```
!python --version

    Python 3.10.11
```

Double-click (or enter) to edit

```
!pip install keras-visualizer
!pip install visualkeras

    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Collecting keras-visualizer
      Downloading keras_visualizer-3.1.2-py3-none-any.whl (6.9 kB)
    Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from keras-visualizer) (0.20.1
    Installing collected packages: keras-visualizer
    Successfully installed keras-visualizer-3.1.2
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Collecting visualkeras
      Downloading visualkeras-0.0.2-py3-none-any.whl (12 kB)
    Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from visualkeras) (8.4.0)
    Requirement already satisfied: numpy>=1.18.1 in /usr/local/lib/python3.10/dist-packages (from visualkeras) (1.22.4
    Collecting aggdraw>=1.3.11 (from visualkeras)
      Downloading aggdraw-1.3.16-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (993 kB)
         ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 993.0/993.0 kB 26.7 MB/s eta 0:00:00
    Installing collected packages: aggdraw, visualkeras
    Successfully installed aggdraw-1.3.16 visualkeras-0.0.2
```

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Import Library

```
import numpy as np
import pandas as pd
import seaborn as sns
import cv2,math,os,glob
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.express as px
import plotly.graph_objects as go
import scipy
from imblearn.over_sampling import RandomOverSampler
import warnings


import visualkeras
from keras_visualizer import visualizer
```

Import/Download the Dataset

```
!wget https://www.dropbox.com/s/rlezn4w74709oum/face_expression_recog.csv.zip

    --2023-05-26 07:48:04--  https://www.dropbox.com/s/rlezn4w74709oum/face_expression_recog.csv.zip
    Resolving www.dropbox.com (www.dropbox.com)... 162.125.5.18, 2620:100:601b:18::a27d:812
    Connecting to www.dropbox.com (www.dropbox.com)|162.125.5.18|:443... connected.
    HTTP request sent, awaiting response... 302 Found
    Location: /s/raw/rlezn4w74709oum/face_expression_recog.csv.zip [following]
    --2023-05-26 07:48:04--  https://www.dropbox.com/s/raw/rlezn4w74709oum/face_expression_recog.csv.zip
    Reusing existing connection to www.dropbox.com:443.
    HTTP request sent, awaiting response... 302 Found
    Location: https://uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com/cd/0/inline/B8z08orsT51wGAYVPaX7Rh_5Ey5Jm
    --2023-05-26 07:48:05--  https://uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com/cd/0/inline/B8z08orsT51wGA
    Resolving uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com (uc9c4cfd64bd7faf7012f874a392.dl.dropboxuserconte
    Connecting to uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com (uc9c4cfd64bd7faf7012f874a392.dl.dropboxuserc
    HTTP request sent, awaiting response... 302 Found
    Location: /cd/0/inline2/B8x9EQ4TO5shtk7sEkA6Vd9CagZ32HEOBd5O737jBZvFsRSbQE1Y6LOcW8HkEXtcbSaIDQLukL41TBgQ3fkzhzk7FF
    --2023-05-26 07:48:06--  https://uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com/cd/0/inline2/B8x9EQ4TO5sht
    Reusing existing connection to uc9c4cfd64bd7faf7012f874a392.dl.dropboxusercontent.com:443.
    HTTP request sent, awaiting response... 200 OK
    Length: 101279992 (97M) [application/zip]
```

```
     Saving to: ‘face_expression_recog.csv.zip’

     face_expression_rec 100%[===================>]  96.59M  22.3MB/s    in 4.4s

     2023-05-26 07:48:11 (22.0 MB/s) - ‘face_expression_recog.csv.zip’ saved [101279992/101279992]
```

```
!unzip face_expression_recog.csv.zip

     Archive:  face_expression_recog.csv.zip
       inflating: fer2013.csv
```

Read/view the Database

```
y1a = pd.read_csv('fer2013.csv')
print(y1a.shape)
print(y1a)

     (35887, 3)
            emotion                                             pixels       Usage
     0            0  70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...     Training
     1            0  151 150 147 155 148 133 111 140 170 174 182 15...     Training
     2            2  231 212 156 164 174 138 161 173 182 200 106 38...     Training
                                23 19 20 30 41 21 22 32 34 21 1...     Training
                                 0 0 0 0 0 3 15 23 28 48 50 58 84...     Training
                                                                ...          ...
     35882        6  50 36 17 22 23 29 33 39 34 37 37 37 39 43 48 5...  PrivateTest
     35883        3  178 174 172 173 181 188 191 194 196 199 200 20...  PrivateTest
     35884        0  17 17 16 23 28 22 19 17 25 26 20 24 31 19 27 9...  PrivateTest
     35885        3  30 28 28 29 31 30 42 68 79 81 77 67 67 71 63 6...  PrivateTest
     35886        2  19 13 14 12 13 16 21 33 50 57 71 84 97 108 122...  PrivateTest

     [35887 rows x 3 columns]
```

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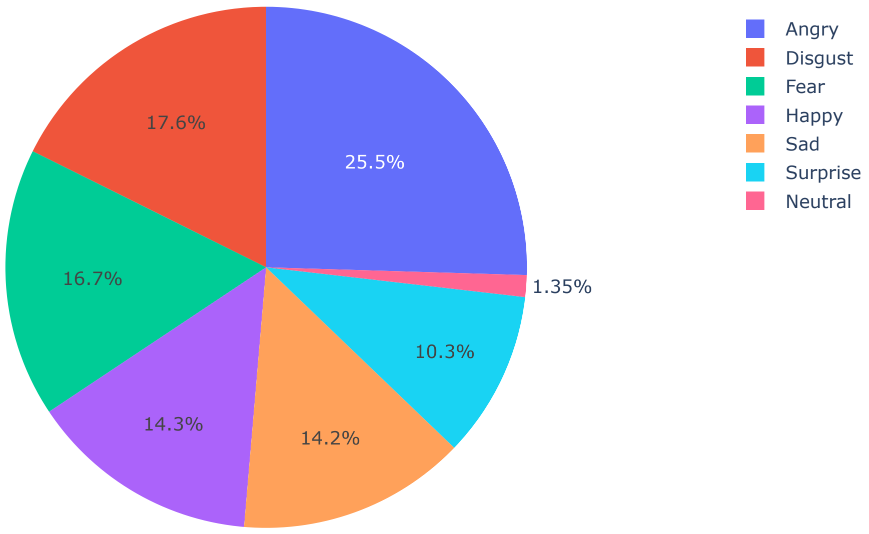
```
y1 = y1a.loc[:3999,:]
print(y1.shape)
print(y1)

     (4000, 3)
           emotion                                             pixels     Usage
     0           0  70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...  Training
     1           0  151 150 147 155 148 133 111 140 170 174 182 15...  Training
     2           2  231 212 156 164 174 138 161 173 182 200 106 38...  Training
     3           4  24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...  Training
     4           6  4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...  Training
     ...       ...                                                ...       ...
     3995        0  25 71 114 80 73 82 94 119 142 156 166 173 172 ...  Training
     3996        6  32 69 63 66 50 53 68 66 67 70 60 83 97 111 127...  Training
     3997        6  140 141 53 29 25 14 56 153 196 208 211 219 220...  Training
     3998        3  58 64 63 33 28 27 29 28 29 34 36 46 66 77 74 7...  Training
     3999        5  133 133 105 79 85 88 94 97 98 100 108 112 116 ...  Training

     [4000 rows x 3 columns]
```

Target/Prediction Class

```
predict_class_count = y1.emotion.value_counts()
display(predict_class_count)

     3    1019
     6     706
     4     668
     2     572
     0     567
     5     414
     1      54
     Name: emotion, dtype: int64
```

```
from plotly.offline import iplot
pred_class = ['Angry','Disgust','Fear','Happy','Sad','Surprise','Neutral' ]
trace = go.Pie(labels = pred_class, values = predict_class_count)
data = [trace]
fig = go.Figure(data = trace)
iplot(fig)
```



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Target CLass representation

0 : Angry, 1 : Disgust, 2 : Fear, 3 : Happy, 4 : Sad, 5 : Surprise, 6 : Neutral

```
xx = y1.pixels  # independent features
yy = y1.emotion # target class
```

Reshaping the values by oversampler

```
data_oversampling = RandomOverSampler(sampling_strategy='auto')

xx_n, yy_n = data_oversampling.fit_resample(xx.values.reshape(-1,1), yy)
print(xx_n.shape," ",yy_n.shape)

    (7133, 1)   (7133,)
```

Value check for target class

```
yy_n.value_counts()

    0    1019
    2    1019
    4    1019
    6    1019
    3    1019
    5    1019
```

```
        1    1019
        Name: emotion, dtype: int64
```

Data Flatten - convert muti Dimension data into 1D

```
xx_n1 = pd.Series(xx_n.flatten())
xx_n1
```

```
        0       70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...
        1       151 150 147 155 148 133 111 140 170 174 182 15...
        2       231 212 156 164 174 138 161 173 182 200 106 38...
        3       24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
        4       4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...
                                     ...
        7128    1 5 9 16 23 12 8 10 13 21 32 42 33 45 67 76 86...
        7129    147 151 154 156 160 117 56 44 64 80 82 84 92 9...
        7130    249 247 246 242 238 235 230 239 113 51 62 65 6...
        7131    83 87 91 92 91 84 78 80 90 85 9 5 3 0 10 21 39...
        7132    120 121 123 120 120 122 127 67 55 86 89 92 96 ...
        Length: 7133, dtype: object
```

Normalization

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```
                          , xx_n1)), np.float32)
xx_n2/=255
xx_n2[:10]
```

```
        array([[0.27450982, 0.3137255 , 0.32156864, ..., 0.41568628, 0.42745098,
                0.32156864],
               [0.5921569 , 0.5882353 , 0.5764706 , ..., 0.75686276, 0.7176471 ,
                0.72156864],
               [0.90588236, 0.83137256, 0.6117647 , ..., 0.34509805, 0.43137255,
                0.59607846],
               ...,
               [0.3019608 , 0.30588236, 0.30980393, ..., 0.49019608, 0.2627451 ,
                0.26666668],
               [0.33333334, 0.32941177, 0.3529412 , ..., 0.22745098, 0.28627452,
                0.32941177],
               [1.        , 0.99607843, 1.        , ..., 0.99607843, 1.        ,
                1.        ]], dtype=float32)
```

Independent features - data reshaping/resizing

```
xx_data_new = xx_n2.reshape(-1, 48, 48, 1)
xx_data_new.shape
```

```
        (7133, 48, 48, 1)
```

convert target class data into array format

```
yy_n1 = np.array(yy_n)
yy_data_new = yy_n1.reshape(yy_n1.shape[0], 1)
yy_data_new.shape
```

```
        (7133, 1)
```

Data Splitting

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
```

```
X_train, X_test, y_train, y_test = train_test_split(xx_data_new, yy_data_new, test_size = 0.15, random_state = 45)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(6063, 48, 48, 1) (6063, 1)
(1070, 48, 48, 1) (1070, 1)
```

Calling Library

```
from tensorflow import keras
from keras.layers import Conv2D, MaxPool2D, AveragePooling2D, Input, BatchNormalization, MaxPooling2D, Activation, Flatt
from keras.models import Sequential
from keras.utils import np_utils
from keras.preprocessing import image
```

```
model1 = Sequential([
    Input((48, 48, 1)),
    Conv2D(32, kernel_size=(3,3), strides=(1,1), padding='valid'),
    BatchNormalization(axis=3),
    Activation('relu'),
    Conv2D(64, (3,3), strides=(1,1), padding = 'same',activation='relu'),
    BatchNormalization(axis=3),
    Activation('relu'),
    [illegible]
Creating a copy...                              , padding = 'valid',activation='relu'),
    [illegible]
    Activation('relu'),
    Conv2D(128, (3,3), strides=(1,1), padding = 'same'),
    BatchNormalization(axis=3),
    Activation('relu'),
    MaxPooling2D((2,2)),
    Conv2D(128, (3,3), strides=(1,1), padding = 'valid'),
    BatchNormalization(axis=3),
    Activation('relu'),
    MaxPooling2D((2,2)),
    Flatten(),
    Dense(200, activation='relu'),
    Dropout(0.6),
    Dense(7, activation = 'softmax') ])
model1.summary()
model1.compile(optimizer="adam", loss='categorical_crossentropy', metrics=['accuracy'])
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 32)        320

 batch_normalization (BatchN  (None, 46, 46, 32)       128
 ormalization)

 activation (Activation)     (None, 46, 46, 32)        0

 conv2d_1 (Conv2D)           (None, 46, 46, 64)        18496

 batch_normalization_1 (Batc  (None, 46, 46, 64)       256
 hNormalization)

 activation_1 (Activation)   (None, 46, 46, 64)        0

 max_pooling2d (MaxPooling2D  (None, 23, 23, 64)       0
 )

 conv2d_2 (Conv2D)           (None, 21, 21, 64)        36928

 batch_normalization_2 (Batc  (None, 21, 21, 64)       256
 hNormalization)

 activation_2 (Activation)   (None, 21, 21, 64)        0

 conv2d_3 (Conv2D)           (None, 21, 21, 128)       73856
 batch_normalization_3 (Batc  (None, 21, 21, 128)      512
 hNormalization)

 activation_3 (Activation)   (None, 21, 21, 128)       0

 max_pooling2d_1 (MaxPooling  (None, 10, 10, 128)      0
 2D)

 conv2d_4 (Conv2D)           (None, 8, 8, 128)         147584

 batch_normalization_4 (Batc  (None, 8, 8, 128)        512
 hNormalization)

 activation_4 (Activation)   (None, 8, 8, 128)         0

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0
 2D)

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 200)               409800

 dropout (Dropout)           (None, 200)               0

 dense_1 (Dense)             (None, 7)                 1407

=================================================================
Total params: 690,055
```

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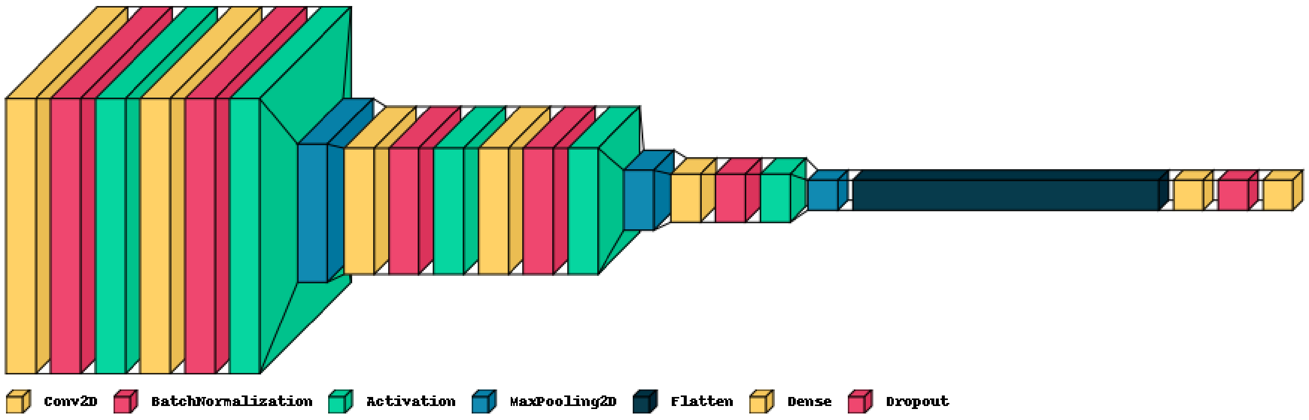
```
from keras_visualizer import visualizer
tf.keras.utils.plot_model(model1, to_file="my_model1.png", show_shapes=True)
visualkeras.layered_view(model1, legend=True) # without custom font
```



Convert Target class (Y_train , Y_test) into catregorical code

```
y_train_n = np_utils.to_categorical(y_train, 7)
y_train_n.shape

     (6063, 7)
```

```
y_test_n = np_utils.to_categorical(y_test, 7)
y_test_n.shape

     (1070, 7)
```

Train the CNN model 1

```
history1 = model1.fit(X_train, y_train_n, epochs = 35, validation_data=(X_test, y_test_n))

     Epoch 1/35
     190/190 [==============================] - 100s 517ms/step - loss: 2.0132 - accuracy: 0.1697 - val_loss: 1.9828
     Epoch 2/35
     190/190 [==============================] - 98s 515ms/step - loss: 1.8214 - accuracy: 0.2116 - val_loss: 2.0326 -
     Epoch 3/35
     190/190 [==============================] - 97s 509ms/step - loss: 1.7210 - accuracy: 0.2636 - val_loss: 1.8525 -
     Epoch 4/35
     190/190 [==============================] - 98s 515ms/step - loss: 1.6430 - accuracy: 0.2905 - val_loss: 1.7006 -
     Epoch 5/35
     190/190 [==============================] - 96s 506ms/step - loss: 1.5774 - accuracy: 0.3182 - val_loss: 1.4642 -
     Epoch 6/35
     190/190 [==============================] - 101s 530ms/step - loss: 1.5176 - accuracy: 0.3431 - val_loss: 1.3610
     Epoch 7/35
     190/190 [==============================] - 100s 526ms/step - loss: 1.4950 - accuracy: 0.3373 - val_loss: 1.5096
     Epoch 8/35
     190/190 [==============================] - 100s 524ms/step - loss: 1.4703 - accuracy: 0.3439 - val_loss: 1.4642
     Epoch 9/35
     190/190 [==============================] - 100s 528ms/step - loss: 1.4443 - accuracy: 0.3508 - val_loss: 1.5359
     Epoch 10/35
     190/190 [==============================] - 98s 519ms/step - loss: 1.4389 - accuracy: 0.3553 - val_loss: 1.2980 -
     Epoch 11/35
     190/190 [==============================] - 100s 525ms/step - loss: 1.4105 - accuracy: 0.3594 - val_loss: 1.5400
     Epoch 12/35
     190/190 [==============================] - 103s 542ms/step - loss: 1.4112 - accuracy: 0.3683 - val_loss: 1.2826
     Epoch 13/35
     190/190 [==============================] - 101s 534ms/step - loss: 1.4021 - accuracy: 0.3706 - val_loss: 1.2932
     Epoch 14/35
     190/190 [==============================] - 100s 527ms/step - loss: 1.3761 - accuracy: 0.3764 - val_loss: 1.4631
     Epoch 15/35
     190/190 [==============================] - 100s 526ms/step - loss: 1.3819 - accuracy: 0.3830 - val_loss: 1.2595
     Epoch 16/35
                             =========] - 100s 527ms/step - loss: 1.3634 - accuracy: 0.3859 - val_loss: 1.2413
  Creating a copy...
                             =========] - 99s 519ms/step - loss: 1.3337 - accuracy: 0.3774 - val_loss: 1.2684 -
     Epoch 18/35
     190/190 [==============================] - 100s 527ms/step - loss: 1.3137 - accuracy: 0.3947 - val_loss: 1.2547
     Epoch 19/35
     190/190 [==============================] - 100s 525ms/step - loss: 1.3197 - accuracy: 0.3940 - val_loss: 1.2918
     Epoch 20/35
     190/190 [==============================] - 100s 526ms/step - loss: 1.3025 - accuracy: 0.4038 - val_loss: 1.1930
     Epoch 21/35
     190/190 [==============================] - 100s 525ms/step - loss: 1.2998 - accuracy: 0.4089 - val_loss: 1.3030
     Epoch 22/35
     190/190 [==============================] - 99s 520ms/step - loss: 1.2962 - accuracy: 0.4054 - val_loss: 1.2022 -
     Epoch 23/35
     190/190 [==============================] - 100s 525ms/step - loss: 1.3004 - accuracy: 0.4207 - val_loss: 1.2209
     Epoch 24/35
     190/190 [==============================] - 99s 523ms/step - loss: 1.3166 - accuracy: 0.4137 - val_loss: 1.3325 -
     Epoch 25/35
     190/190 [==============================] - 100s 524ms/step - loss: 1.2758 - accuracy: 0.4234 - val_loss: 1.3596
     Epoch 26/35
     190/190 [==============================] - 99s 522ms/step - loss: 1.2666 - accuracy: 0.4325 - val_loss: 1.5526 -
     Epoch 27/35
     190/190 [==============================] - 99s 522ms/step - loss: 1.2595 - accuracy: 0.4410 - val_loss: 1.1472 -
     Epoch 28/35
     190/190 [==============================] - 100s 524ms/step - loss: 1.2660 - accuracy: 0.4457 - val_loss: 1.2183
     Epoch 29/35
```

```
#
```

```
history1 = model1.fit(X_train, y_train_n, epochs = 15, validation_data=(X_test, y_test_n))
```

```
     Epoch 1/15
     190/190 [==============================] - 99s 518ms/step - loss: 1.2413 - accuracy: 0.4928 - val_loss: 1.2423 - v
     Epoch 2/15
     190/190 [==============================] - 101s 530ms/step - loss: 1.2139 - accuracy: 0.5011 - val_loss: 1.2092 -
     Epoch 3/15
     190/190 [==============================] - 100s 529ms/step - loss: 1.1942 - accuracy: 0.5176 - val_loss: 1.2125 -
     Epoch 4/15
     190/190 [==============================] - 100s 526ms/step - loss: 1.1725 - accuracy: 0.5214 - val_loss: 1.2142 -
     Epoch 5/15
     190/190 [==============================] - 100s 526ms/step - loss: 1.1889 - accuracy: 0.5265 - val_loss: 1.2364 -
     Epoch 6/15
     190/190 [==============================] - 98s 518ms/step - loss: 1.1623 - accuracy: 0.5324 - val_loss: 1.2011 - v
     Epoch 7/15
     190/190 [==============================] - 99s 520ms/step - loss: 1.1652 - accuracy: 0.5355 - val_loss: 1.2536 - v
     Epoch 8/15
     190/190 [==============================] - 99s 521ms/step - loss: 1.1791 - accuracy: 0.5270 - val_loss: 1.2669 - v
     Epoch 9/15
```

```
    190/190 [==============================] - 99s 520ms/step - loss: 1.1588 - accuracy: 0.5385 - val_loss: 1.2574 - v
    Epoch 10/15
    190/190 [==============================] - 98s 515ms/step - loss: 1.1835 - accuracy: 0.5217 - val_loss: 1.1953 - v
    Epoch 11/15
    190/190 [==============================] - 100s 525ms/step - loss: 1.1576 - accuracy: 0.5390 - val_loss: 1.2817 - v
    Epoch 12/15
    190/190 [==============================] - 99s 521ms/step - loss: 1.1839 - accuracy: 0.5360 - val_loss: 1.2112 - v
    Epoch 13/15
    190/190 [==============================] - 99s 519ms/step - loss: 1.1654 - accuracy: 0.5382 - val_loss: 1.2102 - v
    Epoch 14/15
    190/190 [==============================] - 97s 513ms/step - loss: 1.1482 - accuracy: 0.5430 - val_loss: 1.3151 - v
    Epoch 15/15
    190/190 [==============================] - 99s 520ms/step - loss: 1.1507 - accuracy: 0.5385 - val_loss: 1.2129 - v
```

```
print("Accuracy  : " , model1.evaluate(X_test,y_test_n)[1]*100 , "%")
```

```
    34/34 [==============================] - 5s 139ms/step - loss: 1.2129 - accuracy: 0.5850
    Accuracy  :  58.50467085838318 %
```

```
plt.plot(history1.history['accuracy'])
plt.plot(history1.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

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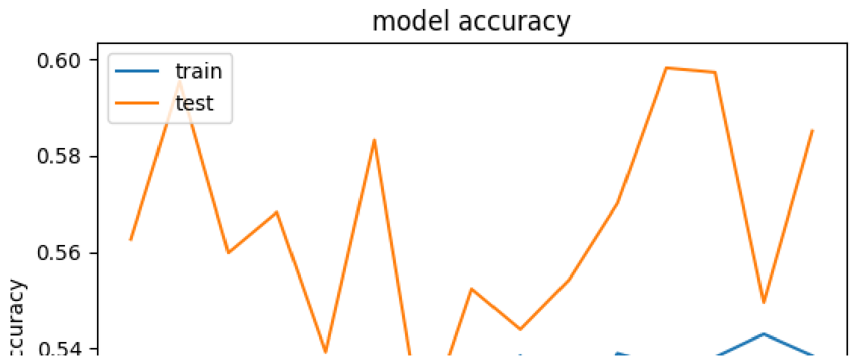
```
plt.plot(history1.history['accuracy'])
plt.plot(history1.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



```
y_pred = model1.predict(X_test)
y_result = []

for pred in y_pred:
    y_result.append(np.argmax(pred))
y_result[:10]

     34/34 [==============================] - 4s 112ms/step
     [2, 2, 3, 0, 3, 6, 3, 6, 6, 4]
```

```
y_actual = []

for pred in y_test_n:
                                           )
```

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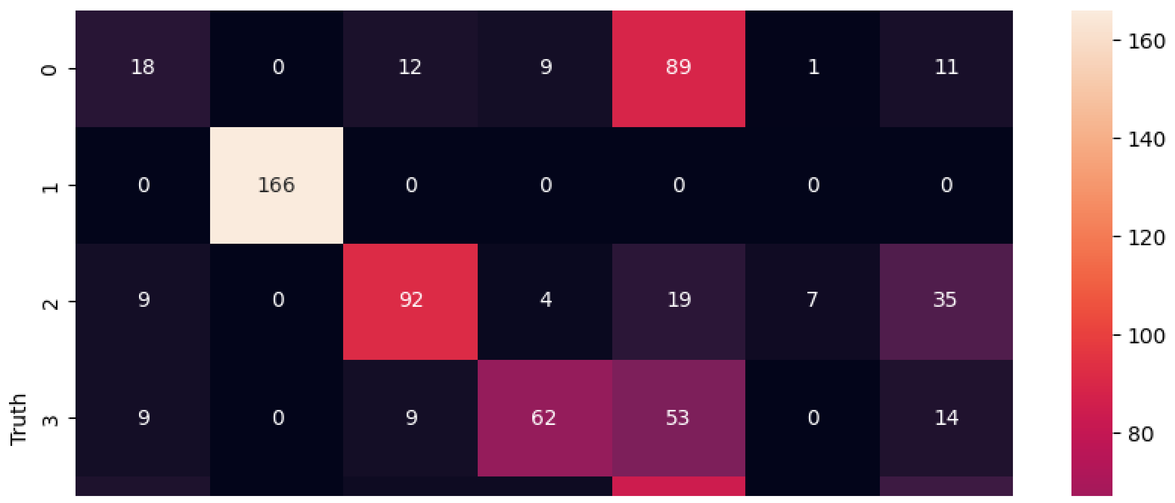
```
     [2, 5, 3, 0, 3, 2, 3, 3, 6, 5]
```

```
from sklearn.metrics import confusion_matrix, classification_report
print(classification_report(y_actual, y_result))

                   precision    recall  f1-score   support

                0       0.25      0.13      0.17       140
                1       1.00      1.00      1.00       166
                2       0.51      0.55      0.53       166
                3       0.76      0.42      0.54       147
                4       0.31      0.62      0.41       136
                5       0.93      0.64      0.76       163
                6       0.53      0.66      0.59       152

         accuracy                           0.59      1070
        macro avg       0.61      0.57      0.57      1070
     weighted avg       0.63      0.59      0.59      1070
```

```
import seaborn as sn
cm = tf.math.confusion_matrix(labels = y_actual, predictions = y_result)

plt.figure(figsize = (10, 7))
sn.heatmap(cm, annot = True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(95.72222222222221, 0.5, 'Truth')
```



Model 2

```
model2 = Sequential()
num_features = 64
#module 1
                    kernel_size=(3, 3), input_shape=(48, 48, 1), data_format='channels_last'))
model2.add(Activation('relu'))
model2.add(Conv2D(2*2*num_features, kernel_size=(3, 3), padding='same'))
model2.add(BatchNormalization())
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

#module 2
model2.add(Conv2D(2*num_features, kernel_size=(3, 3), padding='same'))
model2.add(BatchNormalization())
model2.add(Activation('relu'))
model2.add(Conv2D(2*num_features, kernel_size=(3, 3), padding='same'))
model2.add(BatchNormalization())
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

#module 3
model2.add(Conv2D(num_features, kernel_size=(3, 3), padding='same'))
model2.add(BatchNormalization())
model2.add(Activation('relu'))
model2.add(Conv2D(num_features, kernel_size=(3, 3), padding='same'))
model2.add(BatchNormalization())
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

#flatten
model2.add(Flatten())

#dense 1
model2.add(Dense(2*2*2*num_features))
model2.add(BatchNormalization())
model2.add(Activation('relu'))

#dense 2
model2.add(Dense(2*2*num_features))
model2.add(BatchNormalization())
model2.add(Activation('relu'))

#dense 3
model2.add(Dense(2*num_features))
model2.add(BatchNormalization())
model2.add(Activation('relu'))

#output layer
model2.add(Dense(7, activation='softmax'))
```

Creating a copy...

```
model2.compile(optimizer="adam", loss='categorical_crossentropy', metrics=['accuracy'])
```

```
model2.summary()
```

```
 conv2d_8 (Conv2D)           (None, 23, 23, 128)       147584

 batch_normalization_8 (Batc  (None, 23, 23, 128)      512
 hNormalization)

 activation_8 (Activation)   (None, 23, 23, 128)       0

 max_pooling2d_4 (MaxPooling  (None, 11, 11, 128)      0
 2D)

 conv2d_9 (Conv2D)           (None, 11, 11, 64)        73792

 batch_normalization_9 (Batc  (None, 11, 11, 64)       256
 hNormalization)

 activation_9 (Activation)   (None, 11, 11, 64)        0

 conv2d_10 (Conv2D)          (None, 11, 11, 64)        36928

 batch_normalization_10 (Bat  (None, 11, 11, 64)       256
 chNormalization)

 activation_10 (Activation)  (None, 11, 11, 64)        0

Creating a copy...            (None, 5, 5, 64)         0

 flatten_1 (Flatten)         (None, 1600)              0

 dense_2 (Dense)             (None, 512)               819712

 batch_normalization_11 (Bat  (None, 512)              2048
 chNormalization)

 activation_11 (Activation)  (None, 512)               0

 dense_3 (Dense)             (None, 256)               131328

 batch_normalization_12 (Bat  (None, 256)              1024
 chNormalization)

 activation_12 (Activation)  (None, 256)               0

 dense_4 (Dense)             (None, 128)               32896

 batch_normalization_13 (Bat  (None, 128)              512
 chNormalization)

 activation_13 (Activation)  (None, 128)               0

 dense_5 (Dense)             (None, 7)                 903

=================================================================
Total params: 2,137,991
Trainable params: 2,134,407
Non-trainable params: 3,584
_________________________________________________________________
```

```
history2 = model2.fit(X_train, y_train_n, epochs = 30, validation_data=(X_test, y_test_n))
```

```
190/190 [==============================] - 1006s 5s/step - loss: 1.1934 - accuracy: 0.5576 - val_loss: 2.6229 -
Epoch 3/30
190/190 [==============================] - 972s 5s/step - loss: 0.8849 - accuracy: 0.6936 - val_loss: 1.8242 - v
Epoch 4/30
190/190 [==============================] - 1006s 5s/step - loss: 0.6144 - accuracy: 0.7943 - val_loss: 1.2709 -
Epoch 5/30
190/190 [==============================] - 969s 5s/step - loss: 0.4301 - accuracy: 0.8583 - val_loss: 1.1331 - v
Epoch 6/30
190/190 [==============================] - 1005s 5s/step - loss: 0.2822 - accuracy: 0.9086 - val_loss: 1.1212 -
```

```
190/190 [==============================] - 1005s 5s/step - loss: 0.1703 - accuracy: 0.9441 - val_loss: 1.1476 -
Epoch 9/30
190/190 [==============================] - 971s 5s/step - loss: 0.1429 - accuracy: 0.9550 - val_loss: 1.0807 - v
Epoch 10/30
190/190 [==============================] - 970s 5s/step - loss: 0.0958 - accuracy: 0.9708 - val_loss: 1.0787 - v
Epoch 11/30
190/190 [==============================] - 1006s 5s/step - loss: 0.1033 - accuracy: 0.9680 - val_loss: 1.1782 -
Epoch 12/30
190/190 [==============================] - 1011s 5s/step - loss: 0.1379 - accuracy: 0.9558 - val_loss: 1.1441 -
Epoch 13/30
190/190 [==============================] - 1009s 5s/step - loss: 0.1167 - accuracy: 0.9619 - val_loss: 1.2854 -
Epoch 14/30
190/190 [==============================] - 1016s 5s/step - loss: 0.0939 - accuracy: 0.9692 - val_loss: 1.1830 -
Epoch 15/30
190/190 [==============================] - 1016s 5s/step - loss: 0.0588 - accuracy: 0.9822 - val_loss: 1.5453 -
Epoch 16/30
190/190 [==============================] - 1017s 5s/step - loss: 0.0706 - accuracy: 0.9779 - val_loss: 1.2095 -
Epoch 17/30
190/190 [==============================] - 1017s 5s/step - loss: 0.0688 - accuracy: 0.9771 - val_loss: 1.4023 -
Epoch 18/30
190/190 [==============================] - 1018s 5s/step - loss: 0.0788 - accuracy: 0.9769 - val_loss: 1.3858 -
Epoch 19/30
190/190 [==============================] - 1019s 5s/step - loss: 0.0885 - accuracy: 0.9726 - val_loss: 1.5116 -
Epoch 20/30
190/190 [==============================] - 1020s 5s/step - loss: 0.0842 - accuracy: 0.9713 - val_loss: 1.3830 -
Epoch 21/30
190/190 [==============================] - 1020s 5s/step - loss: 0.0676 - accuracy: 0.9759 - val_loss: 1.5467 -
Epoch 22/30
190/190 [==============================] - 1019s 5s/step - loss: 0.0428 - accuracy: 0.9853 - val_loss: 1.4119 -
Epoch 23/30
Creating a copy...          =========] - 982s 5s/step - loss: 0.0272 - accuracy: 0.9921 - val_loss: 1.4060 - v

190/190 [==============================] - 1018s 5s/step - loss: 0.0525 - accuracy: 0.9825 - val_loss: 1.4745 -
Epoch 25/30
190/190 [==============================] - 1019s 5s/step - loss: 0.0484 - accuracy: 0.9848 - val_loss: 1.4432 -
Epoch 26/30
190/190 [==============================] - 1021s 5s/step - loss: 0.0668 - accuracy: 0.9789 - val_loss: 1.4750 -
Epoch 27/30
190/190 [==============================] - 1021s 5s/step - loss: 0.0526 - accuracy: 0.9845 - val_loss: 1.3802 -
Epoch 28/30
190/190 [==============================] - 987s 5s/step - loss: 0.0401 - accuracy: 0.9871 - val_loss: 1.5773 - v
Epoch 29/30
190/190 [==============================] - 1018s 5s/step - loss: 0.0461 - accuracy: 0.9873 - val_loss: 1.8969 -
Epoch 30/30
190/190 [==============================] - 982s 5s/step - loss: 0.0632 - accuracy: 0.9781 - val_loss: 1.5456 - v
```

```
history2a = model2.fit(X_train, y_train_n, epochs = 5, validation_data=(X_test, y_test_n))
```

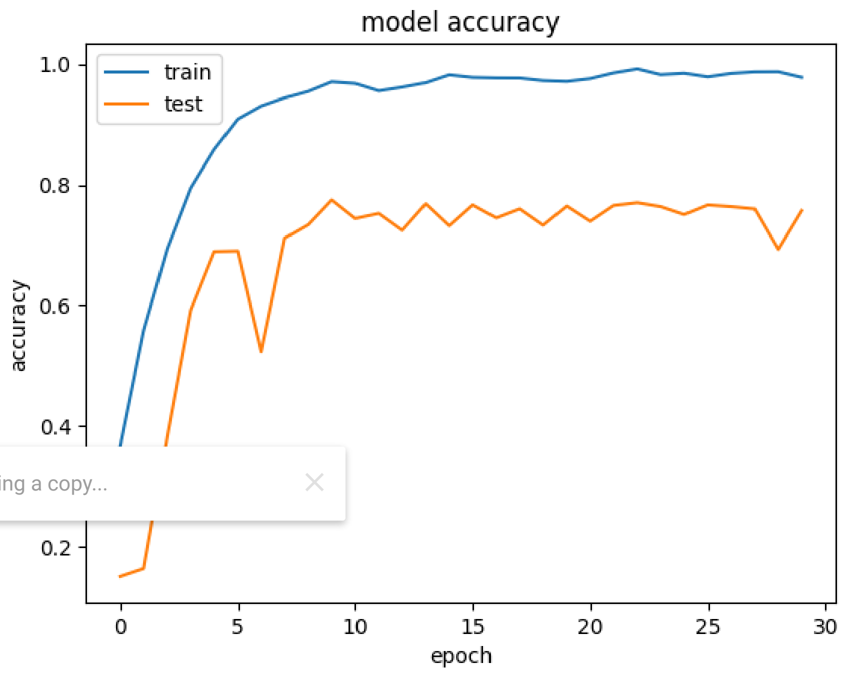
```
Epoch 1/5
190/190 [==============================] - 1018s 5s/step - loss: 0.0822 - accuracy: 0.9731 - val_loss: 1.5254 - va
Epoch 2/5
190/190 [==============================] - 983s 5s/step - loss: 0.0624 - accuracy: 0.9787 - val_loss: 1.3240 - val_
Epoch 3/5
190/190 [==============================] - 1022s 5s/step - loss: 0.0248 - accuracy: 0.9932 - val_loss: 1.2981 - va
Epoch 4/5
190/190 [==============================] - 985s 5s/step - loss: 0.0207 - accuracy: 0.9939 - val_loss: 1.6149 - val_
Epoch 5/5
190/190 [==============================] - 988s 5s/step - loss: 0.0368 - accuracy: 0.9878 - val_loss: 1.4349 - val_
```

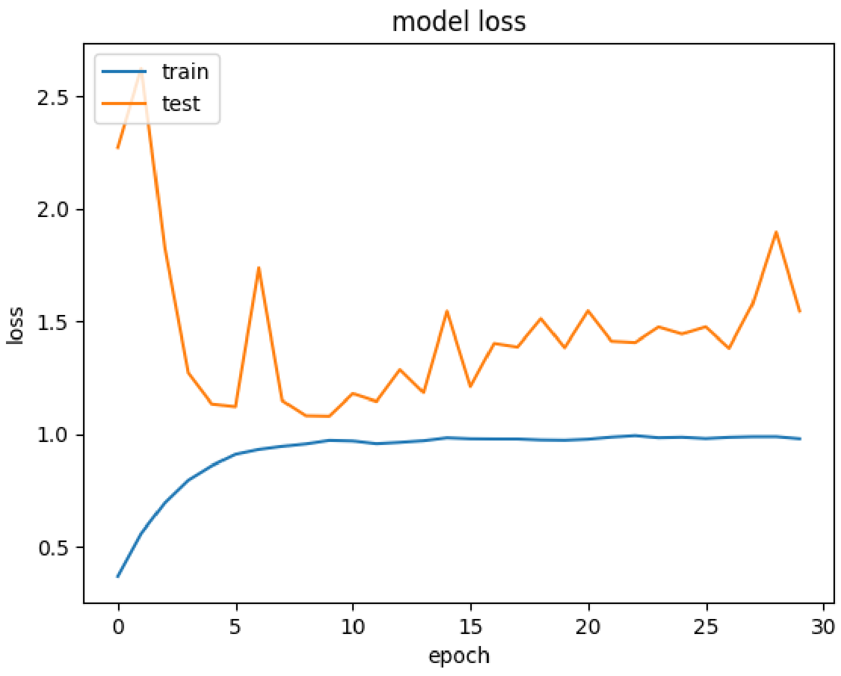
```
print("Accuracy  : " , model2.evaluate(X_test,y_test_n)[1]*100 , "%")
```

```
34/34 [==============================] - 47s 1s/step - loss: 1.5456 - accuracy: 0.7570
Accuracy  :  75.70093274116516 %
```

model 2

```
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```





```
y_pred2 = model2.predict(X_test)
y_result2 = []

for pred1 in y_pred2:
    y_result2.append(np.argmax(pred1))
y_result2[:10]
```

```
34/34 [==============================] - 49s 1s/step
[2, 2, 3, 0, 3, 2, 3, 2, 6, 0]
```

```
y_actual2 = []

for pred1 in y_test_n:
    y_actual2.append(np.argmax(pred1))
y_actual2[:10]
```

```
     [2, 5, 3, 0, 3, 2, 3, 3, 6, 5]
```

```
from sklearn.metrics import confusion_matrix, classification_report
print(classification_report(y_actual2, y_result2))
```

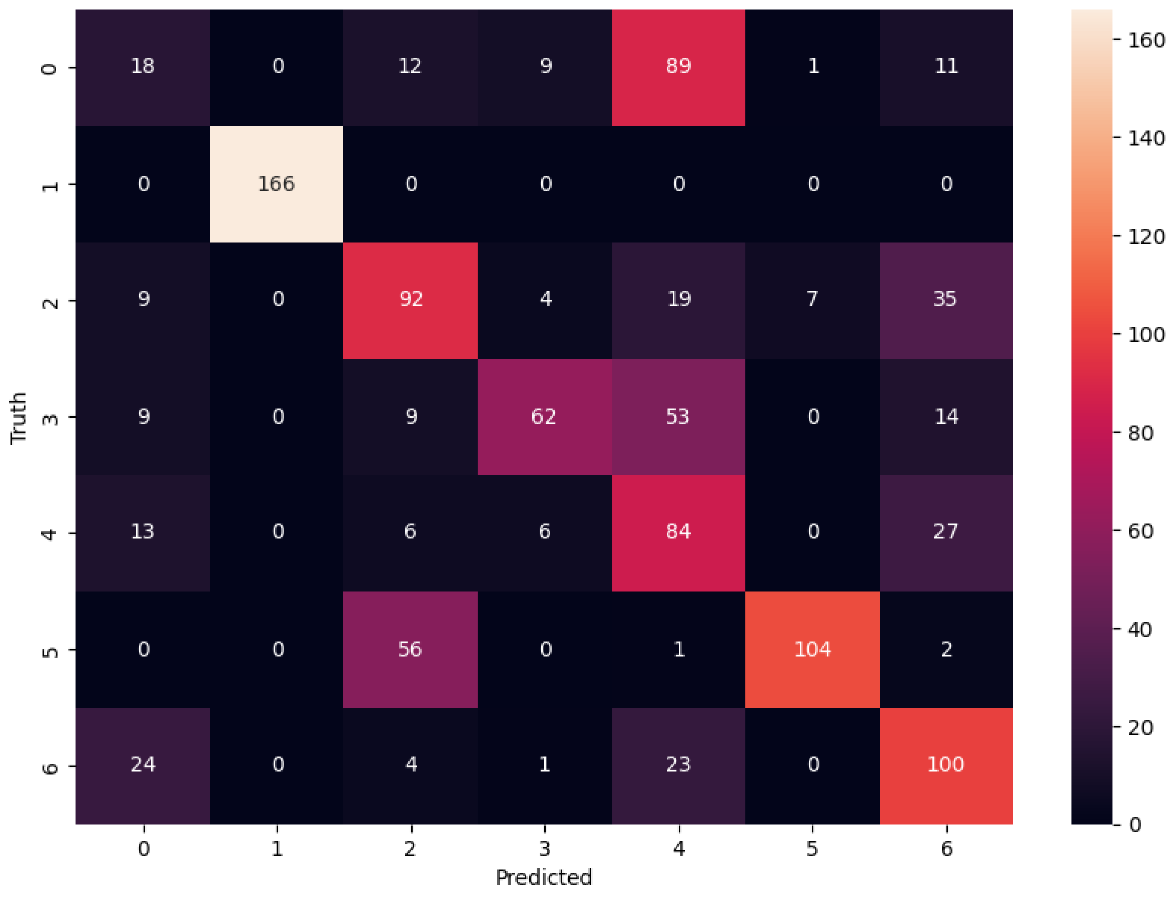
```
                   precision    recall  f1-score   support

                0       0.67      0.80      0.73       140
                1       0.93      1.00      0.96       166
                2       0.70      0.73      0.72       166
                3       0.67      0.55      0.60       147
                4       0.62      0.62      0.62       136
                5       0.90      0.87      0.88       163
                6       0.76      0.67      0.71       152

         accuracy                           0.76      1070
        macro avg       0.75      0.75      0.75      1070
     weighted avg       0.76      0.76      0.75      1070
```

```
import seaborn as sn
```

Creating a copy...

```
ls = y_actual2, predictions = y_result2)

plt.figure(figsize = (10, 7))
sn.heatmap(cm, annot = True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
     Text(95.72222222222221, 0.5, 'Truth')
```



Test Images

```
!wget https://www.dropbox.com/s/6e8bkfigau37u0u/test_images.zip
```

```
--2023-05-26 19:42:25--  https://www.dropbox.com/s/6e8bkfigau37u0u/test_images.zip
Resolving www.dropbox.com (www.dropbox.com)... 162.125.65.18, 2620:100:6022:18::a27d:4212
Connecting to www.dropbox.com (www.dropbox.com)|162.125.65.18|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: /s/raw/6e8bkfigau37u0u/test_images.zip [following]
--2023-05-26 19:42:25--  https://www.dropbox.com/s/raw/6e8bkfigau37u0u/test_images.zip
Reusing existing connection to www.dropbox.com:443.
HTTP request sent, awaiting response... 302 Found
Location: https://uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com/cd/0/inline/B8wpQ2wlXpXyqTlsBvL_3PVBQsoy_
--2023-05-26 19:42:26--  https://uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com/cd/0/inline/B8wpQ2wlXpXyqT
Resolving uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com (uc59edd6c36da7a95c39d7aaf33e.dl.dropboxuserconte
Connecting to uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com (uc59edd6c36da7a95c39d7aaf33e.dl.dropboxuserc
HTTP request sent, awaiting response... 302 Found
Location: /cd/0/inline2/B8xHn1P7X2wTu1e7TxISq2JkKbwrBKjOzBtnUe4chq8GUv9RzweIDg1UfpuPX2P8hGHI_vCBF0ygPZU5PHYkGpYeN-/
--2023-05-26 19:42:26--  https://uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com/cd/0/inline2/B8xHn1P7X2wTu
Reusing existing connection to uc59edd6c36da7a95c39d7aaf33e.dl.dropboxusercontent.com:443.
HTTP request sent, awaiting response... 200 OK
Length: 545335 (533K) [application/zip]
Saving to: ‘test_images.zip’

test_images.zip     100%[===================>] 532.55K  --.-KB/s    in 0.1s

2023-05-26 19:42:26 (5.32 MB/s) - ‘test_images.zip’ saved [545335/545335]
```

Creating a copy...

```
   creating: test_images/
  inflating: test_images/download.jpg
  inflating: test_images/downloadd.png
  inflating: test_images/downloadd1.png
  inflating: test_images/downloadd2.png
  inflating: test_images/downloadd2a.png
  inflating: test_images/downloadd2b.png
  inflating: test_images/images (1).jpg
  inflating: test_images/images (2).jpg
  inflating: test_images/images.jpg
```

Test

```
!wget https://www.dropbox.com/s/852f07npbwjk7pl/play_soundd.zip
```

```
--2023-05-26 19:42:32--  https://www.dropbox.com/s/852f07npbwjk7pl/play_soundd.zip
Resolving www.dropbox.com (www.dropbox.com)... 162.125.65.18, 2620:100:6022:18::a27d:4212
Connecting to www.dropbox.com (www.dropbox.com)|162.125.65.18|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: /s/raw/852f07npbwjk7pl/play_soundd.zip [following]
--2023-05-26 19:42:32--  https://www.dropbox.com/s/raw/852f07npbwjk7pl/play_soundd.zip
Reusing existing connection to www.dropbox.com:443.
HTTP request sent, awaiting response... 302 Found
Location: https://uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com/cd/0/inline/B8xXnUMYvyUIT6zenA-F6XBxSn3Lj
--2023-05-26 19:42:32--  https://uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com/cd/0/inline/B8xXnUMYvyUIT6
Resolving uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com (uc94ef48064ab7c676b4d41126bd.dl.dropboxuserconte
Connecting to uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com (uc94ef48064ab7c676b4d41126bd.dl.dropboxuserc
HTTP request sent, awaiting response... 302 Found
Location: /cd/0/inline2/B8y4gAPKyFB9l54ZoLwbEgqrIlxlyQIq1Pj1Sx_tx8fUgPWGNbxW03tMviCLAftmVDnnENiRELXEQ7Ggm3eHpEJhWC
--2023-05-26 19:42:33--  https://uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com/cd/0/inline2/B8y4gAPKyFB9l
Reusing existing connection to uc94ef48064ab7c676b4d41126bd.dl.dropboxusercontent.com:443.
HTTP request sent, awaiting response... 200 OK
Length: 693741 (677K) [application/zip]
Saving to: ‘play_soundd.zip’

play_soundd.zip     100%[===================>] 677.48K  --.-KB/s    in 0.08s

2023-05-26 19:42:33 (8.29 MB/s) - ‘play_soundd.zip’ saved [693741/693741]
```

```
!unzip play_soundd.zip
```

```
Archive:  play_soundd.zip
  inflating: disgust.mp3
  inflating: fear.mp3
  inflating: happy.mp3
  inflating: neutral.mp3
  inflating: sad.mp3
  inflating: surprise.mp3
  inflating: anger.mp3
```

```
!pip install install playsound==1.2.2
from playsound import playsound
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting install
  Downloading install-1.3.5-py3-none-any.whl (3.2 kB)
Collecting playsound==1.2.2
  Downloading playsound-1.2.2-py2.py3-none-any.whl (6.0 kB)
Installing collected packages: playsound, install
Successfully installed install-1.3.5 playsound-1.2.2
```

```
# read image
images = []
for filename in os.listdir('test_images'):
    path = os.path.join('test_images', filename)
    images.append(cv2.imread(path, -1))
```

Creating a copy...

```
predictions = []
for img in images:
    # change to greyscale
    curr_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    curr_img = cv2.resize(curr_img, (48,48))
    curr_img = np.reshape(curr_img, (1,48, 48,1))
    predictions.append(np.argmax(model2.predict(curr_img)))
```

```
# list of given emotions
EMOTIONS = ['Angry', 'Disgust', 'Fear',
            'Happy', 'Sad', 'Surprise', 'Neutral']

# bgr to rgb
for i in range(9):
    images[i] = cv2.cvtColor(images[i], cv2.COLOR_BGR2RGB)
```

#

```
predictions = [2, 2, 3, 0, 3, 2, 3, 2, 6, 0]
```

```
predictions
```

```
[2, 2, 3, 0, 3, 2, 3, 2, 6, 0]
```

#

```
EMOTIONS
```

```
['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
```

sample audio playing

```
from IPython.display import Audio
```

```
Audio('anger.mp3')
```

0:00 / 0:01

```
Audio('fear.mp3')
```

0:01 / 0:03

```
Audio('surprise.mp3')
```

0:00 / 0:00

```
Audio('disgust.mp3')
```

0:00 / 0:01

Creating a copy... ×

0:00 / 0:15

```
Audio('happy.mp3')
```

0:00 / 0:06

```
Audio('neutral.mp3')
```

0:00 / 0:15

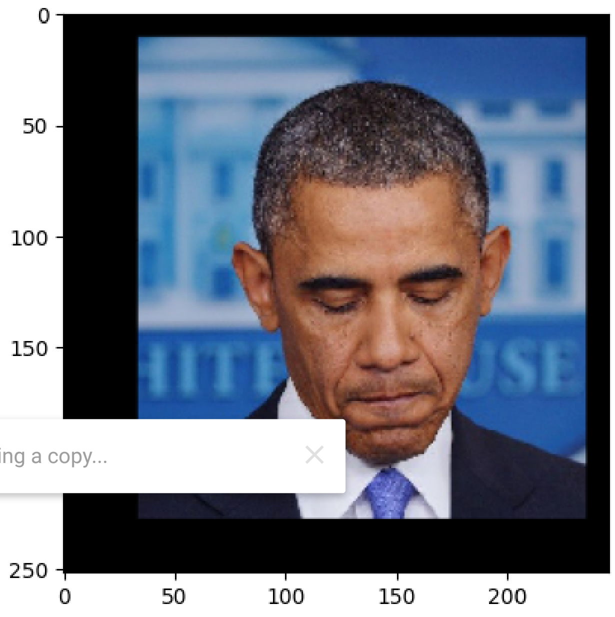
```
#
```

```
range(len(EMOTIONS))

     range(0, 7)
```

```
plt.imshow(images[3])
dataaa = str(EMOTIONS[predictions[3]])
print('Predicted Emotion: ' + dataaa)


if dataaa == 'Angry':
   Audio('anger.mp3')
   print('Angry')
elif dataaa == 'Disgust':
     Audio('disgust.mp3')
     print('Disgust')
elif dataaa == 'Fear':
     Audio('fear.mp3')
     print('fear')
elif dataaa == 'Happy':
     Audio('happy.mp3')
     print('happy')
```

```
elif dataaa == 'Sad':
     Audio('sad.mp3')
     print('sad')
elif dataaa == 'Surprise':
     Audio('surprise.mp3')
     print('surprise')
elif dataaa == 'Neutral':
     Audio('neutral.mp3')
     print('neutral')
```

```
Predicted Emotion: Angry
Angry
```



```
plt.imshow(images[4])
dataaa = str(EMOTIONS[predictions[4]])
print('Predicted Emotion: ' + dataaa)


if dataaa == 'Angry':
   Audio('anger.mp3')
   print('Angry')
elif dataaa == 'Disgust':
     Audio('disgust.mp3')
     print('Disgust')
elif dataaa == 'Fear':
     Audio('fear.mp3')
     print('fear')
elif dataaa == 'Happy':
     Audio('happy.mp3')
     print('happy')
elif dataaa == 'Sad':
     Audio('sad.mp3')
     print('sad')
elif dataaa == 'Surprise':
     Audio('surprise.mp3')
     print('surprise')
elif dataaa == 'Neutral':
     Audio('neutral.mp3')
     print('neutral')
```

```
Predicted Emotion: Happy
happy
```

Creating a copy...

✓ 0s completed at 1:44 AM

Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.