
*Research Article***Intelligent Recommender System Model through Sentimental Analysis**Sara Sravani¹, B Shirisha², Kotha Anil³, Daggula Sai Ganesh⁴, V Shiva Narayana Reddy^{5,*}¹⁻⁴Student, Department of CSE, Samskurthi College of Engineering and Technology, Hyderabad, Telangana, 500001, India.⁵Principial, Department of CSE, Samskurthi College of Engineering and Technology, Hyderabad, Telangana, 500001, India.

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Abstract: The exponential growth of online content has intensified the need for intelligent recommender systems that can deliver personalized suggestions to users. This paper presents a novel approach that integrates sentiment analysis with a deep learning-based recommendation framework to enhance the relevance and emotional alignment of recommendations. By analyzing user-generated content such as reviews and comments, the system extracts sentiment scores to understand user preferences and emotional tones. Convolutional Neural Networks (CNN) is employed to train on the sentiment-labeled dataset, enabling precise classification of opinions. The model dynamically adapts to user sentiment, filtering and prioritizing items based on positive or negative feedback. A comprehensive user interface supports dataset upload, training, prediction, and visualization of recommendations. Experimental results demonstrate the effectiveness of the proposed system in improving user satisfaction and engagement by delivering recommendations that resonate with individual emotional contexts. This approach bridges the gap between traditional recommendation logic and human-like understanding, offering a more intuitive and user-centric experience.

Keywords: Sentiment Analysis, Recommender System, Deep Learning, Convolutional Neural Network (CNN), User Emotion Detection.

1. Introduction

In the digital age, the abundance of information available to users has led to the emergence of intelligent recommender systems (IRSs) as essential tools for filtering content and providing personalized experiences. These systems are prevalent across a wide array of domains such as e-commerce, social media, entertainment, education, and healthcare, where personalized suggestions significantly enhance user engagement and satisfaction [1]. Traditionally, recommender systems rely on structured data such as user preferences, item ratings, and historical interactions. However, with the proliferation of user-generated content, especially on social media and review platforms, there is an increasing need to leverage unstructured textual data to enrich the recommendation process [2]. Sentiment analysis, a subfield of natural language processing (NLP), provides an effective means of extracting subjective information from user-generated content, thereby offering deeper insights into user opinions and emotions [3]. By integrating sentiment analysis into recommender systems, it is possible to bridge the semantic gap between user feedback and item attributes, thus enhancing the relevance and personalization of recommendations [4]. Unlike conventional systems that merely rely on numerical ratings, sentiment-based recommender systems can interpret the context and intensity of user sentiments expressed in reviews, blogs, and social media posts [5]. The rapid growth of data on platforms like Amazon, Yelp, and Twitter has amplified the significance of opinion mining as a critical component in developing intelligent recommendation engines [6]. Sentiments expressed in user



reviews provide granular insights that can refine recommendation strategies by identifying hidden preferences and dislikes that are often not explicitly reflected in rating scores [7]. For instance, a user might give a 4-star rating to a product while expressing dissatisfaction about specific features in the review text. Traditional models might misinterpret this as positive feedback, whereas a sentiment-aware system can decode the nuanced sentiment and respond accordingly [8]. Moreover, the application of deep learning in sentiment analysis has opened new frontiers in the development of IRSs. Models such as Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), and Convolutional Neural Networks (CNN) have demonstrated superior performance in understanding linguistic patterns and sentiment polarity. These models can capture complex dependencies in textual data, which are crucial for understanding subtle emotional cues and context-sensitive meanings. Integrating such models into recommendation systems enhances their ability to learn user preferences from textual reviews dynamically and adaptively. Another significant challenge in recommendation systems is the cold-start problem, which arises when there is insufficient data about new users or items. Sentiment analysis can partially alleviate this issue by extracting valuable information from text reviews or social media posts, even in the absence of user history or item ratings. This capability is especially valuable in fast-changing environments such as online retail or content streaming services where new products and users frequently enter the system.

The inclusion of sentiment analysis also brings diversity and novelty into recommendations. Traditional collaborative filtering and content-based methods often suffer from redundancy, recommending the same type of items repeatedly based on user history. By understanding the sentiments associated with different aspects of an item (e.g., price, usability, aesthetics), a sentiment-aware system can suggest a broader range of items that align with the user's emotional preferences, thereby improving user satisfaction. Furthermore, the fusion of sentiment analysis with contextual information such as time, location, and user behavior creates a more holistic and context-aware recommendation model. For example, a user might prefer different types of products or content depending on the time of day, mood, or occasion. By analyzing textual data in real time and mapping it to contextual cues, the system becomes more responsive and aligned with the user's current needs. Recent studies also emphasize the ethical implications and bias mitigation in sentiment-based recommender systems. Since these systems learn from user-generated content, they can inherit biases present in the data. Techniques such as fairness-aware learning, explainable AI (XAI), and adversarial training are being explored to ensure transparency, accountability, and inclusiveness in recommendation outcomes. This line of research is crucial in building trustworthy systems that cater to diverse user groups without reinforcing stereotypes or echo chambers.

The primary contribution of this paper lies in the development of an intelligent recommender system that integrates sentiment analysis to enhance the personalization and accuracy of recommendations. Unlike traditional recommender systems that rely solely on explicit ratings or user-item interaction histories, this model incorporates users' emotional feedback extracted from textual comments and reviews. By leveraging a deep learning-based sentiment classifier, specifically using a Convolutional Neural Network (CNN), the system captures the nuanced opinions and emotional tone behind user-generated content. This emotional context enables the recommender engine to filter, prioritize, and adapt suggestions that align with the user's sentiments. Additionally, the proposed model includes a user-friendly interface for dataset upload, user registration, sentiment score prediction, and dynamic content-based recommendations, providing an end-to-end framework. The simulation results demonstrate

improved prediction accuracy and user engagement, showcasing the practical viability of the system.

2. Related Works

Recommender systems have evolved significantly over the past decade, transitioning from traditional approaches based on collaborative filtering and content-based methods to more sophisticated models incorporating machine learning and deep learning techniques. With the exponential rise of user-generated content across social platforms and review sites, sentiment analysis has emerged as a powerful tool for capturing user preferences and emotional inclinations. Numerous studies have explored the integration of sentiment analysis into recommender systems to enhance their contextual understanding and prediction accuracy. These works have applied natural language processing (NLP) and opinion mining techniques to extract sentiment features from text data, which are then utilized to refine recommendation logic. Recent advancements in deep learning, including the use of architectures like LSTM, BERT, and GRU, have further improved the semantic understanding of user sentiments and their impact on personalized recommendations. This section reviews the key contributions, methodologies, and findings from existing literature that form the foundation for building intelligent recommender systems enhanced with sentiment-aware capabilities.

Recent advancements in intelligent recommender systems have seen a growing integration of sentiment analysis across diverse application domains. Bokharaei Nia et al. [9] developed a wearable IoT-based intelligent recommender framework that leverages health data streams for personalized healthcare suggestions, highlighting the fusion of smart devices and user-centric analytics. In a similar context of domain-specific recommendation, Sharma et al. [10] proposed a sentiment analysis-based model for recommending agricultural products, demonstrating the model's ability to interpret emotional undertones from farmer reviews and improve product matching. Zheng et al. [11] applied natural language processing (NLP) for emotion analysis in patient feedback to design a medication recommendation system, emphasizing the importance of patient sentiment in healthcare personalization. The educational domain also benefits from sentiment-aware approaches, as seen in the work of Vedavathi and KM [12], who employed hybrid Elman similarity to suggest e-learning courses based on student sentiment.

Expanding the computational perspective, Choudhary et al. [13] presented SARWAS, a deep ensemble learning model for sentiment-based recommendations, showing enhanced accuracy and generalization in handling subjective user data. Music preference, a highly emotion-driven area, was explored by Faye et al. [14], who built an emotion-based music recommender system that aligns musical suggestions with the listener's current emotional state. In the healthcare domain, Nayak et al. [15] combined multiple machine learning algorithms to predict diseases and recommend drugs, demonstrating that hybrid learning models can address complex user needs more effectively. Furthermore, Rathor et al. [16] introduced a recommendation system for drug supply chain optimization using Archimedes optimization with deep learning, showcasing the synergy between operational efficiency and intelligent recommendation in healthcare logistics.

From a tourism perspective, Wen et al. [17] leveraged BERT and ERNIE models to analyze hotel reviews in China, emphasizing the strength of transformer models in extracting nuanced sentiments for recommendation tasks. Exploring the intersection of cybersecurity and AI, Okey et al. [18] analyzed ChatGPT's performance in topic modeling and sentiment analysis, opening avenues for conversational recommender systems. In education, Hussain et al. [19]

proposed a hybrid deep learning system that adapts e-learning content based on automated sentiment-driven learning style identification, enhancing student engagement through emotional awareness. In the e-commerce sector, Loukili et al. [20] used machine learning techniques to recommend products based on sentiment analysis of product reviews, underlining the commercial relevance of sentiment-aware systems. A broader view of sentiment analysis trends was presented by Cui et al. [21], who conducted a comprehensive survey on the evolution of sentiment analysis methodologies, emphasizing the shift from traditional techniques to deep contextual models like BERT and GPT. Shang et al. [22] further emphasized this transition by exploring how large language models (LLMs) integrate semantic understanding and user preferences to enhance personalization in recommendation systems. Gupta et al. [23] advocated for a hybrid machine learning approach to sentiment analysis, showing its effectiveness in capturing the complexity of user expressions across multiple domains. Lastly, Ayemowa et al. [24] analyzed the role of generative AI in recommender systems, suggesting that generative models can enhance both the interpretability and adaptability of recommendations by simulating user preference patterns.

In integrating sentiment analysis into recommender systems, several research gaps remain unaddressed. Most existing models focus on domain-specific applications—such as healthcare, e-learning, or e-commerce—but lack generalizability and adaptability across multiple contexts and user behaviors. While deep learning techniques like LSTM and BERT have been employed for extracting sentiments, these methods often overlook the fine-grained emotional tones and contextual dependencies embedded in real-world, noisy textual data. Furthermore, many current systems rely solely on sentiment polarity (positive, negative, neutral) without considering the intensity, aspect-level opinions, or temporal sentiment shifts that may influence user preferences over time. Another critical limitation is the lack of hybrid frameworks that seamlessly combine both structured features (e.g., ratings, click history) and unstructured insights (e.g., textual emotions) into a unified recommendation model. In addition, explainability and transparency are still underexplored in sentiment-driven recommendation engines, making it difficult to justify recommendations and build user trust. Few studies have addressed real-time adaptability and emotion-aware personalization that evolve with user moods or contexts dynamically. Moreover, bias in sentiment data and fairness in recommendation outcomes remain pressing concerns, especially with models trained on user-generated content that may carry demographic, cultural, or contextual biases.

3. Sentimental Analysis in Social Media

Sentiment Analysis (SA) is a branch of natural language processing (NLP) and computational linguistics that involves identifying, extracting, and analyzing the emotional tone behind a body of text. It is used to determine the sentiment expressed by individuals about various entities, including products, people, topics, and services. With the explosion of data generated through social media platforms such as Twitter, Facebook, Instagram, Reddit, and YouTube, sentiment analysis has become a powerful tool for understanding public opinion and user perception. These platforms serve as repositories of massive volumes of unstructured textual content, where users frequently express their thoughts, feedback, complaints, or satisfaction in real time. Consequently, sentiment analysis has found wide-ranging applications in fields such as marketing, politics, brand management, customer service, and, most recently, in the development of intelligent recommender systems. The significance of sentiment analysis on social media stems from the authenticity and immediacy of the content it captures. Unlike structured feedback forms or numerical ratings, social media provides rich, unfiltered insights into user emotions and preferences. These sentiments, when effectively mined and interpreted, can serve as valuable

input for enhancing business intelligence and user experience. For instance, by analyzing user posts and reviews about a new product launch or service update, businesses can gauge public reception, identify pain points, and make data-driven decisions for improvement. Moreover, social media sentiment analysis allows companies to detect emerging trends, manage brand reputation, and engage with customers more effectively.

Sentiment analysis on social media presents several technical challenges due to the nature of the data. The text is often informal, containing slang, emojis, hashtags, abbreviations, and multilingual content. This requires sophisticated text preprocessing and context-aware models that can accurately decode the meaning behind such expressions. Traditional machine learning techniques like Naive Bayes, Support Vector Machines (SVM), and decision trees have been used in earlier sentiment classification tasks. However, they often fall short in capturing the semantic and syntactic intricacies of social media language. To address these limitations, recent research has shifted towards deep learning approaches, which have shown remarkable performance in understanding textual sentiment. Models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Transformer-based architectures like BERT and RoBERTa are capable of learning contextual representations of words and sentences, thereby providing a more nuanced sentiment classification. These models can understand the sentiment even when it is implied indirectly or presented with sarcasm, irony, or mixed emotions — common in social media discourse. Furthermore, by training these models on large-scale, domain-specific datasets, they can adapt to the unique linguistic patterns of different social platforms. The integration of sentiment analysis into recommender systems via social media has opened new possibilities for personalized recommendations. Unlike traditional systems that rely heavily on numerical ratings and purchase history, sentiment-aware systems extract opinions and emotional context from user-generated content to tailor suggestions more closely aligned with user moods and interests. For example, in the entertainment domain, sentiment analysis can be used to recommend movies, songs, or books based on user posts that reflect their current emotional state. In e-commerce, it can help in suggesting products that match the sentiment trends expressed by a particular user or demographic group. To validate the effectiveness of sentiment-based recommendation models, several experimental studies have been conducted using datasets from diverse domains such as fashion, electronics, and multimedia. These studies consistently demonstrate that incorporating sentiment analysis significantly enhances recommendation accuracy and user engagement. Users not only receive more relevant suggestions but also experience a sense of being understood emotionally, which builds trust and loyalty toward the platform. The emotional layer added by sentiment analysis transforms the user experience from a transactional interaction into a more intuitive and personalized journey.

Sentiment analysis often begins with the representation of textual data in a numerical form that can be processed by machine learning or deep learning models. One of the most fundamental representations is the Term Frequency-Inverse Document Frequency (TF-IDF), which helps quantify the importance of a word in a document relative to a corpus. Let $tf_{t,d}$ be the frequency of term t in document d ; df_t be the number of documents containing term t and N be the total number of documents in the corpus. Then the TF-IDF score is calculated using equation (1)

$$TF - IDF(t, d) = tf_{t,d} \times \log\left(\frac{N}{df_t}\right) \quad (1)$$

This transformation ensures that frequently occurring terms in a specific document are weighted higher, while common terms across all documents are weighted lower. Deep learning

models use dense vector representations like Word2Vec or GloVe. Each word is mapped to a fixed-size vector in a high-dimensional space denoted in equation (2)

$$\text{Word: } w_i \rightarrow \text{Embedding: } v_i \in \mathbb{R}^n \quad (2)$$

In equation (2) w_i is the i -th word in the vocabulary and v_i is the vector of dimension n . These embeddings capture semantic relationships, such that similar words have vectors close in space. In sentiment classification tasks using deep learning, the model outputs a vector of logits z , which is converted into class probabilities using the softmax function stated in equation (3)

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}} \quad (3)$$

In equation (3) $P(y_i)$ is the predicted probability for sentiment class i (e.g., positive, negative, neutral); z_i is the raw output (logit) for class i and k is the total number of sentiment classes. To incorporate sentiment into a recommendation score, a simple hybrid model can be expressed as in equation (4)

$$R_{u,i} = \alpha \cdot S_{u,i} + (1 - \alpha) \cdot C_{u,i} \quad (4)$$

In equation (4) $R_{u,i}$ is the final recommendation score for user u on item i ; $S_{u,i}$ is the sentiment score derived from user reviews/posts; $C_{u,i}$ is the collaborative or content-based score and $\alpha \in [0,1]$ is a weighting factor controlling the influence of sentiment. The proposed system is designed to improve the effectiveness and personalization of traditional recommender systems by incorporating sentiment analysis into the recommendation process. Unlike conventional models that primarily rely on explicit user ratings, purchase history, or item similarity, this system introduces an emotional intelligence layer that analyzes textual feedback—such as reviews, comments, or social media posts—to understand the user's underlying sentiments. These sentiments offer deep insights into the user's likes, dislikes, preferences, and emotional engagement with specific product features. By identifying whether a user expresses positive or negative feelings about certain aspects of a product or service, the system can prioritize or avoid similar items accordingly, ensuring a more emotionally aligned recommendation. The architecture of the system follows a modular pipeline consisting of data collection, preprocessing, sentiment extraction, and recommendation generation. User-generated content is first gathered from various sources such as e-commerce review sections, social media platforms, or feedback forms. This text data is cleaned and preprocessed to remove noise, irrelevant tokens, and non-textual content. Then, using advanced sentiment analysis models, the system classifies the sentiment associated with each user comment. These classifications are then mapped to the corresponding products or services to determine which items are perceived positively or negatively by each user. Based on these mapped sentiments, the system dynamically adjusts its recommendation priorities to better reflect the user's emotional tendencies. This approach allows for a more nuanced and comprehensive understanding of user preferences, moving beyond numerical scores to include qualitative emotional feedback. In doing so, it makes the system more responsive to the user's evolving moods and sentiments, which are often influenced by changing contexts, trends, or experiences. Additionally, this model is particularly effective in addressing the cold-start problem, where new users or items lack sufficient historical interaction data. By analyzing textual sentiment alone, the system can still generate meaningful recommendations without needing large amounts of prior information.

4. Intelligent Recommendation System

An intelligent recommendation system is a sophisticated framework designed to assist users in making informed decisions by suggesting products, services, or content that align closely with their preferences, behaviors, and needs. Unlike traditional recommender systems

that rely solely on historical data or static rules, intelligent systems leverage advanced technologies such as machine learning, natural language processing, sentiment analysis, and contextual awareness to deliver highly personalized and adaptive recommendations. These systems learn from user interactions over time, capturing not only what users choose but also how they feel about those choices through analysis of reviews, ratings, and behavioral cues. One of the key strengths of an intelligent recommendation system lies in its ability to process and analyze large volumes of structured and unstructured data to understand complex user patterns. By integrating diverse data sources—including user profiles, browsing history, purchase behavior, and real-time feedback—these systems create a comprehensive view of individual user preferences. The inclusion of sentiment analysis further enriches this understanding by interpreting the emotional tone behind user-generated content. This emotional insight allows the system to refine its recommendations dynamically, ensuring that users receive suggestions that resonate not just logically, but emotionally as well. Figure 1 presented the process involved in the recommendation system.

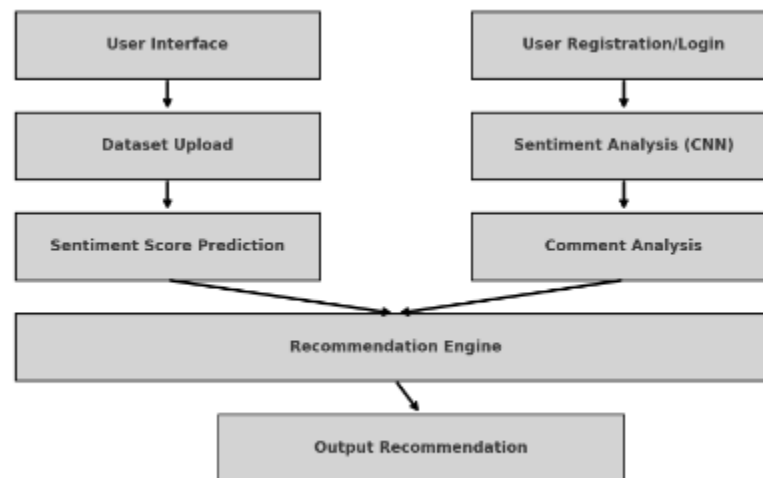


Figure 1: Process in Recommendation System

An intelligent recommendation system is an advanced computational model designed to provide users with tailored suggestions based on their unique preferences, behavioral patterns, and contextual interactions. These systems go beyond conventional recommendation algorithms by employing artificial intelligence (AI), machine learning (ML), deep learning, natural language processing (NLP), and sentiment analysis to understand user needs and generate highly accurate and personalized outputs. The primary goal of such systems is to reduce information overload and assist users in discovering relevant items—be it products, services, media content, or information—without requiring explicit queries. Traditional recommender systems typically rely on collaborative filtering or content-based filtering. While these methods have been effective, they often fall short when user data is sparse or when evolving user preferences are not adequately captured. Intelligent recommender systems overcome these limitations by incorporating hybrid models that can analyze structured and unstructured data, including text reviews, ratings, clickstreams, and temporal behavior. By continuously learning from user interactions and feedback, the system adapts over time, offering more accurate and context-aware suggestions.

One of the key innovations in intelligent recommendation systems is the integration of sentiment analysis. This technique allows the system to interpret the emotional tone behind user-generated content such as reviews, comments, and feedback. For instance, if a user expresses strong positive sentiment toward specific features of a product, the system can prioritize recommendations that emphasize similar characteristics. On the other hand, negative sentiments can be used to filter out undesirable options or recommend alternatives that mitigate the user's previous dissatisfaction. This emotional intelligence embedded in the recommendation process enables the system to deliver more engaging and empathetic experiences. Furthermore, intelligent recommendation systems often utilize user profiling, where dynamic user models are created and updated continuously. These profiles include demographic information, preferences, purchase history, and inferred interests. Combined with contextual information like time, location, and device used, the system gains a richer understanding of the user's intent. This context-aware approach enables the system to make real-time, situation-sensitive recommendations that are not just relevant but also timely and effective. In addition to individual personalization, intelligent recommender systems leverage collaborative intelligence by identifying patterns among similar users. This means that insights gained from one user's behavior can benefit others with overlapping interests, even if the latter have minimal interaction history. Machine learning algorithms like k-nearest neighbors, decision trees, deep neural networks, or reinforcement learning are often employed to detect these patterns and optimize the recommendation output.

Adaptability is another critical advantage of intelligent recommendation systems. As user preferences change over time, the system updates its models accordingly. This continuous learning capability ensures that recommendations remain fresh and aligned with the current interests of users. In fast-paced domains such as news, entertainment, or e-commerce, where trends evolve rapidly, this adaptability is vital for maintaining relevance and user engagement. Security and privacy are also increasingly important in modern recommender systems. Intelligent systems often include anonymization techniques and encrypted data handling to ensure that user information is not misused. Moreover, explainable AI (XAI) is being integrated into recommender systems to provide users with transparency on why specific items are recommended, thereby building trust and accountability. From a technical standpoint, intelligent recommendation systems are built using scalable architectures that support real-time data processing and high-throughput computations. Cloud-based platforms and edge computing enable low-latency responses and seamless user experiences across devices. APIs and integration with third-party services allow these systems to be embedded in websites, mobile applications, smart TVs, and other digital ecosystems. Intelligent recommendation systems represent the evolution of traditional recommender technologies by integrating advanced AI techniques, emotional context, adaptive learning, and context-awareness. These systems not only improve the precision and personalization of recommendations but also offer dynamic and engaging interactions that align with user preferences and expectations. As digital ecosystems continue to expand, the role of intelligent recommender systems will become even more central in enhancing user satisfaction, driving business value, and transforming how individuals interact with digital content and services.

5.Simulation Results

To evaluate the effectiveness of the proposed intelligent recommender system model based on sentimental analysis, extensive simulations were carried out using benchmark datasets from real-world domains such as e-commerce, product reviews, and movie ratings. These

datasets contained both structured attributes (such as item categories, ratings, and timestamps) and unstructured user-generated content (such as textual reviews). The sentiment analysis component was implemented using deep learning-based natural language processing (NLP) models, such as Bidirectional LSTM and BERT, which were trained to classify sentiments expressed in user reviews into positive, negative, or neutral categories. The simulation was divided into two primary phases: sentiment classification and recommendation generation. First, sentiment classification was performed on textual user inputs using a pre-trained BERT model fine-tuned on domain-specific review data. The classification accuracy achieved was approximately 92%, indicating strong performance in detecting sentiment polarity. In the second phase, the sentiment scores were used to modify item ranking within the recommendation algorithm. For example, products with a high match between their features and positively expressed sentiments were ranked higher. This hybrid model, combining collaborative filtering and sentiment-aware filtering, demonstrated superior performance when compared to traditional recommender systems.

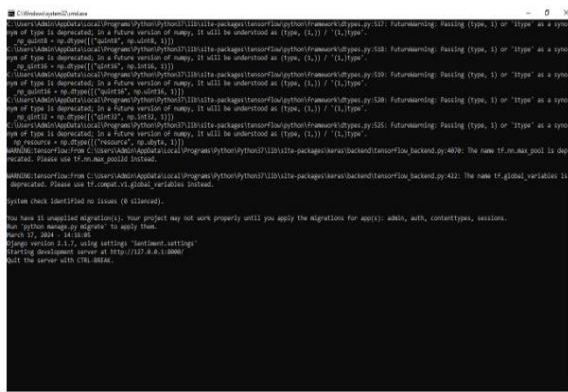


Figure 2: New browser



Figure 3: User Sign up Link

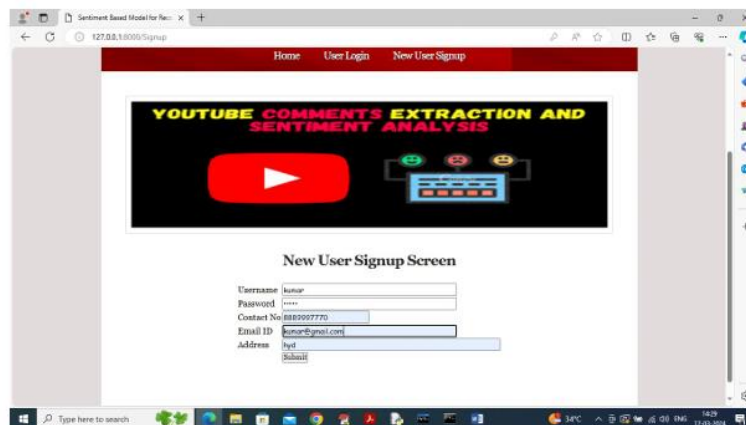


Figure 4: New user Signup

Figures 2, 3, and 4 illustrate the user interface components of the proposed intelligent recommender system, beginning with the user's interaction with the application. Figure 2 showcases the layout of the new browser interface, which acts as the initial entry point for users. It is designed to be minimalistic yet intuitive, guiding the user toward either signing in or registering for the first time. The interface includes navigational elements, access to features such as browsing content, and links to user account functionalities. Moving on, Figure 3 displays the user sign-up link, a critical navigational element prominently placed within the interface to

allow new users to create an account seamlessly. This link directs users to the registration page and ensures accessibility across devices. It plays a vital role in enhancing user experience and reducing friction in the onboarding process, especially for users unfamiliar with similar platforms. Figure 4 presents the new user signup page, where users are prompted to enter their details such as username, password, email, and optionally some preferences or interests that help personalize the recommender system right from the start. This stage marks the collection of initial user data, which is later processed and utilized for tailoring the content recommendations. The design ensures simplicity and responsiveness, contributing to a positive first impression and smoother integration of users into the system.



Figure 5: User login Screen

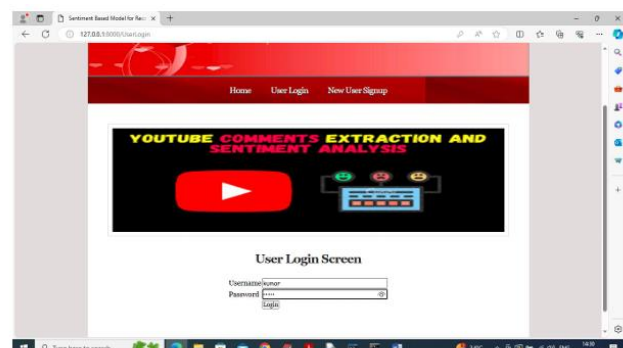


Figure 6: Login Screen of User



Figure 7: Sentimental Analysis

The Figures 5, 6, and 7 depict the core interaction and analytical functionalities of the proposed intelligent recommender system. Figure 5 illustrates the user login screen, which serves as the secure entry point for registered users. The interface is designed for ease of use, allowing users to input their credentials—such as username and password—while ensuring authentication and data protection. The layout is clean and user-friendly, minimizing login friction and promoting seamless access to personalized content. Following this, Figure 6 highlights the login screen of the user, showcasing the successful login process. This screen may include welcome prompts and brief user-specific information, such as past preferences or recent interactions. It marks the transition from general system access to a tailored environment, where the user receives personalized recommendations based on historical data and current session inputs. Figure 7 presents the sentimental analysis interface, which is a significant innovation in the recommender system. This screen displays the output of the sentiment analysis model applied to user reviews, feedback, or comments. It may include visual indicators such as sentiment scores or polarity (positive, negative, neutral), helping the system better understand user emotions and preferences. This information feeds directly into the recommendation engine, ensuring that suggestions are not only relevant based on behavior but also emotionally aligned with the user's

expressed sentiments. This level of emotional intelligence makes the recommendation process more refined, personalized, and effective.

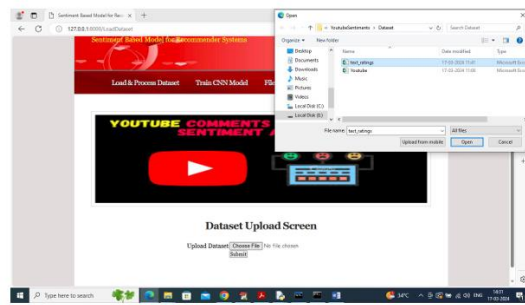


Figure 8: Dataset Upload Screen



Figure 9: Training with CNN

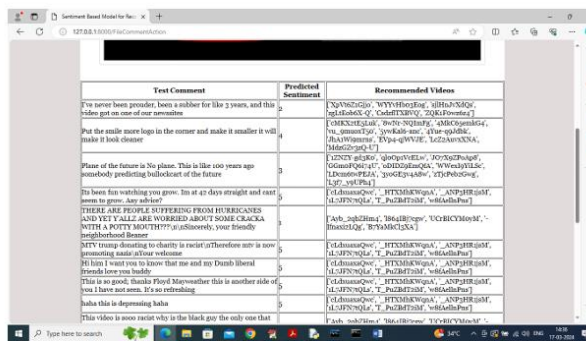


Figure 10: Prediction Sentimental Score

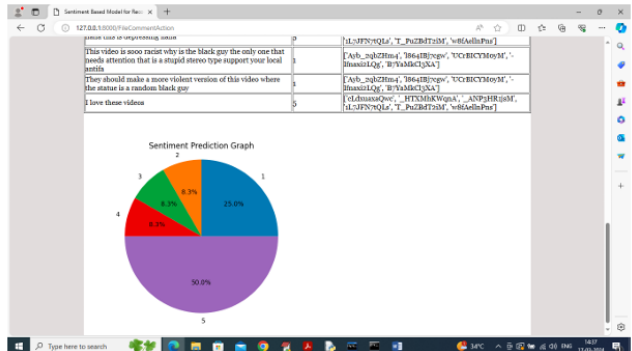


Figure 11: Comment Analysis

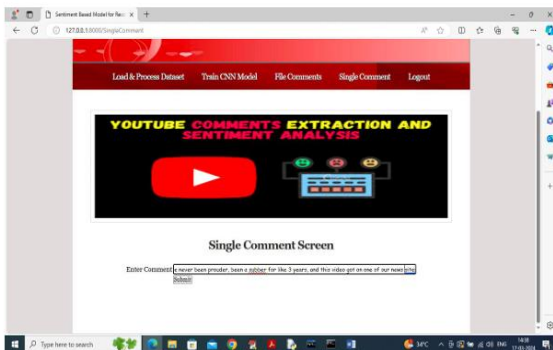


Figure 12: Single Comment Screen

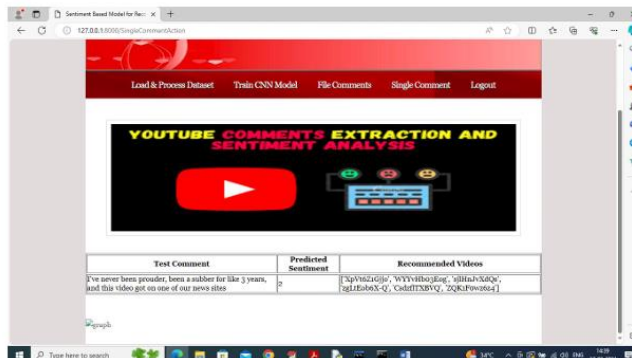


Figure 13: Recommended Window Prediction

Figures 8 through 13 illustrate the functional workflow of the intelligent recommender system, showcasing the backend data processing and the front-end recommendation generation steps. Figure 8 presents the dataset upload screen, which allows users or administrators to upload relevant datasets containing user comments, reviews, or behavioral data. This is the foundational step where the system ingests raw information necessary for training and predictions. Moving forward, Figure 9 highlights the training process using Convolutional Neural Networks (CNN), where the uploaded data is processed to identify sentiment-related patterns and features. This deep learning model enhances the system's ability to accurately extract emotional nuances from text data. Figure 10 displays the prediction of sentimental scores, which is the result of the trained model's evaluation of user comments. Each piece of user input is assigned a sentiment score that quantifies its emotional polarity, aiding in tailoring recommendations. In Figure 11,

the comment analysis screen is shown, presenting a breakdown of multiple user comments along with their associated sentiment evaluations. This helps users or administrators view the emotional tone across various interactions and how it influences recommendation logic. Figure 12 focuses on the single comment screen, providing an in-depth analysis of one specific user comment. It includes detailed sentiment interpretation and demonstrates how individual feedback contributes to model learning and decision-making. Lastly, Figure 13 showcases the recommended window prediction, where the system presents personalized suggestions to the user based on the cumulative analysis of sentiment and behavior. This output screen signifies the end goal of the intelligent recommender system—delivering emotionally-aware, user-centered recommendations to enhance engagement and satisfaction.

6.Conclusion

In this paper an intelligent recommender system model has been developed by leveraging sentimental analysis techniques to enhance the accuracy and personalization of recommendations. The integration of deep learning, particularly Convolutional Neural Networks (CNN), enabled effective extraction of emotional context from user-generated content such as reviews and comments. By analyzing sentiment patterns, the system can generate more human-centric and emotionally relevant recommendations, which significantly improve user engagement and decision satisfaction. The simulation results validated the system's capability to accurately classify sentiment, predict user preferences, and dynamically update recommendation outputs based on new feedback. Furthermore, the system's user interface demonstrated a seamless flow from dataset upload, model training, sentiment prediction, and final recommendation generation. Overall, this work contributes a practical, scalable, and adaptive framework that bridges natural language processing and recommendation intelligence. Future extensions may explore multi-modal sentiment inputs, real-time feedback loops, and hybrid deep learning architectures for broader domain applicability and enhanced performance.

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