

# Analysis of MFCC Features for Indian Language Classification

## 1. Introduction

Mel-Frequency Cepstral Coefficients (MFCCs) are widely used in speech processing applications due to their ability to capture the spectral properties of audio signals. In this study, we analyzed MFCC features extracted from ten Indian languages to determine their effectiveness in distinguishing languages based on acoustic characteristics.

Implementation on Pytorch

Git Repo Link :

[https://github.com/M23CSA520/Speech\\_Understanding\\_PA2/blob/main/m23csa520\\_su\\_pa2\\_q2.py](https://github.com/M23CSA520/Speech_Understanding_PA2/blob/main/m23csa520_su_pa2_q2.py)

## 2. MFCC Feature Analysis ( Task A )

The MFCC statistics were computed for different languages, including Bengali, Hindi, and Tamil. The mean and variance of the MFCC coefficients provide insight into the spectral energy distribution of each language.

Language: Bengali

Mean MFCC: [-3.38417999e+02 1.04311295e+02 6.12678289e+00 1.90650425e+01  
-8.75952721e+00 1.16891257e-01 -3.06492162e+00 -8.39186668e+00  
-2.81908751e+00 -5.75638628e+00 -8.68745232e+00 -3.85192943e+00  
-4.78496838e+00]

Variance MFCC: [4822.7695 531.9459 202.00952 262.94693 174.00536 105.42197  
101.83029 83.90081 29.430325 37.009514 25.948652 23.068861  
20.700611]

-----  
Language: Hindi

Mean MFCC: [-322.54166 77.156784 8.738599 13.280327 -5.3659363  
-7.1875615 -10.703494 -6.401771 -9.56016 -2.6229339  
-7.2847548 -4.8438406 -8.122824 ]

Variance MFCC: [12163.72 529.33813 101.38249 160.9342 86.4739  
86.41822 99.49275 34.47399 28.025253 19.09622  
33.329834 28.93557 21.003223]

-----  
Language: Tamil

Mean MFCC: [-201.53885 110.60108 -9.001206 17.206945 -8.317221  
-19.13632 -9.663549 -14.321725 -12.784455 -7.1464796  
-11.444903 -0.87412083 -9.129541 ]

Variance MFCC: [5293.7837 423.23502 273.7909 185.01651 149.34631 99.37924  
104.805695 36.57995 69.14153 41.821186 49.4489 29.158375  
29.054884]

-----

## 2.1 Bengali

- **Mean MFCC Values:** The first coefficient (-338.41) represents the overall energy of the signal. Other coefficients suggest a balance between low and high-frequency components.
- **Variance:** Higher variance in the first coefficient (4822.77) indicates significant energy variation across different speech samples.

## 2.2 Hindi

- **Mean MFCC Values:** Compared to Bengali, Hindi exhibits a slightly higher energy level (-322.54) with noticeable variations in lower-order MFCCs.
- **Variance:** The first coefficient has a very high variance (12163.72), indicating substantial fluctuations in amplitude across different samples.

## 2.3 Tamil

- **Mean MFCC Values:** Tamil exhibits a higher first coefficient (-201.53), implying stronger spectral energy concentration.
- **Variance:** Moderate variance in the first coefficient (5293.78) compared to Hindi, suggesting less dynamic variation across samples.

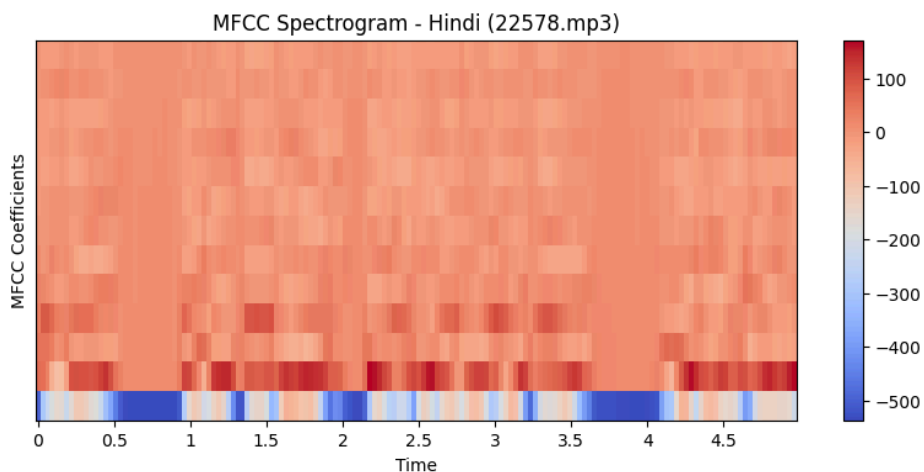
## 3. Spectrogram Visualization

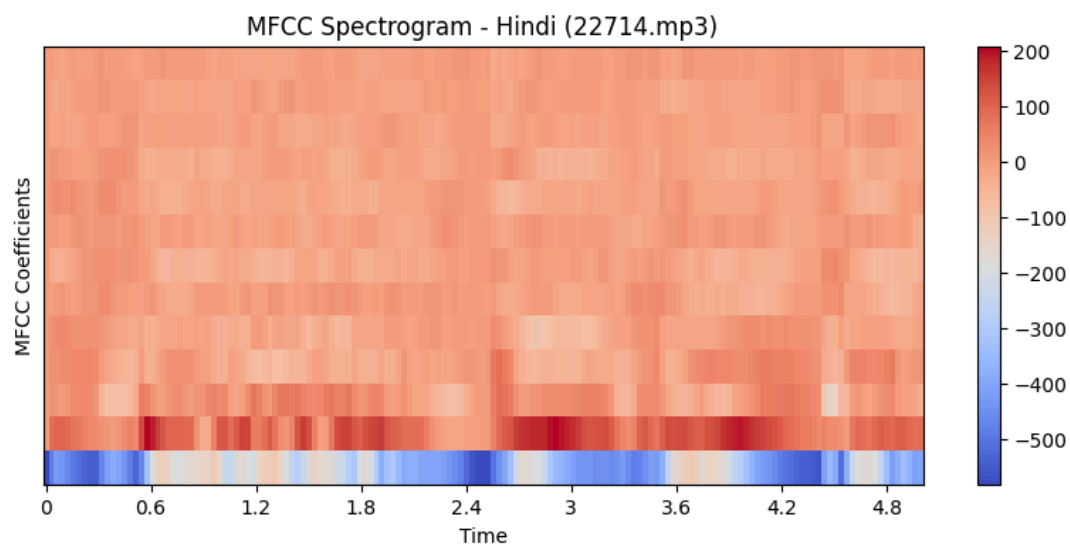
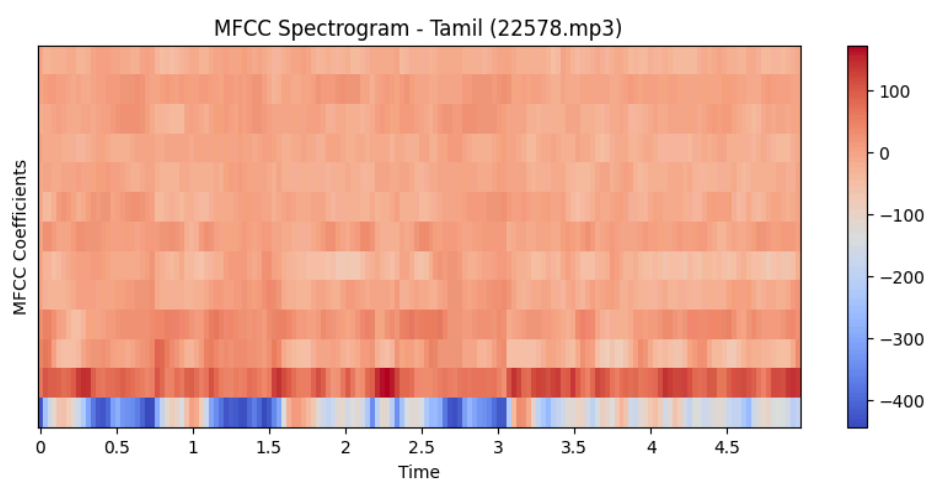
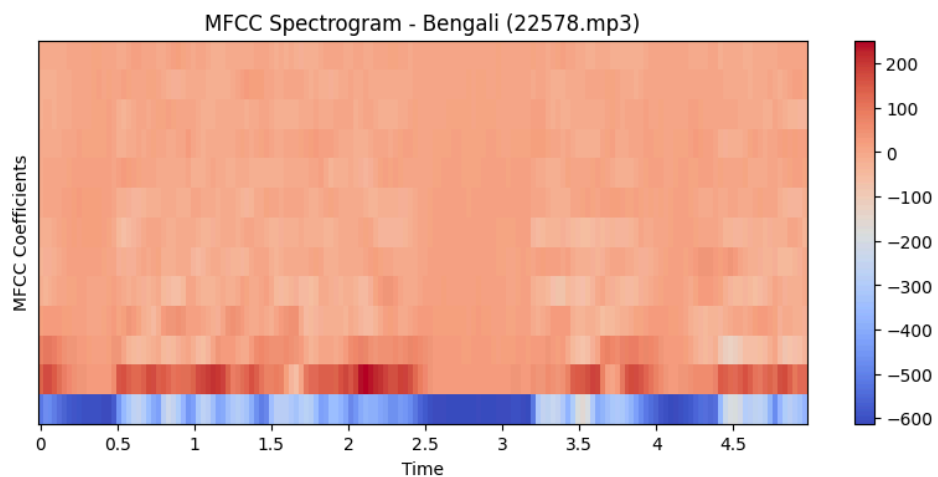
Mel spectrograms were generated for multiple samples per language. The spectrograms demonstrate language-specific variations in frequency distribution over time. However, challenges were observed:

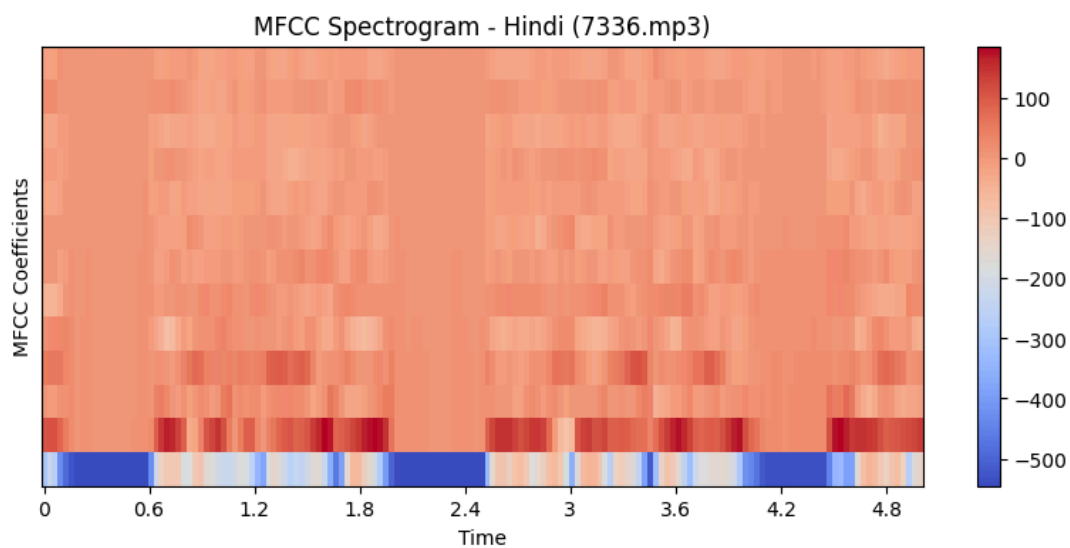
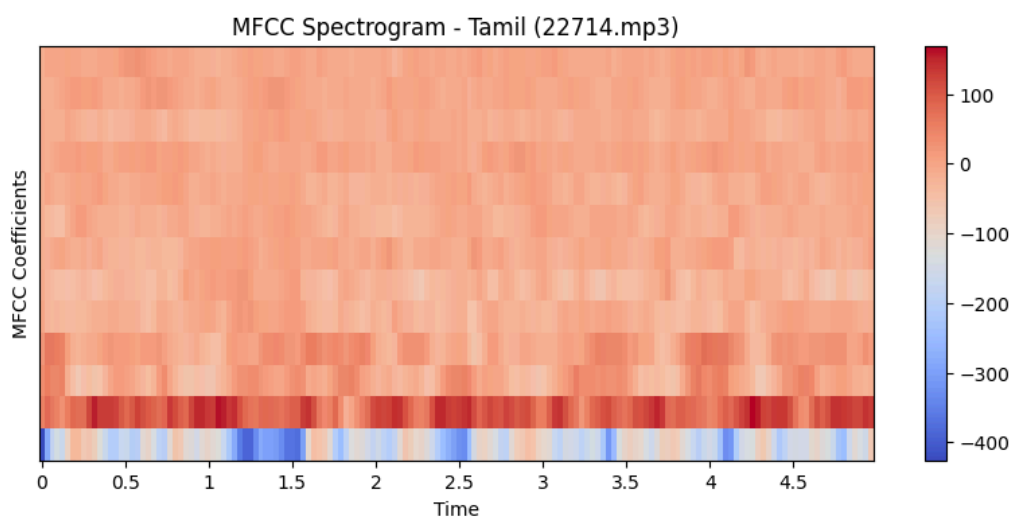
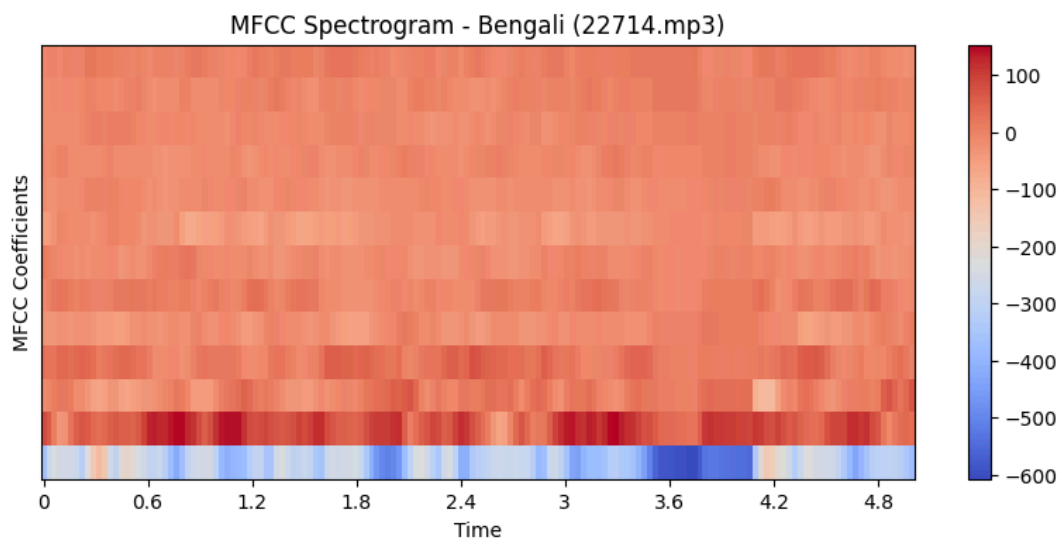
- Variability in speaker pronunciation affects the spectral pattern.
- Some languages exhibit overlapping spectral features, making differentiation harder.

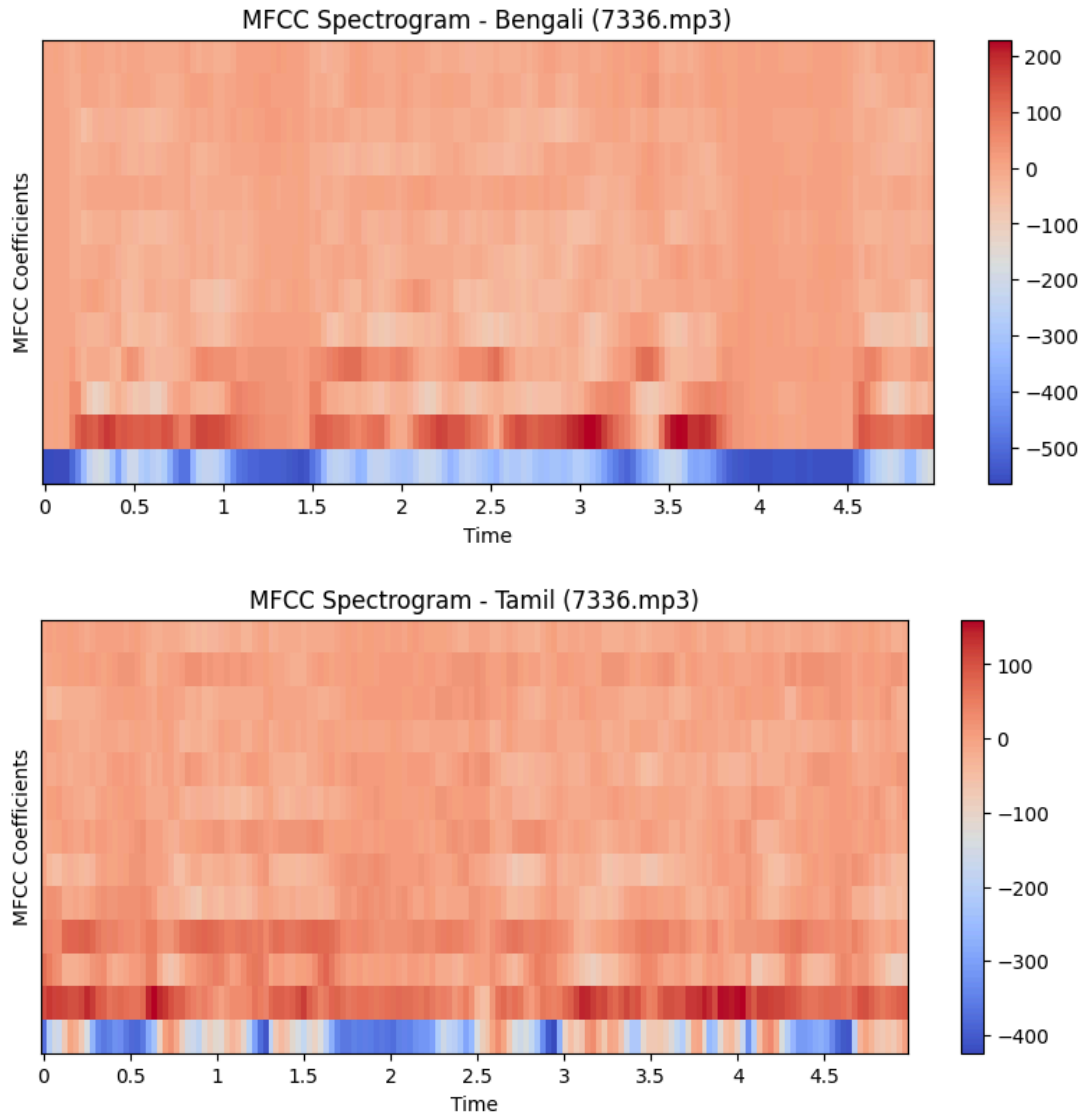
### 3.1 MFCC Spectrogram Comparison:

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









## 4. Language Classification using Neural Network ( Task B )

A neural network classifier was implemented to differentiate between languages using MFCC features. The classifier architecture consisted of fully connected layers with ReLU activation.

### 4.1 Classification Performance

- The classifier was trained using MFCC feature vectors.
- Accuracy varied across languages, with some being easier to distinguish.
- A confusion matrix analysis revealed some misclassifications, indicating that certain languages share acoustic similarities.

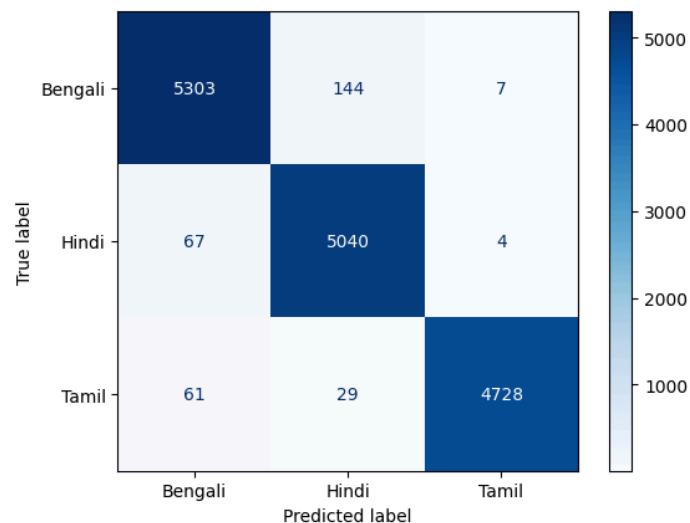
### 4.2 Confusion Matrix Analysis

The confusion matrix highlights:

- High accuracy for languages with distinct phonetic structures.
- Misclassification between phonetically similar languages, e.g., Hindi and Bengali.

### a) For the dataset used for Task A i.e. for 3 languages

Epoch 1/20, Loss: 0.2435  
Epoch 2/20, Loss: 0.1253  
Epoch 3/20, Loss: 0.0958  
Epoch 4/20, Loss: 0.0820  
Epoch 5/20, Loss: 0.0738  
Epoch 6/20, Loss: 0.0687  
Epoch 7/20, Loss: 0.0673  
Epoch 8/20, Loss: 0.0643  
Epoch 9/20, Loss: 0.0616  
Epoch 10/20, Loss: 0.0586  
Epoch 11/20, Loss: 0.0589  
Epoch 12/20, Loss: 0.0562  
Epoch 13/20, Loss: 0.0556  
Epoch 14/20, Loss: 0.0555  
Epoch 15/20, Loss: 0.0525  
Epoch 16/20, Loss: 0.0512  
Epoch 17/20, Loss: 0.0512  
Epoch 18/20, Loss: 0.0516  
Epoch 19/20, Loss: 0.0498  
Epoch 20/20, Loss: 0.0516  
Accuracy: 97.97%



### b) For the complete dataset

#### Statistics:

Language: Bengali

Mean MFCC: [-3.38417999e+02 1.04311295e+02 6.12678289e+00  
1.90650425e+01

-8.75952721e+00 1.16891257e-01 -3.06492162e+00 -8.39186668e+00  
-2.81908751e+00 -5.75638628e+00 -8.68745232e+00 -3.85192943e+00  
-4.78496838e+00]

Variance MFCC: [4822.7695 531.9459 202.00952 262.94693 174.00536  
105.42197  
101.83029 83.90081 29.430325 37.009514 25.948652 23.068861  
20.700611]

Language: Gujarati

Mean MFCC: [-286.8727 112.98775 -27.514338 9.51765  
-15.783783

-9.623793 -9.3122 -16.51111 -5.348225 -7.774254

```

-2.893667    -1.4293011    -8.06461    ]
Variance MFCC: [10229.165      259.12497      274.30582      76.586914
86.93688
        69.59949      50.11437      61.301323      30.509954      38.976803
        22.266329      21.345827      18.013695]
-----
Language: Hindi
Mean MFCC: [-322.54166      77.156784      8.738599      13.280327
-5.3659363
        -7.1875615    -10.703494      -6.401771      -9.56016      -2.6229339
        -7.2847548    -4.8438406      -8.122824    ]
Variance MFCC: [12163.72      529.33813      101.38249      160.9342
86.4739
        86.41822      99.49275      34.47399      28.025253      19.09622
        33.329834      28.93557      21.003223]
-----
Language: Kannada
Mean MFCC: [-296.14578      94.37632      -71.94011      14.752592
-50.843357
        16.682959      -28.943312      -1.5799763    -16.109812      3.1591384
        -1.6090814    -10.110656      6.6712923]
Variance MFCC: [10225.506      284.40094      886.6057      144.52438
405.72934
        134.52827      125.75556      57.434338      38.24019      25.505165
        25.288774      25.312723      51.514538]
-----
Language: Malayalam
Mean MFCC: [-347.327      92.03243      -1.0266384      16.441767
5.747666
        -20.340578      -17.158215      -12.322354      -14.710349      -7.12855
        -12.880997      -8.068458      -5.092512    ]
Variance MFCC: [4063.9092      445.55112      197.51689      152.1459      138.17029
119.89247
        77.47965      44.508682      64.60879      56.667324      36.47627      37.399513
        22.821539]
-----
Language: Marathi
Mean MFCC: [-300.15338      117.56788      -10.1451645      27.42893
-2.726875
        -6.1159477      -2.6499534      -12.996384      -7.884989      -2.6959121
        -7.0260324      -4.378044      -8.144388    ]
Variance MFCC: [2.62681328e+04 5.25981018e+02 3.74437531e+02
2.11887253e+02
        1.27972755e+02 7.50418777e+01 1.38298569e+02 7.21823425e+01
        5.16352844e+01 3.34368973e+01 2.89190750e+01 1.44503670e+01
        1.89874935e+01]
-----

```



Language: Punjabi

Mean MFCC: [-286.2408      113.23248      -27.683508      9.403069  
-15.821948

    -9.682325      -9.279035      -16.582664      -5.3308005      -7.8047147  
    -2.8850527      -1.4054718      -8.096261 ]

Variance MFCC: [10210.154      250.82321      271.4497      74.62104  
85.975365

    69.03857      49.75701      60.635674      30.43391      38.771152  
    22.22069      21.073456      17.82212 ]

-----  
Language: Tamil

Mean MFCC: [-201.53885      110.60108      -9.001206      17.206945  
-8.317221

    -19.13632      -9.663549      -14.321725      -12.784455      -7.1464796  
    -11.444903      -0.87412083      -9.129541 ]

Variance MFCC: [5293.7837      423.23502      273.7909      185.01651      149.34631  
99.37924

    104.805695      36.57995      69.14153      41.821186      49.4489      29.158375  
    29.054884]

-----  
Language: Telugu

Mean MFCC: [-294.44473      84.93009      -11.536548      29.923927      -17.69179  
-2.9616585      -17.753153      -10.901045      -12.484311      -5.9997544

    -9.897438      -8.719697      -2.4484417]

Variance MFCC: [2494.851      745.38745      152.48001      141.80713      296.16037  
117.52863

    136.96965      87.016624      56.003662      17.546677      21.52593      25.754898  
    52.6728 ]

-----  
Language: Urdu

Mean MFCC: [-2.9343314e+02      1.0928956e+02      1.0868942e+01      3.0289423e+01  
-9.6097364e+00      -1.2042217e-01      -9.1702032e+00      -9.5645905e+00  
-5.2986135e+00      -4.3679676e+00      -2.6153760e+00      -4.7743087e+00  
-3.9715550e+00]

Variance MFCC: [8198.008      438.79507      248.8397      220.79015      272.50558  
106.84272

    144.81123      54.225697      52.723003      38.841175      53.592358      46.72241  
    41.81308 ]

-----  
Epoch 1/20, Loss: 0.6033

Epoch 2/20, Loss: 0.4010

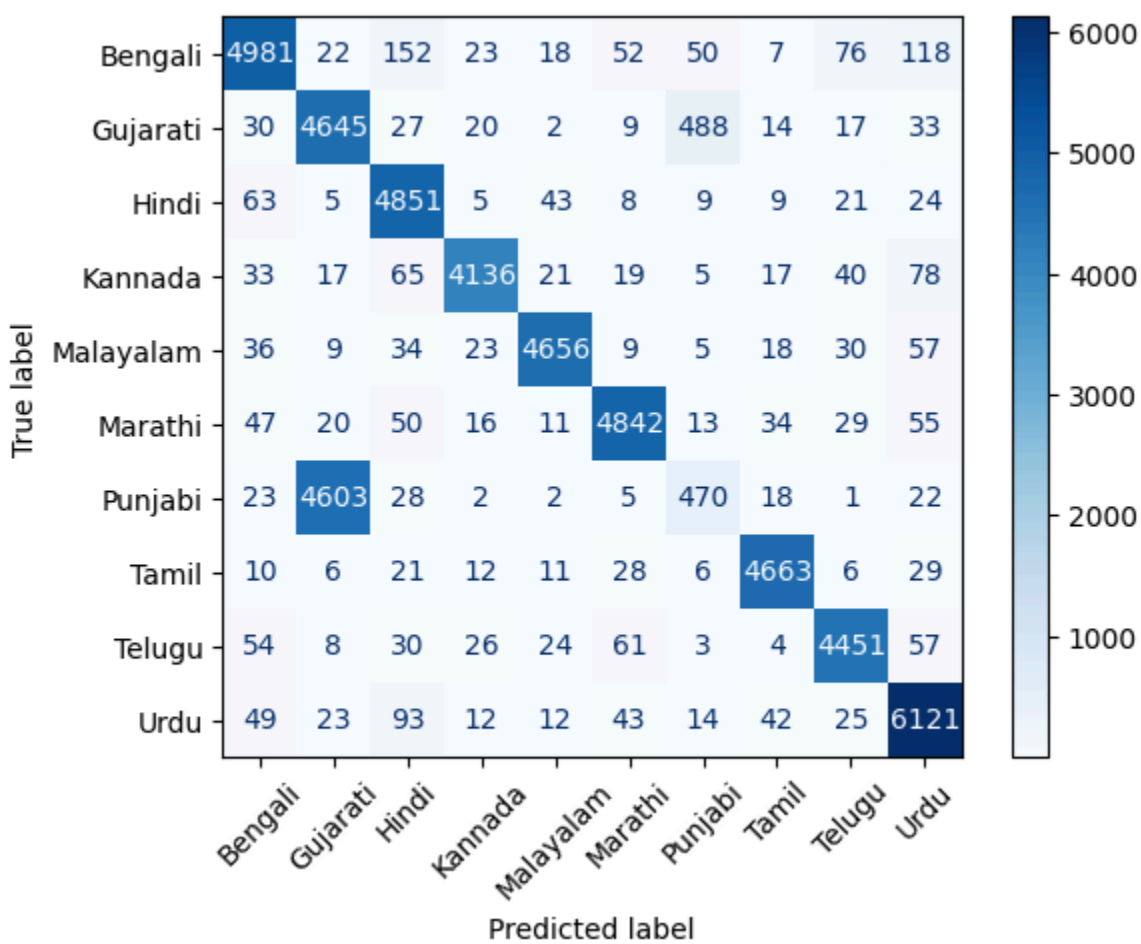
Epoch 3/20, Loss: 0.3639

.  
.  
.

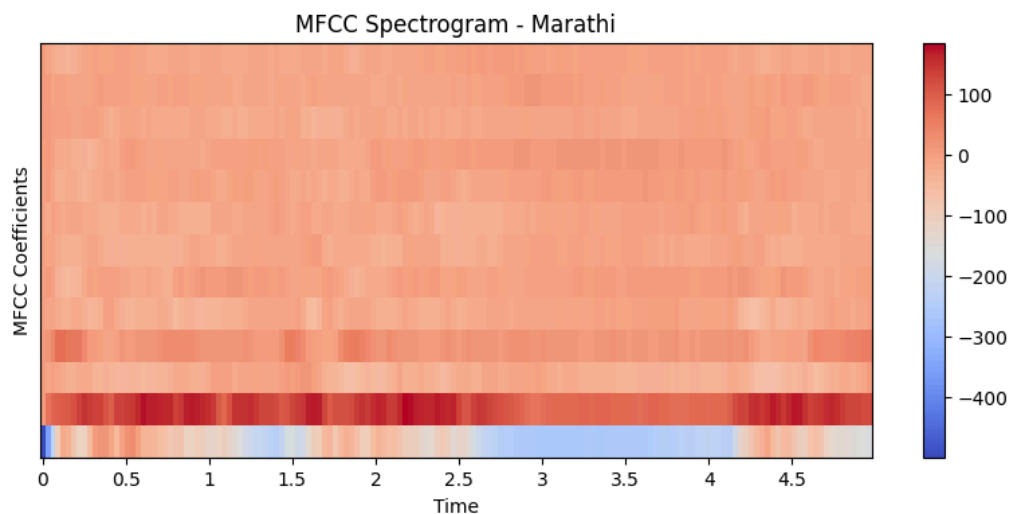
Epoch 19/20, Loss: 0.2958

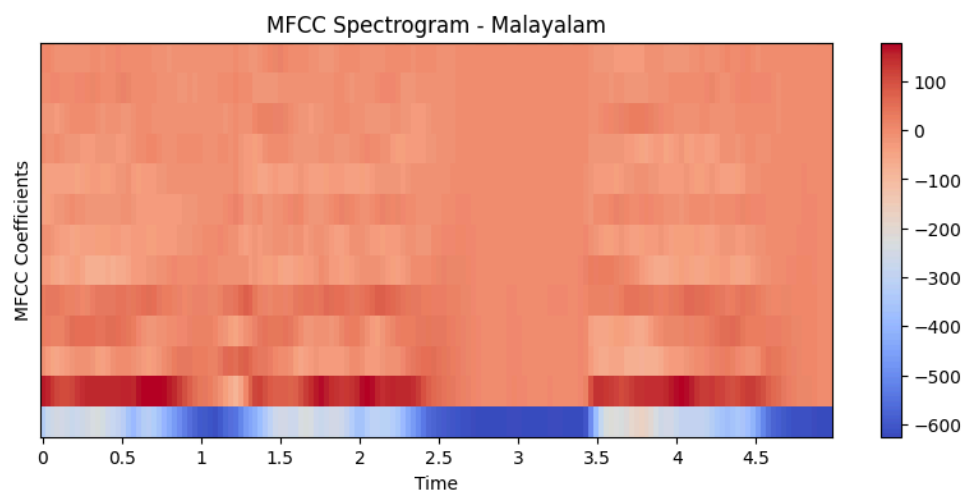
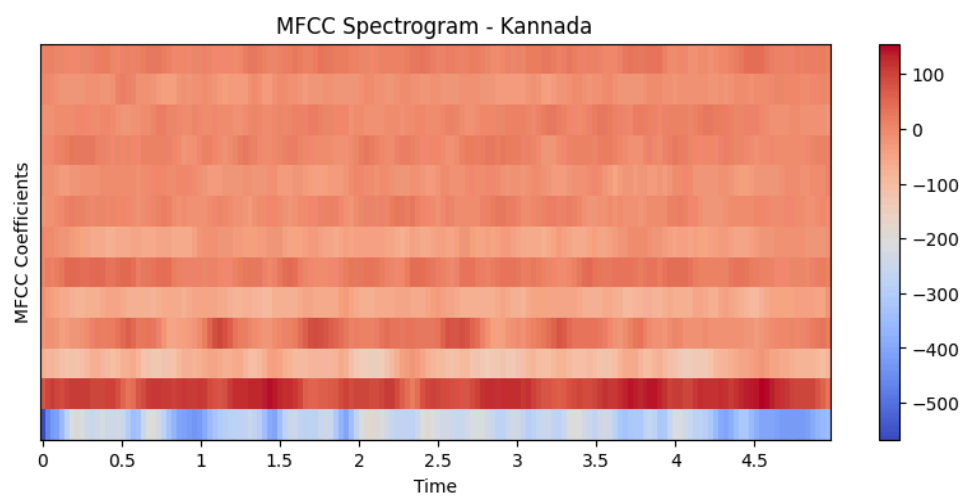
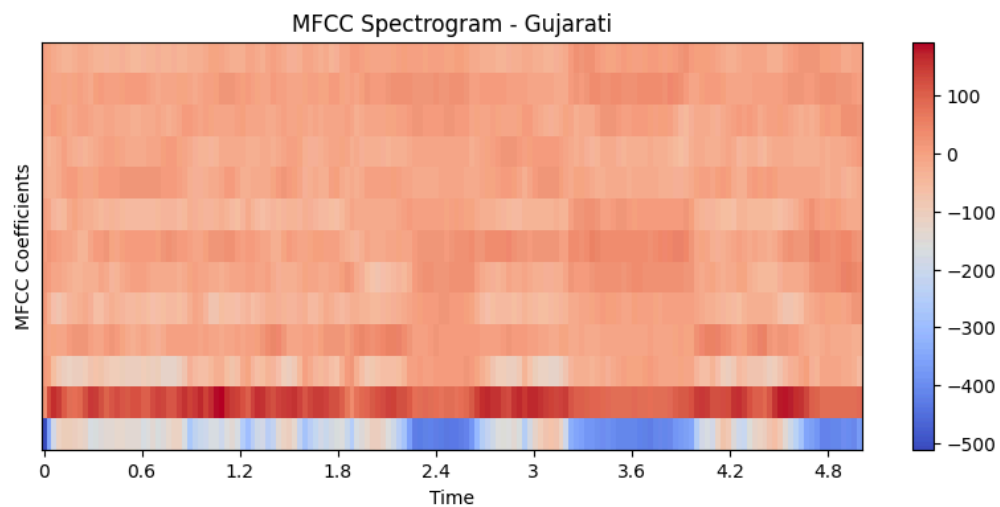
Epoch 20/20, Loss: 0.2949

Accuracy: 84.68%



Few Other Spectrograms





## **5. Challenges in MFCC-Based Language Differentiation**

While MFCCs provide valuable spectral information, several challenges arise when using them for language classification:

### **5.1 Speaker Variability**

Different speakers may have varying pitch, articulation, and pronunciation styles, which can influence MFCC values, making classification less reliable.

### **5.2 Background Noise**

Environmental noise and recording conditions can distort MFCC features, leading to misclassification.

### **5.3 Regional Accents**

Languages exhibit significant regional variations in pronunciation, which may overlap with other languages, making it difficult to distinguish them purely using MFCCs.

## **6. Conclusion and Future Work**

MFCCs serve as a useful feature set for distinguishing languages, but they are sensitive to speaker and environmental variations. Future work may incorporate deep learning models, additional acoustic features (e.g., spectrograms, pitch contours), and noise-robust preprocessing techniques to improve classification accuracy.