```
from google.colab import drive
drive.mount("/content/drive")
     Mounted at /content/drive
import os
import cv2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import shutil
import seaborn as sns
from PIL import Image
%matplotlib inline
from collections import Counter
import cv2
import os
from skimage import color, feature, img as ubyte
from sklearn.metrics import classification_report
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.model selection import GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
from skimage.feature import hog
import tensorflow as tf
from tensorflow.keras.regularizers import 12
from tensorflow.keras.callbacks import EarlyStopping
from torch.utils.data import DataLoader,Dataset,TensorDataset
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input, decode_predictions
from joblib import load, dump
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import to_categorical
from retinaface import RetinaFace
# Lab 09
GOOGLE_DRIVE_PATH_AFTER_MYDRIVE = '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG'
GOOGLE_DRIVE_PATH = os.path.join('drive', 'My Drive', GOOGLE_DRIVE_PATH_AFTER_MYDRIVE)
print(os.listdir(GOOGLE_DRIVE_PATH))
     ['Code', 'Video', 'Models', 'CV2023 CW Dataset']
GOOGLE DRIVE PATH
     '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG'
training_data_path = os.path.join(GOOGLE_DRIVE_PATH, '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/CV2023_CW testing_data_path = os.path.join(GOOGLE_DRIVE_PATH, '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/CV2023_CW_
if os.path.isdir(os.path.join(training_data_path,'all_classes_train')) is False:
  os.mkdir(os.path.join(training_data_path,'all_classes_train'))
if os.path.isdir(os.path.join(testing data path, 'all classes test')) is False:
  os.mkdir(os.path.join(testing_data_path,'all_classes_test'))
train_dataset_path = os.path.join(training_data_path,'all_classes_train')
test_dataset_path = os.path.join(testing_data_path,'all_classes_test')
class_list = ['0', '1', '2']
for i in class_list:
  train_dir=train_dataset_path+'/'+i
  test dir=test dataset path+'/'+i
  if os.path.isdir(train_dir) is False:
    os.mkdir(train_dir)
  if os.path.isdir(test dir) is False:
    os.mkdir(test_dir)
```

```
#Lab 07, the way how to load the images and their respective labels
def import selected data(path):
    train_image_paths, train_labels, test_image_paths, test_labels = [], [], [], []
    for folder in os.listdir(path):
        if folder == "train":
            train_images_path = os.path.join(path, folder, "images")
            train_labels_path = os.path.join(path, folder, "labels")
            for file in sorted(os.listdir(train images path)):
                 if file.endswith(".jpeg"):
                     train_image_paths.append(os.path.join(train_images_path, file))
                     label_path = os.path.join(train_labels_path, file.split(".")[0] + ".txt")
                     with open(label_path, "r") as f:
                         train_labels.append(f.read().strip())
        if folder == "test":
            test_images_path = os.path.join(path, folder, "images")
            test_labels_path = os.path.join(path, folder, "labels")
            for file in sorted(os.listdir(test_images_path)):
                 if file.endswith(".jpeg"):
                     test_image_paths.append(os.path.join(test_images_path, file))
                     label path = os.path.join(test labels path, file.split(".")[0] + ".txt")
                     with open(label_path, "r") as f:
                         test_labels.append(f.read().strip())
    return train_image_paths, train_labels, test_image_paths, test_labels
train image paths, train labels, test image paths, test labels = import selected data('/content/drive/MyDrive/Colab Notebooks/
#Lab 07
print("Number of training images: ", len(train_image_paths))
print("Number of training labels: ", len(train_labels))
print("Number of test images: ", len(test_image_paths))
print("Number of test labels: ", len(test_labels))
    Number of training images: 2393
Number of training labels: 2393
    Number of test images: 458
Number of test labels: 458
# Lab 07
print(Counter(train_labels))
    Counter({'1': 1939, '0': 376, '2': 78})
for k in range(0,len(train_labels)):
    filename = train_image_paths[k].split('/')[len(train_image_paths[k].split('/'))-1]
    label = train labels[k]
    start = os.path.abspath(train_image_paths[k])
    target = os.path.join(train dataset path, label, filename)
    shutil.copyfile(start, target)
for k in range(0,len(test_labels)):
    filename = test_image_paths[k].split(''')[len(test_image_paths[k].split('''))-1]
    label = test labels[k]
    start = os.path.abspath(test_image_paths[k])
    target = os.path.join(test dataset path, label, filename)
    shutil.copyfile(start, target)
def bgr to rgb(image):
    return cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
# Define the data generator with data augmentation
datagen = tf.keras.preprocessing.image.ImageDataGenerator(
    preprocessing_function=bgr_to_rgb, validation_split=0.2)
# Split the training data into a training set and a validation set
train_batches = datagen.flow_from_directory(directory=train_dataset_path,
                                              target size=(size,size),
                                              batch_size=5,
                                              shuffle=True,
```

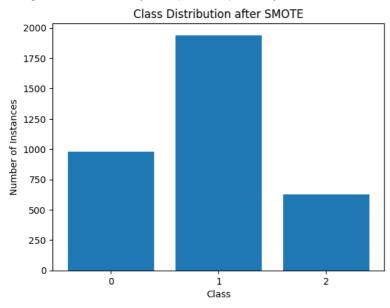
```
# The validation set can be accessed like this:
valid batches = datagen.flow from directory(directory=train dataset path,
                                                                       target_size=(size,size),
                                                                       batch_size=5,
                                                                       shuffle=True.
                                                                        subset="validation",
test_batches =datagen.flow_from_directory(test_dataset_path,
                                                                      target size=(size, size),
                                                                      batch_size=1,
                                                                      shuffle=False.
       Found 2393 images belonging to 3 classes.
        Found 477 images belonging to 3 classes.
       Found 458 images belonging to 3 classes.
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.preprocessing import OneHotEncoder
from imblearn.over_sampling import SMOTE
# Convert directory iterator to arrays
def get_data_from_iterator(iterator, num_samples):
      images, labels = [], []
      for batch in iterator:
            images.extend(batch[0])
            labels.extend(batch[1])
             if len(images) >= num_samples:
                  break
      return np.array(images), np.array(labels)
num train samples = train batches.n
num_valid_samples = valid_batches.n
train_X, train_y = get_data_from_iterator(train_batches, num_train_samples)
valid_X, valid_y = get_data_from_iterator(valid_batches, num_valid_samples)
# Get the number of samples in each class
num samples class0 = np.sum(np.argmax(train y, axis=1) == 0)
num_samples_class1 = np.sum(np.argmax(train_y, axis=1) == 1)
num_samples_class2 = np.sum(np.argmax(train_y, axis=1) == 2)
# Define the desired number of samples for each class after SMOTE
sampling_strategy = {
      0: int(num_samples_class0 * 2.6),
....2: int(num_samples_class2.*.8),
}
# Apply SMOTE
smote = SMOTE(sampling_strategy=sampling_strategy)
train_X_resampled, train_y_resampled = smote.fit_resample(train_X.reshape(train_X.shape[0], -1), np.argmax(train_y, axis=1))
valid X resampled, valid y resampled = smote.fit resample(valid X.reshape(valid X.shape[0], -1), np.argmax(valid y, axis=1))
# Reshape the data back to the original shape
train X resampled = train X resampled.reshape(train X resampled.shape[0], train X.shape[1], train X.shape[2], train X.shape[3]
valid_X_resampled = valid_X_resampled.reshape(valid_X_resampled.shape[0], valid_X.shape[1], valid_X.shape[2], valid_X.shape[3]
# One-hot encode the labels
encoder = OneHotEncoder(sparse=False)
train y resampled = encoder.fit transform(train y resampled.reshape(-1, 1))
valid_y_resampled = encoder.transform(valid_y_resampled.reshape(-1, 1))
# Create new directory iterators with balanced data
datagen = ImageDataGenerator()
train_batches = datagen.flow(train_X_resampled, train_y_resampled, batch_size=5, shuffle=True)
valid_batches = datagen.flow(valid_X_resampled, valid_y_resampled, batch_size=5, shuffle=True)
       /usr/local/lib/python3.9/dist-packages/imblearn/utils/_validation.py:313: UserWarning: After over-sampling, the number of
          warnings.warn(
        /usr/local/lib/python3.9/dist-packages/imblearn/utils/_validation.py:313: UserWarning: After over-sampling, the number of
       /usr/local/lib/python3.9/dist-packages/sklearn/preprocessing/ encoders.py:868: FutureWarning: `sparse` was renamed to `sparse`
          warnings.warn(
original class counts = Counter(np.argmax(train y, axis=1))
unique, counts = np.unique(train_y_resampled.argmax(axis=1), return_counts=True)
```

```
resampled_class_counts = dict(zip(unique, counts))

# Print the counters
print("Original class counts:", original_class_counts)
print("Resampled class counts:", resampled_class_counts)

# Create the bar plot
plt.bar(resampled_class_counts.keys(), resampled_class_counts.values())
plt.xlabel('Class')
plt.ylabel('Number of Instances')
plt.title('Class Distribution after SMOTE')
plt.xticks(list(resampled_class_counts.keys()))
plt.show()
```

Original class counts: Counter({1: 1939, 0: 376, 2: 78})
Resampled class counts: {0: 977, 1: 1939, 2: 624}



- CNN

```
# Define the model
model = models.Sequential([
   layers.Conv2D(64, (3, 3), activation='relu', padding='same', input shape=(100, 100, 3)),
   layers.BatchNormalization(),
   layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.MaxPooling2D((2, 2)),
   layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.MaxPooling2D((2, 2)),
   layers.Conv2D(256, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.Conv2D(256, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.MaxPooling2D((2, 2)),
   layers.Conv2D(512, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.Conv2D(512, (3, 3), activation='relu', padding='same'),
   layers.BatchNormalization(),
   layers.MaxPooling2D((2, 2)),
   layers.Flatten(),
   layers.Dense(512, activation='LeakyReLU', kernel_regularizer=12(0.001)),
   layers.BatchNormalization(),
   layers.Dropout(0.5),
   layers.Dense(256, activation='LeakyReLU', kernel_regularizer=12(0.001)),
   layers.BatchNormalization(),
   layers.Dropout(0.5),
```

1)

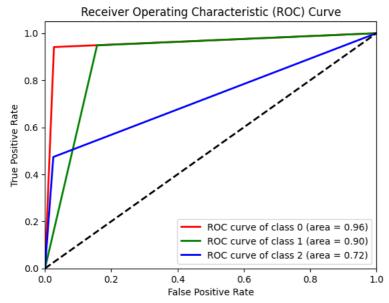
layers.Dense(3, activation='softmax')

```
early stopping = EarlyStopping(monitor='val loss', min delta=0, patience=10, restore best weights=True)
# Compile the model
model.compile(optimizer='adam',
             loss='categorical crossentropy',
             metrics=['accuracy'])
# Train the model
history = model.fit(train_batches,callbacks=[early_stopping], validation_data = valid_batches,epochs=100)
    Epoch 1/100
                              ========= 1 - 33s 31ms/step - loss: 2.3969 - accuracy: 0.7225 - val loss: 1.6400 - val accur
    479/479 [===
    Epoch 2/100
                             =======] - 13s 28ms/step - loss: 1.5630 - accuracy: 0.8491 - val_loss: 1.1053 - val_accur
    479/479 [===
    Epoch 3/100
    479/479 [===
                          :========] - 13s 28ms/step - loss: 1.1091 - accuracy: 0.8692 - val loss: 0.9403 - val accur
    Epoch 4/100
    479/479 [==
                               =======] - 14s 28ms/step - loss: 0.8975 - accuracy: 0.8763 - val_loss: 1.0124 - val_accur
    Epoch 5/100
    479/479 [===
                            :=======] - 14s 28ms/step - loss: 0.8411 - accuracy: 0.8897 - val loss: 0.6602 - val accur
    Epoch 6/100
                              =======] - 14s 29ms/step - loss: 0.7892 - accuracy: 0.8838 - val_loss: 0.7727 - val_accur
    479/479 [===
    Epoch 7/100
                              ========] - 14s 29ms/step - loss: 0.7393 - accuracy: 0.8930 - val_loss: 0.7034 - val_accur
    479/479 [===
    Epoch 8/100
    479/479 [===
                              =======] - 14s 29ms/step - loss: 0.7833 - accuracy: 0.8792 - val_loss: 0.6682 - val_accur
    Epoch 9/100
    479/479 [===
                              =======] - 14s 29ms/step - loss: 0.7803 - accuracy: 0.8796 - val_loss: 0.8861 - val_accur
    Epoch 10/100
    479/479 [====
                             ========] - 14s 29ms/step - loss: 0.7275 - accuracy: 0.8751 - val loss: 0.7880 - val accur
    Epoch 11/100
    479/479 [====
                               ======== 1 - 14s 29ms/step - loss: 0.7321 - accuracy: 0.8918 - val loss: 0.9349 - val accur
    Epoch 12/100
    479/479 [====
                            ======== ] - 14s 29ms/step - loss: 0.7603 - accuracy: 0.8817 - val loss: 0.7149 - val accur
    Epoch 13/100
    479/479 [====
                              =======] - 14s 30ms/step - loss: 0.7188 - accuracy: 0.8897 - val_loss: 0.7637 - val_accur
    Epoch 14/100
    479/479 [====
                              ========] - 14s 29ms/step - loss: 0.7310 - accuracy: 0.8872 - val_loss: 0.6936 - val_accur
    Epoch 15/100
    479/479 [===
                             ========] - 14s 29ms/step - loss: 0.7285 - accuracy: 0.8842 - val_loss: 0.7102 - val_accur
prediction_cnn=model.evaluate(test_batches)
    predictions=model.predict(test_batches)
    458/458 [=========== ] - 2s 4ms/step
# Obtain classification report
v pred=np.argmax(predictions.axis=1)
targetnames=['0','1','2']
y true=test batches.classes
y_true=to_categorical(y_true)
y_pred=to_categorical(y_pred)
report = classification_report(y_true,y_pred,target_names=targetnames)
print("Classification report:\n", report)
    Classification report:
                  precision
                              recall f1-score
                                                support
              0
                      0.83
                               0.88
                                         0.86
                                                     51
                      0.94
                               0.97
                                         0.96
                                                    388
              1
                      0.20
                               0.05
                                         0.08
                                                    19
                      0.92
                               0.92
                                         0.92
                                                    458
       micro avg
       macro avg
                      0.66
                               0.63
                                         0.63
                                                    458
    weighted avg
                      0.90
                               0.92
                                         0.91
                                                    458
     samples avg
                      0.92
                                0.92
                                         0.92
                                                    458
```

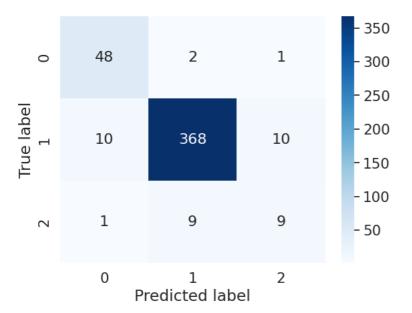
from joblib import load,dump

```
dump(model,'cnn_final_model.joblib')
    ['cnn_final_model.joblib']
dump(model,'/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Models/cnn final model.joblib')
    ['/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Models/cnn final model.joblib']
cnn loaded1 = load('/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Models/cnn final model.joblib')
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label binarize
# Make predictions on the test set
test_predictions = cnn_loaded1.predict(test_batches)
# Convert y_true and test_predictions to binary form
y_true_binary = label_binarize(test_batches.classes, classes=[0, 1, 2])
test_predictions_binary = label_binarize(np.argmax(test_predictions, axis=1), classes=[0, 1, 2])
# Compute ROC curve and AUC for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_true_binary[:, i], test_predictions_binary[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
# Plot ROC curve
plt.figure()
lw = 2
colors = ['red', 'green', 'blue']
for i, color in zip(range(3), colors):
   plt.plot(fpr[i], tpr[i], color=color, lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(i, roc_auc[i]))
plt.plot([0, 1], [0, 1], color='black', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```





```
# Create confusion matrix
y_true = np.argmax(y_true_binary, axis=1)
y_pred = np.argmax(test_predictions_binary, axis=1)
conf_matrix = confusion_matrix(y_true, y_pred)
print("Confusion_matrix.\n" conf_matrix)
```



- HOG+SVM

```
def extract_hog_features(image):
    features,image = hog(image, orientations=8, pixels_per_cell=(16,16), cells_per_block=(1, 1), multichannel =True,visualize=
    return features,image
```

the HOG (Histogram of Oriented Gradients) feature extraction technique to convert each image into a set of features that can be used for training the model.

```
size = 100
train_images = []
train_images_img = []
train_labels = []
test_images = []
test_labels = []
train images orig=[]
counter = 0
# Training data
for imgs, labels in train_batches:
    for img, label in zip(imgs, labels):
        train_images_orig.append(img)
        img = cv2.resize(img,(size,size))
        features,image = extract_hog_features(img)
        train_images_img.append(image)
        train_images.append(features)
        train_labels.append(np.argmax(label))
        counter += 1
    if counter >= train_batches.n:
        break
counter = 0
# Testing data
for imgs, labels in test_batches:
    for img, label in zip(imgs, labels):
        img = cv2.resize(img,(size,size))
        features,image = extract_hog_features(img)
```

```
test_images.append(features)
       test_labels.append(np.argmax(label))
       counter += 1
   if counter >= test_batches.n:
    <ipython-input-58-6017f9a4lc04>:2: FutureWarning: `multichannel` is a deprecated argument name for `hog`. It will be remo
      features, image = hog(image, orientations=8, pixels_per_cell=(16,16), cells_per_block=(1, 1), multichannel =True, visuali
# List files in the directory
image files = os.listdir(image directory)
# Load the first image in the directory
image_file_path = os.path.join(image_directory, image_files[700])
image = cv2.imread(image_file_path)
if image is None:
   print("Error: Image not loaded. Check the file path.")
else:
   gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
   # Compute HOG features
   fd, hog_image = hog(gray_image, orientations=9, pixels_per_cell=(8, 8),
                     cells_per_block=(2, 2), visualize=True, multichannel=False)
   # Normalize the HOG image for better visualization
   hog_image_rescaled = (hog_image - np.min(hog_image)) / (np.max(hog_image) - np.min(hog_image))
   # Visualize the first image and its HOG features
   fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 7), sharex=True, sharey=True)
   ax1.imshow(gray_image, cmap=plt.cm.gray)
   ax1.set_title('Input image')
   ax2.imshow(hog_image_rescaled, cmap=plt.cm.gray)
   ax2.set_title('Histogram of Oriented Gradients')
   plt.show()
```

cipython-input-60-026191c73f59>:15: FutureWarning: `multichannel` is a depreca fd, hog_image = hog(gray_image, orientations=9, pixels_per_cell=(8, 8),





```
from sklearn.model_selection import GridSearchCV
from sklearn import svm

# Set up the parameter grid
param_grid = {
   'C': [0.00001,0.1, 1, 10, 100],
```

```
'kernel': ['linear', 'rbf', 'poly'],
      'gamma': [1, 0.1, 0.01, 0.001]
  # Initialize the SVM classifier
 clf = svm.SVC(random_state=42)
 # Create the GridSearchCV object
 grid_search = GridSearchCV(clf, param_grid, cv=2)
  # Fit the GridSearchCV object to the data
 grid_search.fit(train_images, train_labels)
  # Get the best parameters
 best_params = grid_search.best_params_
 print("Best parameters found: ", best_params)
 # Train the SVM classifier with the best parameters
 best_clf = svm.SVC(**best_params, random_state=42)
 best_clf.fit(train_images, train_labels)
      Best parameters found: {'C': 100, 'gamma': 0.1, 'kernel': 'rbf'}
                         SVC
       SVC(C=100, gamma=0.1, random_state=42)
  from sklearn.metrics import accuracy_score, classification_report
  predicted labels ·= · best clf.predict(test images)
  # Calculate accuracy
  accuracy = accuracy_score(test_labels, predicted_labels)
 print("Accuracy: {:.2f}%".format(accuracy * 100))
  # Obtain classification report
  report = classification_report(test_labels, predicted_labels)
 print("Classification report:\n", report)
      Accuracy: 87.55%
      Classification report:
                     precision recall f1-score
                                                    support
                 0
                         0.57
                                  0.53
                                             0.55
                                                         51
                         0.91
                                   0.95
                                             0.93
                                                        388
                         0.71
                                  0.26
                                             0.38
                                                         19
                                             0.88
                                                        458
          accuracy
                         0.73
                                   0.58
                                             0.62
         macro avq
                                                        458
      weighted avg
                         0.87
                                   0.88
                                             0.87
                                                        458
  dump(best_clf,'/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/Models/svm_final_model.joblib')
      ['/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/Models/svm_final_model.joblib']
  svm_loaded=load('/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/Models/svm_final_model.joblib')
HOG+MLP
  def extract_hog_features(image):
     features, image = hog(image, orientations=8, pixels_per_cell=(16,16), cells_per_block=(1, 1), multichannel =True, visualize=
     return features, image
  def convert_to_rgb(image):
     return cv2.cvtColor(image, cv2.COLOR BGR2RGB)
 size = 100
  train images hog = []
 train_images_img = []
 train_labels_hog= []
 test_images_hog = []
 test_labels_hog = []
 train images orig=[]
 counter = 0
  # Training data
  for imgs, labels in train_batches:
      for img, label in zip(imgs, labels):
```

```
train_images_orig.append(img)
       img = cv2.resize(img,(size,size))
       features,image = extract_hog_features(img)
       train_images_img.append(image)
       train_images_hog.append(features)
       train_labels_hog.append(np.argmax(label))
    if counter >= train_batches.n:
       break
counter = 0
# Testing data
for imgs, labels in test_batches:
    for img, label in zip(imgs, labels):
       img = cv2.resize(img,(size,size))
       features,image = extract_hog_features(img)
       test images hog.append(features)
       test_labels_hog.append(np.argmax(label))
       counter += 1
    if counter >= test_batches.n:
       break
    <ipython-input-78-0f5790cc7810>:2: FutureWarning: `multichannel` is a deprecated argument name for `hog`. It will be remo-
      features, image = hog(image, orientations=8, pixels_per_cell=(16,16), cells_per_block=(1, 1), multichannel =True, visuali
# Lab 07
# Initialize the MLP classifier
mlp = MLPClassifier(random state=42)
# Create the parameter grid
param grid mlp = {
    'hidden_layer_sizes': [(100,), (200,), (300,), (100, 100), (200, 100), (100, 100, 100), (200, 100, 100)],
    'activation': ['relu', 'tanh'],
    'solver': ['adam', 'sgd'],
    'alpha': [0.0001, 0.001, 0.01],
# Create the GridSearchCV object
grid_search_mlp = GridSearchCV(mlp, param_grid_mlp, cv=2)
# Fit the GridSearchCV object to the data
grid_search_mlp.fit(train_images_hog, train_labels_hog)
# Get the best parameters
best_params_mlp = grid_search_mlp.best_params_
print("Best parameters found: ", best_params_mlp)
```

```
/usr/local/lib/python 3.9/dist-packages/sklearn/neural\_network/\_multilayer\_perceptron.py: 686: ConvergenceWarning: Stochast and the stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                     warnings.warn(
                /usr/local/lib/python 3.9/dist-packages/sklearn/neural\_network/\_multilayer\_perceptron.py: 686: Convergence Warning: Stochast and the stochas
                     warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural network/ multilayer perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                     warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                /usr/local/lib/python3.9/dist-packages/sklearn/neural network/ multilayer perceptron.py:686: ConvergenceWarning: Stochast
                    warnings.warn(
                Best parameters found: {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_sizes': (200, 100), 'solver': 'adam'}
     # Initialize MLP classifier with best hyperparameters
     mlp = MLPClassifier(hidden layer sizes=best params mlp['hidden layer sizes'],
                                                    activation=best_params_mlp['activation'],
                                                    solver=best_params_mlp['solver'],
                                                    alpha=best_params_mlp['alpha'],
                                                    random_state=42)
     mlp.fit(train_images_hog, train_labels)
     predicted labels = mlp.predict(test images hog)
     accuracy = accuracy_score(test_labels, predicted_labels)
     print("Accuracy: {:.2f}%".format(accuracy * 100))
     # Obtain classification report
     report = classification report(test labels, predicted labels)
     print("Classification report:\n", report)
                Accuracy: 43.89%
                Classification report:
                                                   precision
                                                                                 recall f1-score
                                                                                                                             support
                                         Ω
                                                             0.09
                                                                                    0.27
                                                                                                            0.14
                                                                                                                                        51
                                         1
                                                             0.82
                                                                                    0.48
                                                                                                            0.61
                                                                                                                                      388
                                          2
                                                             0.00
                                                                                    0.00
                                                                                                            0.00
                                                                                                                                        19
                         accuracy
                                                                                                            0.44
                                                                                                                                      458
                                                             0.30
                                                                                    0.25
                       macro avq
                                                                                                            0.25
                                                                                                                                       458
                weighted avg
                                                             0.71
                                                                                                            0.53
                                                                                                                                       458
                                                                                     0.44
     dump(mlp,'/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Models/mlp final model.joblib')
                ['/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Models/mlp final model.joblib']
     !pip install retinaface --no-deps
                Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
                Requirement already satisfied: retinaface in /usr/local/lib/python3.9/dist-packages (1.1.1)
VIDEO
```

```
# https://medium.com/@stepanfilonov/tracking-your-eyes-with-python-3952e66194a6, TO UNDERSTND BETTER HOT TO IMPLEMNET FOR TH E
#https://www.google.com/search?q=RETINA+LIBRARY+VIDEO+PYTHON+MDEIUM&rlz=1C5CHFA_enGB1052GB1052&ei=ijJFZJ7KMZ-YhbIPoJSimAs&ved=
video path = '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW Folder PG/Video/myvideo.mp4'
output_video_path = '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/Video/myvideo_output.mp4'
retinaface = RetinaFace()
cap = cv2. VideoCapture(video path)
fps = int(cap.get(cv2.CAP_PROP_FPS))
frame_size = (int(cap.get(cv2.CAP_PROP_FRAME_WIDTH)), int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT)))
fourcc = cv2.VideoWriter fourcc(*'XVID')
out = cv2.VideoWriter(output_video_path, fourcc, fps, frame_size)
while True:
    ret, frame = cap.read()
```

```
if not ret:
       break
    faces = retinaface.predict(frame)
    if faces is not None:
        for face in faces:
            x, y, x2, y2 = face['x1'],face['y1'],face['x2'],face['y2']
            face_roi = frame[y:y2, x:x2]
                face_roi = cv2.resize(face_roi, (100, 100))
            except:
                continue
            face_roi = np.expand_dims(face_roi, axis=0)
            video output = cnn loaded.predict(face roi, steps=1,verbose=0)
            video_output = np.argmax(video_output[0])
            if(video_output==0):
                cv2.rectangle(frame, (x, y), (x2, y2), (255, 0, 0), 2)
                cv2.putText(frame, "No Mask", (x, y - 10), cv2.FONT_HERSHEY_PLAIN, 0.9, (0, 255, 0), 2)
            elif(video output==1):
                cv2.rectangle(frame, (x, y), (x2, y2), (0, 255, 0), 2)
cv2.putText(frame, "Proper Mask", (x, y - 10), cv2.FONT_HERSHEY_PLAIN, 0.9, (0, 255, 0), 2)
                cv2.rectangle(frame, (x, y), (x2, y2), (0, 0, 255), 2)
                cv2.putText(frame, "Improper Mask", (x, y - 10), cv2.FONT_HERSHEY_PLAIN, 0.9, (0, 255, 0), 2)
    out.write(frame)
    if cv2.waitKey(1) & 0xFF == ord('q'):
       break
cap.release()
out.release()
cv2.destroyAllWindows()
print("Output video saved successfully.")
    model[normal quality] init ..
    model success !
    Output video saved successfully.
os.environ['DISPLAY'] = ':0'
os.environ['PYVISTA_OFF_SCREEN'] = 'true'
output_video_path = '/content/drive/MyDrive/Colab Notebooks/CV 2023 CW/CW_Folder_PG/Video/myvideo output.mp4'
out_cap = cv2.VideoCapture(output_video_path)
while True:
    # Read the current frame
   ret, frame = out_cap.read()
   if not ret:
   cv2 imshow(frame)
   key = cv2.waitKey(1) & 0xFF
        if key == ord('q'):
        break
out cap.release()
cv2.destroyAllWindows()
```

