```
# Mount to Google Drive for downloading dataset file

from google.colab import drive
drive.mount('/content/gdrive/')
```

```
Mounted at /content/gdrive/
```

```
# Unzip the dataset file

!unzip /content/gdrive/MyDrive/deep-learning-recycle-item-classification-main.zip
```

```
Archive:  /content/gdrive/MyDrive/deep-learning-recycle-item-classification-main.zip
33ae657e01683187bb19c4351555cd56aa5329d3
   creating: deep-learning-recycle-item-classification-main/
  inflating: deep-learning-recycle-item-classification-main/LICENSE
  inflating: deep-learning-recycle-item-classification-main/README.md
   creating: deep-learning-recycle-item-classification-main/code/
  inflating: deep-learning-recycle-item-classification-main/code/deep-learning-real-life-item-classification.ipynb
  inflating: deep-learning-recycle-item-classification-main/code/deep-learning-real-life-item-classification.pdf
   creating: deep-learning-recycle-item-classification-main/dataset/
  inflating: deep-learning-recycle-item-classification-main/dataset/Dataset.zip
   creating: deep-learning-recycle-item-classification-main/images/
  inflating: deep-learning-recycle-item-classification-main/images/accuracy-validation.png
  inflating: deep-learning-recycle-item-classification-main/images/confusion-matrix.png
  inflating: deep-learning-recycle-item-classification-main/images/item-classification-deep-learning.png
  inflating: deep-learning-recycle-item-classification-main/images/loss-validation.png
```

```
import pandas as pd
import numpy as np
import glob
import os
from datetime import datetime
from packaging import version

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.callbacks import ModelCheckpoint, History

from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Conv2D, Lambda, MaxPooling2D, Dense, Dropout, Flatten
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import to_categorical

from skimage.io import imread, imshow
from skimage.transform import resize
from IPython import display
import matplotlib.pyplot as plt
import seaborn as sns
from seaborn import heatmap
from sklearn.metrics import confusion_matrix
```

```
!unzip /content/deep-learning-recycle-item-classification-main/dataset/Dataset.zip
```

```
    inflating: Dataset/Train/Non-recyclable/O_51.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_51.jpg
    inflating: Dataset/Train/Non-recyclable/O_45.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_45.jpg
    inflating: Dataset/Train/Non-recyclable/O_79.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_79.jpg
    inflating: Dataset/Train/Non-recyclable/O_41.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_41.jpg
    inflating: Dataset/Train/Non-recyclable/O_55.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_55.jpg
    inflating: Dataset/Train/Non-recyclable/O_69.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_69.jpg
    inflating: Dataset/Train/Non-recyclable/O_82.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_82.jpg
    inflating: Dataset/Train/Non-recyclable/O_96.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_96.jpg
    inflating: Dataset/Train/Non-recyclable/O_264.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_264.jpg
    inflating: Dataset/Train/Non-recyclable/O_270.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_270.jpg
    inflating: Dataset/Train/Non-recyclable/O_258.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_258.jpg
    inflating: Dataset/Train/Non-recyclable/O_476.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_476.jpg
    inflating: Dataset/Train/Non-recyclable/O_310.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_310.jpg
    inflating: Dataset/Train/Non-recyclable/O_304.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_304.jpg
    inflating: Dataset/Train/Non-recyclable/O_462.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_462.jpg
    inflating: Dataset/Train/Non-recyclable/O_338.jpg
    inflating: __MACOSX/Dataset/Train/Non-recyclable/._O_338.jpg
    inflating: Dataset/Train/Non-recyclable/O_6.jpg
```

```python
# Define train and test image folder path

train_folder = "/content/Dataset/Train"
test_folder = "/content/Dataset/Test"


# Data augmentation for training
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest')


# No augmentation for validation/test
test_datagen = ImageDataGenerator(rescale=1./255)


# Load dataset
train_generator = train_datagen.flow_from_directory(
    train_folder,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary')
```

```
Found 999 images belonging to 2 classes.
```

```python
test_generator = test_datagen.flow_from_directory(
    test_folder,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    shuffle=False)
```

```
Found 1234 images belonging to 2 classes.
```

```python
from sklearn.utils.class_weight import compute_class_weight
# Compute class weights to address imbalance
class_labels = np.array(train_generator.classes)
class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(class_labels), y=class_labels)
class_weight_dict = {i: class_weights[i] for i in range(len(class_weights))}


# Define ResNet model
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
base_model.trainable = False
```

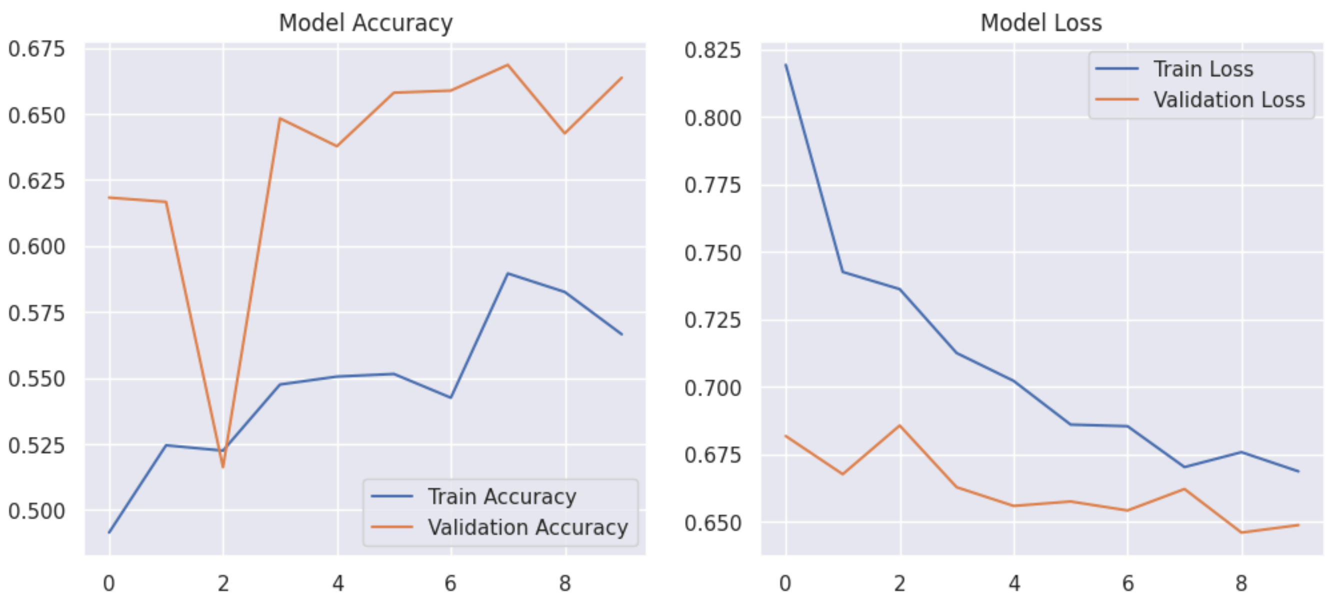
```
model = keras.Sequential([
    base_model,
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(1, activation='sigmoid')
])
```

```
from tensorflow.keras.optimizers import Adam
#Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='binary_crossentropy', metrics=['accuracy'])
```

```
# Train model
history = model.fit(
    train_generator,
    epochs=10,
    validation_data=test_generator,
    class_weight=class_weight_dict)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` c]
  self._warn_if_super_not_called()
Epoch 1/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 483s 15s/step - accuracy: 0.4873 - loss: 0.8619 - val_accuracy: 0.6183 - val_loss: 0.6818
Epoch 2/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 414s 12s/step - accuracy: 0.5169 - loss: 0.7536 - val_accuracy: 0.6167 - val_loss: 0.6677
Epoch 3/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 387s 12s/step - accuracy: 0.5167 - loss: 0.7378 - val_accuracy: 0.5162 - val_loss: 0.6857
Epoch 4/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 386s 12s/step - accuracy: 0.5606 - loss: 0.7103 - val_accuracy: 0.6483 - val_loss: 0.6629
Epoch 5/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 386s 12s/step - accuracy: 0.5302 - loss: 0.7150 - val_accuracy: 0.6378 - val_loss: 0.6560
Epoch 6/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 381s 12s/step - accuracy: 0.5521 - loss: 0.6833 - val_accuracy: 0.6580 - val_loss: 0.6576
Epoch 7/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 388s 12s/step - accuracy: 0.5246 - loss: 0.6927 - val_accuracy: 0.6588 - val_loss: 0.6543
Epoch 8/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 384s 12s/step - accuracy: 0.5854 - loss: 0.6733 - val_accuracy: 0.6686 - val_loss: 0.6622
Epoch 9/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 380s 12s/step - accuracy: 0.5947 - loss: 0.6744 - val_accuracy: 0.6426 - val_loss: 0.6461
Epoch 10/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 381s 12s/step - accuracy: 0.5694 - loss: 0.6741 - val_accuracy: 0.6637 - val_loss: 0.6489
```

```
# Plot accuracy and loss
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
axes[0].plot(history.history['accuracy'], label='Train Accuracy')
axes[0].plot(history.history['val_accuracy'], label='Validation Accuracy')
axes[0].set_title('Model Accuracy')
axes[0].legend()
axes[1].plot(history.history['loss'], label='Train Loss')
axes[1].plot(history.history['val_loss'], label='Validation Loss')
axes[1].set_title('Model Loss')
axes[1].legend()
plt.show()
```

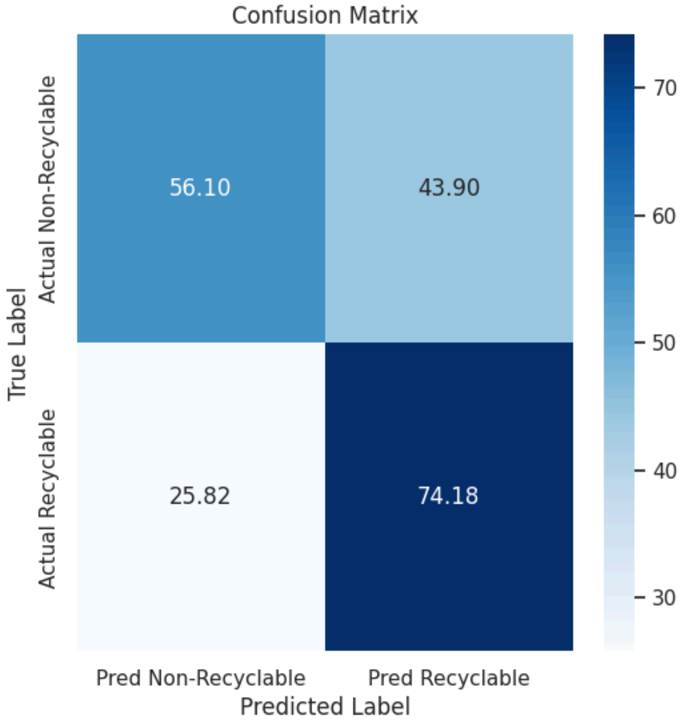


```
# Confusion matrix
y_true = test_generator.classes
y_pred = model.predict(test_generator) > 0.5
cm = confusion_matrix(y_true, y_pred)
```

```
39/39 ━━━━━━━━━━━━━━━━━━━━ 211s 5s/step
```

```
# Display confusion matrix with labels and percentages
fig, ax = plt.subplots(figsize=(6, 6))
cm_percent = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis] * 100
sns.heatmap(cm_percent, annot=True, fmt='.2f', cmap='Blues', xticklabels=['Pred Non-Recyclable', 'Pred Recyclable'],
            yticklabels=['Actual Non-Recyclable', 'Actual Recyclable'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
```

```
Text(0.5, 1.0, 'Confusion Matrix')
```




```
from sklearn.metrics import classification_report
# Classification report
print("Classification Report:")
print(classification_report(y_true, y_pred, target_names=['Non-Recyclable', 'Recyclable']))
```

```
Classification Report:
                precision    recall  f1-score   support

 Non-Recyclable       0.62      0.56      0.59       533
     Recyclable       0.69      0.74      0.71       701

       accuracy                           0.66      1234
      macro avg       0.66      0.65      0.65      1234
   weighted avg       0.66      0.66      0.66      1234
```

```
# Convert accuracy and loss to percentage
train_acc = [x * 100 for x in history.history['accuracy']]
val_acc = [x * 100 for x in history.history['val_accuracy']]
train_loss = [x * 100 for x in history.history['loss']]
val_loss = [x * 100 for x in history.history['val_loss']]
# Print accuracy and loss values
print("Final Training Accuracy: {:.2f}%".format(train_acc[-1]))
print("Final Validation Accuracy: {:.2f}%".format(val_acc[-1]))
print("Final Training Loss: {:.2f}%".format(train_loss[-1]))
print("Final Validation Loss: {:.2f}%".format(val_loss[-1]))
```

```
Final Training Accuracy: 56.66%
Final Validation Accuracy: 66.37%
Final Training Loss: 66.88%
Final Validation Loss: 64.89%
```