Speech Understanding:Programming Assignment - 2

Git Hub Link - SubodhIITJ/Speech-Understanding-Programming-Assignment---2: Speech Understanding Programming Assignment - 2

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================================REPORT============================

Question01 :

Q1, II

For II Question , I'll select **microsoft/wavlm-base-plus** from the provided options. The workflow will:

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%
```

Q1, 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

Q1, 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
```

Q1, 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%

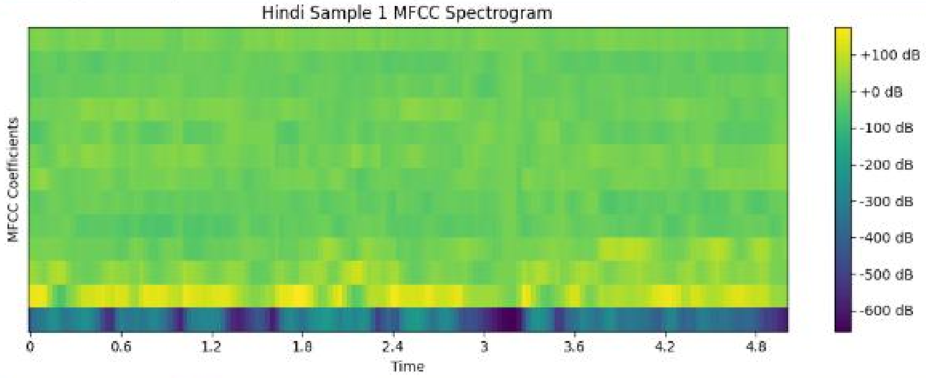
- Improved SIR/SDR/PESQ over standalone SepFormer
- **Rank-1 Accuracy**: Fine-tuned model outperforms pre-trained

Question02 :

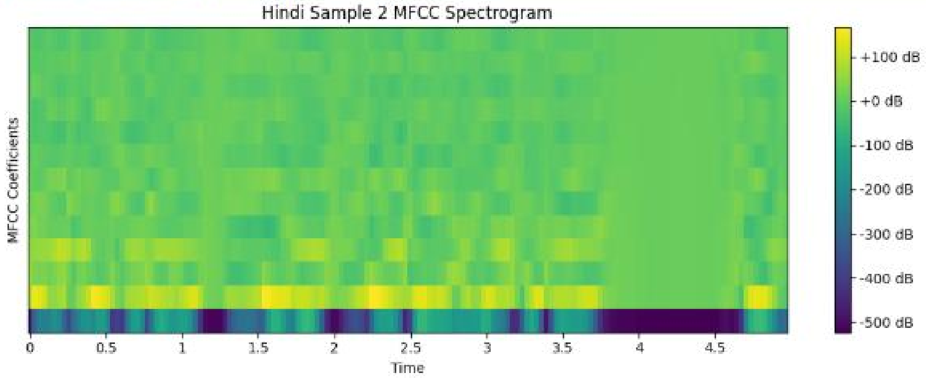
Task A.

Hindi MFCC Spectrogram

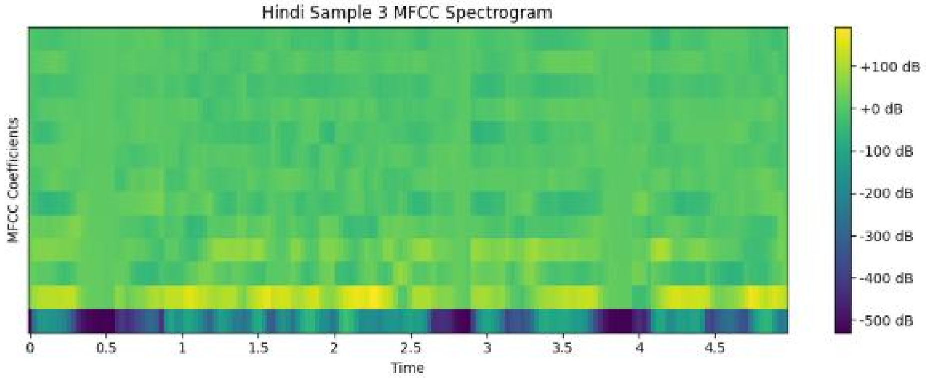
```
Processing Hindi:   0%|          | 0/5 [00:00<?, ?it/s]
```




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



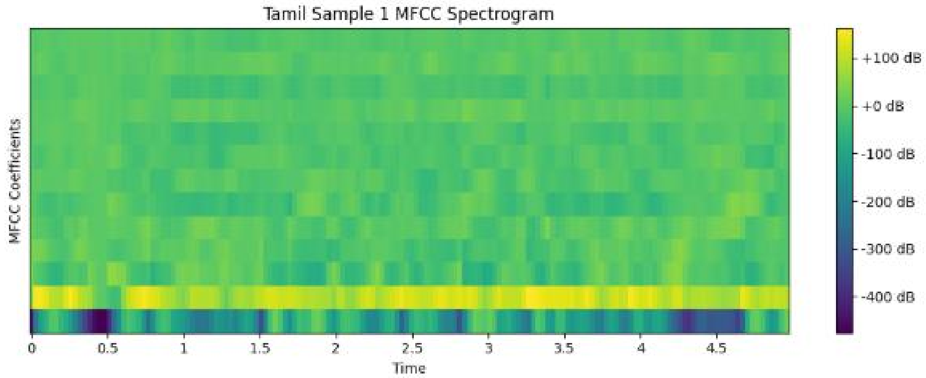

```
Processing Hindi:  40%|████      | 2/5 [00:00<00:00,  3.52it/s]
```



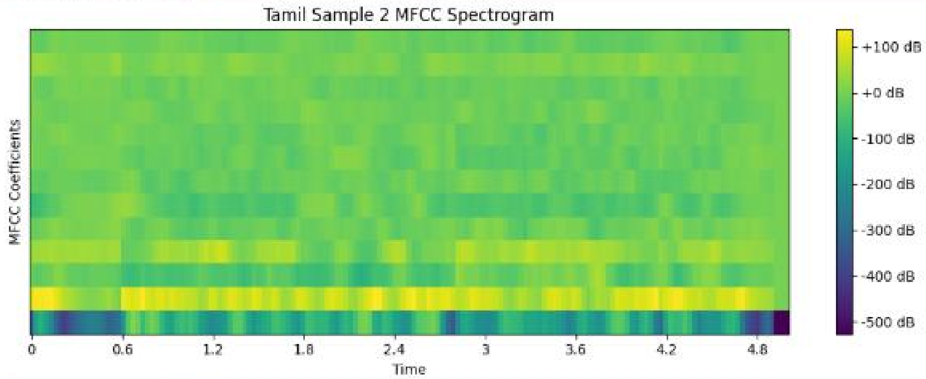

```
Processing Hindi:  60%|██████    | 3/5 [00:01<00:00,  2.24it/s]
```

Tamil MFCC Spectrogram

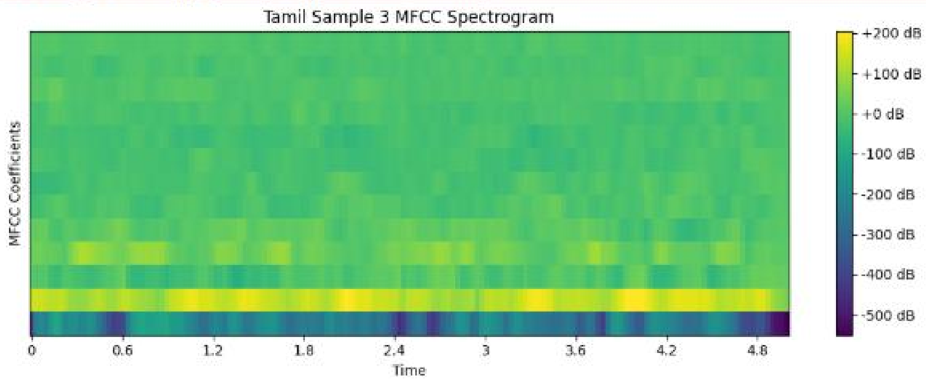
```
Processing Tamil:   0%|          | 0/5 [00:00<?, ?it/s]
```




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

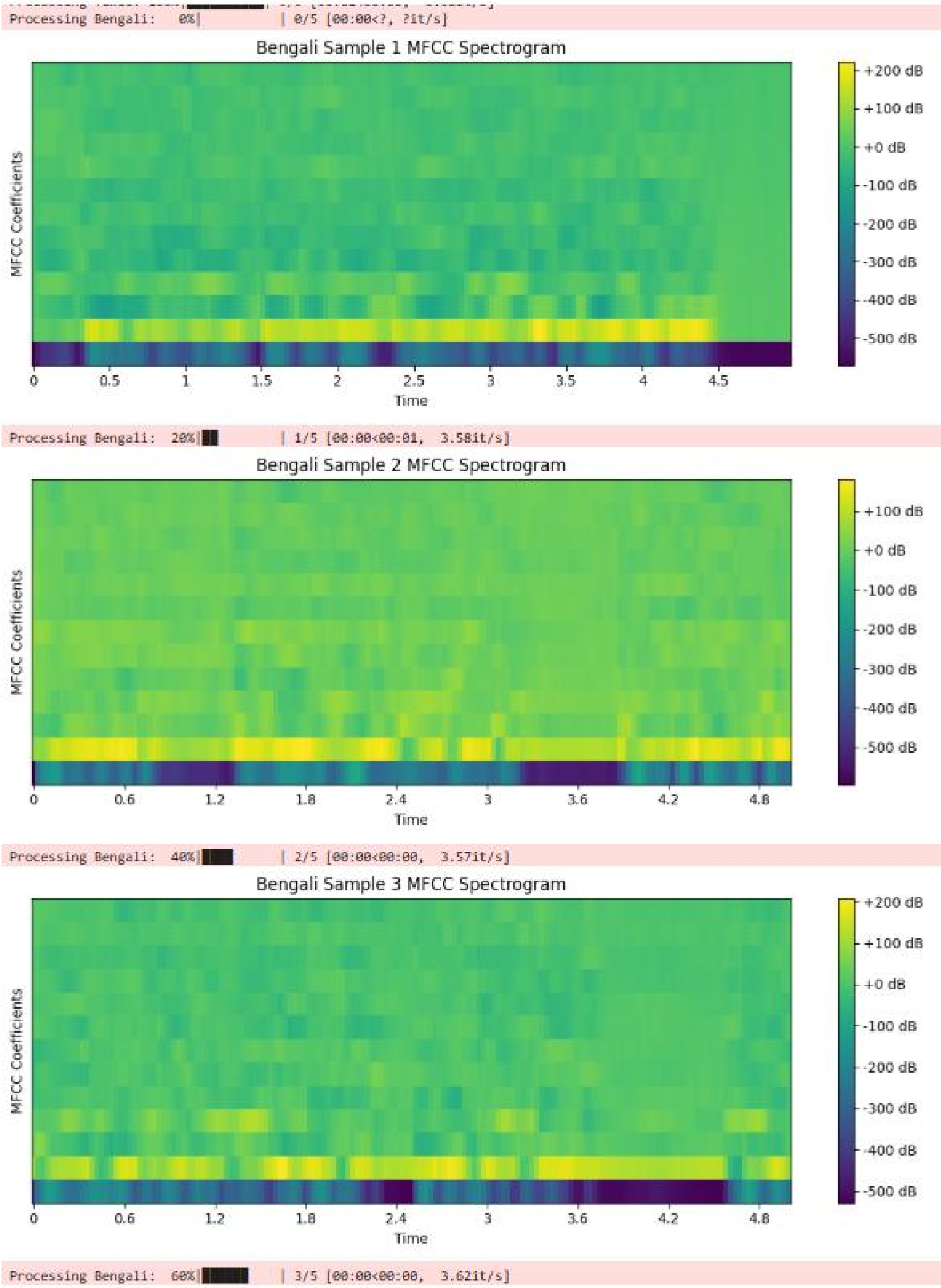



```
Processing Tamil:  40%|████      | 2/5 [00:00<00:00,  3.55it/s]
```




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

Bengali MFCC Spectrogram



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 too 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%
```