Leveraging Machine Learning for Optimal Detection of Retinal Vascular Occlusions Using Fundus Images

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Introduction

Central Retinal Artery Occlusion (CRAO), Central Retinal Vein Occlusion (CRVO), and Branched Retinal Vein Occlusion (BRVO) result from blood flow obstruction in different parts of the retinal vasculature [1].

CRAO cases are ophthalmologic emergencies demanding immediate identification and treatment [2].

Primary care physicians need to distinguish CRAO from non-emergent occlusions like BRVO and CRVO.

The goal of this pilot study is to develop a machine learning model to predict normal, BRVO, CRVO, and CRAO fundoscopy images.

Methods

A dataset of normal, BRVO, CRVO, and CRAO fundus images (120 images in total) was curated [3].

- 38 normal fundus images
- 44 BRVO fundus
- 22 CRVO fundus
- 16 CRAO fundus images

- 120 images & 16 images per batch ⇒ 8 batches.
- Once all 8 batches go through the model, one epoch is complete.

The model was trained on Google Teachable Machine (GTM) for 100 epochs with a batch size of 16.

External validity assessed with a total of 20 separate fundus images [4,5,6]

85% (102 images) of the images were used for training.

15% (18 images) were used for testing the model.

Accuracy, precision, recall and F-1 score calculated from confusion matrix.

Table 1: Metrics generated from confusion matrix

<table>
<thead>
<tr>
<th>Class</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F-1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>BRVO</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>CRVO</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>CRAO</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 2: Prediction accuracy and confidence on external validity assessment

<table>
<thead>
<tr>
<th>Prediction Accuracy</th>
<th>Prediction Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>BRVO</td>
</tr>
<tr>
<td>Normal</td>
<td>BRVO</td>
</tr>
<tr>
<td>Mean</td>
<td>0.00</td>
</tr>
<tr>
<td>STDEV</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Figure 1: Accuracy plots from GTM

Figure 2: Loss plots from GTM

Results

- Collect other pathologic retinal images to make model more complex and clinically useful.
- Expand the study to include other image classification and detection models to generate best model.

Future Studies

- Small number of images to train and test the model ⇒ model is most likely not as generalizable at the moment.
- Only 3 pathologies are tested ⇒ test more pathologic images to make more clinically relevant

Limitations

- Some signs of overfitting present as indicated by loss plots.

Conclusions

GTM can effectively predict various retinal vascular occlusions using a limited dataset according to the metrics.

References

6. Rejath Jose, OMS III, Adriel Abraham, OMS IV, Zain Satti, OMS IV, Thomas Jacob, OMS IV, Himani Jani, OMS IV, Milan Toma., PhD

The model is most likely not as generalizable at the moment.

Accuracy could be significantly impacted by the addition of more fundus images with diverse backgrounds and color combinations.

Figure 3: Normalized confusion matrix