IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 1, June 2025

Impact Factor: 7.67

AI-Enhanced Personalized Content Generator

V. B. Sakanure[1], Yuvrajsingh Shekhawat[2], Pallavi Jadhav[3], Pooja Raut[4], Rucha Rakshe[5]

Professor, Department of Information Technology[1]

Student, Department of Information Technology[2,3,4,5]

Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

Abstract: *With the explosion of digital content and the growing demand for tailored user experiences, personalization technologies have become essential for sustaining user interest across various online platforms. However, conventional recommendation systems typically rely on historical interactions and static user profiles, failing to capture the dynamic and emotional aspects of user behavior. This research introduces a robust AI-powered system—the AI-Enhanced Personalized Content Generator—which bridges this gap by incorporating real-time sentiment analysis and intelligent profiling to recommend emotionally aligned content.*

Utilizing Natural Language Processing (NLP), the system interprets users' emotional states from inputs such as typed text or feedback, and adjusts content recommendations—particularly in the domains of movies and music—accordingly. Unlike static recommendation models, this approach adapts continuously through machine learning, refining its output based on real-time mood detection and evolving user interests. Our experiments indicate a marked improvement in user satisfaction and engagement when emotional intelligence is embedded into recommendation engines. The results advocate for a paradigm shift in personalization strategies, highlighting the need for emotionally adaptive systems in the next generation of content platforms.

Keywords: Analysis, Personalized Recommendation System, Sentiment Analysis, Hybrid Recommendation

I. INTRODUCTION

In the rapidly evolving digital age, content personalization has emerged as a critical factor in maintaining user engagement across various platforms. Recommendation systems play a pivotal role in shaping how users interact with digital content such as movies, music, and news. While existing systems have proven effective to some extent, they often rely heavily on static user data—including viewing history, clicks, and search queries. A major limitation of these traditional approaches is their inability to adapt to users' real-time emotional states or capture evolving personal interests and hobbies, leading to a user experience that can feel impersonal and disconnected. This issue becomes particularly significant in emotionally sensitive contexts, where users seek content that aligns with their current mood. The failure to meet such emotional expectations can result in decreased engagement, satisfaction, and overall platform retention.

i. Problem Significance and Challenges

The primary issue addressed by this project is the absence of real-time emotional intelligence in contemporary recommendation systems. Current platforms—such as Netflix and Spotify—primarily base their recommendations on historical user behavior, overlooking the emotional needs of the user in the moment. This represents a fundamental gap in achieving truly personalized and emotionally resonant user experiences. The core challenge is to develop a system capable of not only interpreting past preferences but also dynamically adjusting recommendations based on real-time sentiment and mood analysis. Overcoming this challenge is essential for building next-generation recommendation systems that prioritize contextual relevance and emotional alignment, ultimately leading to improved user engagement and satisfaction.

ii. Aims and Goals

The primary objective of this project is to develop an AI-Enhanced Personalized Content Generator that utilizes Natural Language Processing (NLP) and sentiment analysis to deliver personalized movie and music recommendations. Unlike traditional systems, this model aims to interpret the user's current emotional state—as well as their ongoing interests and hobbies—to curate content that feels timely, relevant, and emotionally engaging. By embedding emotional intelligence into the recommendation process, the system aspires to deliver a deeper, more immersive, and satisfying user experience, paving the way for future advancements in emotion-aware AI systems.

II. METHODOLOGY

This project adopts an integrated approach combining Natural Language Processing (NLP), Machine Learning (ML), and Full-Stack Web Development to implement a robust, real-time AI-Enhanced Personalized Content Generator. The methodology is divided into the following key components:

A. Data Preprocessing

The initial phase involves cleaning and preparing user-generated text data for model inference. The preprocessing pipeline includes:

Regular expressions (regex) for removing noisy elements such as emojis, hyperlinks, special symbols, and unwanted characters.

Tokenization and lemmatization using libraries such as spaCy or NLTK to normalize input text and reduce it to base word forms.

Stopword removal to eliminate non-informative words and enhance model accuracy.

B. Embedding Techniques

To convert processed text into machine-readable format, the system employs two types of embedding strategies:

TF-IDF (Term Frequency–Inverse Document Frequency): A lightweight embedding approach suitable for real-time inference and deployment in resource-constrained environments.

BERT / DistilBERT Embeddings: For more sophisticated analysis, transformer-based contextual embeddings are generated using the Hugging Face transformers library.

Tokenization is handled by BERT-specific tokenizers.

Embeddings are returned in the format: shape = [batch_size, embedding_dim], allowing input to downstream neural layers.

C. Model Architecture

A modular set of machine learning models is implemented to interpret input data and classify emotional state:

Naive Bayes: Baseline model for fast, initial testing and comparisons.

Logistic Regression: A lightweight classifier, ideal for rapid deployment and scalable inference.

LSTM / GRU (Recurrent Neural Networks): Sequence-based models designed to detect temporal or patterned input (e.g., repeated emotional states or behavior).

BERT with Dense Layers: A deep neural model for high-performance, context-aware sentiment classification and recommendation alignment.

Training and Optimization:

Loss Function: Binary Cross-Entropy for binary classification tasks.

Optimizer: AdamW (a weight-decay variant of Adam) for efficient training.

Evaluation Metrics: F1-Score, ROC-AUC, and Hamming Loss to evaluate classification accuracy and model robustness.

D. Backend Integration

To bridge the AI models with the user-facing system, the backend is structured with the following:

REST API endpoints (/predict) served using Flask or FastAPI to handle real-time inference requests.
MongoDB stores:
Raw input text and user metadata (e.g., ID, IP address, timestamp).
Prediction labels for future analytics and retraining.
The MERN stack (MongoDB, Express.js, React.js, Node.js) enables seamless integration between the frontend and backend components, ensuring a responsive and interactive user interface.

E. Real-Time Interaction Flow

The complete real-time system functions as follows:
The React frontend captures user input (e.g., mood descriptions, hobbies).
Input is sent to the backend inference engine via HTTP requests.
The backend preprocesses the input and routes it through the appropriate ML model for sentiment classification and recommendation generation.
Results are returned instantly and displayed on the frontend interface.
Optional email alerts or notifications are triggered via SMTP or third-party APIs like SendGrid, especially for event-based updates or system monitoring

III. LITERATURE SURVEY

1. Federated Personalized Home BESS Recommender System Based on Neural Collaborative Filtering

Authors: Xiangzhi Guo, Fengji Luo, Zehua Zhao, Yuchen Zhang, Tong Wan
Publication Year: 2024
This paper proposes a federated learning-based recommender system focused on battery energy storage systems. The authors utilize neural collaborative filtering to analyze customer preferences and energy costs. By applying federated learning, the system aims to enhance privacy and user data security while improving the accuracy of recommendations through the aggregation of decentralized data.

2. Music Recommendation System Using Machine Learning

Authors: Varsha Verma, Ninad Marathe, Parth Sanghavi, Dr. Prashant Nitnaware
Publication Year: 2021
This study implements a machine learning-based music recommendation system that suggests songs based on user history. The authors analyze various algorithms to determine which provides the best personalization and user satisfaction. While the system proves effective in recommending music, it primarily relies on historical data and does not account for the user's current emotional state.

3. Content-based Music Recommendation System

Authors: Aldiyar Niyazov, Elena Mikhailova, Olga Egorova
Publication Year: 2021
This research develops a content-based music recommender using acoustic similarity and deep learning techniques. The authors focus on analyzing the acoustic features of music tracks to provide personalized recommendations. Despite its effectiveness, the system lacks integration with user emotional states, making it less responsive to real-time user preferences.

4. Personalized Online Book Recommendation System Using Hybrid Machine Learning Techniques

Authors: S. Rajalakshmi, G. Indumathi, Arun Elias, G. Shanmuga Priya, Vidhya Muthulakshmi
Publication Year: 2024
This paper proposes a hybrid machine learning approach for a personalized online book recommendation system. The authors enhance recommendation accuracy by combining collaborative filtering and content-based techniques.

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Although it shows improved results, the system does not incorporate real-time sentiment analysis to align with the user's emotional state during the recommendation process.

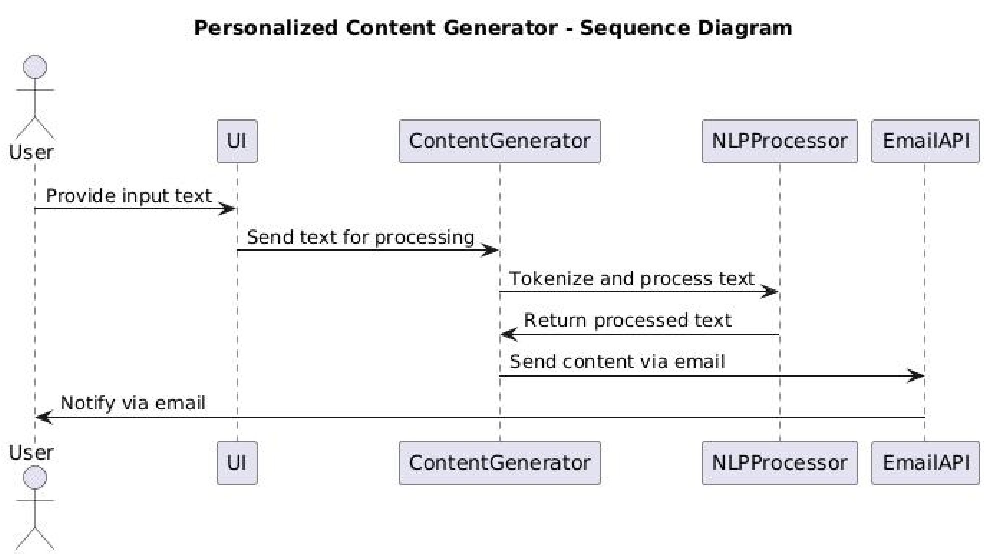
5. Recommender System Using Hybrid Approach
Authors: Sanya Sharma, Aakriti Sharma, Yamini Sharma, Ms. Manjot Bhatia
Publication Year: 2020
This paper introduces a hybrid filtering algorithm that combines multiple recommendation methods to enhance accuracy. The authors emphasize the importance of incorporating both user behavior and content features for effective recommendations. However, the system primarily relies on historical data without addressing the emotional context of the user.

6. Personalized Video Recommendation Model Based on Multi-Graph Neural Network and Attention Mechanism
Authors: Rohan Mehta Joshi, Humphrey St. Clair Dawson, Kunal Roy
Publication Year: 2024
This study proposes a video recommendation model using multi-graph neural networks and attention mechanisms for effective feature extraction. The authors focus on enhancing the relevance of recommendations by incorporating complex relationships within the content. While it offers advanced personalization, the system does not account for the users emotional state during content selection.

7. Intelligent Personalized Content Recommendations Based on Neural Networks
Authors: HeQiang Zhou
Publication Year: 2024
This paper discusses an intelligent content recommendation system utilizing neural networks and self-attention mechanisms to refine content suggestions. The author highlights the benefits of using advanced algorithms for personalization but does not emphasize real-time emotional data, which is crucial for user engagement.

IV. UML DIAGRAM

Sequence Diagram :



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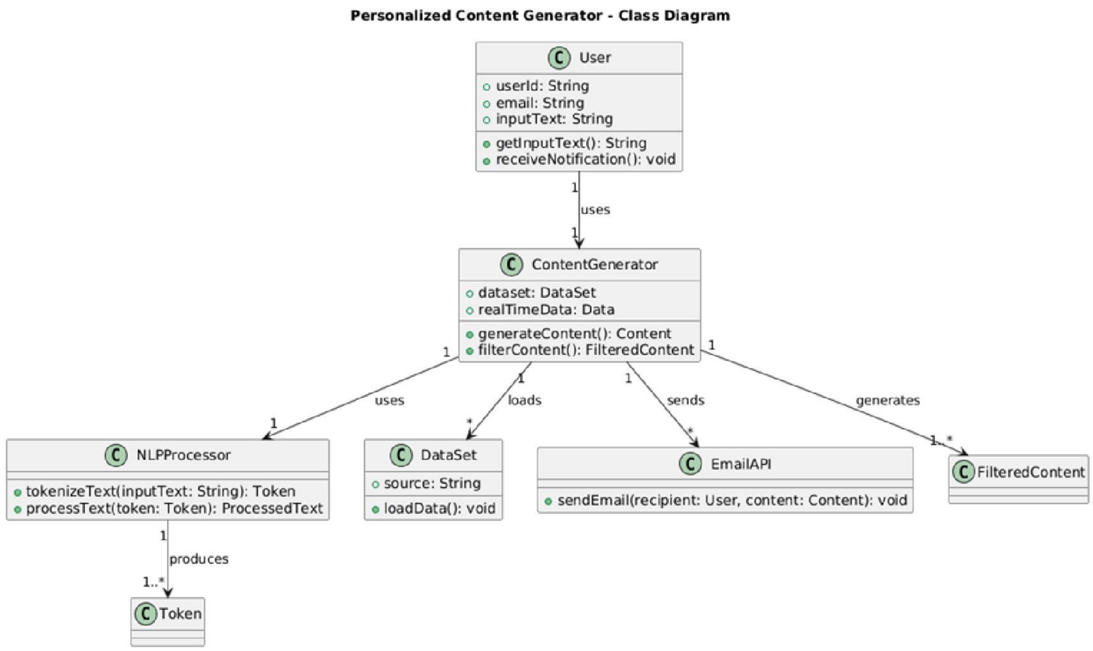
Class Diagram :



V. CONCLUSION

The Personalized Content Generator project successfully demonstrates the feasibility and value of integrating emotionally intelligent computing into content recommendation systems. Designed to deliver context-aware and emotionally resonant suggestions for movies and music, the system effectively combines Machine Learning, Natural Language Processing (NLP), and real-time web technologies to go beyond traditional recommendation models.

A key innovation of the system lies in its real-time sentiment input, which allows recommendations to be dynamically adapted based on the user's current emotional state. Unlike conventional systems that rely exclusively on static behavioral data or popularity metrics, this solution accepts user mood, genre, and language preferences—offering a contextual and flexible discovery experience. This makes the system particularly effective in enhancing engagement and satisfaction, especially in emotionally driven content consumption scenarios.

The architecture, including a lightweight Flask-based backend, leverages custom-trained models using semantic embeddings and cosine similarity to produce tailored recommendations. It also addresses the cold start problem—a common challenge in collaborative filtering—by enabling mood- and query-driven input from even first-time users, ensuring relevant suggestions without requiring extensive user history.

From a technical standpoint, the entire pipeline—from user input to result delivery—is optimized for speed, with response times under one second. The frontend interface, designed for simplicity and responsiveness, ensures seamless interaction across devices and platforms. Thorough functional and non-functional testing has validated the system's robustness, usability, and cross-platform compatibility.

In summary, the Personalized Content Generator fulfills its vision of bridging the gap between emotional context and digital personalization. It sets a new standard for emotion-aware recommendation systems, offering a scalable, intelligent, and user-centric solution for content platforms seeking to elevate their engagement strategies in today's data-driven world.

DOI: 10.48175/IJARSCT-27360

VI. ACKNOWLEDGMENT

We are very thankful to all the teachers who have provided us valuable guidance towards the completion of this project work on **Ai-Enhanced Personalized Content Generator .** We express our sincere gratitude towards cooperative department who has provided us with valuable assistance and requirements for the project work.

We are very grateful and want to express our thanks to **V. B. Sakanure** for guiding us in right manner, correcting our doubts by giving her time whenever we required, and providing her knowledge and experience in making this project work. We are also thankful to the HOD of our Information Technology department **Dr. M. L. Bangare** for his moral support and motivation which has encouraged us in making this project work. We are also thankful to our Vice Principal **Dr. K. R. Borole** and our Principal **Dr. A.V. Deshpande**, who provided his constant support and motivation that made a significant contribution to the success of this project.

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