

November 5, 2024

1 Facial Emotion Recogniton

Facial expressions recognition system has received significant attention among researchers in recent decades mainly because of it is diversified applications, such as human computer interactions, multimedia, surveillance, treatment of mentally retarded patients, and lie detection.

The study of Mehrabian stated that to understand emotion or intention of a person, 55% of the information are conveyed through facial expressions alone, 38% through vocal cues, and the remaining 7% via verbal cues.

This encourages the researchers to explore deeply in the area of facial expressions recognition and analysis (FERA). Ekman et al. asserted after extensive study over facial expressions, that facial expressions are universal and innate. They also concluded that six basic expressions, namely, happiness, sadness, disgust, anger, surprise, and fear are universal in nature.

##Import Libraries

```
[1]: !pip install py-feat
      !pip install opencv-python-headless
```

```
Requirement already satisfied: py-feat in /usr/local/lib/python3.10/dist-
packages (0.6.2)
Requirement already satisfied: pandas>=1.0 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (2.2.2)
Requirement already satisfied: numpy>=1.9 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (1.23.5)
Requirement already satisfied: seaborn>=0.7.0 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (0.13.2)
Requirement already satisfied: matplotlib>=2.1 in
/usr/local/lib/python3.10/dist-packages (from py-feat) (3.8.0)
Requirement already satisfied: nltools>=0.5.1 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (0.5.1)
Requirement already satisfied: numexpr<2.8.5 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (2.8.4)
Requirement already satisfied: scikit-learn>=1.2 in
/usr/local/lib/python3.10/dist-packages (from py-feat) (1.5.2)
Requirement already satisfied: pywavelets>=0.3.0 in
/usr/local/lib/python3.10/dist-packages (from py-feat) (1.7.0)
Requirement already satisfied: h5py>=2.7.0 in /usr/local/lib/python3.10/dist-
packages (from py-feat) (3.12.1)
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Requirement already satisfied: Pillow>=6.0.0 in /usr/local/lib/python3.10/dist-packages (from py-feat) (10.4.0)

Requirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-packages (from py-feat) (0.20.0+cu121)

Requirement already satisfied: scikit-image>=0.19 in /usr/local/lib/python3.10/dist-packages (from py-feat) (0.24.0)

Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from py-feat) (1.4.2)

Requirement already satisfied: easing-functions in /usr/local/lib/python3.10/dist-packages (from py-feat) (1.0.4)

Requirement already satisfied: celluloid in /usr/local/lib/python3.10/dist-packages (from py-feat) (0.2.0)

Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from py-feat) (4.66.6)

Requirement already satisfied: kornia in /usr/local/lib/python3.10/dist-packages (from py-feat) (0.7.4)

Requirement already satisfied: av>=9.2.0 in /usr/local/lib/python3.10/dist-packages (from py-feat) (13.1.0)

Requirement already satisfied: xgboost>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from py-feat) (2.1.2)

Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (1.3.0)

Requirement already satisfied: cycycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (0.12.1)

Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (4.54.1)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (1.4.7)

Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (24.1)

Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (3.2.0)

Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=2.1->py-feat) (2.8.2)

Requirement already satisfied: nibabel>=3.0.1 in /usr/local/lib/python3.10/dist-packages (from nltools>=0.5.1->py-feat) (5.3.2)

Requirement already satisfied: nilearn>=0.6.0 in /usr/local/lib/python3.10/dist-packages (from nltools>=0.5.1->py-feat) (0.10.4)

Requirement already satisfied: scipy>=1.7.0 in /usr/local/lib/python3.10/dist-packages (from nltools>=0.5.1->py-feat) (1.13.1)

Requirement already satisfied: pynv in /usr/local/lib/python3.10/dist-packages (from nltools>=0.5.1->py-feat) (0.3)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0->py-feat) (2024.2)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0->py-feat) (2024.2)

Requirement already satisfied: networkx>=2.8 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.19->py-feat) (3.4.2)

Requirement already satisfied: imageio>=2.33 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.19->py-feat) (2.36.0)

Requirement already satisfied: tifffile>=2022.8.12 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.19->py-feat) (2024.9.20)

Requirement already satisfied: lazy-loader>=0.4 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.19->py-feat) (0.4)

Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.2->py-feat) (3.5.0)

Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.10/dist-packages (from xgboost>=1.6.0->py-feat) (2.23.4)

Requirement already satisfied: kornia-rs>=0.1.0 in /usr/local/lib/python3.10/dist-packages (from kornia->py-feat) (0.1.7)

Requirement already satisfied: torch>=1.9.1 in /usr/local/lib/python3.10/dist-packages (from kornia->py-feat) (2.5.0+cu121)

Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch>=1.9.1->kornia->py-feat) (3.16.1)

Requirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/python3.10/dist-packages (from torch>=1.9.1->kornia->py-feat) (4.12.2)

Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch>=1.9.1->kornia->py-feat) (3.1.4)

Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch>=1.9.1->kornia->py-feat) (2024.10.0)

Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-packages (from torch>=1.9.1->kornia->py-feat) (1.13.1)

Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch>=1.9.1->kornia->py-feat) (1.3.0)

Requirement already satisfied: importlib-resources>=5.12 in /usr/local/lib/python3.10/dist-packages (from nibabel>=3.0.1->nltools>=0.5.1->py-feat) (6.4.5)

Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages (from nilearn>=0.6.0->nltools>=0.5.1->py-feat) (5.3.0)

Requirement already satisfied: requests>=2.25.0 in /usr/local/lib/python3.10/dist-packages (from nilearn>=0.6.0->nltools>=0.5.1->py-feat) (2.32.3)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=2.1->py-feat) (1.16.0)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.25.0->nilearn>=0.6.0->nltools>=0.5.1->py-feat) (3.4.0)

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.25.0->nilearn>=0.6.0->nltools>=0.5.1->py-feat) (3.10)

Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.25.0->nilearn>=0.6.0->nltools>=0.5.1->py-feat) (2.2.3)

Requirement already satisfied: certifi>=2017.4.17 in
 /usr/local/lib/python3.10/dist-packages (from
 requests>=2.25.0->nilearn>=0.6.0->nltools>=0.5.1->py-feat) (2024.8.30)
 Requirement already satisfied: MarkupSafe>=2.0 in
 /usr/local/lib/python3.10/dist-packages (from jinja2->torch>=1.9.1->kornia->py-
 feat) (3.0.2)
 Requirement already satisfied: opencv-python-headless in
 /usr/local/lib/python3.10/dist-packages (4.10.0.84)
 Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-
 packages (from opencv-python-headless) (1.23.5)

```
[2]: import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Convolution2D, Activation,
    ↳BatchNormalization, MaxPooling2D, Dropout, Dense, Flatten, AveragePooling2D
from tensorflow.keras.initializers import RandomNormal

from keras.models import Sequential , load_model
from keras.layers import Convolution2D, Activation, BatchNormalization,
    ↳MaxPooling2D, Dropout, Dense, Flatten, AveragePooling2D
from keras.initializers import RandomNormal
from keras.layers import Conv2D,MaxPooling2D
from keras.optimizers import RMSprop,SGD,Adam
from keras.callbacks import ModelCheckpoint, TensorBoard ,EarlyStopping,
    ↳ReduceLROnPlateau
from sklearn.svm import SVC
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
```

##Import Dataset

```
[3]: from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
[4]: # import os
# import zipfile
```

```
# # Path to the directory containing the zip files
# zip_dir = '/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↳PJT 1 '

# # Iterate through the directory and unzip all zip files
# for filename in os.listdir(zip_dir):
#     if filename.endswith(".zip"):
#         zip_path = os.path.join(zip_dir, filename)
#         with zipfile.ZipFile(zip_path, 'r') as zip_ref:
#             zip_ref.extractall(zip_dir)
#         print(f"Unzipped: {filename}")
```

ImageDataGenerator() tool from Keras that allows for real-time data augmentation on image datasets. It helps improve model generalization by applying various transformations, such as rotation, shifting, zooming, and flipping, to create more diverse training samples from the original dataset.

```
[5]: data_dir = "/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↳PJT 1 "
datagen = ImageDataGenerator()
generator = datagen.flow_from_directory(    data_dir, target_size=(48,48),
↳color_mode="grayscale", subset="training", class_mode='categorical')
```

Found 393 images belonging to 8 classes.

1.0.1 Pre - Process The Images

```
[6]: from feat.detector import Detector

help(Detector)
```

Help on class Detector in module feat.detector:

```
class Detector(builtins.object)
|   Detector(face_model='retinaface', landmark_model='mobilefacenet',
au_model='xgb', emotion_model='resmasknet', facepose_model='img2pose',
identity_model='facenet', device='cpu', n_jobs=1, verbose=False, **kwargs)
|
|   Methods defined here:
|
|   __getitem__(self, i)
|
|   __init__(self, face_model='retinaface', landmark_model='mobilefacenet',
au_model='xgb', emotion_model='resmasknet', facepose_model='img2pose',
identity_model='facenet', device='cpu', n_jobs=1, verbose=False, **kwargs)
|       Detector class to detect FEX from images or videos.
|
|       Detector is a class used to detect faces, facial landmarks, emotions,
```

and action units from images and videos.

```
|
|     Args:
|         n_jobs (int, default=1): Number of processes to use for extraction.
|         device (str): specify device to process data (default='cpu'), can be
|         ['auto', 'cpu', 'cuda', 'mps']
|         verbose (bool): print logging and debug messages during operation
|         **kwargs: you can pass each detector specific kwargs using a
dictionary
|         like: `face_model_kwargs = {...}, au_model_kwargs={...}, ...`
|
|     Attributes:
|         info (dict):
|             n_jobs (int): Number of jobs to be used in parallel.
|             face_model (str, default=retinaface): Name of face detection
model
|             landmark_model (str, default=mobilenet): Name of landmark model
|             au_model (str, default=svm): Name of Action Unit detection model
|             emotion_model (str, default=resmasknet): Path to emotion
detection model.
|             facepose_model (str, default=img2pose): Name of headpose
detection model.
|             identity_model (str, default=facenet): Name of identity
detection model.
|             face_detection_columns (list): Column names for face detection
output (x, y, w, h)
|             face_landmark_columns (list): Column names for face landmark
output (x0, y0, x1, y1, ...)
|             emotion_model_columns (list): Column names for emotion model
output
|             emotion_model_columns (list): Column names for emotion model
output
|             mapper (dict): Class names for emotion model output by index.
|             input_shape (dict)
|
|             face_detector: face detector object
|             face_landmark: face_landmark object
|             emotion_model: emotion_model object
|
|     Examples:
|         >> detector = Detector(n_jobs=1)
|         >> detector.detect_image(["input.jpg"])
|         >> detector.detect_video("input.mp4")
|
|     __repr__(self)
|         Return repr(self).
|
|     change_model(self, **kwargs)
```

```

|         Swap one or more pre-trained detector models for another one. Just pass
in
|         the the new models to use as kwargs, e.g. emotion_model='svm'
|
|         detect_aus(self, frame, landmarks, **au_model_kwargs)
|         Detect Action Units from image or video frame
|
|         Args:
|             frame (np.ndarray): image loaded in array format (n, m, 3)
|             landmarks (array): 68 landmarks used to localize face.
|
|         Returns:
|             array: Action Unit predictions
|
|         Examples:
|             >>> from feat import Detector
|             >>> from feat.utils import read_pictures
|             >>> frame = read_pictures(['my_image.jpg'])
|             >>> detector = Detector()
|             >>> detector.detect_aus(frame)
|
|         detect_emotions(self, frame, facebox, landmarks, **emotion_model_kwargs)
|         Detect emotions from image or video frame
|
|         Args:
|             frame ([type]): [description]
|             facebox ([type]): [description]
|             landmarks ([type]): [description]
|
|         Returns:
|             array: Action Unit predictions
|
|         Examples:
|             >>> from feat import Detector
|             >>> from feat.utils import read_pictures
|             >>> img_data = read_pictures(['my_image.jpg'])
|             >>> detector = Detector()
|             >>> detected_faces = detector.detect_faces(frame)
|             >>> detected_landmarks = detector.detect_landmarks(frame,
detected_faces)
|             >>> detector.detect_emotions(frame, detected_faces,
detected_landmarks)
|
|         detect_facepose(self, frame, landmarks=None, **facepose_model_kwargs)
|         Detect facepose from image or video frame.
|
|         When used with img2pose, returns *all* detected poses, and facebox and
landmarks

```

```

|         are ignored. Use `detect_face` method in order to obtain bounding boxes
|         corresponding to the detected poses returned by this method.
|
|     Args:
|         frame (np.ndarray): list of images
|         landmarks (np.ndarray | None, optional): (num_images, num_faces, 68,
2)         landmarks for the faces contained in list of images; Default None
and
|         ignored for img2pose and img2pose-c detectors
|
|     Returns:
|         list: poses (num_images, num_faces, [pitch, roll, yaw]) - Euler
angles (in
|         degrees) for each face within in each image}
|
|     detect_faces(self, frame, threshold=0.5, **face_model_kwargs)
|         Detect faces from image or video frame
|
|     Args:
|         frame (np.ndarray): 3d (single) or 4d (multiple) image array
|         threshold (float): threshold for detectiong faces (default=0.5)
|
|     Returns:
|         list: list of lists with the same length as the number of frames.
Each list
|         item is a list containing the (x1, y1, x2, y2) coordinates of each
detected
|         face in that frame.
|
|     detect_identity(self, frame, facebox, **identity_model_kwargs)
|         Detects identity of faces from image or video frame using face
representation embeddings
|
|     Args:
|         frame (np.ndarray): 3d (single) or 4d (multiple) image array
|         threshold (float): threshold for matching identity (default=0.8)
|
|     Returns:
|         list: list of lists with the same length as the number of frames.
Each list
|         item is a list containing the (x1, y1, x2, y2) coordinates of each
detected
|         face in that frame.
|
|     detect_image(self, input_file_list, output_size=None, batch_size=1,
num_workers=0, pin_memory=False, frame_counter=0, face_detection_threshold=0.5,
face_identity_threshold=0.8, **kwargs)

```



```

|         Detects FEX from one or more image files. If you want to speed up
detection you
|         can process multiple images in batches by setting `batch_size > 1`.
However, all
|         images must have **the same dimensions** to be processed in batches. Py-
feat can
|         automatically adjust image sizes by using the `output_size=int`. Common
|         output-sizes include 256 and 512.
|
|         **NOTE: Currently batch processing images gives slightly different AU
detection results due to the way that py-feat integrates the underlying models.
You can examine the degree of tolerance by checking out the results of
`test_detection_and_batching_with_diff_img_sizes` in our test-suite**
|
|         Args:
|             input_file_list (list of str): Path to a list of paths to image
files.
|             output_size (int): image size to rescale all image preserving aspect
ratio.
|                                     Will raise an error if not set and batch_size >
1 but images are not the same size
|             batch_size (int): how many batches of images you want to run at one
shot.
|                                     Larger gives faster speed but is more memory-
consuming. Images must be the
|             same size to be run in batches!
|             num_workers (int): how many subprocesses to use for data loading.
``0`` means that the data will be loaded in the main process.
|             pin_memory (bool): If ``True``, the data loader will copy Tensors
into CUDA pinned memory before returning them. If your data elements are a
custom type, or your :attr:`collate_fn` returns a batch that is a custom type
|             frame_counter (int): starting value to count frames
|             face_detection_threshold (float): value between 0-1 to report a
detection based on the
|                                     confidence of the face detector; Default >= 0.5
|             face_identity_threshold (float): value between 0-1 to determine
similarity of person using face identity embeddings; Default >= 0.8
|             **kwargs: you can pass each detector specific kwargs using a
dictionary
|                                     like: `face_model_kwargs = {...},
au_model_kwargs={...}, ...`
|
|         Returns:
|             Fex: Prediction results dataframe
|
|         detect_landmarks(self, frame, detected_faces, **landmark_model_kwargs)
|             Detect landmarks from image or video frame
|

```

```

|     Args:
|         frame (np.ndarray): 3d (single) or 4d (multiple) image array
|         detected_faces (array):
|
|     Returns:
|         list: x and y landmark coordinates (1,68,2)
|
|     Examples:
|         >>> from feat import Detector
|         >>> from feat.utils import read_pictures
|         >>> img_data = read_pictures(['my_image.jpg'])
|         >>> detector = Detector()
|         >>> detected_faces = detector.detect_faces(frame)
|         >>> detector.detect_landmarks(frame, detected_faces)
|
|     detect_video(self, video_path, skip_frames=None, output_size=700,
| batch_size=1, num_workers=0, pin_memory=False, face_detection_threshold=0.5,
| face_identity_threshold=0.8, **kwargs)
|         Detects FEX from a video file.
|
|     Args:
|         video_path (str): Path to a video file.
|         skip_frames (int or None): number of frames to skip (speeds up
| inference,
|         but less temporal information); Default None
|         output_size (int): image size to rescale all imagee preserving
| aspect ratio
|         batch_size (int): how many batches of images you want to run at one
| shot. Larger gives faster speed but is more memory-consuming
|         num_workers (int): how many subprocesses to use for data loading.
| ``0`` means that the data will be loaded in the main process.
|         pin_memory (bool): If ``True``, the data loader will copy Tensors
|                             into CUDA pinned memory before returning them.
| If your data elements
|                             are a custom type, or your :attr:`collate_fn`
| returns a batch that is a custom type
|         face_detection_threshold (float): value between 0-1 to report a
| detection based on the
|                             confidence of the face detector; Default >= 0.5
|         face_identity_threshold (float): value between 0-1 to determine
| similarity of person using face identity embeddings; Default >= 0.8
|
|     Returns:
|         Fex: Prediction results dataframe
|
|     -----
|     Data descriptors defined here:
|

```

```
| __dict__
|     dictionary for instance variables (if defined)
|
| __weakref__
|     list of weak references to the object (if defined)
```

```
[7]: from feat import Detector
import cv2
import matplotlib.pyplot as plt

detector = Detector(au_model='rgb')

image_path = '/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↳PJT 1 /anger/S010_004_00000019.png'
image = cv2.imread(image_path)

image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

plt.imshow(image_rgb)
plt.axis('off')
plt.show()

result = detector.detect_image(image_path)

aus_data = result.aus.iloc[0]

au_labels = aus_data.index
au_values = aus_data.values

plt.figure(figsize=(10, 6))
plt.bar(au_labels, au_values)
plt.title('Detected Action Units (AUs)')
plt.xlabel('AU Label')
plt.ylabel('AU Intensity')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
100%|      | 1.79M/1.79M [00:00<00:00, 22.9MB/s]
100%|      | 12.3M/12.3M [00:00<00:00, 80.3MB/s]
100%|      | 966k/966k [00:00<00:00, 14.4MB/s]
100%|      | 33.6M/33.6M [00:00<00:00, 36.5MB/s]
100%|      | 130k/130k [00:00<00:00, 4.32MB/s]
100%|      | 45.9M/45.9M [00:00<00:00, 138MB/s]
100%|      | 130k/130k [00:00<00:00, 4.33MB/s]
100%|      | 53.9M/53.9M [00:00<00:00, 64.6MB/s]
```

```

100%|      | 130k/130k [00:00<00:00, 4.46MB/s]
100%|      | 167k/167k [00:00<00:00, 4.43MB/s]
100%|      | 531k/531k [00:00<00:00, 9.61MB/s]
100%|      | 494k/494k [00:00<00:00, 8.91MB/s]
100%|      | 207k/207k [00:00<00:00, 5.14MB/s]
100%|      | 1.15M/1.15M [00:00<00:00, 16.3MB/s]
100%|      | 572k/572k [00:00<00:00, 10.3MB/s]
100%|      | 330k/330k [00:00<00:00, 6.79MB/s]
100%|      | 335k/335k [00:00<00:00, 6.64MB/s]
100%|      | 587k/587k [00:00<00:00, 10.4MB/s]
100%|      | 207k/207k [00:00<00:00, 5.08MB/s]
100%|      | 690k/690k [00:00<00:00, 10.7MB/s]
100%|      | 584k/584k [00:00<00:00, 10.3MB/s]
100%|      | 207k/207k [00:00<00:00, 5.11MB/s]
100%|      | 257k/257k [00:00<00:00, 6.07MB/s]
100%|      | 1.08M/1.08M [00:00<00:00, 15.7MB/s]
100%|      | 1.95M/1.95M [00:00<00:00, 23.8MB/s]
100%|      | 312k/312k [00:00<00:00, 7.00MB/s]
100%|      | 524k/524k [00:00<00:00, 9.37MB/s]
100%|      | 77.7k/77.7k [00:00<00:00, 3.12MB/s]
100%|      | 552M/552M [00:04<00:00, 125MB/s]
100%|      | 448/448 [00:00<00:00, 438kB/s]
100%|      | 944/944 [00:00<00:00, 834kB/s]
100%|      | 170M/170M [00:03<00:00, 43.3MB/s]
100%|      | 176/176 [00:00<00:00, 346kB/s]
100%|      | 176/176 [00:00<00:00, 98.5kB/s]
100%|      | 112M/112M [00:01<00:00, 86.7MB/s]
/usr/local/lib/python3.10/dist-
packages/feat/face_detectors/Retinaface/Retinaface_test.py:70: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
    pretrained_dict = torch.load(
/usr/local/lib/python3.10/dist-packages/feat/detector.py:238: FutureWarning: You
are using `torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to construct
malicious pickle data which will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for

```

more details). In a future release, the default value for ``weights_only`` will be flipped to ``True``. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via ``torch.serialization.add_safe_globals``. We recommend you start setting ``weights_only=True`` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
checkpoint = torch.load(
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to
/root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|          | 44.7M/44.7M [00:00<00:00, 125MB/s]
/usr/local/lib/python3.10/dist-
packages/feat/facepose_detectors/img2pose/img2pose_test.py:105: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
```

```
checkpoint = torch.load(model_path, map_location=self.device)
/usr/local/lib/python3.10/dist-
packages/feat/emo_detectors/ResMaskNet/resmasknet_test.py:718: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
```

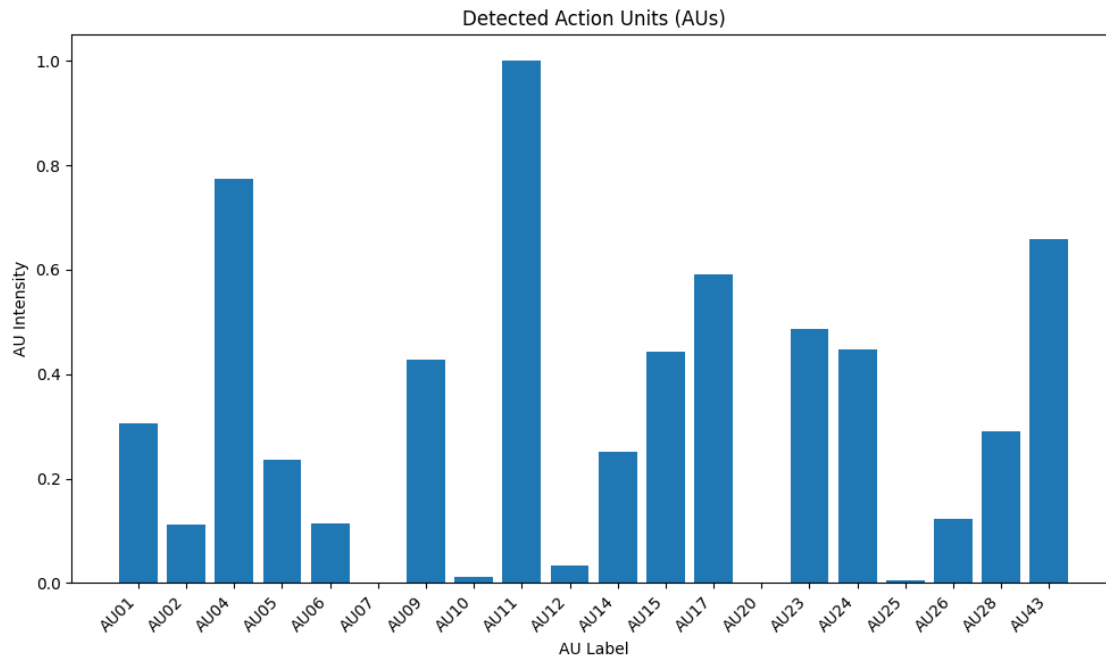
```
torch.load(
/usr/local/lib/python3.10/dist-
packages/feat/identity_detectors/facenet/facenet_model.py:275: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
```

construct malicious pickle data which will execute arbitrary code during unpickling (See <https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models> for more details). In a future release, the default value for ``weights_only`` will be flipped to ``True``. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via ``torch.serialization.add_safe_globals``. We recommend you start setting ``weights_only=True`` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
torch.load(
```



100% | 1/1 [00:06<00:00, 6.35s/it]



1.0.2 Load the Image

Load your image using OpenCV (or any other library) for visualization and processing. For this example, let's assume you have an image named `face_image.jpg`.

```
[8]: from feat import Fex
from feat import Detector
import matplotlib.pyplot as plt
import seaborn as sns
import cv2

image_path = "/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↳PJT 1 /happiness/S010_006_00000015.png"
image = cv2.imread(image_path)
image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

plt.imshow(image_rgb)
plt.axis("off")
plt.title("Original Image")
plt.show()
```

Original Image



1.0.3 Initialize the py-feat Detector

The Detector class in py-feat provides pre-trained models for extracting AUs and other facial attributes.

```
[9]: detector = Detector()
```

```
/usr/local/lib/python3.10/dist-  
packages/feat/face_detectors/Retinaface/Retinaface_test.py:70: FutureWarning:  
You are using `torch.load` with `weights_only=False` (the current default  
value), which uses the default pickle module implicitly. It is possible to  
construct malicious pickle data which will execute arbitrary code during  
unpickling (See  
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for  
more details). In a future release, the default value for `weights_only` will be  
flipped to `True`. This limits the functions that could be executed during  
unpickling. Arbitrary objects will no longer be allowed to be loaded via this  
mode unless they are explicitly allowlisted by the user via  
`torch.serialization.add_safe_globals`. We recommend you start setting  
`weights_only=True` for any use case where you don't have full control of the  
loaded file. Please open an issue on GitHub for any issues related to this  
experimental feature.  
pretrained_dict = torch.load(
```


/usr/local/lib/python3.10/dist-packages/feat/detector.py:238: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See <https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models> for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
checkpoint = torch.load(
/usr/local/lib/python3.10/dist-
packages/feat/facepose_detectors/img2pose/img2pose_test.py:105: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
```

```
checkpoint = torch.load(model_path, map_location=self.device)
/usr/local/lib/python3.10/dist-
packages/feat/emo_detectors/ResMaskNet/resmasknet_test.py:718: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
```

```
torch.load(
/usr/local/lib/python3.10/dist-
packages/feat/identity_detectors/facenet/facenet_model.py:275: FutureWarning:
```

You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See <https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models> for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
torch.load(
```

1.0.4 Extract AUs from the Image

Use the `detect_image` method on the Detector to extract AUs from the image.

```
[10]: results = detector.detect_image(image_path)
      print(results)
```

```
100%|          | 1/1 [00:05<00:00,  5.50s/it]

      FaceRectX  FaceRectY  FaceRectWidth  FaceRectHeight  FaceScore  \
0   249.611787   92.715177     260.082729     336.462964    0.999799

      x_0      x_1      x_2      x_3      x_4  ...  \
0   252.550246   253.873156   257.196233   264.358964   279.218316  ...

      Identity_505  Identity_506  Identity_507  Identity_508  Identity_509  \
0        -0.03535        -0.006768         0.007255        -0.065137        -0.04202

      Identity_510  Identity_511  Identity_512  \
0         0.016652        -0.04152         0.019833

                                     input  frame
0  /content/drive/MyDrive/Colab Notebooks/Shared ...      0

[1 rows x 686 columns]
```

```
[11]: results.columns
```

```
[11]: Index(['FaceRectX', 'FaceRectY', 'FaceRectWidth', 'FaceRectHeight',
            'FaceScore', 'x_0', 'x_1', 'x_2', 'x_3', 'x_4',
            ...,
            'Identity_505', 'Identity_506', 'Identity_507', 'Identity_508',
            'Identity_509', 'Identity_510', 'Identity_511', 'Identity_512', 'input',
            'frame'],
```

```
dtype='object', length=686)
```

1.0.5 View Extracted Action Units (AUs)

The results object now contains extracted AUs and other features. You can visualize these AUs by converting them to a DataFrame and plotting them.

```
[12]: aus = results.aus
      print(aus)
```

	AU01	AU02	AU04	AU05	AU06	AU07	AU09	AU10	\
0	0.28013	0.17168	0.179969	0.251102	0.898776	1.0	0.455161	0.779167	

	AU11	AU12	AU14	AU15	AU17	AU20	AU23	AU24	\
0	1.0	0.966566	0.583662	0.338505	0.138821	1.0	0.074952	0.098609	

	AU25	AU26	AU28	AU43
0	0.9999	0.600634	0.026196	0.065242

1.0.6 Plot Action Units

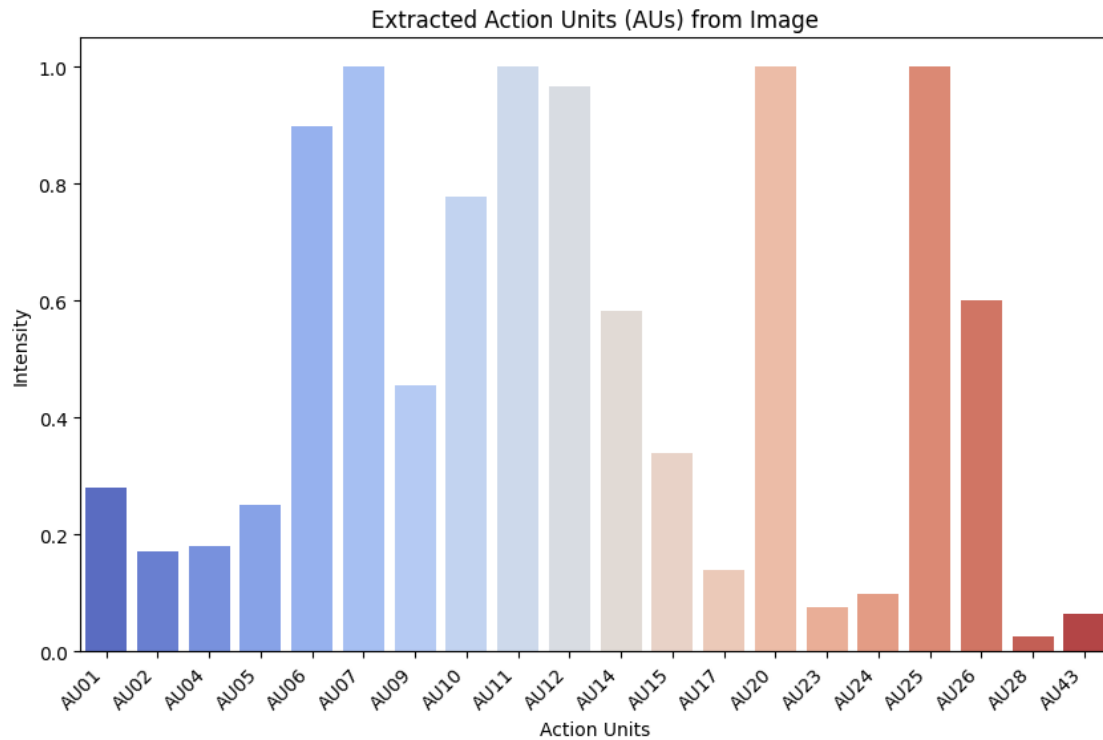
You can create a bar plot or heatmap to visualize the intensities of the extracted AUs.

```
[13]: plt.figure(figsize=(10, 6))
      sns.barplot(x=aus.columns, y=aus.iloc[0], palette="coolwarm")
      plt.title("Extracted Action Units (AUs) from Image")
      plt.xticks(rotation=45, ha="right")
      plt.ylabel("Intensity")
      plt.xlabel("Action Units")
      plt.show()
```

<ipython-input-13-13c2e5230754>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

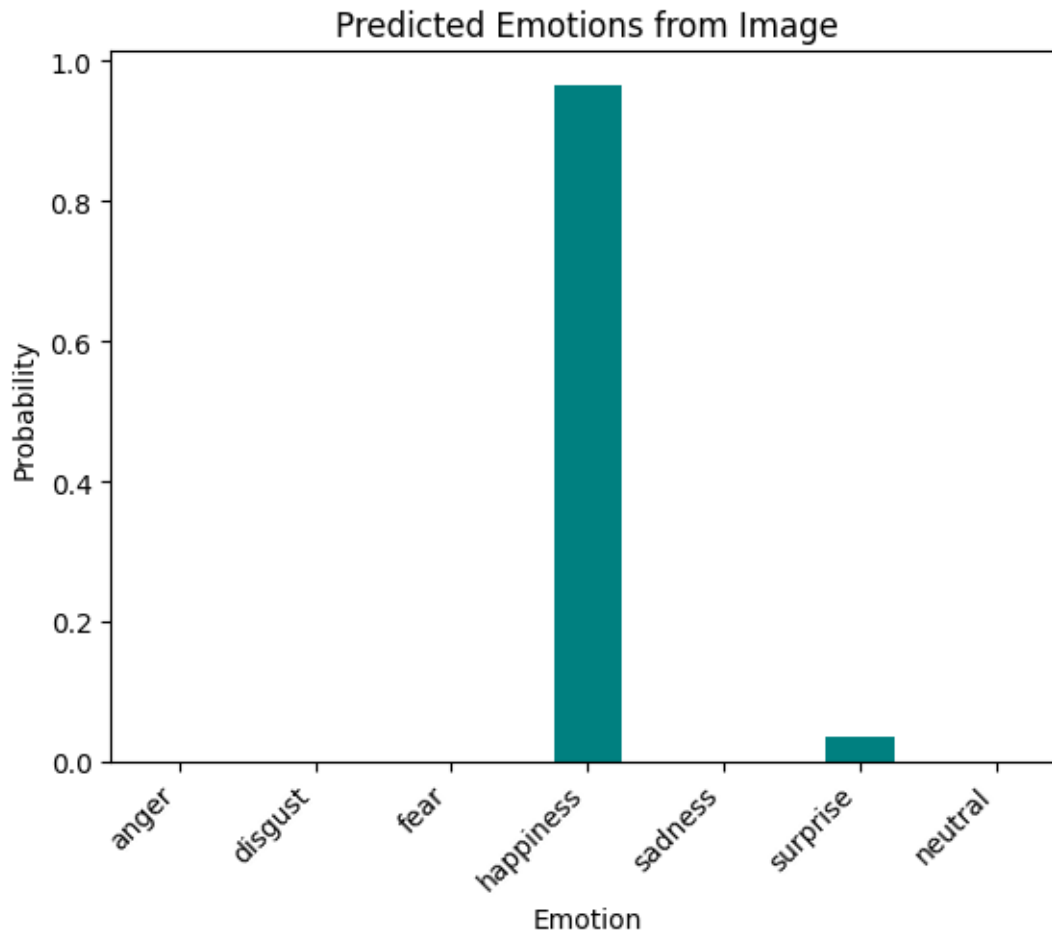
```
sns.barplot(x=aus.columns, y=aus.iloc[0], palette="coolwarm")
```



1.0.7 Display Emotions

If you're also interested in the emotions predicted by py-feat, you can visualize these alongside the AUs.

```
[14]: emotions = results.emotions.iloc[0]
emotions.plot(kind="bar", color="teal")
plt.title("Predicted Emotions from Image")
plt.ylabel("Probability")
plt.xlabel("Emotion")
plt.xticks(rotation=45, ha="right")
plt.show()
```



1.1 Extract the AU's for all the images

```
[15]: # import pandas as pd
# import os
# import cv2
# from feat import Detector
# import matplotlib.pyplot as plt

# def create_dataframe(data_dir):
#     rows = []
#     detector = Detector(au_model='xgb')

#     for class_name in os.listdir(data_dir):
#         class_dir = os.path.join(data_dir, class_name)
#         if os.path.isdir(class_dir):
#             for filename in os.listdir(class_dir):
#                 if filename.endswith(('png', 'jpg', 'jpeg')):
```

```

#             image_path = os.path.join(class_dir, filename)

#             try:
#                 result = detector.detect_image(image_path)
#                 aus_data = result.aus.iloc[0]
#                 row = {'image_path': image_path, 'emotion_class':
↪class_name}
#                 for au_label, au_value in aus_data.items():
#                     row[au_label] = au_value
#                 rows.append(row)
#             except Exception as e:
#                 print(f"Error processing {image_path}: {e}")
#     df = pd.DataFrame(rows)
#     return df

# data_dir = "/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↪PJT 1 "
# df = create_dataframe(data_dir)
# print(df.head())

```

```

[16]: # csv_file_path = '/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/
↪SEM 7/ck+AU.csv'
# df.to_csv(csv_file_path, index=False)

```

1.2 AU's Dataset

```

[17]: data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Capstone Project/
↪ck+AU.csv')

```

1.2.1 Dataset Pre Processing

```

[18]: data['emotion_class'] = data['emotion_class'].replace('newtral', 'neutral')

```

```

[19]: data

```

```

[19]:
           image_path emotion_class \
0  /content/drive/MyDrive/Colab Notebooks/Shared ...      anger
1  /content/drive/MyDrive/Colab Notebooks/Shared ...      anger
2  /content/drive/MyDrive/Colab Notebooks/Shared ...      anger
3  /content/drive/MyDrive/Colab Notebooks/Shared ...      anger
4  /content/drive/MyDrive/Colab Notebooks/Shared ...      anger
..      ...      ...
388 /content/drive/MyDrive/Colab Notebooks/Shared ...    neutral
389 /content/drive/MyDrive/Colab Notebooks/Shared ...    neutral
390 /content/drive/MyDrive/Colab Notebooks/Shared ...    neutral

```

```

391 /content/drive/MyDrive/Colab Notebooks/Shared ... neutral
392 /content/drive/MyDrive/Colab Notebooks/Shared ... neutral

```

	AU01	AU02	AU04	AU05	AU06	AU07	AU09	\
0	0.305341	0.111024	0.774244	0.235994	0.114007	0.0	0.427204	
1	0.410413	0.049372	0.567212	0.263178	0.070896	0.0	0.200582	
2	0.495457	0.126502	0.639733	0.226856	0.148076	0.0	0.572054	
3	0.367992	0.069756	0.186828	0.327858	0.093801	0.0	0.162881	
4	0.352316	0.208684	0.855927	0.275487	0.222181	0.0	0.642084	
..		
388	0.225302	0.244933	0.081000	0.318644	0.127745	0.0	0.124225	
389	0.271004	0.122386	0.135678	0.347571	0.166843	0.0	0.129874	
390	0.183183	0.107340	0.153325	0.315734	0.144561	0.0	0.124810	
391	0.235248	0.157013	0.261249	0.339881	0.168045	0.0	0.126665	
392	0.192613	0.112670	0.280976	0.321234	0.119856	0.0	0.124381	

	AU10	...	AU14	AU15	AU17	AU20	AU23	AU24	\
0	0.011345	...	0.252306	0.443434	0.591958	0.0	0.486583	0.447435	
1	0.000050	...	0.243349	0.155853	0.601341	0.0	0.482076	0.350582	
2	0.021714	...	0.449422	0.482744	0.610026	0.0	0.615954	0.429906	
3	0.001404	...	0.212178	0.760874	0.634899	0.0	0.579455	0.427951	
4	0.026703	...	0.281772	0.256666	0.614216	0.0	0.329869	0.586029	
..		
388	0.003299	...	0.114912	0.124776	0.320067	0.0	0.257766	0.307838	
389	0.003849	...	0.108141	0.205502	0.317284	0.0	0.309154	0.208997	
390	0.001073	...	0.136684	0.109674	0.444846	0.0	0.376766	0.248119	
391	0.002646	...	0.160595	0.050449	0.417870	0.0	0.310338	0.357068	
392	0.000465	...	0.113249	0.312299	0.487511	0.0	0.323831	0.162351	

	AU25	AU26	AU28	AU43
0	0.005062	0.123228	0.290482	0.658306
1	0.002979	0.021886	0.756728	0.149469
2	0.001003	0.078458	0.208640	0.149787
3	0.062809	0.111795	0.427864	0.020686
4	0.005813	0.051902	0.136744	0.153439
..
388	0.166607	0.066789	0.040286	0.048816
389	0.201857	0.107756	0.075074	0.048068
390	0.145572	0.086918	0.023285	0.038345
391	0.081102	0.170520	0.064692	0.048056
392	0.100709	0.072184	0.056132	0.059615

[393 rows x 22 columns]

```
[20]: data['emotion_class'].unique()
```

```
[20]: array(['anger', 'contempt', 'disgust', 'fear', 'happiness', 'sadness',
        'surprise', 'neutral'], dtype=object)
```

```
[21]: data.describe()
```

```
[21]:
```

	AU01	AU02	AU04	AU05	AU06	AU07 \
count	393.000000	393.000000	393.000000	393.000000	393.000000	393.000000
mean	0.475713	0.298907	0.374992	0.394008	0.388405	0.333333
std	0.221700	0.215167	0.274089	0.163547	0.306424	0.472005
min	0.142232	0.045115	0.034763	0.205045	0.056081	0.000000
25%	0.299077	0.133512	0.149638	0.255365	0.148794	0.000000
50%	0.421869	0.232451	0.278704	0.339881	0.241401	0.000000
75%	0.639267	0.398451	0.551263	0.511930	0.586810	1.000000
max	0.943540	0.886387	0.974760	0.773143	0.956136	1.000000

	AU09	AU10	AU11	AU12	AU14	AU15 \
count	393.000000	393.000000	393.000000	393.000000	393.000000	393.000000
mean	0.305837	0.231342	0.498728	0.337682	0.382598	0.338150
std	0.215495	0.330680	0.500636	0.361741	0.255296	0.207795
min	0.072200	0.000050	0.000000	0.011760	0.044774	0.020721
25%	0.129874	0.004978	0.000000	0.052479	0.156868	0.171339
50%	0.203485	0.041824	0.000000	0.148698	0.291349	0.291692
75%	0.467869	0.364032	1.000000	0.586494	0.611708	0.474064
max	0.835468	0.996910	1.000000	0.991688	0.909408	0.895304

	AU17	AU20	AU23	AU24	AU25	AU26 \
count	393.000000	393.000000	393.000000	393.000000	393.000000	393.000000
mean	0.455035	0.435115	0.332925	0.286541	0.550197	0.370722
std	0.159653	0.496404	0.148188	0.241424	0.445823	0.310181
min	0.124127	0.000000	0.058417	0.004934	0.000382	0.021886
25%	0.313230	0.000000	0.220335	0.029868	0.045429	0.111236
50%	0.478728	0.000000	0.307654	0.266593	0.642664	0.227792
75%	0.588354	1.000000	0.441891	0.481251	0.999735	0.668518
max	0.806457	1.000000	0.751106	0.846946	0.999995	0.973897

	AU28	AU43
count	393.000000	393.000000
mean	0.158453	0.185332
std	0.155885	0.225435
min	0.003435	0.012862
25%	0.045899	0.038345
50%	0.101007	0.083097
75%	0.223049	0.219020
max	0.840946	0.926194

```
[22]: data.info()
```



```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 393 entries, 0 to 392
Data columns (total 22 columns):
#   Column          Non-Null Count  Dtype
---  -
0   image_path      393 non-null   object
1   emotion_class   393 non-null   object
2   AU01            393 non-null   float64
3   AU02            393 non-null   float64
4   AU04            393 non-null   float64
5   AU05            393 non-null   float64
6   AU06            393 non-null   float64
7   AU07            393 non-null   float64
8   AU09            393 non-null   float64
9   AU10            393 non-null   float64
10  AU11            393 non-null   float64
11  AU12            393 non-null   float64
12  AU14            393 non-null   float64
13  AU15            393 non-null   float64
14  AU17            393 non-null   float64
15  AU20            393 non-null   float64
16  AU23            393 non-null   float64
17  AU24            393 non-null   float64
18  AU25            393 non-null   float64
19  AU26            393 non-null   float64
20  AU28            393 non-null   float64
21  AU43            393 non-null   float64
dtypes: float64(20), object(2)
memory usage: 67.7+ KB

```

```

[23]: au_columns = ['AU01', 'AU02', 'AU04', 'AU05', 'AU06', 'AU07', 'AU09', 'AU10',
                  'AU11', 'AU12', 'AU14', 'AU15', 'AU17', 'AU20', 'AU23', 'AU24',
                  'AU25', 'AU26', 'AU28', 'AU43']

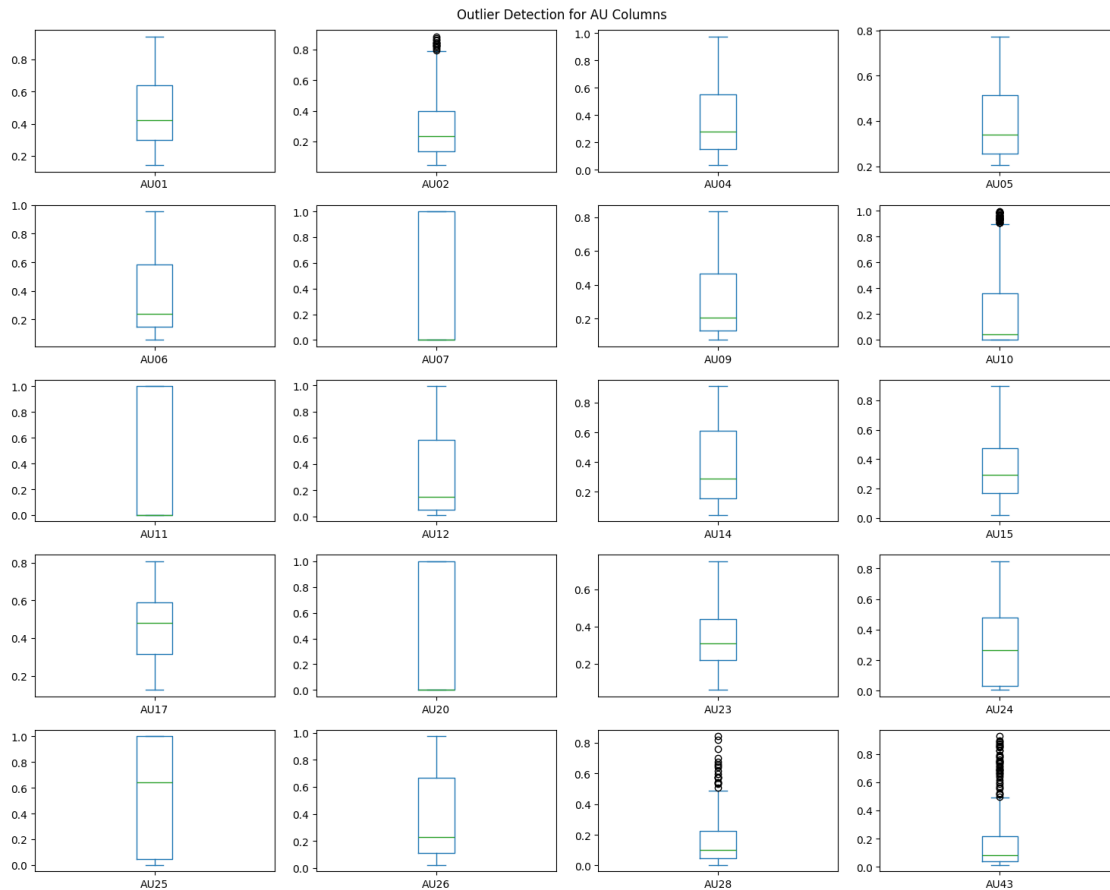
plt.figure(figsize=(20, 10))

data[au_columns].plot(kind='box', subplots=True, layout=(5, 4), figsize=(15, 12),
                      sharex=False, sharey=False, title='Outlier Detection for AU_
                      Columns')

plt.tight_layout()
plt.show()

```

<Figure size 2000x1000 with 0 Axes>



```
[24]: df = data.drop(columns=['image_path'])
```

1.3 Models & Metrics

```
[25]: x = df.drop(columns = ['emotion_class'])
      y = df['emotion_class']
```

```
[26]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
      ↪random_state=42)
```

1.3.1 Basic Multinomial Logistic Model

```
[ ]: from sklearn.linear_model import LogisticRegression
      from sklearn.metrics import accuracy_score, classification_report,
      ↪confusion_matrix
      import seaborn as sns
      import matplotlib.pyplot as plt
      import numpy as np
```

```

model = LogisticRegression(multi_class='multinomial', solver='lbfgs',
    ↪max_iter=500)
model.fit(x_train, y_train)

y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

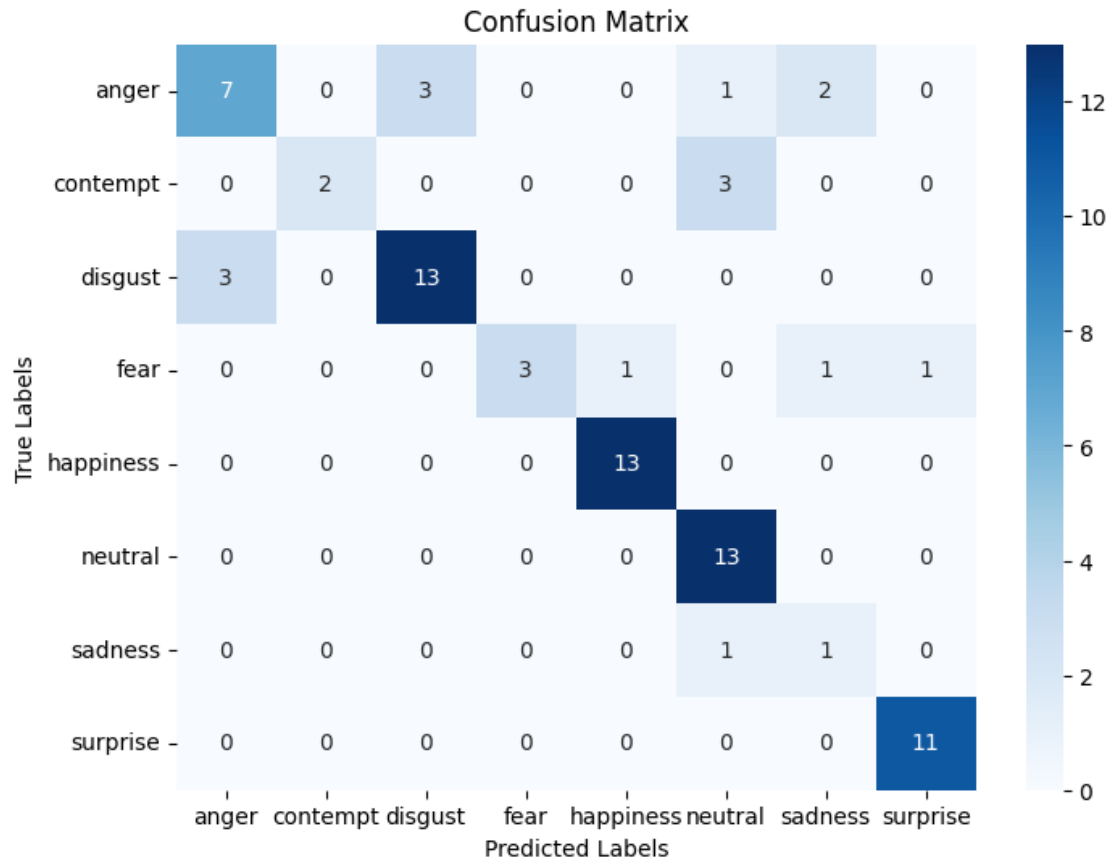
conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    ↪unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)

```

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:1247:
FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed
in 1.7. From then on, it will always use 'multinomial'. Leave it to its default
value to avoid this warning.
warnings.warn(



Accuracy: 79.75%

Classification Report:

	precision	recall	f1-score	support
anger	0.70	0.54	0.61	13
contempt	1.00	0.40	0.57	5
disgust	0.81	0.81	0.81	16
fear	1.00	0.50	0.67	6
happiness	0.93	1.00	0.96	13
neutral	0.72	1.00	0.84	13
sadness	0.25	0.50	0.33	2
surprise	0.92	1.00	0.96	11
accuracy			0.80	79
macro avg	0.79	0.72	0.72	79
weighted avg	0.82	0.80	0.79	79

1.3.2 Modified Multinomial Logistic Model

```
[ ]: from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, classification_report, \
    ↪confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('logreg', LogisticRegression(multi_class='multinomial', max_iter=1000))
])

param_grid = {
    'logreg_C': [0.01, 0.1, 0.2, 1, 9, 10, 11, 100],
    'logreg_solver': ['newton-cg', 'lbfgs', 'sag', 'saga']
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy', \
    ↪n_jobs=-1)
grid_search.fit(x_train, y_train)

best_model = grid_search.best_estimator_

y_pred = best_model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

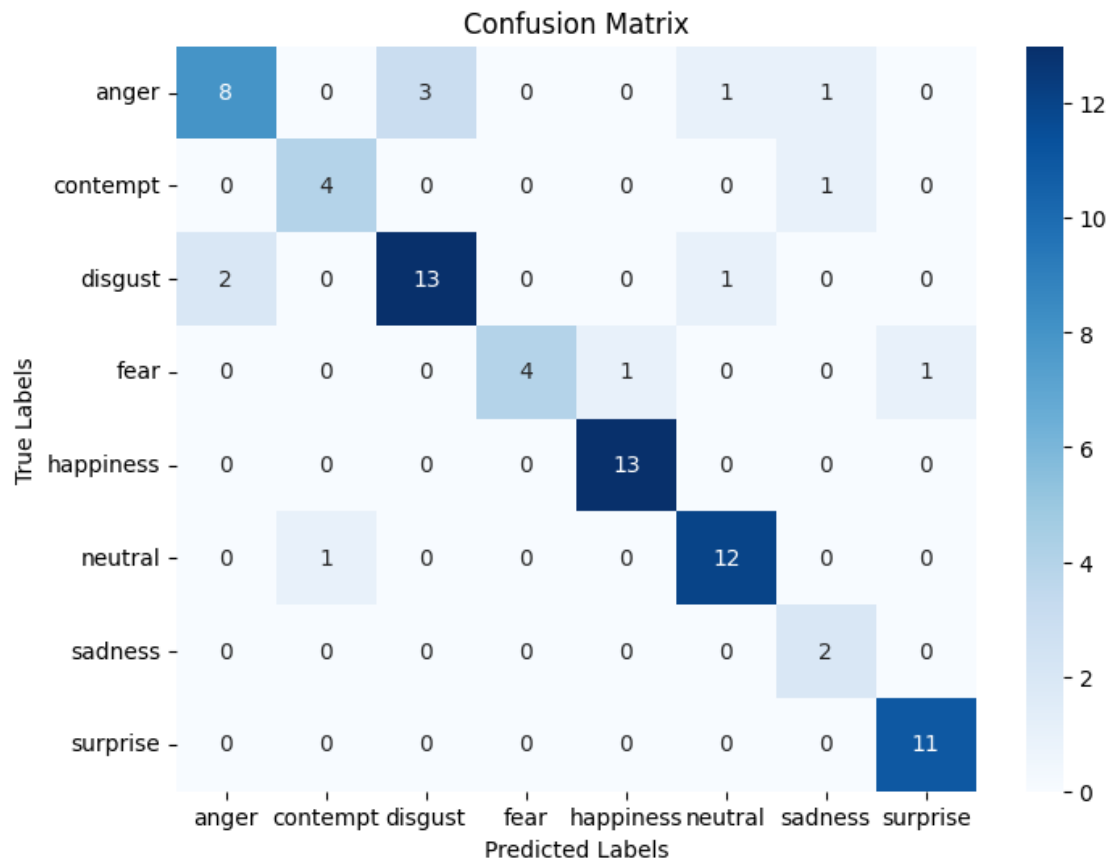
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    ↪unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

print(f"Best Parameters: {grid_search.best_params_}")
print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)
```

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:1247:
FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed

in 1.7. From then on, it will always use 'multinomial'. Leave it to its default value to avoid this warning.

```
warnings.warn(
```



Best Parameters: {'logreg__C': 10, 'logreg__solver': 'lbfgs'}

Accuracy: 84.81%

Classification Report:

	precision	recall	f1-score	support
anger	0.80	0.62	0.70	13
contempt	0.80	0.80	0.80	5
disgust	0.81	0.81	0.81	16
fear	1.00	0.67	0.80	6
happiness	0.93	1.00	0.96	13
neutral	0.86	0.92	0.89	13
sadness	0.50	1.00	0.67	2
surprise	0.92	1.00	0.96	11
accuracy			0.85	79

macro avg	0.83	0.85	0.82	79
weighted avg	0.86	0.85	0.85	79

1.3.3 KNN model

```
[ ]: from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

model = KNeighborsClassifier(n_neighbors=6)

model.fit(x_train, y_train)

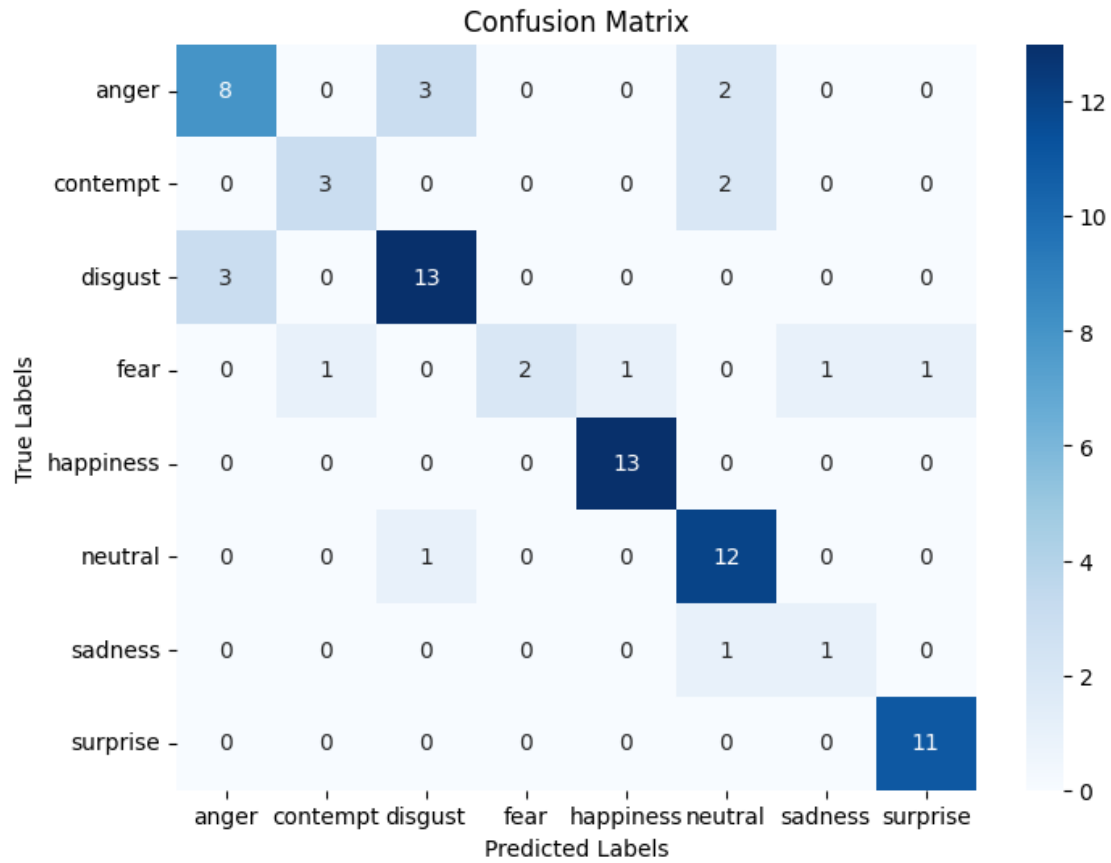
y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    ↪unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)
```



Accuracy: 79.75%

Classification Report:

	precision	recall	f1-score	support
anger	0.73	0.62	0.67	13
contempt	0.75	0.60	0.67	5
disgust	0.76	0.81	0.79	16
fear	1.00	0.33	0.50	6
happiness	0.93	1.00	0.96	13
neutral	0.71	0.92	0.80	13
sadness	0.50	0.50	0.50	2
surprise	0.92	1.00	0.96	11
accuracy			0.80	79
macro avg	0.79	0.72	0.73	79
weighted avg	0.81	0.80	0.79	79


```
[ ]: from sklearn.neighbors import KNeighborsClassifier
      from sklearn.metrics import accuracy_score

      for n_neighbors in range(1, 15):
          model = KNeighborsClassifier(n_neighbors=n_neighbors)
          model.fit(x_train, y_train)
          y_pred = model.predict(x_test)
          accuracy = accuracy_score(y_test, y_pred)
          print(f"Accuracy for n_neighbors={n_neighbors}: {accuracy * 100:.2f}%")
```

```
Accuracy for n_neighbors=1: 77.22%
Accuracy for n_neighbors=2: 74.68%
Accuracy for n_neighbors=3: 75.95%
Accuracy for n_neighbors=4: 78.48%
Accuracy for n_neighbors=5: 78.48%
Accuracy for n_neighbors=6: 79.75%
Accuracy for n_neighbors=7: 70.89%
Accuracy for n_neighbors=8: 75.95%
Accuracy for n_neighbors=9: 72.15%
Accuracy for n_neighbors=10: 75.95%
Accuracy for n_neighbors=11: 73.42%
Accuracy for n_neighbors=12: 74.68%
Accuracy for n_neighbors=13: 74.68%
Accuracy for n_neighbors=14: 74.68%
```

1.3.4 Modified KNN model

```
[ ]: from sklearn.neighbors import KNeighborsClassifier
      from sklearn.model_selection import GridSearchCV
      from sklearn.metrics import accuracy_score, classification_report, \
          confusion_matrix
      import seaborn as sns
      import matplotlib.pyplot as plt
      import numpy as np

      param_grid = {
          'n_neighbors': [3, 5, 6, 7, 9, 11],
          'weights': ['uniform', 'distance'],
          'metric': ['euclidean', 'manhattan', 'minkowski']
      }

      grid_search = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5, \
          scoring='accuracy', n_jobs=-1)
      grid_search.fit(x_train, y_train)

      best_knn = grid_search.best_estimator_
```

```

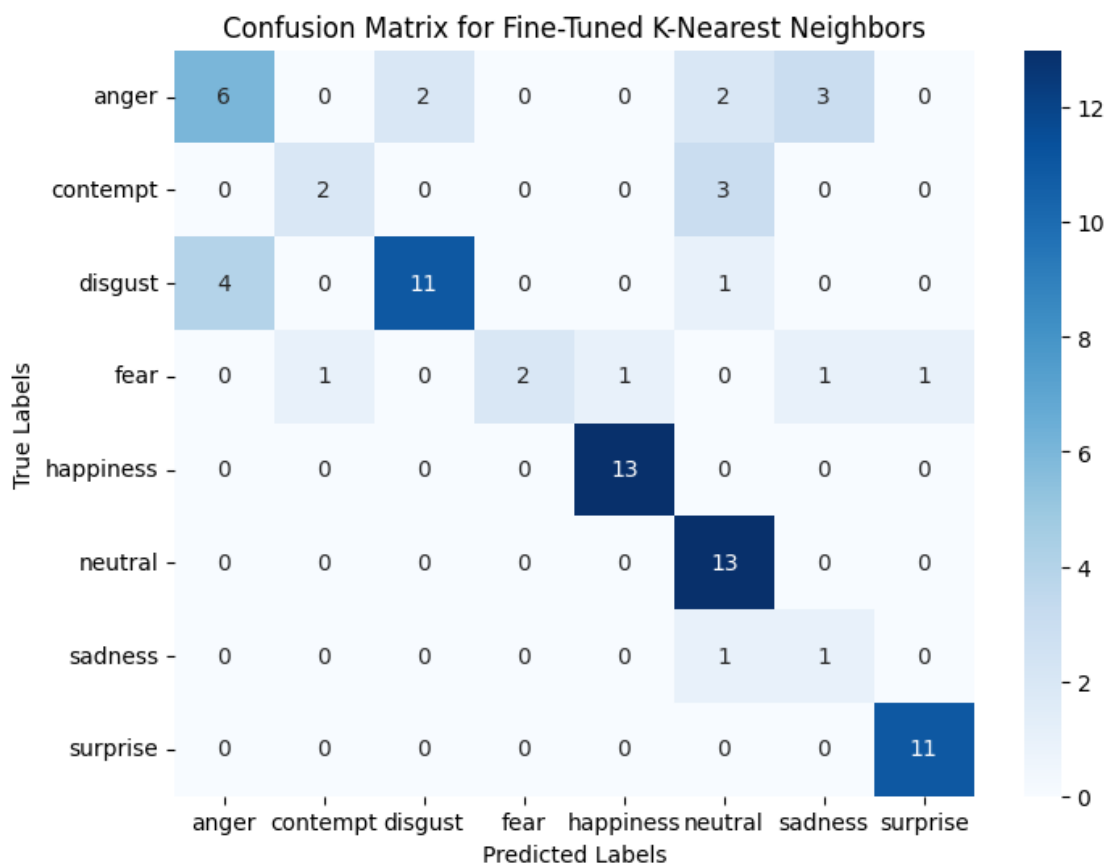
y_pred = best_knn.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix for Fine-Tuned K-Nearest Neighbors")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

print(f"Best Parameters: {grid_search.best_params_}")
print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)

```



Best Parameters: {'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'uniform'}
 Accuracy: 74.68%

Classification Report:

	precision	recall	f1-score	support
anger	0.60	0.46	0.52	13
contempt	0.67	0.40	0.50	5
disgust	0.85	0.69	0.76	16
fear	1.00	0.33	0.50	6
happiness	0.93	1.00	0.96	13
neutral	0.65	1.00	0.79	13
sadness	0.20	0.50	0.29	2
surprise	0.92	1.00	0.96	11
accuracy			0.75	79
macro avg	0.73	0.67	0.66	79
weighted avg	0.78	0.75	0.74	79

1.3.5 KNN Model Visulaization & PCA

```
[ ]: from sklearn.decomposition import PCA
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import LabelEncoder

pca = PCA(n_components=2)
x_train_2d = pca.fit_transform(x_train)
x_test_2d = pca.transform(x_test)

knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(x_train_2d, y_train)

x_min, x_max = x_train_2d[:, 0].min() - 1, x_train_2d[:, 0].max() + 1
y_min, y_max = x_train_2d[:, 1].min() - 1, x_train_2d[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1), np.arange(y_min, y_max, 0.1))

Z = knn_model.predict(np.c_[xx.ravel(), yy.ravel()])

le = LabelEncoder()
Z = le.fit_transform(Z)
Z = Z.reshape(xx.shape)

plt.figure(figsize=(10, 8))
plt.contourf(xx, yy, Z, alpha=0.3, cmap='viridis')
```

```

y_train_numeric = le.transform(y_train)

scatter = plt.scatter(x_train_2d[:, 0], x_train_2d[:, 1], c=y_train_numeric,
                      cmap='viridis', edgecolor='k')

plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.title("KNN Decision Boundary on PCA-Reduced Data")

unique_labels = np.unique(y_train)
colors = plt.cm.viridis(np.linspace(0, 1, len(unique_labels)))

plt.figure(figsize=(10, 8))
plt.contourf(xx, yy, Z, alpha=0.3, cmap='viridis')

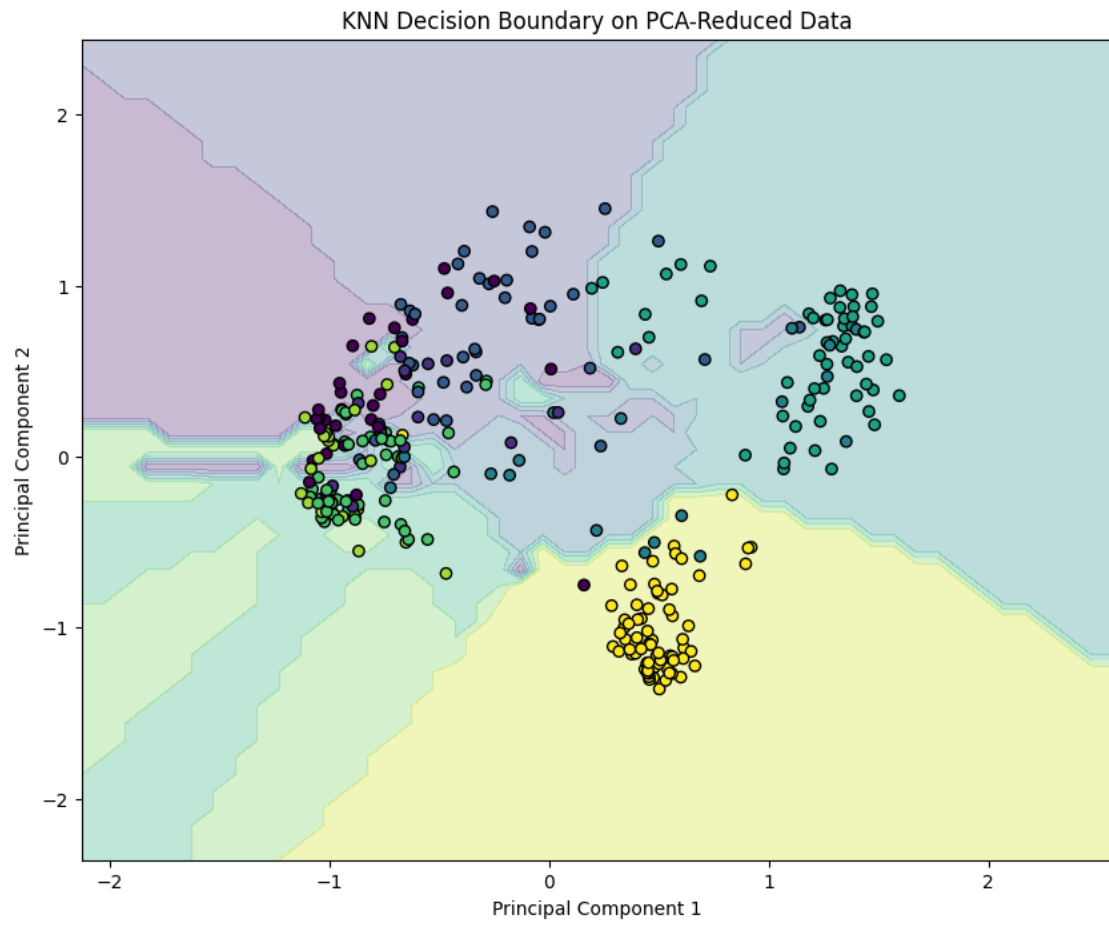
for i, label in enumerate(unique_labels):
    indices = np.where(y_train == label)
    plt.scatter(x_train_2d[indices, 0], x_train_2d[indices, 1],
                c=[colors[i]], label=label, edgecolor='k')

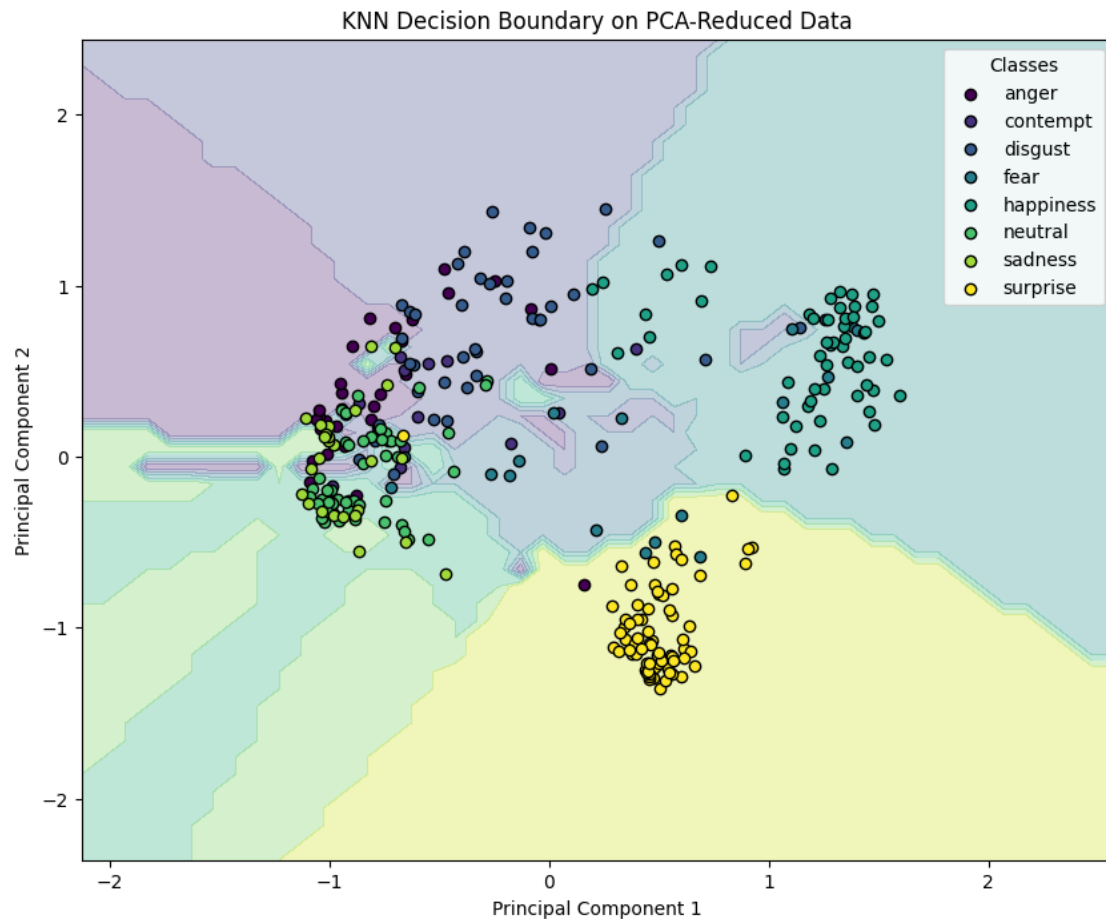
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.title("KNN Decision Boundary on PCA-Reduced Data")

plt.legend(title="Classes")

```

```
[ ]: <matplotlib.legend.Legend at 0x7d7586e80af0>
```





1.3.6 Decision Tree model

```
[ ]: from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

model = DecisionTreeClassifier(random_state=42)

model.fit(x_train, y_train)

y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
```

```

conf_matrix = confusion_matrix(y_test, y_pred)

print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)

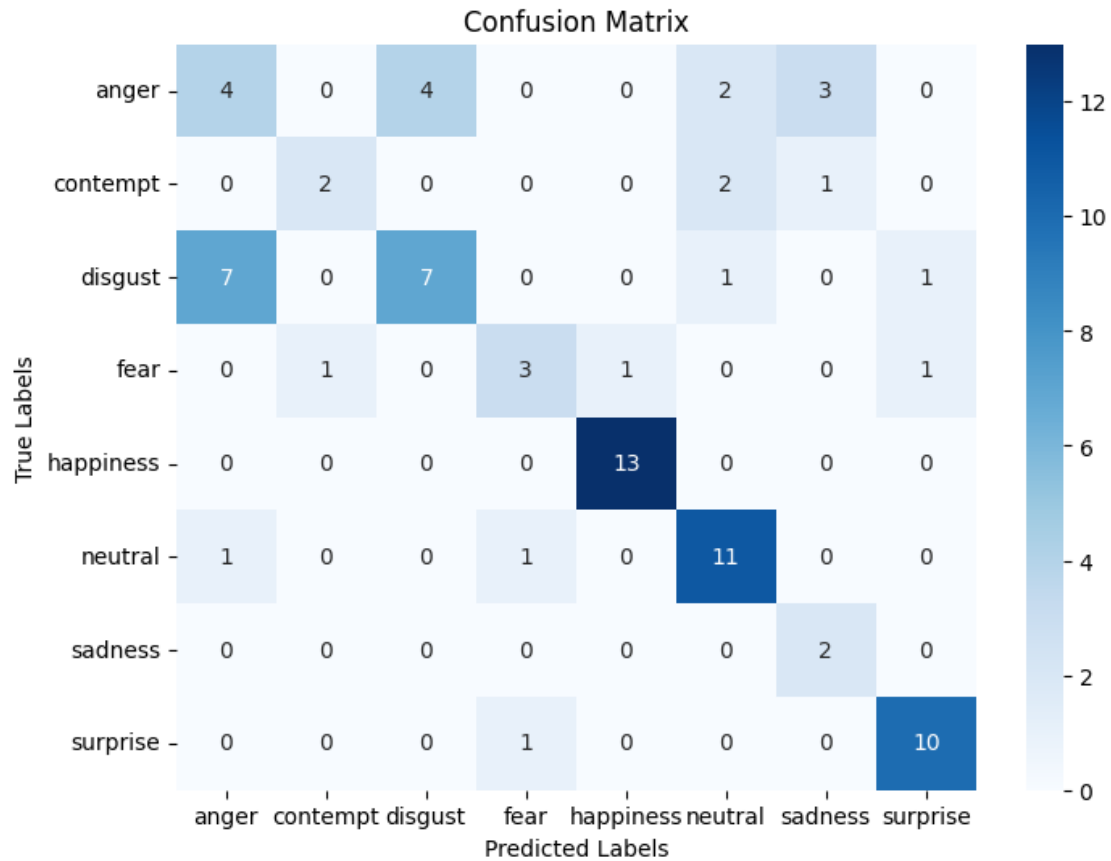
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

```

Accuracy: 65.82%

Classification Report:

	precision	recall	f1-score	support
anger	0.33	0.31	0.32	13
contempt	0.67	0.40	0.50	5
disgust	0.64	0.44	0.52	16
fear	0.60	0.50	0.55	6
happiness	0.93	1.00	0.96	13
neutral	0.69	0.85	0.76	13
sadness	0.33	1.00	0.50	2
surprise	0.83	0.91	0.87	11
accuracy			0.66	79
macro avg	0.63	0.68	0.62	79
weighted avg	0.66	0.66	0.65	79



1.3.7 Modified Decision Tree model

```
[ ]: from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [20],
    'min_samples_split': [1,2,3,4, 5, 10],
    'min_samples_leaf': [1, 2, 3,4,5]
}

grid_search = GridSearchCV(DecisionTreeClassifier(), param_grid, cv=5, \
    scoring='accuracy', n_jobs=-1)
```



```

grid_search.fit(x_train, y_train)

best_model = grid_search.best_estimator_

y_pred = best_model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix for Fine-Tuned Decision Tree")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()

print(f"Best Parameters: {grid_search.best_params_}")
print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:540: FitFailedWarning:
50 fits failed out of a total of 300.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:

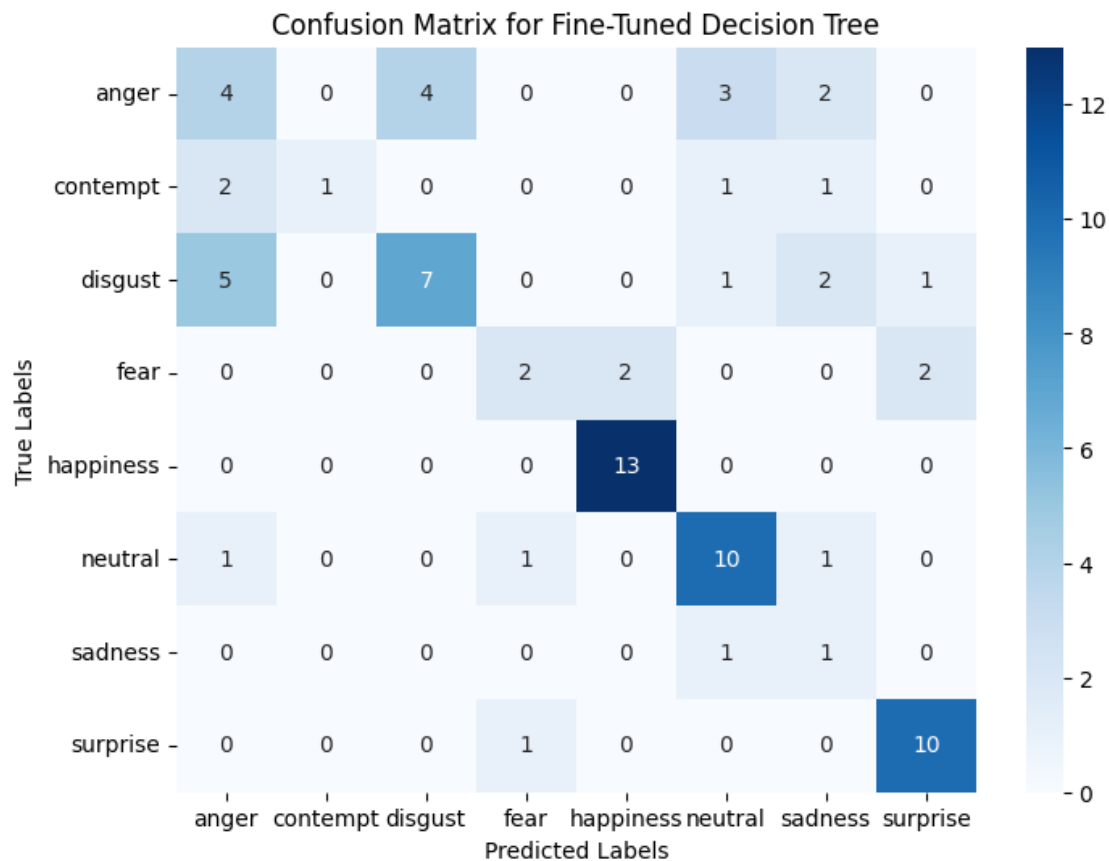
```

-----
50 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 888, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1466, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 666, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py", line 95, in validate_parameter_constraints
    raise InvalidParameterError(

```

```
sklearn.utils._param_validation.InvalidParameterError: The 'min_samples_split'
parameter of DecisionTreeClassifier must be an int in the range [2, inf) or a
float in the range (0.0, 1.0]. Got 1 instead.
```

```
warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py:2820: RuntimeWarning:
invalid value encountered in cast
_data = np.array(data, dtype=dtype, copy=copy,
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:1103:
UserWarning: One or more of the test scores are non-finite: [      nan
0.63056836 0.65606759 0.63701997 0.65289299 0.65289299
nan 0.62104455 0.64961598 0.62099334 0.64004096 0.64654378
nan 0.63051715 0.62744496 0.64331797 0.63051715 0.64659498
nan 0.64971838 0.65289299 0.64971838 0.65289299 0.64654378
nan 0.6625704 0.66574501 0.64654378 0.64971838 0.65924219
nan 0.67199181 0.67834101 0.6656426 0.64966718 0.662468
nan 0.65913978 0.66236559 0.6656426 0.65289299 0.63696877
nan 0.6656938 0.6625192 0.6688172 0.6656938 0.66241679
nan 0.66241679 0.65611879 0.6625192 0.66574501 0.66886841
nan 0.65606759 0.67511521 0.67199181 0.6655914 0.65606759]
warnings.warn(
```



Best Parameters: {'criterion': 'entropy', 'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 3}

Accuracy: 60.76%

Classification Report:

	precision	recall	f1-score	support
anger	0.33	0.31	0.32	13
contempt	1.00	0.20	0.33	5
disgust	0.64	0.44	0.52	16
fear	0.50	0.33	0.40	6
happiness	0.87	1.00	0.93	13
neutral	0.62	0.77	0.69	13
sadness	0.14	0.50	0.22	2
surprise	0.77	0.91	0.83	11
accuracy			0.61	79
macro avg	0.61	0.56	0.53	79
weighted avg	0.64	0.61	0.60	79

1.3.8 Random Forest model

```
[ ]: from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
model = RandomForestClassifier(n_estimators=31, random_state=53)

model.fit(x_train, y_train)

y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

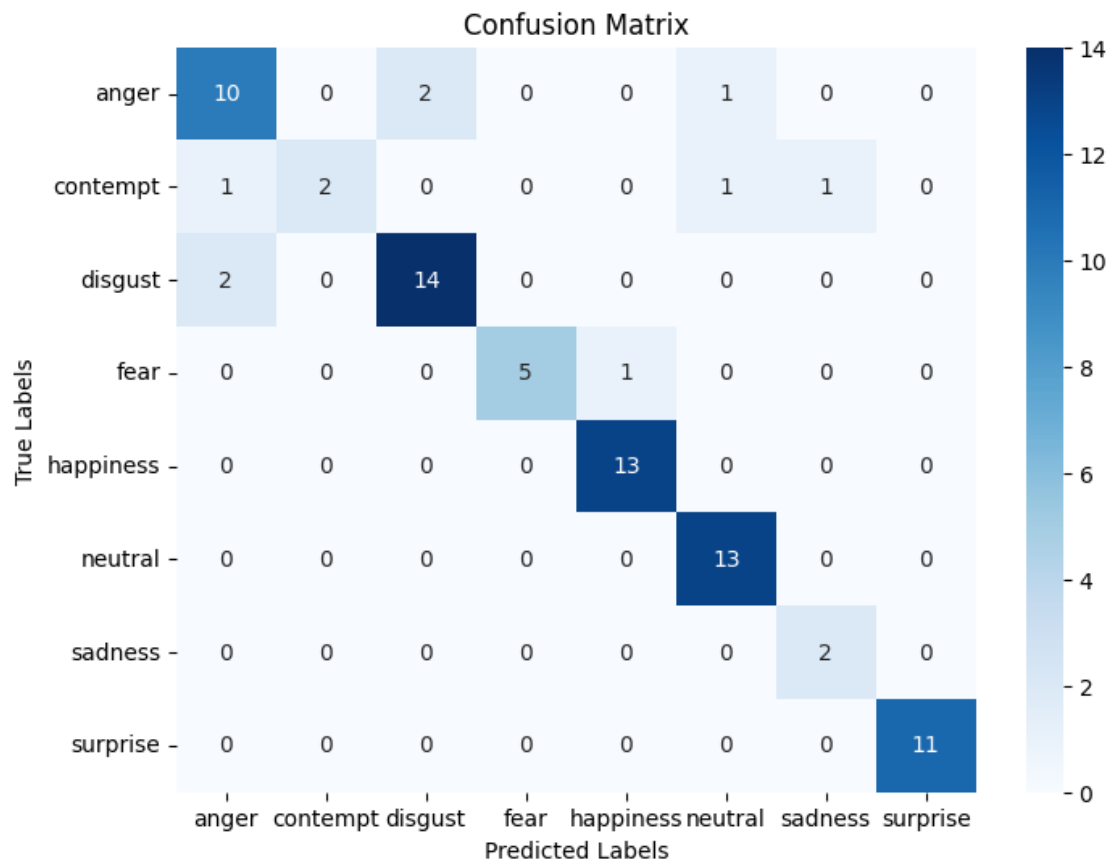
print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", report)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
    ↪unique(y), yticklabels=np.unique(y))
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```

Accuracy: 88.61%

Classification Report:

	precision	recall	f1-score	support
anger	0.77	0.77	0.77	13
contempt	1.00	0.40	0.57	5
disgust	0.88	0.88	0.88	16
fear	1.00	0.83	0.91	6
happiness	0.93	1.00	0.96	13
neutral	0.87	1.00	0.93	13
sadness	0.67	1.00	0.80	2
surprise	1.00	1.00	1.00	11
accuracy			0.89	79
macro avg	0.89	0.86	0.85	79
weighted avg	0.89	0.89	0.88	79

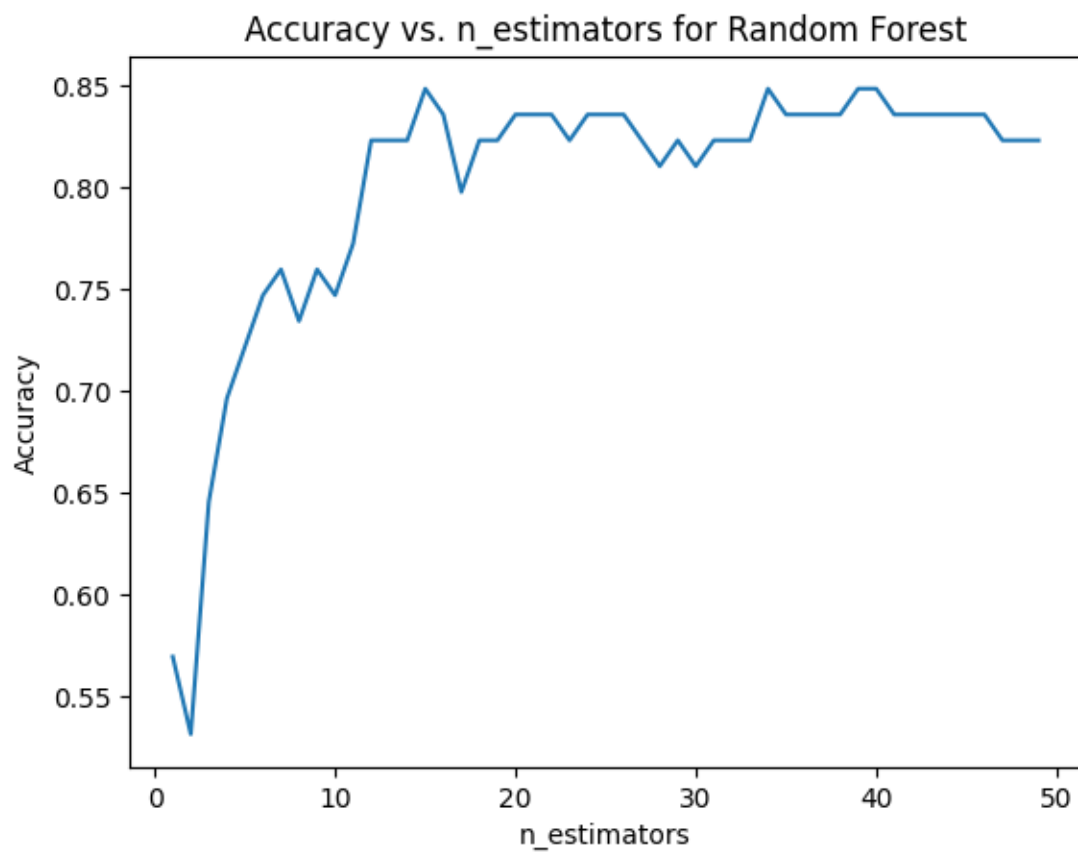


```
[ ]: import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

accuracies = []
n_estimators_values = range(1, 50)

for k in n_estimators_values:
    model = RandomForestClassifier(n_estimators=k, random_state=42)
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)

plt.plot(n_estimators_values, accuracies)
plt.xlabel("n_estimators")
plt.ylabel("Accuracy")
plt.title("Accuracy vs. n_estimators for Random Forest")
plt.show()
```



```
[ ]: from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

best_accuracy = 0
best_params = {'n_estimators': None, 'random_state': None}
accuracies = []

for n in range(1, 101):
    for rs in range(1, 100):
        model = RandomForestClassifier(n_estimators=n, random_state=rs)
        model.fit(x_train, y_train)
        y_pred = model.predict(x_test)
        accuracy = accuracy_score(y_test, y_pred)
        accuracies.append((accuracy, n, rs))

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_params['n_estimators'] = n
            best_params['random_state'] = rs

print("Best Accuracy:", best_accuracy)
print("Best Parameters:", best_params)
```

Best Accuracy: 0.8860759493670886

Best Parameters: {'n_estimators': 31, 'random_state': 53}

1.3.9 Modified Random Forest Model

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,
    cv=5, n_jobs=-1)
grid_search.fit(x_train, y_train)
```

```

best_model = grid_search.best_estimator_
y_pred = best_model.predict(x_test)

report = classification_report(y_test, y_pred, output_dict=True)
conf_matrix = confusion_matrix(y_test, y_pred)

print(f'Accuracy: {accuracy*100:.4f}')
print(report)

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:540: FitFailedWarning: 540 fits failed out of a total of 1620. The score on these train-test partitions for these parameters will be set to nan. If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:

```

-----
540 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 888, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1466, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 666, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.py", line 95, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestClassifier must be an int in the range [1, inf), a float in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto' instead.

```

```
warnings.warn(some_fits_failed_message, FitFailedWarning)
```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:1103:

UserWarning: One or more of the test scores are non-finite: [nan

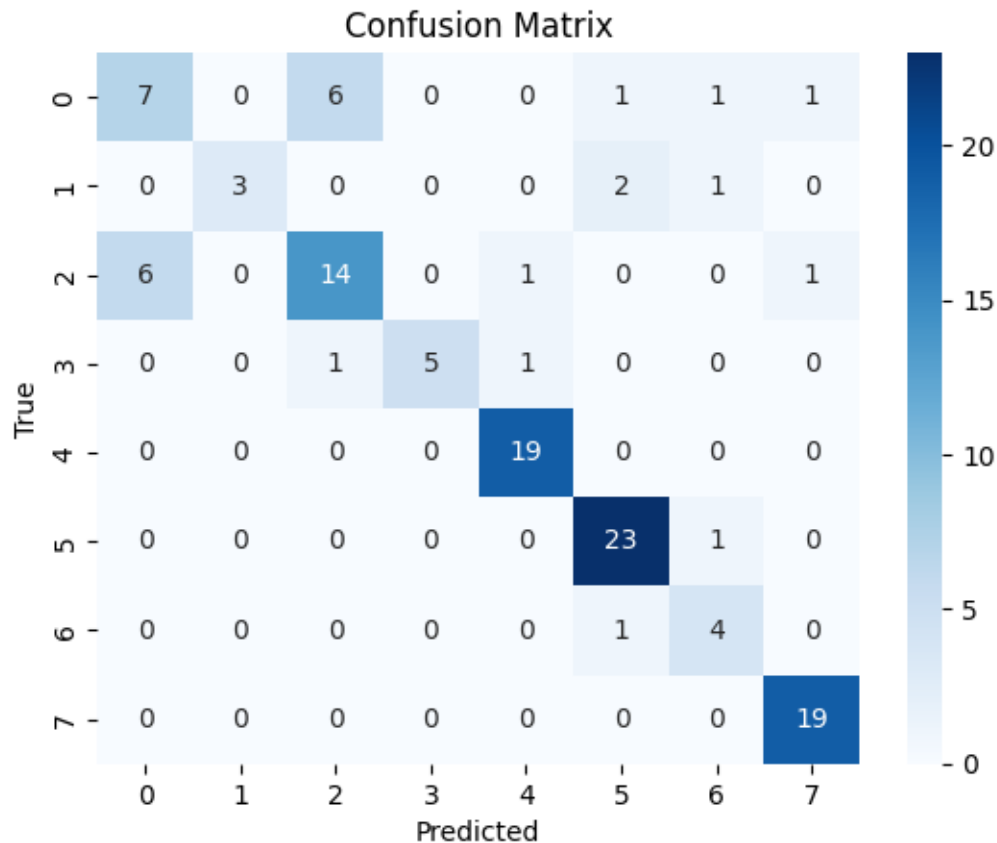
nan	nan	nan	nan	nan		
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	0.81090909	0.81454545	0.82181818
0.81454545	0.81454545	0.81454545	0.82181818	0.80727273	0.82181818	
0.80727273	0.81090909	0.81454545	0.82181818	0.81454545	0.82181818	
0.80363636	0.82181818	0.81454545	0.81090909	0.79636364	0.81090909	
0.81090909	0.79636364	0.81090909	0.79636364	0.80363636	0.80727273	
0.81090909	0.81454545	0.82181818	0.81454545	0.81454545	0.81454545	
0.82181818	0.80727273	0.82181818	0.80727273	0.81090909	0.81454545	
0.82181818	0.81454545	0.82181818	0.80363636	0.82181818	0.81454545	
0.81090909	0.79636364	0.81090909	0.81090909	0.79636364	0.81090909	
0.79636364	0.80363636	0.80727273		nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
0.81818182	0.82545455	0.82545455	0.82545455	0.81090909	0.81454545	
0.81818182	0.8	0.82545455	0.80727273	0.81818182	0.81090909	
0.82181818	0.81090909	0.82181818	0.80363636	0.81818182	0.81454545	
0.81090909	0.79636364	0.81090909	0.81090909	0.79636364	0.81090909	
0.79636364	0.80363636	0.80727273	0.81818182	0.82545455	0.82545455	
0.82545455	0.81090909	0.81454545	0.81818182	0.8	0.82545455	
0.80727273	0.81818182	0.81090909	0.82181818	0.81090909	0.82181818	
0.80363636	0.81818182	0.81454545	0.81090909	0.79636364	0.81090909	
0.81090909	0.79636364	0.81090909	0.79636364	0.80363636	0.80727273	
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	0.81090909	0.81454545	0.82181818
0.81454545	0.81454545	0.81454545	0.82181818	0.80727273	0.82181818	
0.80727273	0.81090909	0.81454545	0.82181818	0.81454545	0.82181818	
0.80363636	0.82181818	0.81454545	0.81090909	0.79636364	0.81090909	
0.81090909	0.79636364	0.81090909	0.79636364	0.80363636	0.80727273	
0.81090909	0.81454545	0.82181818	0.81454545	0.81454545	0.81454545	
0.82181818	0.80727273	0.82181818	0.80727273	0.81090909	0.81454545	
0.82181818	0.81454545	0.82181818	0.80363636	0.82181818	0.81454545	
0.81090909	0.79636364	0.81090909	0.81090909	0.79636364	0.81090909	
0.79636364	0.80363636	0.80727273		nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
	nan	nan	nan	nan	nan	nan
0.81090909	0.81454545	0.82181818	0.81454545	0.81454545	0.81454545	


```

0.82181818 0.80727273 0.82181818 0.80727273 0.81090909 0.81454545
0.82181818 0.81454545 0.82181818 0.80363636 0.82181818 0.81454545
0.81090909 0.79636364 0.81090909 0.81090909 0.79636364 0.81090909
0.79636364 0.80363636 0.80727273 0.81090909 0.81454545 0.82181818
0.81454545 0.81454545 0.81454545 0.82181818 0.80727273 0.82181818
0.80727273 0.81090909 0.81454545 0.82181818 0.81454545 0.82181818
0.80363636 0.82181818 0.81454545 0.81090909 0.79636364 0.81090909
0.81090909 0.79636364 0.81090909 0.79636364 0.80363636 0.80727273]
warnings.warn(

{'anger': {'precision': 0.5384615384615384, 'recall': 0.4375, 'f1-score':
0.4827586206896552, 'support': 16.0}, 'contempt': {'precision': 1.0, 'recall':
0.5, 'f1-score': 0.6666666666666666, 'support': 6.0}, 'disgust': {'precision':
0.6666666666666666, 'recall': 0.6363636363636364, 'f1-score':
0.6511627906976745, 'support': 22.0}, 'fear': {'precision': 1.0, 'recall':
0.7142857142857143, 'f1-score': 0.8333333333333334, 'support': 7.0},
'happiness': {'precision': 0.9047619047619048, 'recall': 1.0, 'f1-score': 0.95,
'support': 19.0}, 'neutral': {'precision': 0.8518518518518519, 'recall':
0.9583333333333334, 'f1-score': 0.9019607843137255, 'support': 24.0}, 'sadness':
{'precision': 0.5714285714285714, 'recall': 0.8, 'f1-score': 0.6666666666666666,
'support': 5.0}, 'surprise': {'precision': 0.9047619047619048, 'recall': 1.0,
'f1-score': 0.95, 'support': 19.0}, 'accuracy': 0.7966101694915254, 'macro avg':
{'precision': 0.8047415547415547, 'recall': 0.7558103354978356, 'f1-score':
0.7628186077959652, 'support': 118.0}, 'weighted avg': {'precision':
0.7963100929202624, 'recall': 0.7966101694915254, 'f1-score':
0.7878258035303338, 'support': 118.0}}

```



```
[ ]: print(f'Accuracy: {accuracy*100:.4f}')
```

Accuracy: 65.2542

1.3.10 Gradient Boosting (e.g., XGBoost, LightGBM, CatBoost)

XGboost

```
[ ]: import xgboost as xgb
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

y_train_encoded = le.fit_transform(y_train)

y_test_encoded = le.transform(y_test)
```

```

model_xgb = xgb.XGBClassifier()
model_xgb.fit(x_train, y_train_encoded)
y_pred_xgb = model_xgb.predict(x_test)

y_pred_original = le.inverse_transform(y_pred_xgb)

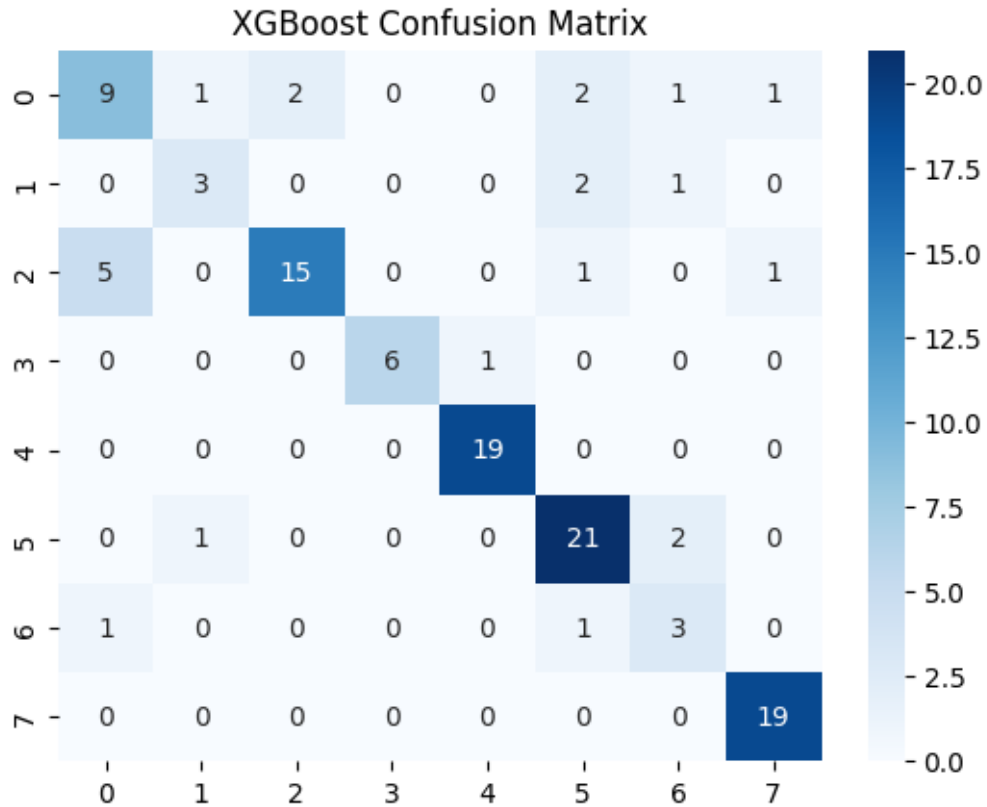
acc_xgb = accuracy_score(y_test_encoded, y_pred_xgb)
print("XGBoost Accuracy:", acc_xgb*100)
print(classification_report(y_test, y_pred_original))

cm_xgb = confusion_matrix(y_test_encoded, y_pred_xgb)
sns.heatmap(cm_xgb, annot=True, fmt="d", cmap="Blues")
plt.title("XGBoost Confusion Matrix")
plt.show()

```

XGBoost Accuracy: 80.50847457627118

	precision	recall	f1-score	support
anger	0.60	0.56	0.58	16
contempt	0.60	0.50	0.55	6
disgust	0.88	0.68	0.77	22
fear	1.00	0.86	0.92	7
happiness	0.95	1.00	0.97	19
neutral	0.78	0.88	0.82	24
sadness	0.43	0.60	0.50	5
surprise	0.90	1.00	0.95	19
accuracy			0.81	118
macro avg	0.77	0.76	0.76	118
weighted avg	0.81	0.81	0.80	118



Modified XGboost Model

```
[ ]: from sklearn.model_selection import GridSearchCV

param_grid = {
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'n_estimators': [100, 200, 300],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

grid_search = GridSearchCV(estimator=xgb.XGBClassifier(),
    param_grid=param_grid, cv=3, scoring='accuracy', n_jobs=-1, verbose=1)
grid_search.fit(x_train, y_train_encoded)

best_model = grid_search.best_estimator_
y_pred_tuned = best_model.predict(x_test)
y_pred_original_tuned = le.inverse_transform(y_pred_tuned)

acc_tuned = accuracy_score(y_test_encoded, y_pred_tuned)
```

```

print("Tuned XGBoost Accuracy:", acc_tuned * 100)
print(classification_report(y_test, y_pred_original_tuned))

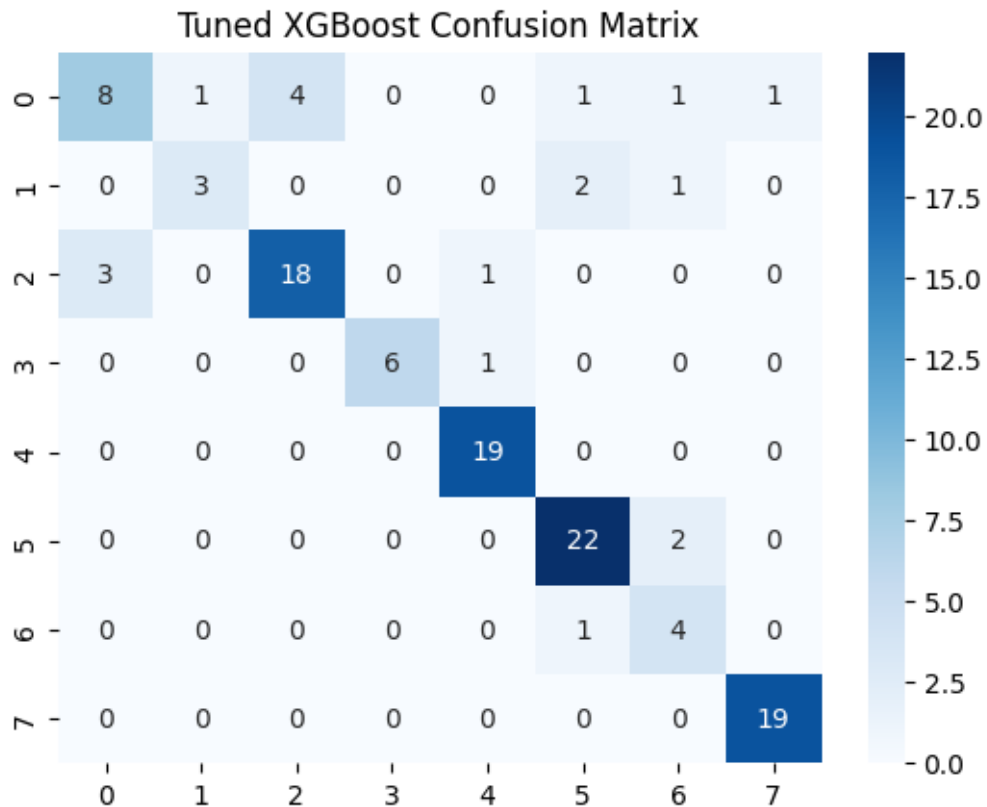
cm_tuned = confusion_matrix(y_test_encoded, y_pred_tuned)
sns.heatmap(cm_tuned, annot=True, fmt="d", cmap="Blues")
plt.title("Tuned XGBoost Confusion Matrix")
plt.show()

```

Fitting 3 folds for each of 108 candidates, totalling 324 fits

Tuned XGBoost Accuracy: 83.89830508474576

	precision	recall	f1-score	support
anger	0.73	0.50	0.59	16
contempt	0.75	0.50	0.60	6
disgust	0.82	0.82	0.82	22
fear	1.00	0.86	0.92	7
happiness	0.90	1.00	0.95	19
neutral	0.85	0.92	0.88	24
sadness	0.50	0.80	0.62	5
surprise	0.95	1.00	0.97	19
accuracy			0.84	118
macro avg	0.81	0.80	0.79	118
weighted avg	0.84	0.84	0.83	118



LightGBM

```
[ ]: import lightgbm as lgb
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

model_lgb = lgb.LGBMClassifier()
model_lgb.fit(x_train, y_train)
y_pred_lgb = model_lgb.predict(x_test)

acc_lgb = accuracy_score(y_test, y_pred_lgb)
print("LightGBM Accuracy:", acc_lgb*100)
print(classification_report(y_test, y_pred_lgb))

cm_lgb = confusion_matrix(y_test, y_pred_lgb)
sns.heatmap(cm_lgb, annot=True, fmt="d", cmap="Greens")
plt.title("LightGBM Confusion Matrix")
plt.show()
```


[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
LightGBM Accuracy: 0.788135593220339

```

	precision	recall	f1-score	support
anger	0.56	0.62	0.59	16
contempt	0.50	0.50	0.50	6
disgust	0.83	0.68	0.75	22
fear	1.00	0.57	0.73	7
happiness	0.95	1.00	0.97	19
neutral	0.83	0.83	0.83	24
sadness	0.38	0.60	0.46	5
surprise	0.95	1.00	0.97	19
accuracy			0.79	118
macro avg	0.75	0.73	0.73	118
weighted avg	0.81	0.79	0.79	118



Catboost

```
[ ]: !pip install catboost
```

Collecting catboost

Downloading catboost-1.2.7-cp310-cp310-manylinux2014_x86_64.whl.metadata (1.2 kB)

Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from catboost) (0.20.3)

Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from catboost) (3.8.0)

Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.26.4)

Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-packages (from catboost) (2.2.2)

Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from catboost) (1.13.1)

Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (from catboost) (5.24.1)

Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from catboost) (1.16.0)

Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2024.2)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2024.2)

Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.3.0)

Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (0.12.1)

Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (4.54.1)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.4.7)

Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (24.1)

Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (10.4.0)

Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (3.2.0)

Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly->catboost) (9.0.0)

Downloading catboost-1.2.7-cp310-cp310-manylinux2014_x86_64.whl (98.7 MB)

98.7/98.7 MB

6.5 MB/s eta 0:00:00

Installing collected packages: catboost

Successfully installed catboost-1.2.7

```
[ ]: from catboost import CatBoostClassifier
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

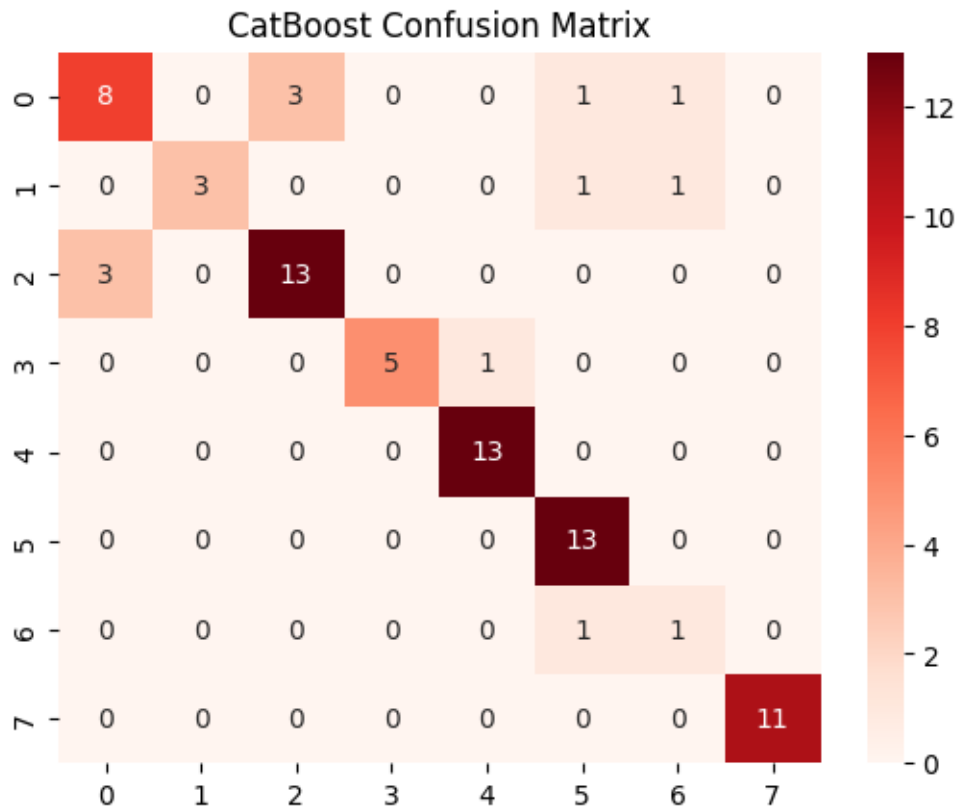
model_cat = CatBoostClassifier(verbose=0)
model_cat.fit(x_train, y_train)
y_pred_cat = model_cat.predict(x_test)

acc_cat = accuracy_score(y_test, y_pred_cat)
print("CatBoost Accuracy:", acc_cat*100)
print(classification_report(y_test, y_pred_cat))

cm_cat = confusion_matrix(y_test, y_pred_cat)
sns.heatmap(cm_cat, annot=True, fmt="d", cmap="Reds")
plt.title("CatBoost Confusion Matrix")
plt.show()
```

CatBoost Accuracy: 84.81012658227847

	precision	recall	f1-score	support
anger	0.73	0.62	0.67	13
contempt	1.00	0.60	0.75	5
disgust	0.81	0.81	0.81	16
fear	1.00	0.83	0.91	6
happiness	0.93	1.00	0.96	13
neutral	0.81	1.00	0.90	13
sadness	0.33	0.50	0.40	2
surprise	1.00	1.00	1.00	11
accuracy			0.85	79
macro avg	0.83	0.80	0.80	79
weighted avg	0.86	0.85	0.85	79



Modified Catboost Model

```
[ ]: from catboost import CatBoostClassifier
from sklearn.model_selection import RandomizedSearchCV
import numpy as np

param_grid = {
    'iterations': np.arange(100, 1001, 100),
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'depth': [4, 6, 8, 10],
    'l2_leaf_reg': [1, 3, 5, 7, 9]
}

model_cat = CatBoostClassifier(verbose=0)

random_search = RandomizedSearchCV(
    estimator=model_cat,
    param_distributions=param_grid,
    n_iter=20,
    scoring='accuracy',
    cv=3,
```

```

        random_state=42,
        n_jobs=-1
    )

    random_search.fit(x_train, y_train)

    best_model_cat = random_search.best_estimator_
    print("Best Parameters:", random_search.best_params_)

    y_pred_cat = best_model_cat.predict(x_test)
    acc_cat = accuracy_score(y_test, y_pred_cat)
    print("Tuned CatBoost Accuracy:", acc_cat * 100)
    print(classification_report(y_test, y_pred_cat))

    cm_cat = confusion_matrix(y_test, y_pred_cat)
    sns.heatmap(cm_cat, annot=True, fmt="d", cmap="Reds")
    plt.title("Tuned CatBoost Confusion Matrix")
    plt.show()

```

1.3.11 Support Vector Machines (SVM) Model

```

[28]: from sklearn.svm import SVC
      from sklearn.metrics import accuracy_score, classification_report, \
      ↪confusion_matrix
      import seaborn as sns
      import matplotlib.pyplot as plt

      model_svm = SVC()
      model_svm.fit(x_train, y_train)
      y_pred_svm = model_svm.predict(x_test)

      acc_svm = accuracy_score(y_test, y_pred_svm)
      print("SVM Accuracy:", acc_svm * 100)
      print(classification_report(y_test, y_pred_svm))

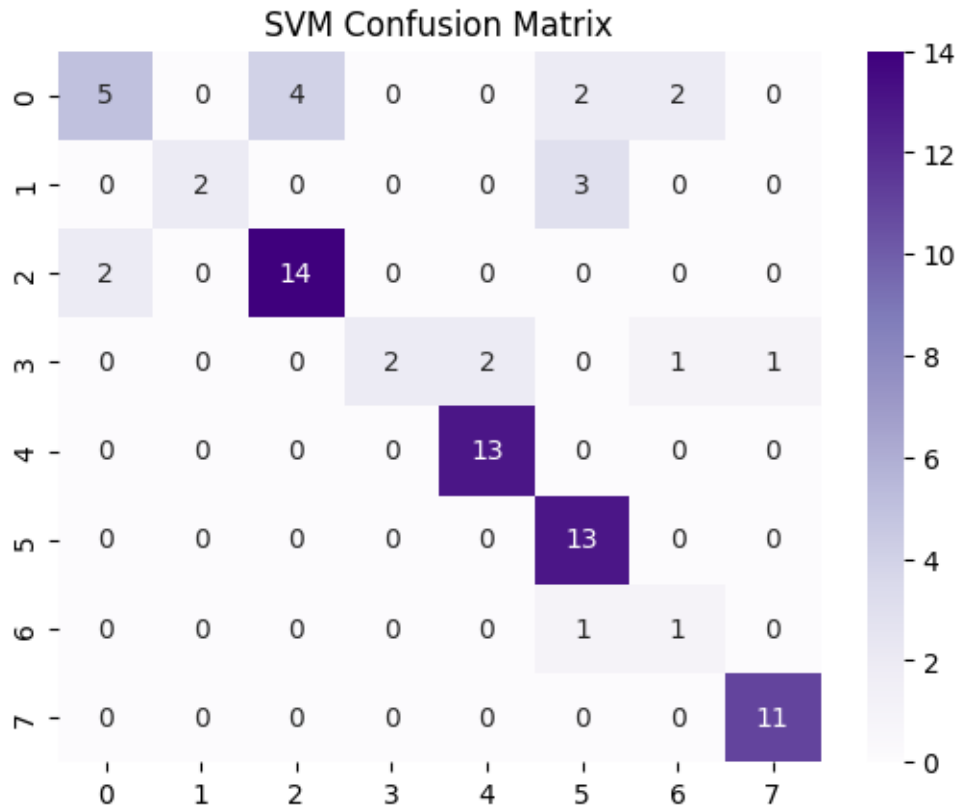
      cm_svm = confusion_matrix(y_test, y_pred_svm)
      sns.heatmap(cm_svm, annot=True, fmt="d", cmap="Purples")
      plt.title("SVM Confusion Matrix")
      plt.show()

```

SVM Accuracy: 77.21518987341773

	precision	recall	f1-score	support
anger	0.71	0.38	0.50	13
contempt	1.00	0.40	0.57	5
disgust	0.78	0.88	0.82	16
fear	1.00	0.33	0.50	6

happiness	0.87	1.00	0.93	13
neutral	0.68	1.00	0.81	13
sadness	0.25	0.50	0.33	2
surprise	0.92	1.00	0.96	11
accuracy			0.77	79
macro avg	0.78	0.69	0.68	79
weighted avg	0.80	0.77	0.75	79



1.3.12 Naive Bayes (GaussianNB) Model

```
[ ]: from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

model_nb = GaussianNB()
model_nb.fit(x_train, y_train)
y_pred_nb = model_nb.predict(x_test)
```

```

acc_nb = accuracy_score(y_test, y_pred_nb)
print("Naive Bayes Accuracy:", acc_nb * 100)
print(classification_report(y_test, y_pred_nb))

cm_nb = confusion_matrix(y_test, y_pred_nb)
sns.heatmap(cm_nb, annot=True, fmt="d", cmap="Oranges")
plt.title("Naive Bayes Confusion Matrix")
plt.show()

```

Naive Bayes Accuracy: 72.03389830508475

	precision	recall	f1-score	support
anger	0.41	0.69	0.51	16
contempt	0.33	0.17	0.22	6
disgust	1.00	0.32	0.48	22
fear	0.83	0.71	0.77	7
happiness	0.95	1.00	0.97	19
neutral	0.64	0.96	0.77	24
sadness	0.00	0.00	0.00	5
surprise	1.00	1.00	1.00	19
accuracy			0.72	118
macro avg	0.65	0.61	0.59	118
weighted avg	0.75	0.72	0.69	118

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.

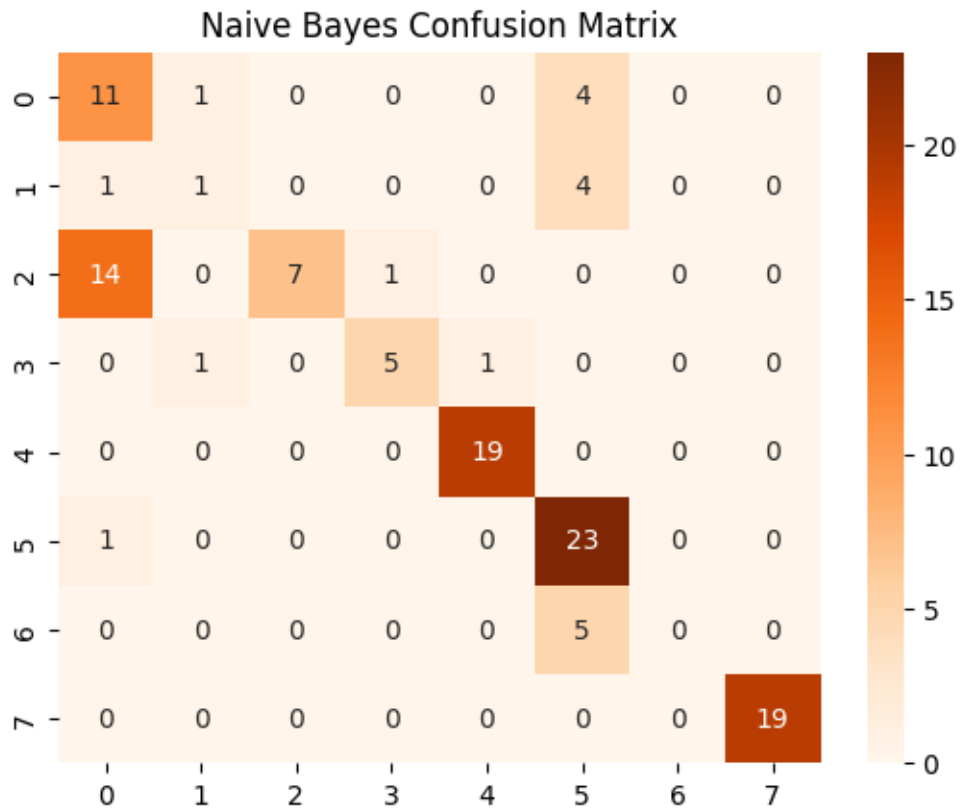
```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



1.3.13 Deep Learning Model

```
[ ]: import tensorflow as tf
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)

x_train, x_test, y_train, y_test = train_test_split(x_scaled, y_encoded,
    ↪ test_size=0.2, random_state=42)

y_train_cat = tf.keras.utils.to_categorical(y_train)
y_test_cat = tf.keras.utils.to_categorical(y_test)
```

```

model = Sequential([
    Dense(64, activation='relu', input_shape=(x_train.shape[1],)),
    Dense(128, activation='relu'),

    Dense(len(label_encoder.classes_), activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy',
    ↪metrics=['accuracy'])

history = model.fit(x_train, y_train_cat, epochs=45, validation_data=(x_test,
    ↪y_test_cat), batch_size=16)

test_loss, test_accuracy = model.evaluate(x_test, y_test_cat)
print(f"Test Accuracy: {test_accuracy*100}")

```

Epoch 1/45

/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
20/20          5s 43ms/step -
accuracy: 0.3431 - loss: 1.8688 - val_accuracy: 0.5570 - val_loss: 1.3582
```

Epoch 2/45

```
20/20          1s 11ms/step -
accuracy: 0.6766 - loss: 1.1538 - val_accuracy: 0.6962 - val_loss: 1.0183
```

Epoch 3/45

```
20/20          0s 10ms/step -
accuracy: 0.7523 - loss: 0.8351 - val_accuracy: 0.7468 - val_loss: 0.7899
```

Epoch 4/45

```
20/20          0s 11ms/step -
accuracy: 0.8136 - loss: 0.6585 - val_accuracy: 0.7848 - val_loss: 0.6776
```

Epoch 5/45

```
20/20          0s 7ms/step -
accuracy: 0.8306 - loss: 0.6035 - val_accuracy: 0.7848 - val_loss: 0.6142
```

Epoch 6/45

```
20/20          0s 12ms/step -
accuracy: 0.8591 - loss: 0.4552 - val_accuracy: 0.8354 - val_loss: 0.5352
```

Epoch 7/45

```
20/20          1s 10ms/step -
accuracy: 0.8418 - loss: 0.4636 - val_accuracy: 0.8228 - val_loss: 0.5195
```

Epoch 8/45

```
20/20          0s 7ms/step -
accuracy: 0.8804 - loss: 0.4175 - val_accuracy: 0.8228 - val_loss: 0.5090
```


Epoch 9/45
20/20 0s 3ms/step -
accuracy: 0.8397 - loss: 0.4008 - val_accuracy: 0.8354 - val_loss: 0.4815
Epoch 10/45
20/20 0s 5ms/step -
accuracy: 0.8599 - loss: 0.3654 - val_accuracy: 0.8608 - val_loss: 0.4745
Epoch 11/45
20/20 0s 4ms/step -
accuracy: 0.9014 - loss: 0.3246 - val_accuracy: 0.8481 - val_loss: 0.4777
Epoch 12/45
20/20 0s 3ms/step -
accuracy: 0.9152 - loss: 0.2622 - val_accuracy: 0.8608 - val_loss: 0.4615
Epoch 13/45
20/20 0s 3ms/step -
accuracy: 0.8925 - loss: 0.3027 - val_accuracy: 0.8481 - val_loss: 0.4617
Epoch 14/45
20/20 0s 5ms/step -
accuracy: 0.9208 - loss: 0.2655 - val_accuracy: 0.8608 - val_loss: 0.4581
Epoch 15/45
20/20 0s 4ms/step -
accuracy: 0.9207 - loss: 0.2561 - val_accuracy: 0.8354 - val_loss: 0.4685
Epoch 16/45
20/20 0s 4ms/step -
accuracy: 0.9303 - loss: 0.2457 - val_accuracy: 0.8354 - val_loss: 0.4659
Epoch 17/45
20/20 0s 3ms/step -
accuracy: 0.9343 - loss: 0.2045 - val_accuracy: 0.8608 - val_loss: 0.4635
Epoch 18/45
20/20 0s 3ms/step -
accuracy: 0.9426 - loss: 0.2238 - val_accuracy: 0.8481 - val_loss: 0.4736
Epoch 19/45
20/20 0s 3ms/step -
accuracy: 0.9353 - loss: 0.2298 - val_accuracy: 0.8354 - val_loss: 0.4817
Epoch 20/45
20/20 0s 3ms/step -
accuracy: 0.9393 - loss: 0.2018 - val_accuracy: 0.8608 - val_loss: 0.4609
Epoch 21/45
20/20 0s 3ms/step -
accuracy: 0.9417 - loss: 0.2014 - val_accuracy: 0.8608 - val_loss: 0.4763
Epoch 22/45
20/20 0s 4ms/step -
accuracy: 0.9375 - loss: 0.2089 - val_accuracy: 0.8481 - val_loss: 0.4826
Epoch 23/45
20/20 0s 4ms/step -
accuracy: 0.9536 - loss: 0.1741 - val_accuracy: 0.8608 - val_loss: 0.4699
Epoch 24/45
20/20 0s 4ms/step -
accuracy: 0.9755 - loss: 0.1552 - val_accuracy: 0.8608 - val_loss: 0.4753

Epoch 25/45
20/20 0s 4ms/step -
accuracy: 0.9460 - loss: 0.1948 - val_accuracy: 0.8481 - val_loss: 0.4940
Epoch 26/45
20/20 0s 4ms/step -
accuracy: 0.9556 - loss: 0.1436 - val_accuracy: 0.8481 - val_loss: 0.4954
Epoch 27/45
20/20 0s 3ms/step -
accuracy: 0.9560 - loss: 0.1431 - val_accuracy: 0.8481 - val_loss: 0.5148
Epoch 28/45
20/20 0s 3ms/step -
accuracy: 0.9826 - loss: 0.1193 - val_accuracy: 0.8608 - val_loss: 0.4958
Epoch 29/45
20/20 0s 4ms/step -
accuracy: 0.9684 - loss: 0.1249 - val_accuracy: 0.8481 - val_loss: 0.5210
Epoch 30/45
20/20 0s 5ms/step -
accuracy: 0.9844 - loss: 0.0999 - val_accuracy: 0.8481 - val_loss: 0.5070
Epoch 31/45
20/20 0s 3ms/step -
accuracy: 0.9813 - loss: 0.1063 - val_accuracy: 0.8481 - val_loss: 0.5311
Epoch 32/45
20/20 0s 5ms/step -
accuracy: 0.9826 - loss: 0.1066 - val_accuracy: 0.8608 - val_loss: 0.5086
Epoch 33/45
20/20 0s 3ms/step -
accuracy: 0.9897 - loss: 0.0863 - val_accuracy: 0.8481 - val_loss: 0.5119
Epoch 34/45
20/20 0s 3ms/step -
accuracy: 0.9653 - loss: 0.1105 - val_accuracy: 0.8608 - val_loss: 0.5205
Epoch 35/45
20/20 0s 4ms/step -
accuracy: 0.9749 - loss: 0.0995 - val_accuracy: 0.8481 - val_loss: 0.5537
Epoch 36/45
20/20 0s 3ms/step -
accuracy: 0.9855 - loss: 0.0786 - val_accuracy: 0.8608 - val_loss: 0.5190
Epoch 37/45
20/20 0s 3ms/step -
accuracy: 0.9699 - loss: 0.0827 - val_accuracy: 0.8481 - val_loss: 0.5552
Epoch 38/45
20/20 0s 4ms/step -
accuracy: 0.9729 - loss: 0.0851 - val_accuracy: 0.8608 - val_loss: 0.5386
Epoch 39/45
20/20 0s 5ms/step -
accuracy: 0.9857 - loss: 0.0702 - val_accuracy: 0.8354 - val_loss: 0.5508
Epoch 40/45
20/20 0s 4ms/step -
accuracy: 0.9883 - loss: 0.0763 - val_accuracy: 0.8734 - val_loss: 0.5432

```

Epoch 41/45
20/20          0s 3ms/step -
accuracy: 0.9888 - loss: 0.0682 - val_accuracy: 0.8354 - val_loss: 0.5735
Epoch 42/45
20/20          0s 3ms/step -
accuracy: 0.9880 - loss: 0.0588 - val_accuracy: 0.8608 - val_loss: 0.5530
Epoch 43/45
20/20          0s 4ms/step -
accuracy: 0.9921 - loss: 0.0662 - val_accuracy: 0.8608 - val_loss: 0.5838
Epoch 44/45
20/20          0s 4ms/step -
accuracy: 0.9894 - loss: 0.0550 - val_accuracy: 0.8608 - val_loss: 0.5650
Epoch 45/45
20/20          0s 3ms/step -
accuracy: 0.9801 - loss: 0.0736 - val_accuracy: 0.8481 - val_loss: 0.5960
3/3            0s 4ms/step -
accuracy: 0.8537 - loss: 0.5823
Test Accuracy: 84.8101258277893

```

```

[ ]: model_filename = f"model_{test_accuracy}.keras"

model.save(model_filename)

print(f"Model saved as {model_filename}")

```

Visualization Of Accuracy Through Epochs

```

[ ]: import matplotlib.pyplot as plt

plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')

plt.tight_layout()

```

```
plt.show()
```



Fine - Tuning The Model

```
[ ]: from tensorflow.keras.layers import Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.regularizers import l2

model = Sequential([
    Dense(64, activation='relu', kernel_regularizer=l2(0.01),
    ↪input_shape=(x_train.shape[1],)),
    Dropout(0.5),
    Dense(128, activation='relu', kernel_regularizer=l2(0.01)),
    Dropout(0.5),
    Dense(64, activation='relu', kernel_regularizer=l2(0.01)),
    Dense(len(label_encoder.classes_), activation='softmax')
])

model.compile(optimizer=Adam(learning_rate=0.001),
    ↪loss='categorical_crossentropy', metrics=['accuracy'])

early_stopping = EarlyStopping(monitor='val_loss', patience=5,
    ↪restore_best_weights=True)
checkpoint = ModelCheckpoint('best_model.keras', save_best_only=True,
    ↪monitor='val_loss')

history = model.fit(x_train, y_train_cat, epochs=50, validation_data=(x_test,
    ↪y_test_cat), batch_size=16, callbacks=[checkpoint, early_stopping])

test_loss, test_accuracy = model.evaluate(x_test, y_test_cat)
print(f"Test Accuracy: {test_accuracy * 100}")
```

Epoch 1/50

20/20 7s 66ms/step -
 accuracy: 0.1634 - loss: 4.0925 - val_accuracy: 0.5190 - val_loss: 3.5787
 Epoch 2/50
 20/20 2s 19ms/step -
 accuracy: 0.4154 - loss: 3.5385 - val_accuracy: 0.6709 - val_loss: 3.1724
 Epoch 3/50
 20/20 0s 20ms/step -
 accuracy: 0.5172 - loss: 3.1689 - val_accuracy: 0.6582 - val_loss: 2.8417
 Epoch 4/50
 20/20 1s 19ms/step -
 accuracy: 0.6490 - loss: 2.7924 - val_accuracy: 0.6709 - val_loss: 2.5681
 Epoch 5/50
 20/20 0s 14ms/step -
 accuracy: 0.6123 - loss: 2.6603 - val_accuracy: 0.6962 - val_loss: 2.3514
 Epoch 6/50
 20/20 0s 11ms/step -
 accuracy: 0.6824 - loss: 2.4230 - val_accuracy: 0.7215 - val_loss: 2.1725
 Epoch 7/50
 20/20 1s 23ms/step -
 accuracy: 0.7334 - loss: 2.2289 - val_accuracy: 0.7342 - val_loss: 2.0586
 Epoch 8/50
 20/20 0s 18ms/step -
 accuracy: 0.7576 - loss: 2.0423 - val_accuracy: 0.7595 - val_loss: 1.9063
 Epoch 9/50
 20/20 1s 20ms/step -
 accuracy: 0.7328 - loss: 2.0370 - val_accuracy: 0.7595 - val_loss: 1.8515
 Epoch 10/50
 20/20 0s 15ms/step -
 accuracy: 0.7229 - loss: 1.9642 - val_accuracy: 0.7595 - val_loss: 1.7707
 Epoch 11/50
 20/20 1s 21ms/step -
 accuracy: 0.7659 - loss: 1.7654 - val_accuracy: 0.7722 - val_loss: 1.6704
 Epoch 12/50
 20/20 0s 10ms/step -
 accuracy: 0.7584 - loss: 1.7069 - val_accuracy: 0.7722 - val_loss: 1.6227
 Epoch 13/50
 20/20 0s 13ms/step -
 accuracy: 0.8143 - loss: 1.6926 - val_accuracy: 0.7975 - val_loss: 1.5453
 Epoch 14/50
 20/20 0s 13ms/step -
 accuracy: 0.7689 - loss: 1.5872 - val_accuracy: 0.7722 - val_loss: 1.4932
 Epoch 15/50
 20/20 1s 16ms/step -
 accuracy: 0.7579 - loss: 1.5862 - val_accuracy: 0.7975 - val_loss: 1.4373
 Epoch 16/50
 20/20 1s 12ms/step -
 accuracy: 0.8048 - loss: 1.4602 - val_accuracy: 0.8101 - val_loss: 1.4135
 Epoch 17/50

20/20 0s 10ms/step -
 accuracy: 0.7358 - loss: 1.5392 - val_accuracy: 0.8101 - val_loss: 1.3642
 Epoch 18/50
 20/20 0s 12ms/step -
 accuracy: 0.7724 - loss: 1.4690 - val_accuracy: 0.7595 - val_loss: 1.3301
 Epoch 19/50
 20/20 0s 13ms/step -
 accuracy: 0.7652 - loss: 1.4122 - val_accuracy: 0.7722 - val_loss: 1.2997
 Epoch 20/50
 20/20 1s 14ms/step -
 accuracy: 0.7943 - loss: 1.3480 - val_accuracy: 0.8228 - val_loss: 1.2471
 Epoch 21/50
 20/20 1s 14ms/step -
 accuracy: 0.7867 - loss: 1.3506 - val_accuracy: 0.7975 - val_loss: 1.2392
 Epoch 22/50
 20/20 0s 12ms/step -
 accuracy: 0.8186 - loss: 1.2745 - val_accuracy: 0.8228 - val_loss: 1.1896
 Epoch 23/50
 20/20 0s 7ms/step -
 accuracy: 0.8071 - loss: 1.1961 - val_accuracy: 0.8354 - val_loss: 1.1624
 Epoch 24/50
 20/20 0s 5ms/step -
 accuracy: 0.8150 - loss: 1.2054 - val_accuracy: 0.8101 - val_loss: 1.1291
 Epoch 25/50
 20/20 0s 5ms/step -
 accuracy: 0.8249 - loss: 1.1515 - val_accuracy: 0.8354 - val_loss: 1.1335
 Epoch 26/50
 20/20 0s 8ms/step -
 accuracy: 0.8038 - loss: 1.1511 - val_accuracy: 0.8228 - val_loss: 1.1133
 Epoch 27/50
 20/20 0s 7ms/step -
 accuracy: 0.8182 - loss: 1.1575 - val_accuracy: 0.8481 - val_loss: 1.0933
 Epoch 28/50
 20/20 0s 5ms/step -
 accuracy: 0.8352 - loss: 1.0971 - val_accuracy: 0.8228 - val_loss: 1.0938
 Epoch 29/50
 20/20 0s 8ms/step -
 accuracy: 0.7955 - loss: 1.1690 - val_accuracy: 0.8354 - val_loss: 1.0485
 Epoch 30/50
 20/20 0s 5ms/step -
 accuracy: 0.7792 - loss: 1.1200 - val_accuracy: 0.8481 - val_loss: 1.0575
 Epoch 31/50
 20/20 0s 5ms/step -
 accuracy: 0.8376 - loss: 1.0347 - val_accuracy: 0.8354 - val_loss: 1.0256
 Epoch 32/50
 20/20 0s 11ms/step -
 accuracy: 0.7768 - loss: 1.0261 - val_accuracy: 0.8228 - val_loss: 1.0067
 Epoch 33/50

20/20 0s 8ms/step -
 accuracy: 0.7985 - loss: 1.1030 - val_accuracy: 0.8608 - val_loss: 0.9897
 Epoch 34/50
 20/20 0s 8ms/step -
 accuracy: 0.8386 - loss: 0.9905 - val_accuracy: 0.7975 - val_loss: 1.0248
 Epoch 35/50
 20/20 0s 11ms/step -
 accuracy: 0.8532 - loss: 0.9728 - val_accuracy: 0.8228 - val_loss: 0.9841
 Epoch 36/50
 20/20 0s 8ms/step -
 accuracy: 0.8233 - loss: 1.0510 - val_accuracy: 0.7975 - val_loss: 0.9927
 Epoch 37/50
 20/20 0s 9ms/step -
 accuracy: 0.8116 - loss: 0.9858 - val_accuracy: 0.8354 - val_loss: 0.9633
 Epoch 38/50
 20/20 0s 10ms/step -
 accuracy: 0.8036 - loss: 0.9739 - val_accuracy: 0.8481 - val_loss: 0.9238
 Epoch 39/50
 20/20 0s 8ms/step -
 accuracy: 0.8258 - loss: 0.9409 - val_accuracy: 0.8354 - val_loss: 0.9384
 Epoch 40/50
 20/20 0s 8ms/step -
 accuracy: 0.8427 - loss: 0.9229 - val_accuracy: 0.8354 - val_loss: 0.9282
 Epoch 41/50
 20/20 0s 10ms/step -
 accuracy: 0.7901 - loss: 0.9671 - val_accuracy: 0.8354 - val_loss: 0.9069
 Epoch 42/50
 20/20 0s 7ms/step -
 accuracy: 0.7873 - loss: 0.9872 - val_accuracy: 0.8101 - val_loss: 0.9110
 Epoch 43/50
 20/20 0s 11ms/step -
 accuracy: 0.7964 - loss: 0.9251 - val_accuracy: 0.8481 - val_loss: 0.8801
 Epoch 44/50
 20/20 0s 9ms/step -
 accuracy: 0.7905 - loss: 0.9145 - val_accuracy: 0.8481 - val_loss: 0.8635
 Epoch 45/50
 20/20 0s 10ms/step -
 accuracy: 0.8400 - loss: 0.8416 - val_accuracy: 0.8354 - val_loss: 0.8913
 Epoch 46/50
 20/20 0s 10ms/step -
 accuracy: 0.7968 - loss: 0.9475 - val_accuracy: 0.8354 - val_loss: 0.8630
 Epoch 47/50
 20/20 0s 11ms/step -
 accuracy: 0.8578 - loss: 0.8244 - val_accuracy: 0.8481 - val_loss: 0.8580
 Epoch 48/50
 20/20 0s 10ms/step -
 accuracy: 0.8117 - loss: 0.8340 - val_accuracy: 0.8354 - val_loss: 0.8510
 Epoch 49/50

```

20/20          0s 11ms/step -
accuracy: 0.8567 - loss: 0.8303 - val_accuracy: 0.8354 - val_loss: 0.8400
Epoch 50/50
20/20          0s 7ms/step -
accuracy: 0.8236 - loss: 0.8384 - val_accuracy: 0.8101 - val_loss: 0.8583
3/3           0s 4ms/step -
accuracy: 0.8435 - loss: 0.8346
Test Accuracy: 83.54430198669434

```

Visualization Of Accuracy Through Epochs

```

[ ]: import matplotlib.pyplot as plt

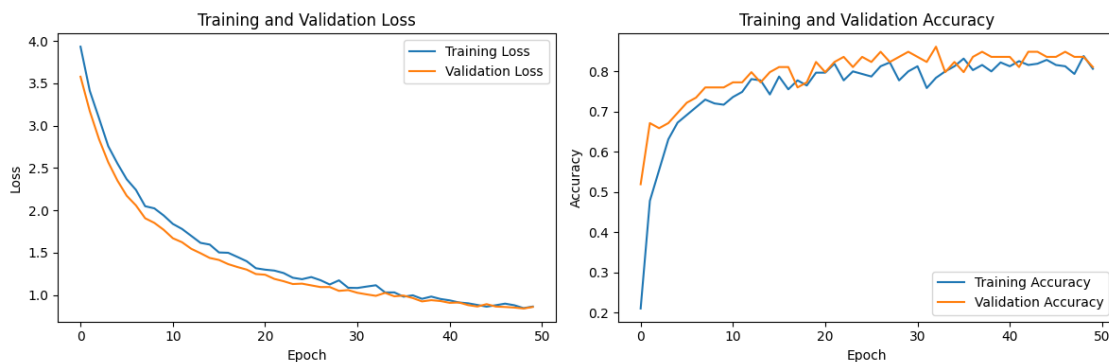
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')

plt.tight_layout()
plt.show()

```



1.4 Comparison % Deduction of Best Model

1.5 Random Forest is the best model here

Let's try to understand this model better.

```
[ ]: from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
model = RandomForestClassifier(n_estimators=31, random_state=53)

model.fit(x_train, y_train)

y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

print(f"Accuracy: {accuracy * 100:.2f}%")
```

Accuracy: 88.61%

1.5.1 1. Feature Importance Visualization

Random Forest models provide feature importance values that can be visualized to understand which features contribute most to the predictions.

```
[ ]: import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(n_estimators=31, random_state=53)
model.fit(x_train, y_train)

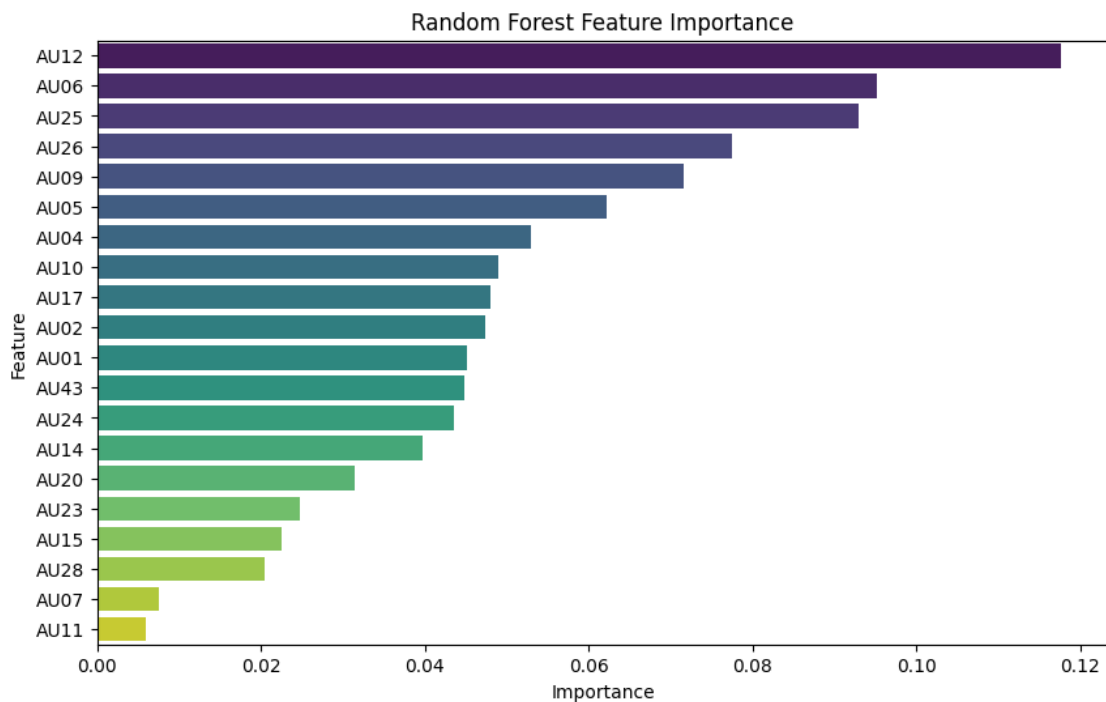
feature_importance = model.feature_importances_
feature_names = x_train.columns if isinstance(x_train, pd.DataFrame) else
    [f"Feature {i}" for i in range(x_train.shape[1])]
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':
    feature_importance})

plt.figure(figsize=(10, 6))
sns.barplot(data=importance_df.sort_values(by="Importance", ascending=False),
    x="Importance", y="Feature", palette="viridis")
plt.title("Random Forest Feature Importance")
plt.show()
```

```
<ipython-input-15-f81adede0802>:14: FutureWarning:
```

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

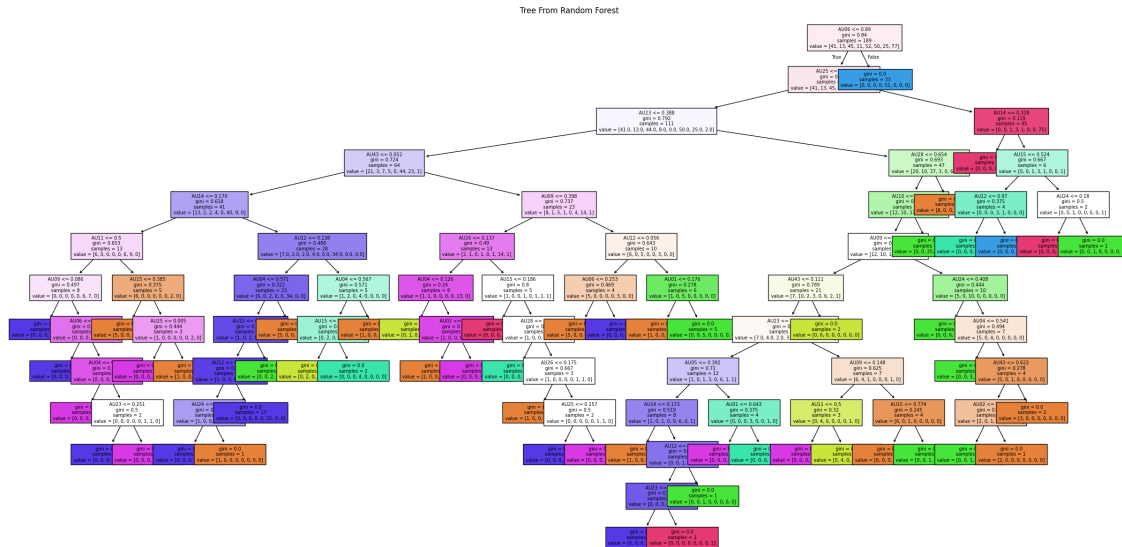
```
sns.barplot(data=importance_df.sort_values(by="Importance", ascending=False),
x="Importance", y="Feature", palette="viridis")
```



###2. Visualizing Individual Decision Trees You can visualize individual trees within the forest using the `plot_tree` function from `sklearn.tree`. Random forests are an ensemble of many trees, so it's often best to visualize only a few trees to understand their structure.

```
[ ]: from sklearn.tree import plot_tree

plt.figure(figsize=(30, 15))
plot_tree(model.estimators_[0], feature_names=feature_names, filled=True,
↪max_depth=15, fontsize=7)
plt.title("Tree From Random Forest")
plt.show()
```



###3. Partial Dependence Plots Partial dependence plots show how the model's predictions change when a specific feature's values change, holding other features constant. These are especially useful in Random Forest to understand feature relationships.

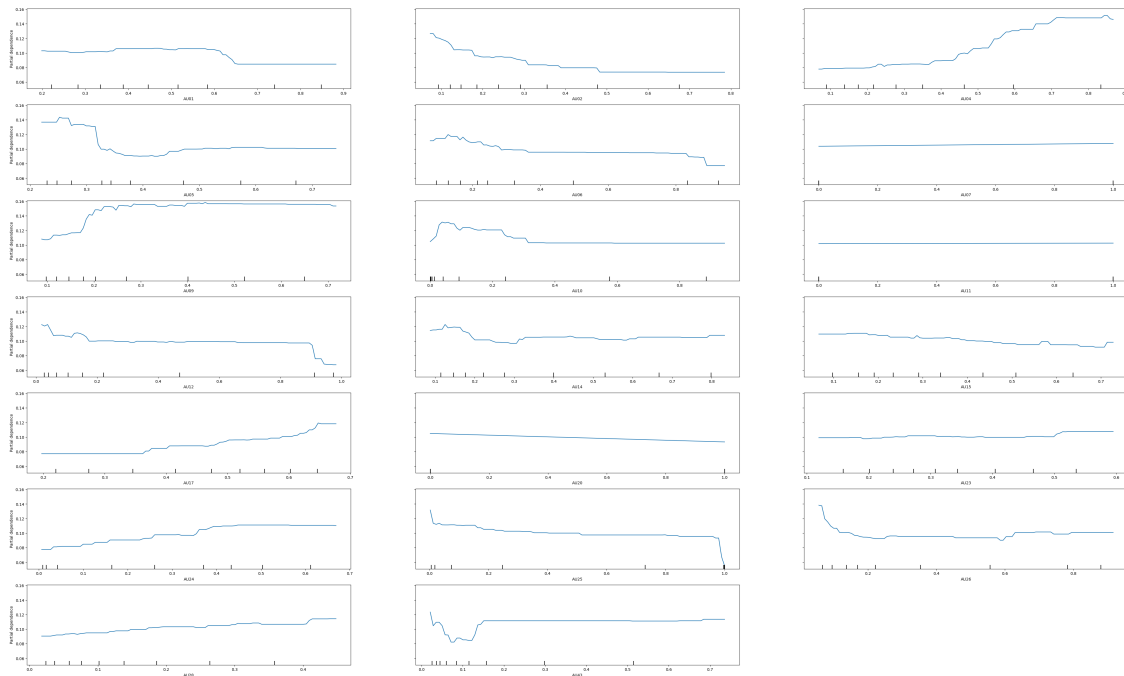
```
[ ]: classes = model.classes_
print(classes)

target_class = classes[0] # F
```

```
['anger' 'contempt' 'disgust' 'fear' 'happiness' 'neutral' 'sadness'
'surprise']
```

```
[ ]: import matplotlib.pyplot as plt
from sklearn.inspection import partial_dependence
from sklearn.inspection import PartialDependenceDisplay

fig, ax = plt.subplots(figsize=(50, 30))
display = PartialDependenceDisplay.from_estimator(
    model,
    x_train,
    features=[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19],
    feature_names=feature_names,
    ax=ax,
    target=target_class
)
plt.show()
```



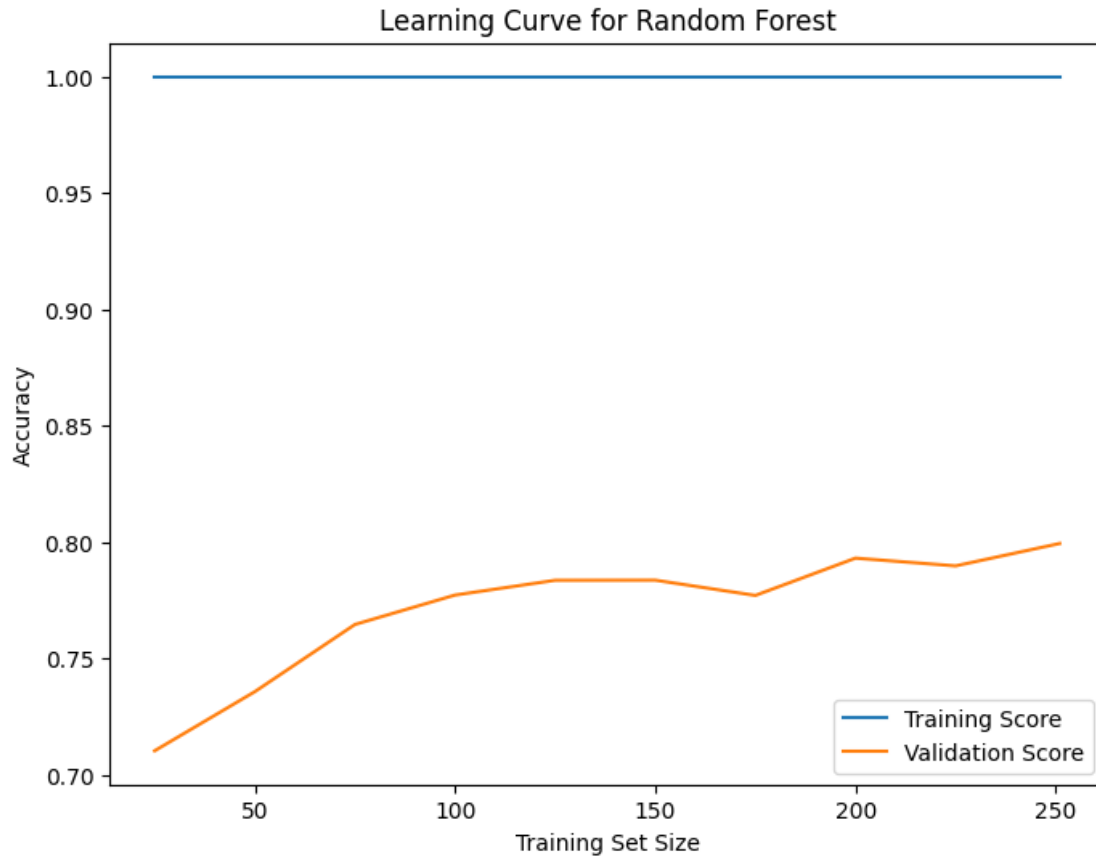
###4. Learning Curves Learning curves plot training and validation accuracy or loss as the model trains on increasingly larger portions of the dataset, helping assess bias vs. variance trade-offs.

```
[ ]: from sklearn.model_selection import learning_curve
import numpy as np

train_sizes, train_scores, test_scores = learning_curve(
    model, x_train, y_train, cv=5, scoring="accuracy", n_jobs=-1,
    train_sizes=np.linspace(0.1, 1.0, 10)
)

train_scores_mean = np.mean(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)

plt.figure(figsize=(8, 6))
plt.plot(train_sizes, train_scores_mean, label="Training Score")
plt.plot(train_sizes, test_scores_mean, label="Validation Score")
plt.xlabel("Training Set Size")
plt.ylabel("Accuracy")
plt.title("Learning Curve for Random Forest")
plt.legend(loc="best")
plt.show()
```



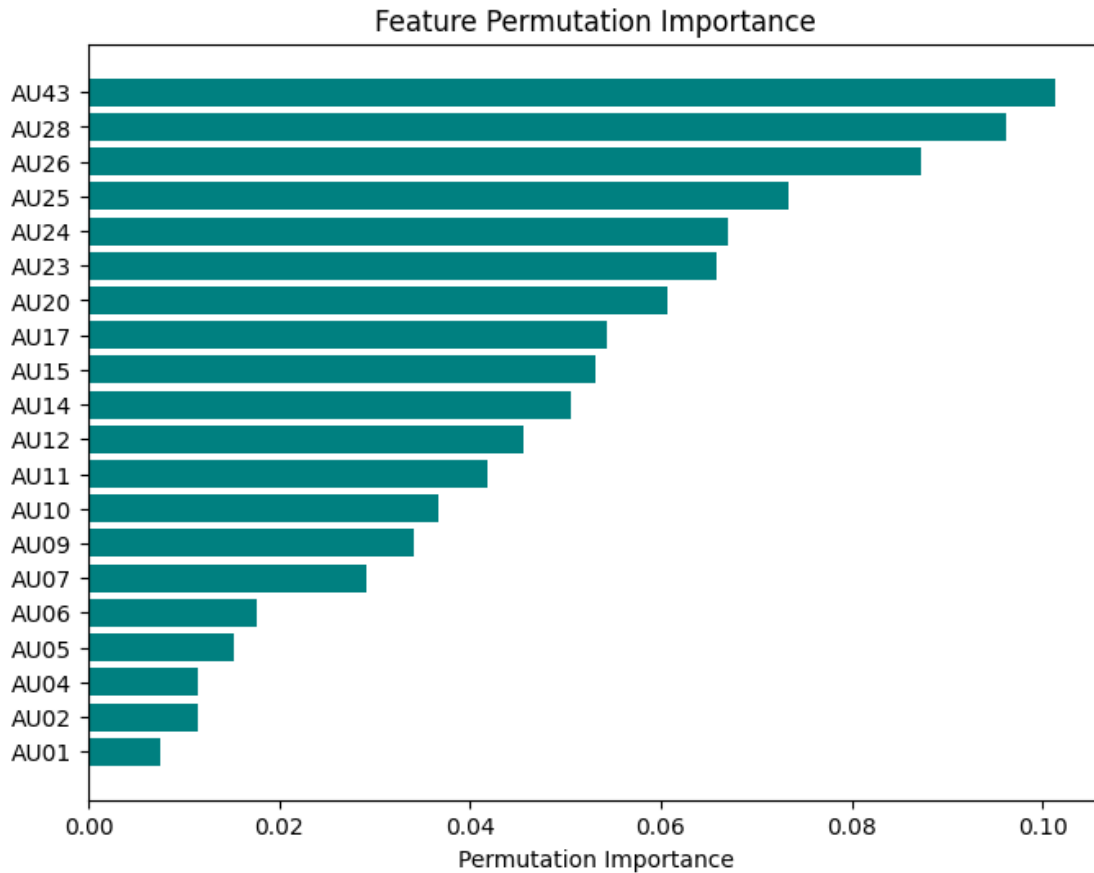
1.5.2 5. Permutation Importance

Permutation importance is another way to assess feature importance by randomly shuffling feature values and measuring the drop in accuracy. This technique helps identify the most influential features in the model.

```
[ ]: from sklearn.inspection import permutation_importance

perm_importance = permutation_importance(model, x_test, y_test, n_repeats=10,
    random_state=53)
sorted_idx = perm_importance.importances_mean.argsort()

plt.figure(figsize=(8, 6))
plt.barh(feature_names, perm_importance.importances_mean[sorted_idx],
    color="teal")
plt.xlabel("Permutation Importance")
plt.title("Feature Permutation Importance")
plt.show()
```



1.5.3 6. Confusion Matrix and Classification Report

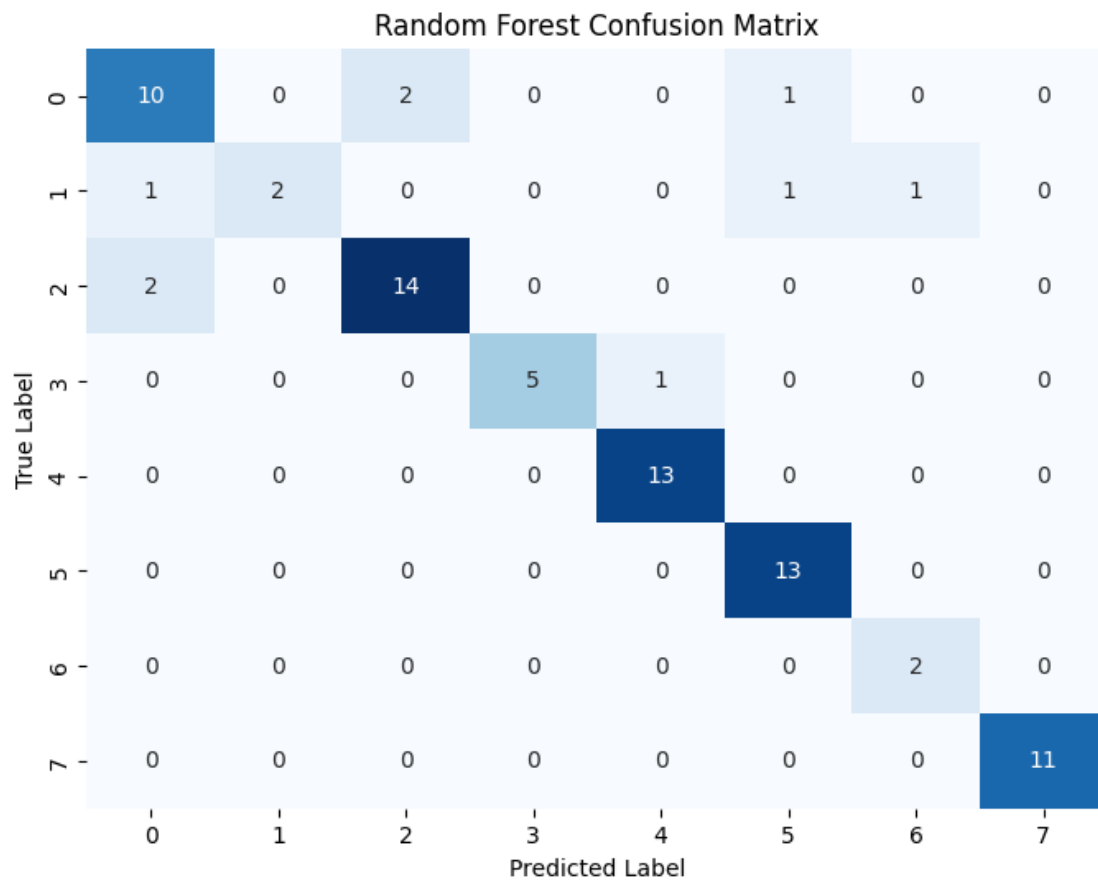
Use the confusion matrix and classification report to visualize prediction performance across classes.

```
[ ]: from sklearn.metrics import confusion_matrix, classification_report

y_pred = model.predict(x_test)
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap="Blues", cbar=False)
plt.title("Random Forest Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()

print(classification_report(y_test, y_pred))
```



	precision	recall	f1-score	support
anger	0.77	0.77	0.77	13
contempt	1.00	0.40	0.57	5
disgust	0.88	0.88	0.88	16
fear	1.00	0.83	0.91	6
happiness	0.93	1.00	0.96	13
neutral	0.87	1.00	0.93	13
sadness	0.67	1.00	0.80	2
surprise	1.00	1.00	1.00	11
accuracy			0.89	79
macro avg	0.89	0.86	0.85	79
weighted avg	0.89	0.89	0.88	79

1.6 User Input Evaluation

```
[ ]: import cv2

def preprocess_image(image_path):

    image = cv2.imread(image_path)

    image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    return image_rgb

[ ]: from feat import Detector

def extract_aus(image_path):
    detector = Detector()
    results = detector.detect_image(image_path)
    aus = results.aus.iloc[0].values
    return aus

[ ]: import pandas as pd
from sklearn.ensemble import RandomForestClassifier

def predict_emotion(aus, model):
    aus_df = pd.DataFrame([aus], columns=x_train.columns)

    prediction = model.predict(aus_df)
    return prediction[0]

[ ]: image = preprocess_image('/content/drive/MyDrive/Colab Notebooks/Shared 15 with_
↳main/SEM 7/PJT 1 /happiness/S026_006_00000013.png')

aus = extract_aus('/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/
↳SEM 7/PJT 1 /happiness/S026_006_00000013.png')

predicted_emotion = predict_emotion(aus, model)
```

/usr/local/lib/python3.10/dist-packages/feat/face_detectors/Retinaface/Retinaface_test.py:70: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See <https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models> for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via

``torch.serialization.add_safe_globals``. We recommend you start setting ``weights_only=True`` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
pretrained_dict = torch.load(  
/usr/local/lib/python3.10/dist-packages/feat/detector.py:238: FutureWarning: You  
are using `torch.load` with `weights_only=False` (the current default value),  
which uses the default pickle module implicitly. It is possible to construct  
malicious pickle data which will execute arbitrary code during unpickling (See  
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for  
more details). In a future release, the default value for `weights_only` will be  
flipped to `True`. This limits the functions that could be executed during  
unpickling. Arbitrary objects will no longer be allowed to be loaded via this  
mode unless they are explicitly allowlisted by the user via  
`torch.serialization.add_safe_globals`. We recommend you start setting  
`weights_only=True` for any use case where you don't have full control of the  
loaded file. Please open an issue on GitHub for any issues related to this  
experimental feature.
```

```
checkpoint = torch.load(  
/usr/local/lib/python3.10/dist-  
packages/feat/facepose_detectors/img2pose/img2pose_test.py:105: FutureWarning:  
You are using `torch.load` with `weights_only=False` (the current default  
value), which uses the default pickle module implicitly. It is possible to  
construct malicious pickle data which will execute arbitrary code during  
unpickling (See  
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for  
more details). In a future release, the default value for `weights_only` will be  
flipped to `True`. This limits the functions that could be executed during  
unpickling. Arbitrary objects will no longer be allowed to be loaded via this  
mode unless they are explicitly allowlisted by the user via  
`torch.serialization.add_safe_globals`. We recommend you start setting  
`weights_only=True` for any use case where you don't have full control of the  
loaded file. Please open an issue on GitHub for any issues related to this  
experimental feature.
```

```
checkpoint = torch.load(model_path, map_location=self.device)  
/usr/local/lib/python3.10/dist-  
packages/feat/emo_detectors/ResMaskNet/resmasknet_test.py:718: FutureWarning:  
You are using `torch.load` with `weights_only=False` (the current default  
value), which uses the default pickle module implicitly. It is possible to  
construct malicious pickle data which will execute arbitrary code during  
unpickling (See  
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for  
more details). In a future release, the default value for `weights_only` will be  
flipped to `True`. This limits the functions that could be executed during  
unpickling. Arbitrary objects will no longer be allowed to be loaded via this  
mode unless they are explicitly allowlisted by the user via  
`torch.serialization.add_safe_globals`. We recommend you start setting  
`weights_only=True` for any use case where you don't have full control of the
```

loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
torch.load(
/usr/local/lib/python3.10/dist-
packages/feat/identity_detectors/facenet/facenet_model.py:275: FutureWarning:
You are using `torch.load` with `weights_only=False` (the current default
value), which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
```

```
torch.load(
100%|          | 1/1 [00:05<00:00,  5.43s/it]
```

Predicted Emotion: happiness

```
[ ]: import matplotlib.pyplot as plt
import cv2

image_path = '/content/drive/MyDrive/Colab Notebooks/Shared 15 with main/SEM 7/
↳PJT 1 /happiness/S026_006_00000013.png'

image = cv2.imread(image_path)

image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

plt.imshow(image_rgb)
plt.axis('off')
plt.show()
```



```
[ ]: print(f"Predicted Emotion: {predicted_emotion}")
```

Predicted Emotion: happiness