Deep Learning-Based Emotion-Aware Chatbot with Personalized Music Recommendation System

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Abstract- The emotion recognition module employs advanced Natural Language Processing techniques using deep learning models such as Bidirectional Long Short-Term Memory (BiLSTM) and transformer-based architectures. These models are trained on publicly available emotion-labeled datasets, enabling accurate identification of subtle emotional cues within conversational text. The music recommendation component adopts a hybrid approach that combines rule-based emotion-to-genre mapping with collaborative filtering to personalize recommendations based on both emotional context and user preferences. Music data sourced from curated mood-based playlists and streaming platforms supports effective recommendation generation. The chatbot interface facilitates seamless real-time interaction, allowing users to express their emotions naturally while receiving empathetic responses and instant music recommendations. Experimental evaluation shows that the proposed system achieves high accuracy in emotion detection and generates music suggestions that align well with users' emotional states. Overall, the project demonstrates the effectiveness of deep learning in developing intelligent, emotion-aware chatbots capable of delivering meaningful and personalized user experiences.

Keywords: Emotion Recognition, Chatbot System, Music Recommendation, Natural Language Processing, Deep Learning, Personalized User Experience

I.INTRODUCTION

In recent years, rapid advancements in artificial intelligence and machine learning have enabled the development of intelligent systems that can understand, interpret, and respond to human emotions. Emotion recognition has become a key component in enhancing human–computer interaction, as it allows machines to move beyond simple command-based responses and engage users in a more natural and empathetic manner. By identifying emotional states such as happiness, sadness, anger, or calmness, systems can adapt their behavior and responses to better suit the user's emotional context.

Among various AI-driven applications, chatbots have gained widespread popularity in domains such as customer service, entertainment, healthcare, and personal assistance due to their ability to provide instant and interactive communication.

Music plays a significant role in influencing human emotions, mood, and mental well- being. Different musical genres and compositions can evoke relaxation, motivation, happiness, or emotional comfort. Music therapy and mood-based listening have been shown to reduce stress and improve emotional balance. Music recommendation systems leverage this emotional connection by suggesting tracks or playlists based on user preferences, listening history, or contextual factors. However, traditional music recommendation systems often fail to consider the user's real-time emotional state, limiting their ability to deliver truly personalized and emotionally relevant content. This project aims to address this limitation by designing and implementing a deep learning–based chatbot that integrates emotion recognition with music recommendation. The chatbot analyzes user emotions through textual conversations using advanced Natural Language Processing techniques. Deep learning models such as Bidirectional Long Short-Term Memory (BiLSTM) networks and transformer-based architectures are employed to capture contextual and semantic patterns in conversational text, enabling accurate classification of user emotions. These models are trained on emotion-labeled datasets to recognize subtle emotional cues expressed through language. Once the user's emotional state is identified, the system recommends music that aligns with or positively influences that emotion. The music recommendation module utilizes a hybrid approach that combines emotion-to-genre mapping with collaborative filtering and content-based techniques. This allows the system to consider both the detected emotional state and individual user preferences while generating recommendations.

Music data sourced from curated mood-based playlists and streaming platforms enhances the diversity and relevance of recommendations. By integrating emotion recognition and music recommendation into a unified chatbot framework, the system delivers empathetic and context-aware interactions. The chatbot not only responds appropriately to user emotions but also enriches the interaction mthrough personalized music suggestions. This approach has strong potential to improve user engagement, satisfaction, and emotional well-being, making it applicable to areas such as entertainment platforms, mental health support systems, and personalized digital assistants.

II.LITERATURE SURVEY

Emotion recognition and music recommendation have independently undergone substantial progress in recent years, primarily due to advancements in deep learning and Natural Language Processing (NLP).

Early emotion recognition systems were largely based on rule-based methods or traditional machine learning algorithms such as Naive Bayes, Decision Trees, and Support Vector Machines (SVM). These approaches depended heavily on handcrafted linguistic or acoustic features, including word frequency, sentiment lexicons, and prosodic cues. While such systems were capable of identifying basic emotional polarity, such as positive or negative sentiment, they struggled to capture subtle emotional nuances and contextual dependencies present in conversational text, leading to limited performance in real-world chatbot applications.

The emergence of deep learning significantly improved the accuracy and robustness of emotion recognition systems. Recurrent neural networks, particularly Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models, demonstrated superior capability in modeling sequential and contextual information within text data.

Convolutional Neural Networks (CNNs) were also applied to emotion classification by extracting high-level semantic features from text representations. More recently, transformer-based architectures such as BERT, RoBERTa, and GPT have revolutionized emotion recognition by enabling contextualized word representations and capturing long-range dependencies in language. These models have shown remarkable performance in fine-grained emotion classification tasks. However, despite their effectiveness, most emotion recognition systems are developed as standalone analytical models and are not fully integrated into interactive chatbot frameworks capable of delivering empathetic and adaptive responses.

In parallel, music recommendation systems have traditionally relied on collaborative filtering and content-based filtering techniques. Collaborative filtering generates recommendations based on similarities between users or items, while content-based filtering uses music attributes such as genre, tempo, and artist information. Although these approaches provide personalized recommendations based on listening history, they largely ignore the listener's real-time emotional state. As a result, recommendations may not always align with the user's current mood or emotional needs. To overcome this limitation, recent studies have explored mood-aware and emotion-based music recommendation systems, incorporating emotional context derived from text, physiological signals, or user feedback. Several research efforts have attempted to integrate emotion recognition with music recommendation to enhance personalization. Systems that detect emotions from text, facial expressions, or physiological signals and map them to corresponding music playlists have demonstrated improved user satisfaction. However, many of these systems rely on predefined rule-based emotion-to-music mappings or a limited set of emotion categories, which restricts flexibility and adaptability. Additionally, such systems often operate independently and lack seamless integration with conversational agents, limiting their ability to provide real-time, interactive, and empathetic user experiences.

Overall, while significant progress has been made in both emotion recognition and music recommendation domains, their deep integration into a unified, real-time chatbot system remains relatively underexplored. Existing solutions often lack contextual depth, emotional granularity, and dynamic personalization. This research addresses these limitations by proposing a deep learning–driven chatbot that combines advanced emotion recognition with personalized music recommendation, enabling adaptive, empathetic, and engaging human–computer interactions.

III.PROPOSED SYSTEM

To accurately detect the emotional state of a user from textual input during chatbot interactions. The system must be capable of analyzing conversational text and classifying emotions into multiple predefined categories such as happiness, sadness, anger, calmness, and neutrality. Once an emotion is identified, the system should automatically recommend music that aligns with or positively influences the user's mood. In addition to emotion detection and music recommendation, the chatbot must support natural language interaction, enabling users to communicate freely and receive relevant, empathetic, and context-aware responses in real time. The system is required to operate efficiently in real time with minimal latency to preserve a smooth and natural conversational experience.

3.1 Data Collection and Preprocessing:

The system begins with collecting datasets for training the emotion recognition model and the music recommendation engine. For emotion recognition, publicly available labeled datasets such as the EmotionLines, SemEval, or ISEAR datasets are used. Text data is cleaned by removing noise like special characters, URLs, and stopwords, followed by tokenization and word embedding using pretrained models like GloVe or BERT embeddings. For the music recommendation, metadata from streaming platforms or curated mood-based playlists is gathered, including genres, moods, and user ratings.

3.2 Emotion Recognition Model Development:

A deep learning model based on transformer architecture (e.g., BERT or RoBERTa) is fine-tuned on the preprocessed emotion-labeled datasets. The model is trained to classify user text input into multiple emotional categories such as happy, sad, angry, or neutral. Techniques like dropout and early stopping are employed to prevent overfitting, while hyperparameter tuning optimizes model performance. The trained model is saved for inference during chatbot interaction.

3.3 Music Recommendation Engine:

The recommendation system uses a hybrid approach combining rule-based emotion- to-genre mappings and collaborative filtering based on user preferences. The rule- based component links detected emotions with corresponding music genres or moods (e.g., sadness → calming or melancholic playlists). Collaborative filtering analyzes user interaction history to personalize recommendations further. A database stores music metadata, playlists, and user profiles to facilitate quick retrieval.

3.4 Chatbot Interface Development:

A conversational interface is developed using chatbot frameworks like Rasa, Microsoft Bot Framework, or custom APIs. The chatbot accepts user input, sends the text to the emotion recognition module, and receives the predicted emotion. Based on this, it queries the music recommendation engine to fetch suitable playlists. The chatbot then responds to the user with empathetic messages and music suggestions. The interface supports real-time interaction and handles conversational context to maintain flow.

3.5 Integration And Deployment

All components—emotion recognition model, music recommendation engine, and chatbot interface—are integrated into a unified system. API endpoints facilitate communication between modules, ensuring low-latency response times. The system is deployed on cloud platforms like AWS, Google Cloud, or Azure to enable scalability and accessibility. Continuous monitoring tools track system performance, user engagement, and errors for ongoing improvements.

IV.RESULTS

In emotion-aware chatbot applications, machine learning enables the system to analyze textual input, identify emotional patterns, and respond empathetically. Deep learning models such as

BiLSTM and transformer architectures enhance the system's ability to understand contextual and semantic nuances in language. By integrating emotion recognition with music recommendation algorithms, machine learning enables personalized, emotionally intelligent interactions that significantly improve user satisfaction and engagement.

In above screen LSTM +GRU got 84% accuracy and can see other metrics also

Figure.1 Confusion Matrix

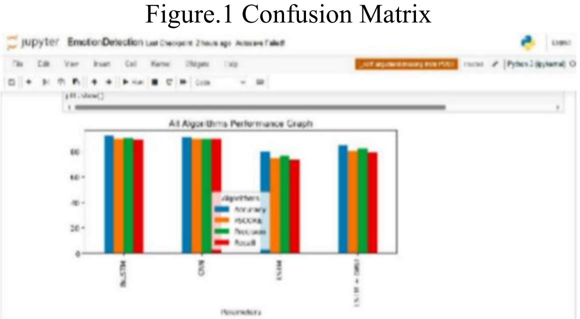
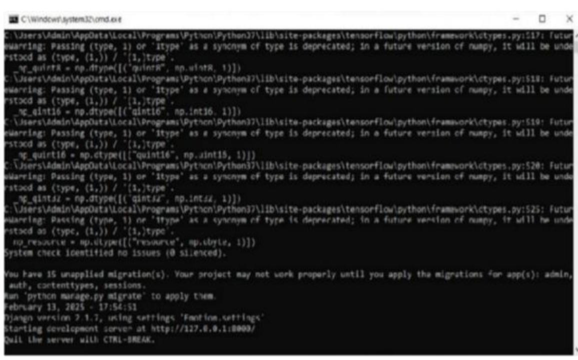


Figure.2 visualizing all algorithms performance



In above screen visualizing all algorithms performance where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars. BILSTM got high accuracy. So in above screen we have seen each algorithm training and testing performance and now double click on 'runWebServer.bat' file to start python server and then will get below page

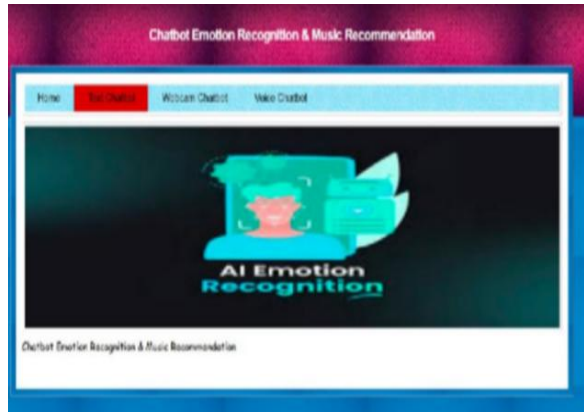
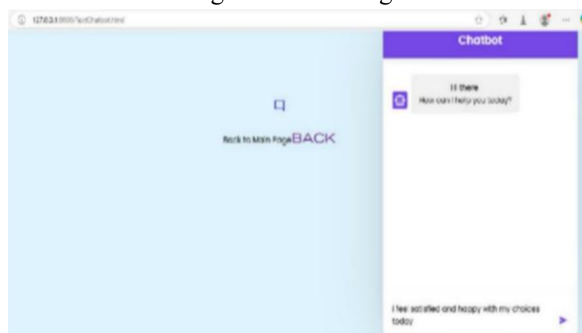


Figure. Admin Page



In above screen click on 'Webcam Chatbot' link to get below page

In above screen in webcam you can show face and then click on 'Take Snapshot' button to capture face and then click on 'Detect Emotion' button to get list of songs

In above screen face is predicted as neutral and now click on 'Voice Chatbot' link to record voice and then recommend songs.

V.CONCLUSION

In this, successfully developed an intelligent emotion-aware chatbot system that integrates deep learning–

based emotion recognition with a personalized music recommendation engine. By using advanced NLP techniques and models such as BiLSTM and transformer-based architectures, the system effectively identifies subtle emotional cues from user conversations. The experimental results indicate strong performance in emotion classification, demonstrating the capability of deep learning to capture contextual and semantic patterns in text. Once the user's emotional state is detected, the system recommends suitable music using a hybrid strategy that combines rule-based emotion-to-genre mapping with collaborative filtering, ensuring both emotional relevance and personalization. The chatbot interface enables smooth real-time interaction by providing empathetic responses along with instant playlist suggestions, improving overall user engagement and satisfaction. The integration of all components into a unified framework highlights the practical feasibility of deploying emotion-sensitive recommendation systems in real-world applications. The achieved results confirm that incorporating emotion recognition into chatbots significantly enhances user experience compared to traditional recommendation systems. Furthermore, the system has strong potential for use in entertainment platforms, stress-relief applications, and mental health support tools. Future work can focus on expanding emotion categories, improving multilingual emotion detection, and incorporating audio or facial emotion cues for higher accuracy. Overall, this work demonstrates that deep learning-driven emotion recognition combined with smart recommendation strategies can deliver meaningful, adaptive, and personalized human–computer interactions.

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