CIDL_project

September 12, 2023

```
[]: import tensorflow as tf
     from tensorflow import keras
     from tensorflow.keras import layers
     import os
     import datetime
     import pandas as pd
     import matplotlib.pyplot as plt
     import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import classification_report, f1_score , confusion_matrix
     import itertools
[]: # from google.colab import drive
     # # drive.mount('/content/drive/Shareddrives/CIDL_Project', force_remount=True)
     # drive.mount('/content/drive', force_remount=True)
     # print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
     print(tf.config.list_physical_devices('GPU'))
     # gpu_devices = tf.config.experimental.list_physical_devices('GPU')
     # for device in gpu_devices:
           tf.config.experimental.set_memory_growth(device, True)
    [PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
    2023-09-12 16:45:11.959905: I
    tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:995]
    successful NUMA node read from SysFS had negative value (-1), but there must be
    at least one NUMA node, so returning NUMA node zero. See more at
    https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-
    pci#L344-L355
    2023-09-12 16:45:12.548703: I
    tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:995]
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pci#L344-L355
```

/home/chuck/Documents/Project/archive
/home/chuck/Documents/Project/models/from_scratch
/home/chuck/Documents/Project/models/feature_extraction
/home/chuck/Documents/Project/models/fine_tuned
/home/chuck/Documents/Project/doc
/home/chuck/Documents/Project/doc/img

```
[]: import shutil
     import random
     # Definisci il percorso della cartella principale del tuo dataset
     dataset_dir = os.path.join(dataPath, "color_prova")
     # Definisci il percorso delle cartelle di addestramento, test e convalida
     train_dir = dataPath + '/train'
     test dir = dataPath + '/test'
     validation_dir = dataPath + '/validation'
     # Definisci le proporzioni per la divisione dei dati
     train_ratio = 0.8
     test_ratio = 0.15
     validation_ratio = 0.15
     # Crea le cartelle di addestramento, test e convalida se non esistono gia'
     os.makedirs(train_dir, exist_ok=True)
     os.makedirs(test_dir, exist_ok=True)
     os.makedirs(validation_dir, exist_ok=True)
     # Itera attraverso le sottocartelle delle classi nel dataset
     for class_folder in os.listdir(dataset_dir):
         class_path = os.path.join(dataset_dir, class_folder)
         # Assicurati che sia una cartella
         if os.path.isdir(class path):
             # Ottieni la lista dei file nella sottocartella
             files = os.listdir(class_path)
             random.shuffle(files) # Mescola i file per rendere la divisione casuale
             # Calcola i punti di divisione
             num_files = len(files)
             num_train = int(num_files * train_ratio)
             valid_test = int(num_files * test_ratio)
             # Suddividi i file nelle cartelle di addestramento, test e convalida
             train_files = files[:num_train]
             validation_files = files[num_train:num_train + valid_test]
             test_files = files[num_train + valid_test:]
             # Crea le sottocartelle delle classi nelle cartelle di addestramento, u
      ⇔test e convalida
             for folder in [train_dir, test_dir, validation_dir]:
                 class_subfolder = os.path.join(folder, class_folder)
                 os.makedirs(class_subfolder, exist_ok=True)
```

```
# Copia i file nelle sottocartelle appropriate
             for file in train files:
                 src_path = os.path.join(class_path, file)
                 dest_path = os.path.join(train_dir, class_folder, file)
                 shutil.copy(src_path, dest_path)
             for file in test files:
                 src_path = os.path.join(class_path, file)
                 dest_.take(1)path = os.path.join(test_dir, class_folder, file)
                 shutil.copy(src_path, dest_path)
             for file in validation_files:
                 src_path = os.path.join(class_path, file)
                 dest_path = os.path.join(validation_dir, class_folder, file)
                 shutil.copy(src_path, dest_path)
     # Rimuovi tutte le altre directory presenti nella cartella principale del⊔
      \rightarrow dataset
     for item in os.listdir(train dir):
         item_path = os.path.join(train_dir, item)
         if os.path.isdir(item path) and (item == "train" or item == "validation" or___
      →item == "test"):
             shutil.rmtree(item_path)
     for item in os.listdir(test_dir):
         item_path = os.path.join(train_dir, item)
         if os.path.isdir(item_path) and (item == "train" or item == "validation" or_u
      ⇔item == "test"):
             shutil.rmtree(item_path)
     for item in os.listdir(validation_dir):
         item_path = os.path.join(train_dir, item)
         if os.path.isdir(item_path) and (item == "train" or item == "validation" or_
      →item == "test"):
             shutil.rmtree(item_path)
[ ]: BATCH SIZE = 32
     IMAGE\_HEIGHT = 256
     IMAGE_WIDTH = 256
[]: diseases = os.listdir(os.path.join(dataPath, "train"))
     nums = \{\}
     for disease in diseases:
         nums[disease] = len(os.listdir(os.path.join(dataPath, "train") + '/' + |

disease))
     img_per_class = pd.DataFrame(nums.values(), index=nums.keys(), columns=["no. of_u

→images"])
     img_per_class
```

```
Strawberry__healthy
                                                                   1824
    Tomato___healthy
                                                                   1926
     Tomato___Septoria_leaf_spot
                                                                   1745
     Cherry_(including_sour)__healthy
                                                                   1826
     Potato__healthy
                                                                   1824
     Peach___Bacterial_spot
                                                                   1838
     Grape___Black_rot
                                                                   1888
     Tomato___Tomato_mosaic_virus
                                                                   1790
     Tomato___Leaf_Mold
                                                                   1882
     Strawberry___Leaf_scorch
                                                                   1774
     Tomato___Late_blight
                                                                   1851
     Corn_(maize)__healthy
                                                                   1859
     Squash___Powdery_mildew
                                                                   1736
     Tomato___Early_blight
                                                                   1920
     Grape__healthy
                                                                   1692
     Cherry_(including_sour)___Powdery_mildew
                                                                   1683
    Pepper, bell healthy
                                                                   1988
    Peach__healthy
                                                                   1728
     Tomato___Tomato_Yellow_Leaf_Curl_Virus
                                                                   1961
     Apple healthy
                                                                   2008
    Potato___Late_blight
                                                                   1939
     Corn_(maize)___Northern_Leaf_Blight
                                                                   1908
     Pepper, bell__Bacterial_spot
                                                                   1913
     Grape__Leaf_blight_(Isariopsis_Leaf_Spot)
                                                                   1722
     Raspberry__healthy
                                                                   1781
     Apple__Cedar_apple_rust
                                                                   1760
     Corn_(maize)___Common_rust_
                                                                   1907
     Soybean___healthy
                                                                   2022
     Tomato___Bacterial_spot
                                                                   1702
     Potato___Early_blight
                                                                   1939
     Grape___Esca_(Black_Measles)
                                                                   1920
     Tomato___Target_Spot
                                                                   1827
     Apple___Apple_scab
                                                                   2016
     Apple Black rot
                                                                   1987
     Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
                                                                   1642
     Tomato Spider mites Two-spotted spider mite
                                                                   1741
     Orange___Haunglongbing_(Citrus_greening)
                                                                   2010
     Blueberry__healthy
                                                                   1816
[]: colors = [
         "#1f77b4", "#ff7f0e", "#2ca02c", "#d62728", "#9467bd",
         "#8c564b", "#e377c2", "#7f7f7f", "#bcbd22", "#17becf",
         "#aec7e8", "#ffbb78", "#98df8a", "#ff9896", "#c5b0d5",
         "#c49c94", "#f7b6d2", "#c7c7c7", "#dbdb8d", "#9edae5",
         "#5254a3", "#6b6ecf", "#bdbdbd", "#8ca252", "#bd9e39",
         "#ad494a", "#8c6d31", "#6b6ecf", "#e7ba52", "#ce6dbd",
```

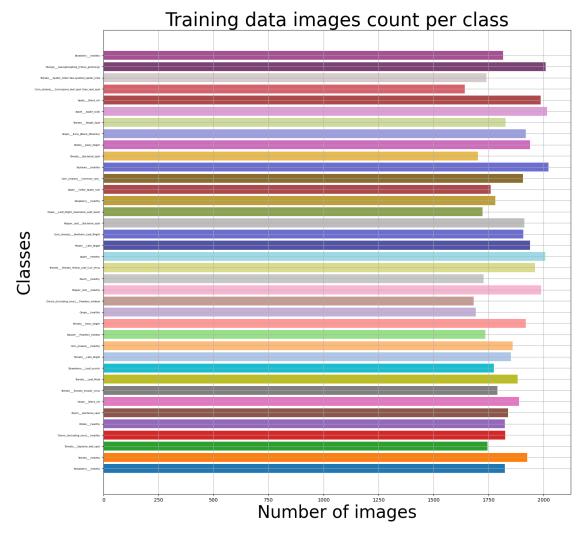
no. of images

[]:

```
"#9c9ede", "#cedb9c", "#de9ed6", "#ad494a", "#d6616b",
    "#d4cbcb", "#7b4173", "#a55194", "#ce6dbd"
]

index = [n for n in range(38)]

plt.figure(figsize=(17,17))
plt.title("Training data images count per class",fontsize=38)
plt.xlabel('Number of images', fontsize=35)
plt.ylabel('Classes', fontsize=35)
plt.yticks(index, diseases, fontsize=5, rotation=0)
plt.barh(index, [n for n in nums.values()], color=colors)
plt.grid(True)
plt.show()
```



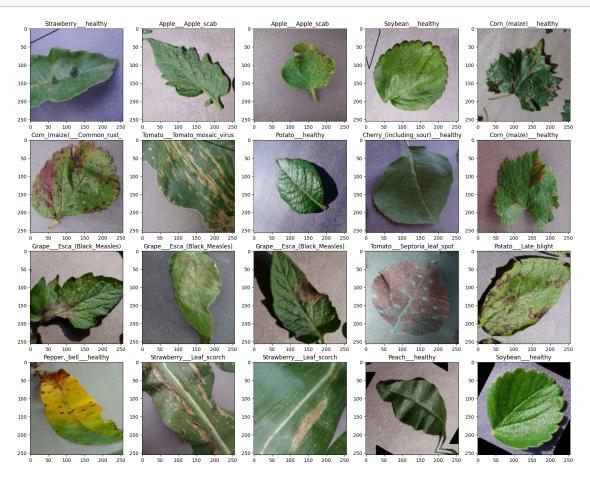
```
[]: train_dataset = keras.utils.image_dataset_from_directory(
         os.path.join(dataPath, 'train'),
         image_size = (IMAGE_HEIGHT, IMAGE_WIDTH),
         batch_size = BATCH_SIZE,
         label_mode = 'categorical'
     valid_dataset = keras.utils.image_dataset_from_directory(
         os.path.join(dataPath, 'valid'),
         image_size = (IMAGE_HEIGHT, IMAGE_WIDTH),
         batch_size = BATCH_SIZE,
         label_mode = 'categorical'
     test_dataset = keras.utils.image_dataset_from_directory(
         os.path.join(dataPath, 'test'),
         image_size = (IMAGE_HEIGHT, IMAGE_WIDTH),
         batch_size = BATCH_SIZE,
         label_mode = 'categorical',
         shuffle=False
     )
```

Found 70295 files belonging to 38 classes. Found 17572 files belonging to 38 classes. Found 5438 files belonging to 38 classes.

1 Data Augmentation

```
[]: plt.figure(figsize=(20, 20))
for images, y_batch in train_dataset.take(1):
    for i in range(20):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(5, 5, i + 1)
        plt.imshow(augmented_images[i].numpy().astype("uint8"))
```

plt.title(diseases[np.where(y_batch[i]==1)[0][0]])



```
[]: from tensorflow.keras import models
     model = keras.Sequential()
     model.add(data_augmentation)
     model.add(layers.Rescaling(1./255))
     model.add(layers.Conv2D(32, kernel_size = 3, activation = "relu6", padding =__

¬"same", input_shape = (256, 256,3))) # TODO see if using IMG_SIZE is correct

     model.add(layers.MaxPooling2D((2, 2)))
     model.add(layers.BatchNormalization())
     model.add(layers.Conv2D(64, kernel_size = 3, activation='relu', padding =__

¬"same"))
     model.add(layers.MaxPooling2D((2, 2)))
     model.add(layers.BatchNormalization())
     model.add(layers.Conv2D(128, kernel_size = 3, activation='relu', padding =_u

¬"same"))
     model.add(layers.MaxPooling2D((2, 2)))
     model.add(layers.BatchNormalization())
```

```
model.add(layers.Conv2D(256, kernel_size = 3, activation='relu', padding = 1

¬"same"))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(512, kernel_size = 3, activation='relu', padding = __

y"same"))

model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(512, kernel_size = 3, activation='relu', padding = __
 ⇔"same"))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Flatten())
model.add(layers.Dropout(0.5))
model.add(layers.Dense(256,activation="relu"))
model.add(layers.Dense(38,activation="softmax"))
model.build(input_shape=(None, 256, 256, 3))
model.compile(loss="categorical_crossentropy",
              optimizer="adam",
              metrics=["accuracy"])
model.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
AugmentationLayer (Sequent ial)	(None, 256, 256, 3)	0
rescaling_3 (Rescaling)	(None, 256, 256, 3)	0
Layer (type)	Output Shape	Param #
AugmentationLayer (Sequent ial)	=======================================	0
AugmentationLayer (Sequent	=======================================	0

<pre>max_pooling2d_6 (MaxPoolin g2D)</pre>	(None, 128, 128, 32)	0
<pre>batch_normalization_9 (Bat chNormalization)</pre>	(None, 128, 128, 32)	128
conv2d_7 (Conv2D)	(None, 128, 128, 64)	18496
<pre>max_pooling2d_7 (MaxPoolin g2D)</pre>	(None, 64, 64, 64)	0
<pre>batch_normalization_10 (Ba tchNormalization)</pre>	(None, 64, 64, 64)	256
conv2d_8 (Conv2D)	(None, 64, 64, 128)	73856
<pre>max_pooling2d_8 (MaxPoolin g2D)</pre>	(None, 32, 32, 128)	0
<pre>batch_normalization_11 (Ba tchNormalization)</pre>	(None, 32, 32, 128)	512
conv2d_9 (Conv2D)	(None, 32, 32, 256)	295168
<pre>max_pooling2d_9 (MaxPoolin g2D)</pre>	(None, 16, 16, 256)	0
<pre>batch_normalization_12 (Ba tchNormalization)</pre>	(None, 16, 16, 256)	1024
conv2d_10 (Conv2D)	(None, 16, 16, 512)	1180160
<pre>max_pooling2d_10 (MaxPooli ng2D)</pre>	(None, 8, 8, 512)	0
<pre>batch_normalization_13 (Ba tchNormalization)</pre>	(None, 8, 8, 512)	2048
conv2d_11 (Conv2D)	(None, 8, 8, 512)	2359808
<pre>max_pooling2d_11 (MaxPooli ng2D)</pre>	(None, 4, 4, 512)	0
<pre>batch_normalization_14 (Ba tchNormalization)</pre>	(None, 4, 4, 512)	2048
flatten_4 (Flatten)	(None, 8192)	0

```
dropout_4 (Dropout)
                          (None, 8192)
    dense_8 (Dense)
                           (None, 256)
                                                2097408
    dense_9 (Dense)
                           (None, 38)
                                                9766
   Total params: 6041574 (23.05 MB)
   Trainable params: 6038566 (23.04 MB)
   Non-trainable params: 3008 (11.75 KB)
[]: modelName = "32relu6_64_128_256_512_512_Drp_256d"
    modelPath = os.path.join(scratchPath, modelName + ".keras")
    save_best_model = tf.keras.callbacks.ModelCheckpoint(modelPath, verbose=True,__
    monitor='val_loss', save_best_only=True, save_weights_only=True)
    earlyStopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',_
    →patience=10)
    reduceLR = tf.keras.callbacks.ReduceLROnPlateau(monitor = 'val_loss', factor = __
     \hookrightarrow0.2, patience = 0.2, mode = 'min')
    history = model.fit(
       train_dataset,
       epochs=20,
       validation_data=valid_dataset,
       validation_steps=len(valid_dataset),
       callbacks=[earlyStopping, save_best_model] #, reduceLR],
     )
   Epoch 1/20
   0.7176
   Epoch 1: val loss improved from inf to 1.89372, saving model to /home/chuck/Docu
   ments/Project/models/from_scratch/32relu6_64_128_256_512_512_Drp_256d.keras
   accuracy: 0.7176 - val_loss: 1.8937 - val_accuracy: 0.6201
   Epoch 2/20
   Epoch 2: val_loss improved from 1.89372 to 0.86715, saving model to /home/chuck/
   Documents/Project/models/from_scratch/32relu6_64_128_256_512_512_Drp_256d.keras
   accuracy: 0.8775 - val_loss: 0.8671 - val_accuracy: 0.7749
```

```
Epoch 3/20
0.9146
Epoch 3: val_loss improved from 0.86715 to 0.47868, saving model to /home/chuck/
Documents/Project/models/from scratch/32relu6 64 128 256 512 512 Drp 256d.keras
accuracy: 0.9146 - val_loss: 0.4787 - val_accuracy: 0.8712
Epoch 4/20
0.9333
Epoch 4: val_loss did not improve from 0.47868
accuracy: 0.9333 - val_loss: 0.7814 - val_accuracy: 0.8090
Epoch 5/20
0.9457
Epoch 5: val_loss improved from 0.47868 to 0.34314, saving model to /home/chuck/
Documents/Project/models/from scratch/32relu6_64_128_256_512_512_Drp_256d.keras
accuracy: 0.9457 - val_loss: 0.3431 - val_accuracy: 0.9105
Epoch 6/20
0.9571
Epoch 6: val_loss did not improve from 0.34314
accuracy: 0.9571 - val_loss: 1.2772 - val_accuracy: 0.7646
Epoch 7/20
0.9605
Epoch 7: val_loss did not improve from 0.34314
accuracy: 0.9605 - val_loss: 0.8003 - val_accuracy: 0.8197
Epoch 8/20
Epoch 8: val_loss did not improve from 0.34314
accuracy: 0.9654 - val_loss: 1.0888 - val_accuracy: 0.7968
Epoch 9/20
0.9694
Epoch 9: val_loss did not improve from 0.34314
2197/2197 [============= ] - 396s 180ms/step - loss: 0.0990 -
accuracy: 0.9694 - val_loss: 0.3893 - val_accuracy: 0.9177
Epoch 10/20
0.9739
Epoch 10: val_loss did not improve from 0.34314
```

```
accuracy: 0.9739 - val_loss: 1.7239 - val_accuracy: 0.7911
Epoch 11/20
0.9762
Epoch 11: val loss did not improve from 0.34314
accuracy: 0.9762 - val_loss: 1.0023 - val_accuracy: 0.8545
Epoch 12/20
0.9781
Epoch 12: val loss improved from 0.34314 to 0.25615, saving model to /home/chuck
/Documents/Project/models/from_scratch/32relu6_64_128_256_512_512_Drp_256d.keras
accuracy: 0.9781 - val_loss: 0.2561 - val_accuracy: 0.9302
Epoch 13/20
Epoch 13: val_loss improved from 0.25615 to 0.14344, saving model to /home/chuck
/Documents/Project/models/from scratch/32relu6 64 128 256 512 512 Drp 256d.keras
accuracy: 0.9790 - val_loss: 0.1434 - val_accuracy: 0.9582
Epoch 14/20
0.9806
Epoch 14: val_loss did not improve from 0.14344
accuracy: 0.9806 - val_loss: 1.7192 - val_accuracy: 0.7169
Epoch 15/20
0.9830
Epoch 15: val_loss did not improve from 0.14344
2197/2197 [============= ] - 389s 177ms/step - loss: 0.0539 -
accuracy: 0.9830 - val_loss: 5.3982 - val_accuracy: 0.7331
Epoch 16/20
0.9836
Epoch 16: val_loss did not improve from 0.14344
accuracy: 0.9836 - val_loss: 0.1652 - val_accuracy: 0.9547
Epoch 17/20
Epoch 17: val_loss did not improve from 0.14344
accuracy: 0.9846 - val_loss: 0.5955 - val_accuracy: 0.9221
Epoch 18/20
```

```
0.9855
   Epoch 18: val_loss did not improve from 0.14344
   2197/2197 [============= ] - 396s 180ms/step - loss: 0.0462 -
   accuracy: 0.9855 - val_loss: 0.7404 - val_accuracy: 0.8638
   Epoch 19/20
   Epoch 19: val_loss did not improve from 0.14344
   accuracy: 0.9859 - val_loss: 0.3681 - val_accuracy: 0.9199
   Epoch 20/20
   0.9877
   Epoch 20: val loss improved from 0.14344 to 0.13112, saving model to /home/chuck
   /Documents/Project/models/from_scratch/32relu6_64_128_256_512_512_Drp_256d.keras
   accuracy: 0.9877 - val_loss: 0.1311 - val_accuracy: 0.9627
[]: # Define needed variables
    tr_acc = history.history['accuracy']
    tr_loss = history.history['loss']
    val_acc = history.history['val_accuracy']
    val_loss = history.history['val_loss']
    index_loss = np.argmin(val_loss)
    val_lowest = val_loss[index_loss]
    index_acc = np.argmax(val_acc)
    acc_highest = val_acc[index_acc]
    Epochs = [i+1 for i in range(len(tr_acc))]
    loss_label = f'best epoch= {str(index_loss + 1)}'
    acc_label = f'best epoch= {str(index_acc + 1)}'
    # Plot training history
    plt.figure(figsize= (20, 8))
    plt.style.use('fivethirtyeight')
    plt.subplot(1, 2, 1)
    plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
    plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
    plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.subplot(1, 2, 2)
    plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
    plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
```



```
* 32relu6_64_128_256_512_512_Drp_256d | val_loss: 0.1311 | val_accuracy: **0.9627**
```

2 Feature extraction

Used model: EfficientNetB5

```
[]: cnn_base = tf.keras.applications.VGG16(
    include_top=False,
    weights="imagenet",
    input_shape=(IMAGE_HEIGHT, IMAGE_WIDTH, 3),
```

```
pooling='max',
)
cnn_base.summary()
```

Model: "vgg16"

100		
Layer (type)	Output Shape	Param #
input_2 (InputLayer)		
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
Layer (type)		Param #
input_2 (InputLayer)		
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080

```
block4_conv1 (Conv2D)
                            (None, 32, 32, 512)
                                                       1180160
block4_conv2 (Conv2D)
                             (None, 32, 32, 512)
                                                       2359808
block4_conv3 (Conv2D)
                             (None, 32, 32, 512)
                                                       2359808
block4_pool (MaxPooling2D)
                            (None, 16, 16, 512)
block5_conv1 (Conv2D)
                             (None, 16, 16, 512)
                                                       2359808
block5_conv2 (Conv2D)
                             (None, 16, 16, 512)
                                                       2359808
block5_conv3 (Conv2D)
                             (None, 16, 16, 512)
                                                       2359808
block5_pool (MaxPooling2D)
                            (None, 8, 8, 512)
global_max_pooling2d_1 (Gl
                            (None, 512)
obalMaxPooling2D)
```

Total params: 14714688 (56.13 MB)
Trainable params: 14714688 (56.13 MB)
Non-trainable params: 0 (0.00 Byte)

This is the number of trainable weights after freezing the conv base: 0

```
[]: pretrained_model = tf.keras.Sequential([
    resize_and_rescale,
    data_augmentation,
    cnn_base,
    layers.Flatten(),
    layers.Dense(256, activation="relu"),
    layers.BatchNormalization(),
    layers.Dropout(0.4),
```

```
layers.Dense(38, activation = 'softmax')
])

pretrained_model.compile(
   loss = 'categorical_crossentropy',
   optimizer = 'adam',
   metrics = ["accuracy"]
)

pretrained_model.build(input_shape=(None, IMAGE_HEIGHT, IMAGE_WIDTH, 3))
pretrained_model.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
sequential_4 (Sequential)	(None, 256, 256, 3)	0
AugmentationLayer (Sequent ial)	(None, 256, 256, 3)	0
vgg16 (Functional)	(None, 512)	14714688
flatten_3 (Flatten)	(None, 512)	0
Laver (type)	Output Shape	 Param #

Layer (type)	Output Shape	Param #
sequential_4 (Sequential)		0
AugmentationLayer (Sequent ial)	(None, 256, 256, 3)	0
vgg16 (Functional)	(None, 512)	14714688
flatten_3 (Flatten)	(None, 512)	0
dense_6 (Dense)	(None, 256)	131328
<pre>batch_normalization_8 (Bat chNormalization)</pre>	(None, 256)	1024
<pre>dropout_3 (Dropout)</pre>	(None, 256)	0
dense_7 (Dense)	(None, 38)	9766

Total params: 14856806 (56.67 MB)
Trainable params: 141606 (553.15 KB)
Non-trainable params: 14715200 (56.13 MB)

Epoch 1/20

2023-09-09 19:44:59.956793: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available. 2023-09-09 19:45:02.991876: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available. 2023-09-09 19:45:02.991944: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

2023-09-09 19:55:34.038381: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

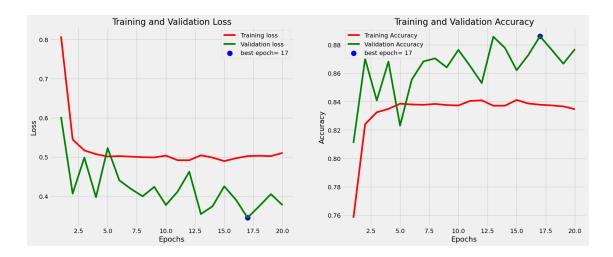
```
2023-09-09 19:55:34.533007: W tensorflow/tsl/framework/bfc_allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 3.25GiB with
freed_by_count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
2023-09-09 19:55:34.533073: W tensorflow/tsl/framework/bfc allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 3.25GiB with
freed by count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
0.7582
Epoch 1: val_loss improved from inf to 0.60236, saving model to
/home/chuck/Documents/Project/models/feature_extraction/FE_base_256d.keras
2197/2197 [============= ] - 789s 354ms/step - loss: 0.8082 -
accuracy: 0.7582 - val_loss: 0.6024 - val_accuracy: 0.8109
Epoch 2/20
0.8241
Epoch 2: val_loss improved from 0.60236 to 0.40663, saving model to
/home/chuck/Documents/Project/models/feature_extraction/FE_base_256d.keras
2197/2197 [============= ] - 775s 353ms/step - loss: 0.5447 -
accuracy: 0.8241 - val_loss: 0.4066 - val_accuracy: 0.8701
Epoch 3/20
0.8325
Epoch 3: val_loss did not improve from 0.40663
accuracy: 0.8325 - val_loss: 0.4986 - val_accuracy: 0.8408
Epoch 4/20
Epoch 4: val_loss improved from 0.40663 to 0.39754, saving model to
/home/chuck/Documents/Project/models/feature_extraction/FE_base_256d.keras
accuracy: 0.8349 - val_loss: 0.3975 - val_accuracy: 0.8681
Epoch 5/20
0.8386
Epoch 5: val_loss did not improve from 0.39754
accuracy: 0.8386 - val_loss: 0.5228 - val_accuracy: 0.8231
Epoch 6/20
0.8380
Epoch 6: val_loss did not improve from 0.39754
2197/2197 [============= ] - 773s 352ms/step - loss: 0.5024 -
accuracy: 0.8380 - val_loss: 0.4406 - val_accuracy: 0.8555
Epoch 7/20
```

```
0.8378
Epoch 7: val_loss did not improve from 0.39754
accuracy: 0.8378 - val_loss: 0.4186 - val_accuracy: 0.8683
Epoch 8/20
0.8384
Epoch 8: val_loss did not improve from 0.39754
accuracy: 0.8384 - val_loss: 0.3998 - val_accuracy: 0.8705
Epoch 9/20
0.8376
Epoch 9: val_loss did not improve from 0.39754
accuracy: 0.8376 - val_loss: 0.4238 - val_accuracy: 0.8642
Epoch 10/20
0.8373
Epoch 10: val_loss improved from 0.39754 to 0.37753, saving model to
/home/chuck/Documents/Project/models/feature extraction/FE base 256d.keras
accuracy: 0.8373 - val_loss: 0.3775 - val_accuracy: 0.8765
Epoch 11/20
0.8405
Epoch 11: val_loss did not improve from 0.37753
accuracy: 0.8405 - val_loss: 0.4118 - val_accuracy: 0.8652
Epoch 12/20
0.8409
Epoch 12: val_loss did not improve from 0.37753
accuracy: 0.8409 - val_loss: 0.4624 - val_accuracy: 0.8531
Epoch 13/20
0.8371
Epoch 13: val_loss improved from 0.37753 to 0.35448, saving model to
/home/chuck/Documents/Project/models/feature_extraction/FE_base_256d.keras
2197/2197 [============= ] - 773s 352ms/step - loss: 0.5044 -
accuracy: 0.8371 - val_loss: 0.3545 - val_accuracy: 0.8857
Epoch 14/20
Epoch 14: val_loss did not improve from 0.35448
2197/2197 [============= ] - 771s 351ms/step - loss: 0.4985 -
```

```
Epoch 15/20
  Epoch 15: val loss did not improve from 0.35448
  2197/2197 [============== ] - 768s 350ms/step - loss: 0.4896 -
  accuracy: 0.8412 - val_loss: 0.4252 - val_accuracy: 0.8622
  Epoch 16/20
  0.8387
  Epoch 16: val_loss did not improve from 0.35448
  2197/2197 [============= ] - 771s 351ms/step - loss: 0.4969 -
  accuracy: 0.8387 - val_loss: 0.3911 - val_accuracy: 0.8729
  Epoch 17/20
  0.8378
  Epoch 17: val_loss improved from 0.35448 to 0.34515, saving model to
  /home/chuck/Documents/Project/models/feature_extraction/FE_base_256d.keras
  accuracy: 0.8378 - val_loss: 0.3451 - val_accuracy: 0.8861
  Epoch 18/20
  0.8373
  Epoch 18: val_loss did not improve from 0.34515
  accuracy: 0.8373 - val_loss: 0.3745 - val_accuracy: 0.8766
  Epoch 19/20
  0.8367
  Epoch 19: val_loss did not improve from 0.34515
  accuracy: 0.8367 - val_loss: 0.4052 - val_accuracy: 0.8668
  Epoch 20/20
  Epoch 20: val_loss did not improve from 0.34515
  accuracy: 0.8346 - val_loss: 0.3773 - val_accuracy: 0.8770
[]: # Define needed variables
   tr_acc = history.history['accuracy']
   tr_loss = history.history['loss']
   val_acc = history.history['val_accuracy']
   val_loss = history.history['val_loss']
   index_loss = np.argmin(val_loss)
   val_lowest = val_loss[index_loss]
   index_acc = np.argmax(val_acc)
```

accuracy: 0.8372 - val_loss: 0.3745 - val_accuracy: 0.8778

```
acc_highest = val_acc[index_acc]
Epochs = [i+1 for i in range(len(tr_acc))]
loss_label = f'best epoch= {str(index_loss + 1)}'
acc_label = f'best epoch= {str(index_acc + 1)}'
# Plot training history
plt.figure(figsize= (20, 8))
plt.style.use('fivethirtyeight')
plt.subplot(1, 2, 1)
plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
plt.scatter(index_acc + 1 , acc_highest, s= 150, c= 'blue', label= acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout
plt.savefig(os.path.join(imgPath, "FExtraction", modelName))
plt.show()
text_to_add = "* " + modelName + " | val_loss: " + "{:.4f}".format(val_lowest)__
 Get " | val_accuracy: **" + "{:.4f}".format(val_acc[index_loss]) + "**\n"
print(text_to_add)
with open(os.path.join(docPath, "accuracies.md"), "a") as file:
    file.write(text_to_add)
```



* FE_base_256d | val_loss: 0.3451 | val_accuracy: **0.8861**

3 Fine Tuning

```
[]: # To recover a specific model
modelName = "FE_base_256d"
modelPath = os.path.join(fExtractorPath, modelName + ".keras")
pretrained_model.load_weights(modelPath)

[]: cnn_base.trainable = True

set_trainable = False

for layer in cnn_base.layers:
    if layer.name == 'block5_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False

cnn_base.summary()
```

```
Model: "vgg16"
```

Layer (type)	Output	Shape			Param #
input 2 (InputLaver)	====== (None	===== . 256.	===== 256.	==== 3)]	0

block1_conv1 (Conv2D)	(None, 256, 256, 64) 1792	
block1_conv2 (Conv2D)	(None, 256, 256, 64) 36928	
block1_pool (MaxPooling2D)	(None, 128, 128, 64) 0	

Layer (type)		Param #
input_2 (InputLayer)		
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1180160
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block5_pool (MaxPooling2D)	(None, 8, 8, 512)	0

```
global_max_pooling2d_1 (Gl (None, 512)
     obalMaxPooling2D)
    Total params: 14714688 (56.13 MB)
    Trainable params: 7079424 (27.01 MB)
    Non-trainable params: 7635264 (29.13 MB)
[]: pretrained_model.compile(
         loss = 'categorical_crossentropy',
         optimizer = tf.keras.optimizers.Adam(learning_rate=0.00001),
         metrics = ["accuracy"]
     )
     pretrained model.build(input_shape=(None, IMAGE_HEIGHT, IMAGE_WIDTH, 3))
     modelName = "FT_base_256d"
     modelPath = os.path.join(fineTunedPath, modelName + ".keras")
     save_best_model = tf.keras.callbacks.ModelCheckpoint(modelPath,__
      monitor='val_loss', verbose = 1, save_best_only=True, save_weights_only=True)
     earlyStopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',_
      →patience=10)
     reduceLR = tf.keras.callbacks.ReduceLROnPlateau(monitor = 'val loss', factor = 1
      →0.2, patience = 2, mode = 'min')
     history = pretrained_model.fit(
         train_dataset,
         epochs=20,
         validation data=valid dataset,
         validation_steps=len(valid_dataset),
         callbacks=[earlyStopping, save_best_model], #, reduceLR],
       )
    Epoch 1/20
    2023-09-10 16:57:55.309117: I
    tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:432] Loaded cuDNN
    version 8904
    2023-09-10 16:57:55.697143: I tensorflow/tsl/platform/default/subprocess.cc:304]
    Start cannot spawn child process: No such file or directory
    2023-09-10 16:57:56.716732: W tensorflow/tsl/framework/bfc_allocator.cc:296]
    Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with
    freed_by_count=0. The caller indicates that this is not a failure, but this may
    mean that there could be performance gains if more memory were available.
```

```
2023-09-10 16:57:59.644636: W tensorflow/tsl/framework/bfc_allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with
freed_by_count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
2023-09-10 16:57:59.644708: W tensorflow/tsl/framework/bfc allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with
freed by count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
2023-09-10 16:58:04.354163: I tensorflow/compiler/xla/service/service.cc:168]
XLA service 0x56075fbe7330 initialized for platform CUDA (this does not
guarantee that XLA will be used). Devices:
2023-09-10 16:58:04.354211: I tensorflow/compiler/xla/service/service.cc:176]
StreamExecutor device (0): NVIDIA GeForce GTX 970, Compute Capability 5.2
2023-09-10 16:58:04.458797: I
tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:255] disabling MLIR
crash reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
2023-09-10 16:58:04.842899: I tensorflow/tsl/platform/default/subprocess.cc:304]
Start cannot spawn child process: No such file or directory
2023-09-10 16:58:04.967816: I ./tensorflow/compiler/jit/device_compiler.h:186]
Compiled cluster using XLA! This line is logged at most once for the lifetime
of the process.
0.8861
2023-09-10 17:09:02.963166: W tensorflow/tsl/framework/bfc_allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with
freed_by_count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
2023-09-10 17:09:03.543243: W tensorflow/tsl/framework/bfc_allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 3.25GiB with
freed_by_count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
2023-09-10 17:09:03.543323: W tensorflow/tsl/framework/bfc_allocator.cc:296]
Allocator (GPU_0_bfc) ran out of memory trying to allocate 3.25GiB with
freed by count=0. The caller indicates that this is not a failure, but this may
mean that there could be performance gains if more memory were available.
0.8861
Epoch 1: val loss improved from inf to 0.17523, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.8861 - val_loss: 0.1752 - val_accuracy: 0.9455
Epoch 2/20
0.9225
Epoch 2: val_loss improved from 0.17523 to 0.15053, saving model to
```

/home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras

```
2197/2197 [============== ] - 800s 364ms/step - loss: 0.2422 -
accuracy: 0.9225 - val_loss: 0.1505 - val_accuracy: 0.9515
Epoch 3/20
0.9402
Epoch 3: val_loss improved from 0.15053 to 0.12264, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.9402 - val_loss: 0.1226 - val_accuracy: 0.9607
Epoch 4/20
Epoch 4: val_loss improved from 0.12264 to 0.11391, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.9494 - val_loss: 0.1139 - val_accuracy: 0.9628
Epoch 5/20
0.9578
Epoch 5: val loss improved from 0.11391 to 0.10958, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.9578 - val_loss: 0.1096 - val_accuracy: 0.9632
Epoch 6/20
Epoch 6: val_loss improved from 0.10958 to 0.09463, saving model to
/home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras
accuracy: 0.9639 - val_loss: 0.0946 - val_accuracy: 0.9709
Epoch 7/20
0.9684
Epoch 7: val_loss improved from 0.09463 to 0.07693, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.9684 - val loss: 0.0769 - val accuracy: 0.9759
Epoch 8/20
0.9727
Epoch 8: val_loss did not improve from 0.07693
accuracy: 0.9727 - val_loss: 0.0782 - val_accuracy: 0.9742
Epoch 9/20
Epoch 9: val_loss did not improve from 0.07693
2197/2197 [============ ] - 786s 358ms/step - loss: 0.0857 -
```

```
accuracy: 0.9759 - val_loss: 0.0790 - val_accuracy: 0.9746
Epoch 10/20
Epoch 10: val loss improved from 0.07693 to 0.06993, saving model to
/home/chuck/Documents/Project/models/fine tuned/FT base 256d.keras
accuracy: 0.9794 - val_loss: 0.0699 - val_accuracy: 0.9779
Epoch 11/20
0.9813
Epoch 11: val_loss did not improve from 0.06993
accuracy: 0.9813 - val_loss: 0.0820 - val_accuracy: 0.9738
Epoch 12/20
0.9833
Epoch 12: val_loss did not improve from 0.06993
2197/2197 [============== ] - 782s 356ms/step - loss: 0.0644 -
accuracy: 0.9833 - val_loss: 0.1011 - val_accuracy: 0.9696
Epoch 13/20
Epoch 13: val loss improved from 0.06993 to 0.06941, saving model to
/home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras
2197/2197 [============= ] - 782s 356ms/step - loss: 0.0598 -
accuracy: 0.9840 - val_loss: 0.0694 - val_accuracy: 0.9776
Epoch 14/20
0.9858
Epoch 14: val_loss did not improve from 0.06941
2197/2197 [============= ] - 777s 353ms/step - loss: 0.0538 -
accuracy: 0.9858 - val_loss: 0.0772 - val_accuracy: 0.9748
Epoch 15/20
0.9865
Epoch 15: val loss improved from 0.06941 to 0.05706, saving model to
/home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras
accuracy: 0.9865 - val_loss: 0.0571 - val_accuracy: 0.9828
Epoch 16/20
Epoch 16: val_loss improved from 0.05706 to 0.05100, saving model to
/home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras
accuracy: 0.9879 - val_loss: 0.0510 - val_accuracy: 0.9843
Epoch 17/20
```

```
0.9889
   Epoch 17: val_loss did not improve from 0.05100
   accuracy: 0.9889 - val_loss: 0.0515 - val_accuracy: 0.9839
   Epoch 18/20
   0.9897
   Epoch 18: val_loss did not improve from 0.05100
   accuracy: 0.9897 - val_loss: 0.0614 - val_accuracy: 0.9801
   Epoch 19/20
   0.9906
   Epoch 19: val_loss improved from 0.05100 to 0.04805, saving model to
   /home/chuck/Documents/Project/models/fine_tuned/FT_base_256d.keras
   2197/2197 [============= ] - 811s 369ms/step - loss: 0.0385 -
   accuracy: 0.9906 - val_loss: 0.0481 - val_accuracy: 0.9847
   Epoch 20/20
   0.9912
   Epoch 20: val loss did not improve from 0.04805
   accuracy: 0.9912 - val_loss: 0.0501 - val_accuracy: 0.9840
[]: # Define needed variables
   tr_acc = history.history['accuracy']
   tr_loss = history.history['loss']
   val_acc = history.history['val_accuracy']
   val_loss = history.history['val_loss']
   index_loss = np.argmin(val_loss)
   val_lowest = val_loss[index_loss]
   index_acc = np.argmax(val_acc)
   acc_highest = val_acc[index_acc]
   Epochs = [i+1 for i in range(len(tr_acc))]
   loss_label = f'best epoch= {str(index_loss + 1)}'
   acc_label = f'best epoch= {str(index_acc + 1)}'
   # Plot training history
   plt.figure(figsize= (20, 8))
   plt.style.use('fivethirtyeight')
   plt.subplot(1, 2, 1)
   plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
   plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
   plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)
   plt.title('Training and Validation Loss')
```

```
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
plt.scatter(index_acc + 1 , acc_highest, s= 150, c= 'blue', label= acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout
plt.savefig(os.path.join(imgPath, "fine-tuning", modelName))
plt.show()
text_to_add = "* " + modelName + " | val_loss: " + "{:.4f}".format(val_lowest)_u
 s+ " | val_accuracy: **" + "{:.4f}".format(val_acc[index_loss]) + "**\n"
print(text to add)
with open(os.path.join(docPath, "accuracies.md"), "a") as file:
    file.write(text_to_add)
```



* FT_base_256d | val_loss: 0.0481 | val_accuracy: **0.9847**

4 Comparison on the test set

[]: cnn_base.summary()

Model: "vgg16"		
Layer (type)	Output Shape	 Param #
input_1 (InputLayer)	[(None, 256, 256, 3)]	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
Layer (type)	Output Shape	Param # =======
<pre>input_1 (InputLayer)</pre>	[(None, 256, 256, 3)]	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1180160

```
block4_conv2 (Conv2D)
                             (None, 32, 32, 512)
                                                        2359808
 block4_conv3 (Conv2D)
                             (None, 32, 32, 512)
                                                        2359808
block4 pool (MaxPooling2D)
                             (None, 16, 16, 512)
block5 conv1 (Conv2D)
                             (None, 16, 16, 512)
                                                        2359808
block5 conv2 (Conv2D)
                             (None, 16, 16, 512)
                                                        2359808
block5_conv3 (Conv2D)
                             (None, 16, 16, 512)
                                                        2359808
 block5_pool (MaxPooling2D) (None, 8, 8, 512)
global_max_pooling2d (Glob (None, 512)
alMaxPooling2D)
Total params: 14714688 (56.13 MB)
```

Trainable params: 0 (0.00 Byte)

Non-trainable params: 14714688 (56.13 MB)

```
[]: # Recovery of the best model from scratch
     scratchName = "32relu6_64_128_256_512_512_Drp_256d"
     path = os.path.join(scratchPath, scratchName + ".keras")
     model.load_weights(path)
     # Recovery of the best model fine-tuned
     fTunedName = "FT_base_256d"
     path = os.path.join(fineTunedPath, fTunedName + ".keras")
     pretrained_model.load_weights(path)
```

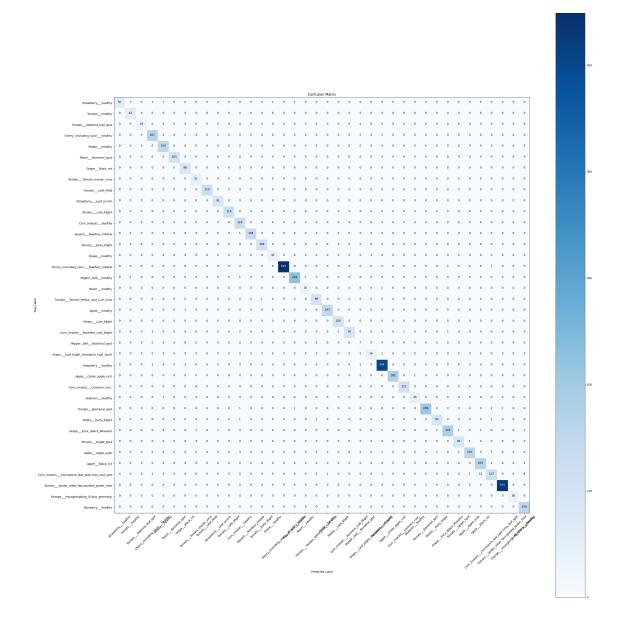
```
[]: # Create an empty list to store the labels
     labels_list = []
     # Iterate through the dataset using a for loop
     for data_item, label in test_dataset:
        labels_list.extend(np.argmax(label.numpy(), axis=1)) # Append the label to_
      →the list
     # Now, labels_list contains all the labels in the dataset
     print(len(labels_list))
```

5438

```
[]: results = model.evaluate(test_dataset, verbose=0)
               Test Loss: {:.5f}".format(results[0]))
     print("
     print("Test Accuracy: {:.2f}%".format(results[1] * 100))
        Test Loss: 0.08954
    Test Accuracy: 97.59%
[ ]: preds = model.predict(test_dataset)
     y_pred = np.argmax(preds, axis=1)
     # Confusion matrix
     cm = confusion_matrix(labels_list, y_pred)
     plt.figure(figsize= (30, 30))
     plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
     plt.title('Confusion Matrix')
     plt.colorbar()
     tick_marks = np.arange(len(diseases))
     plt.xticks(tick_marks, diseases, rotation= 45)
     plt.yticks(tick_marks, diseases)
     thresh = cm.max() / 2.
     for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
         plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' ifu

cm[i, j] > thresh else 'black')
     plt.tight_layout()
     plt.ylabel('True Label')
     plt.xlabel('Predicted Label')
     plt.show()
```

```
89/170 [========>...] - ETA: 3s170/170 [======== ] - 7s 39ms/step
```



```
[]: f1 = f1_score(labels_list, y_pred, average='macro')
print("F1 Score:", f1)
print(classification_report(labels_list, y_pred, target_names=diseases))
```

F1 Score: 0.962158352503775

f1-score	support		precision	recall
0.94	63	Strawberryhealthy	1.00	0.89
0.94	03	Tomatohealthy	0.93	1.00
0.96	62			

		TomatoSeptoria_leaf_spot	1.00	1.00
1.00	28	Cherry_(including_sour)healthy	0.98	0.98
0.98	165			
0.98	150	Potatohealthy	0.96	1.00
1.00	105	PeachBacterial_spot	1.00	1.00
0.92	86	<pre>GrapeBlack_rot</pre>	0.86	1.00
		TomatoTomato_mosaic_virus	0.85	1.00
0.92	52	TomatoLeaf_Mold	1.00	1.00
1.00	119	StrawberryLeaf_scorch	0.99	0.92
0.95	99	•		
1.00	116	TomatoLate_blight	1.00	1.00
0.97	118	Corn_(maize)healthy	0.94	1.00
		SquashPowdery_mildew	1.00	0.99
1.00	139	TomatoEarly_blight	0.99	1.00
1.00	108	Grapehealthy	0.98	0.98
0.98	43	•		
1.00	Cherr 551	y_(including_sour)Powdery_mildew	1.00	1.00
0.99	230	Pepper,_bellhealthy	0.99	0.98
		Peachhealthy	0.97	0.97
0.97	36 Tom	atoTomato_Yellow_Leaf_Curl_Virus	0.94	0.99
0.97	100	Applehealthy	0.99	0.99
0.99	148	-		
0.99	100	PotatoLate_blight	0.98	1.00
0.97	100	Corn_(maize)Northern_Leaf_Blight	1.00	0.95
0.61	15	Pepper,_bellBacterial_spot	0.88	0.47
	Grape	_Leaf_blight_(Isariopsis_Leaf_Spot)	0.97	0.97
0.97	37	Raspberryhealthy	0.98	0.99
0.99	509	AppleCedar_apple_rust	1.00	0.99
0.99	184	whhie oedai ahhie i dar	1.00	0.99

		<pre>Corn_(maize)Common_rust_</pre>	0.99	1.00
1.00	111	Soybeanhealthy	0.96	0.98
0.97	46	boyboannoarony	0.00	0.00
		TomatoBacterial_spot	0.98	0.97
0.97	213	PotatoEarly_blight	0.96	0.94
0.95	100			
0.06	101	<pre>GrapeEsca_(Black_Measles)</pre>	0.99	0.93
0.96	191	TomatoTarget_Spot	0.97	0.99
0.98	95			
0.93	177	AppleApple_scab	0.99	0.88
0.55	111	AppleBlack_rot	0.93	0.97
0.95	168			
Corn_(m	naize)Ce 141	rcospora_leaf_spot Gray_leaf_spot	0.89	0.83
		der_mites Two-spotted_spider_mite	1.00	1.00
1.00	536	Hannel annhime (Citanus annonium)	1 00	1 00
1.00	urange_ 38	Haunglongbing_(Citrus_greening)	1.00	1.00
		Blueberryhealthy	0.93	1.00
0.96	159			
		accuracy		
0.98	5438			
0.96	5438	macro avg	0.97	0.96
	0.200	weighted avg	0.98	0.98
0.98	5438			

```
[]: results = pretrained_model.evaluate(test_dataset, verbose=0)

print(" Test Loss: {:.5f}".format(results[0]))
print("Test Accuracy: {:.2f}%".format(results[1] * 100))
```

2023-09-12 17:58:00.337488: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available. 2023-09-12 17:58:02.676602: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available. 2023-09-12 17:58:02.676664: W tensorflow/tsl/framework/bfc_allocator.cc:296] Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with

freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

2023-09-12 17:58:42.481601: W tensorflow/tsl/framework/bfc_allocator.cc:296]

Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.27GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

2023-09-12 17:58:44.422729: W tensorflow/tsl/framework/bfc_allocator.cc:296]

Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.12GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

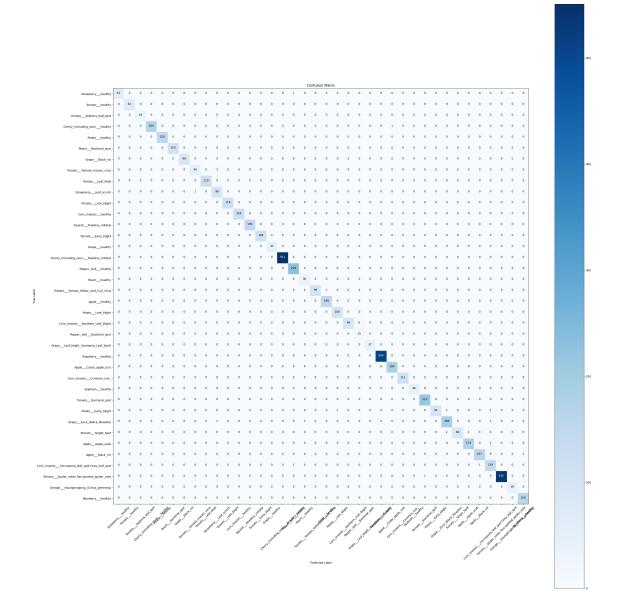
2023-09-12 17:58:44.422790: W tensorflow/tsl/framework/bfc_allocator.cc:296]

Allocator (GPU_0_bfc) ran out of memory trying to allocate 2.12GiB with freed_by_count=0. The caller indicates that this is not a failure, but this may mean that there could be performance gains if more memory were available.

Test Loss: 0.03156
Test Accuracy: 99.01%

```
[]: preds = pretrained_model.predict(test_dataset)
    y_pred = np.argmax(preds, axis=1)
    # Confusion matrix
    cm = confusion_matrix(labels_list, y_pred)
    plt.figure(figsize= (30, 30))
    plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
    plt.title('Confusion Matrix')
    plt.colorbar()
    tick_marks = np.arange(len(diseases))
    plt.xticks(tick_marks, diseases, rotation= 45)
    plt.yticks(tick_marks, diseases)
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' if
     plt.tight_layout()
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()
```

```
49/170 [======>...] - ETA: 25s170/170 [======== ] - 35s 208ms/step
```



```
[]: f1 = f1_score(labels_list, y_pred, average='macro')
print("F1 Score:", f1)
print(classification_report(labels_list, y_pred, target_names=diseases))
```

F1 Score: 0.9836812845075977

f1-score	support		precision	recall
0.00	60	Strawberryhealthy	1.00	0.98
0.99	63	Tomatohealthy	1.00	1.00
1.00	62			

		TomatoSeptoria_leaf_spot	1.00	1.00
1.00	28	Cherry_(including_sour)healthy	1.00	0.99
1.00	165			1 00
1.00	150	Potatohealthy	1.00	1.00
1.00	105	PeachBacterial_spot	1.00	1.00
		<pre>GrapeBlack_rot</pre>	1.00	1.00
1.00	86	TomatoTomato_mosaic_virus	0.98	0.94
0.96	52	TomatoLeaf_Mold	1.00	1.00
1.00	119			
0.98	99	StrawberryLeaf_scorch	0.96	0.99
1.00	116	TomatoLate_blight	1.00	1.00
		Corn_(maize)healthy	1.00	1.00
1.00	118	SquashPowdery_mildew	1.00	1.00
1.00	139	TomatoEarly_blight	1.00	1.00
1.00	108	· ·		
1.00	43	Grapehealthy	1.00	1.00
1.00	Cherr 551	ry_(including_sour)Powdery_mildew	1.00	1.00
1.00		Pepper,_bellhealthy	0.99	0.98
0.99	230	Peachhealthy	0.88	1.00
0.94	36	•		
0.99	10n	natoTomato_Yellow_Leaf_Curl_Virus	1.00	0.99
1.00	148	Applehealthy	0.99	1.00
		PotatoLate_blight	0.99	1.00
1.00	100	Corn_(maize)Northern_Leaf_Blight	1.00	0.94
0.97	100	Pepper,_bellBacterial_spot	0.71	1.00
0.83	15			
1.00	Grape 37	Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00
1.00	509	Raspberryhealthy	1.00	1.00
		AppleCedar_apple_rust	0.99	1.00
1.00	184			

1.00 111 Soybeanhealthy 1.00 1.00 1.00 46 TomatoBacterial_spot 1.00 1.00 1.00 213 PotatoEarly_blight 1.00 0.94 0.97 100 GrapeEsca_(Black_Measles) 0.98 0.98 0.98 191
1.00 46
TomatoBacterial_spot 1.00 1.00 1.00 213 PotatoEarly_blight 1.00 0.94 0.97 100 GrapeEsca_(Black_Measles) 0.98 0.98 0.98 191
1.00 213 PotatoEarly_blight 1.00 0.94 0.97 100 GrapeEsca_(Black_Measles) 0.98 0.98 0.98 191
PotatoEarly_blight 1.00 0.94 0.97 100 GrapeEsca_(Black_Measles) 0.98 0.98 0.98 191
0.97 100 GrapeEsca_(Black_Measles) 0.98 0.98 0.98 191
GrapeEsca_(Black_Measles) 0.98 0.98 0.98
0.98 191
TomatoTarget_Spot 1.00 0.88
0.94 95
AppleApple_scab 0.99 0.98
0.99 177
AppleBlack_rot 0.98 0.93
0.95 168
Corn_(maize)Cercospora_leaf_spot Gray_leaf_spot 0.87 0.99
0.93 141
TomatoSpider_mites Two-spotted_spider_mite 1.00 1.00
1.00 536
OrangeHaunglongbing_(Citrus_greening) 1.00 1.00
1.00 38
Blueberryhealthy 0.99 1.00 0.99 159
0.99 159
accuracy
0.99 5438
macro avg 0.98 0.99
0.98 5438
weighted avg 0.99 0.99
0.99 5438