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An Emoji-Based Movie Recommendation System using Sentimental Analysis and Machine Learning Techniques

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***Abstract*—Currently, movie recommendation systems are predominant intelligent systems that play a crucial role in providing selective information. Conventional approaches in recommending solutions are collaborative filtering and content-based filtering that has certain constraints when involving multiple domains. These existing approaches prerequisites user history and emo- tions to help the user find the desired. In order to address these issues, this paper proposes a Movie Recommendation System (MRS) using sentiment analysis and displays the movie comment review in one word along with emoji by analyzing reviews from the user. We have used various machine learning algorithms for recommendation as well as sentiment analysis. Further, comparative analysis was made to find the better classifier considering certain standard performance metrics. Experimental results showed that the proposed sentiment-based model illus- trates better performance using the Naive Bayes model.**

***Index Terms*—Correlation, Machine learning algorithms, Recommending systems, Sentiment Analysis.**

I. Introduction

The Internet has become the key part of our lives. In this present world, users frequently come across information overload which is a problem. There are many domains that use recommendation systems. MRS helps a user to get a movie of his interest. Movies are one of the major sources of entertainment that provide relief in our day-to-day hectic schedules. The recommendation systems are quite often used in video streaming apps and shopping platforms [1]. Although there exist different recommendation algorithms, the collaborative filtering algorithm is a popular algorithm. The fundamental purpose is to utilize the inclinations of a group with indistinguishable interests to counsel based on user's interest. Users provide a significant extent of response (such as rating) consisting of both positive and negative information to accomplish the need for filtering that helps in giving filtered information. Existing conventional user interest-based recommendation methods are hard to express the requisite information of the data and necessitates manual extraction of features, which consume a lot of time and energy on data labelling and processing [2]. The extraction of the most significant features often determines the efficiency of the algorithm. In recent years, machine learning or deep learning techniques are favoured by researchers as these techniques can accurately express more necessary data information. For instance, the existing recommendation model gets the user ratings to the movie, based on which movies get classified and then recommended to the users. But nowadays users have started giving comment reviews. If a user needs to know about a film, then they have to read the comment completely. Not everyone has the patience to read the whole of the reviews.

In order to address this issue, this paper proposes a MRS using sentiment analysis that shows movies comment review in one word along with emoji by analyzing reviews from the user. It also recommends movies to the user based upon the movie input provided by the user. Firstly, the user needs to enter the name of the movie about which he wants to know the details. The user can read the short description about the movie and also get to know various details like year of release, main actors involved, etc. The user can also learn about a particular actor in the film upon clicking on their picture. A list of similar movies will also be shown to the user with the help of sentimental analysis [3]. Sentimental analysis is done to understand the emotions, opinions of the people. It is a method of classifying the reviews into either "GOOD" or "BAD". If the user likes the movie then they can give a positive reaction using smiley emoji and if they do not like the movie he can give a sad emoji. Based on this, a set of movies are recommended to the user.

The text reviews given by the user are subjected to sentimental analysis and are assigned with polarity scores. The sentimental Analysis of the user reviews helps us to categorize the movies. Polarity points are given to the positive words which occur in the review and based on that score, the review is classified as either positive or negative and we also assign an emoji for the same. We also display the details of the movie in different regional languages apart from English. The trailer of the movie is also available in the description. The key objectives of the proposed MRS are as follows:

- To develop a MRS with improved efficiency to recommend the movies, better than the existing model.
- To design a MRS that provides a mechanism to assist users in classifying movies with similar interests

- Implementation of MRS using sentiment analysis to classify the reviews and recommend movies.
- Analysis of the performance of the proposed MRS using standard performance metrics.

The remainder of this paper is organized as follows: Section IIand SectionIIIwe study the background of Recommendation Systems and its applications. SectionIVgives a brief overview on the existing model of MRS. Then we discuss the development of our proposed MRS in detail in SectionV. In SectionVI, experiment results and discussion are described. Finally, we summarize this paper and the future work is given.

II. Background

MRS is currently one of the top research areas. Due to the impact of high internet speeds, multimedia has become one of the best forms of entertainment. Because of the swift progress in Internet technology, the present community has set foot in the period of Web 2, where information overload has turned into materiality. Video streaming services are more often used by customers to access movie content. Movies are the major source of entertainment but that also comes with the problem of information overload. The proposed MRS deals with the introduction of various concepts related to the recommendation system. The mission of Recommending System is to provide win-win situations for both customers and content providers.

III. Motivation

In this busy world, entertainment is a necessity for each one of us to refresh our mood and energy. Recommendation systems are getting increasingly important in today's extraordinarily hustling world. People never have the time to do extra activities in the given 24 hours in a day. They always find a shortcut for their work. The main point of having a recommendation system firstly is to provide thrilling content which appeals to the user within a less amount of time. In addition, it involves a good number of items to make personalized lists of useful and powerful content new to every individual. Therefore, the MRS is essential as it assists users come up with right choices without the need to vanish their cognitive resources.

IV. Related Work

Many proposed Recommendation Systems have existed over the decades. These systems employ various methods, like Collaborative, Content-Based, Hybrid Filtering, and sentiment analysis, to suggest the preferred items. These existing methods have special attention in Recommendation Systems, and each of them has been discussed as follows.

A. Collaborative-Based, Content-Based, and Hybrid-Based Filtering

Different Recommendation System techniques have been put forward in the literature to counsel based on the user interest [4]. The early-stage utilization of Collaborative Filtering was proposed in [5], which introduced a framework to examine documents and responses gathered from other users.

Katarya et al. [6] proposed a collaborative MRS utilizing fuzzy 'C' mean and grey wolf optimizer clustering techniques. These techniques are implemented employing Movielens data set to obtain a better prediction rate as a Recommendation System. They enhanced the earlier proposed framework in [7] by introducing a k-mean cluster and artificial bee colony framework for collaborative MRS to minimize the scalability and barriers. The amalgamation of the hybrid cluster and optimization method exhibited greater accuracy compared to existing frameworks. Yang et al. [8] deduced implied ratings based on the number of pages the users read. As many times the pages are read by the users, it gives the perception that the users liked the documents. This approach helped them to address the cold start problem in Collaborative Filtering. Zhao et al. [9] proposed a multimodal network representation learn- ing model for a movie recommendation. The result obtained showed that the proposed model performed well on the large dataset.

Content-based Filtering is the widely used RecommendationSystem, which works based on the details of the object and the user's profile [10]. Goossen et al. [11] introduced a novel ap- proach for counselling the news items based on the Term's Fre- quency (TF) and its Inverse Document Frequency (IDF) and a domain ontology, i.e., Collection Frequency and its Inverse Document Frequency (CF-IDF). The analysis showed that TF- IDF outperformed on many evaluation metrics such as recall, accuracy, and the F1-measures for the Athena framework. Ma et al. [12] implemented a recommended approach for social media employing a latent genre-aware micro-video. The key features such as auxiliary features, MovieLens, Yelp data set features, and user-item interaction were utilized and given as input into a neural network to obtain optimal recommendation scores. Nascimento et al. [13] interpreted their work for research manuscript recommendation employing the discrimi- native ability of the words. They inferred by weightage-scheme that title and abstract have discrimination efficiency than the body text. Cantador et al. [14], in their proposed work, focused on the use of item and user profiles explicitly employing loaded lists of social tags to give the music recommendations [15]. Du et al. [16] recommended a framework adopting a video content feature, described as a collaborative embedding regression model, to produce a significant video Recommendation System for multiple content features'.

The experiments conducted using MovieLens, Netflix data sets exhibited the better performance of the model. Meteren and Someren [17] developed a Recommendation System to counsel the articles for home enhancement. This approach computes the similarity between a document and the user profile vector by amalgamat- ing the TF-IDF and the cosine similarity. Contemporaneous research ought to demonstrate that the hybrid approach [18] is far better than conventional methods. The hybrid systems overcome the issues of dependability on single technique because of the amalgamation of multiple recommendation methods. Zhang et al. [19] instigated a framework considering user recommender interaction which procures user's input and suggests 'N' objects of user choice and logs user choice until no suggestion objects favour. Melville et al. [20] applied a content-based type of Collaborative Filtering to obtain refined content-based features in the collaborative framework. Using this technique, they speculated to have the enhanced prediction and the sparsity problem.

B. *Sentimental Analysis*

The primary job in sentimental analysis is to classify the polarity of a given review/text in a paragraph or sentence as whether the expressed feature of the sentence is positive, negative, or neutral by using Natural Language Processing (NLP) and text analysis. Sentimental analysis proved itself to be a beneficial approach for recommender systems [21]. A recommender system focuses on anticipating the choice for an item of the target user. Conventional recommender systems work on exact data sets. Nowadays, users provide their feedback, comment or text reviews to the items in many ecommerce or social networking services. These user's provide feedback or text data containing numerous sentimental opinions towards the item. This drew out feature describes the same as metadata in content-based filtering. For sentiment analysis, Natural Language Processing Toolkit (NLPTK) is a package in python that represents the output which shows each text review or sentence is positive, negative or neutral [22]. To compute at a high pace, we need to write or keep the set of words, and then categorize the expression as positive or negative, which requires a lot of time. The challenge comes when the data is from a language other than English. Wecannot rely on changes which will be inconsistent [23].

V. Proposed Work

The general overview of the architectural framework of the proposed MRS using sentiment to classify reviews and recommend movies with similar interests is represented in Fig.1. In this section, we discuss various components of theproposed MRS.

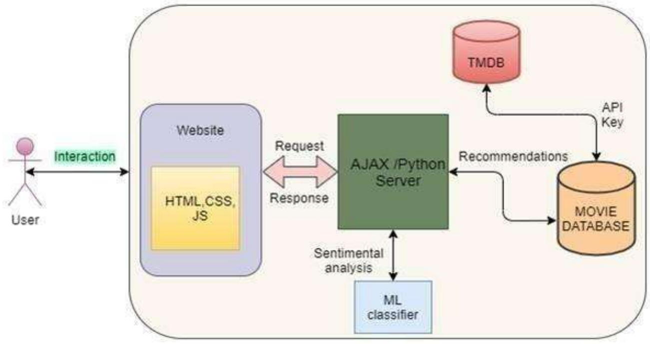

Fig. 1: Architectural overview of the proposed approach

A. *Database Description*

There are public databases available which are employed to recommend the movies and other entertainment media[1]. In our proposed work, the Movie Database (TMDB) Application Programming Interface (API) was used to get more attributes of all the movies by requesting the movie data from TMDB using API key. Upon processing it sends particular movies information along with all the information received from TMDB. After receiving all the necessary information from the TMDB, the Movie Database contains all the below mentioned attributes to be displayed in the website, see Table I

TABLE I: Details related to the movie database

Sl. No.	Attributes	Sl. No.	Attributes
1	Movie Title	6	Movie Release Date
2	Movie Poster	7	Movie Runtime
3	Movie Overview	8	Movie Status
4	Movie Ratings	9	Movie Trailer
5	Movie Genre	10	Movie Cast and Crew Information

The TMDB is a database for collecting different types of information about movies, series, actors etc. It provides a developer API through which developers can fetch information regarding different genres of movies. We mainly focused on movie data. TMDB API gives various endpoints tocollect the data.

We examined the dataset to obtain insight into the movie dataset that assists in developing the proposed MRS using the libraries in Python. We identified patterns such as the number of movies in each genre, most rated genres, the number of movies rated in each rating category, and most rated movies.

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B.Interface Development

We build the website using HyperText Markup Language (HTML) for the skeleton, Cascading Style Sheets (CSS) for stylings of the webpage, and JavaScript (JS) for different functionalities to provide an easy interface of the application to the user. We have hosted the website using port no.:5000 (localhost:5000) and accessed it on the local system to demon-strate the proof of concept of the proposed MRS. In the User Interface (UI), we employ a search engine to search any particular movie of the user choice, and upon clicking the search button a request to Asynchronous JavaScript And XML (AJAX) server is sent as an argument. On receiving the response from AJAX server various details like title, movie poster, overview, ratings, genre, release date, runtime, status, movie trailer, and cast and crew information are displayed. The proposed MRS employs sentiment analysis and displays the movie comment review in one word along with emoji by analyzing reviews from the user. The provision is also made tothe user in the website to view the details of the recommended movies in any regional language the user requires.

C. AJAX Server

AJAX is a set of web development approaches using many web technologies on the client's end to create asynchronous web applications. We will be fetching movie data from a free API and displaying them to the user. There are many API available for movie data on the internet. The title of the movie is sent to the Machine Learning (ML) Classifier to perform sentimental analysis and then a request is sent to the movie database to get the particular movie information and also the recommendation.

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D. ML Classifier

The sentiment in reviews is a paramount aspect in evaluating a movie. It is basically used for data processing to recommend accurate movies to the users. In the proposed MRS, the ML model utilizes the sentimental analysis of text reviews for classifying the reviews as either positive or negative and determining the user's choice for some selected movie.

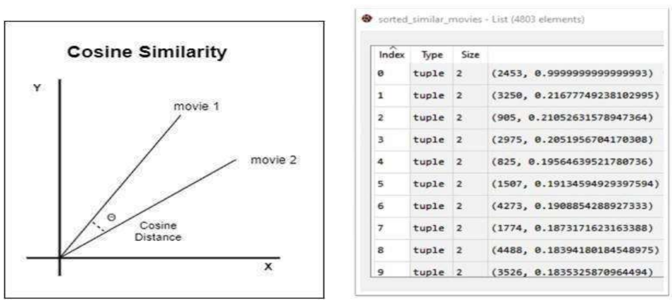
Multinomial Naive Bayes ML classifier performs better for the discrete data (e.g. movie ratings between 1 to 5 where each rating represents a frequency) [24]. However, the Naive BayesML classifier is best suited for text-based learning having onlytwo values to predict the class or label. Since the proposed MRS consists of discrete data to categorize the movie as Good or Bad we have used Multinomial Naive Bayes ML classifier.

E. Multinomial Naive Bayes

The text data which is already mined is fed to the Naive Bayes model that categorizes the text word into either positive and negative. The multinomial model is used to determine the term frequency of a term in a document or sentence. This is useful in sentimental analysis of a particular term, resulting in an effective decision. Term occurrence or frequency helps inanalysing whether the term is helpful in analysis or not. But sometimes, a word or a term in the document is present many times, it may also be a stopword which does not add any meaning to the review or sentence, such words or terms must be eliminated to get better results by using naive bayes algorithm.

Algorithm 1 Pseudo-code of MRS

1: movies = read file movies m_etadata.csv
2: **for** m in movies do **do**
3:Search movie by title m and year then filter by lan-guage=English and section type in this priority:
4:a. Search: query and title are exact match
5:b. Compare: keywords, genre, cast, director is similarto query
6:c. Pqoupeurlyar:movie ratings is popular and similar to
7: **end for**
8: if subtitle is in one of section type then
9:similarity = calculate title similarity and query using Cosine Similarity



(a) (b)

Fig. 2: (a) A similarity measure using Cosine Similarity (b) Snippet of Similarity Calculation Using Cosine Similarity

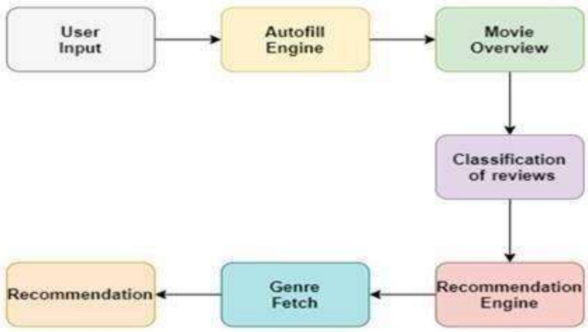


Fig. 3: Data Flow Diagram of the Proposed MRS

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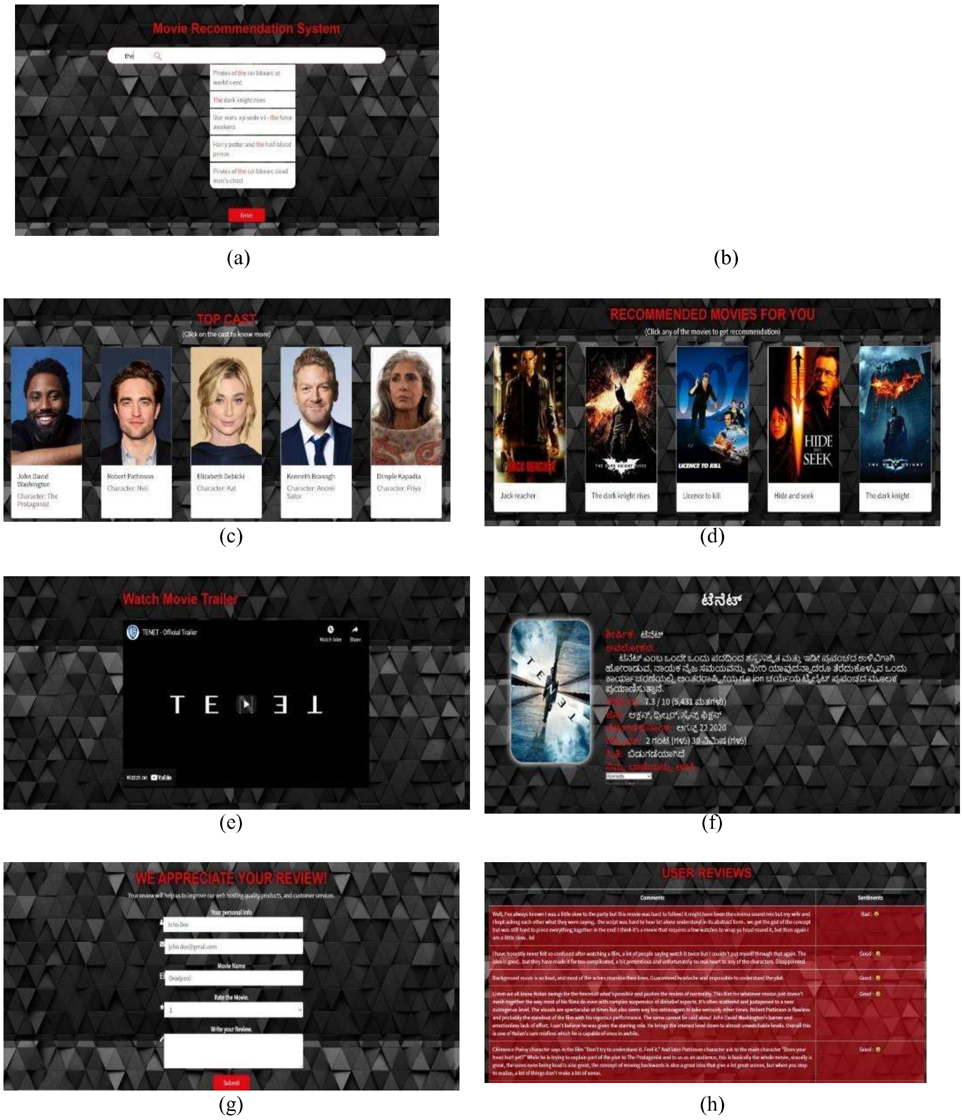

Fig. 4: Screenshot depicting the working functionalities of the proposed MRS

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F. *Cosine similarity*

To provide accurate recommendation and matching to the users, we need a method to define similarity measures [17]. There are some methods like Cosine similarity, Euclidean distance, Pearson coefficient and others. Among them cosine similarity gives good similarity measure and comparatively high precision, which is a very regularly used technique for recommendations. This technique is frequently used in text information processing and natural language processing. It measures similarity between the two n-dimensional vectors which are roughly pointing in the same direction by using the angle between them. It is calculated using below Eq.1, Eq.2, and Eq.3.

$$\cos\theta = \frac{a.\bar{b}}{\|\bar{a}\| . \ \bar{b}} \quad (1)$$

$$\bar{a} = a^2 + a^2 + a^2 + \ .... + a^2 \quad (2)$$

$$\mathrm{B} = + b^2 \ + \ b^2 ...... + b^2 \quad (3)$$

10: movies highest cosine similarity score

11: Display tuple movie index and cosine similarity score

The '·' symbol represents the dot product between two vectors, and *a* represents the European length between the vectors, which is, the square root of itself. The value is less than 1. If the value is nearer to the 1, it means that the cosine similarity is a number that ranges between 0 and π and is 1 because the cosine of 0 is 1 and any angle between the cosine similarity is a number that ranges between 0 and π are similar else two are not similar.

Cosine similarity is most commonly used in information retrieval and text mining. For example, to find how similar the two documents are, based on how many times the terms or words in the document appear, cosine similarity calculateswhether the documents are similar or not. It does not take difference between average scores of items, it takes original cosine similarity values which solves the problem effectively.Pseudocode of the Cosine Similarity measure is described inAlgorithm1and its implementation snippet is shown in Fig. 2.

G. *Recommendations*

Collaborative filtering is a common method followed in the recommendation system. If the movie recommendations are based on the ratings or genres stated by other users it is quite difficult to provide precise results. To make it easy for users and to overcome this drawback, we used another technique for recommendation which is Cosine Similarity. This method helps us in suggesting precise results to the user as the ratings and genres are given by the user himself and depends completely on the user's choice. Previous methods lacked the accuracy of true recommendations as they were dependent on other users.

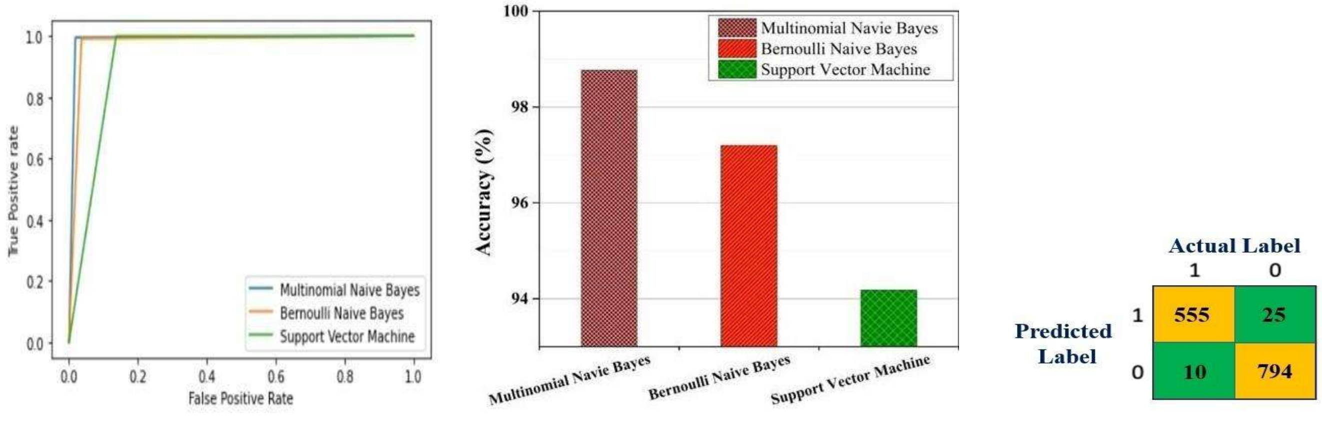
H. *Application Design*

The data flow of the proposed MRS is illustrated in Fig. 7 As shown in Fig.3, the user needs to give an input in the search engine in the user interface. The search engine has auto-complete functionality. On clicking the search button we can see the details of the movie like overview of the movie along with a poster, runtime, status, release date, genre, title, movie cast information along with their pictures, trailer video of the movie, sentiment analysis of the reviews, and the list of recommended movies. The genre of the movie is being taken for recommendation of movies using sentiment analysis. The main features of the proposed MRS are as follows:

- *User Interface* - The user will have a simple user interface where they can search for any movie by typing the name of the movie in the search engine. This search engine has an auto-complete functionality where we get the list of all the movies that start with the letters which we have typed in the search engine.
- Information about searched movies - The data about the movies is fetched from a movie database called TMDB using an API key. Users can get various information regarding the movie that is mentioned in Table I.
- Sentiment Analysis - The reviews of the movie are subjected to sentiment analysis where the whole review is simply represented in one word - "GOOD" or "BAD" along with an emoji.
- Reviews by users - A blog is created at the end where a user can write his/her experience about a movie. User needs to mention his/her email id for the same.

Experimental Analysis

A recommendation system should have higher accuracy and precision. Our proposed work ensures that users are getting the required information about the movie in a convenient and fast manner. In this paper, we used Naive Bayes algorithm for sentiment analysis of the reviews. We performed a com- parative analysis using two other algorithms instead of Naive Bayes, and we inferred that Naive Bayes algorithm gave the best accuracy score compared to the other two. The graph shows the performance analysis of the classification model considered in the proposed work, see Fig.5a. It describes that the true positive rate for multinomial naive bayes algorithm is more/high compared to the other two algorithms which we have implemented and compared with the proposed MRS i.e, Bernoulli naive bayes and Support vector machine algorithms. As we have observed, it is obvious from the accuracy graph and the ROC curve that the performance of Multinomial Naive Bayes is much higher than the performance of Bernoulli Naive Bayes and the Support Vector Machine classifier. Bernoulli Naive Bayes and Support Vector Machine classifiers achieved an accuracy of 97.20%, and 94.18%, respectively which is less than that of Multinomial Naive Bayes Classifier that is 98.77%. It is quite evident from the ROC curve that the true positive rate is higher for Multinomial Naive Bayes which shows the performance wise supremacy of Multinomial Naive Bayes classifier, see Fig.5b. A confusion matrix is a matrix obtained to represent the predicted outcomes of a predicted class in terms of the column, and each row represents the occurrence of instances in an actual class. It is a 2-by-2 matrix that contains the instances of true positives, false positives, true negatives, and false negatives, see Fig.5c. Evaluation metrics such as



(a) (b) (c)

Fig. 5: (a) ROC curve indicating that TPR for Multinomial Naive Bayes algorithm is greater than Bernoulli Naive Bayes and Support Vector Machine ML classifiers (b) Comparison analysis of accuracy obtained by various ML classifiers (C) Confusion Matrix

Precision, Recall, and F1-Score were utilized in this work to appraise the movie recommendation ability of the proposed MRS. An ideal MRS is said to have high Precision and high Recall. However, it is difficult to achieve both. The obtained results for precision, recall, and F1-Score for proposed MRS is as Tabulated in Table II. The demonstration of the proposed work is illustrated in Fig. 4, in terms of screenshots. Fig.4a, shows the autocomplete feature, where we can get a list of movies starting with the letters which we enter. It helps users save time while they are searching for movies with long names. Fig.4h, demonstrates the sentiment analysis part where we analyse

TABLE II: Performance achieved by Multinomial Naive Bayes machine learning-based classifier

Class Label	Precision	Recall	F1-Score
0	0.98	0.96	0.97
1	0.97	0.99	0.98

the whole review and give one word about the whole review that determines whether the review is good or bad. Fig.4d, shows us a list of movies that are recommended to the user based on the genre using sentiment analysis. Fig.4f, shows the content of the whole web-page in any regional language. For demonstration purposes the regional language Kannada is shown. The proposed MRS exhibits other features like the movie trailer (see Fig.4e), details of the topcast in the movie (see Fig.4c), and appreciate the user providing the user review on the movie (see Fig.4g).

Future Directions

MRS proved themselves to be the best solution for addressing the problem of information overload. They help in making choices by preserving time and energy. Future work will focus on enhancement of the existing methods and algorithms used so that the recommendation systems predictions and recommendations quality can be improved. As an additional functionality the ticket booking feature can be added. Finally, MRS can be considered as the best research platform in today's world.

Conclusion

In this paper, we have proposed a MRS that uses senti- ment analysis data to recommend movies. Sentiment analysis imparts data about how the audience responds to a specific movie and how this captured data is useful. The proposed system used cosine similarity score to improve the recom- mendations. Based on our experiments, the proposed sentiment based MRS exhibits better performance using the Multinomial Naive Bayes classification by accomplishing the accuracy of 98.77% compared to other classifiers. We deduce that our proposed MRS recommends more accurately than the other recommendation systems.

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