

07_model_t_tl_fine_tuning_adam

June 10, 2024

1 Model T - Transfer Learning, Fine-tuning, Adaptive Moment Estimation (Adam)

- 128 x 128 x 3 Image size.
 - 64 Batch size.
 - Load our previously trained model with **Transfer Learning, Data Augmentation** and **Adaptive Moment Estimation (Adam)**.
 - **Unfreeze the last 4 convolutional layers** of the VGG16 Convolutional Base.
 - Fine-Tune the Model:
 - Adaptive Moment Estimation (**Adam**) optimizer.
 - **0.0001** Initial Learning rate.
 - **Sparse Categorical Cross-Entropy** loss function.
 - **Reduce Learning Rate on Plateau** callback with a **0.1** factor and patience of **3**.
 - **Early Stopping** callback with patience of **6** and restore best weights.
 - **Model Checkpoint** callback to save the best model based on validation loss.
 - **11 279 370** Trainable Parameters.
 - **30 Epochs** to fine-tune the model.
 - Evaluate the model on the validation set.
 - Test the model on the test set.
-

Imports and Setup

```
[1]: import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import tensorflow as tf
print(f'TensorFlow version: {tf.__version__}')
tf.get_logger().setLevel('ERROR')
tf.autograph.set_verbosity(3)
import matplotlib.pyplot as plt
import pickle
import numpy as np
from tensorflow.keras.utils import image_dataset_from_directory
from tensorflow import keras
from tensorflow.keras import callbacks, optimizers
```

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
    ↪, accuracy_score, precision_score, recall_score, f1_score, roc_curve, auc
from sklearn.preprocessing import label_binarize
from itertools import cycle
```

TensorFlow version: 2.15.0

Group Datasets

```
[2]: IMG_SIZE = 128

train_dirs = [f'../data/train1_resized_{IMG_SIZE}',
              f'../data/train3_resized_{IMG_SIZE}',
              f'../data/train4_resized_{IMG_SIZE}',
              f'../data/train5_resized_{IMG_SIZE}']
validation_dir = f'../data/train2_resized_{IMG_SIZE}'
test_dir = f'../data/test_resized_{IMG_SIZE}'
```

Create Datasets

```
[3]: BATCH_SIZE = 64
NUM_CLASSES = 10

train_datasets = [image_dataset_from_directory(directory, image_size=(IMG_SIZE,
    ↪IMG_SIZE), batch_size=BATCH_SIZE) for directory in train_dirs]

train_dataset = train_datasets[0]
for dataset in train_datasets[1:]:
    train_dataset = train_dataset.concatenate(dataset)

train_dataset = train_dataset.shuffle(buffer_size=1000).prefetch(buffer_size=tf.
    ↪data.AUTOTUNE)
validation_dataset = image_dataset_from_directory(validation_dir,
    ↪image_size=(IMG_SIZE, IMG_SIZE), batch_size=BATCH_SIZE).
    ↪prefetch(buffer_size=tf.data.AUTOTUNE)
test_dataset = image_dataset_from_directory(test_dir, image_size=(IMG_SIZE,
    ↪IMG_SIZE), batch_size=BATCH_SIZE).prefetch(buffer_size=tf.data.AUTOTUNE)

class_names = train_datasets[0].class_names

for data_batch, labels_batch in train_dataset.take(1):
    print('data batch shape:', data_batch.shape)
    print('labels batch shape:', labels_batch.shape)
```

Found 10000 files belonging to 10 classes.

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 Found 10000 files belonging to 10 classes.
 Found 10000 files belonging to 10 classes.
 Found 10000 files belonging to 10 classes.
 Found 10000 files belonging to 10 classes.
 data batch shape: (64, 128, 128, 3)
 labels batch shape: (64,)

- We define the image size of 128 x 128 x 3, batch size of 64 and create an array with the label's names.
- We create the train dataset by concatenating them, we **shuffle** the samples before each epoch and **prefetch** them to memory.
- We do the same for the validation and test dataset except **shuffling** which is **unwanted** for these datasets.

Loading our previously trained Model

```
[4]: model = keras.models.load_model('../models/06_model_t_t1_data_augm_adam.h5')
      model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #

input_2 (InputLayer)	[(None, 128, 128, 3)]	0
sequential (Sequential)	(None, 128, 128, 3)	0
tf.__operators__.getitem (SlicingOpLambda)	(None, 128, 128, 3)	0
tf.nn.bias_add (TFOpLambda)	(None, 128, 128, 3)	0
vgg16 (Functional)	(None, None, None, 512)	14714688
flatten (Flatten)	(None, 8192)	0
dropout (Dropout)	(None, 8192)	0
dense (Dense)	(None, 512)	4194816
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5130

```
=====
Total params: 18914634 (72.15 MB)
Trainable params: 4199946 (16.02 MB)
Non-trainable params: 14714688 (56.13 MB)
-----
```

Previous Model Evaluation

```
[5]: val_loss, val_acc = model.evaluate(validation_dataset)
     print('val_acc:', val_acc)
```

```
157/157 [=====] - 213s 1s/step - loss: 0.4394 -
accuracy: 0.9036
val_acc: 0.9035999774932861
-----
```

Unfreezing the 4 last layers of the VGG16 convolutional base

```
[6]: convbase = model.get_layer("vgg16")
     convbase.trainable = True
     for layer in convbase.layers[:-4]:
         layer.trainable = False
     for i, layer in enumerate(convbase.layers):
         print(i, layer.name, layer.trainable)
```

```
0 input_1 False
1 block1_conv1 False
2 block1_conv2 False
3 block1_pool False
4 block2_conv1 False
5 block2_conv2 False
6 block2_pool False
7 block3_conv1 False
8 block3_conv2 False
9 block3_conv3 False
10 block3_pool False
11 block4_conv1 False
12 block4_conv2 False
13 block4_conv3 False
14 block4_pool False
15 block5_conv1 True
16 block5_conv2 True
17 block5_conv3 True
18 block5_pool True
-----
```

Model Compilation

```
[7]: initial_learning_rate = 0.0001
optimizer = optimizers.Adam(learning_rate=initial_learning_rate)
loss_function = keras.losses.SparseCategoricalCrossentropy()

lr_scheduler = callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.1,
    ↳patience=3, verbose=1)
early_stopping = callbacks.EarlyStopping(monitor='val_loss', patience=6,
    ↳restore_best_weights=True, verbose=1)
save_best_model = callbacks.ModelCheckpoint(filepath='../models/
    ↳07_model_t_t1_fine_tuning_adam.h5', save_best_only=True, monitor='val_loss',
    ↳verbose=1)

callbacks = [lr_scheduler, early_stopping, save_best_model]

model.compile(
    loss=loss_function,
    optimizer=optimizer,
    metrics=["accuracy"])

model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 128, 128, 3)]	0
sequential (Sequential)	(None, 128, 128, 3)	0
tf.__operators__.getitem (SlicingOpLambda)	(None, 128, 128, 3)	0
tf.nn.bias_add (TFOpLambda)	(None, 128, 128, 3)	0
vgg16 (Functional)	(None, None, None, 512)	14714688
flatten (Flatten)	(None, 8192)	0
dropout (Dropout)	(None, 8192)	0
dense (Dense)	(None, 512)	4194816
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5130

```
=====
Total params: 18914634 (72.15 MB)
Trainable params: 11279370 (43.03 MB)
Non-trainable params: 7635264 (29.13 MB)
-----
```

Model Training

```
[8]: history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/30
628/628 [=====] - ETA: 0s - loss: 0.6073 - accuracy:
0.8438
Epoch 1: val_loss improved from inf to 0.42839, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1292s 2s/step - loss: 0.6073 -
accuracy: 0.8438 - val_loss: 0.4284 - val_accuracy: 0.9014 - lr: 1.0000e-04

/usr/local/lib/python3.9/dist-packages/keras/src/engine/training.py:3103:
UserWarning: You are saving your model as an HDF5 file via `model.save()`. This
file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.
    saving_api.save_model(

Epoch 2/30
628/628 [=====] - ETA: 0s - loss: 0.4528 - accuracy:
0.8890
Epoch 2: val_loss improved from 0.42839 to 0.37752, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1287s 2s/step - loss: 0.4528 -
accuracy: 0.8890 - val_loss: 0.3775 - val_accuracy: 0.9130 - lr: 1.0000e-04
Epoch 3/30
628/628 [=====] - ETA: 0s - loss: 0.4027 - accuracy:
0.9082
Epoch 3: val_loss improved from 0.37752 to 0.36604, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1286s 2s/step - loss: 0.4027 -
accuracy: 0.9082 - val_loss: 0.3660 - val_accuracy: 0.9193 - lr: 1.0000e-04
Epoch 4/30
628/628 [=====] - ETA: 0s - loss: 0.3500 - accuracy:
0.9208
Epoch 4: val_loss did not improve from 0.36604
628/628 [=====] - 1287s 2s/step - loss: 0.3500 -
```

```

accuracy: 0.9208 - val_loss: 0.3683 - val_accuracy: 0.9257 - lr: 1.0000e-04
Epoch 5/30
628/628 [=====] - ETA: 0s - loss: 0.3143 - accuracy:
0.9317
Epoch 5: val_loss improved from 0.36604 to 0.35742, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1285s 2s/step - loss: 0.3143 -
accuracy: 0.9317 - val_loss: 0.3574 - val_accuracy: 0.9279 - lr: 1.0000e-04
Epoch 6/30
628/628 [=====] - ETA: 0s - loss: 0.2850 - accuracy:
0.9394
Epoch 6: val_loss did not improve from 0.35742
628/628 [=====] - 1286s 2s/step - loss: 0.2850 -
accuracy: 0.9394 - val_loss: 0.3695 - val_accuracy: 0.9211 - lr: 1.0000e-04
Epoch 7/30
628/628 [=====] - ETA: 0s - loss: 0.2795 - accuracy:
0.9416
Epoch 7: val_loss improved from 0.35742 to 0.35116, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1286s 2s/step - loss: 0.2795 -
accuracy: 0.9416 - val_loss: 0.3512 - val_accuracy: 0.9313 - lr: 1.0000e-04
Epoch 8/30
628/628 [=====] - ETA: 0s - loss: 0.2497 - accuracy:
0.9514
Epoch 8: val_loss improved from 0.35116 to 0.34461, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1286s 2s/step - loss: 0.2497 -
accuracy: 0.9514 - val_loss: 0.3446 - val_accuracy: 0.9299 - lr: 1.0000e-04
Epoch 9/30
628/628 [=====] - ETA: 0s - loss: 0.2318 - accuracy:
0.9560
Epoch 9: val_loss improved from 0.34461 to 0.31969, saving model to
../models/07_model_t_tl_fine_tuning_adam.h5
628/628 [=====] - 1285s 2s/step - loss: 0.2318 -
accuracy: 0.9560 - val_loss: 0.3197 - val_accuracy: 0.9349 - lr: 1.0000e-04
Epoch 10/30
628/628 [=====] - ETA: 0s - loss: 0.2103 - accuracy:
0.9614
Epoch 10: val_loss did not improve from 0.31969
628/628 [=====] - 1285s 2s/step - loss: 0.2103 -
accuracy: 0.9614 - val_loss: 0.3432 - val_accuracy: 0.9319 - lr: 1.0000e-04
Epoch 11/30
628/628 [=====] - ETA: 0s - loss: 0.2073 - accuracy:
0.9622
Epoch 11: val_loss did not improve from 0.31969
628/628 [=====] - 1285s 2s/step - loss: 0.2073 -
accuracy: 0.9622 - val_loss: 0.3902 - val_accuracy: 0.9257 - lr: 1.0000e-04
Epoch 12/30

```

628/628 [=====] - ETA: 0s - loss: 0.1951 - accuracy: 0.9654

Epoch 12: ReduceLROnPlateau reducing learning rate to 9.999999747378752e-06.

Epoch 12: val_loss did not improve from 0.31969

628/628 [=====] - 1285s 2s/step - loss: 0.1951 - accuracy: 0.9654 - val_loss: 0.3228 - val_accuracy: 0.9385 - lr: 1.0000e-04

Epoch 13/30

628/628 [=====] - ETA: 0s - loss: 0.1393 - accuracy: 0.9811

Epoch 13: val_loss improved from 0.31969 to 0.30733, saving model to ../models/07_model_t-tl_fine_tuning_adam.h5

628/628 [=====] - 1286s 2s/step - loss: 0.1393 - accuracy: 0.9811 - val_loss: 0.3073 - val_accuracy: 0.9442 - lr: 1.0000e-05

Epoch 14/30

628/628 [=====] - ETA: 0s - loss: 0.1237 - accuracy: 0.9865

Epoch 14: val_loss did not improve from 0.30733

628/628 [=====] - 1286s 2s/step - loss: 0.1237 - accuracy: 0.9865 - val_loss: 0.3267 - val_accuracy: 0.9455 - lr: 1.0000e-05

Epoch 15/30

628/628 [=====] - ETA: 0s - loss: 0.1183 - accuracy: 0.9873

Epoch 15: val_loss did not improve from 0.30733

628/628 [=====] - 1285s 2s/step - loss: 0.1183 - accuracy: 0.9873 - val_loss: 0.3228 - val_accuracy: 0.9473 - lr: 1.0000e-05

Epoch 16/30

628/628 [=====] - ETA: 0s - loss: 0.1136 - accuracy: 0.9885

Epoch 16: ReduceLROnPlateau reducing learning rate to 9.999999747378752e-07.

Epoch 16: val_loss did not improve from 0.30733

628/628 [=====] - 1279s 2s/step - loss: 0.1136 - accuracy: 0.9885 - val_loss: 0.3323 - val_accuracy: 0.9481 - lr: 1.0000e-05

Epoch 17/30

628/628 [=====] - ETA: 0s - loss: 0.1069 - accuracy: 0.9907

Epoch 17: val_loss did not improve from 0.30733

628/628 [=====] - 1279s 2s/step - loss: 0.1069 - accuracy: 0.9907 - val_loss: 0.3314 - val_accuracy: 0.9492 - lr: 1.0000e-06

Epoch 18/30

628/628 [=====] - ETA: 0s - loss: 0.1071 - accuracy: 0.9910

Epoch 18: val_loss did not improve from 0.30733

628/628 [=====] - 1281s 2s/step - loss: 0.1071 - accuracy: 0.9910 - val_loss: 0.3302 - val_accuracy: 0.9486 - lr: 1.0000e-06

Epoch 19/30

628/628 [=====] - ETA: 0s - loss: 0.1062 - accuracy:

0.9912

Epoch 19: ReduceLROnPlateau reducing learning rate to 9.999999974752428e-08.
Restoring model weights from the end of the best epoch: 13.

Epoch 19: val_loss did not improve from 0.30733
628/628 [=====] - 1279s 2s/step - loss: 0.1062 -
accuracy: 0.9912 - val_loss: 0.3313 - val_accuracy: 0.9489 - lr: 1.0000e-06
Epoch 19: early stopping

Save Model History

```
[9]: with open("../history/07_model_t_t1_fine_tuning_adam.pkl", "wb") as file:  
      pickle.dump(history.history, file)
```

Model Evaluation

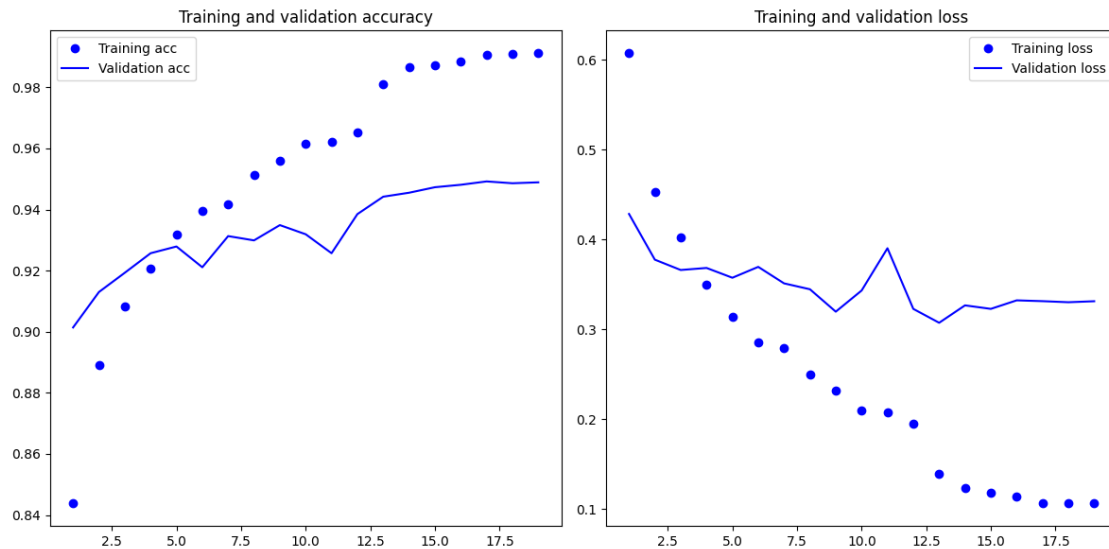
```
[10]: val_loss, val_acc = model.evaluate(validation_dataset)  
      print(f'Classifier Validation Loss: {val_loss:.2f}')  
      print(f'Classifier Validation Accuracy: {val_acc:.2%}')
```

157/157 [=====] - 213s 1s/step - loss: 0.3073 -
accuracy: 0.9442
Classifier Validation Loss: 0.31
Classifier Validation Accuracy: 94.42%

Model Visualization

```
[11]: acc = history.history['accuracy']  
      val_acc = history.history['val_accuracy']  
      loss = history.history['loss']  
      val_loss = history.history['val_loss']  
      epochs = range(1, len(acc) + 1)  
  
      plt.figure(figsize=(12, 6))  
      plt.subplot(1, 2, 1)  
      plt.plot(epochs, acc, 'bo', label='Training acc')  
      plt.plot(epochs, val_acc, 'b', label='Validation acc')  
      plt.title('Training and validation accuracy')  
      plt.legend()  
  
      plt.subplot(1, 2, 2)  
      plt.plot(epochs, loss, 'bo', label='Training loss')  
      plt.plot(epochs, val_loss, 'b', label='Validation loss')  
      plt.title('Training and validation loss')  
      plt.legend()
```

```
plt.tight_layout()
plt.show()
```



- Analyzing the training and validation, accuracy and loss over the epochs:
 - We see that the model begins overfitting on the **6th** epoch.
 - The validation accuracy stops improving significantly after the **13th** epoch while the training accuracy keeps improving.
 - The validation loss stops improving significantly after the **9th** epoch while the training loss keeps improving.
 - The best model, based on validation loss, is saved on the **13th** epoch.
 - The training stops after the **19th** epoch because of the **Early Stopping** callback.

Model Testing

```
[12]: test_labels = []
test_predictions = []
test_probabilities = []

for images, labels in test_dataset:
    test_labels.extend(labels.numpy())
    predictions = model.predict(images)
    test_predictions.extend(np.argmax(predictions, axis=-1))
    test_probabilities.extend(predictions)

test_labels = np.array(test_labels)
test_predictions = np.array(test_predictions)
test_probabilities = np.array(test_probabilities)
```

2/2 [=====] - 1s 694ms/step
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 2/2 [=====] - 1s 697ms/step
 2/2 [=====] - 1s 689ms/step
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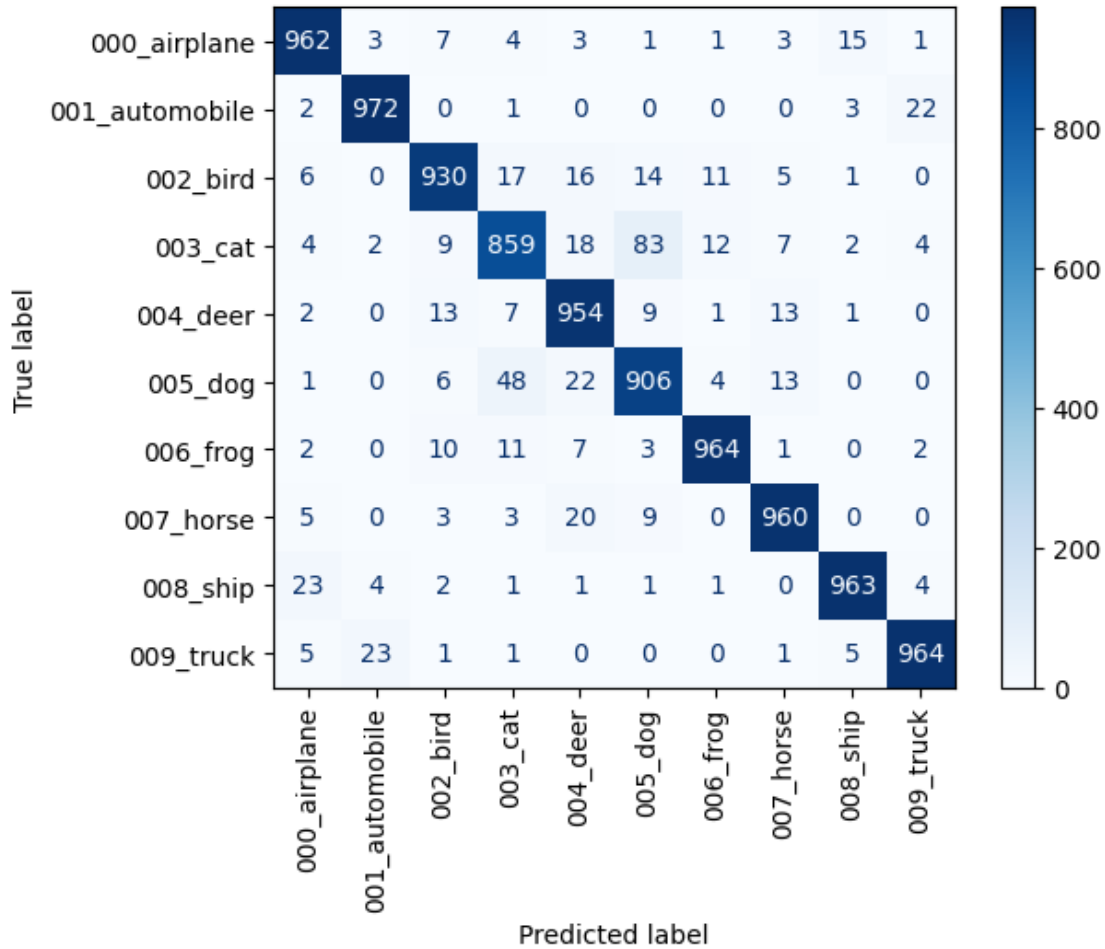
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```
2/2 [=====] - 1s 686ms/step
2/2 [=====] - 1s 688ms/step
2/2 [=====] - 1s 689ms/step
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2/2 [=====] - 1s 687ms/step
2/2 [=====] - 1s 686ms/step
2/2 [=====] - 1s 688ms/step
1/1 [=====] - 0s 413ms/step
```

Confusion Matrix

```
[13]: cm = confusion_matrix(test_labels, test_predictions)
      disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
      disp.plot(cmap=plt.cm.Blues, xticks_rotation=90)
      plt.show()
```



- Looking at the confusion matrix, we see that:
 - The model still has a hard time distinguishing between the categories 003_cat and 005_dog but with less error.
 - The model has a very low performance on the category 003_cat.
 - The model performs better on the vehicle categories than on the animal categories.
 - The model has a below average performance on the categories 002_bird, 003_cat and 005_dog, in which we see a very high false positive rate.
 - The model also has a hard time distinguishing between some other categories but the deviation is not as significant.
 - The model has an above average performance on the categories 000_airplane, 001_automobile, 006_frog, 007_horse 008_ship and 009_truck.
 - Basically, the model has the same error distribution but with higher accuracy.**

ROC Curve Analysis

```

[14]: test_labels_bin = label_binarize(test_labels, classes=range(NUM_CLASSES))

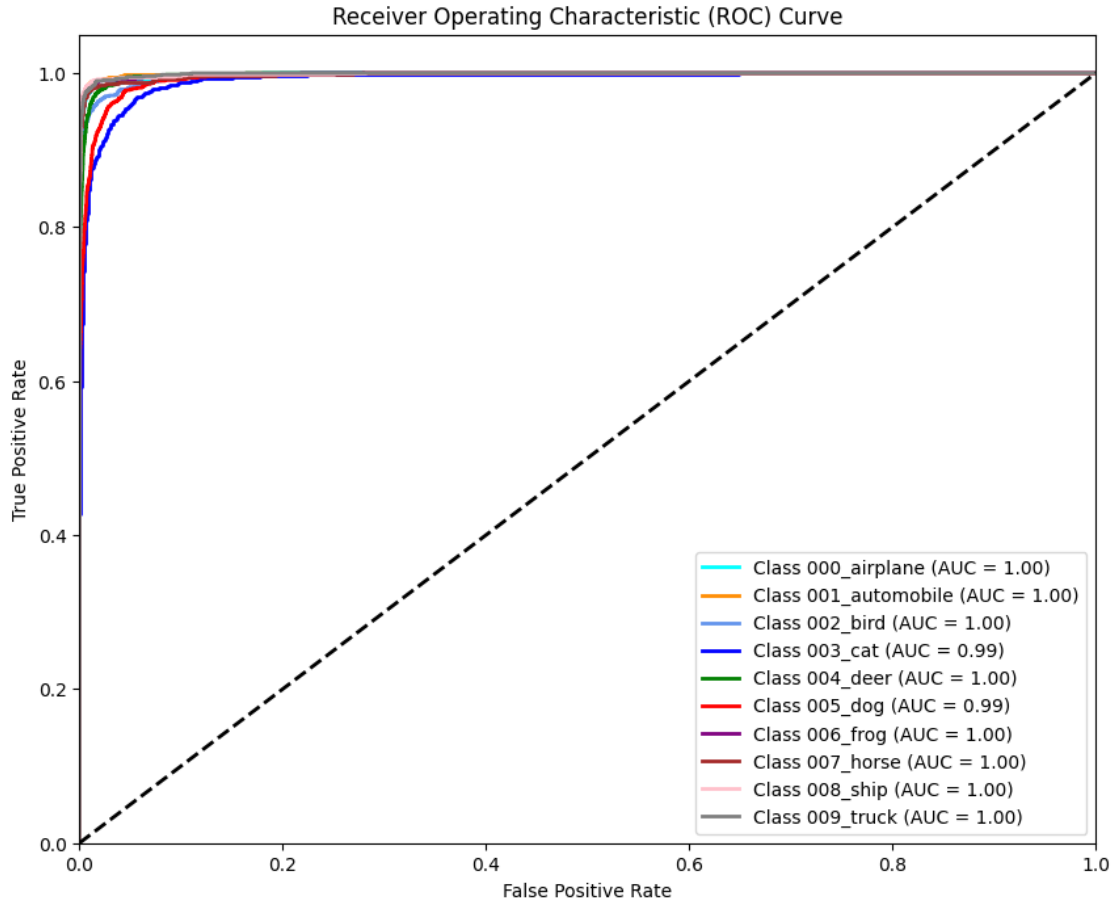
false_positive_rate = dict()
true_positive_rate = dict()
roc_auc = dict()

for i in range(NUM_CLASSES):
    false_positive_rate[i], true_positive_rate[i], _ = \
        roc_curve(test_labels_bin[:, i], test_probabilities[:, i])
    roc_auc[i] = auc(false_positive_rate[i], true_positive_rate[i])

plt.figure(figsize=(10, 8))
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'blue', 'green', 'red', \
    'purple', 'brown', 'pink', 'grey'])
for i, color in zip(range(NUM_CLASSES), colors):
    plt.plot(false_positive_rate[i], true_positive_rate[i], color=color, lw=2, \
        label=f'Class {class_names[i]} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

```

- Looking at the ROC curve:
 - We see that the model has a good performance on the ROC curve for most categories.
 - The categories 003_cat and 005_dog have the worst AUC (Area Under Curve) performance.
 - The other categories have the same performance but with higher AUC.
 - The overall AUC performance increases as the false positive rate decreases and the true positive rate increases.
 - A perfect AUC of 1.0 would mean that the model classifies all images either true positives or true negatives.**

Performance Metrics

- Accuracy** is the proportion of correctly predicted instances out of the total instances.
- Precision** is the ratio of true positive predictions to the total predicted positives. Macro precision calculates this for each class independently and then averages them.

- **Weighted precision** calculates the precision for each class, then averages them, weighted by the number of true instances for each class.
- **Recall** is the ratio of true positive predictions to the total actual positives. Macro recall calculates this for each class independently and then averages them.
- **Weighted recall** calculates the recall for each class, then averages them, weighted by the number of true instances for each class.
- The **F1-score** is the harmonic mean of precision and recall. Macro F1-score calculates this for each class independently and then averages them.
- **Weighted F1-score** calculates the F1-score for each class, then averages them, weighted by the number of true instances for each class.

```
[15]: acc = accuracy_score(y_true = test_labels, y_pred = test_predictions)
print(f'Accuracy : {np.round(acc*100,2)}%')
precision = precision_score(y_true = test_labels, y_pred = test_predictions,
    ↪average='macro')
print(f'Precision - Macro: {np.round(precision*100,2)}%')
recall = recall_score(y_true = test_labels, y_pred = test_predictions,
    ↪average='macro')
print(f'Recall - Macro: {np.round(recall*100,2)}%')
f1 = f1_score(y_true = test_labels, y_pred = test_predictions, average='macro')
print(f'F1-score - Macro: {np.round(f1*100,2)}%')
precision = precision_score(y_true = test_labels, y_pred = test_predictions,
    ↪average='weighted')
print(f'Precision - Weighted: {np.round(precision*100,2)}%')
recall = recall_score(y_true = test_labels, y_pred = test_predictions,
    ↪average='weighted')
print(f'Recall - Weighted: {np.round(recall*100,2)}%')
f1 = f1_score(y_true = test_labels, y_pred = test_predictions,
    ↪average='weighted')
print(f'F1-score - Weighted: {np.round(f1*100,2)}%')
```

```
Accuracy : 94.34%
Precision - Macro: 94.35%
Recall - Macro: 94.34%
F1-score - Macro: 94.33%
Precision - Weighted: 94.35%
Recall - Weighted: 94.34%
F1-score - Weighted: 94.33%
```

- Since the dataset is balanced, the MACRO** average is a good metric to evaluate the model.**

2 Conclusion

2.0.1 Summary

- In this notebook:
 - We loaded our previously trained model with Transfer Learning, Data Augmentation and Adaptive Moment Estimation (Adam).
 - Unfroze the last 4 convolutional layers of the VGG16 Convolutional Base.
 - We fine-tuned the model:
 - * We used Adaptive Moment Estimation (Adam) optimizer.
 - * Initial learning rate of 0.0001.
 - * 30 Epochs with a batch size of 64, to fine-tune the model.
 - We evaluated the model on the validation dataset:
 - * Overfitting was observed after **5 epochs**, but the best model was saved at the **13th epoch**.
 - * Training was intended for 30 epochs but stopped early due to the **Early Stopping** callback.
 - We tested the fine-tuned model on the test set:
 - * We evaluated the model using a confusion matrix to analyze its performance on each category.
 - * We evaluated the model using ROC curves for a deeper performance analysis.
 - * The model achieved an accuracy of 94.34% on the test set which is a good improvement.

2.0.2 Future Work

- We will now implement an application to classify images using our **best model made from scratch**.