In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
```

In [2]:
```
dataset=tf.keras.preprocessing.image_dataset_from_directory("Waste")
```

```
Found 22564 files belonging to 2 classes.
```

IMPORTING LIBRARIES

In [3]:
```
import tensorflow as tf
from tensorflow.keras import models, layers
import matplotlib.pyplot as plt
```

DEFINING PARAMETERS

In [4]:
```
IMAGE_SIZE=(250,250)
BATCH_SIZE=200
CHANNELS=3
EPOCHS=15
```

IMPORTING DATA TO BE USED

In [5]:
```
dataset=tf.keras.preprocessing.image_dataset_from_directory(
    "Waste",
    shuffle=True,
    image_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE
)
```

```
Found 22564 files belonging to 2 classes.
```

GATHERING INSIGHTS

In [6]:
```
class_names=dataset.class_names
class_names
```

Out[6]:
```
['Organic', 'Recyclable']
```

In [7]:
```
len(dataset)
```

Out[7]:
```
113
```

In [8]:
```
for image_batch, label_batch in dataset.take(1):
    print(image_batch.shape)
    print(label_batch.numpy())
```

```
(200, 250, 250, 3)
[1 0 1 0 1 0 1 0 0 1 1 1 1 0 0 0 0 1 0 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0
 0 1 0 1 1 0 0 0 1 0 1 1 1 0 1 0 0 0 0 0 1 1 1 0 0 1 0 1 0 1 0 0 0 1 0 1 0
 1 1 1 0 1 0 1 0 0 0 1 0 0 1 1 1 1 0 1 0 0 0 1 0 1 0 0 1 1 1 0 0 0 0 0 0 0
 0 1 0 1 0 1 0 1 0 0 0 0 0 1 0 0 1 0 1 1 1 1 0 1 1 0 0 0 1 1 1 0 1 1 0 0 1
 0 0 1 0 0 0 0 1 0 0 1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 0 0 0 1 1 0 1 0 1 1 0 1
 1 1 1 1 0 0 1 0 1 0 0 0 1 1 0]
```

In [9]:
```
plt.figure(figsize=(10,10))
for image_batch, label_batch in dataset.take(1):
    for i in range(10):
        ax=plt.subplot(2,5,i+1)
        plt.imshow(image_batch[i].numpy().astype("uint8"))
        plt.title(class_names[label_batch[i]])
        plt.axis("off")
```

SPLITTING OF TRAINING AND TESTING DATA

In [10]:
```
len(dataset)
```
Out[10]: 113

In [11]:
```
train_size=0.8
len(dataset)*train_size
```
Out[11]: 90.4

In [12]:
```
train_ds=dataset.take(90)
len(train_ds)
```
Out[12]: 90

In [13]:
```
test_ds=dataset.skip(90)
len(test_ds)
```
Out[13]: 23

In [14]:
```
val_size=0.1
len(dataset)*val_size
```
Out[14]: 11.3

In [15]:
```
val_ds=test_ds.take(11)
len(val_ds)
```
Out[15]: 11

In [16]:
```
test_ds=test_ds.skip(11)
len(test_ds)
```
Out[16]: 12

DATA PRE-PROCESSING

In [17]:
```
train_ds=train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
val_ds=val_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
test_ds=test_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
```

In [18]:
```
resize_and_rescale=tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(250,250),
```

```
    layers.experimental.preprocessing.Rescaling(1.0/255)
])
```

In [19]:
```
data_augmentation=tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
    layers.experimental.preprocessing.RandomRotation(0.2),
])
```

CREATING CNN MODEL

In [20]:
```
input_shape=(BATCH_SIZE, 250, 250, CHANNELS)
n_classes=2

model=models.Sequential([
    resize_and_rescale,
    data_augmentation,
    layers.Conv2D(32, (3,3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, kernel_size= (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, kernel_size=(3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(32, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(32, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(32, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])

model.build(input_shape=input_shape)
```

In [21]:
```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 sequential (Sequential)     (200, 250, 250, 3)        0         
                                                                 
 sequential_1 (Sequential)   (200, 250, 250, 3)        0         
                                                                 
 conv2d (Conv2D)             (200, 248, 248, 32)       896       
                                                                 
 max_pooling2d (MaxPooling2  (200, 124, 124, 32)       0         
 D)                                                              
                                                                 
 conv2d_1 (Conv2D)           (200, 122, 122, 64)       18496     
                                                                 
 max_pooling2d_1 (MaxPoolin  (200, 61, 61, 64)         0         
 g2D)                                                            
                                                                 
 conv2d_2 (Conv2D)           (200, 59, 59, 64)         36928     
                                                                 
 max_pooling2d_2 (MaxPoolin  (200, 29, 29, 64)         0         
 g2D)                                                            
                                                                 
 conv2d_3 (Conv2D)           (200, 27, 27, 32)         18464     
                                                                 
 max_pooling2d_3 (MaxPoolin  (200, 13, 13, 32)         0         
 g2D)                                                            
                                                                 
 conv2d_4 (Conv2D)           (200, 11, 11, 32)         9248      
                                                                 
 max_pooling2d_4 (MaxPoolin  (200, 5, 5, 32)           0         
 g2D)                                                            
                                                                 
 conv2d_5 (Conv2D)           (200, 3, 3, 32)           9248      
                                                                 
 max_pooling2d_5 (MaxPoolin  (200, 1, 1, 32)           0         
 g2D)                                                            
                                                                 
 flatten (Flatten)           (200, 32)                 0         
                                                                 
 dense (Dense)               (200, 64)                 2112      
                                                                 
 dense_1 (Dense)             (200, 2)                  130       
                                                                 
=================================================================
Total params: 95522 (373.13 KB)
Trainable params: 95522 (373.13 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

MODEL TRAINING(FITTING)

In [22]:
```
model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),
    metrics=['accuracy']
)
```

In [23]:
```
history= model.fit(
    train_ds,
    epochs=EPOCHS,
    batch_size=BATCH_SIZE,
    verbose=1,
    validation_data=val_ds
)
```

```
Epoch 1/15
90/90 [==============================] - 1675s 18s/step - loss: 0.4927 - accuracy: 0.7743 - val_loss: 0.4336 - v
al_accuracy: 0.8223
Epoch 2/15
90/90 [==============================] - 1575s 17s/step - loss: 0.4345 - accuracy: 0.8065 - val_loss: 0.4003 - v
al_accuracy: 0.8259
Epoch 3/15
90/90 [==============================] - 1538s 17s/step - loss: 0.4185 - accuracy: 0.8148 - val_loss: 0.4143 - v
al_accuracy: 0.8168
Epoch 4/15
90/90 [==============================] - 1820s 20s/step - loss: 0.4069 - accuracy: 0.8231 - val_loss: 0.3824 - v
al_accuracy: 0.8432
Epoch 5/15
90/90 [==============================] - 1528s 17s/step - loss: 0.3997 - accuracy: 0.8252 - val_loss: 0.3798 - v
al_accuracy: 0.8368
Epoch 6/15
90/90 [==============================] - 1674s 19s/step - loss: 0.3848 - accuracy: 0.8322 - val_loss: 0.3666 - v
al_accuracy: 0.8523
Epoch 7/15
90/90 [==============================] - 1698s 19s/step - loss: 0.3811 - accuracy: 0.8333 - val_loss: 0.3606 - v
al_accuracy: 0.8509
Epoch 8/15
90/90 [==============================] - 1669s 19s/step - loss: 0.3679 - accuracy: 0.8420 - val_loss: 0.3543 - v
al_accuracy: 0.8614
Epoch 9/15
90/90 [==============================] - 1552s 17s/step - loss: 0.3689 - accuracy: 0.8444 - val_loss: 0.3839 - v
al_accuracy: 0.8282
Epoch 10/15
90/90 [==============================] - 1549s 17s/step - loss: 0.3651 - accuracy: 0.8443 - val_loss: 0.3420 - v
al_accuracy: 0.8591
Epoch 11/15
90/90 [==============================] - 1607s 18s/step - loss: 0.3490 - accuracy: 0.8519 - val_loss: 0.3853 - v
al_accuracy: 0.8391
Epoch 12/15
90/90 [==============================] - 1572s 17s/step - loss: 0.3403 - accuracy: 0.8557 - val_loss: 0.3442 - v
al_accuracy: 0.8627
Epoch 13/15
90/90 [==============================] - 1713s 19s/step - loss: 0.3445 - accuracy: 0.8531 - val_loss: 0.3342 - v
al_accuracy: 0.8673
Epoch 14/15
90/90 [==============================] - 1603s 18s/step - loss: 0.3385 - accuracy: 0.8580 - val_loss: 0.3204 - v
al_accuracy: 0.8686
Epoch 15/15
90/90 [==============================] - 9696s 109s/step - loss: 0.3365 - accuracy: 0.8583 - val_loss: 0.3202 -
val_accuracy: 0.8745
```

In [24]:
```
scores= model.evaluate(test_ds)
```

```
12/12 [==============================] - 42s 2s/step - loss: 0.3376 - accuracy: 0.8613
```

MODEL ACCURACY

INCREASING MODEL ACCURACY IS EASILY ACHIEVABLE BY RUNNING MORE EPOCHS, HOWEVER DUE TO TIME CONSTRAINTS AND AN INEFFICIENT SYSTEM,WE ARE UNABLE TO DO SO.

In [25]:
```
scores
```

Out[25]:
```
[0.3375517427921295, 0.8612521290779114]
```

history

In [27]:
```
history.params
```

Out[27]:
```
{'verbose': 1, 'epochs': 15, 'steps': 90}
```

In [28]:
```
history.history.keys()
```

Out[28]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [29]:
```
len(history.history['accuracy'])
```

Out[29]:
```
15
```

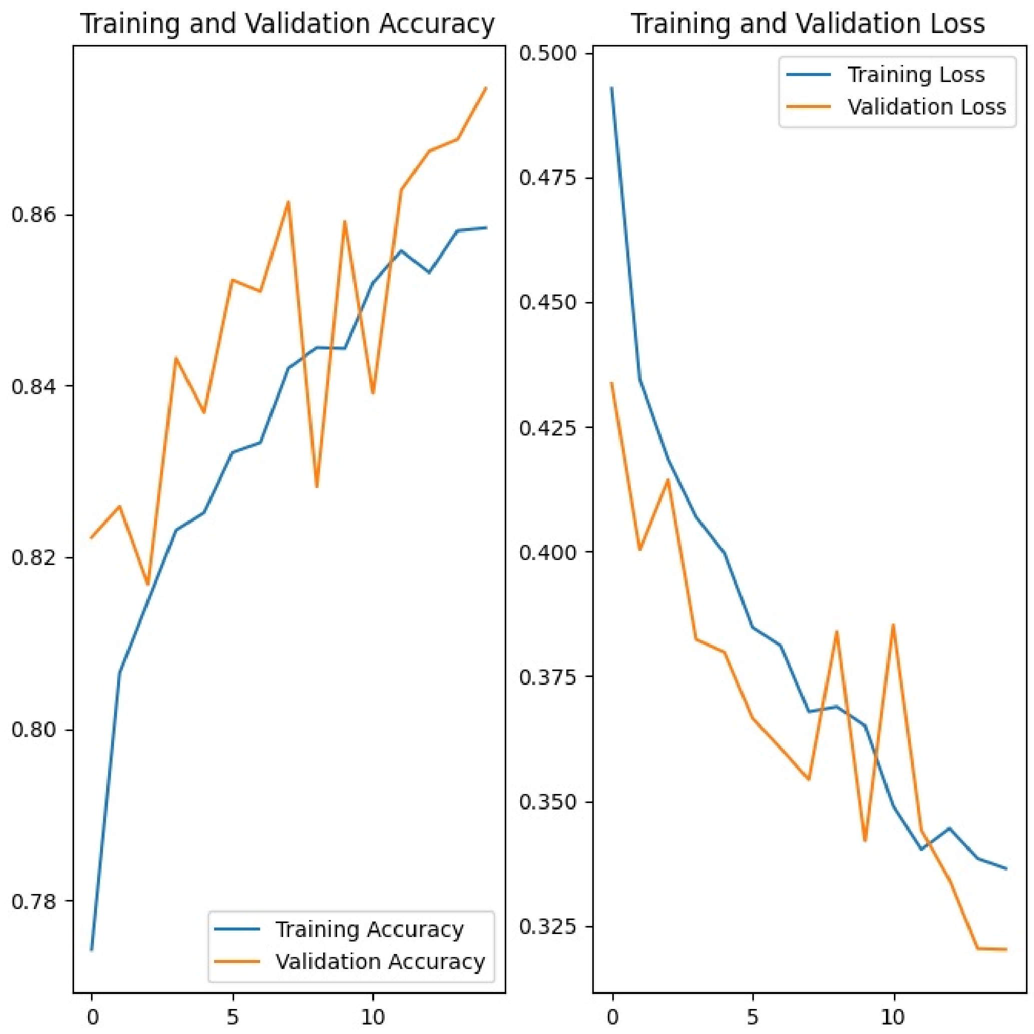
TRAINING DATA ACCURACY VS TESTING DATA ACCURACY

THIS GRAPH SUPPORTING MY ABOVE STATEMENT OF EASILY INCREASING ACCURACY AS WE CAN CLEARLY SEE IN GRAPH ACCURACY OF BOTH TESTING AND TRAINING DATA IS CONTINUOUSLY INCREASING ON RUNNING MORE AND MORE EPOCHS.

In [30]:
```
acc= history.history['accuracy']
```

```
val_acc= history.history['val_accuracy']
loss= history.history['loss']
val_loss= history.history['val_loss']
```

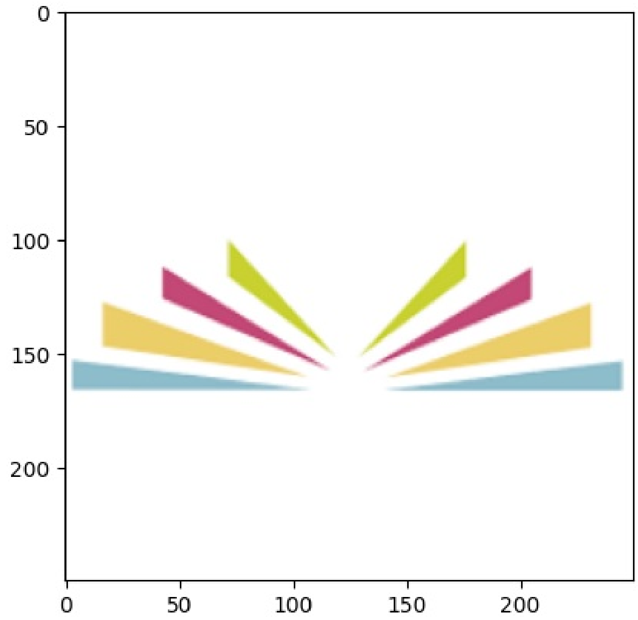
In [31]:
```
plt.figure(figsize=(8,8))
plt.subplot(1,2,1)
plt.plot(range(EPOCHS), acc, label='Training Accuracy')
plt.plot(range(EPOCHS), val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.subplot(1,2,2)
plt.plot(range(EPOCHS), loss, label='Training Loss')
plt.plot(range(EPOCHS), val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



MODEL PREDICTION ON TESTING DATA

In [35]:
```
for images_batch, labels_batch in test_ds.take(1):
    first_image= (images_batch[0].numpy().astype('uint8'))
    first_label= labels_batch[0].numpy()
    print("first image to predict")
    plt.imshow(first_image)
    print("first image's actual label:",class_names[first_label])
    batch_prediction= model.predict(images_batch)
    print("predicted label:",class_names[np.argmax(batch_prediction[0])])
```

```
first image to predict
first image's actual label: Recyclable
7/7 [==============================] - 2s 256ms/step
predicted label: Recyclable
```



In [36]:
```
import numpy as np
```

In [37]:
```
def predict(model, img):
   img_array= tf.keras.preprocessing.image.img_to_array(images[i].numpy())
   img_array= tf.expand_dims(img_array, 0)
   predictions= model.predict(img_array)
   predicted_class= class_names[np.argmax(predictions[0])]
   confidence= round(100*(np.max(predictions[0])), 2)
   return predicted_class, confidence
```

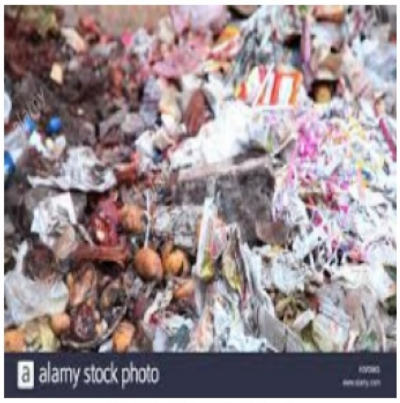
In [43]:
```
plt.figure(figsize=(15,15))
for images, labels in test_ds.take(1):
   for i in range(9):
      ax= plt.subplot(3,3,i+1)
      plt.imshow(images[i].numpy().astype("uint8"))
      predicted_class, confidence = predict(model, images[i].numpy())
      actual_class= class_names[labels[i]]
      plt.title(f"Actual: {actual_class},\n Predicted: {predicted_class}.\n Confidence: {confidence}%")
      plt.axis("off")
```

```
1/1 [==============================] - 0s 61ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 46ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 43ms/step
```

Actual: Organic,
Predicted: Recyclable.
Confidence: 72.01%

Actual: Recyclable,
Predicted: Organic.
Confidence: 89.64%

Actual: Organic,
Predicted: Recyclable.
Confidence: 56.2%



Actual: Organic,
Predicted: Organic.
Confidence: 79.99%

Actual: Recyclable,
Predicted: Recyclable.
Confidence: 94.94%

Actual: Recyclable,
Predicted: Recyclable.
Confidence: 77.98%

Actual: Organic,
Predicted: Recyclable.
Confidence: 93.85%

Actual: Recyclable,
Predicted: Recyclable.
Confidence: 52.46%

Actual: Recyclable,
Predicted: Recyclable.
Confidence: 97.09%

MODEL SAVING

In [42]:
```python
import pickle
```

In [44]:
```python
import pickle
with open("model_pickle",'wb') as file:
    pickle.dump(model,file)
```

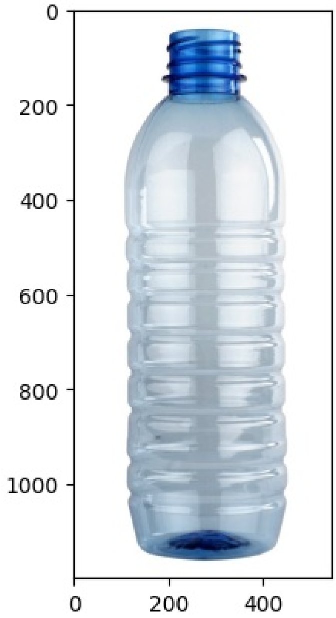
In [45]:
```
with open('model_pickle','rb') as f:
    model=pickle.load(f)
```

MODEL PREDICTION ON IMAGE TAKEN FROM GOOGLE

In [46]:
```
import cv2
```

In [59]:
```
m=plt.imread('plastic.jpg')
```

In [60]:
```
plt.imshow(m)
plt.show()
```



In [61]:
```
m.shape
```

Out[61]:
```
(1199, 547, 3)
```

In [63]:
```
m=cv2.resize(m,(256,256))
```

In [75]:
```
test=m.reshape((1,256,256,3))
```

In [80]:
```
predict(model, test)
```

```
1/1 [==============================] - 0s 147ms/step
```

Out[80]:
```
('Recyclable', 97.09)
```

In [83]:
```
n=plt.imread('OIP.jfif')
```

In [84]:
```
plt.imshow(n)
plt.show()
```

In [85]:
```
n.shape
```
Out[85]:
```
(270, 318, 3)
```
In [87]:
```
n=cv2.resize(m,(256,256))
```
In [92]:
```
test=n.reshape(1,256,256,3)
```
In [93]:
```
predict(model, test)
```
```
1/1 [==============================] - 0s 41ms/step
```
Out[93]:
```
('Recyclable', 97.09)
```
In [ ]:

In [ ]: