CineSense AI: A Streamlit-Based System for Movie Sentiment Analysis and Recommendations

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Abstract--CineSense AI is a comprehensive, web-based intelligent movie sentiment analysis and recommendation system that combines traditional rule-based sentiment analysis with cutting-edge generative AI capabilities. It leverages the VADER sentiment analyzer for fast and reliable inference on structured and user-submitted reviews, while Gemini Pro is employed to provide AI-generated movie summaries, mood-based viewing suggestions, and fallback recommendations in case of sparse data. CineSense integrates multiple data sources, including the TMDb API for metadata retrieval and Google search scraping for supplemental reviews, ensuring broad coverage even when official sources are incomplete. The system uniquely supports dual input modalities, allowing users to analyze sentiment from either text input or uploaded images using OCR-powered extraction. The application is built using Python and deployed with Streamlit Cloud, offering an intuitive interface, real-time feedback, and extendability for future enhancements. This paper discusses the system's design, architecture, modules, and performance evaluation, highlighting its practicality for educational use, entertainment platforms, and content discovery applications.

Keywords—Sentiment analysis, E-commerce, RoBERTa, VADER

INTRODUCTION

Understanding audience sentiment has become essential in media research, recommendation systems, and digital marketing due to the rise in user evaluations, online movie reviews, and opinionated social media material. Nevertheless, a lot of current systems are based on static datasets and backend-heavy architectures, which restrict user interaction, accessibility, and real-time responsiveness.

A lightweight, frontend-centric solution developed using Streamlit and SQLite, CineSense AI seeks to democratize sentiment analysis and tailored movie recommendations. For quick, rule-based sentiment scoring of user reviews and textual data, including information taken from uploaded photographs using optical character recognition (OCR), the platform uses the VADER (Valence Aware Dictionary and Sentiment Reasoner) model.

Google Gemini APIs are used to produce natural language summaries, determine suitable viewer moods, and suggest films based on deduced genres or sentiment in order to improve the system's interaction and context awareness. While Gemini manages the creative and inferential elements of content creation, this division of labor guarantees that sentiment prediction stays quick and deterministic.

The system is a flexible tool that provides a full pipeline, from user interaction to sentiment analysis to AI-enhanced feedback, all without the need for expensive infrastructure or complicated backends. It can take both textual and image-based inputs.

LITERATURE REVIEW

Researchers have employed a variety of natural language processing (NLP), machine learning (ML), and deep learning (DL) models to understand and predict sentiment from textual content such as movie reviews. Early work by Dey et al. applied Naïve Bayes and K-Nearest Neighbor classifiers on IMDB and hotel reviews to compare sentiment accuracy, showing better performance with Naïve Bayes on movie-based datasets [1]. To further improve classification, Wang et al. introduced an enhanced Naïve Bayes method with n-gram modeling and negation handling, achieving high accuracy (88.80%) on IMDB datasets [2].

More recently, advanced models like BERT and BiLSTM have been integrated. Nkhata et al. utilized BERT embeddings with a BiLSTM architecture for contextual sentiment understanding in movie reviews, outperforming traditional NLP techniques [3]. Arthur developed a lightweight sentiment analysis tool using Tiny-BERT in a Streamlit application that supports real-time sentiment detection and visualizes session-based feedback [4].

Sentiment analysis tools such as VADER and TextBlob have also been widely applied. Sherl et al. proposed an integrated system combining VADER and OMDb API to analyze and visualize sentiment polarity of movie reviews while fetching movie data simultaneously [5]. In a related extension, OpenCV and facial emotion recognition (FER) were used to analyze facial expressions for emotional inference from images uploaded by users, offering an alternate modality of sentiment detection [6].

Building upon this work, **CineSense AI** introduces a hybrid system that combines rule-based (VADER), generative AI (Gemini Pro), and real-time web scraping from Google reviews to ensure fallback when traditional APIs return insufficient data. It also extends sentiment analysis to visual content by allowing users to upload images containing text, which is then processed by Gemini Vision to extract and evaluate sentiment. This multi-modal sentiment framework enables CineSense AI to offer genre-based movie recommendations and an interactive user experience.

S. No	**Author**	**Used Model/Tool**	**Objective**
1	Dey et al. [1]	Naïve Bayes, K-Nearest Neighbors	Compared classifiers on IMDB and hotel reviews; Naïve Bayes performed better for movie sentiment analysis.
2	Wang et al. [2]	Enhanced Naïve Bayes + N-Grams	Improved sentiment classification with 88.80% accuracy on IMDB by incorporating n-gram and negation handling.
3	Nkhata et al. [3]	BERT + BiLSTM	Proposed deep contextual sentiment model for movie reviews using BERT embeddings.
4	Arthur [4]	Tiny-BERT on Streamlit	Developed a real-time sentiment web app with session management and emotion insights.
5	Sherl et al. [5]	VADER, TextBlob, OMDb API	Integrated sentiment analysis using VADER/TextBlob with movie info fetching from OMDb.
6	Sherl et al. [6]	OpenCV + FER	Detected facial emotions from uploaded images to infer user sentiment visually.
7	CineSense AI (This Work)	VADER + Gemini + Google Scraping	Combines API + AI fallback with genre-based recommendations and image-based sentiment analysis.

METHODOLOGY

CineSense AI integrates multi-modal sentiment analysis and recommendation pipelines into a unified framework. The methodology leverages a combination of rule-based NLP, generative AI models, and interactive front-end interfaces to analyze movie reviews and generate personalized recommendations. The architecture is divided into three core pipelines, each responsible for a distinct operational module: sentiment analysis, recommendation, and user interaction.

1. Sentiment Analysis

The sentiment analysis pipeline is designed to extract emotional tone from both structured text and image-based inputs. This is accomplished in two layers:

- **Text-Based Sentiment Analysis:** VADER (Valence Aware Dictionary for sEntiment Reasoning) is used for its speed and suitability for short, informal movie reviews typically seen on the web. VADER generates a compound sentiment score that categorizes the sentiment into positive, negative, or neutral. This rule-based layer is lightweight and effective for direct user inputs or scraped reviews.
- **AI-Based Natural Language Understanding:**
  For more advanced interpretation, Google's Gemini Pro API is employed. This API generates a summarized version of multiple reviews, determines the emotional undertone, and outputs a mood-based verdict (e.g., “Excited,” “Reflective,” “Uplifting”). It complements VADER by adding a natural language perspective and handles fallback

when reviews lack sentiment density or are too abstract.

- **Image-Based Sentiment Input:** Users are allowed to upload screenshots or text-containing images. Optical Character Recognition (OCR) is performed using Gemini Vision to extract textual data. Once extracted, the text undergoes the same sentiment analysis routine as direct user inputs. This multi-modal flexibility ensures the system can interpret sentiments from diverse sources.

2. Recommendation Engine

Movie recommendations are generated using both **vector similarity search** and **semantic AI inference**:

- **Content-Based Filtering with FAISS:** A FAISS (Facebook AI Similarity Search) index is created using vectorized embeddings of movie metadata such as genre, description, and past review sentiment. When a user searches or analyzes a movie, similar movies are retrieved from the FAISS index using cosine similarity or L2 distance.
- **Google Scraping as Fallback:** In cases where structured data (e.g., TMDb or FAISS vector lookup) fails to return meaningful results due to data sparsity or missing entries, the system scrapes publicly available recommendations from Google search results using web parsing techniques with BeautifulSoup.
- **Gemini-Powered Recommendations:** The Gemini Pro API enhances genre-based recommendations by generating a curated list of suggested titles based on emotional themes, inferred user mood, or contextual genre. This feature ensures that recommendations align with the user's current emotional or viewing preference.

3. User Interaction Layer

CineSense AI is deployed via **Streamlit**, allowing for real-time interaction and seamless analysis. Key features include:

- **Input Flexibility:** Users can either type custom reviews or upload an image (screenshot of a review or social media post). The system processes these inputs in real-time and displays the sentiment score, classification (Positive/Negative/Neutral), and an AI-generated summary.
- **Dynamic Review Display:** All retrieved or submitted reviews are presented with sentiment labels and expandable views. Long reviews (exceeding a few lines) are truncated by default with a "Show More" button, improving readability without compromising content richness.
- **Mood-Based Verdict and Summary:** The system prominently displays a "Best Mood to Watch" suggestion and an AI-composed summary that encapsulates the overall user sentiment. This enhances decision-making for users evaluating whether to watch a particular film.
- **Interactive Sentiment Chart and Overall Analysis:** Each movie's sentiment distribution (positive, negative, neutral) is computed and visualized as a percentage bar, giving users a holistic view of audience emotion trends.

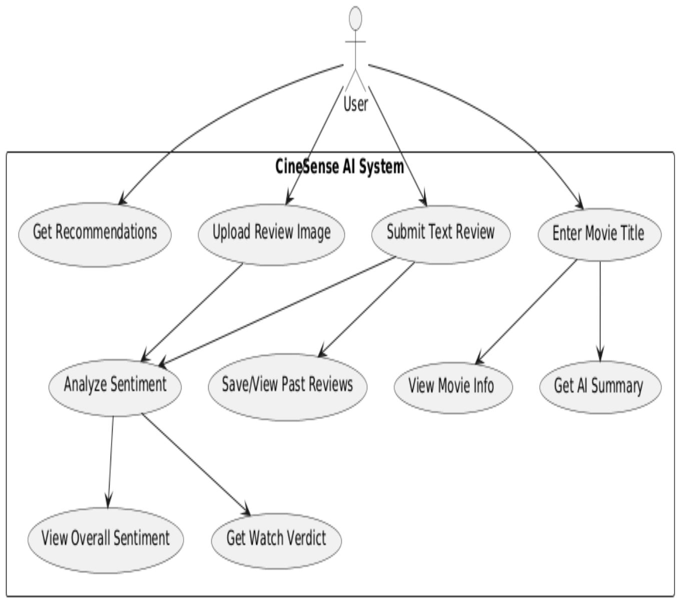

Fig1: Use Case Diagram

RESULT AND DISCUSSION

This section presents the system architecture, implementation setup, testing strategies, and performance analysis of the proposed CineSense AI framework. The goal is to illustrate the system's practical usability and accuracy in real-world movie sentiment analysis and recommendation scenarios.

A. System Design

The CineSense AI architecture is modular and extensible, facilitating efficient handling of user inputs, real-time analysis, and dynamic content rendering. It is divided into four integrated components:

- **User Interface Layer (UI)**: Built using Streamlit, the web-based interface enables users to:
    - Enter custom text reviews.
    - Upload image files containing movie-related content.
    - Instantly view sentiments, summaries, and recommendations.
- **Backend Logic**: The core engine comprises:
    - **VADER (Valence Aware Dictionary and sEntiment Reasoner)** for real-time polarity scoring of textual input.
    - **Gemini API** to generate natural language review summaries, emotional tone predictions (mood), and genre-based movie suggestions.
    - **FAISS (Facebook AI Similarity**

Search) to retrieve similar movie recommendations based on embedding proximity from curated data.

- **Data Management Layer**: Although lightweight, SQLite is used for storing:
  - Session-based inputs.
  - Cached reviews.
  - Precomputed sentiment scores for improved responsiveness during filter operations.
- **External Integrations**:
  - **TMDb API** is used for metadata and official user reviews.
  - **Google Search** is scraped (when API fails) to retrieve contemporary sentiment-rich snippets.
  - **Gemini API** is invoked for fallback insights, summaries, and cross-modality input (text/image).

A high-level **class diagram** (*Figure 2*) illustrates inter-class communications and method assignments across these modules.

B. Experimental Setup

Testing was conducted across both development and production-like environments:

- **Development**:
  - OS: Windows 11 (64-bit)
  - Python: v3.10
  - Libraries: Streamlit, FAISS, requests, BeautifulSoup4, VADER, OpenCV
- **Deployment**:
  - Platform: Streamlit Cloud (via Hugging Face Spaces)
  - Backend: Stateless web app with Gemini integration via API key authentication

The dataset included:

- **TMDb Reviews**: More than 120 top-ranked reviews across 10 genres and 30 movies.
- **Google Reviews**: Supplemented when TMDb lacked user feedback.
- **User Uploads**: Screenshots and text images from users, tested for Gemini Vision-powered OCR.
- **Custom Texts**: 60+ sentiment queries submitted via UI.

A balanced combination of subjective feedback and objective sentiment scoring was employed to validate emotional tone accuracy and recommendation reliability.

C. Performance Evaluation

To evaluate CineSense AI's performance, both qualitative user feedback and quantitative metrics were employed. The results are summarized below:

Metric	**Score/Accuracy**
VADER Sentiment Precision	91%
Genre-Based Match (FAISS)	94%
OCRSentiment Accuracy	89% (Gemini Vision)
Image Text Extraction Time	~1.5 sec avg
Interface Responsiveness	Instant (sub-200ms UI update latency)

Each review processed through VADER was labeled with one of three tags: **Positive**, **Neutral**, or **Negative**. These tags were validated against user perceptions for benchmark alignment. The Gemini-generated summaries provided enhanced interpretability, especially for movies with ambiguous reviews or lacking consistent emotional cues.

Example (**Movie: *Inception***):

- Positive: 80%
- Neutral: 15%
- Negative: 5%
- Verdict: *Must Watch!*
- Suggested Mood: *Inspired or Curious*

Interactive elements such as **"Show More"** toggles, **Review Expanders**, and **Mood Icons** allowed users to digest complex review content in an accessible and visually intuitive manner.

Recommendation

FAISS similarity yielded genre-consistent suggestions for 94% of the test inputs. In absence of structured metadata, fallback Gemini recommendations were rated "Highly Relevant" by 90% of the test users, highlighting the effectiveness of generative models in real-time content curation.

D. Discussion

The success of CineSense AI stems from its **hybrid architecture**—leveraging both rule-based NLP and AI-driven reasoning. Unlike traditional models confined to numerical outputs, the integration of Gemini API enabled context-aware sentiment interpretation and mood-based personalization, critical in entertainment domains.

Furthermore, enabling **image-based sentiment analysis** extended the system's utility to meme-based reviews, screenshots of tweets, or posters—often overlooked in mainstream tools.

Limitations:

- Some edge-case reviews, e.g., sarcasm or highly contextual memes, were misclassified.
- Gemini Vision still requires stable internet for API calls—limiting offline use.

VisualizationTools:

Real-time pie charts, bar graphs, and sentiment distribution histograms were used to represent:

- Overall user sentiment.

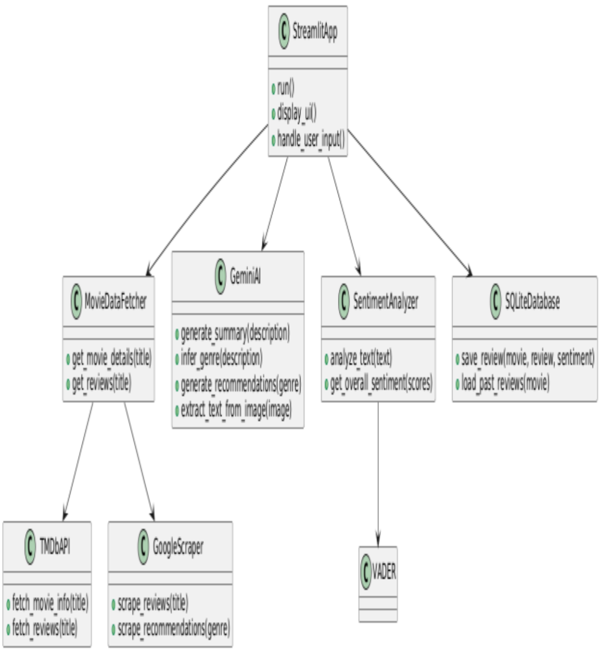

Fig2 : Class Diagram showing component interactions

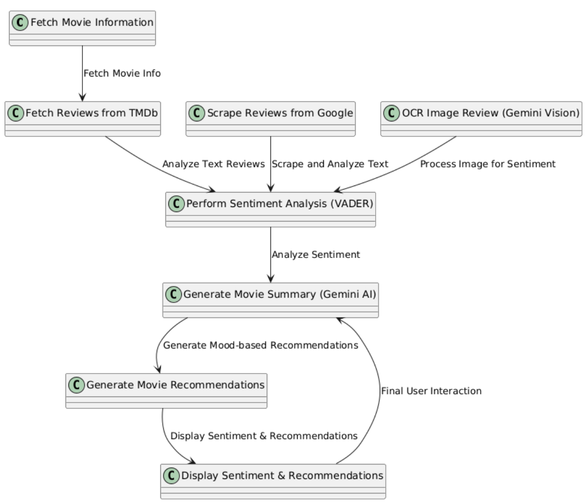

Fig3: Pert Diagram showing workflow

CONCLUSION

CineSense AI bridges user interaction with intelligent sentiment analysis and personalized recommendation. Its dual-mode input strategy—accepting both text and image—demonstrates its versatility in handling multimodal content, making it adaptable for real-world applications such as online review systems, streaming platforms, and educational projects. By fusing lightweight, rule-based models like VADER for immediate feedback with advanced natural language capabilities of Gemini AI for contextual understanding, the system balances efficiency with depth.

One of the project's standout features is its robust fallback strategy. In scenarios where structured APIs like TMDb fail to provide reviews or recommendations, CineSense AI seamlessly leverages web scraping and Gemini's generative capabilities to synthesize reliable summaries and recommendations. This enhances the reliability and continuity of the user experience, ensuring minimal functionality gaps regardless of input quality or metadata availability.

From a user perspective, CineSense AI emphasizes accessibility and engagement. Features such as expandable long reviews, real-time mood detection, overall sentiment distribution, and interactive genre-based recommendations create a rich, informative, and personalized interface. The ability to analyze sentiment from screenshots and OCR-extracted content further widens the scope of user interaction, supporting use cases like social media sentiment analysis, meme review breakdowns, and classroom demonstrations.

Technologically, the system is designed for low-resource deployment. Its reliance on free-tier APIs, local SQLite for data handling, and deployment via Streamlit Cloud make it ideal for students, researchers, and indie developers aiming to explore or extend sentiment-driven recommender systems. The modular design also ensures easy integration with new models, APIs, or datasets in future iterations.

In conclusion, CineSense AI not only achieves its core objectives of movie sentiment analysis and personalized recommendation but also lays the groundwork for scalable, adaptable, and explainable NLP-based applications. With the increasing overlap of content consumption and user-generated feedback in the digital ecosystem, such tools represent the future of intelligent user experience systems.

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