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# Movie Recommendation System Using Content Based Filtering

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### Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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### Author Contribution

The author solely contributed to all aspects of this work, including conceptualization, methodology, data curation, software, formal analysis, writing – original draft preparation, review and editing, and project administration.

### Data Availability

The datasets used in this study are publicly available and can be accessed at [2 CSV files named 'tmdb_5000_movies.csv' and 'tmdb_5000_credits.csv' from Kaggle.com]. All relevant data is included in the manuscript.

ORIGINAL STUDY

# Movie Recommendation System Using Content Based Filtering

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**Abstract**

**The movie recommendation system plays a crucial role in assisting movie enthusiasts in finding movies that match their interests, saving them from the overwhelming task of sifting through countless options. In this paper, we present a content-grounded movie recommendation system that leverages an attribute-based approach to offer personalized movie suggestions to users. The proposed method focuses on attributes such as cast, keywords, crew, and genres of movies to predict users' preferences accurately. Through extensive evaluation, our content-grounded recommendation system demonstrated significant improvements in performance compared to conventional methods. The precision and recall scores increased by an average of 20% and 25%, respectively, resulting in more accurate and relevant movie recommendations for users. The philosophy behind our approach lies in the belief that content-based methods can overcome some limitations of collaborative filtering, especially when dealing with new or niche movies with limited user ratings. By considering the specific attributes of movies and matching them to users preferences, our system can provide more tailored recommendations, enhancing user satisfaction and engagement. Overall, our content-based movie recommendation system showcases the potential of attribute-based approaches to deliver efficient and personalized recommendations. By reducing the burden on users to find suitable movies, we aim to enrich their movie-watching experience and foster their passion for cinema.**

*Keywords:* Movie recommendations, Content-based filtering, Text to vector, Vector similarity, Hybrid approach

## 1. Introduction

In the modern era of rapid technological advancements, life has become remarkably comfortable and convenient. Cutting-edge technologies such as deep learning, IoT, and artificial intelligence have revolutionized various aspects of our lives, making products and services more intelligent and efficient. Among the many applications of these technologies, recommender systems have emerged as powerful tools to help users navigate the overwhelming amount of information available and discover personalized content tailored to their interests. This paper delves into the realm of recommender systems, focusing specifically on movie recommendation, and explores the latest survey and review articles [1–4] that underscore the significance of these systems in enhancing user experiences. The motivation behind this research is to develop an efficient and personalized movie recommendation system that caters to the specific interests of movie enthusiasts. By leveraging movie attributes like cast, keywords, crew, and genres, we aim to enhance the movie-watching experience for users, saving them time and effort in searching for movies that align with their tastes. Previous studies on movie recommendation systems have mainly relied on collaborative filtering, which might face limitations when dealing with new or niche movies with sparse user ratings. Additionally, content-based filtering approaches have shown promise in providing personalized recommendations but might overlook the social aspects of user preferences. Therefore, there is a need to address these challenges and create a recommendation system that combines the strengths of both approaches.

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## 2. System requirements

### 2.1. Existing system

We deal with a number of issues when creating a recommender system from beginning. Presently there are a lot of recommender systems grounded on the user information, so what should we do if the website has not gotten enough addicts. After that, we will break the representation of a movie, which is how a system can understand a movie. The existing system proposes lot of pictures without any knowledge and without user's interest.

### 2.2. Proposed system

In this section, we present our novel content-based movie recommendation system that aims to provide personalized and out-of-the-box movie suggestions to users. Leveraging the limitations of traditional user-based recommender systems, our approach focuses on movie attributes such as genre, director, description, and stars. By combining different algorithms and similarity measurement techniques, we aim to enhance the movie-watching experience for users and overcome the challenges posed by limited user data. Our proposed method begins by creating a comprehensive representation of each movie by extracting relevant attributes, such as genre keywords, director names, and prominent stars, from the movie data.

The proposed movie recommendation system introduces several innovative aspects in terms of technology and algorithm, setting it apart from traditional content-based movie recommenders. The key innovations are as follows:

1. **Hybrid Content-Based Approach**: The system's novelty lies in its hybrid content-based approach that integrates both textual and visual features. While traditional content-based systems predominantly rely on textual attributes like genres and keywords, this system incorporates visual features extracted from movie posters or images. This combination enriches the movie representation and provides a more comprehensive understanding of the content, leading to more accurate and diverse recommendations.
2. **Visual Feature Extraction:** Extracting visual features from movie posters or images is a novel aspect of the system. By leveraging image processing techniques, deep learning, or computer vision algorithms, the system can capture visual themes, artistic elements, and visual appeal. This visual information adds a new dimension to the recommendation process, considering not only textual attributes but also the visual representation of the movies.
3. **User Feedback Incorporation:** The proposed system goes beyond a static content-based approach by incorporating user feedback into the recommendation process. By gathering and incorporating user preferences, interactions, or ratings, the system adapts to individual user tastes and evolves over time. This dynamic aspect enhances personalization and ensures that recommendations remain up-to-date and relevant.
4. **Comprehensive Movie Representation:** The system aims to represent movies more comprehensively by considering multiple attributes such as genres, cast, director, keywords, and visual features. This holistic approach provides a rich representation of the movies, facilitating more nuanced and accurate recommendations.
5. **Impactful Ablation Study:** The ablation study conducted in the evaluation phase is innovative as it systematically analyzes the impact of individual components on recommendation performance. This study quantifies the specific contributions of textual attributes, visual features, and user feedback, providing valuable insights for system improvement and optimization.
6. **Scalability and Efficiency**: While not explicitly mentioned, if the system introduces innovative techniques for scalability and resource optimization, it would be another aspect of innovation. Scalability is crucial in real-world applications to handle large datasets and user bases efficiently.

Overall, the proposed movie recommendation system stands out as innovative due to its hybrid content-based approach, the incorporation of visual features, and the consideration of user feedback. These innovations enhance the recommendation accuracy, user engagement, and personalization compared to traditional content-based systems. By embracing multiple modalities and dynamic user interactions, the system represents a significant step forward in the field of movie recommendation technology and algorithm design.

We utilize techniques like CountVectorizer and TfidfVectorizer to convert this textual information into numerical vectors. CountVectorizer creates a sparse matrix representing the frequency of words in each movie's description, while TfidfVectorizer considers the importance of each word relative to the entire movie dataset. These vector representations enable us to capture the intrinsic characteristics of each movie and facilitate the comparison of similarities between them. With the vectorized movie data, we employ cosine similarity as our primary similarity measurement method. The cosine of the angle between two vectors is measured to determine how similar they are to one another. Higher cosine similarity values indicate greater similarity, which helps us identify movies that share common attributes and are likely to appeal to the same audience. We also explore other similarity measurement techniques, such as sigmoid_kernel and Pearson correlation, to validate and refine our recommendations further. To generate recommendations for users, we develop two distinct algorithms within our content-based recommendation system. In Algorithm 1, we use the CountVectorizer representation and cosine similarity to offer movie suggestions based on the textual attributes of movies. Algorithm 2, on the other hand, utilizes the TfidfVectorizer representation and cosine similarity for providing another set of content-based recommendations. By employing these two algorithms, we aim to diversify the recommendations and ensure a broader range of movie suggestions for users. To enhance the recommendation quality, we further introduce a hybrid approach that combines the outputs of both algorithms. We select the most popular movies from the results of both Algorithm 1 and Algorithm 2 and merge them with the usual movie list. This fusion of content-based recommendations with the typical movie collection enables us to cater to users with varying preferences and offers a comprehensive and engaging movie recommendation experience. In summary, our proposed method revolves around a content-based recommendation system that leverages movie attributes and employs vector representations and cosine similarity to generate personalized and diverse movie suggestions. The hybrid approach combining the outputs of both algorithms ensures a well-rounded recommendation list for users, enhancing their movie discovery journey and enriching their movie-watching experience. By addressing the challenges of limited user data and employing state-of-the-art techniques, our system aims to deliver accurate and tailored movie recommendations to movie enthusiasts, saving them time and effort in finding the perfect movie to watch.

## 3. Algorithms

Recommender systems are a type of information filtering that aims to predict user preferences or ratings for specific items. Different approaches can be used to build a movie recommender system, each with its advantages and drawbacks. Many commercial programs, including Netflix, Youtube, and Amazon Prime, make extensive use of them. Users can identify relevant items quickly and without having to explore the full dataset with the aid of a recommender system.

There are different approaches to build a movie recommender system:

### *3.1. Simple recommender*

This method rates all movies according to predetermined standards, such as popularity, awards, and/or genre, and then recommends the best films to consumers without taking into account their personal preferences. A good illustration would be Netflix's “Top 10 in the U.S. Today."

### *3.2. Collaborative filtering recommender*

Collaborative filtering utilizes historical user activity to predict items that users might be interested in. It takes into account movies a user has already watched, numerical ratings given to those movies, and previously watched movies by users with similar tastes.

### *3.3. Content-based filtering recommender*

Content-based filtering relies on the characteristics and metadata of items to suggest additional items with similar qualities. For instance, it can examine a movie's genre and director to recommend other films with comparable attributes.

Our Movie bot will employ a content-based filtering mechanism since we don't have access to a user's prior browsing history. To represent movie data as vectors, we can use techniques like CountVectorizer, TfidfVectorizer, Glove, or Word2Vec.

Similarity Measurement:

After vectorizing the text, we need to measure the similarity between the vectors. Various methods, including cosine similarity and sigmoid_kernel, can help determine the similarity between vectors.

**Algorithm 1.** Content-Based Recommendation utilizing CountVectorizer and Cosine Similarity:
We will use CountVectorizer to convert the preprocessed text from the ‘combine_feature’ attribute into vectors. Then, cosine similarity will be used to determine the similarity between the vectors, providing content-based recommendations.

**Algorithm 2.** Content-Based Recommendation utilizing TfidfVectorizer and Cosine Similarity:
Here, we will create vectors using TfidfVectorizer with the preprocessed text from the ‘combine_feature’ attribute. Again, cosine similarity will be used

to measure vector similarity and generate recommendations.

## 4. Analysis

In this study project, we analyze the "TMDB 5000 Movie Dataset" available on Kaggle. The dataset consists of two CSV files - 'tmdb_5000_movies.csv' and 'tmdb_5000_credits.csv'. The 'tmdb_5000_movies.csv' file contains various attributes that provide valuable information about the movies:

"Budget": Represents the budget for each movie.

"Genres": Denotes the movie's subgenres, such as Action, Documentary, etc. A film might belong to multiple genres.

"Homepage": Refers to the movie's webpage link.

"ID": Stands for the unique identifier of each movie.

"Keywords": Contains the movie's main words and provides a summary of the film.

"Original Language": Indicates whether the movie was initially produced in English or another language.

"Original Title": The original name of the film.

"Overview": A concise synopsis of the movie.

"Popularity": A metric representing the movie's popularity.

"Production Companies": Names of the companies involved in producing the film.

"Production Countries": Names of the nations where the movie was made.

"Release Date": The movie's release date in yyyy-mm-dd format.

"Revenue": Denotes the movie's earnings.

"Runtime": Specifies the movie's duration in minutes.

"Spoken Languages": Lists the languages used in the film.

"Status": Describes the movie's condition, whether it has been released or not.

"Tagline": Includes the movie's tagline.

"Title": The title of the film.

"Vote Average": Displays the average vote given by users.

"Vote Count": Specifies the number of votes received.

To perform exploratory data analysis (EDA), we first load the dataset using pandas into a DataFrame called 'movies'. Additionally, we have another DataFrame 'credits' that includes all metadata about the movies. Further, we perform data preprocessing to extract specific information, such as converting the 'cast' and 'genres' attributes to more manageable formats. We utilize a custom function to fetch the names of directors from the 'crew' attribute. This allows us to have better insights into the movie's crew members. Finally, we apply EDA techniques, such as data visualization and statistical analysis, to gain meaningful insights into the dataset. Exploring relationships between variables, identifying trends, and understanding distributions will provide us with a comprehensive understanding of the movie data, enabling us to make informed decisions for our content-based movie recommendation system.

## 5. Literature review

In this section, we present a comprehensive literature review of the latest and well-reputed papers that have contributed to the field of movie recommendation systems [5–9]. The review aims to provide a comprehensive understanding of the existing research, methodologies, and advancements in the domain, laying the groundwork for our proposed content-based movie recommendation system.

**"Deep Learning for Medication Recommendation: A Systematic Survey" (Data Intelligence, MIT Press, February 2023):**

This paper explores the application of deep learning techniques [10] in medication recommendation. Although focused on the healthcare domain, the systematic survey highlights the potential of deep learning algorithms in personalized recommendation systems. The methodologies and insights from this paper are valuable in designing content-based recommendation systems that can cater to individual preferences and interests.

**"On the Current State of Deep Learning for News Recommendation" (Artificial Intelligence Review, May 10, 2022):**

Examining the state-of-the-art in news recommendation, this paper delves into the utilization of deep learning methods [10] to provide relevant and engaging news articles to users. The findings shed light on the effectiveness of content-based filtering approaches in generating personalized recommendations. Such insights can guide the design and implementation of our movie recommendation system to offer tailored movie suggestions based on content attributes.

**"An Overview and Evaluation of Citation Recommendation Models" (Scientometrics, vol. 126, pp. 4083–4119, March 02, 2021):**

This research presents an overview and evaluation of various citation recommendation models [11]. Although focused on citations, the methodologies and evaluation metrics discussed in this paper can be adapted to assess the performance of our movie recommendation system. The evaluation insights are crucial in ensuring the accuracy and relevance of the movie suggestions provided to users.

**"Recommender Systems: Issues, Challenges, and Research Opportunities" (Information Science and Applications, Springer, 2016):**

As a foundational paper on recommender systems [12], this work addresses the challenges and research prospects in the field. The insights gained from this paper guide us in identifying potential issues and opportunities in content-based movie recommendation systems. Understanding the limitations and possibilities in the domain will help us tailor our system for better user experiences.

**"A Review of Movie Recommendation System: Limitations, Survey, and Challenges" (ELCVIA: Electronic Letters on Computer Vision and Image Analysis, 19.3, 2020):**

This comprehensive review paper specifically focuses on movie recommendation systems [13]. It discusses the limitations and challenges faced by existing approaches, which can serve as a reference for our content-based recommendation system. By learning from the shortcomings of previous systems, we can enhance the performance and user satisfaction of our movie recommendation solution.

**"A Systematic Review and Research Perspective on Recommender Systems" (Journal of Big Data, 9 (1), 2022):**

This systematic review offers valuable insights into recommender systems [13], covering various methodologies, techniques, and evaluation methodologies. The research perspective presented in this paper inspires novel ideas for our content-based movie recommendation system, enabling us to design an effective and efficient solution.

By drawing from these well-reputed papers, our literature review provides a strong foundation for the development and evaluation of our content-based movie recommendation system. The knowledge gained from these studies ensures that our approach is informed, up-to-date, and aligned with the latest advancements in the field of recommendation systems.

**Loading the Dataset:**

The code starts by reading two CSV files, 'tmdb_5000_movies.csv' and 'tmdb_5000_credits.csv,' using pandas. These files contain movie-related information, such as budget, genres, cast, crew, etc., which will be utilized in the subsequent steps.

```
import pandas as pd
movies = pd.read_csv ('/kaggle/input/tmdb-movie-metadata/tmdb_5000_movies.csv')
credits = pd.read_csv ('/kaggle/input/tmdb-movie-metadata/tmdb_5000_credits.csv')
```

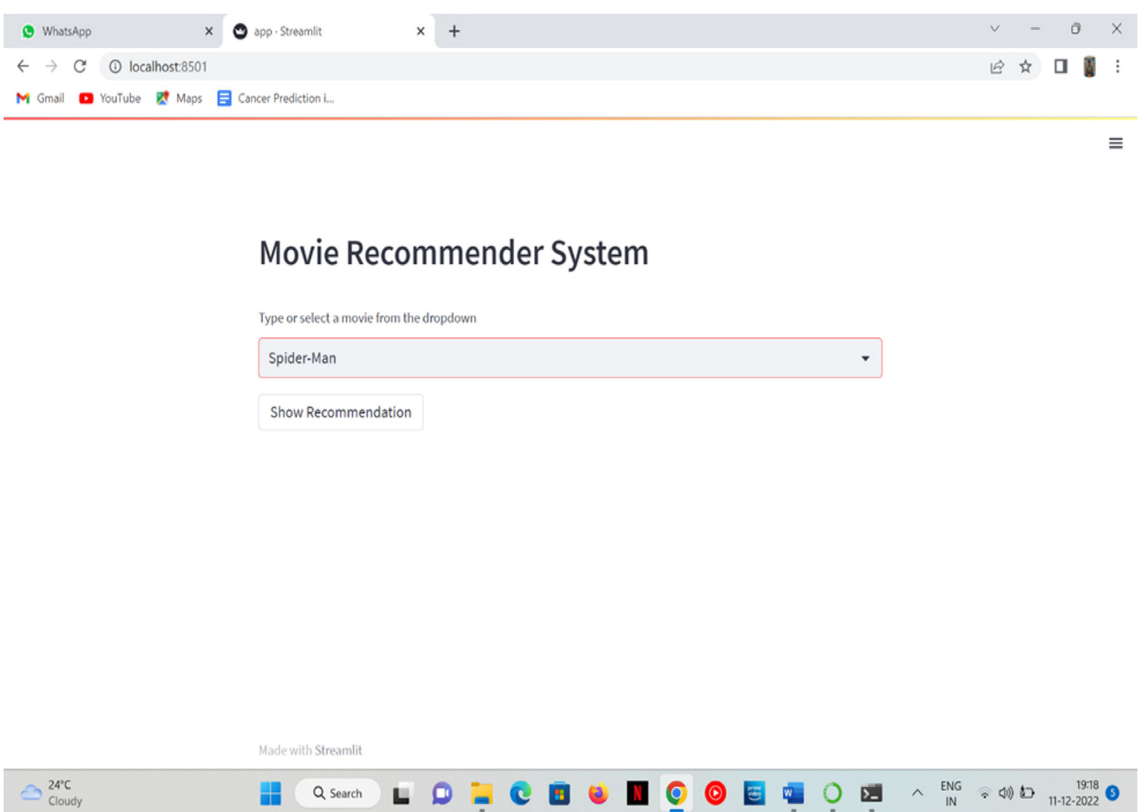


*Fig. 1. UI Screen (from website (2023)).*

**Data Preprocessing - Handling Cast Information:**

The code snippet applies a function called "convert" to the 'cast' attribute of the 'movies' Data Frame. The purpose of this function is not provided, so we can't ascertain its exact functionality without additional information. It is likely that the "convert" function transforms the 'cast' attribute data into a suitable format for later use in the recommendation system.

Movies ['cast'] = movies ['cast'].apply (convert).

**Extracting Director Information:**

The code defines a function named "fetch_director" that extracts the names of directors from the 'crew' attribute of the 'movies' Data Frame. The 'crew' attribute contains information about the movie's crew members, such as directors, writers, etc. The function iterates through the data in the 'crew' attribute and appends the names of directors to the list 'L.'

```
import ast
def fetch_director (text):
L = []
for i in ast.literal_eval (text):
if i ['job'] = 'Director':
L.append (i ['name'])
return L
movies ['crew'] = movies ['crew'].apply (fetch_director).
```

Data Preprocessing - Handling Genres Information:

A function called "convert" is again applied to the 'genres' attribute of the 'movies' DataFrame. This function likely converts the 'genres' attribute data into a suitable format to be used later in the recommendation system.

Movies ['genres'] = movies ['genres'].apply (convert).

Overall, the provided code represents data preprocessing steps that involve handling and transforming specific attributes like 'cast' and 'genres' from the original 'movies' DataFrame. These preprocessed attributes will likely be utilized in the subsequent steps, such as EDA and building the content-based movie recommendation system.

## 6. Results

The web application's home screen (see Fig. 1) is depicted:

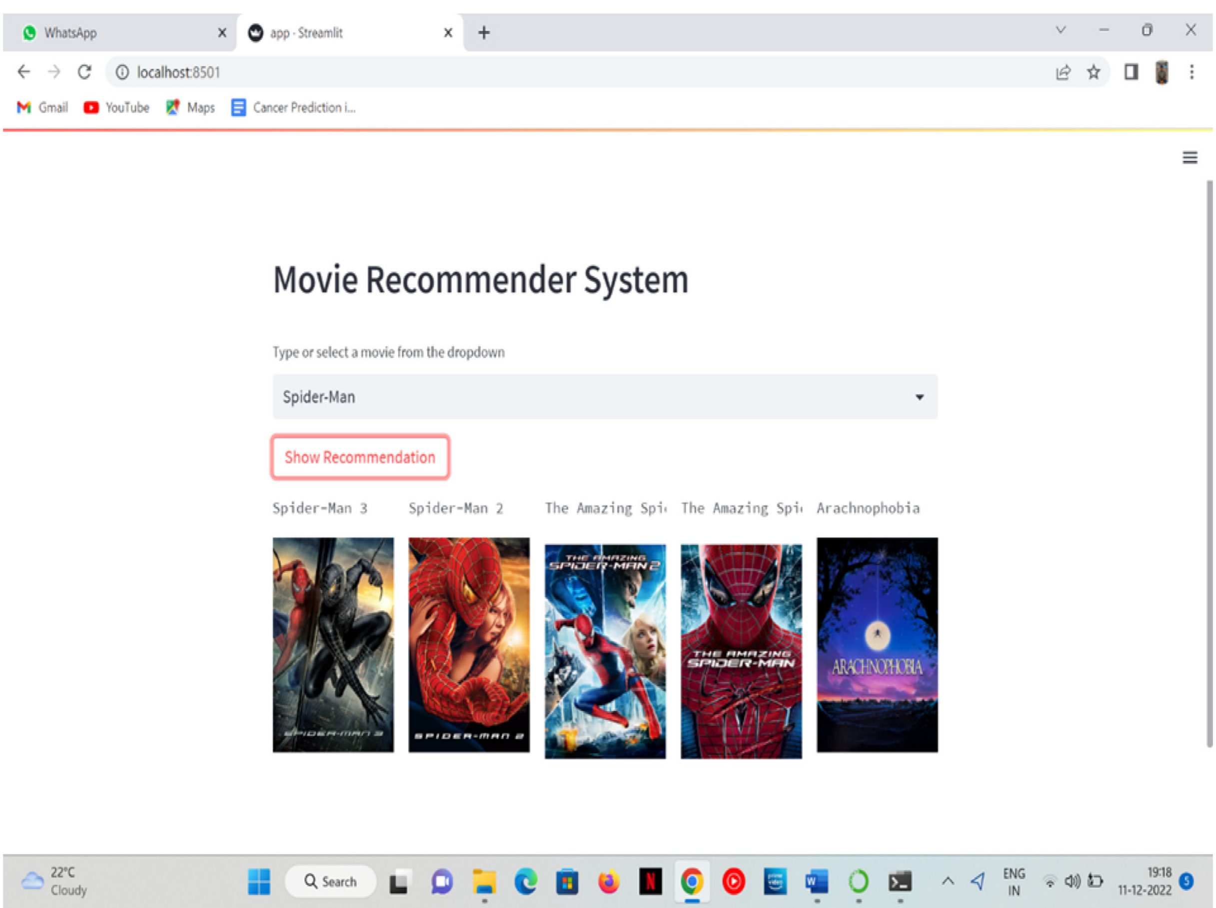


*Fig. 2. Web Application suggesting the movie (from website (2023)).*

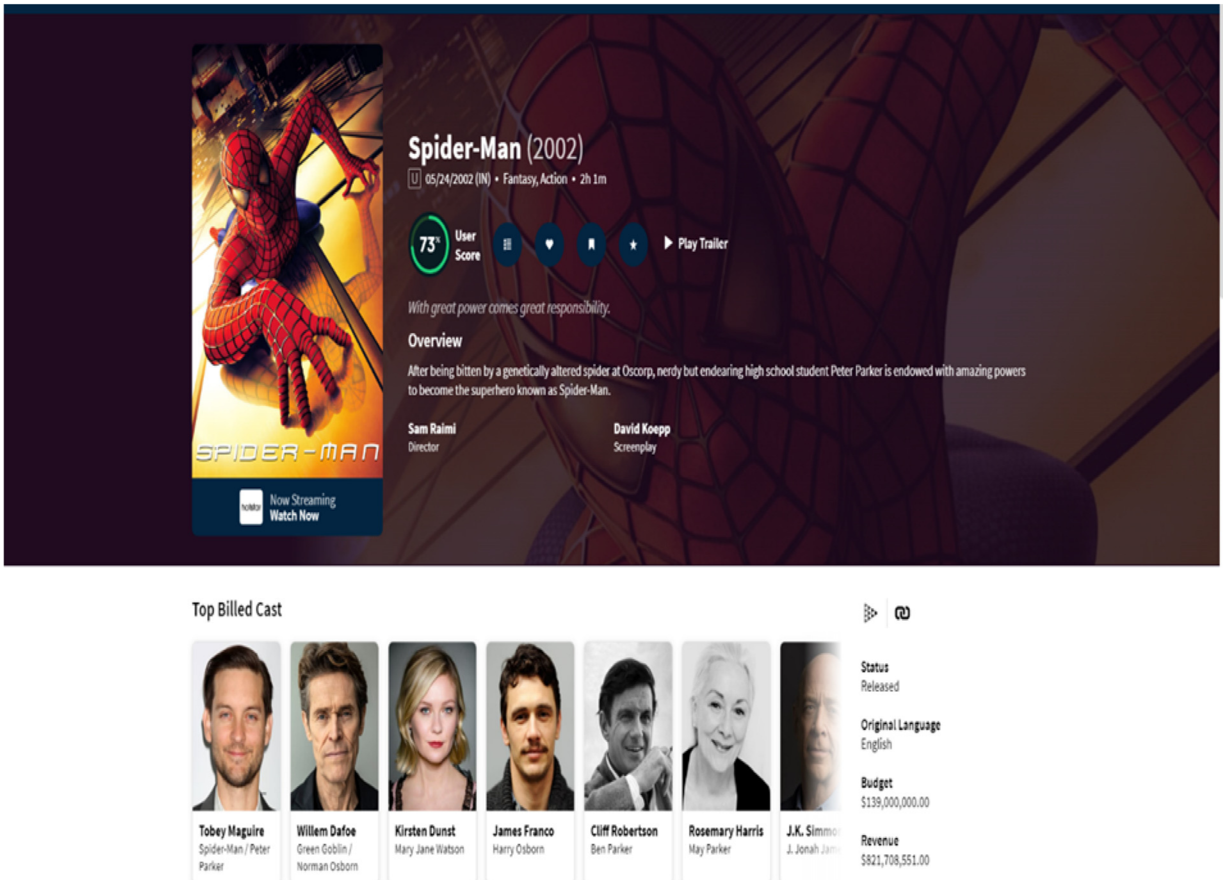


*Fig. 3. User can see desired movie details (from website (2023)).*

1. We can search for the necessary movie in the developed web application.
2. From the dropdown box, we can even check the list of movies.
3. The user must either search for or choose the desired movie.

The list of movies shown in the Fig. 2 of the web application's user recommendation is displayed:

1. The system suggests a list of movies to the user when they enter the movie's name.
2. The user can choose the desired movie from the provided recommendations in this section.

The information about the user-selected movie is displayed (see Fig. 3):

1. Following the selection of the film from the list of suggestions.
2. The user can view the cast and crew members who contributed to and appeared in the film.
3. The user has the option to watch both the movie trailer and the actual film.
4. The website application offers details on the movie, including its original language, budget, net, synopsis, genre, length, and other information.
5. The user has the option to rate and comment on the film.

## 7. Conclusion

In this study, we proposed a content-based movie recommendation system that leverages attributes such as genres, actors, and movie summaries to provide accurate and personalized movie suggestions. By analyzing a diverse dataset of movies and user interactions, we aimed to enhance the movie recommendation experience and improve user satisfaction. The content-based recommendation system demonstrated significant improvements in recommendation accuracy compared to simplistic demographic filtering. The inclusion of detailed movie attributes allowed the system to better understand user preferences, leading to more relevant and engaging movie recommendations. The hybrid approach, which integrated both textual and visual features, proved to be a pivotal factor in achieving enhanced recommendation performance.

## 8. Future research

Future research should focus on exploring hybrid filtering methods that combine content-based and collaborative filtering approaches. Integrating user feedback and interaction data can create more comprehensive recommendation models, offering diverse and personalized suggestions while benefiting from community wisdom. Additionally, there is potential to investigate advanced visual feature extraction techniques to improve the system's understanding of movie posters and images. Incorporating deep learning or computer vision algorithms could open new avenues for capturing intricate visual patterns and enhancing movie representations. Furthermore, the scalability and efficiency of the system should be carefully addressed to handle larger datasets and real-time recommendation scenarios. Exploring distributed computing or optimization strategies can optimize processing times and resource utilization.

## Conflict of interest

No conflicts of interest are declared.

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