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SENTIMENT-SYNC: AI-CURATED MOVIE PICKS

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Abstract: With the era of personalized entertainment, it is essential to get movie recommendations spot on with the user sentiments. Our paper introduces SentimentSync an artificial intelligence-based kannada movie recommendation system that relies on sentimental analysis of YouTube trailer comments and web scraping of dynamic movie listings of the Times of India in contrast to other traditional recommendation systems SentimentSync combines locally hosted sentimental analysis using NLTK's Vader with sophisticated web-scraping techniques through selenium the system generates aggregate sentiment scores for a user-queried film and a group of upcoming releases then rank-filter and returns recommendations based on similarity. An interactive flask web interface shows recommendations with an auto-generated explanation utilizing large language models (llms) through the langchain platform. Experimental outcome shows that our hybrid solution increases recommendation relevance as well as the ease of using an interactive web interface over having to use a paid APIs.

Keywords: Sentiment Analysis, Movie Recommendations, YouTube API, Selenium, Flask, Kannada Movies, Web Scraping, LangChain,NLTK, LLM

I. INTRODUCTION

Personalized movie recommendation engines have become a necessity with the sheer volume of content available on streaming sites. Traditional techniques like collaborative filtering and content-based filtering are now being augmented with sentiment analysis methods that capture emotional reactions of users SentimentSync seeks to offer kannada movie suggestions with high similarity in sentiment profile of a user-queried movie by utilizing social media information pulled from YouTube trailers and dynamically scraping future movie meta data from web sites such as the Times of India.

II. LITERATURE SURVEY

Recent studies have extensively explored the integration of sentiment analysis and dynamic data collection to enhance movie recommendation systems. Ghatora et al. [1] demonstrated that combining traditional machine learning with pre-trained LLMs significantly improves sentiment classification accuracy, supporting the use of advanced NLP techniques for interpreting nuanced opinions in movie trailer comments.

Garapati and Chakraborty [2] introduced the RTG Model, which segments review texts into finer units to extracts sentiment more precisely, a method that informs our detailed analysis of YouTube comments.

In the context of movie recommendations, both Leung et al. [3] and Lee et al. [4] highlighted the benefits of incorporating affective features from media content metadata to provide personalized recommendations.

Chaurasia and Sherekar [5] focused on sentiment analysis in short social media texts, providing valuable insights into preprocessing techniques used to handle YouTube comments, while Patel et al. [6] compared classical and modern text representation models, reinforcing our choice of NLTK's VADER.

Building on these foundations, Gupta and Jain [7] examined regional film recommendations using social media sentiment, focusing specifically on Kannada cinema.

To address the challenge of dynamically extracting movie data, Kumar and Singh [8] presented dynamic web data extraction techniques tailored for movie recommendation systems, validating our use of Selenium for scraping the Times of India.

Rao [9] investigated hybrid recommendation frameworks that integrate collaborative filtering with sentiment analysis, and Mehta and Sinha [10] explored deep learning approaches to personalized film recommendations in regional cinema. Together, these studies justify our hybrid approach in SentimentSync, which leverages YouTube sentiment analysis and dynamic web scraping to deliver context-aware Kannada movie recommendations with LLM-generated explanations.

Summarizing, recent research confirms that integrating sophisticated sentiment analysis methods including pre-trained LLMs and granular text segmentation with dynamic web data extraction significantly enhances movie recommendation systems. Several studies have illustrated that leveraging affective metadata from media sources can improve personalized recommendations, while hybrid and deep learning models refine the accuracy of sentiment-based predictions. These insights validate our approach in SentimentSync, where we combine YouTube trailer sentiment analysis and Selenium-based web scraping to extract real-time Kannada movie data, further enriched by LLM-generated explanations. This comprehensive integration of techniques not only optimizes recommendation relevance but also offers users clear, engaging rationales for the suggested movie

III. SYSTEM DESIGN

SentimentSync is also built as an extensible and scalable system with personalized Kannada movie recommendations facilitated through the collection of multiple sources of data as well as several layers of processing. The system is segmented into the following key elements:

A. Data Collection Layer

- YouTube Data Collection: This one utilizes the YouTube API to get trailer details on movies. This one collects:
  - Video IDs: For the query movie as well as the suggestion movies (in queries such as "movie name trailer").
  - Comments: Up to a certain limit (e.g., 100 for the query movie and 50 for every suggested movie) are pulled out of trailer videos.
  - Video Description Metadata: Trailer description is pulled out to extract more movie metadata (e.g., release dates, cast, or genre cues).
- Web Scraping for Future Movies: With Selenium, the system dynamically extracts movie listings from trusted sources like the Times of India. This module retrieves a list of upcoming Kannada films (targeting a fixed number, say 5) along with minimal metadata (e.g., title and synopsis).

B. Sentiment Analysis Layer

- Sentiment Extraction from YouTube Comments: The system uses NLTK's VADER (Valence Aware Dictionary and sentiment Reasoner) algorithm to process the retrieved YouTube comments. It computes the overall sentiment score for the query movie and all the suggested movies.
- Sentiment Comparison: The calculated overall sentiment score of the searched movie is compared with

the sentiment scores of the future movies. A filtering function then ranks the suggested movies according to how much their sentiment profiles match that of the searched movie.

C. Recommendation Engine

- Hybrid Filtering Approach: While standard collaborative filtering or content-based filtering methods are components of most recommendation systems, SentimentSync is based on a hybrid strategy. The system utilizes the similarity of sentiment (determined in the Sentiment Analysis Layer) to narrow down the top three movie recommendations.
- LLM-Based Explanation Generation: An LLM, accessed through the LangChain framework, generates a human-readable justification of how the suggested movies align with the user's tastes. It generates this based on the movies' sentiment scores, genres, and styles.

D. User Interface and Deployment

- Flask Web Application: The final outputs are rendered as a user-friendly HTML page through Flask. The page consists of:
  - Information of the queried movie (name, trailer video ID, total sentiment score, sentiment label).
  - A list of suggested future movies, including their titles, summaries, calculated sentiment scores, similarities in sentiment, and other metadata from trailer descriptions.
  - An interesting explanation produced by the LLM.
- Scalability and Deployment: The system is scalable by using caching (e.g., Redis) and load balancing when needed. Deployment is managed using Docker to ensure the system operates consistently under various conditions.

E. Architecture Diagram:

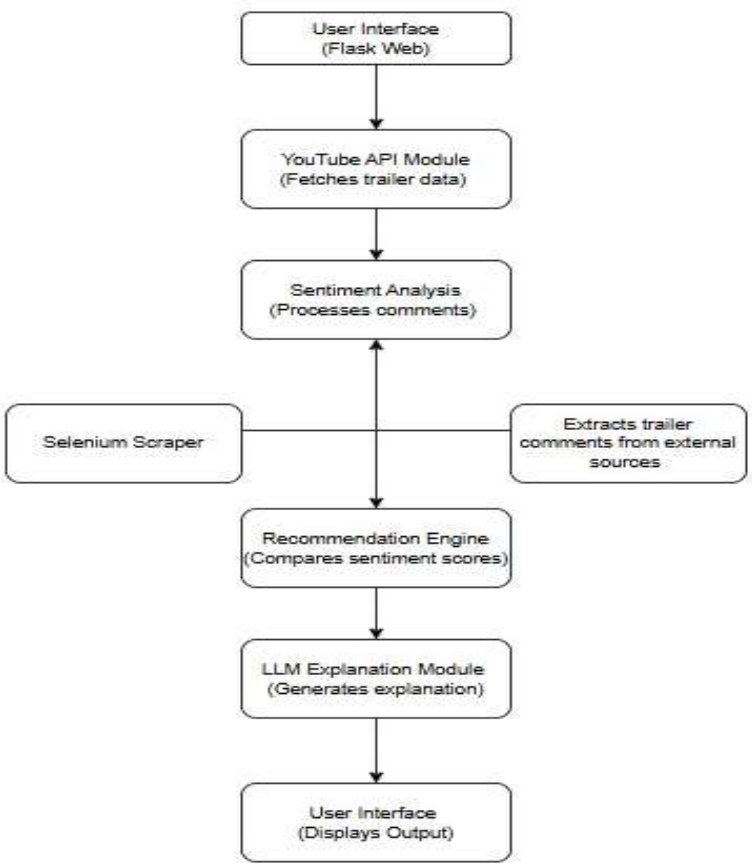


Figure 1: System Architecture Diagram

The Figure 1 illustrates the flow of data from YouTube and web scraping sources through sentiment processing and recommendation filtering, ending in a user-friendly web interface.

IV. METHODOLOGY

Our methodology for building SentimentSync follows a systematic, multi-step process that transforms raw data into personalized movie recommendations. This section details the sequential procedures and techniques employed during development:

A. Data Collection:

- YouTube API Extraction: We begin by fetching trailer data using the YouTube API. For the user-searched movie, the system retrieves the trailer video ID, then extracts up to 100 comments and the video description. This information provides the basis for calculating the movie's overall sentiment.

- Web Scraping with Selenium: We implemented a Selenium-based scraper to extract movie listings from the Times of India website. The scraper collects a list of five upcoming Kannada movies along with basic metadata (e.g., title and overview).

B. Sentiment Analysis:

- Sentiment Extraction using VADER: We utilize NLTK's VADER algorithm to analyse textual data from YouTube comments. For each movie trailer (both for the searched movie and each upcoming movie), we compute an overall sentiment score by averaging the compound sentiment scores of the comments.

- Per-Movie Sentiment Computation: For each upcoming movie, the system fetches its trailer (using the movie title plus "trailer"), retrieves up to 50 comments, and computes an overall sentiment score. This computed score, stored as the movie's estimated sentiment, serves as the basis for similarity comparison.

C. Recommendation Generation and Explanation:

- Similarity Matching: The recommendation engine compares the overall sentiment score of the searched movie with the computed sentiment scores of the upcoming movies. The top three movies with the smallest sentiment difference are selected.

- LLM-Based Explanation: Using the LangChain framework, an LLM generates a natural language explanation. The explanation details why the recommended movies are a good match based on their sentiment similarity, genres, and overall style.

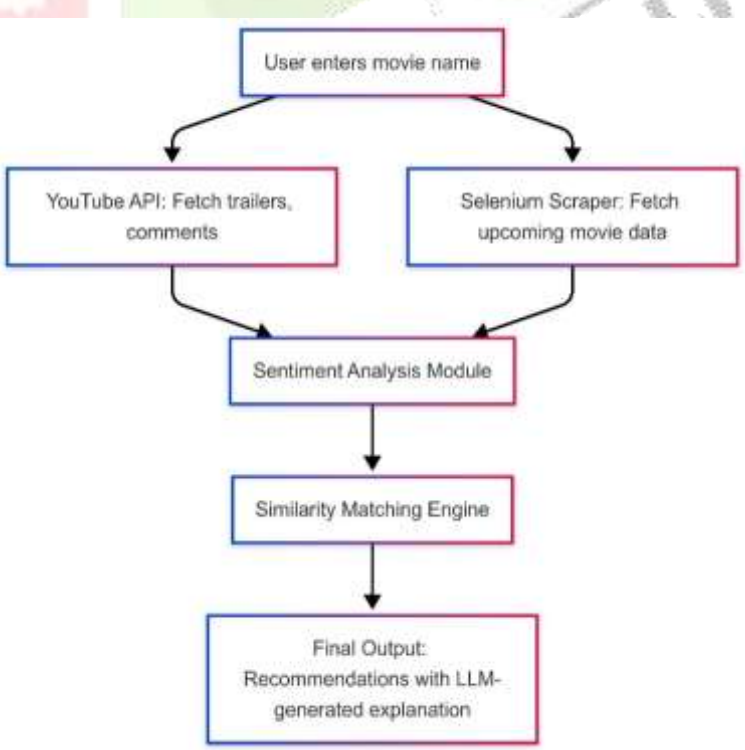


Figure 2: Flowchart of the methodology

Figure 2 is the methodology flowchart where:

- Input: User enters a movie name.
- Branch 1: YouTube API fetches trailer, comments, and computes sentiment.
- Branch 2: Selenium scraper fetches upcoming movie data.
- Both branches flow into the sentiment analysis module and similarity matching engine.
- Final output: Recommendations with LLM-generated explanation.

V. IMPLEMENTATION

A. Software Stack and Tools:

SentimentSync is written in Python, with Flask being the web framework. Major libraries and tools are:

- YouTube API & Google API Client: To fetch trailer IDs, comments, and descriptions.
- NLTK (VADER): To do sentiment analysis on text.
- Selenium: To dynamically scrape future movie data from the Times of India.
- LangChain: To produce human-readable explanations using LLMs.
- Flask: To build the user interface and manage web requests.

B. Module Overview:

- YouTube Scraper Module (youtube_scraper.py): Includes functions such as fetch_youtube_video_id, fetch_youtube_comments, and fetch_video_description to interact with YouTube.
- Web Scraping Module (timesofindia_selenium.py): Utilizes Selenium to scrape movie information from the Times of India site.
- Sentiment Analysis and Recommendation Module: Utilizes VADER for sentiment score and has a filtering function to rank movies based on sentiment similarity.
- LLM Explanation Module: Alters LangChain to create explanations from movie metadata and sentiment similarities.
- Main Application (app.py): Coordinates the overall process: It takes user input, calls the YouTube scraper and Selenium scraper, conducts sentiment analysis, calculates similarities, and displays the results through an HTML/CSS interface.

C. Deployment:

The application is deployed as a Flask web service. Future work includes containerization via Docker and caching with Redis for improved scalability.

VI. RESULT

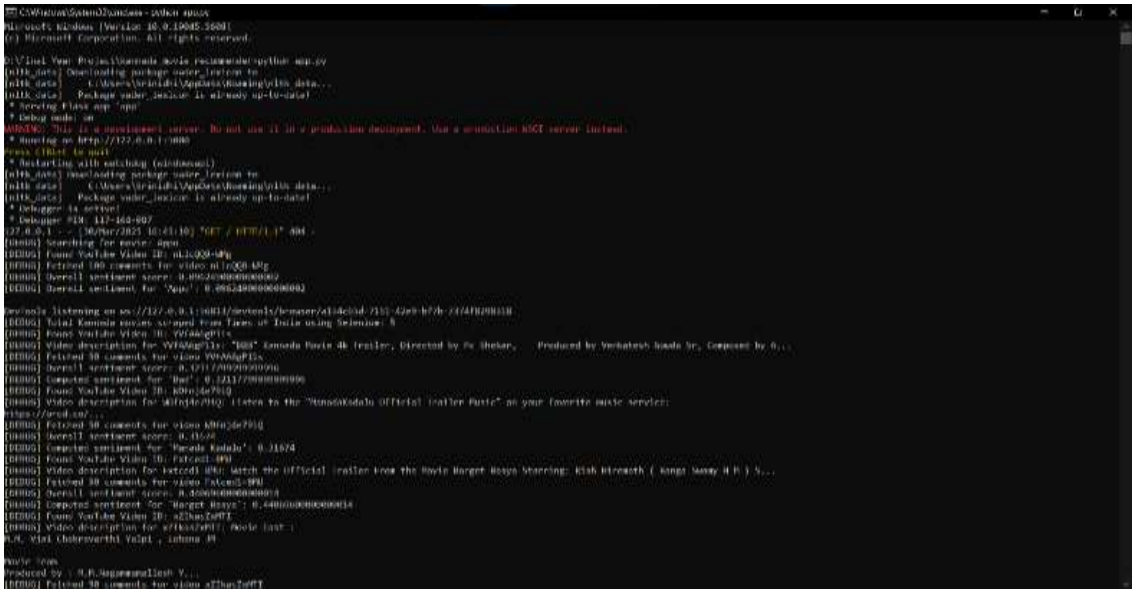
Figure 3: Web Interface Screenshot

Figure 3 shows the following output:

- The searched movie's name, overall sentiment score, sentiment label, and trailer video ID.
- A list of recommended upcoming movies with details such as title, overview, computed estimated sentiment, sentiment similarity, and trailer description metadata.
- The LLM-generated explanation.

Figure 4: Input method to the application

Figure 4 represents how the input is given to the application for processing. Here we are giving the input to the application in the URL of the web page itself by using the URL 'search?movie={movie_name}'. Here we have searched the movie Appu as an Example so the input query will be 'search?movie=Appu'.



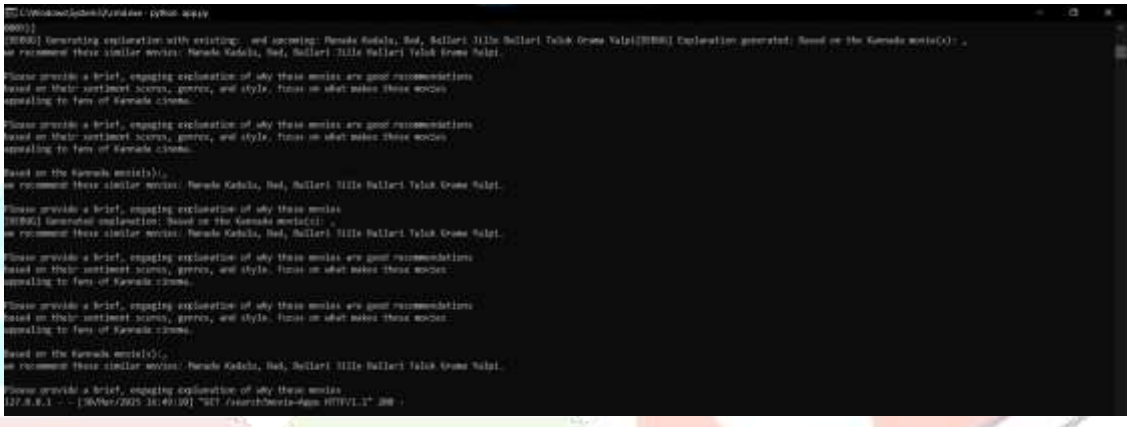


Figure 6: Terminal Output-2

Figure 5 and Figure 6 represent the output displayed in the terminal screens after the performed calculations on the input

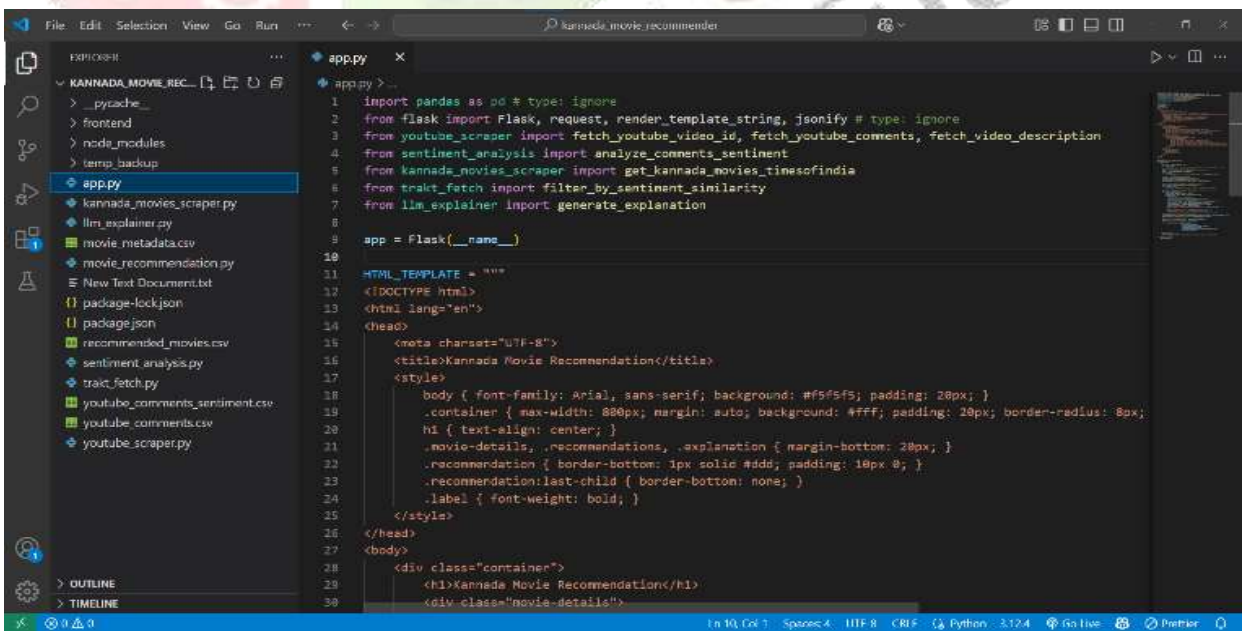


Figure 7: Code Snippet of app.py file

Figure 7 is a code snippet of the main file in the project named as app.py, which contains the main calculations logic.

VII. CONCLUSION

SentimentSync successfully demonstrates the feasibility of combining social media sentiment analysis with dynamic web scraping for personalized movie recommendations. By leveraging YouTube trailer data and scraping the Times of India for upcoming Kannada movies, the system provides updated, context-aware suggestions. The integration of VADER for sentiment extraction and LangChain for explanation generation further enhances recommendation relevance and user engagement. While the system currently relies on pre-collected and scraped data, its modular design allows for future improvements and scalability.

Key contributions of SentimentSync include:

- A novel hybrid approach that marries sentiment analysis from YouTube with real-time web data.
- A robust methodology for computing and comparing sentiment scores across multiple sources.
- An intuitive and user-friendly interface that presents recommendations along with clear, LLM-generated explanations.
- User Personalization: Create user profiles to customize recommendations based on personal viewing history and preferences.
- Multimodal Analysis: Add analysis of images and video content in trailers to provide a richer understanding of movie attributes.
- Make the web interface richer: By using interactive charts and graphs to vividly portray trends in sentiment analysis and reason about recommendations.
- Increasing Dataset Incorporation: Scale the system to embrace more local language coverage and cinema databases to improve the universe of recommendations.

VIII. FUTURE SCOPE

Future research and development on SentimentSync will address the following improvements:

- Real-Time Data Integration: Integrate live streaming data from sites like Twitter to further enhance sentiment analysis and recommendation freshness.
- Improved Metadata Extraction: Use advanced NLP algorithms to extract more dense metadata from trailer descriptions and web pages.
- Scalability and Performance Enhancements: Integrate caching mechanisms and load balancing techniques to support larger user volume and low latency.
- User Personalization: Create user profiles to customize recommendations based on personal viewing history and preferences.
- Multimodal Analysis: Add analysis of images and video content in trailers to provide a richer understanding of movie attributes.
- Make the web interface richer: By using interactive charts and graphs to vividly portray trends in sentiment analysis and reason about recommendations.
- Increasing Dataset Incorporation: Scale the system to embrace more local language coverage and cinema databases to improve the universe of recommendations.

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