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Sequential Pattern Mining and Hybrid Sentiment-based Collaborative Architecture for Rating Prediction

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Abstract
This research presents a novel approach named “Sequential Pattern Mining and Hybrid Sentiment-based Collaborative Architecture for Rating Predictions". This approach overcomes the limitations of traditional techniques by considering multi-dimensional data, including users' past behaviour, buying patterns, and sentiments to enhance the rating predictions and recommendations. The proposed prediction approach incorporates users’ past behaviour i.e. ratings through the Collaborative Filtering technique. The users’ sentiments are included by implementing Hybrid Sentiment Analysis and the sequential buying patterns are considered through the Generalized Sequential Pattern Mining technique. The Hybrid Sentiment Analysis technique combines Lexicon-based and Deep Learning-based Sentiment Analysis methodologies for more comprehensive sentiment evaluation. The proposed Hybrid Rating Prediction System is evaluated using a standardized public dataset and standard evaluation metrics including Accuracy, Precision, Recall, and F1-Score. Therefore, the research study has three primary objectives. The first objective is to identify the existing recommendation techniques through a literature review. The second objective is to propose a hybrid approach that mitigates the limitations of traditional systems by incorporating multi-dimensional information about the user and items. The third objective is to evaluate, validate, and compare the proposed approach against existing state-of-the-art systems and possible hybrid systems. The results demonstrate that the proposed hybrid approach achieves an Accuracy of 79.79%, with significant improvements in Precision and F1-Score compared to existing systems.

Keywords- Book recommendation system, Recommendation systems, Sequential pattern mining, Collaborative filtering, Sentiment analysis, Machine learning, Deep learning, Hybrid sentiment analysis.

1. Introduction

Predictive systems are more inclined towards using Machine Learning (ML) and Deep Learning (DL) techniques to enhance user engagement across various product categories such as books, movies, music, online courses, and research articles. These systems utilized advanced algorithms to analyze users’ past behavior and preferences to provide personalized recommendations. As the online book distribution systems are growing day by day, there is a need for Book Recommender Systems that could target specific user groups, including research scholars, students, and teachers.

Online platforms allow the users to provide numerical ratings to the products and write in-depth text reviews. The numerical ratings are mostly aggregated to provide an overall score, whereas the written reviews are difficult to compile. The textual reviews are generally ignored by Recommendation Systems. However, incorporating textual reviews using Sentiment Analysis could improve Hybrid Recommendation Systems' efficacy by considering the user opinions (Srifi et al., 2020). Further, Hybrid Recommendation System could enhance the recommendation by integrating Sequential Pattern Mining that identifies the trends in user activity, such as reading or buying habits.

Hybrid Recommendation Systems are the most popular recommendation systems in the literature. In Hybridization the Researchers have tried to integrate the Sentiment Analysis technique with other conventional or cutting-edge approaches (Sohail et al., 2018). Sentiment Analysis is a Natural Language Processing (NLP) technique used to identify the emotions and can be implemented using lexicons, Machine Learning, or Deep Learning-based techniques (Medhat et al., 2014). The Lexicon-based approach is primarily based on a sentiment lexicon which is a list of recognized sentiment terms and phrases. It can be further implemented using dictionary-based and corpus-based approaches (Sundari and Subaji, 2020). In the dictionary-based method, the initial set of sentiment terms are often gathered and manually annotated. This set further grows by examining and adding the synonyms and antonyms in the dictionary. In the corpus-based method, Domain-specific dictionaries are provided. These dictionaries are created from a group of "seed" phrases that grow through seeking related words using either statistical or semantic methodologies. The Lexicon-based approach also considers linguistic nuances like negation and modifiers that influence sentiment orientation (Serrano-Guerrero et al., 2015). Recent studies have also tried to implement Sentiment Analysis using Machine Learning and Deep Learning methods (Serrano-Guerrero et al., 2015). As per the literature, both supervised (e.g., Support Vector Machines, Naive Bayes) and unsupervised techniques are used to implement ML-based Sentiment Analysis (Puritat et al., 2021). In DL-based Sentiment Analysis, the Recurrent Neural Networks (RNN) technique is popularly employed to predict the sentiment based on previously trained model (Mahadevaswamy and Swathi, 2023). The RNN technique utilizes text embedding and sequencing to get the model trained on labeled datasets of positive and negative reviews.

Apart from hybrid techniques, researchers have also examined traditional prediction techniques such as Content-based (CB), Collaborative Filtering (CF), Knowledge-based, Social Networking-based, and Context-aware based techniques. The Content-based technique is implemented by building a user profile from his historical interactions and by refining it using user inputs to provide customized recommendations (Wang et al., 2018). Its effectiveness can vary by domain. In contrast to the Content-based technique, the Collaborative Filtering technique is widely accepted in research due to its domain-independent nature. The Collaborative Filtering technique predicts a product's rating based on similar users' or products' previous ratings (Shichang, 2021). Knowledge-based recommendation techniques identify the user-item relationships by acquiring some additional knowledge about users and items for predictions (Tarus et al., 2017a). The Social networking-based recommendation technique utilizes social media data such as hashtags, friend lists, likes, dislikes, and comments to generate recommendations (Margaris et al., 2018). Context-aware recommendation methods systematically monitor contextual factors such as geographic location, family composition, age, and interests to enhance the precision of recommendations (Champiri et al., 2015). The Hybrid Recommendation Technique merges multiple methods to harness their respective strengths and mitigate inherent limitations to provide better recommendations (Elahi et al., 2023).

Within the literature, researchers have explored the Hybrid Recommendation Systems that integrate Sequential Pattern Mining (SPM) in hybridization. The SPM technique can effectively capture users'

historical learning sequences and is commonly employed in sequence mining. In the SPM technique, sequential patterns are identified if they exceed a predetermined minimum support threshold and preserve the order of item occurrence. Literature has introduced algorithms such as SPADE, Generalized Sequential Pattern (GSP), SPAM, and Prefix Span for implementing the Sequential Pattern Mining technique (Anwar and Uma, 2022). Researchers have also tried Deep Learning techniques, such as BERT to identify item sequences (Noorian et al., 2024). Researchers have also investigated Hybrid Recommendation Systems that combine diverse techniques due to their widespread popularity and improved outcomes. A comparison of Book Recommender System proposed by varied researchers is depicted in **Table 1**.

Table 1. Comparison of existing book recommendation systems.

Reference	Implemented techniques	Sequential pattern mining	Ratings considered	Reviews considered	Sentiment analysis technique used
Sohail et al. (2018)	Feature Extraction	No	No	Yes	Feature Extraction
Noorian et al. (2024)	LSTM BERT	Yes	Yes	Yes	LSTM
Chen et al. (2014)	Collaborative Filtering Sequential Pattern Mining	Yes (GSP)	Yes	No	NA
Tarus et al. (2017b)	Collaborative Filtering Ontology Sequential Pattern Mining	Yes (GSP)	Yes	No	NA
Mounika and Saraswathi (2021)	Clustering Sentiment Analysis	No	No	Yes	CNN-Ngram
Kovačević and Mašetić (2022)	Collaborative Filtering	No	Yes	No	NA
Wayesa et al. (2023)	Content-Based Filtering Collaborative Filtering Semantics Patterns using Clustering	Yes (Semantic Pattern Mining using Clustering)	No	No	NA

It is evident from **Table 1** that despite the extensive exploration into the amalgamation of diverse recommendation methodologies, specific lacunae have been identified within Book Recommendation Systems. Firstly, while researchers have developed hybrid frameworks integrating Collaborative Filtering with methods like Content-based, Context-aware data, Association Rule Mining, and Clustering-based semantic relationships, a significant portion of research has overlooked incorporating reviews with Sequential Pattern Mining. Secondly, when reviews are addressed with sentiment analysis, it often involves individual Feature-based, Fuzzy-based, Machine Learning-based, or Deep Learning-based techniques. However, a "Hybrid Sentiment Analysis Technique" that combines Lexicon-based and Deep Learning-based approaches has not been integrated into existing research alongside Sequential Pattern Mining.

In light of these gaps, this research paper represents a crucial adjunct to the prior work (Kumar and Chawla, 2024). It proposes a new approach called "Sequential Pattern Mining and Hybrid Sentiment-based Collaborative Architecture for Rating Prediction". This study aims to integrate diverse recommendation techniques into a unified framework. The framework predicts recommendations by considering quantitative and qualitative information related to the user and item including numerical ratings, sentiments, and sequential behavior. The framework undergoes rigorous validation using standard evaluation parameters. Also, the research aims to merge the "Hybrid Sentiment Analysis Technique" with Sequential Pattern Mining, incorporating enhancers, negations, and modifiers in Lexicon-based Sentiment Analysis. Lastly, the paper seeks to identify the most effective hybrid method by critically assessing

results from combining Lexicon-based Sentiment Analysis with DL-based or ML-based Sentiment Analysis, Collaborative Filtering, and optionally Sequential Pattern Mining as illustrated in **Figure 1**.

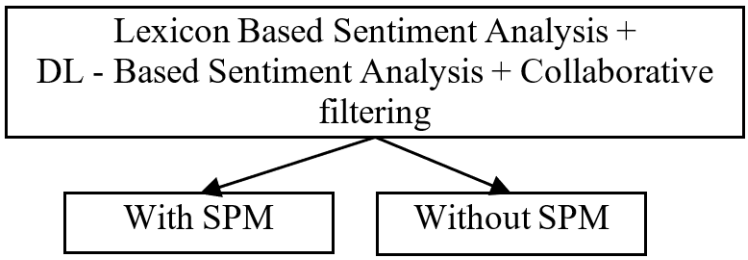

Figure 1. Objective of the research.

In the further sections of this paper, Section 2 outlines the methodology to design a "Sequential Pattern Mining and Hybrid Sentiment-based Collaborative Architecture for Rating Prediction ". 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 "Sequential Pattern Mining and Hybrid Sentiment-based Collaborative Architecture for Rating Prediction" approach is applied in the academic domain for book recommendation. The system is designed with a three-layer architecture consisting of an external layer, a conceptual layer, and an internal layer. The external layer initiates the data flow from a dataset containing user profiles, item sequences, ratings, and reviews. The conceptual layer houses the core logic of the framework, while the internal layer contains the actual dataset to be used in the framework.

The conceptual layer is the primary operational component of the proposed architecture that incorporates various recommendation techniques including the Sentiment Analysis technique, Collaborative Filtering technique, and Sequential Pattern Mining technique as depicted in **Figure 2**. Although each technique has its limitations, their combination enhances system robustness. For example, Lexicon-based Sentiment Analysis relies on annotated dictionary words, whereas Machine Learning and Deep Learning methods learn from labeled datasets, leading to potential variability in outcomes. Similarly, CF relies solely on numerical ratings, and SPM on sequences. Drawing from literature insights, integrating Item-based Collaborative Filtering with the K-nearest neighbors (KNN) approach and using Generalized Sequential Pattern (GSP) mining alongside an integrated Sentiment Analysis approach offers a promising Recommendation System. Thus, this methodology is adopted in this research.

In the three-layered architecture, the user can log in to the system through an external layer i.e. user interface, and can search for a resource. The system generates the search results using the internal layer which contains the Standard Dataset and the Dataset collected from different sources such as Internet sources, web pages, Government Educational Portals, etc. Users can choose from the resource list generated by the conceptual layer. The system shows the resource details along with the recommendations generated by the conceptual layer. Users can submit their ratings or reviews for the selected resource using the User Interface that assists the proposed system in generating better recommendations.

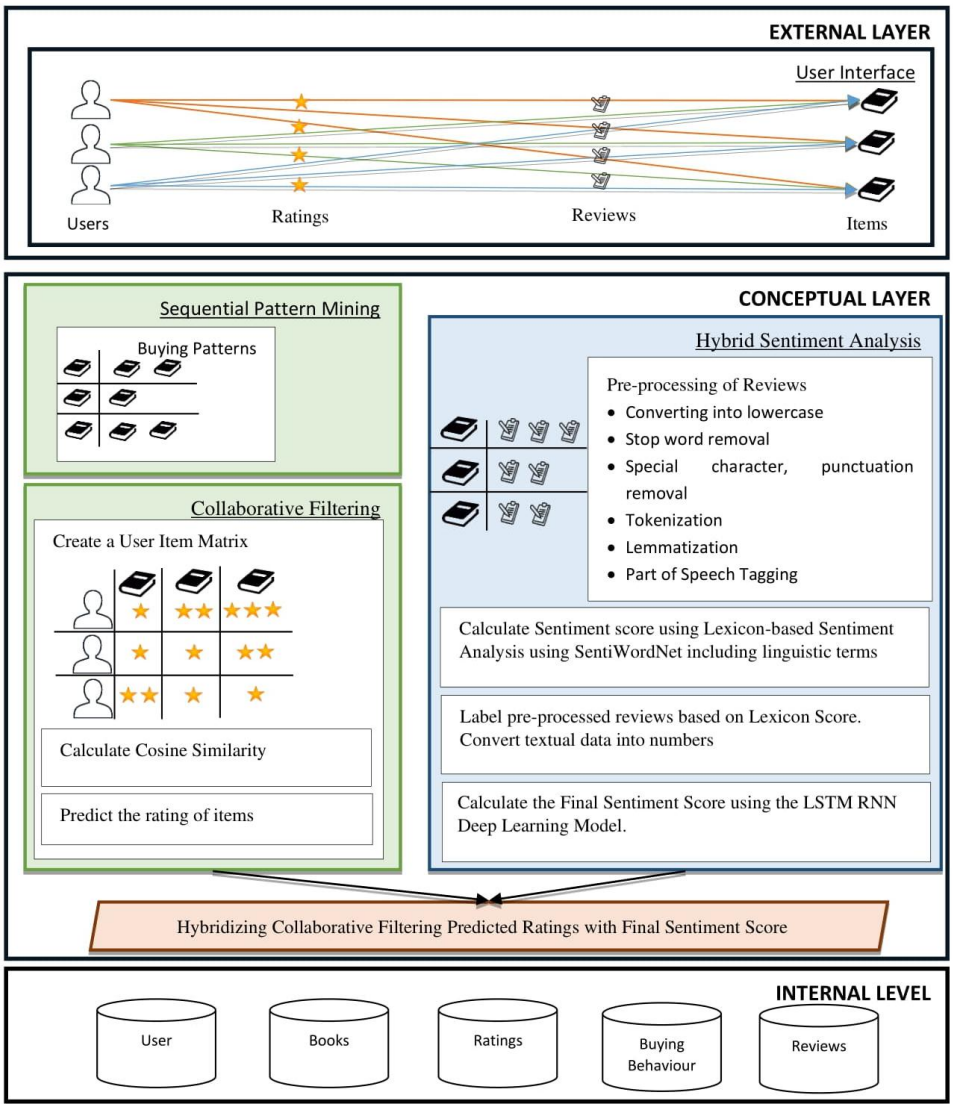

Figure 2. Detailed illustration of proposed hybrid approach.

To implement the proposed framework, an algorithm is detailed in Section 2.2. Given the integration of multiple techniques, the output of one technique serves as the input for another. Initially, input data must be segregated into ratings, reviews, and sequences for use in different techniques. Sequences are analyzed using GSP to identify purchasing or reading patterns. Ratings are used by the Collaborative Filtering technique for similarity and prediction calculations, while textual data (reviews) are utilized by Sentiment Analysis. Reviews undergo preprocessing before being analyzed using Sentiment Analysis techniques. The preprocessing includes converting the case of the reviews and removing unnecessary text such as stop words, and special characters. Preprocessing also performs tokenization, lemmatization, and part-of-speech tagging.

In the proposed framework, each book is associated with a list of co-purchased books for Generalized Sequential Pattern (GSP) analysis. The GSP algorithm identifies patterns within this list based on a

specified support threshold. The output of GSP serves as input for the Collaborative Filtering (CF) technique. When calculating predicted ratings for an item using CF, the support value obtained from GSP is incorporated into the final rating prediction, thus accounting for its significance. In the domain of Sentiment Analysis, pre-processed reviews are utilized, and the Lexicon-based Sentiment Analysis' results act as labeled dataset for Deep Learning-based methods. This Hybrid Sentiment Analysis approach yields sentiment scores for each item, which are then integrated with predicted ratings from CF to determine the final predicted rating value.

2.2 Proposed Algorithm

This section explains the algorithm for the proposed framework.

Algorithm: Hybrid Sentiment-based Collaborative Algorithm for Recommender System

- **Begin**
- **For preprocessing of Dataset, read the Dataset** in JSON or CSV format.
- Convert the datatypes of columns into required data types.
- Filtered out the required category while reading the dataset in chunks.
  a) Convert the category column into lowercase and search for the required category.
  b) Create a new dataset of the required category.
- Drop the non-relevant columns.
- Create a dataset containing item IDs, also buy items, user IDs, ratings, and reviews.
- **For Sequential Pattern Mining, read the pre-processed Dataset in the previous step that contains** information on users, items, ratings, also_buy, and reviews.
  $D = \{ u_i, p_j, r_{ij}, b_{ij}, c_{ij} \}$

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, b_{ij} represents the sequential list of items bought by u_i along with p_j, c_{ij} represents the comment(review) given by u_i to p_j where, $1 \leq i \leq n$, $1 \leq j \leq n$.

- Read the product *p* and the corresponding list of also_buy_items i.e. b.
- Preprocess the also buy items list to convert it into the required datatype.
- Combine the also buy list for every unique item *p*. For every also_buy list $\mathbf{b_{i,p}}$ of a fixed item *p* and $1 \leq i \leq n$.
  a) Combine $b_{i,p}$ to obtain a single list of also_buy_items.
- List of also buy items $b_{i,p}$ for every unique item p is passed to the GSP Algorithm.
  a) In GSP a search value i.e. threshold value between 0.0 to 1.0 is selected for identifying patterns.
  b) GSP will identify the patterns based on the threshold value.
- Create a vector (GP) of the item and the next item that is supposed to be bought based on the patterns having length greater than or equal to 2.
  a) GP is a vector of three values [p, np, *l*] that represents that the item np is bought *l* times after item p where np could be a single item or list of items depending on the length of the GSP pattern.
- **For Collaborative Filtering** Read the user id, item id, and corresponding rating given by the user to the item.
- Remove the duplicate records while keeping the first record.
- Create a user-item matrix where the elements represent the ratings. X is the user-item rating matrix of size *n* x *m* where:
  $X = \left[(r_{ij}, c_{ij})\right]_{nxm}$
- Use the KNN model to identify the similarities among items based on the distances.
- Calculate the similarity among the given fixed item *p* with all other items by varying *l*, $1 \leq l \leq m$.
  $(w_{p,l}) = \cos(\theta) = \frac{p \cdot l}{\|p\| \|l\|}$

- During KNN similarity calculation if the neighbour item is the same as that of the next item in the GSP list (GP) then its similarity value is increased by the number of times the next item appears in buying behaviour i.e. *l* divided by the number of total neighbour items.
  Distance + *l*/K
- Identify the K neighbours using cosine similarity calculations.
- Identified neighbours K are used to calculate the final **Predicted rating** for an item *p* using

$$CP_{u,p} = \frac{\Sigma_{j\in K} r_{u,j} w_{p,j}}{\Sigma_{j\in K} |w_{p,j}|} \quad (1)$$

where, $CP_{u,p}$ is the predicted rating of item *p* for user *u*, K is the neighbours, $r_{u,j}$ is the numerical rating given by *u(user)* for the j^{th}*(item)* in set K, and $w_{p,j}$ is the cosine similarity between items *p* and *j*.

- **For preprocessing of textual reviews:** read the items p and corresponding reviews c_{ij}.
- Combine all the reviews c_{ij} as a single unit for a particular item.
- For all $\mathbf{c_{ij}}$ where, $1 \le i \le n$, $1 \le j \le m$

Preprocess the reviews:

a) Convert the review $\mathbf{c_{ij}}$ into lowercase.
b) Remove special characters, punctuation, and stop words from $\mathbf{c_{ij}}$.
c) Tokenize $\mathbf{c_{ij}}$ to obtain the sequence of tokens.
d) Lemmatize $\mathbf{c_{ij}}$.
e) Use POS tagger on $\mathbf{c_{ij}}$.

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

- **Calculate sentiment score $SL_{i,j}$ using Lexicon-based Sentiment Analysis S**: SentiWordNet is a lexicon providing positive(w_k^+) and negative(w_k^-) scores of a word (w_k).

ModFlag: A binary flag signifying the existence of Modifier.
NegFlag: A binary flag signifying the existence of Negation.
EnFlag: A binary flag signifying the existence of Enhancer.
RedFlag: A binary flag signifying the existence of Reducer.
D = N∪E∪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)
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 w_k^+ and w_k^- from S.
IF $w_k \in$ D
{
Set $mw_k^+ = w_k^+$ and $mw_k^- = w_k^-$ (where mw_k^- and mw_k^+ is modifier's positive and negative score respectively.)
    Set *ModFlag = 1*
    If ($w_k \in$ E)
        Set *EnFlag = 1*
    Else if ($w_k \in$ R)
        Set *RedFlag = 1*
    Else
        NegFlag = 1
}
Else
{   If ModFlag = 1

{ If (NegFlag = 1)
$nw_k^+ = w_k^-$
$nw_k^- = w_k^+$
Else if (EnFlag = 1)
If ($mw_k^+ = mw_k^-$)
{
$nw_k^+ = w_k^+ + mw_k^+$
$nw_k^- = w_k^- + mw_k^-$
}
Else if (mw_k^-=0)
If ($w_k^+ > w_k^-$)
$nw_k^+ = w_k^+ + mw_k^+$
Else
$nw_k^- = w_k^- + mw_k^+$
Else if (RedFlag = 1)
If ($nw_k^+ = 0$)
$nw_k^- = w_k^- + mw_k^-$
Else if($mw_k^+ < w_k^-$)
If($w_k^+ > w_k^-$)
$nw_k^- = w_k^- + mw_k^-$
Else
$nw_k^+ = w_k^+ + mw_k^-$
tps += nw_k^+
tpn += nw_k^-
}
Else
{ *tps* += w_k^+
tpn += w_k^-
}
}

SL_{ij} = *tps* - *tpn*.

SL_{ij} (Lexicon-based Sentiment Analysis) for individual review taken as a labelled dataset for DL-based Sentiment Analysis.

- **For DL-based Sentiment Analysis Train and Save the Model M:**

Tokenize and Convert into Sequence.

Tokenize c_{ij} to obtain the sequence of tokens.

c_{ij} = {w_k} where w_k is the k^{th} token in a review.

E: Embedding Layer, $\mathbf{O_E}$ is the Output of the Embedding Layer:

$O_E = E(c_{ij})$

L: LSTM Layer, $\mathbf{O_L}$ is the Output of the LSTM Layer:

$O_L = L(O_E)$

$\mathbf{D_s}$: Dense Layer with Softmax function, $\mathbf{O_D}$ 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.

- **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≤i≤*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.
$\mathbf{S_H} = \sum DS_k^+ - \sum DS_k^-$, where S_H is the sentiment score based on the hybrid sentiment (Lexicon + Deep Learning) technique for given item *p*.

- **Scaling** the S_H to a value of 0 to 5 using the below formula:

$$S_{Hscaled} = (b-a)\left[\frac{S_H - \min(S_H)}{\max(S_H) - \min(S_H)}\right] + a \quad (2)$$

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

- **A hybridization** of CF, sequential pattern mining, and hybrid sentiment analysis (Lexicon + Deep Learning) is done using equations (1) and (2) to get the final predicted rating ($FP_{u,p}$) value for given item *p* by user *u*.

$FP_{u,p} = CP_{u,p} + S_{Hscaled}$
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 as it is.

- **End**

The Proposed Algorithm begins by preprocessing the data and filtering out relevant information regarding learner behavior (e.g. “also_buy”), ratings, and reviews from standard or non-standard datasets collected from various sources such as Internet sources, web pages, Government Educational Portals, etc. This preprocessing might involve converting the data into required datatypes or dropping out non-relevant columns.

Next, the proposed algorithm identifies buying/reading patterns by implementing the GSP (Generalized Sequential Pattern) Mining Technique. This technique generates a vector of three values [p, np, *l*], where "np" represents the item bought "*l*" times after item "p." "np" could be a single item or a list of items depending on the length of the GSP pattern.

The output of the GSP Pattern Mining Technique, along with numeric ratings, is then processed to perform Item-based Collaborative Filtering using Cosine Similarity with KNN(IBCF). In IBCF, a user-item matrix is constructed. The KNN model utilizes this matrix to identify similarities among items. During similarity calculation, the weight of an item is increased if it appears in the GSP Pattern Vector. The final similarity score is used to predict a user's rating of an item. In the proposed algorithm, till this step, the calculation is done based on numeric values i.e. the quantitative information.

Furthermore, the proposed algorithm processes textual reviews to incorporate qualitative information. The textual reviews are pre-processed. The preprocessing includes converting the case of the reviews and removing unnecessary text such as stop words, and special characters. Preprocessing also performs tokenization, lemmatization, and part-of-speech tagging.

The preprocessed reviews are used as input to perform Lexicon-based Sentiment Analysis. The algorithms start with identifying the linguistic terms such as modifiers (ModFlag), negations (NegFlag), enhancers (EnFlag), or reducers (RedFlag) that may affect the sentiment of the word. If any of these flags are triggered, the algorithm adjusts the word's polarity based on the SentiWordNet Dictionary. The adjusted polarity of individual tokens is summed to calculate the final sentiment score of the sentence. The result of the Lexicon-based Sentiment Analysis (SL_{ij}) serves as the labeled dataset for Deep Learning (DL)-based Sentiment Analysis using the LSTM RNN technique. This approach led to the implementation of Hybrid Sentiment Analysis by combining Lexicon-based Sentiment Analysis and DL-based Sentiment Analysis.

In the DL-based Sentiment Analysis, initially, the tokens are converted into sequences. The sequences are passed to the model through layers to get trained and saved the same. The saved model is used to predict the sentiment score of the new token. This algorithm finally generates S_H i.e. the sentiment score based on the hybrid sentiment (Lexicon + Deep Learning) technique. The S_H is further scaled down to a range of [0,5] to generate ($S_{Hscaled}$).

Finally, the output of the Hybrid Sentiment Analysis ($S_{Hscaled}$) was combined with the output of IBCF ($CP_{u,p}$) to achieve the final Hybrid predicted ratings ($FP_{u,p}$) The user receives the recommendations based on the Hybrid predicted ratings ($FP_{u,p}$).

3. Evaluation Results and Discussion

The proposed algorithm was implemented using the Python language in Google Collab. The framework was evaluated and compared using a publicly available Amazon Book Review Dataset. Specifically, the subset of the dataset focusing on Java books was extracted for evaluation, comprising 12,496 records for Deep Learning training and 873 records from 30 users for hybrid technique evaluation.

For evaluating the proposed framework, the dataset was split into training and testing sets, with proportions of 75% and 25%, respectively. Hybrid recommendation techniques were used to predict product rating values. The evaluation involved comparing predicted ratings with actual ratings using a confusion matrix, constructed with a predefined threshold value. Ratings meeting or exceeding the threshold were labeled as positive predictions, while those below it was considered negative predictions. In this study, a threshold of three was used, as ratings range from 0 to 5. Standard evaluation metrics were computed from the confusion matrix to assess the framework's performance (Anwar et al., 2020).
The proposed framework utilizes a Hybrid Sentiment Analysis approach (Lexicon + DL) with IBCF and GSP techniques. To implement Hybrid Sentiment Analysis, Lexicon-based Sentiment Analysis' result can serve as labeled dataset for ML-based or DL-based Sentiment Analysis. In the proposed framework DL was used. To ensure unbiased evaluation, both ML and DL possibilities were tested using standard evaluation metrics. Additionally, evaluations were conducted with and without GSP.

Therefore, the evaluation of the proposed framework was done in three phases:

- In the first phase, the possibility of using ML techniques in Hybrid Sentiment Analysis was tested. This phase involved comparing and contrasting various ML-based Sentiment Analysis techniques with IBCF to identify the best combination.
- Having identified the most effective ML techniques in the first phase, the next step was to integrate them with Lexicon-based Sentiment Analysis. In the second phase, the proposed framework was compared with a Hybrid approach combining Collaborative Filtering and Hybrid Sentiment Analysis (Lexicon-based + ML), with or without GSP.

- In the third phase, the proposed framework was evaluated and compared, both with and without the integration of GSP, against other approaches documented in the literature and state-of-the-art techniques

3.1 Phase 1

Since ML-based Sentiment Analysis methods require numerical data, therefore feature vectorization techniques such as word count, Term Frequency Inverse Document Frequency (TFIDF), and n-gram are utilized to convert textual data into a numerical format. Moreover, sentiment classification is treated as a binary classification problem therefore Logistic Regression, Support Vector Machine (SVM), and Linear Discriminant Analysis are employed as supervised ML-based sentiment analysis classifiers. This study compares all conceivable combinations of ML classifiers with the mentioned feature vectorization techniques. It is important to note that for testing the ML techniques, dataset labeling was performed by assigning ratings of three or higher as positive, while ratings below three were labeled as negative. The resulting evaluation metrics for different hybrid combinations are presented in **Table 2**. Furthermore, these potential combinations were further hybridized with GSP, and the resulting evaluation metrics are displayed in **Table 3**.

Table 2. Comparison of hybridization of IBCF and ML-based sentiment analysis with proposed technique without considering GSP.

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

** IBCF – Item Based Collaborative Filtering using Cosine Similarity with KNN*
LR – Logistic Regression
SVM – Support Vector Machine
LDA – Linear Discriminant Analysis
NG – n gram Feature Vectorization
WC – Word Count Feature Vectorization
TF – TFIDF Feature Vectorization
SA – Sentiment Analysis

Table 3. Comparison of hybridization of IBCF and ML-based sentiment analysis with proposed technique while considering GSP.

Hybridized techniques	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
IBCF+GSP+LR-NG-SA	68.38	5.09	55.54	9.3306
IBCF+GSP+LR-WC-SA	67.64	5.00	55.82	9.179
IBCF+GSP+LR-TF-SA	56.37	4.15	62.92	7.7924
IBCF+GSP+SVM-NG-SA	33.05	3.17	73.86	6.072
IBCF+GSP+SVM-WC-SA	26.90	3.02	76.99	5.813
IBCF+GSP+SVM-TF-SA	32.53	3.14	73.86	6.028
IBCF+GSP+LDA-NG-SA	71.09	6.16	62.36	11.22
IBCF+GSP+LDA-WC-SA	49.51	4.21	74.72	7.979
IBCF+GSP+LDA-TF-SA	67.17	5.62	64.63	10.343
Proposed Framework (Lexicon + DL + IBCF + GSP)	79.79	6.57	44.60	11.452

In the above tables, the ML-based Sentiment Analysis was combined with IBCF, either with or without GSP. It can be observed that when integrating ML-based sentiment analysis with IBCF, n-gram feature vectorization consistently yields superior results in terms of accuracy, precision, and F1-score. however, compared to these combinations, the proposed framework demonstrates better performance across all metrics except Recall.

3.2 Phase 2

In this evaluation, the Lexicon-based sentiment analysis's result, which includes linguistic terms, serve as labeled datasets for ML-based sentiment analysis. This approach for dataset labeling was considered more appropriate compared to the previous, more simplistic method, which relied on categorizing reviews based on rating thresholds. It is important to note that, given the effectiveness of n-gram feature vectorization identified in prior studies, only n-gram feature vectorization is considered in subsequent **Table 4** and **Table 5**.

Table 4. Comparison of DL and ML techniques in hybridization without considering GSP.

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

Table 5. Comparison of DL and ML techniques in hybridization while considering GSP.

Three hybrid techniques with GSP	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Lexicon+LogisticRegression+IBCF+GSP	66.47	4.38	50.14	8.06
Lexicon+LinearDiscriminantAnalysis+IBCF+GSP	78.21	6.50	48.15	11.46
Lexicon+SupportVectorMachine+IBCF+GSP	78.44	5.74	41.19	10.07
Proposed Framework (Lexicon + DL + IBCF+GSP)	79.79	6.57	44.60	11.45

The tabulated results demonstrate that, aside from recall, the proposed framework consistently exhibits superior performance both with and without the incorporation of GSP (Generalized Sequential Pattern) techniques. It is noteworthy that all techniques discussed in this section were applied to the identical dataset. This suggests that the proposed framework demonstrates heightened efficacy by presenting a greater number of relevant and preferred items in its recommendations, as substantiated by its superior values in accuracy, precision, and F1-Score metrics.

3.3 Phase 3

Finally, **Table 6** shows the comparison of the proposed framework, with and without the integration of GSP, with state-of-the-art techniques and other techniques documented in the literature.

Table 6. Comparison of proposed techniques (with and without GSP) with state-of-the-art techniques.

State of the art techniques	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
IBCF	95.97	04.81	01.98	02.81
Lexicon Based Sentiment Analysis	88.84	08.86	30.25	13.71
Lexicon Based Sentiment Analysis With Modifiers	91.64	09.30	21.16	12.92
Proposed Framework (Lexicon + DL + IBCF)	80.95	07.03	45.02	12.16
Proposed Framework (Lexicon + DL + IBCF+GSP)	79.79	06.57	44.60	11.45

As indicated in **Table 6**, while some parameters exceed those in state-of-the-art techniques, the proposed system achieves the highest recall value. This highlights the effectiveness of the proposed framework in creating a more efficient system, generating a recommended list of items that are both highly preferred and relevant. This superior performance is attributed to the proposed framework's incorporation of multi-dimensional data, which includes ratings, reviews, and buying behavior. Furthermore, the accuracy and recall metrics for the proposed framework without GSP were 80.95% and 45.02%, and with GSP, these metrics were 79.79% and 44.60%, respectively. These results also surpass those of the hybrid model and pattern-based word embedding model recently reported in the literature (Wayesa et al., 2023), which reported accuracy and recall metrics of 52.1% and 37.4%, respectively.

4. Conclusion

The findings of this research affirm that the development of an effective recommendation system is best achieved through the utilization of hybrid methodologies. The proposed novel hybrid approach incorporates hybrid sentiment analysis, IBCF, and GSP techniques. The significant improvement to the intended field is evident in this hybridization, which results in elevated levels of Accuracy, Recall, and F1-score. It is to be noted that the results obtained upon the integration of GSP exhibit comparability to those achieved without GSP. It is also acknowledged that with an increase in dataset size, the outcomes considering GSP may vary due to the augmentation of sequential patterns within the input data. The elevated performance metrics highlight the potential of using a hybrid technique involving both Lexicon and DL-based sentiment analysis alongside IBCF and GSP techniques. Future research will focus on further refining recommendation accuracy by incorporating additional techniques into hybrid models and broadening the evaluation scope to encompass a broader range of products beyond books.

Conflict of Interest

The authors declare that there are no conflicts of interest to declare with this publication.

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