SURFACE RECONSTRUCTION FOR THE MASSES: PIALGCN FOR EFFICIENT SURFACE RECONSTRUCTION

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Introduction

Brain surface reconstruction traditionally relies on Freesurfer for 3D mesh generation but is slow. Recent deep learning methods, using outputs from Freesurfer for supervised learning, significantly improve processing speeds. Our research focuses on enhancing the Pial Surface generation in PialNN using Graph Convolutional Networks (GCNs), improving accuracy and reducing memory consumption, suitable for web-based applications.

Methodology

We used data from 897 patients in the Human Connectome Project, divided into training, validation, and test sets. Our approach integrates GCNs into PialNN, enhancing vertex predictions with neighborhood data and reducing the number of deformation modules for efficiency. We utilized PyTorch Geometric and PyTorch 3D for implementation. The model used for this study is available at this link[1].

The ground truth surfaces used during training were derived from FreeSurfer, which provides detailed cortical surface reconstructions. The training process involved Mean Squared Error (MSE) between the predicted template deformed FreeSurfer White Surface and the ground truth Pial Surface. During training, MSE was used to directly minimize the difference between predicted and ground truth vertex positions. During validation, Chamfer Distance was used as an alternative to measure the distance between point clouds of the predicted and ground truth surfaces.

The impact of GCN depth on memory and accuracy was assessed, with models varying from 2 to 7 GCN layers to find the optimal balance between performance and computational efficiency.

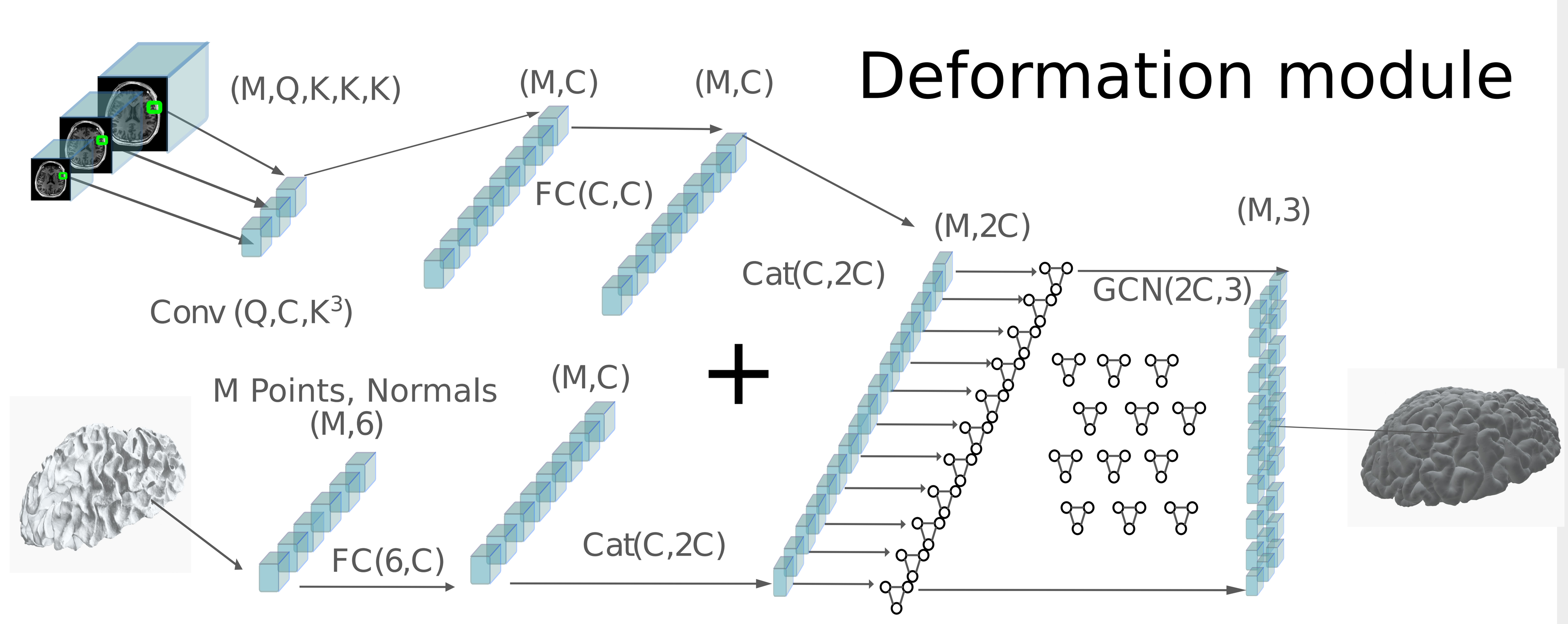

Figure 1: Extension of the PialNN architecture to include GCNs.

Results

Our GCN-enhanced model showed reduced memory usage and improved accuracy compared to traditional methods. Deeper GCN layers increased accuracy but also memory consumption. Visual and quantitative analyses confirmed the benefits of GCNs in reducing Hausdorff distance errors and improving surface reconstruction quality.

[1] https://github.com/neuroneural/cortexGNN/blob/697964e1c15a49ed18523b66ae6e66c74d3f06e5/model/cortexGNN.py

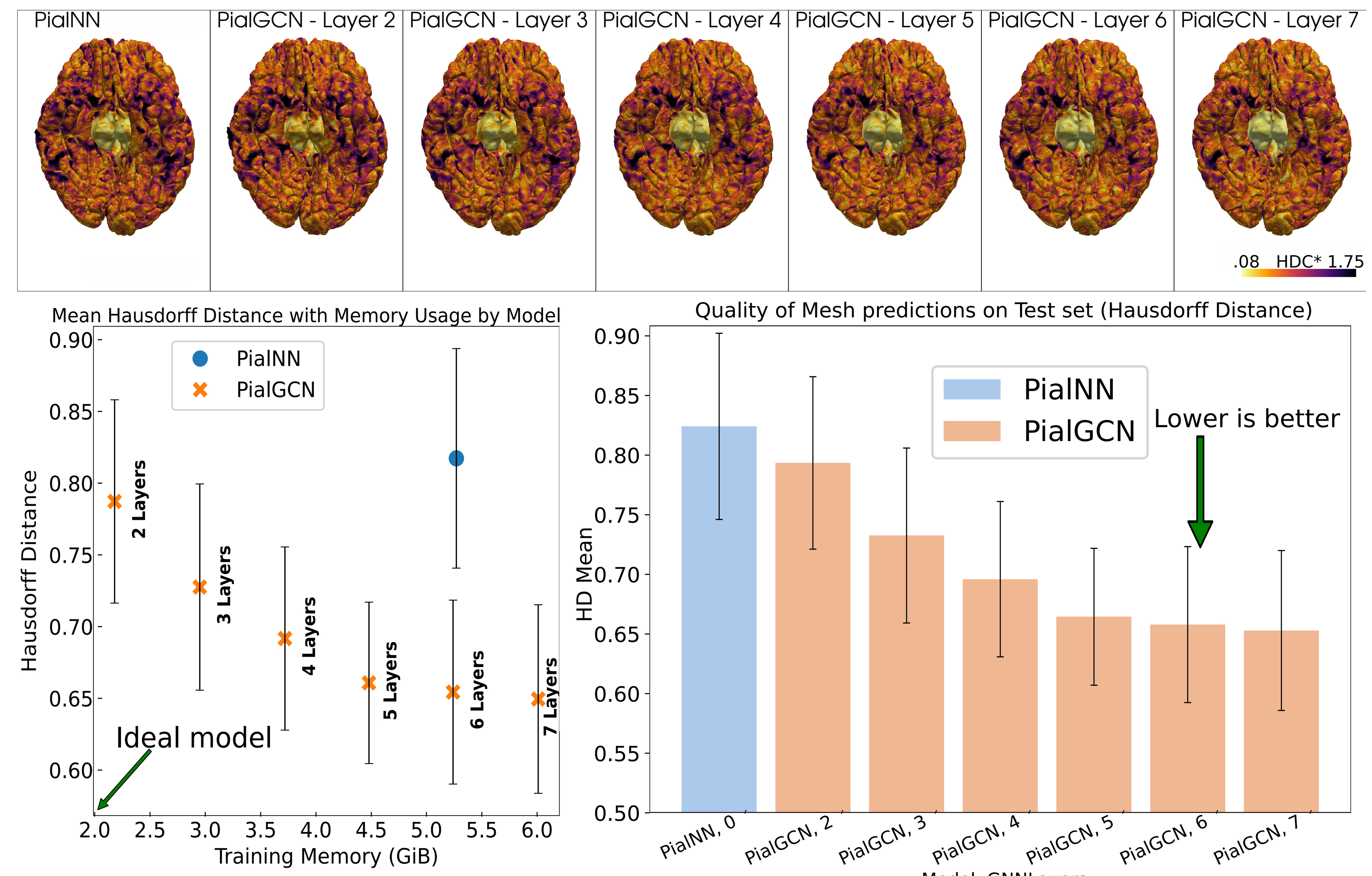

Figure 2: Impact of GCN depth on memory usage and prediction accuracy.

Conclusion

Incorporating GCNs into PialNN significantly enhances brain surface reconstruction, balancing accuracy and memory usage. This advancement supports efficient, high-precision processing for web and mobile applications. Future work will focus on optimizing GCN layers for practical deployment in medical imaging.

References

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