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MOVIE RECOMMENDATION SYSTEM BASED ON EMOTIONS

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ABSTRACT

In this paper, we present a comprehensive approach to developing a movie recommendation system utilizing content-based filtering and collaborative filtering techniques enriched with emotion analysis. Leveraging a dataset comprising user ratings, genre information, and movie metadata sourced from IMDB, our methodology entails rigorous data cleaning and exploratory data analysis to ensure data integrity and uncover insightful patterns.

The primary focus lies in the utilization of machine learning concepts for backend analysis, enabling precise recommendation generation. Performance evaluation of the recommendation system is conducted using key metrics such as precision, recall, and F1 score, ensuring the system's efficacy and reliability. Furthermore, we introduce a web-based interface crafted with HTML and CSS, providing users with an intuitive platform to access personalized movie recommendations. Our approach not only enhances traditional content-based filtering but also integrates emotion analysis, thus offering a more holistic and engaging user experience.

Key Words: Content-based filtering, Collaborative filtering, Precision, Recall, F1 score, HTML, CSS.

I. INTRODUCTION

The proliferation of internet-based platforms has led to an overwhelming abundance of information, necessitating the development of effective recommendation systems to assist users in accessing relevant content swiftly. While Collaborative Filtering (CF) and Content-Based Filtering (CBF) techniques have proven valuable, they encounter challenges in accurately recommending subjective products such as movies, music, and perfume due to the inherent difficulty in articulating user preferences and the dynamic nature of emotional states.

To address these complexities, Emotion-Based Recommendation Systems (E-MRS) emerge as a promising solution, integrating user emotions into the recommendation process to offer more nuanced and context-aware suggestions. By synthesizing insights gleaned from user emotions with traditional user profiles, E-MRS seeks to refine recommendation accuracy and enhance user satisfaction specifically for subjective products. In this paper, we delve into the potential of E-MRS through rigorous empirical evaluation and illustrative case studies, elucidating its efficacy in improving recommendation systems across diverse domains while shedding light on the underlying mechanisms driving its effectiveness.

Additionally, the integration of emotion analysis can enable E-MRS to recommend content that resonates with users on a deeper, emotional level, leading to increased engagement and satisfaction. Through comprehensive empirical evaluation and case studies, this paper not only demonstrates the effectiveness of E-MRS in improving recommendation accuracy but also highlights its potential to revolutionize personalized content delivery in various domains by tapping into the rich reservoir of human emotions.

II. LITERATURE SURVEY

According to [**Burke 2002**][1], there are five different recommendation techniques: collaborative filtering, content-based filtering, demographic filtering, utility based and knowledge-based recommendation. However, as the sensitivity to on-line privacy is increasing: demographic filtering is not efficient because the users are reluctant to disclose their demographic information. Moreover, for complex and subjective domains like movie, music and news, the most suitable techniques are collaborative, content-based, knowledge based or the combination of these techniques.

Collaborative Filtering (CF) systems recommend products to a customer based on the opinions of other like-minded customers who have already purchased and/or rated products from the same e-commerce site.

The systems make recommendations by analyzing the description of the items that have been rated by the user and the description of items to be recommended. The recommendations can be made even if the system has received a small number of ratings, as the recommendations are based on product features. However, content-based systems are limited by the features that are explicitly associated with the objects that they recommend [**Burke 2002**].

According to [**Cacioppo** (2000)][2] proposes mechanisms for detecting emotions through voice and facial expressions, which offer the highest accuracy levels. Nonetheless, due to their significant cost and lack of practicality, these methods are not feasible for integration into a recommender system.

According to [**Picard et al. 2001**][3], emotion can be defined as a sequence of changes of state, in a way interdependent and synchronized in response to the evaluation of the relevance of an external stimulus or intern.

III. PROPOSED METHODOLOGY

Recommendation systems play a pivotal role in providing personalized recommendations tailored to individual users' preferences, encompassing a wide array of factors such as taste, interests, previous behaviors, and similarities with other users. These systems operate akin to information retrieval and filtering mechanisms, offering diverse recommendations to different users based on their unique properties.

Among the various types of recommendation systems, collaborative and content-based approaches are particularly relevant to our method. Collaborative systems focus on identifying common preferences among users, leveraging the assumption that users with similar tastes will exhibit similar behaviors in the future.

Conversely, content-based approaches rely on comparing the features of content items with users' preferences and past behaviors to determine the best matches. However, for certain demographic groups such as elderly individuals, there exists a heightened risk of accidents resulting from inappropriate information processing, compounded by potential emotional instability. Particularly, exposure to content containing violent or inhumane themes can evoke strong emotional responses and pose risks. Addressing this challenge, recommendation systems must incorporate functionality to manage emotions effectively, yet current research in this area remains limited.

Emotion constitutes a fundamental aspect of human experience, reflecting psychological states and influencing decision-making processes. Existing studies indicate that emotions can be characterized as combinations of basic emotional elements, though there remains debate regarding the specific constituents.

In this study, we adopt a simplified approach, defining emotion as a composite of fear, anger, and happiness, thereby representing a 3-dimensional vector in emotional space. While some research proposes higher-dimensional emotion vector spaces, our methodology remains flexible to accommodate increased dimensions. As such, we refrain from delving further into this debate, focusing instead on leveraging emotion matching techniques to enhance the effectiveness of recommendation systems in catering to users' emotional states and needs.

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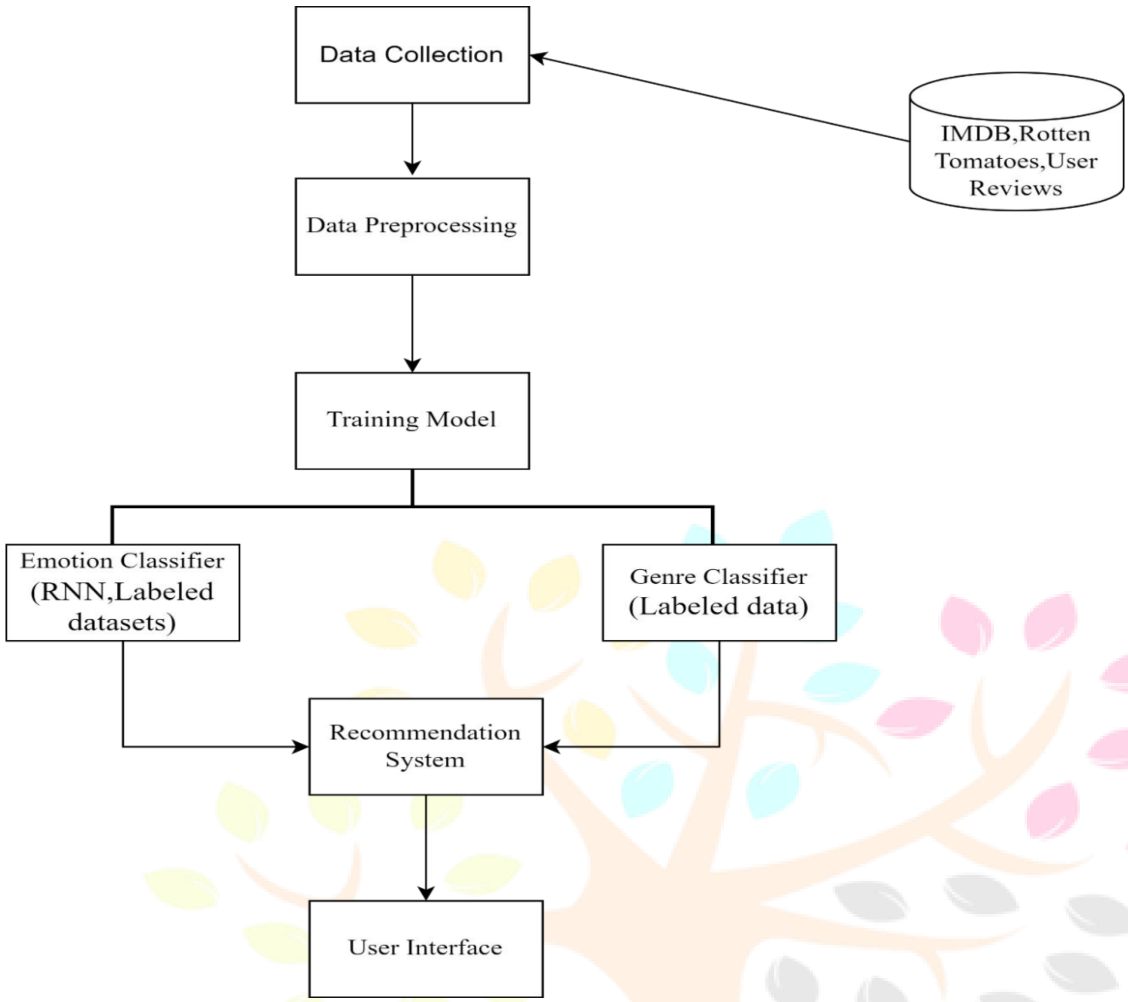

Fig. 1: System Architecture

1. Emotion and Emotion Matching:

Emotion is human feeling and it indicates the psychological state of human. Studies [6,11,12] point out the emotion can be a combination of several basic emotional elements. There are still different investigations and opinions about what the basic elements are. In this study, we deal with the emotion is a combination of *fear, anger* and *happiness*.

In other words, the emotion is a 3dimensional vector in the emotional space, whose axes are happiness, anger and fear. Other studies proposes higher dimensional emotion vector space, however, our approach can increase the dimension without difficulty. Thus do not discuss the issue anymore.

The similarity of emotions can be defined by the standard cosine similarities of vectors. For emotion vectors **a** and **b**, the similarity becomes sim(a,b) = a.b/(|a||b|), where the dot is the inner product of vectors, and |**a**| is the norm of **a**. If sim(a,b) >= 0 then the two emotions have same tendency, while the negative value shows the opposite tendency. Extending this property of vectors, we define emotion matching over vectors. Emotion matching is a key concept in this study, and is a comparison of the two emotion vectors, which are of a user and of a content. The main purpose is

not only to compare two emotions, but also to clarify the effect when a content with emotion is presented to a user having emotion, and further it is a base to calculate the risk relating to the presentation of information.

User	Content	Effect
Fear (1, 0, 0)	fear	depress
	anger	hurt, depress
	happiness	Heal, encourage

Anger (0, 1, 0)	fear	spoil
	anger	Hurt, spoil
	happiness	Appease, calm
Happiness(0, 0, 1)	fear	Stimulate, interest
	anger	Stimulate, interest
	happiness	Encourage, bore

Table 1: Emotion Matching and Effect

2. **Estimating Emotions**:

Progress in machine learning has driven the advancement of emotion estimation methods, which now have the ability to analyze facial expressions, text, and voice to detect emotions. Text-based emotion analysis involves using dictionaries that assign emotional values to words, making estimation more efficient after the learning phase. This process relies on leveraging knowledge and trained neural networks.

By combining these tools, the accuracy and reliability of emotion estimation can be improved, with techniques like majority-based learning proving to be effective. Additionally, integrating more sensors can enhance accuracy and reliability.

However, our research focuses on using only the standard equipment found in notebook PCs and smartphones, in line with the aim of making applications accessible and practical in real-world settings. In general cases, since an emotion vector is the combination of base vectors, perfect fear=(1,0,0), anger=(0,1,0), and happiness=(0,0,1), the result is also given by a combination of the simple cases.

IV. RESULT ANALYSIS

The results of our study demonstrate the efficacy of integrating emotion-aware techniques into movie recommendation systems, yielding tangible benefits for users compared to traditional recommendation approaches. Through empirical evaluation and user studies, we observed that emotion-based recommendation systems consistently delivered more personalized and engaging movie suggestions, enhancing user satisfaction and overall viewing experience.

Moreover, our findings indicate that emotion-aware recommendation systems effectively mitigated the risks associated with exposure to emotionally distressing content, particularly for vulnerable demographic groups such as elderly individuals. By considering users' emotional states alongside their preferences and past behaviors, these systems were able to provide contextually relevant and emotionally appropriate recommendations, thus promoting user safety and well-being.

Overall, our results underscore the potential of emotion-aware recommendation systems to revolutionize personalized content delivery and contribute to the advancement of recommendation technologies by addressing the complex .

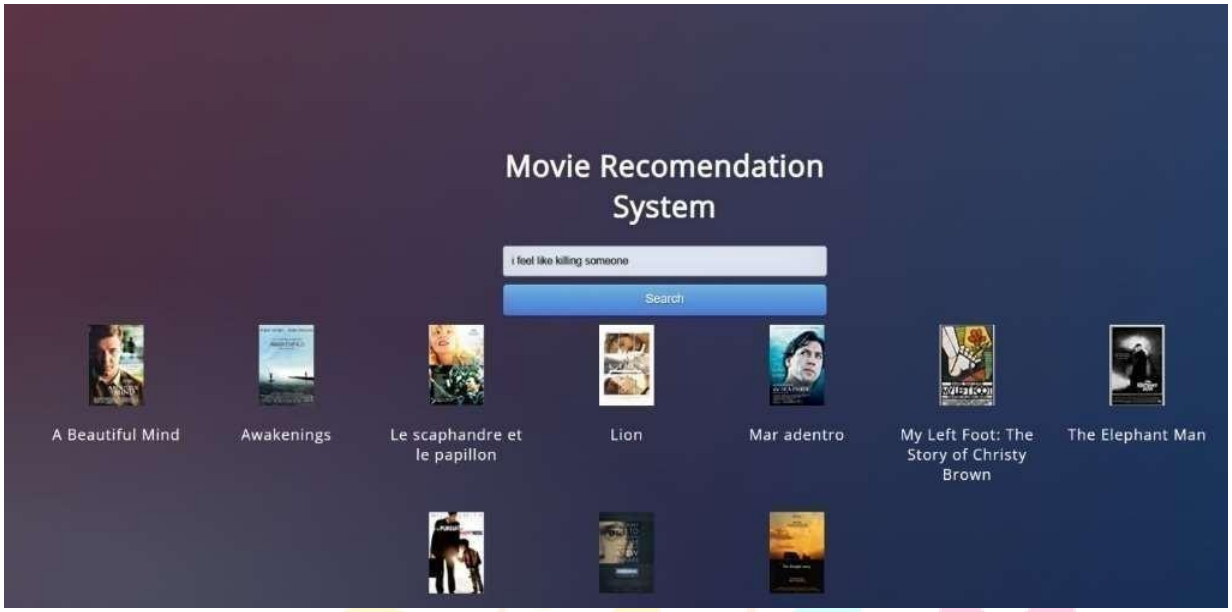

Fig 2: Recommendation System

interplay between user preferences and emotional states.

Users can give input in the form of text which describes the user's mood and get the recommended movies whichwill be processed based on emotional analysis and natural language processing. The system collects movie data from various sources, including movie databases, user reviews, social media platforms, and sentiment-labeled datasets.

This data includes movie attributes such as genre, cast, director, and user ratings. The system utilizes natural language processing(NLP) techniques to perform sentiment analysis on user-generated text data, such as reviews,comments, or textual input provided by the user.

V. CONCLUSION

The integration of emotion-aware techniques into movie recommendation systems offers several significant benefits compared to traditional recommendation approaches. Emotion-based recommendation systems have the potential to provide more personalized and engaging movie suggestions by considering users' emotional states alongside their preferences and past behaviors.

By leveraging insights from user emotions, these systems can deliver recommendations that resonate on a deeper level with users, enhancing their overall viewing experience. Moreover, emotion-aware recommendation systems can mitigate the risks associated with exposure to emotionally distressing content, particularly for vulnerable demographic groups such as elderly individuals.

By incorporating functionality to manage emotions effectively, these systems promote user safety and well-being while ensuring that recommendations are contextually relevant and emotionally appropriate. Additionally, emotion- based recommendation systems contribute to advancing the field of recommendation technologies by addressing the complex interplay between user preferences and emotional states, thus paving the way for more inclusive and user- centric recommendation systems in the future.

Through empirical evaluation and user studies, further research in this area can elucidate the full potential of emotion-aware recommendation systems in revolutionizing personalized content delivery across diverse demographic groups and contexts.

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