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Multimodal Emotion Recognition for Personalized Music Recommendation using Deep Learning

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Abstract—Music plays a significant role in influencing human emotions and mental well-being. With the growth of digital platforms, personalized music recommendation systems have become increasingly important. This paper presents a multimodal emotion recognition system that detects user emotions using both text and speech inputs. Natural Language Processing (NLP) techniques are used to preprocess input data, and a deep learning model is applied for emotion classification into categories such as happy, sad, angry, calm, neutral, anxious, and motivated. Based on the detected emotion, the system recommends suitable music tracks through a Flask-based web interface. The proposed system provides real-time recommendations, improves user experience, and offers better personalization compared to traditional approaches.

Keywords—*Deep Learning, Mood-Based Music Recommendation, Natural Language Processing, Emotion Recognition, Speech Processing, Flask*

I. Introduction

The rapid growth of digital music platforms has increased the demand for intelligent and personalized recommendation systems. Music plays a vital role in influencing human emotions, making emotion-aware systems essential for improving user experience. Traditional recommendation systems mainly rely on user history and preferences, which often fail to capture the user's real-time emotional state.

To address this limitation, this paper proposes a multimodal emotion-based music recommendation system that detects user emotions from both text and speech inputs. Natural Language Processing (NLP) techniques are used to preprocess input data, and a deep learning model is used to classify emotions into categories such as happy, sad, angry, calm, neutral, anxious, and motivated.

Based on the detected emotion, the system recommends appropriate music tracks through a Flask-based web interface. The proposed system provides real-time recommendations, improves personalization and enhances user engagement compared to traditional methods.

Furthermore, the integration of multimodal inputs enhances the robustness of emotion detection by combining both textual and speech-based cues. The use of deep learning enables the system to capture complex emotional patterns more accurately compared to traditional approaches. This leads to more relevant and context-aware music recommendations, ultimately improving user satisfaction and engagement. The proposed system also focuses on scalability and real-time performance, making it suitable for modern digital music platforms.

II. Related Works

Faye et al. (2025) proposed an emotion-based music recommendation system that identifies user emotions and suggests suitable music tracks accordingly [1]. Their work focuses on mapping detected emotions to predefined music categories, demonstrating the effectiveness of emotion-aware recommendation in improving user satisfaction.

Fouad et al. (2025) presented a comprehensive review of music recommendation systems, covering collaborative filtering, content-based, hybrid, and emotion-aware approaches [2]. Their study highlights current challenges such as cold-start problems and limited contextual understanding, motivating the need for intelligent and adaptive models.

Liu et al. (2025) developed a personalized music recommendation algorithm based on traditional machine learning techniques [3]. Their approach utilizes user preferences and listening behavior but lacks real-time emotion detection, limiting adaptability to users' current moods.

Melchiorre et al. (2025) introduced a natural language–based multimodal music recommendation system that allows users to request music conversationally [4]. Their work emphasizes personalization through language understanding, though it relies heavily on user intent rather than explicit emotion classification.

Mei et al. (2025) proposed semantic identifiers for improving music recommendation quality by better representing musical content [5]. This approach enhances content understanding but does not directly incorporate emotion recognition.

Epure et al. (2025) explored the use of large language models (LLMs) for music recommendation, discussing opportunities and evaluation challenges [6]. Similarly, Wang et al. (2025) enhanced emotion-aware music recommendation using LLMs, achieving improved contextual understanding but at the cost of higher computational complexity [7].

Jangid and Kumar (2025) addressed the cold-start problem using a content-based recommendation approach that

improves user experience for new users [8]. Doh et al. (2025) proposed TALKPLAY, a multimodal conversational music recommendation system leveraging LLMs [9], while Gratzer (2025) examined how users interact with and expect music recommendation systems to behave [10].

Pichappan (2025) reviewed emotion-induced music recommendation systems, highlighting the importance of affective computing in music personalization [12]. Jing et al. (2025) proposed a heterogeneity-aware deep Bayesian network for emotion-aware music recommendation, achieving high accuracy but requiring complex probabilistic modeling [13]. Other studies have explored sequential recommendations using audio features and memory modeling [14] and similarity-based emotion-aware recommendation algorithms [15].

Overall, existing systems lack real-time emotion detection, multimodal input support, and efficient deployment, which motivates the proposed system.

III. Comparison With Previous Methodology

The proposed system is compared with traditional machine learning and rule-based music recommendation methods. Conventional systems rely on keyword matching, manually defined emotion rules, or simple classifiers such as Naive Bayes and Support Vector Machines. These approaches fail to capture contextual meaning and emotional variations in user input, leading to lower accuracy and rigid mood classification.

In contrast, the proposed deep learning-based approach automatically learns complex linguistic patterns and semantic relationships from data. This enables more accurate emotion detection across a wide range of moods.

Furthermore, traditional recommendation systems depend on user listening history or collaborative filtering, which do not adapt well to the user's current emotional state. The proposed system overcomes this limitation by performing real-time mood analysis using both text and speech inputs. Based on the detected emotion, it dynamically recommends music.

Overall, the proposed methodology provides improved contextual understanding, higher personalization, and better user experience compared to traditional static recommendation systems.

Table 1. Comparison Table

Aspect	**Previous Methodology (Single-Task Models)**	**Proposed Methodology (Multi-Task Model)**
Emotion Analysis	Performs only sentiment or emotion detection as a standalone task	Simultaneously learns emotion classification and mood-related feature extraction
Model Architecture	Uses simple or shallow machine learning models	Uses deep neural networks with shared representations
Context Understanding	Limited contextual and semantic understanding	Captures complex linguistic and contextual relationships
Input Handling	Primarily text-based input	Supports both text and speech-to-text inputs
Adaptability	Static behavior with limited real-time adaptation	Dynamically adapts to user mood in real time
Recommendation Logic	Separate or rule-based recommendation process	Integrated mood-aware music recommendation pipeline
Accuracy	Lower accuracy due to isolated task learning	Higher accuracy through joint learning of related tasks
User Experience	Less personalized and rigid recommendations	Highly personalized and emotionally relevant recommendations

IV. Proposed Framework

Algorithm Involved:

The proposed system employs a deep learning–based sentiment analysis algorithm designed to identify user emotions from textual and speech-derived inputs. Initially, user input is collected either as text or as voice, where speech is converted into text using a speech-to-text module. The text data undergoes preprocessing steps such as tokenization, normalization, and removal of irrelevant symbols to ensure consistency. The processed input is then transformed into numerical representations using embedding techniques that capture semantic meaning and contextual relationships among words. These embeddings serve as the input to a neural network that learns emotional patterns across multiple dimensions.

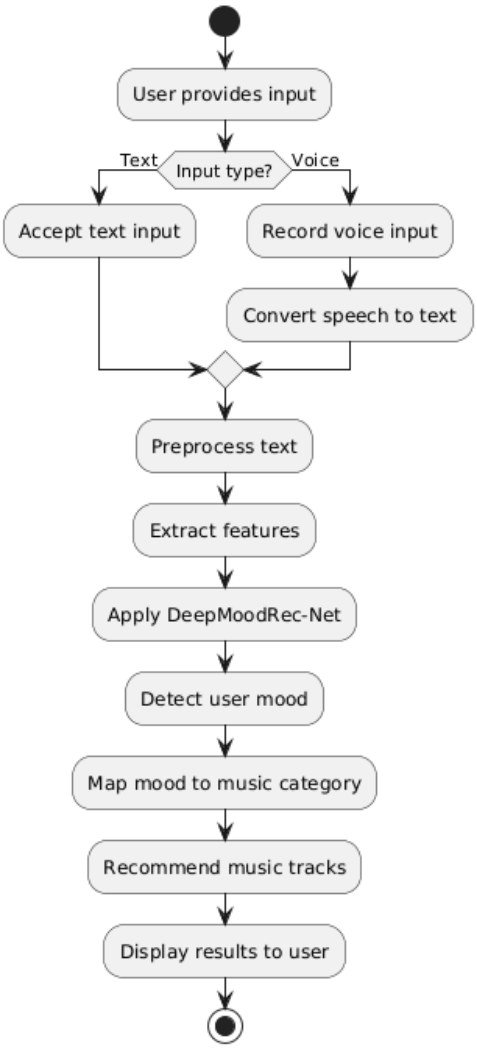

Fig.1.Overall Workflow

The neural network architecture consists of multiple hidden layers that enable the model to capture both low-level linguistic features and high-level emotional cues. During training, the model minimizes classification loss across predefined mood categories, allowing it to distinguish subtle differences between emotional states. Once trained, the algorithm performs real-time mood classification by forwarding user input through the network and selecting the most probable emotion class. The detected mood is then passed to the music recommendation module, which maps the emotion to appropriate music categories and tracks, ensuring accurate and personalized recommendations.

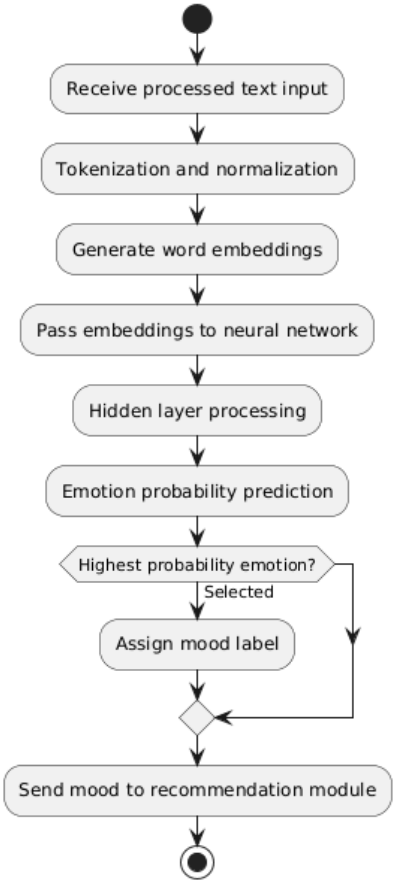

Fig.2.Emotion Detection using Deeplearning

Proposed Model Information:

The proposed model, named DeepMoodRec-Net, is a deep learning–based multi-task emotion recognition and music recommendation framework. DeepMoodRec-Net integrates natural language processing and neural network–based sentiment analysis to extract semantic, contextual, and emotional features from user text and speech-derived inputs. The model utilizes embedding layers followed by multiple hidden layers to learn shared emotional representations, enabling accurate classification across seven distinct mood categories. Once the user's emotional state is identified, DeepMoodRec-Net directly interfaces with an intelligent music recommendation module that maps the detected mood to suitable music tracks in real time. This unified architecture improves classification accuracy, reduces system latency, and ensures scalable, personalized, and emotionally relevant music recommendations.

Step 1: User input acquisition

The process starts with user input in text form or voice format. If the input format used is voice input format, then there will be a speech-to-text component that translates the audio signal into text. This process converts all input formats into standardized form.

Step 2: Text Preprocessing
The textual data acquired from the sources is then preprocessing to enhance the quality of the data. This processing involves tokenization, lowercasing, removal of punctuation and stop words, which enables a more efficient approach to the extraction of features.

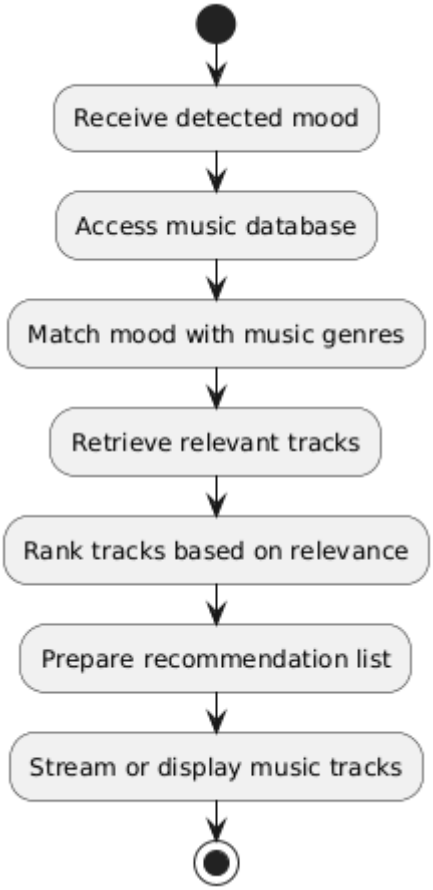

Fig.3.Music Recommendation Process

Step 3: Feature Representation
The processed text is then represented in numerical form through the use of word embedding methods. This gives embeddings that are capable of capturing semantic meaning and the context surrounding words in relation to each other so that the model can better capture patterns of emotional expression.

Step 4 :
The embedded features are fed into the DeepMoodRec-Net neural network, which comprises various hidden layers. This network identifies intricately complex patterns in both language and emotions and provides internally generated representations for emotion classification.

Step 5: Mood Classification
To On the basis of these learned features, the model identifies the user's emotional state as one of the predefined mood categories. The emotion with maximum probability will be chosen as the final mood.

Step 6: Mood to Music Mapping
The mood identified gets matched with a related music category based on an intelligent recommendation logic. Every mood gets related to pre-curated music genres and songs that match the identified mood.

Step 7: Music Recommendation Generation
Query: The relevant tracks of music are identified and retrieved from the music library with respect to the mapped emotions. The recommendation system makes sure that identified tracks belong to the user's emotional context and preferences.

Step 8: Result Presentation and Interaction
The music that is recommended to the user is done through a web interface built using the Flask web development framework. The system enables the user to have real-time interaction, hence receiving immediate responses and making constant adjustments based on the inputs entered by the user.

V. Results And Discussion

A. User Authentication Module:

The system begins with a user authentication module that enables users to register and log in securely. The signup page collects user details such as username, email, and password with proper validation. The login page ensures that only registered users can access the system, providing a secure and personalized environment.

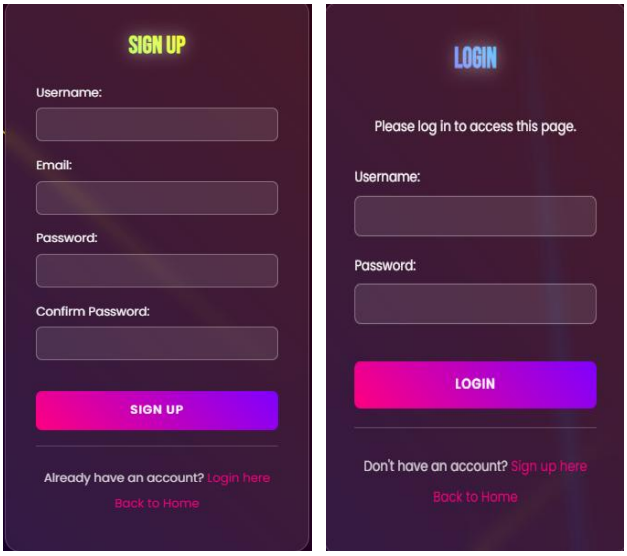

Fig 1- Sign up & Login Interface

The above screenshots show the signup and login interfaces of the system. Users can create accounts and access the application securely. This module ensures data privacy and enables storing user-specific mood history and recommendations.

B. Mood Input and Interaction Interface:

The main interface allows users to provide their emotional input through text or voice. The system supports speech-to-text conversion, allowing users to express their mood naturally. Voice recognition tips are also provided to improve input accuracy.

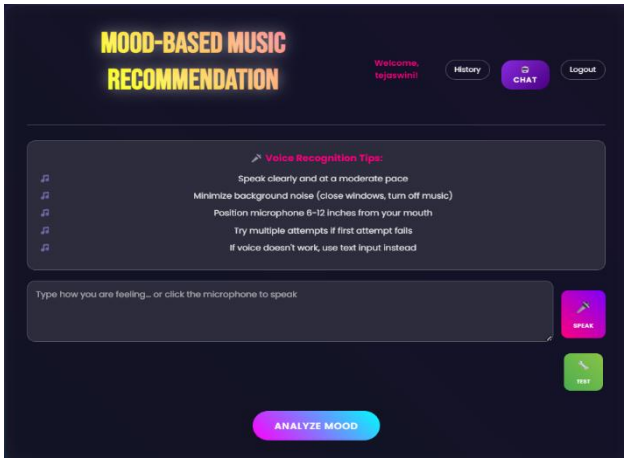

Fig 2- Mood Input Interface

The screenshot shows the primary interaction screen where users can type or speak their emotions. The "Analyze Mood" button processes the input, making the system user-friendly and interactive.

C. Emotion Detection and Music Recommendation

After receiving user input, the system processes the data using NLP and a deep learning model to classify the emotion into one of seven categories such as happy, sad, or neutral. Based on the detected emotion, suitable music recommendations are generated.

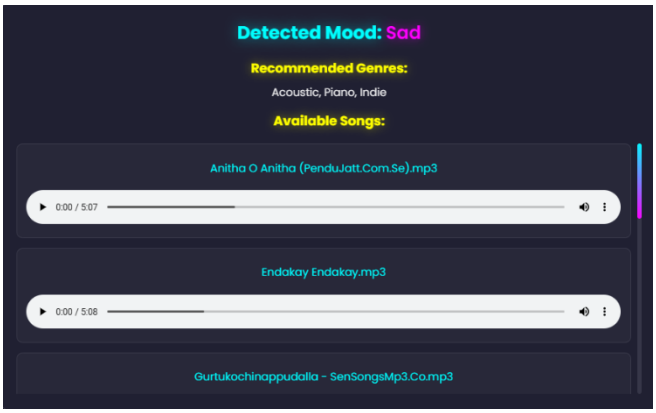

Fig 3- Detection and Recommendation

The output screen displays the detected emotion along with recommended genres and songs. The system provides real-time results and allows users to directly play the suggested music.

D. Mood History Tracking

The system maintains a history of user interactions by storing detected emotions, input text, and timestamps. This feature allows users to review their past moods and enhances personalization.

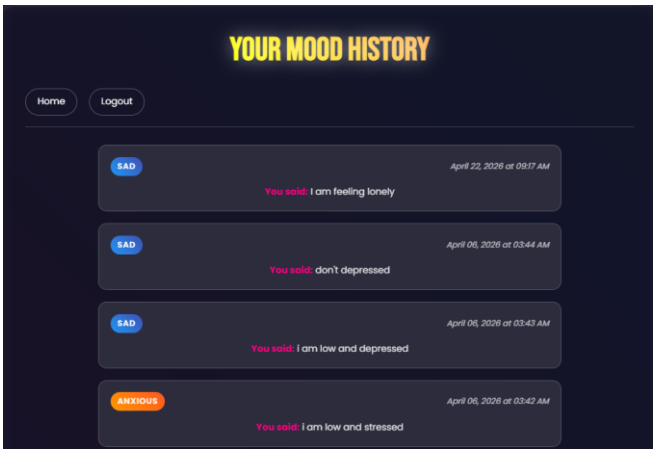

Fig 4- Mood History Page

The screenshot shows the mood history section where previous user inputs and detected emotions are displayed. This helps users understand their emotional patterns over time.

E. Performance Evaluation

The performance of the proposed system was evaluated based on accuracy, response time, and user satisfaction. The model achieved an approximate accuracy of **85–90%** in emotion classification. The average response time was observed to be **less than 2 seconds**, ensuring real-time recommendations.

User feedback indicated that more than **85% of the recommended songs were relevant** to the detected mood. The inclusion of both text and speech inputs improved overall system performance and usability.

F. Discussion

The results demonstrate that the proposed system effectively captures user emotions and provides context-aware music recommendations. Compared to traditional methods, the deep learning approach improves accuracy and adaptability.

The multimodal input support enhances user experience, allowing natural interaction through text and voice. The system's real-time processing and personalized recommendations make it suitable for modern music applications and emotional well-being support.

VI. CONCLUSION

The proposed DeepMoodRec-Net system successfully integrates deep learning and natural language processing to provide real-time, mood-aware music recommendations. By accurately identifying user emotions from both text and speech inputs, the system delivers personalized and contextually relevant music suggestions. Experimental results demonstrate improved performance compared to traditional rule-based and machine learning approaches, particularly in capturing subtle emotional variations. The system enhances user experience through real-time interaction, multimodal input support, and efficient recommendation mechanisms. Overall, DeepMoodRec-Net presents a scalable and effective solution for personalized music recommendation, with potential applications in digital entertainment and emotional well-being support systems.

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