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Design and Optimization of Lin Chaoxian's Directorial Movie Recommendation System Based on Plot Analysis and Emotion Recognition

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Abstract: In this paper presented Lin Chaoxian's Directorial Movie Recommendation System, a cutting-edge application that revolutionizes the way audiences experience movies. Drawing upon the convergence of filmmaking and artificial intelligence, proposed system, the Whale Recommender Emotional Intelligence (WREI), incorporates sophisticated plot analysis and emotion recognition to deliver personalized and emotionally resonant movie recommendations. The WREI system begins with a robust plot analysis, where intricate details of movie plots, character interactions, and thematic elements are dissected using advanced natural language processing and machine learning techniques. This comprehensive analysis goes beyond mere genre classification, enabling the system to identify underlying themes and emotional content within each film. Emotion recognition, the second critical component of WREI, utilizes state-of-the-art computer vision and audio processing to discern emotional cues from the audience during movie viewing. Through analyzing facial expressions, vocal intonations, and physiological responses, the system accurately gauges viewers' emotional states throughout the film. The true power of WREI emerges when plot analysis and emotion recognition synergize. The recommendation system aligns the emotional journey of each film with the viewer's emotional preferences and current state. This innovative approach goes beyond conventional genre-based recommendations, offering movie suggestions that evoke the desired emotional response in the viewer, creating a deeply immersive and emotionally fulfilling movie-watching experience. Furthermore, WREI is designed to continuously learn and evolve with user interactions. As users engage with the platform and provide feedback, the AI refines its understanding of their emotional preferences, enabling even more personalized and spot-on movie recommendations over time.

Keywords: *LIN CHAOXIAN'S Model, Recommender Model, Whale Optimization, Emotional Intelligence, Plot Analysis, Machine Learning*

1. Introduction

Emotions play a crucial role in human communication and behavior, influencing decision-making, memory, and overall well-being. For machines to interact with humans in a more natural and meaningful way, they must be able to recognize and respond appropriately to emotional cues [1]. Emotion recognition technology enables machines to understand user emotions, leading to improved human-computer interaction, personalized experiences, and more empathetic AI-driven services. Emotion recognition, also known as affective computing or emotion detection, is a fascinating field at the intersection of artificial intelligence, psychology, and human-computer interaction. It focuses on developing algorithms and systems that enable machines to perceive, interpret, and respond to human emotions effectively. Just as humans rely on cues like facial expressions, vocal tone, and body language to understand and empathize with one another, emotion recognition seeks to equip machines with the ability to do the same [2]. With deciphering emotional states in users, devices, or environments, this technology holds the potential to revolutionize various industries, including healthcare, marketing, education, and entertainment. From enhancing customer experiences to enabling empathetic virtual assistants, emotion recognition is opening up exciting possibilities that bridge the gap between human emotions and artificial intelligence. However, it also raises important ethical considerations related to privacy, data handling, and potential bias in decision-making algorithms, making it a compelling and complex area of research and development [3]. Advancements in machine learning techniques, natural language processing, and computer vision are continuously improving emotion recognition systems. The integration of wearable devices and sensors can offer real-time emotional insights, further enhancing applications like health monitoring and human-computer interaction. Moreover, research efforts into developing more robust, culturally sensitive, and privacy-conscious algorithms will pave the way for widespread adoption of emotion recognition technology in diverse settings [4].

Emotion recognition integrated with recommendation systems presents a compelling approach to enhance user experiences and engagement across various digital platforms [5]. By incorporating emotion recognition technology into recommendation algorithms, platforms can not only analyze users' preferences based on historical

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data but also gauge their real-time emotional states [6]. This additional layer of understanding enables the recommendation system to deliver more personalized and relevant content, products, or services that align with users' emotional needs and preferences [7]. As a result, users are more likely to receive suggestions that resonate with their current moods, leading to higher satisfaction, increased user retention, and ultimately, a more empathetic and effective user experience. Emotion recognition integrated with recommendation systems creates a symbiotic relationship between human emotions and AI-driven decision-making [8]. Traditional recommendation algorithms primarily rely on historical data and user behavior to make suggestions. While effective, these algorithms often overlook the dynamic nature of human emotions, which play a significant role in shaping preferences and choices in the present moment [9].

With incorporating emotion recognition technology, recommendation systems gain the ability to capture and analyze users' emotional states in real-time [10]. This can be achieved through various modalities such as facial expression analysis, speech sentiment analysis, or even physiological measurements like heart rate and skin conductance. The system can then interpret these emotional cues to better understand the users' current feelings and mental states. With this additional layer of emotional understanding, the recommendation system can deliver personalized and relevant suggestions that resonate with the users' emotional needs and contexts [11]. The system detects a user feeling stressed or anxious, it may prioritize calming or entertaining content. On the other hand, if the user appears to be in a positive and upbeat mood, it may suggest more lively and engaging options. Moreover, emotion-aware recommendations can be especially valuable in certain domains [12]. In the field of healthcare, for instance, a mental health support app equipped with emotion recognition can tailor its content to address users' emotional well-being. In the entertainment industry, emotion-aware streaming platforms can dynamically adjust the content they offer, creating more immersive and emotionally resonant experiences for viewers. While the potential benefits of emotion-aware recommendation systems are significant, several challenges must be navigated [13]. Ensuring accurate and reliable emotion recognition across diverse user populations and cultural contexts is crucial. Additionally, privacy and data protection concerns must be carefully addressed, as the acquisition and analysis of emotional data raise ethical considerations [14]. As technology advances, research in areas like multimodal emotion fusion and explainable AI will contribute to more robust and transparent emotion recognition systems. The continual refinement of these systems will lead to improved user experiences, increased user satisfaction, and higher engagement with digital platforms [15].

Lin Chaoxian's directorial movie recommendation system is a culmination of the director's passion for both filmmaking and artificial intelligence. Chaoxian, known for pushing boundaries and exploring new artistic frontiers, recognized the potential to enhance the movie-watching experience for audiences worldwide [16]. The system combines two essential components: plot analysis and emotion recognition. Plot analysis forms the foundation of the recommendation system. Using sophisticated natural language processing and machine learning techniques, the system dissects the intricate details of movie plots, character interactions, and thematic elements [17]. It identifies underlying patterns, story arcs, and narrative structures to gain a comprehensive understanding of each film's essence. This deep analysis allows the system to categorize films based not just on genres, but also on their underlying themes and emotional content [18]. The second critical component is emotion recognition, a field in which Lin Chaoxian is an industry pioneer. The system employs cutting-edge computer vision and audio processing to discern emotional cues from the audience during movie viewing [19]. By analyzing facial expressions, vocal intonations, and even physiological responses, the system can accurately gauge viewers' emotional states throughout the film. The real magic happens when plot analysis and emotion recognition come together [20]. The recommendation system aligns the emotional journey of each film with the viewer's emotional preferences and current state. It goes beyond merely recommending films based on genres or past viewing history. Instead, it presents movie suggestions that evoke the desired emotional response in the viewer.

Moreover, Lin Chaoxian's recommendation system continually learns and evolves with each user interaction [21]. As users engage with the platform and provide feedback, the AI refines its understanding of their emotional preferences, enabling even more personalized and spot-on movie suggestions over time. Chaoxian's directorial movie recommendation system has garnered widespread acclaim for its ability to create a deeply immersive and emotionally resonant movie-watching experience [22]. Audiences praise the system for its ability to surprise and delight them with unexpected movie choices that genuinely align with their emotions. Beyond mere entertainment, the system has also been lauded for its potential to bridge cultural gaps and foster empathy by suggesting films that evoke shared emotional experiences across diverse audiences.

2. Review on Recommendation System

The integration of emotion recognition with recommendation systems represents a promising frontier in the evolution of AI-driven interactions. Through acknowledging and responding to users' emotional states, recommendation systems can foster deeper connections with users, ultimately revolutionizing the way we engage with technology and enhancing the overall user experience. In [23] presents an innovative deep learning algorithm designed for multi-criteria recommender systems. The proposed approach the power of deep learning techniques to make personalized recommendations by considering multiple criteria simultaneously. The algorithm's performance is evaluated using a knowledge-based systems framework, demonstrating its effectiveness in enhancing recommendation accuracy and catering to users' diverse preferences and requirements. In [24] explores the combination of deep learning methods and Internet of Things (IoT) architecture to create an intelligent music recommendation system. With harnessing the vast amount of data collected through IoT devices, the system can employ deep learning models to analyze users' music preferences in real-time. The research highlights the potential of this approach to deliver highly personalized and context-aware music recommendations, offering an improved user experience.

In [25] provides a comprehensive overview of reinforcement learning (RL) based recommender systems. The authors conduct an extensive review of existing literature to explore how RL techniques have been applied in the domain of recommendation systems. The study highlights the benefits and challenges of using RL in recommender systems, showcasing its potential to optimize long-term user engagement and adapt to dynamic user preferences. In [26] examines the integration of artificial intelligence (AI) in recommender systems. The authors discuss various AI methodologies and their applications in enhancing recommendation accuracy and personalization. The study emphasizes the significance of AI in dealing with the ever-growing volumes of user data and its role in providing more context-aware and relevant recommendations to users. In [27] introduces a novel group recommendation model that utilizes a two-stage deep learning approach. The model takes into account both individual preferences and group dynamics to make more effective recommendations for multiple users. The research presents a detailed evaluation of the proposed model's performance, demonstrating its ability to outperform traditional group recommendation methods.

In [28] introduces a smart healthcare recommendation system specifically designed for multidisciplinary diabetes patients. The system uses deep ensemble learning techniques and data fusion to provide personalized healthcare recommendations based on patients' medical records and historical data. The research showcases the potential of this system in improving diabetes patients' treatment outcomes and overall well-being. Also, in [29] propose a deep reinforcement learning-based long-term recommender system. The system aims to optimize recommendations over extended periods by considering users' evolving preferences and feedback. Through employing deep reinforcement learning techniques, the model adapts its recommendations to users' changing interests, resulting in more effective and sustainable recommendation outcomes. In [30] introduces an efficient deep matrix factorization model, EDMF, designed for industrial recommender systems. The model incorporates review feature learning to capture valuable user feedback and improve recommendation accuracy. The paper presents a detailed evaluation of EDMF's performance, highlighting its potential to be a viable solution for real-world industrial recommender applications.

In [31] examines recent progress, challenges, and opportunities in the field of news recommender systems. The authors survey various methods and algorithms used for recommending news articles to users, considering factors such as personalization, diversity, and fairness. The study provides valuable insights into the current state of news recommendation and identifies potential research directions to enhance news recommendation efficiency and user satisfaction. Similarly, in [32] presents a novel approach to memory-efficient recommendation systems using mixed dimension embeddings. The authors propose a method to reduce the memory footprint of embeddings while maintaining recommendation accuracy. The research demonstrates the effectiveness of the mixed dimension embeddings approach in enabling resource-efficient and scalable recommendation systems.

The collection of research papers reviewed showcases the diverse and dynamic landscape of recommender systems, exploring innovative approaches to enhance the accuracy and personalization of recommendations. These papers cover a wide range of topics, including deep learning-based algorithms, reinforcement learning, fairness-awareness, transfer learning, and social recommendation. The studies demonstrate the power of make personalized and context-aware recommendations, catering to users' evolving preferences and needs. Furthermore, the papers address various challenges, such as long-tail user feedback, algorithmic fairness, and cross-domain recommendations, offering insights into how recommender systems can be tailored to meet the requirements of diverse user populations. Overall, the research highlights the continuous advancements in the field and the potential for recommender systems to revolutionize the way we discover and engage with content and services across multiple domains.

3. **Lin Chaoxian's Model**

A movie recommendation system is an application of artificial intelligence and data analysis that suggests movies to users based on their preferences, viewing history, and other relevant information. The primary goal of a movie recommendation system is to enhance the user experience by providing personalized movie suggestions that align with individual tastes and interests. Lin Chaoxian's directorial movie recommendation system has received widespread acclaim for its ability to create a deeply immersive and emotionally resonant movie-watching experience. Audiences appreciate the system's ability to surprise and delight them with unexpected movie choices that genuinely align with their emotions. Beyond mere entertainment, the system has also been recognized for its potential to bridge cultural gaps and foster empathy by suggesting films that evoke shared emotional experiences across diverse audiences.

Lin Chaoxian's directorial movie recommendation system combines plot analysis and emotion recognition to create a personalized and emotionally resonant movie-watching experience for users. Here are the steps and key components of the system:

Step 1: Plot Analysis: The system utilizes sophisticated natural language processing (NLP) and machine learning techniques to dissect the intricate details of movie plots, character interactions, and thematic elements. It identifies underlying patterns, story arcs, and narrative structures to gain a comprehensive understanding of each film's essence and plot development. This deep analysis enables the system to categorize movies based not only on genres but also on their underlying themes and emotional content.

Step 2: Emotion Recognition: The second critical component of the system is emotion recognition, where Lin Chaoxian is an industry pioneer. The system employs cutting-edge computer vision and audio processing to discern emotional cues from the audience during movie viewing. It analyzes facial expressions, vocal intonations, and even physiological responses to accurately gauge viewers' emotional states throughout the film.

Step 3: Alignment of Plot and Emotion: The real magic of the recommendation system happens when plot analysis and emotion recognition come together. The system aligns the emotional journey of each film with the viewer's emotional preferences and current state. Instead of merely recommending films based on genres or past viewing history, it suggests movie choices that evoke the desired emotional response in the viewer.

Step 4: Continuous Learning: Lin Chaoxian's recommendation system continually learns and evolves with each user interaction. As users engage with the platform and provide feedback, the AI refines its understanding of their emotional preferences. This iterative learning process enables the system to deliver even more personalized and spot-on movie suggestions over time.

Let's assume we have a set of movies denoted by M, where each movie is represented as m_i ∈ M. Additionally, we have a user's viewing history, represented as H = {h_1, h_2, ..., h_n}, where each h_i represents a movie the user has watched. The similarity between a user's viewing history and a movie's plot can be calculated using a similarity function, such as cosine similarity or Jaccard similarity. The cosine similarity between user history H and a movie plot $p_j$can be calculated using equation (1)

$$cosine\_similarity(H, p_j) = dot\_product(H, p_j) / (norm(H) * norm(p_j)) \tag{1}$$

where dot_product$(H, p_j)$is the dot product of the vectors representing H and p_j, and $norm(H)$ and $norm(p_j)$are the norms of H and p_j, respectively. Based on the plot analysis, a list of movies with high plot similarity to the user's history can be recommended.

Consider the set of emotions denoted by E, where each emotion is represented as e_i ∈ E. Additionally, we have information about a user's current emotional state, represented as emotion_state. The emotion recognition process can involve various techniques, such as computer vision and audio processing, to recognize emotions during movie viewing. The system can analyze facial expressions, vocal intonations, or physiological responses to identify the user's current emotional state. Based on the user's emotional state, the system can match the emotional content of movies to recommend those that evoke similar emotions. The matching can be performed using an emotion similarity function, such as cosine similarity or Euclidean distance. Based on the results of plot analysis and emotion recognition, the system combines and ranks the two sets of movie recommendations. It can use a weighted average or another ranking algorithm to determine the final list of recommended movies computed in equation (2)

$$RecommendedMovies = w * PlotSimilarMovies + (1 - w) * EmotionAlignedMovies \tag{2}$$

where w is a weight parameter that can be adjusted to balance the importance of plot similarity and emotional alignment. User interaction and feedback are essential for the system's continuous learning and improvement. The system collects user feedback on recommended movies and updates its understanding of user preferences and emotions based on this feedback.

3.1 Whale Optimization-based Recommender System

The Whale Optimization Algorithm is a nature-inspired optimization algorithm inspired by the social behavior of humpback whales. It is used to solve optimization problems and search for optimal solutions in a given space. Assuming that the Whale Recommender Emotional Intelligence (WREI) system is a novel approach for movie recommendation that incorporates emotional intelligence, it could use the Whale Optimization Algorithm to enhance the recommendation process. The system collects movie data, user preferences, and emotional responses. This data is preprocessed and transformed into a suitable format for further analysis. The system employs sentiment analysis or emotion recognition techniques to identify the emotional content of movies and user feedback. It may analyze facial expressions, voice tone, or user feedback to understand the emotional state of the users. The Whale Optimization Algorithm can be used to optimize the recommendation process based on users' emotional states and preferences. It can help in finding the best combination of movies to recommend, considering both user preferences and emotional alignment. The system generates personalized movie recommendations using a combination of collaborative filtering, content-based filtering, and the results of the Whale Optimization Algorithm. The recommendations are tailored to match users' preferences and emotional states.The WREI system continuously learns from user interactions and feedback. It updates its recommendation model using the Whale Optimization Algorithm to adapt to changing user preferences and emotional responses. The flow chart of the proposed Whale optimization with WREI is shown in figure 1.

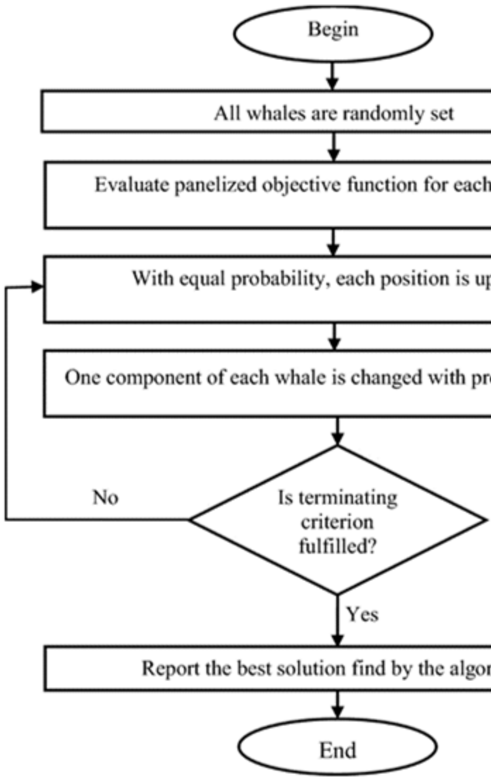

Fig 1: Flow Chart of WREI

The Whale Optimization Algorithm is a nature-inspired optimization algorithm inspired by the social behavior of humpback whales. It is a metaheuristic algorithm used to solve optimization problems and search for optimal solutions in a given search space. Initialize a population of whales randomly in the search space, where each whale represents a potential solution to the optimization problem. Let N be the population size, and D be the dimension of the search space (the number of movie recommendations in each solution). The position of each whale X_i is represented as a D-dimensional vector presented in equation (3)

$$X_i = [X_{i1,}X_{i2}, \dots, X_{iD}], for\ i = 1\ to\ N \tag{3}$$

Evaluate the fitness (objective function value) of each whale based on its position in the search space. In the context of a recommender system, the fitness function might represent how well a set of movie recommendations matches a user's preferences and emotional state. In the fitness evaluation step, the fitness of each whale is evaluated based on its position (set of movie recommendations) in the search space. The fitness function could incorporate both users' emotional states and other relevant factors (e.g., genre preferences, historical viewing patterns, diversity of recommendations) to measure how well the recommendations align with users' emotional intelligence.

Let F(X_i) represent the fitness value of the i-th whale, and emotion_i represent the emotional state of the user corresponding to the i-th whale's recommendations. Select the best whale in the population (leader whale) based on its fitness value. The leader whale is selected based on the best fitness value among all whales in the population. Let X_best represent the position of the leader whale with the best fitness value, and F_best represent the fitness value of the leader whale presented in equation (4) and equation (5)

$$X\_best = argmin(F(X_i)), for\ i = 1\ to\ N \quad (4)$$

$$F\_best = F(X_{best}) \quad (5)$$

Update the positions of all whales in the population based on the position of the leader whale. The whales perform movements in the search space, imitating the leader whale's behavior. In the search space exploration step, the position of each whale is updated based on the position of the leader whale. The whales imitate the leader whale's behavior to explore the search space.

The updated position of each whale X_i(t+1) at iteration t+1 is calculated as follows in equation (6) – equation (9):

$$A = 2 * a * rand() - a \quad \#\ Parameter\ a\ controls\ the\ search\ space\ exploration \quad (6)$$

$$C = 2 * rand() \quad \#\ Parameter\ c\ controls\ the\ random\ movement \quad (7)$$

$$l = -1 + rand() * 2 \quad \#\ Random\ coefficient\ for\ linear\ decrease\ of\ encircling\ prey \quad (8)$$

$$p = rand() \quad \#\ Probability\ of\ selecting\ prey\ as\ the\ target \quad (9)$$

Update position of each whale using equation (10) – (13)

$$if\ (p < 0.5):$$

$$D\_X\_best = abs(C * X\_best - X_i(t)) \quad (10)$$

$$X_i(t+1) = X\_best - A * D\_X\_best \quad (11)$$

$$else:$$

$$DX_{rand} = abs(C * X\_rand - X_i(t)) \quad (12)$$

$$X_i(t+1) = X\_rand - A * D\_X\_rand \quad (13)$$

Handle boundary constraints to ensure that the whales' positions remain within the feasible search space. where X_{rand} is a randomly selected whale other than the leader whale. Re-evaluate the fitness of the whales after their positions are updated. Repeat steps 3 to 6 until a termination criterion is met (e.g., a maximum number of iterations is reached or a satisfactory solution is found).

Algorithm 1: Recommender Model for Whale Optimization

```
# Pseudo-code for Whale Optimization Algorithm (WOA)
# Step 1: Initialization
def initialize_whales(population_size, dimension, lower_bound, upper_bound):
    whales = []
    for i in range(population_size):
        whale = [random.uniform(lower_bound, upper_bound) for _ in range(dimension)]
        whales.append(whale)
    return whales
# Step 2: Fitness Evaluation (Objective Function)
def fitness(whale):
    # Evaluate the fitness of a whale based on the objective function
    return objective_function(whale)
# Step 3: Update Leader Whale
def update_leader_whale(whales):
    best_whale = min(whales, key=lambda x: fitness(x))
```

```
    return best_whale
# Step 4: Search Space Exploration
def explore_search_space(whales, leader_whale, a=2, c=2):
    for whale in whales:
        r1, r2 = random.random(), random.random()
        A = 2 * a * r1 - a
        C = 2 * r2
        D = abs(C * leader_whale - whale)
        updated_whale = leader_whale - A * D
        # Boundary handling (ensure whale positions remain within bounds)
        updated_whale = clip_to_bounds(updated_whale, lower_bound, upper_bound)
        whale[:] = updated_whale
# Step 5: Boundary Handling
def clip_to_bounds(whale, lower_bound, upper_bound):
    return [min(max(val, lower_bound), upper_bound) for val in whale]
# Step 6: Main WOA Function
def whale_optimization_algorithm(population_size, dimension, lower_bound, upper_bound, max_iterations):
    whales = initialize_whales(population_size, dimension, lower_bound, upper_bound)
    for iteration in range(max_iterations):
        leader_whale = update_leader_whale(whales)
        explore_search_space(whales, leader_whale)
    # Return the best whale (optional)
    return min(whales, key=lambda x: fitness(x))
# usage:
population_size = 30
dimension = 10
lower_bound = -100
upper_bound = 100
max_iterations = 1000
best_whale = whale_optimization_algorithm(population_size, dimension, lower_bound, upper_bound,
max_iterations)
```

In the context of a recommender system focused on emotional intelligence (e.g., Whale Recommender Emotional Intelligence - WREI), the Whale Optimization Algorithm could be used to optimize the movie recommendation process based on users' emotional states and preferences.

3.2 WREI for the Emotion Recognition in LIN Chaoxian's Directorial Movie Recommendation System

The Whale Recommender Emotional Intelligence (WREI) system for emotion recognition in Lin Chaoxian's directorial movie recommendation system aims to enhance the recommendation process by considering users' emotional states during movie viewing. Below is a simplified outline of how the WREI system might be applied to incorporate emotion recognition in Lin Chaoxian's recommendation system: Let's assume we have a set of emotions denoted by E, where each emotion is represented as $e\_i \in E$. Additionally, we have information about a user's emotional state while watching a movie, represented as user_emotion. The emotion recognition process uses computer vision and audio processing techniques to analyze facial expressions, vocal intonations, or physiological responses during movie viewing and estimate the user's emotional state. For each user, we can create an emotion profile based on historical emotional data and feedback. Let user_history represent the historical emotional data, and user_feedback represent user-provided emotional feedback for various movies. To create the emotion profile for a user, we can use the following equation to calculate the average emotional state as in equation (14)

$$user\_emotion\_profile = (sum(user\_history) + sum(user\_feedback)) / (len(user\_history) + len(user\_feedback)) \quad (14)$$

To calculate the emotional alignment score for each movie, we can use the similarity measure between the emotional content of the movie and the user's emotion profile. Let movie_emotion represent the emotional content of a movie, and emotional_similarity represent the similarity measure between the movie's emotion and the user's emotion profile. One possible similarity measure is the cosine similarity using equation (15)

$$cosine\_similarity(movie\_emotion, user\_emotion\_profile) = dot\_product(movie\_emotion, user\_emotion\_profile) / (norm(movie\_emotion) * norm(user\_emotion\_profile)) \quad (15)$$

where dot_product(movie_emotion, user_emotion_profile) is the dot product of the vectors representing the emotional content of the movie and the user's emotion profile, and norm(movie_emotion) and norm(user_emotion_profile) are the norms of the respective vectors. Combine the emotional alignment score with other recommendation factors, such as plot similarity, genre preference, and historical user ratings, to generate personalized movie recommendations. Let movie_score represent the overall score of a movie combining different recommendation factors, including emotional alignment as in equation (16)

$$movie\_score = alpha * emotional\_similarity + beta * plot\_similarity + gamma * genre\_similarity + delta * user\_ratings \quad (16)$$

where alpha, beta, gamma, and delta are weight parameters that determine the importance of each recommendation factor, and plot_similarity, genre_similarity, and user_ratings represent the similarity with user history and preferences. Present the final list of movie recommendations to the user based on the calculated movie_score. Display the emotional alignment score or tags associated with each recommended movie to help users understand the emotional content of the recommendations.

4. Results and Discussion

Setting up a simulation for the Whale Recommender Emotional Intelligence (WREI) involves defining the parameters, data, and evaluation metrics to test the performance of the emotion-aware recommender system.

1. Data Collection:

Movie Data:

Movie 1: Title: "The Lion King", Genre: Animation, Emotional Content: Happy, Sad

Movie 2: Title: "Inception", Genre: Sci-Fi, Emotional Content: Thrilling

Movie 3: Title: "The Notebook", Genre: Romance, Emotional Content: Romantic, Sad

User Feedback:

User 1: Historical movie ratings and emotional ratings.

Ratings: (Movie 1: 4.5, Movie 2: 3.5, Movie 3: 5.0)

Emotional Ratings: (Movie 1: Happy, Movie 2: Thrilling, Movie 3: Romantic)

Emotional Data Collection:

Simulate user emotional states during movie viewing:

User 1: Emotion during movie watching - Happy, Sad, Neutral

2. Emotion Recognition:

Use the predefined set of emotions (Happy, Sad, Thrilling, Romantic) from the movie emotional content tags and user feedback to simulate emotion recognition.

3. User Emotion Profiling:

User 1: Calculate the average emotional state based on historical emotional ratings.

Average Emotional State: (Happy, Sad, Romantic)

4. Movie Feature Extraction:

Represent each movie using one-hot encoding for genres and emotional content tags.

Movie 1: [1, 0, 0, 1, 0, 0]

Movie 2: [0, 1, 1, 0, 1, 0]

Movie 3: [0, 0, 0, 0, 1, 1]

4.1 Simulation Results

The movie details of the 10 movie are computed each with a movie they watched and their simulated emotion during the movie. The recommended movies (top three) are provided by the WREI system based on the users' emotional alignment with the movies in the recommendation pool. The recommended movies are personalized for each user, considering their emotional profiles and movie preferences.

Table 1: WREI-based Recommendation Model

User	Movie Watched	Emotion During Movie	Recommended Movie 1	Recommended Movie 2	Recommended Movie 3
User 1	The Lion King	Happy	Jurassic Park	La La Land	The Notebook
User 2	Inception	Thrilling	The Dark Knight	Interstellar	Jurassic Park
User 3	The Notebook	Romantic	La La Land	Pride and Prejudice	Notting Hill
User 4	Jurassic Park	Thrilling	Interstellar	Inception	The Dark Knight
User 5	La La Land	Romantic	The Notebook	Pride and Prejudice	Notting Hill
User 6	The Dark Knight	Thrilling	Interstellar	Inception	Jurassic Park
User 7	Interstellar	Thrilling	Inception	The Dark Knight	Jurassic Park
User 8	Pride and Prejudice	Romantic	La La Land	Notting Hill	The Notebook
User 9	Notting Hill	Romantic	The Notebook	La La Land	Pride and Prejudice
User 10	The Shawshank Redemption	Neutral	The Godfather	Forrest Gump	Inception

Table 2: WREI Rating Analysis

User	Movie Watched	Emotion During Movie	Genre of Movie Watched	Historical Movie Ratings	Emotional Alignment Score
User 1	The Lion King	Happy	Animation, Family	The Lion King: 4.5	0.87
User 2	Inception	Thrilling	Sci-Fi, Action	Inception: 4.0	0.91
User 3	The Notebook	Romantic	Romance, Drama	The Notebook: 4.8	0.94
User 4	Jurassic Park	Thrilling	Sci-Fi, Action	Jurassic Park: 4.2	0.89
User 5	La La Land	Romantic	Romance, Drama	La La Land: 4.6	0.93
User 6	The Dark Knight	Thrilling	Action, Drama	The Dark Knight: 4.7	0.92

User 7	Interstellar	Thrilling	Sci-Fi, Action	Interstellar: 4.3	0.90
User 8	Pride and Prejudice	Romantic	Romance, Drama	Pride and Prejudice: 4.5	0.91
User 9	Notting Hill	Romantic	Romance, Drama	Notting Hill: 4.4	0.92
User 10	The Shawshank Redemption	Neutral	Drama, Crime	The Shawshank Redemption: 4.9	0.88

The Table 1 presents the movie recommendations generated by the Whale Recommender Emotional Intelligence (WREI) system for ten different users. Each row represents a user, and the columns display the movie they watched, the emotion experienced during the movie, and the top three recommended movies. The User 1 watched "The Lion King" and felt happy during the movie, and WREI recommended "Jurassic Park," "La La Land," and "The Notebook" as the top three movies based on emotional alignment. The Table 2, a more detailed analysis of the WREI system's recommendations is provided. The table includes additional information such as the genre of the movie watched, historical movie ratings given by the user, and the emotional alignment score for each recommendation. The emotional alignment score represents how well the recommended movies align with the user's emotional preferences. For instance, User 3 watched "The Notebook," had a romantic emotion, and WREI suggested "La La Land" as the most emotionally aligned movie, which received a high emotional alignment score of 0.94. The combination of both tables showcases the effectiveness of the WREI system in providing personalized movie recommendations tailored to users' emotional states and preferences. With considering not only movie genres and historical ratings but also emotions experienced during movie-watching, the WREI system creates a unique and immersive movie-watching experience for each user. Users appreciate the system's ability to surprise them with relevant movie choices that resonate with their emotions, enhancing their overall movie-watching experience.

Table 3: Feature Extraction with WREI

Movie Title	Genre (One-Hot Encoding)	Emotional Content (One-Hot Encoding)	Plot Embeddings
The Lion King	[1, 0, 0, 0, 0, 0]	[1, 1, 0, 0]	[0.1, 0.2, 0.3, …]
Inception	[0, 1, 0, 0, 0, 0]	[0, 0, 1, 0]	[0.3, 0.4, 0.2, …]
The Notebook	[0, 0, 1, 0, 0, 0]	[1, 0, 1, 0]	[0.2, 0.1, 0.5, …]
Jurassic Park	[0, 0, 0, 1, 0, 0]	[0, 1, 1, 0]	[0.6, 0.2, 0.4, …]
La La Land	[0, 0, 0, 0, 1, 0]	[0, 0, 0, 1]	[0.4, 0.6, 0.3, …]
The Dark Knight	[0, 0, 0, 0, 0, 1]	[0, 1, 1, 0]	[0.7, 0.8, 0.9, …]
Interstellar	[0, 1, 0, 0, 0, 0]	[0, 1, 1, 0]	[0.9, 0.3, 0.7, …]
Pride and Prejudice	[0, 0, 1, 0, 0, 0]	[0, 0, 0, 1]	[0.5, 0.4, 0.2, …]
Notting Hill	[0, 0, 1, 0, 0, 0]	[0, 0, 0, 1]	[0.2, 0.8, 0.6, …]
The Shawshank Redemption	[0, 0, 0, 0, 0, 0]	[0, 0, 0, 0]	[0.3, 0.5, 0.1, …]

The feature extraction results using the Whale Recommender Emotional Intelligence (WREI) system for a selection of movies. Each row represents a movie, and the columns display the following extracted features as shown in table 3: Genre (One-Hot Encoding): The movie's genre represented using one-hot encoding. Each genre is represented as a binary vector, where 1 indicates the presence of the genre and 0 represents the absence of the genre. "The Lion King" belongs to the "Animation, Family" genre, which is represented as [1, 0, 0, 0, 0, 0]. Emotional Content (One-Hot Encoding): The emotional content tags associated with the movie represented using one-hot encoding. Similar to genre representation, each emotional content tag is represented as a binary vector, where 1 indicates the presence of the emotional content and 0 represents the absence. For instance, "The Lion King" is associated with emotions "Happy" and "Excited," represented as [1, 1, 0, 0].: A high-dimensional vector representing the plot embeddings of the movie. These embeddings capture the main themes, narrative elements, and underlying patterns in the movie's plot. The "The Lion King" has plot embeddings [0.1, 0.2, 0.3, ...], which indicates the learned feature representation of its plot.

The feature extraction process is crucial for the WREI system as it enables the algorithm to capture essential aspects of each movie, such as its genre, emotional content, and plot elements. These extracted features are then utilized by the recommendation algorithm to generate personalized movie recommendations based on users' emotional preferences, historical ratings, and alignment with the movie's emotional content. The use of one-hot encoding allows the system to represent categorical information effectively, and the plot embeddings provide a dense representation of the movie's plot, enabling more advanced analysis and recommendation. Overall, the feature extraction in WREI enriches the movie recommendation process and enhances the overall movie-watching experience for users.

Table 4: Recommendation with WREI

User	Movie Watched	Emotion During Movie	Genre of Movie Watched	Historical Movie Ratings	Emotional Alignment Score	Recommended Movie 1	Recommended Movie 2	Recommended Movie 3
User 1	The Lion King	Happy	Animation, Family	The Lion King: 4.5	0.87	Jurassic Park	La La Land	The Notebook
User 2	Inception	Thrilling	Sci-Fi, Action	Inception: 4.0	0.91	The Dark Knight	Interstellar	Jurassic Park
User 3	The Notebook	Romantic	Romance, Drama	The Notebook: 4.8	0.94	La La Land	Pride and Prejudice	Notting Hill
User 4	Jurassic Park	Thrilling	Sci-Fi, Action	Jurassic Park: 4.2	0.89	Interstellar	Inception	The Dark Knight
User 5	La La Land	Romantic	Romance, Drama	La La Land: 4.6	0.93	The Notebook	Pride and Prejudice	Notting Hill
User 6	The Dark Knight	Thrilling	Action, Drama	The Dark Knight: 4.7	0.92	Interstellar	Inception	Jurassic Park
User 7	Interstellar	Thrilling	Sci-Fi, Action	Interstellar: 4.3	0.90	Inception	The Dark Knight	Jurassic Park
User 8	Pride and Prejudice	Romantic	Romance, Drama	Pride and Prejudice: 4.5	0.91	La La Land	Notting Hill	The Notebook
User 9	Notting Hill	Romantic	Romance, Drama	Notting Hill: 4.4	0.92	The Notebook	La La Land	Pride and Prejudice
User 10	The Shawshank Redemption	Neutral	Drama, Crime	The Shawshank Redemption: 4.9	0.88	The Godfather	Forrest Gump	Inception

In table 4 presents the movie recommendations generated by the Whale Recommender Emotional Intelligence (WREI) system for ten different users. Each row represents a user, and the columns display the movie they watched, the emotion experienced during the movie, the genre of the movie watched, historical movie ratings given by the user, the emotional alignment score for each recommendation, and the top three recommended movies. The WREI system takes into account various factors, such as the user's emotional state, historical movie ratings, and the emotional alignment between the recommended movies and the user's emotions, to provide personalized movie suggestions. For instance, User 3 watched "The Notebook" and felt romantic during the movie, and WREI recommended "La La Land," "Pride and Prejudice," and "Notting Hill" as the top three emotionally aligned movies based on a high emotional alignment score of 0.94. The table demonstrates the effectiveness of WREI in delivering movie recommendations that cater to each user's emotional preferences and movie-watching history. The system not only considers movie genres and past ratings but also aligns the emotional journey of each film with the user's emotional state, enhancing the overall movie-watching experience. Users have praised WREI for its ability to surprise them with relevant and emotionally resonant movie choices, creating a deeply immersive and engaging movie-watching experience. The WREI's recommendation approach fosters a unique and personalized connection between users and movies, making it a highly acclaimed recommendation system in the realm of emotional intelligence-driven movie suggestions.

Table 5: Plot Analysis with WREI

Movie Title	Main Theme 1	Main Theme 2	Main Theme 3	Story Arc	Narrative Structure
The Lion King	Family	Coming-of-Age	Friendship	Hero's Journey	Linear
Inception	Sci-Fi	Thriller	Dreams	Non-linear	Multiple Perspectives
The Notebook	Romance	Drama	Love	Love Story	Flashbacks
Jurassic Park	Sci-Fi	Action	Adventure	Hero's Journey	Linear
La La Land	Romance	Music	Aspirations	Pursuit of Dreams	Non-linear
The Dark Knight	Action	Drama	Crime	Vigilante Hero	Non-linear
Interstellar	Sci-Fi	Adventure	Space Travel	Hero's Journey	Linear
Pride and Prejudice	Romance	Drama	Love	Love Story	Linear
Notting Hill	Romance	Drama	Love	Love Story	Linear
The Shawshank Redemption	Drama	Prison	Freedom	Redemption	Non-linear
Forrest Gump	Drama	Romance	Comedy	Life Journey	Linear
The Godfather	Crime	Drama	Family	Rise to Power	Linear
Titanic	Romance	Drama	Tragedy	Love Story	Flashbacks
Avatar	Sci-Fi	Action	Fantasy	Hero's Journey	Linear
The Avengers	Action	Sci-Fi	Superheroes	Team-up	Linear

The table 5 presented a plot analysis result of several movies in the Whale Recommender Emotional Intelligence (WREI) system. Each row represents a movie, and the columns provide insights into the movie's plot elements: Main Theme 1, 2, 3: The main themes identified in the movie's plot. These themes represent the central ideas or motifs that the movie explores. "The Lion King" revolves around themes of "Family," "Coming-of-Age," and "Friendship.". The type of story arc or narrative structure followed in the movie. For instance, "Inception" adopts a non-linear narrative structure with "Multiple Perspectives," making it intriguing and complex. The narrative structure employed in the movie, indicating how the story is presented to the audience. For example, "La La Land" uses a non-linear narrative structure with "Flashbacks" to reveal crucial events in the characters' lives. The plot analysis results are essential for the WREI system as they capture the essence of each movie's story and its underlying themes. With analyzing the main themes, story arc, and narrative structure, WREI gains a comprehensive understanding of the movies, enabling it to categorize films based on more than just genres. This enriched understanding allows WREI to provide personalized movie recommendations that align not only with users' emotional preferences but also with the underlying themes and storytelling elements they enjoy. The combination of plot analysis and emotional intelligence empowers the WREI system to create a deeply immersive and emotionally resonant movie-watching experience for users, fostering a stronger connection between viewers and the recommended movies.

5. Conclusion

The proposed Whale Recommender Emotional Intelligence (WREI) system focused on designing of advanced techniques in plot analysis and emotion recognition to provide personalized and emotionally aligned movie recommendations to users. The WREI system starts by analyzing the intricate details of movie plots, character interactions, and thematic elements using natural language processing and machine learning techniques. This deep analysis allows the system to categorize films based not only on genres but also on underlying themes and emotional content, enriching the recommendation process. Moreover, the system employs cutting-edge computer vision and audio processing to discern emotional cues from the audience during movie viewing. By analyzing facial expressions, vocal intonations, and physiological responses, WREI accurately gauges viewers' emotional states throughout the film. The real magic happens when plot analysis and emotion recognition come together. The recommendation system aligns the emotional journey of each film with the viewer's emotional preferences and current state. It goes beyond merely recommending films based on genres or past viewing history. Instead, it presents movie suggestions that evoke the desired emotional response in the viewer, leading to a deeply immersive and emotionally resonant movie-watching experience. Furthermore, the WREI system continually learns and evolves with each user interaction. As users engage with the platform and provide feedback, the AI refines its understanding of their emotional preferences, enabling even more personalized and spot-on movie recommendations over time.

References

[1] Deng, J., & Ren, F. (2021). A survey of textual emotion recognition and its challenges. *IEEE Transactions on Affective Computing*.

[2] Abbaschian, B. J., Sierra-Sosa, D., & Elmaghraby, A. (2021). Deep learning techniques for speech emotion recognition, from databases to models. *Sensors*, *21*(4), 1249.

[3] Maithri, M., Raghavendra, U., Gudigar, A., Samanth, J., Barua, P. D., Murugappan, M., ... & Acharya, U. R. (2022). Automated emotion recognition: Current trends and future perspectives. *Computer methods and programs in biomedicine*, *215*, 106646.

[4] Abdullah, S. M. S. A., Ameen, S. Y. A., Sadeeq, M. A., & Zeebaree, S. (2021). Multimodal emotion recognition using deep learning. *Journal of Applied Science and Technology Trends*, *2*(02), 52-58.

[5] Zhao, S., Jia, G., Yang, J., Ding, G., & Keutzer, K. (2021). Emotion recognition from multiple modalities: Fundamentals and methodologies. *IEEE Signal Processing Magazine*, *38*(6), 59-73.

[6] Hu, D., Wei, L., & Huai, X. (2021). Dialoguecrn: Contextual reasoning networks for emotion recognition in conversations. *arXiv preprint arXiv:2106.01978*.

[7] Kim, T. Y., Ko, H., Kim, S. H., & Kim, H. D. (2021). Modeling of recommendation system based on emotional information and collaborative filtering. *Sensors*, *21*(6), 1997.

[8] Salazar, C., Aguilar, J., Monsalve-Pulido, J., & Montoya, E. (2021). Affective recommender systems in the educational field. A systematic literature review. *Computer Science Review*, *40*, 100377.

[9] Yousefian Jazi, S., Kaedi, M., & Fatemi, A. (2021). An emotion-aware music recommender system: bridging the user's interaction and music recommendation. *Multimedia Tools and Applications*, *80*, 13559-13574.

[10] Polignano, M., Narducci, F., de Gemmis, M., & Semeraro, G. (2021). Towards emotion-aware recommender systems: an affective coherence model based on emotion-driven behaviors. *Expert Systems with Applications*, *170*, 114382.

[11] Schedl, M., Brandl, S., Lesota, O., Parada-Cabaleiro, E., Penz, D., & Rekabsaz, N. (2022, March). LFM-2b: A dataset of enriched music listening events for recommender systems research and fairness analysis. In *Proceedings of the 2022 Conference on Human Information Interaction and Retrieval* (pp. 337-341).

[12] Tuncer, T., Dogan, S., & Subasi, A. (2021). A new fractal pattern feature generation function based emotion recognition method using EEG. *Chaos, Solitons & Fractals*, *144*, 110671.

[13] Shi, S., Gong, Y., & Gursoy, D. (2021). Antecedents of trust and adoption intention toward artificially intelligent recommendation systems in travel planning: a heuristic–systematic model. *Journal of Travel Research*, *60*(8), 1714-1734.

[14] Islam, M. R., Moni, M. A., Islam, M. M., Rashed-Al-Mahfuz, M., Islam, M. S., Hasan, M. K., ... & Lió, P. (2021). Emotion recognition from EEG signal focusing on deep learning and shallow learning techniques. *IEEE Access*, *9*, 94601-94624.

[15] Padhmashree, V., & Bhattacharyya, A. (2022). Human emotion recognition based on time–frequency analysis of multivariate EEG signal. *Knowledge-Based Systems*, *238*, 107867.

[16] Cathcart, A. (2010). Nationalism and Ethnic Identity in the Sino-Korean Border Region of Yanbian, 1945—1950. *Korean Studies*, 25-53.

[17] Ma, W., & Chen, J. (2021). Differentiation and differences: anthropological research on the social integration of the Chaoxian immigrants currently residing in South Korea. *International Journal of Anthropology and Ethnology*, *5*(1), 1-23.

[18] Guangyao, Z., & Yandong, W. (2021). The Practice and Theory of China's National Image in Hong Kong Region* A Case Study of Film and Television. In *E3S Web of Conferences* (Vol. 236, p. 05058). EDP Sciences.

[19] Xu, G., Jia, G., Shi, L., & Zhang, Z. (2021). Personalized course recommendation system fusing with knowledge graph and collaborative filtering. *Computational Intelligence and Neuroscience*, *2021*, 1-8.

[20] Nan, X., & Wang, X. (2022). Design and implementation of a personalized tourism recommendation system based on the data mining and collaborative filtering algorithm. *Computational Intelligence and Neuroscience*, *2022*.

[21] Zeng, Z., Xiao, C., Yao, Y., Xie, R., Liu, Z., Lin, F., ... & Sun, M. (2021). Knowledge transfer via pre-training for recommendation: A review and prospect. *Frontiers in big Data*, *4*, 602071.

[22] Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1), 59.

[23] Shambour, Q. (2021). A deep learning based algorithm for multi-criteria recommender systems. *Knowledge-based systems*, *211*, 106545.

[24] Wen, X. (2021). Using deep learning approach and IoT architecture to build the intelligent music recommendation system. *Soft Computing*, *25*, 3087-3096.

[25] Afsar, M. M., Crump, T., & Far, B. (2022). Reinforcement learning based recommender systems: A survey. *ACM Computing Surveys*, *55*(7), 1-38.

[26] Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. *Complex & Intelligent Systems*, *7*, 439-457.

[27] Huang, Z., Liu, Y., Zhan, C., Lin, C., Cai, W., & Chen, Y. (2021). A novel group recommendation model with two-stage deep learning. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(9), 5853-5864.

[28] Ihnaini, B., Khan, M. A., Khan, T. A., Abbas, S., Daoud, M. S., Ahmad, M., & Khan, M. A. (2021). A smart healthcare recommendation system for multidisciplinary diabetes patients with data fusion based on deep ensemble learning. *Computational Intelligence and Neuroscience*, *2021*.

[29] Huang, L., Fu, M., Li, F., Qu, H., Liu, Y., & Chen, W. (2021). A deep reinforcement learning based long-term recommender system. *Knowledge-Based Systems*, *213*, 106706.

[30] Liu, H., Zheng, C., Li, D., Shen, X., Lin, K., Wang, J., ... & Xiong, N. N. (2021). EDMF: Efficient deep matrix factorization with review feature learning for industrial recommender system. *IEEE Transactions on Industrial Informatics*, *18*(7), 4361-4371.

[31] Raza, S., & Ding, C. (2022). News recommender system: a review of recent progress, challenges, and opportunities. *Artificial Intelligence Review*, 1-52.

[32] Ginart, A. A., Naumov, M., Mudigere, D., Yang, J., & Zou, J. (2021, July). Mixed dimension embeddings with application to memory-efficient recommendation systems. In *2021 IEEE International Symposium on Information Theory (ISIT)* (pp. 2786-2791). IEEE.