In [1]:
```
import librosa
import os
import glob
import soundfile
import soundfile as sf
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.preprocessing import LabelEncoder
# from keras.utils import np_utils
```

In [2]:
```
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, f1_score
from sklearn.metrics import precision_score, recall_score
import matplotlib.pyplot as plt
import itertools

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Define the scaler object
scaler = StandardScaler()
```

In [4]:
```
print(os.getcwd())

os.listdir()
```

```
C:\Users\asnp2\Project
```

Out[4]:
```
['.ipynb_checkpoints',
 'Combined_Dataset.csv',
 'data',
 'Dataset',
 'main_data.csv',
 'noisy_audio.wav',
 'Ravdess_dataset.ipynb',
 'Ravdess_data_preprocessing.ipynb',
 'Ravdess_df.csv',
 'single_data_preprocessing.ipynb',
 'Speech Emotion Recognition.ipynb',
 'Tess_dataset.ipynb',
 'Tess_df.csv',
 'Test1.ipynb',
 'test_data.csv',
 'Untitled.ipynb']
```

Sampling

In [5]:

```
from pydub import AudioSegment
import os
import shutil

# Set the new sample rate you want
new_sample_rate = 22050  # Change this to your desired sample rate

# Input and output directories
input_dir = 'Dataset\\RAVDESS song_speech Actors_01-24'
output_dir = 'Dataset\\RAVDESS_Demo'

# Create the output directory if it doesn't exist
if not os.path.exists(output_dir):
    os.makedirs(output_dir)

# Iterate through the files in the input directory
for subdir, _, files in os.walk(input_dir):
    for file in files:
        if file.endswith(".wav"):
            # Create the corresponding output subdirectory
            relative_path = os.path.relpath(subdir, input_dir)
            output_subdir = os.path.join(output_dir, relative_path)
            if not os.path.exists(output_subdir):
                os.makedirs(output_subdir)

            # Load the audio file
            audio = AudioSegment.from_file(os.path.join(subdir, file))

            # Resample to the new sample rate
            audio = audio.set_frame_rate(new_sample_rate)

            # Define the output file path
            output_path = os.path.join(output_subdir, file)

            # Export the resampled audio to the output directory
            audio.export(output_path, format="wav")

            print(f"Resampled and saved: {output_path}")

print("Done resampling and saving files.")
```

```
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-01-02-0
1-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-01-02-0
2-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-02-01-0
1-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-02-01-0
2-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-02-02-0
1-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-03-02-02-0
2-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-04-01-01-0
1-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-04-01-01-0
2-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-04-01-02-0
1-01.wav
Resampled and saved: Dataset\RAVDESS_Demo\Actor_01\03-01-04-01-02-0
2-01.wav
```

Creating Dataframe

In [6]:

```
Ravdess_Path='Dataset/RAVDESS_Demo'

ravdess=[]
for directory in os.listdir(Ravdess_Path):
    actors=os.listdir(os.path.join(Ravdess_Path,directory))
    for wav in actors:
        emotion=wav.partition('.wav')[0].split('-')
        emotion_number=int(emotion[2])
        ravdess.append((emotion_number,os.path.join(Ravdess_Path,direct
Ravdess_df=pd.DataFrame.from_dict(ravdess)
Ravdess_df.rename(columns={0:'Emotion',1:'File_Path'},inplace=True)
Ravdess_df['Emotion'].replace({1:'neutral', 2:'neutral', 3:'happy', 4:'
Ravdess_df.head()
```

Out[6]:

	Emotion	File_Path
0	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-01-0...
1	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-01-0...
2	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-02-0...
3	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-02-0...
4	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-02-01-01-0...

In [7]:
```
Ravdess_df
```

Out[7]:

	Emotion	File_Path
0	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-01-0...
1	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-01-0...
2	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-02-0...
3	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-01-01-02-0...
4	neutral	Dataset/RAVDESS_Demo\Actor_01\03-01-02-01-01-0...
...	...	...
2447	fear	Dataset/RAVDESS_Demo\Actor_24\03-02-06-01-02-0...
2448	fear	Dataset/RAVDESS_Demo\Actor_24\03-02-06-02-01-0...
2449	fear	Dataset/RAVDESS_Demo\Actor_24\03-02-06-02-01-0...
2450	fear	Dataset/RAVDESS_Demo\Actor_24\03-02-06-02-02-0...
2451	fear	Dataset/RAVDESS_Demo\Actor_24\03-02-06-02-02-0...

2452 rows × 2 columns

In [8]:
```
Ravdess_df['Emotion'].unique()
```

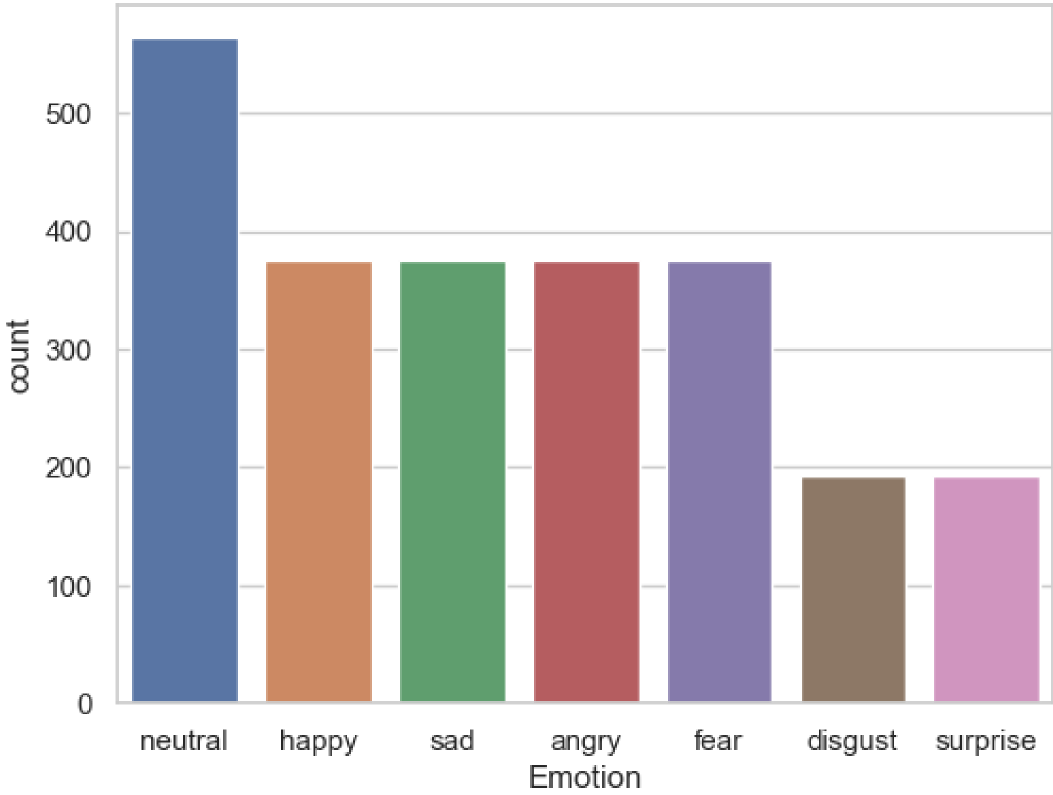
Out[8]:
```
array(['neutral', 'happy', 'sad', 'angry', 'fear', 'disgust', 'surpris
e'],
      dtype=object)
```

In [9]:
```
df = pd.DataFrame(Ravdess_df)

file_name = 'Ravdess_df.csv'

df.to_csv(file_name, index=False)
```

Exploratory Data Analysis

In [10]:
```
import seaborn as sns
sns.set_theme(style="whitegrid")

#df = sns.load_dataset("combined_df")
sns.countplot(data=Ravdess_df, x="Emotion")
```

Out[10]: <Axes: xlabel='Emotion', ylabel='count'>



In [11]:
```
def wave_plot(data,sr,emotion,color):
    plt.figure(figsize=(12,5))
    plt.title(f'Waveplot of {emotion} emotion',size=17)
    librosa.display.waveshow(y=data,sr=sr,color=color)
```

In [12]:
```
def spectogram(data,sr,emotion):
    audio=librosa.stft(data)
    audio_db=librosa.amplitude_to_db(abs(audio))
    plt.figure(figsize=(12,5))
    plt.title(f'Spectrogram of {emotion} emotion',size=17)
    librosa.display.specashow(audio_db,sr=sr,x_axis='time',y_axis='hz')
print("done")
```

done

In [13]:
```
colors={'disgust':'#804E2D','happy':'#F19C0E','sad':'#478FB8','neutral'
```

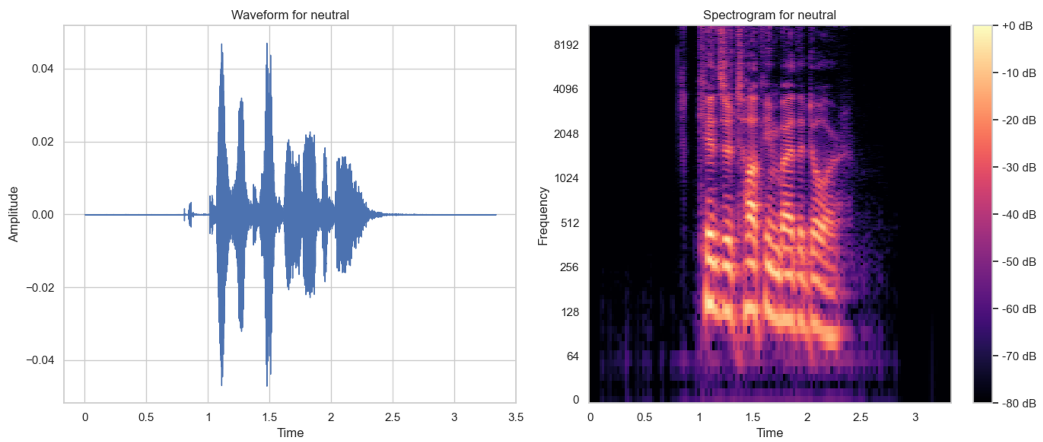
In [14]:
```
emotion_names=Ravdess_df['Emotion'].unique()
emotion_names
```

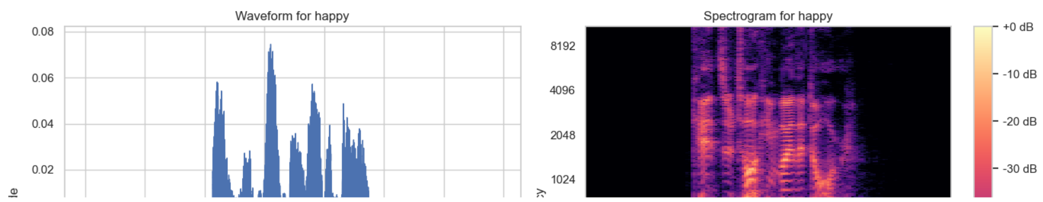
Out[14]:
```
array(['neutral', 'happy', 'sad', 'angry', 'fear', 'disgust', 'surpris
e'],
      dtype=object)
```

In [15]:
```
# import numpy as np
# import librosa
# import librosa.display
# import matplotlib.pyplot as plt

# def spectrogram(data, sr, emotion):
#     plt.figure(figsize=(10, 4))
#     D = librosa.amplitude_to_db(np.abs(librosa.stft(data)), ref=np.ma
#     librosa.display.specshow(D, sr=sr, x_axis='time', y_axis='log')
#     plt.colorbar(format='%+2.0f dB')
#     plt.title(f'Spectrogram for {emotion}')
#     plt.tight_layout()
#     plt.show()

# # Assuming wave_plot function definition is available as well

# # Make sure the 'spectrogram' function is properly defined

# audio_path = []
# for emotion in emotion_names:
#     path = np.array(Ravdess_df['File_Path'][Ravdess_df['Emotion'] == 
#     data, sr = librosa.load(path)
#     wave_plot(data, sr, emotion, colors[emotion])
#     spectrogram(data, sr, emotion)
#     audio_path.append(path)
```

In [16]:

```
import numpy as np
import librosa
import librosa.display
import matplotlib.pyplot as plt

def plot_waveform_spectrogram(data, sr, emotion):
    plt.figure(figsize=(14, 6))

    # Plot Waveform
    plt.subplot(1, 2, 1)
    librosa.display.waveshow(data, sr=sr)
    plt.title(f'Waveform for {emotion}')
    plt.xlabel('Time')
    plt.ylabel('Amplitude')

    # Plot Spectrogram
    plt.subplot(1, 2, 2)
    D = librosa.amplitude_to_db(np.abs(librosa.stft(data)), ref=np.max)
    librosa.display.specshow(D, sr=sr, x_axis='time', y_axis='log')
    plt.colorbar(format='%+2.0f dB')
    plt.title(f'Spectrogram for {emotion}')
    plt.xlabel('Time')
    plt.ylabel('Frequency')

    plt.tight_layout()
    plt.show()

# Assuming wave_plot function definition is available as well

# Make sure the 'plot_waveform_spectrogram' function is properly define

audio_path = []
for emotion in emotion_names:
    path = np.array(Ravdess_df['File_Path'][Ravdess_df['Emotion'] == em
    data, sr = librosa.load(path)
    plot_waveform_spectrogram(data, sr, emotion)
    audio_path.append(path)
```





Feature Extraction

In [17]:
```
def zcr(data,frame_length,hop_length):
    zcr=librosa.feature.zero_crossing_rate(y=data,frame_length=frame_le
    return np.squeeze(zcr)
def rmse(data,frame_length=2048,hop_length=512):
    rmse=librosa.feature.rms(y=data,frame_length=frame_length,hop_lengt
    return np.squeeze(rmse)
def mfcc(data,sr,frame_length=2048,hop_length=512,flatten:bool=True):
    mfcc=librosa.feature.mfcc(y=data,sr=sr)
    return np.squeeze(mfcc.T)if not flatten else np.ravel(mfcc.T)
```

In [18]:
```
def extract_features(data,sr,frame_length=2048,hop_length=512):
    result=np.array([])

    result=np.hstack((result, zcr(data,frame_length,hop_length), rmse(d
    return result
```

In [19]:
```
def get_features(path,duration=2.5, offset=0.6):
    data,sr=librosa.load(path,duration=duration,offset=offset)
    aud=extract_features(data,sr)
    audio=np.array(aud)

    return audio
```

In [20]:
```
import numpy as np
import pandas as pd
import librosa

# Load your dataset into a pandas DataFrame
data_df1 = pd.read_csv('Ravdess_df.csv')  # Replace with the path to yo

X = []  # Initialize the feature matrix
Y = []  # Initialize the emotion label vector

for index, row in data_df1.iterrows():
    file_path1 = row['File_Path']
    emotion_label1 = row['Emotion']

    # Extract features from the audio file
    features = get_features(file_path1)

    # Append the features to X and the label to Y
    X.append(features)
    Y.append(emotion_label1)
```

In [21]:
```
X
```

Out[21]:
```
[array([0.00488281, 0.00683594, 0.0234375 , ..., 1.48098469, 1.3242
6548,
        1.169994  ]),
 array([0.01367188, 0.04589844, 0.06542969, ..., 0.        , 0.
,
        0.        ]),
 array([0.00292969, 0.02148438, 0.02441406, ..., 0.        , 0.
,
        0.        ]),
 array([0.00488281, 0.01953125, 0.02148438, ..., 1.86558366, 1.6781
0977,
        1.49356747]),
 array([ 0.01074219,  0.01269531,  0.01269531, ...,  3.83961153,
         1.24286556, -0.2991249 ]),
 array([0.01171875, 0.01855469, 0.04394531, ..., 0.08538315, 0.1186
6914,
        0.14108332]),
 array([0.01171875, 0.01660156, 0.02246094, ..., 1.87611556, 1.7346
5741,
```

Combining Features and Emotions

In [22]:
```
df = pd.DataFrame({'Emotions': Y, 'Features': X})
df
```

Out[22]:

	Emotions	Features
0	neutral	[0.0048828125, 0.0068359375, 0.0234375, 0.0224...
1	neutral	[0.013671875, 0.0458984375, 0.0654296875, 0.07...
2	neutral	[0.0029296875, 0.021484375, 0.0244140625, 0.02...
3	neutral	[0.0048828125, 0.01953125, 0.021484375, 0.0185...
4	neutral	[0.0107421875, 0.0126953125, 0.0126953125, 0.0...
...	...	...
2447	fear	[0.09765625, 0.13818359375, 0.18115234375, 0.1...
2448	fear	[0.10302734375, 0.17529296875, 0.2421875, 0.27...
2449	fear	[0.1201171875, 0.1826171875, 0.25927734375, 0....
2450	fear	[0.13134765625, 0.1962890625, 0.26220703125, 0...
2451	fear	[0.1591796875, 0.236328125, 0.32080078125, 0.3...

2452 rows × 2 columns

Splitting Features

In [23]:

```
# Find the maximum length of any array in the 'array_column'
max_length = df['Features'].apply(lambda x: len(x)).max()

# Create new column names based on the maximum length
new_columns = [f'Feature_{i+1}' for i in range(max_length)]

# Split the arrays into different columns
for i in range(max_length):
    df[new_columns[i]] = df['Features'].apply(lambda x: x[i] if i < len

# Drop the original 'array_column' if you no longer need it
df.drop(columns=['Features'], inplace=True)
```

In [24]:

```
df
```

Out[24]:

	Emotions	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feat
0	neutral	0.004883	0.006836	0.023438	0.022461	0.022461	0.058594	0.0!
1	neutral	0.013672	0.045898	0.065430	0.071289	0.062500	0.057617	0.0!
2	neutral	0.002930	0.021484	0.024414	0.029297	0.038086	0.054199	0.0
3	neutral	0.004883	0.019531	0.021484	0.018555	0.020996	0.032227	0.0:
4	neutral	0.010742	0.012695	0.012695	0.012695	0.001953	0.015625	0.0:
...	...	...	...	...	...	...	...	
2447	fear	0.097656	0.138184	0.181152	0.169922	0.166016	0.162598	0.1
2448	fear	0.103027	0.175293	0.242188	0.273926	0.300781	0.303223	0.3
2449	fear	0.120117	0.182617	0.259277	0.273438	0.282227	0.296875	0.2!
2450	fear	0.131348	0.196289	0.262207	0.255371	0.237305	0.226074	0.2
2451	fear	0.159180	0.236328	0.320801	0.316895	0.296387	0.284180	0.2

2452 rows × 2377 columns

In [25]:

```
# Names to count occurrences
names_to_count = ['neutral', 'happy', 'sad', 'angry', 'fear', 'disgust'

# Initialize a dictionary to store counts for each name
name_counts = {}

# Loop through the names and count occurrences in DataFrame columns
for name in names_to_count:
    count = (df == name).sum().sum()
    name_counts[name] = count

# 'name_counts' is a dictionary with counts for each name
print("Counts for each name:")
for name, count in name_counts.items():
    print(f"The name '{name}' appears {count} times in the DataFrame.")
```

```
Counts for each name:
The name 'neutral' appears 564 times in the DataFrame.
The name 'happy' appears 376 times in the DataFrame.
The name 'sad' appears 376 times in the DataFrame.
The name 'angry' appears 376 times in the DataFrame.
The name 'fear' appears 376 times in the DataFrame.
The name 'disgust' appears 192 times in the DataFrame.
The name 'surprise' appears 192 times in the DataFrame.
```

Checking Nan Values and Removing

In [26]:

```
null_mask = df.isnull().any(axis=1)
null_rows = df[null_mask]

print(null_rows)
```

```
      Emotions  Feature_1  Feature_2  Feature_3  Feature_4  Feature_5  
\
455       fear   0.054688   0.066895   0.093750   0.091309   0.115723   
470   surprise   0.038086   0.041992   0.067383   0.048340   0.029297   
884   surprise   0.001953   0.042969   0.074219   0.081055   0.081055   
1082      fear   0.000000   0.019531   0.055176   0.090820   0.136719   
1092  surprise   0.042969   0.052246   0.052246   0.030762   0.027832   
1095  surprise   0.079102   0.104004   0.119629   0.083496   0.052734   
1096  surprise   0.021973   0.048828   0.074219   0.053223   0.053223   
1098  surprise   0.034668   0.094727   0.159668   0.209961   0.272949   
1099  surprise   0.182617   0.262695   0.354004   0.359375   0.341309   
1250   neutral   0.075195   0.075195   0.089844   0.046387   0.017578   
1255   neutral   0.059570   0.103516   0.107422   0.062988   0.160156   
1258   neutral   0.000000   0.005859   0.005859   0.005859   0.027832   
1259   neutral   0.043457   0.046387   0.109863   0.142578   0.111328   
1303  surprise   0.053223   0.108887   0.146484   0.150391   0.111328   
1883  surprise   0.005859   0.005859   0.007812   0.003906   0.001953   

      Feature_6  Feature_7  Feature_8  Feature_9  ...  Feature_2367  \
455    0.116211   0.091309   0.062012   0.065430  ...           NaN   
470    0.041016   0.044922   0.092773   0.092773  ...           NaN   
884    0.040527   0.009766   0.004395   0.004395  ...           NaN   
1082   0.167480   0.202148   0.236816   0.266602  ...           NaN   
1092   0.019531   0.039551   0.039551   0.083984  ...           NaN   
1095   0.038086   0.039062   0.042480   0.063965  ...           NaN   
1096   0.028320   0.020996   0.064941   0.070801  ...           NaN   
1098   0.301758   0.318848   0.333008   0.321777  ...           NaN   
1099   0.348633   0.350098   0.350586   0.330566  ...           NaN   
1250   0.078613   0.140625   0.137695   0.177246  ...           NaN   
1255   0.182129   0.243164   0.292969   0.250000  ...           NaN   
1258   0.034180   0.085938   0.124512   0.149902  ...           NaN   
1259   0.124023   0.060059   0.015625   0.015625  ...           NaN   
1303   0.066895   0.029297   0.039551   0.044434  ...           NaN   
1883   0.001953   0.000000   0.000000   0.000000  ...           NaN   

      Feature_2368  Feature_2369  Feature_2370  Feature_2371  Feature_
2372  \
455            NaN           NaN           NaN           NaN  
NaN   
470            NaN           NaN           NaN           NaN  
NaN   
884            NaN           NaN           NaN           NaN  
NaN   
1082           NaN           NaN           NaN           NaN  
NaN   
1092           NaN           NaN           NaN           NaN  
NaN   
1095           NaN           NaN           NaN           NaN  
NaN   
1096           NaN           NaN           NaN           NaN  
NaN   
1098           NaN           NaN           NaN           NaN  
NaN   
1099           NaN           NaN           NaN           NaN  
NaN   
1250           NaN           NaN           NaN           NaN  
NaN   
1255           NaN           NaN           NaN           NaN  
NaN   
1258           NaN           NaN           NaN           NaN  
NaN   
```

```
1259             NaN           NaN           NaN           NaN
NaN
1303             NaN           NaN           NaN           NaN
NaN
1883             NaN           NaN           NaN           NaN
NaN

      Feature_2373  Feature_2374  Feature_2375  Feature_2376
455            NaN           NaN           NaN           NaN
470            NaN           NaN           NaN           NaN
884            NaN           NaN           NaN           NaN
1082           NaN           NaN           NaN           NaN
1092           NaN           NaN           NaN           NaN
1095           NaN           NaN           NaN           NaN
1096           NaN           NaN           NaN           NaN
1098           NaN           NaN           NaN           NaN
1099           NaN           NaN           NaN           NaN
1250           NaN           NaN           NaN           NaN
1255           NaN           NaN           NaN           NaN
1258           NaN           NaN           NaN           NaN
1259           NaN           NaN           NaN           NaN
1303           NaN           NaN           NaN           NaN
1883           NaN           NaN           NaN           NaN

[15 rows x 2377 columns]
```

In [27]:
```
df2=df.dropna(axis=1)
```

In [28]:
```
df2
```

Out[28]:

	Emotions	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feat
0	neutral	0.004883	0.006836	0.023438	0.022461	0.022461	0.058594	0.0!
1	neutral	0.013672	0.045898	0.065430	0.071289	0.062500	0.057617	0.0:
2	neutral	0.002930	0.021484	0.024414	0.029297	0.038086	0.054199	0.0
3	neutral	0.004883	0.019531	0.021484	0.018555	0.020996	0.032227	0.0:
4	neutral	0.010742	0.012695	0.012695	0.012695	0.001953	0.015625	0.0:
...	...	...	...	...	...	...	...	
2447	fear	0.097656	0.138184	0.181152	0.169922	0.166016	0.162598	0.1
2448	fear	0.103027	0.175293	0.242188	0.273926	0.300781	0.303223	0.3
2449	fear	0.120117	0.182617	0.259277	0.273438	0.282227	0.296875	0.2!
2450	fear	0.131348	0.196289	0.262207	0.255371	0.237305	0.226074	0.2
2451	fear	0.159180	0.236328	0.320801	0.316895	0.296387	0.284180	0.2

2452 rows × 2223 columns

In [29]:
```
null_mask = df2.isnull().any(axis=1)
null_rows = df2[null_mask]

print(null_rows)
```

```
Empty DataFrame
Columns: [Emotions, Feature_1, Feature_2, Feature_3, Feature_4, Featur
e_5, Feature_6, Feature_7, Feature_8, Feature_9, Feature_10, Feature_1
1, Feature_12, Feature_13, Feature_14, Feature_15, Feature_16, Feature
_17, Feature_18, Feature_19, Feature_20, Feature_21, Feature_22, Featu
re_23, Feature_24, Feature_25, Feature_26, Feature_27, Feature_28, Fea
ture_29, Feature_30, Feature_31, Feature_32, Feature_33, Feature_34, F
eature_35, Feature_36, Feature_37, Feature_38, Feature_39, Feature_40,
Feature_41, Feature_42, Feature_43, Feature_44, Feature_45, Feature_4
6, Feature_47, Feature_48, Feature_49, Feature_50, Feature_51, Feature
_52, Feature_53, Feature_54, Feature_55, Feature_56, Feature_57, Featu
re_58, Feature_59, Feature_60, Feature_61, Feature_62, Feature_63, Fea
ture_64, Feature_65, Feature_66, Feature_67, Feature_68, Feature_69, F
eature_70, Feature_71, Feature_72, Feature_73, Feature_74, Feature_75,
Feature_76, Feature_77, Feature_78, Feature_79, Feature_80, Feature_8
1, Feature_82, Feature_83, Feature_84, Feature_85, Feature_86, Feature
_87, Feature_88, Feature_89, Feature_90, Feature_91, Feature_92, Featu
re_93, Feature_94, Feature_95, Feature_96, Feature_97, Feature_98, Fea
ture_99, ...]
Index: []

[0 rows x 2223 columns]
```

In [30]:
```
duplicate = df2[df2.duplicated()]

print("Duplicate Rows :")
```

```
Duplicate Rows :
```

MinMax Scaling

In [31]:
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler


# Column to exclude from scaling
column_to_exclude = 'Emotions'

# Create a copy of the DataFrame excluding the specified column
df_scaled = df2.drop(columns=[column_to_exclude]).copy()

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the DataFrame without the excluded column
scaled_data = scaler.fit_transform(df_scaled)

# Create a new DataFrame with the scaled data
scaled_df = pd.DataFrame(scaled_data, columns=df_scaled.columns)

# Add the excluded column back to the scaled DataFrame
scaled_df[column_to_exclude] = df2[column_to_exclude]

# Display the original DataFrame and the Min-Max scaled DataFrame
print("Original DataFrame:")
print(df2)
print("\nScaled DataFrame (Min-Max scaled excluding the specified colum
print(scaled_df)
```

```
1       0.057617   0.081055   0.120117   0.154785  ...       0.000000
2       0.054199   0.071289   0.083984   0.091309  ...       0.000000
3       0.032227   0.038086   0.036133   0.035156  ...       2.604749
4       0.015625   0.022461   0.038086   0.066406  ...       1.562334
...          ...        ...        ...        ...  ...            ...
2447    0.162598   0.142090   0.125000   0.097168  ...       8.355169
2448    0.303223   0.301758   0.303223   0.295898  ...     -10.118071
2449    0.296875   0.291016   0.289062   0.292969  ...       3.604109
2450    0.226074   0.202148   0.184082   0.175781  ...      -6.222557
2451    0.284180   0.247070   0.234863   0.233887  ...     -15.943939

      Feature_2214  Feature_2215  Feature_2216  Feature_2217  Featu
re_2218  \
0         3.834519      3.340515      2.863275   -854.507629
2.556789
1         0.000000      0.000000      0.000000   -859.693542
0.000000
2         0.000000      0.000000      0.000000   -858.044434
0.000000
3         2.278258      1.893247      1.333017   -840.390930      1
```

Splitting Dataset

In [32]:
```
X=scaled_df.drop(labels='Emotions',axis=1)
Y=scaled_df['Emotions']
```

In [33]:
```
X_train,X_test,y_train,y_test=train_test_split(X,Y,random_state=42,test_
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[33]:
```
((1961, 2222), (491, 2222), (1961,), (491,))
```

In [34]:
```
y_train
```

Out[34]:
```
1436         sad
1815     disgust
2157       happy
2037     neutral
736      neutral
          ...   
1638       happy
1095    surprise
1130       angry
1294     disgust
860        angry
Name: Emotions, Length: 1961, dtype: object
```

In [35]:
```
y_test
```

Out[35]:
```
2114      happy
700       happy
1165        sad
2416    neutral
1626    neutral
         ...   
1491      angry
192       angry
289         sad
174     neutral
907       happy
Name: Emotions, Length: 491, dtype: object
```

In [36]:
```
X_train
```

Out[36]:

	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feat
1436	0.660714	0.668275	0.667263	0.668444	0.626043	0.633936	0.612821	0.6
1815	0.003571	0.002413	0.001789	0.001778	0.000000	0.000000	0.000000	0.0
2157	0.328571	0.369119	0.400716	0.434667	0.449917	0.495263	0.483761	0.4
2037	0.332143	0.299156	0.293381	0.262222	0.278798	0.291128	0.263248	0.1
736	0.039286	0.050663	0.095707	0.118222	0.181970	0.211886	0.200855	0.2
...	...	...	...	...	...	...	...	
1638	0.489286	0.507841	0.502683	0.509333	0.472454	0.479759	0.451282	0.3
1095	0.289286	0.256936	0.219141	0.152000	0.090150	0.067183	0.068376	0.0
1130	0.000000	0.031363	0.073345	0.161778	0.287980	0.381568	0.447009	0.4
1294	0.173214	0.266586	0.208408	0.144889	0.153589	0.051680	0.067521	0.1
860	0.142857	0.125452	0.130590	0.117333	0.090150	0.099914	0.111111	0.0

1961 rows × 2222 columns

In [37]:
```
X_test
```

Out[37]:

	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feat
2114	0.407143	0.425814	0.425760	0.434667	0.403172	0.405685	0.405128	0.3
700	0.225000	0.270205	0.288909	0.300444	0.267112	0.246339	0.159829	0.1
1165	0.323214	0.317250	0.313953	0.327111	0.260434	0.254953	0.229915	0.1
2416	0.487500	0.459590	0.454383	0.431111	0.367279	0.372954	0.333333	0.2
1626	0.442857	0.441496	0.427549	0.424889	0.402337	0.400517	0.391453	0.3
...	...	...	...	...	...	...	...	
1491	0.075000	0.154403	0.128801	0.176000	0.259599	0.355728	0.436752	0.4
192	0.219643	0.259349	0.299642	0.331556	0.333055	0.316968	0.302564	0.3
289	0.203571	0.137515	0.101968	0.042667	0.005008	0.005168	0.005128	0.0
174	0.289286	0.287093	0.296959	0.296889	0.297162	0.360896	0.468376	0.5
907	0.164286	0.144753	0.152952	0.152889	0.113523	0.122308	0.106838	0.1

491 rows × 2222 columns

Training Dataset

1. Support Vector Machine

In [38]:
```
pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\asnp2\anaconda
3\lib\site-packages (1.2.1)
Requirement already satisfied: scipy>=1.3.2 in c:\users\asnp2\anaconda
3\lib\site-packages (from scikit-learn) (1.10.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\asnp2\anacond
a3\lib\site-packages (from scikit-learn) (1.1.1)
Requirement already satisfied: numpy>=1.17.3 in c:\users\asnp2\anacond
a3\lib\site-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\asnp2
\anaconda3\lib\site-packages (from scikit-learn) (2.2.0)
Note: you may need to restart the kernel to use updated packages.

WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
```

In [39]:

```
# Import necessary libraries
# import numpy as np
# from sklearn import datasets
# from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score



svm_classifier = SVC(kernel='linear', C=1.0)
svm_classifier.fit(X_train, y_train)

y_pred = svm_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.6334012219959266
```

In [40]:

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

# Define the hyperparameter grid
param_grid = {
    'C': [0.1, 1,10],
    'kernel': ['poly', 'linear','rbf'],
    'gamma': ['auto'] + [0.001, 0.01, 0.1, 1], #scale
}

# Initialize the SVM classifier
base_model = SVC()

# Create a GridSearchCV object with cross-validation
grid_search = GridSearchCV(base_model, param_grid, cv=5, scoring='accur

# Fit the GridSearchCV to your data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)

# Get the best estimator (model)
best_model = grid_search.best_estimator_

# Predict with the best model
y_pred = best_model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy * 100))

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Best Hyperparameters: {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
Accuracy: 72.91%
Precision: 0.73
Recall: 0.73
F1 Score: 0.73
```

In [41]:

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix

# Train an SVM classifier
svm_classifier = SVC(kernel='linear')
svm_classifier.fit(X_train, y_train)

# Get a list of unique emotions in the dataset
unique_emotions = list(set(y_test))

# Create a dictionary to store accuracy for each emotion
emotion_accuracies = {}

for emotion in unique_emotions:
    # Make predictions on the testing set
    y_pred = best_model.predict(X_test)

    # Calculate accuracy for the current emotion
    emotion_indices = [i for i, e in enumerate(y_test) if e == emotion]
    true_positives = sum(1 for i in emotion_indices if y_pred[i] == emo
    false_negatives = len(emotion_indices) - true_positives

    accuracy = true_positives / (true_positives + false_negatives)

    # Store the accuracy in the dictionary
    emotion_accuracies[emotion] = accuracy

# Print accuracies for each emotion
for emotion, accuracy in emotion_accuracies.items():
    print(f'Accuracy for {emotion}: {accuracy:.2f}')
```

```
Accuracy for surprise: 0.57
Accuracy for sad: 0.67
Accuracy for fear: 0.73
Accuracy for disgust: 0.71
Accuracy for happy: 0.67
Accuracy for neutral: 0.82
Accuracy for angry: 0.81
```

In [42]:

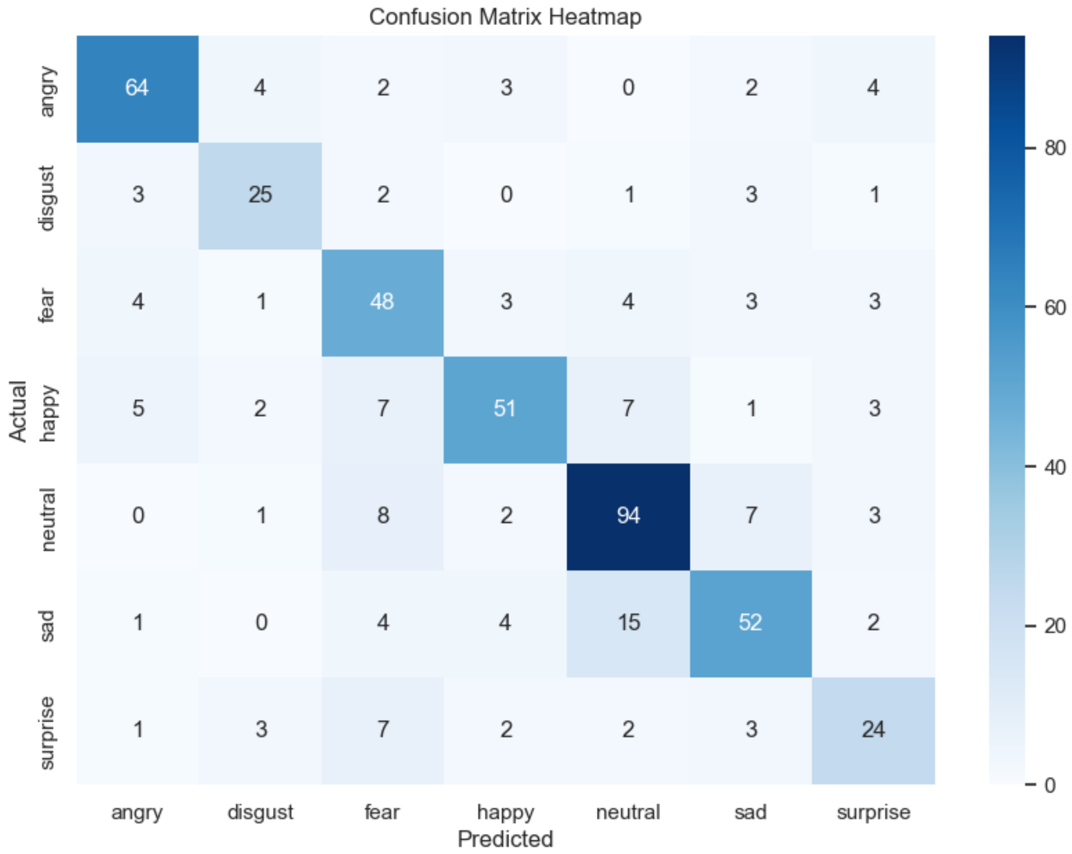
```
confusion = confusion_matrix(y_test, y_pred)

# Printing the confusion matrix
print("Confusion Matrix:")
print(confusion)
```

```
Confusion Matrix:
[[64  4  2  3  0  2  4]
 [ 3 25  2  0  1  3  1]
 [ 4  1 48  3  4  3  3]
 [ 5  2  7 51  7  1  3]
 [ 0  1  8  2 94  7  3]
 [ 1  0  4  4 15 52  2]
 [ 1  3  7  2  2  3 24]]
```

In [43]:
```
a,b=np.unique(y_pred,return_counts=True)
print (a)
print (b)
```

```
['angry' 'disgust' 'fear' 'happy' 'neutral' 'sad' 'surprise']
[ 78  36  78  65 123  71  40]
```

In [44]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Set the labels for the confusion matrix
labels = ['angry', 'disgust' ,'fear', 'happy', 'neutral' ,'sad' ,'surpr
# Create a heatmap
plt.figure(figsize=(10, 7))
sns.heatmap(confusion, annot=True, fmt='d', cmap='Blues', xticklabels=l

# Add labels and a title
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')

plt.show()
```



K - Nearest Neighbour

In [45]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

# Create a KNN classifier (specify the number of neighbors, e.g., 3)
knn_classifier = KNeighborsClassifier(n_neighbors=3)

# Train the KNN classifier on the training data
knn_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = knn_classifier.predict(X_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Accuracy: 0.5437881873727087
Precision: 0.57
Recall: 0.54
F1 Score: 0.53
```

Random Forest

In [46]:

```
# Import necessary libraries
# from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier
# from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Create a Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=4

# Train the Random Forest classifier on the training data
rf_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = rf_classifier.predict(X_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Accuracy: 0.5458248472505092
Precision: 0.56
Recall: 0.55
F1 Score: 0.53
```

Naive Bayes Classifier

In [47]:

```
from sklearn.naive_bayes import GaussianNB

# Create a Gaussian Naive Bayes classifier
naive_bayes_classifier = GaussianNB()

# Train the Naive Bayes classifier on the training data
naive_bayes_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = naive_bayes_classifier.predict(X_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Accuracy: 0.32179226069246436
Precision: 0.54
Recall: 0.32
F1 Score: 0.29
```

Decision Tree Classifier

In [48]:

```
from sklearn.tree import DecisionTreeClassifier

# Create a Decision Tree classifier
decision_tree_classifier = DecisionTreeClassifier(random_state=42)

# Train the Decision Tree classifier on the training data
decision_tree_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = decision_tree_classifier.predict(X_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Accuracy: 0.4093686354378819
Precision: 0.41
Recall: 0.41
F1 Score: 0.41
```

MLP Classifier

In [49]:
```
pip install tensorflow
```

```
Requirement already satisfied: tensorflow in c:\users\asnp2\anaconda3
\lib\site-packages (2.10.1)
Requirement already satisfied: six>=1.12.0 in c:\users\asnp2\anaconda3
\lib\site-packages (from tensorflow) (1.16.0)
Requirement already satisfied: protobuf<3.20,>=3.9.2 in c:\users\asnp2
\anaconda3\lib\site-packages (from tensorflow) (3.19.6)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\asnp2\anacon
da3\lib\site-packages (from tensorflow) (1.4.0)
Requirement already satisfied: h5py>=2.9.0 in c:\users\asnp2\anaconda3
\lib\site-packages (from tensorflow) (3.7.0)
Requirement already satisfied: wrapt>=1.11.0 in c:\users\asnp2\anacond
a3\lib\site-packages (from tensorflow) (1.14.1)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\asnp2\a
naconda3\lib\site-packages (from tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in c:\users\asnp2\anac
onda3\lib\site-packages (from tensorflow) (16.0.6)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\asnp2\anac
onda3\lib\site-packages (from tensorflow) (2.3.0)
Requirement already satisfied: tensorboard<2.11,>=2.10 in c:\users\asn
p2\anaconda3\lib\site-packages (from tensorflow) (2.10.1)
Requirement already satisfied: keras<2.11,>=2.10.0 in c:\users\asnp2\a
naconda3\lib\site-packages (from tensorflow) (2.10.0)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in c:\users\asnp2\a
naconda3\lib\site-packages (from tensorflow) (0.4.0)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
c:\users\asnp2\anaconda3\lib\site-packages (from tensorflow) (0.31.0)
Requirement already satisfied: flatbuffers>=2.0 in c:\users\asnp2\anac
onda3\lib\site-packages (from tensorflow) (23.5.26)
Requirement already satisfied: keras-preprocessing>=1.1.1 in c:\users
\asnp2\anaconda3\lib\site-packages (from tensorflow) (1.1.2)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\asnp2\ana
conda3\lib\site-packages (from tensorflow) (3.3.0)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\as
np2\anaconda3\lib\site-packages (from tensorflow) (4.4.0)
Requirement already satisfied: packaging in c:\users\asnp2\anaconda3\l
ib\site-packages (from tensorflow) (22.0)
Requirement already satisfied: numpy>=1.20 in c:\users\asnp2\anaconda3
\lib\site-packages (from tensorflow) (1.23.5)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\asnp2\a
naconda3\lib\site-packages (from tensorflow) (1.56.2)
Requirement already satisfied: setuptools in c:\users\asnp2\anaconda3
\lib\site-packages (from tensorflow) (65.6.3)
Requirement already satisfied: tensorflow-estimator<2.11,>=2.10.0 in
c:\users\asnp2\anaconda3\lib\site-packages (from tensorflow) (2.10.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\asnp2\ana
conda3\lib\site-packages (from tensorflow) (1.6.3)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\asnp2\an
aconda3\lib\site-packages (from astunparse>=1.6.0->tensorflow) (0.38.
4)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 i
n c:\users\asnp2\anaconda3\lib\site-packages (from tensorboard<2.11,>=
2.10->tensorflow) (0.6.1)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\asnp2\anaco
nda3\lib\site-packages (from tensorboard<2.11,>=2.10->tensorflow) (2.
2.2)
Requirement already satisfied: markdown>=2.6.8 in c:\users\asnp2\anaco
nda3\lib\site-packages (from tensorboard<2.11,>=2.10->tensorflow) (3.
4.1)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
c:\users\asnp2\anaconda3\lib\site-packages (from tensorboard<2.11,>=2.
10->tensorflow) (0.4.6)
```

```
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\asnp2\a
naconda3\lib\site-packages (from tensorboard<2.11,>=2.10->tensorflow)
(2.28.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in c:\users\asnp2
\anaconda3\lib\site-packages (from tensorboard<2.11,>=2.10->tensorflo
w) (2.22.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in c:\use
rs\asnp2\anaconda3\lib\site-packages (from tensorboard<2.11,>=2.10->te
nsorflow) (1.8.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in c:\users\asnp
2\anaconda3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard
<2.11,>=2.10->tensorflow) (5.3.1)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\users\asnp2
\anaconda3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<
2.11,>=2.10->tensorflow) (0.2.8)
Requirement already satisfied: urllib3<2.0 in c:\users\asnp2\anaconda3
\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.11,>=2.1
0->tensorflow) (1.26.14)
Requirement already satisfied: rsa<5,>=3.1.4 in c:\users\asnp2\anacond
a3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.11,>=
2.10->tensorflow) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in c:\users\as
np2\anaconda3\lib\site-packages (from google-auth-oauthlib<0.5,>=0.4.1
->tensorboard<2.11,>=2.10->tensorflow) (1.3.1)
Requirement already satisfied: idna<4,>=2.5 in c:\users\asnp2\anaconda
3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.11,>=2.10
->tensorflow) (3.4)
Requirement already satisfied: charset-normalizer<3,>=2 in c:\users\as
np2\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard
<2.11,>=2.10->tensorflow) (2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\asnp2\an
aconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.11,
>=2.10->tensorflow) (2023.7.22)
Requirement already satisfied: MarkupSafe>=2.1.1 in c:\users\asnp2\ana
conda3\lib\site-packages (from werkzeug>=1.0.1->tensorboard<2.11,>=2.1
0->tensorflow) (2.1.1)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in c:\users\asnp2
\anaconda3\lib\site-packages (from pyasn1-modules>=0.2.1->google-auth<
3,>=1.6.3->tensorboard<2.11,>=2.10->tensorflow) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in c:\users\asnp2\anaco
nda3\lib\site-packages (from requests-oauthlib>=0.7.0->google-auth-oau
thlib<0.5,>=0.4.1->tensorboard<2.11,>=2.10->tensorflow) (3.2.2)
Note: you may need to restart the kernel to use updated packages.
```

```
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\asnp2\anacon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -atplotlib (c:\users\asnp2\anac
onda3\lib\site-packages)
```

In [50]:

```
from sklearn.neural_network import MLPClassifier

#Initialise Multi Layer Perceptron Classifier
model = MLPClassifier(alpha = 0.01, batch_size = 256, epsilon = 1e-08,

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

#Calculate Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy*100))

# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1 Score: {:.2f}".format(f1))
```

```
Accuracy: 62.73%
Precision: 0.63
Recall: 0.63
F1 Score: 0.63
```

Testing recorded data

creating dataframe

In [51]:

```
import pandas as pd
import os
import glob

# Directory containing the WAV files
test_path = 'Dataset/Test_Dataset'

# Get a list of WAV files in the directory
wav_files = glob.glob(os.path.join(test_path, '*.wav'))

# Initialize an empty list to store file paths and emotions
data = []

# Iterate through the WAV files
for file_path in wav_files:
    file_name = os.path.basename(file_path)  # Get the file name
    emotion = file_name.split('_')[-1].split('.')[0]  # Extract the emo
    data.append({ 'Emotion': emotion, 'File_Path': file_path})

# Create a DataFrame from the collected data
test_df = pd.DataFrame(data)

# Display the DataFrame
print(test_df)
```

```
   Emotion                              File_Path
0    happy    Dataset/Test_Dataset\sara_happy.wav
1  neutral  Dataset/Test_Dataset\sara_neutral.wav
```

In [52]:

```
df = pd.DataFrame(test_df)

file_name = 'test_data.csv'

df.to_csv(file_name, index=False)
```

Extracting Features

In [53]:
```
data_df2 = pd.read_csv('test_data.csv')  # Replace with the path to you

X1 = []  # Initialize the feature matrix
Y1 = []  # Initialize the emotion label vector

for index, row in data_df2.iterrows():
    file_path2 = row['File_Path']  # Assuming 'File_path1' is the colum
    emotion_label2 = row['Emotion']  # Assuming 'Emotion' is the column

    # Extract features from the audio file
    features = get_features(file_path2)

    # Append the features to X and the label to Y
    X1.append(features)
    Y1.append(emotion_label2)
```

In [54]:
```
X1
```

Out[54]:
```
[array([ 0.05712891,  0.078125  ,  0.09912109, ...,  0.9903053 ,
        -2.02973127,  2.46071434]),
 array([  0.03222656,   0.05712891,   0.08203125, ...,  -6.19661379,
         -3.43672371, -12.5972538 ])]
```

In [55]:
```
Y1
```

Out[55]:
```
['happy', 'neutral']
```

Combining Features and Emotions

In [56]:
```
df3 = pd.DataFrame({'Emotions': Y1, 'Features': X1})
df3
```

Out[56]:

	Emotions	Features
0	happy	[0.05712890625, 0.078125, 0.09912109375, 0.088...
1	neutral	[0.0322265625, 0.05712890625, 0.08203125, 0.11...

In [57]:
```
# Find the maximum length of any array in the 'array_column'
max_length = df3['Features'].apply(lambda x: len(x)).max()

# Create new column names based on the maximum length
new_columns = [f'Feature_{i+1}' for i in range(max_length)]

# Split the arrays into different columns
for i in range(max_length):
    df3[new_columns[i]] = df3['Features'].apply(lambda x: x[i] if i < l

# Drop the original 'array_column' if you no longer need it
df3.drop(columns=['Features'], inplace=True)
```

In [58]:
```
df3
```

Out[58]:

	Emotions	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_
0	happy	0.057129	0.078125	0.099121	0.088379	0.084961	0.090332	0.0942
1	neutral	0.032227	0.057129	0.082031	0.111328	0.159668	0.212402	0.3232

2 rows × 2377 columns

In [59]:
```
df3['Feature_2223']
```

Out[59]:
```
0    -6.453092
1   -48.336262
Name: Feature_2223, dtype: float64
```

Checking NaN and Null values

In [60]:
```
null_mask = df3.isnull().any(axis=1)
null_rows = df3[null_mask]

print(null_rows)
```

```
Empty DataFrame
Columns: [Emotions, Feature_1, Feature_2, Feature_3, Feature_4, Featur
e_5, Feature_6, Feature_7, Feature_8, Feature_9, Feature_10, Feature_1
1, Feature_12, Feature_13, Feature_14, Feature_15, Feature_16, Feature
_17, Feature_18, Feature_19, Feature_20, Feature_21, Feature_22, Featu
re_23, Feature_24, Feature_25, Feature_26, Feature_27, Feature_28, Fea
ture_29, Feature_30, Feature_31, Feature_32, Feature_33, Feature_34, F
eature_35, Feature_36, Feature_37, Feature_38, Feature_39, Feature_40,
Feature_41, Feature_42, Feature_43, Feature_44, Feature_45, Feature_4
6, Feature_47, Feature_48, Feature_49, Feature_50, Feature_51, Feature
_52, Feature_53, Feature_54, Feature_55, Feature_56, Feature_57, Featu
re_58, Feature_59, Feature_60, Feature_61, Feature_62, Feature_63, Fea
ture_64, Feature_65, Feature_66, Feature_67, Feature_68, Feature_69, F
eature_70, Feature_71, Feature_72, Feature_73, Feature_74, Feature_75,
Feature_76, Feature_77, Feature_78, Feature_79, Feature_80, Feature_8
1, Feature_82, Feature_83, Feature_84, Feature_85, Feature_86, Feature
_87, Feature_88, Feature_89, Feature_90, Feature_91, Feature_92, Featu
re_93, Feature_94, Feature_95, Feature_96, Feature_97, Feature_98, Fea
ture_99, ...]
Index: []

[0 rows x 2377 columns]
```

In [61]:

```
import pandas as pd

# Assume df is your DataFrame
# Find the index of 'Feature_2223' column
start_col_index = df3.columns.get_loc('Feature_2223')

# Remove columns from 'Feature_2223' to the last column
columns_to_remove = df3.columns[start_col_index:]

# Drop columns from 'Feature_2223' to the last column
df3 = df3.drop(columns=columns_to_remove, axis=1)

# Now df contains columns up to 'Feature_2222', excluding columns from
print(df3)
```

```
  Emotions  Feature_1  Feature_2  Feature_3  Feature_4  Feature_5  Fea
ture_6  \
0    happy   0.057129   0.078125   0.099121   0.088379   0.084961   0.
090332
1  neutral   0.032227   0.057129   0.082031   0.111328   0.159668   0.
212402

   Feature_7  Feature_8  Feature_9  ...  Feature_2213  Feature_2214  \
0   0.094238   0.105469   0.102539  ...     -8.158518     -2.653066
1   0.323242   0.395996   0.403809  ...      5.422617    -19.505695

   Feature_2215  Feature_2216  Feature_2217  Feature_2218  Feature_221
9  \
0      -6.25986     -6.310815   -618.352905     36.361511     28.64255
5
1      -1.02990    -13.600679   -255.544266    145.685883    -21.28196
0

   Feature_2220  Feature_2221  Feature_2222
0     20.794819      5.751059     -3.076875
1    -23.968109    -37.248383      5.741776

[2 rows x 2223 columns]
```

In [62]:
```
null_mask = df3.isnull().any(axis=1)
null_rows = df3[null_mask]

print(null_rows)
```

```
Empty DataFrame
Columns: [Emotions, Feature_1, Feature_2, Feature_3, Feature_4, Featur
e_5, Feature_6, Feature_7, Feature_8, Feature_9, Feature_10, Feature_1
1, Feature_12, Feature_13, Feature_14, Feature_15, Feature_16, Feature
_17, Feature_18, Feature_19, Feature_20, Feature_21, Feature_22, Featu
re_23, Feature_24, Feature_25, Feature_26, Feature_27, Feature_28, Fea
ture_29, Feature_30, Feature_31, Feature_32, Feature_33, Feature_34, F
eature_35, Feature_36, Feature_37, Feature_38, Feature_39, Feature_40,
Feature_41, Feature_42, Feature_43, Feature_44, Feature_45, Feature_4
6, Feature_47, Feature_48, Feature_49, Feature_50, Feature_51, Feature
_52, Feature_53, Feature_54, Feature_55, Feature_56, Feature_57, Featu
re_58, Feature_59, Feature_60, Feature_61, Feature_62, Feature_63, Fea
ture_64, Feature_65, Feature_66, Feature_67, Feature_68, Feature_69, F
eature_70, Feature_71, Feature_72, Feature_73, Feature_74, Feature_75,
Feature_76, Feature_77, Feature_78, Feature_79, Feature_80, Feature_8
1, Feature_82, Feature_83, Feature_84, Feature_85, Feature_86, Feature
_87, Feature_88, Feature_89, Feature_90, Feature_91, Feature_92, Featu
re_93, Feature_94, Feature_95, Feature_96, Feature_97, Feature_98, Fea
ture_99, ...]
Index: []

[0 rows x 2223 columns]
```

In [63]:
```
duplicate = df3[df3.duplicated()]

print("Duplicate Rows :")
```

```
Duplicate Rows :
```

Splitting

In [64]:
```
# X1_test=scaled_df1.drop(labels='Emotions',axis=1)
# Y1_test=scaled_df1['Emotions']
```

In [65]:
```
X1_test=df3.drop(labels='Emotions',axis=1)
Y1_test=df3['Emotions']
```

In [66]:
```
X1_test
```

Out[66]:

	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feature
0	0.057129	0.078125	0.099121	0.088379	0.084961	0.090332	0.094238	0.1054
1	0.032227	0.057129	0.082031	0.111328	0.159668	0.212402	0.323242	0.3959

2 rows × 2222 columns

In [67]:
```
Y1_test
```

Out[67]:
```
0      happy
1    neutral
Name: Emotions, dtype: object
```

In [68]:
```
# Import necessary libraries
# import numpy as np
# from sklearn import datasets
# from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score


# Create an SVM classifier (SVC is for classification)
svm_classifier = SVC(kernel='linear', C=1.0)

# Train the SVM classifier on the training data
svm_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = svm_classifier.predict(X1_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(Y1_test, y_pred)
print("Accuracy:", accuracy)
```

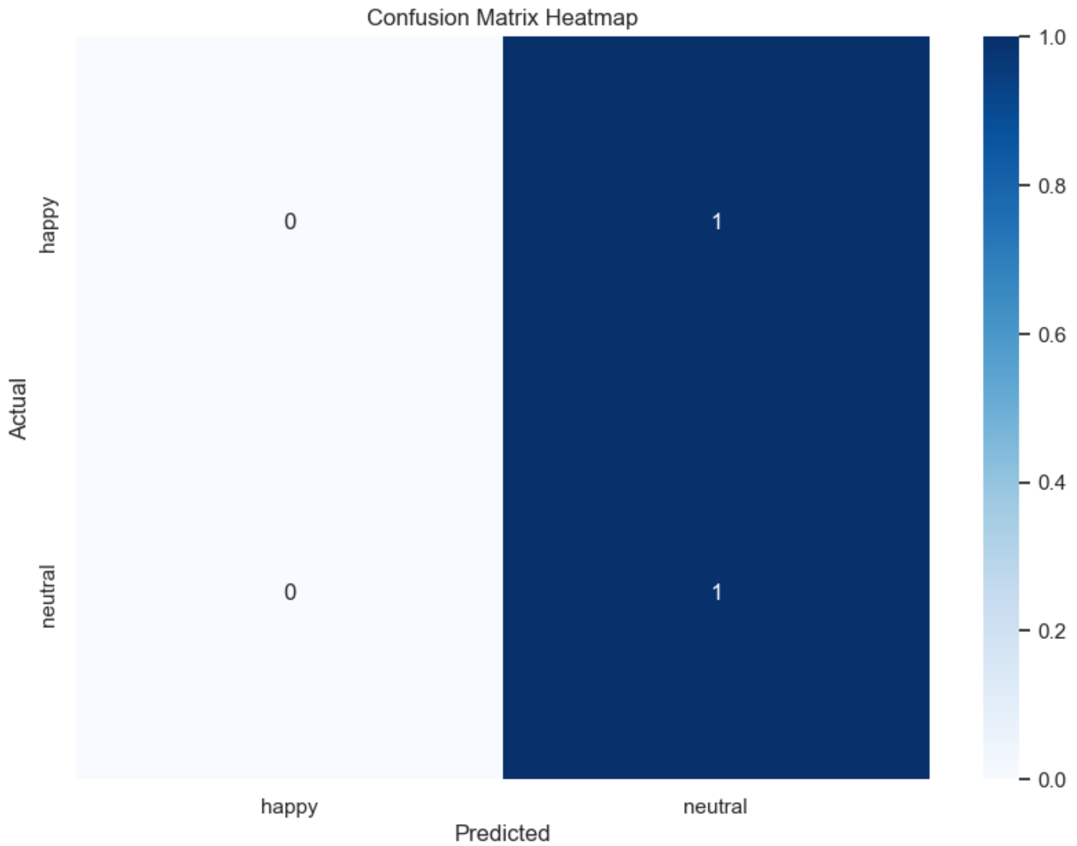
```
Accuracy: 0.5
```

In [69]:
```
confusion = confusion_matrix(Y1_test, y_pred)

# Printing the confusion matrix
print("Confusion Matrix:")
print(confusion)
```

```
Confusion Matrix:
[[0 1]
 [0 1]]
```

In [70]:

```
## import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Assuming you already have a confusion matrix (confusion)
# Replace this with your actual confusion matrix

# Set the labels for the confusion matrix
labels = ['happy', 'neutral']
# Create a heatmap
plt.figure(figsize=(10, 7))
sns.heatmap(confusion, annot=True, fmt='d', cmap='Blues', xticklabels=l

# Add labels and a title
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')

plt.show()
```



In [ ]: