DS 203
E-7

Sound to Structure

Audio Genre Classification

Decoding the beats

Presentated by

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Executive Overview

Problem Statement

- What is given?
  MFCC (Mel-Frequency Cepstral Coefficients) for 116 audio files
- What is to be done?
  Classify these 116 files broadly into 6 categories
  - National Anthem
  - Bhavgeet
  - Lavni
  - Songs of Asha Bhosale
  - Songs of Kishor Kumar
  - Songs of Michael Jackson

But, But, But what exactly is this fancy word ‘MFCC’?

The raw audio data of someone speaking is complex and contains a lot of information.
MFCCs help **simplify** this data

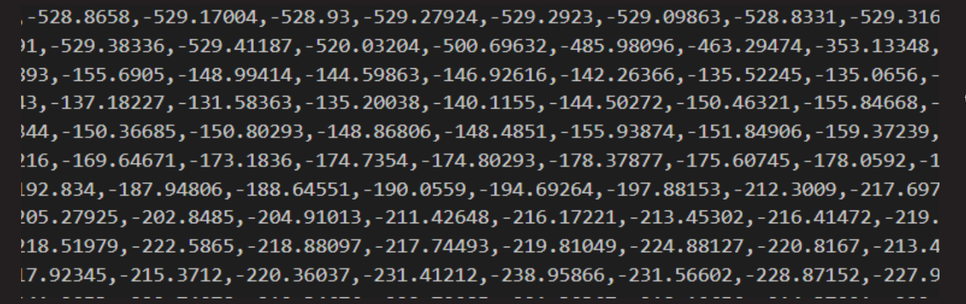
- by focusing on the features that are most important for understanding the speech
- by converting the signal into a set of numbers

What do we want?
Numbers

(Some Magic)

Singers and Genres

The files provided look something like this

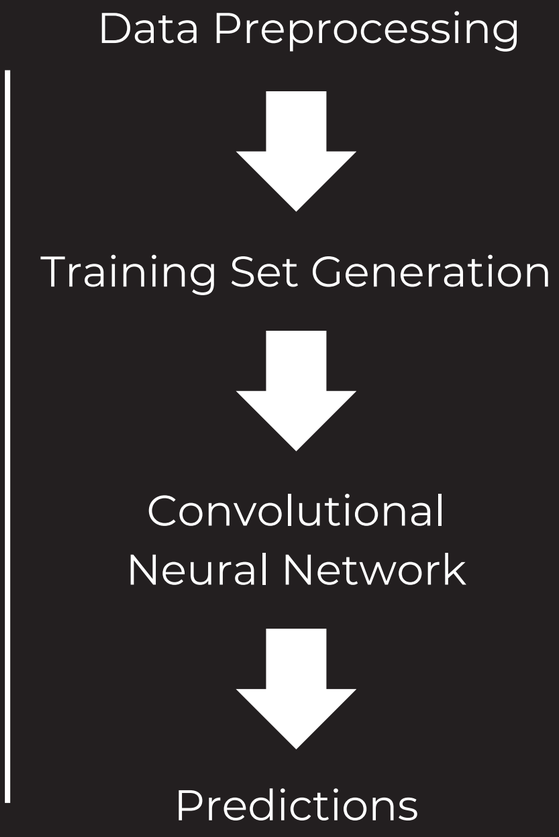


(pretty intimidating)

Executive Overview

How did we tackle this problem?

- 1. Performed **EDA** to understand what our data set actually entails
- 2. Extracted Complex Features from the given files using **CNN** (as just passing the raw data gives poor results)
- 3. Generated a **training data** set of 750 files
- 4. Implemented **hyper-parameter** tunning to tune the neural network as per our data-set
- 5. Implemented techniques to **reduce overfitting**
- 6. Classified the 116 files into 6 categories using our model



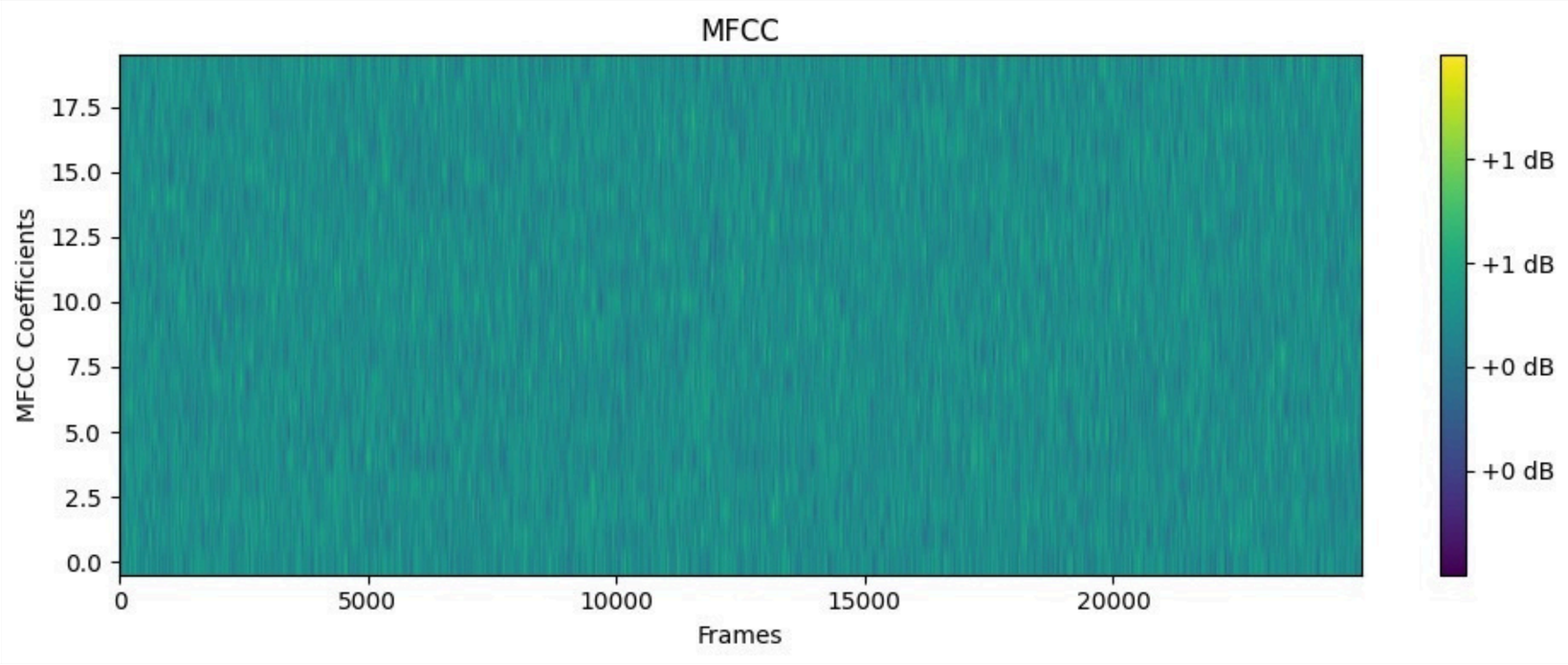
Why choose CNN?

Isn’t it used for images only? nope!

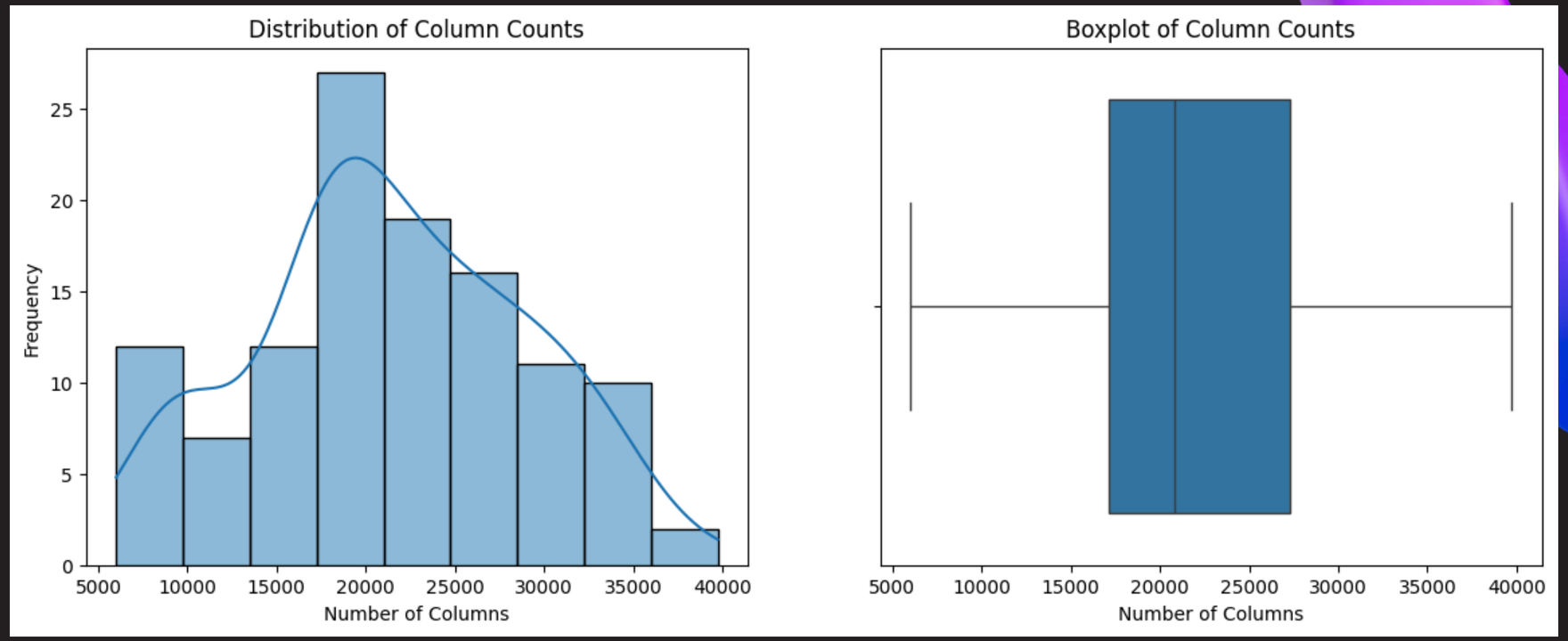
- CNNs learn **hierarchical** representations of data, which can be applied to our data set as to capture,
  - **low-level features** (e.g., pitch, timbre) and
  - **high-level features** (e.g., phonemes, words).
- CNNs recognize patterns regardless of their position in the input.
  Which is especially handy for our classification where we need to essentially identify the voices of 3 different singers.
- This is a **supervised learning** approach, unsupervised learning models won’t perform well on the given data as it
  - lacks clear structure and
  - has high dimensionality.

Exploratory Data Analysis

- **EDA analysis** on test files was done to check Missing values.
  We didnt find any missing values in the our dataset of mfcc csv files.
- This is a **spectrogram**, with time on the x-axis and frequency on the y-axis. The color of each point in the spectrogram represents the **intensity of the signa**l at that point



Column Distribution




```
Column Count Statistics:
25th Percentile: 17155.25
Median (50th Percentile): 20844.5
75th Percentile: 27268.5
90th Percentile: 31972.0
Interquartile Range (IQR): 10113.25
```

We considered the **Median** and **75th Percentile** value and choose **25000** as fixed column size for our all mfcc files to do mean max pooling.

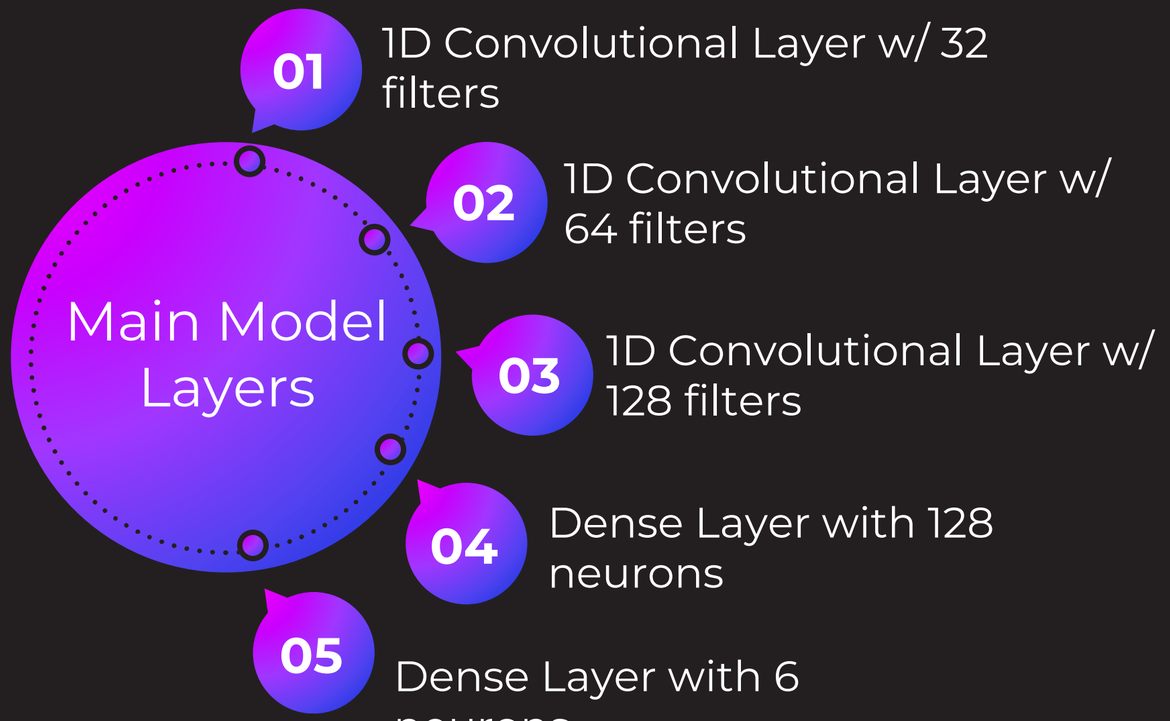
Data Pre-Processing

File sizes of all the test files were analysed. There were a lot of **variations**.

Mean-Max Pooling

- By considering the mean, median and 75th percentile , we chose **20*25000** as the fixed size for Mean-max pooling
- Max pooling emphasizes the **most important features** by retaining the maximum values
- Mean pooling helps retain **global** contextual information by **averaging**

Model Architecture



Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 20, 32)	6,400,032
batch_normalization_4 (BatchNormalization)	(None, 20, 32)	128
max_pooling1d_3 (MaxPooling1D)	(None, 10, 32)	0
dropout_4 (Dropout)	(None, 10, 32)	0
conv1d_4 (Conv1D)	(None, 10, 64)	10,304
batch_normalization_5 (BatchNormalization)	(None, 10, 64)	256
max_pooling1d_4 (MaxPooling1D)	(None, 5, 64)	0
dropout_5 (Dropout)	(None, 5, 64)	0
conv1d_5 (Conv1D)	(None, 5, 128)	41,088
batch_normalization_6 (BatchNormalization)	(None, 5, 128)	512
max_pooling1d_5 (MaxPooling1D)	(None, 3, 128)	0
dropout_6 (Dropout)	(None, 3, 128)	0
flatten_1 (Flatten)	(None, 384)	0
dense_2 (Dense)	(None, 128)	49,280
batch_normalization_7 (BatchNormalization)	(None, 128)	512
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 6)	774

Categorical Crossentropy Loss Function

- Calculates the negative logarithm of the predicted probability for the correct class, penalizing incorrect predictions
- The loss is always non-negative, with **zero indicating perfect accuracy** and increasing as predictions become less accurate

ReduceLROnPlateau

- Used to **reduce the learning rate** when a monitored metric has stopped improving
- It automatically adjusts the learning rate without requiring manual intervention
- It prevents the optimizer from overshooting the optimal solution

HOW DID WE TRAIN THIS MODEL?

We downloaded 50 songs for each of the 6 song categories from the internet. (total **300** songs)

- Converted .mp3 to .csv, which contains the MFCC coefficients

BUT,
Neural Networks typically require a lot of training data.
We used data augmentation to generate **750** MFCC coefficient files.

What's done in **Data Augmentation**?

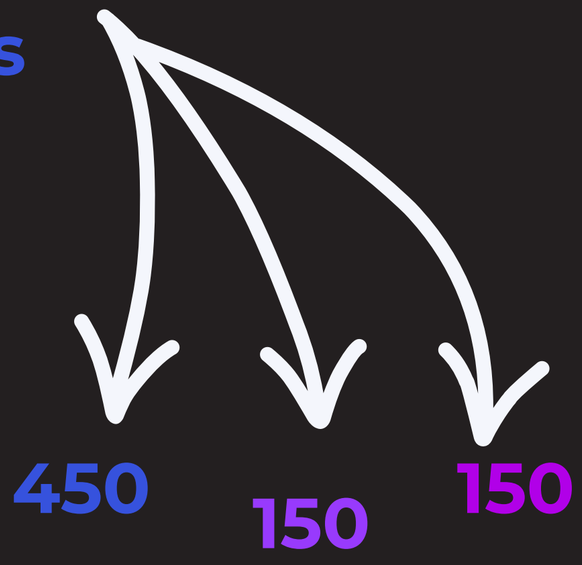
- By augmenting MFCC data, we can increase the dataset size and bring up diversity.
- **Scaling**, **shifting**, and **removing** frames were used to augment the data.

Encoding Technique Used: **Binary Encoding** - for target variables

The final training data set after pre-processing and data augmentation:

Click here for training dataset

Divide
750 files



But why??
three words train, test, validation

VALIDATION SET

- Helps to evaluate the model's performance on data that it has **not seen during training**
- Provides **unbiased** evaluation of model’s performance
- Helps in **tunning the hyperparameters**
  - number of layers
  - learning rate
  - filters in each convolutional layer
  - kernel size of each convolutional layer

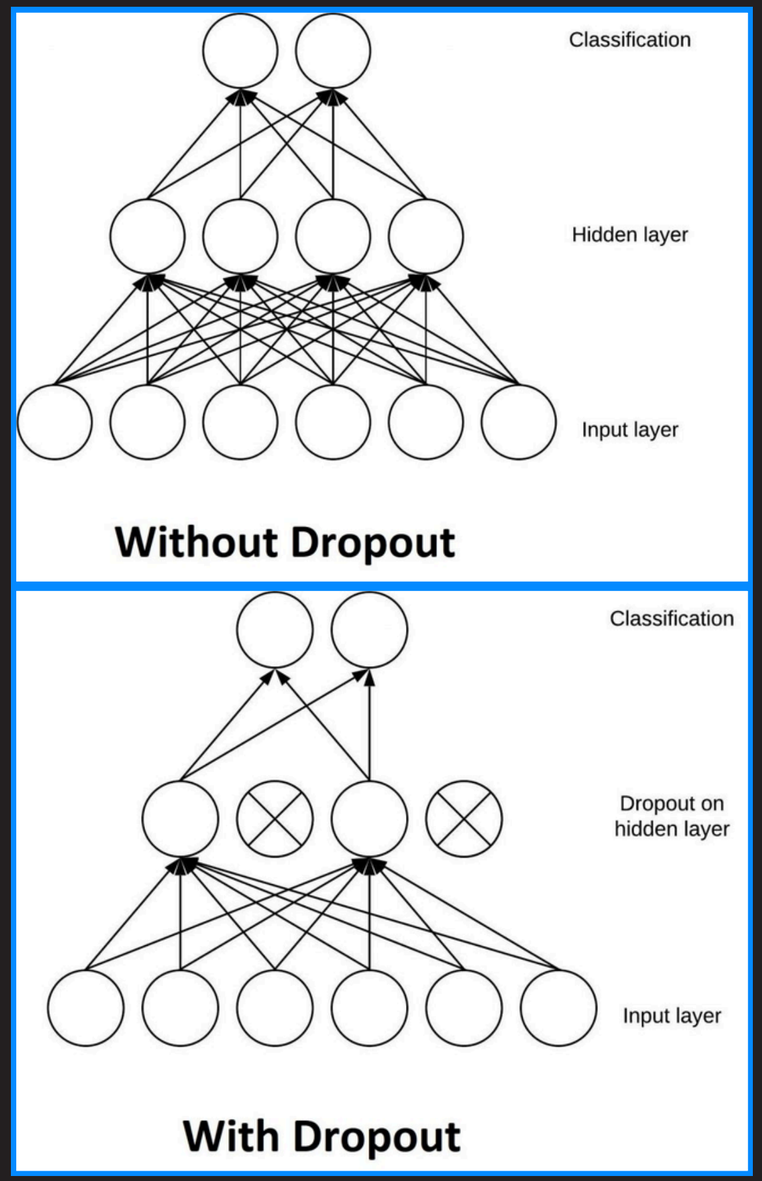
TACKLING OVERFITTING

1. Batch Normalization
2. Dropout Layers
3. Early Stopping

1. BATCH NORMALIZATION

- Used to improve the training of deep neural networks by normalizing the inputs of each layer
- Makes the network more robust to variations in the input data

2. DROPOUT



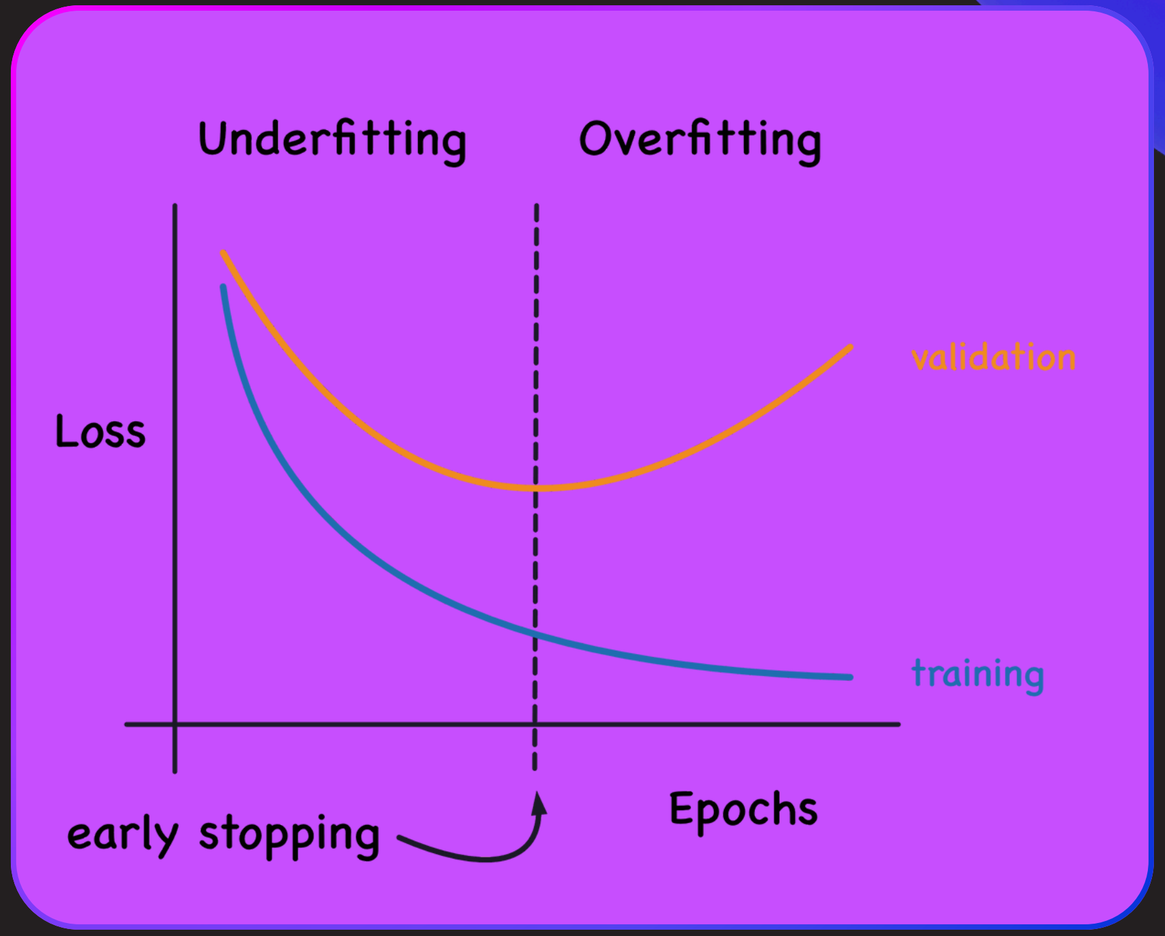
Works by randomly "dropping out" (i.e, setting to zero) a fraction of the neurons during the training process

This forces the network to learn more robust features that are not reliant on specific neurons

Improves generalization to new data

3. EARLY STOPPING

- Works by **monitoring the performance** of the model on a validation set
- Stops training if the metric does not improve for a specified number of **epochs**
- The metric used here to monitor the performance on the validation set is validation accuracy
- Prevents unnecessary training and **saves time**
- Restores the **best model weights**



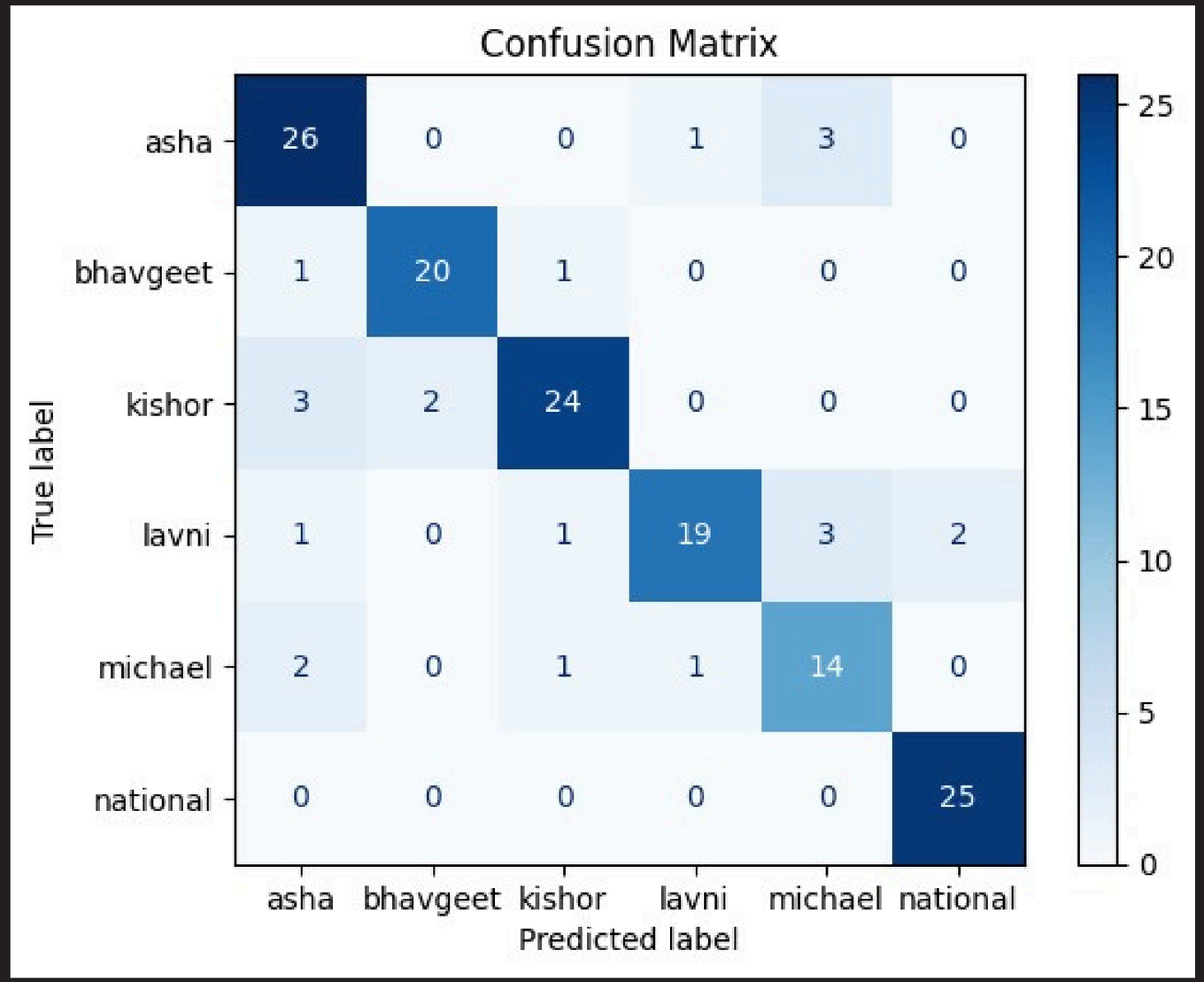
Model Metrics

```
Accuracy: 0.8533333333333334
Precision: 0.8579073272406607
Recall: 0.8533333333333334
F1 Score: 0.8529462909866046
```

	precision	recall	f1-score	support
asha	0.79	0.87	0.83	30
bhavgeet	0.91	0.91	0.91	22
kishor	0.89	0.83	0.86	29
lavni	0.90	0.73	0.81	26
michael	0.70	0.78	0.74	18
national	0.93	1.00	0.96	25
accuracy			0.85	150
macro avg	0.85	0.85	0.85	150
weighted avg	0.86	0.85	0.85	150

- We got a **accuracy of 0.85**, suggesting that the model is giving us appropriate results.
- The values aren't very close to 1, so we can conclude that model **isn't overfitting.**
- Different songs have have different lyrics but **National Anthem** has same for all, so it has high metric measures.

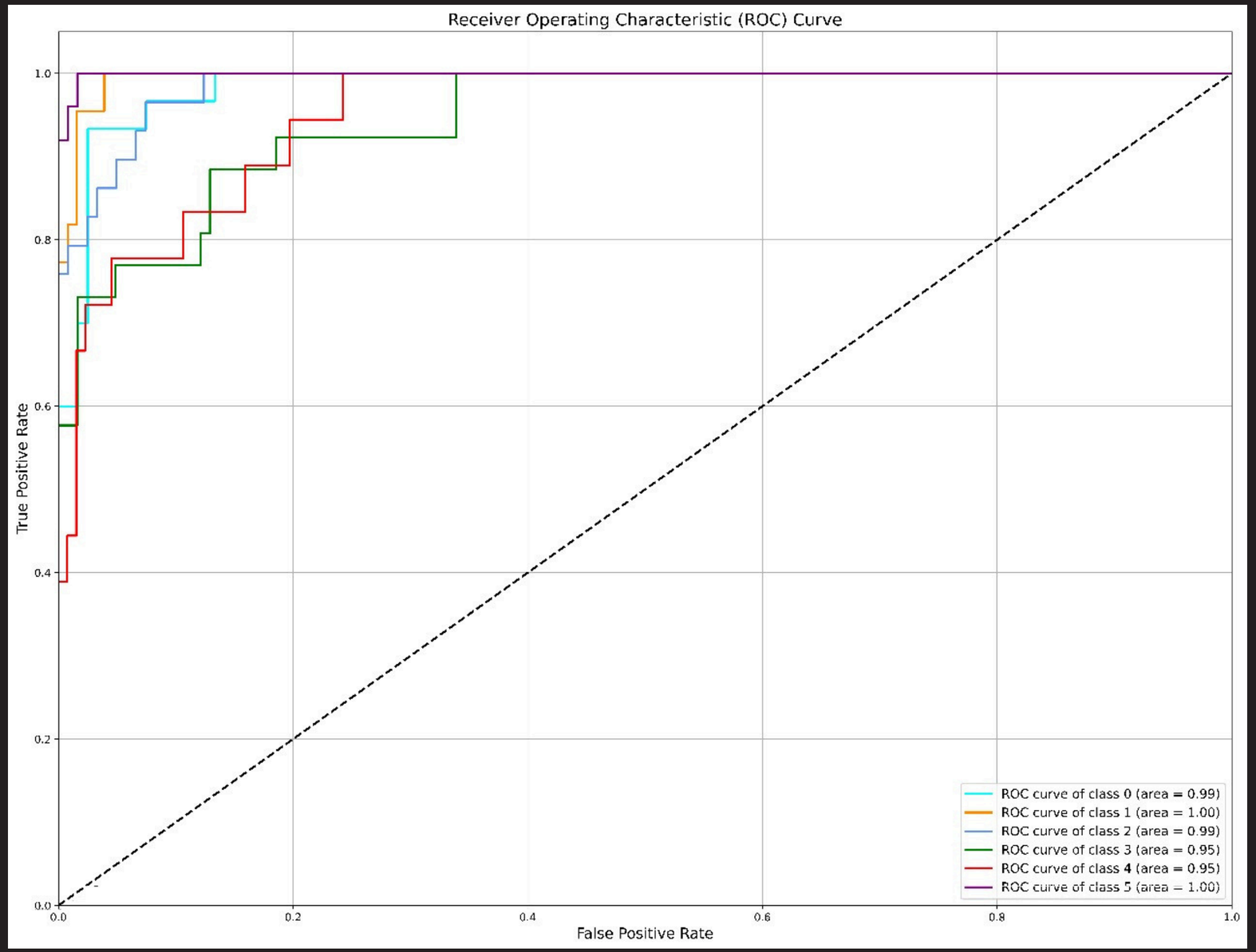
Confusion Matrix




```
Confusion Matrix:
[[26  0  0  1  3  0]
 [ 1 20  1  0  0  0]
 [ 3  2 24  0  0  0]
 [ 1  0  1 19  3  2]
 [ 2  0  1  1 14  0]
 [ 0  0  0  0  0 25]]
```

- **High diagonal values** suggest good accuracy for each class
- Low values are shown for **michael** indicationg that the model is not able to classify the songs of michael jackson
- This could be because there are **more hindi/marathi** songs as compared to english ones as our model is picking up on words

ROC Curve

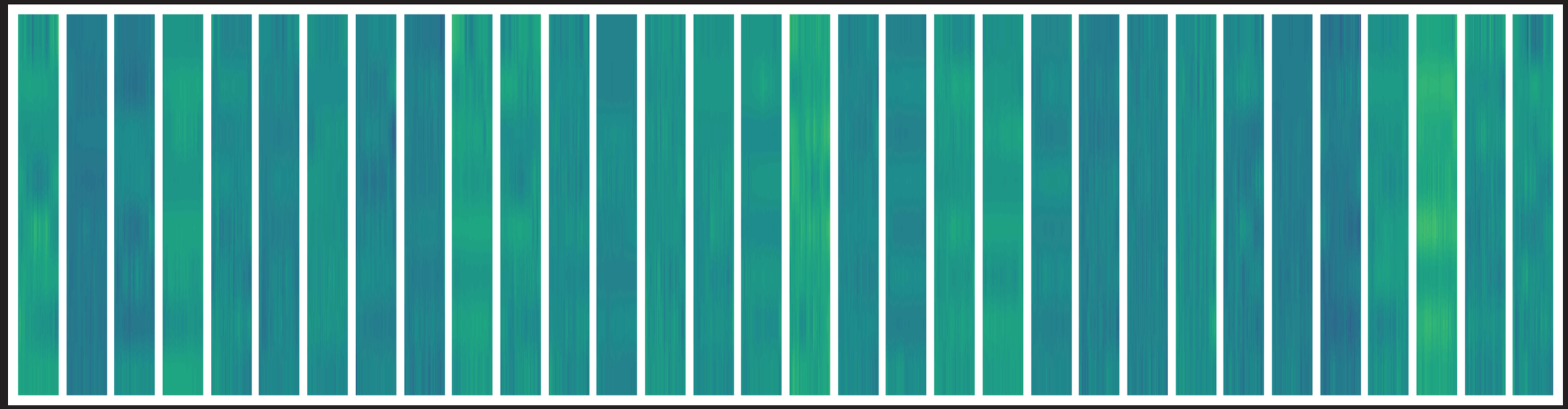



```
AUC for class 0: 0.99
AUC for class 1: 1.00
AUC for class 2: 0.99
AUC for class 3: 0.95
AUC for class 4: 0.95
AUC for class 5: 1.00
Micro-average AUC: 0.98
```

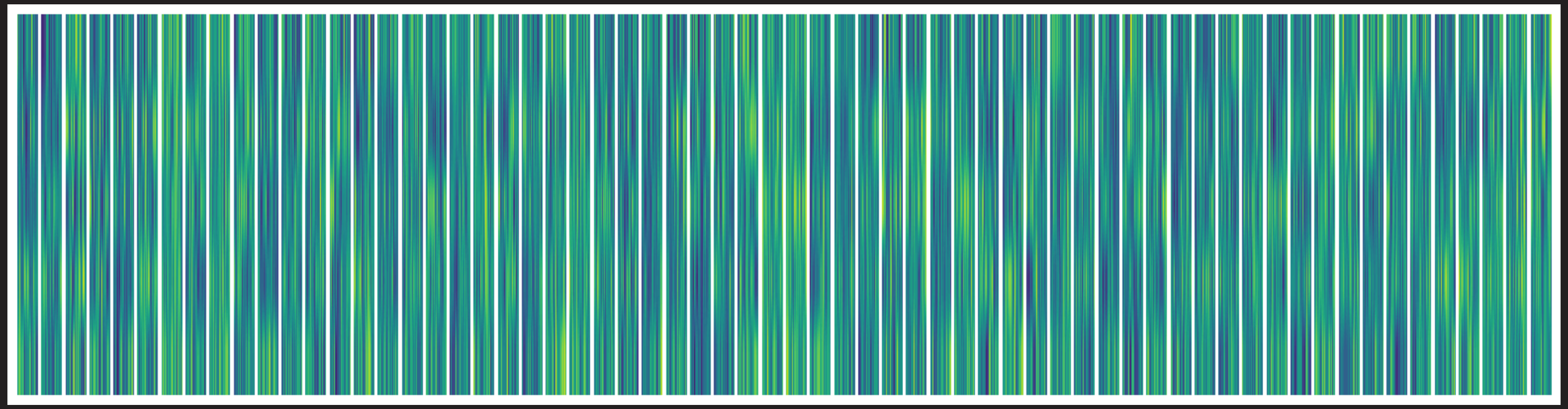
The auc values are close to **1** which indicates that the model is performing well

Visualization of what the CNN layers are actually doing??

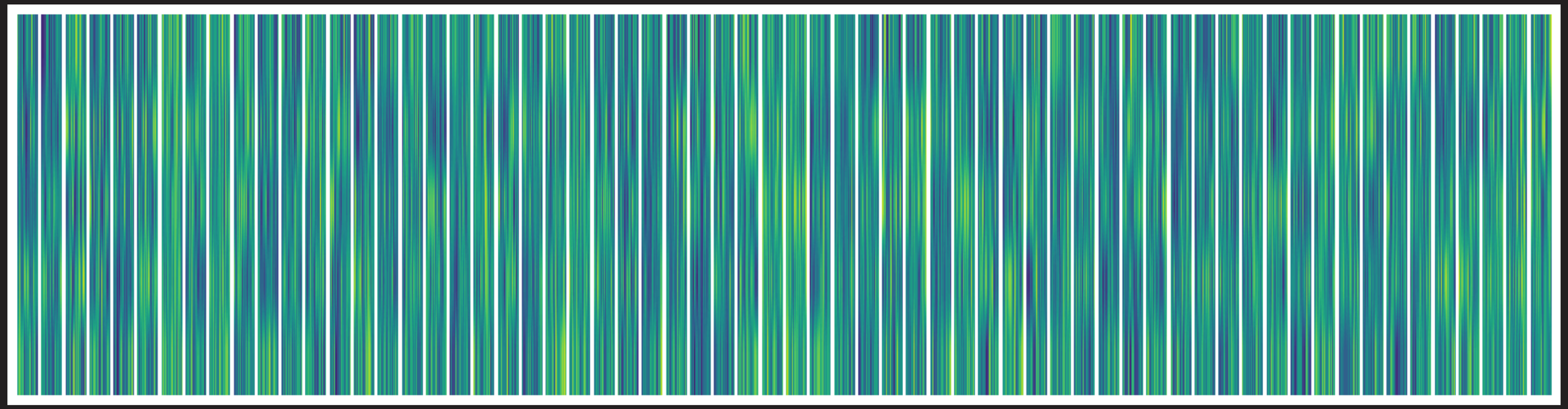
1st Convolutional Layer w/ 32 filters



2nd Convolutional Layer w/ 64 filters



3rd Convolutional Layer w/ 64 filters



Analysis of Graphs

- **Feature Extraction:** Each vertical line represent a specific feature map generated after applying filters in a CNN layer.
- **Activation Patterns:** High activation regions (bright yellow-green areas) indicate areas where the CNN detects prominent features.
- **Impact of Layers:** The maps demonstrate how each CNN Layer refines features from previous layers. (Hierarchial learning process)

Predictions of the Model

File_Name	Category
01-MFCC.csv	national
02-MFCC.csv	national
03-MFCC.csv	michael
04-MFCC.csv	asha
05-MFCC.csv	kishor
06-MFCC.csv	asha
07-MFCC.csv	kishor
08-MFCC.csv	asha
09-MFCC.csv	kishor
10-MFCC.csv	asha
100-MFCC.csv	asha
101-MFCC.csv	kishor
102-MFCC.csv	bhavgeet
103-MFCC.csv	michael
104-MFCC.csv	asha
105-MFCC.csv	asha
106-MFCC.csv	bhavgeet
107-MFCC.csv	national
108-MFCC.csv	national
109-MFCC.csv	kishor
11-MFCC.csv	asha
110-MFCC.csv	asha
111-MFCC.csv	bhavgeet
112-MFCC.csv	lavni
113-MFCC.csv	asha
114-MFCC.csv	asha
115-MFCC.csv	lavni
116-MFCC.csv	national

File_Name	Category
12-MFCC.csv	asha
13-MFCC.csv	asha
14-MFCC.csv	kishor
15-MFCC.csv	asha
16-MFCC.csv	national
17-MFCC.csv	national
18-MFCC.csv	kishor
19-MFCC.csv	lavni
20-MFCC.csv	asha
21-MFCC.csv	michael
22-MFCC.csv	kishor
23-MFCC.csv	asha
24-MFCC.csv	kishor
25-MFCC.csv	bhavgeet
26-MFCC.csv	bhavgeet
27-MFCC.csv	national
28-MFCC.csv	kishor
29-MFCC.csv	bhavgeet
30-MFCC.csv	asha
31-MFCC.csv	national
32-MFCC.csv	asha
33-MFCC.csv	lavni
34-MFCC.csv	kishor
35-MFCC.csv	national
36-MFCC.csv	michael
37-MFCC.csv	asha
38-MFCC.csv	bhavgeet
39-MFCC.csv	lavni

File_Name	Category
40-MFCC.csv	asha
41-MFCC.csv	lavni
42-MFCC.csv	bhavgeet
43-MFCC.csv	lavni
44-MFCC.csv	asha
45-MFCC.csv	asha
46-MFCC.csv	kishor
47-MFCC.csv	lavni
48-MFCC.csv	lavni
49-MFCC.csv	bhavgeet
50-MFCC.csv	bhavgeet
51-MFCC.csv	kishor
52-MFCC.csv	asha
53-MFCC.csv	asha
54-MFCC.csv	kishor
55-MFCC.csv	kishor
56-MFCC.csv	kishor
57-MFCC.csv	lavni
58-MFCC.csv	kishor
59-MFCC.csv	kishor
60-MFCC.csv	asha
61-MFCC.csv	national
62-MFCC.csv	lavni
63-MFCC.csv	kishor
64-MFCC.csv	asha
65-MFCC.csv	kishor
66-MFCC.csv	national
67-MFCC.csv	national

File_Name	Category
68-MFCC.csv	kishor
69-MFCC.csv	asha
70-MFCC.csv	asha
71-MFCC.csv	asha
72-MFCC.csv	lavni
73-MFCC.csv	asha
74-MFCC.csv	asha
75-MFCC.csv	national
76-MFCC.csv	kishor
77-MFCC.csv	lavni
78-MFCC.csv	lavni
79-MFCC.csv	lavni
80-MFCC.csv	asha
81-MFCC.csv	national
82-MFCC.csv	asha
83-MFCC.csv	kishor
84-MFCC.csv	kishor
85-MFCC.csv	lavni
86-MFCC.csv	michael
87-MFCC.csv	national
88-MFCC.csv	lavni
89-MFCC.csv	asha
90-MFCC.csv	national
91-MFCC.csv	lavni
92-MFCC.csv	kishor
93-MFCC.csv	kishor
94-MFCC.csv	bhavgeet
95-MFCC.csv	national
96-MFCC.csv	bhavgeet
97-MFCC.csv	bhavgeet
98-MFCC.csv	michael
99-MFCC.csv	lavni

Files Containing the National Anthem

National Anthem
01-MFCC.csv
02-MFCC.csv
87-MFCC.csv

Solo Songs

Asha Bhosale	Kishor Kumar	Michael Jackson
06-MFCC.csv	05-MFCC.csv	03-MFCC.csv
30-MFCC.csv	18-MFCC.csv	98-MFCC.csv
60-MFCC.csv	46-MFCC.csv	103-MFCC.csv

Optional Problem Statement

Problem Statement:

Need to classify the given songs into songs of **female singers**, **male singers** and **both**

Our Approach:

- Created a training dataset 799 files containing
  - 300 songs of female singers,
  - 300 of male singers and
  - 199 songs of both

  using the methods disccused earlier
- Used the CNN model we had built for the previous problem statement after **fine-tunning** to classify the songs

The **final training data set** after pre-processing and data augmentation: click here

Model Metrics

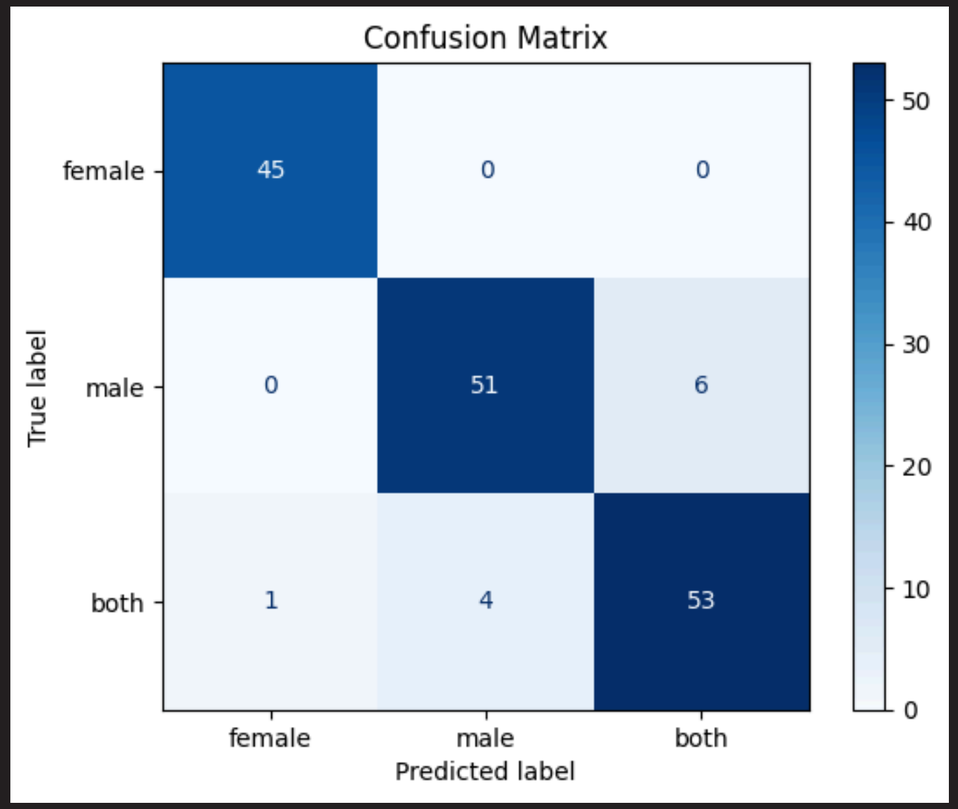
```
Accuracy: 0.93125
Precision: 0.9311123718764656
Recall: 0.93125
F1 Score: 0.9310201083638583
              precision    recall  f1-score   support

        both       0.98      1.00      0.99        45
      female       0.93      0.89      0.91        57
        male       0.90      0.91      0.91        58

    accuracy                           0.93       160
   macro avg       0.93      0.94      0.94       160
weighted avg       0.93      0.93      0.93       160
```

- We have got a **high accuracy** of **0.93**, suggesting that our model has given us good results.
- The Precision and Recall values, suggest that our model was **well trained** and could **recall** very well to make predictions.
- We have got high metric values for the **‘both**’ category, so our model works well with predictions related to songs of both male and female singers.

Confusion Matrix




```
Confusion Matrix:
[[45  0  0]
 [ 0 51  6]
 [ 1  4 53]]
```

- The matrix **summarizes** the performance of our machine learning model on set of test data.
- **High diagonal** values indicate good accuracy for each class

Predictions of the Model for Female-Male Classification

01-MFCC.csv	male
03-MFCC.csv	male
04-MFCC.csv	male
05-MFCC.csv	male
07-MFCC.csv	male
08-MFCC.csv	male
09-MFCC.csv	male
100-MFCC.csv	male
101-MFCC.csv	male
107-MFCC.csv	male
113-MFCC.csv	male
114-MFCC.csv	male
116-MFCC.csv	male
14-MFCC.csv	male
15-MFCC.csv	male
16-MFCC.csv	male
18-MFCC.csv	male
19-MFCC.csv	male
20-MFCC.csv	male
21-MFCC.csv	male
24-MFCC.csv	male
31-MFCC.csv	male
32-MFCC.csv	male
33-MFCC.csv	male
34-MFCC.csv	male
36-MFCC.csv	male
44-MFCC.csv	male
45-MFCC.csv	male

46-MFCC.csv	male
52-MFCC.csv	male
53-MFCC.csv	male
54-MFCC.csv	male
55-MFCC.csv	male
57-MFCC.csv	male
58-MFCC.csv	male
59-MFCC.csv	male
61-MFCC.csv	male
62-MFCC.csv	male
63-MFCC.csv	male
65-MFCC.csv	male
66-MFCC.csv	male
67-MFCC.csv	male
68-MFCC.csv	male
71-MFCC.csv	male
74-MFCC.csv	male
76-MFCC.csv	male
77-MFCC.csv	male
78-MFCC.csv	male
86-MFCC.csv	male
89-MFCC.csv	male
92-MFCC.csv	male
93-MFCC.csv	male
96-MFCC.csv	male
98-MFCC.csv	male

02-MFCC.csv	female
06-MFCC.csv	female
10-MFCC.csv	female
102-MFCC.csv	female
103-MFCC.csv	female
104-MFCC.csv	female
105-MFCC.csv	female
106-MFCC.csv	female
108-MFCC.csv	female
109-MFCC.csv	female
11-MFCC.csv	female
110-MFCC.csv	female
112-MFCC.csv	female
115-MFCC.csv	female
12-MFCC.csv	female
13-MFCC.csv	female
17-MFCC.csv	female
22-MFCC.csv	female
23-MFCC.csv	female
25-MFCC.csv	female
26-MFCC.csv	female
27-MFCC.csv	female
28-MFCC.csv	female
29-MFCC.csv	female
35-MFCC.csv	female
37-MFCC.csv	female
38-MFCC.csv	female
39-MFCC.csv	female
40-MFCC.csv	female
41-MFCC.csv	female
42-MFCC.csv	female
43-MFCC.csv	female
47-MFCC.csv	female

48-MFCC.csv	female
49-MFCC.csv	female
51-MFCC.csv	female
56-MFCC.csv	female
60-MFCC.csv	female
64-MFCC.csv	female
69-MFCC.csv	female
70-MFCC.csv	female
72-MFCC.csv	female
73-MFCC.csv	female
75-MFCC.csv	female
79-MFCC.csv	female
80-MFCC.csv	female
81-MFCC.csv	female
84-MFCC.csv	female
85-MFCC.csv	female
87-MFCC.csv	female
88-MFCC.csv	female
90-MFCC.csv	female
91-MFCC.csv	female
94-MFCC.csv	female
95-MFCC.csv	female
99-MFCC.csv	female

111-MFCC.csv	both
30-MFCC.csv	both
50-MFCC.csv	both
82-MFCC.csv	both
83-MFCC.csv	both
97-MFCC.csv	both

Learnings and Hurdles faced in the project

- We initially tried to solve the problem using **unsupervised** learning but the clusters and predictions weren't accurate enough.
- We tried to use **RBM** layers with CNN model but couldn't get good results as it requires proper initialization of weights.
- Explored different ways to improve the **accuracy** of CNN model, some of them are mentioned after the metrics table in slides.
- Learned about the concepts behind **mffc generation** and how features can be extracted from it.
- We tried **target and binary encoding** techniques. Binary gave us better results in this problem.
- Creation of Large Training data is a important aspect in building a model, we first downloaded songs and then made more data by **data augmentation**.
- We got only 6 songs classified as Michael Jackson because our model was **heavily trained** on hindi songs as compared to english.
- Explored the use of **spark** for big data analysis.

Thank you