Tensorflow-Tiled-Image-Segmentation-Messidor-2-Retinal-Vessel (2025/02/25)

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This is the first experiment of Image Segmentation for **Messidor-2** based on Pretrained HRF Retinal Vessel Model, which was trained by the latest Tensorflow-Image-Segmentation-API, and a **pre-augmented tiled dataset** Augmented-Tiled-HRF-ImageMask-Dataset.zip, which was derived by us from the following dataset:

Download the whole dataset (~73 Mb) in **High-Resolution Fundus (HRF) Image Database**.

Please see also our experiments:

- 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 Strategies

1. LABELS (antillia ground truth) for Messidor-2 master IMAGES
The Messidor-2 dataset contains no LABELS (ground truth) data. Therefore, we created our own master LABELS (ground truth) from the original Messidor-2 IMAGES by using Tiled Image Segmentation method and Pretrained-HRF-Retinal-Vessel UNet Model which was trained by the latest Tensorflow-Image-Segmentation-API, and a **pre-augmented tiled dataset** Augmented-Tiled-HRF-ImageMask-Dataset.zip.

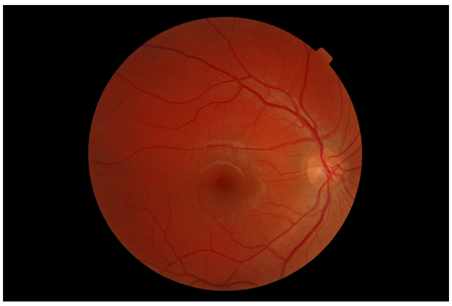
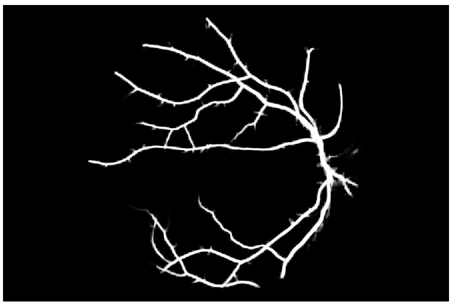
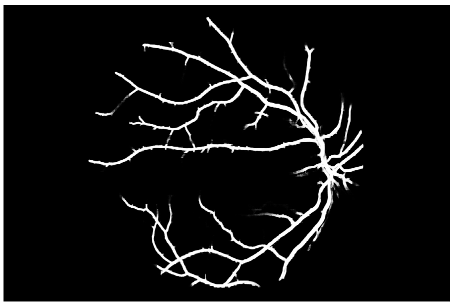
2. Messidor-2 Dataset
We splitted the Messidor-2-master IMAGES and LABELES into test, train and valid subsets.

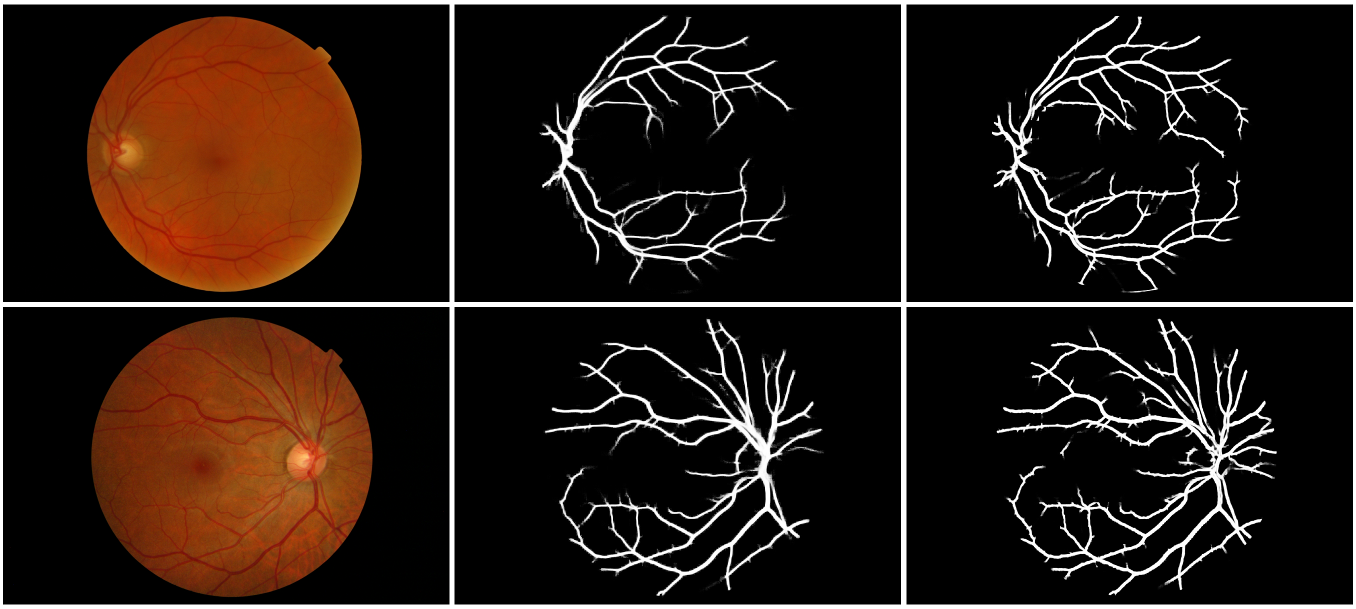
3. Train Messidor-2 Segmentation Model
We trained and validated a TensorFlow UNet model by using the **Messidor-2 train and valid subsets**

4. Evaluate Messidor-2 Segmentation Model
We evaluated the performance of the trained UNet model by using the **Messidor-2 test** dataset by computing the **bce_dice_loss** and **dice_coef**.

5. Tiled Inference
We applied our Tiled Image Segmentation method to infer the Retinal Vessel for the mini_test images of the original Messidor-2 IMAGES of 2240x1488 pixels.

Actual Tiled Image Segmentation for Messidor-2 IMAGES of 2240x1488 pixels
As shown below, the inferred masks look similar to the ground truth masks.

Input: image	Mask (antillia ground_truth)	Prediction: tiled_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

1.1 High-Resolution Fundus (HRF) Image Database

The dataset used here has been taken from the dataset Download the whole dataset (~73 Mb) in **High-Resolution Fundus (HRF) Image Database**.

Introduction
This database has been established by a collaborative research group to support comparative studies on automatic segmentation algorithms on retinal fundus images. The database will be iteratively extended and the webpage will be improved.
We would like to help researchers in the evaluation of segmentation algorithms. We encourage anyone working with segmentation algorithms who found our database useful to send us their evaluation results with a reference to a paper where it is described. This way we can extend our database of algorithms with the given results to keep it always up-to-date.
The database can be used freely for research purposes. We release it under Creative Commons 4.0 Attribution License.

Citation
Robust Vessel Segmentation in Fundus Images
Budai, Attila; Bock, Rüdiger; Maier, Andreas; Hornegger, Joachim; Michelson, Georg.
International Journal of Biomedical Imaging, vol. 2013, 2013

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1.2 Messidor-2 Dataset

We also used Messidor-2 Dataset,

MESSIDOR stands for **M**ethods to **E**valuate **S**egmentation and **I**ndexing **T**echniques in the field of **R**etinal **O**phthalmology (in French).

Messidor-2 Dataset
The Messidor-2 dataset is a collection of Diabetic Retinopathy (DR) examinations, each consisting of two macula-centered eye

fundus images (one per eye). Part of the dataset (Messidor-Original) was kindly provided by the Messidor program partners. The remainder (Messidor-Extension) consists of never-before-published examinations from Brest University Hospital. In the original Messidor dataset, some fundus images came in pairs, some others were single. Messidor-Original consists of all image pairs from the original Messidor dataset, that is 529 examinations (1058 images, saved in PNG format). In order to populate Messidor-Extension, diabetic patients were recruited in the Ophthalmology department of Brest University Hospital (France) between October 16, 2009 and September 6, 2010. Eye fundi were imaged, without pharmacological dilation, using a Topcon TRC NW6 non-mydriatic fundus camera with a 45 degree field of view. Only macula-centered images were included in the dataset. Messidor-Extension contains 345 examinations (690 images, in JPG format).
Overall, Messidor-2 contains 874 examinations (1748 images). The dataset comes with a spreadsheet containing image pairing.
It does not contain annotations such as a diabetic retinopathy “ground truth”. However, some third-parties proposed such annotations, but these are independent from the official Messidor-2 database, and therefore not handled by our services.

Using the database
Messidor-2 can be used, free of charge, for research and educational purposes. Copy, redistribution, and any unauthorized commercial use are prohibited. Any publication relying on this dataset must acknowledge the LaTIM laboratory and the Messidor program partners. Please include the following acknowledgmen.
Kindly provided by the Messidor program partners (see https://www.adcis.net/en/third-party/messidor/).
Decencière et al..
Feedback on a publicly distributed database: the Messidor database.
Image Analysis & Stereology, v. 33, n. 3, p. 231-234, aug. 2014. ISSN 1854-5165.
Available at: http://www.ias-iss.org/ojs/IAS/article/view/1155 or http://dx.doi.org/10.5566/ias.1155. M. D. Abràmoff, J. C. Folk, D. P. Han, J. D. Walker, D. F. Williams, S. R. Russell, P. Massin, B. Cochener,
P. Gain, L. Tang, M. Lamard, D. C. Moga, G. Quellec, and M. Niemeijer,
Automated analysis of retinal images for detection of referable diabetic retinopathy.
JAMA Ophthalmol, vol. 131, no. 3, Mar. 2013, p. 351–357.
Available at: https://doi.org/10.1001/jamaophthalmol.2013.1743.

2. Create LABELS for Messidor-2 IMAGES

2.1 Download Messidor-2 IMAGES Dataset

Please download Messidor-2 Dataset, and place IMAGES under Messidor-2-master folder as shown below.

```
./projects
 └─generator
    └─Messidor-2-master
        └─IMAGES
```

2.2 Download Augmented-Tiled-HRF-Pretrained-Model

Please download our Augmented-Tiled-HRF-Pretrained-Model.zip, expand it and place **best_model.h5** under models folder as shown below.

```
./projects
 └─TensorflowSlightlyFlexibleUNet
    └─Augmented-Tiled-HRF
         └─models
             └─best_model.h5
```

2.3 Run Tiled Inference method

Please move the folder "./projects/TensorflowSlightlyFlexibleUNet/Augmented-Tiled-HRF". and run the following bat file.

```
5.tiled_infer-messidor.bat
```

This will generate our own LABELS (ground truth) for the official Messidor-2 IMAGES by using the HRF-Pretrained-Model, without any human experts.

```
./projects
 └─generator
    └─Messidor-2-master
        ├─IMAGES
        └─LABELS
```

2.4 Split Messidor-2-master

Please move to "./projects/generator" folder and run the following Python script.

```
python spit_master.py
```

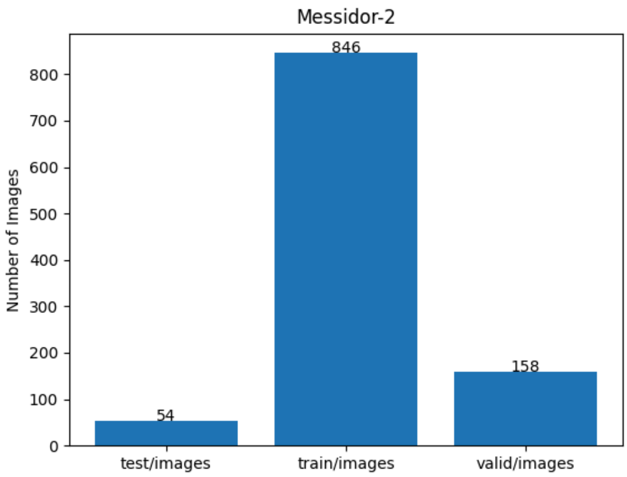
,by which the following Messidor-2 dataset will be created.

```
./dataset
└─Messidor-2
    ├─test
    │  ├─images
    │  └─masks
    ├─train
    │  ├─images
    │  └─masks
    └─valid
        ├─images
        └─masks
```

This is a 2240x1488 pixels images and their corresponding masks dataset.

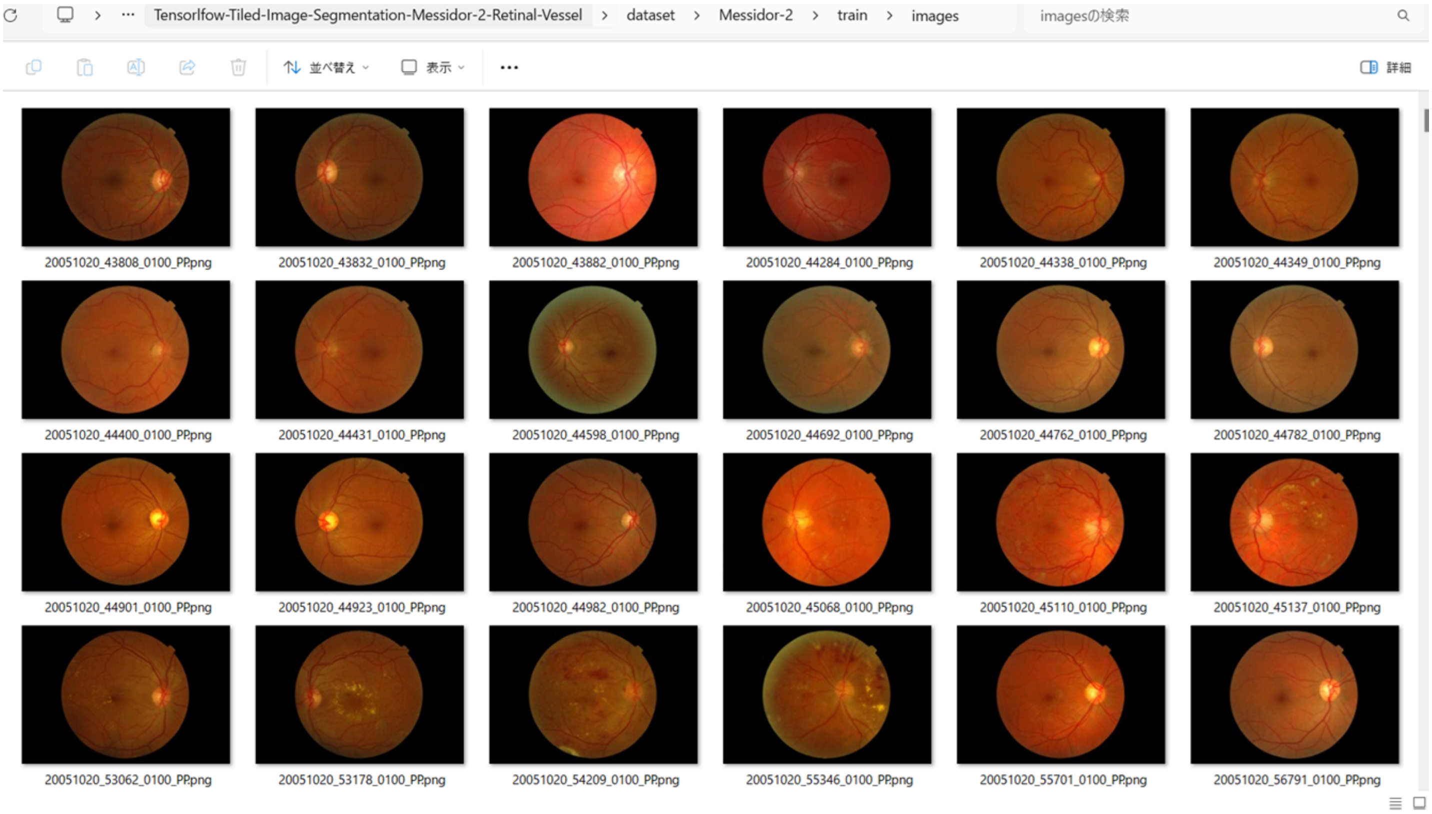
.

Messidor-2 Statistics

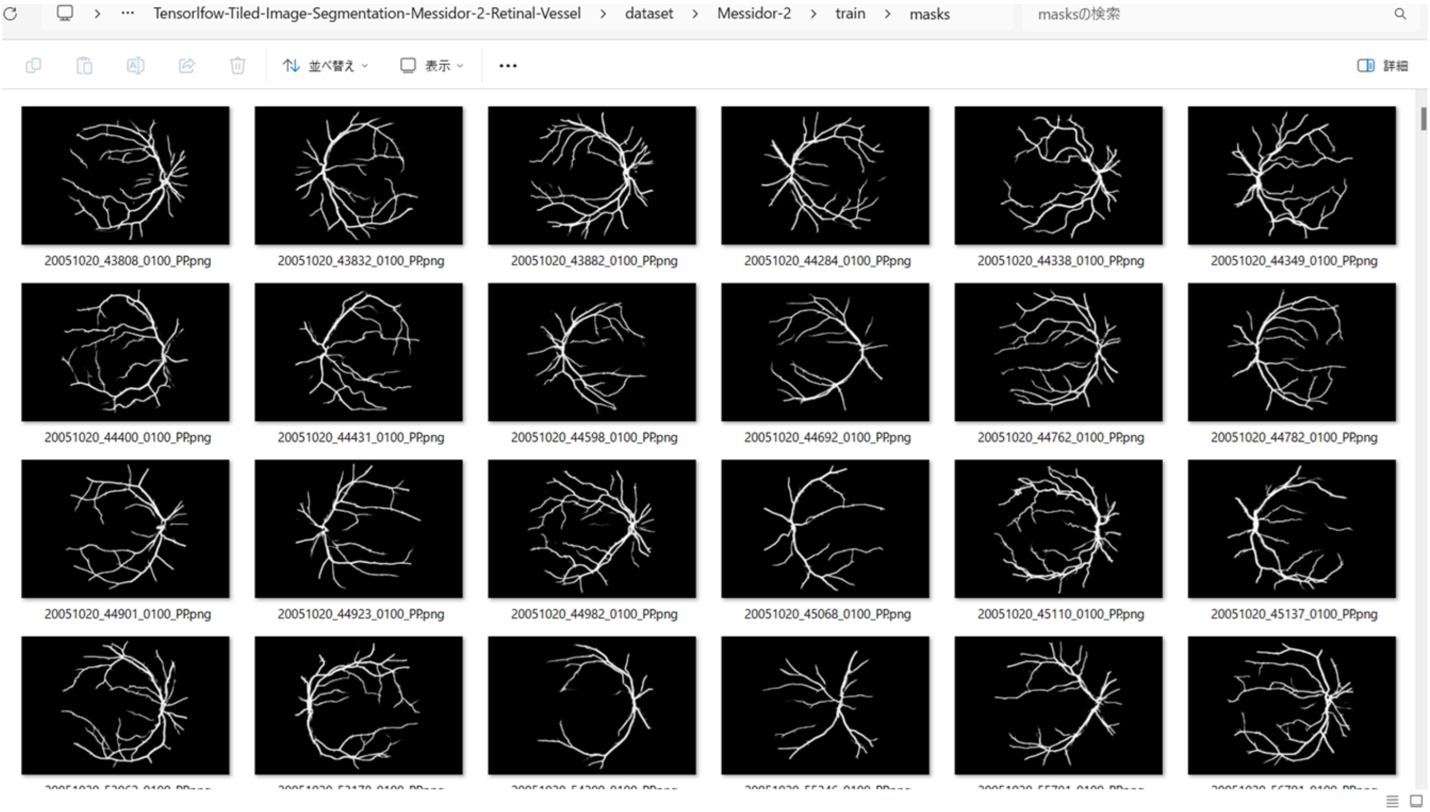


As shown above, the number of images of train and valid datasets is enough to use for a training set of our segmentation model.

Train_images_sample



Train_masks_sample



3 Train TensorflowUNet Model

We have trained HRF TensorflowUNet Model by using the following [train_eval_infer.config](#) file.
Please move to ./projects/TensorflowSlightlyFlexibleUNet/Messidor-2 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=(11,11)** 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   = (11,11)
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
```

Tiled Inference

Used the original Messidor-2 IMAGES as a mini_test dataset for our inference images.

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

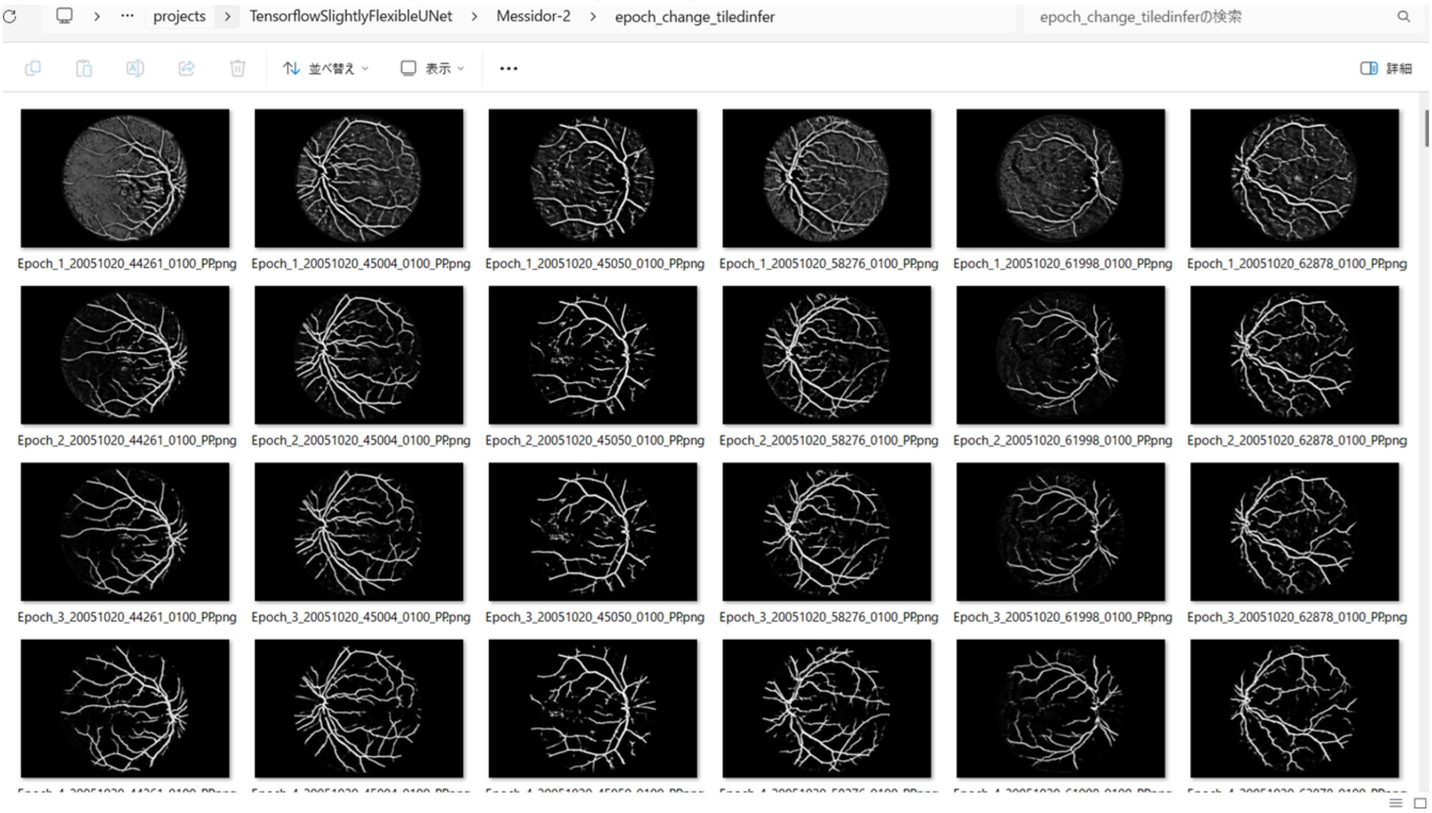
Epoch change inference callbacks

Enabled epoch_change_infer callback.

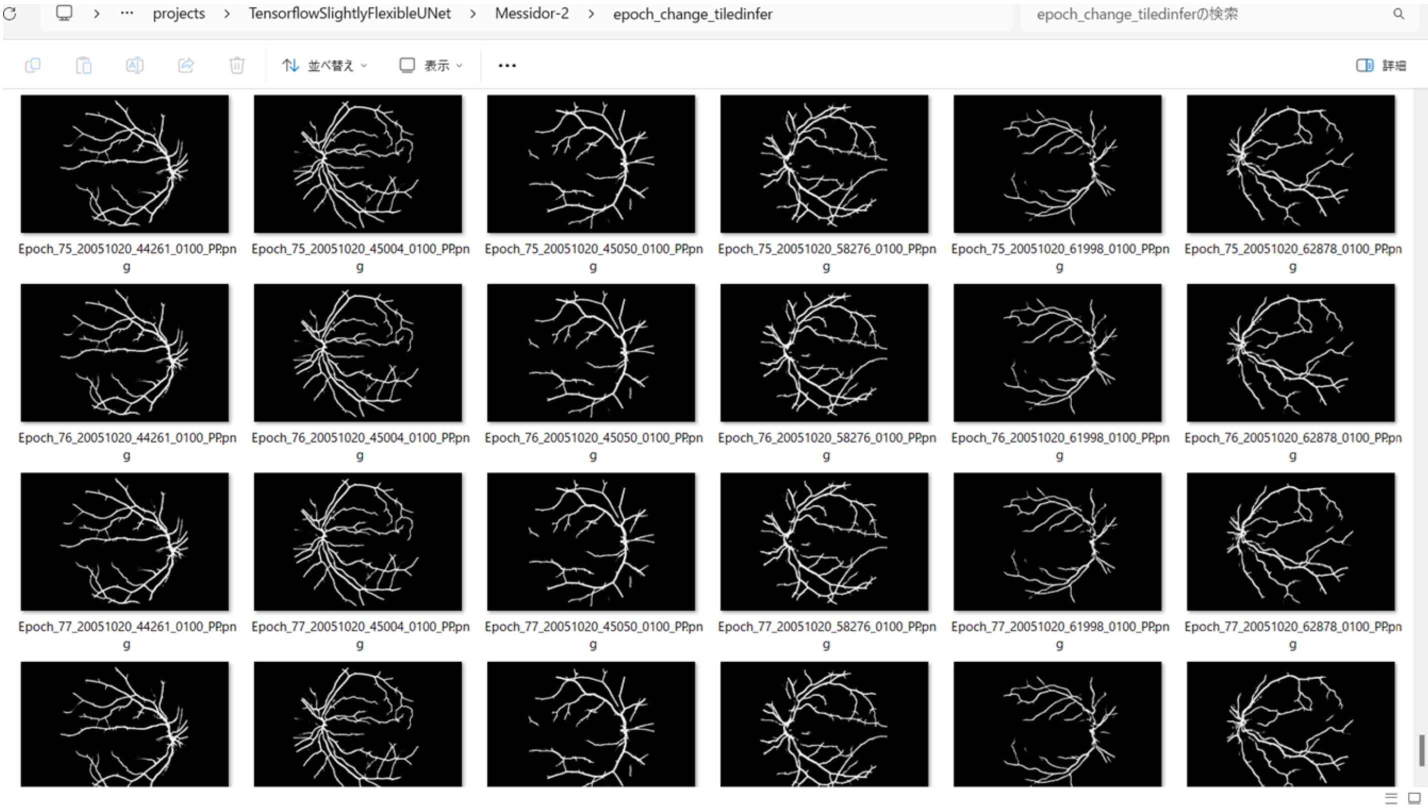
```
[train]
epoch_change_infer      = False
epoch_change_infer_dir  = "./epoch_change_infer"
epoch_change_tiledinfer = True
epoch_change_tiledinfer_dir = "./epoch_change_tiledinfer"
num_infer_images       = 6
```

By using this callback, on every epoch_change, the epoch change 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.

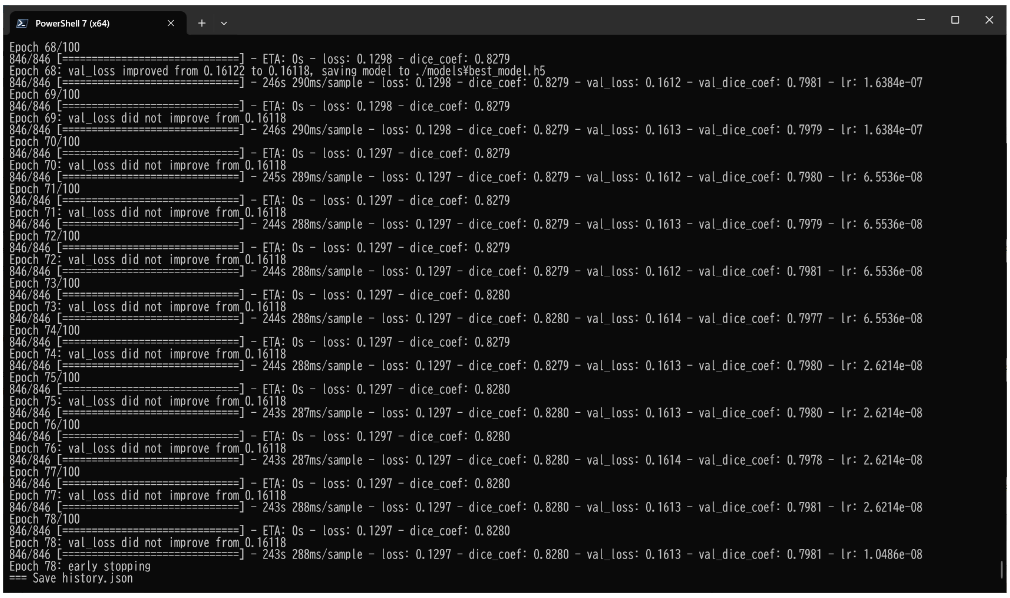
Epoch_change_tiled_inference output at starting (1,2,3,4)



Epoch_change_tiled_inference output at ending (75,76,77,78)

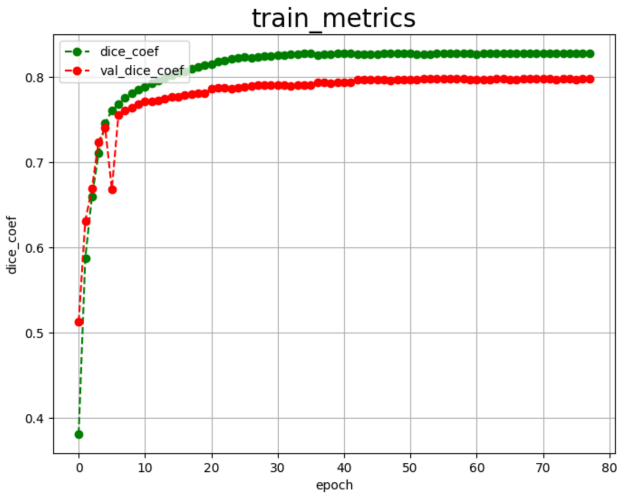


In this experiment, the training process was stopped at epoch 78 by EarlyStopping Callback.

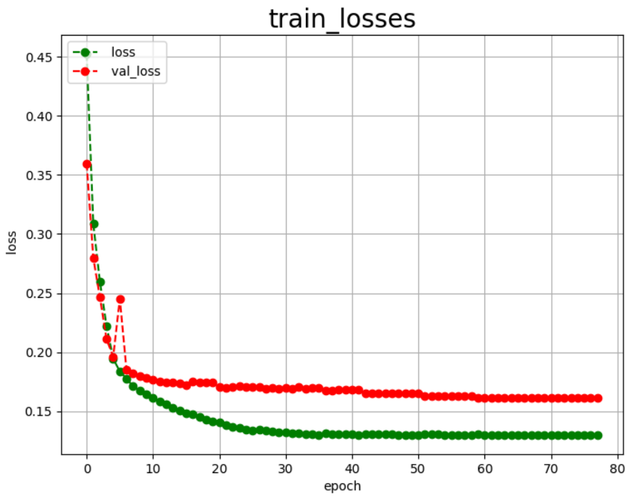


```
PowerShell 7 (x64)
Epoch 68/100
846/846 [==============================] - ETA: 0s - loss: 0.1298 - dice_coef: 0.8279
Epoch 68: val_loss improved from 0.16122 to 0.16118, saving model to ./models¥best_model.h5
846/846 [==============================] - 246s 290ms/sample - loss: 0.1298 - dice_coef: 0.8279 - val_loss: 0.1612 - val_dice_coef: 0.7981 - lr: 1.6384e-07
Epoch 69/100
846/846 [==============================] - ETA: 0s - loss: 0.1298 - dice_coef: 0.8279
Epoch 69: val_loss did not improve from 0.16118
846/846 [==============================] - 246s 290ms/sample - loss: 0.1298 - dice_coef: 0.8279 - val_loss: 0.1613 - val_dice_coef: 0.7979 - lr: 1.6384e-07
Epoch 70/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8279
Epoch 70: val_loss did not improve from 0.16118
846/846 [==============================] - 245s 289ms/sample - loss: 0.1297 - dice_coef: 0.8279 - val_loss: 0.1612 - val_dice_coef: 0.7980 - lr: 6.5536e-08
Epoch 71/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8279
Epoch 71: val_loss did not improve from 0.16118
846/846 [==============================] - 244s 288ms/sample - loss: 0.1297 - dice_coef: 0.8279 - val_loss: 0.1613 - val_dice_coef: 0.7979 - lr: 6.5536e-08
Epoch 72/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8279
Epoch 72: val_loss did not improve from 0.16118
846/846 [==============================] - 244s 288ms/sample - loss: 0.1297 - dice_coef: 0.8279 - val_loss: 0.1612 - val_dice_coef: 0.7981 - lr: 6.5536e-08
Epoch 73/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8280
Epoch 73: val_loss did not improve from 0.16118
846/846 [==============================] - 244s 288ms/sample - loss: 0.1297 - dice_coef: 0.8280 - val_loss: 0.1614 - val_dice_coef: 0.7977 - lr: 6.5536e-08
Epoch 74/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8279
Epoch 74: val_loss did not improve from 0.16118
846/846 [==============================] - 244s 288ms/sample - loss: 0.1297 - dice_coef: 0.8279 - val_loss: 0.1613 - val_dice_coef: 0.7980 - lr: 2.6214e-08
Epoch 75/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8280
Epoch 75: val_loss did not improve from 0.16118
846/846 [==============================] - 243s 287ms/sample - loss: 0.1297 - dice_coef: 0.8280 - val_loss: 0.1613 - val_dice_coef: 0.7980 - lr: 2.6214e-08
Epoch 76/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8280
Epoch 76: val_loss did not improve from 0.16118
846/846 [==============================] - 243s 287ms/sample - loss: 0.1297 - dice_coef: 0.8280 - val_loss: 0.1614 - val_dice_coef: 0.7978 - lr: 2.6214e-08
Epoch 77/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8280
Epoch 77: val_loss did not improve from 0.16118
846/846 [==============================] - 243s 288ms/sample - loss: 0.1297 - dice_coef: 0.8280 - val_loss: 0.1613 - val_dice_coef: 0.7981 - lr: 2.6214e-08
Epoch 78/100
846/846 [==============================] - ETA: 0s - loss: 0.1297 - dice_coef: 0.8280
Epoch 78: val_loss did not improve from 0.16118
846/846 [==============================] - 243s 288ms/sample - loss: 0.1297 - dice_coef: 0.8280 - val_loss: 0.1613 - val_dice_coef: 0.7981 - lr: 1.0486e-08
Epoch 78: early stopping
=== Save history.json
```

train_metrics.csv



[train_losses.csv]



4 Evaluation

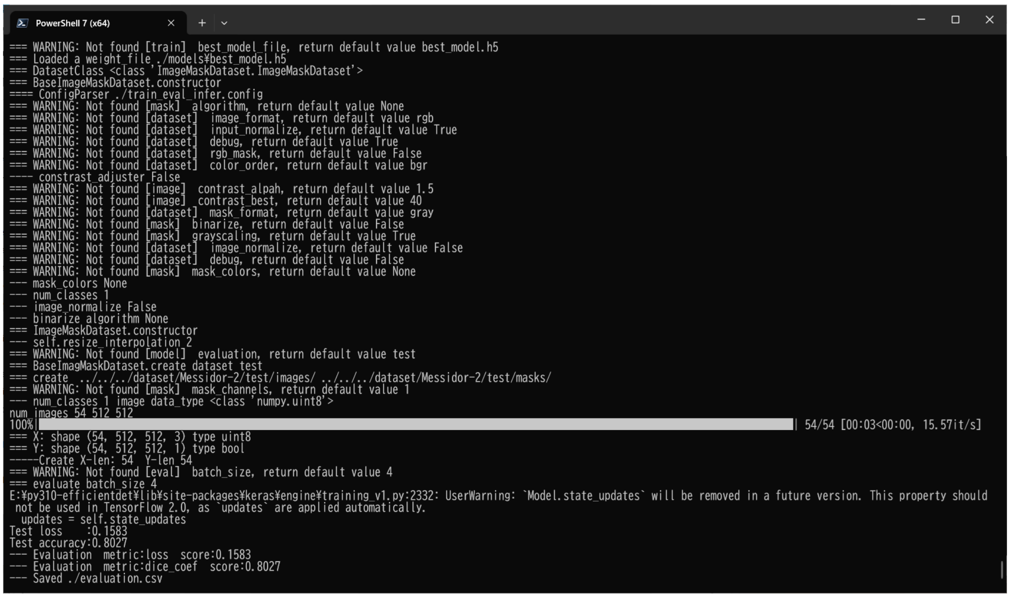
Please move to a **./projects/TensorflowSlightlyFlexibleUNet/Messidor-2** folder,
and run the following bat file to evaluate TensorflowUNet model for Messidor-2/test.

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

This bat file simply runs the following command.

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

Evaluation console output:



```
PowerShell 7 (x64)
=== WARNING: Not found [train]  best_model_file, return default value best_model.h5
=== Loaded a weight_file ./models¥best_model.h5
=== DatasetClass <class 'ImageMaskDataset.ImageMaskDataset'>
=== BaseImageMaskDataset.constructor
==== ConfigParser ./train_eval_infer.config
=== WARNING: Not found [mask]  algorithm, return default value None
=== WARNING: Not found [dataset]  image_format, return default value rgb
=== WARNING: Not found [dataset]  input_normalize, return default value True
=== 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
---- constrast_adjuster False
=== WARNING: Not found [image]  contrast_alpah, return default value 1.5
=== WARNING: Not found [image]  contrast_best, return default value 40
=== WARNING: Not found [dataset]  mask_format, return default value gray
=== WARNING: Not found [mask]  binarize, return default value False
=== WARNING: Not found [mask]  grayscaling, return default value True
=== WARNING: Not found [dataset]  image_normalize, return default value False
=== WARNING: Not found [dataset]  debug, return default value False
=== WARNING: Not found [mask]  mask_colors, return default value None
--- mask_colors None
--- num_classes 1
--- image_normalize False
--- binarize algorithm None
=== ImageMaskDataset.constructor
--- self.resize_interpolation 2
=== WARNING: Not found [model]  evaluation, return default value test
=== BaseImagMaskDataset.create dataset test
=== create  ../../../dataset/Messidor-2/test/images/ ../../../dataset/Messidor-2/test/masks/
=== WARNING: Not found [mask]  mask_channels, return default value 1
--- num_classes 1 image data_type <class 'numpy.uint8'>
num_images 54 512 512
100%|| 54/54 [00:03<00:00, 15.57it/s]
=== X: shape (54, 512, 512, 3) type uint8
=== Y: shape (54, 512, 512, 1) type bool
-----Create X-len: 54  Y-len 54
=== 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
Test loss    :0.1583
Test accuracy:0.8027
--- Evaluation  metric:loss  score:0.1583
--- Evaluation  metric:dice_coef  score:0.8027
--- Saved ./evaluation.csv
```

evaluation.csv

The loss (bce_dice_loss) to this Messidor-2/test was not low, and dice_coef not high as shown below.

```
loss,0.1583
dice_coef,0.8027
```

5 Tiled Inference

Please move to a **./projects/TensorflowSlightlyFlexibleUNet/Messidor-2** folder
,and run the following bat file to infer segmentation regions for images by the Trained-TensorflowUNet model for Messidor-2.

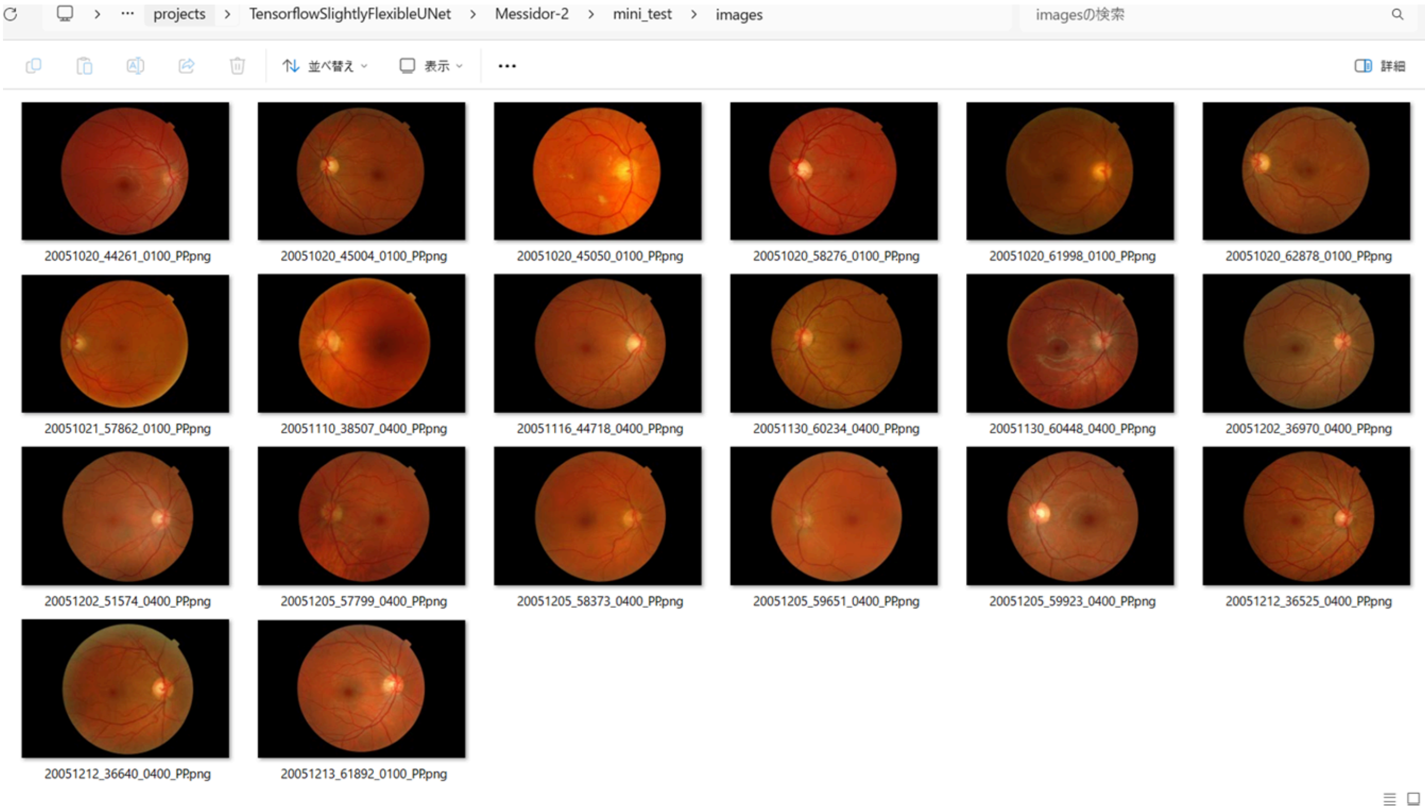
```
./4.tiledinfer.bat
```

This simply runs the following command.

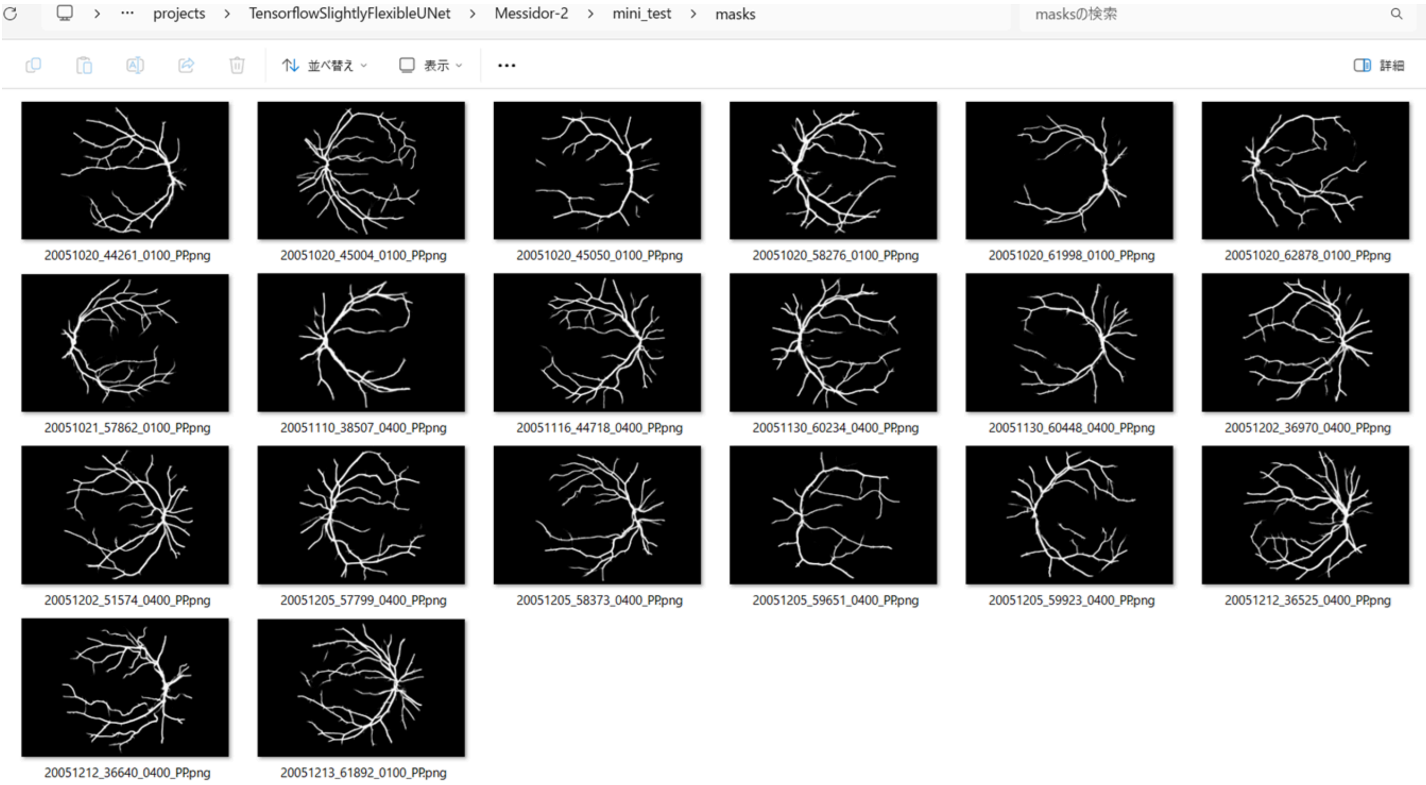
```
python ../../../src/TensorflowUNetTiledInferencer.py ./train_eval_infer.config
```

---

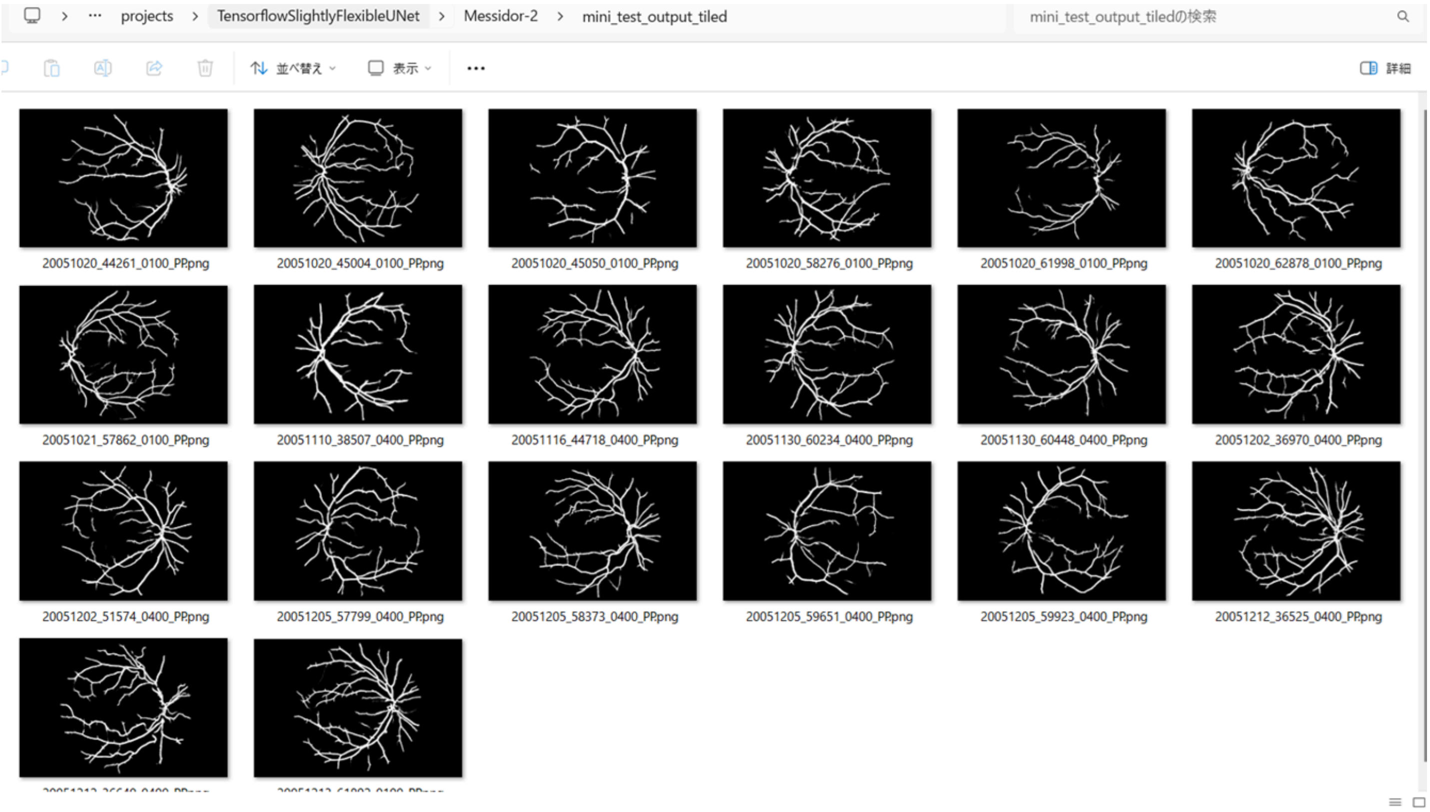
mini_test_images (2240x1488 pixels)



mini_test_mask(antillia ground_truth)

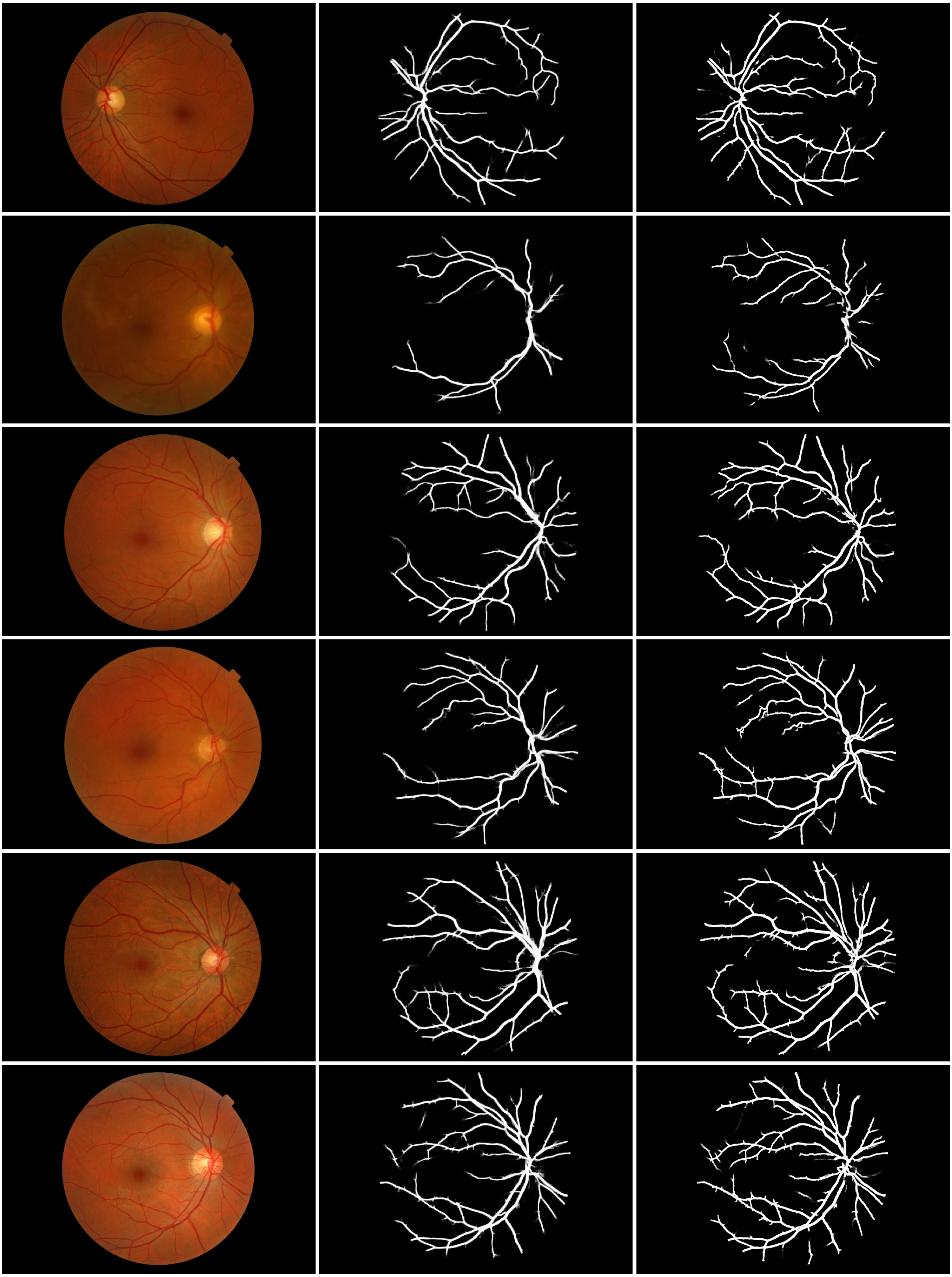


Tiled inferred test masks (2240x1488 pixels)



Enlarged images and masks of 2240x1488 pixels

Image	Mask (antillia 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. High-Resolution Fundus (HRF) Image Database
Budai, Attila; Bock, Rüdiger; Maier, Andreas; Hornegger, Joachim; Michelson, Georg.
https://www5.cs.fau.de/research/data/fundus-images/ .

3. Robust Vessel Segmentation in Fundus Images
Budai, Attila; Bock, Rüdiger; Maier, Andreas; Hornegger, Joachim; Michelson, Georg.
https://onlinelibrary.wiley.com/doi/10.1155/2013/154860

4. 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

5. Retinal blood vessel segmentation using a deep learning method based on modified U-NET model
Sanjeewani, Arun Kumar Yadav, Mohd Akbar, Mohit Kumar, Divakar Yadav
https://www.semanticscholar.org/reader/f5cb3b1c69a2a7e97d1935be9d706017af8cc1a3

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-HRF-Retinal-Vessel
Toshiyuki Arai @antillia.com
https://github.com/sarah-antillia/Tensorflow-Tiled-Image-Segmentation-Pre-Augmented-HRF-Retinal-Vessel