Deep Learning-based Type Identification of Volumetric MRI Sequences

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Introduction

- Magnetic Resonance Imaging (MRI):
  - Analysis of brain tumor progression:
    - Interest on automating the process.
  - MRI sequences must be well identified:
    - However, unstandardized naming protocols.
- Proposed solution:
  - Convolutional Neural Network (CNN) to classify among MRI sequence types.
Related works

● Noguchi et al. (2018):
  ○ MRI classification based on the first or central slice of the volumes;
  ○ Small dataset.

● Ranjbar et al. (2019):
  ○ Single-slice classification;
  ○ No guarantee that slices from the same volume do not occur in train and test sets;
  ○ Missing/contradictory information;

● Also, both works use private datasets, hindering comparability.
Proposed solution

Figure 1: Overview of the proposed method (volume from TCGA-GBM* dataset)

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Proposed solution

Figure 2: Distinction between the main sequence types recognized by the classifier (volume from TCGA-GBM dataset in the overview and from BraTS* dataset in the foreground)

*Publicly available. No license information found.
Experiments

- Datasets:

<table>
<thead>
<tr>
<th></th>
<th>BraTS (pre-processed data)</th>
<th>TCGA-GBM (non-pre-processed data)</th>
<th>BraTS + TCGA-GBM (mixed data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All five classes</td>
<td>-</td>
<td>TCGA5</td>
<td>BRATS+TCGA5</td>
</tr>
<tr>
<td>No “OTHER” class</td>
<td>BRATS4</td>
<td>TCGA4</td>
<td>BRATS+TCGA4</td>
</tr>
</tbody>
</table>

Table 1: Datasets assembled for the experiments
Experiments

- Study on the input volume:
  - $n = 1, 2, \ldots, 16$

Figure 3: Study on the input volume: random $n$-depth subvolume from 1 to 16 slices (volume from TCGA-GBM dataset)

- Study on the use of pre-processed data:

Figure 4: Slices from a pre-processed volume (left; from BraTS dataset) and from a non-pre-processed volume (right; from TCGA-GBM dataset)
Results

- Study on the input volume:
  - Figure 5: Validation macro-accuracy across the considered volume depths ($n$). The highest accuracy is obtained for $n = 4$

- Study on the use of pre-processed data:
  - Figure 6: Test macro-accuracies regarding the use of pre-processed data

No “OTHER” class

<table>
<thead>
<tr>
<th></th>
<th>PP</th>
<th>M</th>
<th>NPP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>PP</td>
<td>M</td>
<td>NPP</td>
</tr>
<tr>
<td>Test</td>
<td>PP</td>
<td>M</td>
<td>NPP</td>
</tr>
</tbody>
</table>

All five classes

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<tbody>
<tr>
<td>Train</td>
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</tr>
<tr>
<td>Test</td>
<td></td>
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</tbody>
</table>
Conclusions

● High accuracy on classifying among MRI sequence types:
  ○ Even considering several acquisition protocols.

● Better generalization by mixing pre-processed and non-pre-processed data;

● Possible improvements:
  ○ Better distinguishing between T1 and T1c;
  ○ Recognition of more sequence types.
Thanks!

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