Feature Selection Methods for Music Genre Classification Models

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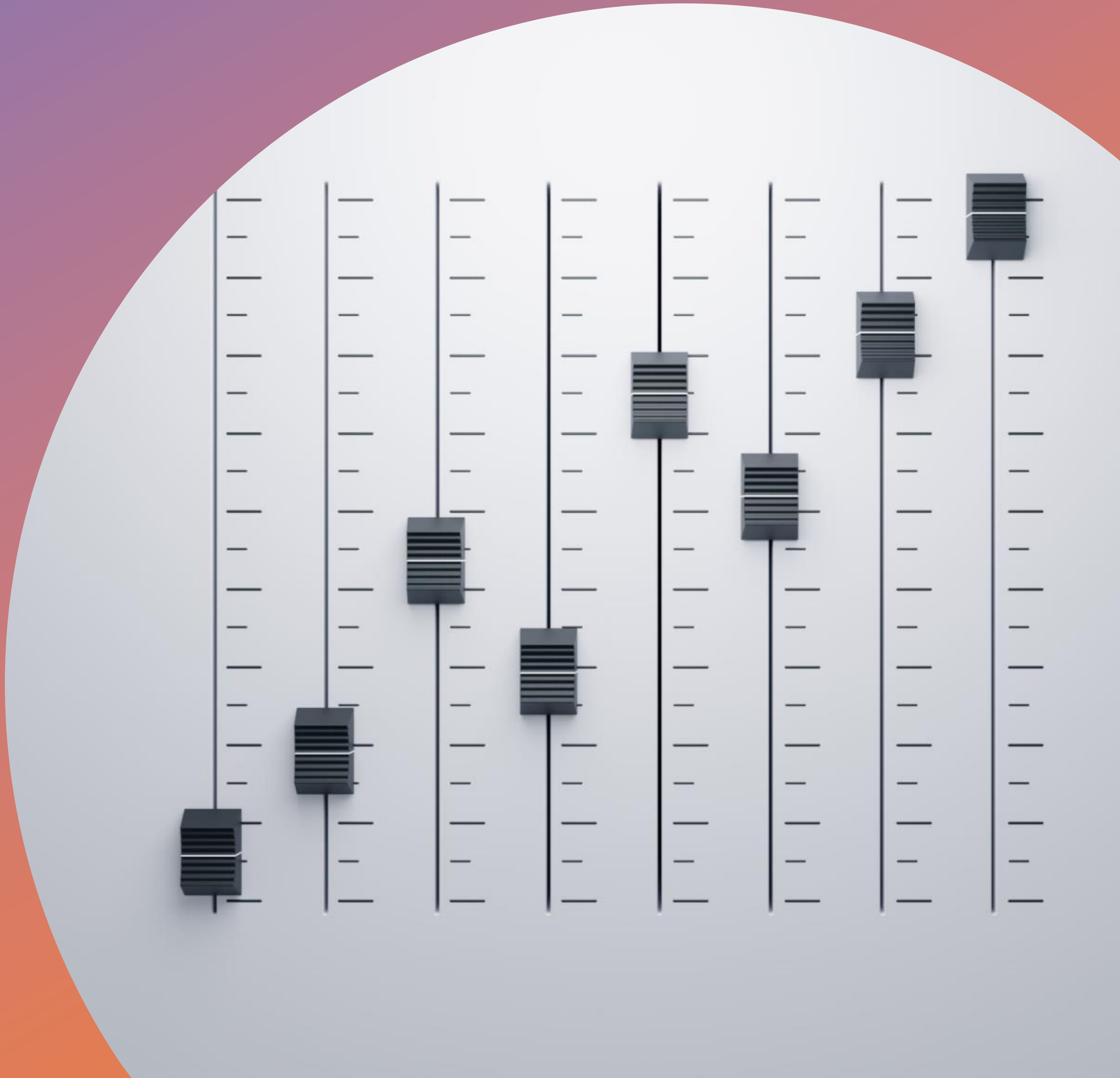
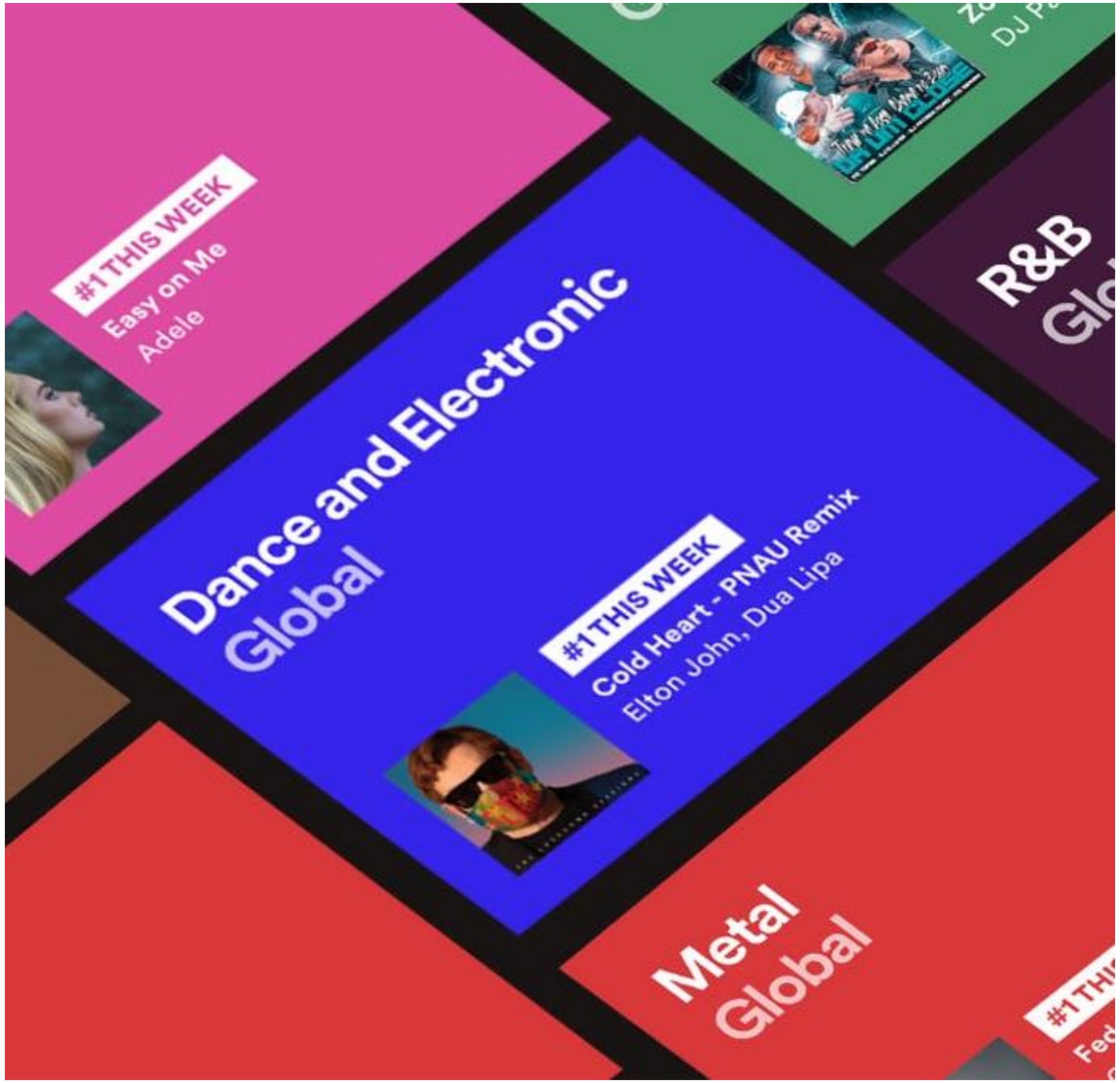


Introduction

- Classifying music is still an ongoing process that has not been perfected.
- Music Genre Classification models analyze various features of the music and identify patterns that are representative of a particular genre.
- Problems to solve in current models include:
  - Subjective evaluation of the genre
  - Not able to keep up with new genres
  - **Not identifying the correct features**

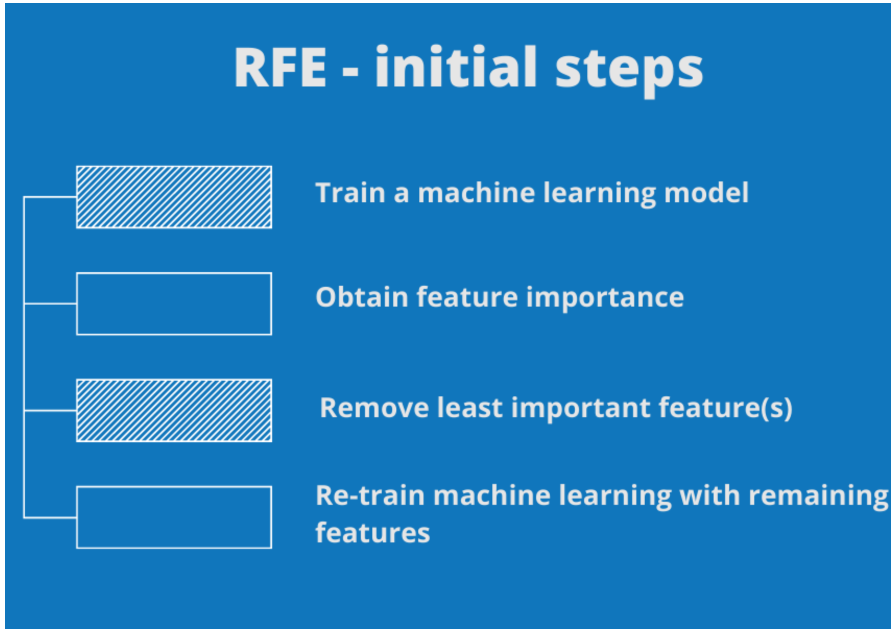


Introduction cont'd.

Previous research explored three main approaches to music genre classification :-

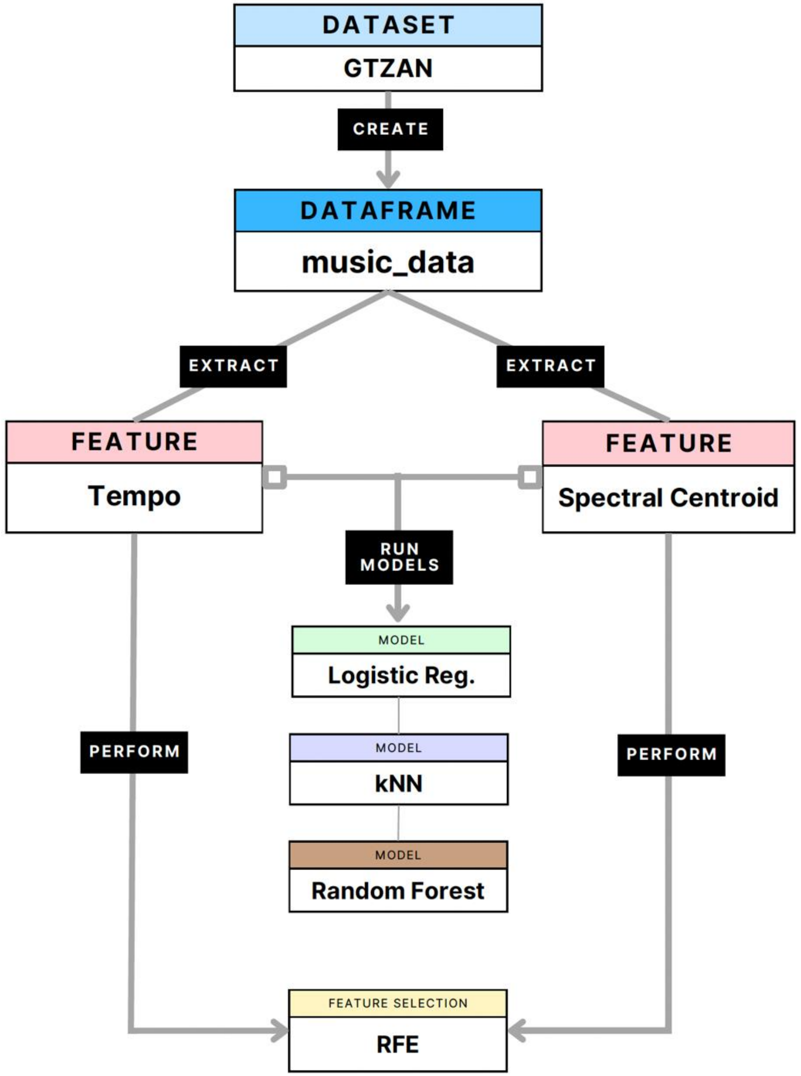
- Content based traditional machine learning models
- CNN's
- RNN's

Feature selection methods such as RFE and Boruta help identify important underlying features and help in reducing the number of features and selecting the most relevant ones.



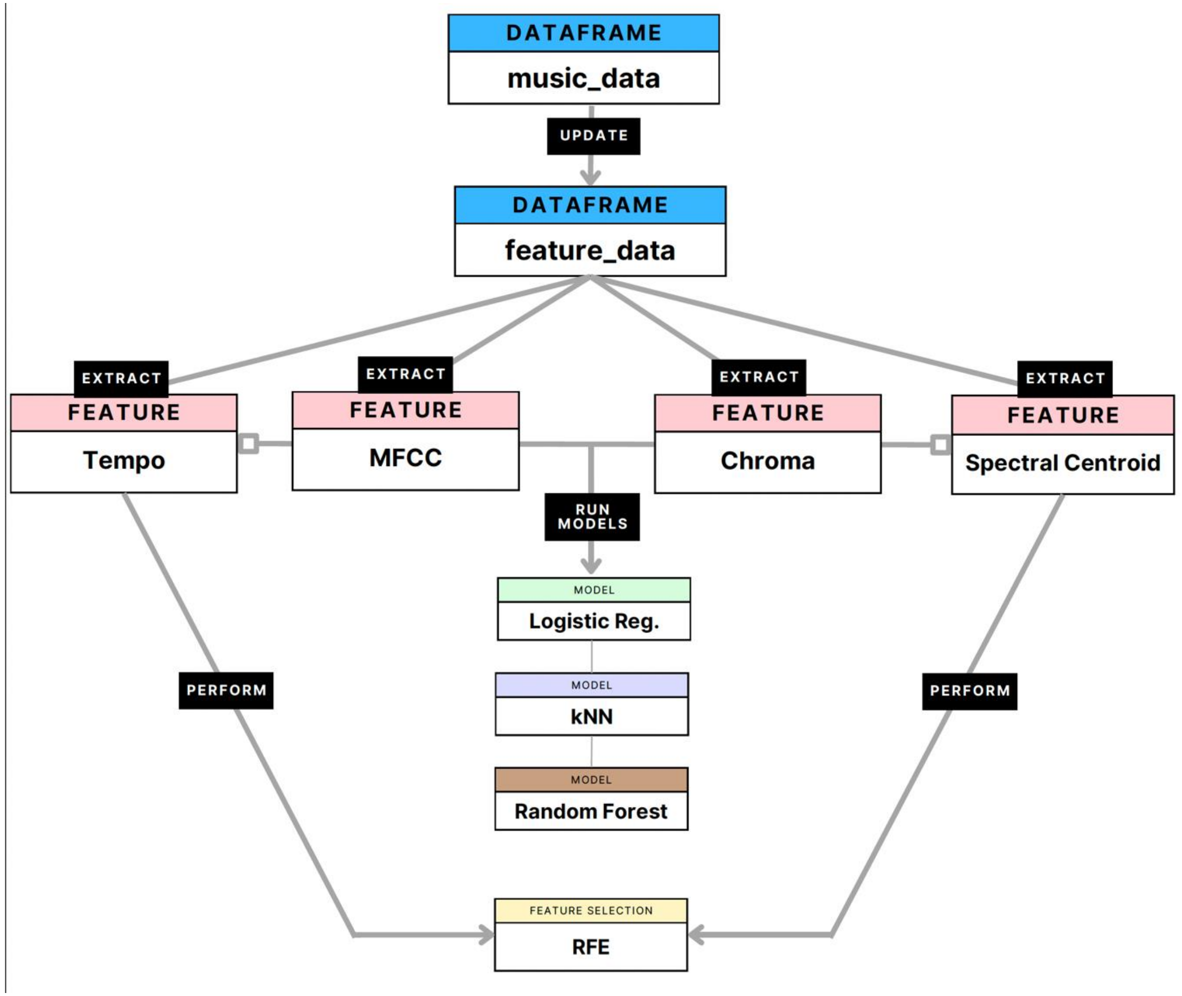
Methods and Materials

- Download GTZAN dataset
- Create "music_data" dataframe and extract tempo and spectral centroid features
- Run models Logistic Regression, Random Forest, k-Nearest Neighbors (kNN)
- Perform RFE using random forest model for tempo and spectral centroid features.



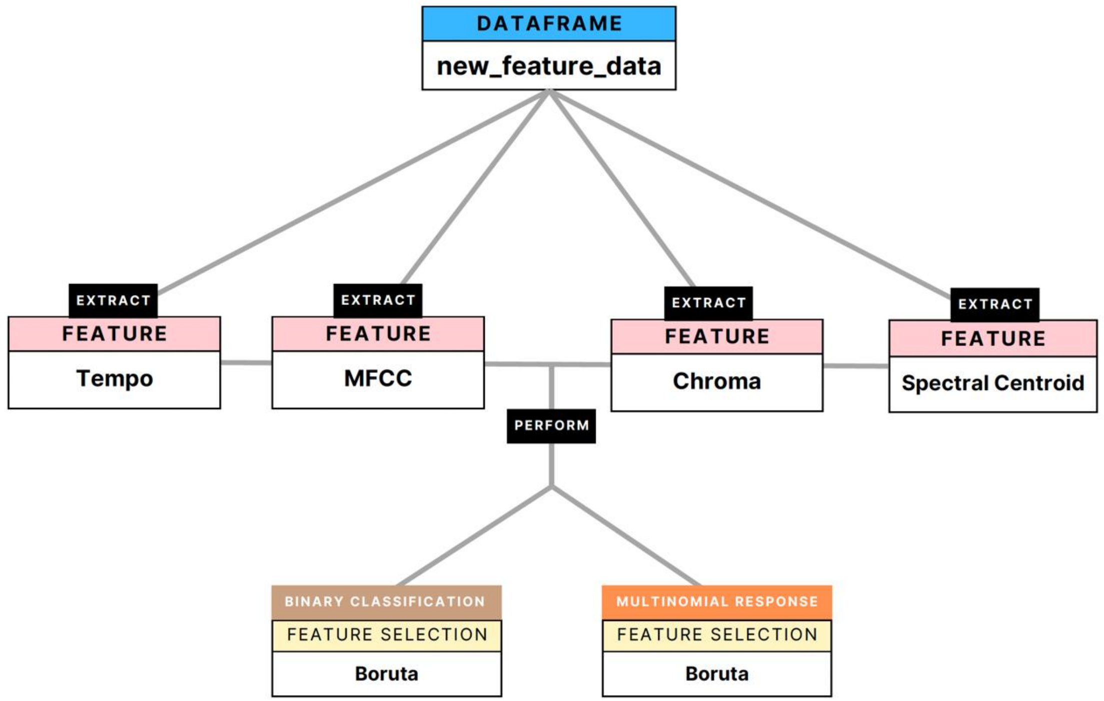
Methods cont’d.

- Incorporate MFCC and Chroma features
- Calculate MFCC and Chroma features
- Add features to feature_data
- Perform RFE with MFCC and Chroma features



Methods cont'd.

- Split updated data into training and test sets (70/30)
- Train and evaluate models again with MFCC and Chroma features
- Create "new_feature_data" dataframe
- Perform Boruta feature selection



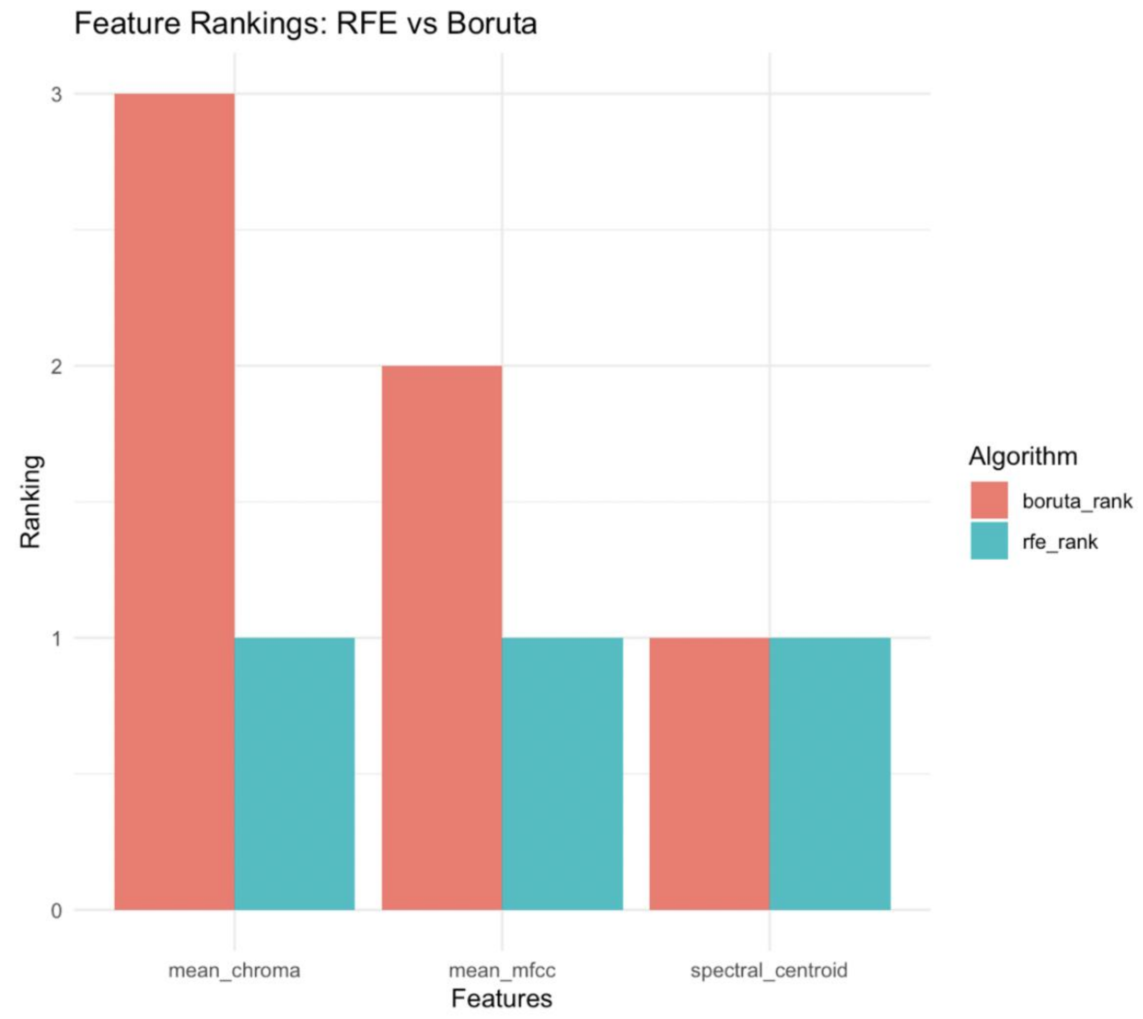
Results

Model Accuracy using 2 features (Tempo, Spectral Centroid)	
Model	**Accuracy Score (%)**
KNN	26.42
Random Forest	28.09
Logistic Regression	29.43

Model Accuracy using 4 features (Tempo, Spectral Centroid, MFCC, Chroma)	
Model	**Accuracy Score (%)**
KNN	57.73
Random Forest	34.54
Logistic Regression	32.57

Results cont’d.

- Boruta method deemed “tempo” as unimportant
- Boruta method highlighted mean_chroma, mean_mfcc, and spectral_centroid as important
- ”Spectral Centroid” feature importance consistent with both methods



Discussion

Main takeaways

- Addition of MFCC and Chroma improved performance of all 3 models
- Boruta method was more consistent with our initial results of model performance.
- Compared to similar studies, kNN performance achieved similar accuracy

Discussion cont'd.

Feature Selection

- **Tempo**: Measures the speed or pace of an audio file
- **Spectral Centroid**: Distinguishes between different types of bright or dull sounds
- **MFCC** : Short-term spectral shape of a sound signal
- **Chroma** : The pitch content of a sound signal in audio files

Discussion cont'd.

Limitations

- Large dataset (computationally expensive)
- Extraction process included limited set of features
- Imputation methods instead of using "na.omit"
- Include hyperparameter tuning
- Ensemble methods could improve performance
- Use advanced techniques, such as deep learning

Conclusion

Feature selection methods help identify relevant and important features

Addition of MFCC and Chroma features improve model

RFE and Boruta methods can be used to create better predicitons for classifying music

Thank you for listening!