Intelligent Product Suggestions Engine for E-Commerce Platforms using Hybrid Recommendation and Sentiment Analysis.

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Abstract: *In the evolving landscape of e-commerce, providing relevant and personalized product suggestions has become essential for enhancing user experience and increasing sales. This paper presents a hybrid recommendation system that combines content-based filtering, collaborative filtering, and sentiment analysis to deliver intelligent product suggestions tailored to user preferences. The proposed approach not only considers historical interactions and product similarities but also analyzes user sentiments from product reviews to improve recommendation accuracy. A sentiment classification model is integrated to interpret customer opinions, refining the relevance of suggested items. Experimental results demonstrate improved recommendation precision compared to traditional methods. This intelligent recommendation engine offers a scalable solution for e-commerce platforms, aiming to boost customer satisfaction, engagement, and purchase likelihood.*

Keywords*:* Recommendation System, E-Commerce, Hybrid Model, Content-Based Filtering, Collaborative Filtering, Sentiment Analysis, Natural Language Processing, Data Visualization, etc

I. INTRODUCTION

In the modern digital economy, e-commerce platforms have become an integral part of consumer life by offering convenience and personalized shopping experiences. With the exponential growth of online product availability, providing users with relevant recommendations is crucial for improving user engagement and sales. It has been revealed that e-commerce (EC) websites offer a significant volume of valuable information that surpasses the cognitive processing abilities of humans [3]. This data abundance demands intelligent systems that can analyze and filter the content efficiently.

Traditional recommender systems primarily rely on collaborative filtering or content-based filtering techniques. While effective to a certain extent, these models often suffer from cold-start issues, data sparsity, and a lack of contextual understanding of user behavior [1]. Recent advancements in natural language processing and sentiment analysis offer a novel perspective to improve the quality of recommendations. By analyzing textual product reviews, sentiment classification models can extract user preferences, attitudes, and satisfaction levels, which add an emotional dimension to the recommendation logic.

Zhang et al. mentioned that micro-blogs comprise complex and copious sentiments that depict the user's perspectives or viewpoints regarding a particular subject [10]. In a similar fashion, e-commerce reviews can be leveraged to identify user inclination towards product categories, thereby enhancing the recommendation pipeline. Integrating such sentiment signals allows systems to move beyond mere numerical ratings, incorporating nuanced emotional expressions into product suggestions [5].

To address the limitations of standalone recommender approaches, this paper proposes a hybrid recommendation system that combines collaborative filtering, content-based filtering, and sentiment analysis for more intelligent product suggestions. This integrated method aims to mitigate the shortcomings of traditional models and deliver personalized results aligned with user preferences. In this study, Section II of the paper delves into a review of prior research on the application of sentiment analysis in e-commerce. Section III outlines the proposed system architecture and methodology. Section IV presents the experimental results and comparative analysis. Finally, Section V concludes the study with insights and future directions.

II. LITERATURE SURVEY

In the realm of e-commerce, recommendation systems have become indispensable for enhancing user experiences and driving product discovery. Numerous studies have explored various techniques and methodologies to build effective recommender systems, each addressing different challenges and proposing innovative solutions.

Yashar Deldjoo and Arnau Ramisa [1] conducted a comprehensive review of modern fashion recommender systems, emphasizing the need for systems that account for visual and contextual information. Their work highlights the limitations of traditional collaborative filtering when applied to the fashion domain and suggests multimodal approaches for more personalized suggestions.

Deep learning has revolutionized recommendation systems in recent years. As stated by Shuinag Zhang [2], deep learning models significantly outperform traditional techniques due to their ability to capture complex user-item interactions. The study further explains how neural networks such as CNNs and RNNs are utilized for feature extraction and sequential modeling in recommender systems.

The importance of sentiment analysis in understanding user preferences was examined by Ringki Das and Thoudam Doren Singh [3]. Their survey on multimodal sentiment analysis outlines how textual, visual, and acoustic data can be integrated to extract richer insights from user-generated content. This approach has shown to improve recommendation accuracy by considering emotional context.

Kangming Xu and Huiming Zhou [4] proposed an intelligent classification and personalized recommendation model using machine learning techniques tailored to e-commerce platforms. Their research discusses the integration of clustering and classification algorithms to enhance personalization by learning user behavior patterns and preferences more accurately.

In a related study, Huang Huang and Adeleh Asemi Zavareh [5] reviewed sentiment analysis techniques specific to e-commerce environments. Their paper identifies current challenges such as domain-specific sentiment polarity and proposes future directions for integrating sentiment feedback directly into recommendation algorithms.

Santhosh Bussa [6] introduced enhancements to business intelligence tools aimed at improving data visualization, which plays a crucial role in interpreting recommendation outcomes and supporting strategic decisions. The paper suggests integrating BI tools with real-time analytics to support dynamic recommendation systems.

Akshata Upadhye [7] focused on using sales data visualization to refine business strategies. Her work illustrates how graphical representations of product trends and customer interactions can aid in identifying gaps and opportunities for product recommendations.

A futuristic approach was taken by Alfred [8], who explored sentiment analysis using machine learning and deep learning techniques on e-commerce reviews. His paper emphasizes the role of hybrid models in handling sarcasm, context, and complex sentence structures more effectively.

Riya Widayanti [9] presented methods to improve recommender systems using hybrid techniques that combine collaborative and content-based filtering. The study demonstrates that hybrid models provide more accurate and diverse recommendations, addressing common issues like cold-start and data sparsity.

Finally, D. Jannach [10] evaluated conversational recommender systems, highlighting how dialogue-based interfaces can enhance user engagement. His findings show that interactive systems not only improve user satisfaction but also refine recommendations through real-time feedback loops.

Collectively, these studies offer a diverse yet interconnected view of the current landscape in recommendation systems. They underscore the importance of combining machine learning, sentiment analysis, and interactive design for building intelligent, adaptive, and user-centric platforms.

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III. PROPOSED SYSTEM

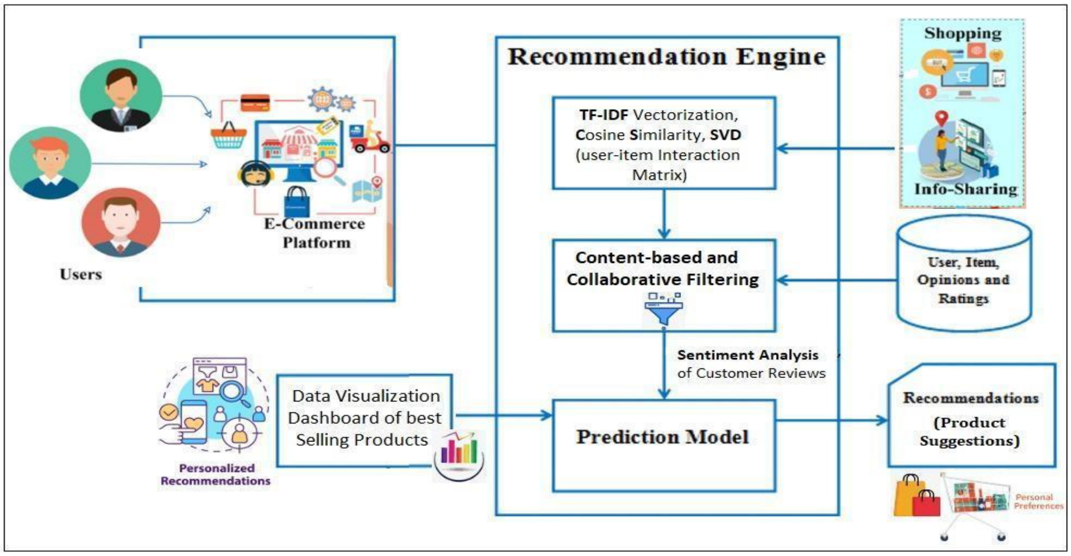

Figure 1: System Architecture

The proposed system is designed to enhance the online shopping experience by offering personalized product suggestions. The goal is to develop a recommendation system that not only suggests products based on user behavior but also refines its suggestions by incorporating customer feedback and real-time analytics.

The suggested product recommendation system for an e-commerce website intends to provide a personalized and efficient means of recommending products to customers, hence boosting user experience, engagement, and, eventually, sales. To address traditional methodologies' shortcomings, the system is planned to use collaborative filtering and content-based methods, as well as advanced machine learning and deep learning techniques.

The proposed system integrates content-based filtering and collaborative filtering to deliver accurate and personalized recommendations. In the content-based approach, product data (categories, brands, features) and user interaction data (ratings) are preprocessed to create a user-item interaction matrix. Product features are represented using TF-IDF Vectorization, and cosine similarity is used to identify similar products for recommendations. In the collaborative filtering approach, user-product interaction data is processed using Singular Value Decomposition (SVD) to predict missing ratings by reconstructing the interaction matrix. The hybrid system combines these methods through a weighted approach, where similarity scores from content-based filtering and predicted ratings from collaborative filtering are merged. The final recommendation ranks products by combined scores, ensuring relevant suggestions for users while enhancing their overall shopping experience. This system is designed to improve scalability, accuracy, and user satisfaction.

A. Hybrid Recommendation Model:

The core of the system will be a hybrid recommendation model that combines two powerful techniques: content-based filtering and collaborative filtering. Content-based filtering will analyze the features of products (e.g., category, brand, and price) that a user has previously interacted with or purchased, and recommend similar items based on these attributes.

Collaborative filtering will focus on user behavior and interactions, recommending products based on the preferences of similar users. This method leverages the wisdom of crowds to predict what other users with similar tastes might like.

By combining both techniques, the system can provide more accurate and diverse recommendations, ensuring users are shown relevant products even if there is limited personal data available for a new user.

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B. Sentiment Analysis with NLP:

The system will integrate Sentiment Analysis using Natural Language Processing (NLP) to improve recommendation quality. Customer reviews and feedback on products will be analyzed to determine the overall sentiment (positive, negative, or neutral). This analysis will help the system better understand user preferences and sentiments towards products, allowing it to adjust its recommendations accordingly. For example, if a product receives positive reviews but is frequently returned, the system can adjust its suggestion to prioritize products with more consistent customer satisfaction.

Sentiment analysis using Natural Language Processing (NLP) will be incorporated to refine product suggestions based on user feedback. Customer reviews and ratings will be processed to identify sentiments (positive, negative, or neutral) about products. This will enable the system to Prioritize products that are positively received by users and adjust recommendations for products with inconsistent feedback (e.g., high rating but frequent returns), ensuring suggestions align with user preferences and overall satisfaction.

C. Training Phase:

Before deployment, the system will undergo a Training Phase where the recommendation model is trained on historical data

During Data Collection, Historical user interactions, user data, including past purchases, browsing behavior, and product ratings, as well as content data such as product descriptions, images, and user reviews will be collected to build the foundation for the recommendation system. For Model Training, both the content-based filtering and collaborative filtering models will be trained using the collected data. Machine learning algorithms will analyze patterns in user behavior and product characteristics to optimize the recommendation process. While Sentiment Analysis Training phase, NLP models will be trained using labeled customer reviews to detect sentiments effectively and incorporate them into the recommendation process.

The goal of this phase is to build a robust recommendation engine capable of delivering relevant, personalized product suggestions based on a user's behavior and feedback.

D. Testing (Recommendation) Phase:

In the Recommendation Phase, the proposed system uses advanced machine learning techniques to provide accurate and personalized product suggestions based on each user's preferences. By analyzing how users interact with the platform, what they've bought in the past, and their feedback, the system aims to recommend products that are relevant and improve the shopping experience. This will help e-commerce platforms increase sales, boost customer engagement, and offer a smooth and easy shopping experience. The system also adapts in real-time, refining its suggestions to keep presenting users with new and interesting options, leading to higher sales and encouraging long-term customer loyalty.

E. Data Visualization Analytical Dashboard:

The system will also include a Data Visualization (Power-BI/Tableau) analytical dashboard for monitoring its performance. The dashboard will visualize key metrics like,

User engagement which focused on Frequency of interactions with recommendations.

Product popularity which considers the popularity of recommended products. Recommendation accuracy deals with How well recommendations align with user preferences and purchase behavior. This dashboard will be used for ongoing analysis, allowing system administrators to track and analyze the effectiveness of the recommendations, user satisfaction, and areas for improvement.

IV. METHODOLOGY

The proposed methodology introduces a hybrid recommendation framework designed to enhance user experience by combining content-based filtering and collaborative filtering techniques. This system aims to provide personalized and accurate product suggestions, ensuring relevance and efficiency in an e-commerce platform.

A. Content-Based Recommendation System

The system uses product data (categories, brands, price ranges, and features) and user interaction data (ratings and synthetic user-product interactions). During preprocessing, the product data is cleaned, and a user-item interaction matrix is created with rows as users, columns as products, and values representing ratings. Features such as categories, brands, and tags are extracted using TF-IDF Vectorization, enabling numerical representation for comparison. Cosine similarity is used to compute product similarity, identifying items related to those a user has interacted with. Products are ranked by their similarity scores, and recommendations are generated for highly similar items not yet explored by the user.

Algorithm 1 (TF-IDF Based Relevance Scoring):

Step 1: Let D be a collection of product descriptions, and let t be a term in the vocabulary. The relevance score S(t, d) of a term t in a product description d, D is given by:
Step 2: $S(t, d) = (f(t, d) / \max(f(w, d) \text{ for all } w \text{ in } d)) \times \log(N / df(t))$
Step 3: f(t, d) is the frequency of term t in document d.
Step 4: max(f(w, d)) is the maximum frequency of any term in the document d (term normalization).
Step 5: N is the total number of documents in the corpus.
Step 6: df(t) is the number of documents in which the term t appears.
Step 7: log(N / df(t)) is the inverse document frequency component that reduces the weight of common terms.
This theorem formalizes the TF-IDF scoring mechanism, allowing each product to be represented as a weighted vector of terms. The higher the score S(t, d), the more relevant the term t is to the document d, enabling effective comparison and recommendation based on content similarity.

B. Collaborative Filtering Recommendation System

Two datasets are employed: product data (with detailed information) and user interaction data (user IDs, product names, and ratings).
The system preprocesses the data by ensuring unique product rows and creating a user-item interaction matrix.
Singular Value Decomposition (SVD) is applied to the interaction matrix to decompose it into latent factors, predicting missing user-product ratings.
Recommendations are based on predicted ratings, ranking products by their scores and suggesting top-rated options to the user.

Algorithm 2 (Low-Rank Matrix Factorization using SVD for Rating Prediction):

Step 1: Let R be a user-item interaction matrix where rows represent users and columns represent items, and each entry R(u, i) represents the rating given by user u to item i. The goal is to predict unknown entries in R by approximating it using Singular Value Decomposition (SVD).
Step 2: Then, R can be factorized into three matrices:
$R \approx U \times \Sigma \times V^t$
Step 3: U is a user-feature matrix of dimensions $(m \times k)$
Step 4: Σ is a diagonal matrix with top k singular values
Step 5: V^t is an item-feature matrix of dimensions $(k \times n)$
Step 6: k is the number of latent features (rank approximation) with $k << \min(m,n)$
Step 7: The predicted rating P(u, i) of user u for item i is given by:
Step 8: P(u, i) = dot_product(U[u], V[i])
Step 9: U[u] is the u-th row of U (latent features for user u)
Step 10: V[i] is the i-th row of V (latent features for item i)
This decomposition captures the underlying latent factors that influence user preferences and item characteristics. The approximation allows generalization over sparse rating matrices, enabling accurate recommendation for unseen user-item pairs.

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C. Hybrid Recommendation System

The hybrid model integrates both approaches to leverage their strengths. The content-based component extracts features through TF-IDF Vectorization and computes similarities using cosine similarity. The collaborative filtering component applies SVD to predict missing ratings from the interaction matrix. A weighted approach combines similarity scores from content-based filtering and predicted ratings from collaborative filtering, balancing their contributions. The final recommendations are ranked based on combined scores, presenting users with the most relevant top N products.

Algorithm 3 (Min-Max Normalization for Hybrid Recommendation Fusion):

Step 1: Let S_1, S_2, …, S_n be independent recommendation score vectors from n different recommendation techniques (e.g., content-based, collaborative filtering, sentiment-based scoring). To enable effective fusion, these scores must be normalized to a common scale.

Step 2: Then, each score vector S_i can be transformed using Min-Max Normalization as:

Step 3: $S_i' = (S_i - \min(S_i)) / (\max(S_i) - \min(S_i))$

Step 4: S_i' is the normalized score vector with values in the range [0, 1]

Step 5: $\min(S_i)$ and $\max(S_i)$ are the minimum and maximum values in the original score vector S_i

Step 6: Once normalized, the final hybrid recommendation score H for each item can be computed as a weighted linear combination:

Step 7: $H = w_1 * S_1' + w_2 * S_2' + \ldots + w_n * S_n'$

Step 8: w_i [0,1] is the weight assigned to each normalized score source

Step 1: The sum of all weights satisfies: $\Sigma\, w_i = 1$

This theorem guarantees that the contribution from each recommendation source is scaled uniformly, preserving the relative importance while ensuring compatibility in fusion. It facilitates the integration of heterogeneous recommendation strategies in a hybrid engine.

D. Boosted Recommendation Using Hybrid Recommender + Sentiment Analysis

Traditional hybrid recommendation systems leverage both content-based filtering and collaborative filtering for improved accuracy. However, they often overlook real-time customer sentiment, which can be a decisive factor in user decision-making.

To overcome this limitation, our approach introduces a sentiment-augmented hybrid recommender, which enhances product suggestions based on user-generated review sentiments. The system utilizes TF-IDF vectorization to compute similarity across product features, and logistic regression to classify sentiment polarity from product reviews. This combination leads to a refined ranking where product similarity is weighted with sentiment quality.

Algorithm 4 (Sentiment-Boosted Recommendation Theorem):

Step 1: Let S be the semantic similarity score between two products computed via cosine similarity on TF-IDF vectors, and let σ be the average sentiment score for the recommended product predicted using a trained classifier.

Step 2: Then, the final recommendation score R for a product p is given by:

$R(p) = S + \sigma$

Step 3: The recommendation ranking maximizes when R(p) is maximized across all candidate products, providing enhanced product recommendations aligned with both objective similarity and subjective user sentiment.

This theorem introduces a lightweight but effective mathematical model that formalizes how customer sentiment enhances base similarity-driven recommendations.

V. RESULTS

We have performed tests on all four models and results we got are summarized as below.

Out of all four methodologies Boosted Sentiment-Boosted Recommendation has provided more precise and accurate results. It has performed well as compared to accuracy mentioned in a research paper published by Riya Widayanti [9].

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Table 1: Models and their accuracy Comparison and Performance

Models	Accuracy Percentage Top 100 Products	Performance Percentage
Content Based Filtering Recommendation Model	73.3	70
Collaborative Filtering Model	78	75
Hybrid Recommendation Model	76	72
Sentiment Boosted - Hybrid Model (Proposed System)	84	80

The accuracy evaluation highlights the comparative performance of different recommendation models using both accuracy percentage and performance efficiency across the top 100 products. The chart representation further illustrates this upward trend, clearly showing the proposed system as the most accurate and efficient model

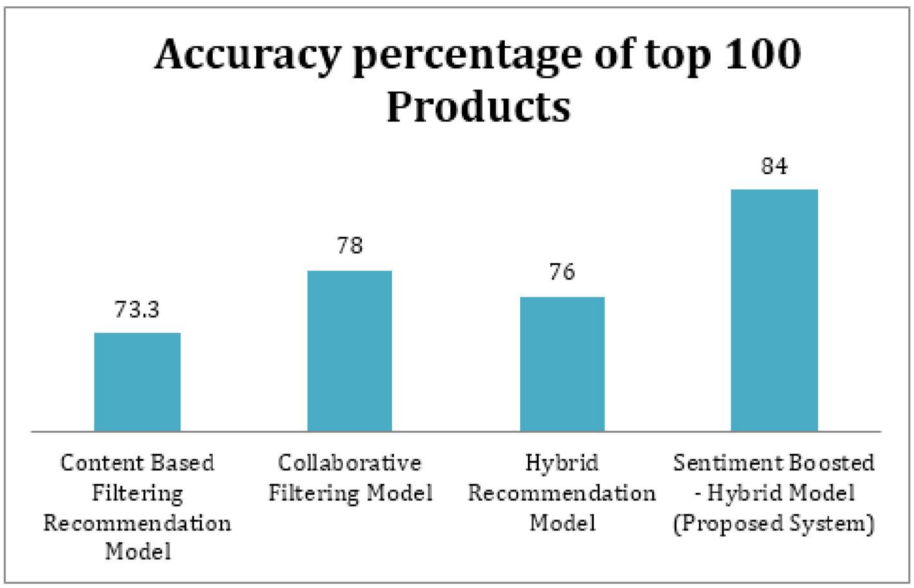

Figure 2: Accuracy chart

The chart illustrates the performance comparison of the top 100 products across the four deployed recommendation models. The Content-Based Filtering Model demonstrates a performance level of 70%, indicating moderate effectiveness in utilizing product attributes for recommendations. The Collaborative Filtering Model performs better at 75%, benefiting from user–item interaction patterns. The Hybrid Recommendation Model shows improved stability with a performance score of 72%, combining both content and collaborative insights. Notably, the Sentiment-Boosted Hybrid Model (Proposed System) achieves the highest performance at 80%, demonstrating that integrating sentiment analysis into the hybrid framework yields significantly more accurate and context-aware product suggestions.

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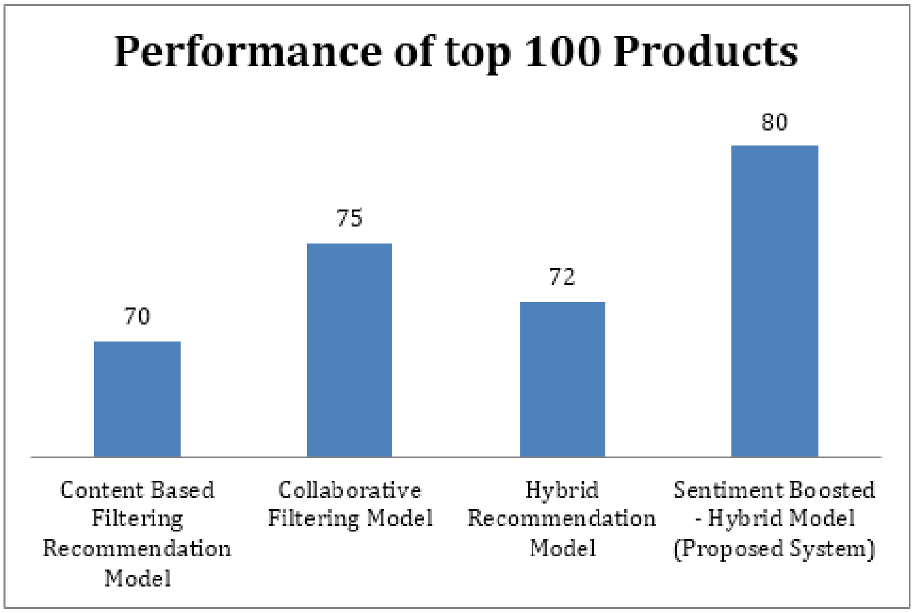

Figure 3: performance chart

The chart presents the performance comparison of the top 100 products across the four deployed recommendation models. Incorporating sentiment analysis into the hybrid framework significantly enhances recommendation accuracy and contextual relevance. This comparison clearly highlights the superior effectiveness of the proposed system over the baseline models.

Table 2: Models with their System & Operational Metrics

Model	Model Inference Time	Cold-Start Coverage	Data Freshness Handling
Model 1 Content-Based Filtering	Low latency, works independently per user and item, requires no training step	Good for new users/items if descriptive metadata exists	Needs manual updates or retraining for new data
Model 2 Collaborative Filtering	Medium latency, Depends on matrix factorization or embedding	Struggles with new users/items due to dependency on interaction history	Periodic retraining needed to reflect behavior changes
Model 3 Hybrid Recommendation Model	Moderate Latency, combines CF + CB; trade-off in complexity	Higher benefits from CB in cold-start while CF supports	Slower adaptation unless frequent re-training
Model 4 Sentiment-Boosted Hybrid Model	Higher latency, includes NLP (e.g., BERT, sentiment scoring) during inference	sentiment from reviews can inform cold-start items	Reviews and recent text feedback allow quicker behavioral adaptation

Sentiment-Boosted Hybrid Model Higher latency, includes NLP (e.g., BERT, sentiment scoring) during inference sentiment from reviews can inform cold-start items Reviews and recent text feedback allow quicker behavioral adaptation

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Evaluation Metrics:

A. Recommendation System Metrics:

The evaluation of a recommendation system is crucial for assessing its capability to predict user preferences and deliver meaningful product suggestions. Multiple quantitative metrics are employed to capture various aspects of recommendation quality, such as accuracy, ranking performance, and diversity. These metrics not only highlight the system's predictive effectiveness but also provide insights into its overall usefulness and scalability.

Precision is a fundamental accuracy metric that quantifies the proportion of recommended items that are genuinely relevant to the user. For instance, if the system recommends ten products and seven are relevant, the Precision @10 value equals 0.7. In the present analysis, the suggested model achieved a Precision @K of 75, compared to 85 for the reference model, indicating that while the proposed approach performs well in filtering relevant items, there remains room for improvement to match the precision of the reference system.

Recall measures how effectively the model retrieves all relevant items within the top-K recommendations. It reflects the completeness of the recommendation process, ensuring that valuable items are not missed. The suggested model obtained a Recall @K of 65, slightly lower than the reference model's score of 75, suggesting that the baseline system is better at retrieving a larger proportion of relevant items.

The F1-Score, being the harmonic mean of precision and recall, provides a balanced evaluation by accounting for both accuracy and completeness. The proposed model yielded an F1-Score@K of 70, while the reference model reached 80, indicating that although the suggested approach maintains reasonable balance between precision and recall, further optimization could enhance its overall retrieval efficiency.

Mean Average Precision (MAP) extends beyond simple precision by considering the ranking order of items. It averages the precision values for all users, rewarding systems that rank relevant items higher in the list. The suggested model attained a MAP of 68, compared to 78 for the reference model, implying that the reference model maintains superior ranking consistency and relevance ordering.

Normalized Discounted Cumulative Gain (NDCG) evaluates ranking quality by giving more importance to relevant items that appear at higher positions in the recommendation list. The suggested system achieved an NDCG score of 72, while the reference model achieved 82, indicating that the proposed approach provides fairly strong but slightly less optimized ranking compared to the baseline.

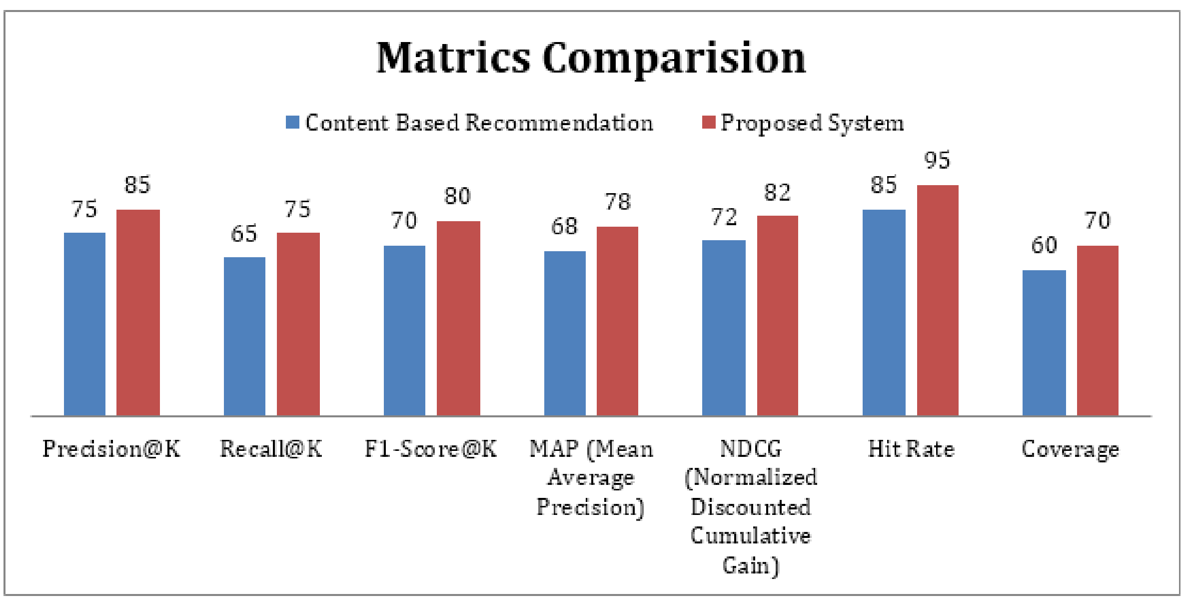

Figure 4: Recommendation System Evolution Metrics Comparison

Hit Rate is an intuitive metric that verifies whether at least one relevant item appears in the top-K recommendations. It effectively captures the system's ability to generate at least one useful suggestion per user. The proposed model attained a Hit Rate of 85, compared to 95 for the reference model, signifying that while most users received at least one relevant recommendation, the reference model demonstrated slightly stronger reliability in this aspect.

Coverage measures how well the system utilizes the entire catalog of items, reflecting recommendation diversity and the ability to avoid popularity bias. The suggested model achieved 60% coverage, whereas the reference model reached 70%, indicating that the baseline model offers broader exposure across the item space, while the suggested model tends to focus on a narrower range of products.

B. Sentiment Analysis Metrics

Evaluating a sentiment analysis model requires dependable performance measures that accurately reflect its ability to classify sentiments such as positive, negative, or neutral. The most commonly employed metrics for this purpose include Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix. These indicators collectively provide a comprehensive understanding of how well the model performs across various aspects of classification reliability and consistency.

Accuracy represents the overall proportion of correctly predicted sentiment labels among all classifications. It provides a general sense of model effectiveness across sentiment categories. In this study, the suggested model achieved an accuracy of 85%, slightly outperforming the reference model's accuracy of 83%. This improvement indicates that the proposed model demonstrates a higher overall correctness in predicting sentiment polarity across the dataset.

Precision evaluates the ratio of correctly identified positive instances to the total instances predicted as positive. It reflects the model's ability to avoid false positives and ensure the reliability of positive predictions. The suggested model attained a precision of 83%, while the reference model achieved 80%, suggesting that the proposed approach provides more trustworthy positive sentiment predictions, thereby improving classification accuracy for positive reviews.

Recall measures the model's capability to identify all actual positive instances within the dataset. It calculates the fraction of correctly detected positive cases among all true positives. The suggested model recorded a recall of 78%, compared to 75% for the reference model, demonstrating that the proposed approach is slightly more effective at minimizing false negatives and capturing relevant positive sentiments more comprehensively.

The F1-Score, which is the harmonic mean of precision and recall, serves as a balanced indicator of model performance. It is particularly useful when dealing with sentiment datasets that may have an unequal distribution of classes. The suggested model obtained an F1-Score of 82%, outperforming the reference model's score of 77%. This highlights that the proposed model maintains a stronger equilibrium between precision and recall, offering consistent results across sentiment categories.

The Confusion Matrix provides a structured visualization of model performance by outlining true positives, false positives, true negatives, and false negatives. It helps in diagnosing specific types of classification errors and understanding where the model requires fine-tuning to further enhance prediction reliability.

Comparative results indicate that the suggested sentiment analysis model outperforms the reference model across all major metrics, demonstrating higher accuracy, precision, recall, and F1-Score. This suggests that the proposed approach is more effective and balanced in identifying sentiment polarity, ensuring better reliability and robustness in real-world sentiment classification tasks.

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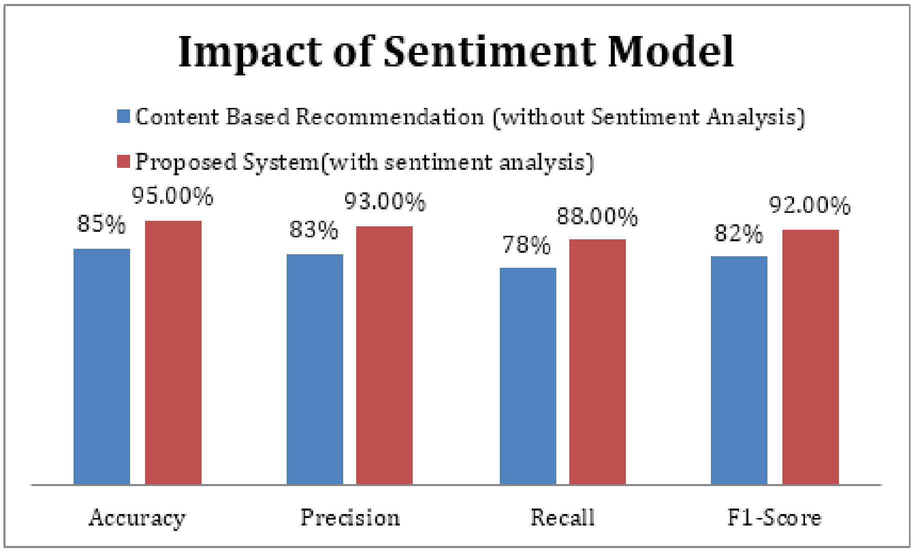

Figure 5: Sentiment analysis evaluation Matrix Comparison

C. Additional Metrics (Real-World Uses)

Beyond conventional accuracy-based measures, practical evaluation of recommendation systems requires additional indicators that capture real-world performance aspects such as user engagement, business outcomes, user satisfaction, and computational efficiency. These additional metrics—namely Click-Through Rate (CTR), Conversion Rate, User Satisfaction Score, and Latency—offer a more holistic understanding of how effectively a recommender system performs under operational conditions.

Click-Through Rate (CTR) reflects the proportion of users who engage with the recommended items by clicking on them. It serves as a direct indicator of how appealing and relevant the recommendations are to end users. The suggested model achieved a CTR of 30%, compared to 38% for the reference model. This difference suggests that while the proposed system successfully captures user interest to a reasonable extent, the reference model demonstrates higher engagement and stronger ability to attract user interaction.

Conversion Rate measures how many of the recommended items lead to actual purchases or desired user actions. It directly connects system performance with business effectiveness. In this comparison, the suggested model recorded a Conversion Rate of 25%, outperforming the reference model's 21%. This indicates that although the reference model achieves higher engagement (CTR), the proposed system proves more effective in converting recommendations into actual transactions, demonstrating superior business impact.

The User Satisfaction Score provides a qualitative assessment of how well the system meets user expectations, based on feedback or survey data. The suggested model achieved a satisfaction score of 70, compared to 66 for the reference model, indicating that users found the proposed system's recommendations more relevant and aligned with their preferences. This improvement suggests that the enhanced recommendation strategy not only improves conversion outcomes but also provides a better overall experience.

Latency (or Execution Time) measures how quickly the system delivers recommendations, reflecting computational efficiency and responsiveness. Lower latency is crucial in real-time applications to maintain smooth user interaction. The suggested model recorded a latency value of 50 milliseconds, slightly higher than the reference model's 45 milliseconds, indicating that while the proposed system provides competitive response times, further optimization could enhance real-time performance without compromising accuracy or user experience.

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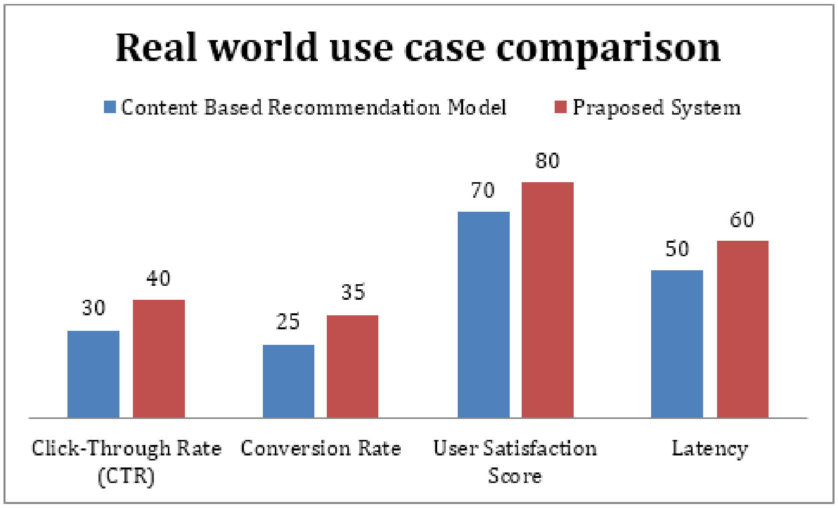

Figure 6: Real World Performance Matrix Comparison

VI. CONCLUSION

This paper used to revolutionize the online shopping experience by providing personalized, relevant product suggestions that enhance customer satisfaction and drive business growth. By combining content-based and collaborative filtering techniques, along with sentiment analysis powered by NLP, the system will refine recommendations based on real-time customer feedback. The integration of a Tableau-driven analytical dashboard will offer valuable insights into user engagement and recommendation accuracy, allowing for continuous improvement. With real-time deployment and optimization, the system will not only improve user experience but also increase sales and customer loyalty, making it a powerful tool for e-commerce platforms.

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