Facial Emotion, Age and Gender Detection from Images

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Problem Statement

- Predicting the emotion from facial images.
- **Keywords:** Classfication, Prediction, Deep Learning, emotion, Neural networks

Data Collection

- Source(url):(https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data)).
- Short Description : The dataset is taken from Kaggle (FER challange). The dataset has approximately 35000 records, with attributes image pixel array and emotion value. There are total 7 emotions in the dataset. The dataset has no attributes related to age and gender.
- Keywords: facial emotion, age, gender, pixels,images, prediction

Required packages

Install the required packages - Most of packages are already installed. The syntax for installing packages is pip install package name.

Next the installed package needs to be imported. The syntax is "import package name" or from "package" import "module name". The packages that are required are:

In [2]:
```
import numpy as np
import pandas as pd
import math
import numpy as np
import pandas as pd
import os
import cv2
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report
import tensorflow as tf
from tensorflow.keras import optimizers
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten, Dense, Conv2D, MaxPooling2D, Dropou
from tensorflow.keras.layers import Dropout, BatchNormalization, LeakyReLU, Acti
from tensorflow.keras.callbacks import Callback, EarlyStopping, ReduceLROnPlatea
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.vgg19 import VGG19
from tensorflow.keras.applications.mobilenet import MobileNet
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.layers import Input
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import RMSprop
```

Load the dataset and check its shape

In [4]:
```
image_df= pd.read_csv('C:/Users/sivay/Downloads/facial-expression-recognitionfer
image_df=image_df[['emotion','pixels']]
print(image_df.head())
print(image_df.shape)
```

```
   emotion                                             pixels
0        0  70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...
1        0  151 150 147 155 148 133 111 140 170 174 182 15...
2        2  231 212 156 164 174 138 161 173 182 200 106 38...
3        4  24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
4        6  4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...
(35887, 2)
```

Download the images from the pixels to a folder named image

In [ ]:
```
os.mkdir("image")
for index,row in image_df.iterrows():
    pixels=np.asarray(list(row['pixels'].split(' ')),dtype=np.uint8)
    img=pixels.reshape((48,48))
    pathname=os.path.join('image',str(index)+'.jpg')
    cv2.imwrite(pathname,img)
```

Check the emotion values

In [5]:
```
image_df.emotion.unique()
```

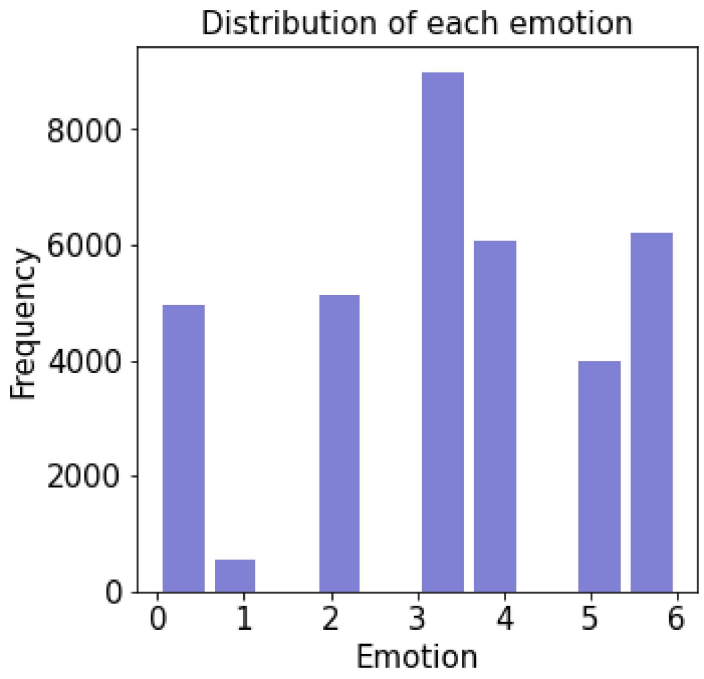
Out[5]:
```
array([0, 2, 4, 6, 3, 5, 1], dtype=int64)
```

Plot the number of images for each emotion

In [6]:
```
emotion_label = {0:'anger', 1:'disgust', 2:'fear', 3:'happiness', 4: 'sadness', !
#checking count of each emotion
print(image_df.emotion.value_counts())
```

```
3    8989
6    6198
4    6077
2    5121
0    4953
5    4002
1     547
Name: emotion, dtype: int64
```

In [7]:
```
%matplotlib inline
plt.figure(figsize=[5,5])
plt.hist(x=image_df.emotion, color='#0504aa',alpha=0.5, rwidth=0.8)
plt.xlabel('Emotion',fontsize=15)
plt.ylabel('Frequency',fontsize=15)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.ylabel('Frequency',fontsize=15)
plt.title('Distribution of each emotion',fontsize=15)
plt.show()
```

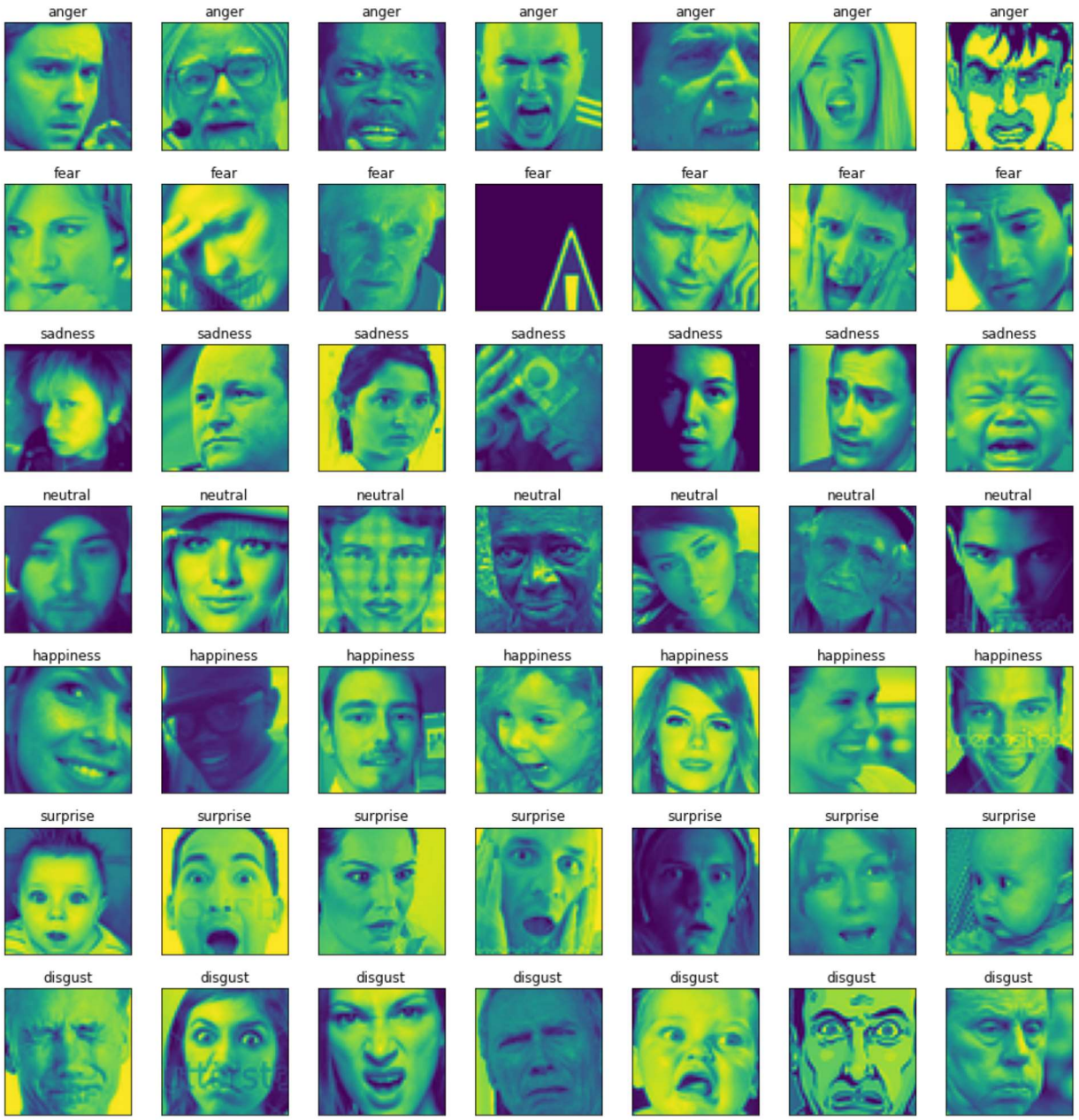


We can see that emotion disguist have very less images

In [ ]:

Plot the images for each emotion

In [8]:
```
ig = plt.figure(1, (14, 14))
i = 0
for l in image_df.emotion.unique():
    for j in range(7):
        px = image_df[image_df.emotion==l].pixels.iloc[i]
        px = np.array(px.split(' ')).reshape(48, 48).astype('float32')
        i += 1
        ax = plt.subplot(7, 7, i)
        ax.imshow(px, cmap=None)
        ax.set_xticks([])
        ax.set_yticks([])
        ax.set_title(emotion_label[l])
        plt.tight_layout()
```



Data Preprocessing

- The dataset contains image pixels stored in string format in a data frame. So, the pixels should be separated and converted to float format.
- The pixels should be reshaped to the required format which is (48,48,1). The depth is one because the images are gray scale images.
- Emotion labels are converted to categorical varaibles using label encoder.
- The data is spilitted into test and train.
- The pixels are normalized by dividing with 255.

Convert the pixels from text format to the required shape of float format

In [9]:
```
image_array = image_df.pixels.apply(lambda x: np.array(x.split(' ')).reshape(48,
image_array = np.stack(image_array, axis=0)
print(image_array.shape)
```

```
(35887, 48, 48, 1)
```

We can see that there are total 35887 grey scale images of size 48*48

Convert the emotions to categorical format

In [10]:
```
le = LabelEncoder()
image_labels = le.fit_transform(image_df.emotion)
image_labels = tf.keras.utils.to_categorical(image_labels)
image_labels.shape
```

Out[10]:
```
(35887, 7)
```

Check the number of classes

In [11]:
```
le.classes_
```

Out[11]:
```
array([0, 1, 2, 3, 4, 5, 6], dtype=int64)
```

Split the data to train and validation in the ration 80:20

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(image_array, image_labels,
                                                    shuffle=True, stratify=image_
                                                    test_size=0.2)
#print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
#print(X_train, X_test, y_train, y_test)
```

Get the image width, height, depth and number of classes to use them while building models

In [13]:
```
img_width = X_test.shape[1]
img_height = X_test.shape[2]
img_depth = X_test.shape[3]
num_classes = y_test.shape[1]
print(img_width,img_height,img_depth,num_classes)
```

```
48 48 1 7
```

Normalize the data by diving with 255

In [14]:
```
# Normalizing
X_train = X_train / 255
X_test = X_test / 255
X_train.shape
y_test.shape
```

Out[14]:
```
(7178, 7)
```

Reshape the train and validation data as required to build models. This is only for thr first 2 models

In [13]:
```
## Run this only for model 1 and 2
X_train = X_train.reshape(len(X_train), 48*48)
X_test = X_test.reshape(len(X_test), 48*48)

## Keras works with floats, so we must cast the numbers to floats
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
```

Methodology

1. To build deep neural networks and convolutional neural networks for emotion detection. To appl transfer learning (VGG) for training the model by making appropriate changes for the VGG model after importing it for emotion detection. To use a pre trained model for gender and age detection.
2. Deep Neural Networks you used in the project

    - ConvNet
        - A convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery(source Wikipedia)
    - VGG model
        - VGG-19 is a trained Convolutional Neural Network. The number 19 stands for the number of layers with trainable weights. 16 Convolutional layers and 3 Fully Connected layers.

3. Keywords
   Keywords: supervised learning, transfer learning, classification, prediction, neural networks.

Model fitting / Validation / Evaluation

1. Model 1 A basic neural network is built. 2 Dense hidden layers with 64 neurons each with relu activation function and dropout of 0.2 after each layer to prevent outfitting. No data augmentation is used.

2. Model 2 6 CNN layers with 32, 64, 128 neurons for each two layers and 2D max pooling layer after every 2 layers. All layers have ‘same’ padding and kernel initializer is ‘he_uniform’ and kernel shape is (3, 3) as the activation function is relu.

3. Model 3 CONV => RELU => POOL, drop out 0.25, (CONV => RELLU) * 2 => POOL , dropout 0.25, set of FC => RELU layers, dropout 0.25 and batch normalization after each layer. Data augumentation is applied which is rotation_range=25,width_shift_range=0.1, height_shift_range=0.1,shear_range=0.2,zoom_range=0.2,horizontal_flip=True, fill_mode="nearest

4. Model 4 Activation function elu, kernel initializer “he_normal”, padding “same”, kernel size (5,5) for first layer and (3,3) for the rest of the layers, dropout 0.4, batch normalization after each layer. Total 6 CNN layers and 2 dense layers at the end. 2D max pooling of (2,2) after every 2 layers. Data augmentation (rotation_range=15,width_shift_range=0.15, height_shift_range=0.15,shear_range=0.15,zoom_range=0.15,horizontal_flip=True)

5. Model 5 Same model 4 with a different output layer that is only for the top 3 emotions.

6. Model Transfer learning (pre trained VGG model) is used. Last 5 layers are removed and 3 dense layers are added as per required. Data augmentation is used.

The optimizer used is Adam optimizer and loss is categorical_crossentropy. Accuracy is used as the performance metrics. Batch size of 64 and 128 are used as required per model. 100 and 25 epochs are used.

Optimal Emotion Detection Model:

- Optimizer: Adam
- Loss Function : Categorical Cross entropy
- Data augmentation : ImageDataGenerator
- Regularization: Drop out, Batch Normalization
- Output Activation Function: Softmax
- Activation Function: Elu
- Kernel size: (3,3) and (5,5)
- Kernel initializer: he_normal
- Pooling Layers: Max Pooling (2D)

Model 1 with only two hidden dense layers

In [14]:
```
model_1 = Sequential()
model_1.add(Dense(64, activation='relu', input_shape=(2304,)))
model_1.add(Dropout(0.2))
model_1.add(Dense(64, activation='relu'))
model_1.add(Dropout(0.2))
model_1.add(Dense(num_classes,
            activation='softmax',
            name='out_layer'))
```

Complie the model with learning rate 0.001 and using Adam optimizer

In [15]:
```
# Let's compile the model
learning_rate = .001
model_1.compile(loss='categorical_crossentropy',
              optimizer=optimizers.Adam(0.001),
              metrics=['accuracy'])
# note that `categorical cross entropy` is the natural generalization
# of the loss function we had in binary classification case, to multi class case
```

Fit the model with a batch size of 100 and 25 epochs

In [16]:
```
# And now let's fit.
batch_size = 128  # mini-batch with 128 examples
epochs = 100
history = model_1.fit(
    X_train, y_train,
    batch_size=batch_size,
    epochs=epochs,
    verbose=1,
    validation_data=(X_test, y_test))
```

```
Train on 28709 samples, validate on 7178 samples
Epoch 1/100
28709/28709 [==============================] - 2s 78us/sample - loss: 1.8473
- accuracy: 0.2387 - val_loss: 1.7891 - val_accuracy: 0.2572
Epoch 2/100
28709/28709 [==============================] - 2s 54us/sample - loss: 1.7952
- accuracy: 0.2576 - val_loss: 1.7632 - val_accuracy: 0.2764
Epoch 3/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.7772
- accuracy: 0.2558 - val_loss: 1.7465 - val_accuracy: 0.2806
Epoch 4/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.7658
- accuracy: 0.2662 - val_loss: 1.7481 - val_accuracy: 0.2828
Epoch 5/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.7666
- accuracy: 0.2626 - val_loss: 1.7577 - val_accuracy: 0.2778
Epoch 6/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.7569
- accuracy: 0.2624 - val_loss: 1.7357 - val_accuracy: 0.2892
```

We can see that the accuracy on train is 35.12% and on validation is 34.75% which indicates that the model is underfitting. Also, the train and the validation loss are very high. Hence we need to build a complex model.

In [ ]:

Model 2 - A basic CNN model

In [ ]:
```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform',
model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform',
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform',
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform',
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(MaxPooling2D((2, 2)))
model.add(Dense(num_classes,
            activation='softmax',
            name='out_layer'))
```

Compile the model

In [19]:
```
# Let's compile the model
learning_rate = .001
model.compile(loss='categorical_crossentropy',
              optimizer=optimizers.Adam(0.001),
              metrics=['accuracy'])
# note that `categorical cross entropy` is the natural generalization
# of the loss function we had in binary classification case, to multi class case
```

Fit the model with 100 epochs and 128 batch size

In [20]:
```
# And now let's fit.

batch_size = 128  # mini-batch with 128 examples
epochs = 100
history = model_1.fit(
    X_train, y_train,
    batch_size=batch_size,
    epochs=epochs,
    verbose=1,
    validation_data=(X_test, y_test))
```

```
Train on 28709 samples, validate on 7178 samples
Epoch 1/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6668
- accuracy: 0.3459 - val_loss: 1.6513 - val_accuracy: 0.3515
Epoch 2/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6647
- accuracy: 0.3482 - val_loss: 1.6674 - val_accuracy: 0.3396
Epoch 3/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6730
- accuracy: 0.3434 - val_loss: 1.6495 - val_accuracy: 0.3519
Epoch 4/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6662
- accuracy: 0.3476 - val_loss: 1.6739 - val_accuracy: 0.3546
Epoch 5/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6687
- accuracy: 0.3458 - val_loss: 1.6623 - val_accuracy: 0.3529
Epoch 6/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6657
- accuracy: 0.3503 - val_loss: 1.6602 - val_accuracy: 0.3526
Epoch 7/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6689
- accuracy: 0.3464 - val_loss: 1.6556 - val_accuracy: 0.3536
Epoch 8/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6683
- accuracy: 0.3483 - val_loss: 1.6467 - val_accuracy: 0.3540
Epoch 9/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6689
- accuracy: 0.3479 - val_loss: 1.6698 - val_accuracy: 0.3495
Epoch 10/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6718
- accuracy: 0.3414 - val_loss: 1.6558 - val_accuracy: 0.3559
Epoch 11/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6730
- accuracy: 0.3449 - val_loss: 1.6656 - val_accuracy: 0.3402
Epoch 12/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6739
- accuracy: 0.3431 - val_loss: 1.6699 - val_accuracy: 0.3473
Epoch 13/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6660
- accuracy: 0.3485 - val_loss: 1.6501 - val_accuracy: 0.3575
Epoch 14/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6580
- accuracy: 0.3497 - val_loss: 1.6411 - val_accuracy: 0.3568
Epoch 15/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6634
```

```
- accuracy: 0.3476 - val_loss: 1.6482 - val_accuracy: 0.3568
Epoch 16/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6631
- accuracy: 0.3493 - val_loss: 1.6701 - val_accuracy: 0.3520
Epoch 17/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6664
- accuracy: 0.3462 - val_loss: 1.6634 - val_accuracy: 0.3437
Epoch 18/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6645
- accuracy: 0.3475 - val_loss: 1.6646 - val_accuracy: 0.3536
Epoch 19/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6640
- accuracy: 0.3456 - val_loss: 1.6430 - val_accuracy: 0.3571
Epoch 20/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6631
- accuracy: 0.3496 - val_loss: 1.6637 - val_accuracy: 0.3504
Epoch 21/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6690
- accuracy: 0.3454 - val_loss: 1.6661 - val_accuracy: 0.3484
Epoch 22/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6636
- accuracy: 0.3477 - val_loss: 1.6430 - val_accuracy: 0.3561
Epoch 23/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6675
- accuracy: 0.3461 - val_loss: 1.6641 - val_accuracy: 0.3497
Epoch 24/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6670
- accuracy: 0.3480 - val_loss: 1.6670 - val_accuracy: 0.3580
Epoch 25/100
28709/28709 [==============================] - 1s 52us/sample - loss: 1.6670
- accuracy: 0.3446 - val_loss: 1.6608 - val_accuracy: 0.3543
Epoch 26/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6604
- accuracy: 0.3484 - val_loss: 1.6447 - val_accuracy: 0.3603
Epoch 27/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6597
- accuracy: 0.3505 - val_loss: 1.6541 - val_accuracy: 0.3514
Epoch 28/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6612
- accuracy: 0.3495 - val_loss: 1.6528 - val_accuracy: 0.3562
Epoch 29/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6651
- accuracy: 0.3457 - val_loss: 1.6631 - val_accuracy: 0.3522
Epoch 30/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6577
- accuracy: 0.3529 - val_loss: 1.6415 - val_accuracy: 0.3571
Epoch 31/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6582
- accuracy: 0.3535 - val_loss: 1.6676 - val_accuracy: 0.3398
Epoch 32/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6633
- accuracy: 0.3498 - val_loss: 1.6498 - val_accuracy: 0.3561
Epoch 33/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6644
- accuracy: 0.3490 - val_loss: 1.6486 - val_accuracy: 0.3559
Epoch 34/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6628
```

```
- accuracy: 0.3463 - val_loss: 1.6471 - val_accuracy: 0.3522
Epoch 35/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6538
- accuracy: 0.3537 - val_loss: 1.6588 - val_accuracy: 0.3493
Epoch 36/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6608
- accuracy: 0.3494 - val_loss: 1.6467 - val_accuracy: 0.3520
Epoch 37/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6528
- accuracy: 0.3561 - val_loss: 1.6572 - val_accuracy: 0.3493
Epoch 38/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6605
- accuracy: 0.3507 - val_loss: 1.6496 - val_accuracy: 0.3559
Epoch 39/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6672
- accuracy: 0.3487 - val_loss: 1.6528 - val_accuracy: 0.3529
Epoch 40/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6606
- accuracy: 0.3507 - val_loss: 1.6522 - val_accuracy: 0.3530
Epoch 41/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6619
- accuracy: 0.3499 - val_loss: 1.6576 - val_accuracy: 0.3546
Epoch 42/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6818
- accuracy: 0.3321 - val_loss: 1.6691 - val_accuracy: 0.3451
Epoch 43/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6598
- accuracy: 0.3508 - val_loss: 1.6445 - val_accuracy: 0.3553
Epoch 44/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6611
- accuracy: 0.3511 - val_loss: 1.6640 - val_accuracy: 0.3433
Epoch 45/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6595
- accuracy: 0.3524 - val_loss: 1.6385 - val_accuracy: 0.3640
Epoch 46/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6560
- accuracy: 0.3542 - val_loss: 1.6522 - val_accuracy: 0.3578
Epoch 47/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6657
- accuracy: 0.3491 - val_loss: 1.6648 - val_accuracy: 0.3488
Epoch 48/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6625
- accuracy: 0.3494 - val_loss: 1.6530 - val_accuracy: 0.3580
Epoch 49/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6558
- accuracy: 0.3505 - val_loss: 1.6492 - val_accuracy: 0.3611
Epoch 50/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6601
- accuracy: 0.3496 - val_loss: 1.6499 - val_accuracy: 0.3583
Epoch 51/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6674
- accuracy: 0.3464 - val_loss: 1.6612 - val_accuracy: 0.3449
Epoch 52/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6644
- accuracy: 0.3483 - val_loss: 1.6748 - val_accuracy: 0.3321
Epoch 53/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6604
```

```
- accuracy: 0.3482 - val_loss: 1.6469 - val_accuracy: 0.3576
Epoch 54/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6538
- accuracy: 0.3533 - val_loss: 1.6561 - val_accuracy: 0.3470
Epoch 55/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6538
- accuracy: 0.3529 - val_loss: 1.6466 - val_accuracy: 0.3558
Epoch 56/100
28709/28709 [==============================] - 2s 53us/sample - loss: 1.6559
- accuracy: 0.3531 - val_loss: 1.6474 - val_accuracy: 0.3596
Epoch 57/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6610
- accuracy: 0.3495 - val_loss: 1.6624 - val_accuracy: 0.3569
Epoch 58/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6553
- accuracy: 0.3531 - val_loss: 1.6502 - val_accuracy: 0.3508
Epoch 59/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6582
- accuracy: 0.3522 - val_loss: 1.6486 - val_accuracy: 0.3529
Epoch 60/100
28709/28709 [==============================] - 1s 52us/sample - loss: 1.6593
- accuracy: 0.3510 - val_loss: 1.6550 - val_accuracy: 0.3497
Epoch 61/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6596
- accuracy: 0.3528 - val_loss: 1.6413 - val_accuracy: 0.3649
Epoch 62/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6553
- accuracy: 0.3483 - val_loss: 1.6823 - val_accuracy: 0.3468
Epoch 63/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6547
- accuracy: 0.3515 - val_loss: 1.6372 - val_accuracy: 0.3589
Epoch 64/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6598
- accuracy: 0.3508 - val_loss: 1.6479 - val_accuracy: 0.3596
Epoch 65/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6658
- accuracy: 0.3478 - val_loss: 1.6419 - val_accuracy: 0.3605
Epoch 66/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6529
- accuracy: 0.3528 - val_loss: 1.6425 - val_accuracy: 0.3541
Epoch 67/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6585
- accuracy: 0.3530 - val_loss: 1.6436 - val_accuracy: 0.3608
Epoch 68/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6529
- accuracy: 0.3551 - val_loss: 1.6627 - val_accuracy: 0.3555
Epoch 69/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6544
- accuracy: 0.3527 - val_loss: 1.6458 - val_accuracy: 0.3622
Epoch 70/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6577
- accuracy: 0.3512 - val_loss: 1.6781 - val_accuracy: 0.3392
Epoch 71/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6580
- accuracy: 0.3531 - val_loss: 1.6446 - val_accuracy: 0.3516
Epoch 72/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6586
```

```
- accuracy: 0.3498 - val_loss: 1.6599 - val_accuracy: 0.3564
Epoch 73/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6546
- accuracy: 0.3563 - val_loss: 1.6484 - val_accuracy: 0.3543
Epoch 74/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6512
- accuracy: 0.3546 - val_loss: 1.6717 - val_accuracy: 0.3355
Epoch 75/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6607
- accuracy: 0.3460 - val_loss: 1.6645 - val_accuracy: 0.3491
Epoch 76/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6566
- accuracy: 0.3523 - val_loss: 1.6801 - val_accuracy: 0.3484
Epoch 77/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6553
- accuracy: 0.3527 - val_loss: 1.6540 - val_accuracy: 0.3459
Epoch 78/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6609
- accuracy: 0.3486 - val_loss: 1.6672 - val_accuracy: 0.3396
Epoch 79/100
28709/28709 [==============================] - 1s 44us/sample - loss: 1.6538
- accuracy: 0.3558 - val_loss: 1.6659 - val_accuracy: 0.3415
Epoch 80/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6593
- accuracy: 0.3521 - val_loss: 1.6434 - val_accuracy: 0.3626
Epoch 81/100
28709/28709 [==============================] - 1s 51us/sample - loss: 1.6519
- accuracy: 0.3557 - val_loss: 1.6360 - val_accuracy: 0.3631
Epoch 82/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6628
- accuracy: 0.3462 - val_loss: 1.6440 - val_accuracy: 0.3587
Epoch 83/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6528
- accuracy: 0.3551 - val_loss: 1.6535 - val_accuracy: 0.3518
Epoch 84/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6448
- accuracy: 0.3574 - val_loss: 1.6440 - val_accuracy: 0.3573
Epoch 85/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6531
- accuracy: 0.3537 - val_loss: 1.6440 - val_accuracy: 0.3626
Epoch 86/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6498
- accuracy: 0.3587 - val_loss: 1.6438 - val_accuracy: 0.3610
Epoch 87/100
28709/28709 [==============================] - 1s 52us/sample - loss: 1.6562
- accuracy: 0.3531 - val_loss: 1.6523 - val_accuracy: 0.3590
Epoch 88/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6495
- accuracy: 0.3575 - val_loss: 1.6394 - val_accuracy: 0.3596
Epoch 89/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6598
- accuracy: 0.3514 - val_loss: 1.6548 - val_accuracy: 0.3593
Epoch 90/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6598
- accuracy: 0.3499 - val_loss: 1.6557 - val_accuracy: 0.3429
Epoch 91/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6537
```

```
- accuracy: 0.3546 - val_loss: 1.6758 - val_accuracy: 0.3541
Epoch 92/100
28709/28709 [==============================] - 1s 49us/sample - loss: 1.6558
- accuracy: 0.3538 - val_loss: 1.6381 - val_accuracy: 0.3647
Epoch 93/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6487
- accuracy: 0.3565 - val_loss: 1.6605 - val_accuracy: 0.3586
Epoch 94/100
28709/28709 [==============================] - 1s 47us/sample - loss: 1.6478
- accuracy: 0.3548 - val_loss: 1.6476 - val_accuracy: 0.3547
Epoch 95/100
28709/28709 [==============================] - 1s 50us/sample - loss: 1.6591
- accuracy: 0.3529 - val_loss: 1.6388 - val_accuracy: 0.3589
Epoch 96/100
28709/28709 [==============================] - 1s 52us/sample - loss: 1.6497
- accuracy: 0.3563 - val_loss: 1.6379 - val_accuracy: 0.3668
Epoch 97/100
28709/28709 [==============================] - 1s 48us/sample - loss: 1.6460
- accuracy: 0.3591 - val_loss: 1.6450 - val_accuracy: 0.3543
Epoch 98/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6511
- accuracy: 0.3552 - val_loss: 1.6535 - val_accuracy: 0.3477
Epoch 99/100
28709/28709 [==============================] - 1s 45us/sample - loss: 1.6497
- accuracy: 0.3555 - val_loss: 1.6386 - val_accuracy: 0.3619
Epoch 100/100
28709/28709 [==============================] - 1s 46us/sample - loss: 1.6525
- accuracy: 0.3560 - val_loss: 1.6696 - val_accuracy: 0.3359
```

We can see that the accuracy on train is 35.60% and on validation is 33.59% which indicates that the model is underfitting. Also, the train and the validation loss are very high. Hence we need to build a complex model with different activation fucntion is required.

In [ ]:

Model 3

In [22]:
```
inputShape = (img_height, img_width,img_depth)
chanDim=-1
model2 = Sequential()
model2.add(Conv2D(64, (3, 3), padding="same",
input_shape=inputShape))
model2.add(Activation("relu"))
model2.add(BatchNormalization(axis=chanDim))
model2.add(MaxPooling2D(pool_size=(3, 3)))
model2.add(Dropout(0.25))
model2.add(Conv2D(128, (3, 3), padding="same"))
model2.add(Activation("relu"))
model2.add(BatchNormalization(axis=chanDim))
model2.add(Conv2D(128, (3, 3), padding="same"))
model2.add(Activation("relu"))
model2.add(BatchNormalization(axis=chanDim))
model2.add(MaxPooling2D(pool_size=(2, 2)))
model2.add(Dropout(0.25))
model2.add(Flatten())
model2.add(Dense(1024))
model2.add(Activation("relu"))
model2.add(BatchNormalization())
model2.add(Dropout(0.25))
model2.add(Dense(num_classes))
model2.add(Activation("softmax"))
```

In [27]:
```

opt = Adam(lr=0.001, decay=0.001 / 100)
model2.compile(loss="categorical_crossentropy", optimizer=opt,metrics=["accuracy
```

In [29]:
```
aug = ImageDataGenerator(rotation_range=25, width_shift_range=0.1,
    height_shift_range=0.1, shear_range=0.2, zoom_range=0.2,
    horizontal_flip=True, fill_mode="nearest")
```

In [36]:
```
History2 = model2.fit_generator(
    aug.flow(X_train, y_train, batch_size=32),
    validation_data=(X_test, y_test),
    steps_per_epoch=len(X_train) // 32,
    epochs=100, verbose=1)
```

```
Epoch 1/100
897/897 [==============================] - 384s 428ms/step - loss: 2.0175 - a
ccuracy: 0.2455 - val_loss: 8.1409 - val_accuracy: 0.1728
Epoch 2/100
897/897 [==============================] - 272s 303ms/step - loss: 1.8094 - a
ccuracy: 0.2946 - val_loss: 4.4035 - val_accuracy: 0.2028
Epoch 3/100
897/897 [==============================] - 225s 251ms/step - loss: 1.7121 - a
ccuracy: 0.3323 - val_loss: 8.1822 - val_accuracy: 0.1115
Epoch 4/100
897/897 [==============================] - 231s 257ms/step - loss: 1.6537 - a
ccuracy: 0.3606 - val_loss: 7.7165 - val_accuracy: 0.0581
Epoch 5/100
897/897 [==============================] - 227s 253ms/step - loss: 1.5722 - a
ccuracy: 0.3941 - val_loss: 2.6653 - val_accuracy: 0.2051
Epoch 6/100
897/897 [==============================] - 226s 251ms/step - loss: 1.5316 - a
ccuracy: 0.4093 - val_loss: 4.5396 - val_accuracy: 0.1641
Epoch 7/100
```

In [37]:
```
print("Done")
```

```
Done
```

In [ ]:
```

```

Model4

In [15]:
```
model4 = Sequential()
model4.add(Conv2D(filters=64,kernel_size=(5,5),input_shape=(img_width, img_height
                      padding='same',kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(Conv2D(
            filters=64,
            kernel_size=(5,5),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2,2)))
model4.add(Dropout(0.4))
model4.add(Conv2D(
            filters=128,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(Conv2D(
            filters=128,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2,2)))
model4.add(Dropout(0.4))
model4.add(Conv2D(
            filters=256,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(Conv2D(
            filters=256,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2,2)))
model4.add(Dropout(0.5, name='dropout_3'))
model4.add(Flatten())
model4.add( Dense(128,activation='elu',kernel_initializer='he_normal'))
model4.add(BatchNormalization())
model4.add(Dropout(0.5))
model4.add(Dense(
            num_classes,
            activation='softmax'))
```

Create Data Augumentation method

In [16]:
```
a3=ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.15,
    height_shift_range=0.15,
    shear_range=0.15,
    zoom_range=0.15,
    horizontal_flip=True,
)
```

Complie the model

In [17]:
```
opt = Adam(lr=0.001, decay=0.001 / 100)
model4.compile(loss="categorical_crossentropy", optimizer=opt,metrics=["accuracy
```

Fit the model using the data augumentation method and the model created

In [30]:
```
History4 = model4.fit_generator(
    a3.flow(X_train, y_train, batch_size=64),
    validation_data=(X_test, y_test),
    steps_per_epoch=len(X_train) // 64,
    epochs=100, verbose=1)
```

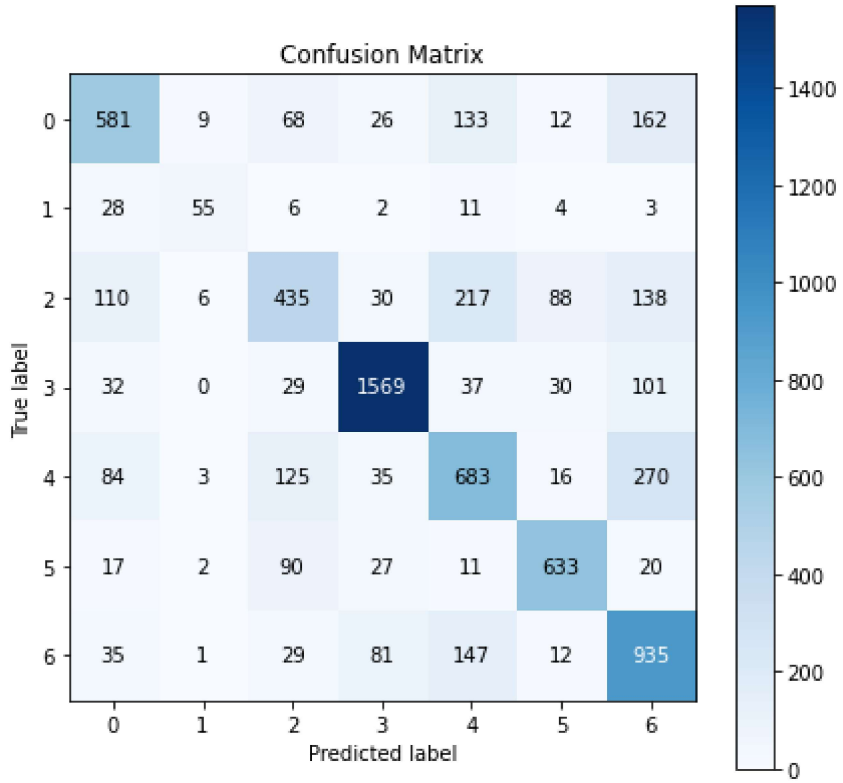
```
Epoch 1/100
448/448 [==============================] - 755s 2s/step - loss: 1.0030 - accu
racy: 0.6279 - val_loss: 0.9666 - val_accuracy: 0.6443
Epoch 2/100
448/448 [==============================] - 779s 2s/step - loss: 0.9908 - accu
racy: 0.6330 - val_loss: 0.9609 - val_accuracy: 0.6445
Epoch 3/100
448/448 [==============================] - 782s 2s/step - loss: 0.9839 - accu
racy: 0.6338 - val_loss: 0.9364 - val_accuracy: 0.6538
Epoch 4/100
448/448 [==============================] - 773s 2s/step - loss: 0.9767 - accu
racy: 0.6381 - val_loss: 0.9430 - val_accuracy: 0.6517
Epoch 5/100
448/448 [==============================] - 780s 2s/step - loss: 0.9701 - accu
racy: 0.6392 - val_loss: 0.9511 - val_accuracy: 0.6481
Epoch 6/100
448/448 [==============================] - 792s 2s/step - loss: 0.9706 - accu
racy: 0.6401 - val_loss: 0.9517 - val_accuracy: 0.6519
Epoch 7/100
```

In [33]:
```
#!pip install scikit-plot
#pip install scikitplot
#import scikitplot
y_valid = model4.predict_classes(X_test)
scikitplot.metrics.plot_confusion_matrix(np.argmax(y_test, axis=1), y_valid, fig

print(f'total wrong validation predictions: {np.sum(np.argmax(y_test, axis=1) !=
print(classification_report(np.argmax(y_test, axis=1), y_valid))
```

```
total wrong validation predictions: 2287
```

	precision	recall	f1-score	support
0	0.66	0.59	0.62	991
1	0.72	0.50	0.59	109
2	0.56	0.42	0.48	1024
3	0.89	0.87	0.88	1798
4	0.55	0.56	0.56	1216
5	0.80	0.79	0.79	800
6	0.57	0.75	0.65	1240
accuracy			0.68	7178
macro avg	0.68	0.64	0.65	7178
weighted avg	0.68	0.68	0.68	7178



We can see that the accuracy on train is 73.27% and on validation is 68.14% whihc is the best model as of now

In [ ]:
```
print("Ok")
```

CONSIDER ONLY THE TOP 3 EMOTIONS AND BUILD MODELS FOR CLASSIFYING THEM

In [59]:
```
Il = [3, 4, 6]
```

In [61]:
```
image_df1 = image_df[image_df.emotion.isin(Il)]
```

Get the required data and reshape as required

In [63]:
```
imagearray = image_df1.pixels.apply(lambda x: np.array(x.split(' ')).reshape(48,
imagearray = np.stack(imagearray, axis=0)
imagearray.shape
le1 = LabelEncoder()
imagelabels = le1.fit_transform(image_df1.emotion)
imagelabels = tf.keras.utils.to_categorical(imagelabels)
imagelabels.shape
X_train1, X_test1, y_train1, y_test1 = train_test_split(imagearray, imagelabels,
                                                        shuffle=True, stratify=image
                                                        test_size=0.3)
imgwidth = X_test1.shape[1]
imgheight = X_test1.shape[2]
imgdepth = X_test1.shape[3]
numclasses = y_test1.shape[1]
print(imgwidth,imgheight,imgdepth,numclasses)
# Normalizing
X_train1 = X_train1 / 255
X_test1 = X_test1 / 255
X_train1.shape
y_test1.shape
```

```
48 48 1 3
```

Out[63]:
```
(6380, 3)
```

Build the same model as model4 but with the top 3 labels

In [65]:
```
model5 = Sequential()
model5.add(Conv2D(filters=64,kernel_size=(5,5),input_shape=(img_width, img_height
                      padding='same',kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(Conv2D(
            filters=64,
            kernel_size=(5,5),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(2,2)))
model5.add(Dropout(0.4))
model5.add(Conv2D(
            filters=128,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(Conv2D(
            filters=128,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(2,2)))
model5.add(Dropout(0.4))
model5.add(Conv2D(
            filters=256,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(Conv2D(
            filters=256,
            kernel_size=(3,3),
            activation='elu',
            padding='same',
            kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(MaxPooling2D(pool_size=(2,2)))
model5.add(Dropout(0.5, name='dropout_3'))
model5.add(Flatten())
model5.add( Dense(128,activation='elu',kernel_initializer='he_normal'))
model5.add(BatchNormalization())
model5.add(Dropout(0.5))
model5.add(Dense(
            3,
            activation='softmax'))
```

Compile the model

In [66]:

```
opt = Adam(lr=0.001, decay=0.001 / 100)
model5.compile(loss="categorical_crossentropy", optimizer=opt,metrics=["accuracy
```

Fit the model

In [67]:
```
History5 = model5.fit_generator(
    a3.flow(X_train1, y_train1, batch_size=64),
    validation_data=(X_test1, y_test1),
    steps_per_epoch=len(X_train1) // 64,
    epochs=25, verbose=1)
```

```
Epoch 1/25
232/232 [==============================] - 767s 3s/step - loss: 1.3141 - accu
racy: 0.3994 - val_loss: 1.0325 - val_accuracy: 0.4715
Epoch 2/25
232/232 [==============================] - 771s 3s/step - loss: 1.0794 - accu
racy: 0.4574 - val_loss: 0.9544 - val_accuracy: 0.5428
Epoch 3/25
232/232 [==============================] - 780s 3s/step - loss: 1.0006 - accu
racy: 0.5088 - val_loss: 0.8799 - val_accuracy: 0.5842
Epoch 4/25
232/232 [==============================] - 903s 4s/step - loss: 0.9405 - accu
racy: 0.5456 - val_loss: 0.7978 - val_accuracy: 0.6259
Epoch 5/25
232/232 [==============================] - 495s 2s/step - loss: 0.8636 - accu
racy: 0.5894 - val_loss: 0.7579 - val_accuracy: 0.6393
Epoch 6/25
232/232 [==============================] - 510s 2s/step - loss: 0.8096 - accu
racy: 0.6165 - val_loss: 0.7682 - val_accuracy: 0.6412
Epoch 7/25
232/232 [==============================] - 514s 2s/step - loss: 0.7582 - accu
racy: 0.6414 - val_loss: 0.7837 - val_accuracy: 0.6382
Epoch 8/25
232/232 [==============================] - 540s 2s/step - loss: 0.7364 - accu
racy: 0.6590 - val_loss: 0.7666 - val_accuracy: 0.6635
Epoch 9/25
232/232 [==============================] - 530s 2s/step - loss: 0.7086 - accu
racy: 0.6807 - val_loss: 0.7987 - val_accuracy: 0.6534
Epoch 10/25
232/232 [==============================] - 521s 2s/step - loss: 0.6854 - accu
racy: 0.6956 - val_loss: 0.7077 - val_accuracy: 0.6978
Epoch 11/25
232/232 [==============================] - 547s 2s/step - loss: 0.6672 - accu
racy: 0.7021 - val_loss: 0.5926 - val_accuracy: 0.7370
Epoch 12/25
232/232 [==============================] - 516s 2s/step - loss: 0.6557 - accu
racy: 0.7110 - val_loss: 0.6190 - val_accuracy: 0.7373
Epoch 13/25
232/232 [==============================] - 515s 2s/step - loss: 0.6410 - accu
racy: 0.7157 - val_loss: 0.5636 - val_accuracy: 0.7561
Epoch 14/25
232/232 [==============================] - 533s 2s/step - loss: 0.6312 - accu
racy: 0.7269 - val_loss: 0.5639 - val_accuracy: 0.7473
Epoch 15/25
232/232 [==============================] - 516s 2s/step - loss: 0.6136 - accu
racy: 0.7325 - val_loss: 0.5920 - val_accuracy: 0.7368
Epoch 16/25
232/232 [==============================] - 551s 2s/step - loss: 0.6006 - accu
racy: 0.7394 - val_loss: 0.5586 - val_accuracy: 0.7583
Epoch 17/25
232/232 [==============================] - 566s 2s/step - loss: 0.6046 - accu
```

```
racy: 0.7388 - val_loss: 0.6045 - val_accuracy: 0.7343
Epoch 18/25
232/232 [==============================] - 513s 2s/step - loss: 0.5920 - accu
racy: 0.7426 - val_loss: 0.5950 - val_accuracy: 0.7353
Epoch 19/25
232/232 [==============================] - 510s 2s/step - loss: 0.5784 - accu
racy: 0.7504 - val_loss: 0.5464 - val_accuracy: 0.7558
Epoch 20/25
232/232 [==============================] - 500s 2s/step - loss: 0.5731 - accu
racy: 0.7546 - val_loss: 0.5940 - val_accuracy: 0.7392
Epoch 21/25
232/232 [==============================] - 510s 2s/step - loss: 0.5662 - accu
racy: 0.7557 - val_loss: 0.5251 - val_accuracy: 0.7697
Epoch 22/25
232/232 [==============================] - 515s 2s/step - loss: 0.5618 - accu
racy: 0.7618 - val_loss: 0.5194 - val_accuracy: 0.7766
Epoch 23/25
232/232 [==============================] - 514s 2s/step - loss: 0.5484 - accu
racy: 0.7690 - val_loss: 0.5913 - val_accuracy: 0.7370
Epoch 24/25
232/232 [==============================] - 514s 2s/step - loss: 0.5515 - accu
racy: 0.7645 - val_loss: 0.6046 - val_accuracy: 0.7364
Epoch 25/25
232/232 [==============================] - 504s 2s/step - loss: 0.5468 - accu
racy: 0.7650 - val_loss: 0.5903 - val_accuracy: 0.7440
```

Transfer learning VGG considering all the emotions

Broadcast the images as required

In [108]:
```
rgb_batch = np.repeat(X_train[..., np.newaxis], 3, -1)
rgb_batch1 = np.repeat(X_test[..., np.newaxis], 3, -1)
rgb_batch=np.array(rgb_batch)
rgb_batch1=np.array(rgb_batch1)
rgb_batch=rgb_batch.reshape(28709,48,48,3)
rgb_batch1=rgb_batch1.reshape(7178,48,48,3)
```

Build model using VGG19

In [118]:
```
model= VGG19(weights="imagenet", include_top=False,pooling='avg',
input_tensor=Input(shape=(img_width, img_height, 3)))
```

In [119]:
```
#The last 5 layers ae removed adnd 3 other layers are added
x = model.layers[-5].output
x = GlobalMaxPool2D(name="global_pool")(x)
x = Dense(100, activation="softmax")(x)
x = Dense(30, activation="softmax")(x)
predictions = Dense(num_classes, activation="softmax")(x)

model = Model(inputs=model.input, outputs=predictions)
```

In [123]:
```
model.summary()
```

```
Model: "model_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_11 (InputLayer)        [(None, 48, 48, 3)]       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 48, 48, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 48, 48, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 24, 24, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 24, 24, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 24, 24, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 12, 12, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 12, 12, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 12, 12, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 12, 12, 256)       590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 12, 12, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 6, 6, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 6, 6, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 3, 3, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 3, 3, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 3, 3, 512)         2359808
_________________________________________________________________
global_pool (GlobalMaxPoolin (None, 512)               0
_________________________________________________________________
dense_28 (Dense)             (None, 100)               51300
_________________________________________________________________
dense_29 (Dense)             (None, 30)                3030
_________________________________________________________________
dense_30 (Dense)             (None, 7)                 217
=================================================================
Total params: 15,359,315
Trainable params: 15,359,315
Non-trainable params: 0
_________________________________________________________________
```

Compile the model

In [124]:
```
model.compile(loss="categorical_crossentropy", optimizer=opt,metrics=["accuracy"
```

Fit the model

In [126]:
```
History6 = model.fit_generator(
    a3.flow(rgb_batch, y_train, batch_size=64),
    validation_data=(rgb_batch1, y_test),
    steps_per_epoch=len(rgb_batch) // 64,
    epochs=25, verbose=1)
```

```
Epoch 1/25
448/448 [==============================] - 1217s 3s/step - loss: 1.8304 - acc
uracy: 0.2499 - val_loss: 1.8134 - val_accuracy: 0.2505
Epoch 2/25
448/448 [==============================] - 1125s 3s/step - loss: 1.8125 - acc
uracy: 0.2504 - val_loss: 1.8106 - val_accuracy: 0.2505
Epoch 3/25
448/448 [==============================] - 1124s 3s/step - loss: 1.8109 - acc
uracy: 0.2505 - val_loss: 1.8101 - val_accuracy: 0.2505
Epoch 4/25
448/448 [==============================] - 1119s 2s/step - loss: 1.8109 - acc
uracy: 0.2500 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 5/25
448/448 [==============================] - 1120s 3s/step - loss: 1.8103 - acc
uracy: 0.2512 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 6/25
448/448 [==============================] - 1116s 2s/step - loss: 1.8105 - acc
uracy: 0.2505 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 7/25
448/448 [==============================] - 1118s 2s/step - loss: 1.8108 - acc
uracy: 0.2505 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 8/25
448/448 [==============================] - 1111s 2s/step - loss: 1.8108 - acc
uracy: 0.2502 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 9/25
448/448 [==============================] - 1104s 2s/step - loss: 1.8103 - acc
uracy: 0.2502 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 10/25
448/448 [==============================] - 1103s 2s/step - loss: 1.8106 - acc
uracy: 0.2510 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 11/25
448/448 [==============================] - 1098s 2s/step - loss: 1.8103 - acc
uracy: 0.2508 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 12/25
448/448 [==============================] - 1096s 2s/step - loss: 1.8097 - acc
uracy: 0.2505 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 13/25
448/448 [==============================] - 1100s 2s/step - loss: 1.8122 - acc
uracy: 0.2497 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 14/25
448/448 [==============================] - 1096s 2s/step - loss: 1.8103 - acc
uracy: 0.2499 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 15/25
448/448 [==============================] - 1093s 2s/step - loss: 1.8102 - acc
uracy: 0.2516 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 16/25
448/448 [==============================] - 1109s 2s/step - loss: 1.8105 - acc
uracy: 0.2504 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 17/25
448/448 [==============================] - 1100s 2s/step - loss: 1.8109 - acc
```

```
uracy: 0.2503 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 18/25
448/448 [==============================] - 1097s 2s/step - loss: 1.8108 - acc
uracy: 0.2501 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 19/25
448/448 [==============================] - 1100s 2s/step - loss: 1.8098 - acc
uracy: 0.2511 - val_loss: 1.8101 - val_accuracy: 0.2505
Epoch 20/25
448/448 [==============================] - 1099s 2s/step - loss: 1.8101 - acc
uracy: 0.2501 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 21/25
448/448 [==============================] - 1097s 2s/step - loss: 1.8107 - acc
uracy: 0.2516 - val_loss: 1.8100 - val_accuracy: 0.2505
Epoch 22/25
448/448 [==============================] - 1097s 2s/step - loss: 1.8103 - acc
uracy: 0.2508 - val_loss: 1.8101 - val_accuracy: 0.2505
Epoch 23/25
448/448 [==============================] - 1100s 2s/step - loss: 1.8111 - acc
uracy: 0.2502 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 24/25
448/448 [==============================] - 1103s 2s/step - loss: 1.8105 - acc
uracy: 0.2494 - val_loss: 1.8099 - val_accuracy: 0.2505
Epoch 25/25
448/448 [==============================] - 1101s 2s/step - loss: 1.8103 - acc
uracy: 0.2499 - val_loss: 1.8099 - val_accuracy: 0.2505
```

In [ ]:
```
model.save("D:\Deep Learning\model")
```

In [ ]:
```
model_1.save("D:\Deep Learning\model1")
```

In [ ]:
```
model2.save("D:\Deep Learning\model2")
```

In [ ]:
```
model3.save("D:\Deep Learning\model3")
```

In [35]:
```
model4.save("D:\Deep Learning\model4")
```

```
INFO:tensorflow:Assets written to: D:\Deep Learning\model4\assets

INFO:tensorflow:Assets written to: D:\Deep Learning\model4\assets
```

In [ ]:
```
model5.save("D:\Deep Learning\model5")
```

In [ ]:
```
#Model1 with basic CNN
N = np.arange(0, 100)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, history.history["loss"], label="train_loss")
plt.plot(N, history.history["val_loss"], label="val_loss")
plt.plot(N, history.history["accuracy"], label="train_acc")
plt.plot(N, history.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy ")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig("D:\Deep Learning\plot1")
```

In [ ]:
```
#Model 2 with little complex CNN model
N = np.arange(0, 100)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, History2.history["loss"], label="train_loss")
plt.plot(N, History2.history["val_loss"], label="val_loss")
plt.plot(N, History2.history["accuracy"], label="train_acc")
plt.plot(N, History2.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig("D:\Deep Learning\plot2")
```

In [ ]:
```
#Model 4 with complex CNN and elu
N = np.arange(0, 25)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, History4.history["loss"], label="train_loss")
plt.plot(N, History4.history["val_loss"], label="val_loss")
plt.plot(N, History4.history["accuracy"], label="train_acc")
plt.plot(N, History4.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig("D:\Deep Learning\plot4")
```

In [ ]:
```
#Model 5 considering only the top 2 lables and complex CNN
N = np.arange(0, 25)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, History5.history["loss"], label="train_loss")
plt.plot(N, History5.history["val_loss"], label="val_loss")
plt.plot(N, History5.history["accuracy"], label="train_acc")
plt.plot(N, History5.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig("D:\Deep Learning\plot5")
```

In [ ]:
```
#model with transfer learning VGG
N = np.arange(0, 25)
plt.style.use("ggplot")
plt.figure()
plt.plot(N, History6.history["loss"], label="train_loss")
plt.plot(N, History6.history["val_loss"], label="val_loss")
plt.plot(N, History6.history["accuracy"], label="train_acc")
plt.plot(N, History6.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig("D:\Deep Learning\plot")
```

Issues / Improvements

1. Lack of effective resources
2. Having only gray scale images for emotion detection.
3. Use cross-validaiton

References

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