RIMeshGNN: A Rotation-Invariant Graph Neural Network for Mesh Classification
Supplementary Material

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1. Ablation Studies

In this section, we evaluate the impact of various design choices on the performance of RIMeshGNN for 3D shape classification. We perform several ablation studies using the Manifold40 dataset to examine the effects of each design element. The network is trained for 500 epochs in all experiments.

Local Pooling Layer: The use of the proposed local pooling layer within our classification network was investigated as one of our design choices. Experiments with the Manifold40 mesh models indicate a small improvement in classification accuracy when the pooling layer is incorporated. It is worth noting that the effect of the local pooling layer may have a greater impact on the classification of datasets with more complex objects or when higher-resolution meshes are used as input.

Number of GNN layers: We employ a series of GNN layers to capture node and edge dependencies over extended distances, enabling information propagation through multiple hops. Our experiments began with two stacked layers and increased to 10 layers. We found that the model achieves the highest accuracy with six stacked layers while maintaining a large receptive field, as detailed in the experimental section. Adding more layers does not enhance accuracy, but increases network size and computation time. Table 1 displays the performance of RIMeshGNN with different numbers of stacked GNN layers when trained on the Manifold40 dataset.

Number of GNN layer	Accuracy
2	80.9%
4	88.1%
6	**90.7**%
8	86.9%
10	62.5%

Table 1. Experimental results on Manifold40 classification for RIMeshGNN with a various number of stacked GNN layers. The bold number indicates the best performance.

Number of spherical bins	Accuracy
2	69.1%
4	87.4%
6	88.0%
8	**90.7** %
10	90.4%
12	83.4%

Table 2. Experimental results for Manifold40 classification for RIMeshGNN with a various number of spherical bins used in the aggregation function. The bold number indicates the best performance.

Number of spherical bins in the aggregation function of the GNN: We performed multiple experiments with RIMeshGNN with 6 stacked GNN layers to determine the optimal number of spherical bins for aggregating node features in our proposed GNN. The findings are presented in Table 2. Based on the results, we selected eight spherical bins for the design of the aggregation function.

Evaluating the Impact of Incorporating Vertices' Coordinates and Normal Vectors: In the input features of RIMeshGNN, vertices' coordinates and normal vectors are the only ones that change under rotation transformation. All other input features are rotation-invariant, and rotating the object does not impact them. To highlight the importance of node-level geometric features to our classification network design, we removed the coordinates and normal information from the input features, which are then fed into a modified version of our GNN layers that do not utilize coordinate and normal information. Specifically, we exclude $\|x_i - x_j\|_2$ and $n_i.n_j$ from Equation 1, remove Equations 2 to 4 and 7 to 9 in the calculation of graph attribute h_g^{l+1} and use the average of invariant nodes features instead in Equation 6. We obtained the classification accuracy of only 68.3% in this

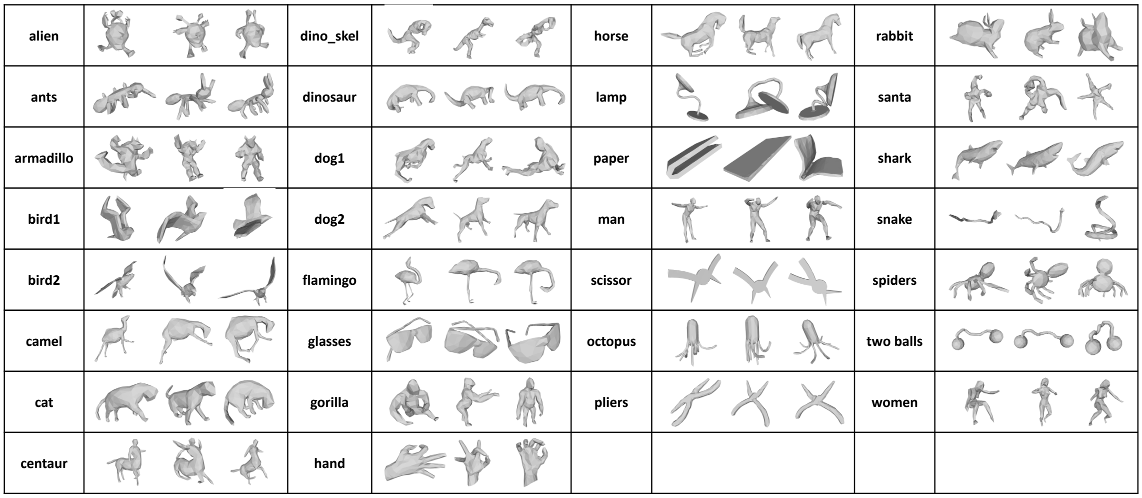

Figure 1. Three typical models from each of the 30 object categories in the SHREC11 dataset [3].

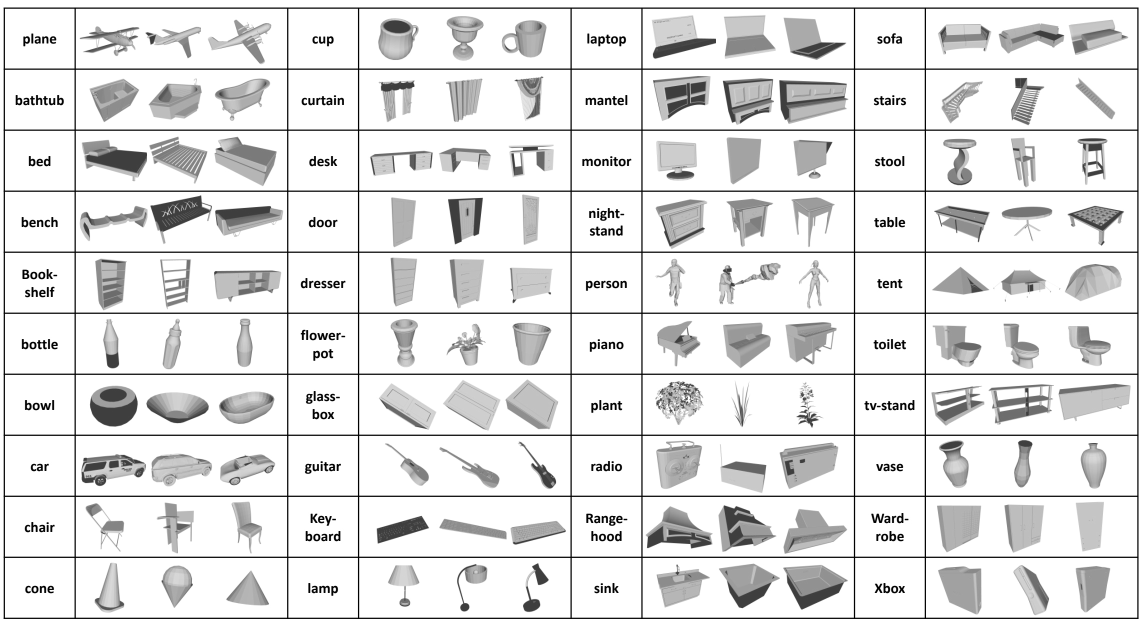

Figure 2. Three typical models from each of the 40 object categories in the ModelNet40 dataset [4].

experiment, which emphasizes the critical contribution of the coordinate and normal information to the classification task.

2. Project Repository

The code and dataset of this project can be found at the project repository:
https://github.com/BSResearch/RIMeshGNN

3. Datasets

In order to visually represent SHREC11 [3] and ModelNet40 [4] datasets, we randomly selected three samples from each of the 30 categories in SHREC11 and 40 categories in ModelNet40, as labelled by the respective datasets. Figures 1 and 2 serve as visual representations, offering researchers an overview of the dataset contents.

Figure 2 also draws attention to the presence of noise and cross-labeling issues in the ModelNet40 dataset. For instance, the second sample in the "stool" class is mislabeled, actually belonging to the "chair" category. Additionally, there are cross-labeling issues between the categories of flowerpot/plant/vase and desk/table as also mentioned in [2] and [1]. These instances shed light on the inherent challenges and complexities of the dataset, emphasizing the importance of careful consideration and evaluation when utilizing the ModelNet40 dataset for research purposes. Finally, it is worth mentioning that the models in this report have been evaluated using the original ground truth provided by ModelNet40.

References

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