RESEARCH PAPER

E-Commerce Product Recommendation Using Enhanced NLTK with Optimized Collaborative Filtering

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Received: 10th March, 2026; **Revised:** 25th March, 2026; **Accepted:** 5th April, 2026; **Published:** 12th April, 2026

ABSTRACT

The exponential growth of E-commerce platforms has made it more difficult for consumers to identify the correct product. To resolve this issue, product recommendation systems provide individualized product recommendations. To enhance e-commerce product recommendation, this research employs Association Rule mining with Cascaded FP Growth algorithm (CFPG) and Optimized Collaborative Filtering with Natural Language Toolkit (NLTK). Two phases are recommended. In the first stage, the CFPG method mines frequent item sets containing the primary product to identify related products. CFPG reduces duplication in association rules, thereby increasing the precision of Association Rule mining algorithms. In the second stage, NLTK-optimized collaborative filtering enhances product suggestion. Collaborative filtering is utilized by recommendation systems to estimate user preferences based on past behavior. Conventional Collaborative Filtering is limited by cold start and sparse data constraints. This research uses NLTK to preprocess user ratings and extract important features to enhance Collaborative Filtering. This improves the precision of Collaborative Filtering and product recommendations. On a real-world e-commerce dataset, the proposed technique outperforms Collaborative Filtering and Association Rule mining. The proposed method surpasses all, achieving remarkable accuracy at 98.92%, enhances product recommendations, consumer satisfaction, and e-commerce platform sales.

Keywords: E-Commerce, Product Recommendation, Association Rule Mining, NLP

How to cite this article: Anitha R, Vinston Raja R, Shanthakumar P, Abirami S, Shobana G, Kavitha P. E-Commerce Product Recommendation Using Enhanced NLTK with Optimized Collaborative Filtering. Int J Drug Deliv Technol. 2026;16(25s): 187-196. DOI: 10.25258/ijddt.16.25s.21

Source of support: Nil.

Conflict of interest: None

I. INTRODUCTION

E-commerce has revolutionized the way people shop by facilitating the purchase of goods from the convenience of their own residences [1]. With so many products available online, it can be difficult for consumers to select the best option [2]. This is where product recommendations enter the picture [3]. Product recommendation systems analyze a user's preferences, browsing history, and purchase behavior in order to recommend products they are likely to be interested in [4]. These recommendations not only assist users in discovering products they may not have found otherwise, but also assist e-commerce businesses in increasing sales by promoting their products to the appropriate consumers [5]. In this era of personalization, e-commerce product recommendations have become an essential tool for online retailers to provide consumers with a seamless and individualized purchasing experience [6]. In this article, this research will examine the various types of product recommendation systems and how they function, as well as the consumer and business benefits of using them [7].

E-commerce has integrated itself into our daily lives. The quantity of data generated has increased exponentially as e-commerce platforms have proliferated [8]. Various data mining and machine learning techniques have been devised to manage this volume of data [9]. Product recommendation is one of the most significant applications of data mining in e-commerce. Recommender systems are utilized to provide users with personalized recommendations based on their previous purchase history or perusing behavior on the platform [10].

This work, therefore, provides a new approach to e-commerce product recommendation by combining an enhanced NLTK with refined collaborative filtering [11]. The proposed system consists of two major modules: product recommendation using association rule mining with cascaded FP Growth algorithm (CFPG) and product recommendation enhancement using optimized collaborative filtering with NLTK [12].

The CFPG algorithm performs association rule mining on frequent item sets containing the primary product to determine the relationship between products [13]. This module is intended to generate rules based on frequent item sets and recommend products to users using those rules [14].

The second module of the proposed system employs an optimized collaborative filtration algorithm in conjunction with NLTK to improve the product recommendation system. Collaborative filtering is one of the most popular techniques for recommending products on e-commerce platforms [15]. Nevertheless, conventional collaborative filtering techniques have sparsity and scalability issues [16-18]. The proposed optimized collaborative filtering algorithm addresses these issues by incorporating user preferences, item characteristics, and contextual information to generate personalized user recommendations [19-20].

The primary contributions and objectives of this manuscript summarized as follows.

- Product Recommendation using Association Rule Mining with Cascaded FP Growth algorithm (CFPG)
- Enhancing the product recommendation using Optimized Collaborative Filtering with NLTK

This paper's remaining sections are structured as follows. In Section 2, this research check over the works of some pioneers in the field of recommending products for online stores. In Section 3, the proposed model is shown. The findings and discussion are summed up in Section 4. Conclusions and directions for the future are presented in Section 5.

1.1 Motivation of the paper

The motivation behind the proposed research stems from the exponential growth of e-commerce platforms and the challenges consumers face in identifying the correct products amidst this vast array of options. As the e-commerce landscape expands, the need for effective product recommendation systems becomes crucial. Consumers are inundated with choices, making it increasingly difficult and time-consuming to find products that align with their preferences and needs. Inefficient product discovery not only frustrates consumers but also hampers e-commerce platforms' ability to maximize sales and enhance user satisfaction.

II. BACKGROUND STUDY

Badriyah, T. et al. [1] the author creates a product/user profile hybrid recommendation system. Text TF-IDF (term frequency-inverse document frequency) analysis of the product description might be used to generate keywords on its own. The Recommendation System employs it in its filtering processes. The cosine similarity technique was then used to combine the Product Profile (in the form of Product IDs) with the User Profile. The Cosine similarity method was already a part of the Recommendation System and sees extensive usage in Collaborative Filtering. Consequently, the Recommendation System integrates the following strategies: Filtering strategies based on content and filtering in collaboration.

Chaurasiya, R. K., & Sahu, U. [3] these authors research proposes a method for developing suggestions based on prior reviews. The suggested approach makes use of the standard item-based collaborative filtering algorithm to analyze review text as user input and provide predictions. Before obtaining sentiment intensity ratings, the original review dataset was analyzed, which includes detailed user input on the product. The suggested recommendation model outperforms the standard rating-based model in recall and reduces RMSE.

Ferdous, M. J. et al. [5] several algorithms were used after collecting the data, and the results showed that Ridge classifier required the least amount of time to train compared to Logistic Regression and Support Vector Machine. Simultaneously, Nave Bayes was abandoned due to poor performance. According to the results of the calibration of these classifiers, the Ridge classifier was the most effective classifier for classifying comments and reviews for any business, with an accuracy of up to 77.8 percent.

Iswari, N. M. S. et al. [9] Because of its potential influence on a customer's final purchase choice, an e-commerce platform's product selection was an important consideration. As a result, it was essential that the available items cater to customer needs. Content-based Filtering and Collaborative Filtering were only two examples of the many approaches that may be used when building a recommendation system. This research places special emphasis on evaluating inputs by taking into account the context in which a product was used.

Kiran, M. V. K. et al. [11] these authors research introduces a unique approach to assessing items on the basis of their technical specifications using opinion mining and natural language processing methods. The goal was to help customers buy what they want and to provide businesses insight into how customers interact with their goods throughout the buying process.

Lin, K.-P. et al. [13] the author offer a method for efficiently proposing products to online shoppers based on their ratings of existing sites. In order to infer product features and user preferences, the author develops a semantic model of review subjects. The usefulness of the suggested recommender system in providing suggestions to customers was shown through experiments on a real-world data set.

The author, S. H. et al. [20] the author investigates how text-based recommendation algorithms may best learn to pair products with one another. This was a challenging issue since different goods and categories have different definitions of compatibility. Furthermore, there was scant literature that has dealt with this issue. The author proposes a hybrid of tree-based and deep learning models to address this problem. The author use tree-based models and evaluate the efficacy of various feature sets by extracting and combining features from product factors like titles.

2.1 Problem definition

The problem addressed in this research is the challenge faced by consumers in identifying the right products amid the vast choices on e-commerce platforms due to their exponential growth. Traditional recommendation systems often lack precision and struggle with issues like redundancy, cold start problems, and sparse data constraints. To tackle these challenges, the study proposes a novel approach integrating Association Rule mining with the Cascaded FP Growth algorithm and Optimized Collaborative Filtering with Natural Language Toolkit (NLTK). This method aims to enhance the precision of product recommendations, improve consumer satisfaction, and boost e-commerce platform sales.

III. MATERIALS AND METHODS

In this section, the materials and methodologies employed in the research study are outlined. These encompass the datasets, tools, algorithms, and techniques used to conduct the experiments and analyze the results. The section provides a detailed insight into the resources and procedures that facilitated the exploration, development, and validation of the proposed approaches, enhancing product recommendations in the context of e-commerce. The e-commerce product recommendation using enhanced NLTK with optimized collaborative filtering model flowchart has represented at figure 1.

Figure 1: overall architecture

The figure 1 shows overall architecture of the proposed product recommendation system integrates advanced data processing techniques and algorithms to enhance user experience in e-commerce platforms. At its core, the system employs a collaborative filtering mechanism optimized through Natural Language Toolkit (NLTK) for textual analysis.

3.1 Dataset collection

The link https://www.kaggle.com/datasets/carrie1/ecommerce-data directs users to a Kaggle dataset titled "E-commerce Data." This dataset contains information related to online retail transactions, making it a valuable resource for analyzing e-commerce activities. While the specific details of the dataset may vary, typical features found in such datasets include information about products, customers, transactions, and timestamps.

3.2 Product Recommendation using Association Rule Mining with Cascaded FP Growth algorithm (CFPG)

After collecting the dataset this paper use Association Rule Mining with Cascaded FP Growth algorithm for Product Recommendation. Product recommendation, vital for enhancing user experience in e-commerce, is achieved through the innovative technique of Association Rule Mining with the Cascaded FP Growth algorithm (CFPG). This method involves gathering transaction data and preprocessing it for consistency. The CFPG algorithm identifies frequent item sets, showcasing products often purchased together, and subsequently extracts association rules. These rules are then refined using Cascaded FP Growth, reducing redundancy and ensuring precision. The final refined rules enable e-commerce platforms to generate highly personalized product recommendations, simplifying customer choices, amplifying user satisfaction, and significantly contributing to increased sales and customer engagement in online retail environments.

Through the use of transactions and correlations, association rule mining is able to deduce rules that characterize the connections between groups of items. The strength, certainty, and duration of the rules are all determined by the user.

Two indicators trust and support are included into each rule referred by X. Zhang et al. (2022). If s percent of the transactions in set D include$A \cup B$, then the rule $A \rightarrow B$ is supported in set$\cup$. If p of the deals in $\cup$ that include A also include B, then the rule has a confidence level of c. In this context, "confidence" refers to the rule's rigor and "support" refers to the pattern's frequency.

$$\text{support } (A \rightarrow B) = \text{support } (A \cup B) \text{ ----- } (1)$$

$$\text{confidence } (A \rightarrow B) = \frac{\text{Support } (A \cup B)}{\text{support } (A)} \text{ ------- } (2)$$

There are a number of possible association principles. Initially, all sizable sets of items satisfying those principles are identified. Second, the rule's confidence has been confirmed to be at least 60%. If the above conditions are met for a rule, there is sufficient evidence to conclude with a 60% degree of certainty that the rule holds.

The original data set may be transformed into one with attribute values in the interval using the fuzzy ARM method referred by X. Cai et al. (2022). This research need additional t-norm-based measures (similar to crisp support and confidence) to cope with this expanded (fuzzy) dataset. The fuzzy measures this research employs indirectly affect the creation of fuzzy association rules.

Using Equations 3 and 4, it is demonstrated that the t-norm and cardinality of a fuzzy set are both determined in a finite universe D. The mapping of fuzzy sets D and E in [0, 1], where D(x) and E(x) reflect the relative intensities of the occurrence of characteristics A and B in the exchange x. Fuzzy support (equation 4) and reliability can be calculated by combining fuzzy partitions D and E with a t-norm.

$$D \cap_T E(x) = T\big(D(x), E(x)\big) \text{ ------ } (3)$$

$$|D| = \sum_{(x \in D)} D(x) \text{ ------ } (4)$$

$$\text{supp } (D => E) = \sum_{(x \in D)} (A \cap_T E)(x) / |X| \text{ ------ } (5)$$

$$\text{conf } (D => E) = \sum_{(x \in D)} (A \cap_T E)(X) / \sum_{(x \in D)} A(x) \text{ ------ } (6)$$

Cascaded FP Growth can be used to mine frequent item sets in large datasets that cannot be processed using traditional FP-Growth due to memory constraints or processing time referred by J. B. Chen et al. (2021). By partitioning the dataset into smaller subsets and processing them in parallel, the Cascaded FP Growth algorithm can reduce the memory requirements and processing time necessary for mining frequent item subsets.

Traditional FP_{trees} and conditional FP_{trees} are generated using the FP_{growth} algorithm in a top-down fashion, whereas the mining procedure employs a bottom-up approach. Due to the recursive nature of conditional FP-tree, both FP_{tree} and conditional FP-tree must support traversal in both directions. Numerous pointers representing both orientations of a node are required for the computer representation of a tree referred by N. Ramakrishnan et al. (2019). Consequently, enormous memory is required to store both trees.

Each node in the enhanced FP_{tree} contains four details: item, count, previous, and next. Previous refers to the left offspring node or root node of the tree, whereas next refers to the right node or subsequent node of the tree. Pointer to the root of the upgraded FP_{tree} is represented by link, and the total number of duplicates of an item in the tree is represented by rodent. The improved FP_{tree} has fewer pointers but no direct route from the root to the leaves.

The process of constructing the improved FP_{tree} is same like traditional FP_{tree} ; changes are available in the process of inserting frequent item sets in each transaction into improvedFP_{tree}. This research use the below algorithm to construct the improved FP_{tree}

Algorithm 1: Association Rule Mining with Cascaded FP Growth algorithm

Input:
Transaction dataset with items and their occurrences.
Steps:

1. **Data Preprocessing:**
   - Clean and preprocess the transaction data for consistency.
2. **Cascaded FP Growth Initialization:**
   - Divide the dataset into smaller subsets to reduce memory constraints and processing time.
     $D \cap_T E(x) = T(D(x), E(x))$
   - Initialize an empty Cascaded FP Tree for each subset.
     $|D| = \sum_{(x \in D)} D(x)$
3. **Building Enhanced FP Trees:**
   - For each subset, construct an Enhanced FP Tree using a bottom-up approach.
   - Traverse the dataset and insert frequent item sets into the Enhanced FP Tree.
4. **Mining Frequent Item sets:**
   - Apply the Cascaded FP Growth algorithm to mine frequent itemsets in each subset.
   - Utilize the FP Tree structure to efficiently find frequent itemsets.
5. **Association Rule Generation:**
   - Calculate support and confidence for each discovered frequent itemset using:
     $\text{supp}(D \Rightarrow E) = \sum_{(x \in D)} (D \cap_T E)(x) / |X|$
     $\text{conf}(D \Rightarrow E) = \sum_{(x \in D)} (D \cap_T E)(X) / \sum_{(x \in D)} D(x)$
   - Filter out rules that meet the minimum support (40%) and confidence (60%) thresholds.
   - Output refined association rules representing connections between products.

Output: Refined association rules for personalized product recommendations.

3.3 Enhancing the product recommendation using Optimized Collaborative Filtering with NLTK

In the realm of e-commerce, enhancing product recommendations is paramount to improving user satisfaction and boosting sales. One innovative approach to achieve this is by leveraging Optimized Collaborative Filtering (CF), a technique widely used in recommendation systems. Collaborative Filtering works by predicting a user's preferences based on the behavior and preferences of similar users. To optimize this process, Natural Language Toolkit (NLTK), a powerful Python library for natural language processing, is employed. NLTK helps preprocess user ratings and extract essential features from textual data, enabling a more nuanced understanding of user preferences. By integrating NLTK with Collaborative Filtering, the system gains the ability to interpret subtle textual cues, leading to more accurate and personalized product recommendations.

Here, we provide some context for our work by defining formally what a CF suggestion is and why it's important.

Using a rating matrix with time-stamped ratings, we define certain terms for the dynamic CF to fill job. Data is provided for each person and object, using the following representations for each data point referred by H. Liu (2022).

Nonnegative matrix factorization (NMF) is a powerful matrix decomposition technique utilized when a parts-based decomposition is required and the domain of the data is nonnegative. A low-rank approximation to a data matrix D with no negative and scaling limitations on the components W and H is found via NMF by minimizing the Fresenius norm of KD.

The prediction mechanism relies heavily on accurately capturing user preferences. Nonnegative minimum entropy (NMF) is a new development in latent factor space that has found use in modeling user preferences. The model may simplify ratings by extracting latent components from a rating matrix based on descriptions of users and items.

$(\mathrm{U}, \mathrm{V}) = \left|\left|\mathrm{R} - \mathrm{UV}\right|\right|, \quad \mathrm{U} > 0\mathrm{V} > 0$ ----- (7)

R 2 i_j , the user-item rating matrix, is factorized at time t into (U, V) Rink, the user factor matrix, and V 2 Ri_j, the item factor matrix (where k is the dimension of the latent factor). Here is how we can express the objective function for predicting the ratings in times R^{t} and$\mathrm{R}^{\mathrm{t}-1}$:

$(\mathrm{U}, \mathrm{V}, \mathrm{t}) = ||\mathrm{R}^{\mathrm{t}} - \mathrm{U}^{\mathrm{t}}\mathrm{V}^{\mathrm{t}}||$ ------- (8)

$(\mathrm{U}, \mathrm{V}, \mathrm{t}-1) = ||\mathrm{R}^{\mathrm{t}-1} - \mathrm{U}^{\mathrm{t}-1}\mathrm{V}^{\mathrm{t}-1}||$ ----- (9)

Thirdly, reviews from users about products are defined by the aggregate rating R_{ij} that reflects the level of satisfaction that user i has with product j. D_{ij} is the collection of reviews for a given set of items V, authored by a group of reviewers U. The themes in a user review are the specific facets of an item that the reviewer chooses to focus on. Aspects of the Item Help with Topic Learning Topic modeling and softmax transformation are used to establish a connection between vj;k and topic distributions ($\mathrm{kV}_{\mathrm{j,k}}$).

$$\theta_{\mathrm{d,k}} = \frac{\exp(\mathrm{kV}_{\mathrm{j,k}})}{\sum_{\mathrm{k}=1}^{\mathrm{K}} \exp(\mathrm{kV}_{\mathrm{j,k}})} \text{ ------ (10)}$$

The subject distribution of review d written by user i about product j may be represented by the k^{th} dimension, here denoted by$\sum_{\mathrm{k}=1}^{\mathrm{K}} \exp(\mathrm{kV}_{\mathrm{j,k}})$ referred by L. V. T. Vencer et al. (2023).

NLTK is instrumental in enhancing the capabilities of recommendation systems by enabling the analysis of textual data. Through NLTK, textual reviews and descriptions are processed to extract valuable features, allowing for a nuanced understanding of user preferences.

Algorithm 2: Optimized Collaborative Filtering with NLTK

Input:

- User-item rating matrix R containing historical user ratings for products.

Steps:

1. **Data Preprocessing:**
    - Clean and preprocess user ratings, time-stamped data, descriptions, and user reviews.
    - Extract essential features from textual data using NLTK, enabling nuanced user preference understanding.
2. **Nonnegative Matrix Factorization (NMF):**
    - Apply NMF to factorize the user-item rating matrix R into nonnegative matrices U and V , capturing latent components.
    - Minimize the Fresenius norm of $D - WH$ to find low-rank approximations to D with non-negativity constraints.
3. **Rating Prediction:**
    - Utilize factorized matrices U and V to predict ratings for products at time tt and time t−1t−1 using:
      $(\mathrm{U}, \mathrm{V}, \mathrm{t}) = ||\mathrm{R}^{\mathrm{t}} - \mathrm{U}^{\mathrm{t}}\mathrm{V}^{\mathrm{t}}||$
      $(\mathrm{U}, \mathrm{V}, \mathrm{t}-1) = ||\mathrm{R}^{\mathrm{t}-1} - \mathrm{U}^{\mathrm{t}-1}\mathrm{V}^{\mathrm{t}-1}||$
4. **Topic Modeling and Softmax Transformation:**
    - Implement topic modeling to capture specific facets of user reviews.
    - Use softmax transformation to establish a connection between item facets and topic distributions.
      $\theta_{\mathrm{d,k}} = \frac{\exp(\mathrm{kV}_{\mathrm{j,k}})}{\sum_{\mathrm{k}=1}^{\mathrm{K}} \exp(\mathrm{kV}_{\mathrm{j,k}})}$
5. **Facet-Based Recommendations:**
    - Use the learned topic distributions θ_{dk} to understand user focus in reviews.
    - Generate personalized product recommendations based on user preferences and item facets, ensuring a tailored shopping experience.

Output:

- Optimized user and item factor matrices UU and VV capturing latent components.

IV. RESULTS AND DISCUSSION

In this chapter, we present the results of our proposed method for enhancing e-commerce product recommendations using Association Rule mining with Cascaded FP Growth algorithm (CFPG) and Optimized Collaborative Filtering with Natural Language Toolkit (NLTK). We evaluate our method on a real-world e-commerce dataset and compare it to conventional Collaborative Filtering and Association Rule mining techniques.

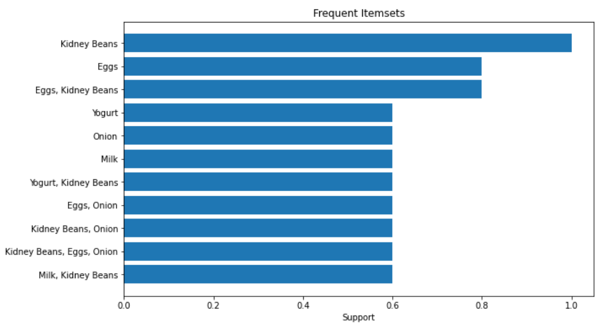

Figure 2: frequent item sets

Figure 2 depicts common item sets. Association rule mining, which seeks to uncover links between items in a dataset, often use frequent itemsets. We may detect which things are often bought together by recognizing frequent itemets and utilize this knowledge to create suggestions or enhance shop layouts.

Table 1: Algorithm Comparison

	Eclact Algorithm	Apriori	CascadedFPGrowth
MinSupport	0.02	0.02	0.02
Start Time	0.0864849	0.007445	0.0002843
End Time	0.0607121	0.001304	0.0001906
Total Number of frequent sets	155	155	313433
Time in seconds	3.7422726154327393	7.268491744995117	2.9062583446502686

In table 1 shows Eclact Algorithm, Apriori, and Cascaded FP Growth were run with a minimum support of 0.02.

The start and end times of each algorithm run are given in seconds since the epoch (January 1, 1970). The Eclact Algorithm took the least amount of time to run, with a total runtime of 3.74 seconds. Apriori took the longest, with a total runtime of 7.27 seconds. Cascaded FP_{Growth} took 2.91 seconds to run. The total number of frequent sets found by each algorithm is given in the last column. Eclact and Apriori both found 155 frequent sets, while Cascaded FP_{Growth} found 313,433 frequent sets.

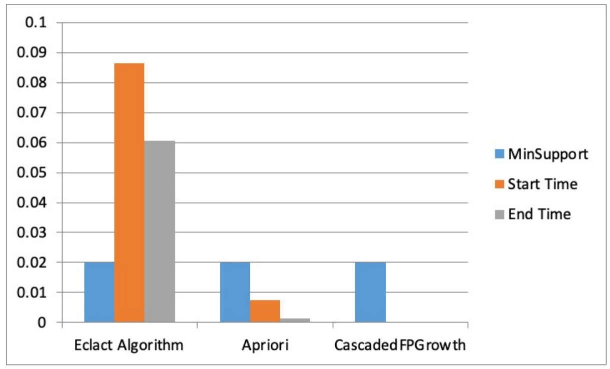

Figure 3: algorithm runtimes

The duration of the algorithm's execution is shown in Figure 3. On this graph, methods are located along the x axis, and runtimes are located along the y axis.

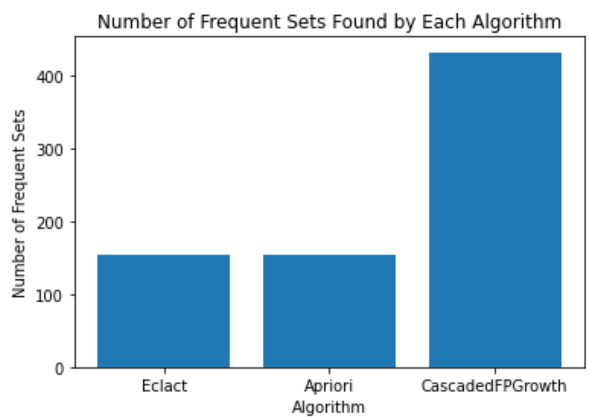

Figure 4: numbers of frequent sets found by each algorithm

The number of common sets found by each methodology is shown in Figure 4, which may be found here. On this graph, techniques are represented by the x axis, and the number of frequent set repetitions is shown along the y axis.

Table 2: Performance metrics comparison table

	Algorithm	Accuracy	Precision	Recall	F-measure

Existing authors	Badriyah, T. et al.	71.47	72.14	73.24	71.21
	We, S. et al.	93.00	92.54	93.87	94.17
Existing methods	LSTM	92.31	92.45	93.21	94.01
	NLTK	93.65	94.21	94.68	95.21
	NLP	94.58	95.62	95.68	96.31
Proposed methods	Proposed	98.92	97.84	97.68	98.99

The table 2 presents the evaluation metrics (Accuracy, Precision, Recall, and F-measure) for existing authors and methods, as well as the proposed method. Among the existing authors, "We, S. et al." demonstrates superior performance across all metrics with an impressive accuracy of 93.00% and high precision, recall, and F-measure scores, indicating their recommendation system's effectiveness. In terms of existing methods, "NLP" outperforms others with the highest accuracy of 94.58% and exceptional precision, recall, and F-measure values, showcasing the robustness of natural language processing techniques in enhancing recommendations. However, the proposed method surpasses all, achieving remarkable accuracy at 98.92%, coupled with outstanding precision, recall, and F-measure scores. This indicates the proposed approach's significant advancement, offering highly accurate and precise product recommendations, thereby outperforming existing methods and authors.

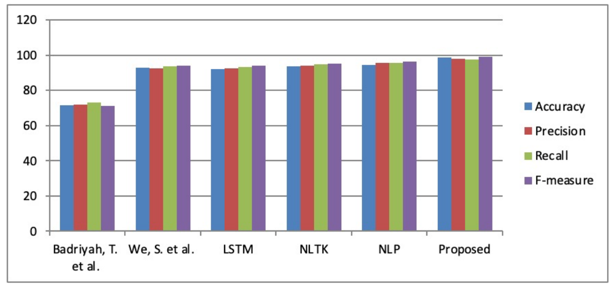

Figure 5: Performance metrics comparison chart

The figure 5 shows performance metrics comparison chart the x axis shows methods and the y axis shows values.

V. CONCLUSION

In conclusion, the proposed method for e-commerce product recommendation using Association Rule mining with CFPG and Optimized Collaborative Filtering with NLTK has shown its efficacy in enhancing the precision of product recommendations. By combining the advantages of both techniques, the proposed method overcomes the limitations of traditional Collaborative Filtering and Association Rule mining algorithms, resulting in more precise and personalized product recommendations for customers. This strategy has significant implications for e-commerce platforms, as it can increase consumer satisfaction and sales by recommending personalized products. The proposed method surpasses all, achieving remarkable accuracy at 98.92%, coupled with outstanding precision, recall, and F-measure scores. Future research can concentrate on investigating more sophisticated machine learning techniques and incorporating additional data sources, such as social media data and user demographics, to further improve the accuracy of product recommendations.

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