

# Final Project on Emotion Detector

Submitted by: **Bushra Khatoon**

```
In [1]: from google.colab import files
files.upload() # upload kaggle.json from your computer
```

No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.  
Saving kaggle.json to kaggle.json

```
Out[1]: {'kaggle.json': b'{"username":"bushrakhattoon","key":"17a83efd40bfd25d5e5f5157cbde8078"}'}
```

```
In [2]: !mkdir -p ~/.kaggle
!mv kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

```
In [3]: !pip -q install kaggle
import kaggle
!kaggle --version
```

Kaggle API 1.7.4.5

```
In [10]: # Download the file from Kaggle Link
# Use the dataset slug from your Link
slug = "ananthu017/emotion-detection-fer"

# Choose a target folder
DATA_DIR = "/content/data/emotion_fer"
!mkdir -p "$DATA_DIR"

# Download and unzip (if --unzip fails on some setups, we unzip manually below)
!kaggle datasets download -d $slug -p "$DATA_DIR" --unzip
```

Dataset URL: <https://www.kaggle.com/datasets/ananthu017/emotion-detection-fer>

License(s): CC0-1.0

Downloading emotion-detection-fer.zip to /content/data/emotion\_fer

0% 0.00/65.2M [00:00<?, ?B/s]

100% 65.2M/65.2M [00:00<00:00, 1.21GB/s]

```
In [22]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import glob
import cv2
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense, Conv2D, MaxPooling2D, Flatten, Activation, BatchNormalization, Drop
from tensorflow.keras import models, layers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.utils import class_weight
import warnings
warnings.filterwarnings('ignore')
```

```
In [6]: # Inspect the directory structure
for dirpath, dirnames, filenames in os.walk("/content/data"):
    print(f"Directory: {dirpath}, Files: {len(filenames)}")
```

```
Directory: /content/data, Files: 0
Directory: /content/data/emotion_fer, Files: 0
Directory: /content/data/emotion_fer/test, Files: 0
Directory: /content/data/emotion_fer/test/surprised, Files: 831
Directory: /content/data/emotion_fer/test/disgusted, Files: 111
Directory: /content/data/emotion_fer/test/angry, Files: 958
Directory: /content/data/emotion_fer/test/sad, Files: 1247
Directory: /content/data/emotion_fer/test/fearful, Files: 1024
Directory: /content/data/emotion_fer/test/neutral, Files: 1233
Directory: /content/data/emotion_fer/test/happy, Files: 1774
Directory: /content/data/emotion_fer/train, Files: 0
Directory: /content/data/emotion_fer/train/surprised, Files: 3171
Directory: /content/data/emotion_fer/train/disgusted, Files: 436
Directory: /content/data/emotion_fer/train/angry, Files: 3995
Directory: /content/data/emotion_fer/train/sad, Files: 4830
Directory: /content/data/emotion_fer/train/fearful, Files: 4097
Directory: /content/data/emotion_fer/train/neutral, Files: 4965
Directory: /content/data/emotion_fer/train/happy, Files: 7215
```

```
In [17]: # Total number of images in train and test folders
total_train_images = sum(train_counts.values())
total_test_images = sum(test_counts.values())

print(f"Total images in train folder: {total_train_images}")
print(f"Total images in test folder: {total_test_images}")
```

```
Total images in train folder: 28709
Total images in test folder: 7178
```

```
In [15]: # Total number of images for all 7-categories in train and test directories.
train_counts = {}
test_counts = {}

train_dir = os.path.join(DATA_DIR, "train")
test_dir = os.path.join(DATA_DIR, "test")

if os.path.isdir(train_dir):
    for emotion_folder in os.listdir(train_dir):
        emotion_path = os.path.join(train_dir, emotion_folder)
        if os.path.isdir(emotion_path):
            train_counts[emotion_folder] = len(glob.glob(os.path.join(emotion_path, "*")))

if os.path.isdir(test_dir):
    for emotion_folder in os.listdir(test_dir):
        emotion_path = os.path.join(test_dir, emotion_folder)
        if os.path.isdir(emotion_path):
            test_counts[emotion_folder] = len(glob.glob(os.path.join(emotion_path, "*")))

print("Train counts:")
for emotion, count in train_counts.items():
    print(f"{emotion}: {count}")

print("\nTest counts:")
for emotion, count in test_counts.items():
    print(f"{emotion}: {count}")
```

Train counts:  
surprised: 3171  
disgusted: 436  
angry: 3995  
sad: 4830  
fearful: 4097  
neutral: 4965  
happy: 7215

Test counts:  
surprised: 831  
disgusted: 111  
angry: 958  
sad: 1247  
fearful: 1024  
neutral: 1233  
happy: 1774

```
In [13]: # ✅ Show random images from the emotion_fer dataset
import glob, random, math
from PIL import Image

# 📍 Change this if your dataset lives elsewhere
DATA_DIR = "/content/data/emotion_fer" # e.g., where you unzipped ananthu017/emotion-detection-fe

# Pick a split folder if it exists; otherwise search the root
base = None
for split in ["train", "validation", "val", "test"]:
    p = os.path.join(DATA_DIR, split)
    if os.path.isdir(p):
        base = p
        break
if base is None:
    base = DATA_DIR # fallback to root

# Collect image paths
exts = ("*.jpg", "*.jpeg", "*.png", "*.bmp", "*.tif", "*.tiff")
paths = []
# common structure: base/<class>/*.jpg
class_dirs = [d for d in os.listdir(base) if os.path.isdir(os.path.join(base, d))]
if class_dirs:
    for cls in sorted(class_dirs):
        for e in exts:
            paths.extend(glob.glob(os.path.join(base, cls, e)))
# fallback: recursive search (in case the structure is different)
if not paths:
    for e in exts:
        paths.extend(glob.glob(os.path.join(DATA_DIR, "**", e), recursive=True))

if not paths:
    raise FileNotFoundError(f"No images found under {DATA_DIR}. Check your dataset path/folders.")

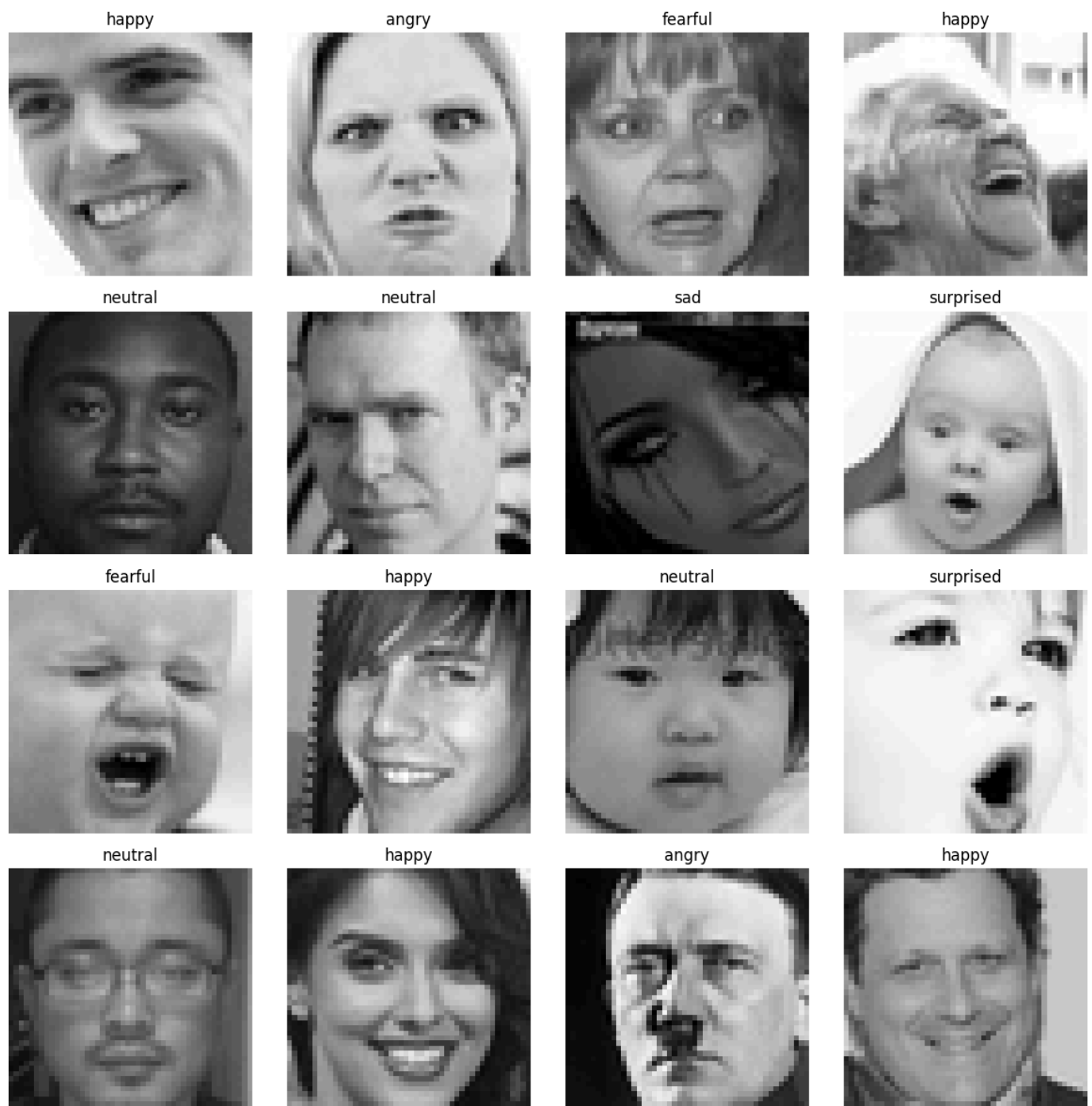
# Show a class balance snapshot (top 10)
labels = [os.path.basename(os.path.dirname(p)) for p in paths]
class_counts = pd.Series(labels).value_counts().head(10)
display(class_counts.to_frame("images"))
```

images	
happy	7215
neutral	4965
sad	4830
fearful	4097
angry	3995
surprised	3171
disgusted	436

```
In [18]: # Sample & plot
K = 16 # number of images to show
sample = random.sample(paths, min(K, len(paths)))

cols = 4
rows = math.ceil(len(sample) / cols)
plt.figure(figsize=(cols * 3, rows * 3))
for i, p in enumerate(sample, 1):
    with Image.open(p) as img:
        img = img.convert("RGB")
        plt.subplot(rows, cols, i)
        plt.imshow(img)
        title = os.path.basename(os.path.dirname(p))
        plt.title(title[:16])
        plt.axis("off")
plt.tight_layout()
plt.show()

print(f"Showing {len(sample)} random images from: {base}")
```



Showing 16 random images from: /content/data/emotion\_fer/train

## Data preparation for CNN model with Tensorflow

### Data generation and data normalization

```
In [21]: # Using IDG to Load images from directory
train_idg = ImageDataGenerator(rescale=1./255, validation_split=0.25)
# 25% validation split for taining
test_idg = ImageDataGenerator(rescale=1./255)

# Specify parameters for data generation
img_size = (100, 100)
batch_size = 64

arg_train = {'target_size': img_size,
             'color_mode': 'grayscale',
             'class_mode' : 'categorical',
             'batch_size': batch_size}
arg_test = {'target_size': img_size,
            'color_mode': 'grayscale',
```

```
'class_mode' : 'categorical',  
'batch_size': batch_size,  
'shuffle': False}
```

```
train = train_idg.flow_from_directory(directory=train_dir, subset='training', **arg_train)  
valid = train_idg.flow_from_directory(directory=train_dir, subset='validation', **arg_train)  
test = test_idg.flow_from_directory(directory=test_dir, **arg_test)
```

Found 21535 images belonging to 7 classes.

Found 7174 images belonging to 7 classes.

Found 7178 images belonging to 7 classes.

```
In [42]: ### Creat CNN Model  
model=Sequential()  
model.add(Conv2D(32,kernel_size=(3,3),padding='valid',activation='relu',input_shape=(100,100,1)))  
model.add(BatchNormalization())  
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))  
  
model.add(Conv2D(64,kernel_size=(3,3),padding='valid',activation='relu'))  
model.add(BatchNormalization())  
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))  
  
model.add(Conv2D(128,kernel_size=(3,3),padding='valid',activation='relu'))  
model.add(BatchNormalization())  
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))  
  
model.add(Flatten())
```

```
In [43]: model.add(Dense(128,activation='relu'))  
model.add(Dropout(0.1))  
model.add(Dense(64,activation='relu'))  
model.add(Dropout(0.1))  
model.add(Dense(7,activation='softmax')) # Changed activation to softmax  
model.summary()
```

Model: "sequential\_6"

Layer (type)	Output Shape	Param #
conv2d_19 (Conv2D)	(None, 98, 98, 32)	320
batch_normalization_19 (BatchNormalization)	(None, 98, 98, 32)	128
max_pooling2d_19 (MaxPooling2D)	(None, 49, 49, 32)	0
conv2d_20 (Conv2D)	(None, 47, 47, 64)	18,496
batch_normalization_20 (BatchNormalization)	(None, 47, 47, 64)	256
max_pooling2d_20 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_21 (Conv2D)	(None, 21, 21, 128)	73,856
batch_normalization_21 (BatchNormalization)	(None, 21, 21, 128)	512
max_pooling2d_21 (MaxPooling2D)	(None, 10, 10, 128)	0
flatten_6 (Flatten)	(None, 12800)	0
dense_18 (Dense)	(None, 128)	1,638,528
dropout_12 (Dropout)	(None, 128)	0
dense_19 (Dense)	(None, 64)	8,256
dropout_13 (Dropout)	(None, 64)	0
dense_20 (Dense)	(None, 7)	455

**Total params:** 1,740,807 (6.64 MB)

**Trainable params:** 1,740,359 (6.64 MB)

**Non-trainable params:** 448 (1.75 KB)

```
In [44]: ### To train the model
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])

history=model.fit(train,epochs=50,validation_data=valid)
```

Epoch 1/50  
337/337 ————— 27s 58ms/step - accuracy: 0.2387 - loss: 2.1775 - val\_accuracy: 0.1781  
- val\_loss: 4.8952

Epoch 2/50  
337/337 ————— 14s 42ms/step - accuracy: 0.3672 - loss: 1.5993 - val\_accuracy: 0.3163  
- val\_loss: 1.6647

Epoch 3/50  
337/337 ————— 15s 45ms/step - accuracy: 0.4331 - loss: 1.4534 - val\_accuracy: 0.3545  
- val\_loss: 1.6969

Epoch 4/50  
337/337 ————— 17s 49ms/step - accuracy: 0.4727 - loss: 1.3406 - val\_accuracy: 0.3914  
- val\_loss: 1.5253

Epoch 5/50  
337/337 ————— 15s 44ms/step - accuracy: 0.5109 - loss: 1.2656 - val\_accuracy: 0.4834  
- val\_loss: 1.3692

Epoch 6/50  
337/337 ————— 18s 54ms/step - accuracy: 0.5606 - loss: 1.1455 - val\_accuracy: 0.4755  
- val\_loss: 1.3738

Epoch 7/50  
337/337 ————— 14s 42ms/step - accuracy: 0.5876 - loss: 1.0743 - val\_accuracy: 0.4898  
- val\_loss: 1.3684

Epoch 8/50  
337/337 ————— 17s 50ms/step - accuracy: 0.6323 - loss: 0.9636 - val\_accuracy: 0.5095  
- val\_loss: 1.3732

Epoch 9/50  
337/337 ————— 14s 42ms/step - accuracy: 0.6721 - loss: 0.8669 - val\_accuracy: 0.4933  
- val\_loss: 1.4446

Epoch 10/50  
337/337 ————— 18s 54ms/step - accuracy: 0.7080 - loss: 0.7710 - val\_accuracy: 0.4962  
- val\_loss: 1.4794

Epoch 11/50  
337/337 ————— 17s 49ms/step - accuracy: 0.7448 - loss: 0.6882 - val\_accuracy: 0.5148  
- val\_loss: 1.5206

Epoch 12/50  
337/337 ————— 15s 43ms/step - accuracy: 0.7640 - loss: 0.6243 - val\_accuracy: 0.5077  
- val\_loss: 1.5753

Epoch 13/50  
337/337 ————— 21s 46ms/step - accuracy: 0.7833 - loss: 0.5811 - val\_accuracy: 0.5096  
- val\_loss: 1.7648

Epoch 14/50  
337/337 ————— 15s 45ms/step - accuracy: 0.7972 - loss: 0.5419 - val\_accuracy: 0.5066  
- val\_loss: 1.7592

Epoch 15/50  
337/337 ————— 17s 49ms/step - accuracy: 0.8140 - loss: 0.5063 - val\_accuracy: 0.5035  
- val\_loss: 1.7623

Epoch 16/50  
337/337 ————— 17s 49ms/step - accuracy: 0.8330 - loss: 0.4551 - val\_accuracy: 0.5171  
- val\_loss: 1.8615

Epoch 17/50  
337/337 ————— 22s 66ms/step - accuracy: 0.8504 - loss: 0.4152 - val\_accuracy: 0.5194  
- val\_loss: 1.8980

Epoch 18/50  
337/337 ————— 18s 52ms/step - accuracy: 0.8524 - loss: 0.4085 - val\_accuracy: 0.5234  
- val\_loss: 1.9531

Epoch 19/50  
337/337 ————— 19s 55ms/step - accuracy: 0.8634 - loss: 0.3752 - val\_accuracy: 0.5061  
- val\_loss: 1.9956

Epoch 20/50  
337/337 ————— 15s 46ms/step - accuracy: 0.8658 - loss: 0.3751 - val\_accuracy: 0.5259  
- val\_loss: 1.9560

Epoch 21/50  
337/337 ————— 14s 42ms/step - accuracy: 0.8767 - loss: 0.3456 - val\_accuracy: 0.5205  
- val\_loss: 2.1393

Epoch 22/50  
337/337 ————— 15s 45ms/step - accuracy: 0.8724 - loss: 0.3566 - val\_accuracy: 0.5173  
- val\_loss: 2.1757

Epoch 23/50



337/337 ————— 20s 45ms/step - accuracy: 0.8789 - loss: 0.3385 - val\_accuracy: 0.5180  
- val\_loss: 2.1820  
Epoch 24/50

337/337 ————— 18s 54ms/step - accuracy: 0.8892 - loss: 0.3176 - val\_accuracy: 0.5217  
- val\_loss: 2.1070  
Epoch 25/50

337/337 ————— 16s 48ms/step - accuracy: 0.8954 - loss: 0.3084 - val\_accuracy: 0.5070  
- val\_loss: 2.2813  
Epoch 26/50

337/337 ————— 21s 63ms/step - accuracy: 0.8944 - loss: 0.3048 - val\_accuracy: 0.5148  
- val\_loss: 2.3842  
Epoch 27/50

337/337 ————— 17s 49ms/step - accuracy: 0.8924 - loss: 0.3041 - val\_accuracy: 0.5091  
- val\_loss: 2.3611  
Epoch 28/50

337/337 ————— 18s 53ms/step - accuracy: 0.8979 - loss: 0.2827 - val\_accuracy: 0.5163  
- val\_loss: 2.3067  
Epoch 29/50

337/337 ————— 18s 53ms/step - accuracy: 0.9057 - loss: 0.2754 - val\_accuracy: 0.5273  
- val\_loss: 2.3673  
Epoch 30/50

337/337 ————— 17s 50ms/step - accuracy: 0.9082 - loss: 0.2697 - val\_accuracy: 0.5195  
- val\_loss: 2.2697  
Epoch 31/50

337/337 ————— 19s 57ms/step - accuracy: 0.9058 - loss: 0.2664 - val\_accuracy: 0.5146  
- val\_loss: 2.5771  
Epoch 32/50

337/337 ————— 16s 49ms/step - accuracy: 0.9105 - loss: 0.2596 - val\_accuracy: 0.5178  
- val\_loss: 2.4784  
Epoch 33/50

337/337 ————— 19s 55ms/step - accuracy: 0.9093 - loss: 0.2615 - val\_accuracy: 0.5244  
- val\_loss: 2.4651  
Epoch 34/50

337/337 ————— 19s 50ms/step - accuracy: 0.9141 - loss: 0.2460 - val\_accuracy: 0.5177  
- val\_loss: 2.6008  
Epoch 35/50

337/337 ————— 18s 53ms/step - accuracy: 0.9153 - loss: 0.2445 - val\_accuracy: 0.5244  
- val\_loss: 2.5011  
Epoch 36/50

337/337 ————— 18s 52ms/step - accuracy: 0.9190 - loss: 0.2270 - val\_accuracy: 0.5059  
- val\_loss: 2.5088  
Epoch 37/50

337/337 ————— 16s 48ms/step - accuracy: 0.9216 - loss: 0.2332 - val\_accuracy: 0.5135  
- val\_loss: 2.6316  
Epoch 38/50

337/337 ————— 19s 55ms/step - accuracy: 0.9207 - loss: 0.2367 - val\_accuracy: 0.5146  
- val\_loss: 2.4045  
Epoch 39/50

337/337 ————— 17s 50ms/step - accuracy: 0.9182 - loss: 0.2387 - val\_accuracy: 0.5142  
- val\_loss: 2.4557  
Epoch 40/50

337/337 ————— 17s 51ms/step - accuracy: 0.9210 - loss: 0.2424 - val\_accuracy: 0.5155  
- val\_loss: 2.8644  
Epoch 41/50

337/337 ————— 18s 53ms/step - accuracy: 0.9260 - loss: 0.2145 - val\_accuracy: 0.5128  
- val\_loss: 2.2657  
Epoch 42/50

337/337 ————— 18s 52ms/step - accuracy: 0.9243 - loss: 0.2157 - val\_accuracy: 0.5294  
- val\_loss: 2.7794  
Epoch 43/50

337/337 ————— 20s 59ms/step - accuracy: 0.9280 - loss: 0.2054 - val\_accuracy: 0.5209  
- val\_loss: 2.6579  
Epoch 44/50

337/337 ————— 17s 51ms/step - accuracy: 0.9261 - loss: 0.2087 - val\_accuracy: 0.5070  
- val\_loss: 2.5789  
Epoch 45/50

337/337 ————— 16s 48ms/step - accuracy: 0.9293 - loss: 0.2076 - val\_accuracy: 0.5191

```

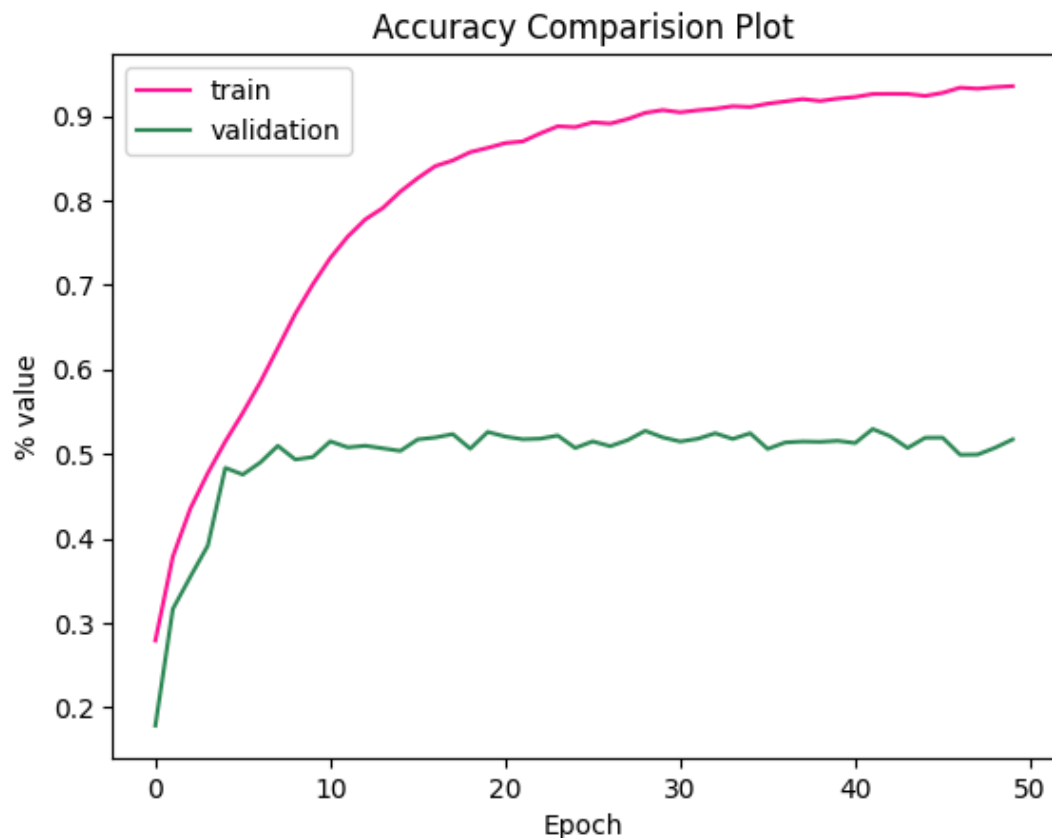
- val_loss: 2.2895
Epoch 46/50
337/337 ————— 18s 54ms/step - accuracy: 0.9295 - loss: 0.2159 - val_accuracy: 0.5192
- val_loss: 2.4035
Epoch 47/50
337/337 ————— 17s 50ms/step - accuracy: 0.9336 - loss: 0.1988 - val_accuracy: 0.4989
- val_loss: 3.0592
Epoch 48/50
337/337 ————— 14s 43ms/step - accuracy: 0.9360 - loss: 0.1870 - val_accuracy: 0.4992
- val_loss: 2.9436
Epoch 49/50
337/337 ————— 14s 42ms/step - accuracy: 0.9330 - loss: 0.1968 - val_accuracy: 0.5072
- val_loss: 2.5851
Epoch 50/50
337/337 ————— 14s 43ms/step - accuracy: 0.9388 - loss: 0.1843 - val_accuracy: 0.5171
- val_loss: 2.6766

```

```

In [51]: # Accuracy comparison chart
plt.plot(history.history['accuracy'],color='deeppink',label='train')
plt.plot(history.history['val_accuracy'],color='seagreen',label='validation')
plt.title('Accuracy Comparision Plot')
plt.ylabel('% value')
plt.xlabel('Epoch')
plt.legend()
plt.show()

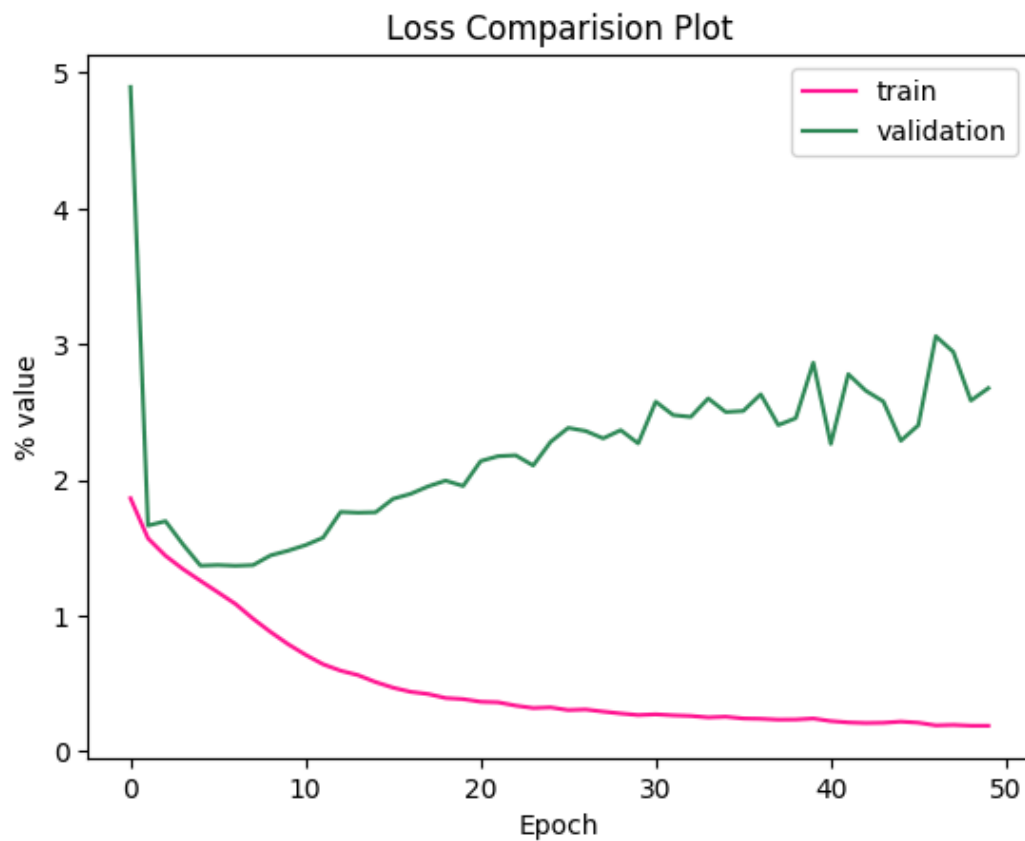
```



```

In [52]: # Loss comparison chart
plt.plot(history.history['loss'],color='deeppink',label='train')
plt.plot(history.history['val_loss'],color='seagreen',label='validation')
plt.title('Loss Comparision Plot')
plt.ylabel('% value')
plt.xlabel('Epoch')
plt.legend()
plt.show()

```

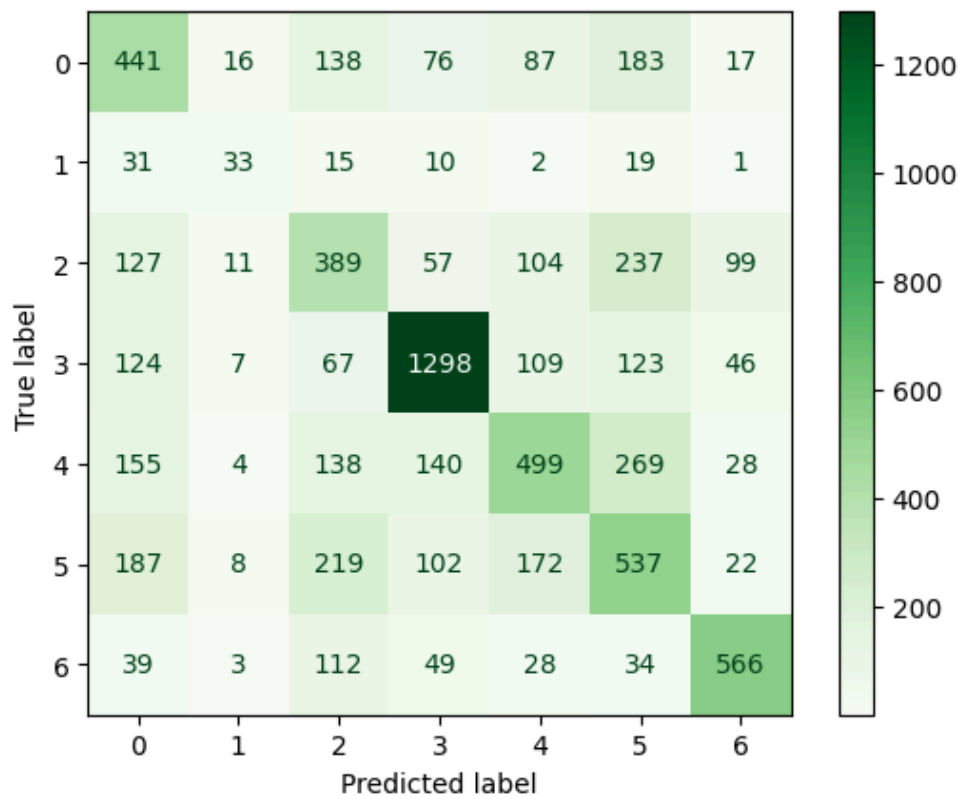


```
In [56]: # Testing and evaluation
from sklearn import metrics # Import metrics module

y_pred = model.predict(test)
y_pred_labels = []
for i in y_pred:
    y_pred_labels.append(np.argmax(i))
y_actual = test.classes[test.index_array]

cm = metrics.confusion_matrix(y_actual, y_pred_labels)
disp = metrics.ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap=plt.cm.Greens)
plt.show()
```

113/113 ————— 5s 47ms/step



```
In [58]: from sklearn.metrics import classification_report # Import classification_report

print(classification_report(y_actual, y_pred_labels, digits=4))
```

	precision	recall	f1-score	support
0	0.3995	0.4603	0.4277	958
1	0.4024	0.2973	0.3420	111
2	0.3609	0.3799	0.3701	1024
3	0.7494	0.7317	0.7404	1774
4	0.4985	0.4047	0.4467	1233
5	0.3830	0.4306	0.4054	1247
6	0.7266	0.6811	0.7031	831
accuracy			0.5242	7178
macro avg	0.5029	0.4837	0.4908	7178
weighted avg	0.5325	0.5242	0.5267	7178

```
In [152]: ### Category recognition
train_gen = train_idg.flow_from_directory(
    '/content/data/emotion_fer/train',
    target_size=(100,100),
    batch_size=32,
    class_mode='categorical'
)

print(train_gen.class_indices)
```

Found 28709 images belonging to 7 classes.

```
{'angry': 0, 'disgusted': 1, 'fearful': 2, 'happy': 3, 'neutral': 4, 'sad': 5, 'surprised': 6}
```

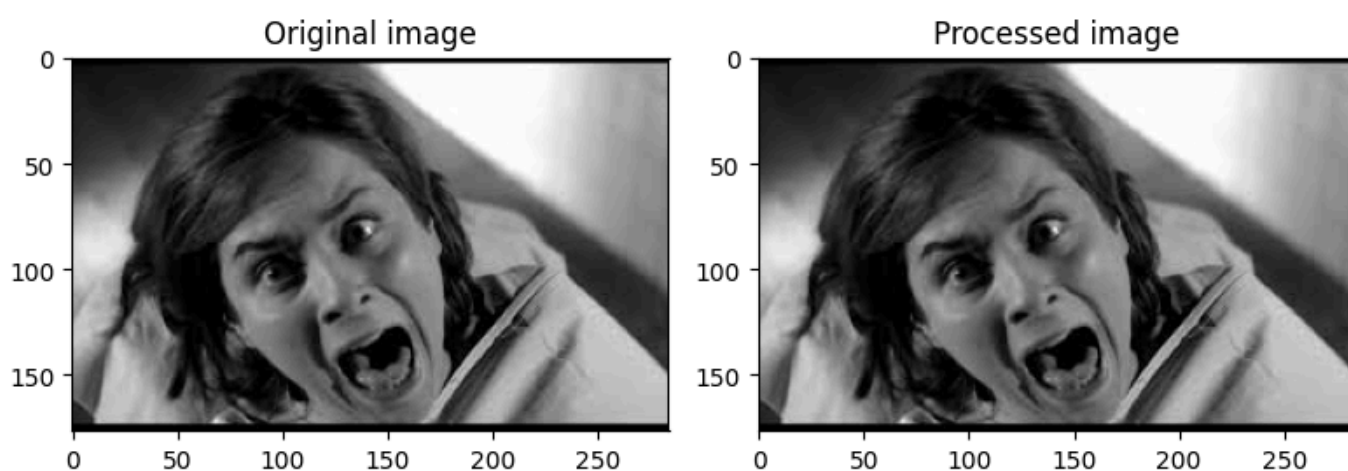
Found 28709 images belonging to 7 classes.

**{'angry': 0, 'disgusted': 1, 'fearful': 2, 'happy': 3, 'neutral': 4, 'sad': 5, 'surprised': 6}**

## Prediction-1

```
In [162]: import cv2
          from matplotlib import pyplot as plt
```

```
In [84]: #reading the original image
test_img2 = cv2.imread('/content/2_fearful_face.jpeg')
#converting the image into grayscale
grey_img2 = rgb2gray(test_img2)
fig, axes = plt.subplots(1, 2, figsize=(8, 4))
ax = axes.ravel()
#setting the axes of the image
ax[0].imshow(test_img2) # Use test_img1 for the original image
ax[0].set_title("Original image")
ax[1].imshow(grey_img2, cmap=plt.cm.gray) # Use grey_img1 for the grayscale image
ax[1].set_title("Processed image")
#display the processed image
fig.tight_layout()
plt.show()
```



```
In [85]: grey_img2_resized = cv2.resize(grey_img2, (100, 100))
          test_input2 = grey_img2_resized.reshape(1, 100, 100, 1)
          test_input2.shape
```

```
Out[85]: (1, 100, 100, 1)
```

```
In [86]: model.predict(test_input2)
```

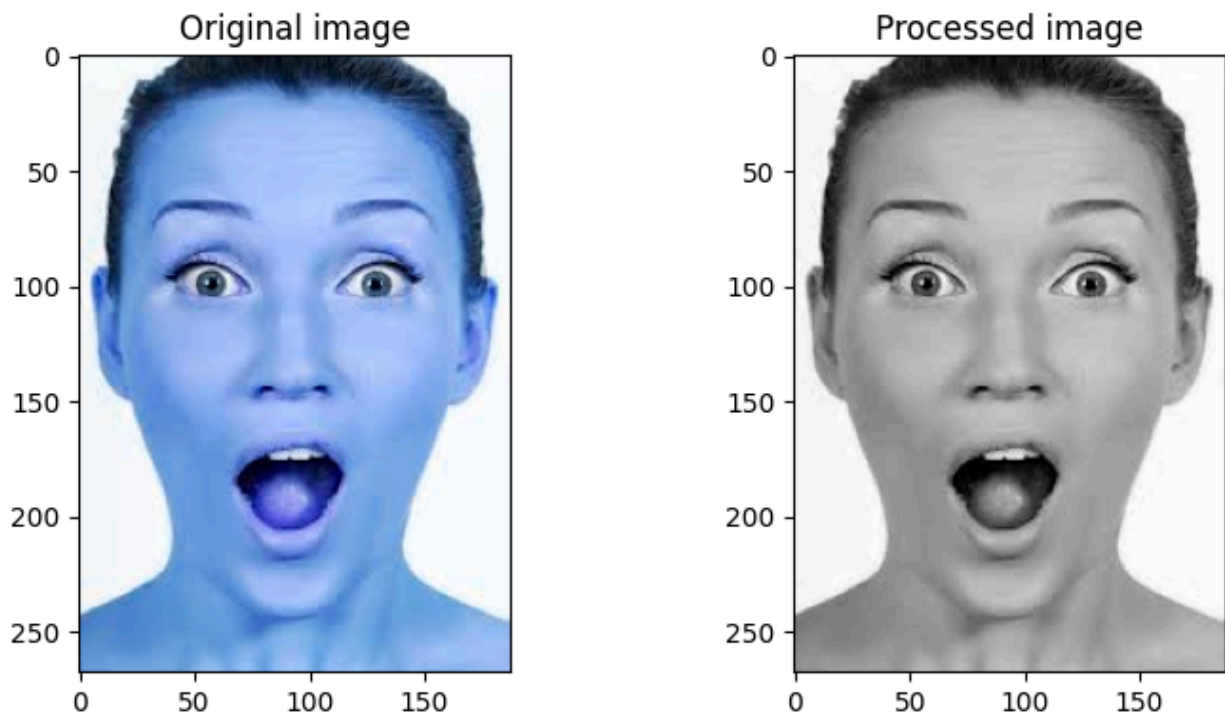
1/1 ————— 0s 34ms/step

```
Out[86]: array([[0.12131992, 0.13538785, 0.6299236 , 0.04644792, 0.00874567,
                  0.04605708, 0.01211797]], dtype=float32)
```

## Prediction-2

```
In [175]: #reading the original image
test_img02 = cv2.imread('/content/surprised_face2.jpeg')
#converting the image into grayscale
grey_img02 = rgb2gray(test_img02)
fig, axes = plt.subplots(1, 2, figsize=(8, 4))
ax = axes.ravel()
#setting the axes of the image
ax[0].imshow(test_img02) # Use test_img1 for the original image
ax[0].set_title("Original image")
ax[1].imshow(grey_img02, cmap=plt.cm.gray) # Use grey_img1 for the grayscale image
ax[1].set_title("Processed image")
#display the processed image
```

```
fig.tight_layout()
plt.show()
```



```
In [176... grey_img02_resized = cv2.resize(grey_img02, (100, 100))
test_input02 = grey_img02_resized.reshape(1, 100, 100, 1)
test_input02.shape
```

```
Out[176... (1, 100, 100, 1)
```

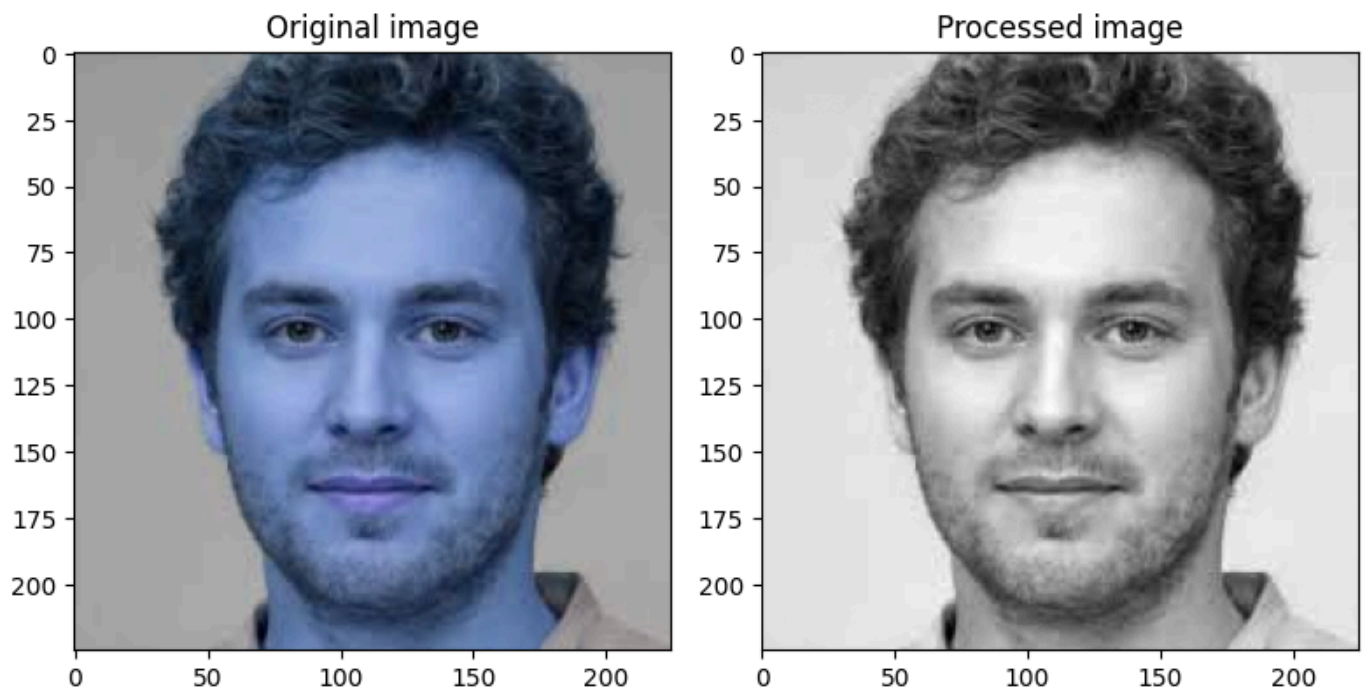
```
In [177... model.predict(test_input02)
```

1/1 ————— 0s 34ms/step

```
Out[177... array([[5.4477328e-01, 5.7460260e-02, 3.7919796e-01, 1.7362081e-02,
        1.5343505e-06, 1.6526741e-04, 1.0397012e-03]], dtype=float32)
```

## Prediction-3

```
In [166... #reading the original image
test_img4 = cv2.imread('/content/nutral_face2.jpeg')
#converting the image into grayscale
grey_img4 = rgb2gray(test_img4)
fig, axes = plt.subplots(1, 2, figsize=(8, 4))
ax = axes.ravel()
#setting the axes of the image
ax[0].imshow(test_img4) # Use test_img1 for the original image
ax[0].set_title("Original image")
ax[1].imshow(grey_img4, cmap=plt.cm.gray) # Use grey_img1 for the grayscale image
ax[1].set_title("Processed image")
#display the processed image
fig.tight_layout()
plt.show()
```



```
In [169... grey_img4_resized = cv2.resize(grey_img4, (100, 100))
test_input4 = grey_img4_resized.reshape(1, 100, 100, 1)
test_input4.shape
```

```
Out[169... (1, 100, 100, 1)
```

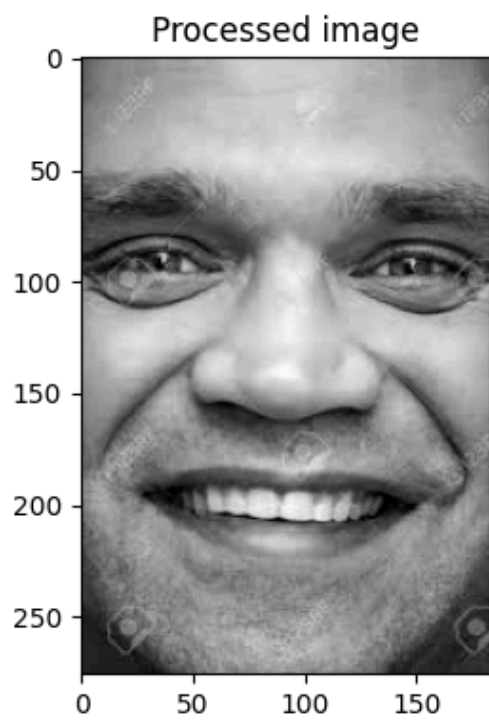
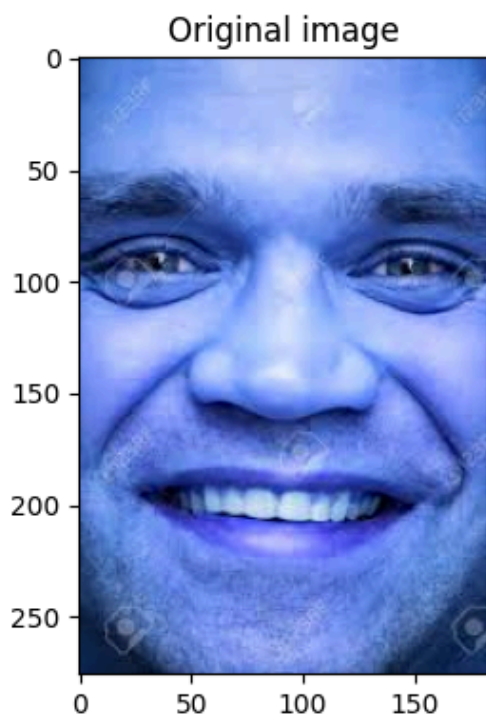
```
In [170... model.predict(test_input4)
```

```
1/1 ————— 0s 53ms/step
```

```
Out[170... array([[6.9924456e-04, 2.5507687e-14, 6.6499088e-06, 5.0905120e-04,
          9.9419051e-01, 4.0052142e-03, 5.8924936e-04]], dtype=float32)
```

## Prediction-4

```
In [178... #reading the original image
test_img5 = cv2.imread('/content/happy_face4.jpeg')
#converting the image into grayscale
grey_img5 = rgb2gray(test_img5)
fig, axes = plt.subplots(1, 2, figsize=(8, 4))
ax = axes.ravel()
#setting the axes of the image
ax[0].imshow(test_img5) # Use test_img1 for the original image
ax[0].set_title("Original image")
ax[1].imshow(grey_img5, cmap=plt.cm.gray) # Use grey_img1 for the grayscale image
ax[1].set_title("Processed image")
#display the processed image
fig.tight_layout()
plt.show()
```



```
In [179... grey_img5_resized = cv2.resize(grey_img5, (100, 100))
test_input5 = grey_img5_resized.reshape(1, 100, 100, 1)
test_input5.shape
```

```
Out[179... (1, 100, 100, 1)
```

```
In [180... model.predict(test_input5)
```

1/1 ————— 0s 36ms/step

```
Out[180... array([[7.3643422e-01, 5.7453119e-11, 1.4249649e-06, 4.0472839e-02,
        6.7381113e-04, 2.2227617e-01, 1.4158608e-04]], dtype=float32)
```