Mood–Based Classifier and Recommender System

Mid Project Presentation

Group-41

INDRAPRASTHA INSTITUTE *of*
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DELHI

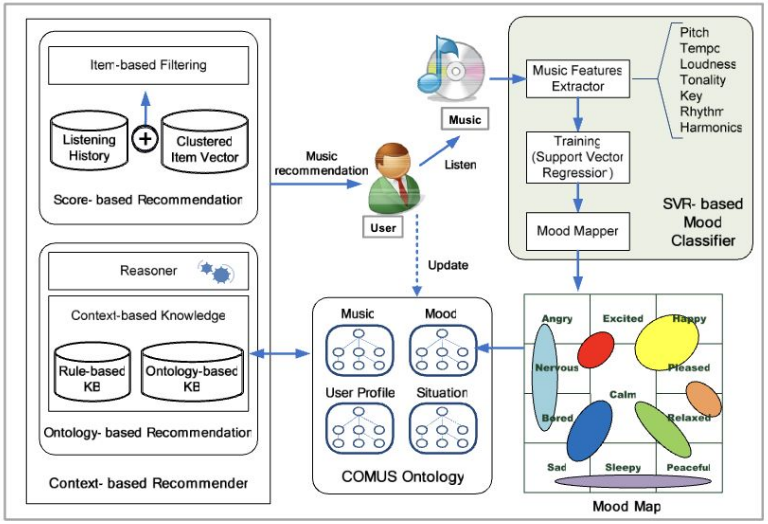
Motivation

Music deeply resonates with our emotions, yet choosing a song to match one's mood in today's vast digital library is daunting. Most platforms only suggest based on user history, neglecting the emotional aspect. Our project offers a **Mood-Based Song Classifier and Recommender System**, using machine learning to discern moods from recent song choices. We aim for a personalized listening experience, bridging the gap between emotions and song recommendations. Our goal is to align every song suggestion with the user's emotional state.

Literature Review

- **SVR-based music mood classification and context-based music recommendation by Seungmin Rho , Byeong-jun Han and Eenjun Hwang.**

This paper focuses on context based music recommendation. The authors first classified the mood after converting it into a regression problem based on **Support Vector Regression** (SVR).For music recommendation, they assess the user's mood and situation using both **collaborative filtering and ontology technology**.



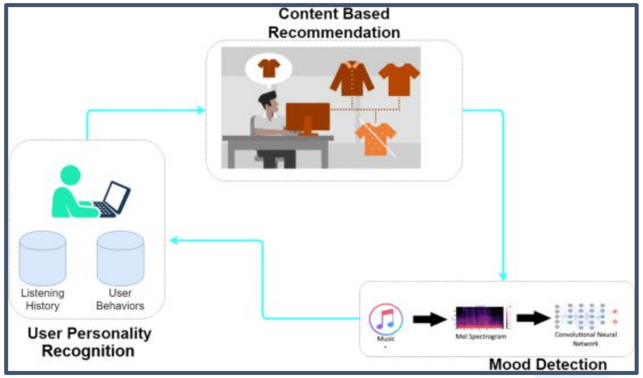
Literature Review

- **Moodplay: Interactive Mood-based Music Discovery and Recommendation by Ivana Andjelkovic, Denis Parra, John O'Donovan.**

  MoodPlay is a **hybrid recommender system**music which integrates content and mood-based filtering in an interactive interface. MoodPlay allows the user to explore a music collection by latent affective dimensions, by integrating user input at recommendation time with predictions **based on a pre-existing user profile**

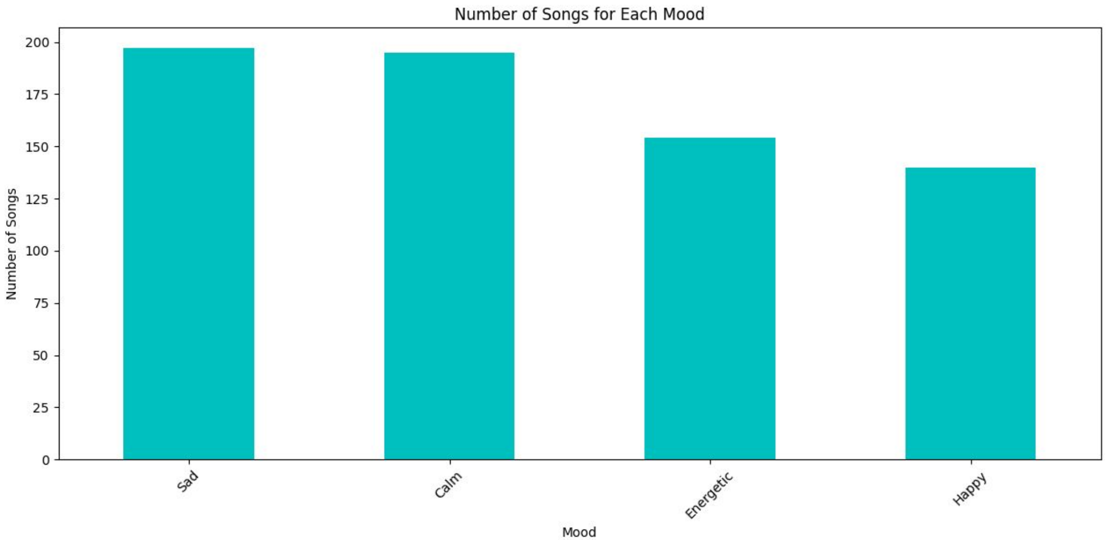
- **An Emotional Recommender System for Music by Vincenzo Moscato, Antonio Picariello and Giancarlo Sperli.**

  In this paper, the authors describe a novel music recommendation technique based on the **identification of personality traits, moods, and emotions of a single user**. It embeds users' personality and mood with a **content -based filtering** approach to obtain accurate and dynamic results.



Dataset Description

We used the Spotify Music data [LINK] which contains **686 songs** different artists and multiple genre. All the songs features were extracted using Spotify API.

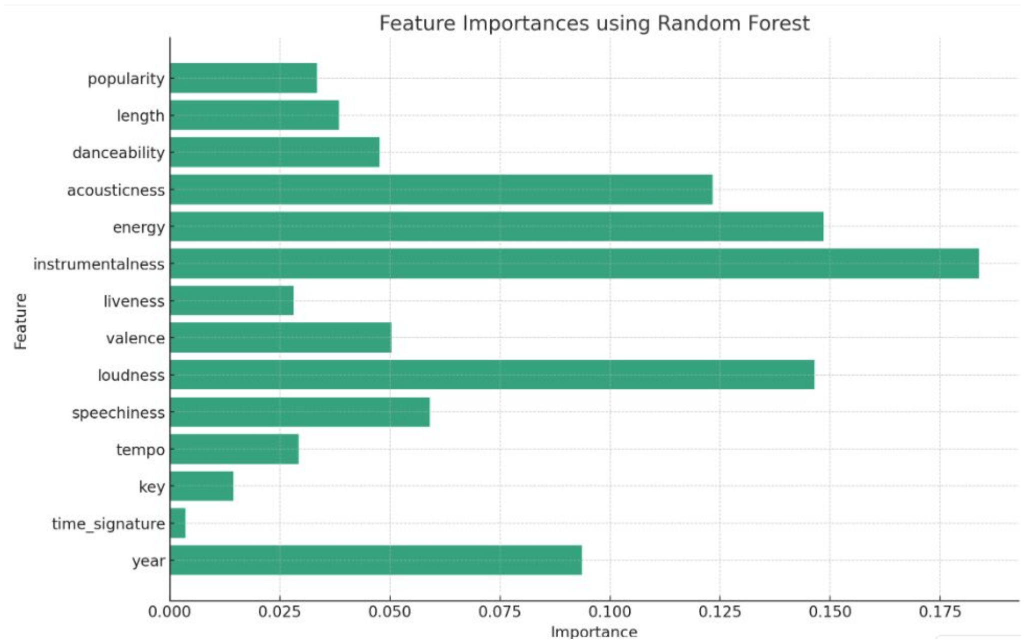


Feature	Type
Name	String
Album	String
Artist	String
Id	String
Release_date	Date
Popularity	Integer
Length	Integer
Danceability	Float
Acousticness	Float
Energy	Float
Instrumentalness	Float
Liveness	Float
Valence	Float
Loudness	Float
Speechiness	Float
Tempo	Float
Key	Integer
Time Signature	Integer

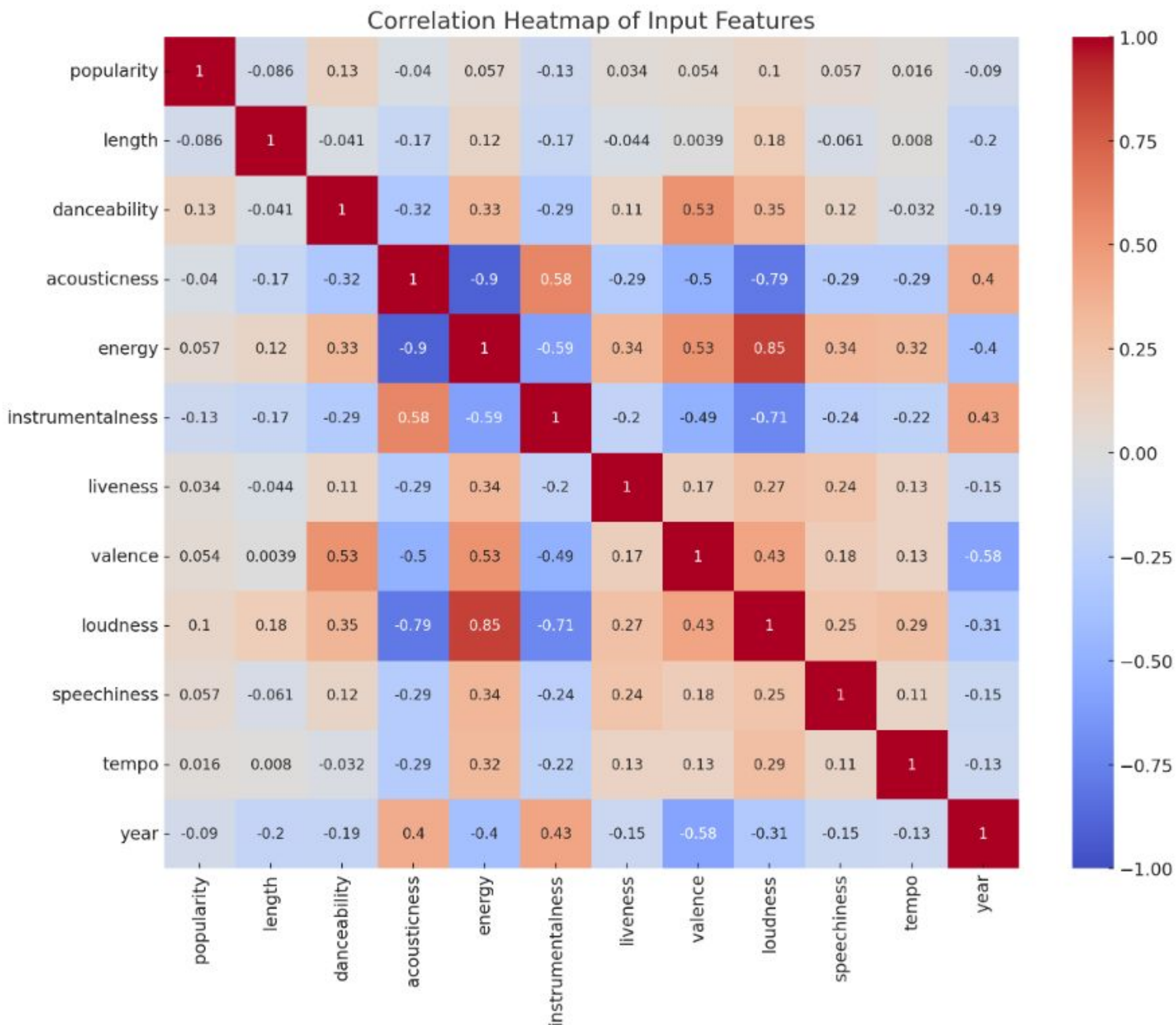
Raw Features

DataSet Preprocessing

- Categorical Features such as name, album, artist, and id are dropped.
- Numerical Features are standardised to ensure they have a mean of 0 and a standard deviation of 1.
- Label encoding of categorical target label mood.
- Feature Selection has been been done using Random Forest and based on the avg. impurity loss time signature and key are dropped.



Dataset Visualisation

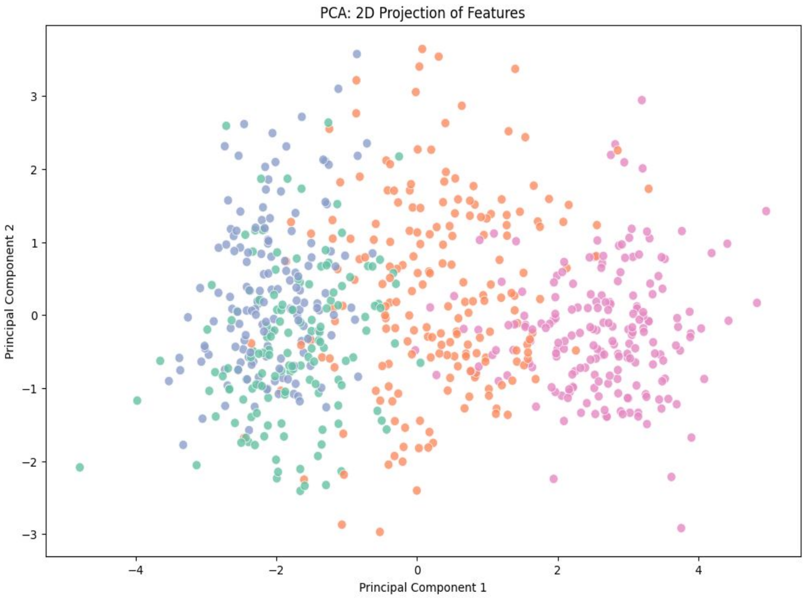


Positive Correlation:
Energy and Loudness

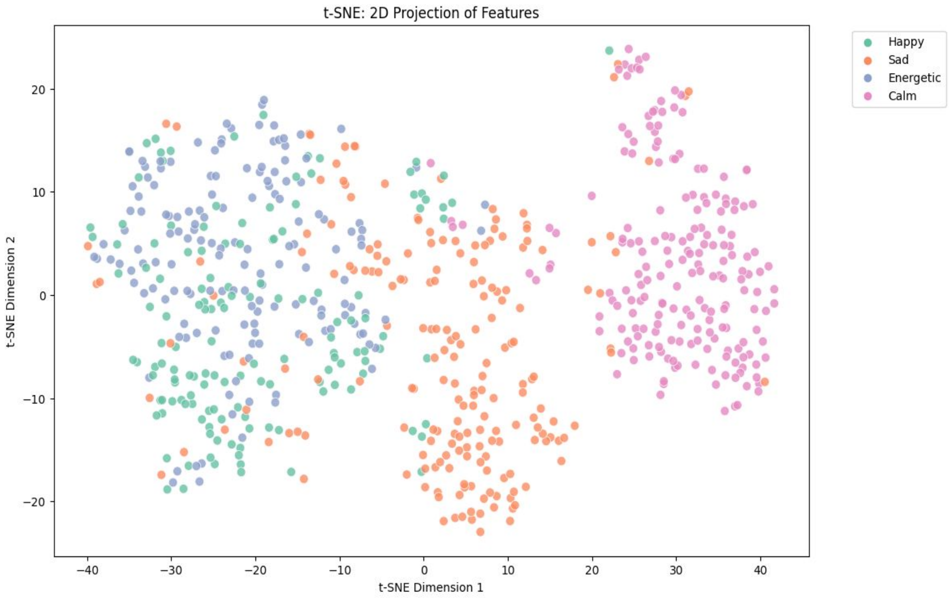
Negative Correlation:
Acousticness and Energy

Data Visualization

Dimensionality Reduction



Principal Component Analysis

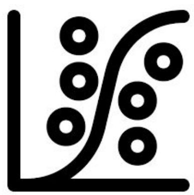


T-distributed Stochastic Neighbor Embedding

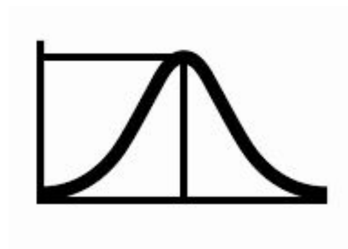
Moods are clearly separable (in separate clusters) except for energetic and happy songs, where there is a some amount of overlap.

Methodology

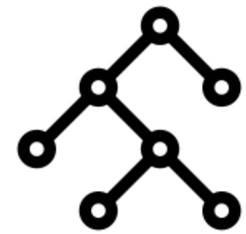
<u>Classifier Models Tested up until now</u>



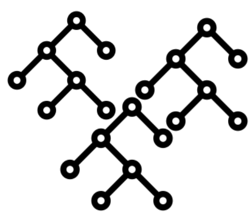
Logistic Regression



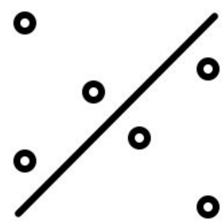
Gaussian Naive Bayes



Decision Tree

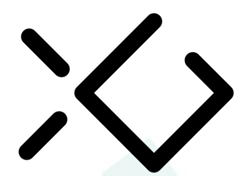


Random Forest



Support Vector Machine

- **Linear**
- **Polynomial**
- **RBF**



XGBoost Classifier

Results and Analysis

- We selected **Gaussian Naive Bayes** and **Decision Tree** as the baseline models because of their minimal complexity.
- We tested the models listed below and obtained the metrics before and after hyperparameter tuning with **cross-validation (k=10)**.
- Decision Trees, in particular, showed noticeable improvement after hyperparameter tuning, emphasizing the value of tuning especially for models with numerous parameters like trees.
- SVM (both Linear and RBF kernel) also improved, suggesting that the default hyperparameters were not optimal for this dataset.

Before Hyper-parameter tuning:

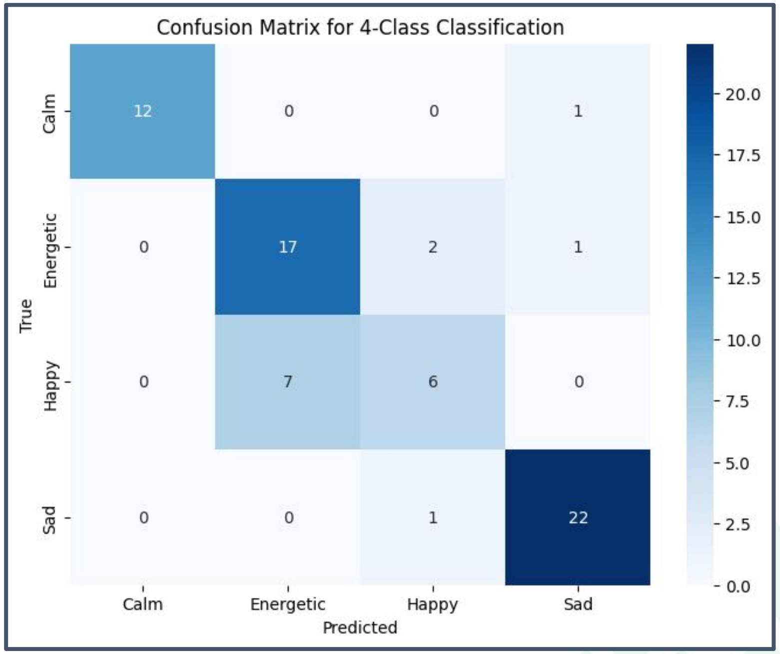
	Accy	Precision	Recall	F1
LR	0.8417	0.8591	0.8417	0.8401
SGD	0.8273	0.8325	0.8273	0.8251
GNB	0.7985	0.8144	0.7985	0.7978
DTs	0.7553	0.7613	0.7553	0.7540
RFC	0.8417	0.8439	0.8417	0.8410
XGB	0.8561	0.8580	0.8561	0.8559
SVM Linear	0.8417	0.8527	0.8417	0.8407
SVM Poly	0.8417	0.8652	0.8417	0.8404
SVM RBF	0.8201	0.8304	0.8201	0.8162

After Hyper-parameter Tuning:

	Accy	Precision	Recall	F1
SGD	0.8269	0.8010	0.7986	0.7969
DTs	0.7769	0.7820	0.7769	0.7755
RFC	0.8533	0.8553	0.8533	0.8528
SVM Linear	0.8545	0.8693	0.8345	0.8321
SVM RBF	0.8273	0.8418	0.8373	0.8248

Results and Analysis

- After hyper parameter tuning with cross-validation, we notice an improvement in the evaluation metrics of Random Forest , SVM, Decision Tree and SGD Classifier. There was no improvement in the evaluation metrics of the XGB model as it is already optimised.
- We get the best results from **XGBoost Classifier and Random Forests** with accuracies of **85.61%** and **85.33%** respectively.
- This is because ensemble models like Random Forest and XGB have higher accuracy and F1 scores compared to simpler models, given their ability to capture complex relationships and reduce overfitting.

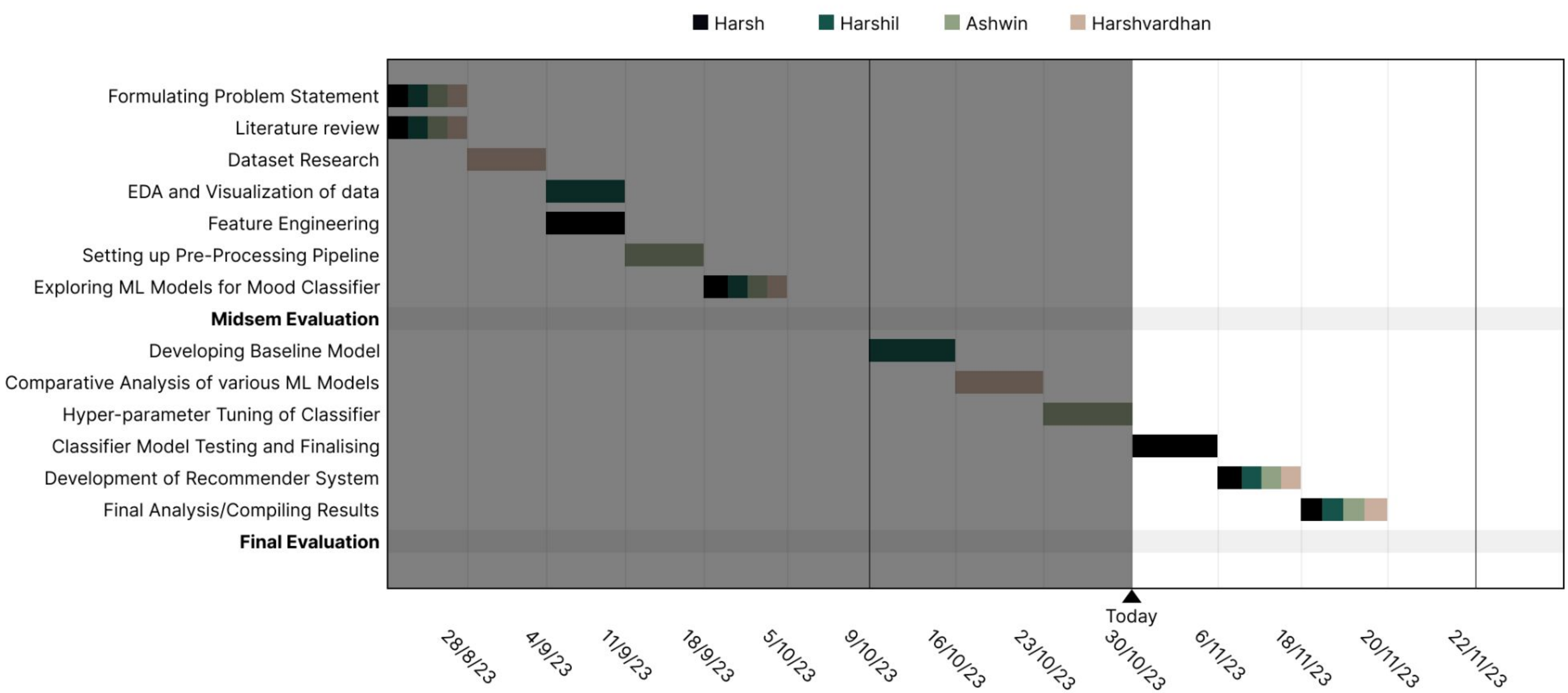


Conclusion

We discovered that the features we have used are highly effective in discerning the mood of a song, and as a result, they can effectively represent the mood of the listener. The **XGB Classifier** model has yielded a promising metric score, which gives us the confidence to move forward and develop a recommender system for songs. This system will be capable of suggesting songs to users based on the mood of the song they are currently listening to.

Timeline

We're ahead of the proposed timeline!



Individual Contribution

Ashwin R Nair

Setting Up and Designing a robust pre-processing pipeline, ensuring data cleaning,feature scaling, and encoding for optimal model performance. Implemented techniques to handle missing values and outliers, enhancing data quality.

Harsh Popat

Enhancing model predictive power by feature selection and hyperparameter used to improve model performance and help to get valuable insights from the data.

Harshil Mital

Performing Exploratory Data Analysis (EDA). Also, experimented with various ML models and conducting performance evaluations, leading to the selection of the most suitable algorithms.

Harshvardhan Singh

Did literature review on related research to inform data selection and model design, ensuring the project's foundation is built on sound empirical and theoretical knowledge. Explored Various ML models to get familiar with the available techniques.

THANK YOU!

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Harshvardhan Singh	(2021052)

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