Chapter 1

User Manual

In this chapter, detailed instructions on how to execute the source code have been provided. All explanations contain screenshots that demonstrate the inputs and outputs of the executable commands. This chapter assumes that the steps listed in the **Maintenance Manual** have been followed and the project repository has been set up.

The *Command Prompt* application for Windows is equivalent to the Linux/macOS *Terminal*. Therefore, the same operations can be performed on Linux and macOS, as well. The appropriate alternative commands will be provided in each example.

Instructions for starting *Command Prompt/Terminal*

To open a Command Prompt window and navigate to a directory:

1. Open the search bar, type '**cmd**' and press the 'ENTER' key on the keyboard to start the application. See Fig. 1. For Linux, the **CTRL** + **ALT** + **T** sequence of keyboard keys can be used to start a terminal window. For macOS, press the **Command** button + **Space** on the keyboard to open Spotlight Search. Then, you can type *Terminal* and hit the **ENTER** key.

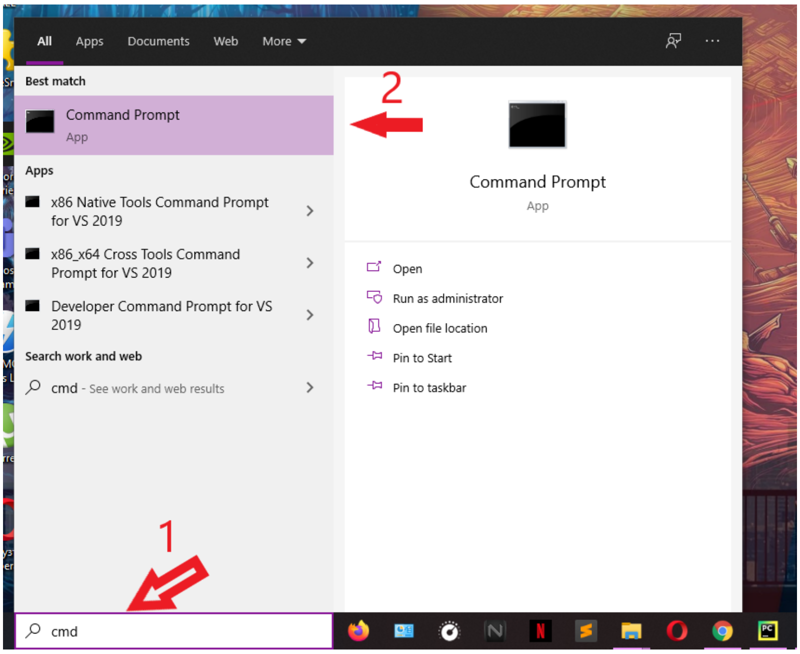
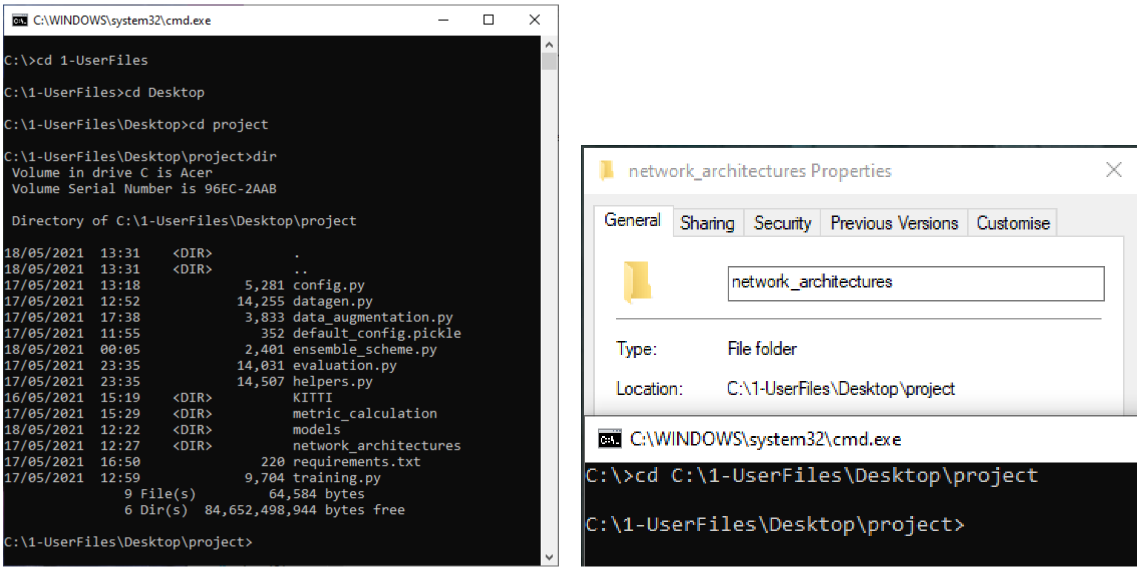


Figure 1: How to start a Command Prompt window

2. Navigate to the project directory created during the installation and setup stage by using two basic commands - *cd* (Change Directory) and **dir** (View Contents of Directory). The difference in Linux/macOS is that the **dir** command is replaced with **ls**. To go back from the current directory use `[cd ..]`. Refer to Figure 2 for visual examples and more detailed instructions.



(a) Example 1 of **cmd** navigation

(b) Example 2 of **cmd** navigation

Figure 2: This figure shows an example of how to navigate within the Command Prompt Interface. In **2a**, we navigate the directories one by one. In **2b**, we right-click on a file/folder inside our project directory and go to **Properties**. From there, the **Location** shows the full path to the parent directory. We can copy that and directly paste it after the **cd** command, clicking **CTRL + V** on the keyboard. Note: Make sure the path is surrounded by double quotes (")

After these steps, you will be able to run all source code files from that Command Prompt/Terminal instance.

Data augmentation

To execute this functionality, you need to open a Command Prompt window or a Terminal and navigate to the project directory (as shown in Section 1). The following instructions will walk you through the process of running the example:

1. Run the command - `python data_augmentation.py -h`. It will display help information about the script. More specifically, it shows what arguments are required in order for the script to be executed. Figure 3 displays the output of this command. It is visible that the script requires 3 positional arguments - directories. That is, arguments that need to be given exactly in the order they are requested.

2. An example of the execution of the data augmentation algorithm is shown in Figure 4. The red numbers shown on the screenshot correspond to the following 4 items:

   (a) Shows the directories residing in a repository, **KITTI_test**, before data augmentation is applied.

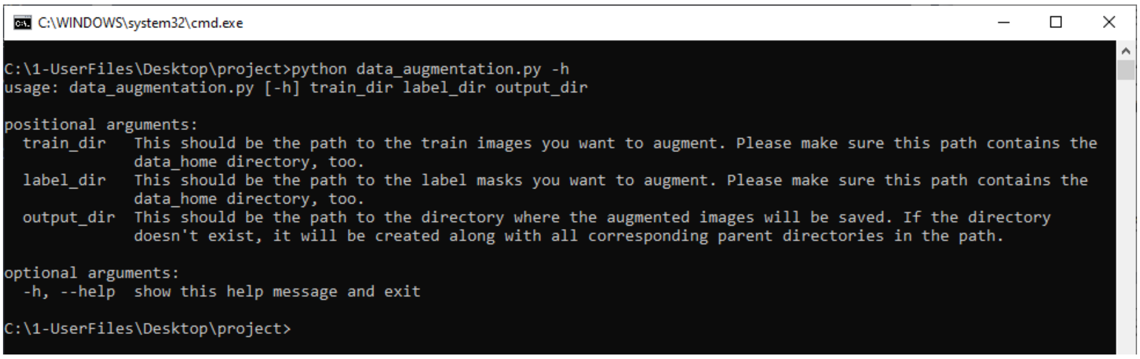


Figure 3: Output of the help information for the **data_augmentation.py** script. It expects a directory with images to augment, the path to the folder containing the corresponding ground-truth masks and an output location where the newly augmented images will be saved.

(b) This part counts the number of available labelled masks - 384.

(c) Here, we execute the script on the training images from the **um_road/** directory which annotated labels are in **enc_gt_image_1/**. The provided output location is a directory **augmented_images** residing in the **data_road/training** folder. Therefore, after the algorithm is completed, we will look for the augmented images there.

(d) The second arrow (4 in the screenshot) shows the newly-created augmented images' directory. A test is also executed to check the number of labels in **enc_gt_image_1/**. The result indicates that the number of samples has increased by 95 - the exact number of **um_road** images.

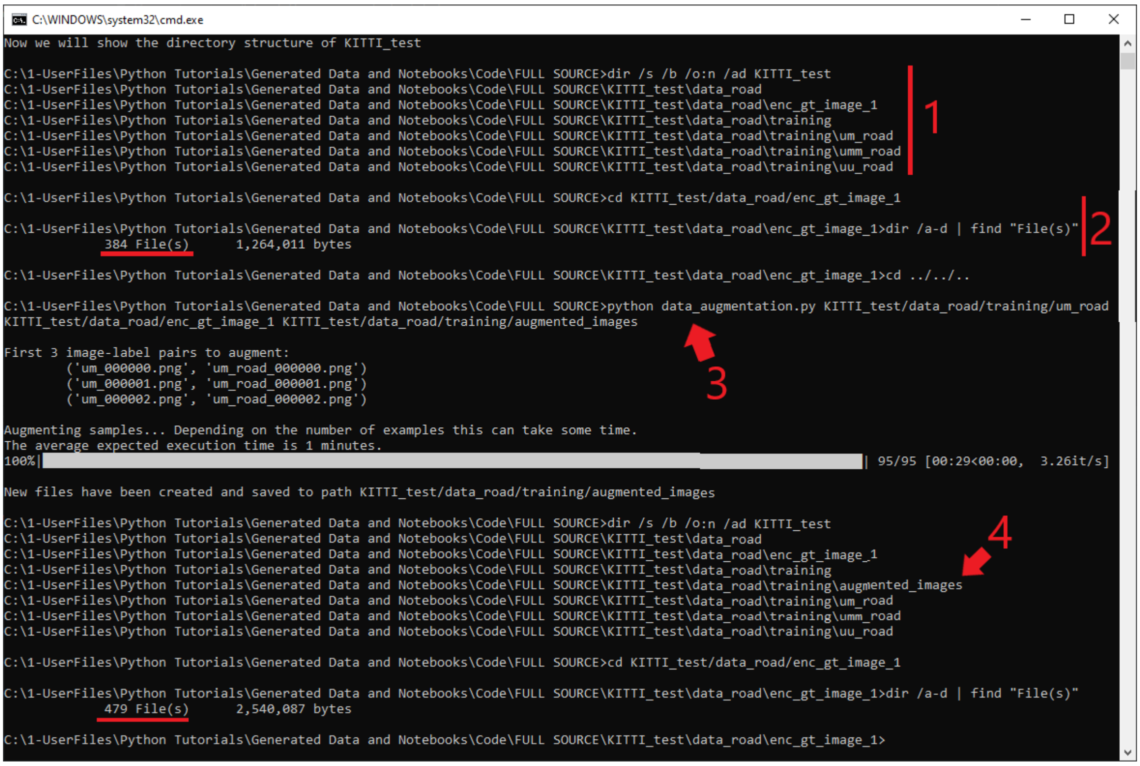


Figure 4: This figure shows the execution and the output of the data augmentation algorithm.

The effect of the augmentation operation is presented in Figure 5. The image on the left

(a) Original KITTI road image

(b) Augmentation using mirroring, rotation and zoom

Figure 5: The effect of applying data augmentation operations on an image from the KITTI data set.

(5a) is the original KITTI image, while the right one (5b) is the augmented version. It is visible how the transformations affected the data - image is rotated, mirrored horizontally and zoomed/cropped.

Note: Currently, augmented samples for all images are included in the data set. The augmented ground-truth masks are located in the **enc_gt_image_1/** directory within **data_road** and have the word '*new*' in their names. The **new_augs/** folder contains all raw images' augmented versions within **data_road/training/**. Creating new augmented images using this method will overwrite the existing labels as they are always saved to the main label directory. The other augmentations will be stored in a directory of your choice and hence the old ones will not be deleted (unless you specify the same output directory as the current one).

Training

This section describes the process of training a model. It is important to note that this may take a long time if the training set contains a lot of images. To get a better idea of how it is performed, a simple training example will be provided below with step-by-step explanations.

Parameter Configuration

To train a model, we need a configuration object (Python dictionary) that contains parameters like batch size, number of epochs, data set paths and many others. Such a dictionary is created using the **config.py** Python script. One dictionary is also provided with this distribution - **default_config.pickle**. This file is a serialised (*pickled*) version of the configuration dictionary object that can be loaded into any script during runtime. It contains all default values of each parameter which are also available in Figure 6. It is similar to the help information received for the data augmentation script. An example script initiation command is given in the first line of the output of the help request. Definitions for each of the optional arguments are also provided along with their default values.

The generation of a configuration file is demonstrated in Fig. 7. It can be seen how the specified arguments, namely batch size, epochs, steps per epoch and configuration filename, are different from the default values. We generate a configuration dictionary that will train a U-net model using 128×128 images as input for the neural network. Additionally, the training process will continue for 2 epochs and during each of them, 2 batches containing 2 images will be presented to the model. The resulting model will be saved in the **models/** directory within the current project folder.

```
C:\WINDOWS\system32\cmd.exe

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>python config.py -h
usage: config.py [-h] [-i IMSIZE] [-b {2,4,8,16,32}] [-c CLASSES] [-e EPOCHS] [-mv {unet,mob_net}] [-v [0.0, 1.0]]
                 [-s STEPS_PER_EPOCH] [-a AUGMENTED_DATA] [-p [0.0, 1.0]] [-d DATA_HOME] [-tr TRAIN_DIR] [-l LABEL_DIR]
                 [-tt TEST_DIR] [-ms MODEL_SAVE_DIR] [-cf CONFIG_FILENAME]

optional arguments:
  -h, --help            show this help message and exit
  -i IMSIZE, --imsize IMSIZE
                        This defines the size of the images inputted to the network. The data must be a tuple of two
                        elements (Width, Height). NOTE: Model will not work if the given size is not compatible with its
                        Input Layer. (default: (128, 128))
  -b {2,4,8,16,32}, --bsize {2,4,8,16,32}
                        The number of samples to load in each batch (the available sizes are shown in curly the brackets
                        - {2,4,...,32}). Depending on the capacity of the GPU or RAM, large "bsize" might terminate
                        execution. (default: 4)
  -c CLASSES, --classes CLASSES
                        Number of object classes the model needs to choose from for each pixel. (default: 2)
  -e EPOCHS, --epochs EPOCHS
                        Number of training epochs. (default: 20)
  -mv {unet,mob_net}, --model_version {unet,mob_net}
                        The model architecture that will be used for training. (default: unet)
  -v [0.0, 1.0], --val_split [0.0, 1.0]
                        What fraction of the data to use for validation during training. (default: 0.2)
  -s STEPS_PER_EPOCH, --steps_per_epoch STEPS_PER_EPOCH
                        Number of batches to iterate over in each epoch. (default: None)
  -a AUGMENTED_DATA, --augmented_data AUGMENTED_DATA
                        Path to the augmented images. The corresponding augmented labels are expected to be in the main
                        ground-truth folder. (default: training/new_augs)
  -p [0.0, 1.0], --partial_sampling [0.0, 1.0]
                        What fraction of the data to use for partial sampling during transfer learning. (default: 0.0)
  -d DATA_HOME, --data_home DATA_HOME
                        Path to directory containing all training and testing sample subdirectories. (default:
                        KITTI/data_road)
  -tr TRAIN_DIR, --train_dir TRAIN_DIR
                        Path to the training images within the "--data_home" directory (default: training/um_road)
  -l LABEL_DIR, --label_dir LABEL_DIR
                        Path to ground-truth labels within "--data_home". This directory must include also the augmented
                        images` labels. (default: enc_gt_image_1)
  -tt TEST_DIR, --test_dir TEST_DIR
                        Path to the testing samples within "--data_home". (default: training/umm_road)
  -ms MODEL_SAVE_DIR, --model_save_dir MODEL_SAVE_DIR
                        Name of the directory where the trained model an its weights will be saved. (default: models/)
  -cf CONFIG_FILENAME, --config_filename CONFIG_FILENAME
                        The name of the file that will be used to save the serialised (pickled) dictionary object. Do
                        not add a file extension - a .pickle one will be added anyway. (default: default_config)

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>
```

Figure 6: This figure shows the help information associated with the **config.py** script.

Model Training

The **training.py** script is responsible for training a model on a given data set. The help information for the script can be accessed using `python training.py -h` and the resulting output is shown in Fig. 8.

The output produced by the training algorithm is illustrated in Fig. 9 and Fig. 10. The output is separated into two screenshots for clearer visualisation. In the first image, we execute the Python file from the *Command Prompt* by specifying the test configuration file created during the previous task.

The different stages of the execution will be briefly described below.

1. The training process begins with the initialisation of a *DataGen* object that will iterate over the images in the directories specified by the paths in the config file. This data generator provides image-label pairs for the training process, creates validation data and testing data generators, normalises images, performs encoding, etc.

2. Tests are executed to check the integrity of the data.

3. The specified model architecture is created and its internal structure defined in terms of layers, output shapes and parameter counts is printed.

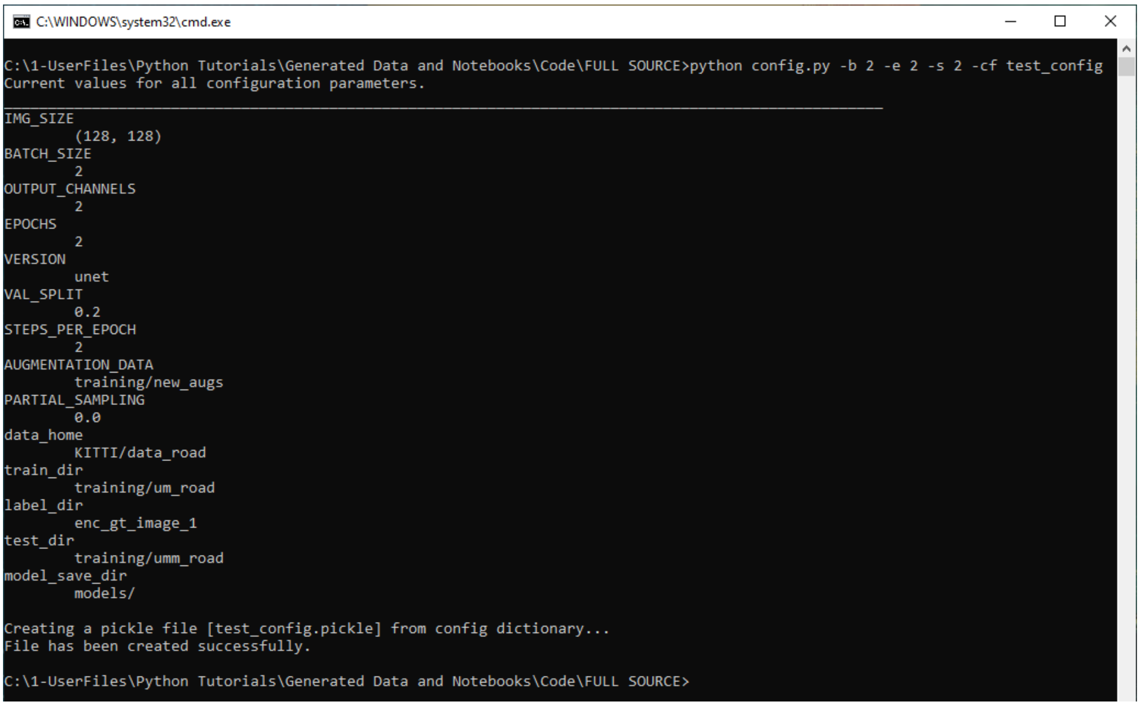


Figure 7: An example execution of the **config.py** file. The different options specified in the command are reflected in given output list.

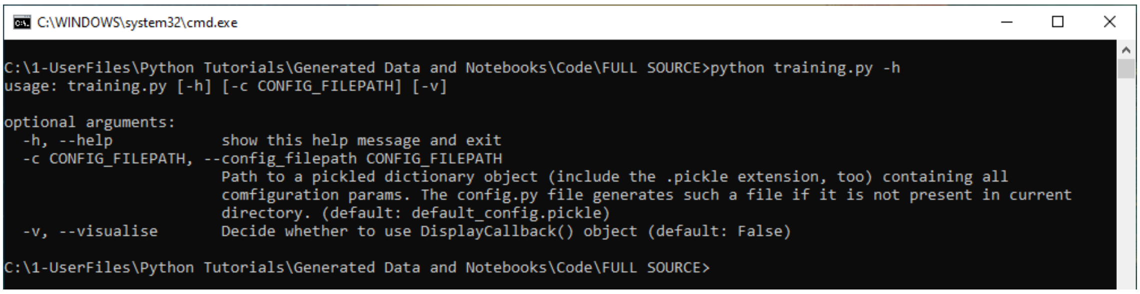


Figure 8: Help information for the **training.py** script file. The '-v' flag if specified, activates a specific callback object (DisplayCallback()). It uses the intermediate state of the model after each epoch to predict several test images. This is useful because it provides us with insight into the current development of the model during a certain epoch.

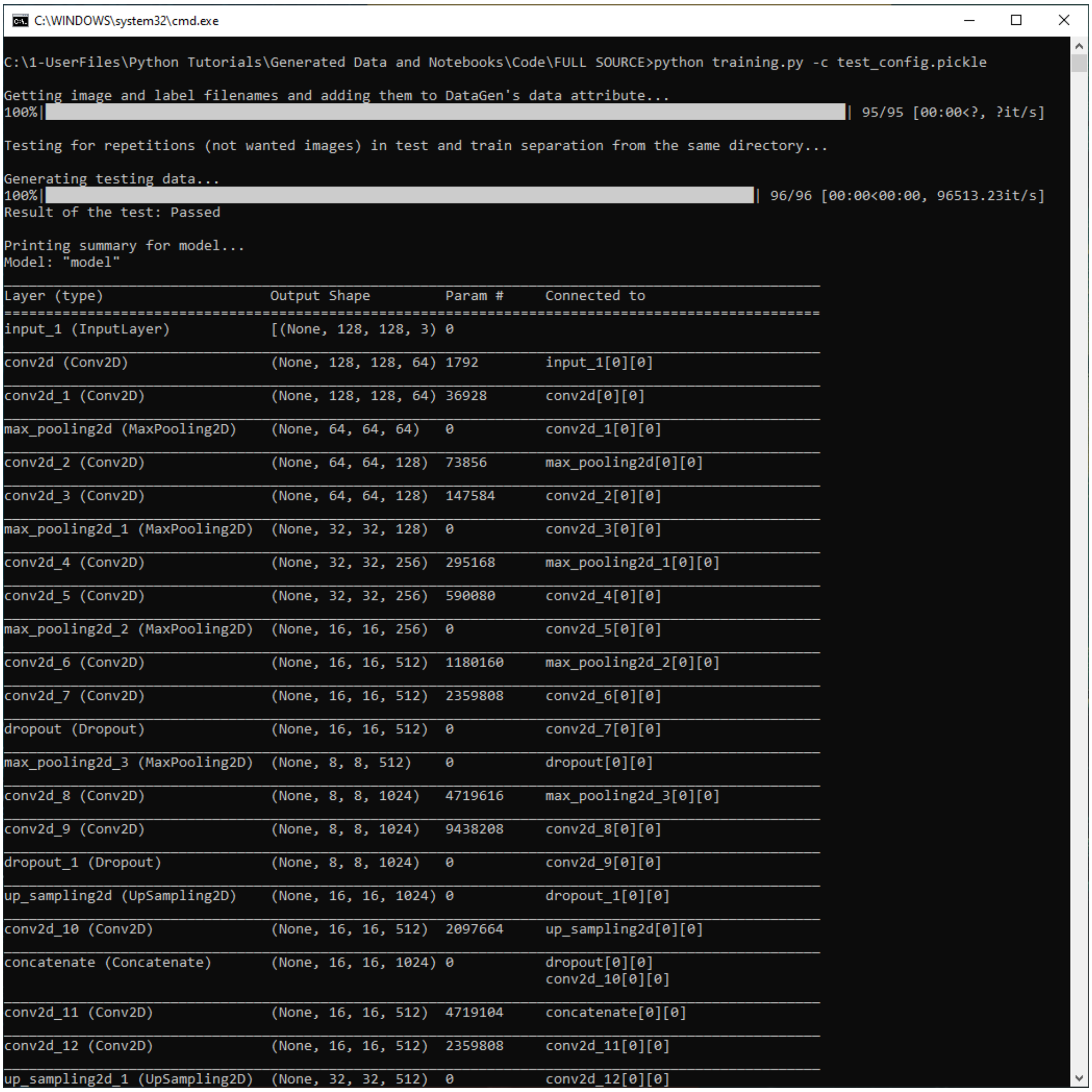
4. A prompt requests a name for the model to be inputted. Make sure that the name starts with 'model' because the evaluation algorithm looks for it.

5. The training starts and epoch-by-epoch the model is trained. After each iteration over the data, a validation stage is initiated.

6. At the end of the training, the model is saved to the directory from the configuration file with the name specified by us. Additional log information like current date and time, metric values, etc. are also appended to the name to allow uniqueness and prevent overriding.

Evaluation

After successfully training and saving a model, it is time to explain how we can evaluate its performance on the testing data. The **evaluation.py** script loads a trained model from a specified



```
C:\WINDOWS\system32\cmd.exe
C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>python training.py -c test_config.pickle

Getting image and label filenames and adding them to DataGen's data attribute...
100%|                                                                  | 95/95 [00:00<?, ?it/s]

Testing for repetitions (not wanted images) in test and train separation from the same directory...

Generating testing data...
100%|                                                                  | 96/96 [00:00<00:00, 96513.23it/s]
Result of the test: Passed

Printing summary for model...
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 128, 128, 3) 0
__________________________________________________________________________________________________
conv2d (Conv2D)                 (None, 128, 128, 64) 1792        input_1[0][0]
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 128, 128, 64) 36928       conv2d[0][0]
__________________________________________________________________________________________________
max_pooling2d (MaxPooling2D)    (None, 64, 64, 64)   0           conv2d_1[0][0]
__________________________________________________________________________________________________
conv2d_2 (Conv2D)               (None, 64, 64, 128)  73856       max_pooling2d[0][0]
__________________________________________________________________________________________________
conv2d_3 (Conv2D)               (None, 64, 64, 128)  147584      conv2d_2[0][0]
__________________________________________________________________________________________________
max_pooling2d_1 (MaxPooling2D)  (None, 32, 32, 128)  0           conv2d_3[0][0]
__________________________________________________________________________________________________
conv2d_4 (Conv2D)               (None, 32, 32, 256)  295168      max_pooling2d_1[0][0]
__________________________________________________________________________________________________
conv2d_5 (Conv2D)               (None, 32, 32, 256)  590080      conv2d_4[0][0]
__________________________________________________________________________________________________
max_pooling2d_2 (MaxPooling2D)  (None, 16, 16, 256)  0           conv2d_5[0][0]
__________________________________________________________________________________________________
conv2d_6 (Conv2D)               (None, 16, 16, 512)  1180160     max_pooling2d_2[0][0]
__________________________________________________________________________________________________
conv2d_7 (Conv2D)               (None, 16, 16, 512)  2359808     conv2d_6[0][0]
__________________________________________________________________________________________________
dropout (Dropout)               (None, 16, 16, 512)  0           conv2d_7[0][0]
__________________________________________________________________________________________________
max_pooling2d_3 (MaxPooling2D)  (None, 8, 8, 512)    0           dropout[0][0]
__________________________________________________________________________________________________
conv2d_8 (Conv2D)               (None, 8, 8, 1024)   4719616     max_pooling2d_3[0][0]
__________________________________________________________________________________________________
conv2d_9 (Conv2D)               (None, 8, 8, 1024)   9438208     conv2d_8[0][0]
__________________________________________________________________________________________________
dropout_1 (Dropout)             (None, 8, 8, 1024)   0           conv2d_9[0][0]
__________________________________________________________________________________________________
up_sampling2d (UpSampling2D)    (None, 16, 16, 1024) 0           dropout_1[0][0]
__________________________________________________________________________________________________
conv2d_10 (Conv2D)              (None, 16, 16, 512)  2097664     up_sampling2d[0][0]
__________________________________________________________________________________________________
concatenate (Concatenate)       (None, 16, 16, 1024) 0           dropout[0][0]
                                                                 conv2d_10[0][0]
__________________________________________________________________________________________________
conv2d_11 (Conv2D)              (None, 16, 16, 512)  4719104     concatenate[0][0]
__________________________________________________________________________________________________
conv2d_12 (Conv2D)              (None, 16, 16, 512)  2359808     conv2d_11[0][0]
__________________________________________________________________________________________________
up_sampling2d_1 (UpSampling2D)  (None, 32, 32, 512)  0           conv2d_12[0][0]
```

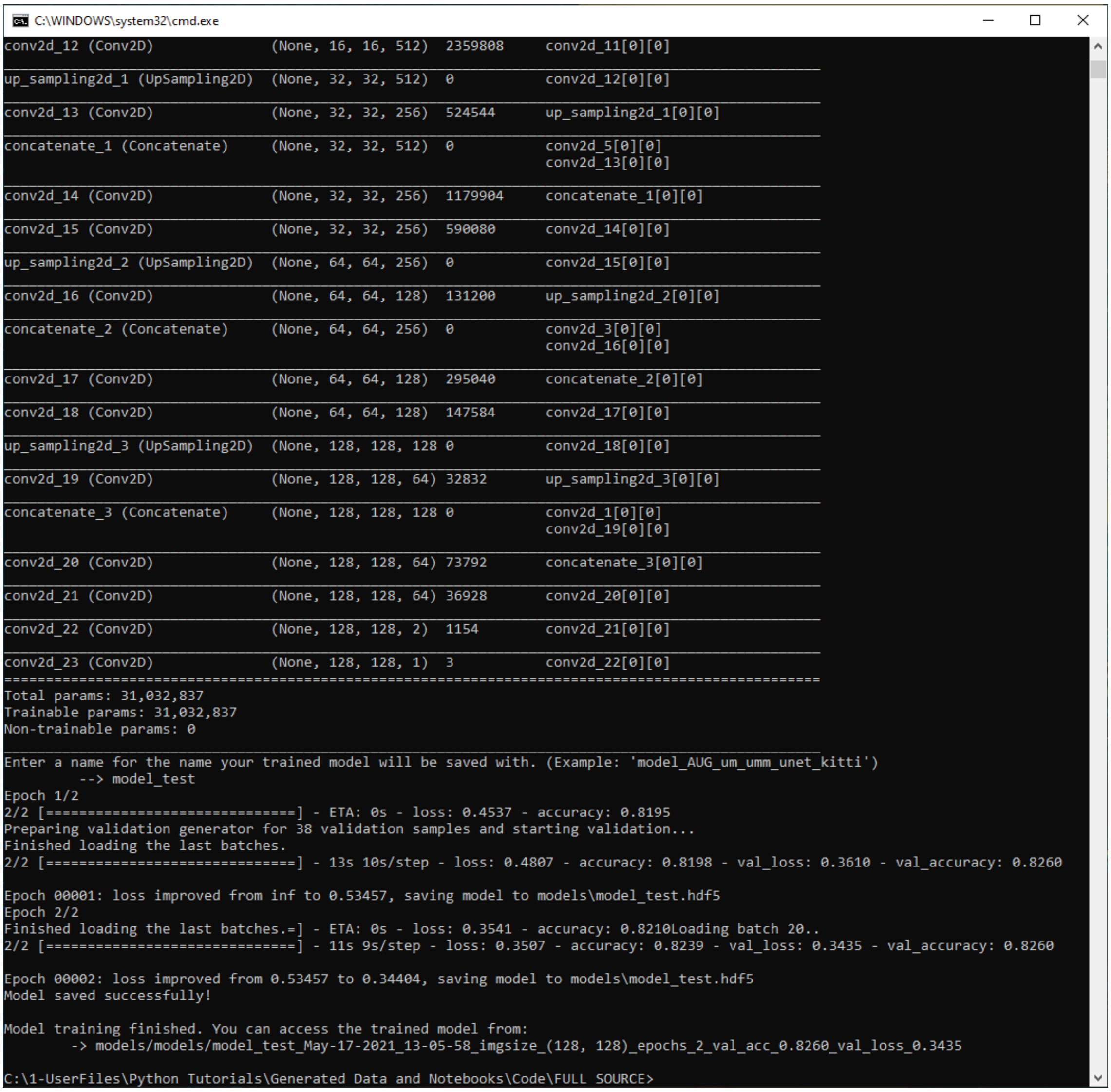
Figure 9: This figure presents a screenshot of the first part of **training.py** script's output. Different messages within the output text describe the executed processes and the resulting output.

directory and generates predictions for the testing data using that model. This file can also perform inference time measurement. Help information is available in Fig. 11.

The process of evaluation will be described similarly to the training pipeline. The output of the execution is provided in Fig. 12, Fig. 13, Fig. 14, respectively. Three screenshots of different sections of the output are presented in these figures.

The first one (12) shows the execution command and the choice of a model to use for inference. The program lists all available models and waits for user input. The selected model (the pretrained '*v3*' model) is loaded into memory and a summary of its structure is printed for reference.

In the second part (13), the user is prompted to decide whether they want to measure accurate inference time. If this option is selected, the model will not produce any visual elements as output (as in real-time applications this is not needed). After the user skips the timing option, they are asked to choose how many testing images should be predicted. We choose 1 here for the



```
C:\WINDOWS\system32\cmd.exe
conv2d_12 (Conv2D)             (None, 16, 16, 512)  2359808     conv2d_11[0][0]
__________________________________________________________________________________________________
up_sampling2d_1 (UpSampling2D)  (None, 32, 32, 512)  0           conv2d_12[0][0]
__________________________________________________________________________________________________
conv2d_13 (Conv2D)             (None, 32, 32, 256)  524544      up_sampling2d_1[0][0]
__________________________________________________________________________________________________
concatenate_1 (Concatenate)    (None, 32, 32, 512)  0           conv2d_5[0][0]
                                                                 conv2d_13[0][0]
__________________________________________________________________________________________________
conv2d_14 (Conv2D)             (None, 32, 32, 256)  1179904     concatenate_1[0][0]
__________________________________________________________________________________________________
conv2d_15 (Conv2D)             (None, 32, 32, 256)  590080      conv2d_14[0][0]
__________________________________________________________________________________________________
up_sampling2d_2 (UpSampling2D)  (None, 64, 64, 256)  0           conv2d_15[0][0]
__________________________________________________________________________________________________
conv2d_16 (Conv2D)             (None, 64, 64, 128)  131200      up_sampling2d_2[0][0]
__________________________________________________________________________________________________
concatenate_2 (Concatenate)    (None, 64, 64, 256)  0           conv2d_3[0][0]
                                                                 conv2d_16[0][0]
__________________________________________________________________________________________________
conv2d_17 (Conv2D)             (None, 64, 64, 128)  295040      concatenate_2[0][0]
__________________________________________________________________________________________________
conv2d_18 (Conv2D)             (None, 64, 64, 128)  147584      conv2d_17[0][0]
__________________________________________________________________________________________________
up_sampling2d_3 (UpSampling2D)  (None, 128, 128, 128 0           conv2d_18[0][0]
__________________________________________________________________________________________________
conv2d_19 (Conv2D)             (None, 128, 128, 64) 32832       up_sampling2d_3[0][0]
__________________________________________________________________________________________________
concatenate_3 (Concatenate)    (None, 128, 128, 128 0           conv2d_1[0][0]
                                                                 conv2d_19[0][0]
__________________________________________________________________________________________________
conv2d_20 (Conv2D)             (None, 128, 128, 64) 73792       concatenate_3[0][0]
__________________________________________________________________________________________________
conv2d_21 (Conv2D)             (None, 128, 128, 64) 36928       conv2d_20[0][0]
__________________________________________________________________________________________________
conv2d_22 (Conv2D)             (None, 128, 128, 2)  1154        conv2d_21[0][0]
__________________________________________________________________________________________________
conv2d_23 (Conv2D)             (None, 128, 128, 1)  3           conv2d_22[0][0]
==================================================================================================
Total params: 31,032,837
Trainable params: 31,032,837
Non-trainable params: 0
__________________________________________________________________________________________________
Enter a name for the name your trained model will be saved with. (Example: 'model_AUG_um_umm_unet_kitti')
         --> model_test
Epoch 1/2
2/2 [==============================] - ETA: 0s - loss: 0.4537 - accuracy: 0.8195
Preparing validation generator for 38 validation samples and starting validation...
Finished loading the last batches.
2/2 [==============================] - 13s 10s/step - loss: 0.4807 - accuracy: 0.8198 - val_loss: 0.3610 - val_accuracy: 0.8260

Epoch 00001: loss improved from inf to 0.53457, saving model to models\model_test.hdf5
Epoch 2/2
Finished loading the last batches.=] - ETA: 0s - loss: 0.3541 - accuracy: 0.8210Loading batch 20..
2/2 [==============================] - 11s 9s/step - loss: 0.3507 - accuracy: 0.8239 - val_loss: 0.3435 - val_accuracy: 0.8260

Epoch 00002: loss improved from 0.53457 to 0.34404, saving model to models\model_test.hdf5
Model saved successfully!

Model training finished. You can access the trained model from:
        -> models/models/model_test_May-17-2021_13-05-58_imgsize_(128, 128)_epochs_2_val_acc_0.8260_val_loss_0.3435

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>
```

Figure 10: This figure presents a screenshot of the second part of **training.py** script's output. Different messages within the output text describe the executed processes and the resulting output.

sake of this example. The mask is predicted and overlaid on top of the real image along with the corresponding ground-truth label. The large overlap is visible (pink colour). The red pixels indicate missed road pixels, while the blue region means that the model incorrectly assumed that this is road. The result is shown on the screen using the *matplotlib* Python package. The prediction of the model trained in this example is also shown in Fig. 15.

In the final part of the output (14), the user is prompted whether they would like to save all the overlays and the associated predicted and true masks to a directory. Fig. 16 shows the contents of the save directory after the predictions have been generated and exported as PNG files.

Metric Calculation and Model Comparison

In order to evaluate the models' performance and their differences. We need to generate overlays and predicted masks using the **evaluation.py** script. At least two images per model are required so that the statistical operations and tests (e.g., mean, standard deviation, t-test) can be

```
C:\WINDOWS\system32\cmd.exe

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>python evaluation.py -h
usage: evaluation.py [-h] [-c CONFIG_FILEPATH] [-s SAVED_MODELS_DIR] [-e] [-i]

optional arguments:
  -h, --help            show this help message and exit
  -c CONFIG_FILEPATH, --config_filepath CONFIG_FILEPATH
                        Path to a pickled dictionary object (include the .pickle extension, too) containing all
                        comfiguration params. The config.py file can be used to generate such a file if it is not
                        present in current directory. This file is required because its config params will be used to
                        create a DataGen object for testing data generation. (default: default_config.pickle)
  -s SAVED_MODELS_DIR, --saved_models_dir SAVED_MODELS_DIR
                        The path where the pretrained models are saved. This will be used to load models into memory
                        for evaluation. (default: models/)
  -e, --ensemble        Enabling this flag option will set the evaluation in ensemble mode. This will require several
                        models to be loaded (specified during model selection process). (default: False)
  -i, --intermediate_path
                        This option allows you to decide whether to save the intermediate outputs during the ensemble
                        voting stage. They are all saved to directory named 'intermediate_outputs' . (default: False)

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>
```

Figure 11: Help information for the **evaluation.py** script file. The '-e' flag, if specified, indicates that several models will be used as a joint ensemble to generate segmentation masks for the test images. The '-i' flag defines whether the script should save the intermediate outputs of the ensemble algorithm - these include each ensemble model's individual prediction, their pixel-wise summed predictions and the final average predicted mask.

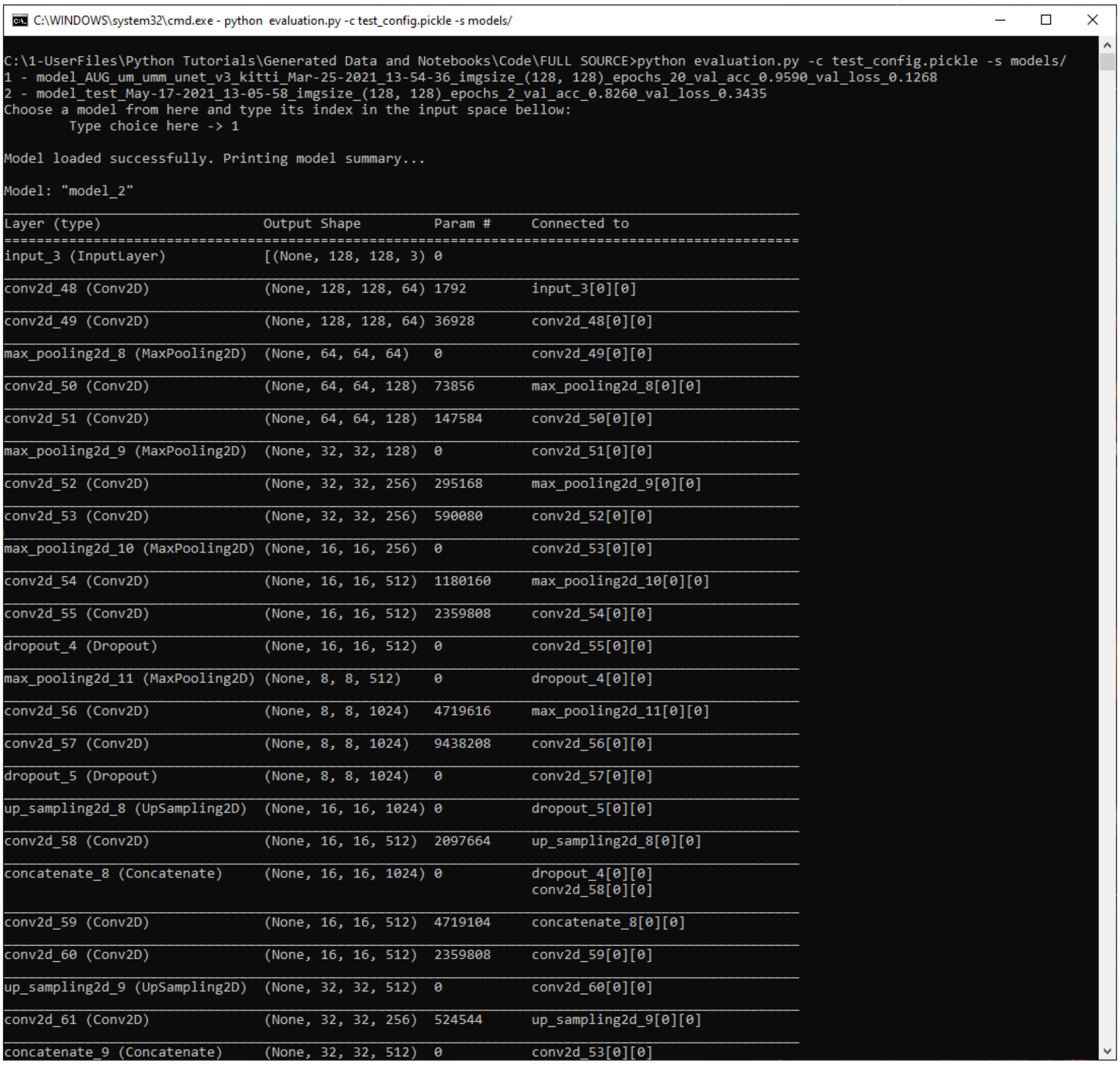
executed.

For this example, the predictions of the trained model for 3 test images were generated and saved in a directory called **test predictions_pred_imgs/**. The name of each directory that contains samples to evaluate must include the sequence 'pred_imgs'. Before running the metric calculation script, we have to copy the **test predictions_pred_imgs/** directory to the corresponding location. The specific folder is called 'ALL PREDICTED IMAGES' and it resides in the **metric_calculation** directory within the project repository. This is demonstrated in Fig. 17.

The last preparation step before executing the algorithms is shown in Fig. 18. We have to specify a name for each model whose predictions are contained in the 'ALL PREDICTED IMAGES' directory. That is why we open the **helpers.py** file with any text editor and type this at the end of the dictionary definition as shown in the figure.

The score calculation process compares all segmentation masks and generates various tables. The printed output (Fig. 19, Fig. 20) shows the computed scores for the given images. At the end of the execution, all the scores are added to a dictionary object which is serialised to a '*.pickle*' file. This file will be used in the next stage, where the scores will be compared and plotted to graphs. This algorithm produces several Excel tables and text files, all containing the scores in different formats. Some contain t-test results and p-values, while others percentage differences in performance between models across all metrics. Figure 21 shows the contents of the produced MS Excel files and the rest of the elements in the output directory.

After these files have been produced, we can use the second script in the **metric_calculation** directory - **score_compare.py**. It is responsible for loading the saved pickled dictionary and creating graphs from the scores where the models are plotted against two metrics. Each time a plot is created, it is shown on the screen and then saved to the 'Figures and Graphs' directory. This file also produces an Excel table where the mean scores of all compared models for all metrics are shown. The sequence of screenshots in Figure 22, Figure 23 and Figure 24 show the discussed outputs and created files.



```
C:\WINDOWS\system32\cmd.exe - python  evaluation.py -c test_config.pickle -s models/

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>python evaluation.py -c test_config.pickle -s models/
1 - model_AUG_um_umm_unet_v3_kitti_Mar-25-2021_13-54-36_imgsize_(128, 128)_epochs_20_val_acc_0.9590_val_loss_0.1268
2 - model_test_May-17-2021_13-05-58_imgsize_(128, 128)_epochs_2_val_acc_0.8260_val_loss_0.3435
Choose a model from here and type its index in the input space bellow:
        Type choice here -> 1

Model loaded successfully. Printing model summary...

Model: "model_2"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 128, 128, 3) 0
__________________________________________________________________________________________________
conv2d_48 (Conv2D)              (None, 128, 128, 64) 1792        input_3[0][0]
__________________________________________________________________________________________________
conv2d_49 (Conv2D)              (None, 128, 128, 64) 36928       conv2d_48[0][0]
__________________________________________________________________________________________________
max_pooling2d_8 (MaxPooling2D)  (None, 64, 64, 64)   0           conv2d_49[0][0]
__________________________________________________________________________________________________
conv2d_50 (Conv2D)              (None, 64, 64, 128)  73856       max_pooling2d_8[0][0]
__________________________________________________________________________________________________
conv2d_51 (Conv2D)              (None, 64, 64, 128)  147584      conv2d_50[0][0]
__________________________________________________________________________________________________
max_pooling2d_9 (MaxPooling2D)  (None, 32, 32, 128)  0           conv2d_51[0][0]
__________________________________________________________________________________________________
conv2d_52 (Conv2D)              (None, 32, 32, 256)  295168      max_pooling2d_9[0][0]
__________________________________________________________________________________________________
conv2d_53 (Conv2D)              (None, 32, 32, 256)  590080      conv2d_52[0][0]
__________________________________________________________________________________________________
max_pooling2d_10 (MaxPooling2D) (None, 16, 16, 256)  0           conv2d_53[0][0]
__________________________________________________________________________________________________
conv2d_54 (Conv2D)              (None, 16, 16, 512)  1180160     max_pooling2d_10[0][0]
__________________________________________________________________________________________________
conv2d_55 (Conv2D)              (None, 16, 16, 512)  2359808     conv2d_54[0][0]
__________________________________________________________________________________________________
dropout_4 (Dropout)             (None, 16, 16, 512)  0           conv2d_55[0][0]
__________________________________________________________________________________________________
max_pooling2d_11 (MaxPooling2D) (None, 8, 8, 512)    0           dropout_4[0][0]
__________________________________________________________________________________________________
conv2d_56 (Conv2D)              (None, 8, 8, 1024)   4719616     max_pooling2d_11[0][0]
__________________________________________________________________________________________________
conv2d_57 (Conv2D)              (None, 8, 8, 1024)   9438208     conv2d_56[0][0]
__________________________________________________________________________________________________
dropout_5 (Dropout)             (None, 8, 8, 1024)   0           conv2d_57[0][0]
__________________________________________________________________________________________________
up_sampling2d_8 (UpSampling2D)  (None, 16, 16, 1024) 0           dropout_5[0][0]
__________________________________________________________________________________________________
conv2d_58 (Conv2D)              (None, 16, 16, 512)  2097664     up_sampling2d_8[0][0]
__________________________________________________________________________________________________
concatenate_8 (Concatenate)     (None, 16, 16, 1024) 0           dropout_4[0][0]
                                                                 conv2d_58[0][0]
__________________________________________________________________________________________________
conv2d_59 (Conv2D)              (None, 16, 16, 512)  4719104     concatenate_8[0][0]
__________________________________________________________________________________________________
conv2d_60 (Conv2D)              (None, 16, 16, 512)  2359808     conv2d_59[0][0]
__________________________________________________________________________________________________
up_sampling2d_9 (UpSampling2D)  (None, 32, 32, 512)  0           conv2d_60[0][0]
__________________________________________________________________________________________________
conv2d_61 (Conv2D)              (None, 32, 32, 256)  524544      up_sampling2d_9[0][0]
__________________________________________________________________________________________________
concatenate_9 (Concatenate)     (None, 32, 32, 512)  0           conv2d_53[0][0]
```

Figure 12: This figure presents a screenshot of the first part of **evaluation.py** script's output. Different messages within the output text describe the executed processes and the resulting output.

Ensemble scheme

Finally, this example will demonstrate the use of the ensemble functionality of the **evaluation.py** script. Refer to Fig. 11 for a refresher of the requirements for executing this program. The example displayed in Fig. 25 shows the interface of the ensemble evaluation algorithm. If the '-i' option was included in the execution command, the model would have produced a directory called **'intermediate_outputs'** which would contain each model's individual prediction, the sum of all predictions and the averaged voted instance.

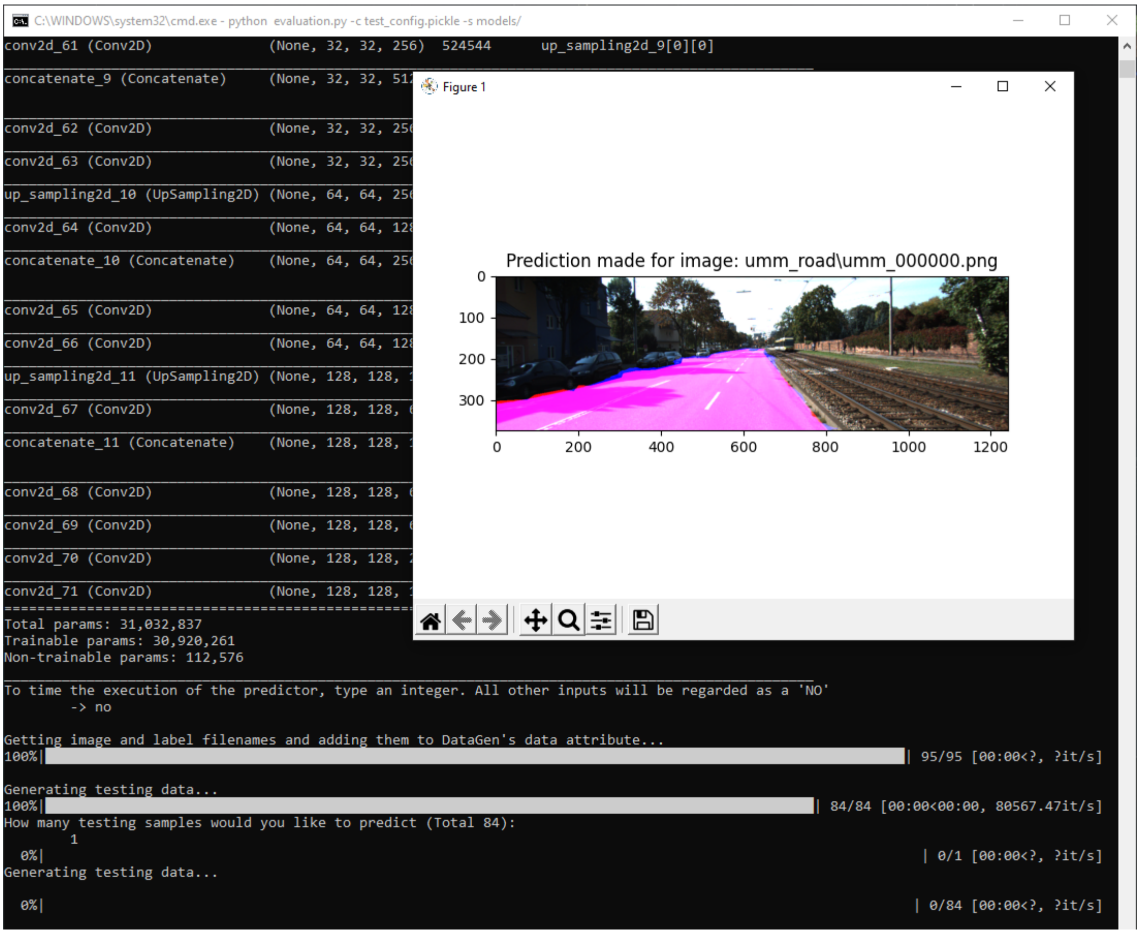
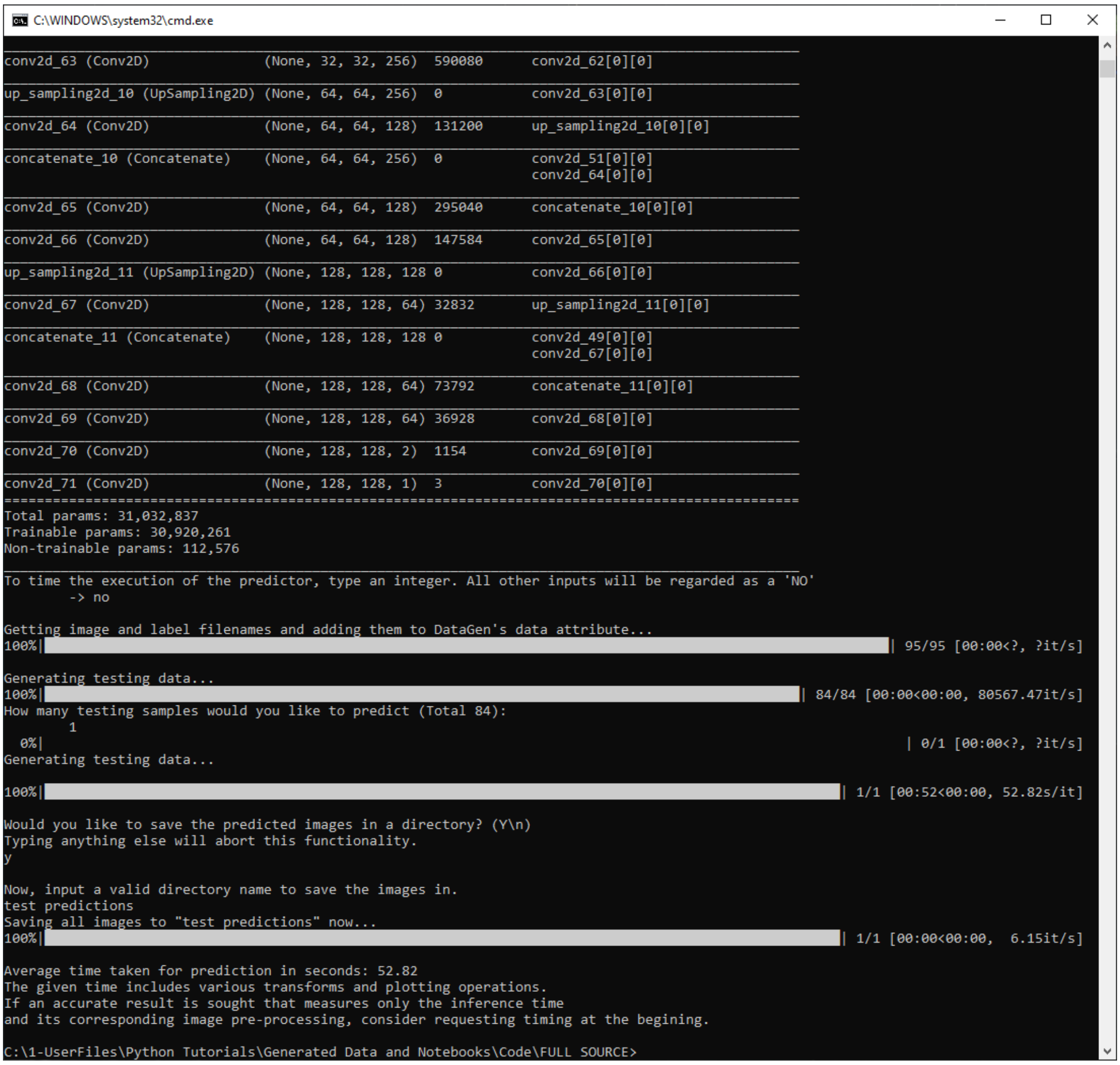


Figure 13: This figure presents a screenshot of the second part of **evaluation.py** script's output. Different messages within the output text describe the executed processes and the resulting output.



```
C:\WINDOWS\system32\cmd.exe
conv2d_63 (Conv2D)              (None, 32, 32, 256)  590080      conv2d_62[0][0]
up_sampling2d_10 (UpSampling2D) (None, 64, 64, 256)  0           conv2d_63[0][0]
conv2d_64 (Conv2D)              (None, 64, 64, 128)  131200      up_sampling2d_10[0][0]
concatenate_10 (Concatenate)    (None, 64, 64, 256)  0           conv2d_51[0][0]
                                                                 conv2d_64[0][0]
conv2d_65 (Conv2D)              (None, 64, 64, 128)  295040      concatenate_10[0][0]
conv2d_66 (Conv2D)              (None, 64, 64, 128)  147584      conv2d_65[0][0]
up_sampling2d_11 (UpSampling2D) (None, 128, 128, 128 0           conv2d_66[0][0]
conv2d_67 (Conv2D)              (None, 128, 128, 64) 32832       up_sampling2d_11[0][0]
concatenate_11 (Concatenate)    (None, 128, 128, 128 0           conv2d_49[0][0]
                                                                 conv2d_67[0][0]
conv2d_68 (Conv2D)              (None, 128, 128, 64) 73792       concatenate_11[0][0]
conv2d_69 (Conv2D)              (None, 128, 128, 64) 36928       conv2d_68[0][0]
conv2d_70 (Conv2D)              (None, 128, 128, 2)  1154        conv2d_69[0][0]
conv2d_71 (Conv2D)              (None, 128, 128, 1)  3           conv2d_70[0][0]
==================================================================================================
Total params: 31,032,837
Trainable params: 30,920,261
Non-trainable params: 112,576
__________________________________________________________________________________________________
To time the execution of the predictor, type an integer. All other inputs will be regarded as a 'NO'
        -> no

Getting image and label filenames and adding them to DataGen's data attribute...
100%|██████████████████████████████████████████████████████████| 95/95 [00:00<?, ?it/s]

Generating testing data...
100%|████████████████████████████████████████████████████| 84/84 [00:00<00:00, 80567.47it/s]
How many testing samples would you like to predict (Total 84):
        1
  0%|                                                          | 0/1 [00:00<?, ?it/s]
Generating testing data...

100%|███████████████████████████████████████████████████████| 1/1 [00:52<00:00, 52.82s/it]

Would you like to save the predicted images in a directory? (Y\n)
Typing anything else will abort this functionality.
y

Now, input a valid directory name to save the images in.
test predictions
Saving all images to "test predictions" now...
100%|███████████████████████████████████████████████████████| 1/1 [00:00<00:00,  6.15it/s]

Average time taken for prediction in seconds: 52.82
The given time includes various transforms and plotting operations.
If an accurate result is sought that measures only the inference time
and its corresponding image pre-processing, consider requesting timing at the begining.

C:\1-UserFiles\Python Tutorials\Generated Data and Notebooks\Code\FULL SOURCE>
```

Figure 14: This figure presents a screenshot of the third part of **evaluation.py** script's output. Different messages within the output text describe the executed processes and the resulting output.

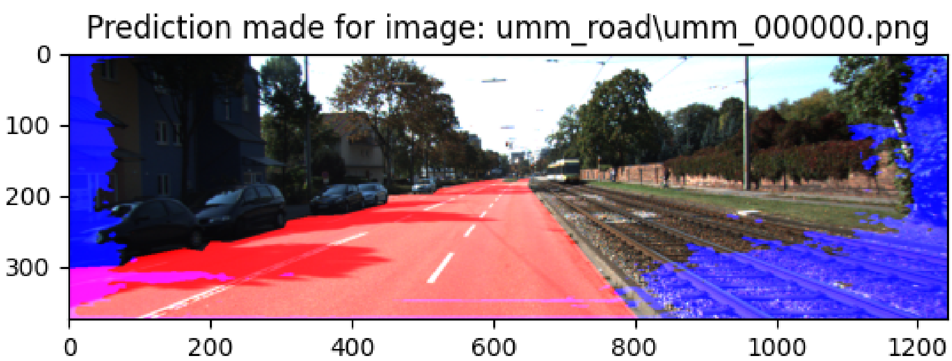


Figure 15: The result of predicting a test image (*umm_000000.png*) using the test model trained in this example.

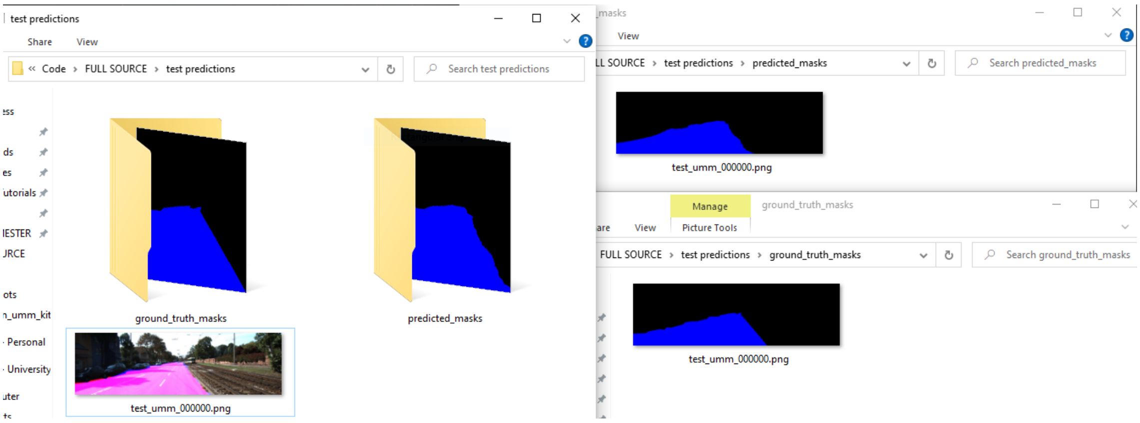


Figure 16: The contents of the directory where the predictions of a model are saved. The overlay and the corresponding true and predicted segmentation masks for each predicted image are saved accordingly.

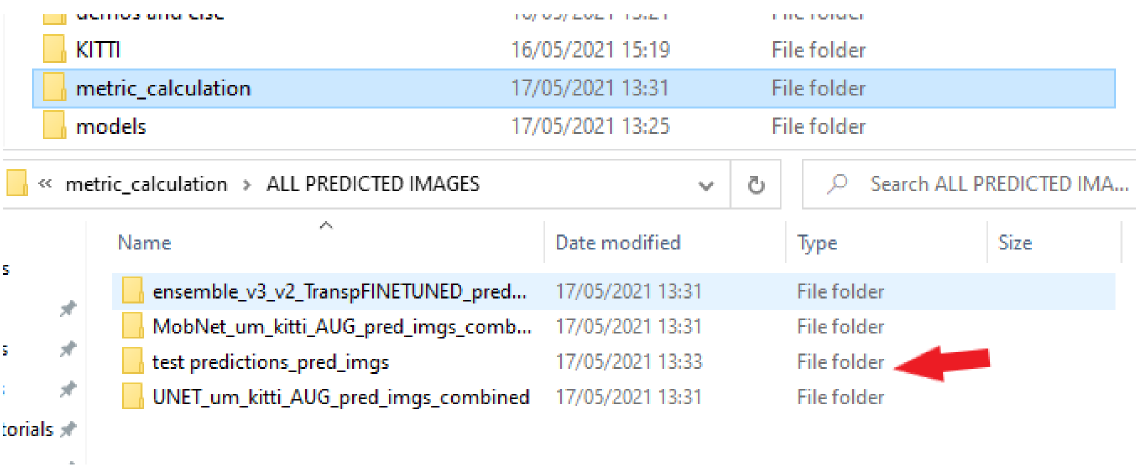
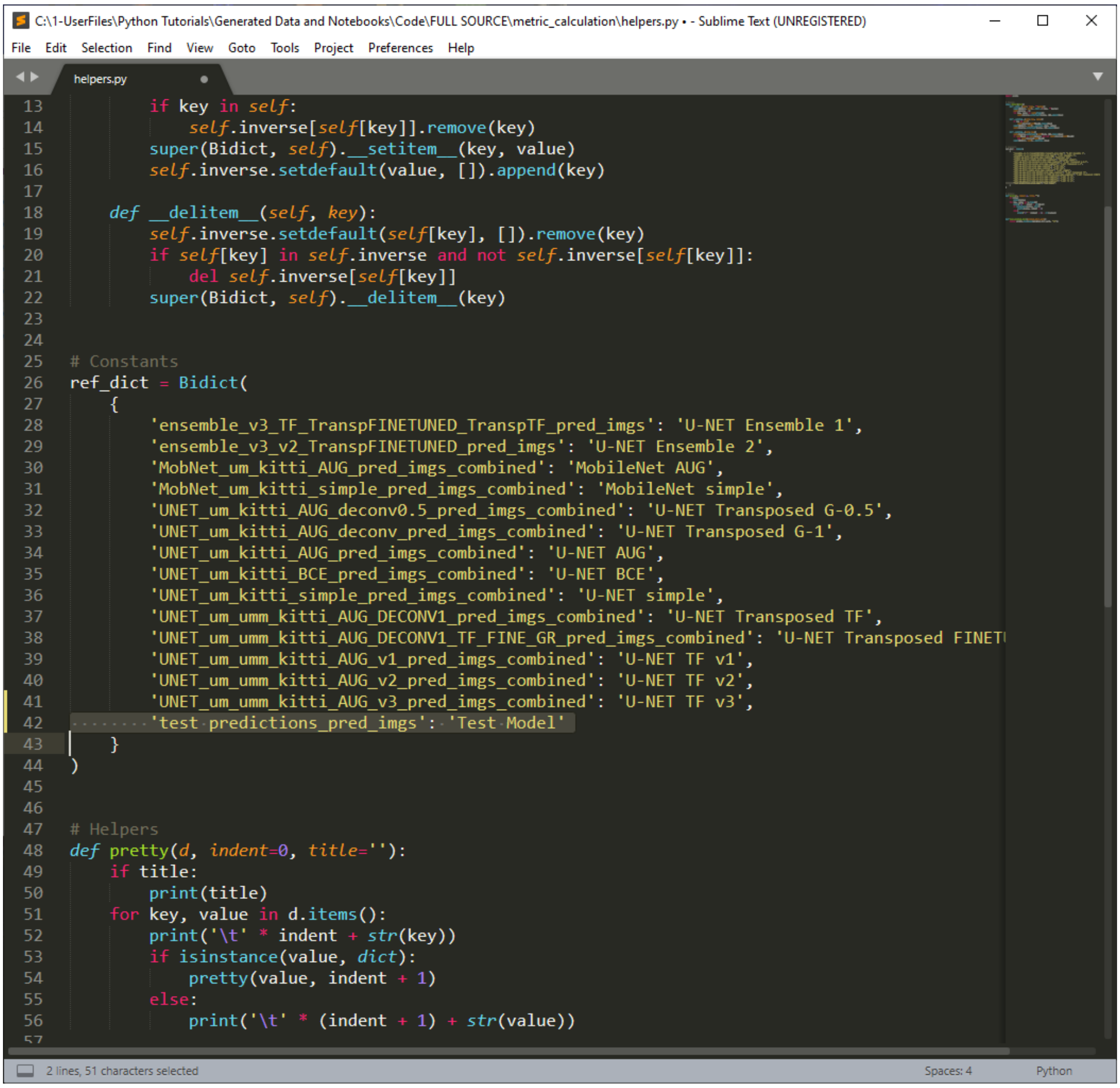


Figure 17: This figure shows the metric calculation directory to which the predicted masks have to be copied prior to score calculation and comparison. The red arrow on the second image points to the directory containing our test model's predictions.




```python
        if key in self:
            self.inverse[self[key]].remove(key)
        super(Bidict, self).__setitem__(key, value)
        self.inverse.setdefault(value, []).append(key)

    def __delitem__(self, key):
        self.inverse.setdefault(self[key], []).remove(key)
        if self[key] in self.inverse and not self.inverse[self[key]]:
            del self.inverse[self[key]]
        super(Bidict, self).__delitem__(key)


# Constants
ref_dict = Bidict(
    {
        'ensemble_v3_TF_TranspFINETUNED_TranspTF_pred_imgs': 'U-NET Ensemble 1',
        'ensemble_v3_v2_TranspFINETUNED_pred_imgs': 'U-NET Ensemble 2',
        'MobNet_um_kitti_AUG_pred_imgs_combined': 'MobileNet AUG',
        'MobNet_um_kitti_simple_pred_imgs_combined': 'MobileNet simple',
        'UNET_um_kitti_AUG_deconv0.5_pred_imgs_combined': 'U-NET Transposed G-0.5',
        'UNET_um_kitti_AUG_deconv_pred_imgs_combined': 'U-NET Transposed G-1',
        'UNET_um_kitti_AUG_pred_imgs_combined': 'U-NET AUG',
        'UNET_um_kitti_BCE_pred_imgs_combined': 'U-NET BCE',
        'UNET_um_kitti_simple_pred_imgs_combined': 'U-NET simple',
        'UNET_um_umm_kitti_AUG_DECONV1_pred_imgs_combined': 'U-NET Transposed TF',
        'UNET_um_umm_kitti_AUG_DECONV1_TF_FINE_GR_pred_imgs_combined': 'U-NET Transposed FINET
        'UNET_um_umm_kitti_AUG_v1_pred_imgs_combined': 'U-NET TF v1',
        'UNET_um_umm_kitti_AUG_v2_pred_imgs_combined': 'U-NET TF v2',
        'UNET_um_umm_kitti_AUG_v3_pred_imgs_combined': 'U-NET TF v3',
        'test predictions_pred_imgs': 'Test Model'
    }
)


# Helpers
def pretty(d, indent=0, title=''):
    if title:
        print(title)
    for key, value in d.items():
        print('\t' * indent + str(key))
        if isinstance(value, dict):
            pretty(value, indent + 1)
        else:
            print('\t' * (indent + 1) + str(value))
```

Figure 18: This is a very important step that specifies to the metric calculation algorithm what name to assign to the scores calculated for the given predictions directory.

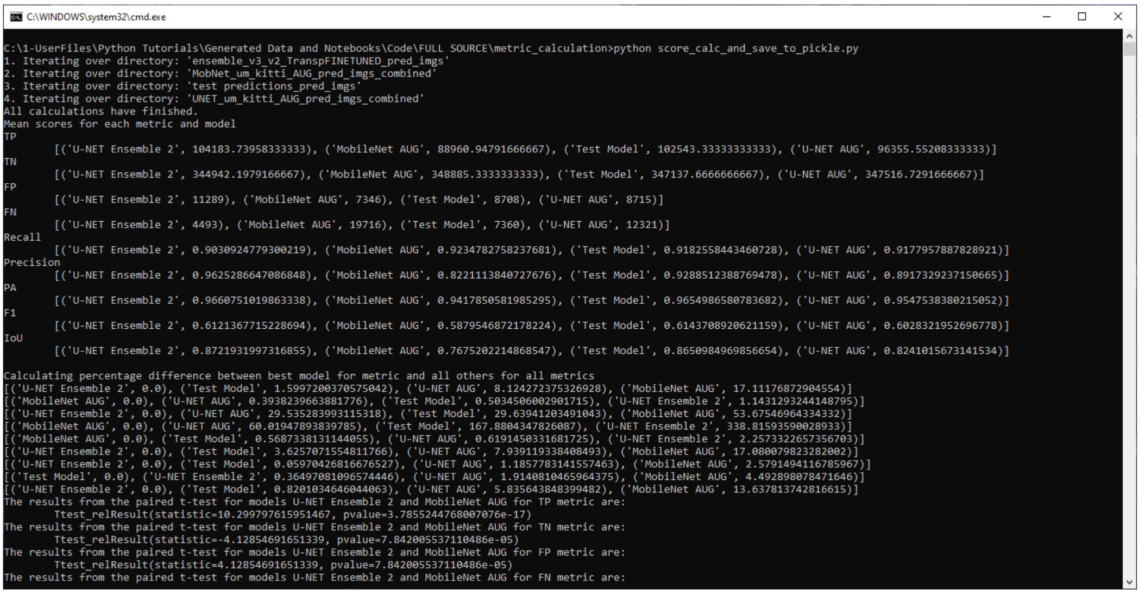


Figure 19: Output of the metric calculation algorithm. The various scores for each model are printed out, as well as, the model-wise comparison scores.

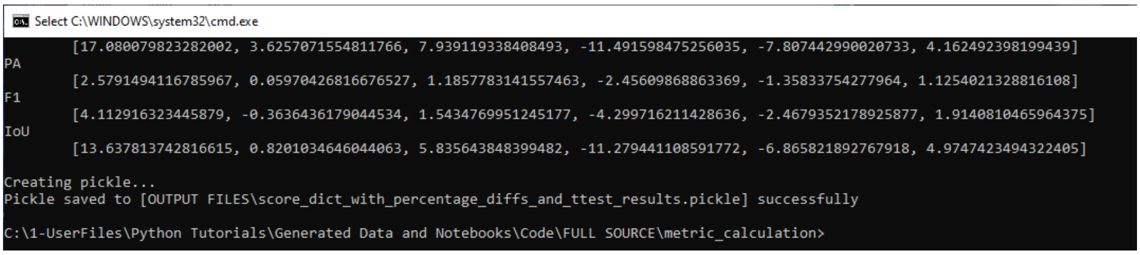


Figure 20: The end of the output of the metric calculation algorithm. All scores are saved to a .pickle file.

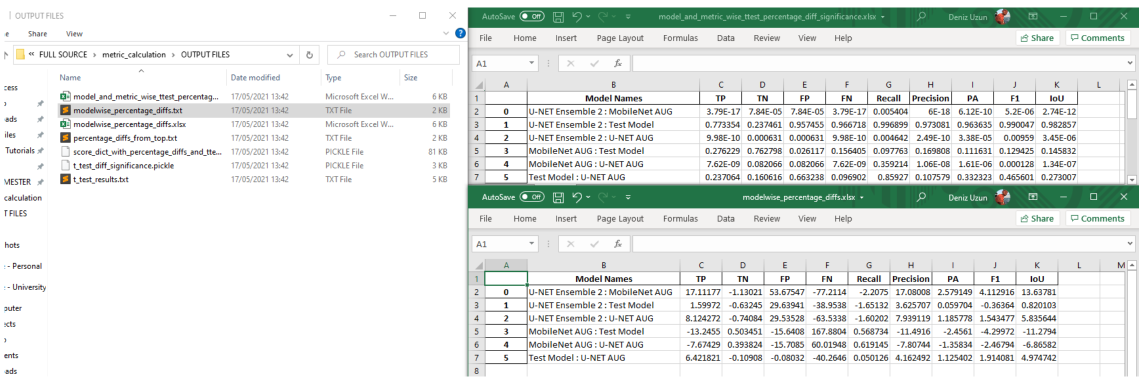


Figure 21: The files produced by the score calculation script. There are two MS Excel tables that contain statistical differences and t-test results for all 2-model combinations.

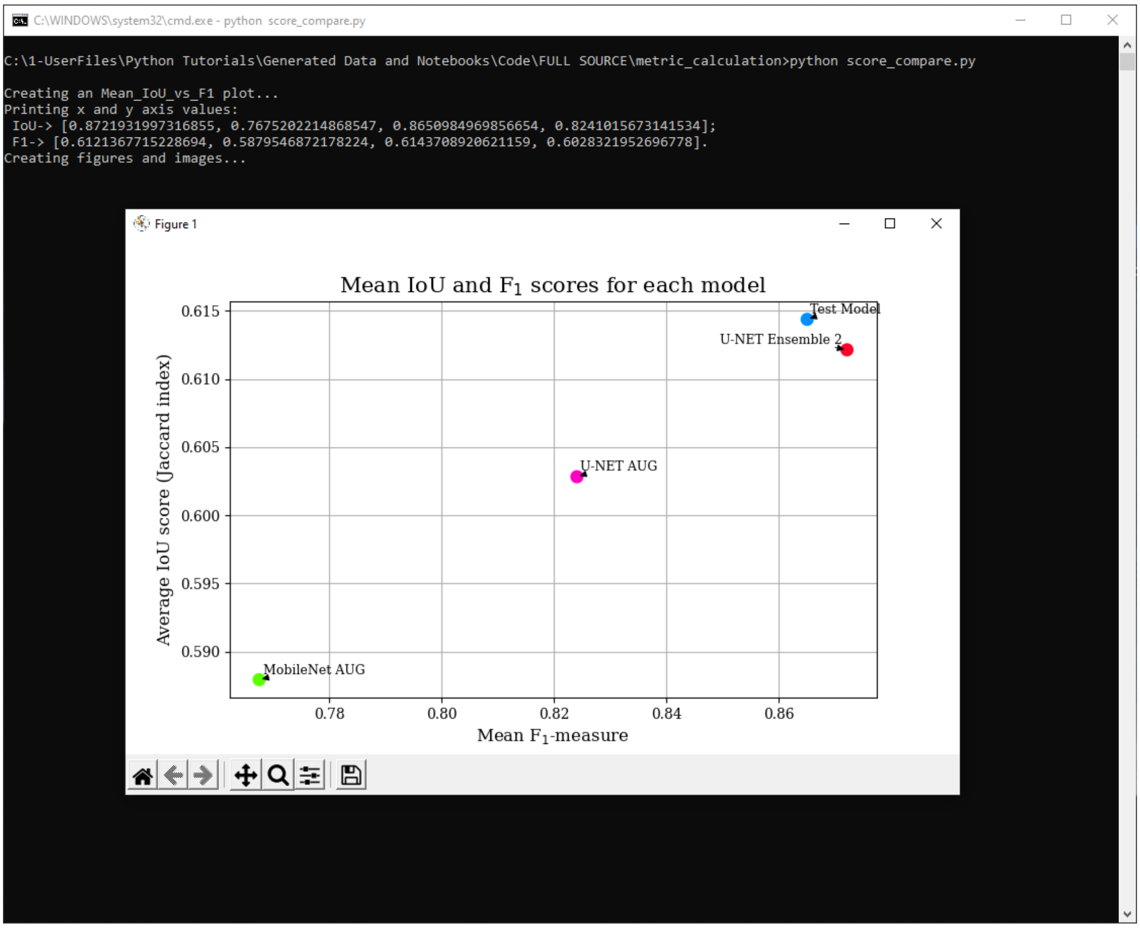


Figure 22: This image shows the first graph that is produced by the **score_compare.py** script. It compares the provided models based on their IoU and F_1 scores.

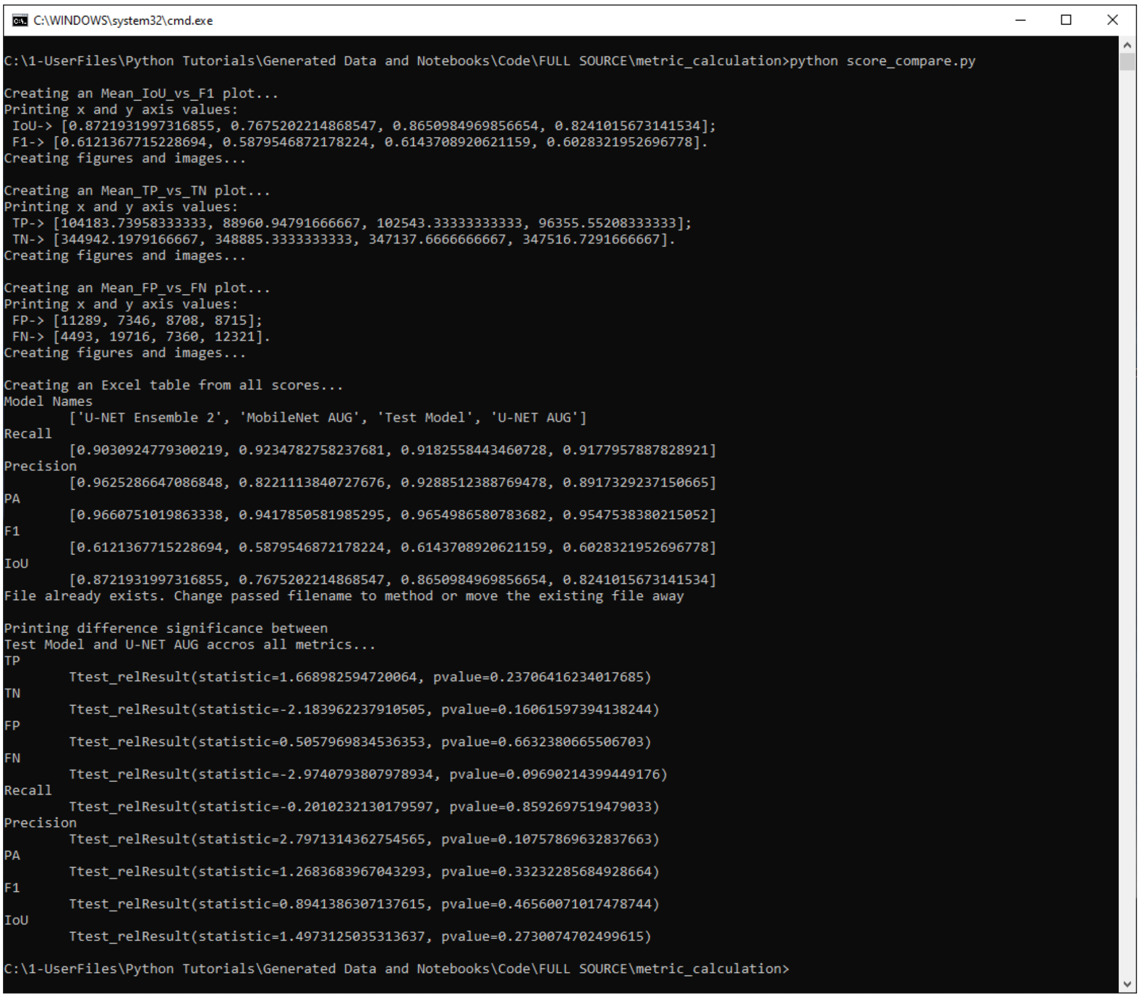


Figure 23: This is the rest of the output of the **score_compare.py** script, which illustrates the generation of two more figures and a table of all mean scores.

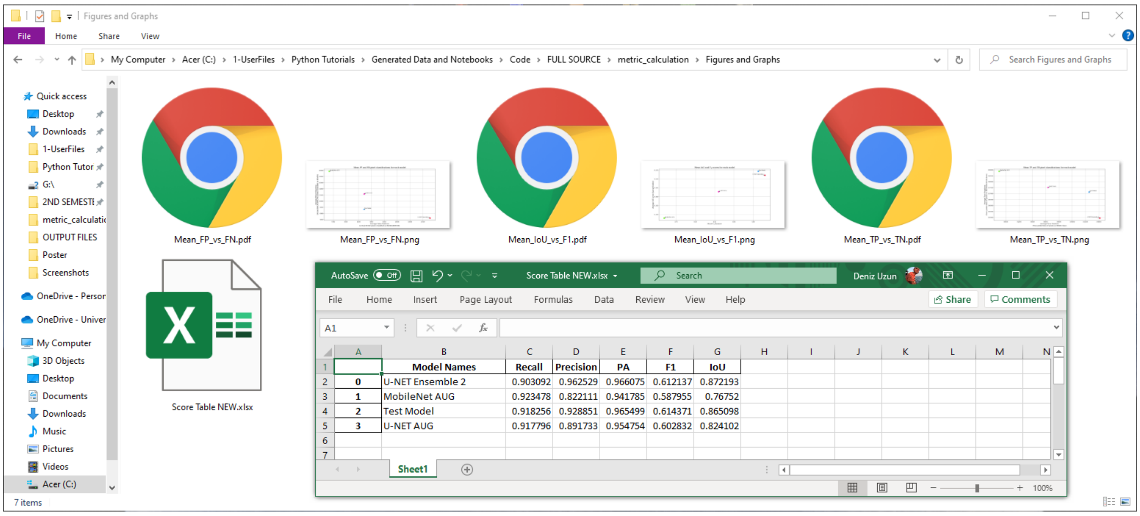


Figure 24: Here, the saved figures (in PDF and PNG format) by the **score_compare.py** script are shown in the directory along with the results summary table.)

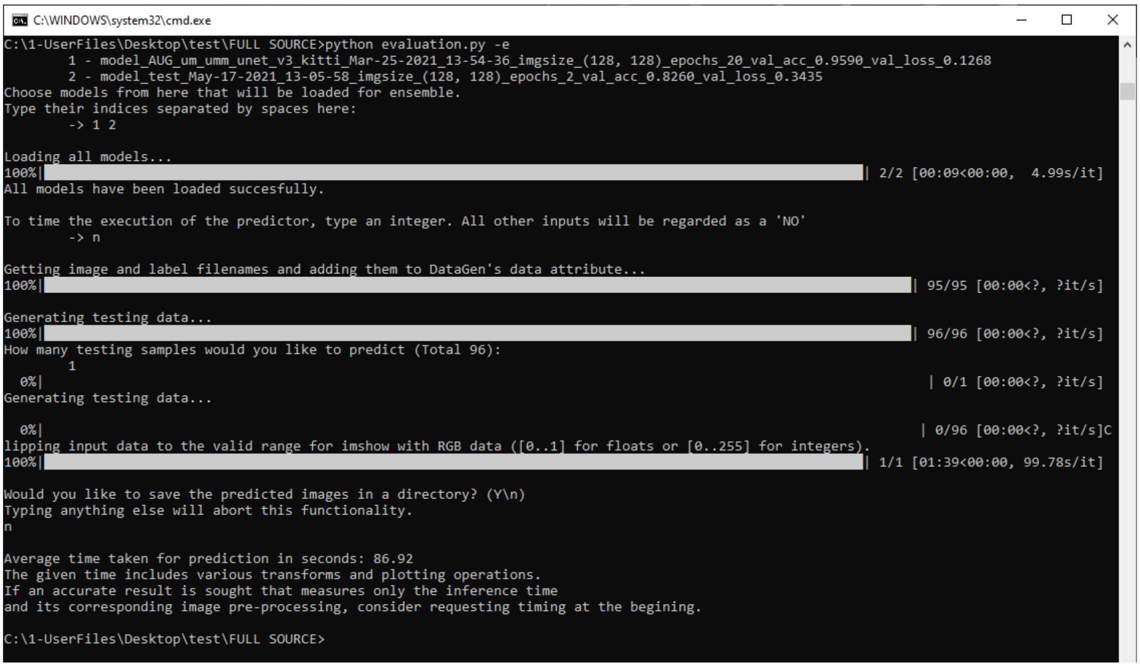


Figure 25: In this image, the evaluation script is executed for an ensemble of models. The default directory, **models/**, is checked for available models. The user is prompted to select the trained models they want to use for the ensemble scheme. The rest of the process is identical to that of normal evaluation for a single network.