Tensorflow-Image-Segmentation-IDRiD-Retinal-Vessel (2025/03/09)

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This is the first experiment of Image Segmentation for **IDRiD Retinal Vessel** based on the latest Tensorflow-Image-Segmentation-API, and our dataset Antillia-Augmented-IDRiD-Dataset.zip (2.06G).

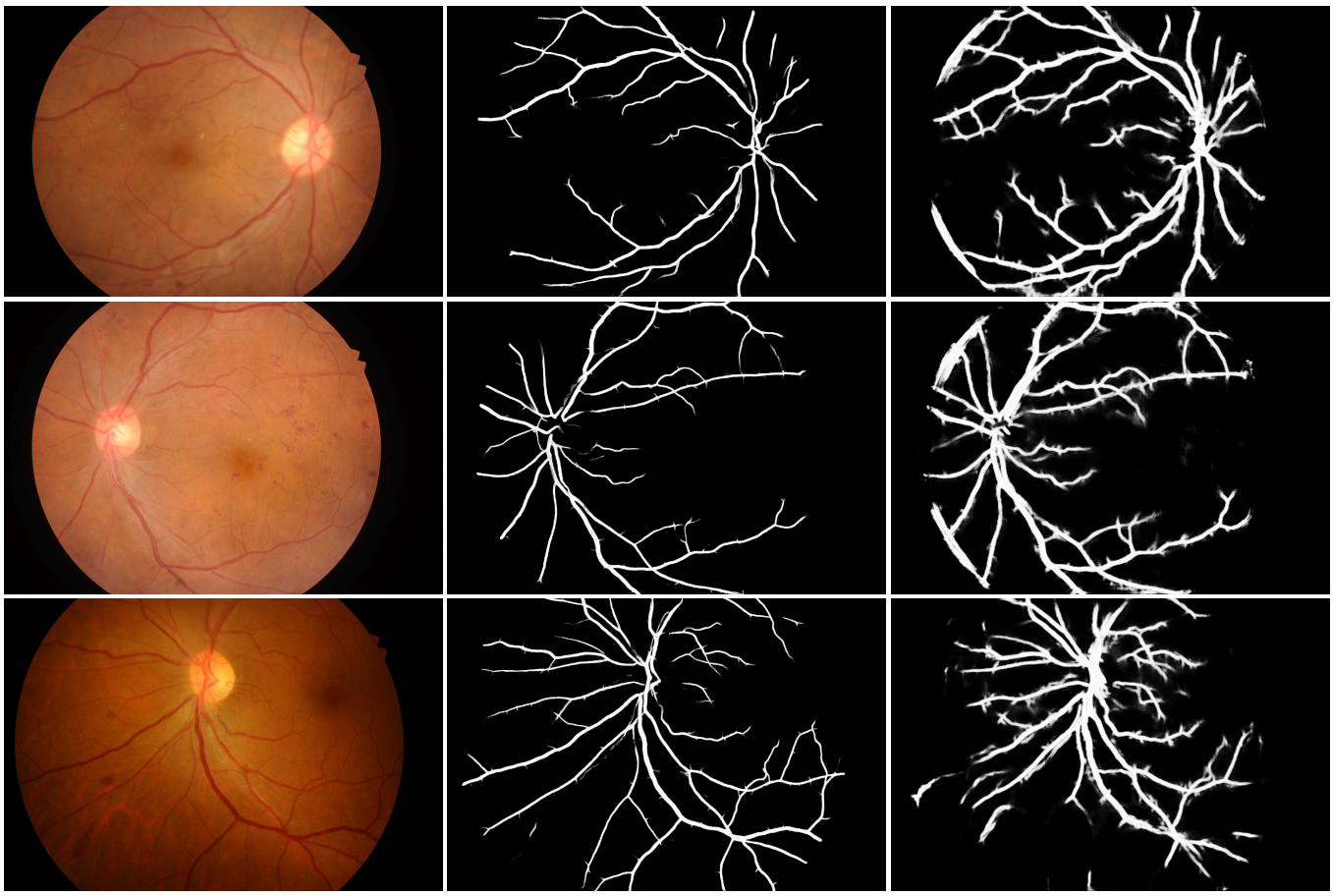
Please see also our experiments:
- Tensorlfow-Tiled-Image-Segmentation-IDRiD-Retinal-Vessel based on Indian Diabetic Retinopathy Image Dataset (IDRiD)
- Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-HRF-Retinal-Vessel based on High-Resolution Fundus (HRF) Image Database.
- Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-DRIVE-Retinal-Vessel based on DRIVE: Digital Retinal Images for Vessel Extraction
- Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-STARE-Retinal-Vessel based on STructured Analysis of the Retina.
- Tensorflow-Image-Segmentation-Retinal-Vessel based on CHASE_DB1 dataset.

Experiment Strategy
As demonstrated in Tensorflow-Image-Segmentation-FIVES-Retinal-Vessel , COLOR SPACE CONVERSION (cv2.COLOR_BGR2Luv) was effective in Non-Tiled Segmentation for Retinal Vessel. Therefore we employed the same method for this IDRiD Segmentation model.

Actual Image Segmentation for IDRiD images of 4288x2848 pixels
Our segementation model infers masks that are similar to the ground truth, but it does not produce satisfactory results in detail. The simple UNet model, which takes input images of 512x512 pixels, does not work well for segmenting of high-resolution images.

For segmentation of large images using UNet, employing a divide and conquer algorithm is a good idea. Since large images cannot be processed all at once, they are divided into small tiles. Segmentation processing is then applied to these divided small images, and finally, they are reassembled to their original size. This is our proposed Tiled Image Segmentation method Tensorlfow-Tiled-Image-Segmentation-IDRiD-Retinal-Vessel

Input: image	Mask (antillia ground_truth)	Prediction: inferred_mask



In this experiment, we used the simple UNet Model TensorflowSlightlyFlexibleUNet for this HRFSegmentation Model.
As shown in Tensorflow-Image-Segmentation-API. you may try other Tensorflow UNet Models:

- TensorflowSwinUNet.py
- TensorflowMultiResUNet.py
- TensorflowAttentionUNet.py
- TensorflowEfficientUNet.py
- TensorflowUNet3Plus.py
- TensorflowDeepLabV3Plus.py

1 Dataset Citation

The dataset used here has been take from the following **IEEE DataPort** web site
Indian Diabetic Retinopathy Image Dataset (IDRiD)

Please see also **DIABETIC RETINOPATHY: SEGMENNTATION AND GRAND CHALLENGE**

Citation Author(s):
Prasanna Porwal, Samiksha Pachade, Ravi Kamble, Manesh Kokare, Girish Deshmukh,
Vivek Sahasrabuddhe, Fabrice Meriaudeau,
April 24, 2018, "Indian Diabetic Retinopathy Image Dataset (IDRiD)", IEEE Dataport,

DOI: https://dx.doi.org/10.21227/H25W98

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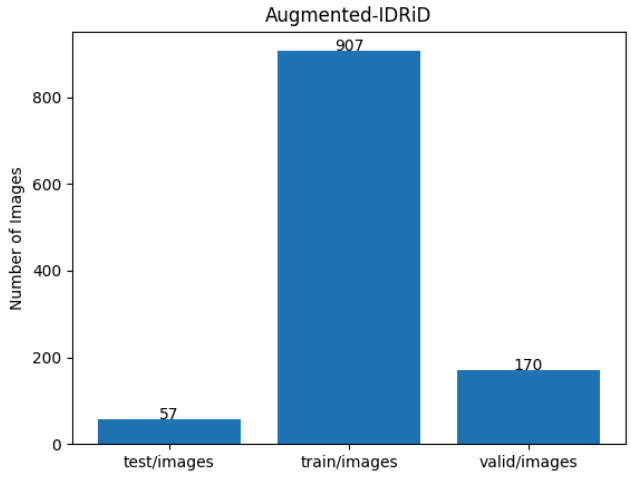
2 Augmented IDRiD Retinal Vessel Dataset

Please download the dataset from the google drive Antillia-Augmented-IDRiD-Dataset.zip (2.06G), expand it and place it under ./dataset to be.

```
./dataset
└─Augmented-IDRiD
    ├─test
    │  ├─images
    │  └─masks
    ├─train
    │  ├─images
    │  └─masks
    └─valid
       ├─images
       └─masks
```

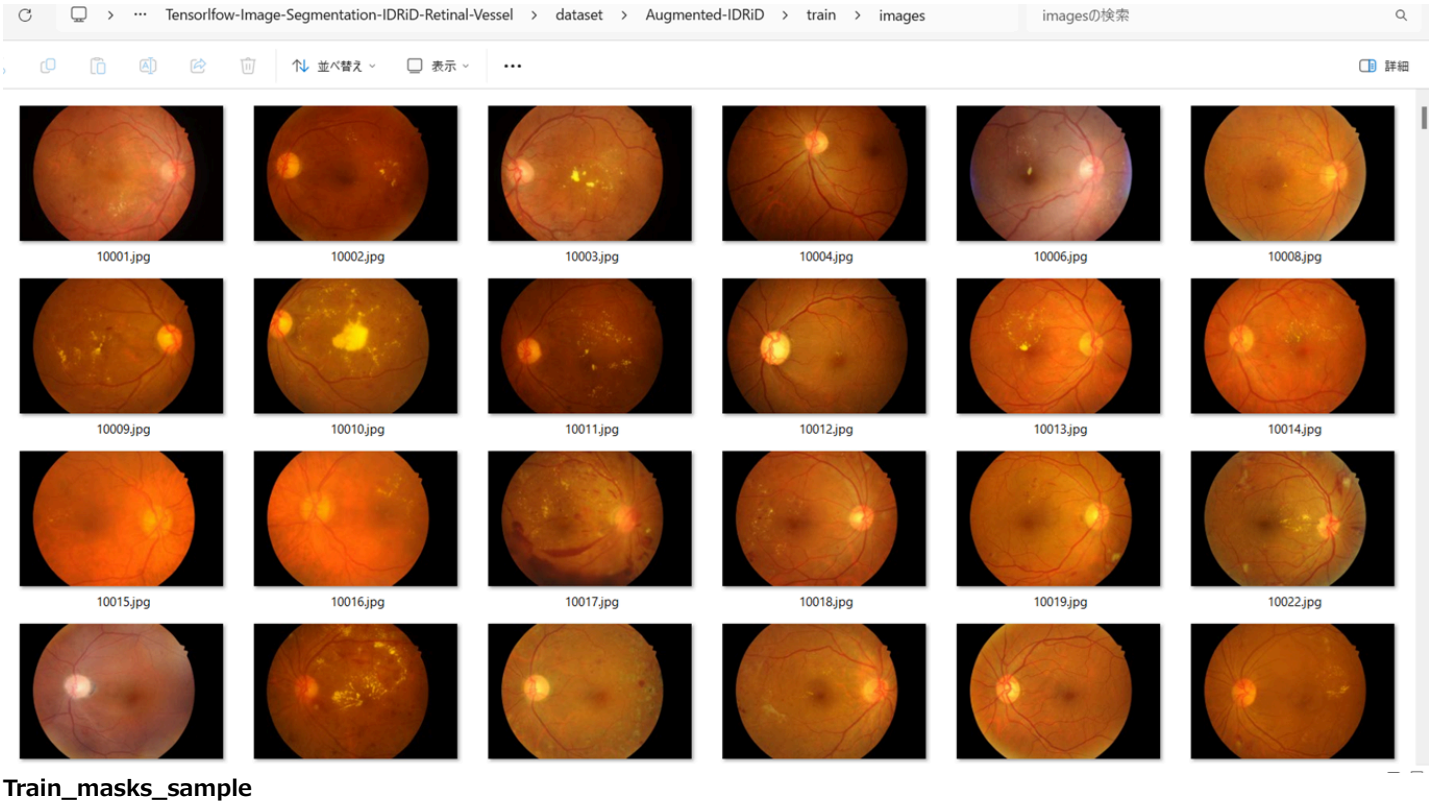
This is a Non-Tiled 4288x2848 pixels images and their corresponding masks dataset for IDRiD Retinal Vessel.

Augmented-IDRiD Statistics

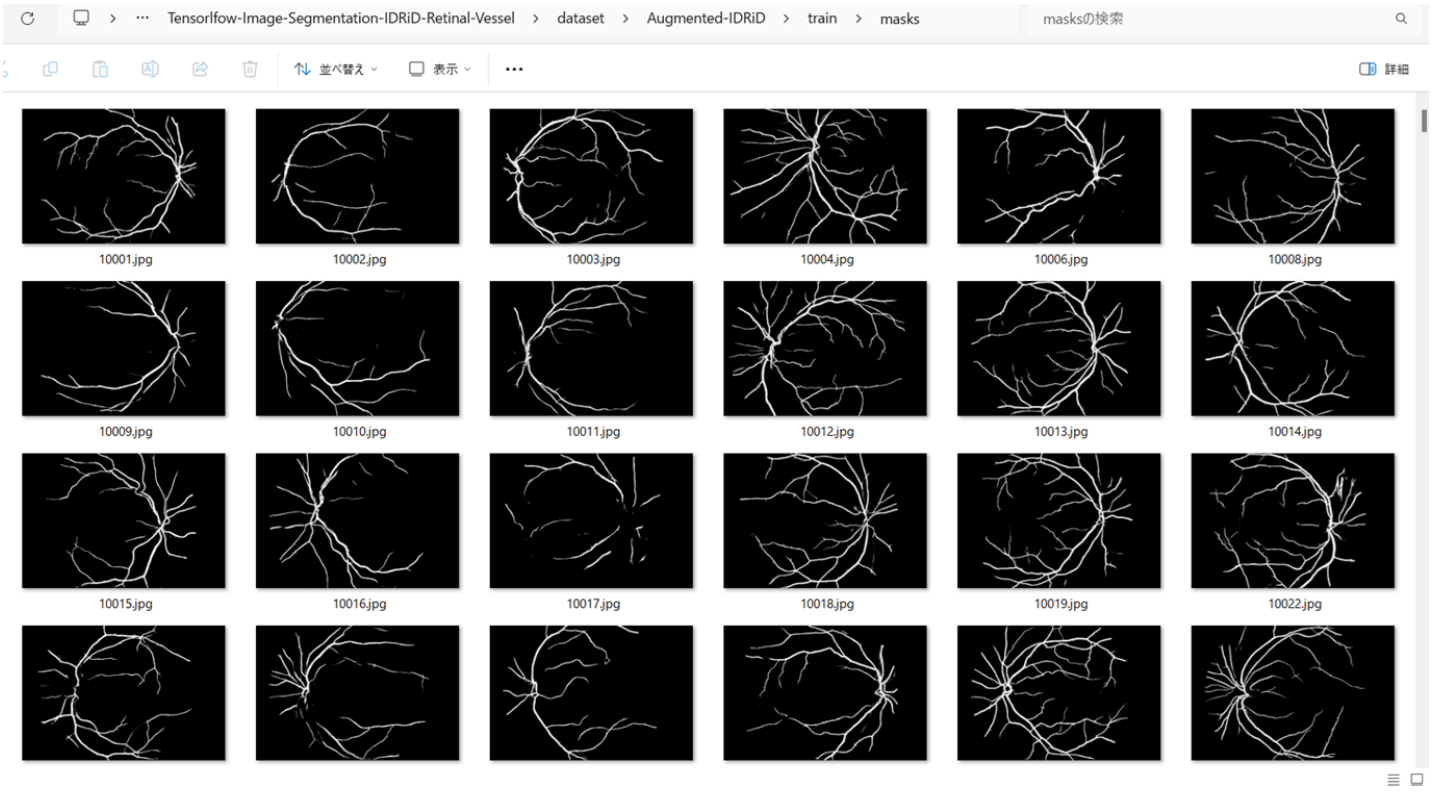


As shown above, the number of images of train and valid datasets is not so large, but enough to use for a training set of our segmentation model.

Train_images_sample



Train_masks_sample



3 Train TensorflowUNet Model

We have trained HRF TensorflowUNet Model by using the following **train_eval_infer.config** file.
Please move to ./projects/TensorflowSlightlyFlexibleUNet/IDRiD and run the following bat file.

```
>1.train.bat
```

, which simply runs the following command.

```
>python ../../../src/TensorflowUNetTrainer.py ./train_eval_infer.config
```

Model parameters

Enabled Batch Normalization.
Defined a small **base_filters=16** and large **base_kernels=(13,13)** for the first Conv Layer of Encoder Block of TensorflowUNet.py and a large num_layers (including a bridge between Encoder and Decoder Blocks).

```
[model]
base_filters   = 16
base_kernels   = (13,13)
num_layers     = 8
dilation       = (1,1)
```

Learning rate

Defined a small learning rate.

```
[model]
learning_rate  = 0.0001
```

Online augmentation

Disabled our online augmentation tool.

```
[model]
model         = "TensorflowUNet"
generator     = False
```

Loss and metrics functions

Specified "bce_dice_loss" and "dice_coef".

```
[model]
loss           = "bce_dice_loss"
metrics        = ["dice_coef"]
```

Learning rate reducer callback

Enabled learing_rate_reducer callback, and a small reducer_patience.

```
[train]
learning_rate_reducer = True
reducer_factor     = 0.4
reducer_patience   = 4
```

Dataset class

Specified ImageMaskDataset class.

```
[dataset]
datasetclass  = "ImageMaskDataset"
resize_interpolation = "cv2.INTER_LINEAR"
```

Early stopping callback

Enabled early stopping callback with patience parameter.

```
[train]
patience      = 10
```

Color space conversion

Used cv2.COLOR_BGR2Luv color converter.

```
[image]
color_converter = "cv2.COLOR_BGR2Luv"
```

Inference

Used the original IDRiD IMAGES as a mini_test dataset for our inference images.

```
[tiledinfer]
images_dir    = "./mini_test/images"
output_dir    = "./mini_test_output_tiled"
```

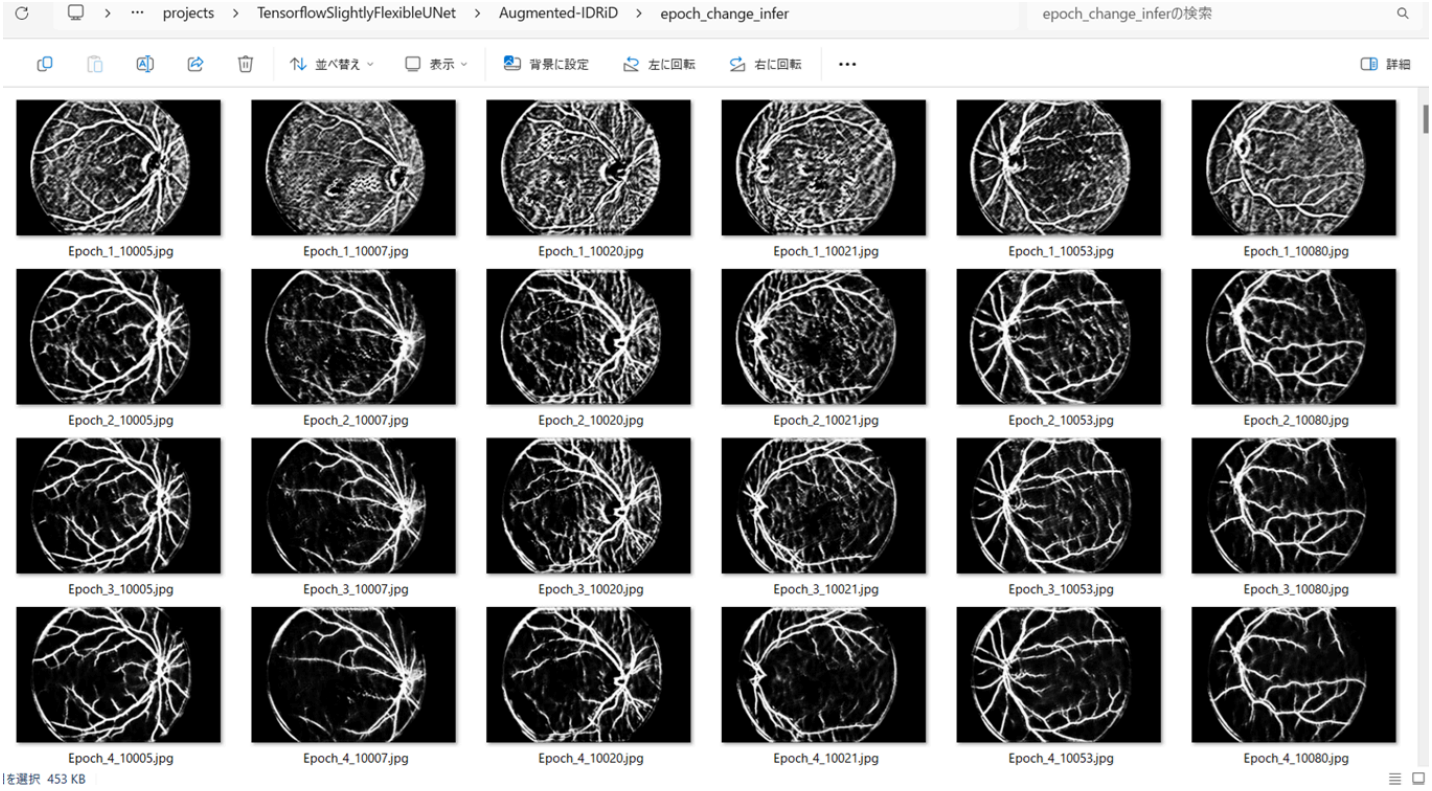
Epoch change inference callbacks

Enabled epoch_change_infer callback.

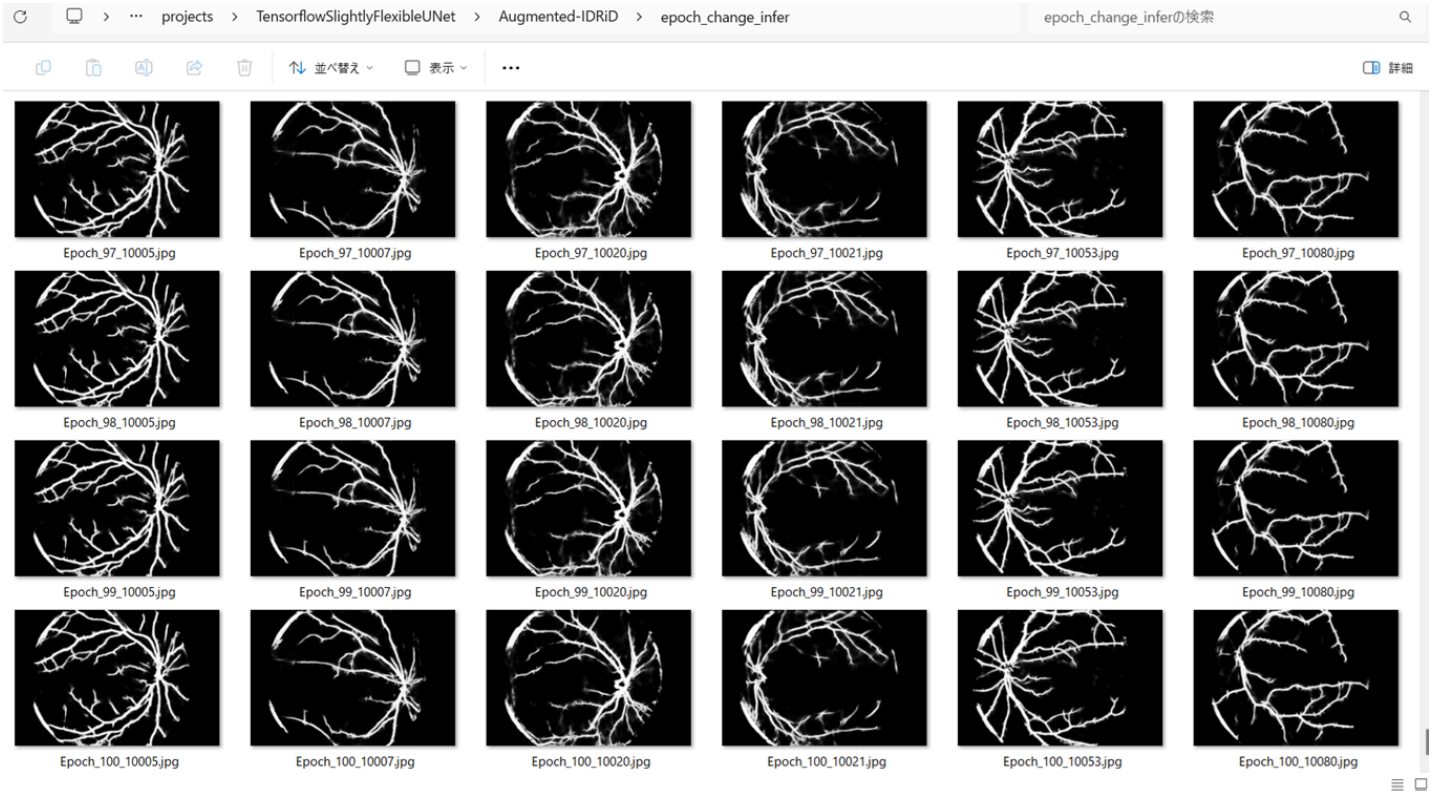
```
[train]
epoch_change_infer      = True
epoch_change_infer_dir  = "./epoch_change_infer"
epoch_change_tiledinfer = False
epoch_change_tiledinfer_dir = "./epoch_change_tiledinfer"
num_infer_images       = 6
```

By using this callback, on every epoch_change, the epoch change tiled inference procedure can be called for 6 images in **mini_test** folder. This will help you confirm how the predicted mask changes at each epoch during your training process.

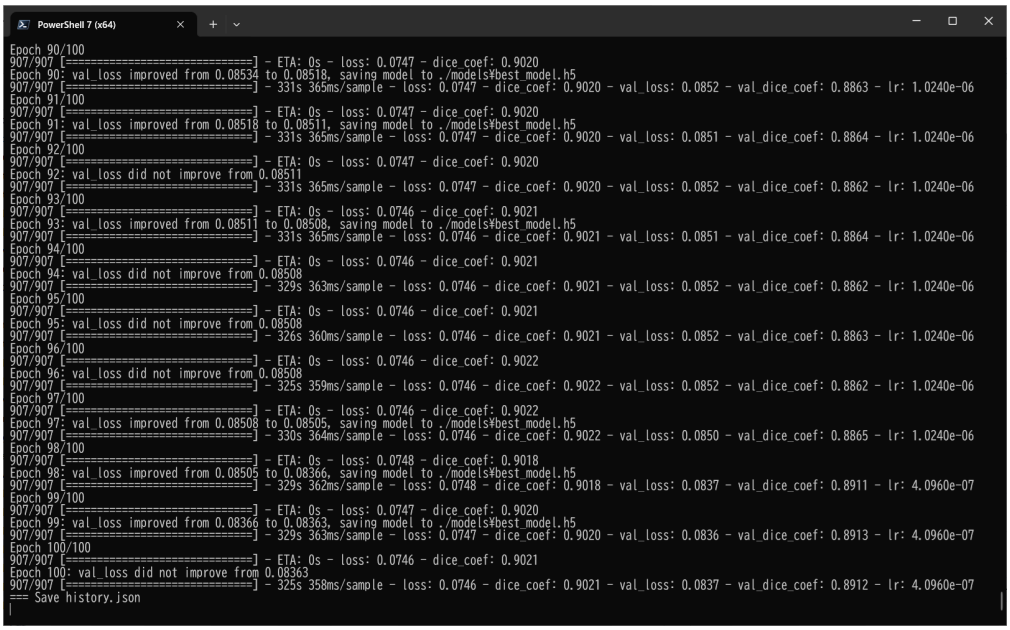
Epoch_change_tiled_inference output at starting (1,2,3,4)



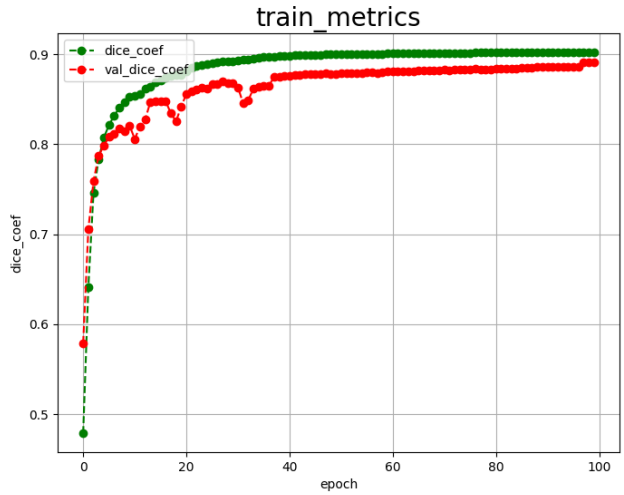
Epoch_change_tiled_inference output at ending (97,98,99,100)



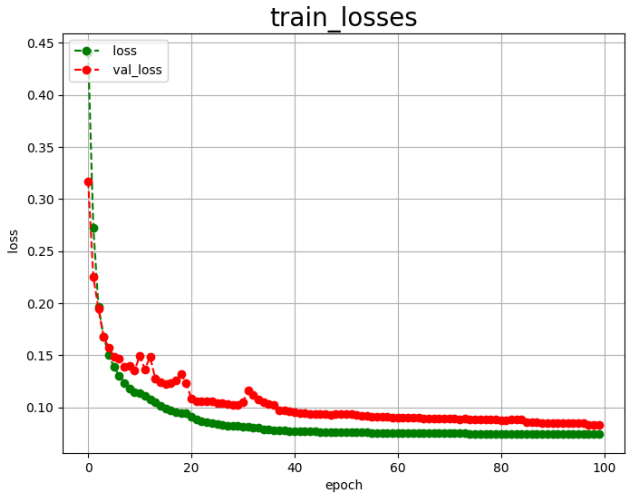
In this experiment, the training process was terminated at epoch 100.



[train_metrics.csv](./projects/TensorflowSlightlyFlexibleUNet/IDRiD/train_metrics.csv)



[train_losses.csv](./projects/TensorflowSlightlyFlexibleUNet/IDRiD/train_losses.csv)



4 Evaluation

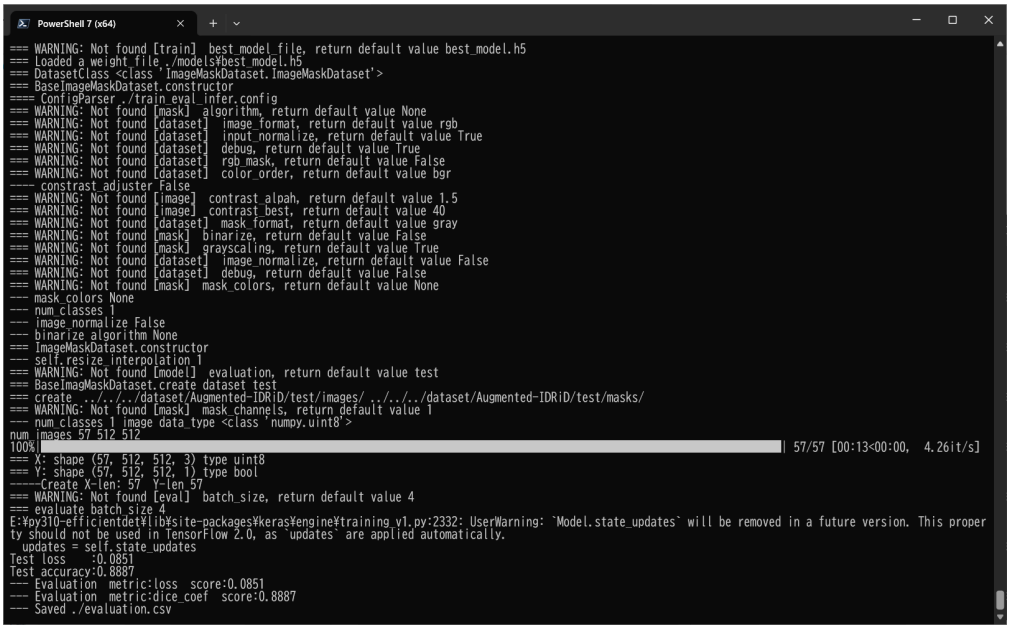
Please move to a **./projects/TensorflowSlightlyFlexibleUNet/IDRiD** folder,
and run the following bat file to evaluate TensorflowUNet model for IDRiD/test.

```
./2.evaluate.bat
```

This bat file simply runs the following command.

```
python ../../../src/TensorflowUNetEvaluator.py ./train_eval_infer.config
```

Evaluation console output:



evaluation.csv

The loss (bce_dice_loss) to this IDRiD/test was low, and dice_coef high as shown below.

```
loss,0.0851
dice_coef,0.8887
```

5 Inference

Please move to a **./projects/TensorflowSlightlyFlexibleUNet/IDRiD** folder
,and run the following bat file to infer segmentation regions for images by the Trained-TensorflowUNet model for IDRiD.

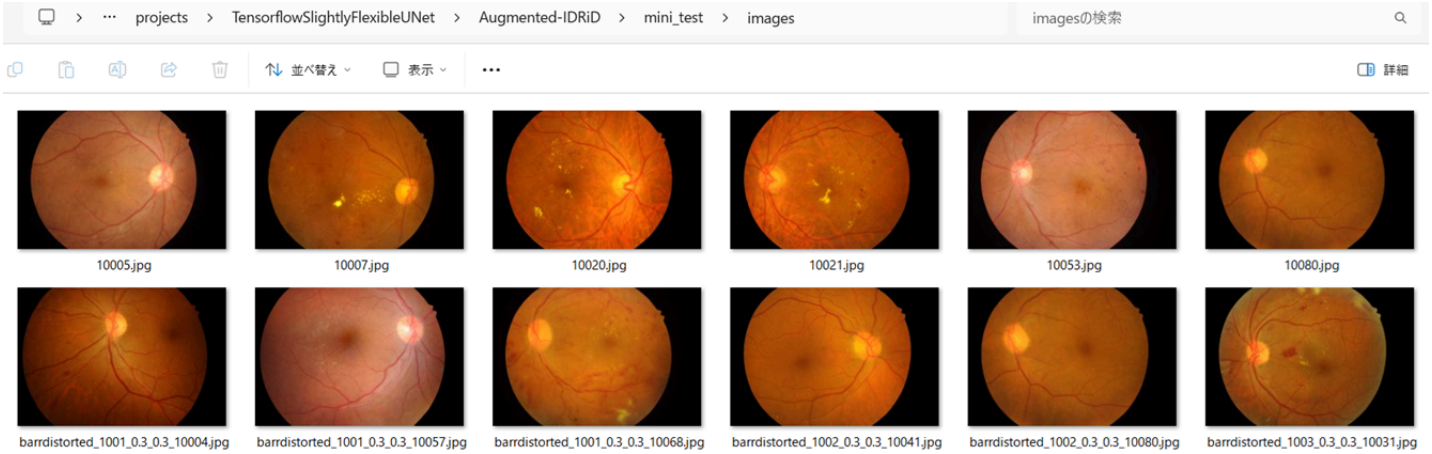
```
./3.infer.bat
```

This simply runs the following command.

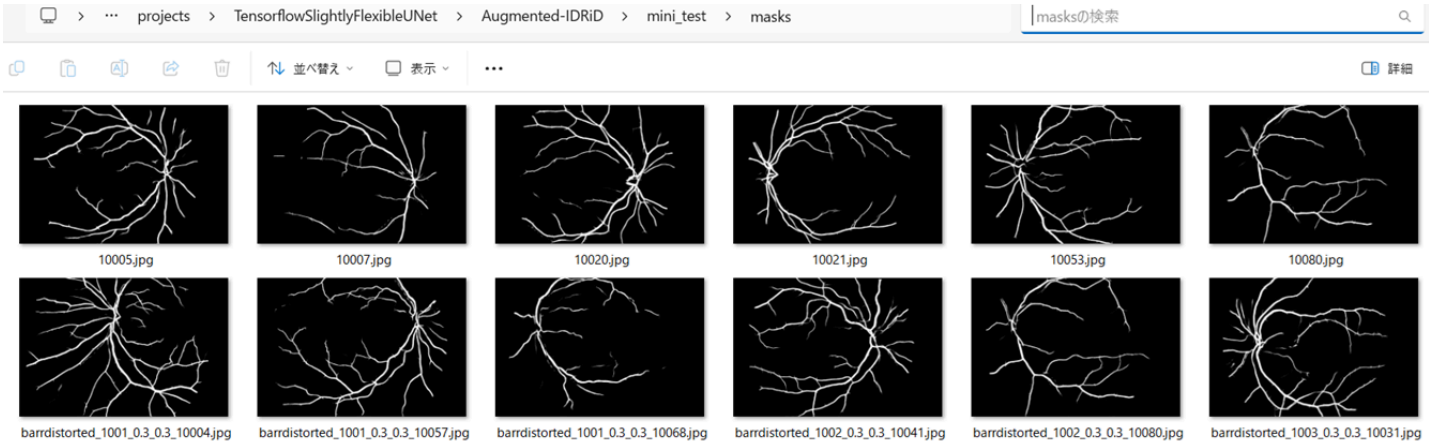
```
python ../../../src/TensorflowUNetInferencer.py ./train_eval_infer.config
```

---

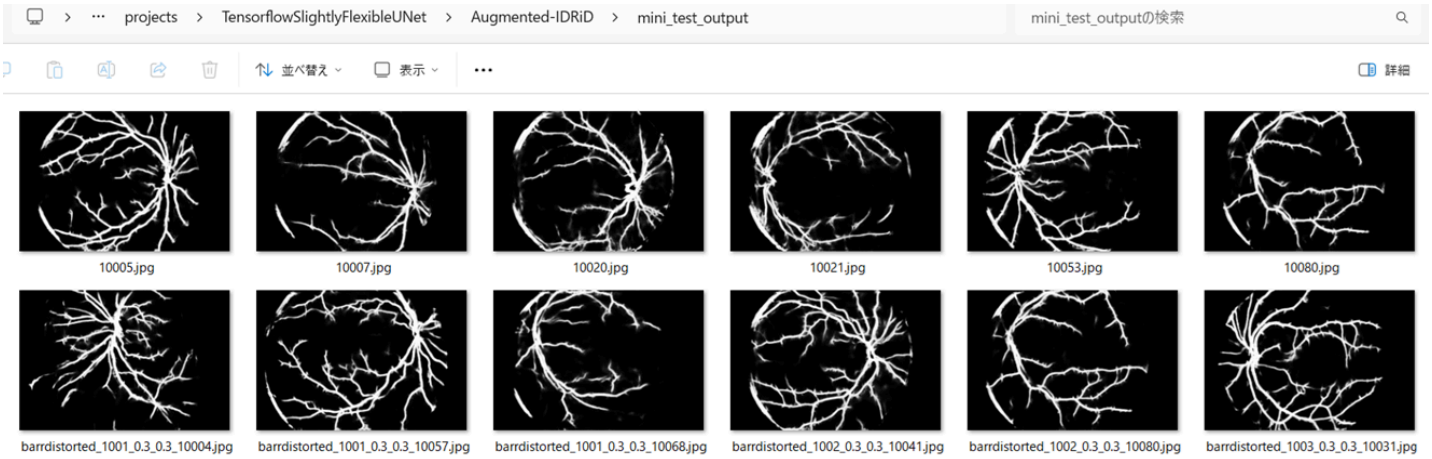
mini_test_images (4288x2848 pixels)



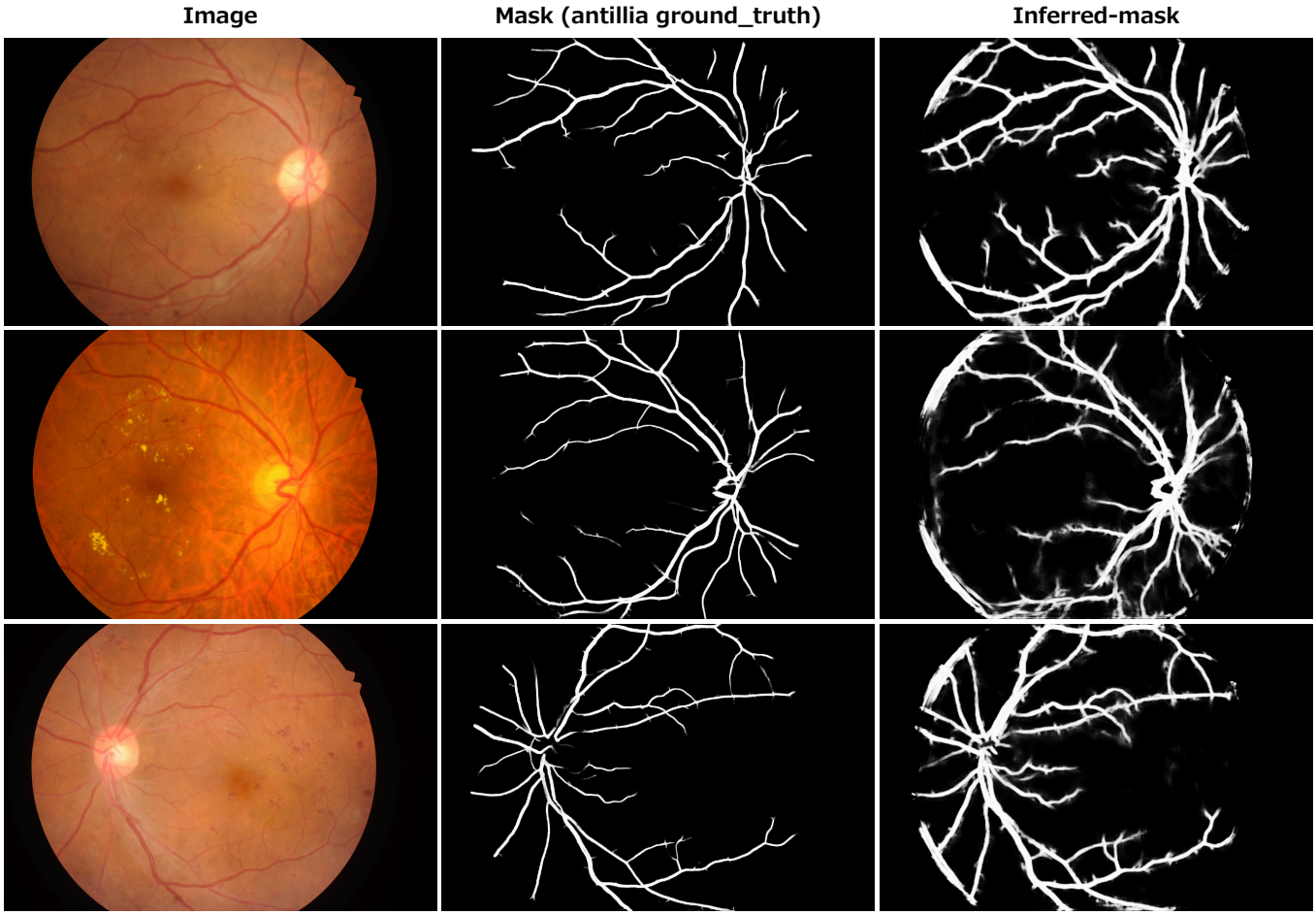
mini_test_mask(antillia ground_truth)

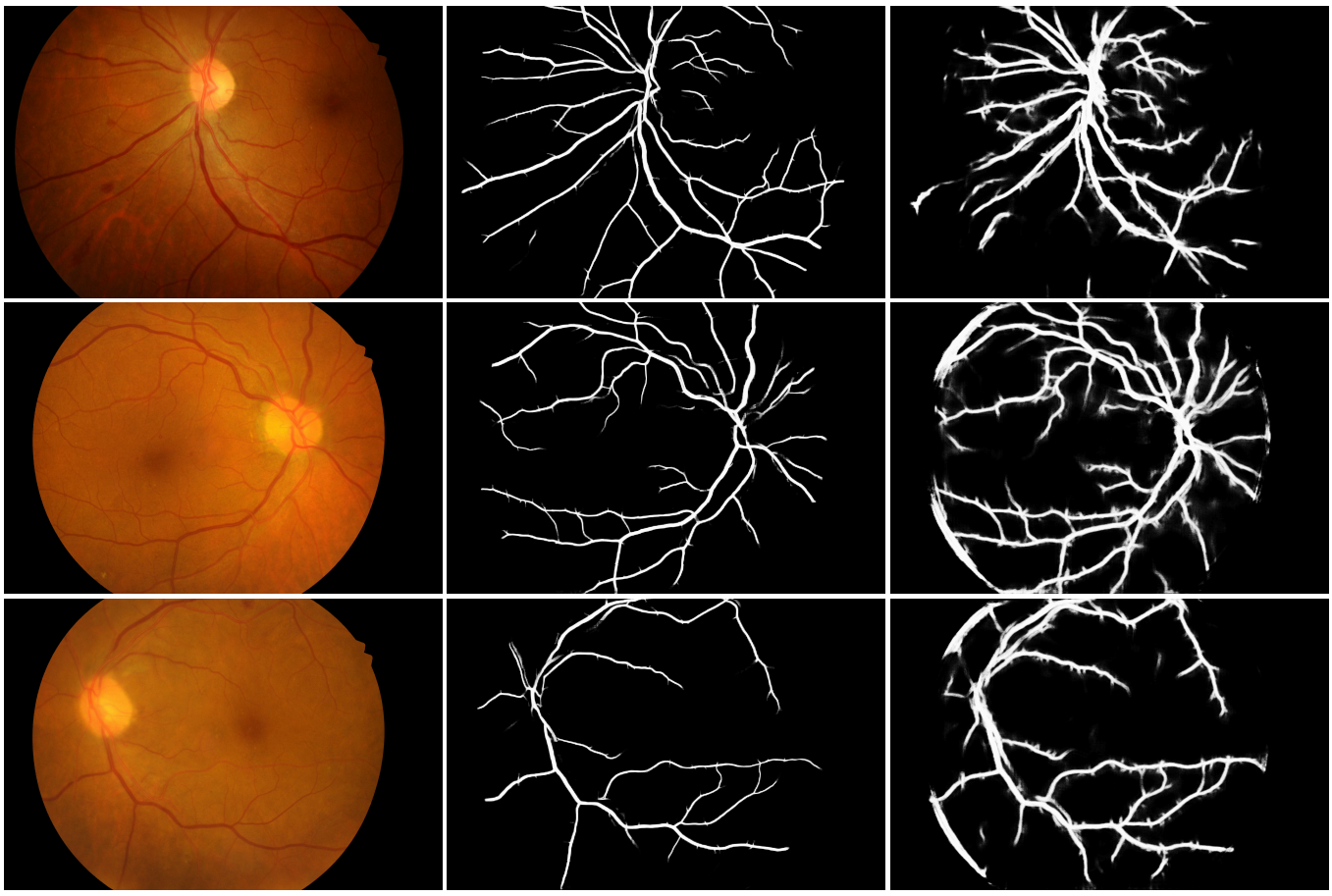


Inferred test masks (4288x2848 pixels)



Enlarged images and masks of 4288x2848 pixels





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Toshiyuki Arai @antillia.com
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