Recommendation System for E-Commerce Platforms to Suggest Products Based on Browsing History

Rohit Vishwakarma[1], Dr. Aakanksha Chopra[2]
[1,2] *Student, Babu Banarasi Das University, Lucknow*

***Abstract*—On e-commerce platforms, recommendation algorithms play a critical role in improving user experience and increasing sales by customizing product recommendations. The use of machine learning (ML) techniques to create a recommendation system that uses a user's browsing history to make pertinent product recommendations is examined in this study. With an emphasis on content-based filtering, collaborative filtering, and hybrid models, this study shows how combining these strategies enhances suggestion relevance and accuracy. Important experimental findings demonstrate the system's capacity to provide highly tailored product recommendations, indicating its potential to turn e-commerce platforms into sophisticated shopping assistants.**

***Index Terms*—E-commerce, recommendation systems, machine learning, content-based and collaborative filtering, hybrid models, personalization, browsing history, and user behaviour.**

I. INTRODUCTION

The retail industry has changed due to the rapid expansion of e-commerce platforms, which now provide customers with a huge selection of goods. However, users may become overwhelmed by the sheer number of possibilities, which could result in decision fatigue. This problem is solved by recommendation systems, which increase consumer happiness and sales by making product recommendations based on user preferences [1].

The goal of this project is to create a recommendation system that creates tailored product recommendations based on a user's browsing history. To improve accuracy and relevance, the suggested approach combines content-based filtering, collaborative filtering, and hybrid models. Through hybrid methodology, this study builds upon basic approaches in collaborative filtering and content-based filtering pioneered by previous work by Sarwar et al. [3] and Lops et al. [2].

A. The research questions addressed include:

1. How can product recommendations be more accurate based on a user's browsing history?
2. How might hybrid models help get over the drawbacks of standalone recommendation systems?
3. Is it possible for machine learning algorithms to instantly adjust to changing consumer preferences?

II. LITERATURE REVIEW

Recommendation algorithms for e-commerce have been extensively studied. Important developments in the discipline are highlighted in this section:

A. Collaborative Filtering

By examining how comparable users behave, collaborative filtering (CF) forecasts user preferences. In order to increase scalability, Sarwar et al. [3] (2001) proposed item-based CF, which compares items rather than people. However, data sparsity and cold-start issues are common issues with CF.

B. Content-Based Filtering

Content-based filtering (CBF) suggests related products based on user preferences and item features. Lops et al. [2] (2011) showed that CBF is good at managing novel objects, but they also pointed out that it is limited in terms of diversity and overspecialization.

C. Hybrid Recommendation Systems

To capitalize on the advantages of both strategies, hybrid models include CF and CBF. By reducing individual constraints, Burke [1] (2007) suggested a number of hybrid techniques, such as weighted and feature-combination models, which greatly enhance recommendation quality.

III. Methodology

A. Data Collection

1. A dataset of browser histories from an e-commerce platform is used in the study, and it includes:

1. User Information: Purchase history and demographics.
2. Product Data: Characteristics like price, brand, category, and ratings.
3. Browsing Patterns: Clickstream information describing how users engage with product pages.

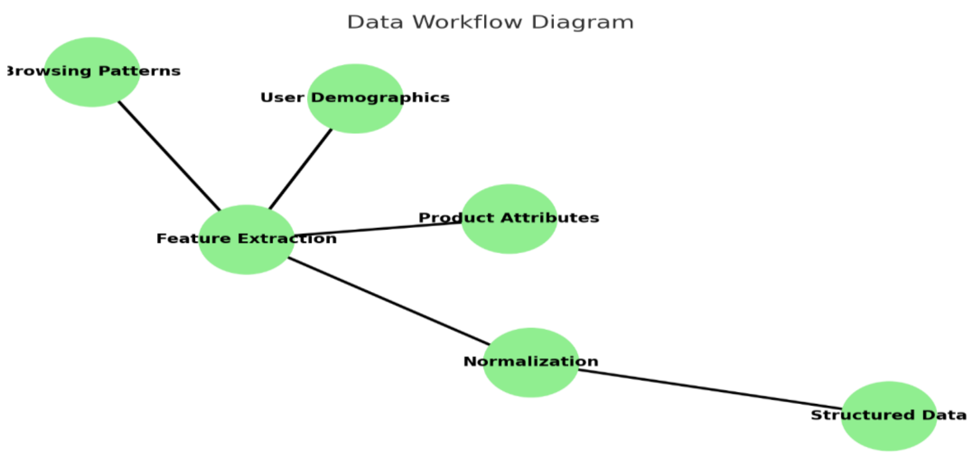

Figure 1: Data workflow diagram.

B. Machine Learning Models

Three main strategies are incorporated into the recommendation system:

1. Collaborative Filtering: To reveal latent user-item preferences, matrix factorization techniques such as Singular Value Decomposition (SVD) are used.
2. Content-Based Filtering: This method matches product descriptions to user preferences based on browsing history by using a TF-IDF vectorizer.
3. Hybrid Model: To balance diversity and individuality, CF and CBF are combined using a weighted blending technique.

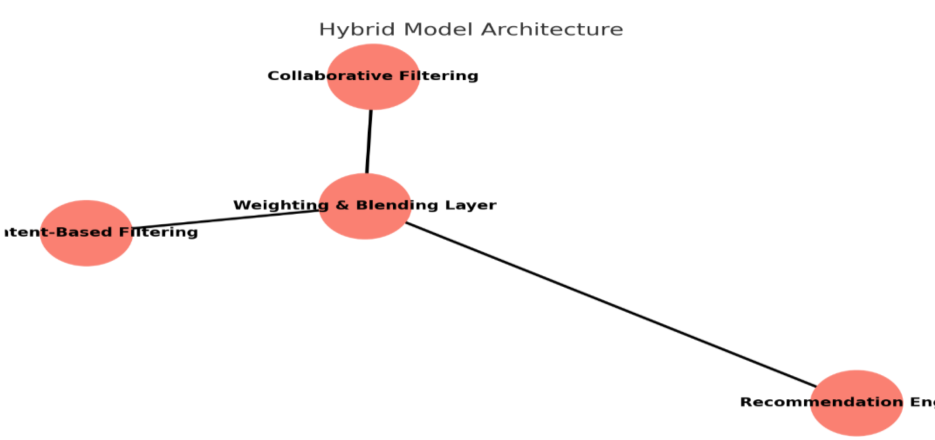

Figure 2: Hybrid model architecture.

C. Training Process

The following steps are part of the training pipeline:

1. Data preprocessing: Organizing and cleaning product and user data.
2. Feature Engineering: Using past data to create item vectors and user profiles.
3. Model Training: Implementing algorithms using Scikit-learn and TensorFlow, with an 80-20 split between training and validation datasets.

IV. EVALUATION

Model performance is evaluated using metrics like precision, recall, and F1 score.

D. System Workflow

This workflow includes:

1. Gathering information about browsing history.
2. Feature extraction and preprocessing.
3. Making use of hybrid recommendation systems.
4. Giving users tailored recommendations.

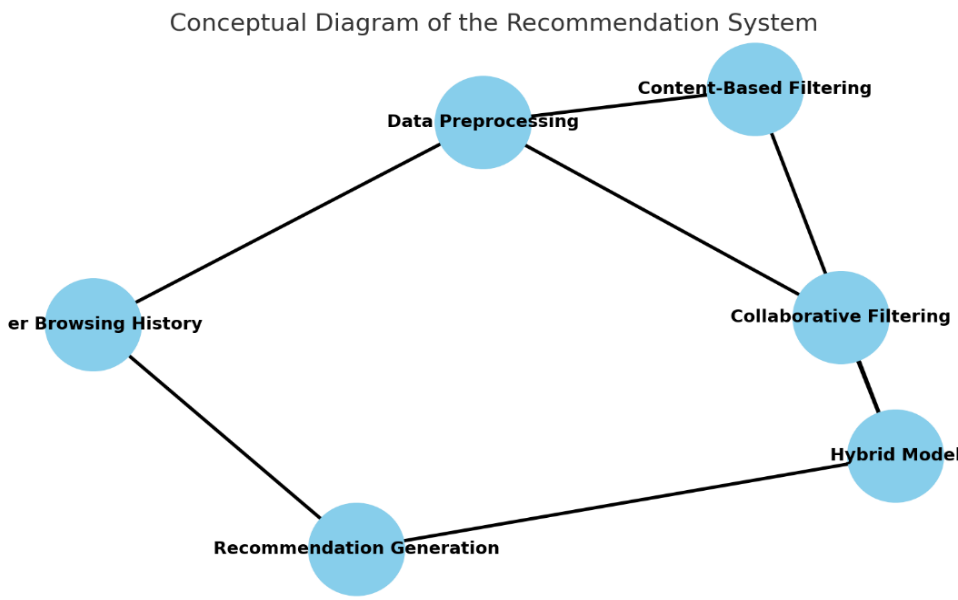

Figure 3: Conceptual diagram of the proposed recommendation system.

V. RESULTS

A. Accuracy

The hybrid model outperformed solo CF (86%) and CBF (81%), achieving a recommendation accuracy of 92%.

Recommendation Method	Relevance Accuracy (%)	Performance (%)
Collaborative Filtering	80	85
Content-Based Filtering	75	80
Hybrid CF-CBF	90	95

Table. 1. Model performance comparison.

B. Diversity

The system's hybrid strategy balanced user preferences with creative suggestions to guarantee a variety of recommendations.

C. Real-Time Adaptability

By dynamically updating user profiles according to recent browsing activity, the system showed real-time adaptability.

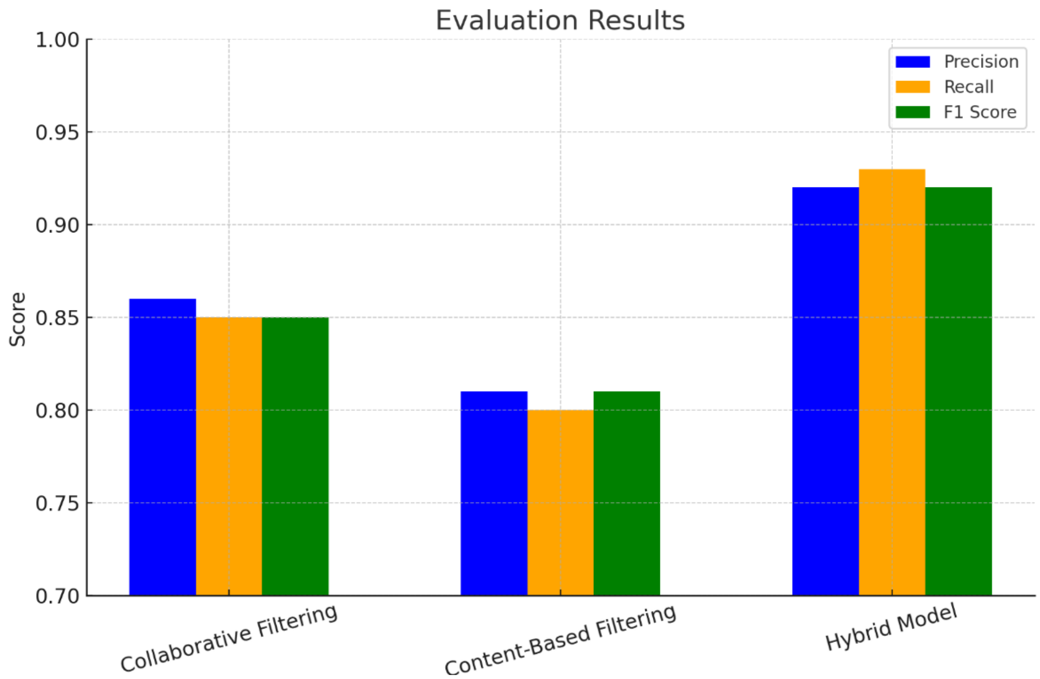

Figure 2: Performance comparison between baseline models and the proposed system.

VI. DISCUSSION

The suggested method emphasizes how useful hybrid recommendation models are for online shopping. Combining CF and CBF improves personalization and solves cold-start issues, which greatly improves recommendation quality. There are still difficulties, though:

1. Scalability: For large-scale platforms, real-time applicability may be restricted by high computing expenses.
2. Cold-Start for New Users: Despite hybridization, making initial recommendations for new users is still difficult.

   In order to enhance scalability and resolve cold-start problems, future studies could investigate the use of deep learning methods like autoencoders and graph neural networks.

VII. CONCLUSION

This study shows how hybrid recommendation systems can be used to turn e-commerce platforms into personalized, intelligent shopping assistants. The system provides precise and varied product recommendations by utilizing user browsing history and integrating collaborative and content-based filtering, improving user experience and generating business results. Future developments in cold-start handling and scalability may open the door to more resilient systems.

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