HAPPY-SAD MODEL CLASSIFIER

Todo: Create a model that Classfier Happy and Sad People

- BUILDING A DATA PIPELINE
- PREPROCESSING IMAGES FOR DL
- CREATING A DEEP NN CLASSIFIER
- EVALUATING MODEL PERFORMANCE
- SAVING THE MODEL FOR DEPLOYMENT

1. Install Dependencies and Setup

```
# pip install numpy --upgrade
# !pip list
```

+ Code + Text

```
import tensorflow as tf
import os
```

```
# gpus = tf.config.experimental.list_physical_devices('GPU')
#for gpu in gpus:
#    tf.config.experimental.set_memory_growth(gpu, True)
```

```
tf.config.list_physical_devices('GPU')
```

```
[]
```

1.2. Remove dodgy images

```
import cv2
import imghdr # Use to check for the image type
import PIL.Image as Image
import matplotlib.pyplot as plt
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Input In [2], in <cell line: 1>()
----> 1 import cv2
      2 import imghdr # Use to check for the image type
      3 import PIL.Image as Image

ModuleNotFoundError: No module named 'cv2'
```

```
data_dir = 'data'
```

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

```
os.listdir('data'), os.path.join('data', 'happy' )
```

```
(['.ipynb_checkpoints',
  'happy',
  'images.jpg',
  'images2.jpg',
  'images3.jpeg',
  'sad'],
 'data\\happy')
```

```
for image_class in os.listdir(data_dir):
    print(image_class)
```

```
.ipynb_checkpoints
happy
images.jpg
images2.jpg
images3.jpeg
sad
```

```
# To get every image in the folrder

os.listdir(os.path.join(data_dir, 'sad' ))
# This return all photos in the happy folder
```

```
['-unhappy-miss-good-chance-dressed-casually-isolated-yellow-wall_273609-37534.jpg',
 '1000_F_124527256_XeXO1Q7xiE39ZcnuCOHTCotlj7p1FYwc.jpg',
 '1000_F_233515059_A3JEmjWEgLcwOAc7aNxa6k3SDXjvvBgv.jpg',
 '12165734.jpg',
 '141203-depression-stock.jpg',
 '360_F_548848756_IlV9Y9HV8chb6mSuc3PBamYRT9gIn8Vo.jpg',
 '360_F_573380015_l5YdjSZuJqET7UWOHBVMhzT7J63O8hPq.jpg',
 '360_F_601507482_RbV0Vk2KSg72LkjkSZBJNpmxu6Y4Hdzw.jpg',
 '39843138-sad-man.jpg',
 '5acf9ed1146e711e008b46d7.jpg',
 '73705bd7debb66c2afc780a22c223804.jpg',
 '7RNXwSxCAKL8vGtXG2ZkyD-1200-80.jpg',
 '8iAb9k4aT.jpg',
 '960x0.jpg',
 'b2ap3_large_happy-sad-unsplash-850x575.jpg',
 'crying-at-work.jpg',
 'DealingwithDepressionwithoutMedication-1.jpg',
 'depressed-man.jpg',
 'depressed-person-standing-alone-bench_23-2150761438.jpg',
 'depression-1020x680.jpg',
 'depression-sad-mood-sorrow-dark-people-wallpaper-7.jpg',
 'Depression-Vs-Sadness-Are-You-Just-Sad-Or-Depressed-2020-960x640.jpg',
 'dreamstime_m_169987253.jpg',
 'dreamstime_s_101440985.jpg',
 'flat-design-sad-person-silhouette_23-2150388109.jpg',
 'image-20160914-4963-19knfh1.jpg',
 'image-asset.jpeg',
 'image22.jpeg',
 'images30.jpg',
 'images42.jpg',
 'images51.jpg',
 'ing-sad-people-worried-people-depression-alone-portrait-woman-girl-thumbnail.png',
 'iStock_000001932580XSmall.jpg',
 'jack-lucas-smith-Zxq0dvmRyIo-unsplash-1024x701.jpg',
 'l-person-disappointed-of-corporate-job-fail-or-mistake-in-studio-fit_400_400.jpg',
 'lonely-depressed-person-sitting-near-brick-wall_181624-30778.jpg',
 'lonely-young-woman-in-the-rain-feeling-sadness-and-hopelessness-generated-by-ai-photo.jpg',
 'Make-someone-sad-happy.jpg',
 'man-sat-bent-his-knees-holding-his-hands-face-base-tree-there-is-water-around_1150-16341.jpg',
 'man-sits-bench-front-cityscape_818261-431.jpg',
 'man-tears-tear-look.jpg',
 'man-with-head-down-300x300.jpg',
 'n-rendering-frustrated-upset-man-sitting-white-people-man-character-53250684.jpg',
 'old-woman-sad-emotions-home-loneliness-89781840.jpg',
 'orried-people-thinking-depression-alone-microphone-finger-shoulder-thumbnail.png',
 'person-super-depressed.jpg',
 'pngtree-woman-looking-sad-in-black-and-white-picture-image_2770858.jpg',
 'pngtree-woman-looking-sad-in-the-rain-picture-image_2771069.jpg',
 'portrait-sensitive-man_23-2149444529.jpg',
 'sad-depressed-man-702x375.jpg',
 'sad-group-people-problems-17033671.jpg',
 'Sad-man-being-consoled-by-friends-in-group-therapy.jpg',
 'sad-people-vector-26812552.jpg',
 'sad-people-worried-people-thinking-depression-alone-shoulder-sitting-joint-png-clipart.jpg',
 'Sad-People.jpg',
 'sad-person-concept-vector-26538685.jpg',
 'sad-wise-woman-at-window.jpg',
 'sad.jpg',
```

```
Image.open(os.path.join(data_dir, 'happy', '1-2.jpg'))
```

```
img = cv2.imread(os.path.join(data_dir, 'happy', '1-2.jpg'))
img.shape
```

```
(350, 590, 3)
```

```
type(img)
```

```
numpy.ndarray
```

```
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.show()
```


```
os.path.join(data_dir, image_class)
os.listdir(data_dir)
#os.path.join(data_dir, image_class)

#for image_class in os.listdir(data_dir):
 #   print(image_class)
    #else:
     #   print(os.listdir(data_dir))
```

```
['.ipynb_checkpoints',
 'happy',
 'images.jpg',
 'images2.jpg',
 'images3.jpeg',
 'sad']
```

```
for image_class in os.listdir(data_dir):
    if '.jp' in image_class:
        continue
    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 in ext list {}'.format(image_path))
                os.remove(image_path)
        except Exception as e:
            print('Issue with image {}'.format(image_path))
            # os.remove(image_path)
```

```
Image not in ext list data\happy\German-Shepherd.webp
```

1.3. Load Data

```
# tf.data.Dataset??
import numpy as np
```

```
# Use to load the data and group them into batch
tf.keras.utils.image_dataset_from_directory(data_dir)     # Abt
```

```
Found 163 files belonging to 2 classes.
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,),
dtype=tf.int32, name=None))>
```

```
# It resize, batch
data =tf.keras.utils.image_dataset_from_directory(data_dir)
# this return a generator, it have to be iterate to get the data
```

```
Found 163 files belonging to 2 classes.
```

```
len(data)
```

```
6
```

```
for i in data:
    print(i)
```

```
(<tf.Tensor: shape=(32, 256, 256, 3), dtype=float32, numpy=
array([[[[180.60938   , 145.92188   ,  17.390625  ],
         [149.125     , 109.578125  ,   0.        ],
         [146.98438   , 100.828125  ,   0.        ],
         ...,
         [121.71875   ,  96.4375    ,  28.328125  ],
         [128.23438   ,  98.8125    ,   7.15625   ],
         [151.90625   , 120.734375  ,   6.96875   ]],

        [[182.07727   , 146.19287   ,  18.587524  ],
         [153.81097   , 113.89148   ,   1.6767883 ],
         [152.56238   , 105.68347   ,   3.8729858 ],
         ...,
         [114.33411   ,  89.36337   ,  22.12909   ],
         [122.266815  ,  93.369995  ,   4.5704956 ],
         [147.3219    , 116.63556   ,   4.7499695 ]],

        [[184.41003   , 146.62354   ,  20.489624  ],
         [161.25787   , 120.746216  ,   4.341522  ],
         [161.42688   , 113.399536  ,  10.027893  ],
         ...,
         [102.59851   ,  78.12125   ,  12.277649  ],
         [112.78323   ,  84.720825  ,   0.46124268],
         [140.0365    , 110.121765  ,   1.2239075 ]],

        ...,

        [[ 81.46289   ,  75.634766  ,  23.065094  ],
         [ 80.80466   ,  75.80466   ,  18.871094  ],
         [ 87.75781   ,  83.61719   ,  21.449219  ],
         ...,
         [165.26437   , 119.93945   ,   0.43304443],
         [179.39655   , 131.4238    ,   1.6344299 ],
         [197.25845   , 147.9909    ,   9.5494995 ]],

        [[ 79.740234  ,  73.91211   ,  22.392181  ],
         [ 78.78592   ,  73.78592   ,  17.722656  ],
         [ 85.46094   ,  81.32031   ,  20.300781  ],
         ...,
         [176.668     , 129.70117   ,   4.2910767 ],
         [189.75043   , 141.46365   ,   7.565033  ],
         [207.4957    , 157.3758    ,  17.78595   ]],

        [[ 78.65625   ,  72.828125  ,  21.96875   ],
         [ 77.515625  ,  72.515625  ,  17.        ],
         [ 84.015625  ,  79.875     ,  19.578125  ],
         ...,
         [183.84375   , 135.84375   ,   6.71875   ],
         [196.26562   , 147.78125   ,  11.296875  ],
         [213.9375    , 163.28125   ,  22.96875   ]]],


       [[[144.22021   , 139.16895   , 138.28418   ],
         [ 95.23291   ,  94.25488   ,  92.88818   ],
         [ 51.01709   ,  72.21387   ,  32.32715   ],
         ...,
         [ 76.58057   ,  93.293945  ,  56.845703  ],
         [ 51.228516  ,  72.978516  ,  24.251953  ],
```

```
data_iterator = data.as_numpy_iterator()
data_iterator
```

```
<tensorflow.python.data.ops.dataset_ops.NumpyIterator at 0x1c3592f9f40>
```

```
# Get batch of data(Image)
batch = data_iterator.next()
```

```
len(batch)
# 1st is for image and
# 2nd is for the label(folder)
```

```
2
```

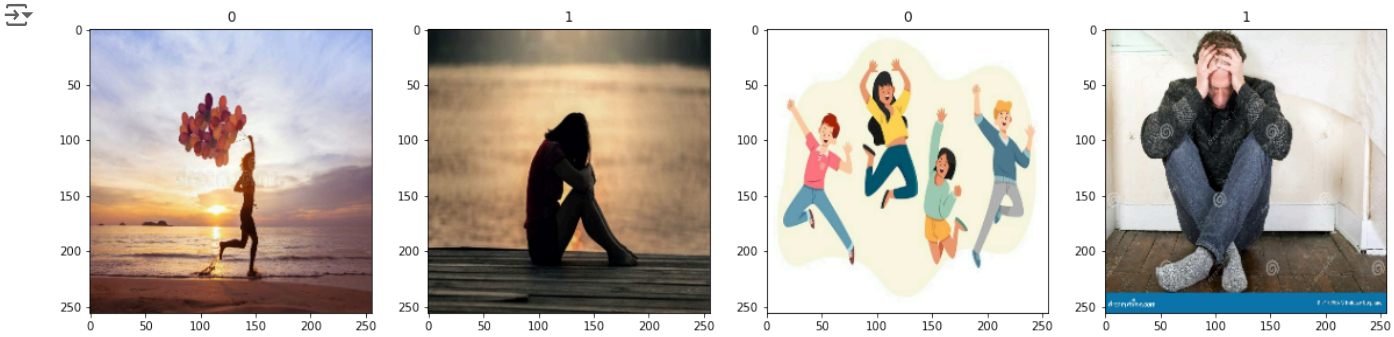
```
# Images represented as numpy array
batch[0].shape
```

```
(32, 256, 256, 3)
```

```
# Label representation
#Class 1 = SAD People
#Class 2 = HAPPY People
batch[1]
```

```
array([0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 0])
```

```
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])
```



2. Preprocess Data

2.1. Scale Data

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

```
data.as_numpy_iterator().next()[0].max()
```

```
1.0
```

```
data
```

```
<_MapDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,),
dtype=tf.int32, name=None))>
```

2.2 Split Data

```
len(data)
```

```
6
```

```
train_size = int(len(data)*.7)
val_size = int(len(data)*.2)
test_size = int(len(data)*.1)+1
```

```
(test_size, val_size, train_size), (test_size + val_size + train_size)
```

```
((1, 1, 4), 6)
```

```
# Use TAKE AND SKIP
train = data.take(train_size)
val = data.skip(train_size).take(val_size)
test = data.skip(train_size+val_size).take(test_size)
```

3.Deep Model

3.1 Build Deep Learning Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
```

```
model = Sequential()
model.add(Conv2D(filters=16, kernel_size=(3,3), strides=(1, 1), activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D())

model.add(Conv2D(16, (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'))
```

```
model.compile('adam', loss=tf.losses.BinaryCrossentropy(), metrics=['accuracy'])
```

```
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, 16)      2320

 max_pooling2d_1 (MaxPoolin  (None, 62, 62, 16)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 16)        2320

 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: 3692001 (14.08 MB)
Trainable params: 3692001 (14.08 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

3.2 Train

```
logdir='logs'
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir)
```

```
hist = model.fit(train, epochs=20, validation_data=val, callbacks=[tensorboard_callback])
```

```
Epoch 1/20
4/4 [==============================] - 13s 3s/step - loss: 1.6252 - accuracy: 0.4219 - val_loss: 0.6481 - val_accuracy: 0.6562
Epoch 2/20
4/4 [==============================] - 11s 2s/step - loss: 0.7273 - accuracy: 0.5625 - val_loss: 0.6630 - val_accuracy: 0.5625
Epoch 3/20
4/4 [==============================] - 12s 2s/step - loss: 0.6410 - accuracy: 0.5781 - val_loss: 0.5843 - val_accuracy: 0.7188
Epoch 4/20
4/4 [==============================] - 10s 2s/step - loss: 0.5686 - accuracy: 0.6484 - val_loss: 0.5162 - val_accuracy: 0.6875
Epoch 5/20
4/4 [==============================] - 10s 2s/step - loss: 0.5530 - accuracy: 0.6719 - val_loss: 0.5438 - val_accuracy: 0.7812
Epoch 6/20
4/4 [==============================] - 10s 2s/step - loss: 0.4678 - accuracy: 0.8516 - val_loss: 0.6051 - val_accuracy: 0.5625
Epoch 7/20
4/4 [==============================] - 10s 2s/step - loss: 0.4448 - accuracy: 0.7578 - val_loss: 0.3890 - val_accuracy: 0.8750
Epoch 8/20
4/4 [==============================] - 10s 2s/step - loss: 0.4142 - accuracy: 0.8750 - val_loss: 0.4931 - val_accuracy: 0.8438
Epoch 9/20
4/4 [==============================] - 10s 2s/step - loss: 0.3818 - accuracy: 0.8750 - val_loss: 0.3747 - val_accuracy: 0.8750
Epoch 10/20
4/4 [==============================] - 10s 2s/step - loss: 0.3073 - accuracy: 0.8906 - val_loss: 0.2708 - val_accuracy: 0.9062
Epoch 11/20
4/4 [==============================] - 10s 2s/step - loss: 0.2517 - accuracy: 0.9062 - val_loss: 0.2662 - val_accuracy: 0.8750
```

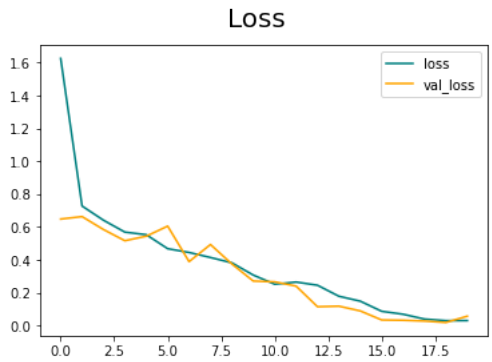
```
Epoch 12/20
4/4 [==============================] - 10s 2s/step - loss: 0.2649 - accuracy: 0.8672 - val_loss: 0.2402 - val_accuracy: 0.9375
Epoch 13/20
4/4 [==============================] - 10s 2s/step - loss: 0.2455 - accuracy: 0.9375 - val_loss: 0.1148 - val_accuracy: 0.9688
Epoch 14/20
4/4 [==============================] - 10s 2s/step - loss: 0.1785 - accuracy: 0.9453 - val_loss: 0.1181 - val_accuracy: 1.0000
Epoch 15/20
4/4 [==============================] - 10s 2s/step - loss: 0.1485 - accuracy: 0.9609 - val_loss: 0.0892 - val_accuracy: 1.0000
Epoch 16/20
4/4 [==============================] - 10s 2s/step - loss: 0.0869 - accuracy: 0.9766 - val_loss: 0.0341 - val_accuracy: 1.0000
Epoch 17/20
4/4 [==============================] - 10s 2s/step - loss: 0.0690 - accuracy: 0.9766 - val_loss: 0.0323 - val_accuracy: 1.0000
Epoch 18/20
4/4 [==============================] - 10s 2s/step - loss: 0.0396 - accuracy: 0.9922 - val_loss: 0.0275 - val_accuracy: 1.0000
Epoch 19/20
4/4 [==============================] - 10s 2s/step - loss: 0.0299 - accuracy: 1.0000 - val_loss: 0.0189 - val_accuracy: 1.0000
Epoch 20/20
4/4 [==============================] - 10s 2s/step - loss: 0.0304 - accuracy: 1.0000 - val_loss: 0.0572 - val_accuracy: 1.0000
```

3.3 Plot Performance

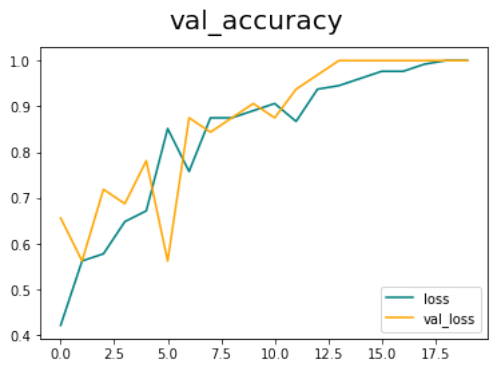
```
import pandas as pd
loss = pd.DataFrame(hist.history)
loss
```

	loss	accuracy	val_loss	val_accuracy
0	1.625167	0.421875	0.648059	0.65625
1	0.727327	0.562500	0.662971	0.56250
2	0.640980	0.578125	0.584350	0.71875
3	0.568602	0.648438	0.516174	0.68750
4	0.552982	0.671875	0.543800	0.78125
5	0.467761	0.851562	0.605093	0.56250
6	0.444844	0.757812	0.389038	0.87500
7	0.414182	0.875000	0.493109	0.84375
8	0.381802	0.875000	0.374737	0.87500
9	0.307299	0.890625	0.270759	0.90625
10	0.251746	0.906250	0.266199	0.87500
11	0.264880	0.867188	0.240211	0.93750
12	0.245460	0.937500	0.114764	0.96875
13	0.178501	0.945312	0.118084	1.00000
14	0.148477	0.960938	0.089230	1.00000
15	0.086906	0.976562	0.034136	1.00000
16	0.069032	0.976562	0.032262	1.00000
17	0.039559	0.992188	0.027544	1.00000
18	0.029919	1.000000	0.018945	1.00000
19	0.030415	1.000000	0.057231	1.00000

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




```
fig = plt.figure()
plt.plot(loss['accuracy'], color='teal', label='loss')
plt.plot(loss['val_accuracy'], color='orange', label='val_loss')
fig.suptitle('val_accuracy', fontsize=20)
plt.legend(loc="lower right")
plt.show()
```



4. Evaluate Performance

4.1 Evaluate

```
from tensorflow.keras.metrics import Precision, Recall, BinaryAccuracy
```

```
pre = Precision()
re = Recall()
acc = BinaryAccuracy()
```

```
len(test)
```

```
1
```

```
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)
    print("passed")
```

```
1/1 [==============================] - 0s 287ms/step
passed
```

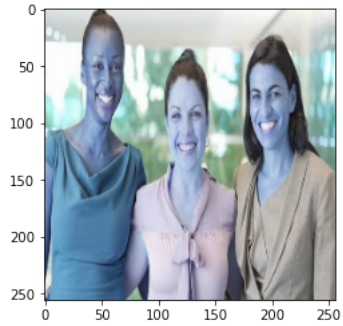
```
print(f"Precision:{pre.result().numpy()}, Recall:{re.result()}, Accuracy:{acc.result()}")
```

```
Precision:1.0, Recall:1.0, Accuracy:1.0
```

4.2 Test

```
img = cv2.imread((os.path.join(data_dir, 'happy','1-2.jpg')))
plt.imshow(img)
plt.show()
#img = cv2.imread(os.path.join(data_dir, 'happy','1-2.jpg'))
#Image.open(os.path.join(data_dir, 'happy','1-2.jpg'))
```


```
resize_image1 = tf.image.resize(img, (256,256))
plt.imshow(resize_image1.numpy().astype(int))
plt.show()
```




```
yhat = model.predict(np.expand_dims(resize_image1/255, 0))
```

```
1/1 [==============================] - 0s 50ms/step
```

```
yhat
```

```
array([[0.9566277]], dtype=float32)
```

```
def res(res):
    if res > 0.5:
        print(f'Predicted class is Sad')
    else:
        print(f'Predicted class is Happy')
```

```
res(yhat), yhat
```

```
Predicted class is Sad
(None, array([[0.9566277]], dtype=float32))
```

```
data_dir
```

```
'data'
```

```
Image.open(os.path.join(data_dir, 'images3.jpeg'))
```

```
#Image.open(os.path.join(data_dir, 'happy','1-2.jpg'))
img2 = cv2.imread(os.path.join(data_dir, 'images3.jpeg'))
resize_image2 = tf.image.resize(img2, (256,256))
#plt.imshow(resize.numpy().astype(int))
#plt.show()

plt.imshow(img2)
plt.show()
yhatt = model.predict(np.expand_dims(resize_image2/255, 0))
```


```
1/1 [==============================] - 0s 51ms/step
```

```
res(yhatt), yhatt
```

```
Predicted class is Happy
(None, array([[0.39176235]], dtype=float32))
```

```
Image.open(os.path.join(data_dir, 'images2.jpg'))
```

```
img3 = cv2.imread(os.path.join(data_dir, 'images2.jpg'))
resize_image3 = tf.image.resize(img3, (256,256))
pred_img3 = model.predict(np.expand_dims(resize_image3/255, 0))
```

```
1/1 [==============================] - 0s 65ms/step
```

```
res(pred_img3), pred_img3
```

```
Predicted class is Sad
(None, array([[0.9974392]], dtype=float32))
```

```
Image.open(os.path.join(data_dir, 'sad', 'very-sad-man-depression-9179354.jpg' ))
```


```
img4 = cv2.imread(os.path.join(data_dir, 'sad', 'very-sad-man-depression-9179354.jpg' ))

resize_image4 = tf.image.resize(img4, (256,256))
pred_img4 = model.predict(np.expand_dims(resize_image4/255, 0))
pred_img4
```

```
1/1 [==============================] - 0s 71ms/step
array([[0.9974362]], dtype=float32)
```

```
res(pred_img4), pred_img4
```

```
Predicted class is Sad
```

```
(None, array([[0.9974362]], dtype=float32))
```

5 Save the Model

5.1 Save the Model

```
from tensorflow.keras.models import load_model
```