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RECOMMENDOMART: EMPOWERING E-COMMERCE WITH INTELLIGENT PRODUCT RECOMMENDATION AND SENTIMENT ANALYSIS

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Abstract: In the rapidly evolving landscape of e-commerce, personalized product recommendations play a pivotal role in enhancing user engagement and driving sales. This research paper presents a comprehensive study on the integration of collaborative filtering techniques and sentiment analysis to deliver more accurate and effective product recommendations. Leveraging a dataset comprising user interactions and product reviews, our recommendation system employs collaborative filtering algorithms, particularly Singular Value Decomposition (SVD), to analyze user behavior and generate personalized recommendations. Additionally, sentiment analysis is applied to user reviews to capture the underlying sentiment associated with products, providing a deeper understanding of user preferences and opinions. We conducted experiments on real-world datasets, including Amazon Electronics and Retail Rocket, to evaluate the performance of our recommendation system. The results demonstrate the superiority of collaborative filtering, especially SVD, when applied to the Amazon Electronics dataset, showcasing its effectiveness in capturing latent user preferences and providing accurate recommendations. Furthermore, our system incorporates aspect-based sentiment analysis to offer more targeted insights into user sentiment, contributing to the refinement of product recommendations. This research contributes to the advancement of recommendation systems in e-commerce by demonstrating the efficacy of combining collaborative filtering and sentiment analysis techniques for personalized and context-aware product recommendations.

Index Terms: Recommender Systems, Collaborative Filtering, SVD(Singular Value Decomposition), User-Item Interactions, Large Datasets, Personalized Recommendations, Comparative Analysis, Scalability, Efficiency, Real-world Implementation, Challenges and Opportunities, Hybrid Models, RMSE, MAE, Precision, Recall, Mean Log Squared Error, Sentiment Analysis, E-commerce Datasets, Amazon electronics ratings datasets, Rule-based approaches.

I. INTRODUCTION

In the era of digital commerce, the ability to offer personalized product recommendations has become a crucial competitive advantage for online retailers. With the abundance of choices available to consumers, the challenge lies in guiding users toward products that align with their preferences and interests. Traditional recommendation systems often rely on collaborative filtering algorithms to analyze user-item interactions and generate recommendations based on similarities between users or items. Recommended systems applied data analysis techniques to the problem of helping users find the items they would like to purchase at e-commerce producing a predicted likeliness score or list of top and recommended items for given users [26]. Recommendation systems are productive customization mechanisms, often up-to-date, and recommendations are based on current consumer preferences. These systems have shown to be extremely helpful in different areas of e-commerce, education, movies, music, books, films, scientific papers, and various products [8].

In the ever-evolving landscape of electronic commerce, the significance of product recommendation systems cannot be overstated. This paper embarks on an exploration of the dynamic realm within this field, with a specific focus on collaborative and content-based filtering techniques. As online platforms increasingly become the go-to for consumers, the role of effective product recommendations becomes crucial for enhancing customer retention and satisfaction. Recommendations can be based on the demographics of the user's overall top-selling items or buying habits of users as a predictor of future items [26].

The synthesis of insights from diverse sources forms the backbone of this exploration. We delve into the current state of research, drawing from various perspectives such as collaborative and content-based filtering. By doing so, we aim to present a comprehensive overview of the evolving landscape of product recommendation systems, with a particular emphasis on electronic products in the realm of e-commerce.

As we navigate through this synthesis, a key motivation behind our investigation is to identify and address existing gaps in the literature. By understanding the nuances and intricacies of collaborative and content-based filtering, we aim to contribute to the ongoing discourse, shedding light on areas where advancements and improvements are needed.

With the development of e-commerce, shopping online is becoming more and more popular. The explosion of reviews has led to a serious problem, information overloading. How to mine user interest from these reviews and understand users' preferences is crucial for us. Traditional recommender systems mainly use structured data to mine user interest preference, such as product category, user's tag, and other social factors [6]. In recent years, sentiment analysis has emerged as a valuable tool for understanding user opinions and sentiments expressed in product reviews. Here we have used sentiment analysis on the text of reviews, to uncover valuable insights into user preferences, sentiments, and opinions towards specific products or brands. Integrating sentiment analysis into recommendation systems improves the efficiency and user retention of recommendations by capturing the nuanced aspects of user preferences.

This research paper explores the integration of collaborative filtering techniques with sentiment analysis to improve the effectiveness of product recommendations in e-commerce settings. Specifically, we investigate the use of collaborative filtering algorithms, including Singular Value Decomposition (SVD), to analyze user behavior and generate personalized recommendations. The SVD provides a numerically stable matrix decomposition that can be used for a variety of purposes and is guaranteed to exist [2]. Additionally, we employ sentiment analysis to extract sentiment features from user reviews, providing a deeper understanding of user preferences and sentiments toward products.

Computer scientists have created powerful and complex mathematical algorithms that derive relatively accurate predictions from behavioral data such as reviews, user profiles, and browsing data [30]. The objectives of this research are to evaluate the effectiveness of collaborative filtering techniques, particularly SVD, in generating personalized product recommendations using real-world e-commerce datasets and to explore the impact of sentiment analysis on enhancing the relevance and accuracy of product recommendations by incorporating user sentiments extracted from product reviews.

II. Related Work

Table 1: Literature Survey

Sr. No.	Paper	Year	Publication	Authors	Methodology	Highlights	Technical gap
1	A new improved KNN-based recommender system [1]	2024	The Journal of Supercomputing	Bahrani, P., Minaei-Bidgoli, B., Parvin, H. et al	Developed **KNN-based Recommender Systems (KRS)** by integrating item-based and user-based methods, incorporating mean and variance of ratings as features, and utilizing ensemble learning. Introduced **EVMRS, EWVMRS, and EWVMRSG, employing weighted averaging and Gaussian mixture model** for improved accuracy.	Enhanced Accuracy: **Ensemble learning methods (EVMRS, EWVMRS, EWVMRSG) achieved 20–30% lower absolute error** compared to mean-based Recommender Systems (MRS). Efficiency: Proposed methods maintained comparable execution time to MRS and demonstrated faster performance than alternative RS techniques.	Further research is needed to assess the scalability and adaptability of proposed methods across diverse datasets and real-world applications. Exploration of techniques to handle larger datasets and dynamic user preferences could enhance practical utility in e-commerce scenarios.
2	A Study on Product Recommendation System based on Deep Learning and Collaborative Filtering [17]	2023	International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)	M. D. Bhagat and P. N. Chatur	Conducted a comprehensive review of recent research and review papers on **AI-based product recommendation systems.** Analysis and Comparison: Critically examined various product recommendation techniques, categorizing them based on fundamental ideas, experimental techniques, and performance assessment criteria, while also highlighting researchers' assertions and identifying flaws.	Thorough Examination: Provides a critical analysis of recent literature on AI-based product recommendation systems, offering insights into different techniques, experimental methods, and performance evaluation criteria. Development of Recommendation System: Proposes a **product recommendation system** based on gathered information about items and users using machine learning algorithms, establishing a linkage between users and products to enhance personalized recommendations.	Need for Comparative Analysis: Highlights the importance of comparing and contrasting different AI-based product recommendation systems to identify strengths, weaknesses, and areas for improvement, laying the groundwork for addressing related challenges.
3	Product Recommedation System Using Deep learning and Collaborative Filtering [12]	2022	International Research Journal of Modernization in Engineering Technology and Science (Peer-Reviewed, Open Access, Fully Refereed International Journal)	Devendra G. Ingale, Dr. R.R. Keole, Dr. A.P. Jadhao	Utilization of Neural Network Architectures: Employed various **neural network architectures** to enhance collaborative filtering models, surpassing limitations of matrix factorization techniques. Evaluation on Real-world Datasets: Tested the developed models on real-world datasets to assess their performance compared to existing state-of-the-art models.	Improved Performance: Demonstrated that the developed neural network models outperformed existing state-of-the-art **collaborative filtering models**, showcasing their efficacy in recommendation tasks. Versatility and Simplicity: Developed models are characterized by their simplicity and versatility, making them applicable across different recommendation scenarios and easy to extend for future research endeavors.	Advancing Recommendation Systems: Addresses limitations of traditional matrix factorization techniques by introducing novel neural network-based approaches, expanding the possibilities for recommendation systems based on deep learning.
4	Personality-Aware Product Recommendation System Based on User Interests	2021	IEEE Transactions on Computational Social Systems	Sahraoui Dhelim; Huansheng Ning; Nyothiri Aung; Runhe Huang;	Meta-Interest System Design: Incorporates **user personality traits** to predict interests and recommend items. Utilizes **interest mining and meta-path discovery**	Novel Approach: Introduces **Meta-Interest, a personality-aware product recommendation system.** Addresses limitations of legacy recommendation systems, particularly cold start and redundancy issues.	Personality Measurement Enhancement: Future direction includes integrating automatic personality recognition systems to improve user personality trait measurement.

	Mining and Metapath Discovery[18]			Jianhua Ma	to suggest items even without user history.		Model Extension and Enhancement: Extending the system to incorporate other personality trait models beyond Big Five, such as the Myers–Briggs type indicator, for broader applicability.
5	A comprehensive approach for the evaluation of recommender systems using implicit feedback [24]	2019	International Journal of Information Technology	Sohail, S.S., Siddiqui, J. & Ali, R.	Utilization of Implicit User Feedback: **Implicit user feedback**, such as product reviews, is utilized for evaluation. Sincerity Check Mechanism: A novel mechanism is proposed to identify and mitigate biased and casual feedback from users. **Mathematical Model for Preference Classification**: A mathematical model is presented to classify product preference criteria. Rank Aggregation Algorithm: **Rank aggregation algorithm** is employed to merge individual product rankings into a final ranking for evaluation.	Comprehensive Evaluation Approach: The proposed approach comprehensively evaluates recommender systems by addressing issues of **biased and casual user feedback.** Enhanced Reliability: By incorporating sincerity checks and mathematical models, the evaluation strategy aims to provide more reliable assessments of recommender system performance. Superiority Over Existing Schemes: Comparative analysis demonstrates the superiority of the proposed approach in terms of various parameters, highlighting its effectiveness in addressing evaluation challenges.	Challenge of Inappropriate Evaluation: Existing evaluation schemes often rely on casual or biased user feedback, leading to inappropriate assessments of recommender system performance. Need for Enhanced Evaluation Methods: There is a need for more robust evaluation strategies that can mitigate the impact of fake and biased feedback, ensuring reliable assessments of recommender systems for users' online shopping experiences.
6	An efficient approach for improving the predictive accuracy of multi-criteria recommender system [23]	2023	International Journal of Information Technology	Anwar, I Zafar, A. Iqbal	Modified Similarity Measure: Proposed a modified similarity measure to enhance accuracy in neighborhood generation and rating prediction within **multi-criteria recommender systems (MCRS).** User Clustering Based on Multi-Criteria Ratings: Implemented user clustering based on multi-criteria ratings to address **issues of data sparsity and multidimensionality in MCRS.**	Enhanced Recommendation Accuracy: The proposed modified similarity measure improves accuracy in neighborhood generation and rating prediction within MCRS, leading to more precise recommendations for users. Addressing Data Sparsity and Multidimensionality: By clustering users based on **multi-criteria ratings**, the approach mitigates issues associated with data sparsity and multidimensionality in MCRS, thereby enhancing system efficiency and recommendation quality.	Challenges with Traditional CF: While collaborative filtering (CF) is widely used, traditional CF suffers from limitations in capturing user preferences effectively, motivating the need for more advanced techniques like multi-criteria recommender systems (MCRS).
7	Flipkart Product Recommendation System [7]	2020	Journal of Engineering Sciences	Keerthana, T., T. Bhavani, N. Suma Priya, V. Sai Prathyusha, and K. Santhi Sri.	They have used **Hybrid ContentCollaborative Based Filtering** and have represented a system which will recommend products to the user based on the customer reviews.	1. Using recommendation algorithms, systems can identify the most often purchased goods by consumers and recommend them to other customers or users.	Cold start problems may arise if review of a particular product is not available.

8	Product Recommendation System: A Systematic Literature Review [8]	2021	International Journal for Research in Applied Science and Engineering Technology.	Kulkarni, Pradhnya & Zore, Anuj & Kinkar, Ketki.	Conducted a comprehensive review of existing literature on recommendation systems. Analyzed various recommendation techniques, algorithms, and their features. Explored potential areas for improvement in current research.	Synthesized insights from diverse articles to understand different recommendation approaches. Emphasized the importance of product quality and diversity in recommendation engines. **Proposed leveraging cognitive computing techniques** for enhanced recommendation system performance.	Limited exploration of novel recommendation algorithms beyond popular product-based approaches. Lack of emphasis on the need for diversity in recommendations to prevent user boredom. Opportunities exist for further research into implementing cognitive computing techniques for improved recommendation system quality.

2.1 Summary of Literature Survey Findings:

1. Enhanced Accuracy: Recent papers highlight improvements in recommendation accuracy compared to traditional methods, leveraging novel approaches like ensemble learning, neural networks, and modified similarity measures [17][12].

2. Efficiency: Proposed methods prioritize computational efficiency alongside accuracy, maintaining comparable execution times to traditional approaches while achieving superior recommendation accuracy [23].

3. Technical Gap: There's a consensus on the need for further research to assess the scalability, adaptability, and real-world applicability of recommendation methods. Additionally, addressing scalability concerns and dynamic user preferences remains a key challenge [18].

4. Evaluation Challenges: Challenges in evaluating recommendation systems, including biased or casual user feedback, are acknowledged. There's a call for more robust evaluation methods to ensure reliable assessments of system performance [24].

5. Addressing Cold Start Issues: Strategies for addressing cold start problems, such as leveraging recommendation algorithms to identify frequently purchased goods, are suggested as ways to mitigate the impact of limited or absent reviews for certain products [7].

6. Diversity in Recommendations: While diversity in recommendations is recognized as important for user satisfaction, there's limited exploration of diverse recommendation strategies beyond popular product-based approaches, presenting opportunities for further research [8].

7. Leveraging Advanced Techniques: The potential of advanced techniques like cognitive computing for enhancing recommendation system performance is acknowledged. However, further exploration and implementation of these techniques are needed to realize improvements in recommendation quality and diversity [1].

III. METHODOLOGY

The different techniques used in recommendation systems are shown in the figure given below - Figure 1

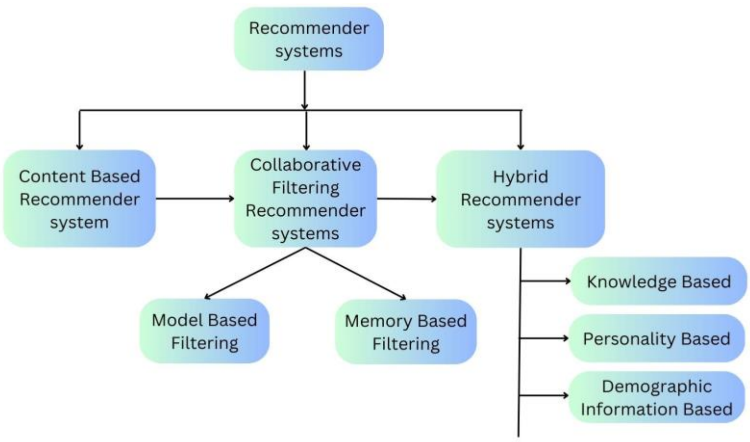


Figure 1: Problem-Solving Methodologies

3.1 Collaborative Filtering:

Collaborative filtering is a recommendation technique that makes predictions about a user's interests by collecting preferences from many users (collaborating). Collaborative Filtering is the process of filtering or evaluating items using the opinions of other people. While the term collaborative filtering (CF) has only been around for a little more than a decade, CF takes its roots from something humans have been doing for centuries - sharing opinions with others [14].

There are two main types:

User-Based Collaborative Filtering:

Recommends items based on the preferences of users with similar tastes.
If User A and User B have similar viewing or purchasing patterns, items liked by User B but not yet seen by User A might be recommended to User A [27].

Item-based Collaborative Filtering:

Item-based techniques first analyze the user-item matrix to identify relationships between different items, and then use these relationships between different items, and then use these relationships to indirectly compute recommendations for users [26]. If a user likes Item X, the system recommends items that are similar to Item X, based on other users' preferences [27].

3.2 Singular Value Decomposition (SVD)

SVD stands for Singular Value Decomposition. It's a fundamental concept in linear algebra and has many applications in various fields such as signal processing, image compression, machine learning, and data analysis. In simple terms, SVD is a way of decomposing a matrix into three simpler matrices [2].
Given a matrix A, SVD expresses it as the product of three matrices:

$$A = U * \Sigma * V^T \qquad \text{… Equation 1}$$

Where:

U is an orthogonal matrix whose columns are called left singular vectors.
Σ (Sigma) is a diagonal matrix containing the singular values of the original matrix.
V^T is the transpose of an orthogonal matrix V, whose columns are called right singular vectors.

IV. Project Design and Implementation

The product recommendation system architecture involves the following major modules based on which further UML diagrams are sketched:

- User Module: Stores user information, purchase history, and personality traits
- Product Module: Stores product information, features, and category relationships.
- Recommendation engine: Combines collaborating filtering and content-based filtering with sentiment analysis of reviews. The algorithm takes into consideration various aspects like negatively reviewed products, positively reviewed products, and their sentiment analysis.
- Sentiment Analysis: Classifies the product reviews into 5 categories namely positive, very positive, negative, very negative, and neutral. A rule-based approach is used for sentiment analysis.

Hardware and Software Requirements for Project Development are:

- System: Pentium i3 Processor
- Hard Disk: 500 GB.
- Monitor: 15'' LED
- Input Devices: Keyboard, Mouse
- Ram: 2 GB
- Operating system: Windows 10
- Coding Language: Java..
- Tool: Netbeans 8.2
- Database: MYSQL

4.1 Use-Case Diagram:

In UML, use-case diagrams model the behavior of a system and help to capture the requirements of the system. Use-case diagrams describe the high-level functions and scope of a system [31]. These diagrams also identify the interactions between the system and its actors. The use cases and actors in use-case diagrams describe what the system does and how the actors use it, but not how the system operates internally [31]. The use case diagram for our implementation is shown in Figure 2 for users, Figure 3 for admin, and Figure 4 for alternate flow.

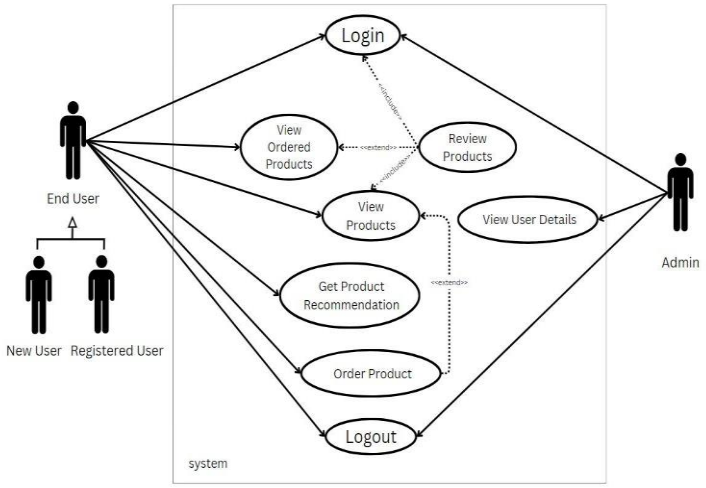


Figure 2: Use-Case Diagram(Users)

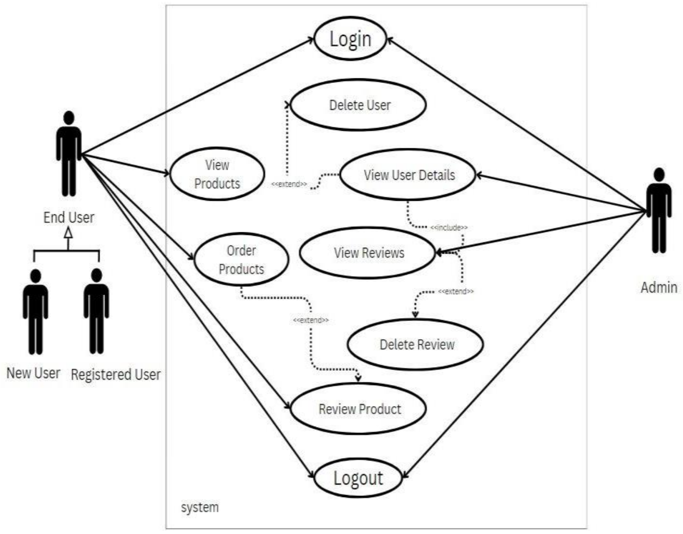


Figure 3: Use-Case Diagram (Admin)

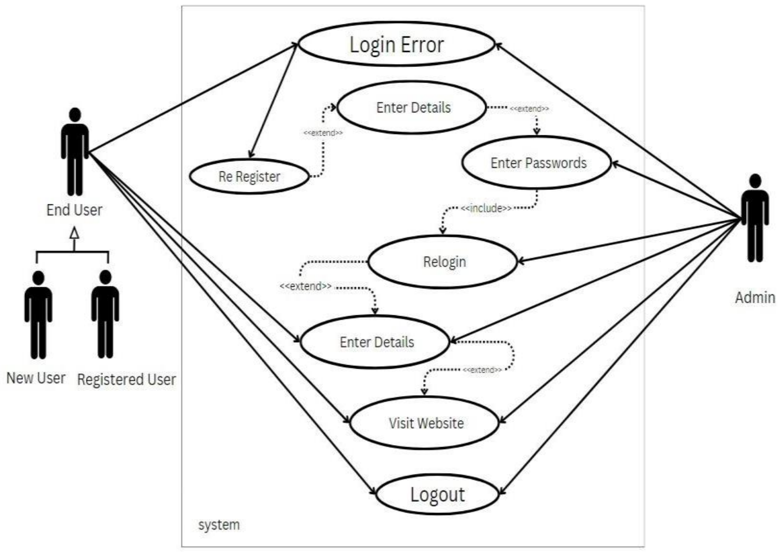


Figure 4: Use-Case Diagram(Alternate Flow)

4.2 Class Diagram:

Class diagrams are a type of UML (Unified Modeling Language) diagram used in software engineering to visually represent the structure and relationships of classes within a system i.e. used to construct and visualize object-oriented systems [34]. The class diagram for our system is shown in Figure 5.

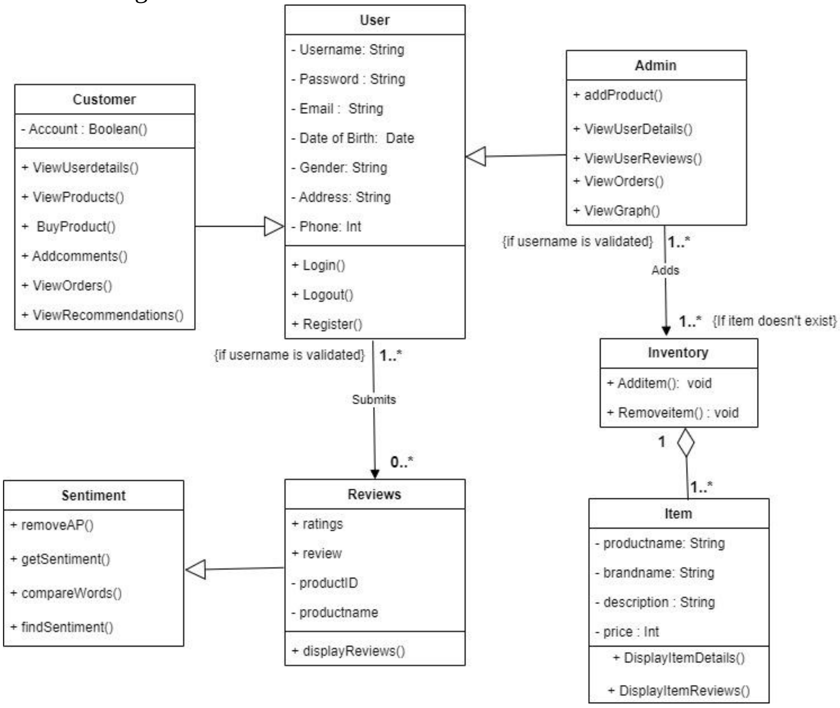


Figure 5: Class Diagram

4.3 Activity Diagram:

Activity Diagrams are used to illustrate the flow of control in a system and refer to the steps involved in the execution of a use case [33]. We can depict both sequential processing and concurrent processing of activities using an activity diagram i.e. an activity diagram focuses on the condition of flow and the sequence in which it happens [33]. The activity diagram for the system is shown in Figure 6.

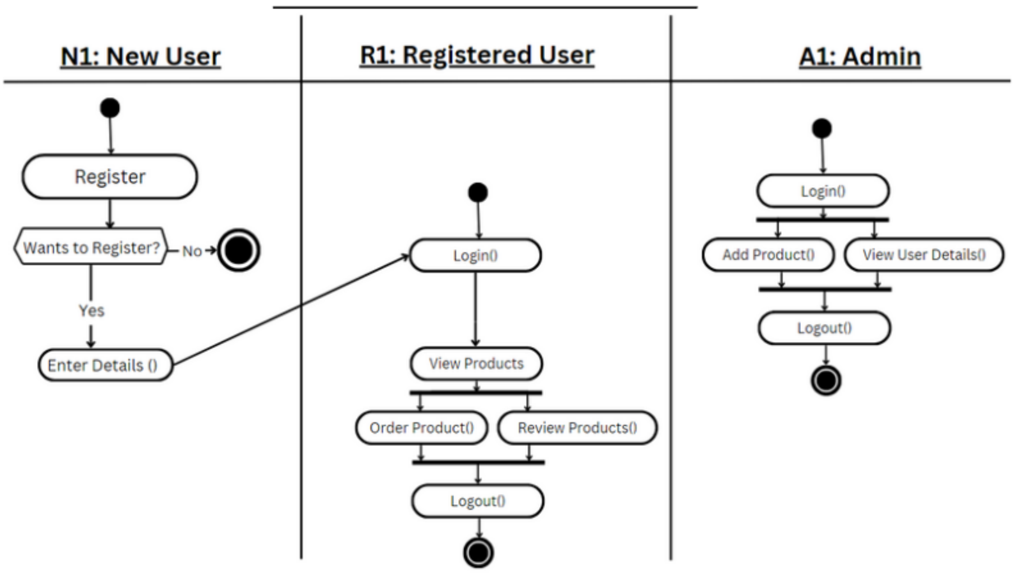


Figure 6: Activity Diagram

4.4 Data Flow Diagram:

DFD is the abbreviation for Data Flow Diagram. The flow of data of a system or a process is represented by DFD. It also gives insight into the inputs and outputs of each entity and the process itself [32]. DFD does not have a control flow and no loops or decision rules are present [32]. Specific operations depending on the type of data can be explained by a flowchart. It is a graphical tool, useful for communicating with users, managers, and other personnel. It is useful for analyzing existing as well as proposed systems [32].

The Level 0 DFD that represents the entire system as a single bubble and provides an overall picture of the system is shown in Figure 7.

Level 0:

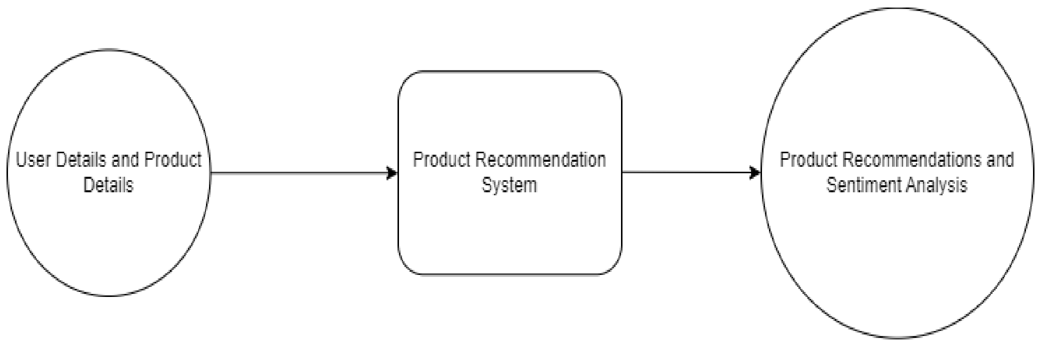


Figure 7: DFD Level 0

The Level 1 DFD that represents the main functions of the system and how they interact with each other is shown in Figure 8.

Level 1:

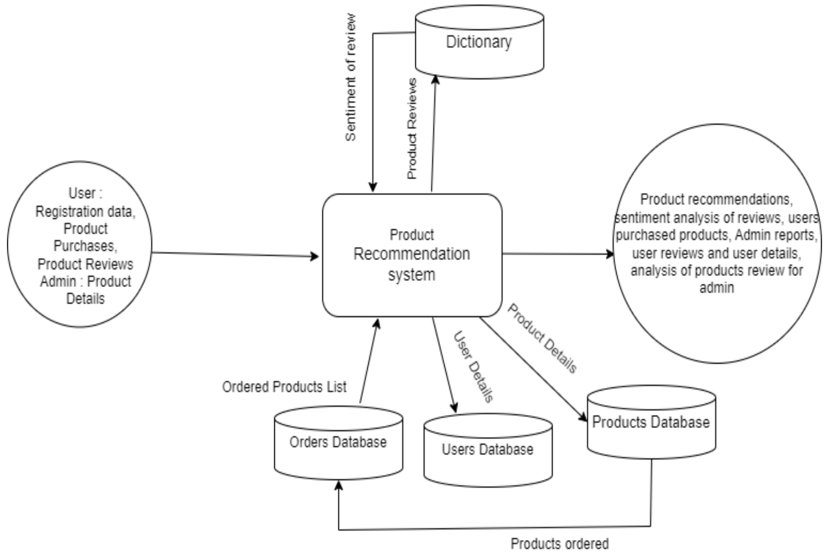


Figure 8: DFD Level 1

The Level 2 DFD that represents the processes within each function of the system and how they interact with each other is shown in Figure 9.

Level 2:

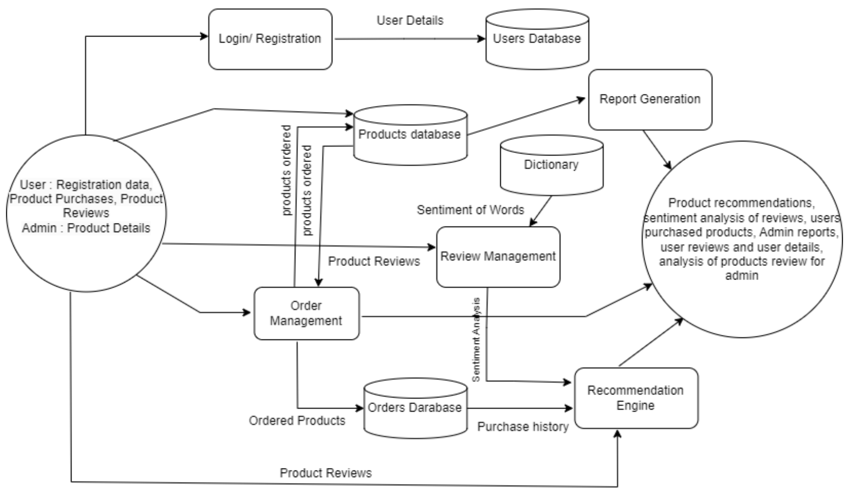


Figure 9: DFD Level 2

V. Dataset Discussion

5.1 Dataset 1: Amazon Electronics -

Context: Online E-commerce websites like Amazon, and Flipkart use different recommendation models to provide personalized suggestions to different users [29]. Amazon currently uses item-to-item collaborative filtering, which scales to massive data sets and produces high-quality recommendations in real-time. We will work with the Amazon product reviews dataset for this project. The dataset contains ratings of different electronic products. It does not include product information or reviews to avoid bias while building the model [29].

The Amazon dataset contains the following attributes:

1. userId: Every user identified with a unique ID

2. productId: Every product identified with a unique ID

3. Rating: Rating of the corresponding product by the corresponding user

4. Timestamp: Time of the rating (ignore this column for this exercise) [29].

5. 2 Dataset 2: Retailrocket recommender system dataset -

Context: The dataset consists of three files: a file with behavior data (events.csv), a file with item properties (item_properties.csv), and a file, that describes the category tree (category_tree.csv). The data has been collected from a real-world ecommerce website. It is raw data, i.e. without any content transformations, however, all values are hashed due to confidential issues. The purpose of publishing is to motivate research in the field of recommender systems with implicit feedback [28].

1. events.csv: This file contains behavior data collected from a real-world e-commerce website. The events include "view," "addtocart," or "transaction." Each row in the file represents a specific event with information such as timestamp, visitor ID, event type, item ID, and, in some cases, transaction ID. The dataset covers 4.5 months, and it includes interactions like clicks, add-to-carts, and transactions. The total number of events is 2,756,101, and 1,407,580 unique visitors produce them. The breakdown of event types is as follows: 2,664,312 "view" events 69,332 "add to cart" events 22,457 "transaction" events [28].

2. item_properties.csv: This file contains item properties and is divided into two parts due to file size limitations. It includes 20,275,902 rows, representing different properties for items. The properties describe 417,053 unique items. Each row has a timestamp, and the file consists of concatenated snapshots for every week in the observed period. If a property of an item is constant over time, only a single snapshot value will be present in the file [28].

3. category_tree.csv: This file describes the category tree for items[28].

VI. Evaluation Metrics For Product Recommendation System

Any product recommendation system is evaluated by measuring the accuracy and coverage of its recommended items. The accuracy measures used for the comparative analysis and evaluation are RMSE, MAE, Precision, Recall, and Mean Log Squared Error (MSLE) measures [3].

What is a confusion matrix?

It is a matrix of size 2×2 for binary classification with actual values on one axis and predicted on another.

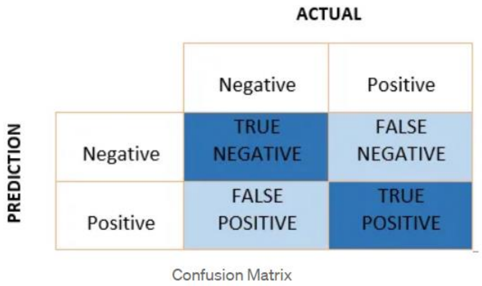


Figure 10: Confusion Matrix

True Positive (TP) — the model correctly predicts the positive class (prediction and actual both are positive).
True Negative (TN) — the model correctly predicts the negative class (prediction and actual both are negative).
False Positive (FP) — model gives the wrong prediction of the negative class (predicted-positive, actual-negative).
False Negative (FN) — model wrongly predicts the positive class (predicted-negative, actual-positive) [3].

Table 2: Evaluation Metrics

Sr. No.	Evaluation Metric	Formula
1.	Precision	Precision = TP/ (TP + FP)
2.	Recall	Recall = TP/ (TP + FN)
3.	Mean Squared Log Error (MSLE)	$MSLE = \frac{1}{n}\sum_{i=1}^{n}(\log(y_i + 1) - \log(\hat{y}_i + 1))^2$
4.	Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$
5.	Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\|y_1 - \hat{y}_i\right\|^2$

VII. Results And Analysis

7.1 Comparative Analysis Results:

In this results chapter, we delve into the outcomes of our comprehensive analysis on recommendation system effectiveness, emphasizing the critical role of dataset selection and algorithmic approaches. Here, we demonstrate a comparative analysis of 2 datasets, the Amazon Electronics dataset, and the Retail Rocket Recommender system dataset, showcasing substantial improvements across various metrics. The following Table gives detailed insights into the values that we get by implementing the SVD algorithm on both datasets [Table 3].

Table 3: Comparison of Datasets using Evaluation Metrics

Evaluation Metrics	Precision	Recall	MSLE	MAE	RMSE
Amazon's electronic product review dataset	**99.5 %**	**7.98 %**	**0.00454**	**0.0077**	**00.136**
RetailRocket Recommender system dataset	66.6 %	50 %	0.565 %	1.1029	1.177

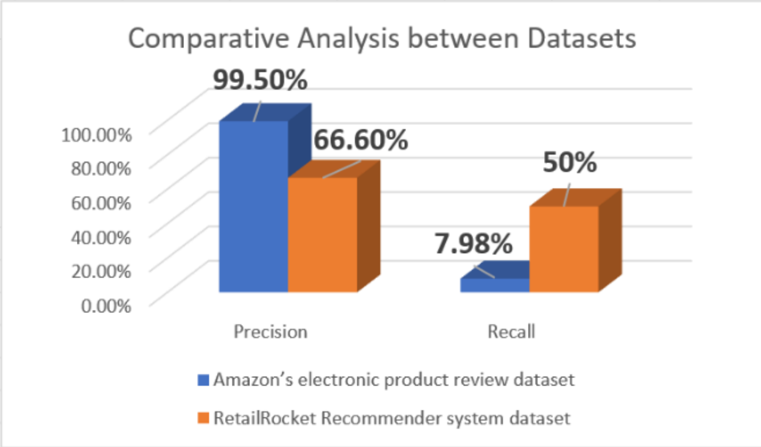


Figure 11: With Metrics Precision and Recall

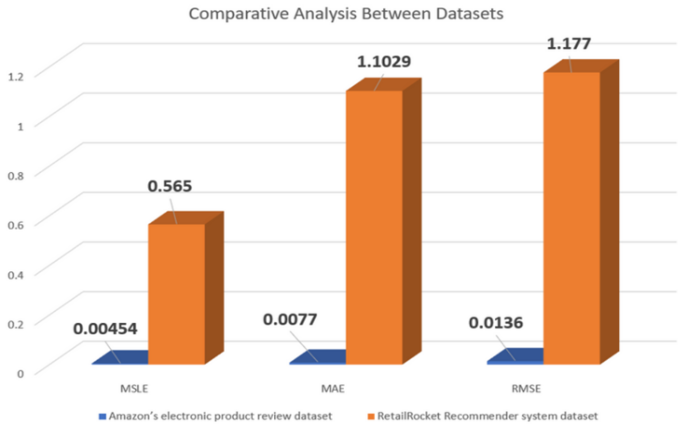


Figure 12: With Metrics RMSE, MSLE, MAE

1. In conclusion, the Amazon Electronics dataset emerges as the superior choice for recommendation system development, owing to its structured format and comprehensive user-product interaction data.
2. By encompassing essential attributes such as user IDs, product IDs, and ratings, this dataset facilitates the generation of interaction matrices, a fundamental component for collaborative filtering techniques.
3. Furthermore, our research highlights the effectiveness of the Singular Value Decomposition (SVD) algorithm when applied to the Amazon Electronics dataset.
4. In summary, the combination of the Amazon Electronics dataset and the SVD algorithm offers a robust framework for developing recommendation systems that deliver personalized and accurate product suggestions to users.
5. Moving forward, leveraging insights gained from our analysis, researchers and practitioners can prioritize dataset quality and algorithmic approaches to enhance the effectiveness of recommendation systems and enrich the online shopping experience for consumers.

Table 4: Variations of different threshold values on Amazon Dataset

Threshold Value	Precision	Recall
3.5	**99.5 %**	**7.98 %**
2.5	98.95%	10.21%
1.5	92.2 %	12.3%
1	76 %	14.8%
0.5	34.85%	20%

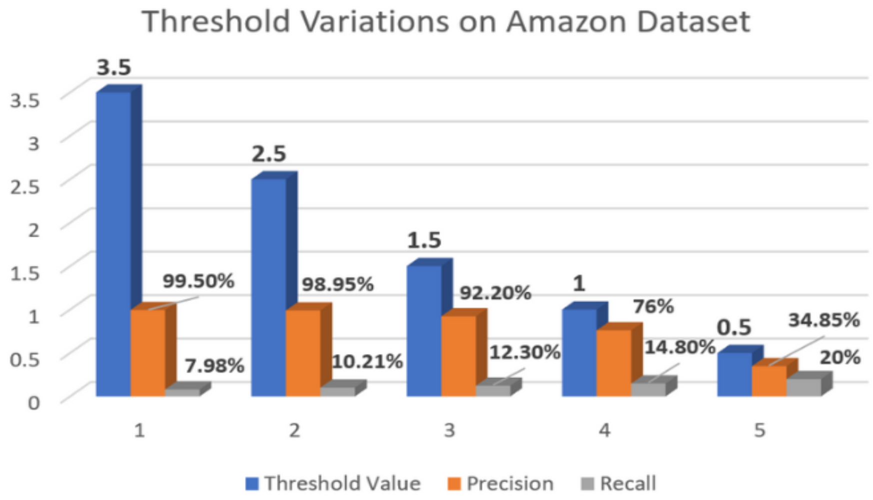


Figure 13: Threshold Variations on Amazon Dataset

From above Figure 13 and Table 4 we can see the variations of different threshold values and how Precision and Recall values change. Here, we found that the values of RMSE, MAE, and MSLE remain constant and hence not included in the table. Further, we can conclude that the best precision is obtained by setting the threshold to 3.5 but we have to compromise recall and poor results are obtained for threshold 0.5, which further states that the threshold value should strictly range between 3.5-1.

7.2 Results of the implemented recommendation system:

In this part, we will focus on the outcomes related to sentiment analysis and the reports generated for the admin. Here's how we can summarize the results:

7.2.1 Sentiment Analysis Results:

- Positive vs. Negative Reviews: Analyzed the sentiment of user reviews to determine the proportion of positive and negative feedback received for the products.
- Sentiment Distribution: Provided a breakdown of sentiment scores across different products or categories, highlighting areas of strength and areas for improvement.
- Impact on User Engagement: Evaluated how sentiment analysis has influenced user engagement and satisfaction with the platform, potentially leading to increased trust and loyalty.
- Graphical overview: For each product along with sentiment analysis of review detailed and real-time pictorial analytics of reviews enhanced user retention and provided more precise insights to the user about the product.

7.2.2 Recommended Products Based on User Behavior:

- Personalized Recommendations: Highlighted the effectiveness of the recommendation system in suggesting products based on user behavior, such as past purchases and reviews.
- Improved User Experience: Assessed how personalized recommendations have enhanced the user experience by helping users discover relevant products more efficiently.
- Increase in Sales: Measured the impact of personalized recommendations on sales conversion rates and revenue generation, demonstrating the system's effectiveness in driving purchases.

7.2.3 Admin Reports:

- Product Performance Analytics: Provided reports on the performance of individual products, including sales figures, user ratings, and sentiment analysis results. This helps admins identify top-selling products and areas for improvement.
- User Engagement Metrics: Presented metrics related to user engagement, such as login frequency, product views, and review submissions, enabling admins to gauge the platform's popularity and user activity.
- Sentiment Analysis Insights: Delivered insights from sentiment analysis, including trends in user sentiment over time, sentiment distribution across products, and identification of products with consistently positive or negative feedback.
- Recommendations Effectiveness: Assessed the performance of the recommendation system by tracking metrics such as click-through rates, conversion rates, and user satisfaction scores for recommended products.

Overall, these results demonstrate the impact of sentiment analysis and personalized recommendations on user engagement, satisfaction, and platform performance. By providing actionable insights to admins, the system empowers them to make informed decisions to optimize the user experience and drive business growth.

Below Figure 14 shows the Home Page of the system.

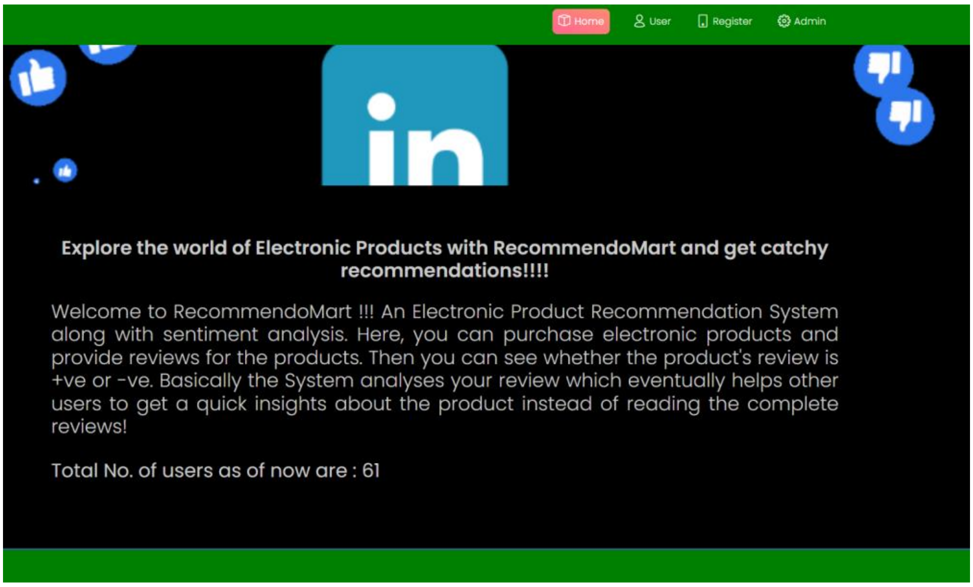


Figure 14. Home Page

Below Figure 15 shows the Admin Home Page that serves as a center for managing all aspects of the website. From here admins can add new products, view all products and orders, can view analytics in detail.

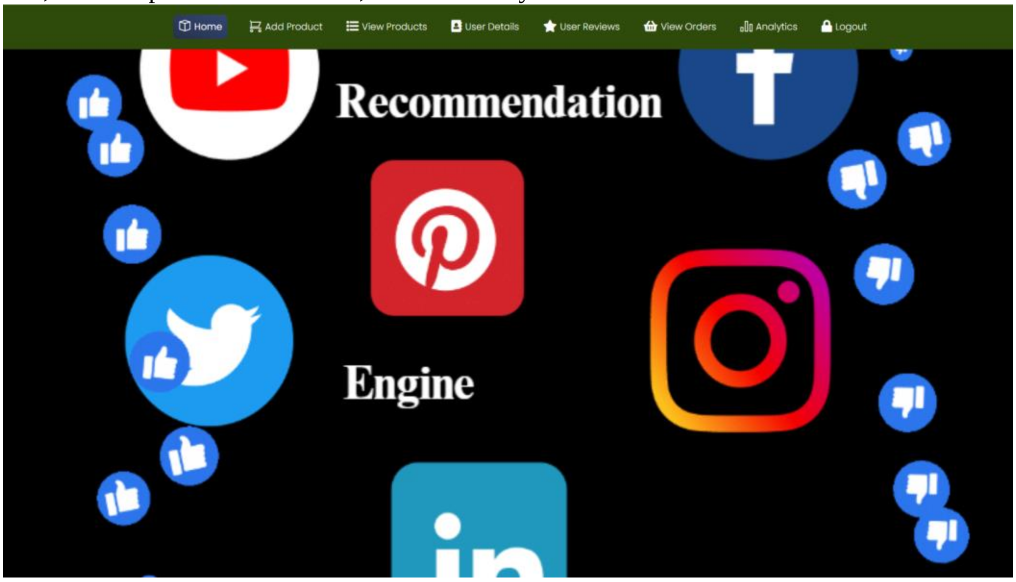


Figure 15: Admin Home Page

Below Figure 16 shows a user page that displays all comments and ratings given to a particular product by different users and also displays Sentiments for each single comment.

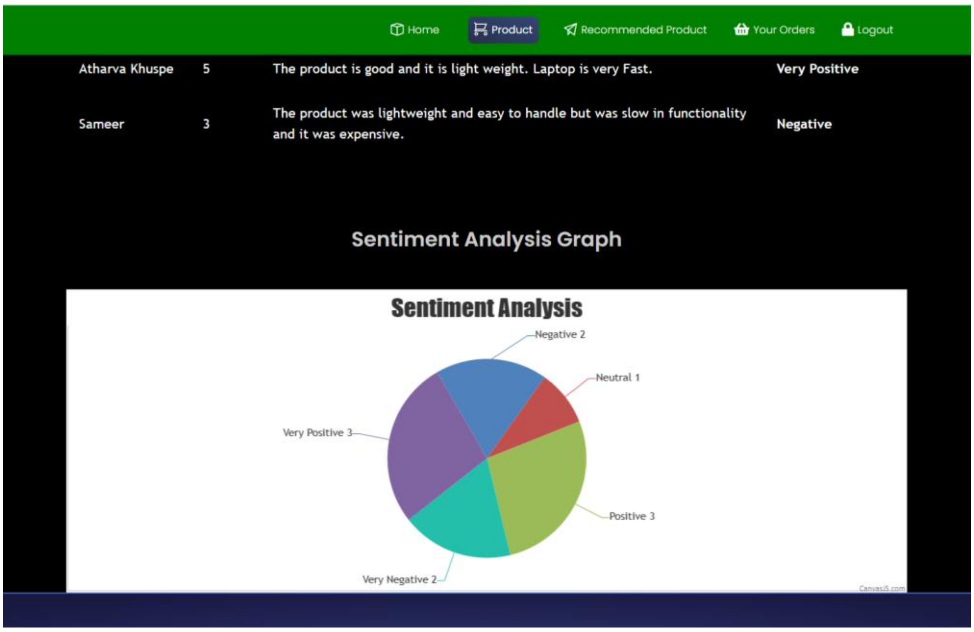


Figure 16: User Page- Sentiment Analysis with Graphical Overview

Below Figure 17 shows various Product recommendations based on the recent purchases made by users.

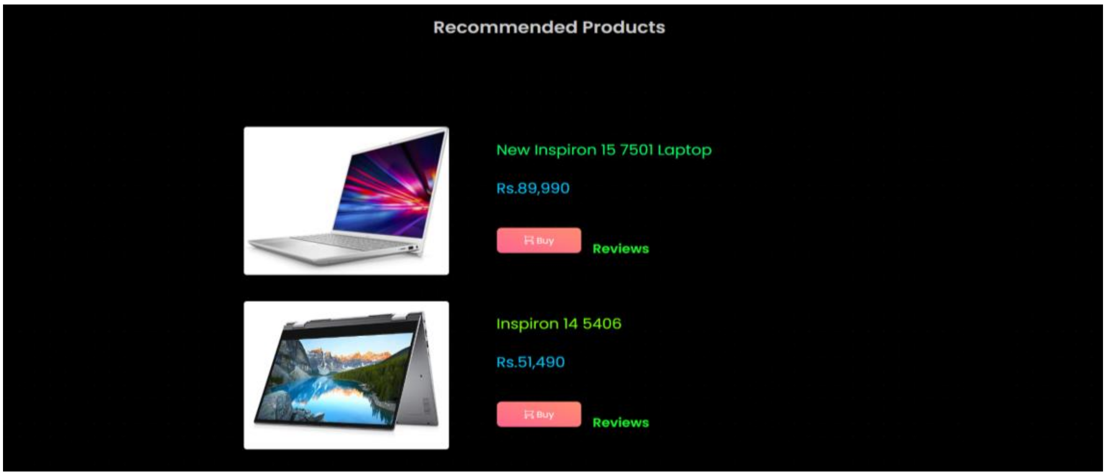


Figure 17: User Product Recommendations

Below Figure 18 shows that users can view all purchases made by them and the time of purchase in a tabular form.

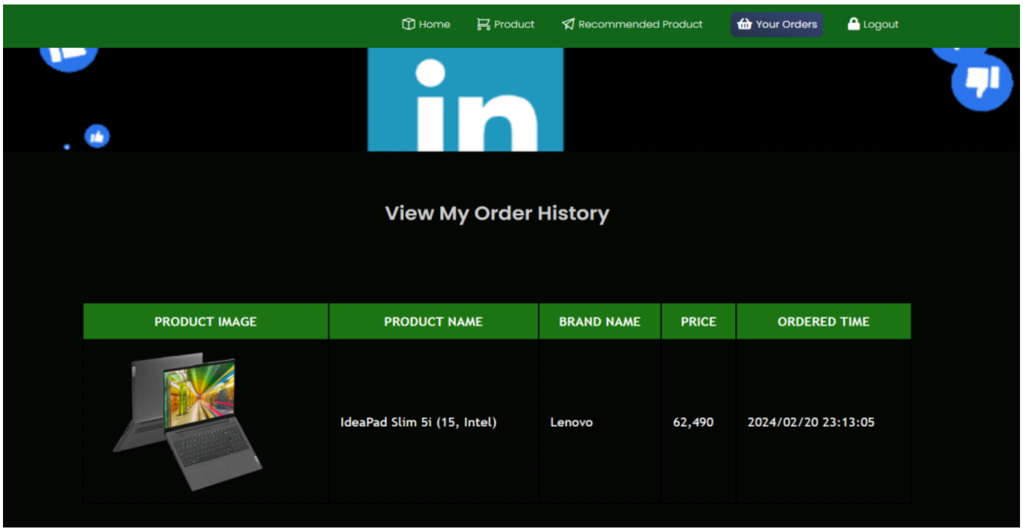
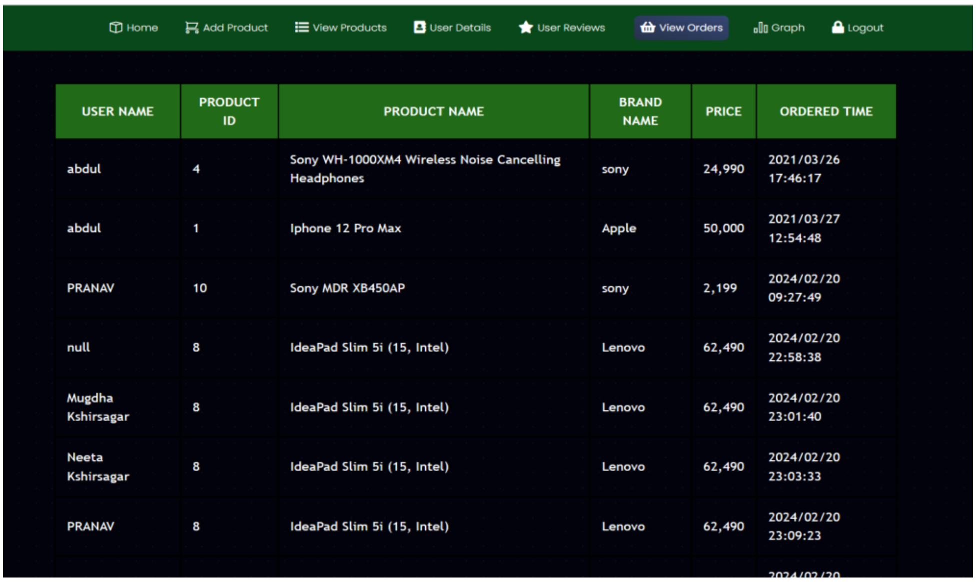


Figure 18: User Order Details

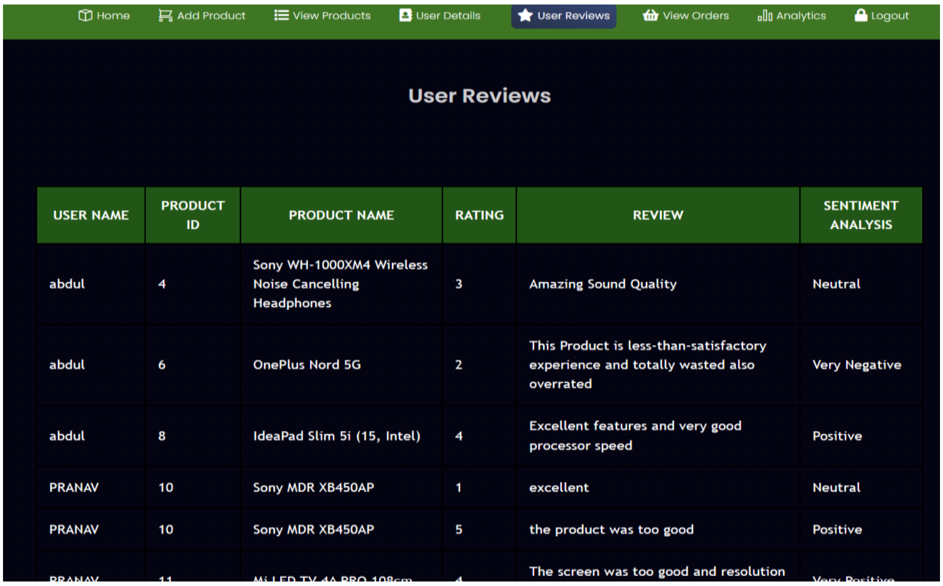
Below Figure 19 shows that the admin can view all user details in a tabular form from his account.



USER NAME	PRODUCT ID	PRODUCT NAME	BRAND NAME	PRICE	ORDERED TIME
abdul	4	Sony WH-1000XM4 Wireless Noise Cancelling Headphones	sony	24,990	2021/03/26 17:46:17
abdul	1	Iphone 12 Pro Max	Apple	50,000	2021/03/27 12:54:48
PRANAV	10	Sony MDR XB450AP	sony	2,199	2024/02/20 09:27:49
null	8	IdeaPad Slim 5i (15, Intel)	Lenovo	62,490	2024/02/20 22:58:38
Mugdha Kshirsagar	8	IdeaPad Slim 5i (15, Intel)	Lenovo	62,490	2024/02/20 23:01:40
Neeta Kshirsagar	8	IdeaPad Slim 5i (15, Intel)	Lenovo	62,490	2024/02/20 23:03:33
PRANAV	8	IdeaPad Slim 5i (15, Intel)	Lenovo	62,490	2024/02/20 23:09:23

Figure 19: Admin Home Page-Order Details

Below Figure 20 shows that the admin can view all user reviews given by various users on various products from his account.



USER NAME	PRODUCT ID	PRODUCT NAME	RATING	REVIEW	SENTIMENT ANALYSIS
abdul	4	Sony WH-1000XM4 Wireless Noise Cancelling Headphones	3	Amazing Sound Quality	Neutral
abdul	6	OnePlus Nord 5G	2	This Product is less-than-satisfactory experience and totally wasted also overrated	Very Negative
abdul	8	IdeaPad Slim 5i (15, Intel)	4	Excellent features and very good processor speed	Positive
PRANAV	10	Sony MDR XB450AP	1	excellent	Neutral
PRANAV	10	Sony MDR XB450AP	5	the product was too good	Positive

Figure 20: Admin Home Page - User Reviews

The below Figure 21 Admin can add new products on the website as well as view all the products available on the website.

PRODUCT IMAGE	PRODUCT NAME	BRAND NAME	DESCRIPTION	PRICE	TAG	CATEGORY
	Iphone 12 Pro Max	Apple	A14 Bionic rockets past every other smartphone chip. The Pro camera system takes low-light photography to the next level — with an even bigger jump on iPhone 12 Pro Max. And Ceramic Shield delivers four times better drop performance.	50,000	Iphone	Mobile
	Oppo OW19W6 Smart Watch	Oppo	Aluminum alloy Watch frame, Magnetic Charging Fluororubber strap, 320 x 360 resolution 4.06 cms (1.6 inch) Rigid AMOLED Screen Display 300mAh (Typical value) /289mAh battery	14,990	Smart Watch	Accessories
	New Inspiron 15 7501 Laptop	Dell	10th Generation IntelÂ®Coreâ?¢ i5-10300H (8MB Cache, up to 4.5 GHz, 4cores) laptop Windows 10 Home Single Language, English video card NVIDIAÂ® GeForce GTXÂ® 1650 Ti 4GB GDDR6 memory 8GB, onboard, DDR4, 2933MHz harddrive 512GB, M.2 PCIe NVMe Solid State Drive color, LCD Back Cover - Silver	89,990	Laptop	Laptop

Figure 21: Admin Page - View Products and Add Products

VIII. CONCLUSION

In summary, our analysis underscores the pivotal role of dataset selection in recommendation system efficacy, with the Amazon Electronics dataset and Singular Value Decomposition (SVD) algorithm emerging as optimal choices. Outperforming the Retail Rocket Recommender system dataset, our approach showcases substantial improvements, ranging from 32.9% to 91.7%, across key metrics. Moving forward, prioritizing quality datasets and algorithmic strategies will augment recommendation system effectiveness, enriching the online shopping experience. Further, our product recommendation system marks a significant stride in enhancing e-commerce by seamlessly integrating user-centric features such as registration, browsing, purchasing, and reviews, alongside sentiment analysis. Setting itself apart, our system offers valuable insights into product sentiment, elevating recommendation relevance. The incorporation of personalized recommendations based on user behavior, coupled with robust administrative features, empowers administrators and lays a foundation for future innovations in personalized recommendation systems, fostering user engagement and satisfaction in the evolving landscape of online shopping.

IX. FUTURE SCOPE

The Future Scope of the project involves the following points:

1. For recommendation algorithms, other factors like age, user personality, and demographic factors can also be taken into consideration to improve recommendations.
2. As the paper shows that SVD on the retail rocket recommender dataset gives less accurate results, we can use neural collaborating filtering(NCF).
3. To tackle with cold start issue, personality-aware product recommendations can be implemented using Big 5 and MBTI personality prediction models [20]

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