model_s_no_data_augm_rmsprop

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1 Model S - From Scratch, No Data Augmentation, RMSProp

- 32 x 32 x 3 Image size.
- **32 Batch size**.
- **No data augmentation**.
- Root Mean Square Propagation **(RMSProp) optimizer**.
- **0.001 Initial Learning rate**.
- 3 x 3 Convolutional kernel size.
- 5 x 5 x 128 Tensor before flatten.
- **40 Epochs**.

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, layers, optimizers, models
from keras import regularizers
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay␣
↪,accuracy_score, precision_score, recall_score, f1_score, roc_curve, auc
```

```python
from sklearn.preprocessing import label_binarize
from itertools import cycle
```

```
TensorFlow version: 2.12.0
```

Group Datasets

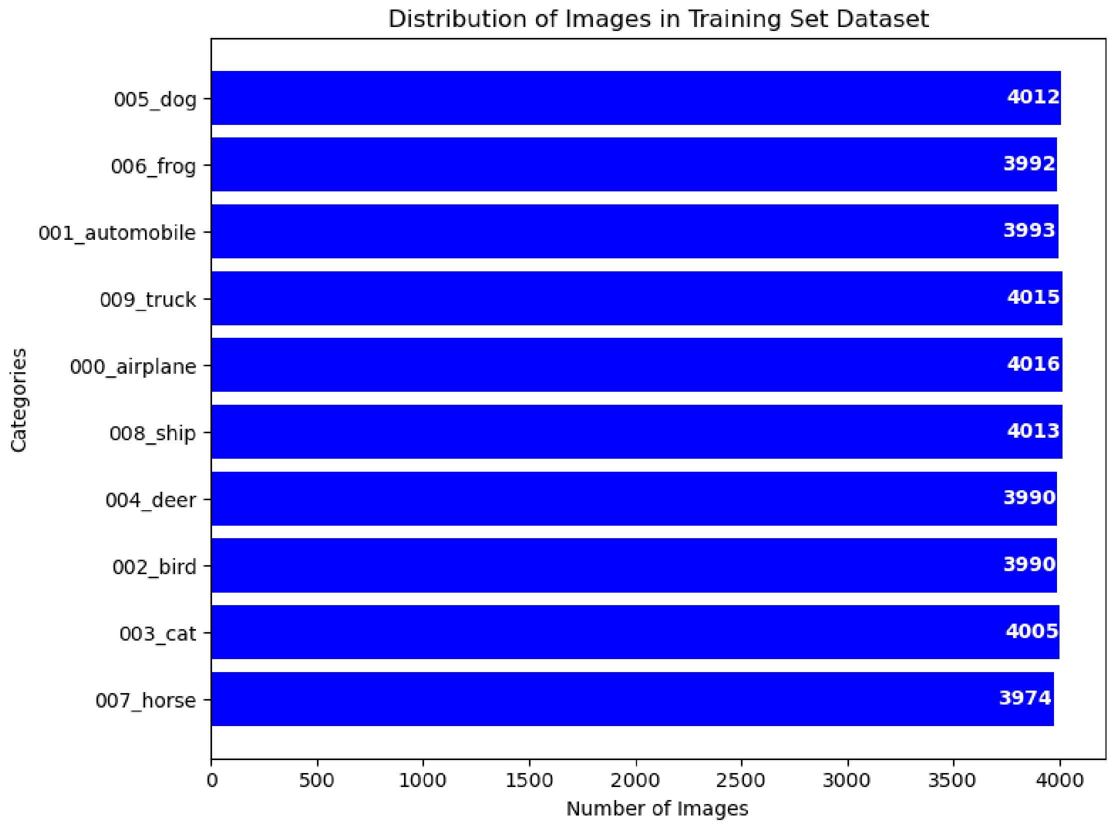
[2]:
```python
train_dirs = ['../data/train1', '../data/train3', '../data/train4', '../data/
↪train5']
validation_dir = '../data/train2'
test_dir = '../data/test'
```

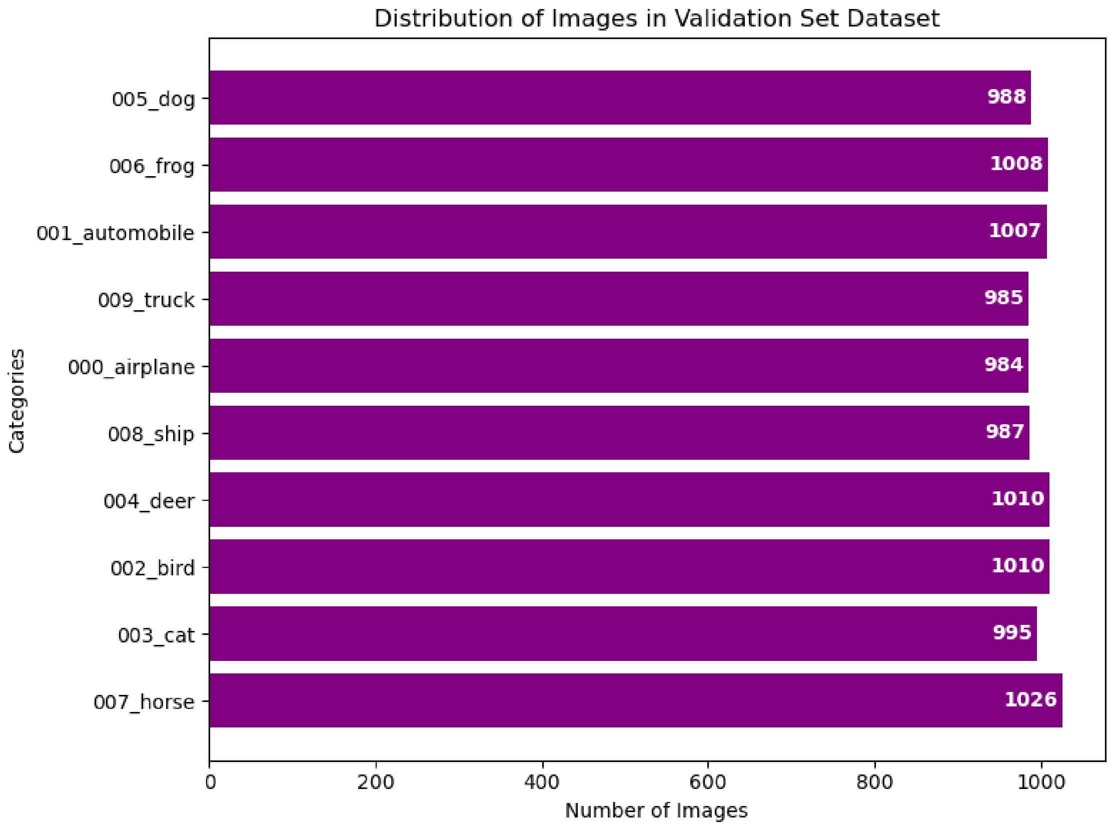
- ((2221985 + 2221986) % 5) + 1 = 2
- **Validation set: train2**.

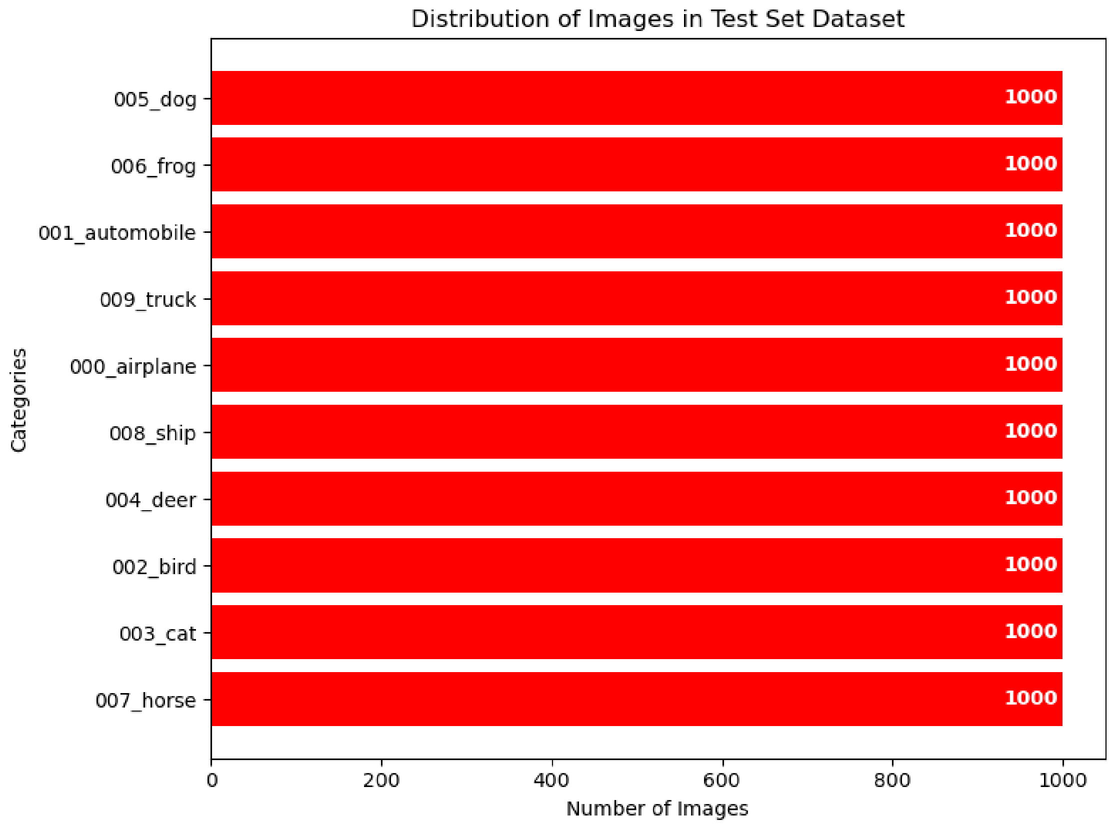
Count Images in Categories

[3]:
```python
def count_images_in_categories(directory):
    categories = os.listdir(directory)
    category_counts = {}
    for category in categories:
        category_counts[category] = len(os.listdir(os.path.join(directory,␣
↪category)))
    return category_counts

train_counts_each_dir = [count_images_in_categories(train_dir) for train_dir in␣
↪train_dirs]
validation_counts = count_images_in_categories(validation_dir)
test_counts = count_images_in_categories(test_dir)
train_counts = {category: sum([count.get(category, 0) for count in␣
↪train_counts_each_dir]) for category in train_counts_each_dir[0]}

def plot_statistics(dataset_name, category_counts, color):
    categories = list(category_counts.keys())
    counts = list(category_counts.values())
    num_categories = len(categories)
    plt.figure(figsize=(8, 6))
    bars = plt.barh(range(num_categories), counts, color=color, alpha=1)

    for bar, count in zip(bars, counts):
        plt.text(bar.get_width() - 5, bar.get_y() + bar.get_height()/2,␣
↪str(count), va='center', ha='right', color='white', fontweight='bold')

    plt.ylabel('Categories')
```

```
    plt.xlabel('Number of Images')
    plt.yticks(range(num_categories), categories)
    plt.title(f'Distribution of Images in {dataset_name} Dataset')
    plt.tight_layout()
    plt.show()

plot_statistics('Training Set', train_counts, 'blue')
plot_statistics('Validation Set', validation_counts, 'purple')
plot_statistics('Test Set', test_counts, 'red')
```




Distribution of Images in Validation Set Dataset
Categories
005_dog
006_frog
001_automobile
009_truck
000_airplane
008_ship
004_deer
002_bird
003_cat
007_horse
988
1008
1007
985
984
987
1010
1010
995
1026
0
200
400
600
800
1000
Number of Images



- We count the images of each category in each folder and plot the distribution.
- We see that there are **minor deviations** the number of samples of each category in the train dataset and a bit **more in the validation dataset**.

Create Datasets

[4]:
```
IMG_SIZE = 32
BATCH_SIZE = 32
NUM_CLASSES = len(train_counts)

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
```

```
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.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
```

- We define the image size of 32 x 32 x 3 and batch size of 32 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 unnecessary.

Dataset Analysis

[5]:
```
for data_batch, labels_batch in train_dataset.take(1):
    print('data batch shape:', data_batch.shape)
    print('labels batch shape:', labels_batch.shape)
```

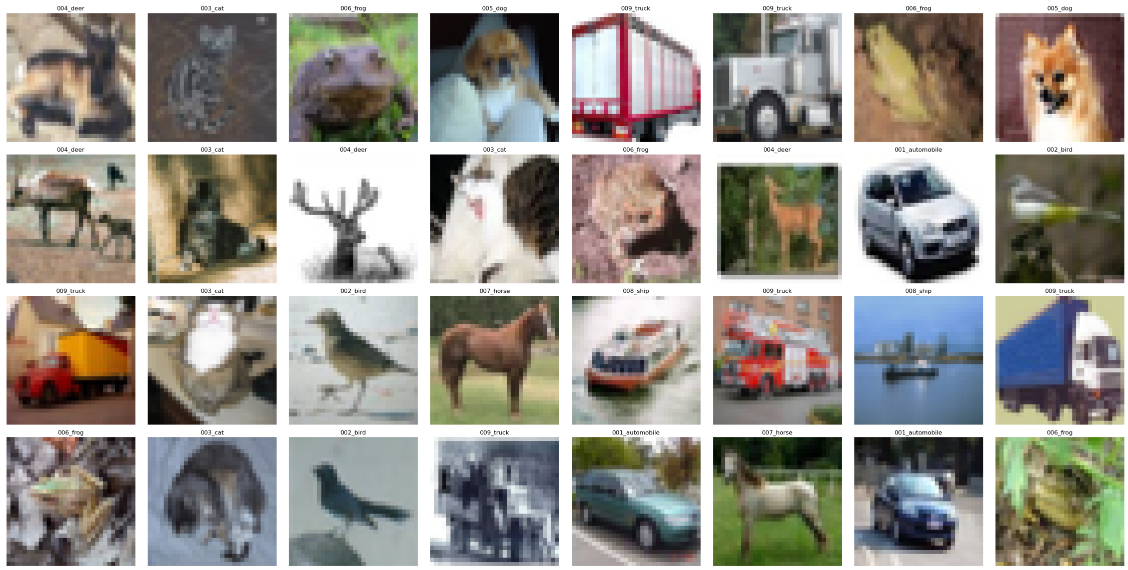
```
data batch shape: (32, 32, 32, 3)
labels batch shape: (32,)
```

- We have batches of 32 images, 32 by 32 pixels with 3 channels (RGB).
- We also have batches of 32 labels, one for each image.

Dataset Visualization

[6]:
```
for images, labels in train_dataset.take(1):
    plt.figure(figsize=(32, 32))
    for i in range(len(images)):
        ax = plt.subplot(8, 8, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i].numpy()])
        plt.axis("off")
        plt.tight_layout()
```

```
plt.show()
```



- We print a random batch of images from the train dataset along with their respective labels.
- We see that the images are of **different categories** and are of **low resolution**.

Model Arquitecture

[7]:
```
inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
x = layers.Rescaling(1./255)(inputs)
x = layers.Conv2D(filters=32, kernel_size=3, kernel_regularizer=regularizers.
 ↪L1L2(0.00001, 0.0001), activation="relu")(x)
x = layers.BatchNormalization()(x)
x = layers.Conv2D(filters=64, kernel_size=3, kernel_regularizer=regularizers.
 ↪L1L2(0.00001, 0.0001), activation="relu")(x)
x = layers.BatchNormalization()(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, kernel_regularizer=regularizers.
 ↪L1L2(0.00001, 0.0001), activation="relu")(x)
x = layers.BatchNormalization()(x)
x = layers.Conv2D(filters=128, kernel_size=3, kernel_regularizer=regularizers.
 ↪L1L2(0.00001, 0.0001), activation="relu")(x)
x = layers.BatchNormalization()(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
```

```
x = layers.Dense(512, activation="relu", kernel_regularizer=regularizers.L1L2(0.
↪001, 0.01))(x)
outputs = layers.Dense(NUM_CLASSES, activation="softmax",␣
↪kernel_regularizer=regularizers.L1L2(0.001, 0.01))(x)
model = models.Model(inputs=inputs, outputs=outputs)
model.summary()
```

```
Model: "model"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 32, 32, 3)]       0

 rescaling (Rescaling)       (None, 32, 32, 3)         0

 conv2d (Conv2D)             (None, 30, 30, 32)        896

 batch_normalization (BatchN  (None, 30, 30, 32)       128
 ormalization)

 conv2d_1 (Conv2D)           (None, 28, 28, 64)        18496

 batch_normalization_1 (Batc  (None, 28, 28, 64)       256
 hNormalization)

 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0
 )

 conv2d_2 (Conv2D)           (None, 12, 12, 128)       73856

 batch_normalization_2 (Batc  (None, 12, 12, 128)      512
 hNormalization)

 conv2d_3 (Conv2D)           (None, 10, 10, 128)       147584

 batch_normalization_3 (Batc  (None, 10, 10, 128)      512
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 128)        0
 2D)

 flatten (Flatten)           (None, 3200)              0

 dropout (Dropout)           (None, 3200)              0

 dense (Dense)               (None, 512)               1638912
```

```
 dense_1 (Dense)             (None, 10)                5130

=================================================================
Total params: 1,886,282
Trainable params: 1,885,578
Non-trainable params: 704
_________________________________________________________________
```

- Input size of 32 x 32 x 3 (RGB).
- No data augmentation.
- Normalize each pixel value in the [0, 1] interval.
- 3 x 3 convolutional kernel size.
- Batch Normalization after each convolutional layer to help stabilize and accelerate learning process.
- L1 regularization 0.00001 and L2 regularization 0.0001 on the convolutional layers.
- Two convolutional layers (32 and 64 kernels each respectively).
- Max pooling with size 2 after the second convolution results in a 14 x 14 x 64 tensor.
- Two convolutional layers (128 kernels each).
- Max pooling with size 2 after the fourth convolution results in a 5 x 5 x 128 tensor.
- Flatten the tensor to a 3200 x 1 tensor.
- A 512 and 10 dense output layer.
- L1 regularization 0.001 and L2 regularization 0.01 on the 512 and 10 dense layer.
- Dropout of 0.5 on the 512 dense layer.
- ReLU activation function on the convolutional and dense layers.
- Softmax activation function on the output layer.
- 10 output neurons, one for each category.

Model Compilation

[8]:
```
initial_learning_rate = 0.001
optimizer = optimizers.RMSprop(learning_rate=initial_learning_rate)
```

```
loss_function = keras.losses.SparseCategoricalCrossentropy()

lr_scheduler = callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.1,␣
↪patience=4, verbose=1)
early_stopping = callbacks.EarlyStopping(monitor='val_loss', patience=8,␣
↪restore_best_weights=True, verbose=1)
save_best_model = callbacks.ModelCheckpoint(filepath='../models/
↪model_s_no_data_augm_rmsprop.h5', save_best_only=True, monitor='val_loss',␣
↪verbose=1)

callbacks = [lr_scheduler, early_stopping, save_best_model]

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

- RMSProp as the optimizer for this model with an initial learning rate of 0.001.
- Sparse categorical cross entropy as the loss function.
- Learning rate scheduler to lower the learning rate by 0.1 on validation loss plateau (patience of 4).
- Early train stopping based on validation loss improvement (stops when validation loss doesn't improve for 8 straight epochs (patience of 8)).
- Checkpoints to save the best model between each epoch based on validation loss.

Model Training

- Training the model during 40 epochs.

[9]:
```
history = model.fit(train_dataset,
                    validation_data=validation_dataset,
                    epochs=40,
                    callbacks=callbacks)
```

```
Epoch 1/40
1251/1252 [============================>.] - ETA: 0s - loss: 5.3191 - accuracy:
0.5260
Epoch 1: val_loss improved from inf to 2.43643, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 56s 44ms/step - loss: 5.3168 -
accuracy: 0.5261 - val_loss: 2.4364 - val_accuracy: 0.6386 - lr: 0.0010
Epoch 2/40
1252/1252 [==============================] - ETA: 0s - loss: 2.3382 - accuracy:
```

```
0.6633
Epoch 2: val_loss improved from 2.43643 to 2.36911, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 64s 51ms/step - loss: 2.3382 -
accuracy: 0.6633 - val_loss: 2.3691 - val_accuracy: 0.6529 - lr: 0.0010
Epoch 3/40
1251/1252 [============================>.] - ETA: 0s - loss: 2.2272 - accuracy:
0.6994
Epoch 3: val_loss improved from 2.36911 to 2.22486, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 58s 46ms/step - loss: 2.2270 -
accuracy: 0.6994 - val_loss: 2.2249 - val_accuracy: 0.7047 - lr: 0.0010
Epoch 4/40
1252/1252 [==============================] - ETA: 0s - loss: 2.1632 - accuracy:
0.7274
Epoch 4: val_loss improved from 2.22486 to 2.18789, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 109s 87ms/step - loss: 2.1632 -
accuracy: 0.7274 - val_loss: 2.1879 - val_accuracy: 0.7228 - lr: 0.0010
Epoch 5/40
1251/1252 [============================>.] - ETA: 0s - loss: 2.1174 - accuracy:
0.7448
Epoch 5: val_loss improved from 2.18789 to 2.18213, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 56s 44ms/step - loss: 2.1173 -
accuracy: 0.7449 - val_loss: 2.1821 - val_accuracy: 0.7199 - lr: 0.0010
Epoch 6/40
1251/1252 [============================>.] - ETA: 0s - loss: 2.0907 - accuracy:
0.7563
Epoch 6: val_loss improved from 2.18213 to 2.13671, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 64s 51ms/step - loss: 2.0906 -
accuracy: 0.7563 - val_loss: 2.1367 - val_accuracy: 0.7449 - lr: 0.0010
Epoch 7/40
1252/1252 [==============================] - ETA: 0s - loss: 2.0614 - accuracy:
0.7685
Epoch 7: val_loss improved from 2.13671 to 2.11626, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 60s 47ms/step - loss: 2.0614 -
accuracy: 0.7685 - val_loss: 2.1163 - val_accuracy: 0.7496 - lr: 0.0010
Epoch 8/40
1251/1252 [============================>.] - ETA: 0s - loss: 2.0244 - accuracy:
0.7789
Epoch 8: val_loss did not improve from 2.11626
1252/1252 [==============================] - 49s 39ms/step - loss: 2.0244 -
accuracy: 0.7788 - val_loss: 2.3273 - val_accuracy: 0.6744 - lr: 0.0010
Epoch 9/40
1252/1252 [==============================] - ETA: 0s - loss: 2.0058 - accuracy:
```

```
0.7849
Epoch 9: val_loss did not improve from 2.11626
1252/1252 [==============================] - 78s 62ms/step - loss: 2.0058 -
accuracy: 0.7849 - val_loss: 2.1230 - val_accuracy: 0.7420 - lr: 0.0010
Epoch 10/40
1252/1252 [==============================] - ETA: 0s - loss: 1.9798 - accuracy:
0.7934
Epoch 10: val_loss did not improve from 2.11626
1252/1252 [==============================] - 64s 51ms/step - loss: 1.9798 -
accuracy: 0.7934 - val_loss: 2.2514 - val_accuracy: 0.7144 - lr: 0.0010
Epoch 11/40
1252/1252 [==============================] - ETA: 0s - loss: 1.9662 - accuracy:
0.7977
Epoch 11: val_loss improved from 2.11626 to 2.10067, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 62s 49ms/step - loss: 1.9662 -
accuracy: 0.7977 - val_loss: 2.1007 - val_accuracy: 0.7577 - lr: 0.0010
Epoch 12/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.9587 - accuracy:
0.8001
Epoch 12: val_loss did not improve from 2.10067
1252/1252 [==============================] - 55s 44ms/step - loss: 1.9591 -
accuracy: 0.8000 - val_loss: 2.1766 - val_accuracy: 0.7346 - lr: 0.0010
Epoch 13/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.9429 - accuracy:
0.8071
Epoch 13: val_loss did not improve from 2.10067
1252/1252 [==============================] - 60s 48ms/step - loss: 1.9428 -
accuracy: 0.8072 - val_loss: 2.1599 - val_accuracy: 0.7375 - lr: 0.0010
Epoch 14/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.9266 - accuracy:
0.8113
Epoch 14: val_loss improved from 2.10067 to 2.03387, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 57s 45ms/step - loss: 1.9266 -
accuracy: 0.8113 - val_loss: 2.0339 - val_accuracy: 0.7786 - lr: 0.0010
Epoch 15/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.9002 - accuracy:
0.8173
Epoch 15: val_loss did not improve from 2.03387
1252/1252 [==============================] - 60s 47ms/step - loss: 1.9000 -
accuracy: 0.8174 - val_loss: 2.1200 - val_accuracy: 0.7503 - lr: 0.0010
Epoch 16/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.8990 - accuracy:
0.8186
Epoch 16: val_loss did not improve from 2.03387
1252/1252 [==============================] - 50s 39ms/step - loss: 1.8989 -
accuracy: 0.8187 - val_loss: 2.2568 - val_accuracy: 0.7242 - lr: 0.0010
```

```
Epoch 17/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.8936 - accuracy:
0.8238
Epoch 17: val_loss improved from 2.03387 to 2.01363, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 49s 39ms/step - loss: 1.8935 -
accuracy: 0.8238 - val_loss: 2.0136 - val_accuracy: 0.7768 - lr: 0.0010
Epoch 18/40
 731/1252 [================>…] - ETA: 18s - loss: 1.8565 - accuracy:
0.8340
Epoch 18: val_loss did not improve from 2.01363
1252/1252 [==============================] - 49s 39ms/step - loss: 1.8875 -
accuracy: 0.8235 - val_loss: 2.0180 - val_accuracy: 0.7864 - lr: 0.0010
Epoch 19/40
1252/1252 [==============================] - ETA: 0s - loss: 1.8713 - accuracy:
0.8300
Epoch 19: val_loss did not improve from 2.01363
1252/1252 [==============================] - 55s 44ms/step - loss: 1.8713 -
accuracy: 0.8300 - val_loss: 2.0424 - val_accuracy: 0.7782 - lr: 0.0010
Epoch 20/40
1252/1252 [==============================] - ETA: 0s - loss: 1.8741 - accuracy:
0.8303
Epoch 20: val_loss did not improve from 2.01363
1252/1252 [==============================] - 62s 49ms/step - loss: 1.8741 -
accuracy: 0.8303 - val_loss: 2.0889 - val_accuracy: 0.7680 - lr: 0.0010
Epoch 21/40
1251/1252 [============================>.] - ETA: 0s - loss: 1.8688 - accuracy:
0.8324
Epoch 21: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.

Epoch 21: val_loss did not improve from 2.01363
1252/1252 [==============================] - 48s 38ms/step - loss: 1.8690 -
accuracy: 0.8324 - val_loss: 2.1838 - val_accuracy: 0.7432 - lr: 0.0010
Epoch 22/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.9676 - accuracy:
0.8867
Epoch 22: val_loss improved from 2.01363 to 1.06088, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 49s 39ms/step - loss: 0.9674 -
accuracy: 0.8868 - val_loss: 1.0609 - val_accuracy: 0.8343 - lr: 1.0000e-04
Epoch 23/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.8523 - accuracy:
0.9055
Epoch 23: val_loss improved from 1.06088 to 1.01488, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 49s 39ms/step - loss: 0.8522 -
accuracy: 0.9056 - val_loss: 1.0149 - val_accuracy: 0.8390 - lr: 1.0000e-04
Epoch 24/40
```

```
1252/1252 [==============================] - ETA: 0s - loss: 0.8028 - accuracy:
0.9133
Epoch 24: val_loss improved from 1.01488 to 0.98787, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 52s 42ms/step - loss: 0.8028 -
accuracy: 0.9133 - val_loss: 0.9879 - val_accuracy: 0.8402 - lr: 1.0000e-04
Epoch 25/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.7698 - accuracy:
0.9192
Epoch 25: val_loss improved from 0.98787 to 0.97554, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7698 -
accuracy: 0.9191 - val_loss: 0.9755 - val_accuracy: 0.8430 - lr: 1.0000e-04
Epoch 26/40
1252/1252 [==============================] - ETA: 0s - loss: 0.7464 - accuracy:
0.9229
Epoch 26: val_loss improved from 0.97554 to 0.96204, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 50s 40ms/step - loss: 0.7464 -
accuracy: 0.9229 - val_loss: 0.9620 - val_accuracy: 0.8431 - lr: 1.0000e-04
Epoch 27/40
1252/1252 [==============================] - ETA: 0s - loss: 0.7254 - accuracy:
0.9281
Epoch 27: val_loss improved from 0.96204 to 0.96051, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 79s 63ms/step - loss: 0.7254 -
accuracy: 0.9281 - val_loss: 0.9605 - val_accuracy: 0.8430 - lr: 1.0000e-04
Epoch 28/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.7099 - accuracy:
0.9310
Epoch 28: val_loss improved from 0.96051 to 0.95747, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7099 -
accuracy: 0.9310 - val_loss: 0.9575 - val_accuracy: 0.8406 - lr: 1.0000e-04
Epoch 29/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6947 - accuracy:
0.9337
Epoch 29: val_loss improved from 0.95747 to 0.95078, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 54s 43ms/step - loss: 0.6948 -
accuracy: 0.9337 - val_loss: 0.9508 - val_accuracy: 0.8432 - lr: 1.0000e-04
Epoch 30/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6801 - accuracy:
0.9369
Epoch 30: val_loss improved from 0.95078 to 0.94690, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 59s 47ms/step - loss: 0.6802 -
accuracy: 0.9369 - val_loss: 0.9469 - val_accuracy: 0.8426 - lr: 1.0000e-04
```

```
Epoch 31/40
1252/1252 [==============================] - ETA: 0s - loss: 0.6694 - accuracy:
0.9393
Epoch 31: val_loss did not improve from 0.94690
1252/1252 [==============================] - 56s 44ms/step - loss: 0.6694 -
accuracy: 0.9393 - val_loss: 0.9491 - val_accuracy: 0.8435 - lr: 1.0000e-04
Epoch 32/40
1252/1252 [==============================] - ETA: 0s - loss: 0.6577 - accuracy:
0.9414
Epoch 32: val_loss did not improve from 0.94690
1252/1252 [==============================] - 67s 53ms/step - loss: 0.6577 -
accuracy: 0.9414 - val_loss: 0.9488 - val_accuracy: 0.8413 - lr: 1.0000e-04
Epoch 33/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6423 - accuracy:
0.9445
Epoch 33: val_loss did not improve from 0.94690
1252/1252 [==============================] - 48s 38ms/step - loss: 0.6422 -
accuracy: 0.9445 - val_loss: 0.9508 - val_accuracy: 0.8413 - lr: 1.0000e-04
Epoch 34/40
1252/1252 [==============================] - ETA: 0s - loss: 0.6353 - accuracy:
0.9466
Epoch 34: val_loss improved from 0.94690 to 0.94530, saving model to
../models/model_s_no_data_augm_rmsprop.h5
1252/1252 [==============================] - 51s 40ms/step - loss: 0.6353 -
accuracy: 0.9466 - val_loss: 0.9453 - val_accuracy: 0.8412 - lr: 1.0000e-04
Epoch 35/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6271 - accuracy:
0.9480
Epoch 35: val_loss did not improve from 0.94530
1252/1252 [==============================] - 49s 39ms/step - loss: 0.6270 -
accuracy: 0.9481 - val_loss: 0.9467 - val_accuracy: 0.8366 - lr: 1.0000e-04
Epoch 36/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6146 - accuracy:
0.9522
Epoch 36: val_loss did not improve from 0.94530
1252/1252 [==============================] - 48s 38ms/step - loss: 0.6146 -
accuracy: 0.9522 - val_loss: 0.9488 - val_accuracy: 0.8394 - lr: 1.0000e-04
Epoch 37/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.6065 - accuracy:
0.9539
Epoch 37: val_loss did not improve from 0.94530
1252/1252 [==============================] - 51s 40ms/step - loss: 0.6065 -
accuracy: 0.9538 - val_loss: 0.9502 - val_accuracy: 0.8378 - lr: 1.0000e-04
Epoch 38/40
1252/1252 [==============================] - ETA: 0s - loss: 0.5998 - accuracy:
0.9546
Epoch 38: val_loss improved from 0.94530 to 0.94426, saving model to
../models/model_s_no_data_augm_rmsprop.h5
```

```
1252/1252 [==============================] - 62s 49ms/step - loss: 0.5998 -
accuracy: 0.9546 - val_loss: 0.9443 - val_accuracy: 0.8363 - lr: 1.0000e-04
Epoch 39/40
1252/1252 [==============================] - ETA: 0s - loss: 0.5900 - accuracy:
0.9568
Epoch 39: val_loss did not improve from 0.94426
1252/1252 [==============================] - 58s 46ms/step - loss: 0.5900 -
accuracy: 0.9568 - val_loss: 0.9526 - val_accuracy: 0.8356 - lr: 1.0000e-04
Epoch 40/40
1251/1252 [============================>.] - ETA: 0s - loss: 0.5860 - accuracy:
0.9565
Epoch 40: val_loss did not improve from 0.94426
1252/1252 [==============================] - 49s 39ms/step - loss: 0.5860 -
accuracy: 0.9565 - val_loss: 0.9465 - val_accuracy: 0.8358 - lr: 1.0000e-04
```

Save Model History

[10]:
```python
with open("../history/model_s_no_data_augm_rmsprop.pkl", "wb") as file:
    pickle.dump(history.history, file)
```

Model Evaluation

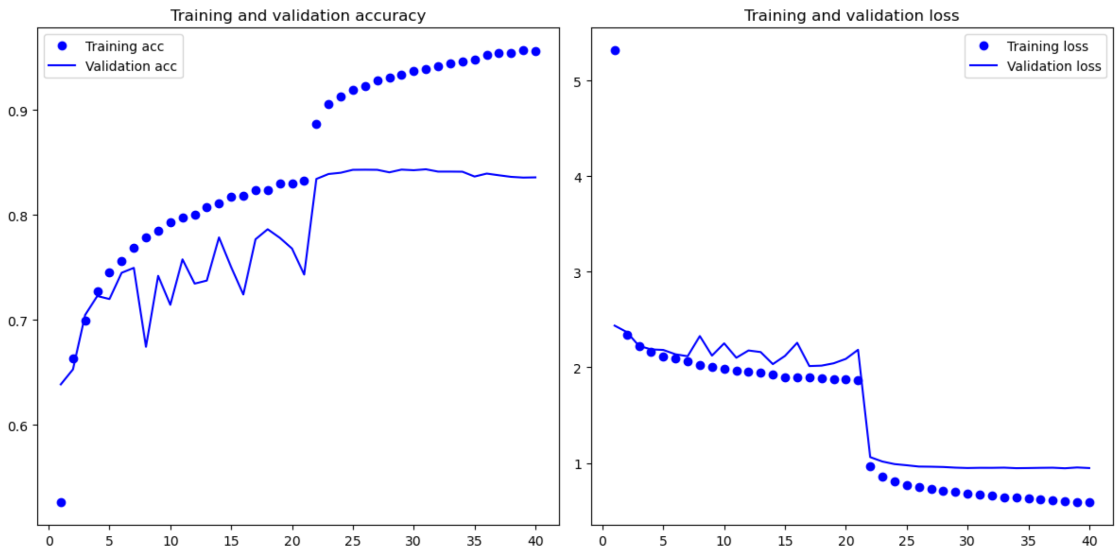
[11]:
```python
val_loss, val_acc = model.evaluate(validation_dataset)
print('Model Validation Loss: ', val_loss)
print('Model Validation Accuracy: ', val_acc)
```

```
313/313 [==============================] - 2s 7ms/step - loss: 0.9465 -
accuracy: 0.8358
Model Validation Loss:  0.9465024471282959
Model Validation Accuracy:  0.8357999920845032
```

Model Training Visualization

[12]:
```python
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()
```



- We see that the model begins overfitting after 22 epochs.

- The validation accuracy stops improving significantly after the 22th epoch while the training accuracy keeps improving.

- The validation loss stops improving significantly after the 22th epoch while the training loss keeps improving.
- However, the best model is saved on the 38th epoch.

Model Testing

[13]:
```
test_labels = []
test_predictions = []
test_probabilities = []

for images, labels in test_dataset:
    test_labels.extend(labels.numpy())
    predictions = model.predict(images)
```

```python
    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)
```

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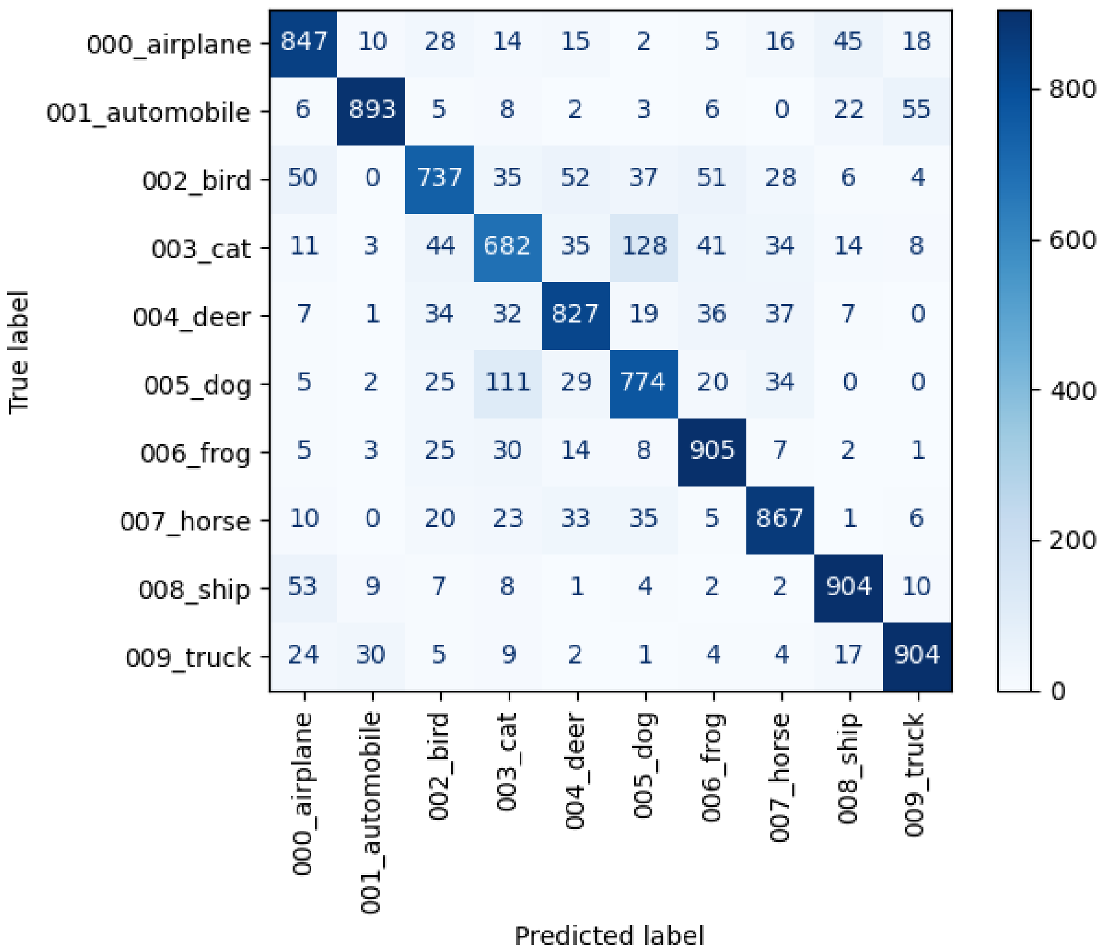
Confusion Matrix

[14]:
```
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 has some trouble distinguishing between some categories.

- The model has a hard time distinguishing between the categories 003_cat and 005_dog.

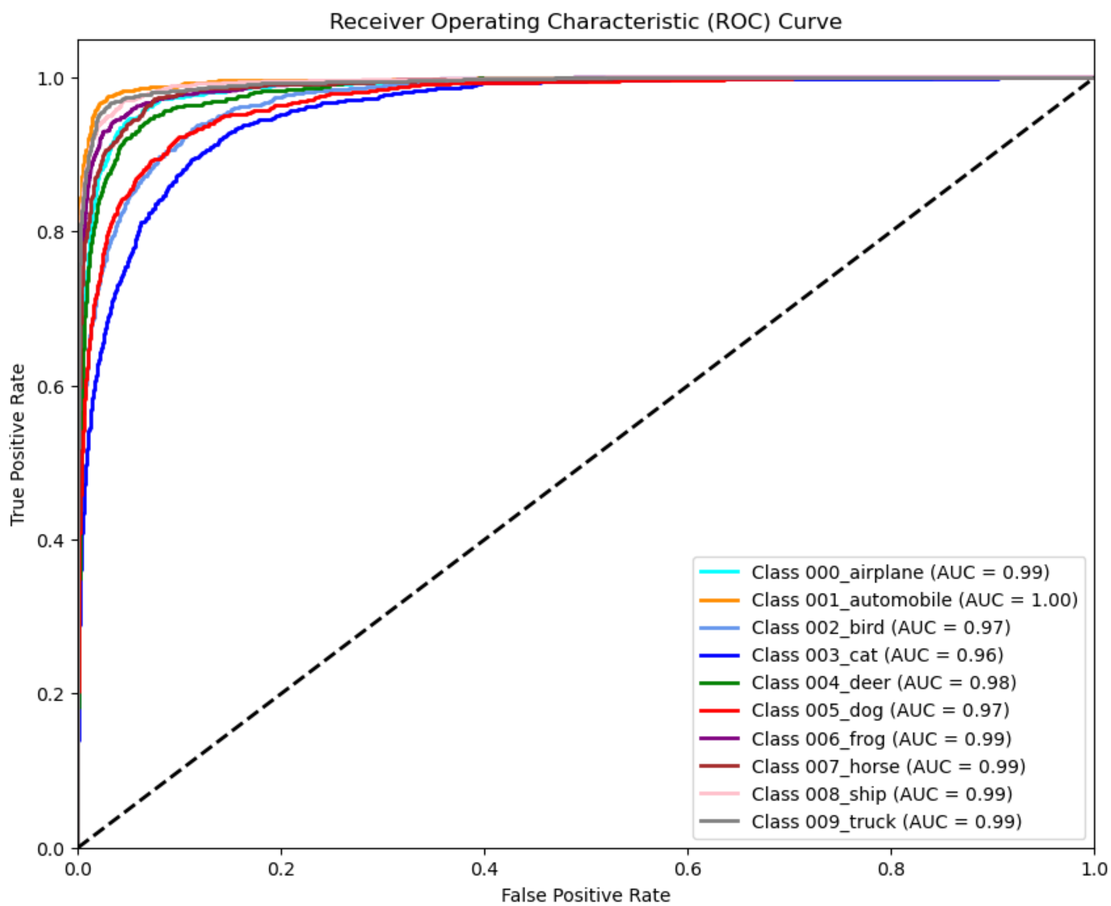
- The model also has a hard time distinguishing between some other categories but the error is not as significant.

- The model has an acceptable performance on the categories 001_automobile, 006_frog, 008_ship and 009_truck.

ROC Curve Analysis

[15]:
```
test_labels_bin = label_binarize(test_labels, classes=range(NUM_CLASSES))

fpr = dict()
```

```
tpr = dict()
roc_auc = dict()

for i in range(NUM_CLASSES):
    fpr[i], tpr[i], _ = roc_curve(test_labels_bin[:, i], test_probabilities[:,␣
↪i])
    roc_auc[i] = auc(fpr[i], tpr[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(fpr[i], tpr[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()
```



- We see that the model has a good performance on the ROC curve for most categories.

- The categories 003_cat, 003_bird, 005_dog and 004_deer have the worst AUC (Area Under Curve) performance.
- A perfect AUC of 1.0 would mean that the model classifies all true positives and true negatives correctly.

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.

[16]:
```
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 : 83.4%
Precision - Macro: 83.35%
Recall - Macro: 83.4%
F1-score - Macro: 83.34%
Precision - Weighted: 83.35%
Recall - Weighted: 83.4%
F1-score - Weighted: 83.34%
```

2 Conclusion

- We have trained a model with no data augmentation, using the Sparse Categorical Crossentropy loss function and the RMSProp optimizer.

- We experimented with various architectures, and this one yielded the best results:
  - Different learning rates were tested; this rate performed best.

- Various batch sizes were explored; this size was optimal.

- Multiple optimizers were evaluated; RMSProp was the most effective.
- Several regularization values were tried; these values worked best.
- Different dropout rates were assessed; this rate provided the best results.
- Various epoch counts were tested; 40 epochs were optimal.
- Different kernel sizes were considered; this size was most effective.
- Various numbers of kernels were tested; this configuration was best.
- Different numbers of layers were evaluated; this architecture was optimal.

- For the next notebook, we will retain this architecture to test data augmentation techniques.
- We opted to add Batch Normalization after each convolutional layer.
- We used L1 and L2 regularization on both convolutional and dense layers.
- Dropout was applied to the dense layers.
- The model showed some difficulty distinguishing between certain categories, particularly cats and dogs.
- Overfitting was observed after 22 epochs, but the best model was saved at the 40th epoch.
- The model achieved an accuracy of 83.4% 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.
- Performance on the test set was good, with:
  - Macro F1-score: 83.34%
  - Weighted F1-score: 83.34%
  - Macro precision: 83.35%
  - Weighted precision: 83.35%
  - Macro recall: 83.4%
  - Weighted recall: 83.4%

2.0.1 Future Work

- In the next phase, we will:
  - Implement and test various data augmentation techniques to further improve model generalization.
  - Explore additional regularization methods to address overfitting.