Causality-Driven One-Shot Learning for Prostate Cancer Grading from MRI

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Motivation

• Find a way to exploit intrinsic information: weak causal signals
• Work in low-data scenario, as in the medical domain: Few-Shot Learning

Methods

1) Extract features

\[F_1, F_2, \ldots, F_k\]

2) Compute causality maps

\[P(F_i|F_j) = \frac{P(F_i, F_j)}{P(F_i)}\]

Max

\[P(F_i|F_j) = \sum_{x \in \mathcal{X}} \frac{P_i(x) \cdot P_j(x)}{P(F_i)}\]

Lehmer

\[P(F_i|F_j) = \frac{LM_{ij}(F_i \times F_j)}{LM(F_j)}\]

E.g. F0 F1 F2 F3

\[\begin{array}{cccc}
F_0 & 0.51 & 0.55 & 0.46 & 0.85 \\
F_1 & 0.94 & 0.55 & 0.61 & 0.72 \\
F_2 & 0.94 & 0.55 & 0.61 & 0.72 \\
F_3 & 0.85 & 0.72 & 0.13 & 0.50 \\
\end{array}\]

Conditional asymmetries

\[P(F_0|F_2) > P(F_2|F_0) \implies F_0 \rightarrow F_2\]

\[P(F_1|F_2) > P(F_2|F_1) \implies F_1 \rightarrow F_2\]

\[P(F_2|F_3) > P(F_3|F_2) \implies F_2 \rightarrow F_3\]

3) Determine causality factors

4) Multiply and concatenate

Results

<table>
<thead>
<tr>
<th>Setting</th>
<th>2-way 1-shot</th>
<th>4-way 1-shot</th>
<th>4-way 1-shot*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main experiments</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non causality-driven</td>
<td>0.539 (0.141)</td>
<td>0.585 (0.068)</td>
<td>0.586 (0.118)</td>
</tr>
<tr>
<td>Causality-driven mulcat</td>
<td>0.550 (0.144)</td>
<td>0.611 (0.069)</td>
<td>0.712 (0.118)</td>
</tr>
<tr>
<td>Causality-driven mulcatbool</td>
<td>0.556 (0.141)</td>
<td>0.614 (0.067)</td>
<td>0.713 (0.119)</td>
</tr>
</tbody>
</table>

Ablation study

| Ablation mulcat              | 0.535 (0.143)| 0.557 (0.063)| 0.557 (0.111)|
| Ablation mulcatbool          | 0.540 (0.139)| 0.571 (0.068)| 0.612 (0.119)|

*: trained to distinguish four classes (ISUP 2 − 5), but the AUROC is computed between ISUP 2 vs. rest.

Conclusion

Integrating causality into a CNN model can:

• Enhance performance (classification metrics)
• Help the model focus more accurately on the critical regions of the image, leading to more reliable and robust predictions.