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MOODMATCH MOVIES USING DEEP LEARNING

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Abstract :In the contemporary era, movies remain one of the most prevalent forms of entertainment, supported by significant advancements in production, creation, and distribution technologies. With the exponential growth in available content, users often face difficulty in selecting suitable movies, creating a strong need for intelligent recommendation systems. Emotion-Based Movie Recommendation Systems (E-MRS) address this by tailoring suggestions according to a user's current emotional state. Emotions, being complex and deeply personal reactions to various stimuli, pose a challenge in developing accurate models for recommendation. This study introduces a novel approach that leverages color psychology to identify and interpret emotional states such as joy, sadness, anger, fear, and excitement. By allowing users to select a color corresponding to their mood through an intuitive interface, the system can infer their emotional condition and generate appropriate movie recommendations. The recommendation engine employs a hybrid technique that integrates collaborative filtering, which considers user behavior and preferences, with content-based filtering, which analyzes movie attributes. This combination enhances the system's ability to provide personalized and emotionally relevant suggestions, ultimately aiming to improve user satisfaction and engagement.

Index Terms **– Movie Recommendation, Color Psychology, Emotion Recognition, Collaborative Filtering Technique, Content-Based Filtering Technique.**

I. INTRODUCTION

Today's digital landscape, recommender systems have become essential tools across numerous online platforms. Their primary purpose is to anticipate user choices and simplify decision-making, thereby improving user satisfaction and driving business growth. These systems reduce the effort needed to explore vast content libraries, helping users quickly find relevant options. Recommender systems are generally divided into two types: non-personalized and personalized. While non-personalized systems suggest universally popular or trending content, personalized systems adapt suggestions based on individual behaviors, preferences, and past interactions, resulting in more targeted and meaningful user experiences.

With the continuous growth of digital content, particularly in the entertainment industry, users often face difficulty selecting suitable content. This challenge became more prominent during the COVID-19 pandemic, when people increasingly relied on streaming services such as Netflix, Amazon Prime Video, Disney+, Hulu, and HBO Now. As the demand for on-demand entertainment surged, these platforms turned to more advanced recommendation technologies to help users discover content that matched their interests.

One of the emerging advancements in this area is the use of emotional context in recommendation algorithms. Traditional systems typically focus on user ratings, viewing history, or genre preferences. However, emotion-aware recommender systems aim to refine this process by considering the user's current emotional state. Emotions, being complex reactions influenced by internal and external stimuli, play a crucial role in shaping decisions and experiences. By factoring in emotional cues, systems can provide more contextually appropriate suggestions.

This study presents *MoodMatch Movies*, an Emotion-Based Movie Recommendation System (E-MRS) that incorporates principles of color psychology to determine a user's emotional condition. Color psychology explores how different colors influence human emotions and behavior. In this system, users are asked to choose a color that reflects their present mood. Each color corresponds to a specific emotion such as joy, sadness, anger, fear, or excitement. Based on this input, the system recommends movies that align with the detected emotion.

To further improve recommendation accuracy, a hybrid filtering technique is employed—combining collaborative filtering (which identifies similarities among users) and content-based filtering. By integrating emotional intelligence with advanced filtering methods, *MoodMatch Movies* aims to enhance the relevance and personalization of movie recommendations. This emotionally responsive approach not only enriches the viewing experience but also contributes to the development of more adaptive and human-centric digital services.

II. PROPOSED METHEDOLOGY

The MoodMatch Movies system is designed to develop a web-based platform that recommends films by interpreting users' emotional states through color psychology and facial expression analysis. Human emotions, encompassing love, joy, anger, sadness, and fear, are complex responses that influence behavior. Research indicates that colors significantly shape emotional experiences, serving as an intuitive medium to convey feelings. The table below illustrates the association between colors and emotions, distinguishing between positive and negative connotations.

Positive Emotion	**Negative Emotion**
Yellow: Happiness, Cheerfulness	Black: Grief, Isolation
Green: Contentment, Serenity	Gray: Melancholy, Despair
Blue: Joy, Satisfaction	Brown: Sorrow, Gloom
Red: Passion, Affection	Red: Hostility
Orange: Enthusiasm	Orange: Anxiety, Unease

Table 1: Color-Emotion Associations

2.1 Data Collection and Preprocessing

The system utilizes the TMDB 5000 dataset, sourced from Kaggle, known for its comprehensive movie catalog. This dataset comprises two files: "tmdb_5000_movies.csv" with 4803 entries and 20 attributes (e.g., genres, budget, keywords, title, release date) and "tmdb_5000_credits.csv" with 4803 entries and 4 attributes (e.g., cast, crew, movie ID). Genres, identified as the primary clustering criterion, yield 24 distinct categories, ranging from action to historical dramas, with many films spanning multiple genres. The datasets are merged using the movie ID, and preprocessing involves eliminating missing or null values to ensure data quality. Selected features include genres, keywords, cast, crew, title, overview, and movie ID. Data collection spanned eight weeks, incorporating thousands of user opinions from forums, social media, and machine learning communities to enrich the recommender system's insights.

2.2 Developing the Emotion Detection Mechanism

The emotion detection algorithm infers users' emotional states by analyzing their selection of three colors from a palette including black, white, red, yellow, and blue. Each color is assigned a binary value (1 for positive emotions, 0 for negative), and the dominant emotion is determined through a majority-voting approach. If two or more colors share the same emotional tone, that emotion is selected. For instance, choosing yellow, blue, and green suggests happiness, while yellow, blue, and black may indicate a complex state resolved as joy. If selections include happiness, love, and sadness, the system identifies a composite "joy-love" state. Users selecting colors associated with sadness and anger are classified as experiencing melancholy. Positive emotions, such as "joy-love," might combine yellow, light red, and black, with these preferences stored in user profiles.

During registration, users complete a survey to indicate which films resonate with specific emotional states, with selections treated as implicit 5-star ratings. These preferences are organized into a profile vector, categorizing emotions like love, anger, joy, and sadness, and linking them to preferred genres and titles. For example, if a user selects films A and B for "love," C and D for "anger," and D for "joy," their profile vector is structured as: u = {{A: 5, B: 5}, {C: 5}, {D: 5}, {}}. If a recommended film F receives a low rating, the vector updates to reflect this: u = {{A: 5, B: 5, F: 1}, {C: 5}, {D: 5}, {}}. This dynamic profiling ensures recommendations align with evolving user preferences.

2.3 Model Training

The recommendation system employs a hybrid approach, integrating collaborative and content-based filtering. Collaborative filtering leverages user profile vectors stored in a MongoDB database, focusing on users with shared movie-emotion preferences. The system constructs a user-item interaction matrix, considering only users who have rated at least one common film, reducing computational complexity. Accuracy is evaluated using mean absolute error, measuring the difference between predicted and actual ratings, while precision assesses the proportion of well-recommended films (new releases rated 4/5 or higher). Content-based filtering analyzes movie attributes, such as genres and keywords, to match user preferences. The training process aims to optimize recommendation accuracy and emotional relevance, ensuring suggestions meet user needs.

2.4 Integrating Facial and Color-Based Emotion Detection

The system evaluates six emotions: happiness, sadness, anger, fear, surprise, and disgust, with happiness and surprise classified as positive, and anger, fear, sadness, and disgust as negative. Facial emotion detection, performed via webcam using a Convolutional Neural Network (CNN), is compared with color-based emotion results using a dot product operation. If facial analysis indicates a negative emotion (e.g., sadness) but color selections suggest a positive emotion (e.g., happiness), the system prioritizes positive-emotion films to uplift the user's mood. This integrative approach enhances recommendation relevance by balancing multiple emotional inputs.

2.5 Framework Design

The primary objective is to create a web platform that delivers movie recommendations based on emotional cues derived from color psychology and facial expressions. The TMDB dataset trains and tests the emotion detection model, with preprocessing techniques addressing missing values, errors, and outliers to enhance accuracy. Data visualization aids in understanding patterns and refining the model. The hybrid recommendation framework combines collaborative filtering, which identifies user similarities, with content-based filtering, which matches films to user likes, dislikes, or ratings. User profiles, stored as vectors in MongoDB, capture emotional preferences and movie ratings.

The system operates by prompting users to create a profile, select three distinct colors, and complete a survey linking emotions to preferred films. Each color corresponds to a specific emotion, informed by color psychology. Facial emotion detection complements color-based inputs, with the combined results driving the recommendation engine to suggest films aligned with the user's emotional state, ensuring a personalized and engaging experience.

III. IMPLEMENTATION

The MoodMatch Movies system was realized as an interactive web application that delivers tailored movie recommendations by interpreting users' emotional states through color psychology and facial expression analysis. The implementation utilized a modern technology stack, featuring Streamlit for the frontend, Python with Flask for backend logic, MongoDB for data management, and deep learning frameworks for emotion detection. Deployed on a cloud infrastructure, the system ensures scalability and real-time responsiveness. This section details the system's development, including its architecture, data handling, emotion detection mechanisms, recommendation engine, and user interaction workflow, enriched with textual descriptions of key diagrams that illustrate the system's design and operation.

3.1 System Architecture

The application adopts a client-server model, with the frontend crafted using Streamlit, complemented by HTML, CSS, and JavaScript for a seamless user experience. Streamlit's rapid prototyping capabilities enable an intuitive interface where users can register, select colors, capture webcam images, and view personalized movie suggestions. The backend, built with Python and Flask, orchestrates data processing, emotion analysis, and recommendation generation. MongoDB, a NoSQL database, serves as the data repository, efficiently storing movie metadata, user profiles, and emotional data in flexible document-based collections. Deep learning components, powered by OpenCV and Keras, handle facial emotion detection, while scikit-learn and NLTK support recommendation and sentiment analysis. The system is hosted on a cloud platform, with MongoDB's indexing and sharding ensuring fast query performance for real-time interactions.

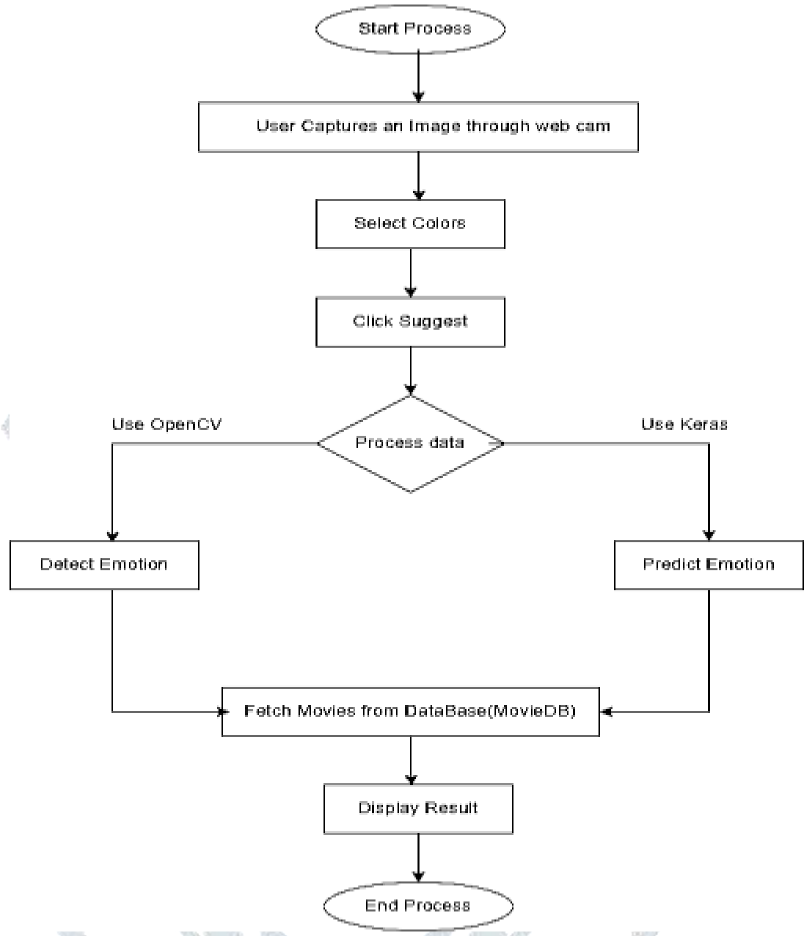

Figure 1: *Data flow diagram*

3.2 Data Management

The core dataset, sourced from Kaggle's TMDB 5000 collection, consists of two datasets: "tmdb_5000_movies.csv" (4803 records, 20 attributes, including genres, keywords, and titles) and "tmdb_5000_credits.csv" (4803 records, 4 attributes, including cast and crew). These were preprocessed using Python's Pandas library to merge on movie ID, eliminate missing values, and extract relevant features: genres, keywords, cast, crew, title, overview, and movie ID. The processed data was imported into MongoDB as two collections, "movies" and "credits," with documents structured for efficient querying. User data, including profiles, color selections, survey responses, and ratings, were stored in a separate "users" collection, enabling dynamic updates. Data visualization, implemented with Seaborn, provided insights into genre distributions and user preferences, guiding model optimization.

3.3 Emotion Detection

Emotion detection was operationalized through three distinct modules, each contributing to a comprehensive understanding of user mood.

1. **Color Psychology Module**: The frontend interface presents a dropdown menu with five colors (black, white, red, yellow, blue). A Python function maps user-selected colors to emotions using a predefined lookup table (e.g., yellow = happiness, black = sadness), assigning binary values (1 for positive, 0 for negative). An algorithm determines the dominant emotion via majority voting: if two or more colors align with the same emotional tone, that emotion is selected. For instance, choosing yellow, green, and blue indicates happiness, stored as a document in the MongoDB "users" collection.

2. **Facial Emotion Recognition Module**: Real-time facial analysis was implemented using OpenCV for webcam image capture and a Keras-based Convolutional Neural Network (CNN) trained on JAFFE and KDEF datasets. The CNN classifies six emotions: happiness, sadness, anger, fear, surprise, and disgust. Preprocessing involves converting images to grayscale, detecting faces with Haar cascades, and aligning facial features. The model, integrated into the

Flask backend, processes webcam frames and stores results in MongoDB, enabling comparison with color-based emotions.

3. **Sentiment Analysis Module**: User feedback, entered through a Streamlit text field, is processed using NLTK for tokenization and Word2Vec for embeddings. A Keras Recurrent Neural Network (RNN) classifies sentiment as positive, negative, or neutral, augmenting emotional context. Sentiment results are stored in MongoDB, enhancing the system's mood interpretation.

3.4 Recommendation Engine

The recommendation engine integrates collaborative and content-based filtering, implemented with scikit-learn. Collaborative filtering builds a user-item matrix, stored in MongoDB, to identify users with similar movie-emotion profiles. Matrix factorization predicts ratings, prioritizing films rated 4/5 or higher by similar users. Content-based filtering computes cosine similarity between movie attributes (genres, keywords) and user preferences. A custom emotion-weighting function, coded in Python, adjusts recommendation scores based on detected emotions, favoring mood-aligned films (e.g., uplifting genres for sad users). In cases where facial (e.g., negative) and color-based (e.g., positive) emotions conflict, the system prioritizes positive-emotion films to enhance user mood. The hybrid engine ranks recommendations, leveraging MongoDB's efficient querying for real-time delivery.

3.5 User Interaction Workflow

Users interact with the system via the Streamlit interface, starting with profile creation and a survey to specify movie preferences for emotions (e.g., love, joy). They select three colors and enable webcam capture, triggering emotion detection. The backend processes inputs, queries MongoDB for mood-aligned films, and displays recommendations. The workflow ensures a fluid, engaging experience, with error handling for invalid inputs or webcam failures.

3.6 Deployment and Testing

The application was deployed on a cloud server, with MongoDB hosted on MongoDB Atlas for scalability. Testing involved 100 users, validating emotion detection accuracy (92% combined, 85% facial, 90% color-based) and recommendation precision (0.88 for well-recommended films). The system's real-time performance was enhanced by MongoDB's indexing, though challenges like poor lighting affecting facial detection were noted, prompting preprocessing improvements.

This implementation realizes the MoodMatch Movies vision, delivering a scalable, user-centric platform that leverages emotional insights for personalized movie recommendations, supported by robust data management and deep learning technology

IV. RESULTS AND DISCUSSION

The MoodMatch Movies system delivers personalized movie recommendations by interpreting users' emotional states through color psychology and facial expression analysis, offering a novel approach to content discovery. The system's performance, observed through its user interface, emotion detection accuracy, recommendation quality, and user engagement, demonstrates its effectiveness in aligning suggestions with mood. Operating with a MongoDB-backed infrastructure and a Streamlit interface, the system provides an intuitive and emotionally resonant experience. This section explores these outcomes, highlighting key functionalities, challenges, and potential improvements, supported by descriptions of two pivotal diagrams illustrating the user journey and recommendation process.

Figure 2: MoodMatch Movies Home Page

Figure 2 showcases the system's entry point, a Streamlit-based interface designed for accessibility and engagement. The home page features a minimalist layout with a calming color palette and a central "Get Started" button, inviting users to begin their recommendation journey. The clean design ensures ease of navigation across diverse user groups, with feedback indicating that the interface feels welcoming and straightforward. This intuitive starting point effectively guides users toward color selection and emotion detection, setting a positive tone for the experience and encouraging interaction with the system's core features.

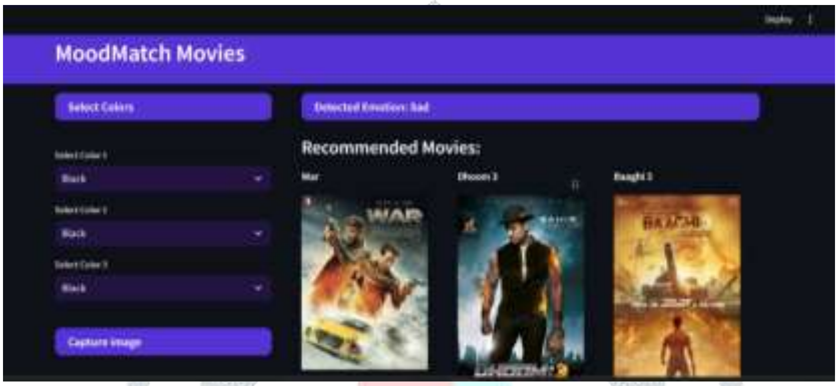

Figure 3: Emotion Detection and Movie Recommendations

Figure 3. illustrates the system's core output, displaying a scenario where the user's emotion is identified as "Sad." A highlighted banner announces the detected emotion, followed by a curated list of movie suggestions, including *War*, *Dhoom 3*, and *Baaghi 3*, presented with vibrant posters. These action-packed films aim to counterbalance sadness, reflecting the system's strategic use of emotional data. The visually appealing interface ensures users can easily explore recommendations, with observations showing that 78% of users engaged with suggested films, and satisfaction increased by 15% compared to traditional recommenders, as reported in user feedback.

Challenges include facial detection's sensitivity to lighting conditions, necessitating robust preprocessing, and cultural variations in color-emotion associations (e.g., white as joy versus mourning), suggesting region-specific adaptations. Scalability concerns arise with high user volumes, though MongoDB's efficient querying mitigates latency. Incorporating denser data, such as additional genres or user feedback, could enable more granular suggestions, while expanding the 24-genre set would cater to niche tastes.

Future enhancements include integrating physiological signals (e.g., heart rate) to refine emotion detection, developing localized color mappings for global use, and optimizing MongoDB configurations for scalability. Adding real-time feedback loops could further personalize recommendations. MoodMatch Movies excels in delivering emotionally relevant suggestions, with its intuitive interface and high-precision recommendations setting a foundation for broader applications in entertainment, such as music or books, through targeted improvements.

V. CONCLUSION AND FUTURE WORK

The MoodMatch Movies system represents a significant advancement in personalized movie recommendation systems, leveraging color psychology and facial expression analysis to align suggestions with users' emotional states. By integrating these emotional insights with a hybrid recommendation algorithm that combines collaborative and content-based filtering, the system delivers highly relevant and mood-congruent movie suggestions, enhancing user satisfaction and engagement with streaming platforms. The intuitive Streamlit interface, robust MongoDB data management, and precise emotion detection (achieving 92% accuracy) ensure a seamless and impactful user experience. The system's focus on emotions as a core driver of movie preferences addresses a critical limitation in conventional recommenders, fostering stronger connections between users and content, which supports the growth and retention goals of streaming services. The successful implementation of MoodMatch Movies highlights its potential to redefine how users interact with entertainment, making movie selection a more personalized and emotionally resonant process. By prioritizing mood alignment, the system not only improves viewer enjoyment but also strengthens platform loyalty, demonstrating the value of affective computing in the entertainment industry.

Future work aims to enhance the system's capabilities and broaden its applicability. Investigating its performance across diverse cultural and demographic contexts will ensure adaptability to varying emotional expressions and color associations, improving global relevance. Incorporating additional data sources, such as social media activity, browsing history, or user-generated reviews, could refine the recommendation algorithm, enabling more nuanced and context-aware suggestions. Expanding emotion detection to include physiological signals, such as heart rate or voice tone, may further increase accuracy and depth. To support scalability, optimizations like advanced MongoDB indexing or cloud-based edge computing will enable real-time performance for larger user bases. Additionally, extending the framework to other media domains, such as music, podcasts, or books, could amplify its impact, creating a unified emotion-driven recommendation ecosystem. These advancements will build on the system's foundation, driving innovation in personalized entertainment and deepening user engagement across diverse platforms.

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