deep-cnn-image-classifier

February 16, 2024

1 Deep CNN Image Classifier with ANY Images.

1.0.1 1. Install Dependencies and Setup

[1]:
```
import tensorflow as tf
import os

# Avoid OOM errors by setting GPU Memory Consumption Growth
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
  tf.config.experimental.set_memory_growth(gpu, True)
```

[2]:
```
gpus
```

[2]:
```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

[3]:
```
gpus = tf.config.experimental.list_physical_devices('CPU')
gpus
```

[3]:
```
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU')]
```

1.1 2. Remove Dodgy images

[4]:
```
import cv2
import imghdr
```

[5]:
```
data_dir = 'drive/MyDrive/Project 13 Classification/data'
```

[6]:
```
# cheking no of images in the dataset
total_images = 0

# Loop over each subdirectory
for folder_name in os.listdir(data_dir):
    folder_path = os.path.join(data_dir, folder_name)

    # Ensure the path is a directory before counting images
    if os.path.isdir(folder_path):
```

```
        num_images = len(os.listdir(folder_path))
        total_images += num_images

print(f'Total number of images: {total_images}')
```

```
Total number of images: 225
```

[7]:
```
image_exts = ['jpeg','jpg','bmp','png']
```

This code is used to read and process images from a directory. It checks the file type of each image and deletes any images that are not of the expected file type or cannot be read.

[8]:
```
for image_class in os.listdir(data_dir):
  for image in os.listdir(os.path.join(data_dir, image_class)):
    image_path = os.path.join(data_dir, image_class, image)
    try:
      img = cv2.imread(image_path)
      tip = imghdr.what(image_path)
      if tip not in image_exts:
        print('Image not ext list {}'.format(image_path))
        os.remove(image_path)
    except Exception as e:
      print('Issue with image {}'.formt(image_path))
      os.remove(image_path)
```

1.1.1 3. Load Data

[9]:
```
import numpy as np
from matplotlib import pyplot as plt
```

[10]:
```
data = 'drive/MyDrive/Project 13 Classification/data'
```

Using the Keras.Utilit function to preprocess the data into shape and size that I need in its default formart

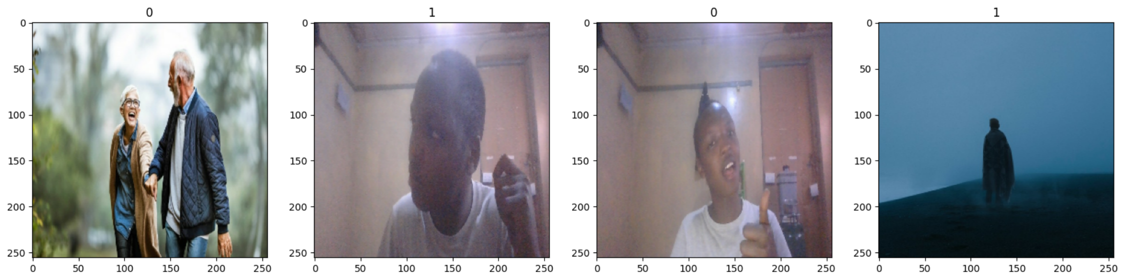
[11]:
```
data = tf.keras.utils.image_dataset_from_directory(data)
```

```
Found 225 files belonging to 2 classes.
```

[12]:
```
data_iterator = data.as_numpy_iterator()
```

[13]:
```
batch = data_iterator.next()
```

[14]:
```
fig, ax = plt.subplots(ncols = 4, figsize = (20,20))
for idx, img in enumerate(batch[0][:4]):
  ax[idx].imshow(img.astype(int))
  ax[idx].title.set_text(batch[1][idx])
```



1 represents Sad people and 0 represents Happy people

1.1.2 4. Scale The data

[15]:
```
data = data.map(lambda x, y: (x/255, y))
```

[16]:
```
data.as_numpy_iterator().next()
```

[16]:
```
(array([[[[0.08583793, 0.12127757, 0.23587623],
          [0.0723269 , 0.11285233, 0.25447303],
          [0.05271906, 0.10660999, 0.28235295],
          …,
          [0.1279565 , 0.1279565 , 0.2769761 ],
          [0.12941177, 0.12941177, 0.2714614 ],
          [0.12941177, 0.12941177, 0.27058825]],

         [[0.08583793, 0.11662266, 0.22897713],
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          …,
          [0.12612872, 0.12571232, 0.27556473],
          [0.12716758, 0.12716758, 0.26921722],
          [0.12716758, 0.12716758, 0.26834404]],

         [[0.09159287, 0.115437  , 0.22269455],
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         …,

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```

```
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```

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  …,
```

```
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```

```
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       0, 0, 1, 0, 1, 0, 0, 0, 0, 1], dtype=int32))
```

1.1.3 5. Split Data

[17]:
```
train_size = int(len(data)*.7)
val_size = int(len(data)*.2)
test_size = int(len(data)*.1)
```

[18]:
```
train_size
```

[18]: 5

[19]:
```
train = data.take(train_size)
val = data.skip(train_size).take(val_size)
test = data.skip(train_size + val_size).take(test_size)
```

1.2 6. Build Deep Learning Model

[20]:
```
train
```

[20]:
```
<_TakeDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32,
name=None))>
```

[21]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten,␣
↪Dropout
```

[22]:
```
model = Sequential()
```

[23]:
```
model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D())
model.add(Conv2D(32, (3,3), 1, activation='relu'))
model.add(MaxPooling2D())
model.add(Conv2D(16, (3,3), 1, activation='relu'))
model.add(MaxPooling2D())
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

[24]:
```
# Compiling the model
model.compile('adam', loss=tf.losses.BinaryCrossentropy(), metrics=['accuracy'])
```

[25]:
```
# Models summary
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 16)      448

 max_pooling2d (MaxPooling2  (None, 127, 127, 16)      0
 D)

 conv2d_1 (Conv2D)           (None, 125, 125, 32)      4640

 max_pooling2d_1 (MaxPoolin  (None, 62, 62, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 16)        4624

 max_pooling2d_2 (MaxPoolin  (None, 30, 30, 16)        0
 g2D)

 flatten (Flatten)           (None, 14400)             0

 dense (Dense)               (None, 256)               3686656

 dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 3696625 (14.10 MB)
Trainable params: 3696625 (14.10 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

1.3 7. Train

[26]:
```
#save the view the logs
logdir = 'logs'
```

[27]:
```
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir = logdir)
```

[28]:
```
hist = model.fit(train, epochs = 60, validation_data = val, callbacks =␣
↪[tensorboard_callback])
```

```
Epoch 1/60
5/5 [==============================] - 12s 877ms/step - loss: 1.3285 - accuracy:
0.5375 - val_loss: 1.1755 - val_accuracy: 0.3750
Epoch 2/60
5/5 [==============================] - 6s 820ms/step - loss: 0.8052 - accuracy:
0.5375 - val_loss: 0.6359 - val_accuracy: 0.6562
Epoch 3/60
5/5 [==============================] - 8s 850ms/step - loss: 0.7123 - accuracy:
0.5625 - val_loss: 0.6619 - val_accuracy: 0.5938
Epoch 4/60
```

```
5/5 [==============================] - 8s 1s/step - loss: 0.6366 - accuracy:
0.6187 - val_loss: 0.5146 - val_accuracy: 0.7812
Epoch 5/60
5/5 [==============================] - 7s 840ms/step - loss: 0.6036 - accuracy:
0.5875 - val_loss: 0.5359 - val_accuracy: 0.6875
Epoch 6/60
5/5 [==============================] - 9s 1s/step - loss: 0.5356 - accuracy:
0.7125 - val_loss: 0.5782 - val_accuracy: 0.5938
Epoch 7/60
5/5 [==============================] - 6s 826ms/step - loss: 0.4605 - accuracy:
0.7688 - val_loss: 0.3986 - val_accuracy: 0.7500
Epoch 8/60
5/5 [==============================] - 10s 1s/step - loss: 0.3928 - accuracy:
0.8313 - val_loss: 0.3784 - val_accuracy: 0.8125
Epoch 9/60
5/5 [==============================] - 8s 1s/step - loss: 0.3527 - accuracy:
0.8125 - val_loss: 0.2903 - val_accuracy: 0.9062
Epoch 10/60
5/5 [==============================] - 8s 1s/step - loss: 0.3291 - accuracy:
0.8625 - val_loss: 0.2573 - val_accuracy: 0.8750
Epoch 11/60
5/5 [==============================] - 8s 940ms/step - loss: 0.2518 - accuracy:
0.9375 - val_loss: 0.1856 - val_accuracy: 0.9375
Epoch 12/60
5/5 [==============================] - 9s 1s/step - loss: 0.2275 - accuracy:
0.9187 - val_loss: 0.1235 - val_accuracy: 0.9375
Epoch 13/60
5/5 [==============================] - 8s 1s/step - loss: 0.1761 - accuracy:
0.9125 - val_loss: 0.1292 - val_accuracy: 0.9062
Epoch 14/60
5/5 [==============================] - 6s 828ms/step - loss: 0.1685 - accuracy:
0.9500 - val_loss: 0.1338 - val_accuracy: 0.9375
Epoch 15/60
5/5 [==============================] - 7s 1s/step - loss: 0.1241 - accuracy:
0.9375 - val_loss: 0.1961 - val_accuracy: 0.8750
Epoch 16/60
5/5 [==============================] - 8s 1s/step - loss: 0.1392 - accuracy:
0.9312 - val_loss: 0.0911 - val_accuracy: 0.9688
Epoch 17/60
5/5 [==============================] - 7s 849ms/step - loss: 0.1219 - accuracy:
0.9438 - val_loss: 0.0902 - val_accuracy: 0.9688
Epoch 18/60
5/5 [==============================] - 8s 1s/step - loss: 0.0904 - accuracy:
0.9750 - val_loss: 0.0655 - val_accuracy: 1.0000
Epoch 19/60
5/5 [==============================] - 7s 842ms/step - loss: 0.0767 - accuracy:
0.9688 - val_loss: 0.0686 - val_accuracy: 0.9688
Epoch 20/60
```

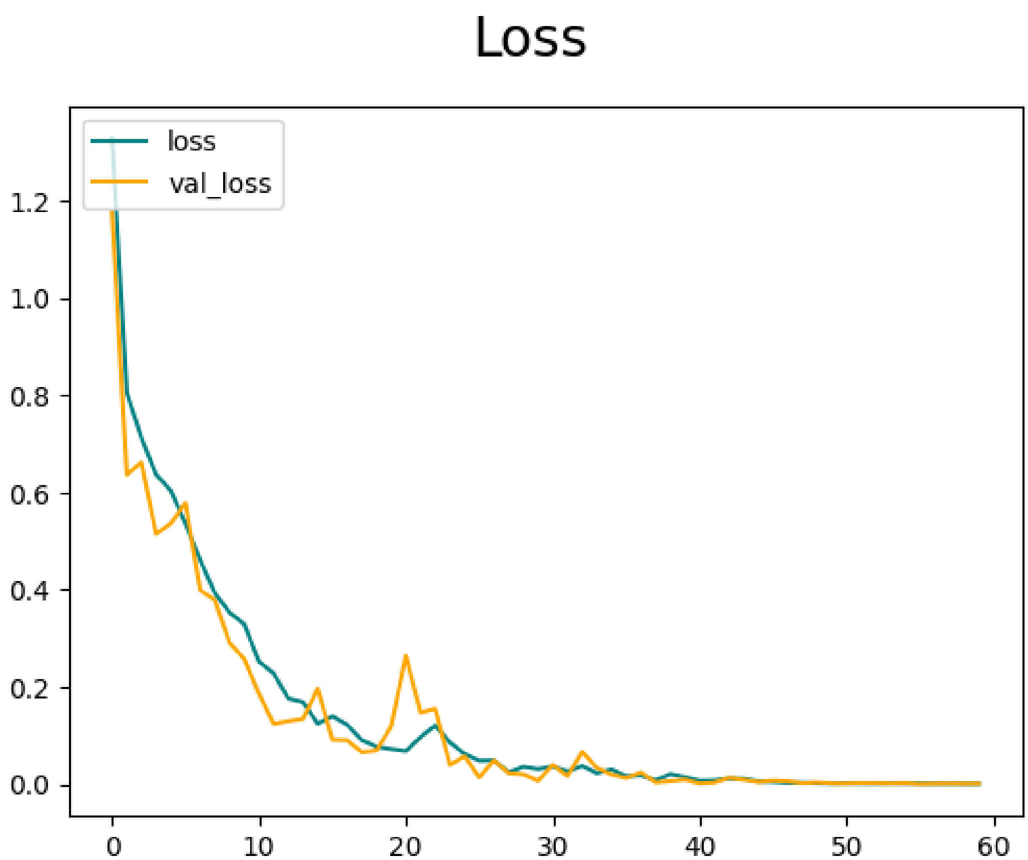
```
5/5 [==============================] - 7s 1s/step - loss: 0.0718 - accuracy:
0.9750 - val_loss: 0.1184 - val_accuracy: 0.9062
Epoch 21/60
5/5 [==============================] - 6s 857ms/step - loss: 0.0676 - accuracy:
0.9688 - val_loss: 0.2638 - val_accuracy: 0.8125
Epoch 22/60
5/5 [==============================] - 8s 953ms/step - loss: 0.0964 - accuracy:
0.9750 - val_loss: 0.1467 - val_accuracy: 1.0000
Epoch 23/60
5/5 [==============================] - 9s 1s/step - loss: 0.1204 - accuracy:
0.9750 - val_loss: 0.1550 - val_accuracy: 0.9062
Epoch 24/60
5/5 [==============================] - 6s 826ms/step - loss: 0.0857 - accuracy:
0.9812 - val_loss: 0.0392 - val_accuracy: 1.0000
Epoch 25/60
5/5 [==============================] - 7s 1s/step - loss: 0.0617 - accuracy:
0.9750 - val_loss: 0.0569 - val_accuracy: 1.0000
Epoch 26/60
5/5 [==============================] - 6s 837ms/step - loss: 0.0482 - accuracy:
0.9937 - val_loss: 0.0135 - val_accuracy: 1.0000
Epoch 27/60
5/5 [==============================] - 7s 998ms/step - loss: 0.0488 - accuracy:
0.9937 - val_loss: 0.0490 - val_accuracy: 1.0000
Epoch 28/60
5/5 [==============================] - 8s 1s/step - loss: 0.0237 - accuracy:
1.0000 - val_loss: 0.0221 - val_accuracy: 1.0000
Epoch 29/60
5/5 [==============================] - 6s 821ms/step - loss: 0.0355 - accuracy:
0.9875 - val_loss: 0.0199 - val_accuracy: 1.0000
Epoch 30/60
5/5 [==============================] - 7s 1s/step - loss: 0.0308 - accuracy:
0.9937 - val_loss: 0.0065 - val_accuracy: 1.0000
Epoch 31/60
5/5 [==============================] - 6s 841ms/step - loss: 0.0362 - accuracy:
0.9937 - val_loss: 0.0394 - val_accuracy: 1.0000
Epoch 32/60
5/5 [==============================] - 7s 999ms/step - loss: 0.0258 - accuracy:
0.9937 - val_loss: 0.0161 - val_accuracy: 1.0000
Epoch 33/60
5/5 [==============================] - 6s 822ms/step - loss: 0.0373 - accuracy:
0.9875 - val_loss: 0.0664 - val_accuracy: 0.9688
Epoch 34/60
5/5 [==============================] - 8s 901ms/step - loss: 0.0224 - accuracy:
1.0000 - val_loss: 0.0334 - val_accuracy: 1.0000
Epoch 35/60
5/5 [==============================] - 6s 826ms/step - loss: 0.0299 - accuracy:
0.9875 - val_loss: 0.0194 - val_accuracy: 1.0000
Epoch 36/60
```

```
5/5 [==============================] - 7s 822ms/step - loss: 0.0161 - accuracy:
0.9937 - val_loss: 0.0125 - val_accuracy: 1.0000
Epoch 37/60
5/5 [==============================] - 7s 864ms/step - loss: 0.0177 - accuracy:
0.9937 - val_loss: 0.0236 - val_accuracy: 1.0000
Epoch 38/60
5/5 [==============================] - 7s 847ms/step - loss: 0.0078 - accuracy:
1.0000 - val_loss: 0.0035 - val_accuracy: 1.0000
Epoch 39/60
5/5 [==============================] - 9s 1s/step - loss: 0.0202 - accuracy:
0.9937 - val_loss: 0.0060 - val_accuracy: 1.0000
Epoch 40/60
5/5 [==============================] - 6s 844ms/step - loss: 0.0143 - accuracy:
1.0000 - val_loss: 0.0091 - val_accuracy: 1.0000
Epoch 41/60
5/5 [==============================] - 9s 1s/step - loss: 0.0067 - accuracy:
1.0000 - val_loss: 0.0013 - val_accuracy: 1.0000
Epoch 42/60
5/5 [==============================] - 6s 826ms/step - loss: 0.0074 - accuracy:
1.0000 - val_loss: 0.0032 - val_accuracy: 1.0000
Epoch 43/60
5/5 [==============================] - 9s 1s/step - loss: 0.0114 - accuracy:
1.0000 - val_loss: 0.0129 - val_accuracy: 1.0000
Epoch 44/60
5/5 [==============================] - 7s 1s/step - loss: 0.0108 - accuracy:
1.0000 - val_loss: 0.0088 - val_accuracy: 1.0000
Epoch 45/60
5/5 [==============================] - 6s 830ms/step - loss: 0.0054 - accuracy:
1.0000 - val_loss: 0.0044 - val_accuracy: 1.0000
Epoch 46/60
5/5 [==============================] - 7s 1s/step - loss: 0.0047 - accuracy:
1.0000 - val_loss: 0.0070 - val_accuracy: 1.0000
Epoch 47/60
5/5 [==============================] - 6s 817ms/step - loss: 0.0026 - accuracy:
1.0000 - val_loss: 0.0057 - val_accuracy: 1.0000
Epoch 48/60
5/5 [==============================] - 9s 1s/step - loss: 0.0028 - accuracy:
1.0000 - val_loss: 0.0018 - val_accuracy: 1.0000
Epoch 49/60
5/5 [==============================] - 8s 1s/step - loss: 0.0018 - accuracy:
1.0000 - val_loss: 0.0033 - val_accuracy: 1.0000
Epoch 50/60
5/5 [==============================] - 7s 834ms/step - loss: 0.0013 - accuracy:
1.0000 - val_loss: 0.0016 - val_accuracy: 1.0000
Epoch 51/60
5/5 [==============================] - 8s 1s/step - loss: 0.0017 - accuracy:
1.0000 - val_loss: 0.0013 - val_accuracy: 1.0000
Epoch 52/60
```

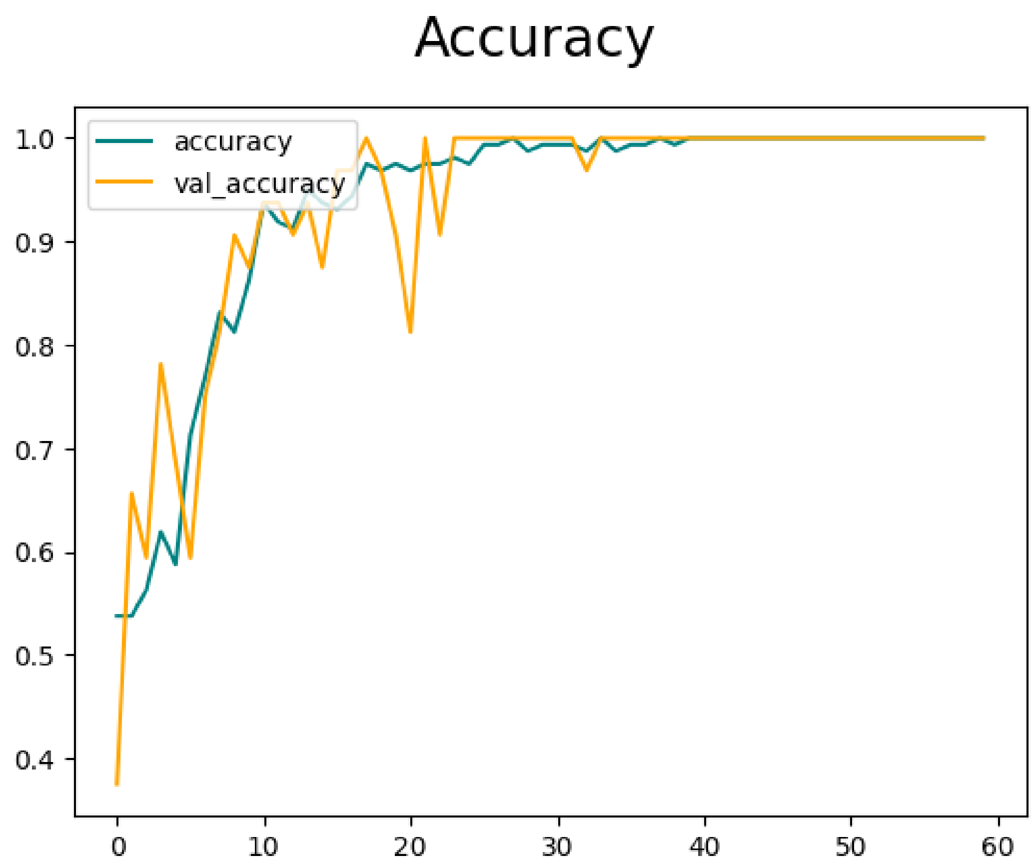
```
5/5 [==============================] - 6s 834ms/step - loss: 0.0013 - accuracy:
1.0000 - val_loss: 0.0020 - val_accuracy: 1.0000
Epoch 53/60
5/5 [==============================] - 7s 830ms/step - loss: 0.0011 - accuracy:
1.0000 - val_loss: 0.0017 - val_accuracy: 1.0000
Epoch 54/60
5/5 [==============================] - 7s 1s/step - loss: 0.0016 - accuracy:
1.0000 - val_loss: 0.0014 - val_accuracy: 1.0000
Epoch 55/60
5/5 [==============================] - 6s 830ms/step - loss: 0.0013 - accuracy:
1.0000 - val_loss: 0.0018 - val_accuracy: 1.0000
Epoch 56/60
5/5 [==============================] - 8s 1s/step - loss: 0.0012 - accuracy:
1.0000 - val_loss: 2.4022e-04 - val_accuracy: 1.0000
Epoch 57/60
5/5 [==============================] - 7s 835ms/step - loss: 9.6568e-04 -
accuracy: 1.0000 - val_loss: 9.5465e-04 - val_accuracy: 1.0000
Epoch 58/60
5/5 [==============================] - 7s 841ms/step - loss: 9.1853e-04 -
accuracy: 1.0000 - val_loss: 0.0012 - val_accuracy: 1.0000
Epoch 59/60
5/5 [==============================] - 8s 1s/step - loss: 7.4237e-04 - accuracy:
1.0000 - val_loss: 9.1980e-04 - val_accuracy: 1.0000
Epoch 60/60
5/5 [==============================] - 7s 837ms/step - loss: 5.8313e-04 -
accuracy: 1.0000 - val_loss: 9.6101e-04 - val_accuracy: 1.0000
```

1.4 Plot Performance

[29]:
```
fig = plt.figure()
plt.plot(hist.history['loss'], color='teal', label='loss')
plt.plot(hist.history['val_loss'], color='orange', label='val_loss')
fig.suptitle('Loss', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```



[30]:
```
fig = plt.figure()
plt.plot(hist.history['accuracy'], color='teal', label='accuracy')
plt.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')
fig.suptitle('Accuracy', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```



1.5 Evaluate

[31]:
```
from tensorflow.keras.metrics import Precision, Recall, BinaryAccuracy
```

[32]:
```
pre = Precision()
re = Recall()
acc = BinaryAccuracy()
```

[33]:
```
for batch in test.as_numpy_iterator():
    X, y = batch
    yhat = model.predict(X)
    pre.update_state(y, yhat)
    re.update_state(y, yhat)
    acc.update_state(y, yhat)
```

[34]:
```
print(pre.result(), re.result(), acc.result())
```

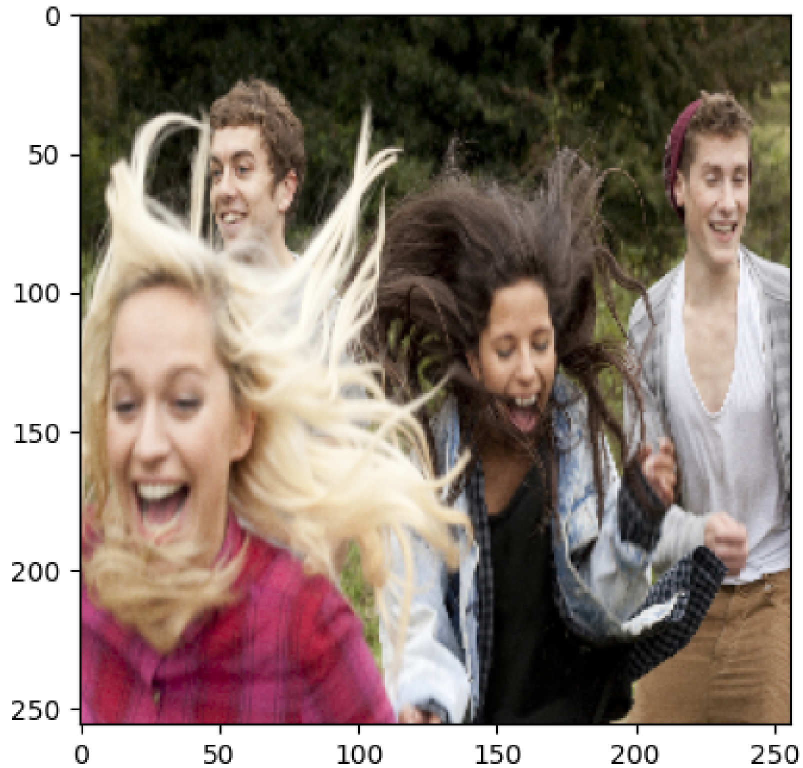
```
tf.Tensor(0.0, shape=(), dtype=float32) tf.Tensor(0.0, shape=(), dtype=float32)
tf.Tensor(0.0, shape=(), dtype=float32)
```

1.6 10. Test

[35]:
```
import cv2
```

[36]:
```
img = cv2.imread('drive/MyDrive/Project 13 Classification/154006829.jpg')
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
if img is None:
    print("Image not loaded")
else:
    plt.imshow(img)
    plt.show()
```

[37]:
```
resize =tf.image.resize(img, (256,256))
plt.imshow(resize.numpy().astype(int))
plt.show()
```



[38]:
```
yhat = model.predict(np.expand_dims(resize/255, 0))
```

```
1/1 [==============================] - 0s 323ms/step
```

[39]:
```
yhat
```

[39]:
```
array([[7.7254776e-07]], dtype=float32)
```

[40]:
```
if yhat > 0.5:
  print(f'Predicted class is Sad')
else:
  print (f'Predicted Class is happy')
```

```
Predicted Class is happy
```

Function for predicting images if happy or sad

[41]:
```
def predict_emotion(image_path, model):
    # Load and convert the image
    img = cv2.imread(image_path)
    if img is None:
        print("Image not loaded")
        return
```

```
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

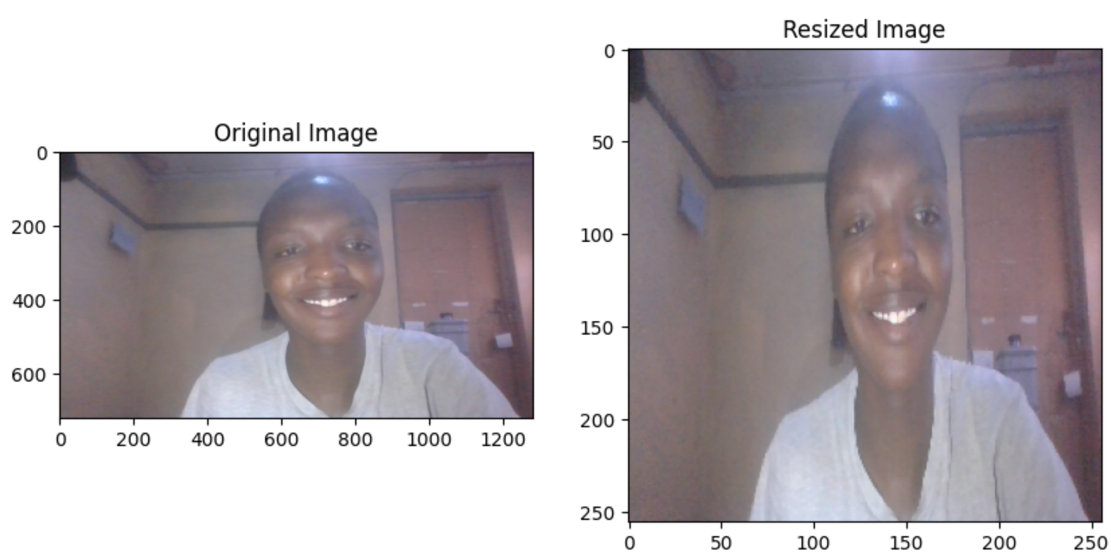
    # Resize the image
    resize = tf.image.resize(img, (256,256))

    # Predict the class
    yhat = model.predict(np.expand_dims(resize/255, 0))
    print(yhat)
    if yhat > 0.5:
        print('Predicted class is Sad')
    else:
        print('Predicted class is Happy')

    # Show the original and resized images
    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.imshow(img)
    plt.title('Original Image')
    plt.subplot(1, 2, 2)
    plt.imshow(resize.numpy().astype(int))
    plt.title('Resized Image')
    plt.show()
```

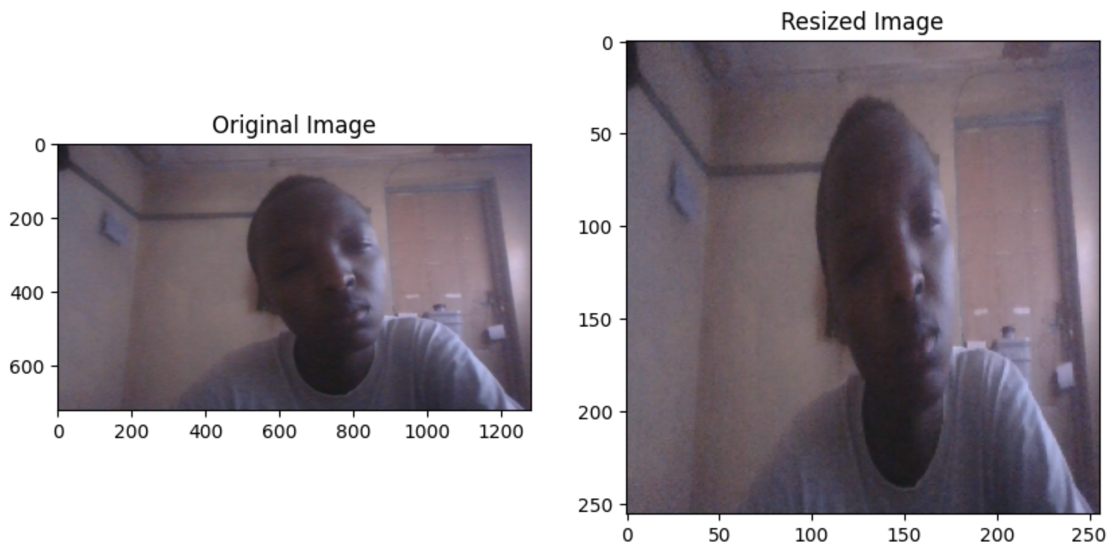
[42]:
```
image_path = 'drive/MyDrive/Project 13 Classification/WIN_20240216_13_46_13_Pro.
 ↪jpg'
predict_emotion(image_path, model)
```

```
1/1 [==============================] - 0s 36ms/step
[[0.00483828]]
Predicted class is Happy
```



```
[43]: image_path = 'drive/MyDrive/Project 13 Classification/WIN_20240216_13_14_07_Pro.
        ↪jpg'
      predict_emotion(image_path, model)
```

```
1/1 [==============================] - 0s 18ms/step
[[0.71629643]]
Predicted class is Sad
```



1.7 Save The Model

```
[44]: from tensorflow.keras.models import load_model
```

```
[45]: model.save(os.path.join('models', 'drive/MyDrive/Project 13 Classification/
        ↪model/imageclassifier.h5'))
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103:
UserWarning: You are saving your model as an HDF5 file via `model.save()`. This
file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```