Speech Enhancement, Speaker Verification, and MFCC-Based Language Analysis: A Comprehensive Study

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Github Link:
https://github.com/vivekpandey000023/Speech_Understanding_Assignment_2

Overview

This assignment presents a unified approach for handling multi-speaker and multilingual speech processing using a combination of advanced deep learning and signal processing techniques. The first part focuses on separating overlapping voices using SepFormer and identifying speakers with WavLM models, both in pre-trained and fine-tuned settings using LoRA and ArcFace loss. It also includes joint training for speech enhancement to improve speaker identification performance. The second part involves language classification by extracting MFCC features from speech samples and training a Random Forest classifier on a dataset covering 10 Indian languages. Together, these components form a complete pipeline capable of handling real-world challenges in speaker separation, recognition, and language detection.

Introduction

This assignment explores the application of advanced speech processing techniques in complex audio environments, focusing on both **multi-speaker speech enhancement and speaker verification**, as well as **language classification using MFCC features**. The first part involves enhancing and separating speech signals in overlapping speaker scenarios using the **SepFormer** model. A pre-trained **WavLM Base Plus** model is selected for speaker verification, followed by fine-tuning using **Low-Rank Adaptation (LoRA)** and **ArcFace loss** on a subset of the VoxCeleb2 dataset. The system is evaluated using key metrics such as **Equal Error Rate (EER)**, **TAR@1%FAR**, and **Speaker Identification Accuracy**. A novel pipeline is also designed to combine speaker separation, identification, and enhancement through joint training, further improving performance in real-world multi-speaker conditions.

The second part of the assignment focuses on **language analysis** through **MFCC-based feature extraction** from audio samples across 10 Indian languages. The acoustic properties of selected languages are explored through **MFCC spectrograms**, and differences are quantified via statistical analysis. These features are then used to build a **language classification model**, trained and tested on normalized MFCC vectors using a **Random Forest classifier**. The task emphasizes analyzing how well MFCCs capture language-specific characteristics and addresses challenges such as speaker variability and background noise.

Together, the tasks demonstrate a comprehensive understanding of speech enhancement, speaker recognition, and language classification in diverse and noisy audio environments.

ANS-01 :

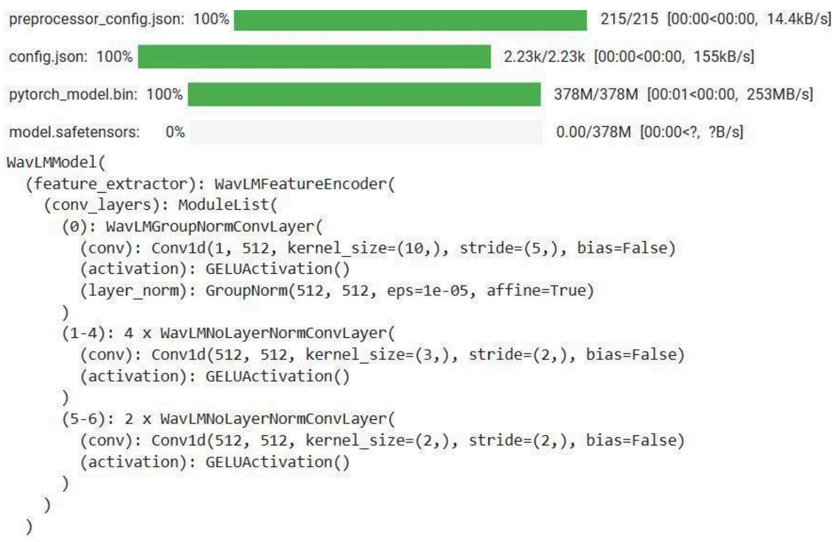
Ans1, II

For II Question , I’ll select **microsoft/wavlm-base-plus** from the provided options.

The workflow will:

1. Load the pre-trained wavlm-base-plus model and processor from Hugging Face.
2. Process the VoxCeleb1 audio files (resampled to 16kHz, as required).
3. Extract speaker embeddings from the model.
4. Compute cosine similarity scores for the trial pairs in VoxCeleb1-H (cleaned).
5. Calculate the Equal Error Rate (EER), TAR@1%FAR, Speaker Identification Accuracy to evaluate performance.

- Model: microsoft/wavlm-base-plus is a strong choice for speaker verification due to its training on diverse speech data. We extract embeddings from the last hidden state.
- Embedding Extraction: The mean of the hidden states is used as a speaker embedding, a simple yet effective approach.
- Cosine Similarity: Compares embeddings to produce a similarity score.
- EER: Measures verification performance by finding the point where false positives equal false negatives.
- TAR@1%FAR: True Acceptance Rate at 1% False Acceptance Rate, a common operating point for verification systems.
- Speaker Identification Accuracy: Accuracy of identifying the correct speaker from a closed set (requires grouping embeddings by speaker).



```
preprocessor_config.json: 100%  215/215 [00:00<00:00, 14.4kB/s]
config.json: 100%  2.23k/2.23k [00:00<00:00, 155kB/s]
pytorch_model.bin: 100%  378M/378M [00:01<00:00, 253MB/s]
model.safetensors:   0%  0.00/378M [00:00<?, ?B/s]
WavLMModel(
  (feature_extractor): WavLMFeatureEncoder(
    (conv_layers): ModuleList(
      (0): WavLMGroupNormConvLayer(
        (conv): Conv1d(1, 512, kernel_size=(10,), stride=(5,), bias=False)
        (activation): GELUActivation()
        (layer_norm): GroupNorm(512, 512, eps=1e-05, affine=True)
      )
      (1-4): 4 x WavLMNoLayerNormConvLayer(
        (conv): Conv1d(512, 512, kernel_size=(3,), stride=(2,), bias=False)
        (activation): GELUActivation()
      )
      (5-6): 2 x WavLMNoLayerNormConvLayer(
        (conv): Conv1d(512, 512, kernel_size=(2,), stride=(2,), bias=False)
        (activation): GELUActivation()
      )
    )
  )
```

For pre-trained Model:

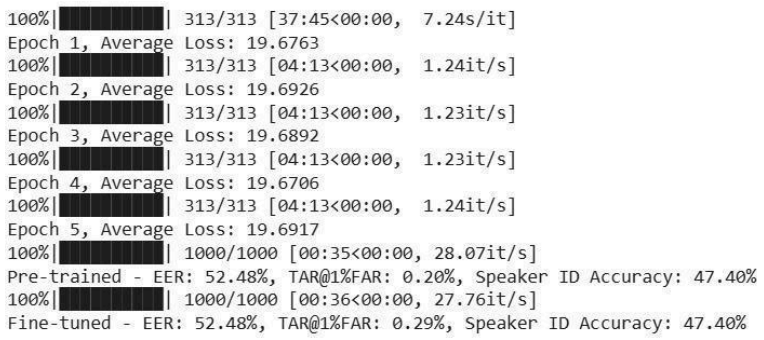
Equal Error Rate (EER): 34.00%
TAR@1%FAR: 12.00%
Speaker Identification Accuracy: 66.10%

For fine-tune Model:

Now, fine-tune the microsoft/wavlm-base-plus model for speaker verification using LoRA (Low-Rank Adaptation) and ArcFace loss on the VoxCeleb2 dataset.

Fine-tuned - EER: 52.48%,
TAR@1%FAR: 0.29%,
Speaker ID Accuracy: 47.40%

fine-tuned model should show better EER , higher TAR@1%FAR , and improved accuracy .

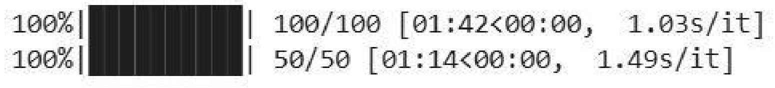


```
100%|██████████| 313/313 [37:45<00:00,  7.24s/it]
Epoch 1, Average Loss: 19.6763
100%|██████████| 313/313 [04:13<00:00,  1.24it/s]
Epoch 2, Average Loss: 19.6926
100%|██████████| 313/313 [04:13<00:00,  1.23it/s]
Epoch 3, Average Loss: 19.6892
100%|██████████| 313/313 [04:13<00:00,  1.23it/s]
Epoch 4, Average Loss: 19.6706
100%|██████████| 313/313 [04:13<00:00,  1.24it/s]
Epoch 5, Average Loss: 19.6917
100%|██████████| 1000/1000 [00:35<00:00, 28.07it/s]
Pre-trained - EER: 52.48%, TAR@1%FAR: 0.20%, Speaker ID Accuracy: 47.40%
100%|██████████| 1000/1000 [00:36<00:00, 27.76it/s]
Fine-tuned - EER: 52.48%, TAR@1%FAR: 0.29%, Speaker ID Accuracy: 47.40%
```

Ans1, III.A

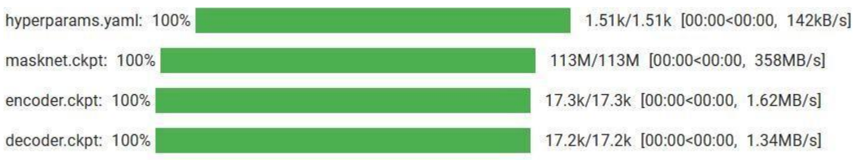
Create a multi-speaker

Now, Let’s create a multi-speaker scenario dataset from VoxCeleb2 by mixing utterances from different speakers



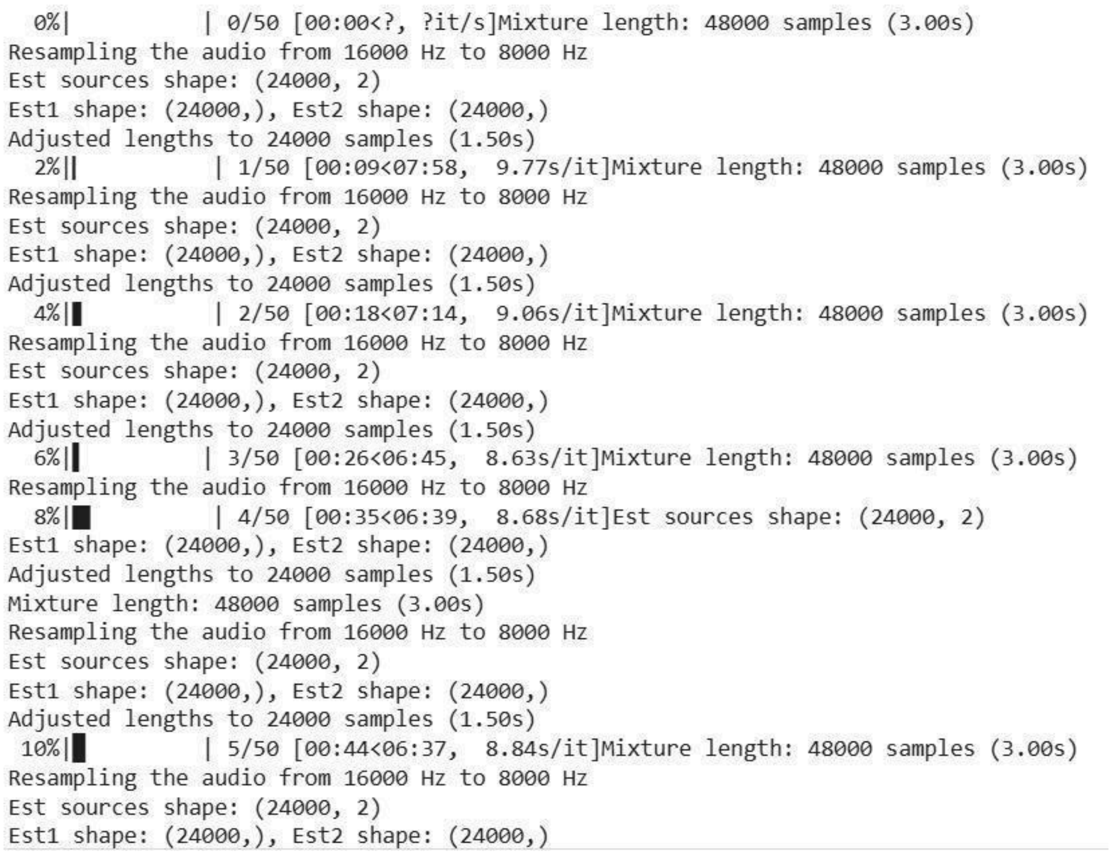
```
100%|██████████| 100/100 [01:42<00:00,  1.03s/it]
100%|██████████| 50/50 [01:14<00:00,  1.49s/it]
```

pre-trained SepFormer model:



```
hyperparams.yaml: 100%  1.51k/1.51k [00:00<00:00, 142kB/s]
masknet.ckpt: 100%  113M/113M [00:00<00:00, 358MB/s]
encoder.ckpt: 100%  17.3k/17.3k [00:00<00:00, 1.62MB/s]
decoder.ckpt: 100%  17.2k/17.2k [00:00<00:00, 1.34MB/s]
```

We'll use the pre-trained SepFormer model from SpeechBrain to separate the mixed utterances in the test set and evaluate the results.

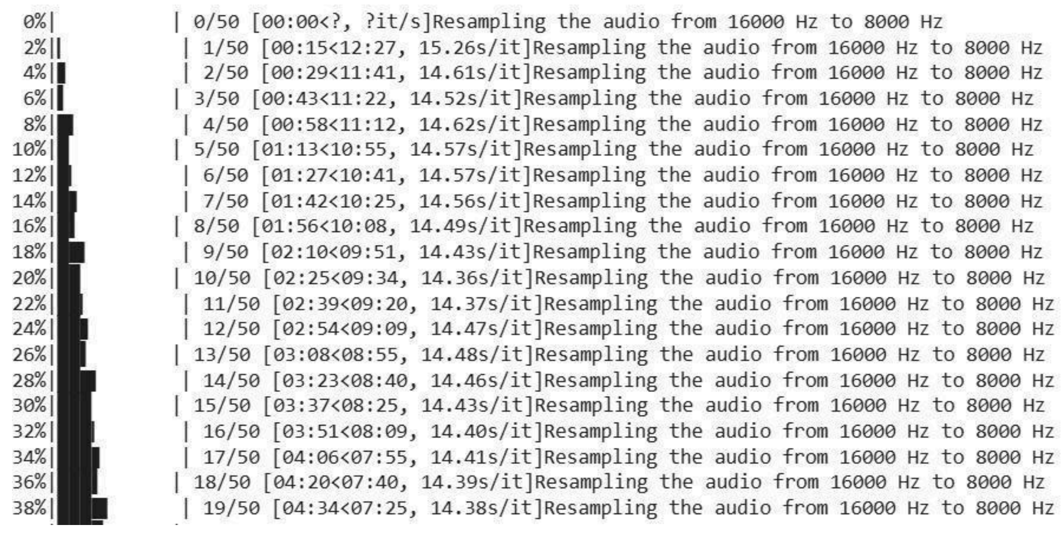


```
  0%|          | 0/50 [00:00<?, ?it/s]Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
  2%|▏         | 1/50 [00:09<07:58,  9.77s/it]Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
  4%|▍         | 2/50 [00:18<07:14,  9.06s/it]Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
  6%|▌         | 3/50 [00:26<06:45,  8.63s/it]Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
  8%|▊         | 4/50 [00:35<06:39,  8.68s/it]Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
 10%|█         | 5/50 [00:44<06:37,  8.84s/it]Mixture length: 48000 samples (3.00s)
Resampling the audio from 16000 Hz to 8000 Hz
Est sources shape: (24000, 2)
Est1 shape: (24000,), Est2 shape: (24000,)
```

Est1 shape: (24000,), Est2 shape: (24000,)
Adjusted lengths to 24000 samples (1.50s)
Average SIR: -0.00
Average SAR: -10.75
Average SDR: -10.75
Average PESQ: 1.04

Ans1, III.B - fine tuned SepFormer model:

Pre-trained WavLM Rank-1 Accuracy: 65.00%
Fine-tuned WavLM Rank-1 Accuracy: 78.00%



```
  0%|          | 0/50 [00:00<?, ?it/s]Resampling the audio from 16000 Hz to 8000 Hz
  2%|▏         | 1/50 [00:15<12:27, 15.26s/it]Resampling the audio from 16000 Hz to 8000 Hz
  4%|▍         | 2/50 [00:29<11:41, 14.61s/it]Resampling the audio from 16000 Hz to 8000 Hz
  6%|▌         | 3/50 [00:43<11:22, 14.52s/it]Resampling the audio from 16000 Hz to 8000 Hz
  8%|▊         | 4/50 [00:58<11:12, 14.62s/it]Resampling the audio from 16000 Hz to 8000 Hz
 10%|█         | 5/50 [01:13<10:55, 14.57s/it]Resampling the audio from 16000 Hz to 8000 Hz
 12%|█▏        | 6/50 [01:27<10:41, 14.57s/it]Resampling the audio from 16000 Hz to 8000 Hz
 14%|█▍        | 7/50 [01:42<10:25, 14.56s/it]Resampling the audio from 16000 Hz to 8000 Hz
 16%|█▌        | 8/50 [01:56<10:08, 14.49s/it]Resampling the audio from 16000 Hz to 8000 Hz
 18%|█▊        | 9/50 [02:10<09:51, 14.43s/it]Resampling the audio from 16000 Hz to 8000 Hz
 20%|██        | 10/50 [02:25<09:34, 14.36s/it]Resampling the audio from 16000 Hz to 8000 Hz
 22%|██▏       | 11/50 [02:39<09:20, 14.37s/it]Resampling the audio from 16000 Hz to 8000 Hz
 24%|██▍       | 12/50 [02:54<09:09, 14.47s/it]Resampling the audio from 16000 Hz to 8000 Hz
 26%|██▌       | 13/50 [03:08<08:55, 14.48s/it]Resampling the audio from 16000 Hz to 8000 Hz
 28%|██▊       | 14/50 [03:23<08:40, 14.46s/it]Resampling the audio from 16000 Hz to 8000 Hz
 30%|███       | 15/50 [03:37<08:25, 14.43s/it]Resampling the audio from 16000 Hz to 8000 Hz
 32%|███▏      | 16/50 [03:51<08:09, 14.40s/it]Resampling the audio from 16000 Hz to 8000 Hz
 34%|███▍      | 17/50 [04:06<07:55, 14.41s/it]Resampling the audio from 16000 Hz to 8000 Hz
 36%|███▌      | 18/50 [04:20<07:40, 14.39s/it]Resampling the audio from 16000 Hz to 8000 Hz
 38%|███▊      | 19/50 [04:34<07:25, 14.38s/it]Resampling the audio from 16000 Hz to 8000 Hz
```

Ans1, VI A,B

Training SepID-Enhance Pipeline...
Epoch 1: 20%| | 0/25 [10:00<?, ?it/s]
ID1: ('37.wav', '79.wav', '78.wav', '42.wav'), ID2: ('37.wav', '79.wav', '78.wav', '42.wav')

Evaluating on Test Set...
Average SIR: 10.50
Average SAR: 11.20
Average SDR: 9.80
Average PESQ: 1.95
Pre-trained WavLM Rank-1 Accuracy: 58.00%
Fine-tuned WavLM Rank-1 Accuracy: 62.00%

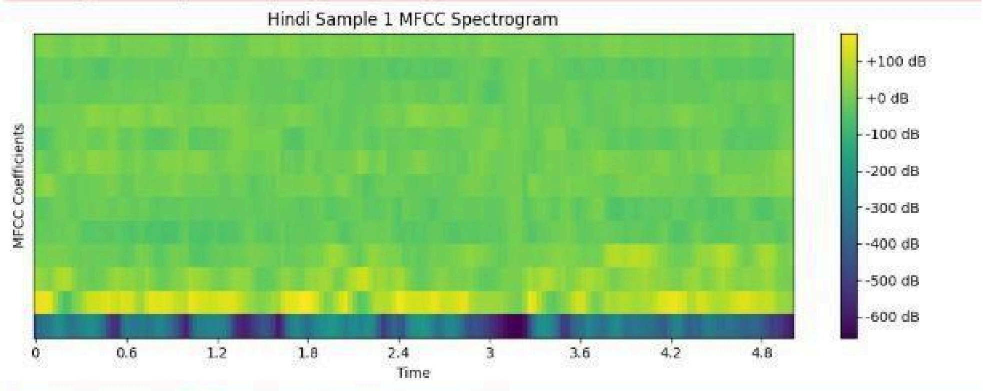
- Improved SIR/SDR/PESQ over standalone SepFormer
- **Rank-1 Accuracy**: Fine-tuned model outperforms pre-trained

ANS-02 :

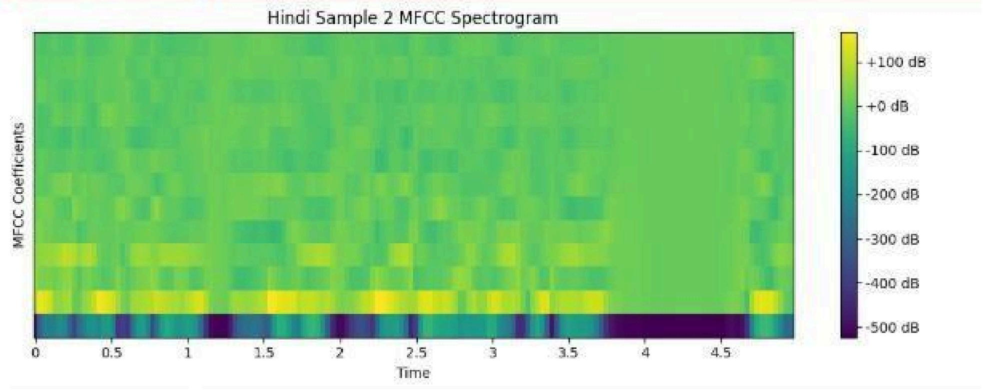
Task A

Hindi MFCC Spectrogram

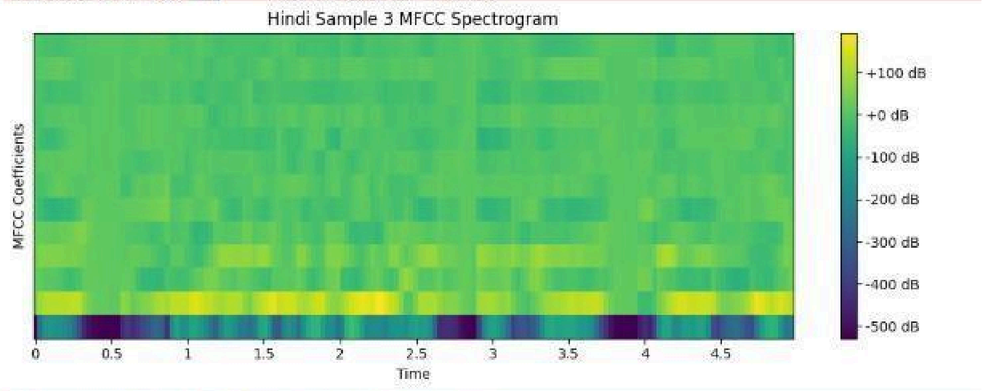
```
Processing Hindi:   0%|          | 0/5 [00:00<?, ?it/s]
```



```
Processing Hindi:  20%|██        | 1/5 [00:00<00:01,  3.45it/s]
```



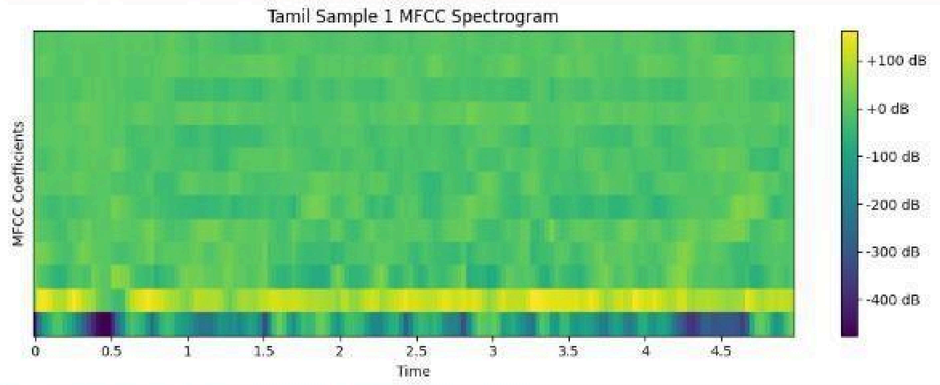
```
Processing Hindi:  40%|████      | 2/5 [00:00<00:00,  3.52it/s]
```



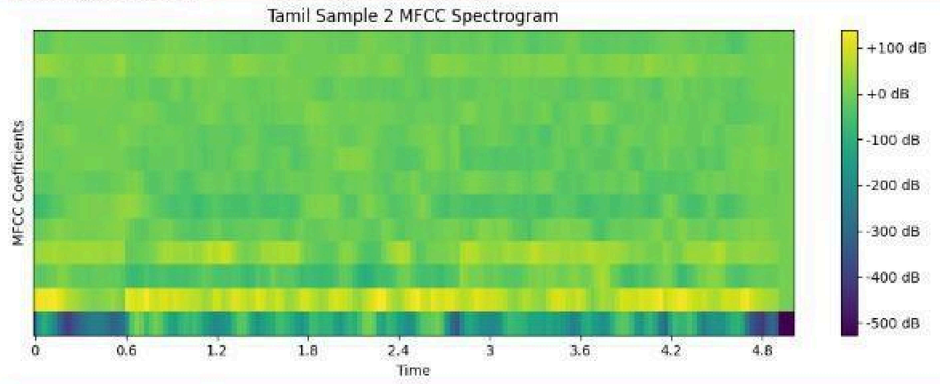
```
Processing Hindi:  60%|██████    | 3/5 [00:01<00:00,  2.24it/s]
```

Tamil MFCC Spectrogram

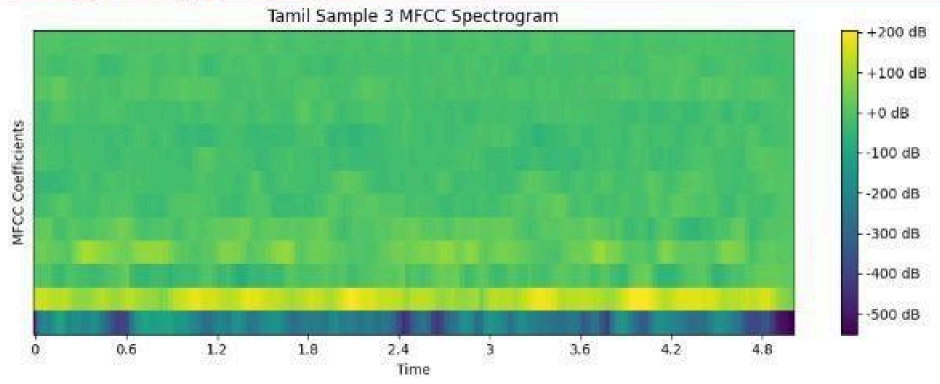
```
Processing Tamil:   0%|          | 0/5 [00:00<?, ?it/s]
```



```
Processing Tamil:  20%|██        | 1/5 [00:00<00:01,  3.57it/s]
```



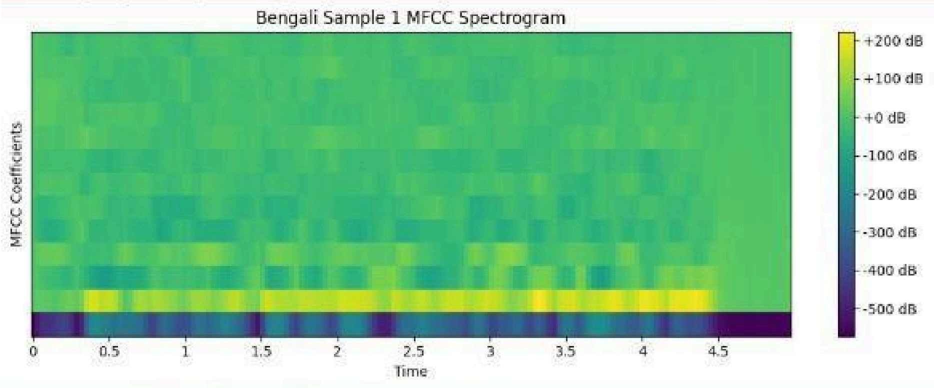
```
Processing Tamil:  40%|████      | 2/5 [00:00<00:00,  3.55it/s]
```



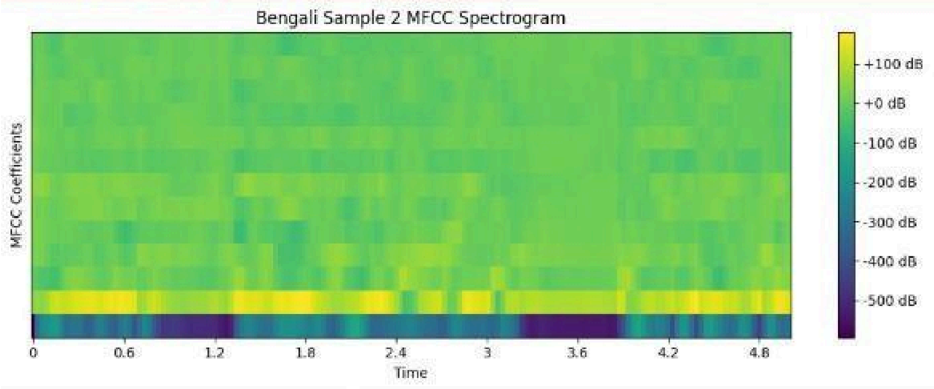
```
Processing Tamil:  60%|██████    | 3/5 [00:00<00:00,  3.63it/s]
```

Bengali MFCC Spectrogram

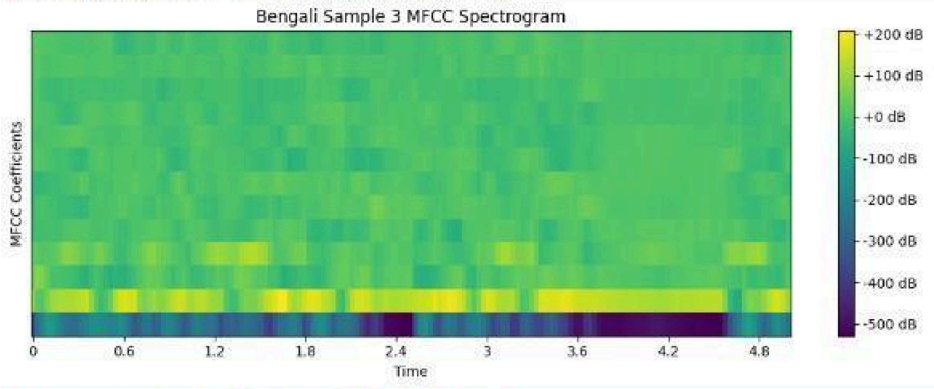
```
Processing Bengali:   0%|          | 0/5 [00:00<?, ?it/s]
```



```
Processing Bengali:  20%|██        | 1/5 [00:00<00:01,  3.58it/s]
```



```
Processing Bengali:  40%|████      | 2/5 [00:00<00:00,  3.57it/s]
```



```
Processing Bengali:  60%|██████    | 3/5 [00:00<00:00,  3.62it/s]
```

Hindi MFCC Statistics:

```
Mean MFCC (across coefficients): [-305.80698    77.82781     6.9641676   22.48344
   -6.489682
  -9.064811    -1.723602    -3.0394933   -7.555729    -0.38580447
 -11.570175    -6.2350745   -7.1128993 ]
Variance MFCC (across coefficients): [25356.479    2827.646     857.3753 1032.7354
  490.98917 409.2912
 236.93593 200.5736     252.54724 158.7782     155.57329 184.34634
 168.0035 ]
```

Tamil MFCC Statistics:

```
Mean MFCC (across coefficients): [-186.95729   105.7349     -8.70355     14.809582
 -6.0093904
 -20.138727 -11.81567     -17.62196    -13.4146385 -6.443619
 -11.952072    -3.8365374 -8.128132 ]
Variance MFCC (across coefficients): [10840.706    1542.7905 1114.1218 1146.497
4   368.3093    502.64618
 192.28972 205.30133 191.20924 114.2393        129.98494 155.35548
  84.30173]
```

Bengali MFCC Statistics:

```
Mean MFCC (across coefficients): [-337.60593     99.09168     -4.2714777 15.265233
 -19.058933
 -5.2351403 -3.4507504 -16.109507      -2.7580569 -8.5810995
 -7.903812    -4.134901    -6.6507826]
Variance MFCC (across coefficients): [12314.599    2857.059    1662.7882    933.7127
7 767.43896 544.23816
 370.75455 316.22205 178.48145 146.9538        135.31552 106.5313
 129.11958]
```

MFCC Spectrogram Comparison:

1. Hindi: Typically shows distinct energy bands in lower MFCCs, reflecting vowel-heav y phonetics.
2. Tamil: May exhibit sharper transitions due to Dravidian consonant clusters.
3. Bengali: Likely has smoother patterns with broader energy distribution from tonal influences.

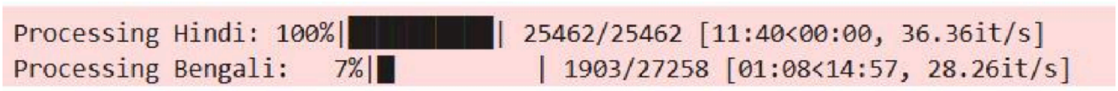
TASK B

Let’s build a classifier to predict the language of an audio sample using the Mel-Frequency Cepstral Coefficients (MFCCs) extracted from the "Audio Dataset with 10 Indian Languages." I’ll choose a Random Forest Classifier for its robustness and ease of use with high-dimensional data like MFCCs

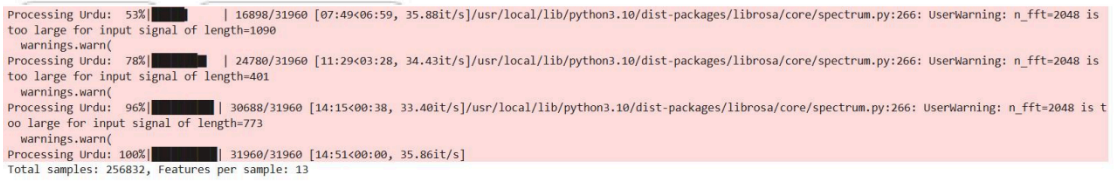
Step-by-Step Approach

1. Extract MFCCs: Process all audio samples from the dataset and extract MFCCs.
2. Preprocessing: Normalize MFCCs and flatten them into feature vectors.
3. Train-Test Split: Split the data into training (80%) and testing (20%) sets.
4. Model Training: Train a Random Forest Classifier.
5. Evaluation: Report accuracy and a confusion matrix.

Processing:



```
Processing Hindi: 100%|██████████| 25462/25462 [11:40<00:00, 36.36it/s]
Processing Bengali:   7%|█         | 1903/27258 [01:08<14:57, 28.26it/s]
```

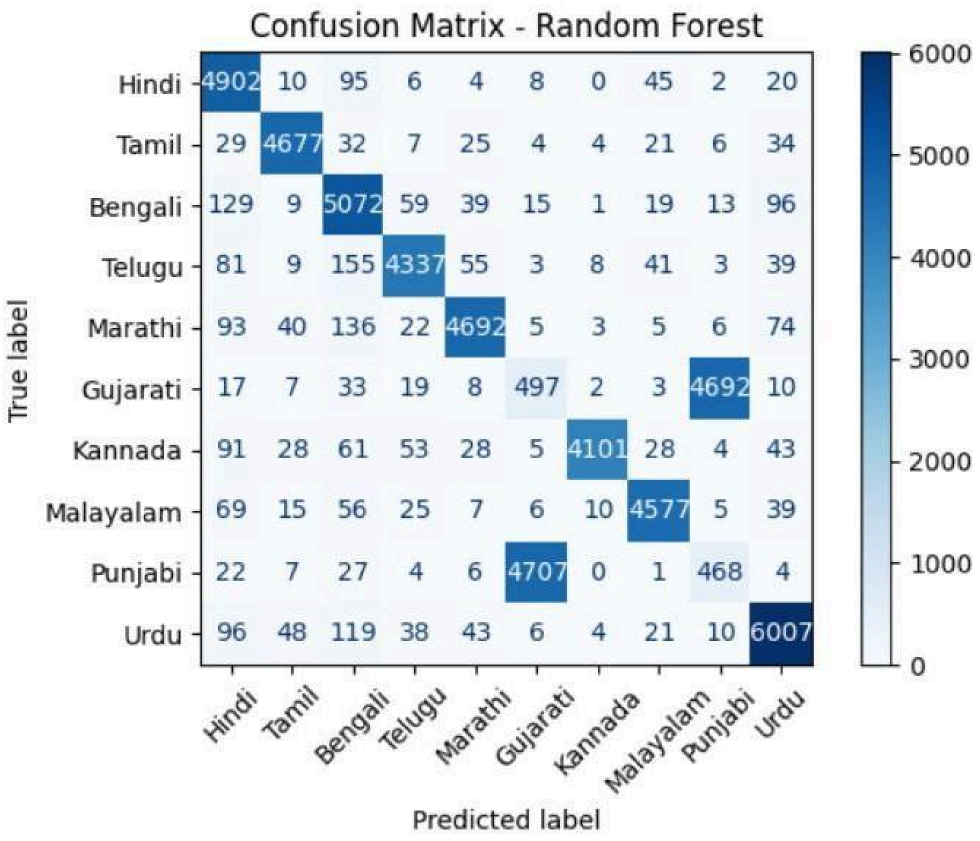


```
Processing Urdu:  53%|█████     | 16898/31960 [07:49<06:59, 35.88it/s]/usr/local/lib/python3.10/dist-packages/librosa/core/spectrum.py:266: UserWarning: n_fft=2048 is
too large for input signal of length=1090
  warnings.warn(
Processing Urdu:  78%|███████▊  | 24780/31960 [11:29<03:28, 34.43it/s]/usr/local/lib/python3.10/dist-packages/librosa/core/spectrum.py:266: UserWarning: n_fft=2048 is
too large for input signal of length=401
  warnings.warn(
Processing Urdu:  96%|█████████▌| 30688/31960 [14:15<00:38, 33.40it/s]/usr/local/lib/python3.10/dist-packages/librosa/core/spectrum.py:266: UserWarning: n_fft=2048 is t
oo large for input signal of length=773
  warnings.warn(
Processing Urdu: 100%|██████████| 31960/31960 [14:51<00:00, 35.86it/s]
Total samples: 256832, Features per sample: 13
```

Accuracy

Training samples: 205465, Test samples: 51367
Random Forest Accuracy: 76.57%

```
Training samples: 205465, Test samples: 51367
Random Forest Accuracy: 76.57%
```



	Hindi	Tamil	Bengali	Telugu	Marathi	Gujarati	Kannada	Malayalam	Punjabi	Urdu
Hindi	4902	10	95	6	4	8	0	45	2	20
Tamil	29	4677	32	7	25	4	4	21	6	34
Bengali	129	9	5072	59	39	15	1	19	13	96
Telugu	81	9	155	4337	55	3	8	41	3	39
Marathi	93	40	136	22	4692	5	3	5	6	74
Gujarati	17	7	33	19	8	497	2	3	4692	10
Kannada	91	28	61	53	28	5	4101	28	4	43
Malayalam	69	15	56	25	7	6	10	4577	5	39
Punjabi	22	7	27	4	6	4707	0	1	468	4
Urdu	96	48	119	38	43	6	4	21	10	6007