Classification of Intestinal Gland Cell-Graphs Using Graph Neural Networks

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Why Graphs?
Pathologists consider morphological changes in tissue, spatial relationship between cell (sub-) types, density of certain cells etc.

Graphs are able to represent the geometrical and topological properties of colorectal glands

Graph Neural Networks (GNNs)

- Message Passing (Graph Convolution): Send message of features to all neighbors → update hidden state according to graph convolution type. More layers = larger neighborhood to collect information from
- Read-out phase: Compute vector representation of the whole graph $v_G$ → used to perform classification

Experimental Setup

- Graph convolutional layers: Graph Convolution Network (GCN), GraphSAGE, Graph Attention Networks (GAT), Edge Network (enn), Graph Isomorphism Network (GIN), 1-dimensional GNN (1-GNN)
- Compare two node feature sets: 4 features used by baseline versus full features set (33)
- 4-fold cross-validation
- Binary classification: normal or dysplastic gland

PT1-Gland Graph Dataset

- 26 well-defined glands extracted from H&E stained images from 20 different patients (13 dysplastic, 13 normal) → 520 in total
- Graph representations: one node for each cell. Every node is connected to its spatially two closest neighbours.

33 node features extracted using QuPath (based on the cytoplasm staining, cell, and nucleus)

Results

Table 1: Average accuracy and standard deviation achieved by the different GNN architectures on the full and baseline node feature set, along with the Graph Edit Distance (GED) baseline and a additional CNN baseline (with and without image rotation data augmentation).

<table>
<thead>
<tr>
<th># Node Features</th>
<th>1-GNN</th>
<th>4 (baseline)</th>
<th>3 (all)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GED-Baseline\textsuperscript{[1]}</td>
<td>83.3 (\pm) 1.7%</td>
<td>89.1 (\pm) 3.7%</td>
<td>93.7 (\pm) 3.0%</td>
</tr>
<tr>
<td>CNN (VGG-16)</td>
<td>91.8 (\pm) 5.5%</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>CNN (VGG-16-Rotation)</td>
<td>92.0 (\pm) 5.1%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\textsuperscript{[1]} Graph-based Classification of Intestinal Glands in Colorectal Cancer Tissue Images, Studer et al., COMPAY workshop, MICCAI 2019

Conclusion

- Different types of GNNs achieve similarly good results
- GNNs can profit from the full 33 node feature set
- Beat SOTA results achieved with Graph Edit Distance (GED)

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