Computer Engineering Department

G47 Application for Stress Management: A Mood-Based Recommendation System

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Introduction

In today's fast-paced world, mental stress adversely affects individuals of all ages, leading to significant health concerns such as depression and anxiety. Our web application tackles the need for personalized stress management by using advanced machine learning to analyze users' moods through a questionnaire, offering tailored recommendations for movies, music, and activities. This approach enhances user engagement by adjusting suggestions based on feedback, aiming to significantly improve mental well-being with customized entertainment solutions.

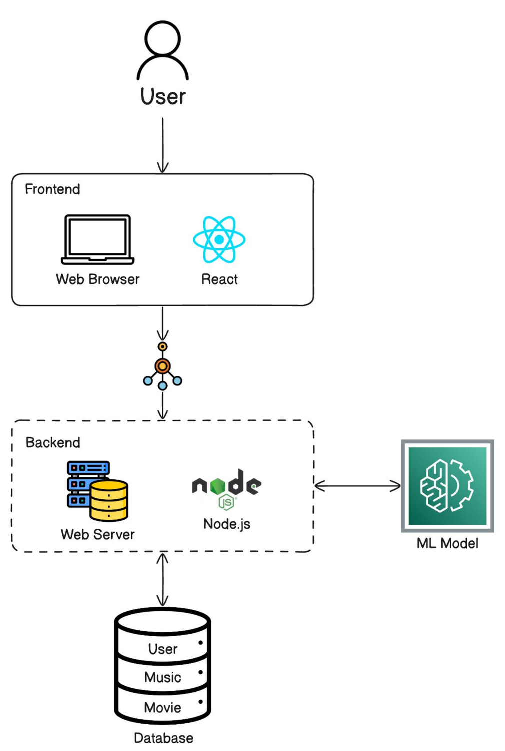

Fig.1: High-level architecture diagram

Methodology

System Architecture

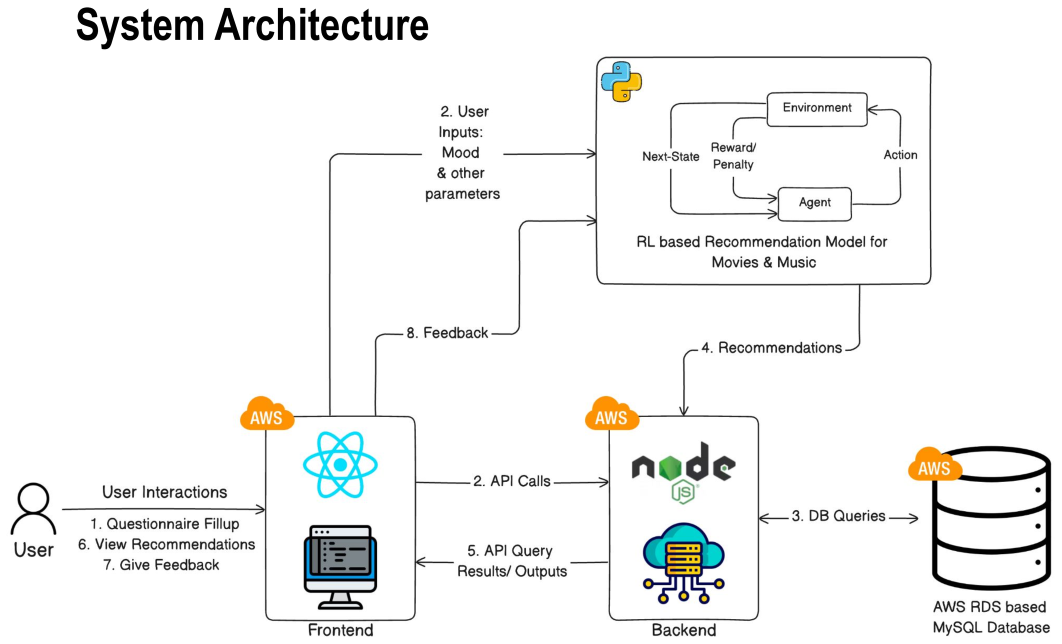

Fig.2: System Architecture Diagram

New users register for our web application by providing basic details such as name, email, password, and date of birth, and then select their preferred genres and mood indicators. Upon sign-in, they are prompted to complete a questionnaire about their current mood and preferences, which include the type of recommendations they desire, such as movies or music. This input is processed by our backend, stored in the database, and analyzed by machine learning models to generate personalized entertainment recommendations. The recommendations are displayed on the user dashboard, where feedback can be submitted to refine future suggestions. Users can update their preferences at any time, ensuring that the recommendations remain aligned with their current interests and moods.

Analysis and Results

Music Recommendation Model:

- A music dataset from the Spotify API, including track metadata and audio features, is loaded with pandas, followed by data cleaning and EDA.
- Songs are categorized into eras ('latest', 'mid', 'old') based on the 'Release_Date'.
- Mood labels are generated from audio features such as 'Valence', 'Energy', and 'Danceability'.
- Features (X) are defined for model training and labels (Y) extracted, with the dataset split into training and testing sets.
- A Random Forest Classifier with 100 estimators is trained and its feature importance analyzed.
- The trained model undergoes testing and is integrated with a rule-based filter for mood and time preferences.
- Filtered song recommendations are uploaded to the web application.

Movie Recommendation Model:

- The movie dataset is loaded with features like average votes, vote counts, popularity, IDs, titles, and genres. It also includes user's preferred genres and watch history.
- Movie eras are determined from release years, and genres are transformed into lists for vectorization.
- User moods influence genre preferences, which are then expanded into a dataframe, treating each genre linked to a mood separately.
- Genres are converted into a binary format using the MultiLabelBinarizer, creating a matrix for similarity calculations.
- Cosine similarity measures alignment between the user's genre vector and movie genres.
- Genre preference and voting scores refine similarity scores.
- Popularity and voting scores are normalized and merged with weighted similarity scores to improve recommendations.
- Previously watched movies are excluded, and the rest are ranked by final scores to determine top recommendations.
- The system displays recommended movies along with their genres, tailored to the user's current preferences.

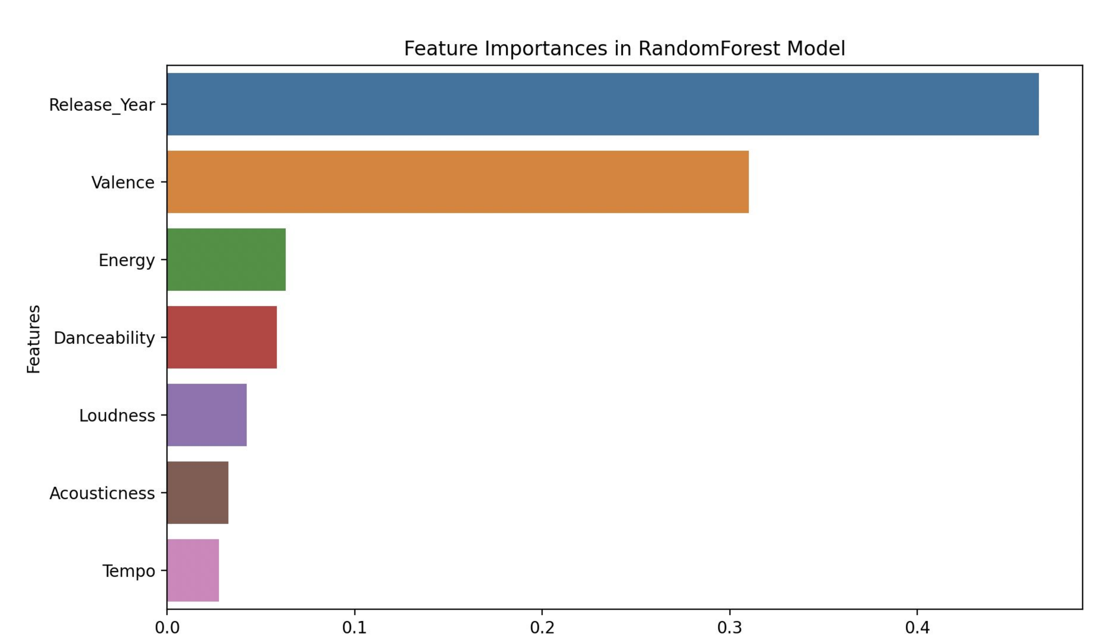

Fig.3: Plot for Feature Importance in Random Forest Model

EDA:

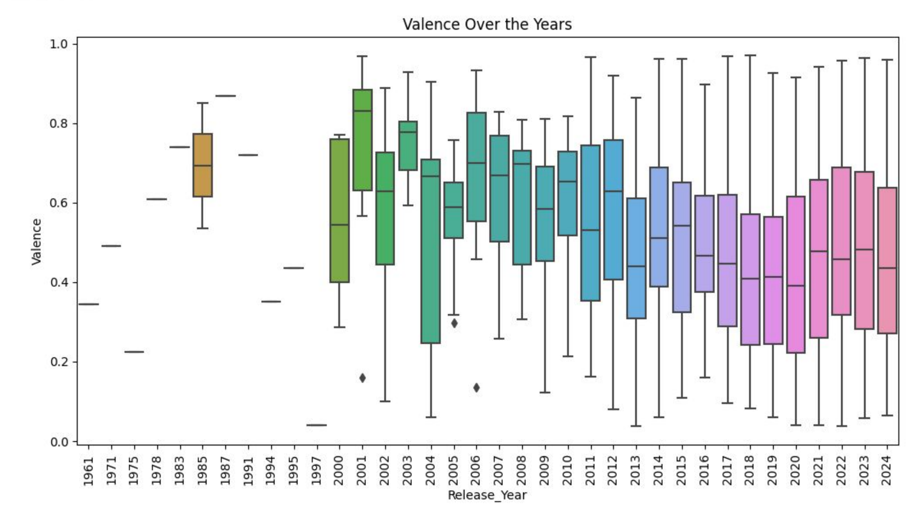

Fig.4: Valence over the Years Plot

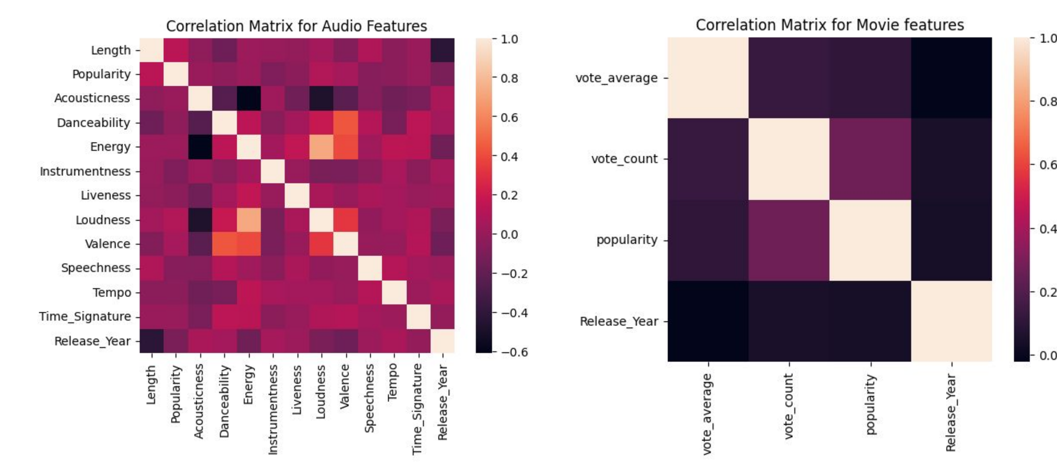

Fig.5: Correlation matrices for Audio and Movie features

Performance of Recommendation Models:

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Classification Report:
              precision    recall  f1-score   support

       happy       0.96      0.95      0.96        82
     neutral       0.96      0.96      0.96       150
         sad       0.76      0.78      0.77        40

    accuracy                           0.93       272
   macro avg       0.89      0.90      0.89       272
weighted avg       0.93      0.93      0.93       272
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Fig.6: Classification Report for Music recommendation model

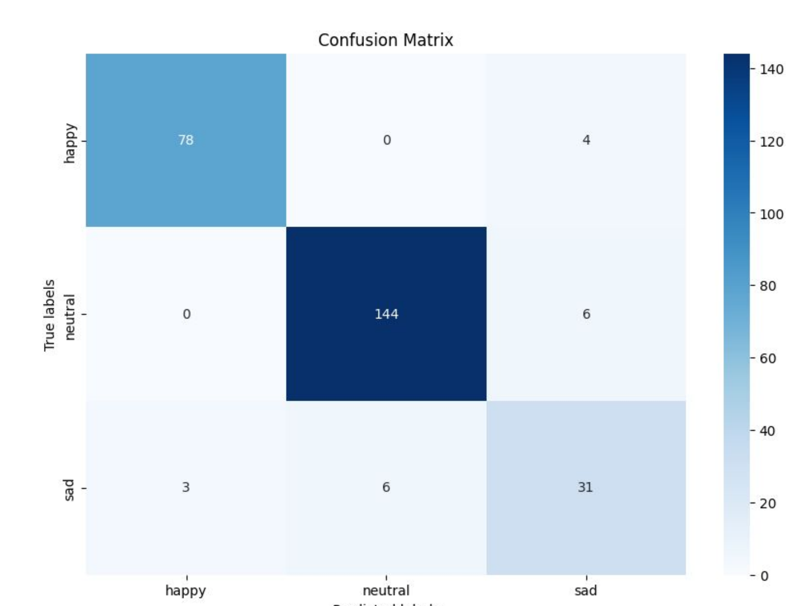

Fig.7: Confusion matrix for Movie recommendation model

K-Fold Cross Validation:

We conducted a five-fold cross-validation to assess our model's performance and stability, dividing the dataset into five parts and training and testing each part in turn. The cross-validation scores were 0.915, 0.941, 0.893, 0.901, and 0.526, with an average score of 0.835, providing a realistic indication of the model's effectiveness.

Model	Content-Based	DNN
Metric		
F1 Score	1.0	0.613
Precision	1.0	0.678
Recall	1.0	0.560

Fig.3: Correlation matrix for Movie features

MSE/RMSE:

The actual movie rating was taken from **50 users** and MSE and RMSE were calculated, this gave us a MSE of **3.72** and a RMSE of **1.929**. This shows that most predictions are close to the actual user rating. With the bigger dataset and user information, and fine tuning the model there is room for improvement.

$$\begin{aligned} \textit{Predicted Rating} &= \textit{Adjusted to 10 scale}(\alpha \times \textit{Normalized Similarity Score} \\ &\quad + \beta \times \textit{Normalized Popularity} + \gamma \times \textit{Normalized Vote Average}) \end{aligned}$$

Summary/Conclusions

Our findings highlight how subtle differences in mood and preferences significantly affect relaxation strategies. By employing advanced, user-centered machine learning, we've developed a system that tailors responses to individual needs, offering comprehensive stress relief through music and movies. We've also emphasized the importance of interdisciplinary collaboration in crafting effective solutions, integrating machine learning with psychological insights to uniquely address the nuanced role of emotions.

Key References

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