semantic segmentation neural network

Figure 6 portrays the accuracy and IoU of different elements of the designed PointNet point cloud semantic segmentation neural network model:

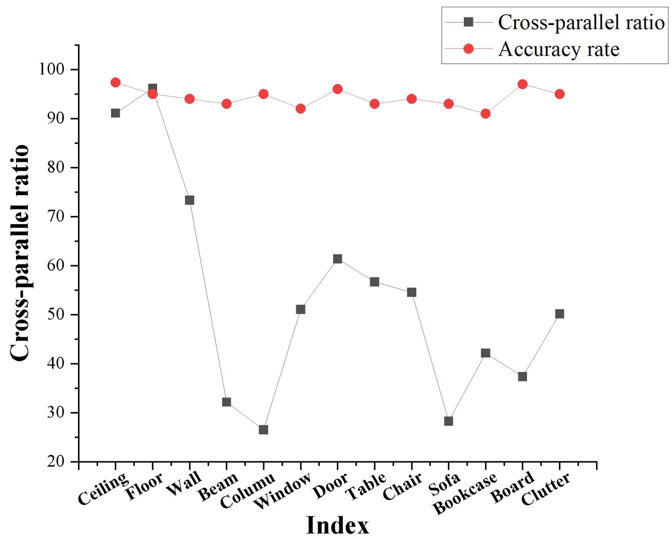


Figure. 6 Accuracy and IoU of different elements of the designed network model

Figure 6 describes that the accuracy of different elements in the test process is above 95%, the highest segmentation accuracy is 97.23% for the ceiling. The highest IoU is the floor at 96.13%, followed by the ceiling at 91.09%. This indicates that points in ancient architectural carvings can be accurately identified in the AI environment through the neural network PointNet for restoration. The variation of convergence speed under different learning rates in the outdoor test process is illustrated in Figure 7:

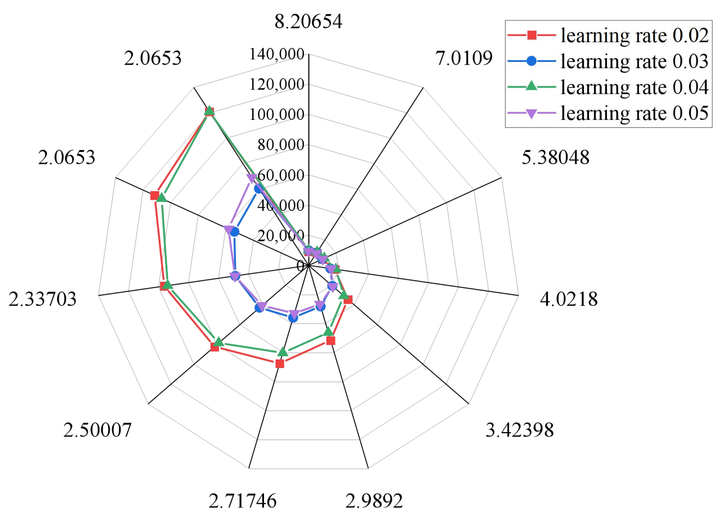


Figure. 7 Change of convergence speed with various learning rate

Figure 7 expresses that during the outdoor scene test, the convergence step is the shortest when the learning rate is 0.03, and the overall model is relatively stable. The learning rate during outdoor data collection is finally determined to be 0.03, and the segmentation result is more accurate. The comparison between the predicted and experimental values of the outdoor test is presented in Figure 8:

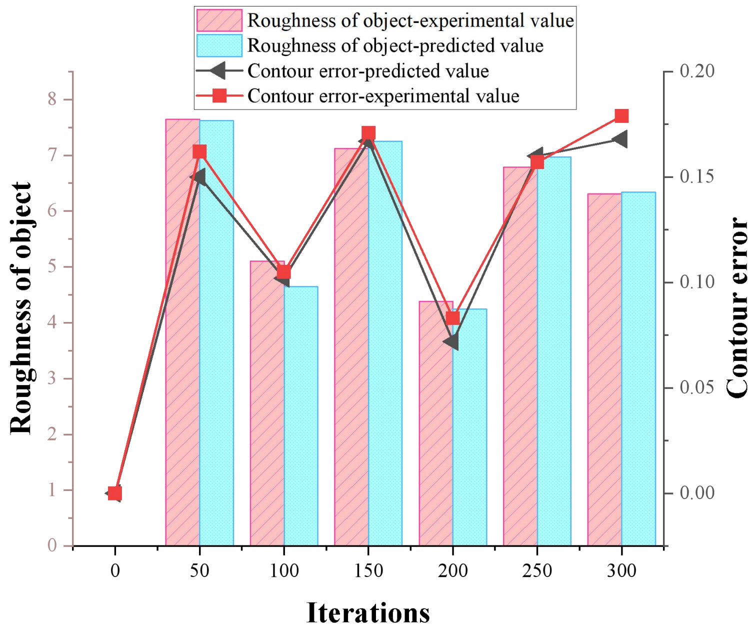


Figure. 8 Comparison of predicted and actual outdoor test values

Figure 8 details that in the process of outdoor testing, two indexes of object roughness and contour error are selected for testing. The results show that the object roughness error is only 0.01, and the contour segmentation and recognition error is 0.398. This means that in the context of AI, the application of the designed DNN PointNet in ancient architectural carving is feasible and highly accurate, offering a new method and idea for ancient architectural carvings' restoration and protection.

4.5 Discussion

Cui et al. used DNN to extract and classify the features of the 3D scanning data of cultural heritage and realized ancient architectural elements' identification and style classification (Cui, Liu, Liu, Zhang, Zare & Fan, 2021). Croce et al. proposed PointNet as a point cloud processing network extensively used in scene analysis, object recognition, and other fields. Its classification and feature extraction capabilities on point cloud data provide strong support for applying ancient architectural carving (Croce, Caroti, De Luca, Jacquot, Piemonte & Véron, 2021). Zhang et al. focused on the ancient buildings' digitization and preservation, covering these buildings' digital reconstruction using 3D laser scanning technology. This laid the foundation for the digital application and data acquisition of ancient architectural carvings (Zhang, Dai & Sun, 2020). The loss rate of the DLNN-based point cloud semantic segmentation model proposed in this study is ultimately stable at 0.05, the overall accuracy is 88.7%, and the MIoU is 73.7%. The accuracy rate of the designed network model is above 95%. During the outdoor scene test, when the learning rate is 0.03, the overall model stability is the highest, the object roughness error is only 0.01. The error of contour segmentation recognition is 0.398. Compared with previous studies, this study can quickly and accurately identify the carving style and elements through automatic detection and classification, which provides essential reference information for conservation work. The application of PointNet can realize the quantitative assessment of the damage of ancient architectural carving and more objectively assess the difficulty and priority of restoration.

5. CONCLUSION

5.1 Research contribution

In this study, the PointNet model in DL is applied to the field of ancient architectural carving, and according to the characteristics of point cloud data, the automatic detection, classification, and damage assessment of ancient architectural carving are realized. This innovative technology offers a new idea and method for restoring and protecting ancient architectural carvings. The feature extraction and classification results based on PointNet can help restorers develop more efficient and accurate restoration schemes for ancient architectural carvings. This is conducive to reducing labor and time costs in the repair process and guarantees the accuracy and stability of the repair effect.

5.2 Future works and research limitations

The point cloud data of ancient architectural carvings are often noisy and incomplete, such as missing data due to scanning equipment limitations or time erosion. These problems may affect PointNet's feature extraction and classification and require better data preprocessing and remediation methods. In the future, it is necessary to establish a larger and diversified point cloud dataset of ancient architectural carving, covering samples of different styles, periods, and damage conditions, to improve the generalization ability and accuracy of the model.、

ETHICS DECLARATIONS

Disclosure statement

No potential conflict of interest was reported by the authors.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

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