Personal Project_04_v10_test1_3conv-layer_run16_advanced control 1

May 2, 2025

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     %matplotlib inline
     import matplotlib.image as mpimg
     import tensorflow as tf
[2]: # default initial values of DOE factors:
     # learning_rate = 0.001
     # dropout_value = 0.3
     # #n-conv_layers = 3
     \# n\_units\_last\_layer = 2048
     # n filters l1 = 32
     # n_filters_l2 = 16
[3]: # DOE factors:
     learning_rate = 0.0005
     dropout value = 0.5
     \# n\text{-}conv\_layers = 4
     n_units_last_layer = 4096
     n_filters_l1 = 8
     n_filters_12 = 64
[4]: # other factors:
     img_size = 130
     batch_size = 32
     validation_split = 0.1 # 10% for validation
     test_split = 0.00 # 0% for testing
     shuffle_buffer_size = 1000
     seed_num = 101
     desired_accuracy = 0.99 # it should be active if EarlyStoppingCallback is_
      \hookrightarrow activated
     loss = 'binary_crossentropy'
     #optimizer = tf.keras.optimizers.RMSprop(learning_rate=learning_rate)
     optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)
     metrics = ['accuracy']
```

```
epochs = 20
     f_mode = 'nearest' # fill_mode in image augmentation
    My dataset_root/
       woman/
          woman_1.jpg
          woman_2.jpg
      man/
          man_1.jpg
          man_2.jpg
          . . .
[6]: import os
     DATA DIR = "D:\\CS online courses\\Free DataSets\\Free Images\\Easier portrait_
      →images_GPU_03"
     # Subdirectories for each class
     data_dir_woman = os.path.join(DATA_DIR, 'woman')
     data_dir_man = os.path.join(DATA_DIR, 'man')
     # os.listdir returns a list containing all files under the given dir
     print(f"There are {len(os.listdir(data dir_woman))} images of woman.")
     print(f"There are {len(os.listdir(data_dir_man))} images of man.")
    There are 471 images of woman.
    There are 472 images of man.
[7]: | image_size = (img_size, img_size) # Resize images to this size
     # Load train dataset (excluding validation & test set):
     train_dataset = tf.keras.utils.image_dataset_from_directory(
         directory = DATA_DIR,
         image_size = image_size,
         batch_size = batch_size,
         label_mode='binary',
         validation_split = validation_split + test_split, # Total split for val +_
         subset = "training",
         seed = seed_num
     # Load validation dataset
     val_dataset = tf.keras.utils.image_dataset_from_directory(
         directory = DATA DIR,
         image_size = image_size,
         batch_size = batch_size,
```

```
label_mode='binary',
         validation_split = validation_split + test_split,
         subset = "validation",
         seed = seed_num
     # Further manually split validation dataset to extract test dataset
     val_batches = tf.data.experimental.cardinality(val_dataset)
     # Compute test dataset size (number of batches)
     test_size = round(val_batches.numpy() * (test_split / (validation_split +__
     →test_split)))
     # Split validation dataset into validation and test subsets
     test_dataset = val_dataset.take(test_size)
     val_dataset = val_dataset.skip(test_size)
     print(f"Train batches: {tf.data.experimental.cardinality(train_dataset).
      →numpy()}")
     print(f"Validation batches: {tf.data.experimental.cardinality(val_dataset).
      →numpy()}")
     print(f"Test batches: {tf.data.experimental.cardinality(test_dataset).numpy()}")
     # Optimize for performance
     AUTOTUNE = tf.data.AUTOTUNE
     training_dataset = train_dataset.cache().shuffle(shuffle_buffer_size).
      prefetch(buffer_size = AUTOTUNE)
     validation dataset = val dataset.cache().prefetch(buffer size = AUTOTUNE)
     test_dataset = test_dataset.cache().prefetch(buffer_size = AUTOTUNE)
    Found 943 files belonging to 2 classes.
    Using 849 files for training.
    Found 943 files belonging to 2 classes.
    Using 94 files for validation.
    Train batches: 27
    Validation batches: 3
    Test batches: 0
[8]: # Get the first batch of images and labels
     for images, labels in training_dataset.take(1):
             example_batch_images = images
             example_batch_labels = labels
     max_pixel = np.max(example_batch_images)
     print(f"Maximum pixel value of images: {max_pixel}\n")
     print(f"Shape of batch of images: {example_batch_images.shape}")
     print(f"Shape of batch of labels: {example_batch_labels.shape}")
```

Maximum pixel value of images: 255.0

```
Shape of batch of images: (32, 130, 130, 3)
     Shape of batch of labels: (32, 1)
 [9]: '''
      class\ Early Stopping Callback (tf.keras.callbacks.Callback):
          def on_epoch_end(self, epoch, logs=None):
              train_accuracy = logs.get('accuracy')
              val_accuracy = logs.get('val_accuracy')
              if train_accuracy >= desired_accuracy and val_accuracy >=_
       \rightarrow desired accuracy:
                  self.model.stop_training = True
                  print(f"\nReached {desired_accuracy}% accuracy so cancelling_
       ⇔training!")
 [9]: '\nclass EarlyStoppingCallback(tf.keras.callbacks.Callback):\n
                                                                          def
      on_epoch_end(self, epoch, logs=None):\n
                                                      train_accuracy =
      logs.get(\'accuracy\')\n
                                     val_accuracy = logs.get(\'val_accuracy\')\n
      if train_accuracy >= desired_accuracy and val_accuracy >= desired_accuracy:\n
      self.model.stop_training = True\n
                                                    print(f"\nReached
      {desired_accuracy}% accuracy so cancelling training!")\n'
[10]: '''
      from tensorflow.keras.callbacks import EarlyStopping
      early_stop = EarlyStopping(monitor='val_loss', patience=3)
      I I I
[10]: "\nfrom tensorflow.keras.callbacks import EarlyStopping\nearly_stop =
      EarlyStopping(monitor='val_loss', patience=3)\n"
[11]: from tensorflow.keras.callbacks import LearningRateScheduler
      # Reduce LR every 10 epochs (Learning rate decay factor)
      def scheduler(epoch, lr):
          if epoch < 10:</pre>
              if epoch % 5 == 0 and epoch > 0:
                  return lr / 1
              return lr
          elif epoch < 30:</pre>
              if epoch \% 5 == 0 and epoch > 0:
                  return lr / 1.2
              return lr
          elif epoch < 40:</pre>
              if epoch \% 5 == 0 and epoch > 0:
                  return lr / 1.1
              return lr
          else:
```

```
return lr
lr_callback = LearningRateScheduler(scheduler)
```

```
[12]: # augmentation_model
      def augment_model():
          """Creates a model (layers stacked on top of each other) for augmenting \Box
       ⇒images of woman and man.
          Returns:
              tf.keras.Model: The model made up of the layers that will be used to_{\sqcup}
       ⇒augment the images of woman and man.
          augmentation_model = tf.keras.Sequential([
              # Specify the input shape.
              tf.keras.Input(shape = (img_size, img_size, 3)),
              tf.keras.layers.RandomFlip("horizontal"),
              tf.keras.layers.RandomRotation(0.1, fill_mode = f_mode),
              #tf.keras.layers.RandomTranslation(0.1, 0.1, fill_mode = f_mode),
              #tf.keras.layers.RandomZoom(0.1, fill_mode=f_mode)
              ])
          return augmentation_model
```

```
[13]: def create_and_compile_model():
          """Creates, compiles and trains the model to predict woman and man images.
          Returns:
              tf.keras.Model: The model that will be trained to predict woman and manu
       \hookrightarrow images.
          11 11 11
          augmentation_layers = augment_model()
          model = tf.keras.Sequential([
              # Note: the input shape is the desired size of the image: 150x150 with
       →3 bytes for color
              tf.keras.layers.InputLayer(shape = (img_size, img_size, 3)),
              augmentation_layers,
              tf.keras.layers.Rescaling(1./255),
                        CONV_LAYER_1:
                                          #####
              tf.keras.layers.Conv2D(n_filters_11, (4, 4), activation = 'linear'),
              tf.keras.layers.MaxPooling2D(2, 2),
              #####
                        CONV_LAYER_2:
                                          #####
              tf.keras.layers.Conv2D(n_filters_12, (3, 3), activation = 'relu'),
```

```
tf.keras.layers.MaxPooling2D(2, 2),
      #####
                CONV_LAYER_3:
                                  #####
      tf.keras.layers.Conv2D(64, (3, 3), activation = 'relu'),
      tf.keras.layers.MaxPooling2D(2, 2),
      #####
                CONV_LAYER_4:
      tf.keras.layers.Conv2D(64, (3, 3), activation = 'relu'),
      tf.keras.layers.MaxPooling2D(2, 2),
      tf.keras.layers.Flatten(),
      tf.keras.layers.Dropout(dropout_value),
               BEFORE_LAST_LAYER:
                                      #####
      tf.keras.layers.Dense(n_units_last_layer, activation = 'relu'),
      # It will contain a value from 0-1 where 0 for the class 'female' and 1_{\sqcup}
⇔for the 'male'
      tf.keras.layers.Dense(1, activation = 'sigmoid')])
  model.compile(
      loss = loss,
      optimizer = optimizer,
      metrics = metrics
  )
  return model
```

```
[14]: # Create the compiled but untrained model
model = create_and_compile_model()
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 130, 130, 3)	0
rescaling (Rescaling)	(None, 130, 130, 3)	0
conv2d (Conv2D)	(None, 127, 127, 8)	392
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 63, 63, 8)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	4,672
<pre>max_pooling2d_1 (MaxPooling2D)</pre>	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 64)	36,928
<pre>max_pooling2d_2 (MaxPooling2D)</pre>	(None, 14, 14, 64)	0

```
conv2d_3 (Conv2D)
                                        (None, 12, 12, 64)
                                                                        36,928
      max_pooling2d_3 (MaxPooling2D) (None, 6, 6, 64)
                                                                             0
                                        (None, 2304)
      flatten (Flatten)
                                                                             0
      dropout (Dropout)
                                        (None, 2304)
                                                                             0
      dense (Dense)
                                        (None, 4096)
                                                                     9,441,280
      dense_1 (Dense)
                                        (None, 1)
                                                                         4,097
      Total params: 9,524,297 (36.33 MB)
      Trainable params: 9,524,297 (36.33 MB)
      Non-trainable params: 0 (0.00 B)
[15]: '''
      training_history = model.fit(
          training_dataset,
          epochs = epochs,
          validation_data = validation_dataset,
          callbacks = [EarlyStoppingCallback()],
          verbose = 2
      111
[15]: '\ntraining_history = model.fit(\n training_dataset,\n
                                                                   epochs = epochs,\n
      validation_data = validation_dataset,\n
                                                 callbacks =
      [EarlyStoppingCallback()], \n verbose = 2\n)\n'
[16]: '''
      training_history = model.fit(
```

training_dataset,
epochs = epochs,

verbose = 2

111

callbacks=[early_stop],

validation_data = validation_dataset,

```
validation_data = validation_dataset,\n callbacks=[early_stop],\n
                                                                              verbose
      = 2\n)\n'
[17]: training_history = model.fit(
          training_dataset,
          epochs = epochs,
          validation_data = validation_dataset,
          callbacks = [lr_callback],
          verbose = 2
      )
     Epoch 1/20
     27/27 - 5s - 171ms/step - accuracy: 0.5913 - loss: 0.6845 - val_accuracy: 0.5532
     - val_loss: 0.7082 - learning_rate: 5.0000e-04
     Epoch 2/20
     27/27 - 2s - 87ms/step - accuracy: 0.6867 - loss: 0.5977 - val_accuracy: 0.7021
     - val_loss: 0.5649 - learning_rate: 5.0000e-04
     Epoch 3/20
     27/27 - 2s - 85ms/step - accuracy: 0.7102 - loss: 0.5627 - val_accuracy: 0.7447
     - val_loss: 0.5695 - learning_rate: 5.0000e-04
     Epoch 4/20
     27/27 - 2s - 89ms/step - accuracy: 0.7479 - loss: 0.5288 - val_accuracy: 0.7553
     - val_loss: 0.5102 - learning_rate: 5.0000e-04
     Epoch 5/20
     27/27 - 2s - 87ms/step - accuracy: 0.7432 - loss: 0.5101 - val_accuracy: 0.8085
     - val_loss: 0.4816 - learning_rate: 5.0000e-04
     Epoch 6/20
     27/27 - 2s - 85ms/step - accuracy: 0.7432 - loss: 0.5080 - val_accuracy: 0.8404
     - val_loss: 0.4814 - learning_rate: 5.0000e-04
     Epoch 7/20
     27/27 - 2s - 84ms/step - accuracy: 0.7797 - loss: 0.4703 - val_accuracy: 0.8085
     - val_loss: 0.4981 - learning_rate: 5.0000e-04
     27/27 - 2s - 85ms/step - accuracy: 0.7762 - loss: 0.4494 - val_accuracy: 0.7872
     - val_loss: 0.4463 - learning_rate: 5.0000e-04
     27/27 - 2s - 86ms/step - accuracy: 0.7939 - loss: 0.4376 - val_accuracy: 0.8298
     - val_loss: 0.3891 - learning_rate: 5.0000e-04
     27/27 - 2s - 85ms/step - accuracy: 0.8092 - loss: 0.3927 - val_accuracy: 0.7660
     - val_loss: 0.6258 - learning_rate: 5.0000e-04
     Epoch 11/20
     27/27 - 2s - 86ms/step - accuracy: 0.8104 - loss: 0.4184 - val_accuracy: 0.8191
     - val_loss: 0.4744 - learning_rate: 4.1667e-04
     Epoch 12/20
     27/27 - 2s - 84ms/step - accuracy: 0.8292 - loss: 0.3838 - val_accuracy: 0.8298
     - val_loss: 0.4207 - learning_rate: 4.1667e-04
```

[16]: '\ntraining_history = model.fit(\n training_dataset,\n

epochs = epochs, \n

```
Epoch 13/20
     27/27 - 2s - 85ms/step - accuracy: 0.8375 - loss: 0.3758 - val_accuracy: 0.8191
     - val_loss: 0.3963 - learning_rate: 4.1667e-04
     Epoch 14/20
     27/27 - 2s - 85ms/step - accuracy: 0.8563 - loss: 0.3515 - val accuracy: 0.8404
     - val_loss: 0.4095 - learning_rate: 4.1667e-04
     27/27 - 2s - 86ms/step - accuracy: 0.8398 - loss: 0.3508 - val_accuracy: 0.8404
     - val_loss: 0.3723 - learning_rate: 4.1667e-04
     Epoch 16/20
     27/27 - 2s - 86ms/step - accuracy: 0.8716 - loss: 0.3308 - val_accuracy: 0.8936
     - val_loss: 0.4032 - learning_rate: 3.4722e-04
     Epoch 17/20
     27/27 - 2s - 85ms/step - accuracy: 0.8339 - loss: 0.3587 - val_accuracy: 0.8617
     - val_loss: 0.3863 - learning_rate: 3.4722e-04
     Epoch 18/20
     27/27 - 2s - 85ms/step - accuracy: 0.8528 - loss: 0.3291 - val_accuracy: 0.8723
     - val_loss: 0.4041 - learning_rate: 3.4722e-04
     Epoch 19/20
     27/27 - 2s - 85ms/step - accuracy: 0.8634 - loss: 0.3008 - val accuracy: 0.7979
     - val_loss: 0.3761 - learning_rate: 3.4722e-04
     Epoch 20/20
     27/27 - 2s - 85ms/step - accuracy: 0.8563 - loss: 0.3114 - val_accuracy: 0.8723
     - val_loss: 0.3607 - learning_rate: 3.4722e-04
[18]: #from tensorflow.keras.models import load model
      #model.save('gender_recognition_project04_v10.h5')
[19]: model.metrics names
[19]: ['loss', 'compile_metrics']
[20]: result_history = pd.DataFrame(model.history.history)
      result_history.head(15)
[20]:
                       loss val_accuracy val_loss learning_rate
         accuracy
      0
         0.591284 0.684490
                                 0.553191 0.708180
                                                          0.000500
         0.686690 0.597668
                                 0.702128 0.564949
                                                          0.000500
      1
      2
         0.710247 0.562719
                                 0.744681 0.569503
                                                          0.000500
      3
         0.747939 0.528787
                                 0.755319 0.510222
                                                          0.000500
      4
         0.743227 0.510139
                                 0.808511 0.481564
                                                          0.000500
      5
         0.743227 0.508042
                                 0.840426 0.481415
                                                          0.000500
      6
         0.779741 0.470272
                                 0.808511 0.498130
                                                          0.000500
      7
         0.776207 0.449389
                                 0.787234 0.446304
                                                          0.000500
      8
         0.793875 0.437624
                                 0.829787 0.389065
                                                          0.000500
         0.809187 0.392655
                                 0.765957 0.625812
      9
                                                          0.000500
      10 0.810365 0.418447
                                                          0.000417
                                 0.819149 0.474382
      11 0.829211 0.383821
                                 0.829787 0.420678
                                                          0.000417
```

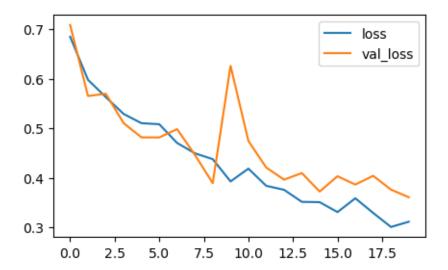
```
    12
    0.837456
    0.375755
    0.819149
    0.396266
    0.000417

    13
    0.856302
    0.351455
    0.840426
    0.409475
    0.000417

    14
    0.839812
    0.350824
    0.840426
    0.372253
    0.000417
```

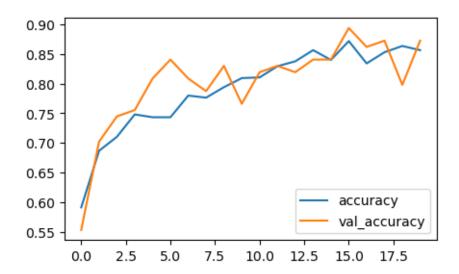
```
[21]: result_history[['loss', 'val_loss']].plot(figsize=(5, 3))
```

[21]: <Axes: >



[22]: result_history[['accuracy', 'val_accuracy']].plot(figsize=(5, 3))

[22]: <Axes: >



```
print(model.evaluate(validation_dataset))
     ['loss', 'compile metrics']
     3/3
                     Os 41ms/step -
     accuracy: 0.8580 - loss: 0.3955
     [0.3606766164302826, 0.8723404407501221]
[24]: from sklearn.metrics import classification_report, confusion_matrix
      y_true = np.concatenate([y.numpy() for _, y in validation_dataset])
      y_pred_prob = model.predict(validation_dataset)
      # Convert probabilities to class labels (0:Female or 1:Male)
      y_pred = (y_pred_prob > 0.5).astype(int).flatten()
      print("Classification Report:\n", classification_report(y_true, y_pred,_
       →target_names=['Female', 'Male']))
     3/3
                     0s 71ms/step
     Classification Report:
                    precision recall f1-score
                                                     support
           Female
                        0.82
                                  0.90
                                            0.86
                                                         41
             Male
                        0.92
                                  0.85
                                            0.88
                                                         53
                                            0.87
                                                         94
         accuracy
        macro avg
                        0.87
                                  0.88
                                            0.87
                                                         94
     weighted avg
                        0.88
                                  0.87
                                            0.87
                                                         94
[25]: import tensorflow as tf
      import numpy as np
      import matplotlib.pyplot as plt
      from tensorflow.keras.models import Model
      from tensorflow.keras.utils import load_img, img_to_array
      img_size = img_size
      model = tf.keras.models.load_model("gender_recognition_project04_v10.h5")
      # Load your personal image if you are interested to predict:
      your_image_path = "D:\\Hossein's desktop files in Microsoft Studio⊔
       →Laptop\\Personal Photos\\Hossein_10.jpg"
      img = load_img(your_image_path, target_size=(img_size, img_size))
      final_img = img_to_array(img)
      # Adding a batch dimension:
      final_img = np.expand_dims(final_img, axis=0)
      prediction = model.predict(final_img)
```

[23]: print(model.metrics_names)

```
result = "Female" if prediction > 0.5 else "Male"
if result=="Female":
    confidence = (model.predict(final_img)[0][0])*100
    confidence = (1-model.predict(final_img)[0][0])*100
print(f"Prediction result: {result} (confidence= {confidence:.2f} %)")
# Visualize CNN Layers
successive feature maps = visualization model.predict(final img)
layer_names = [layer.name for layer in model.layers]
for layer_name, feature_map in zip(layer_names, successive_feature_maps):
    if len(feature_map.shape) == 4: # Only visualize conv/maxpool layers
       n_features = feature_map.shape[-1] # Number of filters
        size = feature_map.shape[1] # Feature map size
        display_grid = np.zeros((size, size * n_features))
        for i in range(n_features):
           x = feature_map[0, :, :, i]
            x -= x.mean()
           x \neq (x.std() + 1e-8) # Normalize
            x *= 64
            x += 128
            x = np.clip(x, 0, 255).astype('uint8') # Convert to image format
            display_grid[:, i * size: (i + 1) * size] = x
        scale = 20. / n_features
       plt.figure(figsize=(scale * n_features, scale))
       plt.title(layer_name)
       plt.grid(False)
        plt.imshow(display_grid, aspect='auto', cmap='cividis')
       plt.show()
```

WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.

```
NameError Traceback (most recent call last)
Cell In[25], line 26
23 print(f"Prediction result: {result} (confidence= {confidence:.2f} %)")
25 # Visualize CNN Layers
---> 26 successive_feature_maps = visualization_model.predict(final_img)
27 layer_names = [layer.name for layer in model.layers]
```

	29 for layer_name, feature_map in zip(layer_names, successive_feature_maps
	NameError: name 'visualization_model' is not defined
[]:[
[]:[
[]:[