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RESEARCH ARTICLE

HSBRS: Hybrid Sentiment-based Collaborative Architecture for Book Recommendation System

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Abstract

Objectives: This study presents an efficient approach "Hybrid Sentiment-based Collaborative Architecture" to enhance book recommendation systems. This novel approach integrates sentiment analysis methodologies that encompass Lexicon-based and Deep Learning-based techniques, in conjunction with Collaborative Filtering to offer a more personalized recommendation experience. **Methods**: This study outlines the methodology for comparing and analyzing various Collaborative Filtering and sentiment analysis techniques to identify an optimal combination. A public dataset "Amazon book review dataset" is employed for the experimental work. In this experimental study, 75% of the dataset serves as the training dataset, and 25% is designated as the testing set. Evaluation of the proposed hybrid approach involves standard metrics such as accuracy, precision, recall, and F1-Score. **Findings**: The proposed hybrid architecture overcomes the drawbacks of traditional recommendation systems by using users' past behavior and preferences through Collaborative Filtering, and incorporating sentiment analysis to understand the emotional tone of reviews. Results and conclusions derived from evaluating the effectiveness of the hybrid architecture in book recommendations provide insights into potential advancements in recommendation system paradigms. The proposed approach improves the recognition accuracy by 80.95% as compared to other existing systems in literature and possible hybridizations. The proposed methodology demonstrates significant enhancements in precision and F1-Score. **Novelty**: The proposed framework employs numerical ratings and sentiments to prognosticate recommendations, with the ultimate suggestion incorporating the relative significance of product sentiments and numerical ratings using the Collaborative Filtering technique and sentiment analysis technique incorporating Lexicon-based and Deep Learning-based techniques.

Keywords: Recommendation Systems; Book Recommendation System; Machine Learning; Sentiment Analysis; Deep Learning

1 Introduction

Recommendation systems are integral for enhancing user engagement across diverse product categories such as books, movies, music, online courses, and research articles. Employing advanced algorithms and analytical methods, these systems analyze user preferences and behaviors to deliver personalized suggestions, aiming to streamline the selection process and optimize the user experience. With the surge in online book distribution, the application of recommender systems in recommending books to specific user groups, including research scholars, students, and teachers, is an ongoing area of research. Various techniques, such as Content-based (CB), Collaborative Filtering (CF), Knowledge-based, Social Networking-based, Context-aware, and hybrid recommendation techniques, have been explored in the literature.

In the Content-Based approach, the system constructs a user profile through historical interactions, refining it over time with user inputs and actions to provide tailored recommendations aligned with the user's preferences. The efficacy of this method is contingent on the specific domain.

Conversely, the Collaborative Filtering technique gains widespread acceptance in research owing to its domain-independent characteristics. This technique projects a product's rating based on prior ratings from analogous users or the previous ratings of comparable products [(1)]. Similarity metrics such as Cosine similarity, Pearson correlation coefficient, and Jaccard similarity are employed to ascertain the likeness between distinct users or items, enabling the prediction of item ratings and subsequent personalized recommendations to the user. For instance, an online book recommendation system using item-based CF using Jaccard Similarity is presented [(2)], while a library book recommendation system utilizing Collaborative Filtering and user interest degrees is proposed, incorporating cosine similarity based on user attributes or common borrowing groups [(3)].

Knowledge-based recommendation technique establishes user-item relationships by procuring additional knowledge about the user and item. Social networking-based recommendation relies on social media information such as hashtags, friend lists, likes, dislikes, and comments [(4)]. The context-aware recommendation technique systematically tracks additional contextual details, including geographic information, family dynamics, ages, and relevant interests, to enhance the precision of recommendations. An example is a book recommendation system presented that employs "Rapid Miner" for data mining, integrating a user K-nearest neighbors (KNN) prediction model with Pearson-based similarity to suggest recommendations based on user location, age, and area of interest [(5)].

The hybrid recommendation technique, widely embraced and favored among researchers, involves a strategic amalgamation of two or more techniques, capitalizing on the strengths of each method while mitigating the limitations inherent in the hybridized techniques. Researchers have attempted to hybridize diverse methods, including Association Rule Mining, clustering techniques, and sentiment analysis, with Collaborative Filtering. The appeal of Collaborative Filtering lies in its domain independence, albeit reliant on numerical ratings.

As online platforms frequently enable users to provide comprehensive perspectives on products through textual reviews, users often rely on numerical ratings and textual reviews for decision-making. While numerical ratings are commonly aggregated for an overall assessment, a parallel approach is not consistently applied to textual reviews. Given the impracticality of manually reviewing every text, recommendation systems incorporate sentiment analysis to assess reviews alongside ratings, ensuring a more comprehensive and informed recommendation process. The challenge arises when solely considering either ratings or reviews, necessitating a hybrid framework capable of analyzing both components for generating valid and accurate recommendations. This hybrid approach discerns user requirements and furnishes pertinent results accordingly.

In existing literature, some researchers have explored the hybridization of sentiment analysis with recommendation techniques [(6)]. Sentiment analysis, a natural language processing (NLP) method, discerns emotional tones in reviews through Lexicon-based or Machine Learning (ML) and Deep Learning (DL)-based approaches. The Lexicon-based method relies on sentiment lexicons, i.e., a collection of known and precompiled sentiment terms, phrases, and even idioms, produced for traditional genres of communication. This approach can be implemented using either a dictionary-based or a corpus-based strategy. In the dictionary-based approach, an initial set of terms (seeds) is manually collected and annotated, expanding through the exploration of synonyms and antonyms within the dictionary. The corpus-based strategy involves utilizing domain-specific dictionaries formed from a set of seed phrases, which proliferate through the identification of related words using statistical or semantic methodologies. The lexicon approach can also address linguistic nuances, such as negation and modifiers, influencing sentiment orientation. Negations like "not" and "n't" reverse the polarity of the subsequent sentiment word, and the polarity of the sentiment word is recalibrated when close to modifiers like "very" or "really". Enhancers and reducers, two types of modifiers, either amplify or diminish the weight of the nearest opinion word, impacting the subsequent sentiment word's polarity positively or negatively. The Machine Learning approach can be classified as supervised and unsupervised. Supervised learning techniques, such as Support Vector Machines (SVM), Naive Bayes, and Maximum Entropy, are employed by training the model on a labeled dataset of text samples and corresponding sentiment labels. Unsupervised techniques are applied when labeled documents for classification are unavailable. In both cases, feature vectorization is employed to convert the textual data into numerical form for processing by Machine Learning algorithms Deep Learning-based techniques, particularly the Recurrent Neural Network (RNN) method, can predict the sentiment of new text based on prior model training. In RNN, the embedding and sequencing of text facilitate training on a labeled dataset of positive and negative reviews.

Given the widespread popularity and improved outcomes associated with hybrid recommendation systems, numerous studies have explored the hybridization of diverse recommendation techniques. The table below presents a comparative analysis of these relevant studies in the context of book recommendation systems.

Table 1. Comparison of existing book recommendation systems

Reference	Implemented Techniques	Outcomes	Limitations	Ratings Considered	Reviews Considered	Sentiment Analysis Technique Used
(2)	Collaborative Filtering with Jaccard Similarity	Predicted ratings are superior in comparison to actual user ratings based on the RMSE (Root Mean Square Error) value	It does not consider the rating values rather it considers two books to be similar if it is rated by more common users. Only the RMSE evaluation technique is used.	Yes	No	NA
(3)	Collaborative Filtering User Interest	A better result is obtained in comparison to traditional single cosine similarity Collaborative Filtering.	Limited comparison with state-of-the-art algorithms. Evaluation of the system was done using MAE (Mean Absolute Error) and RMSE only.	Yes	No	NA
(5)	KNN, Demographic Data (User age, Location, and interest)	Provides better evaluation results based on RMSE, MAE, and NMAE (Normalized Mean Absolute Error).	Not benchmarked against state of art algorithms. Limited evaluation. The system solely considered ratings.	Yes	No	NA
(6)	Feature Extraction	Given better results in terms of various evaluation metrics in comparison to PAS(positional aggregation-based technique), OWA(Ordered Weighted Aggregation), and ORWA (ordered ranked weighted aggregation)	The proposed approach is not compared with other opinion mining techniques.	No	Yes	Feature Extraction
(7)	Feature-based Opinion Mining	Features were identified, and the product's ranking was determined based on the weighting of each respective feature.	Not evaluated using standard evaluation techniques.	No	Yes	Weighted Feature Extraction

Continued on next page

Table 1 continued

[8]	Link Mining, ORWA	The proposed methodology yields superior ranking outcomes compared to OWA, which fails to account for the evaluative contributions of rankers.	Compared with OWA only.	No	Yes	Fuzzy Quantifiers
[9]	OWA	In the proposed approach, among the three linguistic quantifiers ('At least half', 'most', 'as many as possible'), 'as many as possible' yields superior results in terms of precision.	Evaluation is conducted solely utilizing precision as the metric.	No	Yes	Fuzzy Linguistic Quantifiers
[10]	PAS, OWA	All three linguistic quantifiers ('At least half', 'most', 'as many as possible') provide identical recommendations for the top two rankings.	Limited evaluation.	No	Yes	Fuzzy Linguistic Quantifiers
[11]	PAS, OWA	Provides comparable outcomes in terms of Precision, MAP (Mean Average Precision), and FPR (False Positive Rate) when contrasted with the results obtained from Amazon.	Not compared with other opinion mining techniques	No	Yes	Fuzzy Linguistic Quantifiers
[12]	Collaborative Filtering Association Rule Mining	Precision and Recall exhibit improvements when compared with user-based CF	Limited evaluation.	Yes	No	NA
[13]	SVM	The survey, conducted on a five-point Likert scale, exhibits a favorable inclination toward the proposed system.	The evaluation exclusively comprises a survey employing a five-point Likert scale. Similarity calculation is specifically performed for "The Thai Language"	No	No	NA
[14]	Clustering Sentiment Analysis	Better accuracy is achieved using KNN Clustering	Limited evaluation of the system.	No	Yes	CNN-Ngram
[15]	K Means Clustering Algorithm	Claimed to be better based on sensitivity, specificity, and F1 Score	Not compared with state-of-the-art algorithms. A rating above four was considered	Yes	No	NA

Continued on next page

Table 1 continued

[16]	User Based Collaborative Filtering, Matrix Factorization	Conducted a comparison between User-Based CF, Item-Based CF, and Matrix Factorization and found Matrix Factorization technique better based on MAE and RMSE.	Tested for only Arab Readers	Yes	No	NA
[17]	Collaborative Filtering	Examines several commonly used Collaborative Filtering such as neighborhood-based and matrix factorization-based recommendation algorithms and finds matrix factorization-based Singular value decomposition (SVD++) approach to be the best performant model based on MAE and RMSE	Examines the book recommendation systems that use CF only	Yes	No	NA

1.1 Research Gaps

Table 1 reveals that while numerous studies have delved into the hybridization of various recommendation techniques, certain research gaps have been identified within the realm of book recommendation systems.

- Although researchers have endeavored to implement hybrid frameworks by combining Collaborative Filtering with various other methodologies, such as context-aware data, association rule mining, and Deep Learning, a significant portion of research has ignored the inclusion of reviews and the incorporation of sentiment analysis.
- If researchers have addressed sentiment analysis, it predominantly involves the adoption of individual Feature-based, Fuzzy-based, Aspect-based, Machine Learning-based, or Deep Learning-based techniques. However, a hybrid sentiment analysis technique instantiated through a combination of Lexicon-based and Deep Learning-based approaches has not been incorporated into existing research.
- The existing systems are evaluated using only a subset of the standard evaluation metrics.

1.2 Contributions

In light of identified research gaps, a clear inference emerges, suggesting that a novel approach involving the integration of sentiment analysis methodologies 'encompassing Lexicon-based and Deep Learning-based techniques' in conjunction with Collaborative Filtering presents a promising avenue for research. This integration exhibits the potential to generate optimal outcomes in the advancement of recommendation system paradigms. Notably, a considerable portion of hybridization efforts has overlooked this specific combination. Therefore, this research article makes the following key contributions:

- First and foremost, the proposed approach utilizes numerical ratings and sentiments to forecast recommendations, with the ultimate suggestion incorporating the relative significance of product sentiments and numerical ratings.
- The proposed study embraces a novel approach by integrating sentiment analysis methodologies that encompass Lexicon-based and Deep Learning-based techniques, in conjunction with Collaborative Filtering
- Beyond simply considering Lexicon-based sentiment analysis, the study also incorporates the importance of linguistic terms, including negations and modifiers, for recommendations.
- To identify the optimal hybrid approach, the study scrutinizes the outcomes resulting from the hybridization of Lexicon-based sentiment analysis with either Deep Learning-based or Machine Learning-based sentiment analysis in conjunction with Collaborative Filtering.

- The proposed hybrid approach is validated using various standard evaluation metrics, including accuracy, precision, recall, and F1-Score.

The subsequent sections of this paper are structured as follows: Section 2 delineates the methodology to design a "Hybrid Sentiment-based Collaborative Architecture" to enhance book recommendation systems. Section 3 presents the experimental procedures undertaken in the research study. Lastly, Section 4 delivers conclusive remarks.

2 Methodology

2.1 Proposed Framework

The proposed framework for Hybrid Sentiment-based Collaborative Architecture for Book Recommender Systems (HSBRS) initiates the data flow process from a dataset. The detailed depiction of the proposed framework is presented in Figure 1.

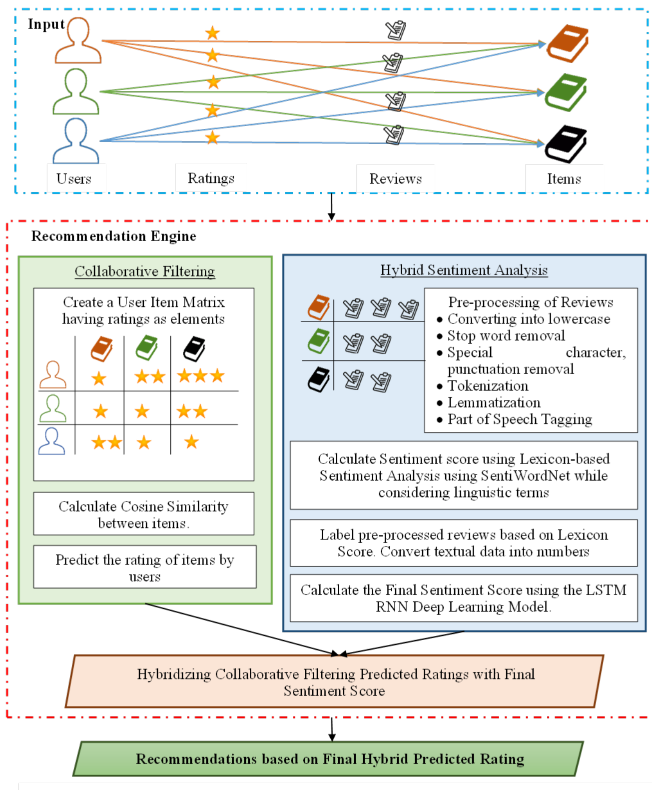

Fig 1. Detailed Illustration of Proposed HSBRS

The input dataset could be either standard or nonstandard and must encompass user profiles, item descriptors, ratings, and reviews. The techniques elucidated in the previous section shall be amalgamated into the construction of the HSBRS. There is a potential variation in outcomes, as Lexicon-based sentiment analysis relies on human-annotated dictionary words, while Machine Learning and Deep Learning techniques autonomously learn from initially labeled datasets of positive and negative reviews. By incorporating the output of Lexicon-based sentiment analysis as labeled data into DL-based sentiment analysis, a more robust system can be devised. By insights gleaned from the literature review, the item-based Collaborative Filtering technique utilizing the K-nearest neighbors (KNN) approach was identified for Collaborative Filtering, the SentiWordNet dictionary for Lexicon-based Sentiment analysis, and the Long Short-Term Memory Recurrent Neural Network (LSTM RNN) technique for DL-based sentiment analysis. The integration of these techniques in a hybrid fashion constitutes the formulation of a comprehensive framework for HSBRS.

Facilitating a seamless transition and coherent data flow necessitates preprocessing of the data. Primarily, the segregation of ratings and reviews is imperative, as Collaborative Filtering in recommendation systems considers numerical values (ratings) for similarity and prediction calculations, while textual data (reviews) are designated for sentiment analysis. Within Collaborative Filtering techniques, various algorithms are employed for similarity calculations, such as adjusted cosine similarity [12], Pearson similarity, Euclidean similarity, Jaccard similarity, cosine similarity [18], and correlation similarity [19]. The latter two, correlation and cosine similarity, emerge as particularly prominent in Collaborative Filtering-based recommendation systems, generating similarity values within the range of 0 to 1 [19]. Given the likelihood of encountering numerous zero values in the dataset, a comparative analysis of correlation and cosine similarity is conducted in this research. The findings indicate that the accuracy rate of cosine similarity surpasses that of correlation similarity. Consequently, the proposed architecture incorporates cosine-based similarity in the Collaborative Filtering process.

In the realm of sentiment analysis, reviews undergo preprocessing to transform unstructured data into a structured format. This preprocessing encompasses several steps, including converting reviews to lowercase, removing stop words, tokenization, lemmatization, and Part-of-speech (POS) tagging. The reviews undergo the elimination of punctuation marks, spaces, special characters, and stop words, as they lack sentiment Tokenization involves splitting sentences into words, while lemmatization aims to derive a word's fundamental meaning. During POS tagging, words are identified with their respective parts of speech, such as nouns, verbs, adverbs, adjectives, etc. This tagging is crucial for pinpointing words carrying sentiment. Subsequently, sentiment analysis techniques, such as Lexicon-based and Deep Learning-based methods, are applied to the preprocessed reviews to compute sentiment scores. These scores are then hybridized with predicted ratings generated through Collaborative Filtering to yield the final predicted rating value. The recommendation system outputs item suggestions to the user based on these predicted ratings.

In the proposed framework, the Lexicon-based sentiment analysis employs the SentiWordNet dictionary, which contains synsets and scores for positivity, negativity, and subjectivity of words [20]. For Deep Learning-based sentiment analysis, the Long Short-Term Memory (LSTM) technique of Recurrent Neural Network (RNN) is employed. LSTM effectively learns sentiments by retaining essential keywords and discarding less relevant ones as new words are encountered. Recurrent Neural Networks exhibit proficiency in handling sequential data, specifically designed to comprehend the inherent order and context within such data. By incorporating a memory element, RNNs capture information about preceding steps in a sequence, thereby exerting influence on the generation of subsequent outputs within the sequence [21]. Traditional RNNs face challenges in capturing long-term dependencies due to the vanishing gradient problem, wherein the gradient diminishes progressively and may reach zero during weight updates in backpropagation. To overcome this limitation, an advanced RNN architecture, namely LSTM, is utilized. LSTM incorporates a gating mechanism that addresses the vanishing gradient problem, enabling the model to capture long-term dependencies more effectively.

2.2 Proposed Algorithm

To operationalize the depicted research framework, as illustrated in Figure 1 and expounded upon earlier, an algorithm has been devised.

Algorithm: Hybrid Sentiment-based Collaborative Algorithm for Recommender System

Input: Actual rating and review of an item p by a user u.

Output: Predicted rating for an item p by a user u

1. Begin

2. Read DataSet containing information on users, items, ratings, and reviews.

D = { u_i, p_j, r_{ij}, c_{ij}}

u_i represents the i^{th} user, p_j represents the j^{th} item(product), r_{ij} represents the ratings given by u_i to p_j, c_{ij} represents the comment(review) given by u_i to p_j where $1 \le i \le n$, $1 \le j \le n$

3. X Is the user-item rating matrix of size n x m where

X = $[(r_{ij}, c_{ij})]_{n\ x\ m}$

4.Calculate the similarity among given fixed item p with all other items by varying l, $1 \le l \le m$

$(w_{p,l}) = \cos(\theta) = \frac{p.l}{\|p\|\|l\|}$

5. Predict the rating for an item p using

$CP_{u,p} = \frac{\sum_{j \in K} r_{u,j} w_{p,j}}{\sum_{j \in K} \left| w_{p,j} \right|}$

Where $CP_{u,p}$ the predicted rating of item p for user u, K is the neighborhood of most similar items, $r_{u,j}$ is the rating given by user u for the item j in set K, and $w_{p,j}$ is the cosine similarity between item p and j.

6. Calculate sentiment score $SL_{i,j}$ using Lexicon-based sentiment analysis for all **cij** where $1 \le i \le n,\ 1 \le j \le m$

Preprocess the reviews

- Convert the review $\mathbf{c}_{ij}$ into lowercase
- Remove special characters, punctuation, and stop words from $\mathbf{c}_{ij}$
- Tokenize $\mathbf{c}_{ij}$ to obtain the sequence of tokens
- Lemmatize $\mathbf{c}_{ij}$
- Use POS tagger on $\mathbf{c}_{ij}$

$\mathbf{c}_{ij} = \{w_k\}$ where w_k is the k^{th} word with POS Tag

S: SentiWordNet is a lexicon providing positive(w_k^+) and negative(w_k^-) score of a word (w_k)

ModFlag: A binary flag indicating the presence of a Modifier.

NegFlag: A binary flag indicating the presence of Negation.

EnFlag: A binary flag indicating the presence of Enhancer.

RedFlag: A binary flag indicating the presence of Reducer.

$\mathbf{D} = \mathbf{N} \cup \mathbf{E} \cup \mathbf{R}$ (Where D is a set of modifiers, N is a set of Negations, E is a set of Enhancers, and R is a set of Reducers) (Refer Table 2)

For $\forall\, \mathbf{w_k} \in \mathbf{c}_{ij}$ repeat the below steps

Initialize tps = 0,tpn =0,nw_k^- = 0,nw_k^+ = 0, ModFlag = 0, NegFlag = 0, EnFlag =0, RedFlag = 0 (where tps is the total positive score, tpn is the total negative score, nw_k^- is new negative score of a word, nw_k^+ is a new positive score of a word)

```
Get wk+ and wk- from S
IF wk∈ D
{  Set mwk+ = wk+ and mwk- = wk- (Where mwk- and mwk+ is modifier's positive and negative score respectively)
   Set ModFlag = 1
   If (wk∈ E)
     Set EnFlag = 1
   Else if (wk∈ R)
     Set RedFlag = 1
   Else
     NegFlag = 1
}
Else
{  If ModFlag = 1
   {  If (NegFlag = 1)
        nwk+ = wk-
        nwk- = wk+
      Else if (EnFlag = 1)
        If (mwk+ = mwk-)
          nwk+ = wk+ + mwk+
          nwk- = wk- + mwk-
        Else if ( mwk-=0)
          If (wk+> wk-)
            nwk+ = wk+ + mwk+
          Else
            nwk- = wk- + mwk+
      Else if (RedFlag = 1)
        If (nwk+ = 0)
          nwk- = wk- +mwk-
        Else if(mwk+< mwk-)
          If(wk+>wk-)
            nwk- = wk- + mwk-
          Else
            nwk+ = wk+ + mwk-
   tps += nwk+
   tpn += nwk-
   }
   Else
```

{ tps += w_k^+
tpn += w_k^-
}
}
SL_{ij} = tps - tpn.
SL_{ij} (Lexicon-based sentiment analysis) for individual review taken as a labeled dataset for Deep Learning-based sentiment analysis

7. Train and Save the Model M
Tokenize and Convert into Sequence
Tokenize $\mathbf{c}_{ij}$ to obtain the sequence of tokens
$\mathbf{c}_{ij} = \{w_k\}$ where w_k is the k^{th} token in a review
E: Embedding Layer, $\mathbf{O}_\mathbf{E}$ is the Output of the Embedding Layer
$O_E = E(c_{ij})$
L: LSTM Layer, $\mathbf{O}_\mathbf{L}$ is the Output of the LSTM Layer
$O_L = L(O_E)$
$\mathbf{D_s}$: Dense Layer with Softmax function, $\mathbf{O}_\mathbf{D}$ is the output of Dense Layer
$O_D = D_s(O_L)$
Compile
M = compile (Optimizer$_{rmsprop}$, Loss$_{categoricalcrossentropy}$, Metric$_{accuracy}$) where M is the final Model
M.fit (c_{ij}, SL_{ij}, epoch =5) where SL_{ij} is the sentiment score of a review as per lexicon analysis
M.save (Path), save the model

8. Predict Deep Learning-based sentiment analysis S_H using Trained Model M
Tokenize and Convert the Reviews into Sequence for given item p
For every review $\mathbf{c}_{i,p}$ of a fixed item p and $1 \leq i \leq n$
Tokenize $\mathbf{c}_{i,p}$ to obtain the sequence of tokens
$\mathbf{c}_{i,p} = \{w_k\}$ where w_k is the k^{th} token in a review
Load pre-trained LSTM RNN Model
LOAD M
Predict Sentiment Score
$DS_k = M(\mathbf{c}_{i,p}) = [DS_k^+, DS_k^-]$
DS^k is a vector of two predicted values $[DS_k^+, DS_k^-]$ that represent Deep Learning-based positive and negative sentiment scores respectively.
$\mathbf{S}_\mathbf{H} = \sum DS_k^+ - \sum DS_k^-$, where S_H is the sentiment score based on the hybrid sentiment (Lexicon + Deep Learning) technique for given item p.

9. Scaling the S_H to a scale of 0 to 5 using the below formula:-

$$S_{Hscaled} = (b-a)\left[\frac{S_H - min(S_H)}{max(S_H) - min(S_H)}\right] + a$$

Where $S_{Hsclaed}$ is the scaled sentiment score S_H for the given item p in the range of [a, b] i.e. [0, 5].

10. A hybridization of CF and hybrid sentiment analysis(Lexicon + Deep Learning) is done to get the final predicted rating ($FP_{u,p}$) value for given item p by user u.

$$FP_{u,p} = P_{u,p} + S_{Hscaled}$$

The final value of $FP_{u,p}$ must be in the range of [0, 5]. If the value is negative, it is taken as 0 and if it is greater than 5, it is taken as 5, and if lies between 0 and 5 use it as it is.

11. End

The presented algorithm is instantiated through the utilization of the Python programming language. Python is selected for its extensive range of libraries and is widely favored among data scientists for tasks such as Machine Learning, data manipulation, and data visualization, owing to its straightforward and easily comprehensible syntax. Various Python libraries are employed in this research to execute the proposed algorithm. Notably, libraries like pandas are utilized for data analysis and manipulation, Numpy for mathematical functions, and Scipy for a specialized data structure involving sparse matrices. For the incorporation of sentiment analysis within the algorithm, the NLTK toolkit is employed. The Deep Learning-based sentiment analysis is realized through the utilization of Keras.

Table 2. Partial List of modifiers affecting the polarity of the next word

Word	Modifier Type	Positive Score	Negative Score	Calculation of Polarity
not or n't	Negation	0	0.625	Negation words reverse the polarity of the subsequent sentiment word, causing an exchange between the negative and positive polarities of the following sentiment word.
very	Enhancer	0.25	0.25	Enhancers possess equal positive and negative polarities; hence, a value of 0.25 is added to the prevailing polarity of the subsequent sentiment word.
really	Enhancer	0.625	0	These enhancers have only positive polarity; therefore, the positive polarity of the enhancer is added to the dominating polarity of the subsequent sentiment word, i.e., if the positive polarity of the subsequent sentiment word is greater than the negative polarity, then the positive polarity of the enhancer is added to the positive polarity of the subsequent sentiment word, and vice versa.
even	Enhancer	0.125	0	
actually	Enhancer	0.375	0	
highly	Enhancer	0.625	0	
pretty	Reducer	0.125	0.25	These reducers have a higher negative polarity; therefore, if the subsequent sentiment word has a higher positive polarity value, its negative polarity is increased by the negative polarity of the reducer, or else its positive polarity is increased by the positive polarity of the reducer.
fairly	Reducer	0.125	0.25	
still	Reducer	0	0.125	These reducers have only negative polarity, which increases the negative polarity of the next sentiment word. Therefore, the negative polarity of the reducer is added to the negative polarity of the next sentiment word.

3 Results and Discussion

The assessment and comparison of HSBRS is conducted using the Amazon book review dataset, which is publicly accessible at http://jmcauley.ucsd.edu/data/amazon/. Specifically, the dataset pertaining to Java books was extracted for evaluation, resulting in a total of 12,496 records. Only the relevant fields (user_id, book_id, book_title, review_body, star_rating) crucial to the research investigation were considered for analysis.

To assess and validate the efficacy of the HSBRS a comparative analysis between the HSBRS and the systems employing traditional sentiment analysis techniques and a hybrid sentiment analysis technique combining Lexicon-based with ML-based Sentiment Analysis techniques based on accuracy, precision, recall, and F1-Score [22]. Accuracy gauges the effectiveness of the recommendation system, precision assesses the utility of the suggestions to the user, recall measures the presence of desirable and pertinent items in the suggested sequence, and F1-Score represents the weighted average and harmonic mean of precision and recall.

To ensure impartial evaluation, the system is systematically tested across all conceivable combinations of Collaborative Filtering recommendation techniques either with a traditional sentiment analysis technique or a hybrid Sentiment Analysis technique, encompassing the fusion of Lexicon-based sentiment analysis with various ML-based Sentiment Analysis techniques.

Initially, an examination is undertaken to compare hybridizations involving only two techniques, specifically Collaborative Filtering and various ML-based Sentiment Analysis techniques. As ML-based Sentiment Analysis techniques necessitate numerical data, various feature vectorization methods such as word count, n-gram, and Term Frequency Inverse Document Frequency (TFIDF) are employed to transform textual data into a numerical format. TFIDF quantifies the frequency of a word in a review relative to the total number of words in that review containing the specific word [23]. N-gram involves utilizing two or three-word sequences or features, enhancing prediction accuracy. Word count considers the frequency of word occurrences in a review, with the likelihood of a review being positive or negative increasing with the frequency of positive or negative words.

Given that sentiment classification is a binary classification problem, logistic regression, Support Vector Machine (SVM), and Linear Discriminant Analysis are utilized as supervised ML-based sentiment analysis classifiers. Logistic regression estimates the probability of a review being positive or negative, ranging between 0 and 1 [24]. The SVM approach creates a decision boundary between positive and negative features and chooses the extreme cases i.e. support vectors of positive and negative features. Based on support vectors, SVM will classify features as positive or negative [13]. Linear Discriminant Analysis serves as a dimensionality reduction technique for identifying and selecting features that describe a review as positive or negative.

The comparison in this study encompasses all possible combinations of ML classifiers with the aforementioned feature vectorization techniques. It is essential to highlight that, for the evaluation of ML techniques, the dataset is labeled by categorizing reviews with a rating equal to or above three as positive and the rest as negative. The dataset is then partitioned into training and testing sets at proportions of 75% and 25%, respectively. The resulting evaluation metrics for various hybridizations are presented in the subsequent Table 3.

The potential hybrid techniques are designed to forecast the rating value of a product. Therefore, the assessment of a hybrid technique involves comparing the predicted rating to the actual rating. This comparison is facilitated through the construction of a confusion matrix, which is generated using a predetermined threshold value. Ratings equal to or exceeding the threshold are classified as positive predictions, while those below the threshold are deemed negative predictions. In this investigation, a threshold value of three is employed. Evaluation metrics for each conceivable hybrid technique are derived from the values within the confusion matrix, encompassing true positive, true negative, false positive, and false negative values.

Table 3. Comparison of Hybridization of CF and ML based sentiment analyis with HSBRS Technique

Hybridized Techniques*	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
CF + LR-NG-SA	68.74	5.18	55.96	9.49
CF + LR-WC-SA	68.34	5.17	56.53	9.47
CF + LR-TF-SA	56.15	4.16	63.49	7.82
CF + SVM-NG-SA	32.58	3.15	74	6.04
CF + SVM-WC-SA	27.13	3.04	77.41	5.86
CF + SVM -TF-SA	32.54	3.15	74.28	6.06
CF + LDA-NG-SA	70.5	6.1	63.06	11.13
CF + LDA-WC-SA	49.55	4.24	75.28	8.04
CF + LDA-TF-SA	67.17	5.66	65.19	10.42
Proposed HSBRS (Lexicon + DL + CF)	80.95	7.03	45.02	12.16

* CF+LR-NG-SA (Collaborative Filtering + Logistic Regression using n-gram feature vectorization-based sentiment analysis)
CF+LR-WC-SA (Collaborative Filtering + Logistic Regression using word count feature vectorization-based sentiment analysis)
CF+LR-TF-SA (Collaborative Filtering + Logistic Regression using TFIDF feature vectorization-based sentiment analysis)
CF+SVM-NG-SA (Collaborative Filtering + Support Vector Machine using n-gram feature vectorization-based sentiment analysis)
CF+ SVM-WC-SA (Collaborative Filtering + Support Vector Machine using word count feature vectorization-based sentiment analysis)
CF+ SVM-TF-SA (Collaborative Filtering + Support Vector Machine using TFIDF feature vectorization-based sentiment analysis)
CF+LDA-NG-SA (Collaborative Filtering + linear discriminant analysis using n-gram feature vectorization-based sentiment analysis)
CF+ LDA -WC-SA (Collaborative Filtering linear discriminant analysis using word count feature vectorization-based sentiment analysis)
CF+ LDA -TF-SA (Collaborative Filtering + linear discriminant analysis using TFIDF feature vectorization-based sentiment analysis)

Examining Table 3, it is evident that within the realm of hybridizations involving Machine Learning-based sentiment analysis techniques and Collaborative Filtering, the linear discriminant analysis technique utilizing n-gram feature vectorization (CF + LDA-NG-SA) yields optimal outcomes across all parameters. This configuration achieves a notable 70.50% accuracy, 6.10% precision, 63.06% recall, and 11.13% F1-Score. Hence, it is asserted that CF + LDA-NG-SA emerges as the most efficacious system. This system provides users with valuable recommendations, delivering a sequence of preferred and relevant items that surpasses other hybrid techniques incorporating Machine Learning-based sentiment analysis with Collaborative Filtering.

The hybrid technique of Collaborative Filtering with linear discriminant analysis based sentiment analysis technique using n-gram feature vectorization approach (CF + LDA-NG-SA), word count feature vectorization (CF + LDA-WC-SA), and TFIDF approach (CF + LDA-TF-SA) yields superior outcomes in comparison to the hybrid technique of Collaborative Filtering with SVM using n-gram feature vectorization (CF + SVM-NG-SA), word count feature vectorization (CF + SVM-WC-SA), TFIDF feature vectorization (CF + SVM -TF-SA). The Hybrid technique of Collaborative Filtering with logistic regression using n-gram feature vectorization (CF + LR-NG-SA), word count feature vectorization (CF + LR-WC-SA), and TFIDF feature vectorization (CF + LR-TF-SA) outperforms hybridization with SVM concerning accuracy, precision, and F1-Score. The recall value in a hybrid technique incorporating SVM surpasses that of the linear discriminant analysis and logistic regression-based hybridization, owing to the inverse relationship between precision and recall. It can be deduced that, within the context of hybridizing Machine Learning-based sentiment analysis techniques with Collaborative Filtering, the utilization of the n-gram feature vectorization technique consistently yields superior results.

Secondly, the conducted study encompassed a comprehensive comparative analysis involving the hybridization of three distinct techniques namely, Collaborative Filtering, Lexicon-based Sentiment Analysis, and ML-based sentiment analysis with the proposed HSBRS. It is crucial to emphasize that, the evaluation focused on a hybrid sentiment analysis technique integrating Lexicon-based sentiment analysis and ML-based sentiment analysis techniques, in contrast to HSBRS, which constitutes a hybridization of Collaborative Filtering with a sentiment analysis technique combining Lexicon-based sentiment analysis and DL-based sentiment analysis techniques. Lexicon-based Sentiment analysis utilized the SentiWordNet dictionary. In this investigation, the results of Lexicon-based sentiment analysis, incorporating linguistic terms, were integrated into Machine

Learning classifiers to form a labeled dataset. This strategy for generating a labeled dataset is considered justified when contrasted with the prior simplistic method, which involved categorizing reviews with a rating equal to or exceeding three as positive, and the remainder as negative. Notably, as the n-gram feature vectorization technique was identified as the most effective in Machine Learning classifiers in a preceding study, only n-gram feature vectorization is considered in the subsequent Table 4.

Table 4. Comparison of Deep Learning and Machine Learning Techniques in Hybridization

Three Hybrid Techniques	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Lexicon+LogisticRegression+CF	66.55%	4.45%	50.99%	8.20%
Lexicon+LinearDiscriminantAnalysis+CF	77.34%	6.40%	49.43%	11.33%
Lexicon+SupportVectorMachine+CF	79.84%	6.18%	41.47%	10.76%
Proposed HSBRS (Lexicon + DL + CF)	80.95%	7.03%	45.02%	12.16%

The tabulated results distinctly illustrate that, except recall, the proposed "Hybrid Sentiment-based Collaborative Architecture," to enhance book recommendation systems (HSBRS) consistently outperforms the hybridization of Collaborative Filtering with a hybrid sentiment analysis technique incorporating Lexicon-based sentiment analysis and Machine Learning-based sentiment analysis techniques. This implies that the proposed HSBRS exhibits heightened efficacy by delivering more relevant and preferred items in its recommendations, as evidenced by superior values in accuracy, precision, and F1-Score.

HSBRS is also evaluated and compared with other proposed approaches in the literature. According to Table 4, the accuracy and recall metrics for HSBRS were determined to be 80.95 % and 45.02%, respectively, surpassing the corresponding values for the recently documented Hybrid Model and Pattern-based Word Embedding model [(25)]. Specifically, the accuracy and recall metrics for the Hybrid Model and Pattern-based Word Embedding model are documented as 52.1% and 37.4%. This implies that HSBRS is a more efficient system, providing more preferred and relevant items in the recommended list.

4 Conclusion

Conclusions drawn from the research study affirm that the development of an effective recommendation system is better achieved through the adoption of hybrid techniques, specifically involving a new novel approach of fusing Lexicon-based Sentiment Analysis with Deep Learning-based sentiment analysis and Collaborative Filtering. Such hybridization demonstrates notable advantages across the accuracy, recall, and F1-Score parameters. The findings also underscore the efficacy of employing hybrid techniques when constructing recommendation frameworks based on ratings and reviews, surpassing the performance of singular techniques. The heightened values of accuracy, recall, and F1, as evident in the results, illuminate the potential of hybridization involving Lexicon-based and DL-based sentiment analysis alongside Collaborative Filtering techniques. Future endeavors will focus on further enhancing recommendation accuracy by integrating additional techniques into hybrid models and extending the system evaluation to products beyond books.

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