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A Study On The Sentiment Analysis Based Hybrid Collaborative Filtering Recommendation Algorithm

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Abstract

Since Internet data is growing, recommender systems must be developed and improved to provide a list of suitable favourites. Recent years have seen a rise in the popularity of review-based recommender systems, in large part due to the proliferation of social networking sites. The idea behind these kinds of systems is to put to good use the insights gained from users' written comments. The development of opinion mining and sentiment analysis has grown significantly in recent years. Hence, it led to an increase in the amount of work that has been put into the improvement of recommendation systems. The purpose of this study is to present a comparative study on sentiment analysis based on a hybrid collaborative filtering recommender system. The approach under consideration is broken down into two stages: the phase of sentiment analysis, and the phase of recommendation. The first part, "sentiment analysis," involves the estimation of sentiment scores by employing datasets collected from a variety of social media sites. The second phase involves the use of hybrid collaborative filtering. This research shows a significant increase in recommender system performance by combining sentiment analysis and other such systems. Further, we evaluated the efficacy of our hybrid collaborative filtering methods to that of alternative methods traditionally employed in sentiment analysis. From the findings, we may conclude that our suggested hybrid collaborative filtering recommendation algorithm for sentiment analysis is superior to the state-of-the-art methods already available with an accuracy of 99.2%.

Keywords: Sentiment Analysis, Collaborative Filtering, Recommender Systems.

1. Introduction

More people are interested in review-based recommender systems now than ever before due to the expansion of social networking sites. Social settings with shared resources require recommender systems [1]. The fact that essential user qualities including a person's history, special interests, and level of experience can vary widely from one user to the next creates significant challenges when it comes to suggesting a resource that is engaging, helpful, and understandable for a specific user. Numerous industries, from e-commerce and media to banking and utilities, have made use of recommender systems. This type of technology makes unique recommendations for each user based on massive volumes of data. Clients benefit from these recommendations because they aid in product selection, while businesses benefit because they boost product use.

Using sentiment analysis in recommender systems helps get insight into users' opinions and feelings in the setting of social media, ultimately leading to more trustworthy recommendations [2]. On the one hand, this data can supplement customers' written reviews of items. Sentiment analysis of items obtained from online news sources, social media, blogs, and even the recommender systems themselves is regarded to be viable for better choices for users [3]. In this study, we propose and analyze a recommendation system that incorporates sentiment analysis with Collaborative Filtering (CF) approaches. Figure 1 given below shows the sentiment polarity analysis.

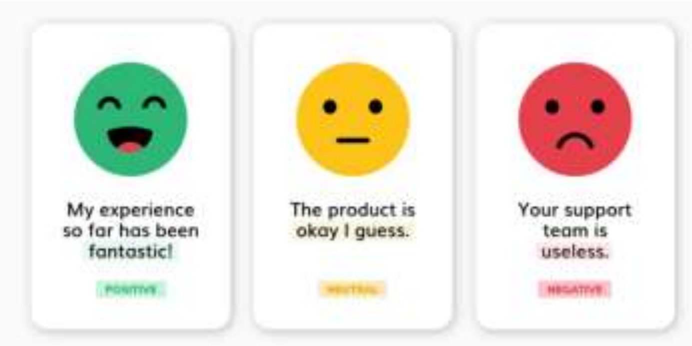

Figure 1. sentiment analysis [4].

Explicit user ratings used in CF methods may not accurately reflect users' perceptions of the relative importance of different criteria when evaluating a specific resource [5]. However, stigmergy phenomena may affect access-pattern-analyzing methods. Thus, at any one time, the community tends to propose to prospective users the resources that are currently the most popular or highly valued [6]. There is no one-to-one correlation between how popular a resource is and how useful or effective it is. This means that analyzing user behavior might result in inadequate recommendations that spread as users stick to their tried-and-true methods of navigating the available material.

With Web 2.0's advancements users are now able to provide much more detail on their experiences. It is possible to learn a lot about a resource's reliability, popularity, and usefulness by reading comments, conversations, and evaluations from actual users. The usage of user-generated reviews on the sources of a repository of educational content is suggested to address the problem of implicit ratings and to uncover qualitative information about a specific resource and the impression it left on the users that visited it. In order to do this, the comments made on educational content using sentiment analysis are analyzed. Next, we evaluated the reliability of the results and the extent to which the comments reflected the degree to which users felt their needs were met by the information. At this point in the process, a system for CF and recommendation was developed; nevertheless, the qualities and attributes of the material were not considered in the analysis. The development of such systems has its goal of the utilization of useful information, which can be gained from the textual reviews provided by users. The purpose of this study is to provide a CF recommender system that makes use of sentiment analysis.

1.1 Sentiment Analysis

Sentiment analysis aids in identifying user attitudes by analytically evaluating textual expressions of opinion as negative, positive, or neutral. Three distinct levels of information extraction are available for use in sentiment analysis: the document level, the aspect or feature level, and the sentence level. It's a method for automatically detecting any of an entity's subjectivities based on data that's been extracted about it. The intention is to determine whether the user-generated content is expressing good, negative, or neutral sentiments. There are now three methods for tackling the issue of sentiment analysis [7]: machine learning-based methods, lexicon-based methods, and combined lexicon/ML/AI methods.

Corpus-based methods and Dictionary-based methods are the two categories that fall under the category of the lexicon-based technique [8]. They were initially used to the task of labeling emotions. Traditional and deep learning-based machine learning algorithms [9] have both been presented for sentiment analysis. The hybrid strategies integrate machine learning with lexicon-based methods [10]. Incorporating the important information contained in reviews and understanding how a specific review impacts the customer are two ways in which sentiment analysis may improve the quality of a recommender system. The use of sentiment analysis lays the way for the creation of a targeted recommendation system. Figure 2 illustrates a framework for sentiment analysis based on CF.

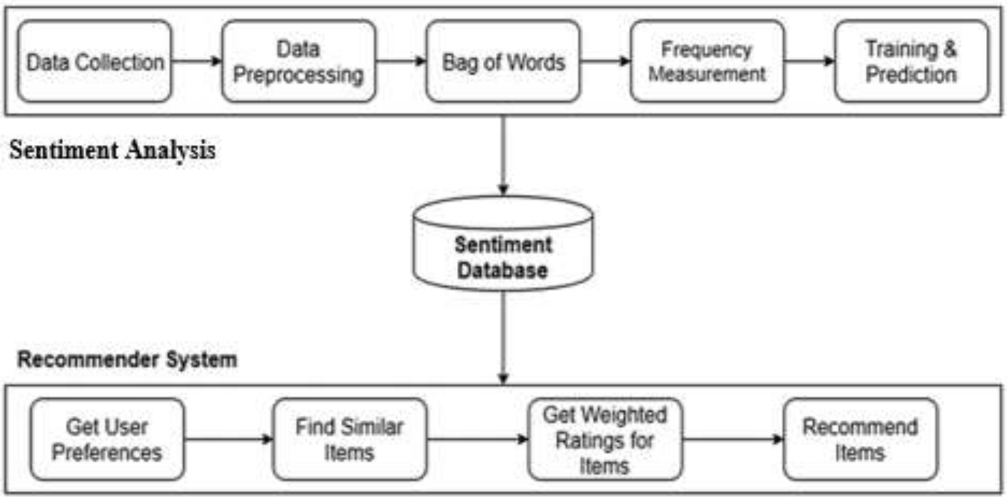

Figure 2. Sentiment analysis based on collaborative filtering [11]

1.2 Collaboration filtering

Collaborative filtering is a type of recommendation system that generates a forecast for a user based on that person's past actions and the behaviors of other users. Predicting individuals' interests based on their known preferences across a large user base is called "collaboration filtering ". It takes into account both the user and the object while calculating similarity [12]. It utilizes the cosine similarity approach in addition to the Pearson correlation method. The process of deciding whether a consumer would like a product based on the views of other individuals who share similar interests is referred to as "collaborative filtering." It finds a subset of individuals who share a user's interests by searching a huge population of people. It takes into account their preferences and creates a sorted list of recommendations. For recommender algorithms to function, we need data that includes both things and users. When processing such information, the matrix contains the responses of a group of users to specific objects inside a larger group of items. A user's ratings would be shown in rows, while the items' average ratings would be displayed in columns [13]. The proposed sentiment-based CF recommended system is shown in Figure 3 given below.

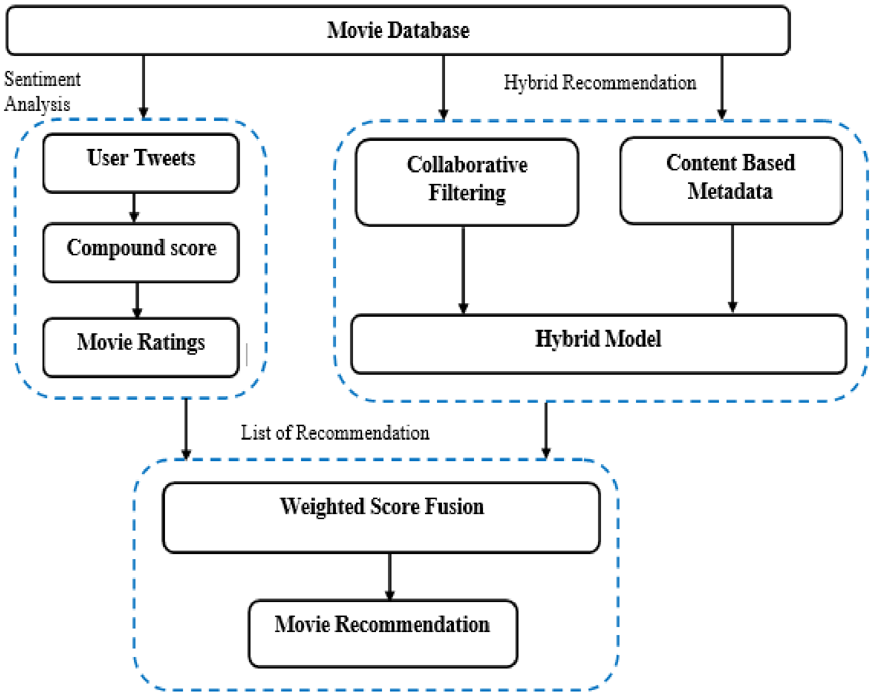

Figure 3. Collaborative Filtering [14]

Data sparsity, scalability, and the "cold start problem" are the primary obstacles that CF seeks to overcome. Model-based CF, Memory-based CF, and hybrid CF are the three primary algorithms introduced by CF, and they are used to integrate CF with other recommendation approaches and their strength to tackle the difficulties. It is often regarded as the simplest and most fundamental approach to discovering suggestions and making sales forecasts. There are drawbacks, which prompted the discovery of other approaches.

1.2.1 Hybrid Collaborative Filtering based recommender System

Hybrid recommender systems combine multiple recommender methods (often content-based approaches) with the strengths of collaborative recommendation systems to get optimal results. The use of a hybrid strategy allows for the avoidance of issues such as cold start, data sparsity, and scalability. The following are examples of how CF may be used with other recommendation methods:

- Hybrid Recommenders incorporating CF and Other Recommender Systems
- Hybrid Recommenders Integrating CF and Content-Based Features
- Hybrid Recommenders Combining CF Algorithms [15].

Figure 4 illustrates the workflow of a hybrid Collaborative Filtering Recommender System.

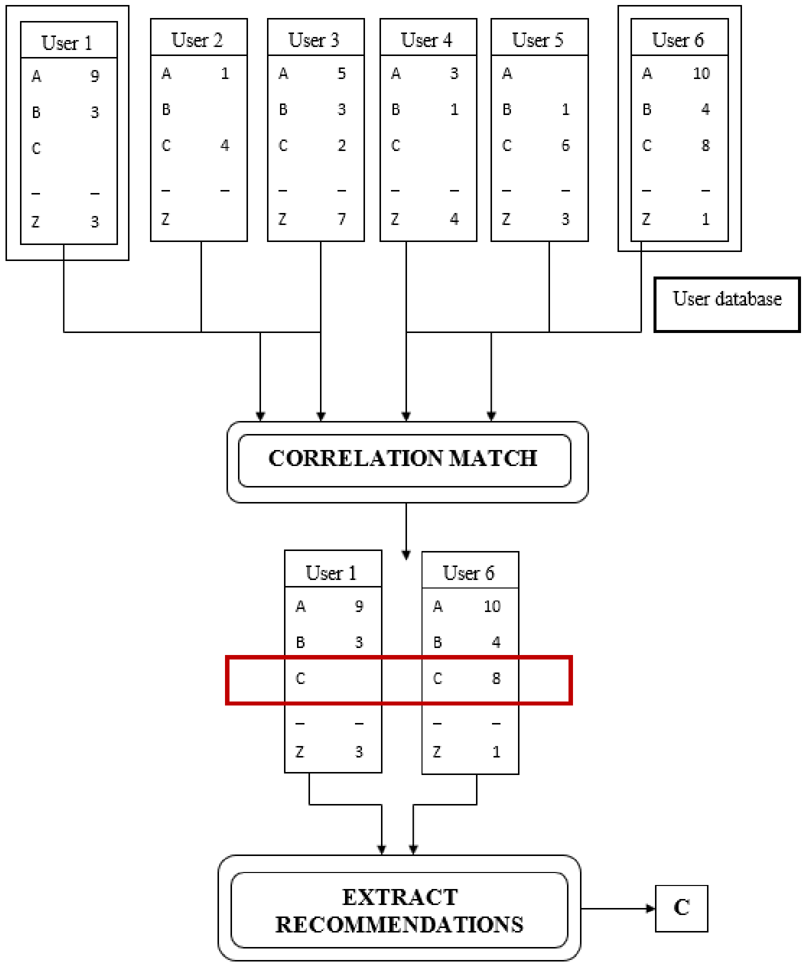

Figure 4. Hybrid Collaborative Filtering based recommender System [16]

It illustrates how collaborative filtering makes product recommendations based only on the numerical ratings offered by various people. Customer feedback is collected and kept in a database for future use. Users 1 and 6 exhibit some overlap in their behaviors, and their profiles are located close to one another, indicating that they share some common interests. Due to this resemblance, the estimation of User 6's rating for an unrated product by analyzing the ratings given by User 1 for that product could be predicted. Therefore, based on the information at hand, a forecast is produced predicting User 6's rating of product C. Recommendations are drawn from these forecasts and presented to the user. In an effort to overcome the shortcomings of both CF and content-based recommender systems, the hybrid recommender system is introduced [17].

2. Literature of review

Ghosh et al., (2021) [18] observed that the application of sentiment analysis on data that was created by a big number of people is quite helpful for expressing the viewpoint of the general public in terms of product reviews. Analyzing a piece of text in order to determine the intended tone or attitude is known as sentiment analysis. Sentiment analysis could be sometimes referred to as opinion mining. It identifies the individual's feelings about a piece of content and provides an explanation for them. Product reviews, tweets, blogs, status updates, posts, etc. all provide massive volumes of sentiment data that may be mined from social media. In this study, a very precise model of sentiment analysis for Amazon purchase evaluations, IMDB movie reviews, and Yelp restaurant reviews is proposed. The study aims to provide greater accuracy scores to their classifications of these reviews as either positive or negative using a combination of classifiers including support vector machine, decision tree, and logistic regression.

Hidayat et al., (2021) [19] assumed that Twitter is extremely popular for users to voice their thoughts on the topic at large. The study was carried out in order to undertake an analysis of how the general public feels about this new development, which was afterward categorized as either positive, negative, or neutral. This study makes use of two different Doc2Vec models—classification strategies such as logistic regression and support vector machines, as well as the dispersed model and dispersed bag of words. The distributed model and the distributed bag of words are both described below. Each model and classifier combination has an accuracy rate that is greater than 75%, and the results demonstrate that practically all of them are opposed to the development of Rinca Island. This study's methodology and findings could be used by the government to poll the Indonesian public on their feelings about the planned development of Rinca Island, or they can be applied to other settings.

Kaur et al., (2021) [20] explained that the Sentimental Analysis model is often used for the analysis of a user's thoughts, feelings, and the subjective nature of the text as expressed by the user. The field of data mining known as sentiment analysis (or "opinion mining") is based on the careful examination of people's expressions of emotion in online forums and online reviews. As demonstrated by experience, websites are the best medium for gathering client feedback. The currently used approaches, which are focused on emotional analysis, are inefficient. Hence, a unique hybrid framework that is built on three classifiers is suggested in this study. The support vector machine, logistic regression, and random forest are examples of such classifiers. The hybrid model acts as a powerful classifier, allowing for more precise categorization outcomes based on user input or past data. The proposed model has also performed well when compared to other approaches using a variety of performance criteria (including accuracy, precision, recall, and recall rate).

Panchal et al., (2021) [21] analyzed that over the past few decades, both the number of users and the number of products on the market have grown, making recommendation systems more and more essential. However, there are two significant obstacles for recommendation systems, which are data sparsity and data scalability, that result in inefficient time utilization and Low prediction quality. In this study, the authors suggest a unified strategy for evaluating review quality by combining Sentiment Analysis with Item-Based Collaborative Filtering. This method makes use of dimension reduction to enhance prediction accuracy and recommendation proficiency, and item-based collaborative filtering to assess review quality. It can forecast the most relevant movies for consumers by filtering out irrelevant information and focusing on conventional and comparable things. The experimental findings show that this strategy significantly affects offering increased prediction accuracy and a lot faster execution time compared to conventional content-based filtering algorithms. Useful information may be gleaned through sentiment analysis, such as how moviegoers feel about a certain film. The conclusions of this study improve the quality of recommendation systems by employing collaborative filtration and sentiment analysis.

Chopra et al., (2021) [22] develop a system that can be used by a large number of people to provide high-quality suggestions for expanding sales. The research applies a new strategy to the consumer review dataset that introduces an improved clustering algorithm called the modified density peak clustering algorithm. The detection of these assaults in the hybrid RS, which combines collaborative filtering and content-based RS, is suggested using an enhanced recurrent neural network method. The outcomes are compared to other cutting-edge methods. The suggested strategy is more suited to e-commerce platforms with fast expanding user bases and product catalogues.

Wang et al., (2021) [23] concentrate on the issue of information expiry while utilising the classic collaborative filtering method and offer a novel collaborative filtering algorithm by integrates the time factor (ITWCF). Authors then present a hybrid collaborative filtering model (TWCHR) that combines item-based and user-based collaborative filtering based on the enhanced K-means clustering technique. Finally, experimental findings demonstrate that the proposed technique can enhance the model's predictive accuracy by accounting for the time impact and doing sentiment analysis on suggestions.

Bhaskaran et al., (2021) [24] development and evaluation of a novel transudative support vector machine-based hybrid personalised hybrid recommender for use on publicly available data sets in machine learning. Learners' routines have enabled them to acquire the necessary skills. Based on the results of the experiments, it can be said that the improved clustering technique finds clusters of random sizes. In comparison to traditional approaches, the presented recommendation strategies significantly outperform them in terms of key metrics including predicted absolute error, accuracy, ranking score, recall, and precision. Using simulations, the authors demonstrate the suggested generalised recommender's potential to significantly boost efficiency and effectiveness.

Abbasi et al., (2021) [25] introduces a recommendation engine that takes user feedback into account via collaborative filtering. Findings indicated that the sentiment analysis of user reviews improves the effectiveness of recommender systems and the rate at which users recommend popular products. These findings demonstrate that online shops can utilise sentiment analysis for analysis of unstructured data to inform policy decisions and provide fresh recommendations to their consumers. A further benefit is that customers are better able to make educated purchases thanks to this system.

Aufar et al., (2020) [26] observed that YouTube is one of the many social networks that continue to have significant local engagement. YouTube has a lot of videos, and it's also a popular place to advertise products, has become increasingly popular. Case studies are public remarks made about Nokia's products that are drawn from studies conducted by academics. A sentiment analysis was conducted, in which various opinions about Nokia's Products were categorized according to whether they are good, negative, or neutral. A conclusion about the product's overall quality may be drawn from this analysis. The remarks, however, are dominantly labeled as neutral. In this study, the steps of sentiment analysis are divided into three distinct phases: gathering data, analyzing data, and drawing conclusions. Accuracy, precision, recall, and Fl-measure are measured and compared to test the final model. Decision

Tree and Random Forest Algorithms were utilized for the analysis of sentiment. In comparison to Random Forest's 88.2% accuracy, Decision Tree's is just a little better at 89.4%.

Maulana et al., (2020) [27] evaluated that Reviews and ratings from past audiences are reliable indicators of a film's quality. Reviews are sorted here according to whether they are positive or negative. The Support Vector Machine is a popular data mining algorithm used in the study because of its efficacy as a text classification technique, despite it being a very sensitive shortcoming in feature selection. When used as a feature selection technique, the Information Gain approach yields faster and more consistent problem-solving and convergence. Two datasets, from Cornell and Stanford, were used for testing, and they contained reviews of movies. An accuracy of 83.05% was achieved using the Support Vector Machine technique on the Cornell dataset. Improved precision reached 0.166%. When applied to the problem of analyzing the tone of movie reviews, Support Vector Machine-based Information Gain was shown to yield more reliable results.

Alharbi et al., (2019) [28] indicated that understanding user sentiment on social media platforms like Twitter has rapidly become a crucial and complex endeavor. The sentiment analysis procedure in such a setting is different from the standard for several reasons, including the short duration of tweets, the prevalence of spelling errors, the use of abbreviations, and the presence of special characters. Social media sentiment analysis is vital and has many relevant applications. Most algorithms for analyzing social media sentiment only consider textual content. This study presents a neural network model that considers past user actions inside a text (tweet). In this study, a Convolutional Neural Network (CNN) was deployed. Two datasets from the SemEval-2016 Workshop were used to assess the performance of the system. Sentiment categorization is improved by going beyond a tweet's topic content, as demonstrated by the proposed model's superior performance compared to the current baseline approach including Support Vector Machine (SVM) and Naive Bayes.

Rehman et al., (2019) [29] concluded that both the CNN model and the Long Short-Term Memory (LSTM) model have shown impressive and successful outcomes when used in various Natural Language Processing (NLP) applications. So, to address this challenge in sentiment analysis, a model that combines LSTM with a very deep CNN model was presented i.e., the Hybrid CNN-LSTM Model. The Word to Vector (Word2Vc) method is used to train the first-word embeddings. Word2Vc takes a string of text and converts it into a vector of numbers, using those numbers to determine the distance between words and classify them with similar meanings. When it comes time for embedding, the suggested model integrates the features retrieved in the preceding convolution and global max-pooling layers with the long-term relationships between them. The proposed model employs normalization, dropout technology, and a rectified linear unit to improve precision. The proposed Hybrid CNN-LSTM Model significantly outperforms the state-of-the-art in deep learning and machine learning on several metrics, including recall, precision, accuracy, and f-measure.

Preethi et al., (2017) [30] determined that it is difficult to do sentiment analysis on short texts such as single lines and reviews that can be found on various social networking sites due to the limited amount of contextual information that is accessible. In this study, a novel method for analyzing review sentiment using a deep learning system built on top of Recursive Neural

Networks (RNN) is presented. RNN-based Deep-learning Sentiment Analysis (RDSA) is presented to recommend nearby places based on user sentiment. The recommendations are fine-tuned using Deep Learning based on the results of a sentiment analysis done on the collected reviews from various social media platforms. According to the results of the experiments, the RNN-based Deep learning Sentiment Analysis (RDSA) improves the behavior by improving the accuracy of the sentiment analysis, which aids in making more useful suggestions for the user and removing a solution that fits their unique set of circumstances.

Ramadhani et al., (2017) [31] mentioned that when compared to other services, social media's massive and growing popularity stands out. A wide variety of tasks, from prediction to sentiment analysis, can benefit from Social Network Service data. Twitter is a social networking service (SNS) that contains a large quantity of data due to user postings. As Twitter has such a lot of data, it has the ability to be the topic of study connected to text mining and might be analyzed based on users' emotions. However, managing such a large quantity of unstructured data is a challenging undertaking, and machine learning is required in order to manage such a large quantity of data. Deep learning is a subfield of machine learning that makes use of the Deep Neural Network (DNN), which is characterized by having many hidden layers. The results of experiments using deep learning have shown that it is around 75% effective. Table 1 summarised the reviewed literature from different authors' their techniques and outcomes were also described below:

Table 1. Summarize the reviewed literature

Authors	**Techniques**	**Outcomes**
Ghosh et al., (2021) [18]	Decision Tree, Logistic Regression, and SVM	Classifiers such as logistic regression, SVM, and decision trees were used to categorize reviews as positive or negative, and their accuracies were compared in this study.
Hidayat et al., (2021) [19]	Logistic regression	The study was performed to assess public opinion, which was broken down into pro, con, and neutral groups. The accuracy rate for every model and classifier combination is more than 75%.
Kaur et al., (2021) [20]	Hybrid classifier	This study proposes a unique hybrid framework consisting of three classifiers: SVM, logistic regression, and random forest. They have been compared to existing approaches using a variety of performance criteria.

Panchal et al., (2021) [21]	Hybrid Collaborative Filtering	In order to enhance predictive performance, recommendations efficiency, and Sentiment analysis, this study proposed a unified method based on item-based collaborative filtering that makes use of dimension reduction.
Chopra et al., (2021) [22]	ARNN	Precision, recall, F-measure, false alarm rate, and accuracy are some of the metrics used to assess performance, with corresponding values of 98.50, 98.83, 98.67, 1.33, and 98.66%. It is also determined that the suggested algorithm provides the best results compared to the alternatives.
Wang et al., (2021) [23]	ITWCF and TWCHR	The proposed approach is validated by two tests, the results of which demonstrate that the system can effectively take into consideration both the passage of time and the sentiment tendency to enhance prediction performance.
Bhaskaran et al., (2021) [24]	SVM	The suggested datasets have an accuracy of 82%-98%. For the mock datasets, the MAE ranges from 5% to 19.2%.
Abbasi et al., (2021) [25]	Logistic Regression	Findings indicated that the sentiment analysis of user ratings improves the effectiveness of recommender systems and the rate at which users recommend popular products.
Aufar et al., (2020) [26]	Decision Tree Random forest	The values of precision, accuracy, recall, and Fl-measure for the Decision Tree and Random Forest classifiers are compared. The decision Tree has higher accuracy of 89.4% than the Random Forest algorithm.
Maulana et al., (2020) [27]	SVM	The findings of this study showed that the SVM method, applied to the Cornell dataset, yielded an accuracy of 83.05%, with an improvement in accuracy of 0.166%. An SVM-based approach to sentiment analysis was shown to be more effective.

Alharbi et al., (2019) [28]	CNN	In this study, CNN based system that takes into account data on user behavior inside a document (tweet) is utilized. Current baseline models are surpassed by the suggested model (including Naive Bayes and SVM).
Rehman et al., (2019) [29]	CNN -LSTM	Results showed that the proposed Hybrid CNN-LSTM Model excels above state-of-the-art deep learning and ML methods in all metrics tested including precision, f-measure, recall, and accuracy.
Preethi et al., (2017) [30]	RNN	The findings show that RDSA enhances behavior by improving the accuracy of sentiment analysis, which in turn leads to enhanced user suggestions and assists the user in identifying a certain attitude.
Ramadhani et al., (2017) [31]	DNN	For the purpose of sentiment analysis, this study made use of Deep Learning, which employs the usage of a deep feed-forward neural network with multiple hidden layers. The findings of the experiment indicate that the accuracy is around 75%.

3. Comparative analysis

In this study, we offer a comparative analysis of various techniques used for sentiment analysis. In this section, we have conducted a comparative study in which five studies that used datasets from various social media platforms, such as products, films, restaurants, and other reviews from Amazon, Twitter, Facebook, blogs, etc., are considered for analysis. The sentiment analysis is done through five different techniques which include SVM, Random Forest, Hybrid Collaborative Filtering, Logistic Regression, and Decision Tree. Further, these techniques are compared based on the accuracy of sentiment analysis. The objective was to examine how each approach performed against the others and find ways to advance the approaches in sentiment analysis.

The analysis illustrated in Figure 5 shows that Logistic Regression shows the least accuracy of 75.83% while Decision Tree shows a slightly higher accuracy of 78%, SVM shows an accuracy of 83.05% and Random Forest shows an accuracy of 88.2%. The technique that outperformed all previous techniques utilized for sentiment analysis is Hybrid Collaborative Filtering with a maximum accuracy of 99.2%. Table 2 depicts the comparative analysis of various techniques utilized for sentiment analysis on the basis of accuracy.

Table 2. Comparison based on the accuracy of different techniques

Authors	**Techniques**	**Accuracy**
Ghosh et al., (2021) [18]	Decision Tree	78%
Hidayat et al., (2021) [19]	Logistic Regression	75.83%
Panchal et al., (2021) [21]	Hybrid Collaborative Filtering	99.2%
Chopra et al., (2021) [22]	ARNN	98.66%
Wang et al., (2021) [23]	TWCHR	77%
Bhaskaran et al., (2021) [24]	SVM	95%
Abbasi et al., (2021) [25]	Logistic Regression	79%
Aufar et al., (2020) [26]	Random forest	88.2%
Maulana et al., (2020) [27]	SVM	83.05%

Figure 5 given below illustrates the graphical representation of the Comparison of different techniques used for sentiment analysis.

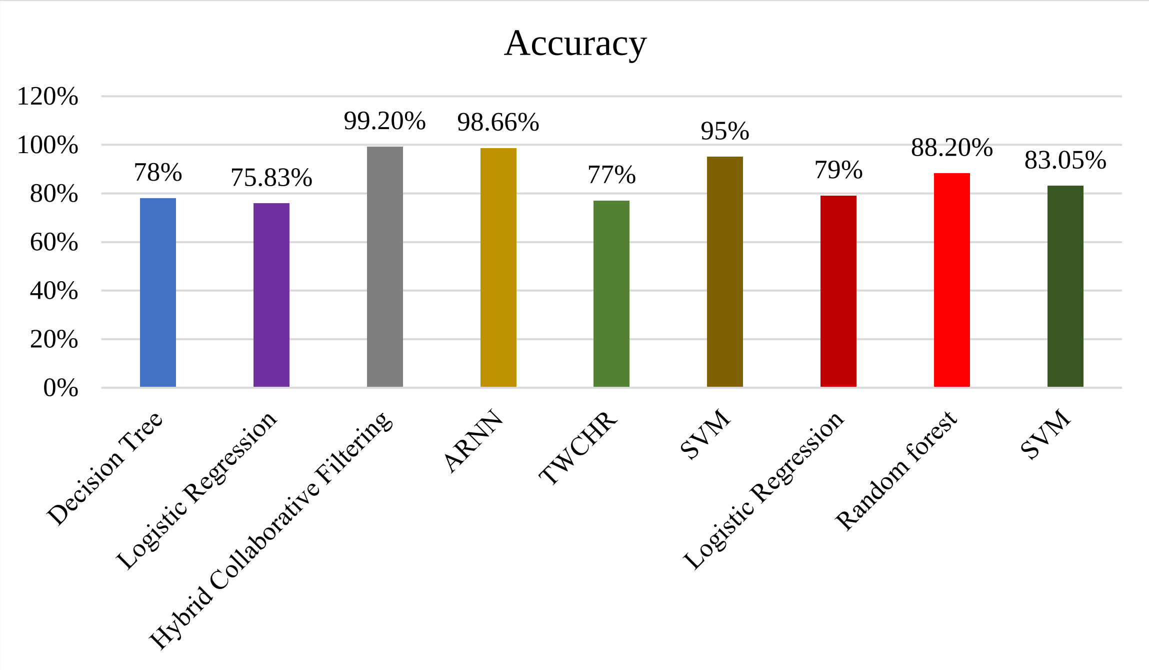

Figure 5. Comparison of different techniques used for sentiment analysis

4. Conclusion and Future scope

The development of opinion mining and sentiment analysis methods in recent years has led to a substantial increase in the amount of work that has been put into the improvement of recommendation systems. The most popular sentiment analysis models include SVM, Random Forest, Hybrid Collaborative Filtering, Logistic Regression, and Decision Tree. Another finding from the study was that popular strategies stated above are often individually evaluated in these studies on different datasets, but there is no comparison analysis. Hence, in this study, a comparative analysis of various methods that have been utilized for sentiment analysis to a dataset of various social media sites is presented. This study presents a comparative analysis of sentiment analysis based on a hybrid collaborative filtering recommender system and other techniques including support vector machines, random forests, hybrid collaborative filtering, logistic regression, and decision tree. Additionally, the relative efficacy of each method is evaluated in terms of sentiment analysis. The goal was to assess how each approach performed against the others and find ways to advance the various methods in sentiment analysis. Analysis indicates that Logistic Regression has the lowest accuracy, at 75.83%, compared to Decision Tree at 78%, Support Vector Machines at 83.15%, and Random Forest at 88.2%. With a maximum accuracy of 99.2 percent, Hybrid Collaborative Filtering has outperformed any and all other approaches used for sentiment analysis. It is possible that future studies might want to look more into hybrid methods, in which different models and techniques are combined to improve the accuracy of sentiment classification that could be achieved by the existing framework or methods while simultaneously minimizing the amount of computing power required.

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