Learn to Segment Retinal Lesions and Beyond

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Abstract

This paper focuses on simultaneously pixel-level retinal lesion segmentation and image-level disease classification. Following discussions are in the context of:

1. **Five grades diabetic retinopathy (DR) classification**
   - no DR, mild NPDR, moderate NPDR, severe NPDR, PDR

2. **Eight DR-related lesions segmentation**
   - MA, iHE, HaEx, CWS, vHE, pHE, NV, FiP

Three challenges:

1. Lesions lacking objective boundaries;
2. Clinical importance of lesions are irrelevant to their size;
3. Lesions and disease classes have no one-to-one correspondence.

Our solutions, accordingly:

1. Lesion-Net with adjustable expansive path;
2. Dual loss that combine segmentation loss and classification loss;
3. Multi-task network that harnesses lesions to improve disease classification.

Lesion-Net for Lesion Segmentation

- **Natural object segmentation**: objects with precise boundaries ⇒ cutting-edge contracting path + carefully designed expansive path
- **Retinal lesion segmentation**: lesions have no objective boundaries ⇒ learn to segment with imprecise boundaries
- **Lesion-Net**: adjustable expansive path + dual loss

**Dual loss**: $\text{loss}_\text{dual} = \lambda \cdot \text{loss}_\text{seg} + (1 - \lambda) \cdot \text{loss}_\text{clf}$

$\lambda \in [0,1]$: hyper parameter to strike a balance between the two sub-losses $\text{loss}_\text{seg}$ and $\text{loss}_\text{clf}$; lesion segmentation loss and lesion classification loss. $\text{loss}_\text{clf}$ can indicate mis-classification of small lesions.

Image-level lesion classification are generated by global max pooling on the segmentation results.

Multi-task Network

Three tasks in one model:

1. lesion segmentation
2. lesion classification
3. DR grading

Main branch (top, Inception-v3): feature extraction

Side-attention branch (down, Lesion-Net-16s): injecting semantic and spatial information contained in the 8 lesion segmentation maps into the main branch.

Experiments

Dataset: 12,252 images from local hospitals and EyePACS dataset. Each image is annotated with image-level DR grade and pixel-level lesions. EyePACS part of the test set has been released on [https://github.com/WeiQijie/retinal-lesions](https://github.com/WeiQijie/retinal-lesions)

Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Lesion segmentation</th>
<th>Lesion classification</th>
<th>DR grading</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCN-8s</td>
<td>0.586</td>
<td>0.778</td>
<td>-</td>
</tr>
<tr>
<td>U-Net</td>
<td>0.570</td>
<td>0.757</td>
<td>-</td>
</tr>
<tr>
<td>DeepLabv3+</td>
<td>0.553</td>
<td>0.794</td>
<td>-</td>
</tr>
<tr>
<td>DANet</td>
<td>0.585</td>
<td>0.775</td>
<td>-</td>
</tr>
<tr>
<td>Inception-v3</td>
<td>-</td>
<td>-</td>
<td>0.774</td>
</tr>
<tr>
<td>ABN</td>
<td>-</td>
<td>-</td>
<td>0.797</td>
</tr>
<tr>
<td>Multi-task network</td>
<td>0.591</td>
<td>0.801</td>
<td>0.803</td>
</tr>
</tbody>
</table>

Take-home message

1. Lesion-Net is effective for segmenting retinal lesions with imprecise boundaries;
2. Multi-task network can simultaneously achieve three tasks;
3. Multi-task network gets better performance in all three tasks.

Segmentation examples