Classification of Alzheimer's Disease Using Improved MeshCNN based on Residuals Connection

Yuankun Liu[1], Duanyang Feng[1], Lumin Xing[2,1], Wenjian Liu[1]*

[1]City University of Macau, Macau S.A.R., China
[2]The First Affiliated Hospital of Shandong First Medical University, Shandong Provincial Qianfoshan Hospital, Jinan, China

澳門城市大學
Universidade da Cidade de Macau
City University of Macau

山东第一医科大学第一附属医院
THE FIRST AFFILIATED HOSPITAL OF SHANDONG FIRST MEDICAL UNIVERSITY
山东省千佛山医院
SHANDONG PROVINCIAL QIANFOSHAN HOSPITAL

Background

Significance:

- **The number of people with Alzheimer's disease（AD） is rapidly increasing.**
- **This disease severely affects patients' memory, intelligence, behavior, and emotions, among other aspects.**
- **Currently, no proven effective treatment has been found for this disease.**
- **At present, the only approach is to delay the progression of the disease through early intervention.**

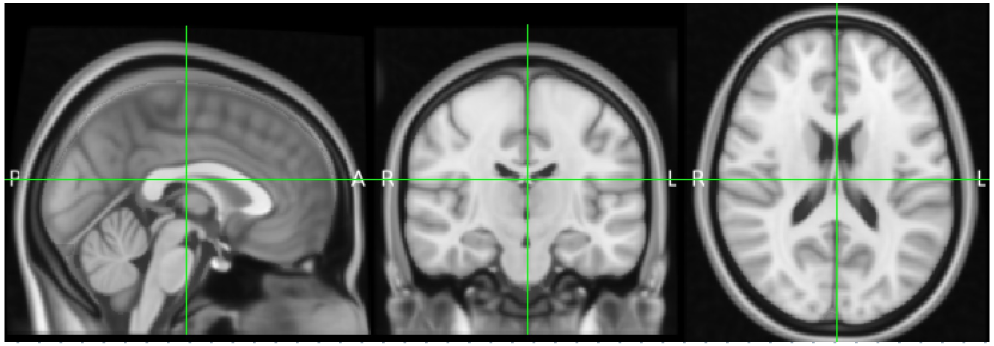
Background

Magnetic Resonance Imaging (MRI):

- **MRI is a medical imaging technique that can non-invasively obtain high-quality images of internal tissues of the human body. Its basic principle is to use contrast agents or external magnetic fields to cause water molecules in the human body to spin in resonance, generating magnetic resonance signals, which are then converted into images.**

Advantages of MRI:

- **High resolution**
- **Good image quality**
- **No radiation**
- **Non-invasive**
- **…**



Mesh

Why?

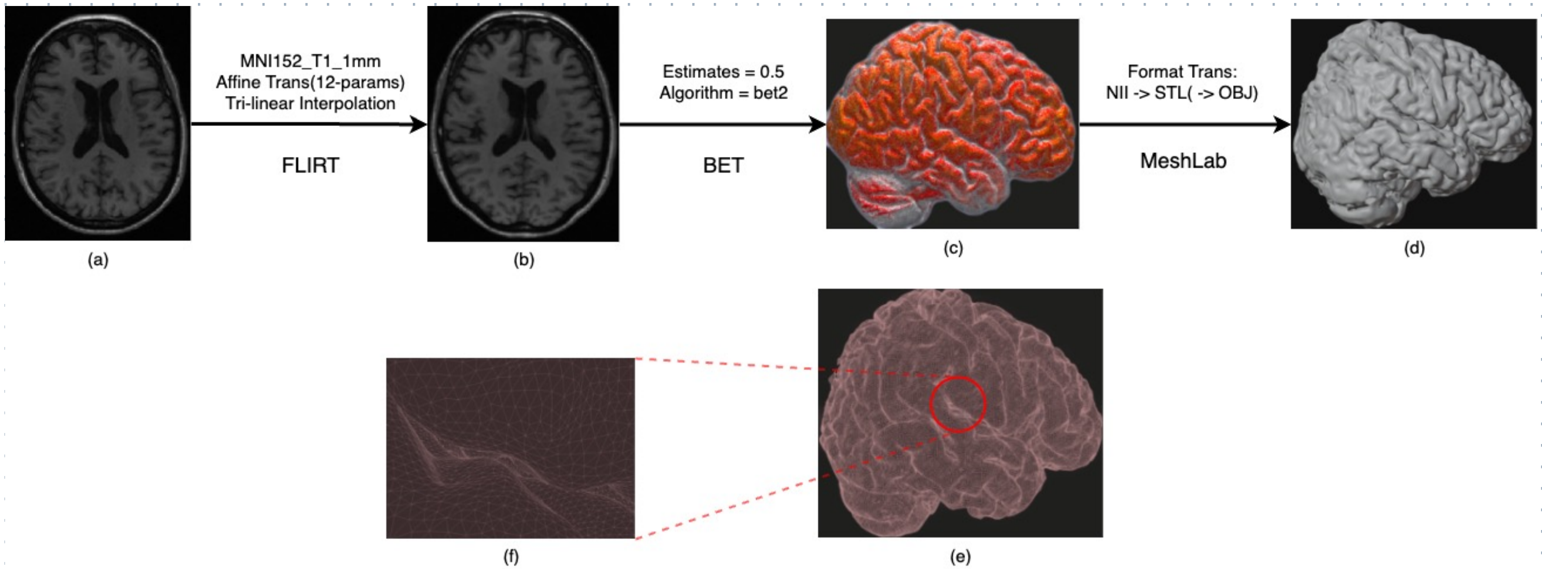
1. **Topological Structure: Compared to point cloud types, Mesh can better represent the details of objects.**
2. **Smaller File Size: Mesh data files tend to be smaller than point cloud data files because mesh data only stores the vertices and polygons needed to define the model.**
3. **Better Rendering: Mesh data can be rendered in real-time more easily compared to point cloud data.**
4. **Editing: Mesh data can be edited more easily compared to point cloud data.**
5. **Texturing: Applying textures to mesh data is easier than to point cloud data. Textures can be applied to the surfaces of polygons in the mesh, giving the model a more realistic and detailed appearance.**

Dataset

The dataset used in this study comes from ADNI. Since 2004, the ADNI dataset has gone through four versions, namely ADNI-1, ADNI-GO, ADNI-2, and ADNI-3. This study uses the ADNI-1 data from the ADNI subset. The total sample size is 1,473, of which 841 are males and 632 are females; 731 belong to the MCI category, 397 belong to the CN category, and 345 belong to the AD category.

Preprocessing

The original image format is DICOM, and the open-source software dcm2niix was used to convert it to NIFTI format. The Flirt algorithm provided by the FSL software was used for registration (aligning the original MRI images with a template), with the MNI152 serving as the registration template. The BET algorithm provided by FSL was used for segmentation (referred to as "skull stripping", preserving the complete brain and cerebellum structures). Subsequently, the MeshLab software was used to convert the NIFTI format image data into STL Mesh format.



Method

Mesh Block is the basic structure of the network, where the main part of the network consists of N blocks, and residual connections are added to it. The residual connections are placed before pooling because the convolution of the MeshCNN does not change the number of edges and vertices, while pooling does, and placing them here allows us to disregard the changes in the feature map.

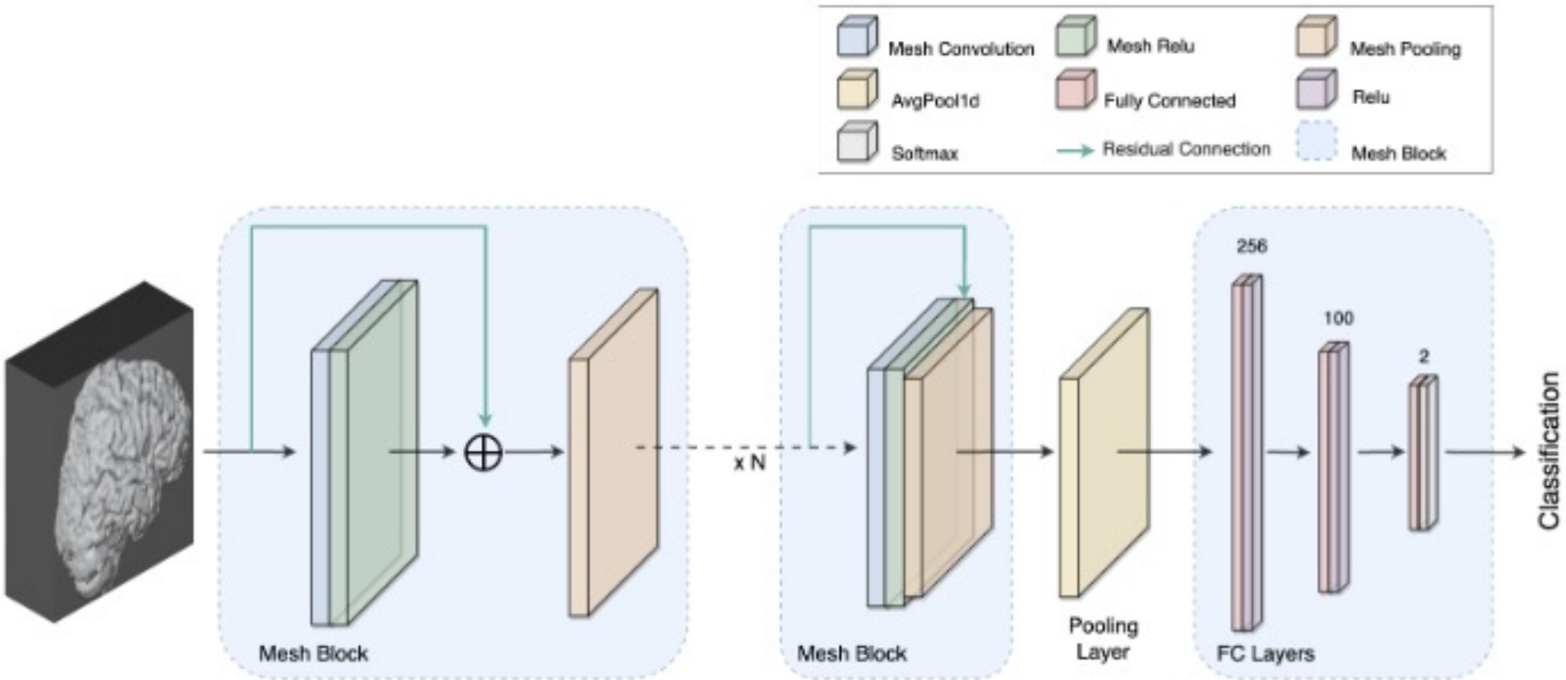


Fig. 2. Network Architecture

$$x_{l+1} = Pool_{Mesh}(Relu(Conv_{Mesh}(x_l) + x_l)) \qquad (1)$$

Method

The Mesh data first passes through a Mesh convolution layer after entering the first Mesh block, which does not affect the image size, and outputs the weighted sum of the current edge and the four non-common edges of its neighboring triangles as the value of the new common edge, therefore, the values of all common edges are generated. Once activated by the Relu function, the output of the convolutional layer enters the Mesh pooling layer.

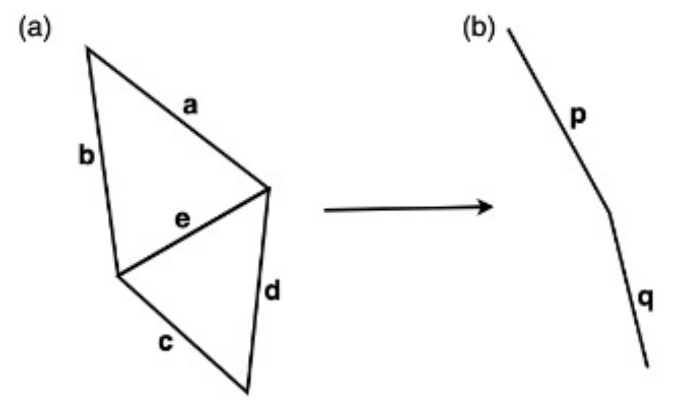


Fig. 4. Mesh convolution(a) and pooling(b)

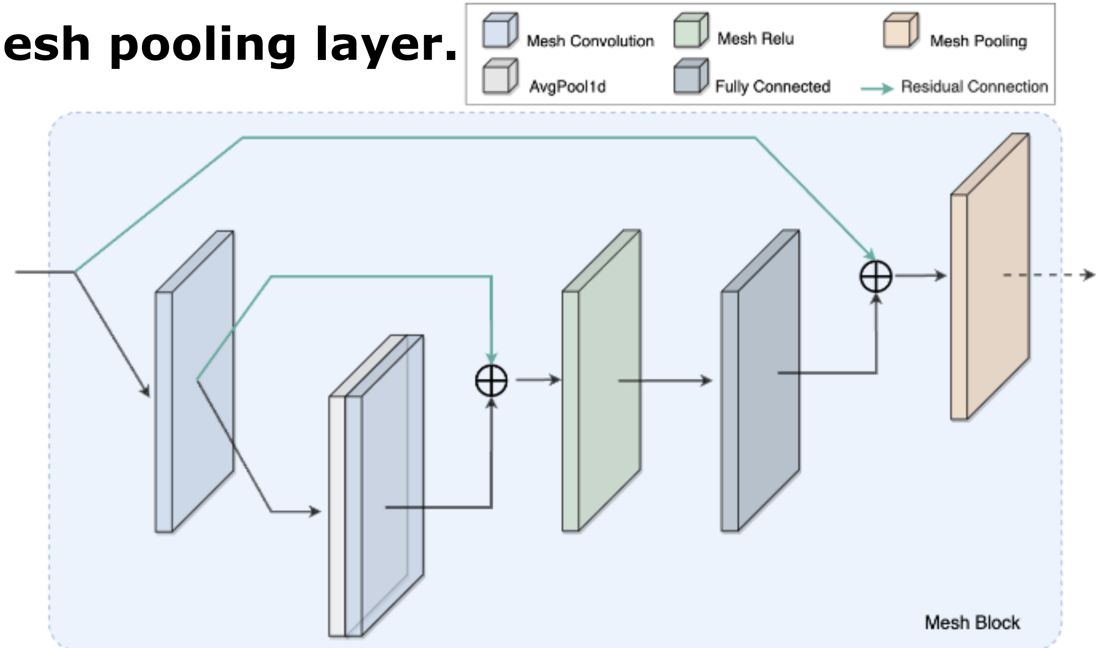


Fig. 3. MeshBlock details with residual connections included

$$Pool_{Mesh}(x_l) = (p, q) = (\sqrt{a^2+b^2+e^2}, \sqrt{c^2+d^2+e^2})$$

R. Hanocka, A. Hertz, N. Fish, R. Giryes, S. Fleishman, and D. CohenOr, "MeshCNN: a network with an edge," Acm T Graphic, vol. 38, no. 4, p. 90:1-90:12, Jul. 2019, doi: 10.1145/3306346.3322959.

Method

TABLE I

RANDOM PARAMETER SEARCH FOR OPTIMAL PARAMETER SELECTION (AD/CN)

Param	Scope
Batch Size	[1, 8, 16, **32**, 64]
Learning Rate	[0.0001, 0.0005, **0.001**, 0.005, 0.01]
Dropout	[0.3, 0.4, **0.5**, 0.6, 0.7]
Optim	[RAdam, SGD, **Adam**, RMSprop]

In this experiment, we adopted a random parameter search method to determine the optimal parameters, as shown in Table 1. In the table, we set the value ranges for different parameters, including batch size, learning rate, dropout probability, and optimizer type, among others. We randomly generated parameter combinations within these ranges and trained the model and evaluated its performance for each combination. Ultimately, we selected the parameter combination with the best performance for the model execution in this study.

Results

TABLE II

PROPOSED COMPARED WITH THE ORIGINAL MESHCNN (ALL VALUES ARE THE AVERAGE AFTER 10 ROUNDS OF PROGRAM CYCLING)

	Acc	Recall	F1	Notes
AD/CN	**0.99**	**0.99**	**0.98**	**proposed**
AD/CN	0.97	0.98	0.97	MeshCNN
AD/MCI/CN	**0.94**	**0.93**	**0.92**	**proposed**
AD/MCI/CN	0.93	0.94	0.91	MeshCNN

Table 2 displays the performance of our model in the AD/CN and AD/MCI/CN classification tasks. Compared to similar models, we can see that our model achieves a higher accuracy rate. It can be observed that classification for MCI still presents challenges.

Results

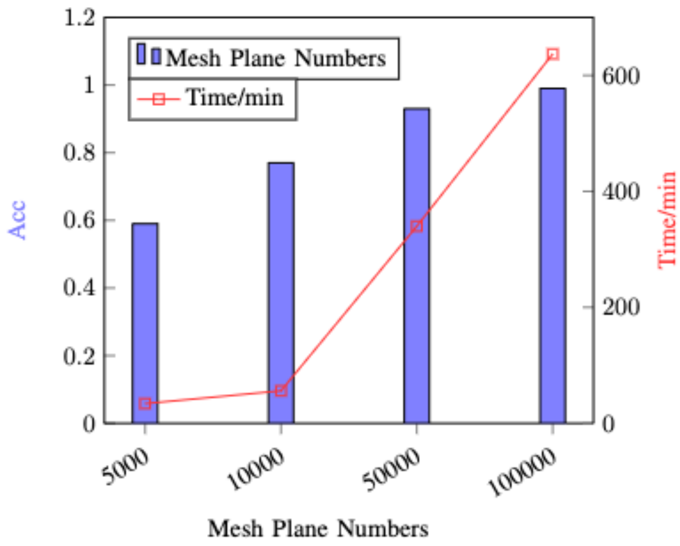


Fig. 5. The effect of different mesh plane numbers on the classification accuracy of AD/CN and the computational time under the optimal parameter settings

The data format used in this study is in mesh format. Therefore, it's necessary to consider the impact of different numbers of mesh planes on classification accuracy, training time, and the computational capability and memory of GPU devices. As shown in Figure 5, with the increase in the number of mesh image planes, the accuracy improves, and the relationship between the number of planes and time follows a linear trend. Hence, it can be concluded that finer images contain more information, which is consistent with the impact of Alzheimer's disease on brain morphology.

Conclusion

This study indicates that, compared to partial brain mesh data, using the complete brain mesh data can provide a more comprehensive view of the overall brain changes, thereby enhancing the classification accuracy for Alzheimer's disease. The potential of the complete brain mesh data in Alzheimer's disease classification warrants further investigation. While the method adopted in this study has been proven to enhance classification accuracy, it demands significant computational power. Future research could address this by reducing computational requirements. Efforts have also begun to explore the classification of Alzheimer's disease using multimodal data, which might further boost accuracy. Future studies can pay more attention to this domain. It's worth noting that this study is confined to MRI images of Alzheimer's disease and might not be applicable to other neurodegenerative diseases or imaging techniques.

https://github.com/lyk7539511/MeshCNNwithRes

Thank you for listening!

Classification of Alzheimer’s Disease Using Improved MeshCNN based on Residuals Connection