An Anime Recommendation System Integrating Sentiment Analysis and Metadata Similarity

Yikang Liao
Faculty of Information Networking for Innovation and Design (INIAD)
Toyo University
Tokyo, Japan
s3f102200134@iniad.org

M. Fahim Ferdous Khan
Faculty of Information Networking for Innovation and Design (INIAD)
Toyo University
Tokyo, Japan
khan@iniad.org

Ken Sakamura
Faculty of Information Networking for Innovation and Design (INIAD)
Toyo University
Tokyo, Japan
sakamura@iniad.org

***Abstract*—In recent years, Japanese anime has gained increasing popularity worldwide, attracting many viewers who were previously unfamiliar with anime culture. For many new audiences, streaming platforms serve as the primary gateway to anime consumption, where recommendation systems play a crucial role in suggesting anime titles. However, such systems often prioritize currently popular works, which may not necessarily align with individual user preferences. In various domains, recommendation systems have proven effective in helping users navigate large volumes of information and identify content that matches their interests, and anime recommendation is no exception. Nevertheless, most existing anime recommendation systems still exhibit notable limitations. One significant drawback is that many systems overlook the similarity of emotional experiences evoked by different anime during the recommendation process, despite the fact that emotional experience is an important factor in recommendation. To address this issue, this study introduces sentiment analysis techniques into traditional algorithms, proposing a recommendation algorithm that integrates metadata similarity and emotional experience similarity calculations to generate more rational recommendations that align with user emotional preferences. Based on the proposed algorithm, an anime recommendation system is further developed to provide users with more satisfying and personalized anime recommendations.**

Keywords—Recommendation System, Anime, Metadata similarity, Sentiment analysis, Transformer

I. Introduction

Japanese anime has gained immense popularity in recent years, particularly among younger audiences [24]. With the rapid development of the Internet, a growing number of viewers now watch anime through online streaming platforms. These platforms typically employ recommendation systems to present users with anime suggestions. Although there has been considerable research on movie recommendation systems [1][2][3], relatively few studies have focused specifically on recommendation systems for Japanese anime [4]. Moreover, most existing anime recommendation systems rely solely on the similarity of metadata [14], such as directors, genres, or production studios. When generating recommendations. However, when users search for anime they wish to watch, they often hope to relive the emotional experiences they felt from previous works. The emotional similarity between anime, that is, how similarly two works resonate emotionally with viewers, is an essential factor that many existing systems fail to consider. To address this limitation, this study proposes a novel recommendation framework that integrates both metadata-based similarity and emotional experience similarity derived from user comments. By combining these two dimensions, the system can more accurately align with users' preferences while introducing innovative and emotionally compatible works that may fall outside their usual viewing habits. This dual consideration of content and emotional experience aims to enrich the recommendation results and provide users with a more personalized, emotionally coherent, and satisfying anime recommendation experience.

The rest of this paper is organized as follows: Section II reviews related work. Section III describes the dataset used in this study. Section IV explains the proposed anime recommendation algorithm. Section V presents the performance evaluation experiments of the proposed algorithm. Section VI introduces the user interface of the system. Section VII discusses the limitations of this study and outlines directions for future work. Finally, Section VIII summarizes the contributions of this research.

II. Related Work

Numerous studies have been conducted in the domain of movie recommendation systems. Sudhanshu Kumar et al. [1] proposed a recommendation method that combines sentiment analysis with content-based similarity. Their system analyzes movie-related tweets to derive an emotional score for each film. The emotional similarity between movies computed based on these scores is then combined with metadata similarity (such as actors, directors, release year, and producers) to generate more precise recommendations. Jiang Zhang et al. [18] proposed a simple yet highly efficient recommendation algorithm that partitions users into multiple clusters based on their profile attributes. For each cluster, a virtual opinion leader is constructed to represent the entire cluster, thereby significantly reducing the dimensionality of the original user–item matrix. Subsequently, a Weighted Slope One-VU method is designed and applied to the virtual opinion leader–item matrix to generate movie recommendations. This approach achieves comparable recommendation performance while substantially reducing computational time complexity. In addition, a variety of other techniques, such as deep learning, neural networks and hybrid approaches [21], have also been applied in movie recommendation systems.

Compared to the field of movie recommendation systems, research on anime recommendation systems remains relatively limited. Christopher Gavra Reswara et al. [4] proposed a BERT-based framework for generating anime recommendations. Their approach extracts feature representations from anime titles and genres using the BERT model [5] and compares these representations with user preference information derived from sentiment analysis of anime reviews using the same BERT-based method. Putri, Helmy Dianti et al. [22] aimed to identify the optimal approach for providing personalized anime recommendations by comparing collaborative filtering and content-based filtering methods. Furthermore, they integrated these techniques into mobile applications, enhancing the user experience by delivering faster and more interactive recommendations. Although these approaches [1] [22] [23] demonstrate the potential of incorporating emotional information into recommender systems, the aforementioned studies primarily focus on sentiment analysis of texts in English. To date, only a limited number of studies have applied this concept specifically to Japanese anime reviews. Japanese anime reviews often contain complex emotional expressions, including sarcasm, irony, and culturally specific nuances. This gap highlights the necessity of developing a system capable of effectively processing Japanese text and more accurately reflecting users' emotional experiences. User-generated textual reviews contain rich emotional information that can be utilized not only to infer user preferences but also to analyze the emotional value conveyed by works to their audiences. By integrating such emotional cues into recommendation algorithms, the system can generate more precise recommendations. Incorporation of sentiment analysis in Japanese-language context has been proven effective in other domains as well, for instance, book recommendation [6] and visualization of product reviews [12]. In this study, we utilize a BERT-based approach to perform sentiment analysis on Japanese user reviews, and the extracted emotional features are combined with traditional recommendation methods to develop an anime recommender system. The proposed system aims to provide recommendations that better align with user preferences and, from the perspective of users' emotional experiences, to generate relatively novel recommendation results compared with existing algorithms.

III. DATASET

A. *WRIME Dataset*

To train and fine-tune the Japanese sentiment analysis model (bert-base-japanese-whole-word-masking) described in Section IV-B), this study employed the WRIME dataset. The WRIME dataset, which is publicly available on GitHub, contains Japanese tweets annotated with emotional labels and intensity scores from both subjective and objective perspectives. This dual-annotation structure enables the model to learn fine-grained emotional representations and better understand variations between the writer's intended emotion and the readers' perceived emotion. The dataset contains tens of thousands of samples, providing sufficient linguistic diversity for training a sentiment analysis model capable of handling Japanese expressions such as irony and emotional nuance [10][11].

B. *Anime Metadata Dataset*

To compute the similarity between anime based on metadata, as well as the similarity in emotional experiences they evoke for users, this study also utilizes two self-constructed datasets. The first dataset is an anime metadata dataset, which was constructed using web scraping techniques from Filmarks Anime, which is a well-known Japanese anime information and review website (https://filmarks.com/animes) and Wikipedia.

This dataset contains metadata for 1,930 anime titles, including Title, Director, Series composition, Script, Character design, Voice actors, Genre and Production studio. Furthermore, this dataset includes user reviews and ratings obtained from Filmarks Anime, which were used as the basis for calculating emotional experience similarity in later stages.

C. *Anime Emotion Probability Distribution Dataset*

In addition to metadata, the emotional dimension of anime was modeled through sentiment analysis of user reviews.

All user reviews collected in Anime Metadata Dataset were processed using the Japanese sentiment analysis model introduced in section IV-B). For each review, the model outputs a probability distribution across the eight basic emotions. The sum of the probability values of these eight basic emotions is equal to 1.

Each review thus produces a unique emotion probability distribution value representing the intensity and composition of emotions expressed by the user. After processing all reviews corresponding to a single anime, the average emotion probability distribution is calculated for that title. This provides an aggregate emotional profile reflecting how the anime is perceived by its audience.

The resulting dataset, the Anime Emotion Probability Distribution Dataset contains each anime's title and the averaged probability values for the eight emotions.

IV. PROPOSED ANIME RECOMMENDATION SYSTEM

This study proposes an anime recommendation algorithm that simultaneously considers both metadata similarity and emotional experience similarity between anime titles[1]. The similarity between any two anime is determined by these two factors, and the final similarity score is obtained by integrating both. The overall workflow of the system's recommendation algorithm is shown in Fig.1.

A. *Metadata Similarity Calculation*

- After loading the data and preprocessing, a binary content-feature matrix C of size $N \times M$ will be created, where N is the number of anime and M is the total number of unique metadata features. Each element C_{ij} takes a value of 1 if anime i possesses feature j, and 0 otherwise.

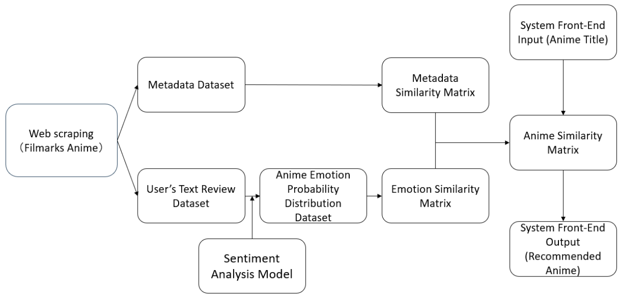

Fig. 1. The overall workflow of the system's recommendation algorithm

- When calculating the similarity between anime titles, the importance of each metadata feature varies. Therefore, when computing anime similarity based on metadata, it is necessary to assign each feature a weight q, representing its relative importance in the similarity computation. Following the approach proposed by Sudhanshu Kumar et al.[1], the feature weights can be inferred using the content-feature matrix and the co-occurrence frequency between anime pairs. To compute q, it is also necessary to construct an N × N anime co-occurrence matrix O. Here, N denotes the total number of anime titles in the dataset, and each element O_{ij} represents the number of viewers who have watched both anime i and anime j.

- To determine the relative importance of each content feature when computing the similarity between anime titles, this study constructs the following linear model:

$$S(i,j) = q \cdot F_{ij} \tag{1}$$

This equation can be expanded as follows:

$$S(i,j) = q_1 \cdot f_1(A_{1i}, A_{1j}) + q_2 \cdot f_2(A_{2i}, A_{2j}) + \cdots + q_n \cdot f_n(A_{ni}, A_{nj}) \tag{2}$$

In these equations, $S(i,j)$ represents the co-occurrence strength between anime i and j. In this study, it is expressed as the number of times the two anime titles co-occur in users' viewing histories. F_{ij} denotes the feature similarity vector composed of the interaction results of each metadata feature. f is a binary function that determines whether a given feature is shared between anime i and j. If the feature co-occurs in both anime, the function returns 1; otherwise, it returns 0. $q = [q_1, q_2, \ldots, q_n]$ is the feature weight vector to be estimated.

- According to (2), use the anime co-occurrence matrix and the content-feature matrix, the feature weight vector q can be obtained by solving a linear system. However, considering computational efficiency and hardware constraints, this study aggregates all feature similarity vectors F_{ij} and co-occurrence values $S(i,j)$, resulting in the following normal equation in matrix form:

$$F^T F_{\text{sum}} \cdot q = F^T S_{\text{sum}} \tag{3}$$

The feature weight vector q can then be estimated as:

$$q = (F^T F_{\text{sum}})^{-1} \cdot F^T S_{\text{sum}} \tag{4}$$

In this implementation, the accumulated matrix of F_{ij} is denoted as $F^T F_{\text{sum}}$, and the accumulated vector of $S(i,j)$ is denoted as $F^T S_{\text{sum}}$. To ensure that the resulting feature weights remain non-negative, the Non-Negative Least Squares (NNLS) method is applied to solve for the optimal feature weight vector q.

- After obtaining the content-feature matrix and the feature weights, the next step is to compute the weighted similarity matrix.

Each column of the content-feature matrix C is multiplied by its corresponding feature weight q, resulting in a weighted content-feature matrix, denoted as C_{weighted}. Subsequently, the metadata-based anime similarity matrix is calculated by multiplying the weighted content-feature matrix C_{weighted} with its transpose C_{weighted}^T:

$$H = C_{\text{weighted}} \times C_{\text{weighted}}^T \tag{5}$$

The metadata-based anime similarity matrix H is of size $N \times N$, where N denotes the total number of anime titles. Each element H_{ij} represents the metadata-based similarity score between anime i and anime j.

B. Computation of Emotional Similarity

In addition to metadata-based similarity, we also consider the emotional similarity between anime titles [13] [15]. In this section, we explain how this emotional similarity is computed based on user review data processed leveraging a BERT-based sentiment analysis model and the WRIME dataset.

1) Sentiment Analysis Model

In this study, a sentiment analysis model[19] [20] is first required to analyze user comments . Sudhanshu Kumar et al. [1] conducted sentiment analysis on English-language movie-related tweets using the VADER method [7], and the resulting sentiment outputs were subsequently transformed into sentiment scores for each movie through a formula proposed by the authors.

In contrast to prior studies, the present work focuses on sentiment analysis of Japanese user reviews. A training program was implemented to develop the sentiment analysis model required in this study. The program is based on the "bert-base-japanese-whole-word-masking" model [5], which is available on Hugging Face Transformers (https://huggingface.co/). After downloading the model from Hugging Face Transformers, we fine-tuned it using the *AutoModelForSequenceClassification* class and related components provided by the Transformers library, together with the WRIME dataset [9], in order to enable the model to analyze text and output probability distributions across different sentiment categories. WRIME is a Japanese corpus specifically designed for estimating emotional intensity. The performance of the fine-tuned sentiment analysis model is presented in Table I. The validation loss and accuracy are tallied for every 200 steps.

Although the overall accuracy is not high, the model has reached a level (around 75%) sufficient for practical application. Moving forward, we will adjust the number of training steps and epochs to further improve its performance.

The WRIME dataset allows the model to output a probability distribution across eight basic emotions, derived from psychologist Robert Plutchik's human emotion framework [8]: Anger, Fear, Anticipation, Surprise, Joy, Sadness, Trust, and Disgust.

By applying this fine-tuned sentiment model to user reviews collected from Filmarks Anime, the system can obtain emotion probability distributions for each comment. These emotion distributions form the foundation for calculating the emotional similarity between anime titles in later sections.

TABLE I. THE ACCURACY OF THE FINE-TUNED SENTIMENT ANALYSIS MODEL

Step	Validation loss	Accuracy
200	0.268855	0.577228
400	0.251281	0.612533
600	0.235337	0.691085
800	0.229703	0.696381
1000	0.219611	0.708737
1200	0.212794	0.732568
1400	0.210345	0.738746
1600	0.205455	0.751985
1800	0.203310	0.751985
2000	0.203867	0.748455

2) Computation of the Average Emotional probability Distribution

Each anime's user reviews were analyzed using the sentiment analysis model described in the above section. Through this analysis, the system derives a probability distribution across the eight basic emotions: Joy, Sadness, Anger, Fear, Anticipation, Surprise, Trust, and Disgust for every textual review. For example, consider the following user review: "The story is too serious and heavy for children, but I really love it, including the animation quality." After applying sentiment analysis to this comment, the model outputs the emotional probability distribution likes: [Joy: 0.348111, Sadness: 0.174356, Anger: 0.018738, Fear: 0.091049, Anticipation: 0.10671, Surprise: 0.124391, Disgust: 0.114654, Trust: 0.021992].

By performing sentiment analysis on all reviews of each anime, the system obtains the emotional probability distribution for every review. Subsequently, the average value of emotional probability distribution for each anime is computed by taking the mean of these probabilities across all its reviews, as expressed below:

$$\bar{E}_A = \frac{1}{n_A}\sum_{r=1}^{n_A} E_r \quad (6)$$

Where $\bar{E}_A$ represents the average emotion distribution vector for anime A, E_r is the emotion probability vector of review r, and n_A is the number of reviews corresponding to anime A. The resulting average emotional distribution for each anime quantitatively represents how viewers emotionally perceive that work.

3) Computation of Emotional Similarity

After obtaining the average emotional probability distributions for all anime titles, the Euclidean distance is used to measure the emotional distance between every pair of anime. This distance serves as an indicator of how dissimilar their emotional experiences are. The Euclidean distance between two anime A and B is defined as follows:

$$\mathrm{d(A,B)} = \sqrt{\sum_{\mathrm{i}=1}^{8} (\mathrm{a_i} - \mathrm{b_i})^2} \quad (7)$$

Where a_i and b_i represent the probabilities of the i-th emotion for anime A and anime B, respectively, and $d(A,B)$ denotes the emotional distance between them. A smaller Euclidean distance indicates that the two anime evoke more similar emotional experiences for viewers. In this study, the Euclidean distance values fall within the range $[0,\sqrt{2}]$.

Once all pairwise Euclidean distances between anime titles have been calculated, they are normalized to a similarity scale within the range $[0,1]$using (8):

$$s = 1 - \frac{d}{\sqrt{2}} \quad (8)$$

Here, s represents the emotional similarity score between two anime, and d is the corresponding Euclidean distance between the two anime.

C. Computation of Overall Anime Similarity

After calculating both the metadata-based similarity and the emotion-based similarity, the final similarity between two anime titles is computed by integrating these two components. Let H denote the similarity matrix of anime titles based on metadata, and D denote the similarity matrix of anime titles based on emotional experience. The final anime similarity matrix S_{final} is computed as (9):

$$S_{\mathrm{final}} = H + (\mathrm{D} \times k) \quad (9)$$

Because the values in D fall within a normalized range of $[0,1]$, they are typically smaller than the corresponding metadata similarity scores in H. Therefore, the scaling coefficient k (also referred to as the emotion weight) is applied to ensure that the emotional similarity has an appropriate impact on the final result[1].

The resulting matrix $\mathrm{S_{final}}$ is an $\mathrm{N \times N}$ symmetric matrix, where N is the total number of anime titles. Each element $\mathrm{S_{final,ij}}$ represents the integrated similarity between anime i and anime j, combining both production-related metadata and audience emotional experience. Formally, for any two anime A and B:

$$\mathrm{S_{final}(A,B) = H(A,B) + k \times D(A,B)} \quad (10)$$

Higher values of $\mathrm{S_{final}(A,B)}$ indicate that the two anime are similar not only in terms of their metadata but also in the emotions they evoke among viewers. This final similarity matrix $\mathrm{S_{final}}$ serves as the core foundation of the proposed anime recommendation system in this study, determining the final recommendation results presented to users.

V. EVALUATION EXPERIMENT

As described at the end of Section IV, the recommendation system proposed in this study computes the similarity between anime titles using (10). To determine an appropriate emotion weighting coefficient k, one that yields the most balanced recommendation results by maintaining sufficient consistency with metadata-based recommendations while incorporating the influence of users' emotional experiences, the authors conducted an experiment evaluating multiple values of k (e.g., $k = 1$, 100, 200, 300, 400). The recommendation lists generated by the proposed method were compared against those produced solely based on metadata similarity. For each anime title in the dataset, the following two recommendation lists were generated:

1) List 1: Generated using metadata similarity H only.

2) List 2: Generated using the proposed hybrid similarity $H + (D \times k)$.

TABLE II. THE AVERAGE SIMILARITY BETWEEN THE ANIMATION LIST RECOMMENDED SOLELY BASED ON METADATA SIMILARITY AND THE RECOMMENDED ANIMATION LIST OBTAINED USING THE PROPOSED METHOD

Number of recommended anime	Average similarity of recommendation lists H : (H + D)	Average similarity of recommendation lists H : (H + D * 50)	Average similarity of recommendation lists H : (H + D * 100)	Average similarity of recommendation lists H : (H + D * 200)	Average similarity of recommendation lists H : (H + D * 300)	Average similarity of recommendation lists H : (H + D * 400)	Average similarity of recommendation lists H : (H + D * 500)
5	82.05%	77.19%	74.08%	68.21%	63.47%	59.15%	55.96%
10	84.83%	80.60%	77.63%	72.10%	67.20%	63.12%	59.41%
15	85.94%	81.94%	78.85%	73.25%	68.35%	63.98%	60.25%

The similarity between these two lists was then measured to quantify how the inclusion of emotional similarity affected the recommendation results. To evaluate the similarity between the two recommendation methods[1][16], we computed the average overlap ratio of the two lists under different values of k. This metric reflects how much the hybrid system's recommendations diverge from the metadata-only results. We consider an ideal balance is achieved when the overlap ratio is approximately 60%–70%, ensuring that recommendations remain relevant to the user's known preferences while introducing new titles that align with their emotional tastes.

The experimental results are shown in Table II. This experimental findings confirm that incorporating emotional similarity significantly enhances the diversity and personalization of anime recommendations. When k is too small, the system's behavior closely resembles the metadata-only approach, failing to capture the emotional nuances of user preferences. Conversely, when k is excessively large, emotional similarity dominates, leading to recommendations that may stray too far from the user's original interests. As shown in TABLE II, the empirically determined value of $k = 300$ provides a practical balance, ensuring that emotional similarity contributes meaningfully to the recommendation process without overpowering metadata-based relevance. This weighting factor ($k = 300$) is adopted as the default parameter in the anime recommendation system described in the following section. As shown in Fig. 2, when the parameter $k = 300$, the same anime title was used as input for two recommendation systems. The list on the left presents the recommendations generated by the system that relies solely on metadata-based similarity, whereas the list on the right illustrates the results produced by the system proposed in this study. The top three recommendations generated by our approach are identical to those produced by the traditional metadata-only method. However, after incorporating sentiment similarity into the hybrid recommendation framework, the proposed system yields two anime titles that differ from those suggested by the prior approach. These results indicate that the proposed system not only ensures that the recommendations remain aligned with the user's original preferences but also provides novel suggestions that evoke stronger emotional resonance.

VI. USER INTERFACE

A. System Overview

The main interface of the system (Fig. 3) serves as the entry point for users to input anime or keyword and obtain recommendation results [16].

B. Adjustable Emotion Similarity Weight

One of the core interactive features of this system is the ability for users to adjust the influence of emotional similarity on the recommendation results. A slider control labeled "Emotion Similarity Weight" as you can see in Fig.3 allows users to modify the value of the emotion weight parameter in real time. This parameter determines the relative influence of sentiment similarity when obtaining recommendation results. By default, the emotion weight is set to 300, as determined through the evaluation experiment in section V. By adjusting the emotional similarity weights to influence the system's recommendation results, this functionality enables users to personalize their recommendation experience, allowing them to explore anime either by metadata or by emotional resonance.

VII. DISCUSSION AND FUTURE WORK

Despite the effectiveness of the proposed system, several limitations remain to be addressed in future research. One of the primary issues lies in the computation of metadata-based similarity between anime titles. In the current implementation, the weight of each metadata feature used to compute the similarity between anime titles is determined based on the co-occurrence frequency of the anime as well as the occurrence of the feature across all pairs of anime. When new anime titles or metadata are added to the database, or when the co-occurrence statistics among anime titles change, the feature weights must be recalculated in order to obtain updated metadata-based similarity scores between anime titles. This requirement substantially increases the computational complexity [18]. The optimization and scalability of this metadata similarity computation method [17] will therefore be considered an important subject for future work. For example, future work may adopt an incremental learning strategy to update metadata feature weights and subsequently compute updated metadata-based similarity between anime titles, rather than recomputing the feature weights from scratch. When estimating the metadata feature weight vector q using the Non-Negative Least Squares (NNLS) method, it is unnecessary to solve the optimization problem from the beginning. Instead, the previously learned weight vector can be used as a warm-start initialization, allowing the optimization to converge to an updated solution with only a small number of additional iterations. By adopting this strategy, the computational cost required to update anime metadata-based similarity can be significantly reduced when new anime titles are added to the system.

Furthermore, from a functional perspective, as a user-oriented anime recommendation platform, the proposed system still lacks certain interactive and usability-related features. For instance, the system does not provide a filtering function for recommendation results, which prevents users from refining the recommended anime list based on criteria such as release year or genre. In addition, a watchlist feature could be incorporated to allow users to bookmark anime titles they are interested in but have not yet viewed. Incorporating these functionalities in future system

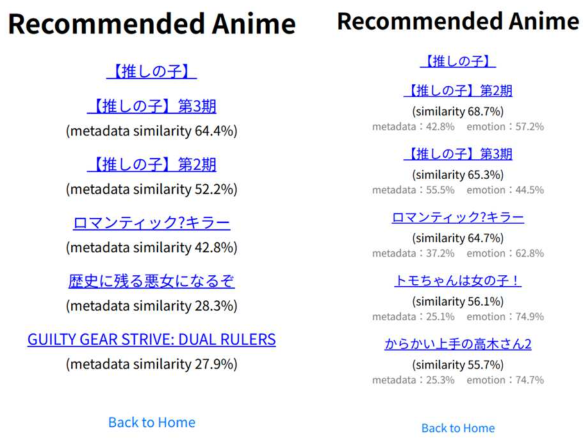

Fig. 2. For the same anime title, two sets of recommendation results were generated using different methods.

updates to enhance the overall user experience [22] constitutes another important issue to be addressed in this anime recommendation system.

VIII. Conclusion

In this paper, we have proposed a recommendation algorithm that integrates anime metadata similarity with emotional experience similarity, and developed a simple and user-friendly anime recommendation system based on the proposed algorithm. Through comparative experiments with baseline algorithms, we have demonstrated that the proposed method extends conventional recommendation approaches that rely solely on metadata similarity, producing balanced recommendation results that are relatively novel while remaining not entirely dissimilar.

References

[1] S. Kumar, K. De and P. P. Roy, "Movie Recommendation System Using Sentiment Analysis From Microblogging Data," in *IEEE Transactions on Computational Social Systems*, vol. 7, no. 4, pp. 915-923, Aug. 2020, doi: 10.1109/TCSS.2020.2993585.

[2] M. Goyani and N. Chaurasiya, "A Review of Movie Recommendation System: Limitations, Survey and Challenges," Electronic Letters on Computer Vision and Image Analysis 19(3):18-37, 2020.

[3] U. Thakker, R. Patel and M. Shah, "A comprehensive analysis on movie recommendation system employing collaborative filtering," Multimedia Tools and Applications (2021) 80:28647–28672, https://doi.org/10.1007/s11042-021-10965-2.

[4] C. G. Reswara, J. Nicolas, M.o Ananta and F. I. Kurniadi, "Anime recommendation system using bert and cosine similarity," 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS).

[5] B. Juarto and A. Suganda Girsang, "Neural Collaborative with Sentence BERT for News Recommender System," JOIV : International Journal on Informatics Visualization, vol. 5, no. 4, p. 448, Dec. 2021, doi: 10.30630/joiv.5.4.678.

[6] M. F. F. Khan, K. Negoro and K. Sakamura, "EmoSync: Synchronizing AI-Mediated Book Recommendation with Reader'' Emotions," 2025 IEEE 13th Region 10 Humanitarian Technology Conference (R10-HTC), Chiba, Japan, 2025, pp. 1-6.

[7] C. J. Hutto and E. Gilbert, "Vader: A parsimonious rule-based model for sentiment analysis of social media text," in Proc. 8th Int. Conf. Weblogs Social Media, 2014, pp. 216–225.

[8] R. Plutchik. A General Psychoevolutionary Theory of Emotion. Theories of Emotion, Vol. 1, pp. 3–31, 1980

[9] T. Kajiwara et al., "WRIME: A New Dataset for Emotional Intensity Estimation with Subjective and Objective Annotations," In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2095–2104.

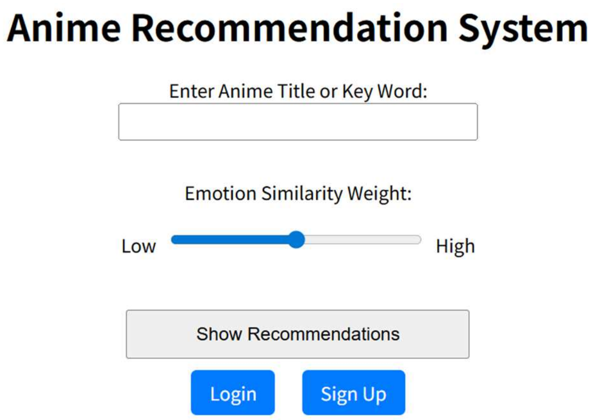

Fig. 3. The main interface of the system

[10] Oxana Vitman, Yevhen Kostiuk, Grigori Sidorov, and Alexander Gelbukh. 2023. Sarcasm detection framework using context, emotion and sentiment features. Expert Syst. Appl. 234, C (Dec 2023). https://doi.org/10.1016/j.eswa.2023.121068

[11] Babanejad, Nastaran, et al. "Affective and contextual embedding for sarcasm detection." Proceedings of the 28th international conference on computational linguistics. 2020.

[12] M. F. F. Khan, S. Seki and K. Sakamura, "Visualization of Online Product Reviews Written in Japanese Based on Entity Sentiment Analysis for Enhanced Customer Experience," International Conference on Cloud Computing and Internet of Things (CCIOT), Okinawa, Japan, 2023, ACM, pp. 64-70.

[13] Handi, Kaluwa, and Chirath Malaka. "Anime Recommendation System Based on User's Emotions." IIT, 2023.

[14] Prakash, Varun, et al. "Deep Anime Recommendation System: Recommending Anime Using Collaborative and Content-based Filtering." *2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*. IEEE, 2022.

[15] Antal, Lidia-Monica, and László Barna Iantovics. "Advanced Data Analysis for Machine Learning-powered Recommender Systems." *Procedia Computer Science* 246 (2024): 3957-3966.

[16] Soni, Badal, et al. "RikoNet: A Novel Anime Recommendation Engine." *Multimedia Tools and Applications* 82.21 (2023): 32329-32348.

[17] Rajarajeswari, S., et al. "Movie recommendation system," *Emerging Research in Computing, Information, Communication and Applications: ERCICA 2018, Volume 1*. Singapore: Springer Singapore, 2019. 329-340.

[18] Zhang, Jiang, et al. "Personalized real-time movie recommendation system: Practical prototype and evaluation." *Tsinghua Science and Technology* 25.2 (2019): 180-191.

[19] Wankhade, Mayur, Annavarapu Chandra Sekhara Rao, and Chaitanya Kulkarni. "A survey on sentiment analysis methods, applications, and challenges," *Artificial Intelligence Review* 55.7 (2022): 5731-5780.

[20] Tan, Kian Long, Chin Poo Lee, and Kian Ming Lim. "A survey of sentiment analysis: Approaches, datasets, and future research." *Applied Sciences* 13.7 (2023): 4550.

[21] Darban, Zahra Zamanzadeh, and Mohammad Hadi Valipour. "GHRS: Graph-based hybrid recommendation system with application to movie recommendation." *Expert Systems with Applications* 200 (2022): 116850.

[22] Putri, Helmy Dianti, and Muhammad Faisal. "Analyzing the effectiveness of collaborative filtering and content-based filtering methods in anime recommendation systems." *Jurnal Komtika (Komputasi dan Informatika)* 7.2 (2023): 124-133.

[23] Mutteppagol, Vidyashree Mahaling. *A deep learning recommender system for anime*. Diss. Dublin, National College of Ireland, 2021.

[24] M. F. F. Khan, R. Masuda and K. Sakamura, "Developing a Voice Analysis System for Novice Anime Voice Actors: A Fundamental Frequency Based Approach," 2024 10th International Conference on Applied System Innovation (ICASI), Kyoto, Japan, 2024, pp. 326-328, doi: 10.1109/ICASI60819.2024.10547927.