International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Personalized Online Book Recommendation System Using Hybrid Machine Learning Techniques

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Submitted: 10/12/2023 **Revised:** 22/01/2024 **Accepted:** 01/02/2024

Abstract: Recently, the scientific world has become interested in recommender systems research due to its exponential development. The COVID-19 pandemic has caused an exponential increase in the number of books available online, making it extremely difficult for readers to identify relevant books within the large e-book sector. According to user ratings and interests, personal recommendation systems have developed as an efficient way to search for relevant books. Recommendation systems are robust emerging technologies that aid consumers in finding products that they wish to purchase. Recommendation systems are often implemented to suggest proper goods to end customers. Recently, websites that offer books online contest with one another based on a wide range of criteria. One of the best methods to boost profits and keep customers is a recommendation system. Users are not satisfied with the current systems since they extract unnecessary information from them. To generate highly effective and productive recommendations, this study proposes the Personalized Online Book Recommendation System (PO-BRS), which is based on machine learning techniques. The authors proposed hybrid machine learning approaches that combine two or more algorithms to improve the recommendation system's ability to suggest books based on the interests of the reader. As a result, recommendations based on a specific book are found to be more accurate and profitable than systems that depend on user input.

Keywords: *Personalized Book, Recommendation System, e-book, Machine Learning, Filtering; Classification*

1. Introduction

The majority of our day-to-day activities are being carried out by technology-driven things in this era of rapidly advancing computer and internet technologies. The rate at which information is being exchanged has resulted in us referring to this period as the "era of data overload." A wide range of computational systems have been established to address the issue of information overload and assist with the analysis of information, hence lowering its impact on humans. A type of expert system called a recommender system (RS) analyses the enormous quantity of information available online, applies a set of criteria for filtering, and then provides recommendations to users. Most businesses that sell goods online include a recommendation process in place. Unfortunately, the majority of websites are not created with the interests of the user in view; instead, businesses drive customers to purchase add-ons by promoting products that are useless or unrelated. From a vast array of products, a personalized recommendation system (PRS) supports individual users in finding mysterious and practical products [1]. The proliferation of e-commerce websites has given consumers an enormous number of options when it comes to products. It can be quite difficult for customers to identify the appropriate goods at the right moment. Users can locate books, stories, films, sounds, online courses, and academic articles with the aid of a personalized recommendation system. Technological advancements in disciplines such as artificial intelligence (AI), quantum computing, and the Internet of Things (IoT) give rise to the 4th revolution in industry. People's purchasing power increases and their standard of living rises as a result of the current financial crisis.

Because of their hectic schedules and the COVID-19 pandemic, personal trips to stores and libraries have decreased significantly in recent years [2]. Rather, e-libraries and electronic markets gained popularity as gathering places. Online shopping behaviors and e-book reading systems helped people find their favorite books among a wide selection of products. Because of this, users typically use expert systems to make quick and informed decisions from an unprecedented array of options. To personalize users' searches and present the most optimal results from a variety of options, recommendation systems were introduced. The algorithms used in recommendation systems are usually created using associative rules, collaborative filtering, multi-model ensembles, and content-based filtering [3]. Personalized recommendation systems may improve from multi-model

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ensemble techniques; however, content-based filtering requires a large volume of real-time information to train the model for predictions. Multiple classifiers are common for multi-model-based RS. In that instance, two distinct frameworks may be implemented: in the initial stage, a few basic classifiers are trained, and in the next phase, the basic classifiers are merged by applying ensemble techniques such as XGBoost or AdaBoost. A multi-model ensemble technique is a common tool in spatial pattern detection. It may determine the spatial anomaly correlation with each other and may cluster the anomaly correlations. The apriori technique is implemented to identify the association rules and level of dependencies among standards.

To find patterns of spatial noise, the method of clustering functions as a filter [4]. Items are filtered collaboratively based on similar responses. It seems through an extensive number of people and finds a select few users who share an interest in collecting things. One important part of collaborative filtering is the similarity measure. It can identify the user groups that exhibit the item selection behavior [5]. The development of recommendation systems usually involves one of four primary approaches: collaborative, content-based, hybrid, or cross-domain filtering algorithms. Initially, collaborative filtering provides product recommendations based on user information and opinions. Both comprehensive and restricted senses have been included in it. It may merge data from numerous users in a specific way to generate automated predictions according to user preferences. Collaborative filtering generally entails working with a lot of different sources, individuals, and various points of perspective. It might be used in web applications, e-commerce, weather forecasting, and mineral exploration anywhere that large amounts of data are required to be processed to produce predictions.

Collaborative filtering has the disadvantage of requiring a large amount of user data, so it's appropriate for certain applications where information is not used. Conversely, object similarity is the basis for recommendation in content-based filtering, which uses object information. Content-based filtering is generally helpful in situations where we lack relevant data. When recommending, the products' similarities are taken into consideration. Machine learning algorithms, both supervised and unsupervised, are used to gauge how identical goods are to one another. Although the content can be unstructured, semi-structured, or structured, the Similarity calculation requires that it be synchronized into a structured format. The output of a hybrid recommendation system is generated by combining two or more filtering methods. When compared to content-based and collaborative filtering, hybrid filtering performs better.

Domain dependencies are not taken into account by collaborative filtering, and user preferences are not taken into account by content-based filtering. To achieve better predictions, collaborative and content-based filtering techniques must work together. By working together, the common knowledge in content-based filtering with user preferences and collaborative filtering with content data is increased. Information from several domains can be accessed by cross-domain filtering algorithms. By examining the source domain, cross-domain filtering algorithms enhance their prediction in the target domain. A collaborative, hybrid, content-based, knowledge-based, and utility-based filtering system utilizing a multitude of techniques is described in this article as a novel solution to the problem of book recommendation. Using the rating and user preference datasets, clustering enables the grouping of all books. When used in a personalized book recommendation system, this kind of clustering demonstrates exceptional prediction ability. The main goal of this study is to develop a better model for adjusting the recommendation system.

The remaining part of this paper is organized as follows: Section II provides the related of this work. Section III describes the model of the hybrid proposed system. Section IV evaluates the results of our experiments and Section V discusses the conclusion of this work and the future work.

2. Related Works

Several methods for recommendation systems can offer more detailed suggestions. The two most commonly used types are content-based (CBF) and collaborative (CF). To modify an element's content according to the user description, the CBF method is aware of what the element contains. Whereas content is a determining factor in collaborative filtering, ideas are matched according to specific criteria, some users have already agreed upon these criteria in the past, and more users may agree on these criteria in the future. The ratings you provide for the products can be used to gather information about your preferences [6].

A highly accurate hybrid recommendation system built in Java that combines the best aspects of content-based, collaborative, and demographic approaches [7]. An expert tool for recommending books to e-users is the book recommendation engine that has been introduced. There's no doubt that the recommender feature will be an excellent Java web application. For the extremely demanding websites used for online purchases these days, this kind of web application could be advantageous. Due to its integration of various recommendation techniques, this hybrid recommender system exhibits higher accuracy and efficiency. The least amount of work involved in selecting the best books from the abundance should be done by the book's recommendation system.

Suggested a method for recommending news on Bing that used the SVD framework and CCF, and it turned out to be more effective than other techniques. By utilizing some of the rich contexts and concentrating on long-tail users, the proposed CCF combines the benefits of the Content-based (CBF) Filtering method with the features of the Collaborative (CF) Filtering approach. This CCF is intended for use in scenarios where a news item may be interpreted by rich contexts, like query findings, for instance, the recommendation of a Bing news subject [8].

In [9] reviewed some issues and difficulties with current recommender systems and concluded that new methods should be used to put recommender systems into practice. to search the books list according to its contents and ranking, cooperative and content-based filtering techniques were used. Existing users' ratings and recommendations for book value are the main sources of information for the recommendation system.

[10] Presented the study provides a comparative analysis of recommendation systems, highlighting the distinctions between Content-Based Filtering (CBF) and Collaborative Filtering (CF). The collaborative algorithm in this paper uses "User Behaviour" to suggest items. When it comes to rating systems, transaction histories, and details about products and purchases, they take advantage of other people and their behaviors. When suggesting products to new users, the expectations and past experiences of other users are taken into account. For content-based filtering to

work, we must be aware of the users and the item's content. The content of the shared attribute space is typically used to build user and item profiles.

[11] Uses the CF algorithm's cosine similarity and quick sort to create an online recommender system. It recommended a method that used Django, NOSQL, an improved collaborative filtering technique, and a successful fast-sort technique to show efficiency and scalability. The approach leveraged OOADM (Object-Oriented Analysis and Design Methodology). In this paper, it is explained that recommendation systems based on content, hybrid, and collaborative filtering techniques have been proposed, but they have numerous problems that are inherent in research endeavors [12]. Research in this field is required to investigate and develop new techniques that can reduce barriers and offer direction for working together to filter a variety of applications while taking confidentiality and dependability concerns into account. A hybrid recommendation system for an online book portal used KNN and associative rule mining to determine which books would be best for each user. It explains different methods of measuring similarity and comes to the conclusion that item-based methods are more accurate than user-based methods. Recommendations that depend on article similarity were made using the content-based filtering approach. This method's main issue is that it suggests new things without taking into account the ratings of existing users. However, user reviews are important when suggesting new books or journals. The current book or journal recommendation's content-based filtering is not very accurate because user rating data is absent from the papers.

AI powers the majority of the algorithms, which search for objects based on book content, popularity, and correlation [13]. The recommendation algorithm is abnormally affected by online searches. For instance, clicking on books with high rankings has no effect, but clicking on books with low rankings provides an advantage [14]. Another significant issue with the conventional book recommendation system is data sparsity, which may be resolved with a neural network and a personal rank algorithm. Both k-nearest neighbor and frequent pattern tree are particularly efficient for recommending scientific journals for academic journal readers. Furthermore, the recommendation systems may be developed with a variety of context-aware rule-based approaches, as well as their more modern pattern-based evaluation, classification-based methods [15-17], or rule-based belief prediction [18]. To get the best accuracy in this paper, a clustering-based recommendation system was implemented.

3. Proposed System

The recommender system in this paper was developed using a clustering technique. For this study, the datasets were gathered from Kaggle's Goodreads books repository. Although there are seven datasets in the Kaggle Goodreads book repository, only four were taken into consideration for this experiment. After combining all the datasets, we used the preprocessing procedure to eliminate the books with lower ratings and create a new dataset for analysis. At last, the method of clustering had been implemented to suggest books to customers who frequent a certain cluster. Additionally, a query interface allows a user to search for a book and returns a list of suggested books.

3.1 Personalized Recommendation System

A recommendation system may be personalized to the specific needs of the intended user. Based on a single user's perspective, the personalized recommendation system makes recommendations based on each user's unique activity [19].

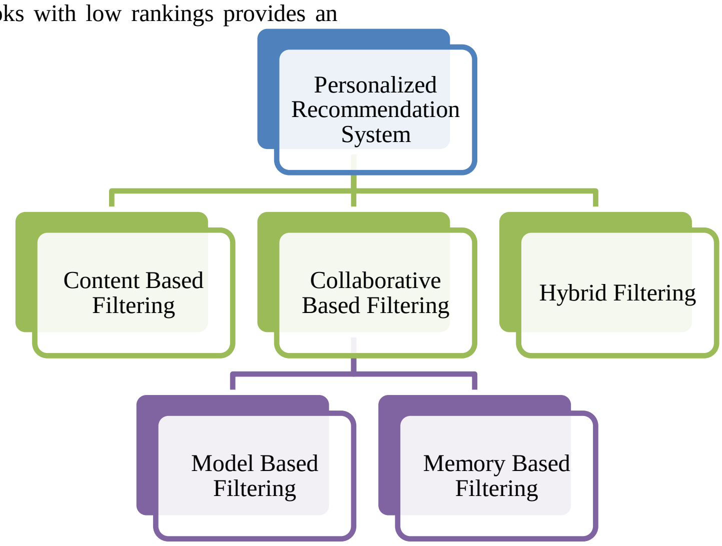

Fig. 3.1. Approaches To Personalized Recommendations that Depend on Data Filtering.

User ratings for identical products, user purchasing patterns, etc., are examples of the activity. For improved suggestions, the personalized recommender additionally considers user activity that is comparable to its own. Personalized recommendation systems are used by online retailers to offer various products to users based on their industry. Recommendation systems may be broadly classified into a content-based approach and a collaborative filtering approach.

3.1.1. Content-Based Filtering

The content-based method suggests a product to a user based on how the user has previously interacted with similar products. The objects' contents are used to evaluate similarity in this case. An instance of a suggestion based on content is the movie recommendation that appears on several websites. The various filtering mechanisms applied to recommendation systems are shown in Figure 3.1. For a content-based system to generate accurate predictions, item descriptions must be organized effectively. Let's examine the Figure 3.2 book recommendation system. It indicates that a user showed interest in and bought the book "A." Now, the content-based recommender locates book "B" that shares characteristics or content with book "A" and recommends it to the user.

When valuable content cannot be extracted from a variety of data elements, such as text, photos, audio, video, etc., content analysis becomes a problem. The quality of recommendations declines as a result of inaccurate content information. The issue of overspecialization arises from the recommendation of only products that closely resemble the products that the user prefers. This limits the user from receiving some interesting and accidental recommendations that they would have appreciated or that corresponded to those requirements. Owing to its drawbacks, CBF is rarely utilized in its pure form; instead, it is combined with another method.

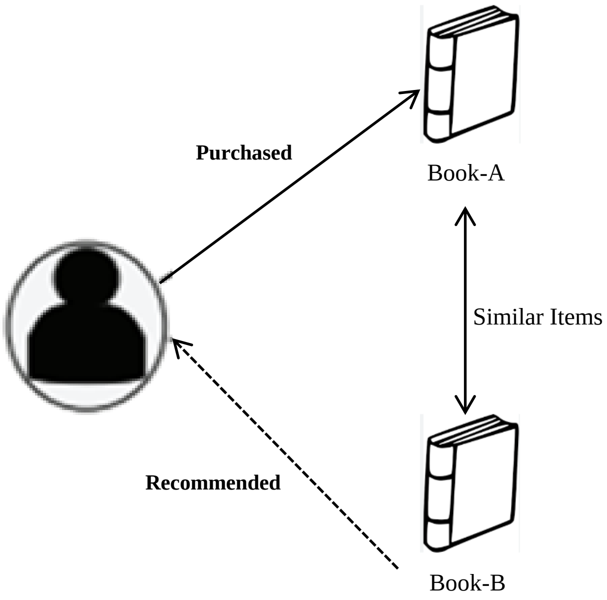

Fig. 3.2. Content-driven filtering system for Personalized Book Recommendation

3.1.2. Collaborative Based Filtering

To accurately determine the user's needs, the collaborative filtering technique combines the use of model-based [20, 21] and memory-based methods [22]. Using this approach, products are recommended to a new user based on the actions and inclinations of previous users. This strategy is seen on e-commerce sites such as Amazon and Flipkart, where a recommendation engine recommends products that the customer could find interesting or buy. This recommendation is based on product specs and other customers' purchase habits [23]. To have a deeper comprehension, let us examine the data presented in Figure 3.3. It indicates that there are three books and three users. In this situation, the book's purchase by the user is shown by the strong line connecting them. Comparably, the dashed arrow extending from the user to the book signifies that the buyer needs to read the book. The system regards to propose a new book to user-1, who has already purchased Book-A. When the system compares the preferences of users 1 and 2, it discovers that user 2 has purchased books A and C and that user 1 has comparable book interests. Thus, it suggests Book-C to user 1.

The correlation and cosine approach may be used to calculate the similarity between users in collaborative filtering [22]. The amounts of items for which both X and Y have provided comparable ratings or feedback determines the correlation between the two users, X and Y. The ratings of X and Y may be expressed via two vectors if they contain n items.

$X_{review} = [x_1,\ x_2, \dots, x_n]$ and $Y_{review} = [y_1,\ y_2, \dots, y_n]$

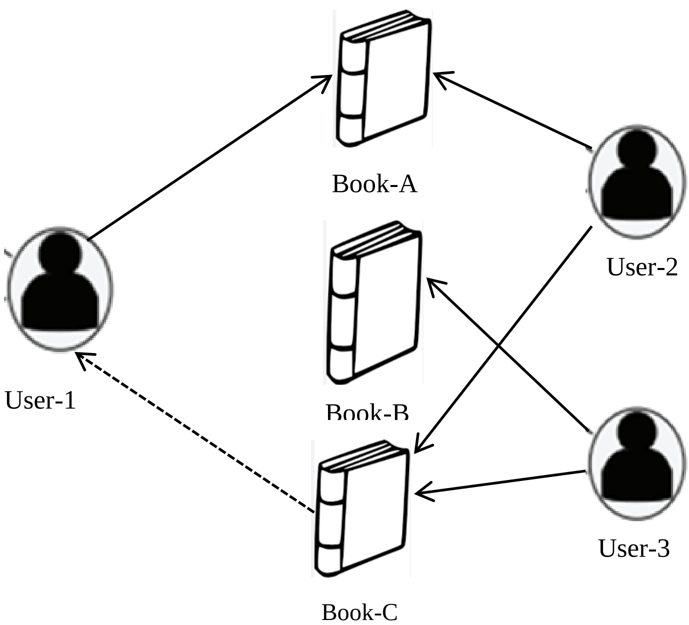

Fig. 3.3. Collaborative-driven filtering system for Personalized Book Recommendation

The correlation among X and Y can be determined by, if the mean values of these ratings are x_c and y_c, respectively,

$$F_{correlation}\ (\mathrm{X, Y}) = \frac{\sum_{g=1}^{n}(x_g - x_c)\,(y_g - y_c)}{\sqrt{\sum_{g=1}^{n}(x_g - x_c)^2}\sqrt{\sum_{g=1}^{n}(y_g - y_c)^2}} \qquad \text{(i)}$$

The Euclidean dot product approach is used in a similar way to calculate the cosine similarity. It is shown as,

$$F_{cosine}\ (\mathrm{X, Y}) = \cos(\theta) = \frac{\sum_{g=1}^{n}(x_g)\,(y_g)}{\sqrt{\sum_{g=1}^{n}(x_g)^2}\sqrt{\sum_{g=1}^{n}(y_g)^2}} \qquad \text{(ii)}$$

The angle between X and Y in an n-dimensional environment is represented by the symbol Θ in the equation ahead.

3.1.3. Hybrid Recommendation Techniques

The hybrid recommendation methodology that is used by businesses today combines several different recommendation methods [19]. The benefits of collaborative and content-based filtering are combined in a hybrid method [22, 24]. It aids to the recommendation's improved overall performance. This method may be used to improve upon the book recommendation system that was previously provided, in which a book recommendation is based on the customers' similarity to the recommended book and the correlation between the two. For recommender systems, both of the most crucial goals of design are scalability and accuracy. Although one of the most often used recommendation strategies in recommender systems is collaborative filtering (CF), it lacks both scalability and accuracy. Furthermore, content-based filtering by itself has several issues and produces inaccurate results. Conventional algorithms function effectively when concise and accurate data is provided; nevertheless, as more items and users are added to the rating matrix, the CF algorithm eventually reveals several faults.

For instance, to predict the ranking of a test item, content-based filtering methods take advantage of all of the things rated by users. Therefore, to generate an effective prediction of a test item, it requires a hybrid algorithm that adapts to the dynamic changes in a rating matrix and takes into consideration only items that are similar to the test item. For an involved user, these forecasts are utilized to generate beneficial recommendations. The content-based technique in this variant of the proposed method depends on a target item's neighbors. Here, R is a set or grouping of every item in the training set, and R is a set of things that the current user has rated. The suggested approach initially examines through the R set's scope for the K-nearest movies of a target item to forecast the rating of that item for active users. The equation shown below is used to calculate the adjusted cosine similarity between the target item and every item in the R set.

$$\cos(\mathrm{x, y}) = \frac{\sum_{c\epsilon C}(\mathrm{P}_{c,x} - P_c)(\mathrm{P}_{c,y} - P_c)}{\sqrt{\sum_{c\epsilon C}(\mathrm{P}_{c,x} - P_c)^2}\sqrt{\sum_{c\epsilon C}(\mathrm{P}_{c,y} - P_c)^2}}$$

$\mathrm{P}_{c,x}$, represents a user's rating for item x, P_c represents the average rating of user C, and $\mathrm{P}_{c,y}$, corresponds to a user's rating for item y. In this scenario, x remains a test item, y corresponds to one of the items from the R set, and C represents the users in the training set who have watched both films x and y.

The content-based technique in this instance of the proposed algorithm depends on objects that have been rated by a target user's neighbors. The suggested technique immediately finds out the K users in the domain of the R^ set who are closest to the target user to predict the rating of a target item for the active user. The following equation is used to calculate the adjusted cosine similarity between the target user and every user in the dataset:

$$\cos(\mathrm{x, y}) = \frac{\sum_{c\epsilon X_{x,y}}(\mathrm{P}_{x,c} - P_x)(\mathrm{P}_{y,c} - P_y)}{\sqrt{\sum_{c\epsilon Goods}(\mathrm{P}_{x,c} - P_x)^2}\sqrt{\sum_{c\epsilon Goods}(\mathrm{P}_{y,c} - P_y)^2}}$$

Where, the average rating for users x and y is represented by P_x and, P_y, accordingly, and the set of items rated by both users x and y is designated by, $X_{x,y}$. After doing examinations, the developers discovered that this was a poor strategy because the outcomes were not better.

4. Experimental Result and Analysis

One of the most important aspects of evaluation is determining the predictive accuracy of the book recommendation system. For analyzing the accuracy of the classifiers, receiver operation characteristic (ROC) is frequently utilized. The development of machine learning techniques, atmospheric research, and all aspects of finance depend significantly on forecasting. A graphical approach for summarising the classifiers' accuracy is provided by the ROC curve. It is extensively utilized in statistical training and education.

A typical approach to generate the predictions is binary prediction. The useful components of a ROC curve are included. Two classes exist for each classification task. Two sets, (P and N), of positive and negative class labels, respectively, comprise each instance (I). The following kinds can be present in a classifier instance. True Positive (TP) is the classification given to the positive case if it is accurately identified. However, if it is incorrectly classified, it is considered a false negative (FN). Assuming accurate classification, the negative instance is considered a true negative (TN). In addition, it is deemed to be a false positive (FP) if it is diagnosed wrongly. Table 4.1 illustrates performance evaluation findings for our proposed method before partitioning the training dataset. There are 1,500 strings in the test, of which 610 are negative and 390 are affirmative. The suggested RS classifies 240 strings incorrectly and correctly detects 760 strings. A common tool for evaluating classifier performance is the confusion matrix. The research's confusion matrix is shown in Table I.

4.1 Performance Metrics

Enhancing the user experience is the primary goal of any RS. Numerous evaluation criteria are used to evaluate the user experience. These metrics calculate an RS's different performance criteria. F-measures, precision, and recall are several instances of different assessment metrics that have been applied in survey research.

The confusion matrix is used in the typical accuracy methodology to evaluate performance. To determine accuracy, one must consider Precision, Recall, and F-Measure score. The equations that follow can be used to determine such statistics.

A. Precision

The precision measure is the proportion of the appropriate goods recommended to the entire quantity of objects the PO-BRS is authorized to. Let TR indicate the total amount of items the PO-BRS has access to, and TN is the number of relevant items the PO-BRS has recommended. An excellent recommender demonstrates a great regard for accuracy. Equation (4.1) represents mathematical precision.

$$\text{Precision (P)} = \frac{T_R}{T_N} \qquad (4.1)$$

B. Recall

Recall is the ratio of the overall number of relevant things to the number of relevant items that RS recommends. If TR denotes the total number of relevant things and TR indicates the number of relevant items that RS has recommended. The recall mathematical notation is then provided by equation (4.2).

$$\text{Recall (R)} = \frac{T_R}{T_R} \tag{4.2}$$

C. F-Measure

The precision and recall harmonic mean is called the F-measure. It is expressed as follows in mathematical notation by equation (4.3).

$$\text{F-Measure} = \frac{2*Precision*Recall}{Precision+Recall} \tag{4.3}$$

Table 4.1. Confusion Matrix

Hypothesized Class	True Class		
	Positive (P)	**Negative (N)**	**Total**
True (T)	850	150	1000
False (F)	150	350	500
Total	**1000**	**500**	**1500**

Let's expand the above description to consist of the terms "specificity = 1-FNR" and "sensitivity = 1-FPR." Specificity is referred to as the real negative rate, and sensitivity is the actual positive rate.

For the classification system, Table 4.2 displays Sensitivity, Specificity, and F1 Score. A user's preferred percentage of books is determined by sensitivity. The percentage of books that are dull for a certain user is determined by specificity. The desired and boring books that are accurately identified are then calculated to find their harmonic mean using the F1 Score. An F1 Score of one is the maximum value that is possible. Based on Table 4.2, the results indicate that 85.29%, 86.49%, and 86.27% have the highest sensitivity, specificity, and F1 Score. When compared to other datasets, dataset 3's sensitivity is higher, indicating a larger likelihood of an intriguing book list being predicted. For the average dataset, the reader's ability to identify uninterested books is 80% specific. Accuracy is not as useful as the F-score. It discovers a balanced relationship between specificity and sensitivity.

Table 4.2. Results of Performance Metrics for various Datasets

Datasets	Precision (%)	Recall (%)	F1-Score (%)
D1	76.42	70.02	76.24
D2	79.27	80.16	81.15
D3	85.29	86.49	86.27
D4	72.41	79.20	81.47
D5	80.27	70.43	80.53
Average	**78.732**	**77.26**	**81.132**

The trade-off between the sensitivity and specificity of the five distinct datasets is shown in Table 4.2 through a receiver's operating characteristic curve. From Figure 4.1, it is shown that every dataset we have used remains around the optimal diagonal path. Table 4.2 illustrates the classifier's F1 Score, Specificity, and Sensitivity. Compared to other datasets, dataset 3 has a higher sensitivity, indicating a high prediction of the chance for an interesting book collection. For dataset 5, the reader's ability to identify uninteresting books is 80% specific. Accuracy is not as useful as the F-score. It establishes a balanced relationship between specificity and sensitivity.

Parallel to the linear optimal classifier lines was probable for the majority of datasets. Every dataset remained within the worst classifier boundary.

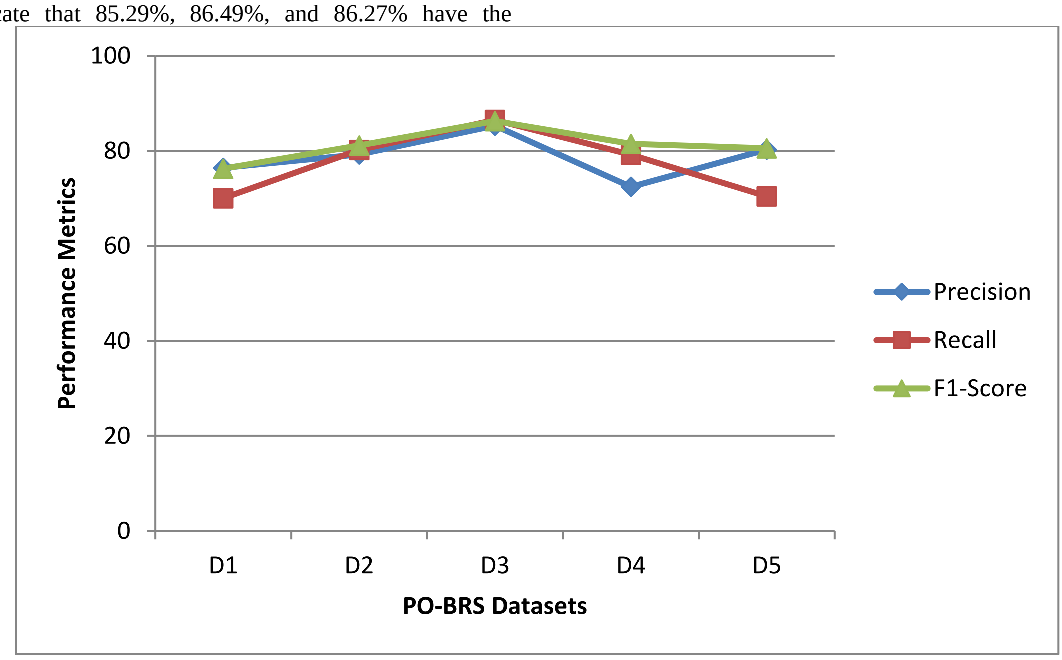

Fig. 4.1. Performance Analysis of Proposed PO-BRS

To evaluate the accuracy of the books that our proposed recommender system accurately suggests to the user, people performed several kinds of studies. Based on ratings, historical data, and user interests, one can develop a personalized recommendation system. On the text crossing file, the recommendation engine is working. The performance analysis of

KNN, RBM, SVD [25], Hybrid, and content and collaborative filtering-based similarity constitute the recommendation algorithm are shown in figure 4.2.

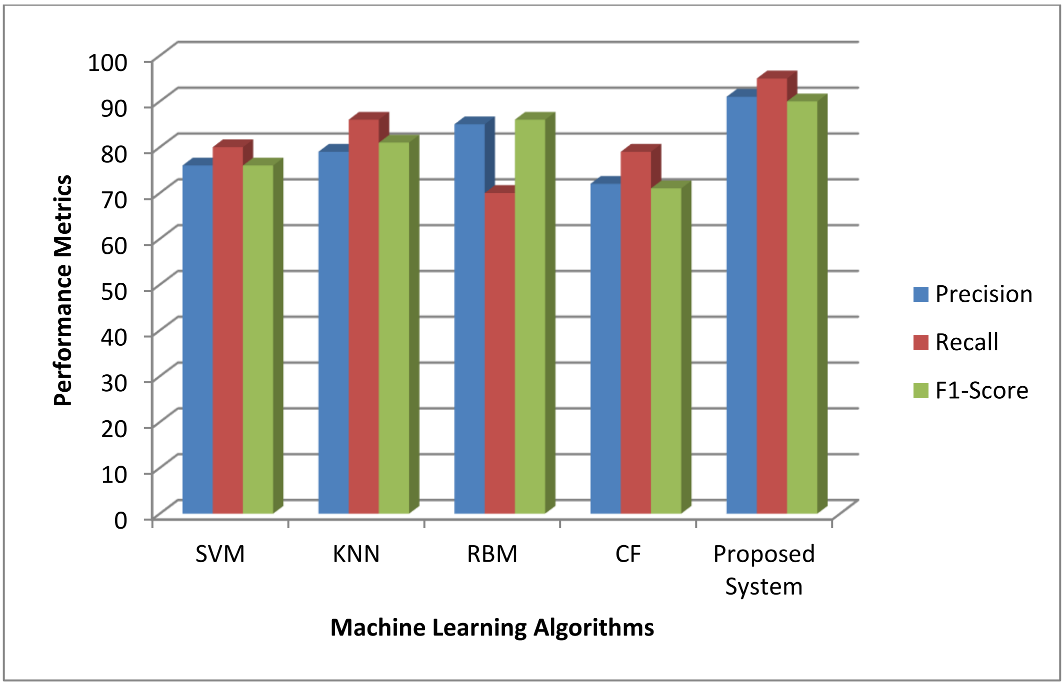

Fig. 4.2. Comparison of various Machine Learning Techniques with Proposed Hybrid RecommendationSystem

On the web application, personalized suggestions are displayed. In this experiment, a few different kinds of technology are involved. Several people and multiple books across all categories made up the modest portion of the book-crossing dataset that was used for the initial run of this experiment. To achieve the best results; we have used various hybrid algorithms.

5. Conclusion

The recommendation system has become more significant in popularity in recent years. The book recommendation system saves recommendations in the customer's online account and suggests books to customers based on their interests. In addition to decreasing the main issue, our method will provide highly personalized and accurate recommendations, doing away with the limitations of rating-based recommendation systems. The system makes use of a variety of contemporary strategies in addition to the conventional Collaborative and Content-based filtering methods. The proposed system implements a hybrid algorithm that combines collaborative and content-based techniques. Also applied is demographic evaluation, which aids in providing more individualized recommendations. As the article explains, the approach integrates several algorithms to improve the precision and calibre of customized outcomes and suggestions. The authors aim to use convolutional neural networks (CNNs) in their future work to develop a recommendation system for online course recommendations.

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