MACHINE LEARNING FOR COMMUNICATION SYSTEMS

LAB REPORT

MEIC501P

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Task 1: Performance Analysis of Supervised and Unsupervised Learning

Part A: Performance Analysis of Supervised learning

```
#TASK 1(a) : PERFORMANCE ANALYSIS OF SUPERVISED LEARNING
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import pandas as pd
# pandas library is imported to do data manipulation and analysis. Making dataframes and changing it as per we want

import numpy as np
# to perform mathematical operations

import librosa
# python library for audio and music analysis. It extracts features from the audio files and process for further use in ML .

from glob import glob
# finds all the pathnames matching a specified pattern

audio_files =glob('Downloads\Actor_01/*.wav')
# collects all .wav extension file from Actor_01 folder from Downloads folder


from matplotlib import pyplot as plt
# Importing pyplot module from matplotlib library for plotting
```

```
lst = []
# creates an empty array to append the audio files

length=len(audio_files)
# finds the length Of the audio_files

for i in range (length):
    # the commands inside the for loop is to append the audio files to lst array
    y,sr = librosa.load(audio_files[i])
    # The librosa.load() function is used to load an audio file.
    #It returns two values:
    # 1.y, which is a NumPy array containing the audio time series
    # 2.sr, which is the sampling rate of the audio.
    lst.append(y.max()*1000)
    #y.max() computes the highest amplitude in the audio file.
lst.sort()
# sorts the lst in asencding order default. For reverse/descending order , use lst.sort(reverse=True)

df2=pd.DataFrame(lst)
# here the pandas library is called and used to make a dataframe of lst

df2.columns=["freq"]
# naming the column as freq

df2.to_csv("rec.csv")
# converting the dataframe to csv file and saving it as rec.csv file

print(df2)
# printing the dataframe
```

Output: Fig 1: Recorded frequency

	freq
0	22.052493
1	22.440949
2	26.036292
3	26.980430
4	28.652139
5	29.932763
6	31.419680
7	33.317581
8	35.650913
9	35.884488
10	36.971465
11	38.234800
12	39.725669
13	41.008729
14	41.546766
15	43.814741
16	44.969343
17	45.787793
18	47.185149
19	47.394369
20	50.119177
21	58.528956
22	58.665499
23	58.744207
24	60.015172
25	61.159208
26	61.836861
27	64.025983
28	66.383295
29	67.772545
30	70.323378
31	72.601795
32	75.142853
33	81.278026
33	81.278026
34	104.997635
35	107.536800
36	107.564509
37	112.748325
38	115.064815
39	116.749868
40	126.323208
41	126.476616
42	130.580217
43	142.322689
44	149.627343
45	166.032284
46	169.806391
47	175.272003
48	178.138345
49	178.688705
50	179.265440
51	202.122718
52	327.279150
53	485.229164
54	506.704867
55	510.604560
56	551.321268
57	579.006553
58	813.333809
59	989.103734

```
data=pd.read_csv("rec.csv")
#This is a function provided by Pandas to read a CSV (Comma Separated Values) file.

Range = data.freq
#assign all frequencies from rec.csv file to Range

y,sr = librosa.load("abnormal.wav")
#loading the abnormal.wav file

fre = y.max()*1000
#calculating frequency, that is from the all frequency, finding the max amplitude of the signal

y, sr = librosa.load(audio_files[0])

pd.Series(y).plot(figsize=(10, 5), lw=1, title='Test 1 - wave plot')

# Add a grid to the plot (note: this line should call the function with parentheses)
plt.grid()

# Display the plot
plt.show()

# Compute the Short-Time Fourier Transform (STFT) of the audio signal
D = librosa.stft(y)

# Convert the amplitude of the STFT to decibels
S_db = librosa.amplitude_to_db(np.abs(D), ref=np.max)

# Create a figure and axis for the plot
fig, ax = plt.subplots(figsize=(10, 5))

# Display the spectrogram with a logarithmic frequency axis
```

```
# Display the spectrogram with a logarithmic frequency axis
img = librosa.display.specshow(S_db, x_axis='time', y_axis='log', ax=ax)

# Set the title of the spectrogram plot
plt.title("spectrum")

# Display the spectrogram plot
plt.show()


print(" The given audiosfrequency is ",fre)
# printing the frequency of the uploaded 'abnormal.wav' file

if(fre>0 and fre<Range[30]):
  print("THE GIVEN SAMPLE IS CALM")
# here all the frequencies that we saved in rec.csv file is saved in Range, so comparing the value from the range of frequencies.

elif(fre>Range[30] and fre<Range[50]):
 print("THE GIVEN SAMPLE IS NORMAL")
# if the fre is greater than 30 and less than 50 ,then the audio signal is Normal.

elif(fre>Range[50]):
 print("THE GIVEN SAMPLE IS ABNORMAL")
# if the fre is greater than 50 then the audio signal is Abnormal.
```

PLOTS:

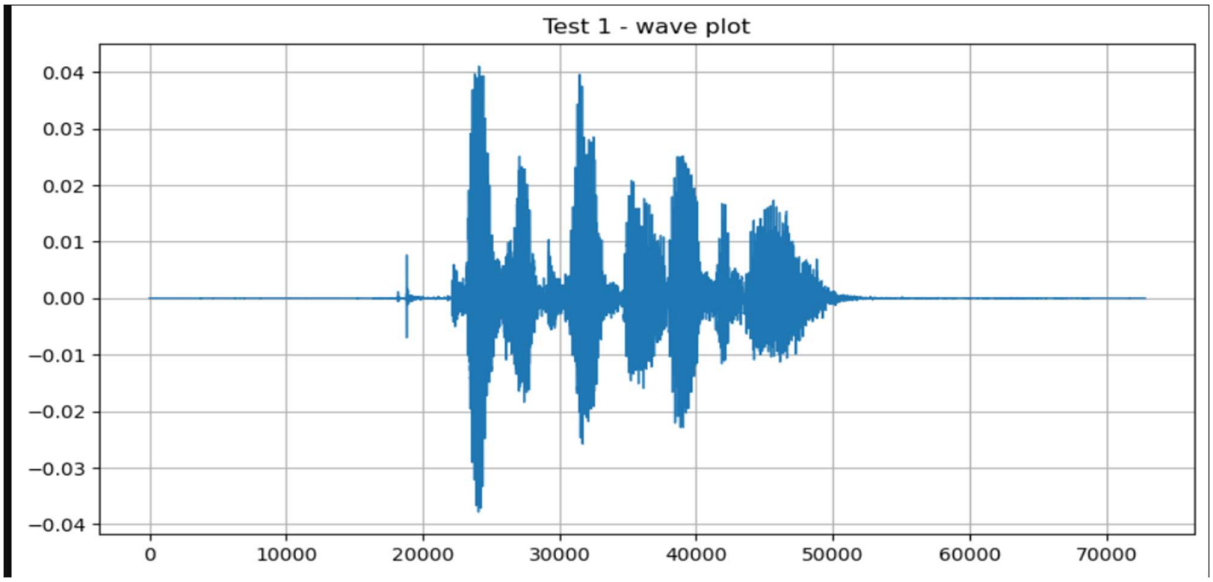

Fig 2: Test signal: “Abnormal” - Wave plot and its Spectrum

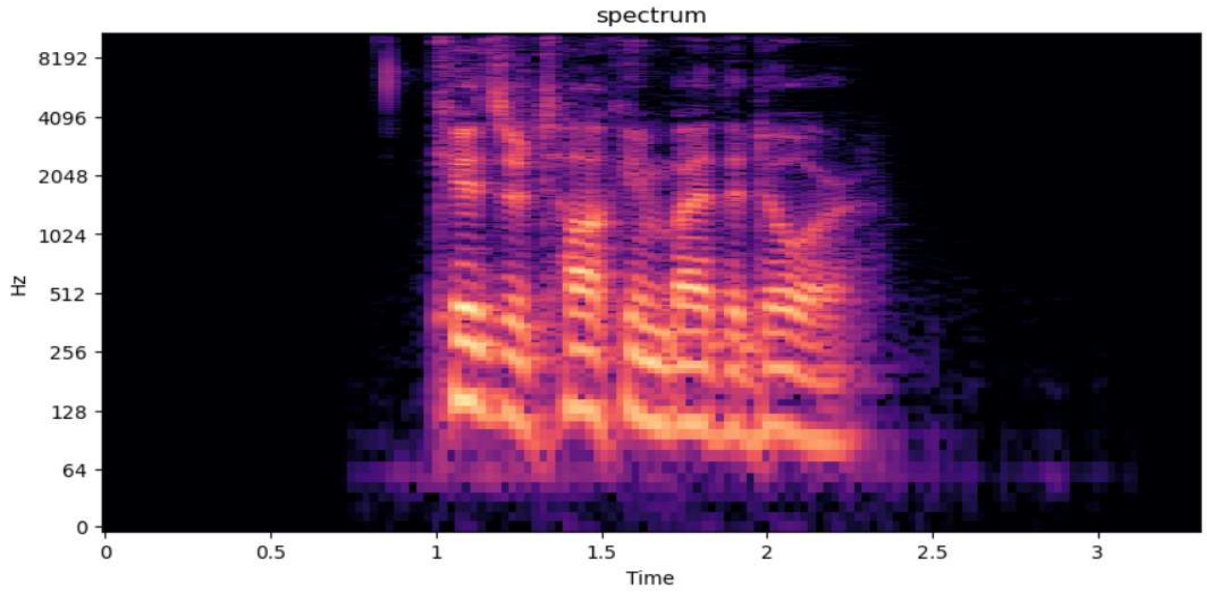

Fig 3: The spectrum of the signal or waveform

Output:

```
 The given audiosfrequency is  241.27447605133057
THE GIVEN SAMPLE IS ABNORMAL
```

Inference:

Feature Extraction:

- For each audio file, librosa.load is used to load the audio data and sampling rate .
- The maximum amplitude of the audio signal is extracted and multiplied by 1000 for scaling.
- These scaled maximum amplitude values are appended to a list.

Data Sorting and Storage:

- The list of maximum amplitudes is sorted.
- A Data Frame is created from the sorted list and labeled with the column name Freq.
- This Data Frame is saved to a CSV file named rec.csv.

Labelling:

- Audio samples are labelled as "Calm," "Normal," or "Abnormal" based on amplitude ranges, creating target variables for supervised learning.

Classification:

- The provided audio sample (abnormal.wav) is classified by comparing its maximum amplitude to the stored ranges, simulating how a supervised model makes predictionsThe resulting Data Frame is printed.

Task 1b: Performance Analysis of Unsupervised Learning

```python
#TASK 1(b) : PERFORMANCE ANALYSIS OF UNSUPERVISED LEARNING
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#MEIC501P

import pandas as pd
# Importing the pandas library for data manipulation and analysis

import librosa
# Importing the librosa library for audio and music processing

import numpy as np
# Importing the numpy library for numerical operations on arrays

from sklearn.cluster import KMeans
# Importing the KMeans clustering algorithm from scikit-learn library

from sklearn.preprocessing import StandardScaler
# Importing StandardScaler for feature scaling from scikit-learn library

from matplotlib import pyplot as plt
# Importing pyplot module from matplotlib library for plotting

from glob import glob
# Importing glob module to find all pathnames matching a specified pattern

import warnings
# Importing warnings library to manage warnings
```

```python
warnings.filterwarnings("ignore")
# Ignores all warnings to prevent them from being displayed

audio_files =glob('Downloads\Actor_01/*.wav')
# Finds all .wav audio files in the specified directory using glob

mfccs = []
# Initializes an empty list to store MFCC (Mel-frequency cepstral coefficients) features

spectral_centroid =[]
# Initializes an empty list to store spectral centroid features

l=len(audio_files)
```

```
mfccs = []
spectral_centroid = []

# Iterate over the range of audio files
for i in range(1):
    # Load the audio file and its sample rate
    animal, sr = librosa.load(audio_files[i])
    # Extract MFCC features with 20 coefficients
    mfccs_anim = librosa.feature.mfcc(y=animal, sr=sr, n_mfcc=20)
    # Extract spectral centroid features
    spectral_centroids_anims = librosa.feature.spectral_centroid(y=animal, sr=sr)
    # Append the maximum value of the 10th MFCC coefficient to the list
    mfccs.append(max(mfccs_anim[9]))
    # Append the maximum spectral centroid value to the list
    spectral_centroid.append(max(max(spectral_centroids_anims)))

# Create a DataFrame with MFCC and spectral centroid values
df = pd.DataFrame()
df['mfcc'] = mfccs
df['spectral'] = spectral_centroid

# Generate descriptive statistics for the DataFrame
stats_summary = df.describe()

# Standardize the MFCC and spectral centroid values
scaler = StandardScaler()
df[['mfcc_t', 'spectral_t']] = scaler.fit_transform(df[['mfcc', 'spectral']])

# Apply KMeans clustering with 2 clusters
KM = KMeans(n_clusters=2)
y_predict = KM.fit_predict(df[['mfcc', 'spectral']])
```

```
df['cluster'] = y_predict

# Print the DataFrame with the cluster labels
print(df)

# Plot the standardized MFCC vs. spectral centroid with cluster coloring
plt.scatter(df['mfcc_t'], df['spectral_t'], c=df['cluster'])
#This line plots the standardized MFCC values (df['mfcc_t']) against the standardized spectral centroid values (df['spectral_t']).
#The c=df['cluster'] argument uses the cluster labels generated by the KMeans algorithm to color the points.
#Each unique value in df['cluster'] will be assigned a different color.
plt.grid()
plt.xlabel('MFCC')
plt.ylabel('SPECTRAL_CENTROID')
plt.title("CLUSTER PLOT")
plt.show()

# Generate descriptive statistics again (if needed for later use)
stats_summary = df.describe()


# Create a dictionary to store the summary statistics
summary_stats = {
    'mean': stats_summary.loc['mean', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    'std': stats_summary.loc['std', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    'min': stats_summary.loc['min', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    '25%': stats_summary.loc['25%', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    '50%': stats_summary.loc['50%', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    '75%': stats_summary.loc['75%', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']],
    'max': stats_summary.loc['max', ['mfcc', 'spectral', 'mfcc_t', 'spectral_t', 'cluster']]
}

# Convert the dictionary to a DataFrame
summary_df = pd.DataFrame(summary_stats)
```

```
# Print the summary DataFrame
print(summary_df)
```

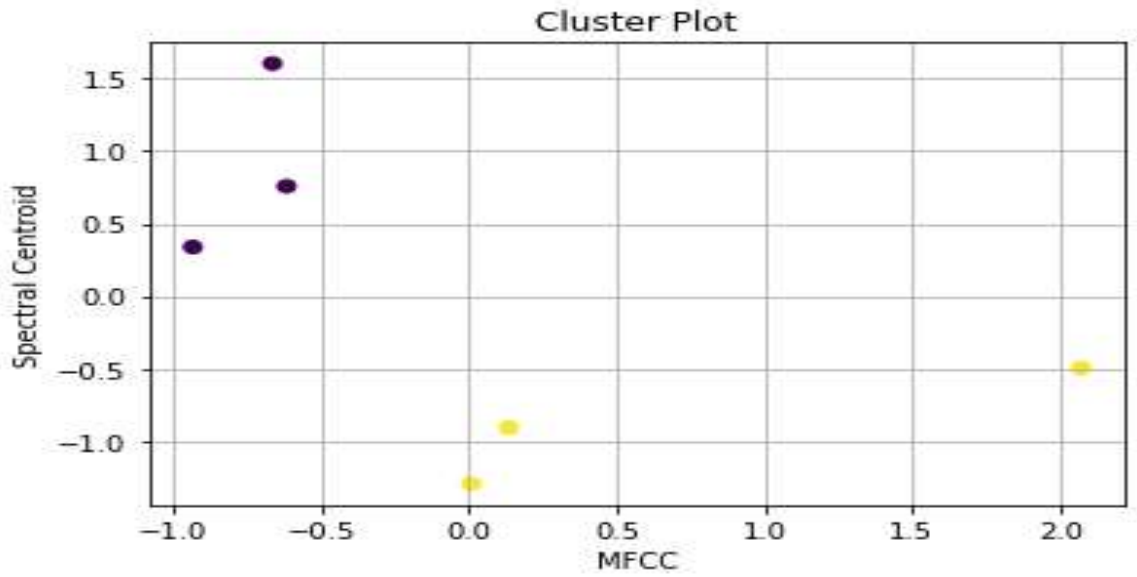
```
:
  # Compute MFCC (Mel-frequency cepstral coefficients) from the audio signal
  mfc = librosa.feature.mfcc(y=y, sr=sr)

  # Create a new figure for the plot with specified figure size
  plt.figure(figsize=(10, 4))

  # Display the MFCC spectrogram with time on the x-axis
  librosa.display.specshow(mfc, x_axis='time')

  # Add a colorbar to the plot with formatting for the decibel scale
  plt.colorbar(format='%+2.0f dB')

  # Set the title of the plot to 'MFCCs'
  plt.title('MFCCs')

  # Display the plot
  plt.show()
```

Output:

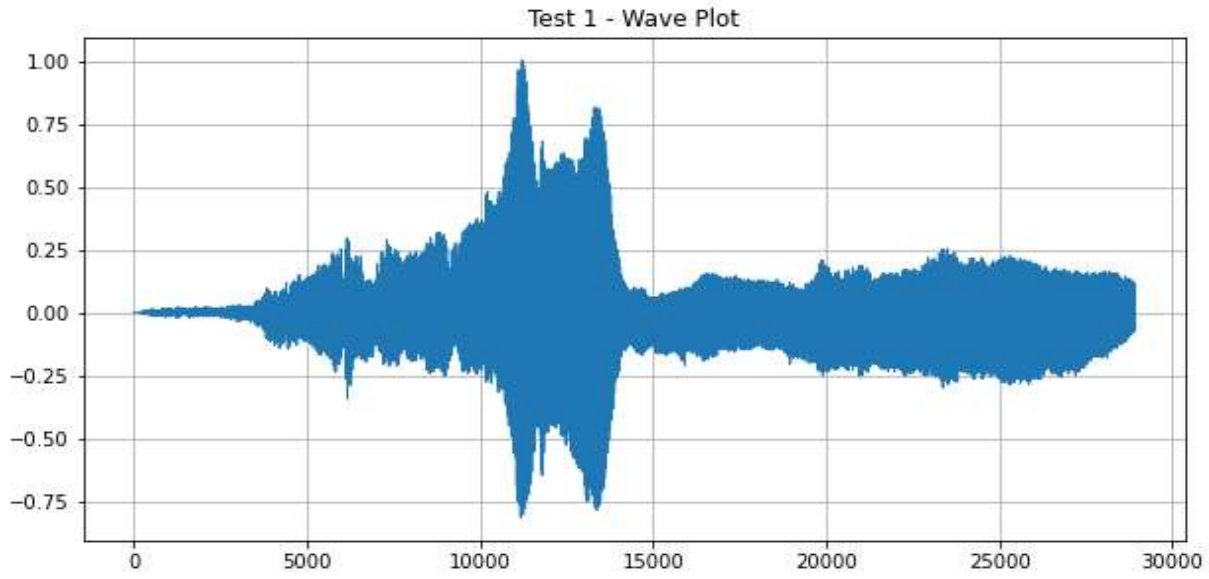
MFCC, Spectral, MFCC transform, Spectral Transform, Mean and Variance:

	mfcc	spectral	mfcc_t	spectral_t	cluster
0	68.688110	2410.670365	2.071106	-0.496861	1
1	33.581944	2185.434301	0.134933	-0.907513	1
2	31.278986	1973.660512	0.007921	-1.293619	1
3	19.093607	3562.220285	-0.664126	1.602649	0
4	19.957205	3098.451969	-0.616497	0.757105	0
5	14.212361	2868.710377	-0.933336	0.338239	0
	mfcc	spectral	mfcc_t	spectral_t	cluster
mean	31.135368	2683.191301	0.000000	-4.163336e-16	0.500000
std	19.862318	600.835141	1.095445	1.095445e+00	0.547723
min	14.212361	1973.660512	-0.933336	-1.293619e+00	0.000000
25%	19.309506	2241.743317	-0.652219	-8.048498e-01	0.000000
50%	25.618095	2639.690371	-0.304288	-7.931108e-02	0.500000
75%	33.006204	3041.016571	0.103180	6.523885e-01	1.000000
max	68.688110	3562.220285	2.071106	1.602649e+00	1.000000

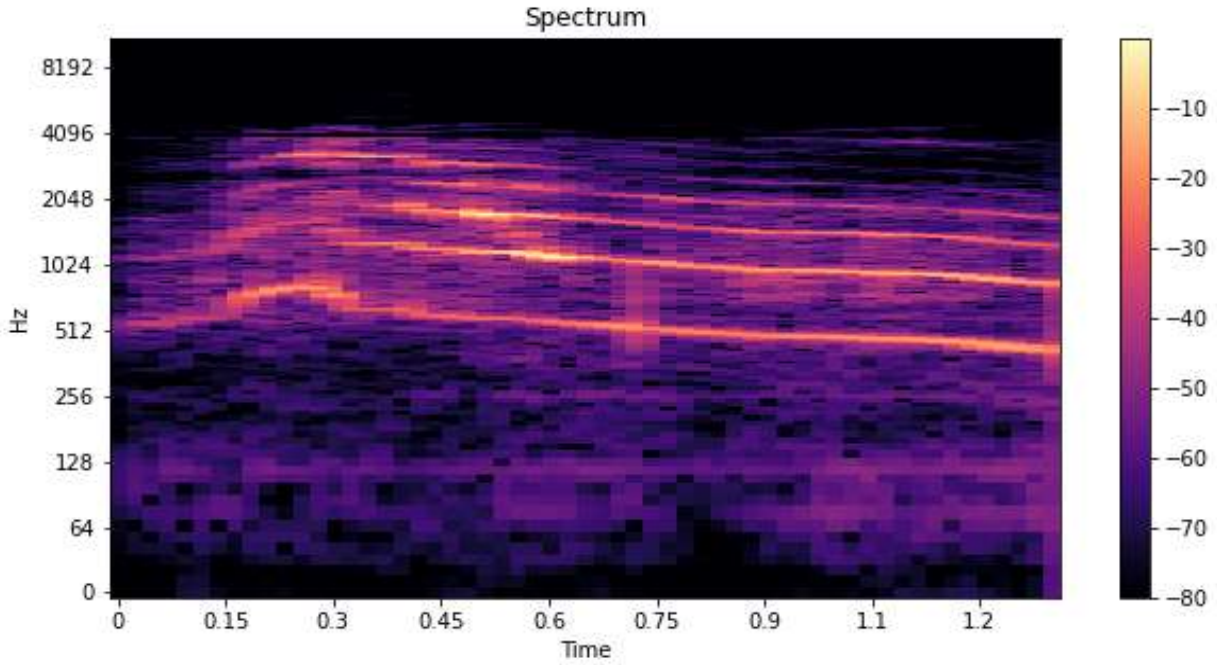
PLOTS:



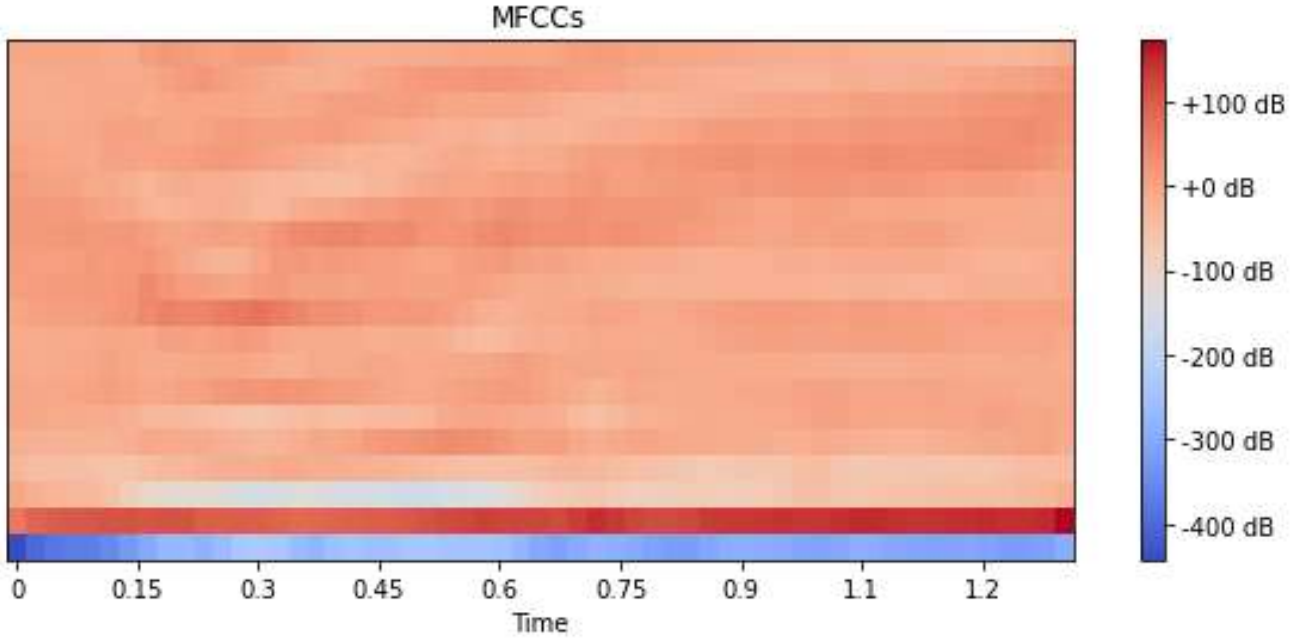
Plot: a: Cluster Plot



b: Wave plot



C: Spectrum



d: MFCC spectrum

Inferences

Frequency Classification:

- The maximum amplitude of the abnormal.wav file is calculated and compared against the frequency range from rec.csv.
- The audio sample is classified as "CALM", "NORMAL", or "ABNORMAL" based on predefined thresholds.

Feature Extraction and Clustering:

- MFCC and spectral centroid features are extracted from each audio file.
- The data is normalized and clustered using K Means.

The clustering results and feature distributions are visualized, indicating potential patterns or

Extract Features:

- For each audio file, extract MFCCs and spectral centroids using `librosa`.
- Store the maximum values of these features in lists.

Create Data Frame:

- Create a Data Frame with the extracted features.
- Normalize the features using `StandardScaler`.
- Apply K Means clustering with 2 clusters and store the cluster labels.

Plot Clusters:

- Plot the clustered data.

Calculate Statistics:

- Calculate and display various statistics (mean, std, min, max, etc.) for the features and clusters.

Plot Waveform, Spectrogram, and MFCCs:

- Plot the waveform, spectrogram, and MFCCs for the first audio file.

- groupings in the data.

Task 1c: Supervised Learning - Analysing Support Vector Machine working

```python
import numpy as np  # Linear algebra operations
import pandas as pd  # Data processing and CSV file I/O
import os  # Operating system interface
import shutil  # High-level file operations
import matplotlib.pyplot as plt  # Plotting and visualization
import librosa  # Audio processing library
import librosa.display  # Visualization utilities for librosa
import IPython.display as ipd  # Display utilities for IPython

import soundfile as sf  # Reading and writing sound files
import tensorflow as tf  # TensorFlow library for machine learning
from sklearn.model_selection import train_test_split  # Splitting data into training and test sets
from sklearn.preprocessing import LabelEncoder, StandardScaler  # Encoding labels and standardizing features
from sklearn.svm import SVC  # Support Vector Classifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix  # Evaluation metrics
import seaborn as sns  # Data visualization library

# Output directory to clear
output_dir = "op"

# Clear the contents of the output directory if it exists, and recreate it
shutil.rmtree(output_dir, ignore_errors=True)
os.makedirs(output_dir, exist_ok=True)

print(f"Contents of {output_dir} cleared.")

# Path to the dataset
dataset_path = "16000_pcm_speeches"

# Output directory to save the combined files
output_dir = "op"

# Create the output directory if it doesn't exist
os.makedirs(output_dir, exist_ok=True)

# List of speaker folders
speaker_folders = [
    "Benjamin_Netanyau",
    "Jens_Stoltenberg",
    "Julia_Gillard",
    "Magaret_Tarcher",
    "Nelson_Mandela"
]
```

```python
# Number of files to combine for each speaker
num_files_to_combine = 120

# Iterate over each speaker's folder
for speaker_folder in speaker_folders:
    # Construct the path to the speaker's folder
    speaker_folder_path = os.path.join(dataset_path, speaker_folder)

    # List the first num_files_to_combine WAV files in the speaker's folder
    wav_files = [f"{i}.wav" for i in range(num_files_to_combine)]

    # Combine all WAV files into a single long file
    combined_audio = []
    for wav_file in wav_files:
        # Construct the path to the current WAV file
        wav_file_path = os.path.join(speaker_folder_path, wav_file)
        # Load the audio file
        audio, sr = librosa.load(wav_file_path, sr=None)
        # Append the audio data to the combined audio list
        combined_audio.extend(audio)

    # Save the combined audio file
    output_file_path = os.path.join(output_dir, f"{speaker_folder}_combined.wav")
    sf.write(output_file_path, combined_audio, sr)

print("Combination complete. Combined files saved in:", output_dir)
```

```python
# Set the parent directory for speaker folders
parent_dir = "16000_pcm_speeches"

# List of speaker folders
speaker_folders = [
    "Benjamin_Netanyau",
    "Jens_Stoltenberg",
    "Julia_Gillard",
    "Magaret_Tarcher",
    "Nelson_Mandela"
]

def extract_features(parent_dir, speaker_folders):
    features = []
    labels = []

    for i, speaker_folder in enumerate(speaker_folders):
        # Construct the path to the speaker's folder
        speaker_folder_path = os.path.join(parent_dir, speaker_folder)

        for filename in os.listdir(speaker_folder_path):
            if filename.endswith(".wav"):
                # Construct the path to the current WAV file
                file_path = os.path.join(speaker_folder_path, filename)
                # Load the audio file
                audio, sr = librosa.load(file_path, sr=None, duration=1)
                # Extract MFCC features from the audio file
                mfccs = librosa.feature.mfcc(y=audio, sr=sr, n_mfcc=13)

                # Normalize MFCC features
                mfccs = StandardScaler().fit_transform(mfccs)
                # Append the normalized MFCC features to the features list
                features.append(mfccs.T)
                # Append the label (index of the speaker folder) to the labels list
                labels.append(i)

    return np.array(features), np.array(labels)

# Extract features and labels from the dataset
X, y = extract_features(parent_dir, speaker_folders)

# Print the first few features
for feature in X[:1]:
    print(feature)
```

```
# Encode labels with explicit classes
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
label_encoder.classes_ = np.array(speaker_folders)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Print the shapes of training and test data
print("Training Data Shape:", X_train.shape)
print("Test Data Shape:", X_test.shape)

# Flatten the input data for the SVM classifier
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)

# Initialize and train the SVM classifier
svm_classifier = SVC(kernel='rbf', C=1.0, gamma='scale')
svm_classifier.fit(X_train_flat, y_train)

# Make predictions on the test set
y_pred = svm_classifier.predict(X_test_flat)

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

# Compute the confusion matrix
confusion_mat = confusion_matrix(y_test, y_pred)

# Generate a classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:")
print(class_report)

# Plot the confusion matrix
plt.figure(figsize=(7, 5))
sns.heatmap(confusion_mat, annot=True, fmt="d", cmap="Blues", xticklabels=speaker_folders, yticklabels=speaker_folders)

# Rotate x-axis labels by 45 degrees
plt.xticks(rotation=45, ha="right")

plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

Output:

Output of the features

```
[[-3.46410155e+00  2.88717210e-01  2.88714826e-01  2.88710833e-01
   2.88705289e-01  2.88698137e-01  2.88689405e-01  2.88679123e-01
   2.88667232e-01  2.88653851e-01  2.88638890e-01  2.88622409e-01
   2.88604409e-01]
 [-3.46410155e+00  2.88697690e-01  2.88696378e-01  2.88694263e-01
   2.88691312e-01  2.88687497e-01  2.88682818e-01  2.88677305e-01
   2.88670957e-01  2.88663775e-01  2.88655698e-01  2.88646817e-01
   2.88637102e-01]
 [-3.46410179e+00  2.88694620e-01  2.88693517e-01  2.88691700e-01
   2.88689107e-01  2.88685828e-01  2.88681775e-01  2.88677037e-01
   2.88671494e-01  2.88665295e-01  2.88658351e-01  2.88650692e-01
   2.88642257e-01]
 [-3.41496515e+00  4.01689023e-01 -5.24658784e-02  6.99484289e-01
   2.78740376e-01  2.13533744e-01  3.30969393e-01  3.79182965e-01
   6.90628365e-02  2.89402425e-01  2.54391849e-01  3.14149350e-01
   2.36824706e-01]
 [-3.32731915e+00  5.34021258e-01 -3.14830184e-01  9.45635557e-01
   3.05575788e-01  2.24249974e-01  2.92698741e-01  3.76336753e-01
  -1.32886805e-02  3.65403891e-01  2.44651034e-01  2.79899329e-01
   8.69657174e-02]
 [-3.23038697e+00  8.90019298e-01 -3.46914947e-01  1.10863638e+00
   2.96282619e-01  2.35278338e-01  9.70718488e-02  2.90819615e-01
  -4.99448590e-02  3.50138187e-01  1.68837532e-01  1.79412916e-01
   1.07501615e-02]
 [-3.16701508e+00  1.22869194e+00 -2.03374133e-01  1.05991554e+00
   2.82521576e-01  2.85676718e-01  1.37484465e-02  3.10726494e-01
  -1.95084754e-02  1.77726954e-01  3.78287919e-02  4.10158709e-02
  -4.79545370e-02]
 [-3.17857456e+00  1.26100934e+00 -1.13383844e-01  9.87116039e-01
   2.86108345e-01  3.20463330e-01  1.30498549e-02  2.98770070e-01
  -7.00799108e-04  1.64008319e-01  5.48957661e-02  2.79900339e-02
  -1.20752044e-01]
 [-3.21629834e+00  1.11208773e+00 -9.15348902e-02  9.55695570e-01
   3.06024373e-01  4.73935425e-01 -5.80192916e-02  2.68428385e-01
  -1.05882689e-01  2.81351179e-01  5.61841577e-02  7.82225057e-02
  -6.01940714e-02]
```

Output of the test accuracy, classification report and average:

```
  7.22828155e-02]]
Training Data Shape: (6000, 32, 13)
Test Data Shape: (1501, 32, 13)
Test Accuracy: 0.9713524317121919
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.98      0.95       310
           1       0.98      0.91      0.94       310
           2       0.99      0.99      0.99       283
           3       0.99      0.98      0.98       283
           4       1.00      1.00      1.00       315

    accuracy                           0.97      1501
   macro avg       0.97      0.97      0.97      1501
weighted avg       0.97      0.97      0.97      1501
```

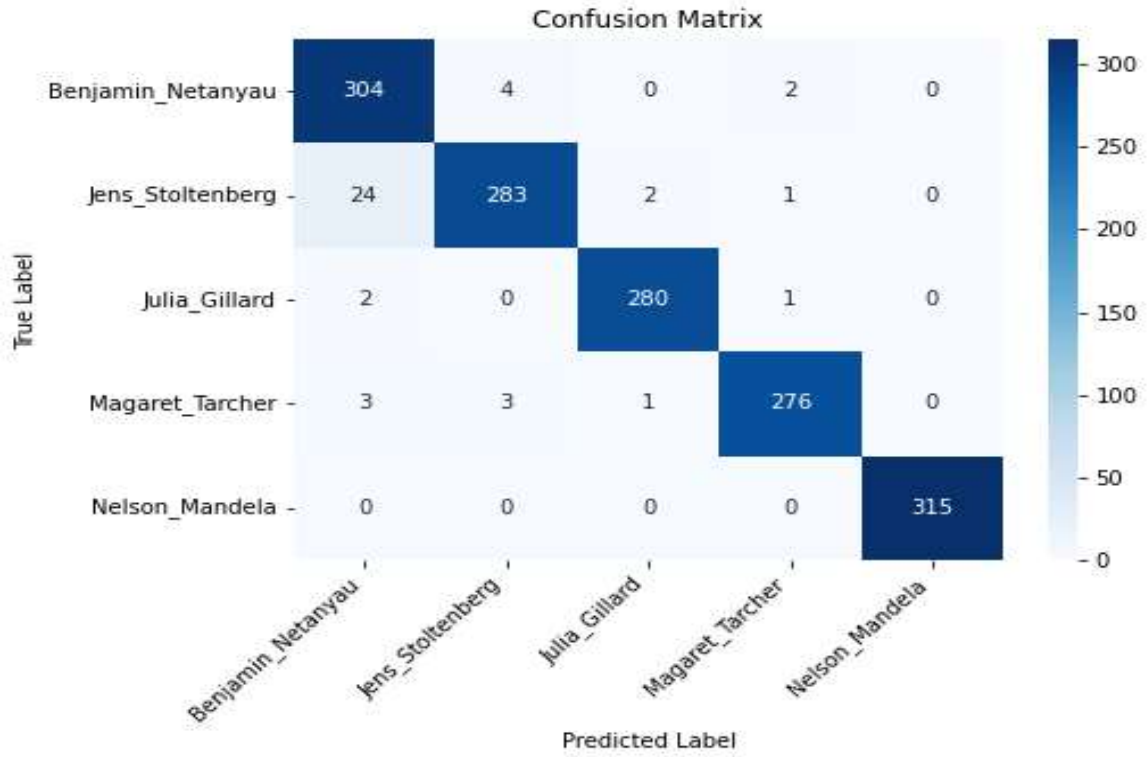


Fig 5: Output showing the graph of the confusion matrix

Inference:

Feature Extraction:

- This code uses the librosa library to extract features from audio files, specifically focusing on MFCC (Mel-Frequency Cepstral Coefficients) features. These MFCCs are crucial for capturing the unique characteristics of the audio signals.

Data Preparation:

- The extracted MFCC features are collected in lists and then converted into a NumPy array. This structured data is split into training and testing sets using train_test_split, ensuring that the model is trained and evaluated on different subsets of data.

Label Encoding:

- The labels representing different speakers are transformed into numerical format using Label Encoder. This conversion is necessary for the machine learning model to process and understand the categorical data.

Data Flattening:

- The input data is reshaped into a 2D array where each row represents a sample with its corresponding features. This format is required by the SVM classifier.

SVM Classification:

- An SVM (Support Vector Machine) classifier is initialized and trained using the training data. The training process involves finding the optimal hyperplane that separates the classes (different speakers) in the feature space.

Prediction and Evaluation:

- The trained SVM model makes predictions on the test set. The model's performance is evaluated using various metrics:
- Accuracy Score: Measures the proportion of correctly classified samples.
- Classification Report: Provides detailed metrics such as precision, recall, and F1-score for each class.
- Confusion Matrix: Shows the number of correct and incorrect predictions for each class, offering deeper insights into the model's performance.

Visualization:

- A heatmap of the confusion matrix is created to visualize the classifier's performance. The heatmap illustrates the true labels on the y-axis and the predicted labels on the x-axis, with color intensity indicating the number of samples in each category