DS203-Project E7

Link for folder containing Train data

https://iitbacin-my.sharepoint.com/:f:/g/personal/23b0312_iitb_ac_in/EnomrKcxO4pAi6OHpylzMnUBhr2YYjyQP1zr0L8BMSGslw?e=mc0alT


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EXECUTIVE OVERVIEW

- **PROBLEM FRAMING:** We decided to solve only the mandatory problems understood the problem as a classification problem with 3 objectives. Broad classification of songs and classification songs based on if they belong to the following categories or not (National Anthem, Asha Bhosale, Kishore Kumar, Michael Jackson) .
- **DATA ACQUISITION:** For training our model we downloaded various songs and converted them into MFCC files using the given code.
- **DOMAIN KNOWLEDGE:** Research into MFCC useful for feature selection.
- **DATA PREPARATION:** Data was scaled and EDA was performed. Coupling EDA and domain knowledge we selected various relevant features.
- **MODELS:** RandomForrest and SVM were chosen for classification and were trained and then used to predict song classes.

DATA COLLECTION

- **Song Selection:** Curated relevant songs from YouTube playlists, focusing on specific artists and genres.
- **Audio Conversion:** Converted selected YouTube videos into audio files for analysis.
- **Feature Extraction:** Generated training data by extracting MFCC coefficients from audio files using the provided code.
- **Dataset Composition:**

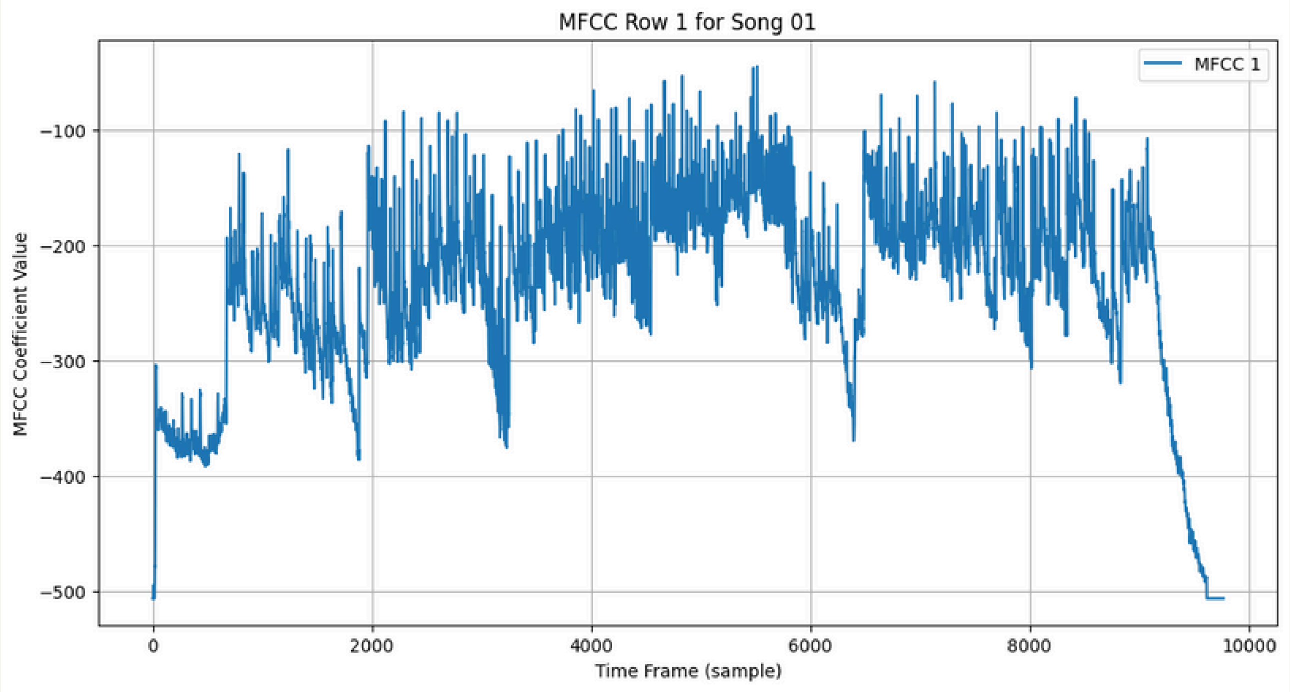
Asha Bhosle Songs: ~350
Kishore Kumar Songs: ~200
Michael Jackson Songs: ~250
Marathi Lavni Geet: ~250
Marathi Bhav Geet: ~100

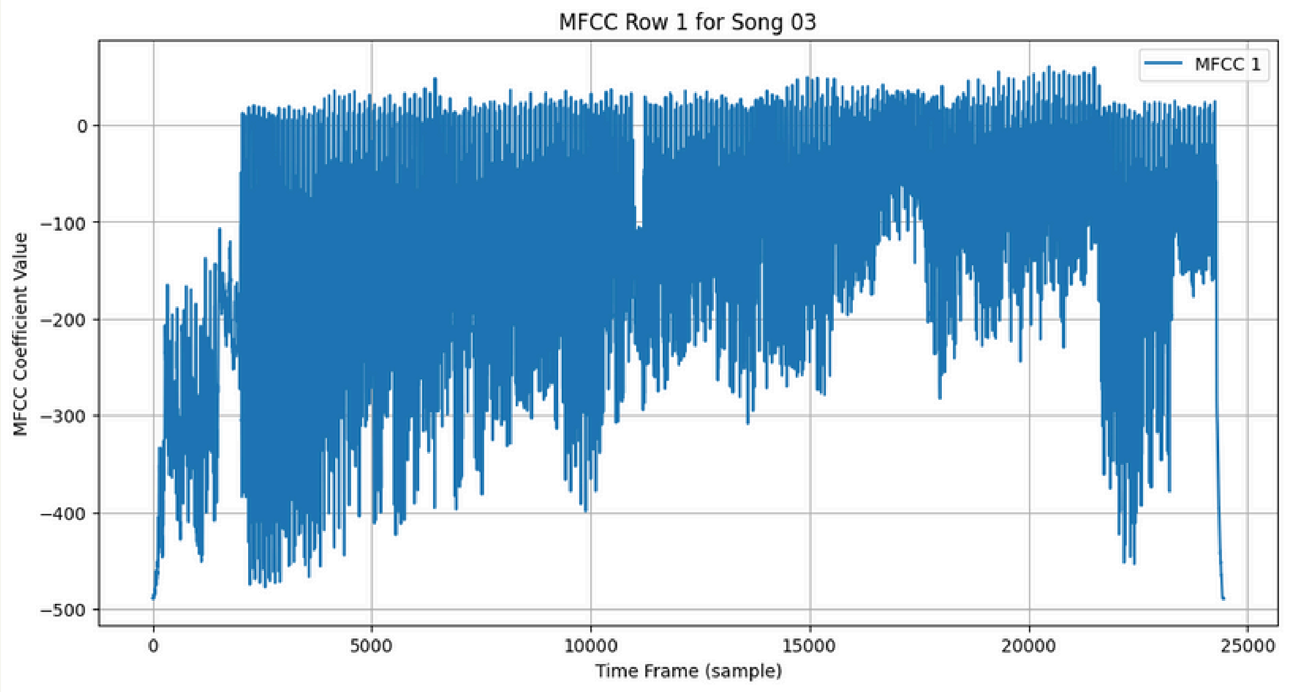
DATASET PRE-PROCESSING

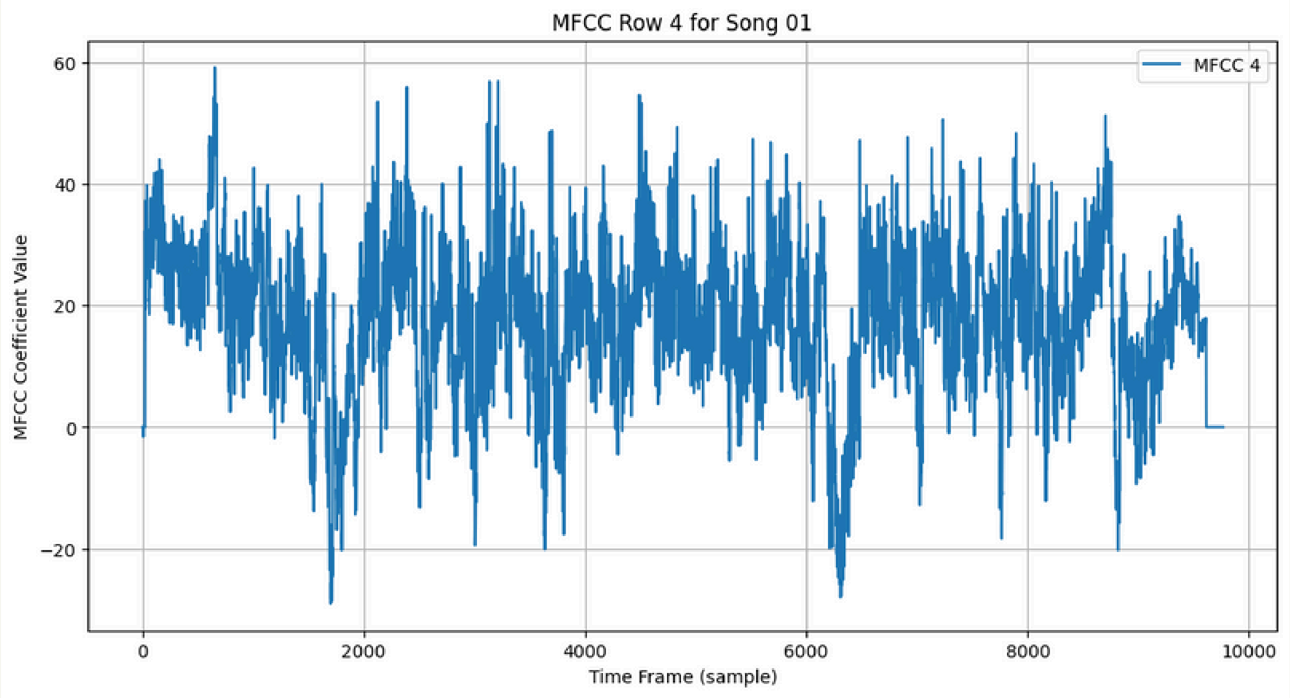
- Scaled all the data for consistent feature scaling.
- Performed EDA to gain insights required for feature creation so as to successfully differentiate between songs belonging to different artists and genres

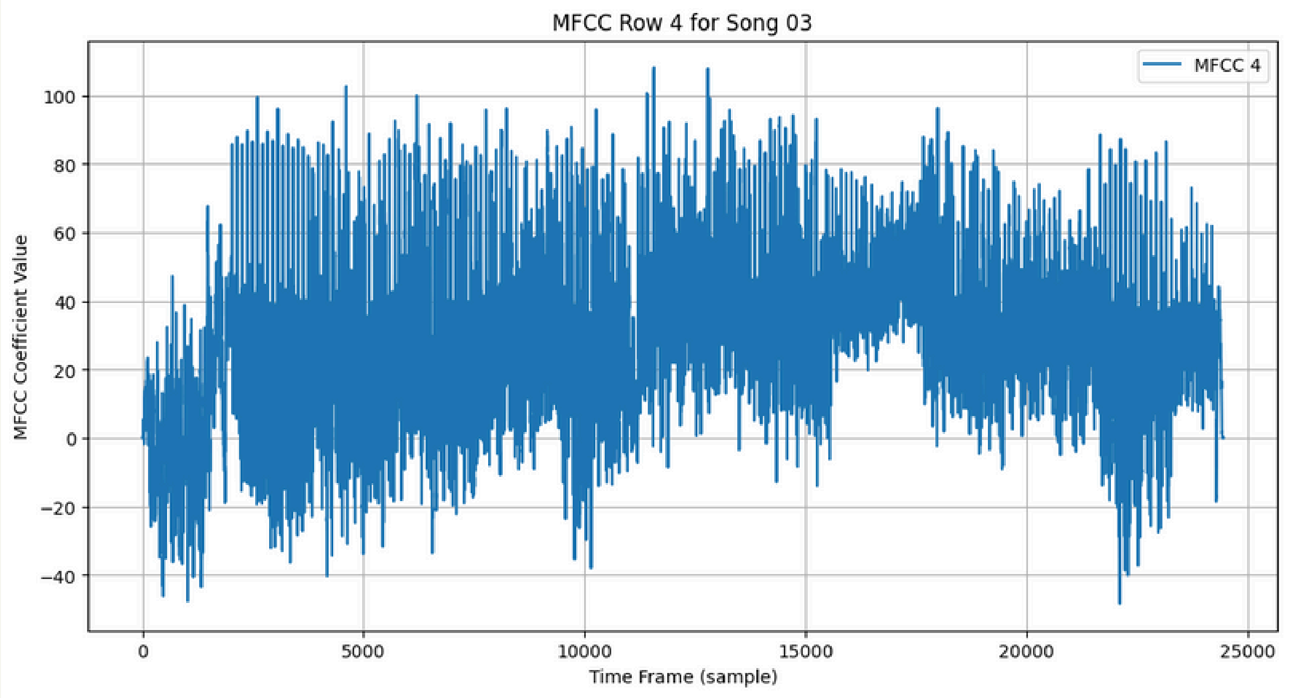
EDA

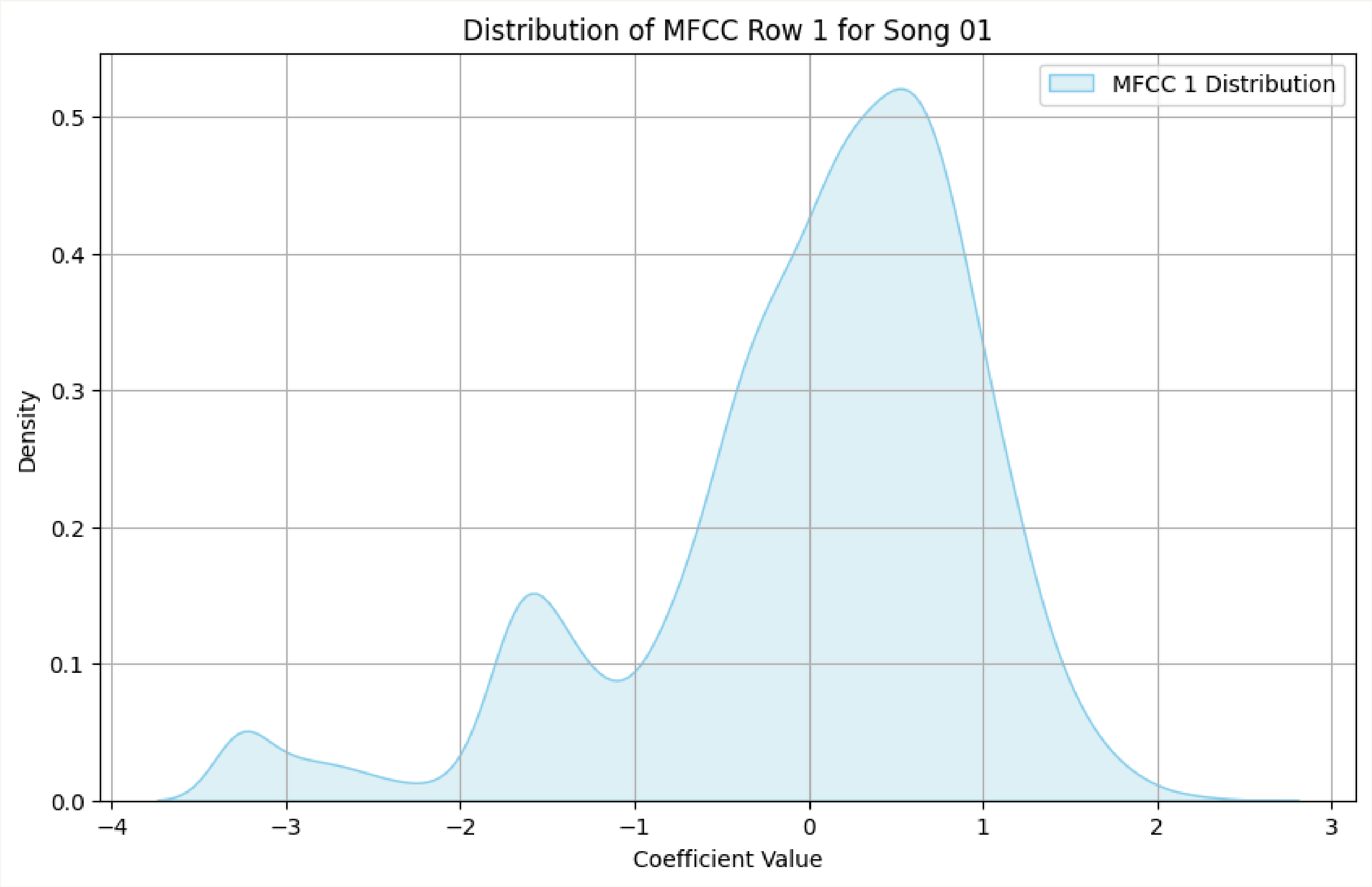
We plotted various MFCC features on the time and frequency scale.

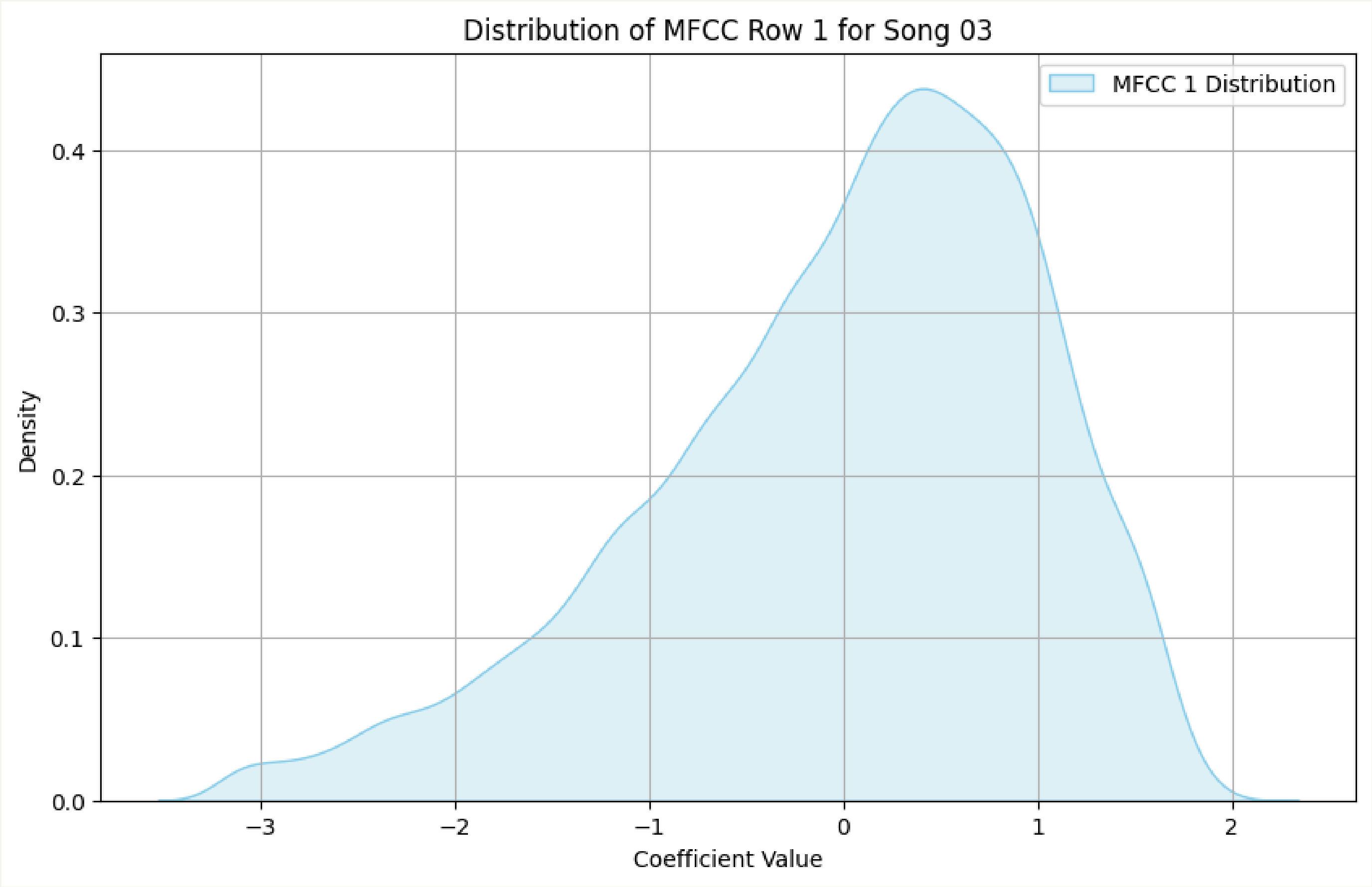


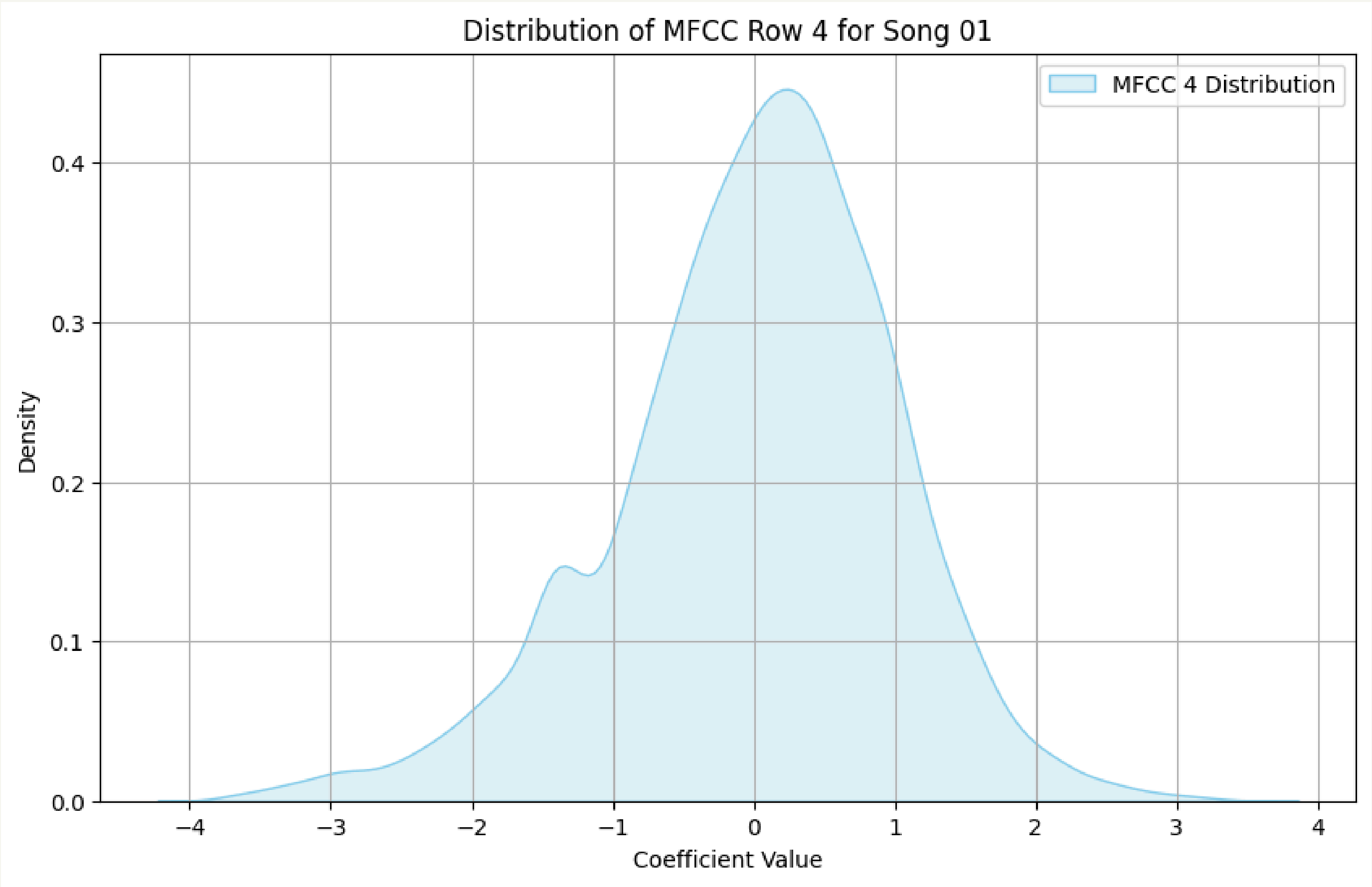


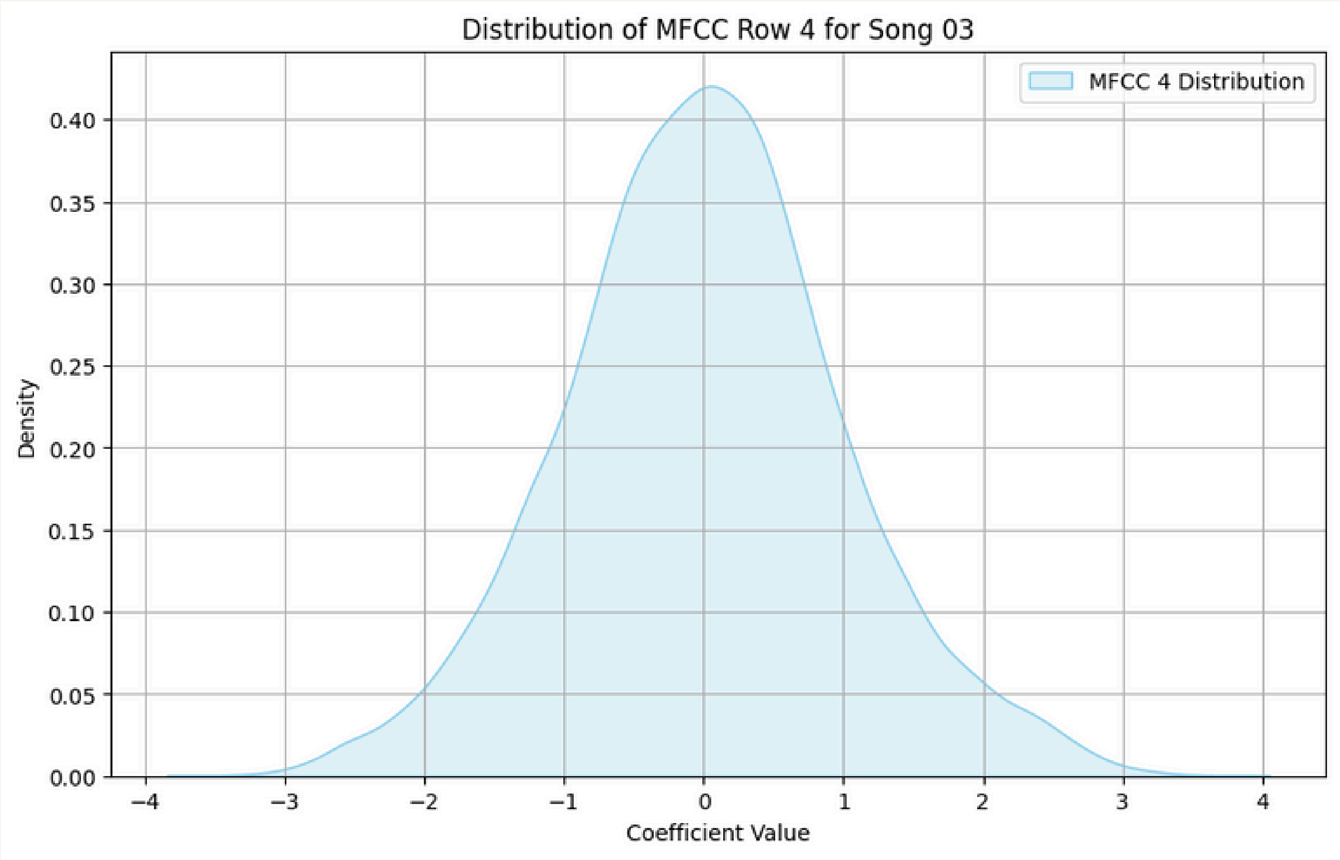












frequency scale

Feature Selection

Using this and our research into MFCC coefficients we decided on using **mean**, **energy**, **entropy**, **homogenity**, **contrast** and **correlation** of MFCC(provided), **delta** MFCC and **delta delta** MFCC(calculated from MFCC data) as our features.
Following are reasons as to why we decided on using specific features.

Means: Mean of he MFCC feature is the most basic feature that summarizes the whole MFCC features created on the time-scale into one feature.

Energy: Indicates the intensity of the MFCC coefficient transitions over time, helping identify songs with strong tonal consistency versus those with more complex or varied timbre.

- High Energy: Found in **Michael Jackson**'s English pop songs and **Marathi Lavni** songs due to their energetic beats, instrumentation, and dynamic performances.
- Low Energy: Found in **Bhav Geet** and **Indian National Anthem**, which are typically softer, more melody-focused, and lack intense rhythmic elements.

Entropy: Captures the randomness in the temporal patterns of MFCC coefficients, which can differentiate tracks with complex or varied sounds (high entropy) from those with repetitive, simple patterns (low entropy).

- High Entropy: Likely in **Michael Jackson**'s songs and **Asha Bhosale**'s Hindi songs, where varied instrumentation and vocal modulation introduce greater complexity in the frequency distribution.
- Low Entropy: Seen in **Indian National Anthem** and possibly **Bhav Geet**, as these songs often have simpler, smoother melodies and fewer tonal variations.

Homogeinity: Homogeneity assesses the uniformity of frequencies by examining how closely each component aligns with the overall mean. Higher homogeneity implies a consistent, harmonious sound, whereas lower homogeneity suggests more variability.

- High Homogeneity: Likely observed in **Indian National Anthem** and **Bhav Geet**, as these songs have more consistent and smooth melodic patterns without frequent changes in frequency.
- Low Homogeneity: Seen in **Michael Jackson**'s songs and **Lavni** songs, where instrumentation and vocal dynamics introduce greater frequency variability.

Contrast: evaluates the variance around the mean frequency, with larger contrast indicating greater disparities between frequency peaks and troughs.

- High Contrast: Found in **Marathi Lavni** songs and **Michael Jackson**'s pop songs due to the distinct shifts between beats, vocals, and instrumental elements.
- Low Contrast: Likely in **Indian National Anthem** and **Bhav Geet**, which tend to have more uniform frequency distributions without sharp tonal shifts.

Correlation: reflects how well the frequency components follow a consistent relationship across the spectrum. It measures the similarity between adjacent frequency bins and is indicative of recurring patterns or harmonics.

- High Correlation: Observed in **Indian National Anthem** and **Bhav Geet**, as these songs maintain a more consistent tonal pattern, reflecting structured melodies with minimal abrupt changes.
- Low Correlation: Likely in **Michael Jackson**'s songs and **Lavni** songs, which often feature more diverse elements and dynamic structures, reducing frequency component consistency.

Finally, we created these features for MFCC, **delta** MFCC and **delta delta** MFCC coefficients. Since, our approach basically takes one value for each feature for a song, it might be incapable of accounting for the time dependent features for this we have used delta and delta delta MFCC features which are basically derivative and double derivative of MFCC features in an attempt to better account for **temporal** variations in the songs.

Using the above feature engineering we have finally created a set of 20(MFCC coeffs) *6 (feature creation)*3(delta) that is **360** feature set.

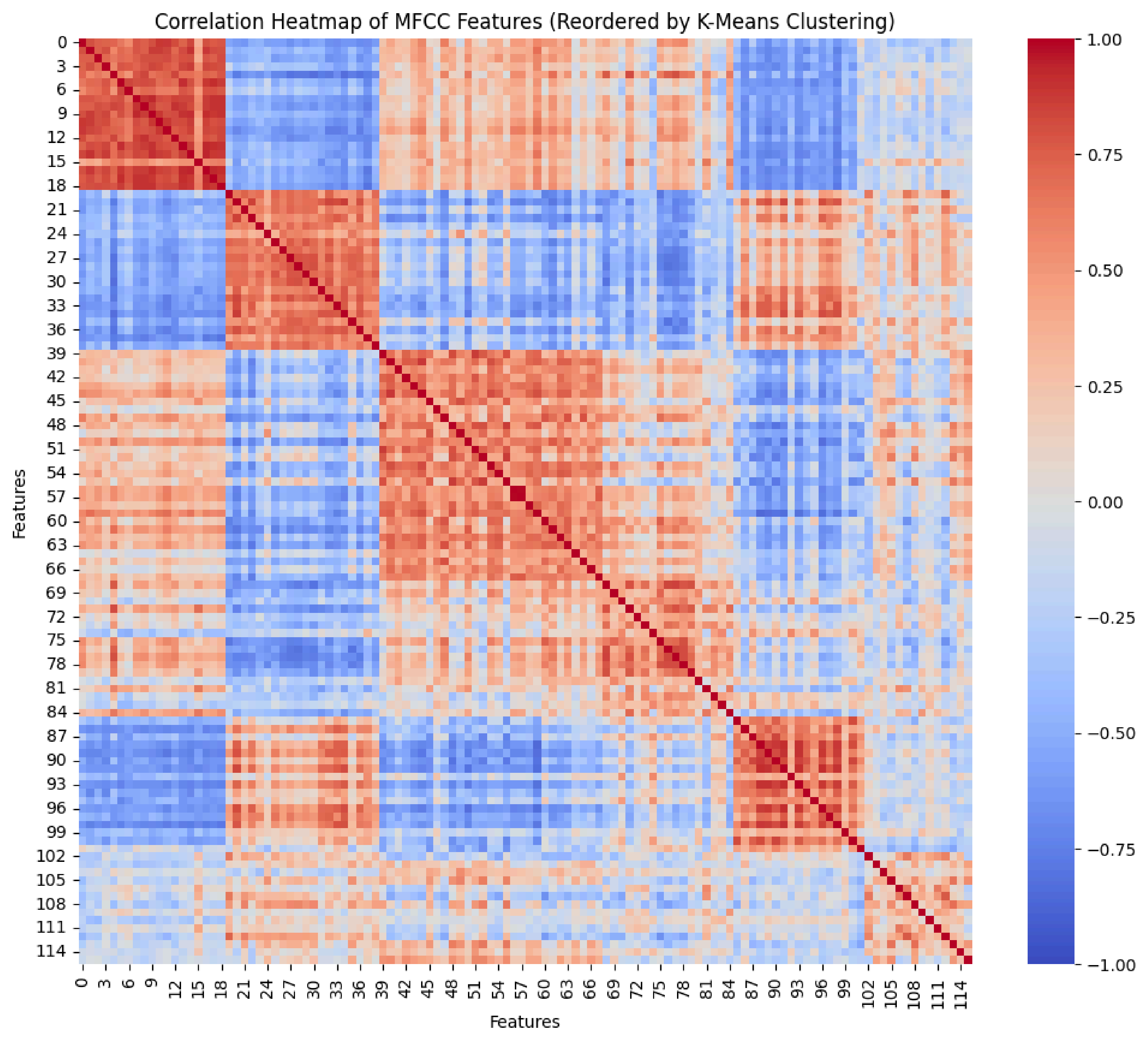
Since our dataset is extremely large creating these features is extremely computationally demanding. Therefore, in order to speed up the process we have used **Fast Fourier Transform (FFT)**.

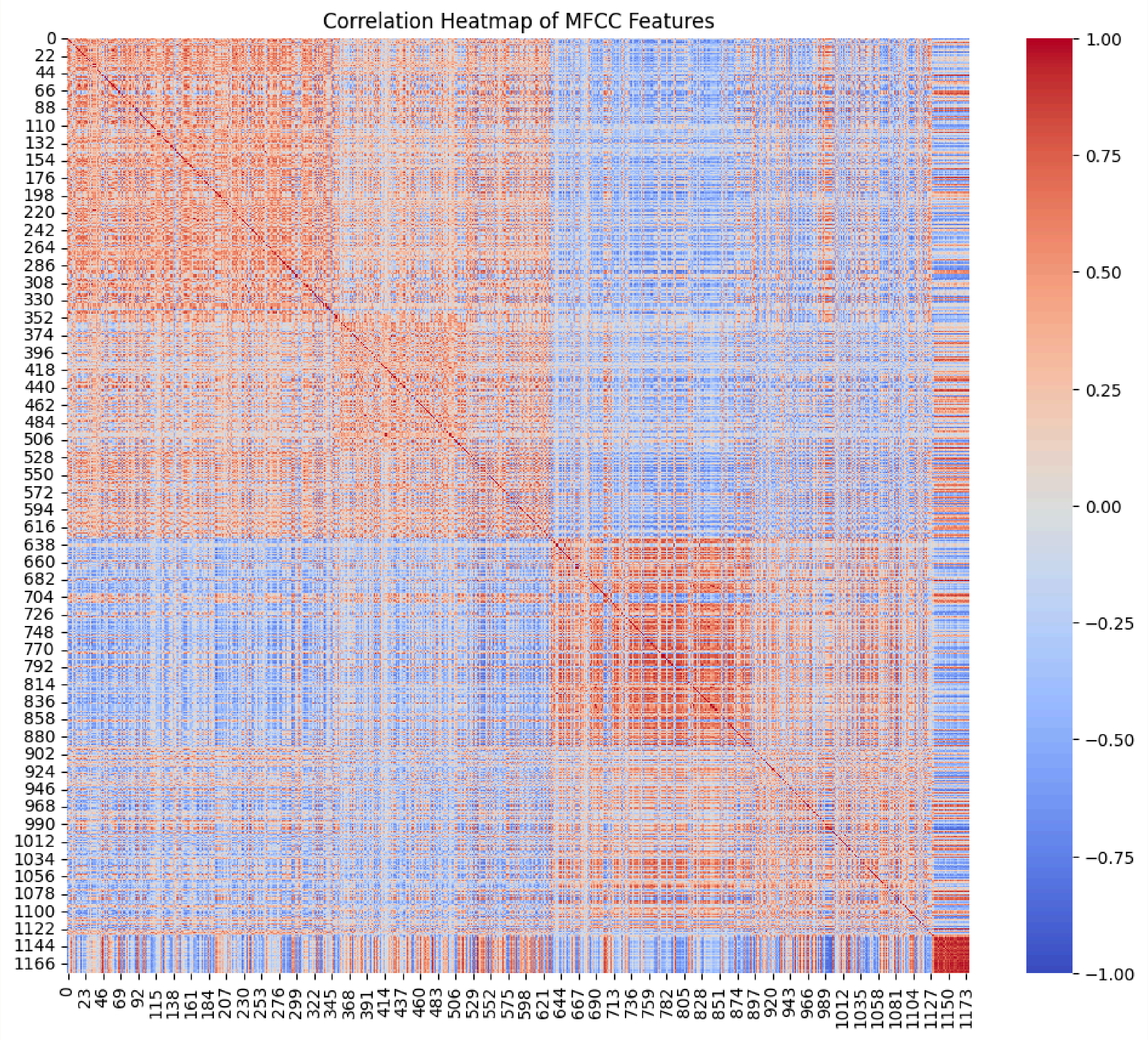
EDA 2

Now that we have a set of features we can do some more analysis on our dataset. We can start by clustering to help us visualize the classes in the given

Then we applied K-means clustering and visualized using feature heatmap.

6 clusters can be clearly visualized from this map. Which indicate strong presence of 6 classes in the dataset that we already know there are.





For context, this is the same heatmap for our train data , some similarity is clearly visible between the two. Similar structure can be seen

Classification

For classification we have decided to use **RandomForrest** and **SVM** classifiers. For classifier evaluation we have divided our downloaded songs into a **70-30** train test split.
For problem 1 we have used **general multi-class** classification and for Problem 2 and 3 i.e to identify atleast 3 songs for the 4 artists we have used **1 vs All** classification i.e we have classified wether the songs is sung by a particular artist or not and this has been done 4 times 1 time each for each artist.

SMOTE

Classification models are biased towards majority class balanced data to **fix class imbalance** in our training dataset we have used **Synthetic Minority Oversampling Techniques (SMOTE)** this is especially necessary in 1 vs all classification as well as for National Anthem. We have compared results for classifiers bith with SMOTE and without.

Problem 1

Analyze MFCC files to organize the 115 files into groups broadly corresponding to those listed above

The class wise precision recall and f1-score is tabulated for these classifiers and the one performing best is chosen for final results. The confusion matrix for the same is also tabulated.

In order to broadly classify the songs into the given categories we have classified them. For this we have used RF and SVM classifier with and without smote giving us 4 final set of predictions.

Problem 1

RandomForestClassifier (SMOTE: False) Metrics:
Accuracy: 0.8050847457627118

Class	Precision	Recall	F1-Score	Support
AB	0.80	0.89	0.84	111
KK	0.67	0.82	0.74	51
MB	0.54	0.34	0.42	38
MJ	0.99	0.86	0.92	80
ML	0.84	0.83	0.83	64
NA	0.90	0.90	0.90	10
Accuracy			0.81	354
Macro avg	0.79	0.77	0.78	354
Weighted avg	0.80	0.81	0.80	354

	AB	KK	MB	MJ	ML	NA
AB	99	5	4	0	3	0
KK	5	42	3	0	0	1
MB	12	10	13	0	3	0
MJ	2	4	1	69	4	0
ML	6	1	3	1	53	0
NA	0	1	0	0	0	9

RF classifier without SMOTE performs poorly for Marathi Bhav Geet songs giving unacceptable Precision, Recall and F1-score values.

RandomForestClassifier (SMOTE: True) Metrics:
Accuracy: 0.8107344632768362

Class	Precision	Recall	F1-Score	Support
AB	0.83	0.85	0.84	111
KK	0.69	0.82	0.75	51
MB	0.55	0.47	0.51	38
MJ	0.96	0.89	0.92	80
ML	0.84	0.84	0.84	64
NA	0.89	0.80	0.84	10
Accuracy			0.81	354
Macro avg	0.79	0.78	0.78	354
Weighted avg	0.81	0.81	0.81	354

	AB	KK	MB	MJ	ML	NA
AB	94	3	10	0	4	0
KK	5	42	3	0	0	1
MB	7	9	18	1	3	0
MJ	1	5	0	71	3	0
ML	5	1	2	2	54	0
NA	1	1	0	0	0	8

Again a similar pattern is noticed. Poor values for Marathi Bhav Geet.

Random Forest Predictions (without SMOTE)

Label	Files
NA	02-MFCC.csv, 108-MFCC.csv, 116-MFCC.csv, 16-MFCC.csv, 17-MFCC.csv, 27-MFCC.csv, 35-MFCC.csv, 66-MFCC.csv, 67-MFCC.csv, 75-MFCC.csv, 81-MFCC.csv, 87-MFCC.csv, 90-MFCC.csv, 95-MFCC.csv
AB	06-MFCC.csv, 10-MFCC.csv, 102-MFCC.csv, 105-MFCC.csv, 106-MFCC.csv, 110-MFCC.csv, 115-MFCC.csv, 13-MFCC.csv, 21-MFCC.csv, 23-MFCC.csv, 25-MFCC.csv, 28-MFCC.csv, 30-MFCC.csv, 33-MFCC.csv, 36-MFCC.csv, 38-MFCC.csv, 40-MFCC.csv, 43-MFCC.csv, 56-MFCC.csv, 57-MFCC.csv, 72-MFCC.csv, 77-MFCC.csv, 79-MFCC.csv, 80-MFCC.csv, 82-MFCC.csv, 91-MFCC.csv, 94-MFCC.csv, 96-MFCC.csv
KK	05-MFCC.csv, 07-MFCC.csv, 09-MFCC.csv, 101-MFCC.csv, 18-MFCC.csv, 29-MFCC.csv, 46-MFCC.csv, 50-MFCC.csv, 51-MFCC.csv, 58-MFCC.csv, 59-MFCC.csv, 63-MFCC.csv, 65-MFCC.csv, 84-MFCC.csv, 92-MFCC.csv, 93-MFCC.csv, 97-MFCC.csv
MB	100-MFCC.csv, 111-MFCC.csv, 48-MFCC.csv, 83-MFCC.csv
ML	01-MFCC.csv, 04-MFCC.csv, 104-MFCC.csv, 107-MFCC.csv, 109-MFCC.csv, 11-MFCC.csv, 112-MFCC.csv, 113-MFCC.csv, 12-MFCC.csv, 14-MFCC.csv, 15-MFCC.csv, 19-MFCC.csv, 22-MFCC.csv, 24-MFCC.csv, 26-MFCC.csv, 31-MFCC.csv, 32-MFCC.csv, 39-MFCC.csv, 41-MFCC.csv, 42-MFCC.csv, 47-MFCC.csv, 49-MFCC.csv, 52-MFCC.csv, 54-MFCC.csv, 55-MFCC.csv, 60-MFCC.csv, 61-MFCC.csv, 62-MFCC.csv, 64-MFCC.csv, 70-MFCC.csv, 71-MFCC.csv, 73-MFCC.csv, 76-MFCC.csv, 85-MFCC.csv, 89-MFCC.csv, 99-MFCC.csv
MJ	03-MFCC.csv, 08-MFCC.csv, 103-MFCC.csv, 114-MFCC.csv, 20-MFCC.csv, 34-MFCC.csv, 37-MFCC.csv, 44-MFCC.csv, 45-MFCC.csv, 53-MFCC.csv, 68-MFCC.csv, 69-MFCC.csv, 74-MFCC.csv, 78-MFCC.csv, 86-MFCC.csv, 88-MFCC.csv, 98-MFCC.csv

Random Forest Predictions (with SMOTE)

Label	Files
NA	02-MFCC.csv, 108-MFCC.csv, 116-MFCC.csv, 16-MFCC.csv, 17-MFCC.csv, 27-MFCC.csv, 67-MFCC.csv, 75-MFCC.csv, 81-MFCC.csv, 87-MFCC.csv, 90-MFCC.csv, 95-MFCC.csv
AB	06-MFCC.csv, 102-MFCC.csv, 105-MFCC.csv, 106-MFCC.csv, 110-MFCC.csv, 115-MFCC.csv, 13-MFCC.csv, 15-MFCC.csv, 23-MFCC.csv, 28-MFCC.csv, 32-MFCC.csv, 33-MFCC.csv, 40-MFCC.csv, 42-MFCC.csv, 50-MFCC.csv, 56-MFCC.csv, 72-MFCC.csv, 77-MFCC.csv, 79-MFCC.csv, 80-MFCC.csv, 91-MFCC.csv, 94-MFCC.csv, 96-MFCC.csv
KK	05-MFCC.csv, 100-MFCC.csv, 111-MFCC.csv, 18-MFCC.csv, 22-MFCC.csv, 24-MFCC.csv, 29-MFCC.csv, 37-MFCC.csv, 46-MFCC.csv, 51-MFCC.csv, 57-MFCC.csv, 58-MFCC.csv, 59-MFCC.csv, 63-MFCC.csv, 65-MFCC.csv, 84-MFCC.csv, 92-MFCC.csv, 93-MFCC.csv, 97-MFCC.csv
MB	09-MFCC.csv, 10-MFCC.csv, 113-MFCC.csv, 21-MFCC.csv, 36-MFCC.csv, 38-MFCC.csv, 48-MFCC.csv, 82-MFCC.csv, 83-MFCC.csv, 89-MFCC.csv
ML	01-MFCC.csv, 04-MFCC.csv, 104-MFCC.csv, 107-MFCC.csv, 109-MFCC.csv, 11-MFCC.csv, 112-MFCC.csv, 12-MFCC.csv, 14-MFCC.csv, 19-MFCC.csv, 25-MFCC.csv, 26-MFCC.csv, 30-MFCC.csv, 31-MFCC.csv, 35-MFCC.csv, 39-MFCC.csv, 41-MFCC.csv, 43-MFCC.csv, 47-MFCC.csv, 49-MFCC.csv, 52-MFCC.csv, 54-MFCC.csv, 55-MFCC.csv, 60-MFCC.csv, 61-MFCC.csv, 62-MFCC.csv, 64-MFCC.csv, 66-MFCC.csv, 68-MFCC.csv, 70-MFCC.csv, 71-MFCC.csv, 73-MFCC.csv, 76-MFCC.csv, 85-MFCC.csv, 99-MFCC.csv
MJ	03-MFCC.csv, 07-MFCC.csv, 08-MFCC.csv, 101-MFCC.csv, 103-MFCC.csv, 114-MFCC.csv, 20-MFCC.csv, 34-MFCC.csv, 44-MFCC.csv, 45-MFCC.csv, 53-MFCC.csv, 69-MFCC.csv, 74-MFCC.csv, 78-MFCC.csv, 86-MFCC.csv, 88-MFCC.csv, 98-MFCC.csv

These are the final results of RF classification models run on the provided dataset of 116 songs

SVC (SMOTE: False) Metrics:
Accuracy: 0.8785310734463276

Class	Precision	Recall	F1-Score	Support
AB	0.87	0.94	0.90	111
KK	0.84	0.92	0.88	51
MB	0.73	0.63	0.68	38
MJ	0.95	0.89	0.92	80
ML	0.92	0.89	0.90	64
NA	1.00	0.80	0.89	10
Accuracy			0.88	354
Macro avg	0.88	0.84	0.86	354
Weighted avg	0.88	0.88	0.88	354

	AB	KK	MB	MJ	ML	NA
AB	104	2	2	0	3	0
KK	3	47	1	0	0	0
MB	6	6	24	2	0	0
MJ	1	1	5	71	2	0
ML	5	0	1	1	57	0
NA	1	0	0	1	0	8

Overall metrics of SVC outperform RF significantly and shows impressive precision values NA i.e no other songs are incorrectly classsified as NA

SVC (SMOTE: True) Metrics:
Accuracy: 0.8615819209039548

Class	Precision	Recall	F1-Score	Support
AB	0.86	0.93	0.89	111
KK	0.81	0.92	0.86	51
MB	0.70	0.55	0.62	38
MJ	0.95	0.88	0.91	80
ML	0.88	0.88	0.88	64
NA	1.00	0.80	0.89	10
Accuracy			0.86	354
Macro avg	0.86	0.83	0.84	354
Weighted avg	0.86	0.86	0.86	354

	AB	KK	MB	MJ	ML	NA
AB	103	2	2	0	4	0
KK	3	47	1	0	0	0
MB	7	8	21	2	0	0
MJ	1	1	4	70	4	0
ML	5	0	2	1	56	0
NA	1	0	0	1	0	8

Again similar results to SVC without SMOTE but Marathi Bhav Geet metric fall unexpectedly leading u to finally choose our **final model** for problem **1** as **SVC(NO SMOTE).**

SVM Predictions (without SMOTE)

Label	Files
NA	02-MFCC.csv, 116-MFCC.csv, 16-MFCC.csv, 17-MFCC.csv, 27-MFCC.csv, 67-MFCC.csv, 75-MFCC.csv, 81-MFCC.csv, 87-MFCC.csv, 90-MFCC.csv, 95-MFCC.csv
AB	05-MFCC.csv, 10-MFCC.csv, 102-MFCC.csv, 105-MFCC.csv, 111-MFCC.csv, 112-MFCC.csv, 115-MFCC.csv, 13-MFCC.csv, 15-MFCC.csv, 21-MFCC.csv, 22-MFCC.csv, 23-MFCC.csv, 24-MFCC.csv, 26-MFCC.csv, 28-MFCC.csv, 30-MFCC.csv, 32-MFCC.csv, 33-MFCC.csv, 36-MFCC.csv, 40-MFCC.csv, 41-MFCC.csv, 42-MFCC.csv, 48-MFCC.csv, 51-MFCC.csv, 71-MFCC.csv, 79-MFCC.csv, 80-MFCC.csv, 82-MFCC.csv, 83-MFCC.csv, 96-MFCC.csv, 97-MFCC.csv, 99-MFCC.csv
KK	07-MFCC.csv, 09-MFCC.csv, 100-MFCC.csv, 18-MFCC.csv, 29-MFCC.csv, 46-MFCC.csv, 50-MFCC.csv, 57-MFCC.csv, 58-MFCC.csv, 59-MFCC.csv, 63-MFCC.csv, 66-MFCC.csv, 84-MFCC.csv, 93-MFCC.csv
MB	106-MFCC.csv, 107-MFCC.csv, 108-MFCC.csv, 54-MFCC.csv, 65-MFCC.csv, 72-MFCC.csv, 88-MFCC.csv, 89-MFCC.csv, 91-MFCC.csv, 92-MFCC.csv
ML	01-MFCC.csv, 04-MFCC.csv, 06-MFCC.csv, 104-MFCC.csv, 109-MFCC.csv, 11-MFCC.csv, 110-MFCC.csv, 113-MFCC.csv, 12-MFCC.csv, 19-MFCC.csv, 25-MFCC.csv, 31-MFCC.csv, 35-MFCC.csv, 38-MFCC.csv, 39-MFCC.csv, 43-MFCC.csv, 45-MFCC.csv, 47-MFCC.csv, 49-MFCC.csv, 55-MFCC.csv, 60-MFCC.csv, 61-MFCC.csv, 62-MFCC.csv, 64-MFCC.csv, 68-MFCC.csv, 70-MFCC.csv, 73-MFCC.csv, 76-MFCC.csv, 79-MFCC.csv, 95-MFCC.csv
MJ	03-MFCC.csv, 104-MFCC.csv, 114-MFCC.csv, 113-MFCC.csv, 20-MFCC.csv, 34-MFCC.csv, 53-MFCC.csv, 74-MFCC.csv, 77-MFCC.csv, 86-MFCC.csv, 88-MFCC.csv

SVM Predictions (with SMOTE)

Label	Files
NA	02-MFCC.csv, 116-MFCC.csv, 16-MFCC.csv, 17-MFCC.csv, 27-MFCC.csv, 67-MFCC.csv, 75-MFCC.csv, 81-MFCC.csv, 87-MFCC.csv, 90-MFCC.csv, 95-MFCC.csv
AB	05-MFCC.csv, 10-MFCC.csv, 102-MFCC.csv, 105-MFCC.csv, 111-MFCC.csv, 112-MFCC.csv, 115-MFCC.csv, 13-MFCC.csv, 15-MFCC.csv, 21-MFCC.csv, 22-MFCC.csv, 23-MFCC.csv, 24-MFCC.csv, 26-MFCC.csv, 28-MFCC.csv, 30-MFCC.csv, 32-MFCC.csv, 33-MFCC.csv, 36-MFCC.csv, 40-MFCC.csv, 41-MFCC.csv, 42-MFCC.csv, 48-MFCC.csv, 51-MFCC.csv, 71-MFCC.csv, 79-MFCC.csv, 80-MFCC.csv, 82-MFCC.csv, 83-MFCC.csv, 96-MFCC.csv, 97-MFCC.csv, 99-MFCC.csv
KK	07-MFCC.csv, 09-MFCC.csv, 100-MFCC.csv, 18-MFCC.csv, 29-MFCC.csv, 46-MFCC.csv, 50-MFCC.csv, 57-MFCC.csv, 58-MFCC.csv, 59-MFCC.csv, 63-MFCC.csv, 66-MFCC.csv, 84-MFCC.csv, 93-MFCC.csv
MB	106-MFCC.csv, 107-MFCC.csv, 108-MFCC.csv, 54-MFCC.csv, 65-MFCC.csv, 72-MFCC.csv, 88-MFCC.csv, 89-MFCC.csv, 91-MFCC.csv, 92-MFCC.csv
ML	01-MFCC.csv, 04-MFCC.csv, 06-MFCC.csv, 104-MFCC.csv, 109-MFCC.csv, 11-MFCC.csv, 110-MFCC.csv, 113-MFCC.csv, 12-MFCC.csv, 19-MFCC.csv, 25-MFCC.csv, 31-MFCC.csv, 35-MFCC.csv, 38-MFCC.csv, 39-MFCC.csv, 43-MFCC.csv, 45-MFCC.csv, 47-MFCC.csv, 49-MFCC.csv, 55-MFCC.csv, 60-MFCC.csv, 61-MFCC.csv, 62-MFCC.csv, 64-MFCC.csv, 68-MFCC.csv, 70-MFCC.csv, 73-MFCC.csv, 76-MFCC.csv, 79-MFCC.csv, 95-MFCC.csv
MJ	03-MFCC.csv, 104-MFCC.csv, 114-MFCC.csv, 113-MFCC.csv, 20-MFCC.csv, 34-MFCC.csv, 53-MFCC.csv, 74-MFCC.csv, 77-MFCC.csv, 86-MFCC.csv, 88-MFCC.csv

These are the final results of SVC classification models run on the provided dataset of 116 songs.
The left table SVM(without SMOTE) is chosen as our **final answer for problem 1**

PROBLEM 2&3

2. Identify at least 3 files containing the National Anthem
3. Identify at least 3 files (each) containing solo songs by Asha Bhosale, Kishor Kumar, and Michael Jackson

For this purpose we have used **1 vs all** classification as previously mentioned same metrics have been used.

Since our goal is to have maximum confidence on our final results and not necessary classify all the songs for these problems. We have used the intersection of results given by all classification models as our final result i.e. **only** songs classified as a particular **class by all 4 models** will be present in our final "answer"

RandomForestClassifier (SMOTE: False) Metrics:
Accuracy: 0.9915254237288136

Class	Precision	Recall	F1-Score	Support
Other	0.99	1.00	1.00	344
NA	0.89	0.80	0.84	10
Accuracy	**0.99**			**354**
Macro avg	0.94	0.90	0.92	354
Weighted avg	0.99	0.99	0.99	354

SVC (SMOTE: False) Metrics:
Accuracy: 0.9971751412429378

Class	Precision	Recall	F1-Score	Support
Other	1.00	1.00	1.00	344
NA	1.00	0.90	0.95	10
Accuracy	**1.00**			**354**
Macro avg	1.00	0.95	0.97	354
Weighted avg	1.00	1.00	1.00	354

RandomForestClassifier (SMOTE: True) Metrics:
Accuracy: 0.9915254237288136

Class	Precision	Recall	F1-Score	Support
Other	0.99	1.00	1.00	344
NA	0.89	0.80	0.84	10
Accuracy	**0.99**			**354**
Macro avg	0.94	0.90	0.92	354
Weighted avg	0.99	0.99	0.99	354

SVC (SMOTE: True) Metrics:
Accuracy: 0.9971751412429378

Class	Precision	Recall	F1-Score	Support
Other	1.00	1.00	1.00	344
NA	1.00	0.90	0.95	10
Accuracy	**1.00**			**354**
Macro avg	1.00	0.95	0.97	354
Weighted avg	1.00	1.00	1.00	354

	RandomForestClassifier (SMOTE: False)	SVC (SMOTE: False)	RandomForestClassifier (SMOTE: True)	SVC (SMOTE: True)
	[Other, NA]	[Other, NA]	[Other, NA]	[Other, NA]
Other	[343, 1]	[344, 0]	[343, 1]	[344, 0]
NA	[2, 8]	[1, 9]	[2, 8]	[1, 9]

In this case the metrics relevant are only those of the class classified as one there fore only those will be used for evaluation

Using that it is clear that **SVC** is the **best** performer with both SMOTE = True and False showing identical metrics

Model	Files
Random Forest (without SMOTE)	'02-MFCC.csv', '116-MFCC.csv', '17-MFCC.csv', '27-MFCC.csv', '35-MFCC.csv', '67-MFCC.csv', '75-MFCC.csv', '81-MFCC.csv', '87-MFCC.csv', '95-MFCC.csv'
SVM (without SMOTE)	'02-MFCC.csv', '108-MFCC.csv', '116-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '27-MFCC.csv', '31-MFCC.csv', '35-MFCC.csv', '67-MFCC.csv', '75-MFCC.csv', '81-MFCC.csv '87-MFCC.csv', '90-MFCC.csv', '95-MFCC.csv'
Random Forest (with SMOTE)	'02-MFCC.csv', '116-MFCC.csv', '17-MFCC.csv', '27-MFCC.csv', '35-MFCC.csv', '75-MFCC.csv', '81-MFCC.csv', '87-MFCC.csv', '90-MFCC.csv', '95-MFCC.csv'
SVM (with SMOTE)	'02-MFCC.csv', '108-MFCC.csv', '116-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '27-MFCC.csv', '35-MFCC.csv', '67-MFCC.csv', '75-MFCC.csv', '81-MFCC.csv', '87-MFCC.csv '90-MFCC.csv', '95-MFCC.csv'
Common Predictions by All Models	'75-MFCC.csv', '27-MFCC.csv', '81-MFCC.csv', '116-MFCC.csv', '02-MFCC.csv', '95-MFCC.csv', '17-MFCC.csv', '35-MFCC.csv', '87-MFCC.csv'

RandomForestClassifier (SMOTE: False) Metrics:
Accuracy: 0.9096045197740112

Metric	Precision	Recall	F1-Score	Support
Others	0.91	0.97	0.94	243
AB	0.92	0.78	0.84	111
Accuracy	**0.91**			354
Macro Avg	0.91	0.88	0.89	354
Weighted Avg	0.91	0.91	0.91	354

SVC (SMOTE: False) Metrics:
Accuracy: 0.9463276836158192

Metric	Precision	Recall	F1-Score	Support
Others	0.97	0.95	0.96	243
AB	0.90	0.94	0.92	111
Accuracy	**0.95**			354
Macro Avg	0.93	0.94	0.94	354
Weighted Avg	0.95	0.95	0.95	354

RandomForestClassifier (SMOTE: True) Metrics:
Accuracy: 0.9067796610169492

Metric	Precision	Recall	F1-Score	Support
Others	0.93	0.93	0.93	243
AB	0.85	0.86	0.85	111
Accuracy	**0.91**			354
Macro Avg	0.89	0.89	0.89	354
Weighted Avg	0.91	0.91	0.91	354

SVC (SMOTE: True) Metrics:
Accuracy: 0.9322033898305084

Metric	Precision	Recall	F1-Score	Support
Others	0.97	0.93	0.95	243
AB	0.85	0.95	0.90	111
Accuracy	**0.93**			354
Macro Avg	0.91	0.94	0.92	354
Weighted Avg	0.94	0.93	0.93	354

	RandomForestClassifier (SMOTE: False)	SVC (SMOTE: False)	RandomForestClassifier (SMOTE: True)	SVC (SMOTE: True)
	[Other, AB]	[Other, AB]	[Other, AB]	[Other, AB]
Other	[235, 8]	[231, 12]	[226, 17]	[225, 18]
AB	[24, 87]	[7, 104]	[16, 95]	[6, 105]

Using previous criteria **SVC**(SMOTE=False) is the **best** model

Model	Songs Belonging to 'AB'
Random Forest (without SMOTE)	'102-MFCC.csv', '105-MFCC.csv', '106-MFCC.csv', '115-MFCC.csv', '23-MFCC.csv', '33-MFCC.csv', '79-MFCC.csv', '80-MFCC.csv', '94-MFCC.csv'
SVM (without SMOTE)	'05-MFCC.csv', '100-MFCC.csv', '102-MFCC.csv', '105-MFCC.csv', '111-MFCC.csv', '115-MFCC.csv', '15-MFCC.csv', '18-MFCC.csv', '23-MFCC.csv', '26-MFCC.csv', '28-MFCC.csv', '29-MFCC.csv', '30-MFCC.csv', '31-MFCC.csv', '41-MFCC.csv', '42-MFCC.csv', '51-MFCC.csv', '70-MFCC.csv', '71-MFCC.csv', '79-MFCC.csv', '82-MFCC.csv', '84-MFCC.csv', '93-MFCC.csv', '94-MFCC.csv', '96-MFCC.csv', '99-MFCC.csv'
Random Forest (with SMOTE)	'10-MFCC.csv', '102-MFCC.csv', '105-MFCC.csv', '106-MFCC.csv', '115-MFCC.csv', '21-MFCC.csv', '23-MFCC.csv', '33-MFCC.csv', '40-MFCC.csv', '56-MFCC.csv', '72-MFCC.csv', '77-MFCC.csv', '79-MFCC.csv', '80-MFCC.csv', '94-MFCC.csv'
SVM (with SMOTE)	'05-MFCC.csv', '100-MFCC.csv', '102-MFCC.csv', '105-MFCC.csv', '109-MFCC.csv', '111-MFCC.csv', '115-MFCC.csv', '15-MFCC.csv', '18-MFCC.csv', '23-MFCC.csv', '26-MFCC.csv', '28-MFCC.csv', '30-MFCC.csv', '31-MFCC.csv', '32-MFCC.csv', '33-MFCC.csv', '41-MFCC.csv', '42-MFCC.csv', '50-MFCC.csv', '51-MFCC.csv', '56-MFCC.csv', '70-MFCC.csv', '75-MFCC.csv', '79-MFCC.csv', '82-MFCC.csv', '83-MFCC.csv', '84-MFCC.csv', '93-MFCC.csv', '94-MFCC.csv', '96-MFCC.csv', '99-MFCC.csv'
Common Predictions by All Models	'102-MFCC.csv', '23-MFCC.csv', '105-MFCC.csv', '94-MFCC.csv', '115-MFCC.csv', '79-MFCC.csv'

RandomForestClassifier (SMOTE: False) Metrics:
Accuracy: 0.923728813559322

Metric	Precision	Recall	F1-Score	Support
Others	0.94	0.97	0.96	303
KK	0.79	0.65	0.71	51
Accuracy	**0.92**			354
Macro Avg	0.86	0.81	0.83	354
Weighted Avg	0.92	0.92	0.92	354

SVC (SMOTE: False) Metrics:
Accuracy: 0.96892655367231640

Metric	Precision	Recall	F1-Score	Support
Others	0.99	0.98	0.98	303
KK	0.87	0.92	0.90	51
Accuracy	**0.97**			354
Macro Avg	0.93	0.95	0.94	354
Weighted Avg	0.97	0.97	0.97	354

RandomForestClassifier (SMOTE: True) Metrics:
Accuracy: 0.9491525423728814

Metric	Precision	Recall	F1-Score	Support
Others	0.96	0.98	0.97	303
KK	0.85	0.78	0.82	51
Accuracy	**0.95**			354
Macro Avg	0.91	0.88	0.89	354
Weighted Avg	0.95	0.95	0.95	354

SVC (SMOTE: True) Metrics:
Accuracy: 0.9632768361581920

Metric	Precision	Recall	F1-Score	Support
Others	0.99	0.97	0.98	303
KK	0.84	0.92	0.88	51
Accuracy	**0.96**			354
Macro Avg	0.91	0.95	0.93	354
Weighted Avg	0.97	0.96	0.96	354

	RandomForestClassifier (SMOTE: False)	SVC (SMOTE: False)	RandomForestClassifier (SMOTE: True)	SVC (SMOTE: True)
	[Other, KK]	[Other, KK]	[Other, KK]	[Other, KK]
Other	[294, 9]	[296, 7]	[296, 7]	[294, 9]
KK	[18, 33]	[4, 47]	[11, 40]	[4, 47]

Model	Songs Belonging to 'KK'
Random Forest (without SMOTE)	'09-MFCC.csv', '18-MFCC.csv', '29-MFCC.csv', '46-MFCC.csv', '51-MFCC.csv', '59-MFCC.csv', '63-MFCC.csv', '84-MFCC.csv', '93-MFCC.csv', '97-MFCC.csv'
SVM (without SMOTE)	'01-MFCC.csv', '02-MFCC.csv', '09-MFCC.csv', '100-MFCC.csv', '116-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '18-MFCC.csv', '27-MFCC.csv', '29-MFCC.csv', '46-MFCC.csv', '50-MFCC.csv', '51-MFCC.csv', '58-MFCC.csv', '59-MFCC.csv', '63-MFCC.csv', '66-MFCC.csv', '67-MFCC.csv', '81-MFCC.csv', '84-MFCC.csv', '87-MFCC.csv', '90-MFCC.csv', '93-MFCC.csv', '95-MFCC.csv', '97-MFCC.csv'
Random Forest (with SMOTE)	'29-MFCC.csv', '46-MFCC.csv', '58-MFCC.csv', '59-MFCC.csv', '93-MFCC.csv'
SVM (with SMOTE)	'01-MFCC.csv', '02-MFCC.csv', '09-MFCC.csv', '100-MFCC.csv', '116-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '18-MFCC.csv', '27-MFCC.csv', '29-MFCC.csv', '32-MFCC.csv', '46-MFCC.csv', '50-MFCC.csv', '51-MFCC.csv', '58-MFCC.csv', '59-MFCC.csv', '63-MFCC.csv', '65-MFCC.csv', '66-MFCC.csv', '67-MFCC.csv', '80-MFCC.csv', '81-MFCC.csv', '84-MFCC.csv', '87-MFCC.csv', '90-MFCC.csv', '93-MFCC.csv', '95-MFCC.csv', '97-MFCC.csv'
Common Predictions by All Models	'46-MFCC.csv', '93-MFCC.csv', '59-MFCC.csv', '29-MFCC.csv'

SMOTE shows significant improvement in the case of RF classifier although SVM has no noticeable change

SVC without SMOTE gives best metrics for the required data.

RandomForestClassifier (SMOTE: False) Metrics:
Accuracy: 0.96045197740113

Metric	Precision	Recall	F1-Score	Support
Others	0.95	1.00	0.97	274
MJ	0.99	0.84	0.91	80
Accuracy	**0.96**			354
Macro Avg	0.97	0.92	0.94	354
Weighted Avg	0.96	0.96	0.96	354

SVC (SMOTE: False) Metrics:
Accuracy: 0.9661016949152542

Metric	Precision	Recall	F1-Score	Support
Others	0.97	0.99	0.98	274
MJ	0.95	0.90	0.92	80
Accuracy	**0.97**			354
Macro Avg	0.96	0.94	0.95	354
Weighted Avg	0.97	0.97	0.97	354

RandomForestClassifier (SMOTE: True) Metrics:
Accuracy: 0.9519774011299436

Metric	Precision	Recall	F1-Score	Support
Others	0.95	0.99	0.97	274
MJ	0.97	0.81	0.88	80
Accuracy	**0.95**			354
Macro Avg	0.96	0.90	0.93	354
Weighted Avg	0.95	0.95	0.95	354

SVC (SMOTE: True) Metrics:
Accuracy: 0.9774011299435028

Metric	Precision	Recall	F1-Score	Support
Others	0.99	0.98	0.99	274
MJ	0.93	0.97	0.95	80
Accuracy	**0.98**			354
Macro Avg	0.96	0.98	0.97	354
Weighted Avg	0.98	0.98	0.98	354

	RandomForestClassifier (SMOTE: False)	SVC (SMOTE: False)	RandomForestClassifier (SMOTE: True)	SVC (SMOTE: True)
	[Other, MJ]	[Other, MJ]	[Other, MJ]	[Other, MJ]
Other	[273, 1]	[270, 4]	[272, 2]	[268, 6]
MJ	[13, 67]	[8, 72]	[15, 65]	[2, 78]

Model	Songs Belonging to 'MJ'
Random Forest (without SMOTE)	'03-MFCC.csv', '08-MFCC.csv', '103-MFCC.csv', '114-MFCC.csv', '20-MFCC.csv', '34-MFCC.csv', '44-MFCC.csv', '45-MFCC.csv', '53-MFCC.csv', '69-MFCC.csv', '74-MFCC.csv', '78-MFCC.csv', '86-MFCC.csv', '88-MFCC.csv', '98-MFCC.csv'
SVM (without SMOTE)	'01-MFCC.csv', '02-MFCC.csv', '03-MFCC.csv', '07-MFCC.csv', '08-MFCC.csv', '101-MFCC.csv', '103-MFCC.csv', '107-MFCC.csv', '108-MFCC.csv', '114-MFCC.csv', '14-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '20-MFCC.csv', '31-MFCC.csv', '35-MFCC.csv', '37-MFCC.csv', '59-MFCC.csv', '61-MFCC.csv', '68-MFCC.csv', '74-MFCC.csv', '75-MFCC.csv', '78-MFCC.csv', '86-MFCC.csv', '87-MFCC.csv', '90-MFCC.csv', '93-MFCC.csv', '95-MFCC.csv', '98-MFCC.csv'
Random Forest (with SMOTE)	'03-MFCC.csv', '08-MFCC.csv', '103-MFCC.csv', '114-MFCC.csv', '20-MFCC.csv', '34-MFCC.csv', '44-MFCC.csv', '45-MFCC.csv', '53-MFCC.csv', '69-MFCC.csv', '74-MFCC.csv', '86-MFCC.csv', '88-MFCC.csv', '98-MFCC.csv'
SVM (with SMOTE)	'01-MFCC.csv', '02-MFCC.csv', '03-MFCC.csv', '07-MFCC.csv', '08-MFCC.csv', '100-MFCC.csv', '101-MFCC.csv', '102-MFCC.csv', '107-MFCC.csv', '108-MFCC.csv', '11-MFCC.csv', '116-MFCC.csv', '14-MFCC.csv', '16-MFCC.csv', '17-MFCC.csv', '22-MFCC.csv', '25-MFCC.csv', '27-MFCC.csv', '29-MFCC.csv', '31-MFCC.csv', '35-MFCC.csv', '37-MFCC.csv', '41-MFCC.csv', '42-MFCC.csv', '43-MFCC.csv', '58-MFCC.csv', '59-MFCC.csv', '61-MFCC.csv', '66-MFCC.csv', '67-MFCC.csv', '68-MFCC.csv', '74-MFCC.csv', '75-MFCC.csv', '78-MFCC.csv', '81-MFCC.csv', '85-MFCC.csv', '87-MFCC.csv', '90-MFCC.csv', '93-MFCC.csv', '95-MFCC.csv'
Common Predictions by All Models	'74-MFCC.csv', '08-MFCC.csv', '03-MFCC.csv'

SMOTE shows significant improvement in the case of SVM classifier and final metrics are extremely impressive. Which indicates high separability of Michael Jackson songs from other classes.

RESULTS

Following slides encompass the final results generated by the whole process

For problem 1 we have listed the classified songs for the best performing model i.e. SVM(w/o SMOTE).

For the 2nd and 3rd Problem Intersection set of all models are used to give the final classified songs since our goal is to maintain maximum accuracy and not high numbers

P1 Final Results

SVM Predictions (without SMOTE)

Label	Files
NA	02-MFCC.csv, 116-MFCC.csv, 16-MFCC.csv, 17-MFCC.csv, 27-MFCC.csv, 67-MFCC.csv, 75-MFCC.csv, 81-MFCC.csv, 87-MFCC.csv, 90-MFCC.csv, 95-MFCC.csv
AB	05-MFCC.csv, 10-MFCC.csv, 102-MFCC.csv, 105-MFCC.csv, 111-MFCC.csv, 112-MFCC.csv, 115-MFCC.csv, 13-MFCC.csv, 15-MFCC.csv, 21-MFCC.csv, 22-MFCC.csv, 23-MFCC.csv, 24-MFCC.csv, 26-MFCC.csv, 28-MFCC.csv, 30-MFCC.csv, 32-MFCC.csv, 33-MFCC.csv, 36-MFCC.csv, 40-MFCC.csv, 41-MFCC.csv, 42-MFCC.csv, 48-MFCC.csv, 51-MFCC.csv, 71-MFCC.csv, 79-MFCC.csv, 80-MFCC.csv, 82-MFCC.csv, 83-MFCC.csv, 96-MFCC.csv, 97-MFCC.csv, 99-MFCC.csv
KK	07-MFCC.csv, 09-MFCC.csv, 100-MFCC.csv, 18-MFCC.csv, 29-MFCC.csv, 46-MFCC.csv, 50-MFCC.csv, 57-MFCC.csv, 58-MFCC.csv, 59-MFCC.csv, 63-MFCC.csv, 66-MFCC.csv, 84-MFCC.csv, 93-MFCC.csv
MB	106-MFCC.csv, 107-MFCC.csv, 108-MFCC.csv, 54-MFCC.csv, 65-MFCC.csv, 72-MFCC.csv, 88-MFCC.csv, 89-MFCC.csv, 91-MFCC.csv, 92-MFCC.csv
ML	01-MFCC.csv, 04-MFCC.csv, 06-MFCC.csv, 104-MFCC.csv, 109-MFCC.csv, 11-MFCC.csv, 110-MFCC.csv, 113-MFCC.csv, 12-MFCC.csv, 19-MFCC.csv, 25-MFCC.csv, 31-MFCC.csv, 35-MFCC.csv, 38-MFCC.csv, 39-MFCC.csv, 43-MFCC.csv, 45-MFCC.csv, 47-MFCC.csv, 49-MFCC.csv, 55-MFCC.csv, 60-MFCC.csv, 61-MFCC.csv, 62-MFCC.csv, 64-MFCC.csv, 68-MFCC.csv, 70-MFCC.csv, 73-MFCC.csv, 76-MFCC.csv, 79-MFCC.csv, 95-MFCC.csv
MJ	03-MFCC.csv, 104-MFCC.csv, 114-MFCC.csv, 113-MFCC.csv, 20-MFCC.csv, 34-MFCC.csv, 53-MFCC.csv, 74-MFCC.csv, 77-MFCC.csv, 86-MFCC.csv, 88-MFCC.csv

1. Analyze MFCC files to organize the 115 files into groups broadly corresponding to those listed below:
• Files containing rendition of the Indian National Anthem
• Files containing Marathi 'Bhav Geet' – sung by various artistes, male and female
• Files containing Marathi Lavni songs – sung by various artistes, predominantly female
• Hindi film songs sung by Asha Bhosale
• Hindi film songs sung by Kishor Kumar • English songs by Michael Jackson

P2 Final Results

2. Identify at least 3 files containing the National Anthem

Target Label	Common Predictions Across All Models
NA	'75-MFCC.csv', '27-MFCC.csv', '81-MFCC.csv', '116-MFCC.csv', '02-MFCC.csv', '95-MFCC.csv', '17-MFCC.csv', '35-MFCC.csv', '87-MFCC.csv'

P3 Final Results

3. Identify at least 3 files (each) containing solo songs by Asha Bhosale, Kishor Kumar, and Michael Jackson

Target Label	Common Predictions Across All Models
AB	'102-MFCC.csv', '23-MFCC.csv', '105-MFCC.csv', '94-MFCC.csv', '115-MFCC.csv', '79-MFCC.csv'
KK	'46-MFCC.csv', '93-MFCC.csv', '59-MFCC.csv', '29-MFCC.csv'
MJ	'74-MFCC.csv', '08-MFCC.csv', '03-MFCC.csv'

Number of problems correctly solved

- We successfully organized the provided dataset of 115 audio files into the six specified groups outlined in the problem statement.
- Successfully identified at least three audio files containing the National Anthem within the dataset.
- Accurately categorized at least three solo songs each by Asha Bhosle, Kishore Kumar, and Michael Jackson.

Creative thinking and innovation:

- We applied the Fourier Transform to the MFCC features to capture key frequency patterns in each song, helping us better identify unique musical traits and improve classification accuracy.
- We included Delta MFCC and Delta-Delta MFCC features to track changes and quick shifts in audio patterns, helping the model detect subtle differences in music style and emotion.
- We used SMOTE to balance the data, treating each target singer or genre as "1" and all others as "0," improving accuracy for rare categories.
- Using a "one-vs-all" classification approach, we focused on identifying each target group separately, making it easier to accurately classify specific songs.

Quality of feature engineering:

- In our project, we tried different features and chose the most relevant ones: mean, energy, entropy, homogeneity, contrast, and correlation. By testing different options, we made sure the selected features were the best fit, improving the model's accuracy for the task.

Relevant metrics on which we have focused:

- RandomForestClassifier (SMOTE: False) Metrics: Accuracy
- RandomForestClassifier (SMOTE: True) Metrics: Accuracy
- SVC (SMOTE: False) Metrics: Accuracy
- SVC (SMOTE: True) Metrics: Accuracy
- Classification metrics like precision, recall, f1-score, support and confusion matrix.

HURDLES FACED	HOW WE APPROACHED THEM
A major challenge was the small dataset, with fewer songs from Marathi Bhav Geet and Lavni genres, leading to an imbalance, as Asha Bhosale and Kishore Kumar had more entries while National Anthem and Marathi Bhav Geet had fewer.	To address the first hurdle, we expanded our dataset to over 800 songs, ensuring a more balanced representation by adding enough Marathi Bhav Geet and Lavni songs to resolve the data imbalance.
Another challenge was the long runtime of our code, as it was computationally heavy due to the large dataset and complex feature extraction. This required optimization to speed up the process.	To overcome the long computation times, we used the Fourier Transform (FFT) to speed up the process. This reduced the complexity of feature extraction, improving efficiency.
A challenge we faced was accurately identifying a specific number of audio files in the dataset belonging to a target cluster.	To address the third hurdle, we fine-tuned the "one-vs-all" classification approach to manage its computational intensity, balancing accuracy with efficiency for better performance.

Key Learning’s:

- One of the most important learnings from this project was gaining hands-on experience with the full data analysis process.

- Starting from a defined problem, we handled data acquisition, preparation, model planning, and model building ourselves, giving us valuable insight into the complete project cycle.

- We applied the Exploratory Data Analysis (EDA) techniques learned in our course to this project, using them to understand patterns in the data and make informed decisions for feature selection and model building.

- A key learning was understanding MFCC features, as they formed the foundation of our project. We explored how these features represent audio signals and how to use them effectively for analyzing and classifying songs.

- We learned to work with various features like mean, energy, entropy, and correlation to capture essential patterns in audio data, helping us improve classification accuracy.

- Additionally, we gained experience using SMOTE to handle data imbalance, ensuring a more balanced and accurate model.