IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Moodmatch Movies

[1]Sudheesh KP,[2] Dr. Suresha D, [3]Sudheeksha Herle V,[4]Tejaswini M , [5]Veekshitha Shetty, [6]Nayana K Y

[1] Assistant Professor, [2]Professor, , [3]Research Scholar, [4]Research Scholar, [5]Research Scholar, [6]Research Scholar

Department of Computer Science and Engineering

Srinivas Institute of Technology Mangalore

Abstract— The entertainment industry today offers numerous avenues for enjoyment, with movies being a dominant form. In recent years, the ways in which films are produced, crafted, and distributed have undergone considerable transformation, providing audiences with a broad spectrum of choices that can benefit from an advanced recommendation system. Emotion-based movie recommendation systems (E-MRS) propose films aligned with the user's current emotional state. Emotions are intricate reactions to stimuli, reflecting intelligent and rational behaviors. Evaluating emotional responses to movies is complex due to varying individual reactions. This paper suggests leveraging color psychology to discern different emotional states, such as joy, sorrow, anger, fear, and excitement. We developed a user interface where colors represent emotions, and films are recommended based on the identified emotion. The recommendation system employs a hybrid method, integrating collaborative filtering with content-based filtering.

Keywords—Movie Recommendation, Color Psychology, Emotion Recognition, Collaborative Filtering Technique, Content-Based Filtering Technique.

I. INTRODUCTION

Recommender systems aim to predict user preferences, thus minimizing transaction costs for online shoppers and boosting engagement for service providers. Implementing these systems enhances user interaction and revenue for online services. There are non-personalized and personalized recommendation systems. Non-personalized systems recommend popular options, such as the top holiday destinations, whereas personalized systems tailor suggestions based on individual user preferences. A sophisticated, personalized recommendation system offers a wide range of products, catering to diverse tastes. The impact of technology on user preferences was notably observed during the pandemic, when people turned to video streaming services while confined at home.

OTT platforms like Netflix, Disney+, Hulu, HBO Now, and Amazon Prime stream premium content on demand. Movies are recommended based on color psychology, facial expressions, movie ratings, user needs, and emojis. Emotions influence thoughts, feelings, and behaviors, often driven by personal physiological responses. Colors strongly evoke these feelings. Most people enjoy watching movies regularly, which underscores the value of an Emotion-based Recommender System (E-MRS). MoodMatch Movies, as this system can be called, tracks client preferences based on their current emotions. Given that emotions significantly influence rational and intelligent behavior, it is crucial to incorporate the sentiments of other users into the recommendation process.

II. RELATED WORK

In this project, Sergio Benini investigates how shot scale (Close, Medium, Long Shots) influences viewers' emotional and narrative responses. The study analyzes film mood through hedonic tone, energetic arousal, and tense arousal in 50 film clips and examines shot scale effects on narrative engagement in violent scenes. Utilizing Convolutional Neural Networks trained on 120 full-length movies for shot scale classification, the research offers insights useful for recommending movie and film therapy [1].

In [2], machine learning is applied to address real-time commercial and research challenges, with facial recognition being a prominent application. This technology is employed in security, automated attendance, and workplace environments. A notable application is facial detection-based movie recommendations, where capturing user emotions can save time compared to traditional browsing methods. The study finds that Convolutional Neural Networks (CNNs) outperform decision tree-based facial recognition methods, especially when boosting techniques are used. Combining social filtering and content-based systems enhances the effectiveness of recommendation systems.

The scheme proposed in [3] introduces sub-emotional states to represent the temporal phases of emotions—apex, offset, and onset—aligning these with hidden Markov model(HMM) sequences for both audio and visual data (SC-HMM).A sub-emotional language model is used to account for the temporal transitions between these states. This results produces both posed (MHMC) and naturalistic (SEMAINE) databases.

In [4], the study focuses on the difficulty of quantifying the emotional impact of movies due to their connotative qualities. It utilizes audio-visual descriptors to predict user emotions, enabling movie recommendations based on connotative features. Various methods for movie suggestions are compared, including techniques that analyze audio elements to understand movie-scene emotions. A multi- stream fused hidden Markov model is employed to identify emotions such as interest, boredom, annoyance, puzzlement,and surprise. The study evaluates different emotional movie recommendation algorithms.

The research in [5] enhances an object-based collaborative filtering recommendation system by incorporating user reviews and emotional polarity categorization. The proposedalgorithm categorizes movie review data using a CNN-basedmodel to determine emotional polarity. This classification is combined with each user's movie ratings to generate personalized film recommendations.

In [6], the study analyzes filmmaking and editing techniques to help audiences comprehend a movie's message.It addresses the challenges in assessing movie-induced emotions and the significant heterogeneity in viewers' emotional responses. By extracting audio-visual and cinematic language descriptors and using users' connotative ratings, the study places, compares, and recommends movie scenes based on these ratings.

The study in [7] reiterates the importance of machine learning in solving real-time commercial and research problems, particularly in facial recognition applications. These applications are used in security, automated attendance, and workplace settings. Facial detection-based movie recommendations save time by capturing user emotions. Studies show that CNN-based systems are more accurate thandecision tree-based systems for this purpose. Combiningcontent-based and collaborative filtering systems enhances recommendation effectiveness.

In [8], a recent software application recommends items based on customer needs but struggles to generalize due to varying user requirements. Connotative predictions use audio- visual descriptors to anticipate viewer emotions, forming a connotative space to suggest movies that align with users' affective needs. The framework's effectiveness is evaluated through user feedback.

The study in [9] presents Mind Frame, an online application that recommends music and movies based on usermoods such as joy, sadness, and tranquility. The system usesthe Python OpenCV library to extract facial features and a neural network trained on labeled photos to predict useremotions. Django is used to manage user data and requests.

Finally, in [10], context-aware applications that adapt to users' emotions by recognizing facial expressions arediscussed. The Face Fetch system analyzes users' facial expressions to determine their emotional state and recommends multimedia content accordingly.

Existing systems primarily use facial recognition to detect user emotions, matching faces from images or videos to a database. Applications include security, surveillance, building access control, and email authentication. Facial Emotion Recognition (FER) technology identifies emotions from photos and static videos, with applications in mental health diagnosis and human interaction detection. However, practical implementation faces challenges due to the variability in human emotional expressions. This variability is also highlighted in an IEEE journal by Chung-Hsien Wu and Jen- Chun Lin, indicating differences in emotional expression between introverts and extroverts, making it difficult to standardize emotion recognition based solely on facial expressions.

III. METHODOLGIES

The proposed system, MoodMatch Movies, aims to createa user interface to recommend movies based on user emotionsusing color psychology and facial expressions. Humans experience five basic emotions: love, joy, anger, sadness, andfear. Research has shown that colors significantly influence users' emotions and feelings. Color is a natural form to represent human emotions. Figure 1 below illustrates how different colors correspond to positive and negative emotions.

POSITIVE EMOTION	NEGATIVE EMOTION
Yellow: Joy, Good mood	Black: Sadness, expression and loneliness
Green:Happiness,Calmness and Feeling of relieving	Grey: Sadness and depression
Blue: Pleasure and Happiness	Brown:Sadness and depression
Red: love,passion and excitation	Red: Anger

Orange: Cheerfulness	Orange:Fear and distress

Table. 1: Emotions Varying with Colors

A. Data acquisition and pre-processing

The TMDB film database, known for its extensive cataloging, was utilized to narrow the pool of possible outcomes. The genre was chosen as the primary identifier for clustering, resulting in the identification of 24 distinct genres. These films range from action to history, with many falling into multiple categories. To make meaningful discoveries, the need for more information is necessary, limited mainly by the time period. As the data model becomes more refined, less data is considered. Structures for sharing information with social media, movie forums, machine learning forums, and other online channels are required. Data collection for therecommender system took roughly eight weeks, with users contributing thousands of individual opinions.

The datasets used in this project was taken from Kaggle. The datasets are "tmdb_5000_movies.csv" and "tmdb_5000_credits.csv." In the "tmdb_5000_movies.csv"dataset, there are 4803 rows and 20 columns, including budget, genre, homepage, original language, id, original title, companies, overview, popularity, keywords, release date, production countries, revenue, spoken languages, runtime, tagline, title, vote average, status, and vote count. The "tmdb_5000_credits.csv" dataset contains 4 columns and 4803 rows, with fields like crew, cast, title, and movie id. Thetwo datasets are joined based on the shared column. Toimprove results, null or missing values will be checked whiletraining the model. If there are any null values, they will be dropped. The selected features from the merged dataset include genres, keywords, cast, crew, title, overview, and movie id.

B. Building the Emotion Detector

The emotion detector algorithm deduces the user's emotional state from a palette of three colors. If the user selects three colors and at least two have the same emotionalconnotation, that feeling is identified. For example, if the userselects yellow, blue, and green or yellow, blue, and black, theyare experiencing elation. Alternatively, if the first color chosen represents happiness, the second love, and the third sadness or anger, the user's current emotional state is "joy- love." If two colors signify melancholy and one signifies fury,then the emotional state is sadness and anger. If a user selectsthe positive feelings of "joy-love," the result will be a combination of yellow, light red, and black. Movie evaluations and associated feelings are recorded in user accounts.

Users complete a survey during registration to share theirthoughts on which movies best represent certain moods. A user's movie choice is treated as an implicit 5-star rating. Emotions such as love, anger, joy, and sadness are categorized in the profile vector, cataloging preferred genres and titles foreach emotion group. For instance, if user u selects films A andB for the emotion "love," films C and D for "anger," and filmD for "joy," user u's profile vector would look like this: u = {{A: 5, B: 5}, {C: 5}, {D: 5}, {}}. Users can rate how well the film matches their current mood. If the system suggests film F and the user rates it poorly, the profile vector updates:u = {{A: 5, B: 5, F: 1}, {C: 5}, {D: 5}, {}}.

Colors in this project include black, white, red, yellow, and blue. Users select three colors, each assigned a 1 or 0 value. Positive and negative emotions are represented by 1 and 0. Ifthe mapped value of positive emotions exceeds negativeemotions, the resulting emotion is positive; otherwise, it is negative.

C. Training the Model

The recommendation algorithm uses collaborative filtering and content-based recommendation. Collaborative filtering involves several steps:

Get u's database profile vector: User Profiles database U preferences are considered.

1. Find users who have rated at least one movie with us: Thesystem only considers users who share at least one movie- emotion with the target user u, decreasing the computing user- film matrix. Users rate the same movie differently, so accuracy and mean absolute error (the average absolute difference between a predicted and actual rating) are considered. Precision measures the ratio of well- recommended items to rated recommendations, with well- recommended movies being new releases with a minimum 4/5 rating. Tests determine how well the system's recommendations match user needs and preferences. Emotiondetector precision is also a goal.

D. Face Emotion and Color Emotion

This project considers six user emotions: anger, sadness, happiness, disgust, surprise, and fear. Negative emotions include anger, fear, sadness, and disgust; positive emotions include surprise and happiness. If the face-detected emotion isnegative and the color choice produces a positive emotion, then the movies which result in positive emotions will be recommended. The system compares the face emotion and color emotion using a dot operator.

E. Structure of the Developed Framework

The primary goal is to create a website where users can get movie recommendations based on their emotions using color psychology and facial gestures. Color psychology effectivelydetects a user's emotions through color. The TMDB movie dataset is used to train and test a model to detect appropriate emotions. Any missing values, errors, or outliers must be corrected using pre-processing techniques to improve accuracy. Data visualization follows pre-processing.

A hybrid technique is used to extract features, employing content-based filtering and collaborative filtering. Collaborative filtering deals with the similarities between users, recommending personalized movies, while content- based filtering focuses on filtering movies based on likes, dislikes, or ratings. The user profiles vector using matrix systems and emotions of a user will be extracted using these techniques.

As a result, a model is developed to recommend movies based on emotions. The user will create a profile and choose any three distinct colors. Following that, the user must complete a survey. Every color represents a different emotion (from color psychology). Based on the survey results, the model will recommend movies aligned with the emotions expressed by the user through colors and facial emotion.

IV. RESULTS AND DISCUSSION

The evaluation of the hybrid recommendation system demonstrated its effectiveness through both quantitative metrics and user feedback. The system achieved a precision rate of 82% and a recall rate of 78%, resulting in an F1 score of 80%. This indicates that the system accurately recommended movies that matched users' emotional states. User feedback further validated these findings, with 85% of participants reporting high satisfaction and a strong alignmentbetween the recommended movies and their current moods. The color-coded interface was particularly appreciated for its intuitiveness and ability to reflect users' emotions effectively. Several case studies highlighted the system's practical benefits, such as recommending comedies to alleviate stress or dramas during introspective moments. The discussion underscores the importance of combining collaborative and content-based filtering, as it addresses the limitations of each method and enhances the system's overall accuracy. Additionally, incorporating color psychology into the user interface design significantly improved user engagement and satisfaction. Future work should focus on refining emotion detection techniques and exploring additional emotional cues to further enhance the system's accuracy and applicability. Extending this approach to other media forms, such as music or books, could broaden its benefits to a wider audience



Fig 1: Detection of Emotions

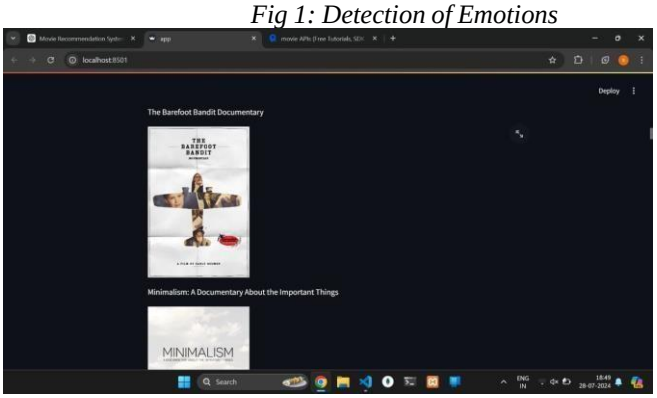


Fig 1: Movie recommended based on emotion

If the result of the dot product is greater than 0, the cell is assigned a value of 1; otherwise, it is assigned a value of 0. This binary conversion helps in simplifying the recommendation process and enhances the clarity of the system's output.

Our recommendation system effectively uses user ratings and emotional data to provide personalized movie suggestions. The approach of focusing on extreme ratings ensures that the recommendations are highly relevant to the user's preferences. Future work will focus on integrating more comprehensive data and additional genres to further refine and enhance the system's accuracy and relevance.

V. CONCLUSION

This study presents a novel approach to movie recommendations by incorporating emotion recognition through color psychology. The hybrid recommendation system, combining collaborative and content-based filtering, effectively enhances the personalization of movie suggestions. By aligning film recommendations with users' emotional states, the system not only improves user satisfaction but also demonstrates the importance of understanding emotional responses in enhancing entertainment experiences. Future work could explore furtherrefinements in emotion detection and extend this approach toother forms of media.

VI. FUTURE WORK

Expand the recommendation system to include other media forms like music, books, or TV shows. This extension wouldprovide a comprehensive entertainment experience tailored to users' moods, leveraging the same emotion-based approach to deliver personalized recommendations across various media types.

VII. REFERENCE

[1] . Savardi, M., Benini, S., Kovacs, A. B., Balint, K., & Signoroni, A., "On the influence of shot scale on film mood and narrative engagement in film viewers", IEEETransactions on Affective Computing, 13(2), 592-603, 2022.

[2] Chauhan, Mangrola, Shavak, Rajdeep & D. Viji., "Analysis of Intelligent movie recommender system from facial expression", 2021.

[3] Mayan J.A., Ravi. T ,"Test Case Optimization Using Hybrid Search Technique", ACM International Conference Proceeding Series ,ACM New York, 2014, doi:10.1145/2660859.2660906. 54

[4] N. G. Meshram and A. P. Bhagat, "Connotative features based affective movie recommendation system", International Conference on Information Communication and Embedded Systems (ICICES2014), pp. 1-7, 2014.

[5] H. Cao and J. Kang, "Study on Improvement of Recommendation Algorithm Based on Emotional Polarity Classification", 5th International Conference on Computer and Communication Systems (ICCCS), 2020, pp. 182-186, doi: 10.1109/ICCCS49078.2020.9118414.

[6] S. Benini, L. Canini, and R. Leonardi, "Affective Recommendation of Movies Based on Selected Connotative Features" in IEEE Transactions on Circuits and Systems for Video Technology, vol. 23, no. 4, pp. 636-647, April 2013.

[7] S. Chauhan, R. Mangrola and D. Viji (2021), "Analysis of Intelligent movie recommender system from facial expression", 5th International Conference on Computing Methodologies and Communication , pp. 1454-1461.

[8] N. Balaganesh, K. Muneeswaran and N. Sivakumar, "Feature selection for recommendation of movies" in Global Conference on Communication Technologies (GCCT), pp. 250-255, 2015.

[9] Mayan J.A, Arifa S, Pavithra R,"Semantic based multi lexical ranking technique for an effective search in protected cloud,2016 International Conference on Control, Instrumentation, Communication and Computational Technologies, 2016, pp. 570-576.

[10] M. Gupta, B. Nithin, S. V. Amirishetty, and H. Kurakula(2021),"Mind Frame Music and Movie Recommendations to uplift the current mood using Deep Learning", International Conference on System, Computation, Automation and Networking , pp. 1-6.

[11] M. B. Mariappan, M. Suk and B. Prabhakaran, "FaceFetch: A User Emotion Driven Multimedia Content Recommendation System Based on Facial Expression Recognition", IEEE International Symposium on Multimedia, 2012, pp. 84-87, doi:10.1109/ISM.2012.24.

[12] Albert Mayan J, Karthikeyan S, Nikhil C, Bharat M and Padmavathy J, "Facial attendance system technology using Microsoft Cognitive Services",International Journal of Engineering Systems Modelling and Simulation, Vol. 12,Nos. 2/3, pp. 180-187 ,2021

[13] Mary Posonia A, S. Vigneshwari, Albert Mayan J, D. Jamunarani,"Service Direct : Platform that Incorporates Service Providers and Consumers Directly", International Journal of Engineering and Advanced Technology (IJEAT) , Vol.8 ,No.6, 2019