port_operations

May 3, 2024

Note: In this document, MarkDown sections marked with a vertical bar (like the current section) correspond to user inputs. All other sections are the transcribed requirements of the assignment

[ ]:
```
import tensorflow as tf
from keras import Sequential, Model
from keras.layers import␣
↪Dense,Conv2D,MaxPooling2D,BatchNormalization,Dropout,GlobalAveragePooling2D,Input
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import sklearn as sk
import numpy as np
```

[ ]:
```
# Display the version of tensorflow, sklearn, and the GPU
print(f'TensorFlow: {tf.__version__}')
print(f'Scikit-learn: {sk.__version__}')
gpus = tf.config.list_physical_devices('GPU')
print(f'GPUs: {gpus if gpus else "None"}')
```

```
TensorFlow: 2.16.1
Scikit-learn: 1.2.2
GPUs: None
```

0.1 Perform the following steps:

1. Build a CNN network to classify the boat.
    1. Split the dataset into train and test in the ratio 80:20, with shuffle and random state=43.

Note that the data split is done with the default scikit-learn train_test_split function with stratification, in order to keep consistent ratios across classes.

[ ]:
```
import os, shutil
import pandas as pd
from sklearn.model_selection import train_test_split

# find all the jpg files one layer deeper in the 'data/source/' folder
files = pd.Series()
```

```
folders = pd.Series()
idx = 0
for root, dirs, fs in os.walk('./data/source'):
    for f in fs:
        if (f.endswith('.jpg')):
            files.at[idx] = os.path.join(root, f).replace('\\', '/')
            folders.at[idx] = os.path.basename(root)
            idx += 1

# Copy the files to the correct folders
def copy_files(files, dest):
    destpath = f"./data/{dest}"
    if os.path.exists(destpath):
        shutil.rmtree(destpath)
    os.makedirs(destpath)
    for f in files:
        f_target = f.replace('source', dest)
        if (not os.path.exists(os.path.dirname(f_target))):
            os.makedirs(os.path.dirname(f_target))
        shutil.copy(f, f_target)

# Split the files and folders into train and test sets
def split_files(files, folders, test_size, train_folder, test_folder,␣
 ↪random_state):
    files_train, files_test, folders_train, folders_test = train_test_split(
        files, folders, test_size=test_size, shuffle = True,␣
 ↪random_state=random_state, stratify=folders)
    # Create and display a dataframe of file counts by folder for the train and␣
 ↪test sets (columns)
    df = pd.DataFrame()
    df['train'] = folders_train.value_counts()
    df['test'] = folders_test.value_counts()
    display(df)
    copy_files(files_train, train_folder)
    copy_files(files_test, test_folder)

split_files(files, folders, 0.2, 'train', 'test', 43)
```

	train	test
sailboat	311	78
kayak	162	41
gondola	154	39
cruise_ship	153	38
ferry_boat	50	13
buoy	42	11
paper_boat	25	6
freight_boat	19	4

```
inflatable_boat     13     3
```

1. …

    2. Use Keras ImageDataGenerator to initialize the train generator with validation_split=0.2 and test generator. Generators are required to avoid out of memory issues while training.
    3. Both generators will be initialized with data normalization. *(Hint: rescale=1./255).*
    4. Load train, validation and test dataset in batches of 32 using the generators initialized in the above step.

    Note 1: While a batch size of 32 makes sense for stabilizing backprop feedback into the layers, there's no reason to do that for the test dataset. To retain the ability to easily look at individual test samples, the batch size for the test set is set to 1.
    Note 2: This is a pretty small training data set for computer vision, so image augmentation is being added to the training dataset. This augmentation is intended to be consistent with seaport realities (e.g., no vertical flip, and minimal rotation range).
    Note 3: The requirement is to use the (deprecated) `ImageDataGenerator` class with generators set with the `validation_split` parameter. This does **not** *maintain ratios across classes, which could negatively impact the quality of the training. Conversely, the data set is quite imbalanced and one should probably focus on data augmentation for the smaller classes to achieve best results. However, this falls outside the requirements for this assignment.*

[ ]:
```python
from random import shuffle


def create_generators(train_dir: str, test_dir: str, val_split: float,␣
 ↪image_size: int):
    train_datagen = ImageDataGenerator(
        rescale=1./255,
        zoom_range=0.2,
        rotation_range=5,
        width_shift_range=0.1,
        height_shift_range=0.1,
        brightness_range=[0.8,1.2],
        horizontal_flip=True,
        fill_mode='nearest',
        validation_split=val_split)
    train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=(image_size, image_size),
        batch_size=32,
        class_mode='categorical',
        subset='training',
        shuffle=True,
        seed=43)
    validation_generator = train_datagen.flow_from_directory(
```

```
        train_dir,
        target_size=(image_size, image_size),
        batch_size=32,
        class_mode='categorical',
        subset='validation',
        shuffle=False,
        seed=43)
    test_datagen = ImageDataGenerator(rescale=1./255)
    test_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=(image_size, image_size),
        batch_size=1,
        class_mode='categorical',
        shuffle=False,
        seed=43)
    return (train_generator, validation_generator, test_generator)

train_generator, validation_generator, test_generator = create_generators('./
 ↪data/train', './data/test', 0.2, 150)
```

```
Found 747 images belonging to 9 classes.
Found 182 images belonging to 9 classes.
Found 233 images belonging to 9 classes.
```

1. …

5. Build a CNN network using Keras with the following layers
   - Cov2D with 32 filters, kernel size 3,3, and activation relu, followed by MaxPool2D
   - Cov2D with 32 filters, kernel size 3,3, and activation relu, followed by MaxPool2D
   - GLobalAveragePooling2D layer
   - Dense layer with 128 neurons and activation relu
   - Dense layer with 128 neurons and activation relu
   - Dense layer with 9 neurons and activation softmax.

[ ]:
```
cnn = Sequential()

cnn.add(Input(shape=(150, 150, 3)))
cnn.add(Conv2D(32, (3, 3), activation='relu', padding='valid'))
cnn.add(MaxPooling2D((2, 2), strides=2, padding='valid'))
cnn.add(Conv2D(32, (3, 3), activation='relu', padding='valid'))
cnn.add(MaxPooling2D((2, 2), strides=2, padding='valid'))
cnn.add(GlobalAveragePooling2D())
cnn.add(Dense(128, activation='relu'))
cnn.add(Dense(128, activation='relu'))
cnn.add(Dense(9, activation='softmax'))
```

1. …

6. Compile the model with Adam optimizer, categorical_crossentropy loss, and with metrics accuracy, precision, and recall.

[ ]:
```
cnn.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy', 'precision', 'recall'])

cnn.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 32)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 32)	0
dense (Dense)	(None, 128)	4,224
dense_1 (Dense)	(None, 128)	16,512
dense_2 (Dense)	(None, 9)	1,161

Total params: 32,041 (125.16 KB)

Trainable params: 32,041 (125.16 KB)

Non-trainable params: 0 (0.00 B)

1. …

7. Train the model for 20 epochs and plot training loss and accuracy against epochs.
8. Evaluate the model on test images and print the test loss and accuracy.

Note: the test loss and accuracy are included in the plots below

[ ]:
```
import warnings
warnings.filterwarnings("ignore")
```

```
history_cnn = cnn.fit(train_generator, validation_data=validation_generator,␣
↪epochs=20)
```

```
Epoch 1/20
24/24             29s 874ms/step -
accuracy: 0.2481 - loss: 2.0699 - precision: 0.3198 - recall: 0.0043 -
val_accuracy: 0.3407 - val_loss: 1.7349 - val_precision: 1.0000 - val_recall:
0.0110
Epoch 2/20
24/24             15s 469ms/step -
accuracy: 0.3212 - loss: 1.8067 - precision: 0.2400 - recall: 3.4767e-04 -
val_accuracy: 0.3407 - val_loss: 1.7409 - val_precision: 0.0000e+00 -
val_recall: 0.0000e+00
Epoch 3/20
24/24             15s 466ms/step -
accuracy: 0.3214 - loss: 1.8135 - precision: 0.2400 - recall: 0.0014 -
val_accuracy: 0.3407 - val_loss: 1.7326 - val_precision: 0.0000e+00 -
val_recall: 0.0000e+00
Epoch 4/20
24/24             15s 466ms/step -
accuracy: 0.3437 - loss: 1.7712 - precision: 0.6820 - recall: 0.0197 -
val_accuracy: 0.3407 - val_loss: 1.7247 - val_precision: 1.0000 - val_recall:
0.0055
Epoch 5/20
24/24             15s 488ms/step -
accuracy: 0.3285 - loss: 1.8326 - precision: 0.4484 - recall: 0.0081 -
val_accuracy: 0.3407 - val_loss: 1.7366 - val_precision: 0.0000e+00 -
val_recall: 0.0000e+00
Epoch 6/20
24/24             15s 501ms/step -
accuracy: 0.3512 - loss: 1.8033 - precision: 0.7521 - recall: 0.0190 -
val_accuracy: 0.3407 - val_loss: 1.7066 - val_precision: 0.5000 - val_recall:
0.0055
Epoch 7/20
24/24             15s 479ms/step -
accuracy: 0.3445 - loss: 1.7413 - precision: 0.8935 - recall: 0.0104 -
val_accuracy: 0.3407 - val_loss: 1.7051 - val_precision: 0.5000 - val_recall:
0.0055
Epoch 8/20
24/24             16s 509ms/step -
accuracy: 0.3148 - loss: 1.7446 - precision: 0.7689 - recall: 0.0193 -
val_accuracy: 0.3407 - val_loss: 1.6852 - val_precision: 0.7143 - val_recall:
0.0275
Epoch 9/20
24/24             15s 470ms/step -
accuracy: 0.3508 - loss: 1.7245 - precision: 0.6302 - recall: 0.0364 -
val_accuracy: 0.4121 - val_loss: 1.6341 - val_precision: 0.7143 - val_recall:
0.0275
```

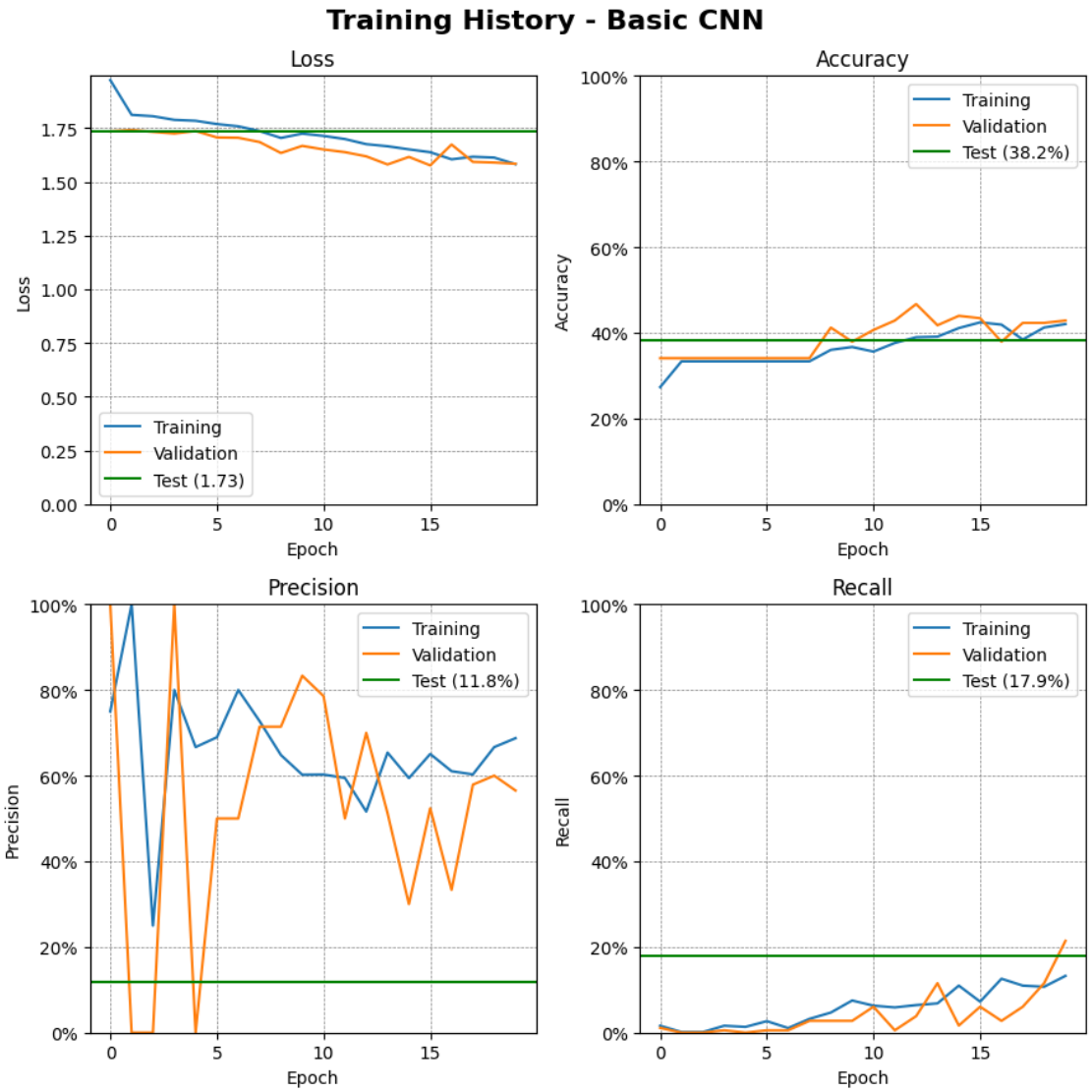
```
Epoch 10/20
24/24            15s 484ms/step -
accuracy: 0.4117 - loss: 1.6910 - precision: 0.6104 - recall: 0.0902 -
val_accuracy: 0.3791 - val_loss: 1.6674 - val_precision: 0.8333 - val_recall:
0.0275
Epoch 11/20
24/24            15s 485ms/step -
accuracy: 0.3558 - loss: 1.7006 - precision: 0.6283 - recall: 0.0592 -
val_accuracy: 0.4066 - val_loss: 1.6506 - val_precision: 0.7857 - val_recall:
0.0604
Epoch 12/20
24/24            15s 483ms/step -
accuracy: 0.3781 - loss: 1.6730 - precision: 0.6053 - recall: 0.0567 -
val_accuracy: 0.4286 - val_loss: 1.6381 - val_precision: 0.5000 - val_recall:
0.0055
Epoch 13/20
24/24            15s 494ms/step -
accuracy: 0.3886 - loss: 1.6744 - precision: 0.5838 - recall: 0.0581 -
val_accuracy: 0.4670 - val_loss: 1.6185 - val_precision: 0.7000 - val_recall:
0.0385
Epoch 14/20
24/24            15s 499ms/step -
accuracy: 0.3717 - loss: 1.7342 - precision: 0.7567 - recall: 0.0620 -
val_accuracy: 0.4176 - val_loss: 1.5807 - val_precision: 0.5122 - val_recall:
0.1154
Epoch 15/20
24/24            15s 493ms/step -
accuracy: 0.4190 - loss: 1.6287 - precision: 0.6445 - recall: 0.1432 -
val_accuracy: 0.4396 - val_loss: 1.6159 - val_precision: 0.3000 - val_recall:
0.0165
Epoch 16/20
24/24            15s 476ms/step -
accuracy: 0.4306 - loss: 1.6540 - precision: 0.6616 - recall: 0.0660 -
val_accuracy: 0.4341 - val_loss: 1.5765 - val_precision: 0.5238 - val_recall:
0.0604
Epoch 17/20
24/24            15s 497ms/step -
accuracy: 0.4460 - loss: 1.5636 - precision: 0.6581 - recall: 0.1362 -
val_accuracy: 0.3791 - val_loss: 1.6736 - val_precision: 0.3333 - val_recall:
0.0275
Epoch 18/20
24/24            15s 491ms/step -
accuracy: 0.3752 - loss: 1.6060 - precision: 0.6629 - recall: 0.0906 -
val_accuracy: 0.4231 - val_loss: 1.5928 - val_precision: 0.5789 - val_recall:
0.0604
Epoch 19/20
24/24            15s 481ms/step -
accuracy: 0.4248 - loss: 1.5922 - precision: 0.7199 - recall: 0.1053 -
```

```
val_accuracy: 0.4231 - val_loss: 1.5896 - val_precision: 0.6000 - val_recall:
0.1154
Epoch 20/20
24/24             15s 511ms/step -
accuracy: 0.4129 - loss: 1.6117 - precision: 0.6804 - recall: 0.1204 -
val_accuracy: 0.4286 - val_loss: 1.5839 - val_precision: 0.5652 - val_recall:
0.2143
```

[ ]:
```python
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
from sklearn.metrics import accuracy_score, precision_score, recall_score
from typing import Dict

def quality_scores(model: Model, generator: ImageDataGenerator) -> Dict[str,␣
↪float]:
    pred = model.predict(generator)
    pred_labels = np.argmax(pred, axis=1) # Turn "one-hot encoding"-like␣
↪probabilities into integer encoding for easier comparison with true labels
    retval = {}
    retval['accuracy'] = accuracy_score(generator.labels, pred_labels)
    retval['precision'] = precision_score(generator.labels, pred_labels,␣
↪average='macro')
    retval['recall'] = recall_score(generator.labels, pred_labels,␣
↪average='macro')
    loss_func = tf.keras.losses.SparseCategoricalCrossentropy()
    retval['loss'] = loss_func(generator.labels, pred)
    return retval

def training_subplot(hist, metric: str, plotnum: int, lim = None, test_val =␣
↪None):
    sp = plt.subplot(2, 2, plotnum)
    plt.plot(hist.history[metric], label='Training')
    plt.plot(hist.history['val_' + metric], label='Validation')
    if (test_val is not None):
        test_lbl = 'Test ' + (f'({test_val:.1%})' if (lim == 1) else␣
↪f'({test_val:.2f})')
        plt.axhline(y=test_val, label=test_lbl, color='green', linestyle='-')
    plt.xlabel('Epoch')
    plt.ylabel(metric.capitalize())
    plt.ylim(0, lim)
    plt.xlim(0, len(hist.history[metric]) - 1)
    if (lim == 1):
        sp.yaxis.set_major_formatter(ticker.PercentFormatter(xmax=1.0))
    plt.legend()
    plt.grid(visible=True, which='both', axis='both', linestyle='--',␣
↪linewidth=0.5, color='grey')
    plt.title(metric.capitalize())
```

```
def training_plot(hist, model: Model, generator: ImageDataGenerator,␣
 ↪title='Training History'):
    quality = quality_scores(model, generator)
    # Plot the training history (loss and accuracy) in two subplots
    plt.figure(figsize=(9, 9))
    plt.suptitle(title, fontsize=16, fontweight='bold')
    training_subplot(hist, 'loss', 1, test_val=quality['loss'])
    training_subplot(hist, 'accuracy', 2, 1, test_val=quality['accuracy'])
    training_subplot(hist, 'precision', 3, 1, test_val=quality['precision'])
    training_subplot(hist, 'recall', 4, 1, test_val=quality['recall'])
    plt.tight_layout()
    plt.show()

training_plot(history_cnn, cnn, test_generator, "Training History - Basic CNN")
```

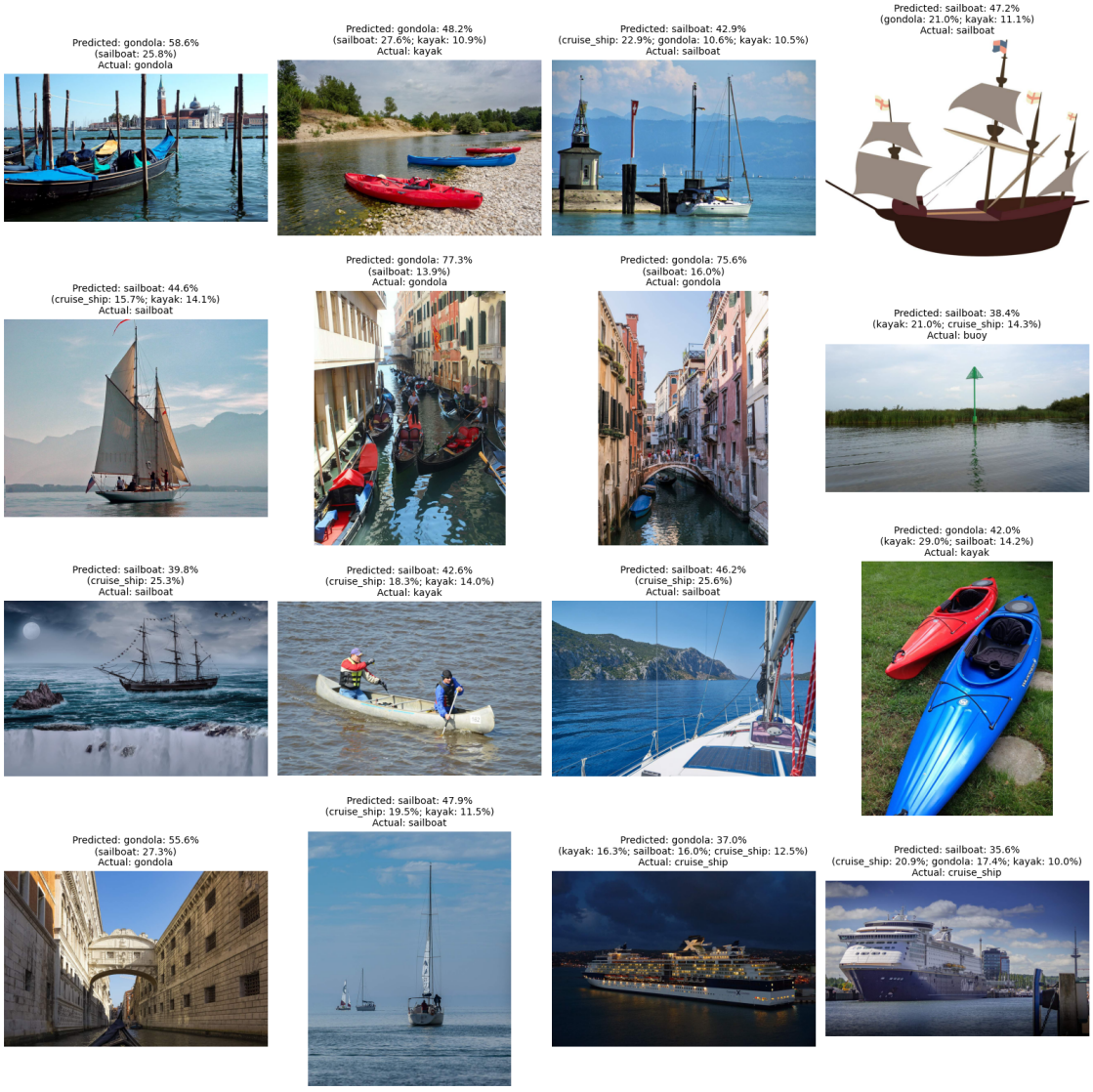
```
233/233             5s 20ms/step
```




```
[ ]: def predict_and_display(model: Model, generator: ImageDataGenerator, path: str):
    pred = model.predict(generator)
    class_names = [k for k in generator.class_indices.keys()]
    if not path.endswith('/'):
        path += '/'

    plt.figure(figsize=(16, 16))
    picked_image_indexes = []
    for i in range(16):
        # pick a random image index that hasn't been picked yet
        idx = None
        while (idx is None or idx in picked_image_indexes):
            idx = np.random.randint(0, len(generator.filenames))
```

```
        picked_image_indexes.append(idx)
        # Show top probability(ies) greater than 10%
        top_preds = [(str(k), f"{round(float(v),3):.1%}") for k, v in␣
↪zip(generator.class_indices.keys(), pred[idx]) if v >= 0.1]
        top_preds.sort(key=lambda x: x[1], reverse=True)
        top_pred_str = f"{top_preds[0][0]}: {top_preds[0][1]}"
        if (len(top_preds) > 1):
            top_pred_str += "\n(" + "; ".join([f"{k}: {v}" for k, v in␣
↪top_preds[1:]]) + ")"
        # Show image
        ax = plt.subplot(4, 4, i+1)
        plt.imshow(plt.imread(f"{path}{generator.filenames[idx]}"))
        plt.title(f"Predicted: {top_pred_str}\nActual: {class_names[generator.
↪labels[idx]]}", fontsize=10)
        plt.axis('off')
    plt.tight_layout()
    plt.show()

predict_and_display(cnn, test_generator, "./data/test")
```

```
233/233             3s 13ms/step
```



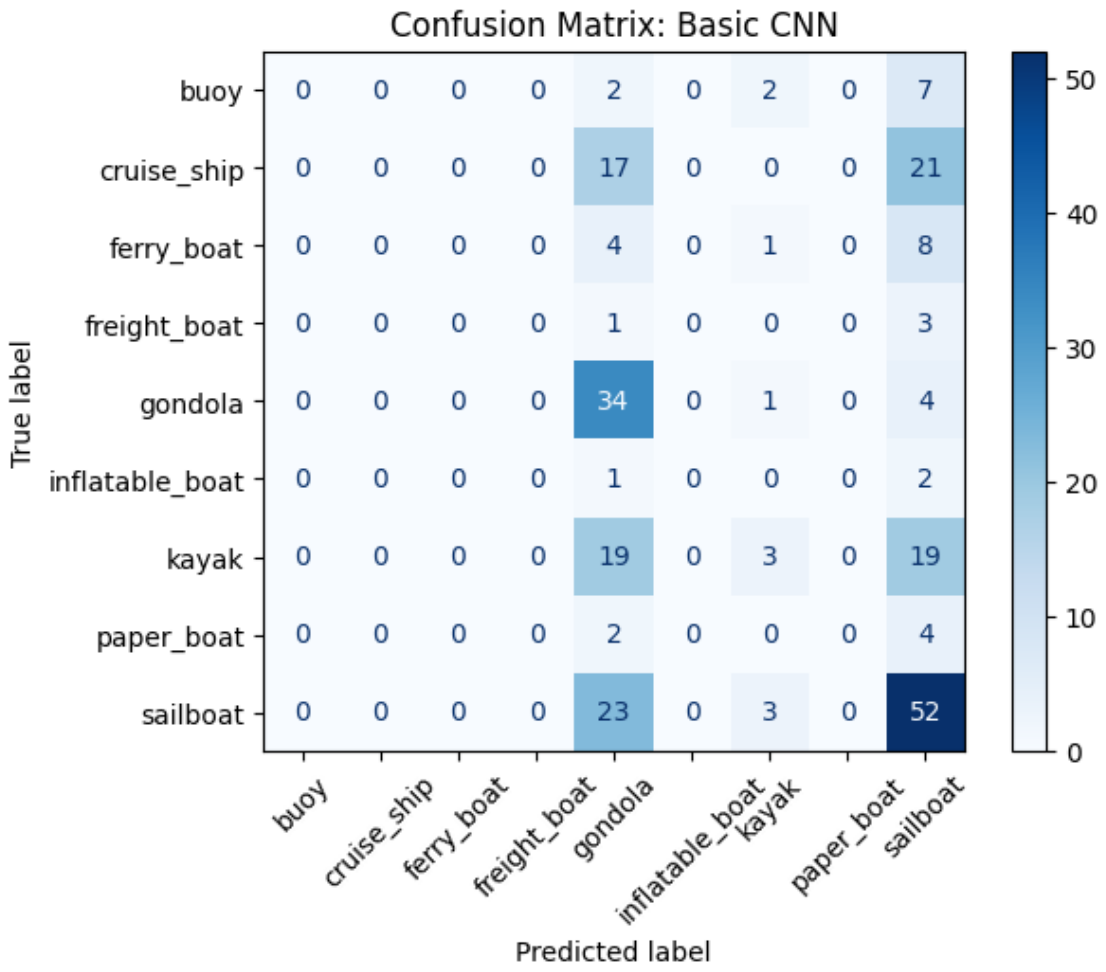
1. ...

9. Plot heatmap of the confusion matrix and print classification report

```
[ ]: from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
      ↪classification_report

     def confusion_matrix_and_classification_report(model: Model, generator: tf.
      ↪keras.preprocessing.image.DirectoryIterator, title: str):
         # Generate predictions
         test_pred = model.predict(generator)
         predicted_labels = test_pred.argmax(axis=1)
         class_names = generator.class_indices.keys()
         # Compute the confusion matrix
```

```
    cm = confusion_matrix(generator.labels, predicted_labels)
    # Plot the confusion matrix
    cm_display = ConfusionMatrixDisplay(cm, display_labels=class_names)
    cm_display.plot(cmap='Blues', values_format='d', xticks_rotation=45)
    plt.title('Confusion Matrix: ' + title)
    plt.show()
    # Display the classification report
    print(classification_report(generator.labels, predicted_labels,␣
 ↪target_names=class_names))

confusion_matrix_and_classification_report(cnn, test_generator, 'Basic CNN')
```

```
233/233                3s 13ms/step
```




```
              precision    recall  f1-score   support

       buoy       0.00      0.00      0.00        11
```

```
     cruise_ship       0.00      0.00      0.00        38
      ferry_boat       0.00      0.00      0.00        13
    freight_boat       0.00      0.00      0.00         4
         gondola       0.33      0.87      0.48        39
inflatable_boat       0.00      0.00      0.00         3
           kayak       0.30      0.07      0.12        41
      paper_boat       0.00      0.00      0.00         6
        sailboat       0.43      0.67      0.53        78

        accuracy                           0.38       233
       macro avg       0.12      0.18      0.12       233
    weighted avg       0.25      0.38      0.28       233
```

2. Build a lightweight model with the aim of deploying the solution on a mobile device using transfer learning. You can use any lightweight pre-trained model as the initial (first) layer. MobileNetV2 is a popular lightweight pre-trained model built using Keras API.
    1. Split the dataset into train and test datasets in the ration 70:30, with shuffle and random state=1.

[ ]:
```
split_files(files, folders, 0.3, 'lm_train', 'lm_test', 1)
```

```
                train  test
sailboat          272   117
kayak             142    61
gondola           135    58
cruise_ship       134    57
ferry_boat         44    19
buoy               37    16
paper_boat         22     9
freight_boat       16     7
inflatable_boat    11     5
```

2. …

    2. Use Keras ImageDataGenerator to initialize the train generator with validation_split=0.2 and test generator. Generators are required to avoid out-of-memory issues while training.

    3. Both generators will be initialized with data normalization. *(Hint: rescale=1./255).*

    4. Load train, validation and test datasets in batches of 32 using the generators initialized in the above step.

Note: MobileNetV2 uses an image size of 224, so this value is used here instead of the 150 setting used earlier.

[ ]:
```
train_lm_generator, validation_lm_generator, test_lm_generator =␣
↪create_generators('./data/lm_train', './data/lm_test', 0.2, 224)
```

```
Found 654 images belonging to 9 classes.
Found 159 images belonging to 9 classes.
Found 349 images belonging to 9 classes.
```

2. …

5. Build a CNN network using Keras with the following layers.
   - Load MobileNetV2 - Light Model as the first layer *(Hint: Keras API Doc)*
   - GLobalAveragePooling2D layer
   - Dropout(0.2)
   - Dense layer with 256 neurons and activation relu
   - BatchNormalization layer
   - Dropout(0.1)
   - Dense layer with 128 neurons and activation relu
   - BatchNormalization layer
   - Dropout(0.1)
   - Dense layer with 9 neurons and activation softmax

[ ]:
```
from keras.applications import MobileNetV2

base_model = MobileNetV2(weights='imagenet', include_top=False,␣
↪input_shape=(224, 224, 3))
base_model.trainable = False

lm_cnn = Sequential()
lm_cnn.add(base_model)
lm_cnn.add(GlobalAveragePooling2D())
lm_cnn.add(Dropout(0.2))
lm_cnn.add(Dense(256, activation='relu'))
lm_cnn.add(BatchNormalization())
lm_cnn.add(Dropout(0.1))
lm_cnn.add(Dense(128, activation='relu'))
lm_cnn.add(BatchNormalization())
lm_cnn.add(Dropout(0.1))
lm_cnn.add(Dense(9, activation='softmax'))
```

2. …

6. Compile the model with Adam optimizer, categorical_crossentropy loss, and metrics accuracy, Precision, and Recall.

[ ]:
```
lm_cnn.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy', 'precision', 'recall'])

lm_cnn.summary()
```

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Functional)	?	2,257,984
global_average_pooling2d_1 (GlobalAveragePooling2D)	?	0 (unbuilt)
dropout (Dropout)	?	0
dense_3 (Dense)	?	0 (unbuilt)
batch_normalization (BatchNormalization)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0
dense_4 (Dense)	?	0 (unbuilt)
batch_normalization_1 (BatchNormalization)	?	0 (unbuilt)
dropout_2 (Dropout)	?	0
dense_5 (Dense)	?	0 (unbuilt)

Total params: 2,257,984 (8.61 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 2,257,984 (8.61 MB)

2. …

7. Train the model for 50 epochs and Early stopping while monitoring validation loss.

Note: I'm assuming that this means **at most** *50 epochs of training with early stopping to occur before these 50 epochs (if at all)*

[ ]:

```
early_stopping = tf.keras.callbacks.EarlyStopping(patience=20,␣
 ↪restore_best_weights=True, monitor='val_loss', verbose=1,␣
 ↪start_from_epoch=25)
```

[ ]:
```
import warnings
warnings.filterwarnings("ignore")

history_lm_cnn = lm_cnn.fit(train_lm_generator,␣
 ↪validation_data=validation_lm_generator, epochs=50,␣
 ↪callbacks=[early_stopping])
```

```
Epoch 1/50
21/21             43s 1s/step -
accuracy: 0.3969 - loss: 1.8439 - precision: 0.5811 - recall: 0.2848 -
val_accuracy: 0.7421 - val_loss: 0.8475 - val_precision: 0.8718 - val_recall:
0.6415
Epoch 2/50
21/21             21s 799ms/step -
accuracy: 0.8118 - loss: 0.6176 - precision: 0.8699 - recall: 0.7497 -
val_accuracy: 0.7799 - val_loss: 0.7344 - val_precision: 0.9016 - val_recall:
0.6918
Epoch 3/50
21/21             21s 785ms/step -
accuracy: 0.8461 - loss: 0.4853 - precision: 0.9234 - recall: 0.7860 -
val_accuracy: 0.8050 - val_loss: 0.7013 - val_precision: 0.8864 - val_recall:
0.7358
Epoch 4/50
21/21             22s 798ms/step -
accuracy: 0.8867 - loss: 0.3646 - precision: 0.9248 - recall: 0.8388 -
val_accuracy: 0.8050 - val_loss: 0.6519 - val_precision: 0.8705 - val_recall:
0.7610
Epoch 5/50
21/21             22s 821ms/step -
accuracy: 0.9099 - loss: 0.2981 - precision: 0.9366 - recall: 0.8797 -
val_accuracy: 0.8302 - val_loss: 0.6317 - val_precision: 0.8707 - val_recall:
0.8050
Epoch 6/50
21/21             22s 810ms/step -
accuracy: 0.9260 - loss: 0.2443 - precision: 0.9476 - recall: 0.9016 -
val_accuracy: 0.8050 - val_loss: 0.6839 - val_precision: 0.8288 - val_recall:
0.7610
Epoch 7/50
21/21             21s 796ms/step -
accuracy: 0.9086 - loss: 0.3070 - precision: 0.9336 - recall: 0.8628 -
val_accuracy: 0.8113 - val_loss: 0.6014 - val_precision: 0.8929 - val_recall:
0.7862
Epoch 8/50
21/21             21s 796ms/step -
```

```
accuracy: 0.9012 - loss: 0.2769 - precision: 0.9194 - recall: 0.8716 -
val_accuracy: 0.8365 - val_loss: 0.6697 - val_precision: 0.8767 - val_recall:
0.8050
Epoch 9/50
21/21             21s 820ms/step -
accuracy: 0.9393 - loss: 0.2010 - precision: 0.9575 - recall: 0.9163 -
val_accuracy: 0.8365 - val_loss: 0.6842 - val_precision: 0.8431 - val_recall:
0.8113
Epoch 10/50
21/21             21s 778ms/step -
accuracy: 0.9539 - loss: 0.1783 - precision: 0.9705 - recall: 0.9428 -
val_accuracy: 0.8302 - val_loss: 0.6520 - val_precision: 0.8553 - val_recall:
0.8176
Epoch 11/50
21/21             21s 789ms/step -
accuracy: 0.9401 - loss: 0.1786 - precision: 0.9588 - recall: 0.9226 -
val_accuracy: 0.8050 - val_loss: 0.7666 - val_precision: 0.8467 - val_recall:
0.7987
Epoch 12/50
21/21             21s 815ms/step -
accuracy: 0.9598 - loss: 0.1381 - precision: 0.9739 - recall: 0.9467 -
val_accuracy: 0.8239 - val_loss: 0.6695 - val_precision: 0.8497 - val_recall:
0.8176
Epoch 13/50
21/21             22s 792ms/step -
accuracy: 0.9619 - loss: 0.1509 - precision: 0.9718 - recall: 0.9369 -
val_accuracy: 0.7987 - val_loss: 0.7299 - val_precision: 0.8267 - val_recall:
0.7799
Epoch 14/50
21/21             21s 781ms/step -
accuracy: 0.9624 - loss: 0.1253 - precision: 0.9752 - recall: 0.9468 -
val_accuracy: 0.7736 - val_loss: 0.7498 - val_precision: 0.7857 - val_recall:
0.7610
Epoch 15/50
21/21             22s 801ms/step -
accuracy: 0.9636 - loss: 0.1004 - precision: 0.9694 - recall: 0.9580 -
val_accuracy: 0.8050 - val_loss: 0.7332 - val_precision: 0.8312 - val_recall:
0.8050
Epoch 16/50
21/21             21s 776ms/step -
accuracy: 0.9694 - loss: 0.0973 - precision: 0.9736 - recall: 0.9660 -
val_accuracy: 0.7987 - val_loss: 0.7189 - val_precision: 0.8301 - val_recall:
0.7987
Epoch 17/50
21/21             22s 788ms/step -
accuracy: 0.9657 - loss: 0.1135 - precision: 0.9787 - recall: 0.9516 -
val_accuracy: 0.8428 - val_loss: 0.6397 - val_precision: 0.8627 - val_recall:
0.8302
```

```
Epoch 18/50
21/21             21s 802ms/step -
accuracy: 0.9703 - loss: 0.0845 - precision: 0.9781 - recall: 0.9658 -
val_accuracy: 0.8239 - val_loss: 0.6452 - val_precision: 0.8533 - val_recall:
0.8050
Epoch 19/50
21/21             21s 774ms/step -
accuracy: 0.9702 - loss: 0.0882 - precision: 0.9795 - recall: 0.9669 -
val_accuracy: 0.8050 - val_loss: 0.6261 - val_precision: 0.8467 - val_recall:
0.7987
Epoch 20/50
21/21             21s 770ms/step -
accuracy: 0.9647 - loss: 0.1111 - precision: 0.9710 - recall: 0.9590 -
val_accuracy: 0.8239 - val_loss: 0.6592 - val_precision: 0.8609 - val_recall:
0.8176
Epoch 21/50
21/21             22s 809ms/step -
accuracy: 0.9736 - loss: 0.0987 - precision: 0.9788 - recall: 0.9693 -
val_accuracy: 0.7987 - val_loss: 0.7691 - val_precision: 0.8278 - val_recall:
0.7862
Epoch 22/50
21/21             21s 798ms/step -
accuracy: 0.9694 - loss: 0.0915 - precision: 0.9764 - recall: 0.9651 -
val_accuracy: 0.8428 - val_loss: 0.7219 - val_precision: 0.8562 - val_recall:
0.8239
Epoch 23/50
21/21             23s 874ms/step -
accuracy: 0.9846 - loss: 0.0709 - precision: 0.9856 - recall: 0.9771 -
val_accuracy: 0.8113 - val_loss: 0.7780 - val_precision: 0.8301 - val_recall:
0.7987
Epoch 24/50
21/21             21s 823ms/step -
accuracy: 0.9688 - loss: 0.0999 - precision: 0.9720 - recall: 0.9669 -
val_accuracy: 0.8302 - val_loss: 0.7585 - val_precision: 0.8377 - val_recall:
0.8113
Epoch 25/50
21/21             23s 898ms/step -
accuracy: 0.9806 - loss: 0.0721 - precision: 0.9856 - recall: 0.9761 -
val_accuracy: 0.8113 - val_loss: 0.8559 - val_precision: 0.8247 - val_recall:
0.7987
Epoch 26/50
21/21             23s 874ms/step -
accuracy: 0.9839 - loss: 0.0642 - precision: 0.9853 - recall: 0.9839 -
val_accuracy: 0.8428 - val_loss: 0.7349 - val_precision: 0.8600 - val_recall:
0.8113
Epoch 27/50
21/21             22s 800ms/step -
accuracy: 0.9722 - loss: 0.0750 - precision: 0.9817 - recall: 0.9610 -
```

```
val_accuracy: 0.8365 - val_loss: 0.6079 - val_precision: 0.8431 - val_recall:
0.8113
Epoch 28/50
21/21            22s 817ms/step -
accuracy: 0.9821 - loss: 0.0714 - precision: 0.9848 - recall: 0.9729 -
val_accuracy: 0.8302 - val_loss: 0.6782 - val_precision: 0.8487 - val_recall:
0.8113
Epoch 29/50
21/21            22s 821ms/step -
accuracy: 0.9795 - loss: 0.0786 - precision: 0.9857 - recall: 0.9782 -
val_accuracy: 0.8302 - val_loss: 0.6749 - val_precision: 0.8442 - val_recall:
0.8176
Epoch 30/50
21/21            21s 783ms/step -
accuracy: 0.9704 - loss: 0.0822 - precision: 0.9704 - recall: 0.9691 -
val_accuracy: 0.8239 - val_loss: 0.6808 - val_precision: 0.8258 - val_recall:
0.8050
Epoch 31/50
21/21            21s 778ms/step -
accuracy: 0.9721 - loss: 0.0877 - precision: 0.9752 - recall: 0.9713 -
val_accuracy: 0.8491 - val_loss: 0.6718 - val_precision: 0.8516 - val_recall:
0.8302
Epoch 32/50
21/21            22s 839ms/step -
accuracy: 0.9848 - loss: 0.0509 - precision: 0.9866 - recall: 0.9848 -
val_accuracy: 0.8553 - val_loss: 0.6053 - val_precision: 0.8654 - val_recall:
0.8491
Epoch 33/50
21/21            23s 900ms/step -
accuracy: 0.9769 - loss: 0.0775 - precision: 0.9768 - recall: 0.9749 -
val_accuracy: 0.8176 - val_loss: 0.6635 - val_precision: 0.8431 - val_recall:
0.8113
Epoch 34/50
21/21            24s 947ms/step -
accuracy: 0.9739 - loss: 0.0915 - precision: 0.9760 - recall: 0.9695 -
val_accuracy: 0.8553 - val_loss: 0.5865 - val_precision: 0.8824 - val_recall:
0.8491
Epoch 35/50
21/21            26s 1s/step -
accuracy: 0.9855 - loss: 0.0613 - precision: 0.9854 - recall: 0.9785 -
val_accuracy: 0.8113 - val_loss: 0.7410 - val_precision: 0.8411 - val_recall:
0.7987
Epoch 36/50
21/21            26s 1s/step -
accuracy: 0.9833 - loss: 0.0497 - precision: 0.9833 - recall: 0.9833 -
val_accuracy: 0.8428 - val_loss: 0.6523 - val_precision: 0.8627 - val_recall:
0.8302
Epoch 37/50
```

```
21/21            25s 959ms/step -
accuracy: 0.9813 - loss: 0.0757 - precision: 0.9827 - recall: 0.9811 -
val_accuracy: 0.8742 - val_loss: 0.5414 - val_precision: 0.8839 - val_recall:
0.8616
Epoch 38/50
21/21            27s 1s/step -
accuracy: 0.9779 - loss: 0.0759 - precision: 0.9823 - recall: 0.9758 -
val_accuracy: 0.8491 - val_loss: 0.7626 - val_precision: 0.8758 - val_recall:
0.8428
Epoch 39/50
21/21            27s 1s/step -
accuracy: 0.9865 - loss: 0.0457 - precision: 0.9906 - recall: 0.9865 -
val_accuracy: 0.8616 - val_loss: 0.5502 - val_precision: 0.8726 - val_recall:
0.8616
Epoch 40/50
21/21            27s 1s/step -
accuracy: 0.9873 - loss: 0.0396 - precision: 0.9882 - recall: 0.9824 -
val_accuracy: 0.8365 - val_loss: 0.7917 - val_precision: 0.8462 - val_recall:
0.8302
Epoch 41/50
21/21            24s 938ms/step -
accuracy: 0.9809 - loss: 0.0496 - precision: 0.9906 - recall: 0.9799 -
val_accuracy: 0.8176 - val_loss: 0.8196 - val_precision: 0.8366 - val_recall:
0.8050
Epoch 42/50
21/21            24s 933ms/step -
accuracy: 0.9849 - loss: 0.0522 - precision: 0.9849 - recall: 0.9849 -
val_accuracy: 0.8553 - val_loss: 0.6253 - val_precision: 0.8553 - val_recall:
0.8553
Epoch 43/50
21/21            23s 909ms/step -
accuracy: 0.9854 - loss: 0.0454 - precision: 0.9874 - recall: 0.9850 -
val_accuracy: 0.8302 - val_loss: 0.6117 - val_precision: 0.8516 - val_recall:
0.8302
Epoch 44/50
21/21            23s 887ms/step -
accuracy: 0.9711 - loss: 0.0793 - precision: 0.9784 - recall: 0.9711 -
val_accuracy: 0.8679 - val_loss: 0.6030 - val_precision: 0.8790 - val_recall:
0.8679
Epoch 45/50
21/21            23s 900ms/step -
accuracy: 0.9795 - loss: 0.0650 - precision: 0.9795 - recall: 0.9795 -
val_accuracy: 0.8239 - val_loss: 0.6034 - val_precision: 0.8506 - val_recall:
0.8239
Epoch 46/50
21/21            22s 838ms/step -
accuracy: 0.9881 - loss: 0.0526 - precision: 0.9881 - recall: 0.9881 -
val_accuracy: 0.8491 - val_loss: 0.7359 - val_precision: 0.8599 - val_recall:
```

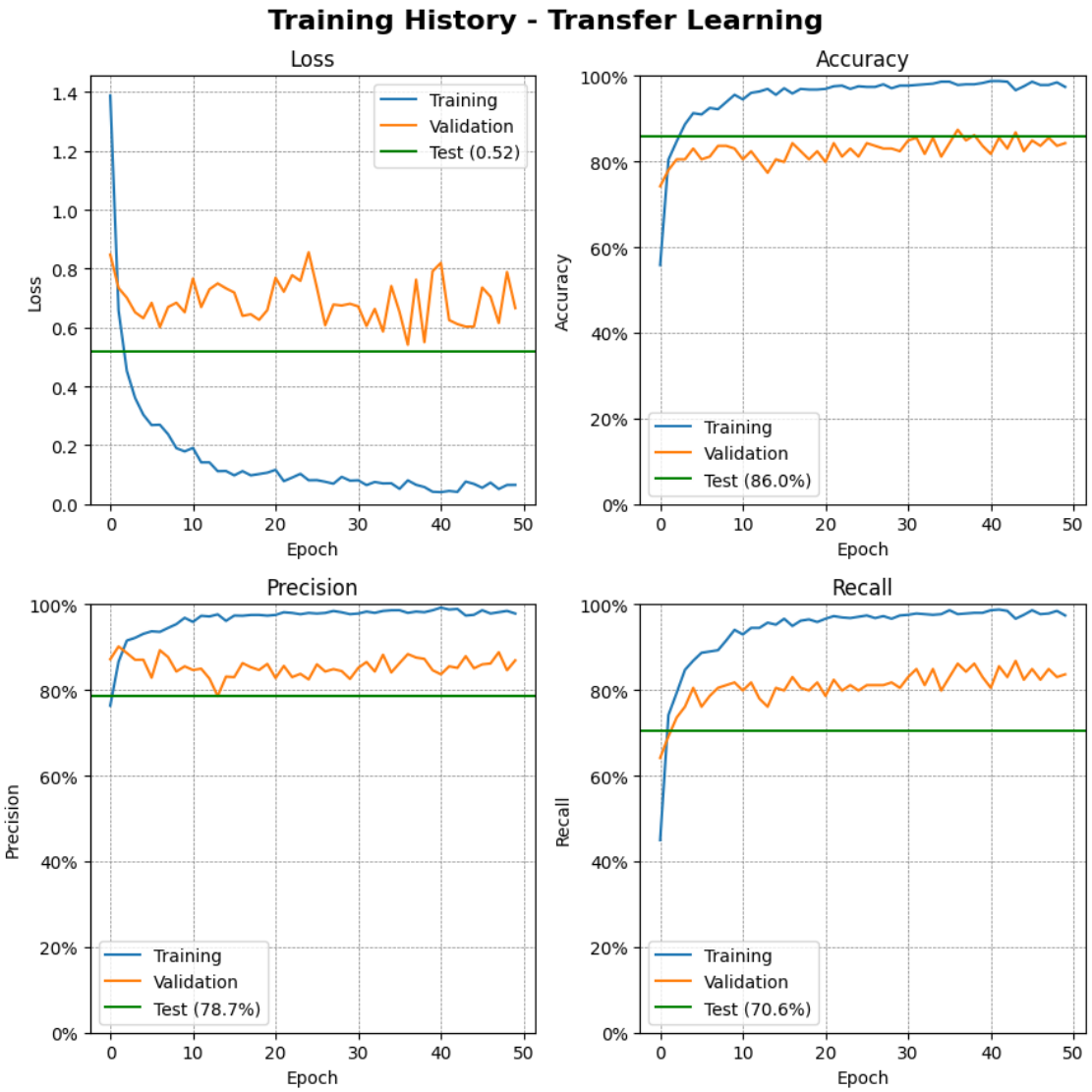
```
0.8491
Epoch 47/50
21/21             26s 1s/step -
accuracy: 0.9735 - loss: 0.0771 - precision: 0.9735 - recall: 0.9733 -
val_accuracy: 0.8365 - val_loss: 0.7051 - val_precision: 0.8618 - val_recall:
0.8239
Epoch 48/50
21/21             24s 911ms/step -
accuracy: 0.9898 - loss: 0.0301 - precision: 0.9908 - recall: 0.9898 -
val_accuracy: 0.8553 - val_loss: 0.6151 - val_precision: 0.8882 - val_recall:
0.8491
Epoch 49/50
21/21             25s 965ms/step -
accuracy: 0.9813 - loss: 0.0692 - precision: 0.9813 - recall: 0.9813 -
val_accuracy: 0.8365 - val_loss: 0.7887 - val_precision: 0.8462 - val_recall:
0.8302
Epoch 50/50
21/21             23s 871ms/step -
accuracy: 0.9690 - loss: 0.0745 - precision: 0.9759 - recall: 0.9690 -
val_accuracy: 0.8428 - val_loss: 0.6660 - val_precision: 0.8693 - val_recall:
0.8365
Restoring model weights from the end of the best epoch: 37.
```

2. …

8. Evaluate the model on test images and print the test loss and accuracy.

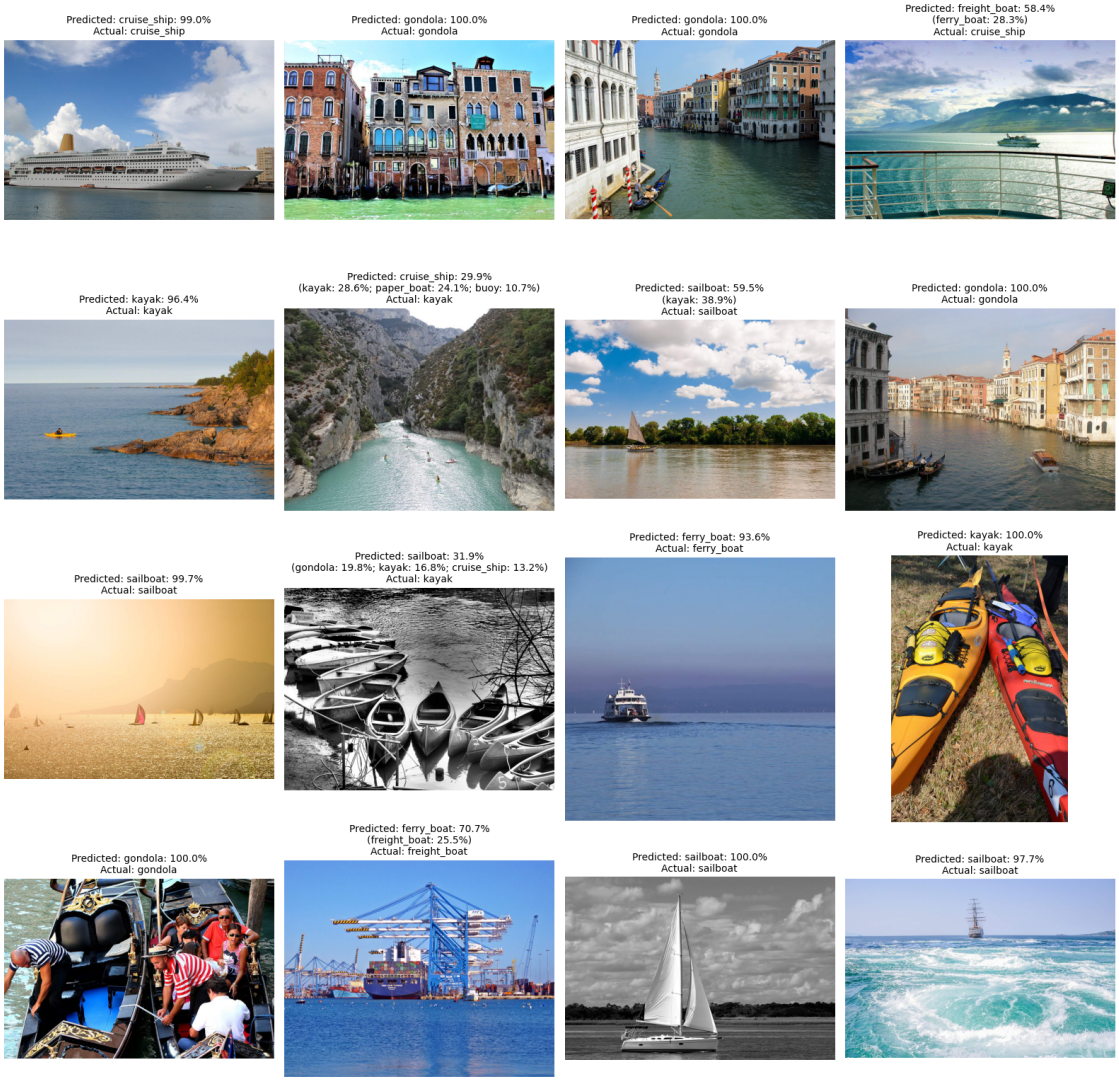
[ ]:
```
training_plot(history_lm_cnn, lm_cnn, test_lm_generator, "Training History -␣
↪Transfer Learning")
```

```
349/349             11s 27ms/step
```



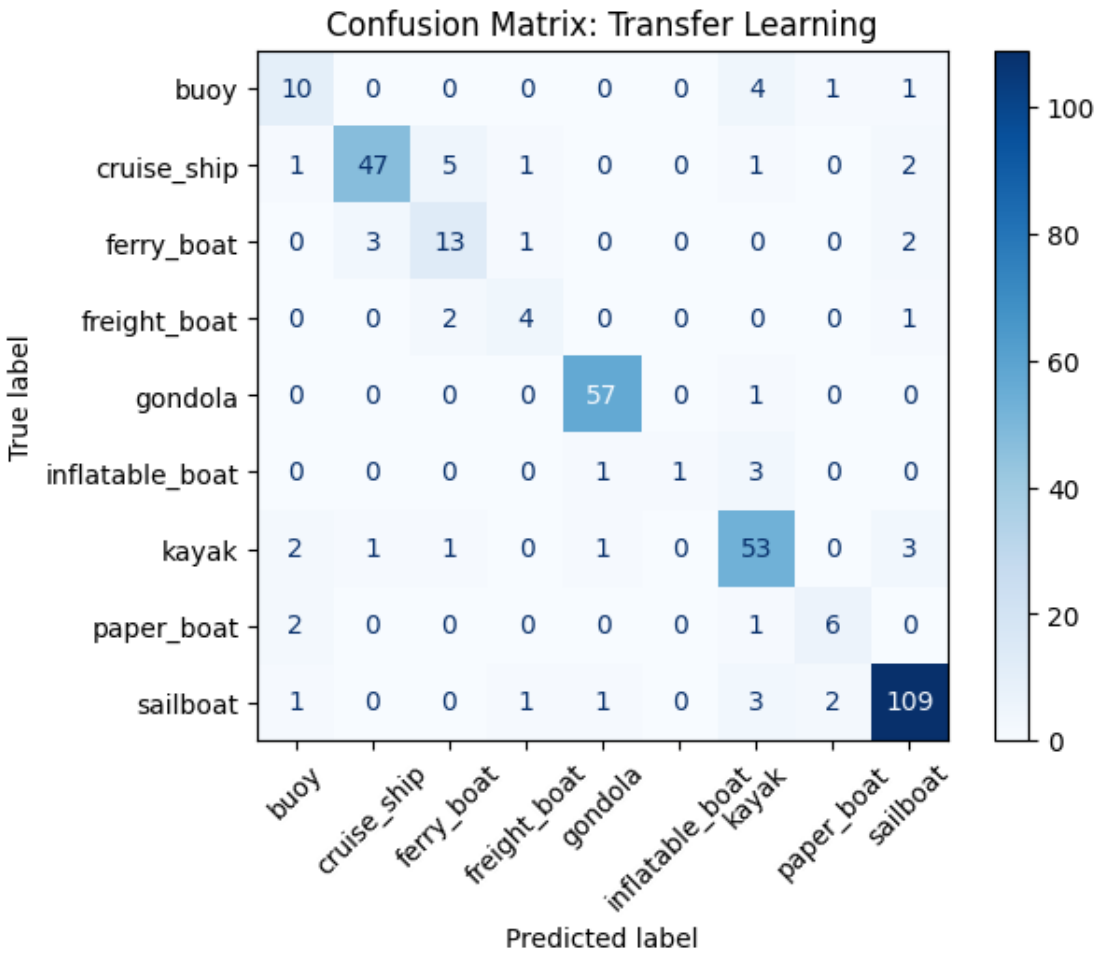
[ ]:
```
predict_and_display(lm_cnn, test_lm_generator, "./data/lm_test")
```

```
349/349              8s 22ms/step
```



[ ]:
```
confusion_matrix_and_classification_report(lm_cnn, test_lm_generator, 'Transfer␣
↪Learning')
```

```
349/349             7s 21ms/step
```

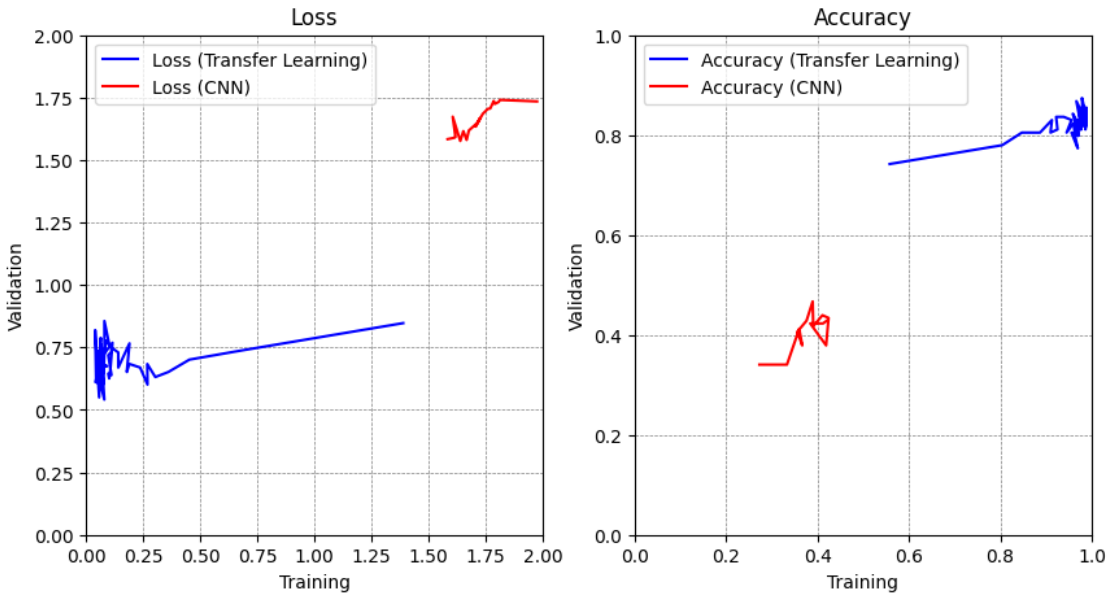


	precision	recall	f1-score	support
buoy	0.62	0.62	0.62	16
cruise_ship	0.92	0.82	0.87	57
ferry_boat	0.62	0.68	0.65	19
freight_boat	0.57	0.57	0.57	7
gondola	0.95	0.98	0.97	58
inflatable_boat	1.00	0.20	0.33	5
kayak	0.80	0.87	0.83	61
paper_boat	0.67	0.67	0.67	9
sailboat	0.92	0.93	0.93	117
accuracy			0.86	349
macro avg	0.79	0.71	0.72	349
weighted avg	0.86	0.86	0.86	349

2. ...

9. Plot Train loss Vs Validation loss and Train accuracy Vs Validation accuracy.

[ ]:
```
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.plot(history_lm_cnn.history['loss'], history_lm_cnn.history['val_loss'],␣
 ↪label='Loss (Transfer Learning)', color='blue', marker=None)
plt.plot(history_cnn.history['loss'], history_cnn.history['val_loss'],␣
 ↪label='Loss (CNN)', color='red', marker=None)
plt.xlim(0, 2)
plt.ylim(0, 2)
plt.title('Loss')
plt.xlabel('Training')
plt.ylabel('Validation')
plt.grid(visible=True, which='both', axis='both', linestyle='--', linewidth=0.
 ↪5, color='grey')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history_lm_cnn.history['accuracy'], history_lm_cnn.
 ↪history['val_accuracy'], label='Accuracy (Transfer Learning)', color='blue',␣
 ↪marker=None)
plt.plot(history_cnn.history['accuracy'], history_cnn.history['val_accuracy'],␣
 ↪label='Accuracy (CNN)', color='red', marker=None)
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.title('Accuracy')
plt.xlabel('Training')
plt.ylabel('Validation')
plt.grid(visible=True, which='both', axis='both', linestyle='--', linewidth=0.
 ↪5, color='grey')
plt.legend()

plt.show()
```



3. Compare the results of both models built in steps 1 and 2 and state your observations.

0.1.1 Basic CNN

The basic convolutional neural network built and trained in step one achieves behaves horribly, as expected, barely achieving an accuracy of 38.2%. This is in large part due to the fact that training was limited to 20 epochs. Even for a very small CNN (64 3x3 filter split over 2 Conv2D layers, followed by 2 128-node classification layers), training the feature extraction (Conv2Ds) *and* classification (the dense layers) requires definitely more training than that.
Indeed, the confusion matrix for the basic CNN clearly shows that the only thing that was "learned" is that most images are sailboats (primarily), gondolas, or kayaks. Most of the predictions fall into one of these 3 classes. The confusion matrix looks like 2 columns (sailboats and gondolas), instead of looking like a diagonal. There are 2 primary things that could be done to alleviate this issue, even with such a simple network:
* More training epochs should be run, maybe with an `EarlyStopping` callback so that training stops before overfitting occurs. * Lower-count classes should be augmented so that the network learns to recognize them. This could be done by either using some keras-based augmentation algorithms or, better, searching the internet for matching images and adding them to the dataset

0.1.2 Transfer Learning

Using Mobile Net (V2) frozen and simply training the classifier subnetwork significantly improves to about 85%, and the confusion matrix looks like a diagonal.
This clearly shows the advantage of using pre-trained networks for image classification: the feature extraction is already present, and it's mostly just the classifier that needs to be re-trained (i.e., the dense layers).

Having said that, however, 85% accuracy is still less than desirable for commercial applications, especially if there are large costs (monetary or otherwise) associated with mis-classifications. To improve accuracy and recall, hence the following further work could be done:
* As noted for the Basic CNN above, the class imbalance in the source data *should* very much be alleviated (with some computational or actual data augmentation for the smaller classes)
* Further training should be done of the overall network, maybe by increasing early stopping `patience` and decreasing the learning rate when a plateau occurs. * Once the classifier is trained, un-freeze the feature extractor (or parts thereof) to allow for fine-tuning of Mobile Net V2 for boat identification.