

IMPLEMENTATION

Face mask :

MobileNetV2 :

Training :

```
# import the necessary packages
# Main modules - keras(for deep learning) , tensorflow(deep learning) , numpy(math , matrix) , sklearn (prediction)
import numpy as np
import os
import matplotlib.pyplot as plt
from imutils import paths

from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.utils import to_categorical
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
```

```
# importing the dataset form machine

dataset='/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset'
imagePaths=list(paths.list_images(dataset))

# grab the list of images in our dataset directory, then initialize
# the list of data (i.e., images) and class images
```

```
imagePaths
```

```
data=[]
labels=[]
```

```
for i in imagePaths:
    # construct the path to the image and load it into memory
    # using OpenCV
    image = cv2.imread(i)

    # extract the class label from the filename
    # assuming that our model has 2 output classes: face
    # and not face, with filenames having the format
    # "label_X_Y.jpg" where "X" is 0 or 1
    label = i.split(os.path.sep)[-2]

    # update the data and labels lists, respectively
    data.append(image)
    labels.append(label)
```

```
data
```



```
array([[[[-0.654902 , -0.7647059 , -0.7882353 ],
        [-0.654902 , -0.7647059 , -0.7882353 ],
        [-0.654902 , -0.7647059 , -0.7882353 ],
        ...,
        [-0.60784316, -0.6862745 , -0.69411767],
        [-0.60784316, -0.6862745 , -0.69411767],
        [-0.6156863 , -0.69411767, -0.7019608 ]],  
[[[-0.6627451 , -0.77254903, -0.79607844],
        [-0.6627451 , -0.77254903, -0.79607844],
        [-0.6627451 , -0.77254903, -0.79607844],
        ...,
        [-0.6156863 , -0.69411767, -0.7019608 ],
        [-0.6156863 , -0.69411767, -0.7019608 ],
        [-0.62352943, -0.7019608 , -0.70980394]]],
```

```
labels
```

```
array(['with_mask', 'with_mask', 'with_mask', ..., 'without_mask',
       'without_mask', 'without_mask'], dtype='<U12')
```

```
# perform one-hot encoding on the labels
```

```
lb=LabelBinarizer()
labels=lb.fit_transform(labels)
labels=to_categorical(labels)
```

```
labels
```

```
array([[1., 0.],
       [1., 0.],
       [1., 0.],
       ...,
       [0., 1.],
       [0., 1.],
       [0., 1.]], dtype=float32)
```

```
train_X,test_X,train_Y,test_Y=train_test_split(data,labels,test_size=0.20,stratify=labels,r
```

```
train_X
```

```
array([[[[-0.17647058, -0.14509803, -0.05098039],
         [-0.17647058, -0.14509803, -0.05098039],
         [-0.15294117, -0.12156862, -0.02745098],
         ...,
         [-0.18431371, -0.15294117, -0.05882353],
         [-0.20784312, -0.17647058, -0.08235294],
         [-0.20784312, -0.17647058, -0.08235294]],

        [[-0.17647058, -0.14509803, -0.05098039],
         [-0.17647058, -0.14509803, -0.05098039],
         [-0.15294117, -0.12156862, -0.02745098],
         ...,
         [-0.18431371, -0.15294117, -0.05882353],
         [-0.20784312, -0.17647058, -0.08235294],
         [-0.20784312, -0.17647058, -0.08235294]],

        [[-0.16862744, -0.1372549 , -0.04313725],
         [-0.16862744, -0.1372549 , -0.04313725],
         [-0.12941176, -0.09803921, -0.00392157],
         ...,
```

```
test_X
```

```
array([[[[-0.4352941 , -0.31764704,  0.12941182],
         [-0.4588235 , -0.34117645,  0.10588241],
         [-0.4588235 , -0.34117645,  0.10588241],
         ...,
         [-0.7254902 , -0.6627451 , -0.27843136],
         [-0.7254902 , -0.6627451 , -0.27843136],
         [-0.70980394, -0.64705884, -0.26274508]],

        [[-0.4352941 , -0.31764704,  0.12941182],
         [-0.4588235 , -0.34117645,  0.10588241],
         [-0.4588235 , -0.34117645,  0.10588241],
         ...,
         [-0.7254902 , -0.6627451 , -0.27843136],
         [-0.7254902 , -0.6627451 , -0.27843136],
         [-0.7176471 , -0.654902 , -0.27058822]],

        [[-0.4352941 , -0.31764704,  0.12941182],
         [-0.45098037, -0.3490196 ,  0.082353  ],
         [-0.45098037, -0.3490196 ,  0.082353  ],
         ...,
```

```

train_X.shape

(3066, 224, 224, 3)

test_X.shape

(767, 224, 224, 3)

# construct the training image generator for data augmentation
# creates multiple images from a single image

aug=ImageDataGenerator(rotation_range=20,
                      zoom_range=0.15,           # rotate , flip , mirror , zoom
                      width_shift_range=0.2,
                      height_shift_range=0.2,
                      shear_range=0.15,
                      horizontal_flip=True,
                      vertical_flip=True,
                      fill_mode='nearest')

baseModel = MobileNetV2(weights="imagenet", include_top=False, input_tensor=Input(shape=(224, 224, 3)))

print(baseModel.summary())

Model: "mobilenetv2_1.00_224"

```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[None, 224, 224, 3]	0	
Conv1_pad (ZeroPadding2D)	(None, 225, 225, 3)	0	input_1[0][0]
Conv1 (Conv2D)	(None, 112, 112, 32)	864	Conv1_pad[0][0]
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)	128	Conv1[0][0]
Conv1_relu (ReLU)	(None, 112, 112, 32)	0	bn_Conv1[0][0]
expanded_conv_depthwise (Depthwise)	(None, 112, 112, 32)	288	Conv1_relu[0][0]
expanded_conv_depthwise_BN (Batch Normalization)	(None, 112, 112, 32)	128	expanded_conv_depthwise[0][0]
expanded_conv_depthwise_relu (ReLU)	(None, 112, 112, 32)	0	expanded_conv_depthwise_BN[0][0]
expanded_conv_project (Conv2D)	(None, 112, 112, 16)	512	expanded_conv_depthwise_relu[0][0]
expanded_conv_project_BN (Batch Normalization)	(None, 112, 112, 16)	64	expanded_conv_project[0][0]

block_16_expand (Conv2D)	(None, 7, 7, 960)	153600	block_15_add[0][0]
block_16_expand_BN (Batch Normalization)	(None, 7, 7, 960)	3840	block_16_expand[0][0]
block_16_expand_relu (ReLU)	(None, 7, 7, 960)	0	block_16_expand_BN[0][0]
block_16_depthwise (Depthwise)	(None, 7, 7, 960)	8640	block_16_expand_relu[0][0]
block_16_depthwise_BN (Batch Normalization)	(None, 7, 7, 960)	3840	block_16_depthwise[0][0]
block_16_depthwise_relu (ReLU)	(None, 7, 7, 960)	0	block_16_depthwise_BN[0][0]
block_16_project (Conv2D)	(None, 7, 7, 320)	307200	block_16_depthwise_relu[0][0]
block_16_project_BN (Batch Normalization)	(None, 7, 7, 320)	1280	block_16_project[0][0]
Conv_1 (Conv2D)	(None, 7, 7, 1280)	409600	block_16_project_BN[0][0]
Conv_1_bn (Batch Normalization)	(None, 7, 7, 1280)	5120	Conv_1[0][0]
out_relu (ReLU)	(None, 7, 7, 1280)	0	Conv_1_bn[0][0]

```

Total params: 2,257,984
Trainable params: 2,223,872
Non-trainable params: 34,112

```

None

```

# construct the head of the model that will be placed on top of the
# the base model
headModel = baseModel.output
headModel = AveragePooling2D(pool_size=(7, 7))(headModel)
headModel = Flatten(name="flatten")(headModel)
headModel = Dense(128, activation="relu")(headModel)
headModel = Dropout(0.5)(headModel)
headModel = Dense(2, activation="softmax")(headModel)

```

```

# place the head FC model on top of the base model (this will become
# the actual model we will train)
model = Model(inputs=baseModel.input, outputs=headModel)

```

```

# loop over all layers in the base model and freeze them so they will
# *not* be updated during the first training process
for layer in baseModel.layers:
    layer.trainable = False

```

```
print(model.summary())
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[None, 224, 224, 3] 0		
Conv1_pad (ZeroPadding2D)	(None, 225, 225, 3) 0		input_1[0][0]
Conv1 (Conv2D)	(None, 112, 112, 32) 864		Conv1_pad[0][0]
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32) 128		Conv1[0][0]
Conv1_relu (ReLU)	(None, 112, 112, 32) 0		bn_Conv1[0][0]
expanded_conv_depthwise (Depthwise (None, 112, 112, 32) 288			Conv1_relu[0][0]
expanded_conv_depthwise_BN (BatchNorm (None, 112, 112, 32) 128			expanded_conv_depthwise[0][0]
expanded_conv_depthwise_relu (ReLU (None, 112, 112, 32) 0			expanded_conv_depthwise_BN[0][0]
block_16_expand (Conv2D)	(None, 7, 7, 960) 153600		block_15_add[0][0]
block_16_expand_BN (BatchNormal (None, 7, 7, 960) 3840			block_16_expand[0][0]
block_16_expand_relu (ReLU) (None, 7, 7, 960) 0			block_16_expand_BN[0][0]
block_16_depthwise (DepthwiseCo (None, 7, 7, 960) 8640			block_16_expand_relu[0][0]
block_16_depthwise_BN (BatchNor (None, 7, 7, 960) 3840			block_16_depthwise[0][0]
block_16_depthwise_relu (ReLU) (None, 7, 7, 960) 0			block_16_depthwise_BN[0][0]
block_16_project (Conv2D)	(None, 7, 7, 320) 307200		block_16_depthwise_relu[0][0]
block_16_project_BN (BatchNorma (None, 7, 7, 320) 1280			block_16_project[0][0]
Conv_1 (Conv2D)	(None, 7, 7, 1280) 409600		block_16_project_BN[0][0]
Conv_1_bn (BatchNormalization)	(None, 7, 7, 1280) 5120		Conv_1[0][0]
out_relu (ReLU)	(None, 7, 7, 1280) 0		Conv_1_bn[0][0]
average_pooling2d (AveragePooli (None, 1, 1, 1280) 0			out_relu[0][0]
flatten (Flatten)	(None, 1280) 0		average_pooling2d[0][0]
dense (Dense)	(None, 128) 163968		flatten[0][0]
dropout (Dropout)	(None, 128) 0		dense[0][0]
dense_1 (Dense)	(None, 2) 258		dropout[0][0]
Total params: 2,422,210			
Trainable params: 164,226			
Non-trainable params: 2,257,984			

```
# initialize the initial learning rate, number of epochs to train for,
# and batch size
learning_rate=0.001
Epochs=20
BS=12
```

```
# compile our model
print("[INFO] compiling model...")
opt=Adam(lr=learning_rate,decay=learning_rate/EPOCHS)
model.compile(loss='binary_crossentropy',optimizer=opt,metrics=['accuracy'])
```

[INFO] compiling model...

```
# train the head of the network
print("[INFO] training head...")
H=model.fit(
    aug.flow(train_X,train_Y,batch_size=BS),
    steps_per_epoch=len(train_X)//BS,
    validation_data=(test_X,test_Y),
    validation_steps=len(test_X)//BS,
    epochs=Epochs)
```

[INFO] training head...
Train for 255 steps, validate on 767 samples
Epoch 1/20
255/255 [=====] - 130s 510ms/step - loss: 0.3702 - accuracy: 0.8386 - val_loss: 0.3579 - val_accuracy: 0.8677
Epoch 2/20
255/255 [=====] - 126s 495ms/step - loss: 0.2593 - accuracy: 0.8946 - val_loss: 0.3319 - val_accuracy: 0.8730
Epoch 3/20
255/255 [=====] - 124s 486ms/step - loss: 0.2015 - accuracy: 0.9172 - val_loss: 0.2699 - val_accuracy: 0.9048
Epoch 4/20
255/255 [=====] - 124s 486ms/step - loss: 0.1923 - accuracy: 0.9204 - val_loss: 0.3203 - val_accuracy: 0.8929
Epoch 5/20
255/255 [=====] - 124s 487ms/step - loss: 0.1858 - accuracy: 0.9227 - val_loss: 0.4504 - val_accuracy: 0.8664
Epoch 6/20
255/255 [=====] - 125s 489ms/step - loss: 0.1885 - accuracy: 0.9221 - val_loss: 0.8745 - val_accuracy: 0.8188
Epoch 7/20
255/255 [=====] - 124s 488ms/step - loss: 0.1668 - accuracy: 0.9391 - val_loss: 0.7256 - val_accuracy: 0.8135
Epoch 8/20
255/255 [=====] - 125s 490ms/step - loss: 0.1551 - accuracy: 0.9388 - val_loss: 0.7927 - val_accuracy: 0.8188
Epoch 9/20
255/255 [=====] - 125s 489ms/step - loss: 0.1587 - accuracy: 0.9391 - val_loss: 0.5994 - val_accuracy: 0.8611
Epoch 10/20
255/255 [=====] - 125s 490ms/step - loss: 0.1698 - accuracy: 0.9332 - val_loss: 0.5402 - val_accuracy: 0.8770
Epoch 11/20
255/255 [=====] - 126s 496ms/step - loss: 0.1501 - accuracy: 0.9453 - val_loss: 0.6855 - val_accuracy: 0.8519
Epoch 12/20
255/255 [=====] - 129s 505ms/step - loss: 0.1436 - accuracy: 0.9434 - val_loss: 0.5045 - val_accuracy: 0.8836
Epoch 13/20
255/255 [=====] - 125s 491ms/step - loss: 0.1525 - accuracy: 0.9453 - val_loss: 0.7014 - val_accuracy: 0.8519
Epoch 14/20
255/255 [=====] - 125s 489ms/step - loss: 0.1486 - accuracy: 0.9430 - val_loss: 0.7949 - val_accuracy: 0.8347
Epoch 15/20
255/255 [=====] - 126s 492ms/step - loss: 0.1302 - accuracy: 0.9519 - val_loss: 0.5703 - val_accuracy: 0.8704
Epoch 16/20
255/255 [=====] - 126s 494ms/step - loss: 0.1296 - accuracy: 0.9502 - val_loss: 0.5905 - val_accuracy: 0.8624
Epoch 17/20
255/255 [=====] - 125s 492ms/step - loss: 0.1294 - accuracy: 0.9473 - val_loss: 0.8137 - val_accuracy: 0.8307
Epoch 18/20
255/255 [=====] - 125s 491ms/step - loss: 0.1294 - accuracy: 0.9476 - val_loss: 0.5925 - val_accuracy: 0.8558
Epoch 19/20
255/255 [=====] - 126s 493ms/step - loss: 0.1346 - accuracy: 0.9479 - val_loss: 0.7837 - val_accuracy: 0.8439
Epoch 20/20
255/255 [=====] - 126s 493ms/step - loss: 0.1251 - accuracy: 0.9565 - val_loss: 0.7262 - val_accuracy: 0.8452

```
# make predictions on the testing set
print("[INFO] evaluating network...")
predIdxs = model.predict(test_X, batch_size=BS)
```

[INFO] evaluating network...

```
# for each image in the testing set we need to find the index of the
# label with corresponding largest predicted probability
predIdxs = np.argmax(predIdxs, axis=1)
```

```
print(classification_report(test_Y.argmax(axis=1),predIdxs,target_names=lb.classes_))
```

	precision	recall	f1-score	support
with_mask	0.98	0.70	0.82	383
without_mask	0.77	0.99	0.87	384
accuracy			0.85	767
macro avg	0.88	0.85	0.84	767
weighted avg	0.88	0.85	0.84	767

```
# serialize the model to disk
print("[INFO] saving mask detector model...")
model.save("/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/mask_detector.model", save_format="h5")
```

[INFO] saving mask detector model...

```
# plot the training loss and accuracy
N = EPOCHS
```

```
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, N), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend(loc="lower left")
```

<matplotlib.legend.Legend at 0x7ff02cb73250>



```
plt.savefig("/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/plot.png")
```

<Figure size 432x288 with 0 Axes>

```
# training of the machine is done now lets go for testing.....
```

Testing :

```
# import the necessary packages

from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.models import load_model
from imutils.video import VideoStream
import numpy as np
import imutils
import time
import cv2
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
```

```
def detect_and_predict_mask(frame, faceNet, maskNet):
    # grab the dimensions of the frame and then construct a blob
    # from it
    (h, w) = frame.shape[:2]
    blob = cv2.dnn.blobFromImage(frame, 1.0, (224, 224),
        (104.0, 177.0, 123.0))

    # pass the blob through the network and obtain the face detections
    faceNet.setInput(blob)
    detections = faceNet.forward()
    print(detections.shape)

    # initialize our list of faces, their corresponding locations,
    # and the list of predictions from our face mask network
    faces = []
    locs = []
    preds = []

    # loop over the detections
    for i in range(0, detections.shape[2]):
        # extract the confidence (i.e., probability) associated with
        # the detection
        confidence = detections[0, 0, i, 2]

        # filter out weak detections by ensuring the confidence is
        # greater than the minimum confidence
        if confidence > 0.5:
            # compute the (x, y)-coordinates of the bounding box for
            # the object
            box = detections[0, 0, i, 3:7] * np.array([w, h, w, h])
            (startX, startY, endX, endY) = box.astype("int")

            # ensure the bounding boxes fall within the dimensions of
            # the frame
            (startX, startY) = (max(0, startX), max(0, startY))
            (endX, endY) = (min(w - 1, endX), min(h - 1, endY))
```

```

# ensure the bounding boxes fall within the dimensions of
# the frame
(startX, startY) = (max(0, startX), max(0, startY))
(endX, endY) = (min(w - 1, endX), min(h - 1, endY))

# extract the face ROI, convert it from BGR to RGB channel
# ordering, resize it to 224x224, and preprocess it
face = frame[startY:endY, startX:endX]
face = cv2.cvtColor(face, cv2.COLOR_BGR2RGB)
face = cv2.resize(face, (224, 224))
face = img_to_array(face)
face = preprocess_input(face)

# add the face and bounding boxes to their respective
# lists
faces.append(face)
locs.append((startX, startY, endX, endY))

# only make a predictions if at least one face was detected
if len(faces) > 0:
    # for faster inference we'll make batch predictions on *all*
    # faces at the same time rather than one-by-one predictions
    # in the above `for` loop
    faces = np.array(faces, dtype="float32")
    preds = maskNet.predict(faces, batch_size=32)

# return a 2-tuple of the face locations and their corresponding
# locations
return (locs, preds)

```

```

# load our serialized face detector model from disk

prototxtPath = "/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/face_detector/deploy.prototxt"
weightsPath = "/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/face_detector/res10_300x300_ssd_iter_140000.caffemodel"
faceNet = cv2.dnn.readNet(prototxtPath, weightsPath)

```

```

# load the face mask detector model from disk

maskNet = load_model("/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/pre trained file/mask_detector.model")

```

```
# initialize the video stream
```

```
print("[INFO] starting video stream...")
vs = VideoStream(src=0).start()
```

```
[INFO] starting video stream...
```

```

# loop over the frames from the video stream
while True:
    # grab the frame from the threaded video stream and resize it
    # to have a maximum width of 400 pixels
    frame = vs.read()
    frame = imutils.resize(frame, width=400)

    # detect faces in the frame and determine if they are wearing a
    # face mask or not
    (locs, preds) = detect_and_predict_mask(frame, faceNet, maskNet)

    # loop over the detected face locations and their corresponding
    # locations
    for (box, pred) in zip(locs, preds):
        # unpack the bounding box and predictions
        (startX, startY, endX, endY) = box
        (mask, withoutMask) = pred

        # determine the class label and color we'll use to draw
        # the bounding box and text
        label = "Mask" if mask > withoutMask else "No Mask"
        color = (0, 255, 0) if label == "Mask" else (0, 0, 255)

        # include the probability in the label
        label = "{}: {:.2f}%".format(label, max(mask, withoutMask) * 100)

        # display the label and bounding box rectangle on the output
        # frame
        cv2.putText(frame, label, (startX, startY - 10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.45, color, 2)
        cv2.rectangle(frame, (startX, startY), (endX, endY), color, 2)

    # show the output frame
    cv2.imshow("Frame", frame)
    key = cv2.waitKey(1) & 0xFF

    # if the `q` key was pressed, break from the loop
    if key == ord("q"):
        break

# do a bit of cleanup
cv2.destroyAllWindows()
vs.stop()

```

VGG 16 :

Training :

```
from keras.layers import Input, Lambda, Dense, Flatten
from keras.models import Model
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt

Using TensorFlow backend.

IMAGE_SIZE = [224, 224] #for resizing all image

train_path = '/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset/train'
valid_path = '/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset/test'

# add preprocessing layer to the front of VGG
vgg = VGG16(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)

Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.1/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [=====] - 182s 3us/step

# don't train existing weights
for layer in vgg.layers:
    layer.trainable = False

# useful for getting number of classes
folders = glob('/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset/train/*')

# our layers - you can add more if you want
x = Flatten()(vgg.output)

# x = Dense(1000, activation='relu')(x)
prediction = Dense(len(folders), activation='softmax')(x)

# create a model object
model = Model(inputs=vgg.input, outputs=prediction)

# view the structure of the model
model.summary()

Model: "model_1"
-----  

Layer (type)          Output Shape         Param #
-----  

input_1 (InputLayer)   (None, 224, 224, 3)   0  

block1_conv1 (Conv2D)  (None, 224, 224, 64)  1792  

block1_conv2 (Conv2D)  (None, 224, 224, 64)  36928  

block1_pool (MaxPooling2D) (None, 112, 112, 64)  0  

block2_conv1 (Conv2D)  (None, 112, 112, 128)  73856  

block2_conv2 (Conv2D)  (None, 112, 112, 128)  147584  

block2_pool (MaxPooling2D) (None, 56, 56, 128)  0  

block3_conv1 (Conv2D)  (None, 56, 56, 256)  295168  

block3_conv2 (Conv2D)  (None, 56, 56, 256)  590080  

block3_pool (MaxPooling2D) (None, 28, 28, 256)  0  

block4_conv1 (Conv2D)  (None, 28, 28, 512)  1180160  

block4_conv2 (Conv2D)  (None, 28, 28, 512)  2359808  

block4_conv3 (Conv2D)  (None, 28, 28, 512)  2359808  

block4_pool (MaxPooling2D) (None, 14, 14, 512)  0  

block5_conv1 (Conv2D)  (None, 14, 14, 512)  2359808  

block5_conv2 (Conv2D)  (None, 14, 14, 512)  2359808  

block5_conv3 (Conv2D)  (None, 14, 14, 512)  2359808  

block5_pool (MaxPooling2D) (None, 7, 7, 512)  0  

flatten_1 (Flatten)   (None, 25088)        0  

dense_1 (Dense)      (None, 2)            50178  

-----  

Total params: 14,764,866
Trainable params: 50,178
Non-trainable params: 14,714,688
```

```

# tell the model what cost and optimization method to use
model.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)

from keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale = 1./255,
                                    shear_range = 0.2,
                                    zoom_range = 0.2,
                                    horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale = 1./255)

training_set = train_datagen.flow_from_directory('/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset/train',
                                                target_size = (224, 224),
                                                batch_size = 32,
                                                class_mode = 'categorical')

Found 1178 images belonging to 2 classes.

test_set = test_datagen.flow_from_directory('/Users/vishnudinesh/Desktop/6th sem btech project/face mask detection/dataset/test',
                                            target_size = (224, 224),
                                            batch_size = 32,
                                            class_mode = 'categorical')

```

Found 194 images belonging to 2 classes.

```

# fit the model
r = model.fit_generator(
    training_set,
    validation_data=test_set,
    epochs=5,
    steps_per_epoch=len(training_set),
    validation_steps=len(test_set)
)

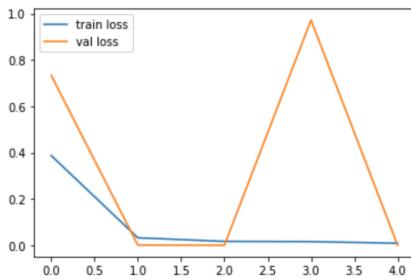
Epoch 1/5
37/37 [=====] - 370s 10s/step - loss: 0.3855 - accuracy: 0.8447 - val_loss: 0.7329 - val_accuracy: 0.9588
Epoch 2/5
37/37 [=====] - 366s 10s/step - loss: 0.0323 - accuracy: 0.9932 - val_loss: 7.9201e-04 - val_accuracy: 0.9639
Epoch 3/5
37/37 [=====] - 365s 10s/step - loss: 0.0166 - accuracy: 0.9983 - val_loss: 2.3115e-04 - val_accuracy: 0.9639
Epoch 4/5
37/37 [=====] - 366s 10s/step - loss: 0.0158 - accuracy: 0.9975 - val_loss: 0.9720 - val_accuracy: 0.9742
Epoch 5/5
37/37 [=====] - 362s 10s/step - loss: 0.0087 - accuracy: 0.9992 - val_loss: 9.2983e-06 - val_accuracy: 0.9742

```

```

# loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

```

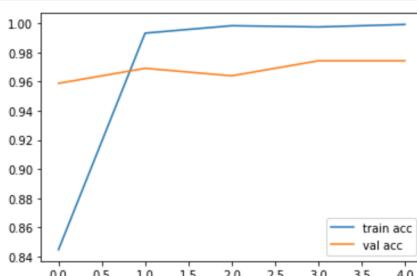


<Figure size 432x288 with 0 Axes>

```

# accuracies
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')

```



<Figure size 432x288 with 0 Axes>

```
import tensorflow as tf
```

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

```
model.save('Mask_detector_model.h5')
```

Testing (image and video) :

```
import cv2
import numpy as np
from keras.models import load_model
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array

Using TensorFlow backend.

# Function to load and prepare the image in right shape
def load_image(filename):
    # Load the image
    img = load_img(filename, target_size=(224, 224))
    # Convert the image to array
    img = img_to_array(img)
    img = np.expand_dims(img, axis=0)
    return img

# Load an image and predict the apparel class
filepath='/Users/vishnudinesh/Desktop/123.jpg'
img = load_image(filepath)
# Load the saved model
model = load_model('Mask_detector_model.h5')
# Predict the apparel class
prediction = model.predict(img)

#loading the cascades
face_cascade=cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
image = cv2.imread(filepath)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
faces = face_cascade.detectMultiScale(gray, 1.3, 5)
for (x,y,w,h) in faces:
    cv2.rectangle(image, (x,y), (x+w,y+h), (127,0,255), 2)

    if(prediction[0][0]>0.5):
        pred='Mask'
        #print(pred)
        cv2.putText(image,pred,(50,50),cv2.FONT_HERSHEY_SIMPLEX,1,(0,255,0),2)
    else:
        pred='No Mask'
        #print(pred)
        cv2.putText(image,pred,(50,50),cv2.FONT_HERSHEY_SIMPLEX,1,(0,0,255),2)
    cv2.imshow('Face Detection', image)
    cv2.waitKey(0) & 0xFF==ord('q')
#Map apparel category with the numerical class
'''if (prediction[0][0]>0.5):
    pred = "Mask"
else:
    pred = "No Mask"'''

print(pred)

cv2.destroyAllWindows()
```

```
import cv2
from keras.models import load_model
import numpy as np
from keras.preprocessing import image
from PIL import Image

#load the model
model=load_model('Mask_detector_model.h5')

#loading the cascades
face_cascade=cv2.CascadeClassifier('haarcascade_frontalface_default.xml')

#webcam face recognition
video_capture=cv2.VideoCapture(0)
while True:
    frame=video_capture.read()
    faces=face_cascade.detectMultiScale(frame,1.3,5)

    for (x,y,w,h) in faces:
        cv2.rectangle(frame,(x,y),(x+w,y+h),(0,255,255),2)
        face=frame[y:y+h,x:x+w]
        cropped_face=face

        if type(face) is np.ndarray:
            face=cv2.resize(face,(224,224))
            im=Image.fromarray(face,'RGB')
            img_array=np.array(im)
            img_array=np.expand_dims(img_array,axis=0)
            pred=model.predict(img_array)
            print(pred)

            if(pred[0][0]>0.5):
                prediction='Mask'
                cv2.putText(cropped_face,prediction,(50,50),cv2.FONT_HERSHEY_COMPLEX,1,(0,255,0),2)
            else:
                prediction='No Mask'
                cv2.putText(cropped_face,prediction,(50,50),cv2.FONT_HERSHEY_COMPLEX,1,(0,0,255),2)
            else:
                cv2.putText(frame,'No Face Found',(50,50),cv2.FONT_HERSHEY_COMPLEX,1,(255,0,0),2)

        cv2.imshow('Video',frame)
        if cv2.waitKey(1) & 0xFF==ord('q'):
            break
video_capture.release()
cv2.destroyAllWindows()
```

Facial emotion :

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import tensorflow as tf
from keras import models , Sequential
from keras.layers import Input, Conv2D, MaxPooling2D, Dropout, BatchNormalization, Dense, Flatten, Activation
from keras.optimizers import Adam
from keras.callbacks import Callback, EarlyStopping, ReduceLROnPlateau , ModelCheckpoint
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import to_categorical
from keras.utils.vis_utils import plot_model
import pydot
import graphviz
import visualkeras
```

```
data = pd.read_csv(r"D:\Project\fer2013.csv")
data.head(1)
```

	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

```
data.shape
```

```
(35887, 3)
```

```
data[ "Usage" ].value_counts()
```

```
Training      28709
PrivateTest   3589
PublicTest    3589
Name: Usage, dtype: int64
```

```
data[ "emotion" ].value_counts()
```

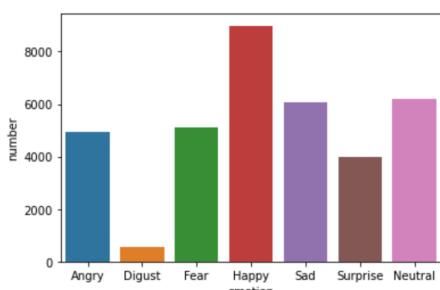
```
3     8989
6     6198
4     6077
2     5121
0     4953
5     4002
1     547
Name: emotion, dtype: int64
```

```
emotion_l = {0: 'Angry', 1: 'Digust', 2: 'Fear', 3: 'Happy', 4: 'Sad', 5: 'Surprise', 6: 'Neutral'}
emotion_counts = data[ 'emotion' ].value_counts(sort=False).reset_index()
emotion_counts.columns = [ 'emotion' , 'number' ]
emotion_counts[ 'emotion' ] = emotion_counts[ 'emotion' ].map(emotion_l)
emotion_counts
```

	emotion	number
0	Angry	4953
1	Digust	547
2	Fear	5121
3	Happy	8989
4	Sad	6077
5	Surprise	4002
6	Neutral	6198

```
sns.barplot(emotion_counts[ 'emotion' ], emotion_counts[ 'number' ])
```

```
<AxesSubplot:xlabel='emotion', ylabel='number'>
```



```
training = data.loc[data["Usage"] == "Training"]
testing = data.loc[data["Usage"] == "PublicTest"]
validation = data.loc[data["Usage"] == "PrivateTest"]
```

```
training.shape , testing.shape , validation.shape
```

```
((28709, 3), (3589, 3), (3589, 3))
```

```
x_train = training["pixels"].str.split(" ").tolist()
x_train = np.uint8(x_train)
x_train = x_train.reshape((28709, 48, 48, 1))
x_train = x_train.astype("float32") / 255

y_train = training["emotion"]
y_train = to_categorical(y_train)

x_test = testing["pixels"].str.split(" ").tolist()
x_test = np.uint8(x_test)
x_test = x_test.reshape((3589, 48, 48, 1))
x_test = x_test.astype("float32") / 255

y_test = testing["emotion"]
y_test = to_categorical(y_test)

x_val = validation["pixels"].str.split(" ").tolist()
x_val = np.uint8(x_val)
x_val = x_val.reshape((3589, 48, 48, 1))
x_val = x_val.astype("float32") / 255

y_val = validation["emotion"]
y_val = to_categorical(y_val)
```

```
x_train.shape , y_train.shape
```

```
((28709, 48, 48, 1), (28709, 7))
```

```
x_test.shape , y_test.shape
```

```
((3589, 48, 48, 1), (3589, 7))
```

```
x_val.shape , y_val.shape
```

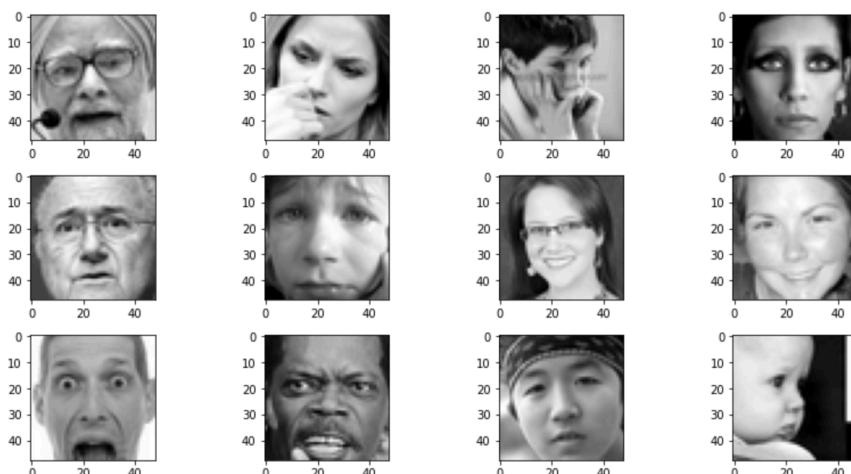
```
((3589, 48, 48, 1), (3589, 7))
```

```
x_test.dtype , y_test.dtype
```

```
(dtype('float32'), dtype('float32'))
```

```
plt.figure(0, figsize=(12,6))
for i in range(1, 13):
    plt.subplot(3,4,i)
    plt.imshow(x_train[i, :, :, 0], cmap="gray")

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



```

model = Sequential()

# Block-1: The First Convolutional Block

model.add(Conv2D(filters=32, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu", input_shape=(48,48, 1)))
model.add(BatchNormalization())
model.add(Conv2D(filters=32, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.5))

# Block-2: The Second Convolutional Block

model.add(Conv2D(filters=64, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu"))
model.add(BatchNormalization())
model.add(Conv2D(filters=64, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.5))

# Block-3: The Third Convolutional Block

model.add(Conv2D(filters=128, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu"))
model.add(BatchNormalization())
model.add(Conv2D(filters=128, kernel_size=(3,3), padding='same', kernel_initializer='he_normal', activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.5))

# Block-4: The Fully Connected Block

model.add(Flatten())
model.add(Dense(64, activation="relu", kernel_initializer='he_normal'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

# Block-5: The Output Block

model.add(Dense(7, activation="softmax", kernel_initializer='he_normal'))

```

```
x_train.shape
```

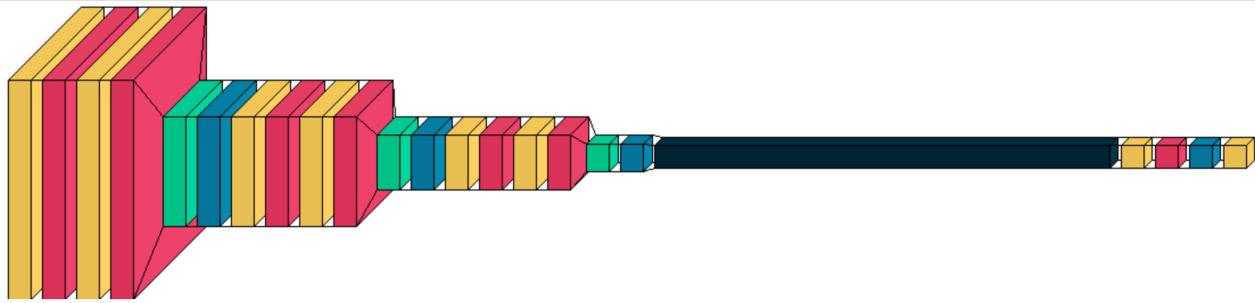
```
(28709, 48, 48, 1)
```

```
model.summary()
```

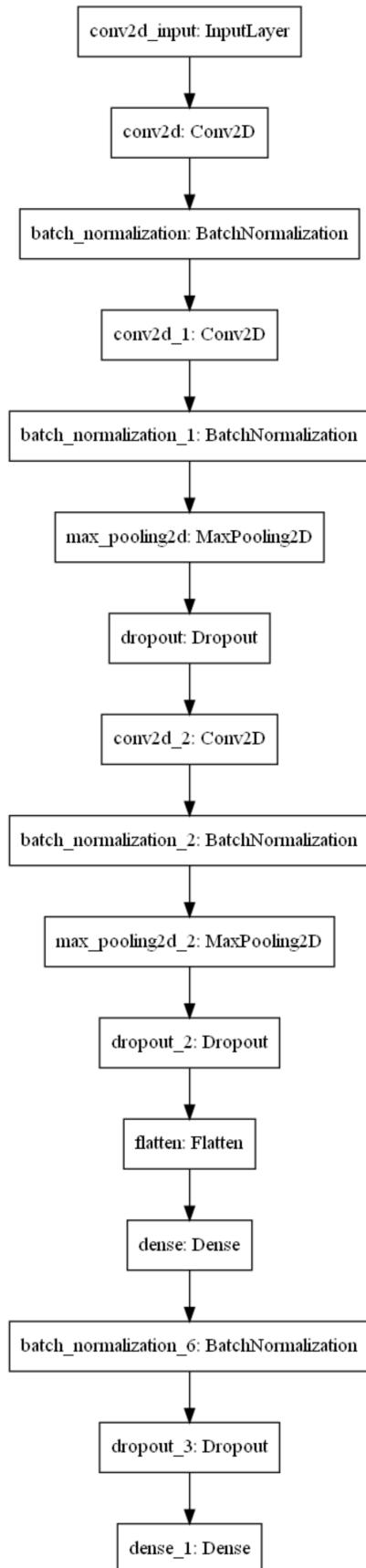
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 32)	320
batch_normalization (BatchNormalizat	(None, 48, 48, 32)	128
conv2d_1 (Conv2D)	(None, 48, 48, 32)	9248
batch_normalization_1 (BatchNormalizat	(None, 48, 48, 32)	128
max_pooling2d (MaxPooling2D)	(None, 24, 24, 32)	0
dropout (Dropout)	(None, 24, 24, 32)	0
conv2d_2 (Conv2D)	(None, 24, 24, 64)	18496
batch_normalization_2 (BatchNormalizat	(None, 24, 24, 64)	256
conv2d_3 (Conv2D)	(None, 24, 24, 64)	36928
batch_normalization_3 (BatchNormalizat	(None, 24, 24, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 64)	0
dropout_1 (Dropout)	(None, 12, 12, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 128)	73856
batch_normalization_4 (BatchNormalizat	(None, 12, 12, 128)	512
conv2d_5 (Conv2D)	(None, 12, 12, 128)	147584
batch_normalization_5 (BatchNormalizat	(None, 12, 12, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
dropout_2 (Dropout)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 64)	294976
batch_normalization_6 (BatchNormalizat	(None, 64)	256
dropout_3 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 7)	455

Total params: 583,911
Trainable params: 582,887
Non-trainable params: 1,024

```
visualkeras.layered_view(model)
```



```
plot_model(model, to_file='model.png', show_layer_names=True)
```



```

model.compile(optimizer = Adam(lr=0.001, beta_1=0.9,
                             beta_2=0.999, epsilon=1e-7),
              loss = "categorical_crossentropy", metrics = ["accuracy"])

lr_reducer = ReduceLROnPlateau(monitor='val_accuracy', factor=0.9, patience=3, verbose=1)
early_stopping = EarlyStopping(monitor='val_accuracy', min_delta=0, patience=8, verbose=1, mode='auto')
checkpointer = ModelCheckpoint('emotions2.h5', monitor='val_accuracy', verbose=1, save_best_only=True)

```

```

history = model.fit(x_train, y_train, batch_size = 64, epochs = 100,
                     verbose=1, validation_data = (np.array(x_test),np.array(y_test)),
                     callbacks = [early_stopping , lr_reducer,checkpointer],
                     shuffle=True)

Epoch 1/100
449/449 [=====] - 317s 703ms/step - loss: 2.3856 - accuracy: 0.2101 - val_loss: 1.7418 - val_accuracy: 0.3115
Epoch 00001: val_accuracy improved from -inf to 0.31151, saving model to emotions2.h5
Epoch 2/100
449/449 [=====] - 317s 707ms/step - loss: 1.6747 - accuracy: 0.3637 - val_loss: 1.4481 - val_accuracy: 0.4366
Epoch 00002: val_accuracy improved from 0.31151 to 0.43661, saving model to emotions2.h5
Epoch 3/100
449/449 [=====] - 322s 717ms/step - loss: 1.4753 - accuracy: 0.4276 - val_loss: 1.4211 - val_accuracy: 0.4458
Epoch 00003: val_accuracy improved from 0.43661 to 0.44581, saving model to emotions2.h5
Epoch 4/100
449/449 [=====] - 315s 702ms/step - loss: 1.4014 - accuracy: 0.4599 - val_loss: 1.3073 - val_accuracy: 0.5010
Epoch 00004: val_accuracy improved from 0.44581 to 0.50098, saving model to emotions2.h5
Epoch 5/100
449/449 [=====] - 320s 714ms/step - loss: 1.3605 - accuracy: 0.4767 - val_loss: 1.2520 - val_accuracy: 0.5143
Epoch 00005: val_accuracy improved from 0.50098 to 0.51435, saving model to emotions2.h5
Epoch 6/100
449/449 [=====] - 313s 697ms/step - loss: 1.2816 - accuracy: 0.5115 - val_loss: 1.2072 - val_accuracy: 0.5497
Epoch 00006: val_accuracy improved from 0.51435 to 0.54974, saving model to emotions2.h5
Epoch 7/100
449/449 [=====] - 322s 718ms/step - loss: 1.2507 - accuracy: 0.5250 - val_loss: 1.1876 - val_accuracy: 0.5492
Epoch 00007: val_accuracy did not improve from 0.54974
Epoch 8/100
449/449 [=====] - 308s 686ms/step - loss: 1.2134 - accuracy: 0.5401 - val_loss: 1.1570 - val_accuracy: 0.5612
Epoch 00008: val_accuracy improved from 0.54974 to 0.56116, saving model to emotions2.h5
Epoch 9/100
449/449 [=====] - 314s 700ms/step - loss: 1.1950 - accuracy: 0.5496 - val_loss: 1.1894 - val_accuracy: 0.5559
Epoch 00009: val_accuracy did not improve from 0.56116
Epoch 10/100
449/449 [=====] - 305s 679ms/step - loss: 1.1762 - accuracy: 0.5584 - val_loss: 1.1366 - val_accuracy: 0.5737
Epoch 00010: val_accuracy improved from 0.56116 to 0.57370, saving model to emotions2.h5
Epoch 11/100
449/449 [=====] - 302s 673ms/step - loss: 1.1523 - accuracy: 0.5686 - val_loss: 1.1128 - val_accuracy: 0.5846
Epoch 00011: val_accuracy improved from 0.57370 to 0.58456, saving model to emotions2.h5
Epoch 12/100
449/449 [=====] - 319s 710ms/step - loss: 1.1249 - accuracy: 0.5757 - val_loss: 1.0956 - val_accuracy: 0.5915
Epoch 00012: val_accuracy improved from 0.58456 to 0.59153, saving model to emotions2.h5
Epoch 13/100
449/449 [=====] - 320s 713ms/step - loss: 1.1160 - accuracy: 0.5784 - val_loss: 1.0683 - val_accuracy: 0.5988
Epoch 00013: val_accuracy improved from 0.59153 to 0.59877, saving model to emotions2.h5
Epoch 14/100
449/449 [=====] - 341s 759ms/step - loss: 1.0890 - accuracy: 0.5949 - val_loss: 1.0790 - val_accuracy: 0.5921

*****  

Epoch 00070: val_accuracy did not improve from 0.65784
Epoch 71/100
449/449 [=====] - 294s 656ms/step - loss: 0.6497 - accuracy: 0.7588 - val_loss: 1.0510 - val_accuracy: 0.6553
Epoch 00071: ReduceLROnPlateau reducing learning rate to 0.0003486784757114947.
Epoch 00071: val_accuracy did not improve from 0.65784
Epoch 72/100
449/449 [=====] - 295s 658ms/step - loss: 0.6486 - accuracy: 0.7632 - val_loss: 1.0655 - val_accuracy: 0.6514
Epoch 00072: val_accuracy did not improve from 0.65784
Epoch 73/100
449/449 [=====] - 301s 670ms/step - loss: 0.6631 - accuracy: 0.7591 - val_loss: 1.0533 - val_accuracy: 0.6495
Epoch 00073: val_accuracy did not improve from 0.65784
Epoch 74/100
449/449 [=====] - 313s 697ms/step - loss: 0.6535 - accuracy: 0.7616 - val_loss: 1.0474 - val_accuracy: 0.6570
Epoch 00074: ReduceLROnPlateau reducing learning rate to 0.00031381062290165574.
Epoch 00074: val_accuracy did not improve from 0.65784
Epoch 75/100
449/449 [=====] - 294s 655ms/step - loss: 0.6542 - accuracy: 0.7587 - val_loss: 1.0563 - val_accuracy: 0.6567
Epoch 00075: val_accuracy did not improve from 0.65784
Epoch 76/100
449/449 [=====] - 294s 654ms/step - loss: 0.6423 - accuracy: 0.7637 - val_loss: 1.0594 - val_accuracy: 0.6570
Epoch 00076: val_accuracy did not improve from 0.65784
Epoch 00076: early stopping

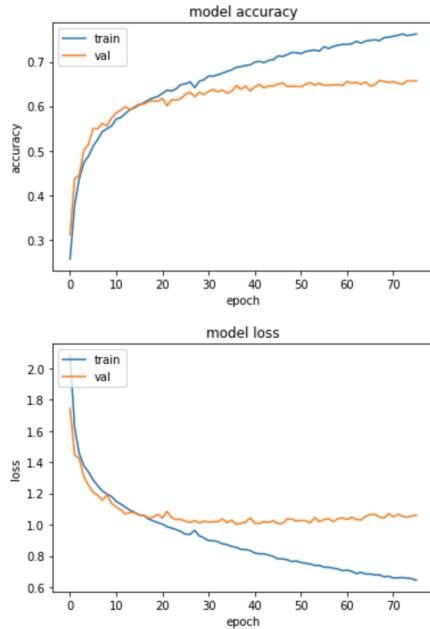
```

```

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

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

```



Testing :

```

from tensorflow.keras.models import load_model
import tensorflow as tf
from time import sleep
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.models import model_from_json
from tensorflow.keras.preprocessing import image
import cv2
import numpy as np

emotion_model =load_model('emotions2.h5')

face_haar_cascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
class_labels = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
cap = cv2.VideoCapture(0)
while True:
    # Grab a single frame of video
    ret, frame = cap.read()
    labels = []
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = face_haar_cascade.detectMultiScale(gray, 1.3, 5)

    for (x,y,w,h) in faces:
        cv2.rectangle(frame,(x,y),(x+w,y+h),(255,0,0),2)
        roi_gray = gray[y:y+h,x:x+w]
        roi_gray = cv2.resize(roi_gray,(48,48),interpolation=cv2.INTER_AREA)

        if np.sum([roi_gray])!=0:
            roi = roi_gray.astype('float')/255.0
            roi = img_to_array(roi)
            roi = np.expand_dims(roi,axis=0)

            preds = emotion_model.predict(roi)[0]
            label=class_labels[preds.argmax()]
            percen = f'{round(np.max(preds)*100)}%'
            print("\nlabel:{0} {1}%".format(label,round(np.max(preds)*100)))
            label_position = (x,y-10)
            cv2.putText(frame,f'{label}:{percen}',label_position, cv2.FONT_HERSHEY_SIMPLEX,1,(0,255,0),2)

    cv2.imshow('Emotion Detector',frame)
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

cap.release()
cv2.destroyAllWindows()

```

Implementation for both face mask and face emotion (for mixing) : Emotion :

```
import pickle
from tqdm import tqdm
import cv2
import os
from keras.preprocessing import image
import numpy as np
import pandas as pd
from tensorflow.keras.utils import to_categorical
from sklearn.utils import shuffle as sk_shuffle
from sklearn.model_selection import train_test_split
from keras.applications.mobilenet_v2 import preprocess_input
from keras.applications.vgg16 import preprocess_input as vgg16_preprocess

from keras.preprocessing.image import ImageDataGenerator
from keras.layers import AveragePooling2D, Dropout, Flatten, BatchNormalization, Dense, Input, GlobalAveragePooling2D, Conv2D, MaxPooling2D
from keras import regularizers
from keras.models import Model, Sequential
from keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import numpy as np
import pickle
import os
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
import cv2
from keras.models import load_model
from keras.preprocessing.image import ImageDataGenerator

def get_image_value(path, dim, bw, model_type):
    '''This function will read an image and convert to a specified version and resize depending on which algorithm is being used. If edge is set to True, it will convert the image to grayscale. If model_type is set to 'Normal', it will stack the image three times along the axis. If model_type is set to 'MobileNet', it will use the mobile preprocess function. If model_type is set to 'VGG16', it will use the vgg16 preprocess function. The image will then be resized to the specified dimension.'''
    img = image.load_img(path, target_size = dim)
    img = image.img_to_array(img)
    if bw == True:
        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    if model_type.upper() != 'Normal':
        img = np.stack((img,)*3, axis = -1)
    else:
        img = img.reshape(img.shape[0], img.shape[1],1)

    if model_type.upper() == 'MOBILENET':
        img = mobile_preprocess(img)
        return img
    elif model_type.upper() == 'VGG16':
        img = vgg16_preprocess(img)
        return img
    return img/255

def get_emotion_classes(class_type):
    angry_paths = [f'D:/Project/FER/{class_type}/angry/{i}' for i in os.listdir(f'D:/Project/FER/{class_type}/angry')]
    angry_labels = [0 for i in range(len(angry_paths))]

    happy_paths = [f'D:/Project/FER/{class_type}/happy/{i}' for i in os.listdir(f'D:/Project/FER/{class_type}/happy')]
    happy_labels = [1 for i in range(len(happy_paths))]

    neutral_paths = [f'D:/Project/FER/{class_type}/neutral/{i}' for i in os.listdir(f'D:/Project/FER/{class_type}/neutral')]
    neutral_labels = [2 for i in range(len(neutral_paths))]

    labels = np.array(angry_labels + happy_labels + neutral_labels)

    print(f'{class_type.upper()} Value Count')
    print(pd.Series(labels).value_counts())
    print('-----')
    labels = to_categorical(labels)
    paths = np.array(angry_paths + happy_paths + neutral_paths)
    paths, labels = sk_shuffle(paths, labels)
    return paths, labels
#0: angry // 1: happy // 2: neutral

def get_emotion_splits(dim, pick_name, model_type = 'normal', bw = False, max_values = 6000):

    #Train
    train_paths, train_labels = get_emotion_classes('train')
    test_paths, test_labels = get_emotion_classes('test')

    train_images = np.array([get_image_value(i, dim, bw, model_type) for i in tqdm(train_paths, desc = 'Getting Emotion Train Images')])
    test_images = np.array([get_image_value(i, dim, bw, model_type) for i in tqdm(test_paths, desc = 'Getting Emotion Test Images')])

    tts = (train_images, test_images, train_labels, test_labels)

    return tts
dim = (48,48)
tts = get_emotion_splits(dim, pick_name = 'normal', bw = False)
```

```
Getting Emotion Train Images: 2%|| 252/16175 [00:00<00:06, 2502.10it/s]
```

```
TRAIN Value Count
1    7215
2    4965
0    3995
dtype: int64
```

```
TEST Value Count
1    1774
2    1233
0    958
dtype: int64
```

```
Getting Emotion Train Images: 100%|██████████| 16175/16175 [00:06<00:00, 2676.19it/s]
Getting Emotion Test Images: 100%|██████████| 3965/3965 [00:01<00:00, 2623.77it/s]
```

```
x_train, x_test, y_train, y_test = get_emotion_splits(dim = (48,48), pick_name = 'normal', bw = True)
print(x_train.shape, x_test.shape)
print(y_train.shape, y_test.shape)
```

```
Getting Emotion Train Images: 3%|| 462/16175 [00:00<00:07, 2184.28it/s]
```

```
TRAIN Value Count
1    7215
2    4965
0    3995
dtype: int64
```

```
TEST Value Count
1    1774
2    1233
0    958
dtype: int64
```

```
Getting Emotion Train Images: 100%|██████████| 16175/16175 [00:07<00:00, 2271.50it/s]
Getting Emotion Test Images: 100%|██████████| 3965/3965 [00:01<00:00, 2214.82it/s]
(16175, 48, 48, 3) (3965, 48, 48, 3)
(16175, 3) (3965, 3)
```

```
x_train.shape
```

```
(16175, 48, 48, 3)
```

```
x_train.shape[1],x_train.shape[2],x_train.shape[3]
```

```
(48, 48, 3)
```

```
def get_conv_model(dim):
    model = Sequential()
    model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu', input_shape = dim))
    model.add(Conv2D(64, kernel_size = (3,3), activation = 'relu'))
    model.add(MaxPooling2D(pool_size = (2,2)))
    model.add(Dropout(.25))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Flatten())
    model.add(Dense(1024, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(3, activation = 'softmax', name = 'Output'))
    model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
    return model
```

```
early_stopping = EarlyStopping(monitor='val_loss', verbose = 1, patience=5, min_delta = .00075)
model_checkpoint = ModelCheckpoint(f'N_Emotions_only3.h5', verbose = 1, save_best_only=True,
                                    monitor = 'val_loss')
```

```
lr_plat = ReduceLROnPlateau(patience = 5, mode = 'min')
epochs = 2000
batch_size = 32
augment = False
```

```
dim = (x_train.shape[1], x_train.shape[2], x_train.shape[3])
cnn = get_conv_model(dim=dim)
```

```
if augment == True:
    train_aug = ImageDataGenerator(rotation_range = 40, width_shift_range = .2, height_shift_range = .2,
                                    horizontal_flip = True, shear_range = .15,
                                    fill_mode = 'nearest', zoom_range = .15)
    # augmentation.fit(x_train)
    cnn_history = cnn.fit_generator(train_aug.flow(x_train, y_train, batch_size = batch_size),
                                    epochs = epochs,
                                    callbacks = [early_stopping, model_checkpoint, lr_plat], validation_data = (x_test, y_test), verbose= 1)

else:
    cnn_history = cnn.fit(x_train, y_train, batch_size = batch_size,
                          epochs = epochs,
                          callbacks = [early_stopping, model_checkpoint, lr_plat], validation_data = (x_test, y_test), verbose= 1)
```

```

Epoch 1/2000
506/506 [=====] - 108s 188ms/step - loss: 1.0611 - accuracy: 0.4498 - val_loss: 0.8656 - val_accuracy: 0.5997
Epoch 00001: val_loss improved from inf to 0.86558, saving model to N_Emotions_only3.h5
Epoch 2/2000
506/506 [=====] - 105s 207ms/step - loss: 0.8350 - accuracy: 0.6154 - val_loss: 0.6964 - val_accuracy: 0.6913
Epoch 00002: val_loss improved from 0.86558 to 0.69637, saving model to N_Emotions_only3.h5
Epoch 3/2000
506/506 [=====] - 103s 203ms/step - loss: 0.7108 - accuracy: 0.6911 - val_loss: 0.6609 - val_accuracy: 0.7117
Epoch 00003: val_loss improved from 0.69637 to 0.66090, saving model to N_Emotions_only3.h5
Epoch 4/2000
506/506 [=====] - 102s 201ms/step - loss: 0.6607 - accuracy: 0.7095 - val_loss: 0.5946 - val_accuracy: 0.7435
Epoch 00004: val_loss improved from 0.66090 to 0.59465, saving model to N_Emotions_only3.h5
Epoch 5/2000
506/506 [=====] - 109s 216ms/step - loss: 0.6166 - accuracy: 0.7412 - val_loss: 0.5853 - val_accuracy: 0.7473
Epoch 00005: val_loss improved from 0.59465 to 0.58528, saving model to N_Emotions_only3.h5
Epoch 6/2000
506/506 [=====] - 113s 223ms/step - loss: 0.5844 - accuracy: 0.7540 - val_loss: 0.5708 - val_accuracy: 0.7498
Epoch 00006: val_loss improved from 0.58528 to 0.57076, saving model to N_Emotions_only3.h5
Epoch 7/2000
506/506 [=====] - 104s 206ms/step - loss: 0.5637 - accuracy: 0.7601 - val_loss: 0.5474 - val_accuracy: 0.7654
Epoch 00007: val_loss improved from 0.57076 to 0.54741, saving model to N_Emotions_only3.h5
Epoch 8/2000
506/506 [=====] - 102s 201ms/step - loss: 0.5336 - accuracy: 0.7704 - val_loss: 0.5615 - val_accuracy: 0.7612
Epoch 00008: val_loss did not improve from 0.54741
Epoch 9/2000
506/506 [=====] - 108s 213ms/step - loss: 0.5014 - accuracy: 0.7942 - val_loss: 0.5442 - val_accuracy: 0.7776
Epoch 00009: val_loss improved from 0.54741 to 0.54423, saving model to N_Emotions_only3.h5
Epoch 10/2000
506/506 [=====] - 108s 214ms/step - loss: 0.4923 - accuracy: 0.7943 - val_loss: 0.5715 - val_accuracy: 0.7574
Epoch 00010: val_loss did not improve from 0.54423
Epoch 11/2000
506/506 [=====] - 111s 220ms/step - loss: 0.4747 - accuracy: 0.8056 - val_loss: 0.5403 - val_accuracy: 0.7793
Epoch 00011: val_loss improved from 0.54423 to 0.54033, saving model to N_Emotions_only3.h5
Epoch 12/2000
506/506 [=====] - 103s 203ms/step - loss: 0.4619 - accuracy: 0.8100 - val_loss: 0.5261 - val_accuracy: 0.7879
Epoch 00012: val_loss improved from 0.54033 to 0.52609, saving model to N_Emotions_only3.h5
Epoch 13/2000
506/506 [=====] - 104s 206ms/step - loss: 0.4443 - accuracy: 0.8178 - val_loss: 0.5623 - val_accuracy: 0.7637
Epoch 00013: val_loss did not improve from 0.52609
Epoch 14/2000
506/506 [=====] - 113s 223ms/step - loss: 0.4323 - accuracy: 0.8233 - val_loss: 0.5216 - val_accuracy: 0.7796
Epoch 00014: val_loss improved from 0.52609 to 0.52158, saving model to N_Emotions_only3.h5
Epoch 15/2000
506/506 [=====] - 120s 238ms/step - loss: 0.4094 - accuracy: 0.8350 - val_loss: 0.5363 - val_accuracy: 0.7869
Epoch 00015: val_loss did not improve from 0.52158
Epoch 16/2000
506/506 [=====] - 114s 225ms/step - loss: 0.3869 - accuracy: 0.8387 - val_loss: 0.5455 - val_accuracy: 0.7770
Epoch 00016: val_loss did not improve from 0.52158
Epoch 17/2000
506/506 [=====] - 114s 225ms/step - loss: 0.3818 - accuracy: 0.8425 - val_loss: 0.5327 - val_accuracy: 0.7897
Epoch 00017: val_loss did not improve from 0.52158
Epoch 18/2000
506/506 [=====] - 106s 210ms/step - loss: 0.3725 - accuracy: 0.8490 - val_loss: 0.5664 - val_accuracy: 0.7753
Epoch 00018: val_loss did not improve from 0.52158
Epoch 19/2000
506/506 [=====] - 107s 212ms/step - loss: 0.3559 - accuracy: 0.8585 - val_loss: 0.5466 - val_accuracy: 0.7834
Epoch 00019: val_loss did not improve from 0.52158
Epoch 00019: early stopping

```

Mask :

```

import pickle
from tqdm import tqdm
import cv2
import os
from keras.preprocessing import image
import numpy as np
import pandas as pd
from tensorflow.keras.utils import to_categorical
from sklearn.utils import shuffle as sk_shuffle
from sklearn.model_selection import train_test_split
from keras.applications.mobilenet_v2 import preprocess_input
from keras.applications.vgg16 import preprocess_input as vgg16_preprocess

from keras.preprocessing.image import ImageDataGenerator
from keras.layers import AveragePooling2D, Dropout, Flatten, BatchNormalization, Dense, Input, GlobalAveragePooling2D, Conv2D, MaxPooling2D
from keras import regularizers
from keras.models import Model, Sequential
from keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import numpy as np
import pickle
import os
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
import cv2
from keras.models import load_model
from keras.preprocessing.image import ImageDataGenerator
#from PyFunctions import Viz
#from PyFunctions import Functions as func

```

```

def get_image_value(path, dim, bw, model_type):
    '''This function will read an image and convert to a specified version and resize depending on which algorithm is being used. If edge is
    img = image.load_img(path, target_size = dim)
    img = image.img_to_array(img)
    if bw == True:
        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
        img = img.reshape(img.shape[0], img.shape[1],1)
    if model_type == 'mobilenet':
        img = preprocess_input(img)
    return img
return img/255

```

```

def get_mask_classes(class_type):
    mask_paths = [f'/Face_Mask_Dataset/{class_type}/WithMask/{i}' for i in os.listdir(f'/Face_Mask_Dataset/{class_type}/WithMask')]
    mask_labels = [1 for i in range(len(mask_paths))]

    nomask_paths = [f'/Face_Mask_Dataset/{class_type}/WithoutMask/{i}' for i in os.listdir(f'/Face_Mask_Dataset/{class_type}/WithoutMask')]
    nomask_labels = [0 for i in range(len(nomask_paths))]

    labels = np.array(mask_labels + nomask_labels)
    print(f'{class_type.upper()} Value Counts')
    print(pd.Series(labels).value_counts())
    print('-----')
    paths = np.array(mask_paths + nomask_paths)
    labels = to_categorical(labels)
    paths, labels = sk_shuffle(paths, labels)
    return paths, labels

def get_mask_splits(dim, pick_name, model_type = 'Mobilenet', bw = False):

    #Train Set
    train_paths, train_labels = get_mask_classes('Train')
    train_images = np.array([get_image_value(i, dim, bw, model_type) for i in tqdm(train_paths, desc = 'Getting Train Images')])
    train_dict = dict(images = train_images, labels = train_labels)

    #Test Set
    test_paths, test_labels = get_mask_classes('Test')
    test_images = np.array([get_image_value(i, dim, bw, model_type) for i in tqdm(test_paths, desc = 'Getting Test Images')])
    test_images, test_labels = sk_shuffle(test_images, test_labels)

    #Validation Set
    val_paths, val_labels = get_mask_classes('Validation')
    val_images = np.array([get_image_value(i, dim, bw, model_type) for i in tqdm(val_paths, desc = 'Getting Validation Images')])
    val_images, val_labels = sk_shuffle(val_images, val_labels)

    tts = train_images, test_images, train_labels, test_labels, val_images, val_labels

    return tts

dim = (244,244)
tts = get_mask_splits(dim, pick_name = 'Normal1',model_type = 'Normal', bw = False )

```

```

Getting Train Images:  0% | 31/10000 [00:00<00:33, 301.37it/s]
TRAIN Value Counts
0  5000
1  5000
dtype: int64
-----
```

```

Getting Train Images: 100%|██████████| 10000/10000 [00:27<00:00, 363.95it/s]
Getting Test Images:  4%|| 36/992 [00:00<00:02, 353.24it/s]
TEST Value Counts
0  509
1  483
dtype: int64
-----
```

```

Getting Test Images: 100%|██████████| 992/992 [00:02<00:00, 391.00it/s]
Getting Validation Images:  4%|| 35/800 [00:00<00:02, 346.30it/s]
VALIDATION Value Counts
0  400
1  400
dtype: int64
-----
```

```

Getting Validation Images: 100%|██████████| 800/800 [00:01<00:00, 424.51it/s]
```

```

dim = (224,224)

x_train, x_test, y_train, y_test, x_val, y_val = get_mask_splits(dim,'Normal1',bw=True)
```

```

Getting Train Images:  0% | 39/10000 [00:00<00:25, 389.16it/s]
TRAIN Value Counts
0  5000
1  5000
dtype: int64
-----
```

```

Getting Train Images: 100%|██████████| 10000/10000 [00:23<00:00, 422.09it/s]
Getting Test Images:  5%|| 54/992 [00:00<00:01, 539.81it/s]
TEST Value Counts
0  509
1  483
dtype: int64
-----
```

```

Getting Test Images: 100%|██████████| 992/992 [00:01<00:00, 636.20it/s]
Getting Validation Images:  7%|| 58/800 [00:00<00:01, 568.37it/s]
VALIDATION Value Counts
0  400
1  400
dtype: int64
-----
```

```

Getting Validation Images: 100%|██████████| 800/800 [00:01<00:00, 624.61it/s]
```

```

def get_mobilenet(dim):
    model = Sequential()
    optimizer = Adam(lr = .0005)
    baseModel = MobileNetV2(weights="imagenet", include_top=False,
                           input_tensor=Input(shape=dim))

    model.add(baseModel)
    model.add(AveragePooling2D(pool_size=(7, 7)))
    model.add(Flatten(name="flatten"))
    model.add(Dense(256, activation="relu"))
    model.add(Dropout(0.6))
    model.add(Dense(2, activation="sigmoid", name = 'Output'))

    for layer in baseModel.layers:
        layer.trainable = False

    model.compile(loss = 'binary_crossentropy', optimizer = optimizer, metrics = ['accuracy'])
    return model

```

```

x_train.shape

```

```

(10000, 224, 224, 1)

```

```

x_train.shape[1] , x_train.shape[2],x_train.shape[3]

```

```

(224, 224, 1)

```

```

dim = (224,224)

x_train, x_test, y_train, y_test, x_val, y_val = func.get_mask_splits(dim)

```

```

early_stopping = EarlyStopping(monitor='val_loss', verbose = 1, patience=5, min_delta = .00075)
model_checkpoint = ModelCheckpoint('Mobilenet_Masks_1.h5', verbose = 1, save_best_only=True,
                                   monitor = 'val_loss')
lr_plat = ReduceLROnPlateau(patience = 5, mode = 'min')
epochs = 2000
batch_size = 64

dim = (x_train.shape[1], x_train.shape[2], x_train.shape[3])
mobilenet = get_mobilenet(dim=dim)

augmentation = ImageDataGenerator(rotation_range = 20, width_shift_range = .2, height_shift_range = .2,
                                  horizontal_flip = True, shear_range = .15,
                                  fill_mode = 'nearest', zoom_range = .15)
augmentation.fit(x_train)
mobilenet_history = mobilenet.fit_generator(augmentation.flow(x_train, y_train, batch_size = batch_size),
                                             epochs = epochs,
                                             callbacks = [early_stopping, model_checkpoint, lr_plat], validation_data = (x_test, y_test), verbose= 1)

```

```

Epoch 00005: val_loss improved from 0.14802 to 0.13957, saving model to ModelWeights/Mobilenet_Masks.h5
Epoch 6/2000
157/157 [=====] - 90s 573ms/step - loss: 0.0641 - acc: 0.9779 - val_loss: 0.2344 - val_acc: 0.9047

Epoch 00006: val_loss did not improve from 0.13957
Epoch 7/2000
157/157 [=====] - 93s 592ms/step - loss: 0.0622 - acc: 0.9785 - val_loss: 0.1219 - val_acc: 0.9395

Epoch 00007: val_loss improved from 0.13957 to 0.12195, saving model to ModelWeights/Mobilenet_Masks.h5
Epoch 8/2000
157/157 [=====] - 91s 578ms/step - loss: 0.0565 - acc: 0.9798 - val_loss: 0.0544 - val_acc: 0.9798

Epoch 00008: val_loss improved from 0.12195 to 0.05442, saving model to ModelWeights/Mobilenet_Masks.h5
Epoch 9/2000
157/157 [=====] - 90s 574ms/step - loss: 0.0582 - acc: 0.9790 - val_loss: 0.0747 - val_acc: 0.9677

Epoch 00009: val_loss did not improve from 0.05442
Epoch 10/2000
157/157 [=====] - 91s 580ms/step - loss: 0.0571 - acc: 0.9801 - val_loss: 0.0426 - val_acc: 0.9869

Epoch 00010: val_loss improved from 0.05442 to 0.04260, saving model to ModelWeights/Mobilenet_Masks.h5
Epoch 11/2000
157/157 [=====] - 91s 580ms/step - loss: 0.0512 - acc: 0.9801 - val_loss: 0.0371 - val_acc: 0.9894

Epoch 00011: val_loss improved from 0.04260 to 0.03707, saving model to ModelWeights/Mobilenet_Masks.h5
Epoch 12/2000
157/157 [=====] - 91s 581ms/step - loss: 0.0520 - acc: 0.9802 - val_loss: 0.0797 - val_acc: 0.9662

Epoch 00012: val_loss did not improve from 0.03707
Epoch 13/2000
157/157 [=====] - 91s 577ms/step - loss: 0.0468 - acc: 0.9832 - val_loss: 0.0659 - val_acc: 0.9698

Epoch 00013: val_loss did not improve from 0.03707
Epoch 14/2000
157/157 [=====] - 90s 575ms/step - loss: 0.0448 - acc: 0.9838 - val_loss: 0.0643 - val_acc: 0.9728

Epoch 00014: val_loss did not improve from 0.03707
Epoch 15/2000
157/157 [=====] - 90s 576ms/step - loss: 0.0494 - acc: 0.9823 - val_loss: 0.0421 - val_acc: 0.9849

Epoch 00015: val_loss did not improve from 0.03707
Epoch 16/2000
157/157 [=====] - 91s 579ms/step - loss: 0.0518 - acc: 0.9815 - val_loss: 0.0518 - val_acc: 0.9824

Epoch 00016: val_loss did not improve from 0.03707
Epoch 00016: early stopping

```

Testing :

```
import cv2
import numpy as np
from keras.models import load_model
from keras.applications.mobilenet_v2 import preprocess_input as mobile_preprocess
from keras.applications.vgg16 import preprocess_input as vgg_preprocess

#live video

classifier = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
mask_model = load_model('Mobilenet_Masksl.h5')
emotion_model = load_model('emotions/N_Emotions_only3.h5')

emotion_dim = (48,48)
mask_dim = (224,224)

mask_dict = {0: 'No Mask', 1: 'Mask'}
mask_dict_color = {0: (0,0,255), 1: (0,255,0)} #colors for bounding boxes

emotion_dict = {0: 'Angry', 1: 'Happy', 2:'Neutral'}
vid_frames = []
cap = cv2.VideoCapture(0)

while True:
    ret, frame = cap.read()
    frame = cv2.flip(frame, 1,1)
    clone = frame.copy()
    bboxes = classifier.detectMultiScale(clone)
    for i in bboxes:
        x, y, width, height = i[0], i[1], i[2], i[3]
        x2, y2 = x+width, y+height
        mask_roi = clone[y:y2, x:x2]
        emotion_roi = mask_roi.copy()
        emotion_roi = cv2.resize(emotion_roi, emotion_dim, interpolation = cv2.INTER_CUBIC)
        mask_roi = cv2.resize(mask_roi, mask_dim, interpolation = cv2.INTER_CUBIC)

        #preprocess mask input
        mask_roi= mobile_preprocess(mask_roi)

        #preprocess emotion input
        emotion_roi = emotion_roi/255

        #resize emotion and mask to feed into nn
        mask_roi = mask_roi.reshape(1, mask_roi.shape[0], mask_roi.shape[1], mask_roi.shape[2])
        emotion_roi = emotion_roi.reshape(1, emotion_roi.shape[0], emotion_roi.shape[1], emotion_roi.shape[2])

        #mask predictions
        mask_predict = mask_model.predict(mask_roi)[0]
        mask_idx = np.argmax(mask_predict)
        mask_conf = f'{round(np.max(mask_predict)*100)}%'
        mask_cat = mask_dict[mask_idx]
        mask_color = mask_dict_color[mask_idx]
        if mask_idx == 0: #if there is no mask detected --> move onto emotions
            #emotion predictions
            emotion_predict = emotion_model.predict(emotion_roi)[0]
            emotion_idx = np.argmax(emotion_predict)
            emotion_cat = emotion_dict[emotion_idx]
            emotion_conf = f'{round(np.max(emotion_predict)*100)}%'
            cv2.putText(clone, f'{mask_cat}: {mask_conf}', (x, y-15), cv2.FONT_HERSHEY_SIMPLEX, .5, mask_color, 2)
            cv2.rectangle(clone, (x,y), (x2,y2), mask_color, 1)
            continue
        cv2.putText(clone, f'{mask_cat}: {mask_conf}', (x, y-15), cv2.FONT_HERSHEY_SIMPLEX, .5, mask_color, 2)
        cv2.rectangle(clone, (x,y), (x2,y2), mask_color, 1)

    cv2.imshow('Face Mask Emotion Detector', clone)
    vid_frames.append(clone)

    if cv2.waitKey(1) & 0xFF ==ord('q'):
        break
cap.release()
cv2.destroyAllWindows()

mask_roi.shape

(1, 224, 224, 3)

emotion_roi

array([[[[0.08627451, 0.0745098 , 0.08235294],
       [0.0745098 , 0.05490196, 0.05882353],
       [0.07843137, 0.05882353, 0.05490196],
       ...,
       [0.1254902 , 0.08235294, 0.07058824],
       [0.1372549 , 0.08235294, 0.0745098 ],
       [0.1372549 , 0.09803922, 0.09019608]],

      [[0.09411765, 0.0745098 , 0.07843137],
       [0.07843137, 0.05882353, 0.05882353],
       [0.09411765, 0.06666667, 0.05882353],
       ...,
       [0.15294118, 0.09411765, 0.08235294],
       [0.16862745, 0.10196078, 0.09019608],
       [0.1372549 , 0.09019608, 0.0745098 ]],


     [[0.10588235, 0.06666667, 0.09019608],
       [0.10196078, 0.0627451 , 0.07058824],
       [0.09803922, 0.08235294, 0.0627451 ],
       ...,
       [0.1372549 , 0.10588235, 0.08235294],
       [0.16078431, 0.12156863, 0.10980392],
       [0.15294118, 0.11764706, 0.10588235]],
```

```
emotion_roi.shape  
(1, 48, 48, 3)  
  
mask_roi.shape[0], mask_roi.shape[1], mask_roi.shape[2]  
(1, 224, 224)  
  
for idx, i in enumerate(vid_frames):  
    cv2.imwrite(f'Test/{idx}.png', i)
```