

Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-CHASEDB1-Retinal-Vessel (2025/02/13)

This is the third experiment of Tiled Image Segmentation for **CHASEDB1 Retinal Vessel** based on the latest [Tensorflow-Image-Segmentation-API](#), and a **pre-augmented tiled dataset** [Augmented-Tiled-CHASEDB1-ImageMask-Dataset.zip](#), which was derived by us from the following dataset:

[CHASE DB1 retinal vessel reference dataset](#)

In this experiment, we retried image segmentation for the CHASEDB1 retinal vessel using our Tile Image Segmentation method to improve the segmentation performance of the previous unsatisfactory results from the [Tensorflow-Image-Segmentation-Retinal-Vessel](#)

Please see also our experiments:

- [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](#) baased on [Structured Analysis of the Retina](#).

Experiment Strategies

As demonstrated in our experiments [Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-STARE-Retinal-Vessel](#) and [Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-IDRID-HardExudates](#), the Tiled Image Segmentation based on a simple UNet model trained by a tiledly-splitted images and masks dataset, is an effective method for the large image segmentation over 4K pixels. Furthermore, as mentioned in [Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-STARE-Retinal-Vessel](#), it is difficult to precisely segment Retinal Blood Vessels in small images using a simple UNet model, because these vessels are typically very thin. Therefore, we generate a high-resolution retinal image dataset by upscaling the original images and use it to train the UNet model to improve segmentation performance.

In this experiment, we employed the same strategies in this project as we did in the [STARE-Retinal-Vessel](#).

1. Enlarged Dataset

We generated a 3x enlarged dataset of 28 JPG images and masks, each with 2997x2880pixels, from the original CHASEDB1 999x960 pixels JPG image and PNG mask files using bicubic interpolation.

2. Pre Augemtned Tiled CHASEDB1 ImageMask Dataset

We generated a pre-augmented image mask dataset from the enlarged dataset, which was tiledly-splitted to 512x512 pixels and reduced to 512x512 pixels image and mask dataset.

3. Train Segmentation Model

We trained and validated a TensorFlow UNet model by using the [Pre Augmented Tiled CHASEDB1 ImageMask Dataset](#)

4. Tiled Image Segmentation

We applied our Tiled-Image Segmentation inference method to predict the CHASEDB1 Retinal Vessel for the mini_test images with a resolution of 2997x2880pixels of the Enlarged Dataset.

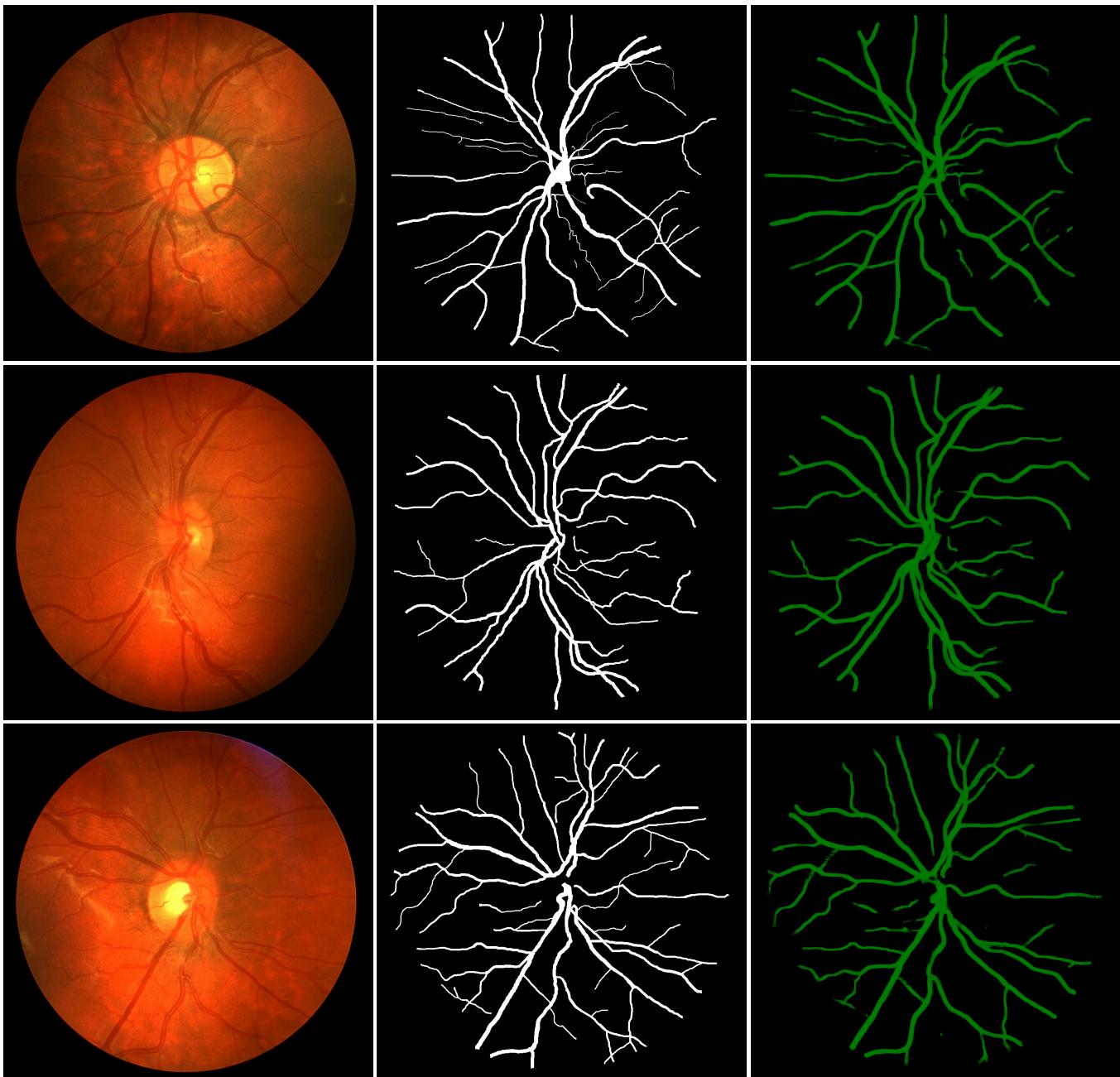
Actual Tiled Image Segmentation for Images of 2997x2880 pixels

As shown below, the inferred masks look similar to the ground truth masks.

Input: image

Mask (ground_truth)

Prediction: inferred_mask



In this experiment, we used the simple UNet Model [TensorflowSlightlyFlexibleUNet](#) for this CHASEDB1Segmentation 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 taken from the following web site of Kingston University Research [CHASE_DB1 retinal vessel reference dataset](#)

Fraz, Muhammad Moazam [Creator], Remagnino, Paolo, Hoppe, Andreas, Uyyanonvara, Bunyarat, Rudnicka, Alicja R [Creator], Owen, Christopher G [Creator] and Barman, Sarah A [Creator] (2012) CHASE_DB1 retinal vessel reference dataset. [Data Collection]

Official URL: <https://doi.org/10.1109/TBME.2012.2205687>

Lay Summary

A public retinal vessel reference dataset CHASE_DB1 made available by Kingston University, London in collaboration with St. George's, University of London. This is a subset of retinal images of multi-ethnic children from the Child Heart and Health Study in England (CHASE) dataset. This subset contains 28 retinal images captured from both eyes from 14 of the children recruited in the study. In this subset each retinal image is also accompanied by two ground truth images. This is provided in the form of two manual vessel segmentations made by two independent human observers for each of the images, in which each pixel is assigned a "1" label if it is part of a blood vessel and a "0" label otherwise. Making this subset publicly available allows for the scientific community to train and test computer vision algorithms (specifically vessel segmentation methodologies). Most importantly this subset allows for performance comparisons - several algorithms being evaluated on the same database allows for direct comparisons of their performances to be made.

2 Augmented-Tiled-CHASEDB1 ImageMask Dataset

If you would like to train this CHASEDB1 Segmentation model by yourself, please download the pre-augmented dataset from the google drive [Augmented-Tiled-CHASEDB1-ImageMask-Dataset.zip](#), expand the downloaded ImageMaskDataset and put it under **./dataset** folder to be

```
./dataset
  └── Augmented-Tiled-CHASEDB1
      ├── test
      │   ├── images
      │   └── masks
      ├── train
      │   ├── images
      │   └── masks
      └── valid
          ├── images
          └── masks
```

This is a 512x512 pixels pre augmented tiles dataset generated from 2997x2880 pixels 28 **Enlarged-images** and their corresponding **Enlarged-masks**.

- The folder structure of the original **CHASEDB1/training** dataset is the following.

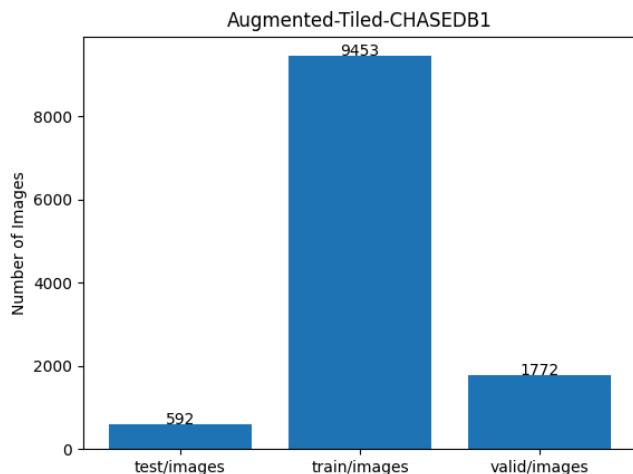
```
./CHASEDB1
  ├── Image_01L.jpg
  ├── Image_01L_1stH0.png
  ├── Image_01L_2ndH0.png
  ├── Image_01R.jpg
  ├── Image_01R_1stH0.png
  └── Image_01R_2ndH0.png
  ...
  ├── Image_14L.jpg
  ├── Image_14L_1stH0.png
  ├── Image_14L_2ndH0.png
  ├── Image_14R.jpg
  ├── Image_14R_1stH0.png
  └── Image_14R_2ndH0.png
```

We used the ***_2ndH0.png** as the ground truth (mask)files for our dataset, and excluded all black (empty) masks and their corresponding images to generate our tiled dataset from the original CHASEDB1.

On the derivation of the dataset, please refer to the following Python scripts.

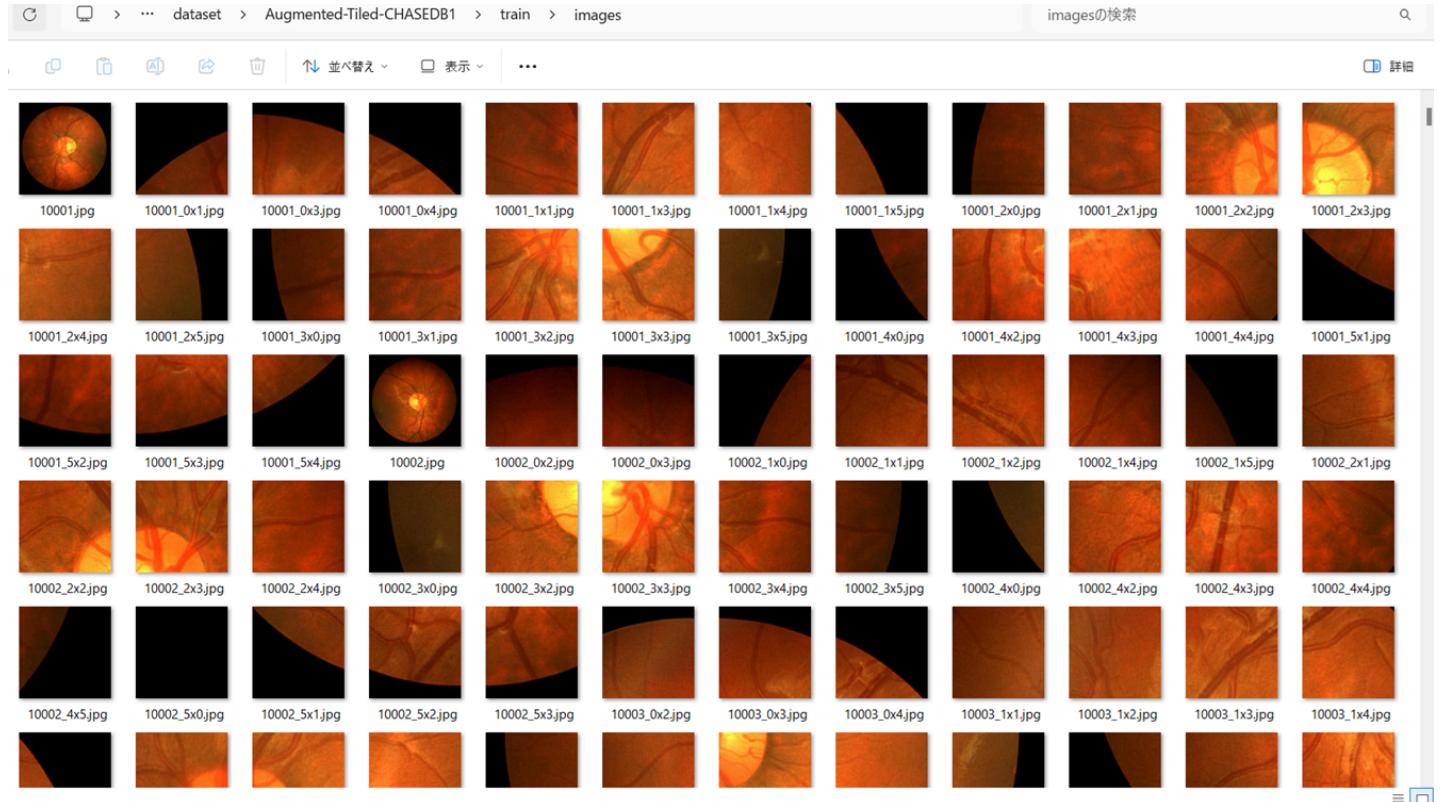
- [Preprocessor.py](#)
- [TiledImageMaskDatasetGenerator.py](#)
- [split_tiled_master.py](#)

Augmented-Tiled-CHASEDB1 Statistics



As shown above, the number of images of train and valid datasets is enough to use for a training set of our segmentation model.

Train_images_sample



Train_masks_sample



3 Train TensorflowUNet Model

We have trained CHASEDB1 TensorflowUNet Model by using the following [train_eval_infer.config](#) file.

Please move to ./projects/TensorflowSlightlyFlexibleUNet/Augmented-Tiled-CHASEDB1 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=(9,9)** 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 = (9, 9)
num_layers = 8
dilation = (3, 3)
```

Learning rate

Defined a small learning rate.

```
[model]
learning_rate = 0.00007
```

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 learning_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
```

Tiled inference

We used 2997x2880pixels enlarged images and masks generated by [Preprocessor.py](#) as a mini_test dataset for our TiledInference.

```
[tiledinfer]
overlapping = 64
images_dir = "./mini_test/images"
output_dir = "./mini_test_output_tiled"
```

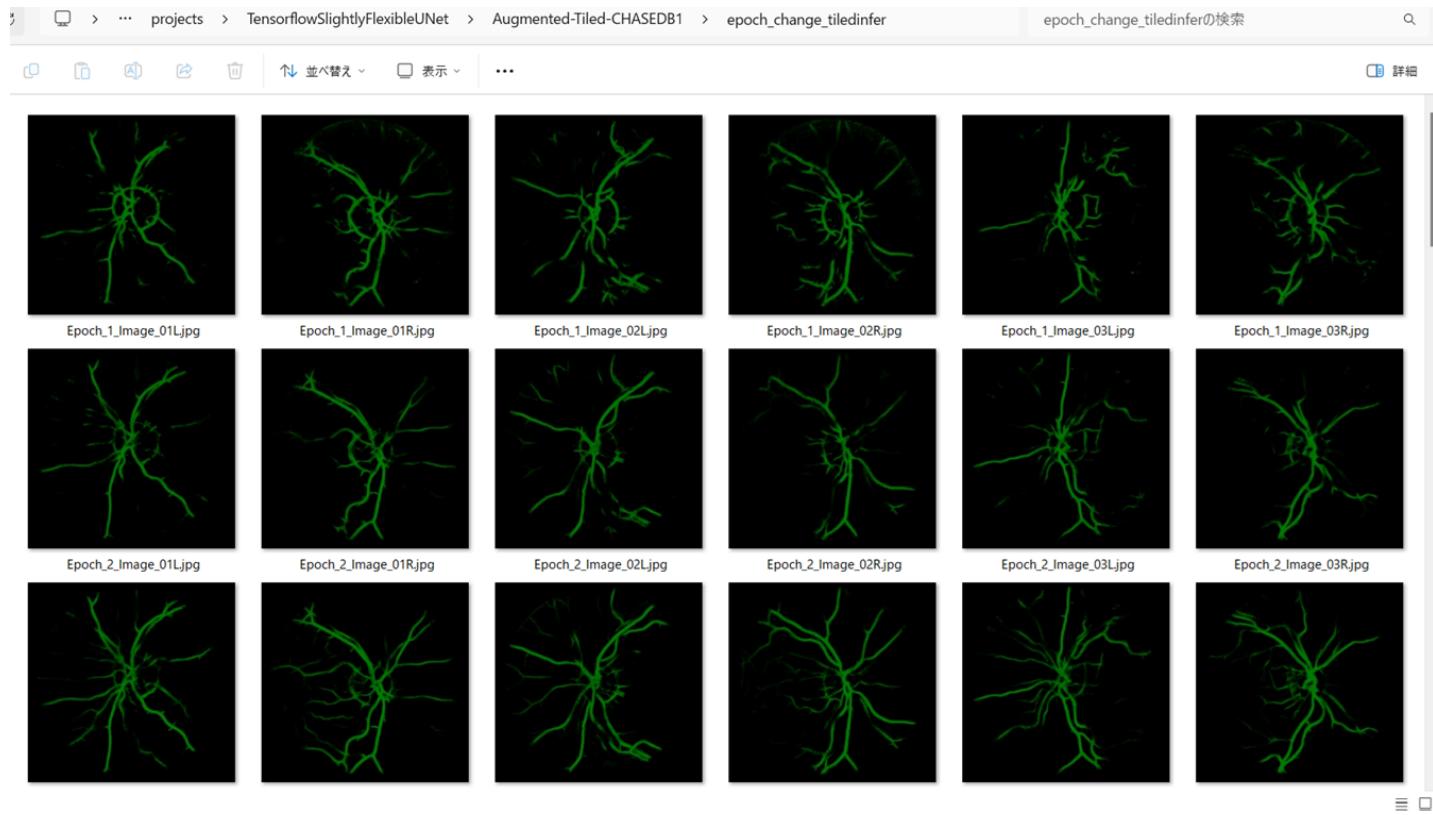
Epoch change inference callbacks

Enabled epoch_change_infer callback.

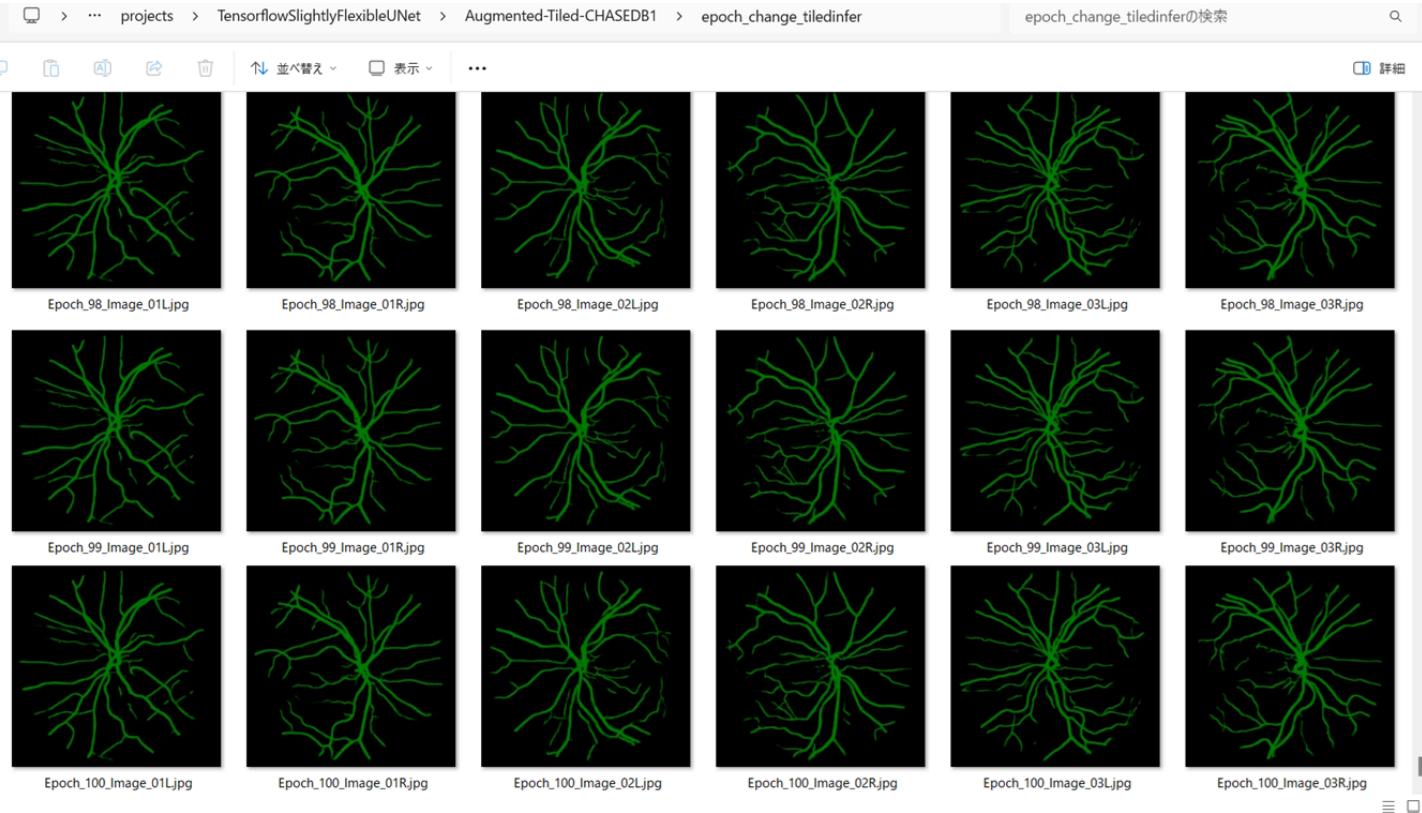
```
[train]
epoch_change_infer = False
epoch_change_infer_dir = "./epoch_change_infer"
epoch_change_tiledinfer = True
epoch_change_tiledinfer_dir = "./epoch_change_tiledinfer"
num_infer_images = 6
```

By using this callback, on every epoch_change, the epoch change tiledinfer 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_inference output at starting (1,2,3)



Epoch_change_inference output at ending (98,99,100)



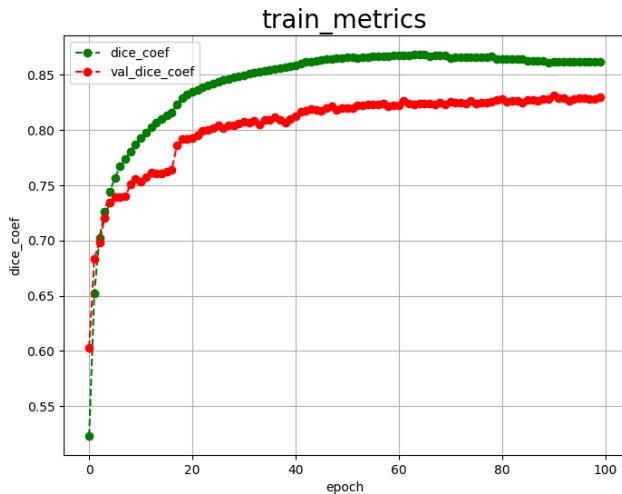
In this experiment, the training process was terminated at epoch 100.

```

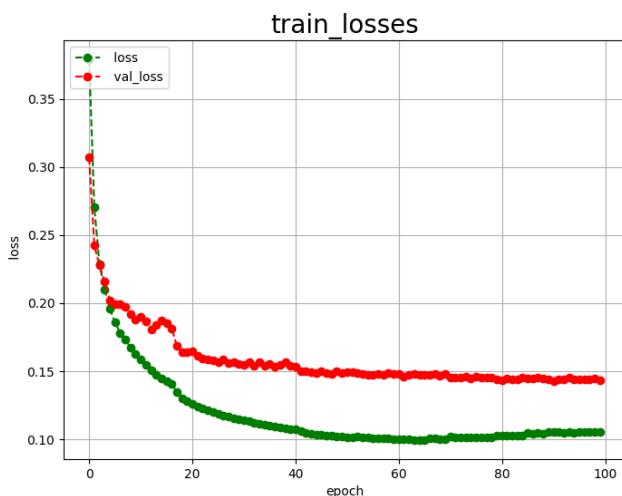
PowerShell 7 (x64) + -
9453/9453 [=====] - ETA: 0s - loss: 0.1053 - dice_coef: 0.8614
Epoch 90: val_loss did not improve from 0.14359
9453/9453 [=====] - 2623s 277ms/sample - loss: 0.1053 - dice_coef: 0.8614 - val_loss: 0.1442 - val_dice_coef: 0.8282 - lr: 4.5875e-08
Epoch 91/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8617
Epoch 91: val_loss improved from 0.14359 to 0.14286, saving model to ./models/best_model.h5
9453/9453 [=====] - 2616s 277ms/sample - loss: 0.1051 - dice_coef: 0.8617 - val_loss: 0.1429 - val_dice_coef: 0.8311 - lr: 4.5875e-08
Epoch 92/100
9453/9453 [=====] - ETA: 0s - loss: 0.1052 - dice_coef: 0.8618
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2627s 278ms/sample - loss: 0.1052 - dice_coef: 0.8618 - val_loss: 0.1439 - val_dice_coef: 0.8291 - lr: 4.5875e-08
Epoch 93/100
9453/9453 [=====] - ETA: 0s - loss: 0.1050 - dice_coef: 0.8621
Epoch 93: val_loss did not improve from 0.14286
9453/9453 [=====] - 2630s 278ms/sample - loss: 0.1050 - dice_coef: 0.8621 - val_loss: 0.1438 - val_dice_coef: 0.8293 - lr: 4.5875e-08
Epoch 94/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8620
Epoch 94: val_loss did not improve from 0.14286
9453/9453 [=====] - 2631s 278ms/sample - loss: 0.1051 - dice_coef: 0.8620 - val_loss: 0.1452 - val_dice_coef: 0.8267 - lr: 4.5875e-08
Epoch 95/100
9453/9453 [=====] - ETA: 0s - loss: 0.1050 - dice_coef: 0.8621
Epoch 95: val_loss did not improve from 0.14286
9453/9453 [=====] - 2631s 278ms/sample - loss: 0.1050 - dice_coef: 0.8621 - val_loss: 0.1443 - val_dice_coef: 0.8284 - lr: 4.5875e-08
Epoch 96/100
9453/9453 [=====] - ETA: 0s - loss: 0.1052 - dice_coef: 0.8615
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2628s 278ms/sample - loss: 0.1052 - dice_coef: 0.8615 - val_loss: 0.1438 - val_dice_coef: 0.8292 - lr: 1.8350e-08
Epoch 97/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8617
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2628s 278ms/sample - loss: 0.1051 - dice_coef: 0.8617 - val_loss: 0.1438 - val_dice_coef: 0.8291 - lr: 1.8350e-08
Epoch 98/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8619
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2635s 279ms/sample - loss: 0.1051 - dice_coef: 0.8619 - val_loss: 0.1442 - val_dice_coef: 0.8284 - lr: 1.8350e-08
Epoch 99/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8619
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2680s 284ms/sample - loss: 0.1051 - dice_coef: 0.8619 - val_loss: 0.1444 - val_dice_coef: 0.8279 - lr: 1.8350e-08
Epoch 100/100
9453/9453 [=====] - ETA: 0s - loss: 0.1051 - dice_coef: 0.8617
9453/9453 [=====] - val_loss did not improve from 0.14286
9453/9453 [=====] - 2850s 302ms/sample - loss: 0.1051 - dice_coef: 0.8617 - val_loss: 0.1436 - val_dice_coef: 0.8296 - lr: 7.3400e-09
Save history.json

```

[train_metrics.csv](#)



[train_losses.csv](#)



4 Evaluation

Please move to a [./projects/TensorflowSlightlyFlexibleUNet/Augmented-Tiled-CHASEDB1](#) folder, and run the following bat file to evaluate TensorflowUNet model for CHASEDB1.

`./2.evaluate.bat`

This bat file simply runs the following command.

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

Evaluation console output:

```
PowerShell 7 (x64) + - x
--- DatasetClass <class 'ImageMaskDataset.ImageMaskDataset'>
--- BaseImageMaskDataset.constructor
--- ConfigParser /train_eval_infer.config
--- WARNING: Not found [dataset] image format, return default value None
--- WARNING: Not found [dataset] input normalize, return default value rgb
--- WARNING: Not found [dataset] debug, return default value True
--- WARNING: Not found [dataset] rgb mask, return default value False
--- WARNING: Not found [dataset] color order, return default value bgr
--- contrast adjusted False
--- Not found [image] contrast alphah, return default value 1.5
--- Not found [image] contrast best, return default value 40
--- Not found [dataset] mask format, return default value gray
--- Not found [mask] binarize, return default value False
--- Not found [mask] grayscaling, return default value True
--- Not found [dataset] image normalize, return default value False
--- Not found [dataset] debug, return default value False
--- Not found [mask] mask_colors, return default value None
mask colors None
num classes 1
image normalize False
binarize algorithm None
ImageMaskDataset.constructor
--- Dataset /dataset
--- Not found [model] evaluation, return default value test
BaseImageMaskDataset.create dataset test
create ../../dataset/Augmented-Tiled-CHASEDB1/test/images/ ../../dataset/Augmented-Tiled-CHASEDB1/test/masks/
--- WARNING: Not found [mask] mask channels, return default value 1
num classes 1 image data type <class 'numpy.uint8'>
num images 592 512 int8
100% | 592/592 [00:05<00:00, 112.58it/s]
X: shape (592, 512, 512, 3) type uint8
Y: shape (592, 512, 512, 1) type bool
--- Create X-len: 592 Y-len 592
--- WARNING: Not found [eval] batch size, return default value 4
evaluate batch size 4
E:\py310\efficientdet\lib\site-packages\keras\engine\training_v1.py:2332: UserWarning: `Model.state_updates` will be removed in a future version. This property should not be used in Tensorflow 2.0, as `updates` are applied automatically.
  updates = self.state_updates
Updates = self.state_updates
Test loss :0.1452
Test accuracy:0.8302
--- Evaluation metric:loss score:0.1452
--- Evaluation metric:dice_coef score:0.8302
--- Saved ./evaluation.csv
```

Image-Segmentation-CHASEDB1 [evaluation.csv](#)

The loss (bce_dice_loss) to this Augmented-Tiled-CHASEDB1/test was not so low, and dice_coef not so high as shown below, which were better than our second experiment [Tensorflow-Image-Segmentation-Retinal-Vessel](#) .

```
loss,0.1452
dice_coef,0.8302
```

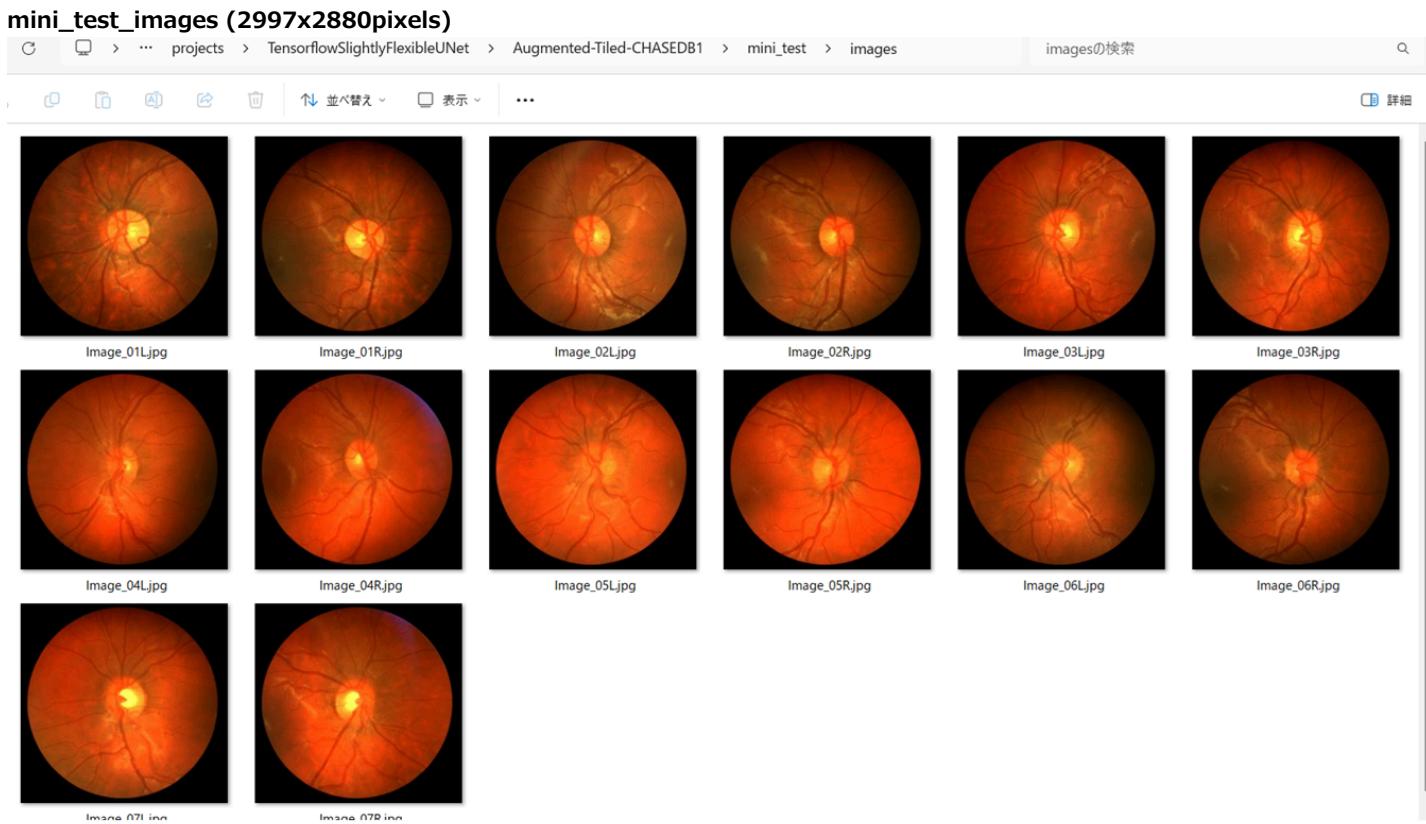
5 Tiled inference

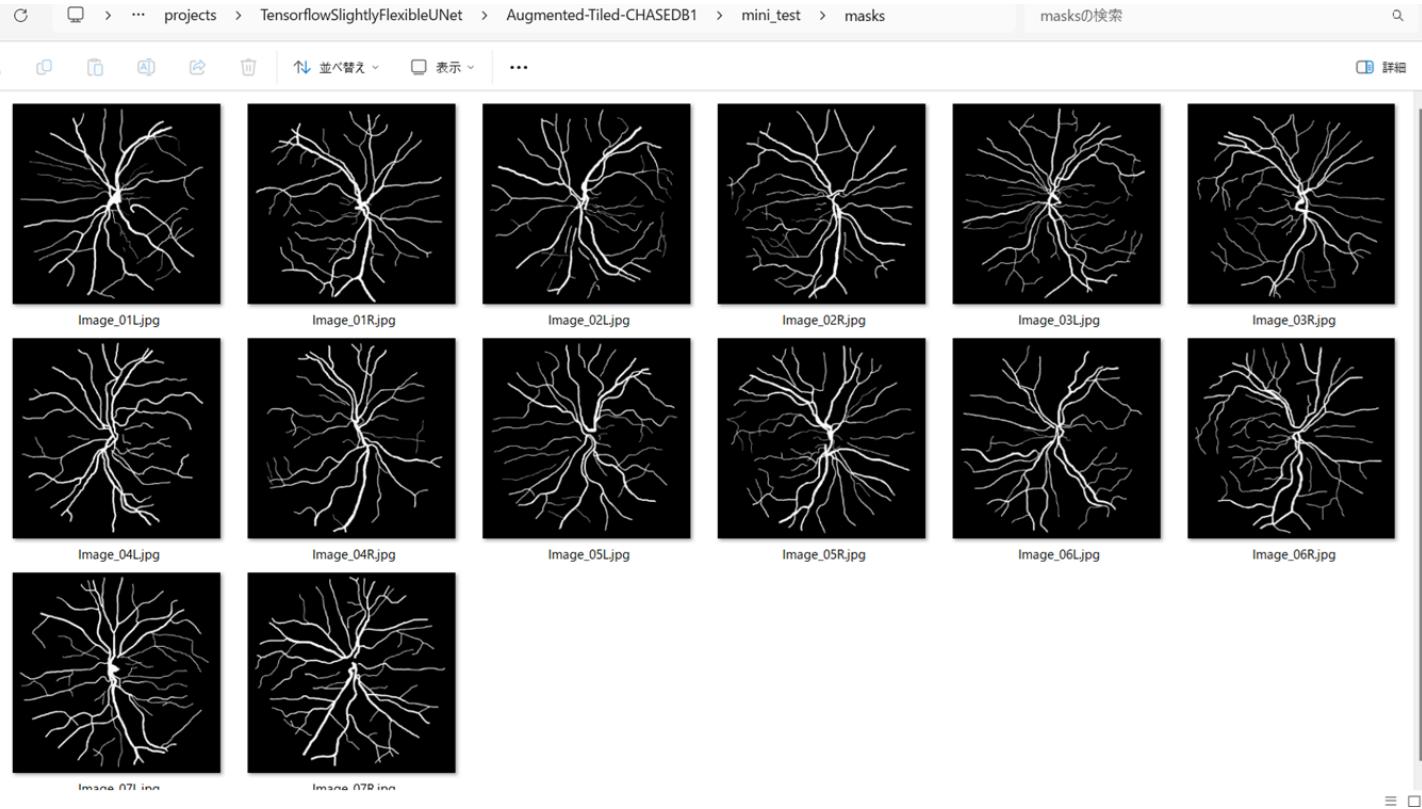
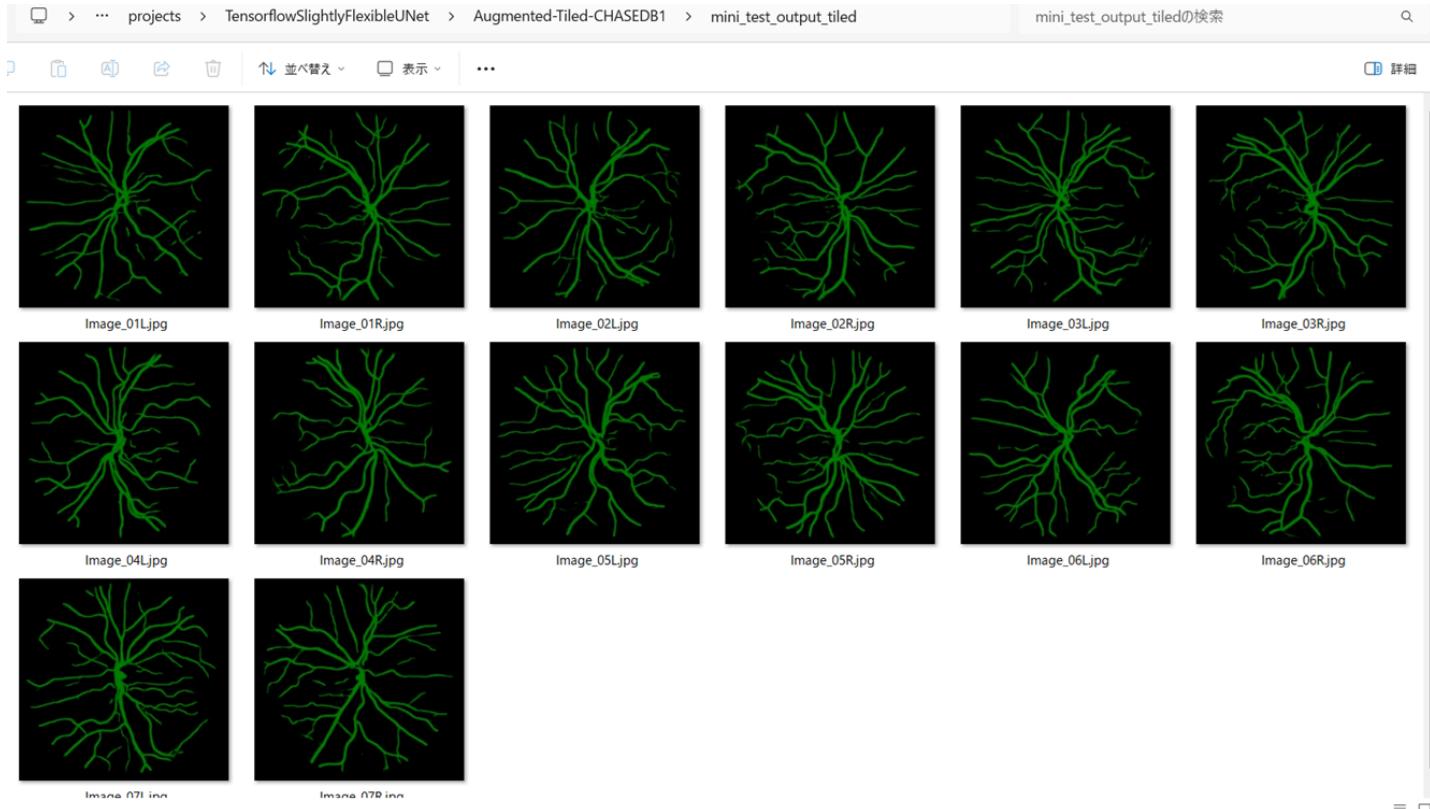
Please move to a **./projects/TensorflowSlightlyFlexibleUNet/Augmented-Tiled-CHASEDB1** folder ,and run the following bat file to infer segmentation regions for images by the Trained-TensorflowUNet model for CHASEDB1.

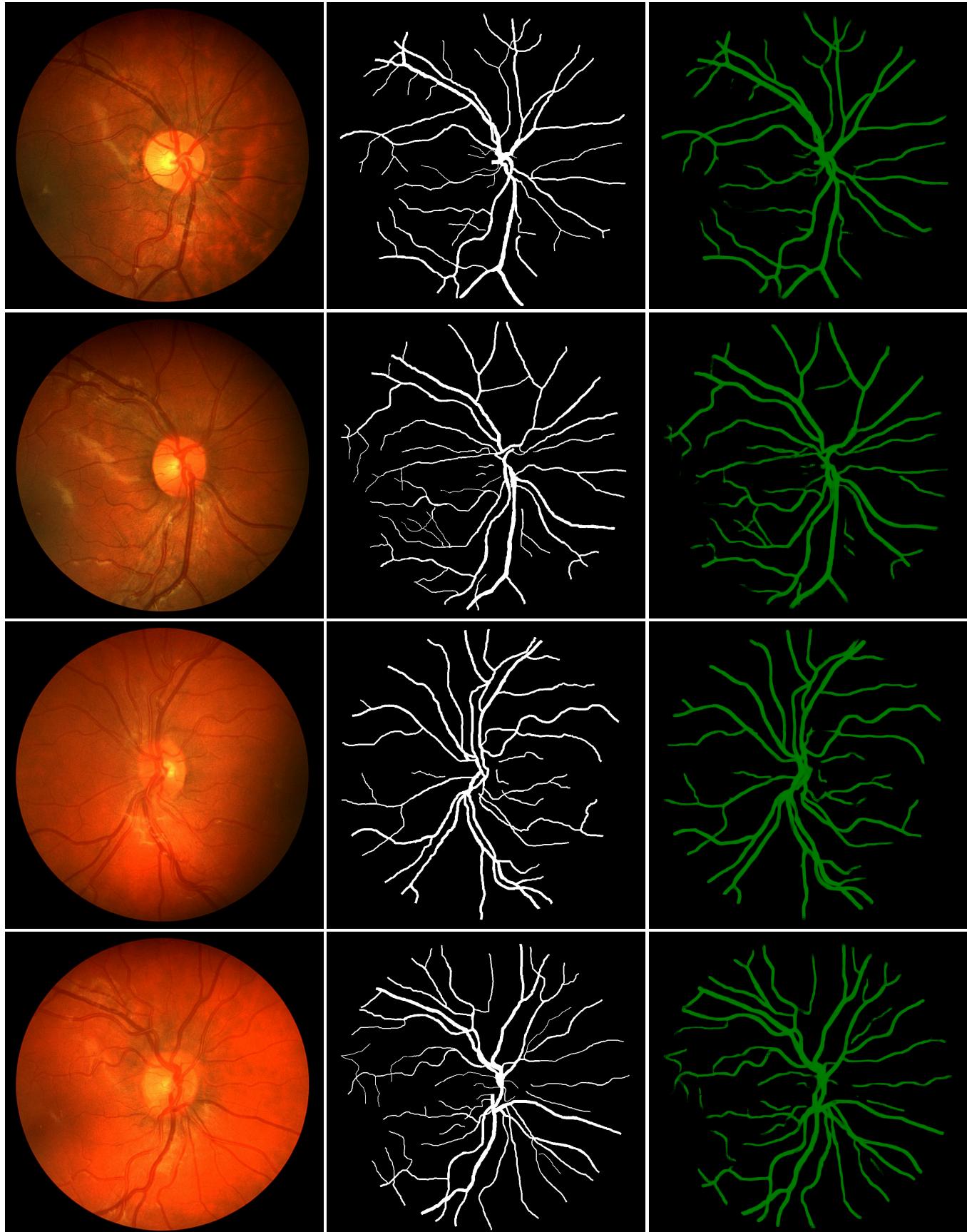
```
./4.tiled_infer.bat
```

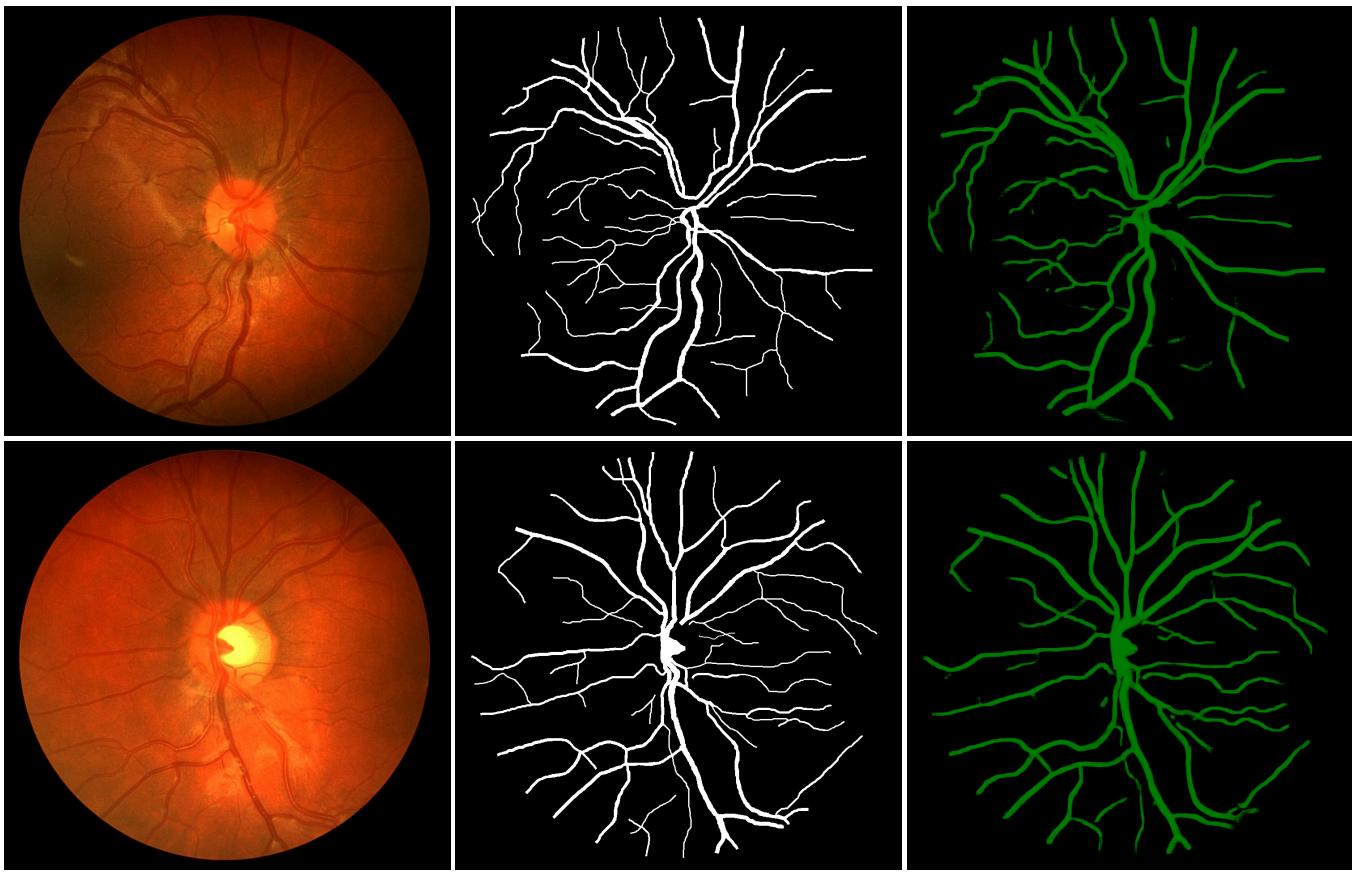
This simply runs the following command.

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



mini_test_mask(ground_truth)**Tiled inferred test masks (2997x2880pixels)****Enlarged images and masks of 2997x2880pixels****Image****Mask (ground_truth)****Tiled-inferred-mask**





References

1. Locating Blood Vessels in Retinal Images by Piecewise Threshold Probing of a Matched Filter Response

Adam Hoover, Valentina Kouznetsova, and Michael Goldbaum

<https://www.uhu.es/retinopathy/General/000301IEEETransMedImag.pdf>

2. CHASE_DB1 retinal vessel reference dataset

Fraz, Muhammad Moazam [Creator], Remagnino, Paolo, Hoppe, Andreas, Uyyanonvara, Bunyarat, Rudnicka, Alicja R [Creator], Owen, Christopher G [Creator] and Barman, Sarah A [Creator] (2012) CHASE_DB1 retinal vessel reference dataset. [Data Collection]

Official URL: <https://doi.org/10.1109/TBME.2012.2205687>

3. State-of-the-art retinal vessel segmentation with minimalistic models

Adrian Galdran, André Anjos, José Dolz, Hadi Chakor, Hervé Lombaert & Ismail Ben Ayed

<https://www.nature.com/articles/s41598-022-09675-y>

4. Retinal blood vessel segmentation using a deep learning method based on modified U-NET model

Sanjeevani, Arun Kumar Yadav, Mohd Akbar, Mohit Kumar, Divakar Yadav

<https://www.semanticscholar.org/reader/f5cb3b1c69a2a7e97d1935be9d706017af8cc1a3>

5. Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-HRF-Retinal-Vessel

Toshiyuki Arai @antillia.com

<https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-HRF-Retinal-Vessel>

6. Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-STARE-Retinal-Vessel

Toshiyuki Arai @antillia.com

<https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-STARE-Retinal-Vessel>

7, Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-DRIVE-Retinal-Vessel

Toshiyuki Arai @antillia.com

<https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-DRIVE-Retinal-Vessel>

8. Tensorflow-Tiled-Image-Segmentation-Augmented-Skin-Cancer

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<https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Augmented-Skin-Cancer>

9. Tensorflow-Tiled-Image-Segmentation-Augmented-MultipleMyeloma

Toshiyuki Arai @antillia.com

<https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Augmented-MultipleMyeloma>

10. Tiled-ImageMask-Dataset-Breast-Cancer

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<https://github.com/sarah-antillia/Tiled-ImageMask-Dataset-Breast-Cancer>