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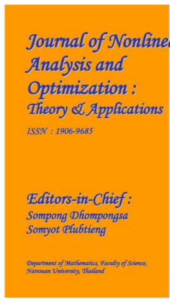

CINEMATIC INSIGHTS A TAILORED RECOMMENDATION

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ABSTRACT

Recommendation systems (RSs) have garnered immense interest for applications in e-commerce and digital media. Traditional approaches in RSs include such as collaborative filtering (CF) and content-based filtering (CBF) through these approaches that have certain limitations, such as the necessity of prior user history and habits for performing the task of recommendation. To minimize the effect of such limitation, this article proposes a hybrid RS for the movies that leverage the best of concepts

used from CF and CBF along with sentiment analysis of tweets from microblogging sites. The purpose to use movie tweets is to understand the current trends, public sentiment, and user response of the movie. Experiments conducted on the public database have yielded promising results.

1. INTRODUCTION

Given the huge amount of movies are available all over the world, it is challenging for a user to find the appropriate movies suitable for his/her tastes. Different users like different movies or actors. It is important to find a method of filtering irrelevant movies and/or find a set of relevant movies. Movie recommendation system is a process of exactly doing above tasks. Such a system has lot of implications and is inspired by the success of recommendation systems in different domains such as books [1], TV program [9], jokes [4], news articles [1]. It is one of the most important research in the digital television domain [4]. The most well known recommendation systems are mainly based on Collaborative Filtering (CF) [3] and Content-based Filtering [2]. CF first tries to find out the groups of similar users automatically from a set of active users. The similarities between users are computed using correlation measure. It then recommends items to a user based on the opinions of the users groups. Although CF is successful in many domains, however, it has shortcomings such as, sparsity and scalability [1]. CF uses user ratings to find similar users. However, it is very difficult to find such since very few movies have ratings. Given the huge amount of movies are available all over the world, it is challenging for a user to find the appropri- ate movies suitable for his/her tastes. Different users like different movies or actors. It is important to find a method of filtering irrelevant movies and/or find a set of relevant movies. Movie recommendation system is a process of exactly doing above tasks. Such a system has lot of implications and is inspired by the success of recommendation systems in different domains such as books [8], TV program [9], [5], jokes [4], news articles [1]. It is one of the most important research in the digital television domain [1]. The most well known recommendation systems are mainly based on Collaborative Filtering (CF) [3] and Content-based Filtering [2]. CF first tries to find out the groups of similar users automatically from a set of active users. The similarities between users are computed using correlation measure. It then recommends items to a user based on the opinions of the users groups. Although CF is successful in many domains, however, it has shortcomings such as, sparsity and scalability [2]. CF uses user ratings to find similar users. However, it is very difficult to find such since very few movies have ratings. Given the huge amount of movies are available all over the world, it is challenging for a user to find the appropri- ate movies suitable for his/her tastes. Different users like different movies or actors. It is important to find a method of filtering irrelevant movies and/or find a set of relevant movies.

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Video Streaming Services: Services like Netflix and YouTube use recommendation systems to suggest movies, TV shows, and videos based on a user's viewing history, preferences, and ratings. This keeps users engaged and encourages them to discover new content they might enjoy.
Personalized Learning: In the realm of online learning, recommendation systems are employed to suggest relevant courses, tutorials, or learning materials based on a student's past learning behavior and preferences. This ensures a more personalized and effective learning experience.
Music and Book Recommendations: Platforms like Spotify and Goodreads leverage recommendation systems to suggest music tracks and books, respectively, based on a user's listening or reading history and preferences. Overall, recommendation systems have become an integral part of the modern digital landscape, enhancing user experiences by efficiently delivering personalized and relevant content amidst the vast sea of information available online. They continue to evolve and improve with advancements in artificial intelligence and machine learning techniques [9].

2. LITERATURE SURVEY

In this project, we propose a movie recommendation system that leverages both collaborative filtering and content-based filtering techniques to provide personalized movie recommendations to users. Collaborative filtering is widely used in recommendation systems to identify users with similar preferences and interests, thereby suggesting movies that like-minded users have enjoyed. Content-based filtering, on the other hand, focuses on the characteristics of the movies themselves, analyzing features like genres, actors, directors, and plot summaries to recommend movies with similar attributes. By combining both methods, our system aims to enhance recommendation accuracy and offer diverse movie choices that align with the user's taste.

This project presents a hybrid movie recommender system that utilizes matrix factorization and deep learning techniques to generate personalized movie recommendations for users. Matrix factorization is employed to discover latent features in the user-item interaction matrix, capturing the underlying preferences of users for various movie attributes. Simultaneously, a deep learning model is trained on movie metadata, such as posters, summaries, and genre information, to extract high-level representations of the movies. These learned representations are then combined to provide a comprehensive and accurate recommendation, catering to each user's unique movie preferences.

In this project, we propose a movie recommendation system that incorporates sentiment analysis and natural language processing (NLP) techniques to provide insightful and sentiment-aware movie recommendations. The system analyzes user reviews and ratings to determine the sentiment associated with each movie, understanding the user's emotional response to the film. NLP is used to extract key features from the reviews, enabling the system to recommend movies that align with the user's expressed sentiments and preferences. This approach enhances the user experience by suggesting movies that resonate positively with the user's emotional state, making the movie-watching journey more enjoyable and satisfying [8].

This project introduces a graph-based movie recommender system that leverages network analysis to identify movie similarities and recommend relevant choices to users. Movies and users are represented as nodes in a graph, and their interactions are modeled as edges, creating a comprehensive network of movie-user connections. By employing graph algorithms, such as community detection and centrality measures, the system identifies movie clusters and influential movies, offering suggestions based on the user's position within the movie network. This approach ensures diverse and unexpected movie recommendations, encouraging users to explore a wide range of films [10].

In this project, we propose a context-aware movie recommender system that considers contextual factors and provides real-time updates for improved recommendation accuracy. The system takes into account situational variables, such as time of day, user location, weather conditions, and social context, to tailor movie suggestions to the current environment and user preferences. Moreover, it continuously updates recommendations based on user feedback and behavior, ensuring that the recommendations remain relevant and up-to-date. By incorporating real-time context and user interactions, our system offers an enriched movie recommendation experience, satisfying the user's evolving interests and preferences.

3. PROBLEM STATEMENT

Many RSs have been developed over the past decades. These systems use different approaches, such as CF, CBF, hybrid, and sentiment analysis to recommend the preferred items. These approaches are discussed as follows. A. Collaborative, Content-Based, and Hybrid Filtering Various RS approaches have been proposed in the literature for recommending items [8]. The primordial use of CF was introduced in [8], which proposed a search system based on document contents and responses collected from other users. Yang et al. [5] inferred implicit ratings from the number of pages the users read. The more pages read by the users, the more they are assumed to like the documents. This concept is helpful to overcome the cold start problem in CF. Optimizing the RS is an ill-posed problem. Researchers have proposed several optimization algorithms, such as gray wolf optimization [6], artificial bee colony [2], particle swarm optimization [4], and genetic algorithms [6]. Katarya et al. and Verma [2] developed a collaborative movie RS based on gray wolf optimizer and fuzzy c-mean clustering techniques. Both techniques are applied to the Movielens data set and predicted a better RS. They improved the existing framework in [2] proposing an artificial bee colony and k-mean cluster (ABC-KM) framework for a collaborative movie RS to reduce the scalability and cold start complication.

3.1 LIMITATIONS

The existing users not only receive information according to their social links but also gain access to other user-generated information. The necessity of prior user history and habits for performing the task of recommendation.

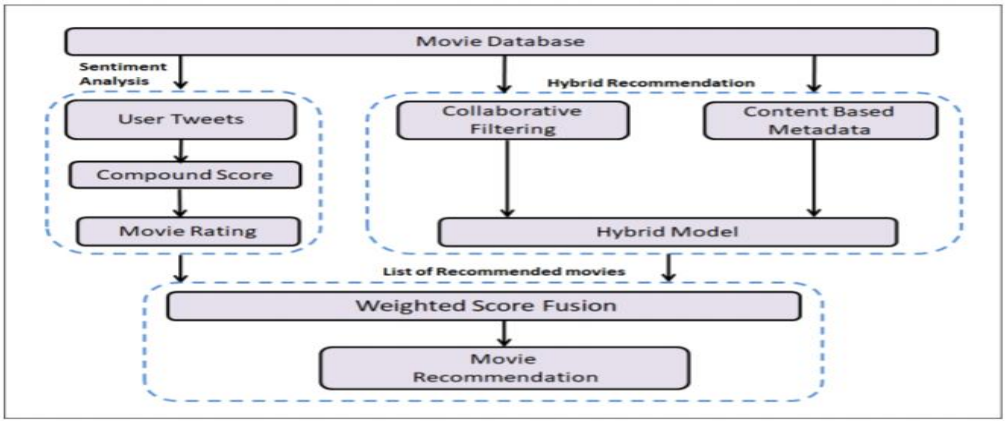
4. PROPOSED SYSTEM

The proposed sentiment-based RS is shown in Fig. 1. In this section, we describe various components of the proposed RS. A. Data Set Description The proposed system needs two types of databases. One is a user-rated movie database, where ratings for relevant movies are present, and another is the user tweets from Twitter. **Public Databases:** There are many popular public databases available, which have been widely used to recommend the movies and other entertainment media. To incorporate the sentiment analysis in the proposed framework, the tweets of movies were extracted from Twitter against the movies that were available in the database. Experiments conducted using various public databases, such as the Movielens 100K,2 Movielens 20M,3 Internet Movie Database (IMDb,4) and Netflix database,5 that were not found suitable for our work due to the absence of microblogging data. After a thorough assessment of the abovementioned databases, the MovieTweetings database [1] was finally selected for the proposed system. MovieTweetings is widely considered as a modern version of the MovieLens database. The purpose of this database is to provide an up-to-date movie rating so that it contains more realistic data for sentiment analysis. Table I displays the relevant details of the MovieTweetings database. **Modified MovieTweetings Database:** In the proposed work, the MovieTweetings database is modified to implement the RS. The primary objective to modify the database was to use sentiment analysis of tweets by the users, in the prediction of the movie RS. The MovieTweetings database contains the movies with published years from 1894 to 2017. Due to the scarcity of tweets for old movies, we only considered the movies that were released in or after the year 2014 and extracted a subset of the database which complied with our objective.

4.1 Advantages:

To use movie tweets is to understand the current trends, public sentiment, and user response of the movie. Experiments conducted on the public database have yielded promising results.

5. SYSTEM ARCHITECTURE



6. IMPLEMENTATION

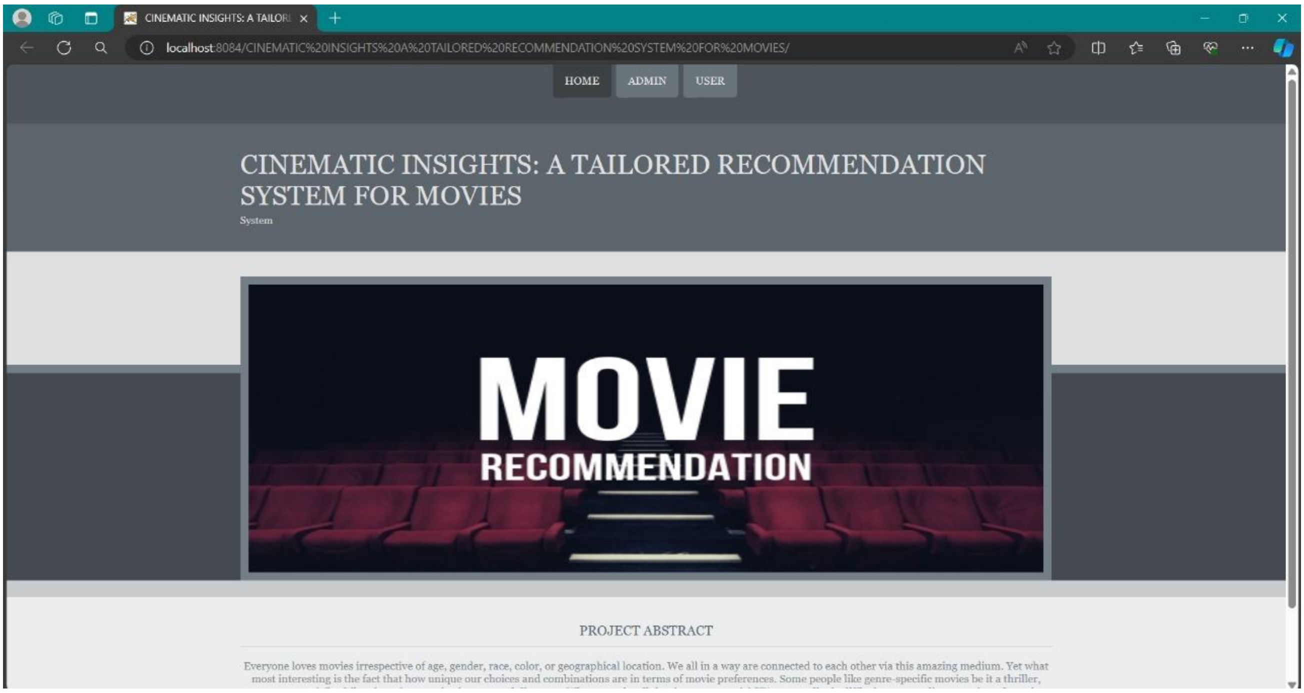
6.1 Admin

We can access and view the Users and who are registering in our applications

6.2 User

we can view posts and we can view the profiles in the application

7. SCREENSHOTS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HOME
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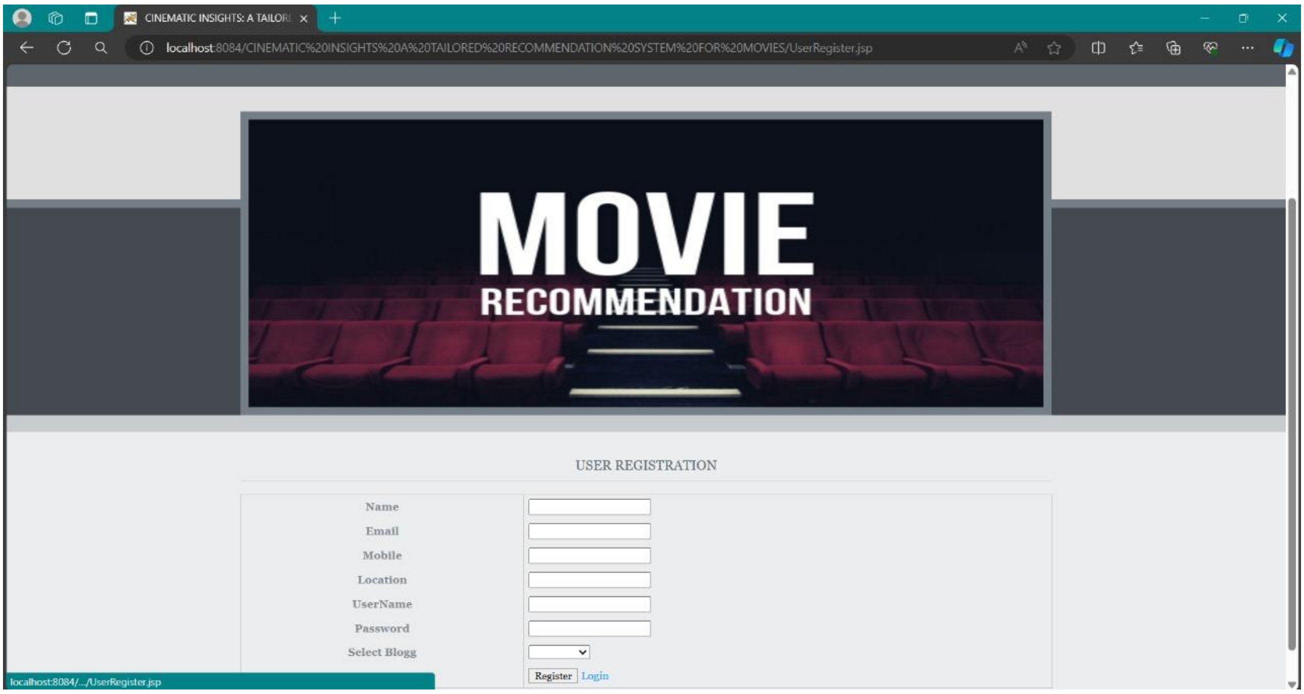
USER
CINEMATIC INSIGHTS: A TAILORED RECOMMENDATION SYSTEM FOR MOVIES
System
MOVIE
RECOMMENDATION
PROJECT ABSTRACT
Everyone loves movies irrespective of age, gender, race, color, or geographical location. We all in a way are connected to each other via this amazing medium. Yet what most interesting is the fact that how unique our choices and combinations are in terms of movie preferences. Some people like genre-specific movies be it a thriller,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Password
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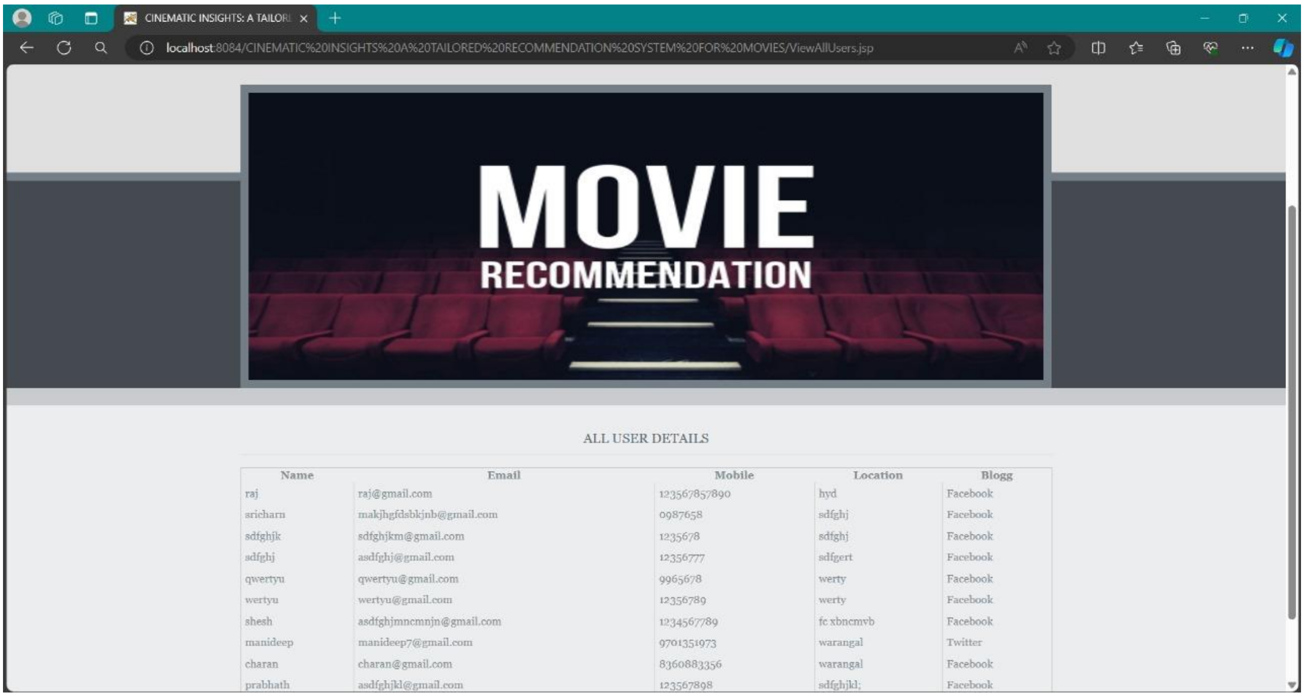
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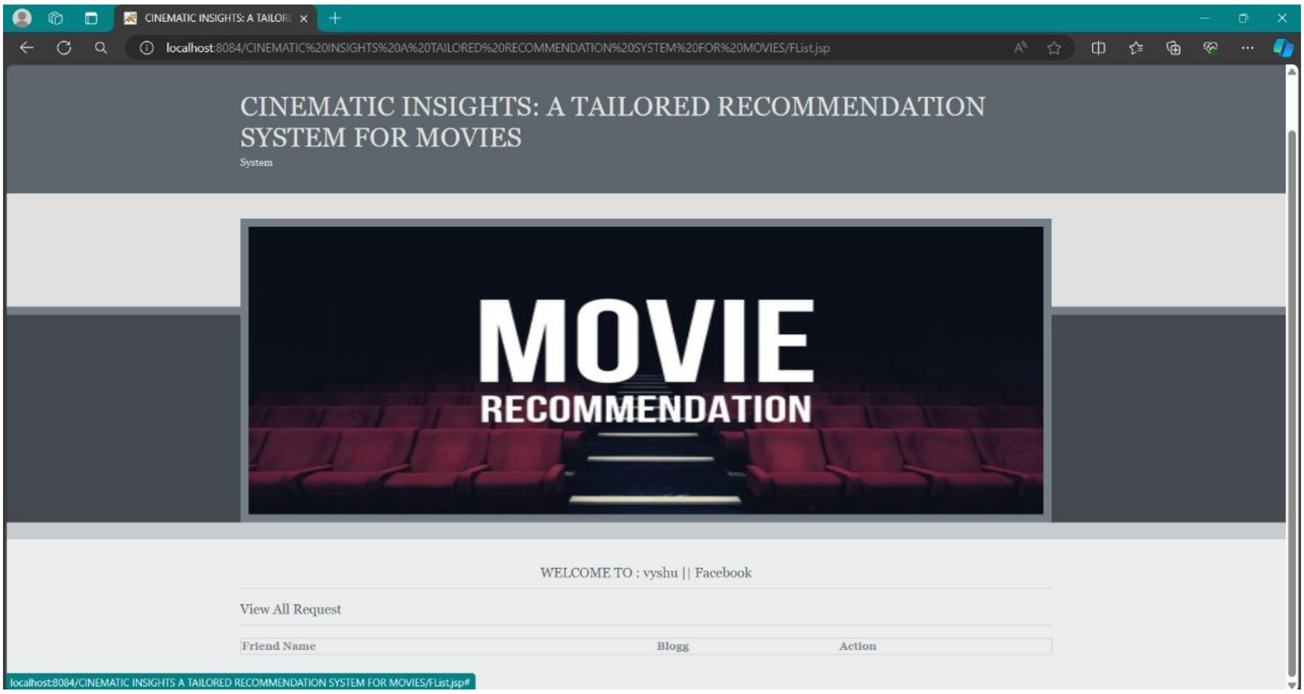
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RECOMMENDATION
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View All Request
Friend Name Blogg Action
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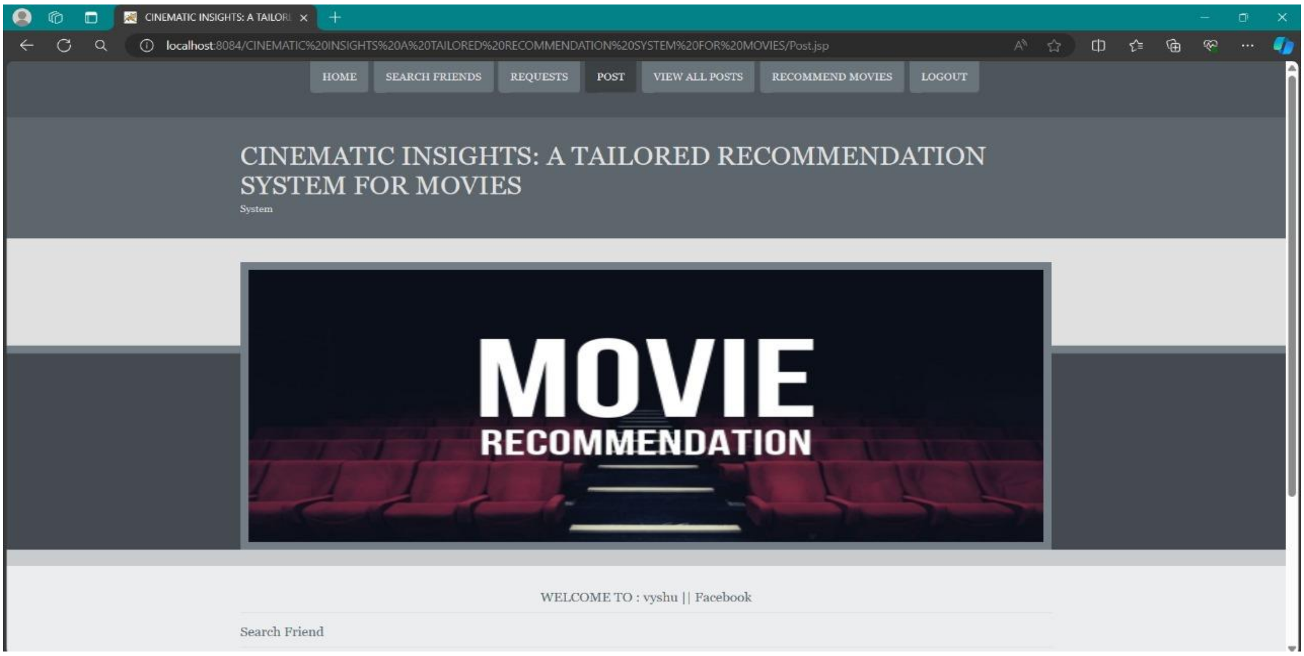
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HOME
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REQUESTS
POST
VIEW ALL POSTS
RECOMMEND MOVIES
LOGOUT
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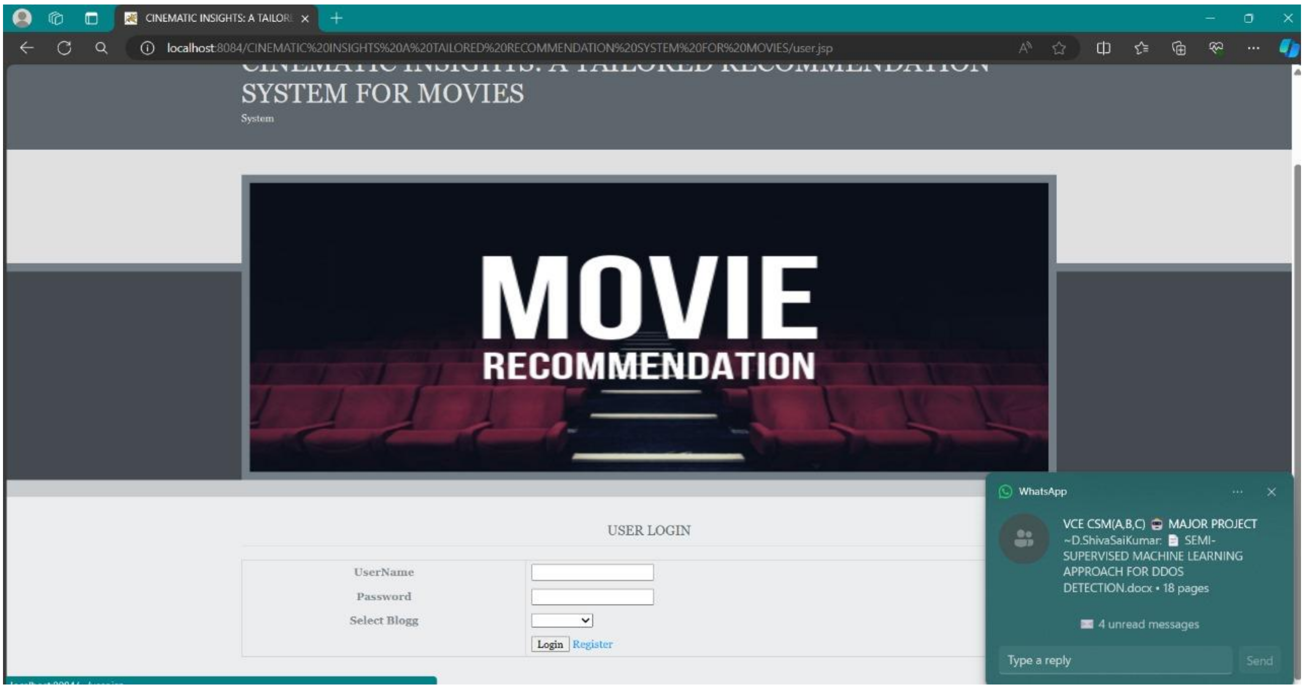
System
MOVIE
RECOMMENDATION
WELCOME TO : vyshu || Facebook
Search Friend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SYSTEM FOR MOVIES
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MOVIE
RECOMMENDATION
USER LOGIN
UserName
Password
Select Blogg
Login
Register
WhatsApp
VCE CSM(A,B,C) MAJOR PROJECT
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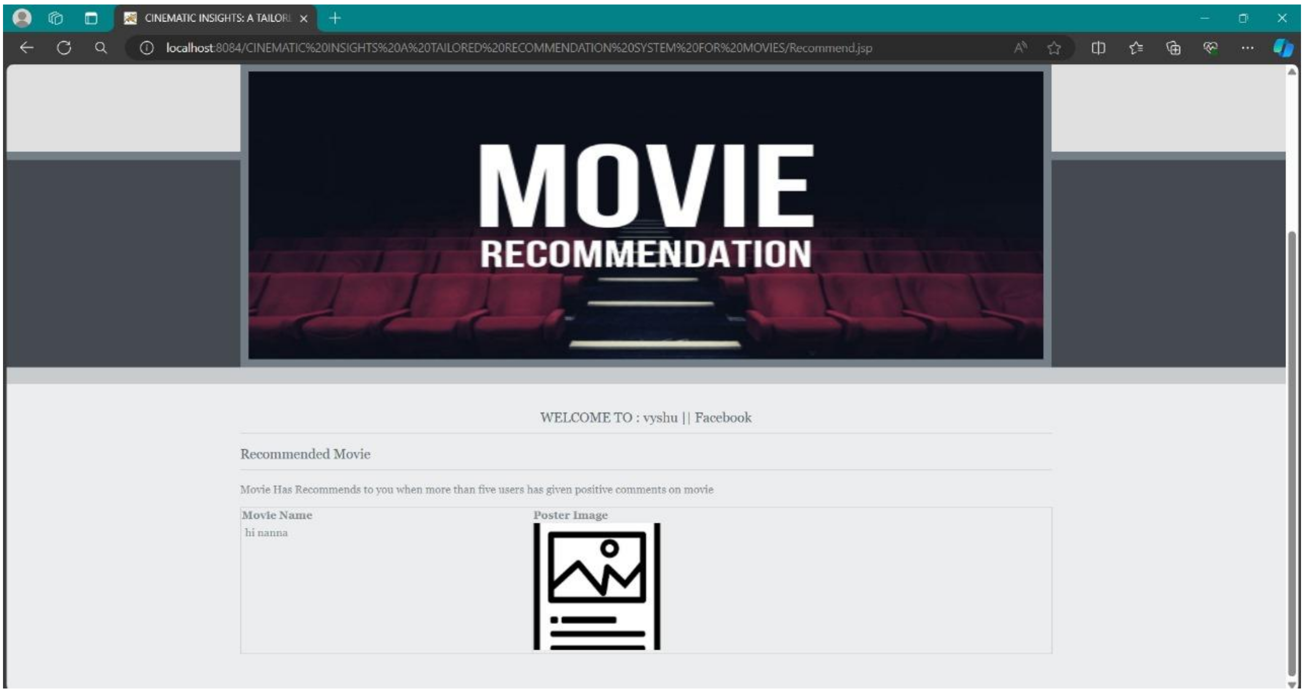
Type a reply
Send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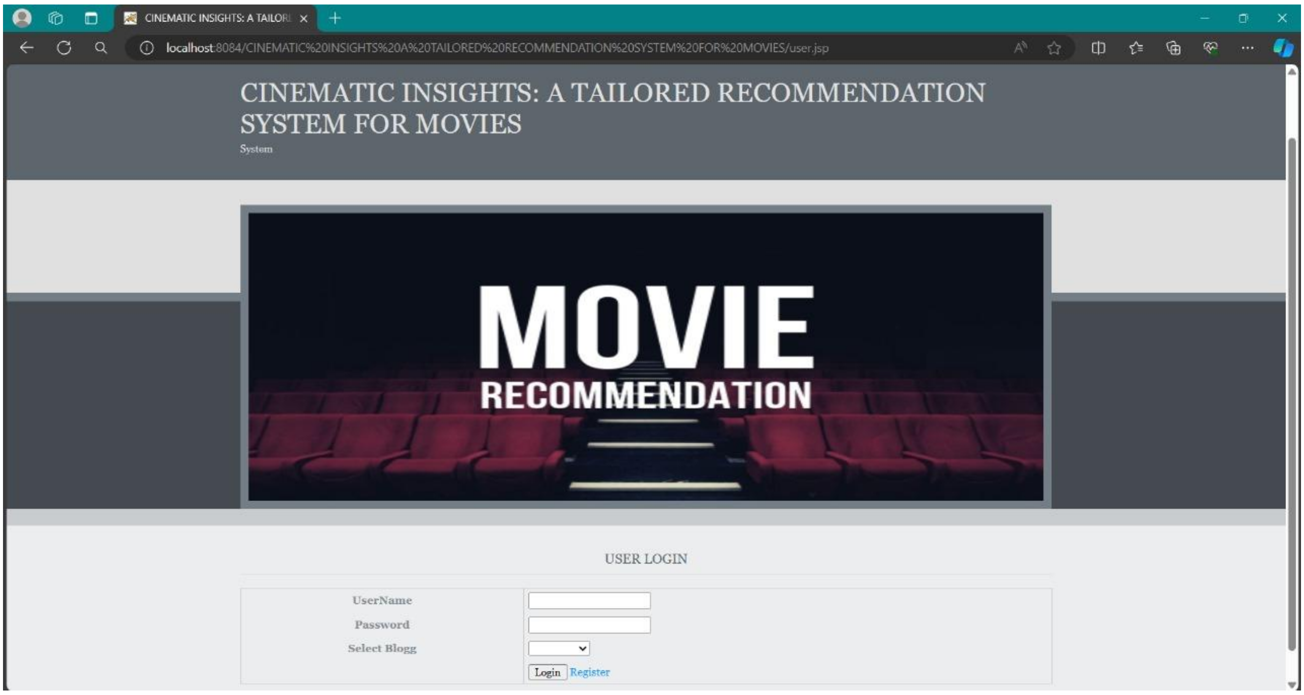
Recommended Movie
Movie Has Recommends to you when more than five users has given positive comments on movie
Movie Name
Poster Image
hi nanna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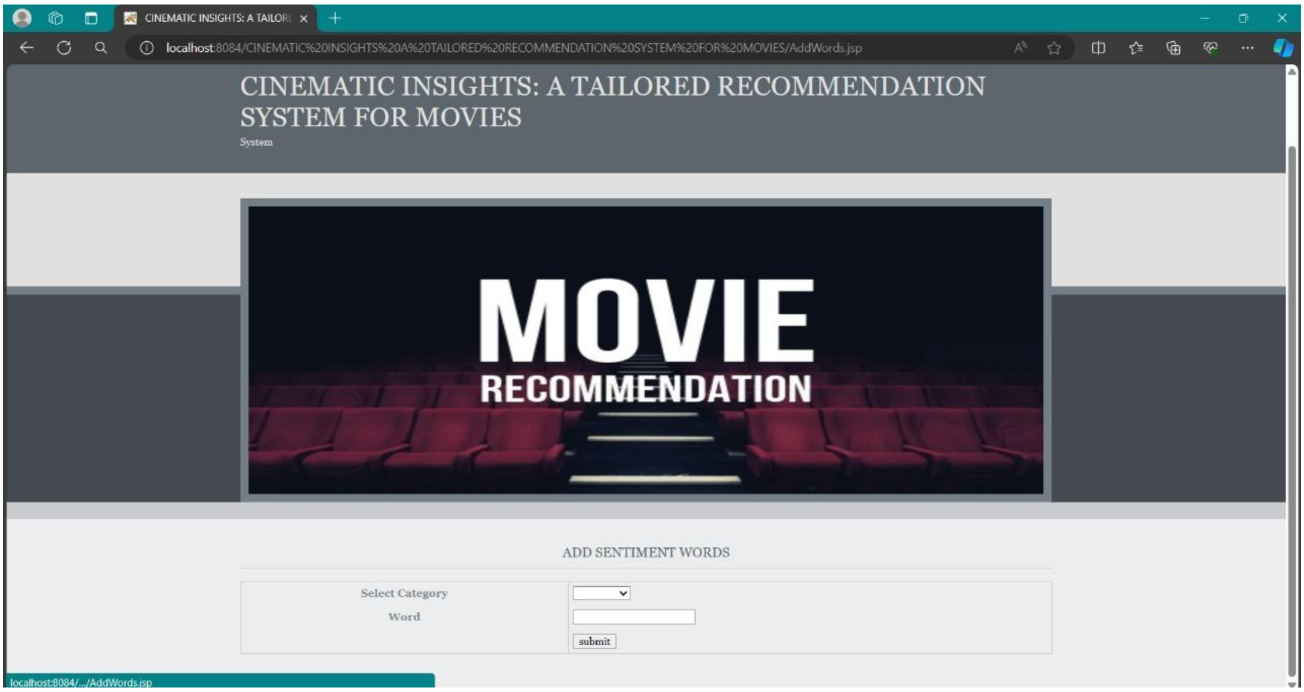
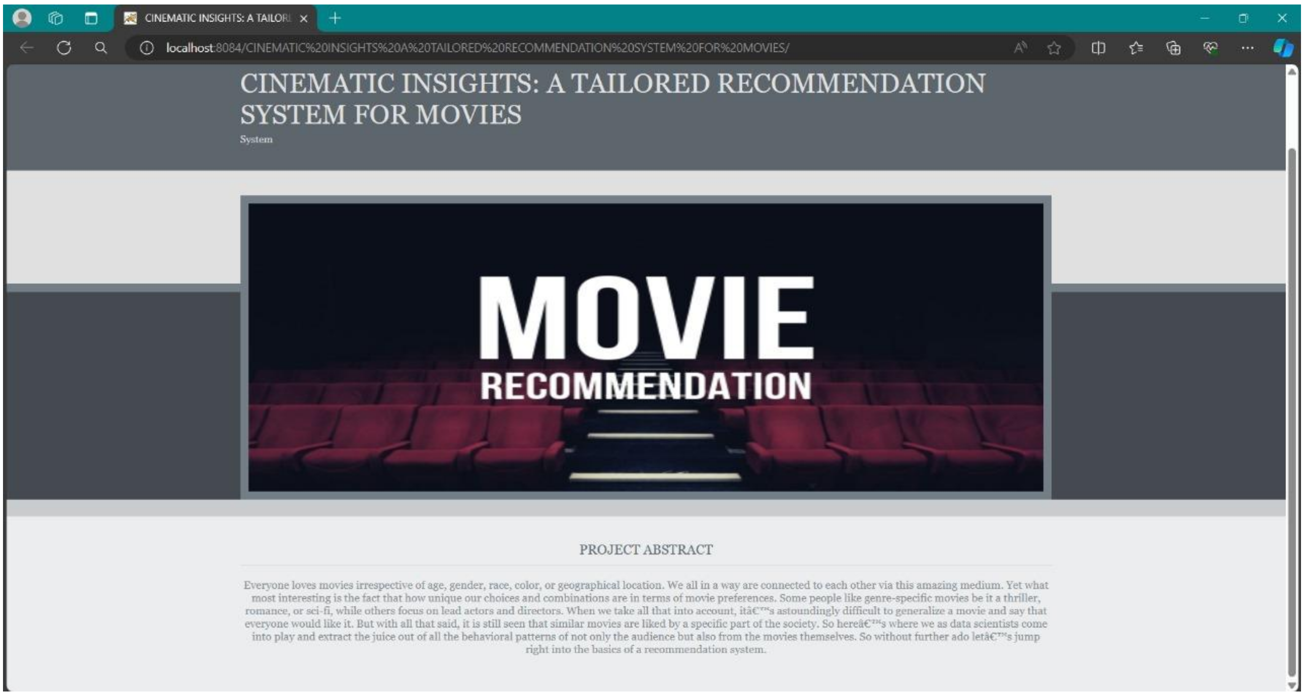
System
MOVIE
RECOMMENDATION
USER LOGIN
UserName
Password
Select Blogg
Login
Register


CINEMATIC INSIGHTS: A TAILORED RECOMMENDATION SYSTEM FOR MOVIES
System
MOVIE
RECOMMENDATION
ADD SENTIMENT WORDS
Select Category
Word
submit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PROJECT ABSTRACT
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8. CONCLUSION

RSs are an important medium of information filtering systems in the modern age, where the enormous amount of data is readily available. In this article, we have proposed a movie RS that uses sentiment analysis data from Twitter, along with movie metadata and a social graph to recommend movies. Sentiment analysis provides information about how the audience is respond to a particular movie and how this information is observed to be useful. The proposed system used weighted score fusion to improve the recommendations. Based on our experiments, the average precision in Top-5 and Top-10 for sentiment similarity, hybrid, and proposed model are 0.54 and 1.04, 1.86 and 3.31, and 2.54 and 4.97, respectively. We found that the proposed model recommends more precisely than the other models. In the future, we plan to consider more information about the emotional tone of the user from different social media platforms and non-English languages to further improve the RS.

9. FUTURE SCOPE

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