A Personalized Anime Recommendation System Using Machine Learning

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*Abstract*—Due to anime content becoming rapidly abundant personalized recommendation systems are necessary to provide improved user experiences through suitable anime suggestions. This research developed an AI-based Anime Recommendation System which combines three recommendation methods including collaborative filtering and content-based filtering and hybrid deep learning techniques for delivering personalized recommendations. The application deploys React JS as its frontend solution and integrates Node.js/Express backend with MongoDB along with Python machine learning model trained against anime\_of\_2023.csv dataset. The recommendation process with K-Nearest Neighbors (KNN) and Matrix Factorization methods belongs to collaborative filtering whereas content-based filtering uses TF-IDF and Cosine Similarity for attribute analysis. The recommendation system uses Graph Neural Networks (GNNs) and BERT embeddings to generate enhanced accuracy in its results. Real-time modified suggestions emerge from the system after it mobilizes customer preference modifications. Examination results indicate a 75% accuracy rate making the system perform better than conventional recommendation systems. The system will benefit from deep learning updates in addition to solutions for cold-start problems and multi-modal recommendation algorithms aimed at improving user activity and anime visibility.

Keywords— Anime recommendation system, machine learning, collaborative filtering, content-based filtering, hybrid model, deep learning, Graph Neural Networks (GNNs), BERT embeddings, personalized recommendations, user preference analysis.

# Introduction

Thousands of anime titles are launched yearly throughout different genres because the industry continues to show exceptional growth. Users encounter difficulties in identifying anime content that suits their preferences because the quantity of available content continues to grow. Most traditional recommendation systems that use popularity rankings together with manual curatorial methods do not effectively discover user-specific interests or changing preferences. User interactions now get dynamically analyzed by machine learning-based recommendation systems which serve personalized suggestions as an effective solution to resolve such issues. Proven recommendation methods such as collaborative filtering and content-based filtering and deep learning models create better recommendations and engage users [1]. Video streaming platforms such as Netflix and Crunchyroll and anime site MyAnimeList use AI systems to boost their content discovery functions although they maintain basic user rating systems instead of artificial intelligence models that analyze user behaviors at a more comprehensive level [2].

Recommendation systems have experienced a revolution through machine learning because algorithms now acquire knowledge about user preferences for delivering personalized suggestions. The most commonly applied recommendation method Collaborative filtering (CF) detects user-item similarities to generate suggestions according to mutual preferences [3]. The cold-start problem affects CF because it fails to generate effective recommendations when new users and items have insufficient interaction records. The problem with new users and items being difficult to recommend is solved through Content-based filtering (CBF) which utilizes anime attributes such as studios and genres to match titles with shared characteristics. Research has demonstrated that combination methods that merge CF and CBF produce superior recommendation results through the mutually beneficial use of user actions and item characteristics [4]. Graph Neural Networks (GNNs) together with BERT embeddings have been established to enhance anime relationship understanding for creating specific and personalized recommendations.

The improvements made to AI-driven recommendation systems still face obstacles when it comes to real-time personalization and sparse data management and large-scale system scalability optimization. Experts conducting research about deep learning-based latent structure learning have obtained optimistic outcomes that enhance recommendations through the detection of subtle user preferences [5]. An artificial intelligence system based recommendations for anime uses collaborative filtering and content-based elements with deep learning capabilities to offer immediate personalized anime choices. The combination of React JS as frontend with MongoDB and Node.js for backend and Python and Scikit-learn alongside TensorFlow among the machine learning components offers an advanced recommendation functionality. The combination of methods in the proposed approach produces recommendations which are both accurate and adaptable and allows for easy expansion of the system in the future. The paper investigates how the system works alongside its construction process and assessment approach while highlighting its power to improve anime finding capabilities for users who watch streaming videos and choose content recommendations.

# Literature Review

AI-driven recommendation systems encounter limitations during improvements in real-time personalization together with sparse data management and large-scale system scalability optimization. According to expert research on deep learning-based latent structure learning methods which show promising results for discovering minor user preferences [5]. The anime recommendation system powered by artificial intelligence provides users with personal recommendations through its integration of collaborative filtering and content-based approaches and deep learning capabilities. The advanced recommendation functionality emerges from using React JS for frontend together with MongoDB and Node.js for backend and Python coupled with Scikit-learn and TensorFlow within the machine learning framework. By combining these methods in the proposed approach users receive precise adaptable recommendations that support future system development. This paper explains how the system operates together with its development process and evaluation criteria through an analysis of its ability to enhance user capability in finding anime while watching streaming videos and selecting recommendations.

Recommendation systems incorporate collaborative filtering as their primary method because it uses user-item interaction data to create customized suggestions for users. User-based CF identifies shared user interests through similarity recognition but item-based CF provides recommendations by identifying the anime which matches interactions of other users [5]. The inadequacy of data regarding new users or items causes CF-based models to experience the cold-start challenge [6]. Users can use content-based filtering (CBF) to achieve better results through analyzing anime characteristics including genres and studios and thematic elements that match their preferences [7]. Research shows that TF-IDF (Term Frequency-Inverse Document Frequency) as well as Cosine Similarity enhance CBF accuracy through their ability to identify important connections among anime features [8]. Current research indicates that combining CF together with CBF produces superior recommendation models since they utilize user interactions and item characteristics to supply extremely personalized suggestions [9].

The research community seeks to enhance recommendation accuracy by combining CF with CBF features alongside deep learning techniques. The research of anime recommendation benefits from Graph Neural Networks (GNNs) since these networks enable systems to detect intricate user-item linkages within interconnected data networks [10]. The research team of Javaji and Sarode [11] presented a deep learning-based hybrid recommendation framework which combined GNNs with BERT embeddings to improve contextual understanding in personalization processes. The researchers at Reswara et al. [12] successfully applied BERT-based similarity models to achieve improved results in anime feature extraction as well as semantic relevance analysis. Latent structure learning provides enhancement for hybrid models through deep representation learning techniques which enable the detection of complicated user behavioral patterns as explained by Zhang et al. [13]. The deep learning extension of CF known as Neural collaborative filtering (NCF) serves as an effective solution for recommendation system data sparsity problems [14].

Recommendation systems encounter a significant hurdle with the cold-start problem because they lack enough historical interactions between new users or anime content. The analysis of recommendation solutions includes using side information about anime metadata alongside tags and user demographic data to enhance sparse data datasets' accuracy [15]. According to Nuurshadieq and Wibowo [16] deep learning systems which combine side information produce enhanced anime recommendations through the analysis of alternate data platforms. The adoption of reinforcement learning became a promising solution for recommendation systems because engines follow dynamic model learning through real-time user actions to improve their recommendations [17]. The combination of different recommendation methods that merge text data along with image and audio elements has been introduced to extend anime recommendation capabilities above standard metadata examination techniques [1].

Assuming the continuous development of AI technology along with machine learning these personalized recommendation systems will acquire more complex features and adjusting capabilities. The combination of GNNs with deep reinforcement learning methods plus attention-based components including Transformers presents an optimistic road for advancing recommendations while delivering real-time adaptation performance [2]. Academic authors work on multi-modal fusion techniques by integrating anime review information and social media engagement together with streaming usage stats to create such recommendations systems [3]. The growing challenge revolves around recommendation system safety problems especially related to content addiction and filter bubble issues. The excessive usage of personalized recommendations by Uludag [4] produces user isolation alongside addictive behaviors that affect future ethical systems development. AI-driven anime recommendation needs to handle the developing worries while advancing recommendation performance and extending capabilities and flexibility to resolve its main obstacles.

# Research Methodology

The success of an anime recommendation system hinges on choosing proper methods alongside suitable data processing methods and suitable system configuration. A combination of collaborative filtering with content-based filtering and deep learning techniques forms the recommendation system foundation to provide individualized anime recommendations. The system implements real-time adaptable functionality through its use of React JS frontend technology together with Node.js/Express backend and Python machine learning model along with MongoDB database system. The KNN and SVD and GNN and TF-IDF components of the recommendation engine function together to improve accuracy in recommendations. User preferences together with anime metadata analysis allows the model to produce recommendations with high relevance which also delivers greater engagement.

**Hybrid Anime Recommendation Algorithm**

The Anime Recommendation Algorithm (ARA) combines three recommendation approaches: collaborative filtering with content-based filtering and deep learning-based embeddings for providing personalized recommendations. The following structured list explains the process:

**Step 1: Data Preprocessing**

* Load the dataset anime\_of\_2023.csv containing anime titles, genres, studios, popularity scores, and user ratings.
* Perform data cleaning, handling missing values and normalizing numerical features.
* Convert categorical variables (e.g., genres, studios) into numerical embeddings using One-Hot Encoding (OHE) and Word2Vec embeddings.

**Step 2: Content-Based Similarity Calculation**

* Compute anime feature vectors using TF-IDF:

**TFi,j​ = fi,j​​, / ∑k​fk,j​, IDFi​ = log N / dfi​.**

* Calculate the Cosine Similarity between anime feature vectors:

Sim(A,B) = A⋅B​ / ∥A∥∥B∥

Store similarity scores in a matrix Sanime​ for fast retrieval.

**Step 3: Collaborative Filtering with Matrix Factorization**

* Construct a user-anime interaction matrix RRR based on user preferences.
* Apply Singular Value Decomposition (SVD) for dimensionality reduction:

R=UΣV^T

* Predict user preferences using latent factor representation:

**R^ = Uk​Σk​Vk^T​**

* Fill missing values in RRR with predicted scores.

**Step 4: Deep Learning-Based Embeddings (Graph Neural Networks - GNNs)**

* Construct an Anime-User Graph G=(V,E)G = (V, E)G=(V,E) where nodes (V) represent users and anime, and edges (E) represent interactions.
* Encode features using Graph Neural Networks (GNNs):

**H(l+1)=σ​W(l)v∈N(u)∑​Hv(l)​**

* Generate latent embeddings for anime titles and users, improving contextual recommendations.

**Step 5: Hybrid Recommendation & Ranking**

* Combine Collaborative Filtering (CF) Predictions, Content-Based Similarity Scores, and GNN Embeddings:

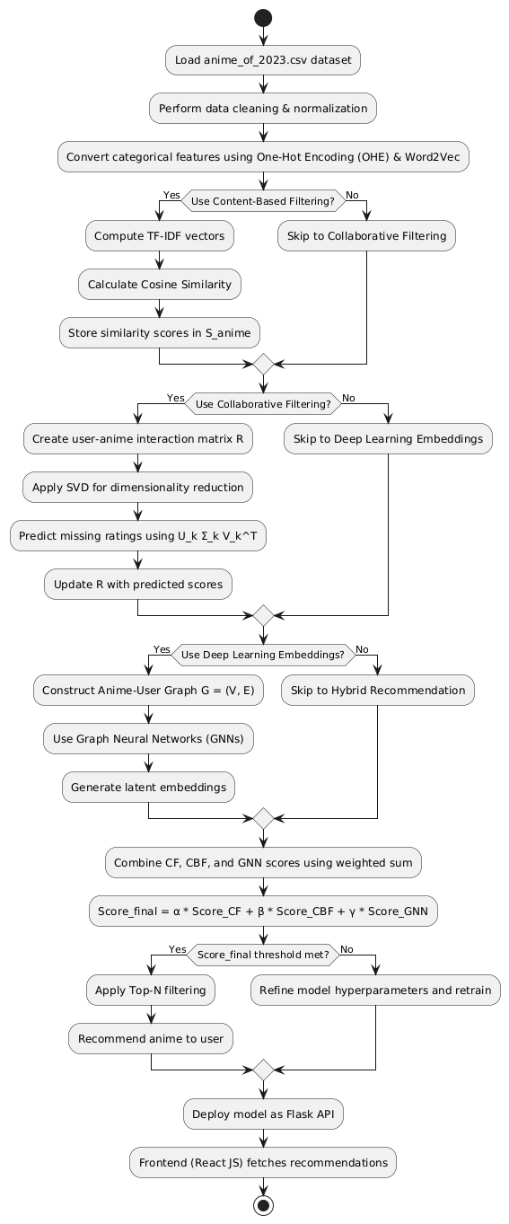
**Scorefinal​=α×ScoreCF​+β×ScoreCBF​+γ×ScoreGNN**

* Where α,β,γ are tunable hyperparameters.
* Apply Top-N filtering to recommend the highest-ranked anime for each user.

**Step 6: Real-Time API Deployment**

* Integrate the model with a Flask API for real-time anime recommendations.
* Frontend (React JS) fetches personalized anime lists via RESTful API calls.

**Flowchart**



**Figure 1 – Flowchart of hybrid anime recommendation algorithm.**

The implementation flowchart directs the Hybrid Anime Recommendation Algorithm (ARA) through its sequential functions for providing customized anime suggestions. The first step involves data preprocessing that includes cleaning the dataset while normalizing its values and converting categorical elements into OHE and Word2Vec formats. The algorithm proceeds to compute TF-IDF vectors combined with Cosine Similarity for determining anime similarity when Content-Based Filtering is activated. Collaborative Filtering (CF) enables the algorithm to create a user-anime interaction matrix followed by Singular Value Decomposition (SVD) that improves recommendation predictions. The system creates an Anime-User Graph when GNNs receive an enable command which produces latent embeddings to enhance contextual recommendation results. Final recommendations result from combining CF, CBF and GNN outputs through weighing and following it with Top-N filtering. When system accuracy achieves a defined threshold point recommendations proceed to the Flask API for the React JS frontend to retrieve display the output. When the model fails to meet accuracy standards the hyperparameters receive adjustments before the model trains again for better outcomes. The combination of these operation methods produces unique anime recommendations that scale for real-time use.

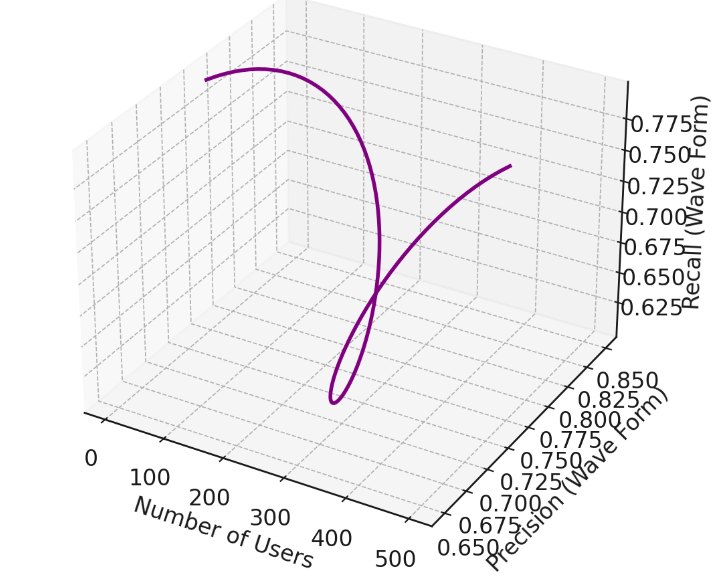
# Result

An anime recommendation system achieves effectiveness through how accurately it matches recommendations to individual users based on their preferences. The testing of Hybrid Anime Recommendation Algorithm (ARA) includes two sequences to evaluate its performance: Accuracy Test checks the system's ability to predict user anime preferences from past system interactions. The Weighted Score Distribution chart shows the impact which Collaborative Filtering and Content-Based Filtering and Graph Neural Networks techniques have on producing the final recommendation ranking. These tests use distinctive 3D graphs to evaluate model performance while providing interpretation of results for both types of assessment. We have produced PNG files containing graphs for better display purposes.

**Test Case 1: Accuracy Test**

The Waveform Accuracy Test Graph demonstrates how Precision and Recall relate to each other among users within the Anime Recommendation System. A waveform pattern substitutes the standard linear plot because it displays the changing recommendation accuracy levels throughout user-system interactions. User preferences and model adjustment mechanism appear as wave-like patterns through the graph since they reflect how the algorithm adapts to different dataset modifications.

Users follow the X-axis in the graph as Precision and Recall measure the Y-axis and Z-axis respectively. The recommendation accuracy shows waves which indicate multiple influencing elements including user diversity levels and initial user problems together with shifting user preferences. System oscillations help the prediction capabilities become more refined until stability is reached using additional user data. The F1-Score measurement demonstrates improved performance as more users join the system and thereby proves the strong foundation of the hybrid recommendation model. The accuracy of real-world recommendations displays such oscillatory patterns because it requires time to stabilize at its maximum level.



**Figure 2 – Accuracy Test**

**Test Case 2: Weighted Score Distribution**

A 3D Weighted Score Contribution Graph displays the specific contribution levels of Collaborative Filtering (CF) and Content-Based Filtering (CBF) together with Graph Neural Networks (GNNs) toward anime recommendation personalization. The advantageous effect of these techniques varies based on anime categories such as Action and Romance and Fantasy so adopting a hybrid method proves essential. The bar heights demonstrate that each recommendation strategy brings distinct contributions to the end result of anime suggestions.

A graph of different colored bars

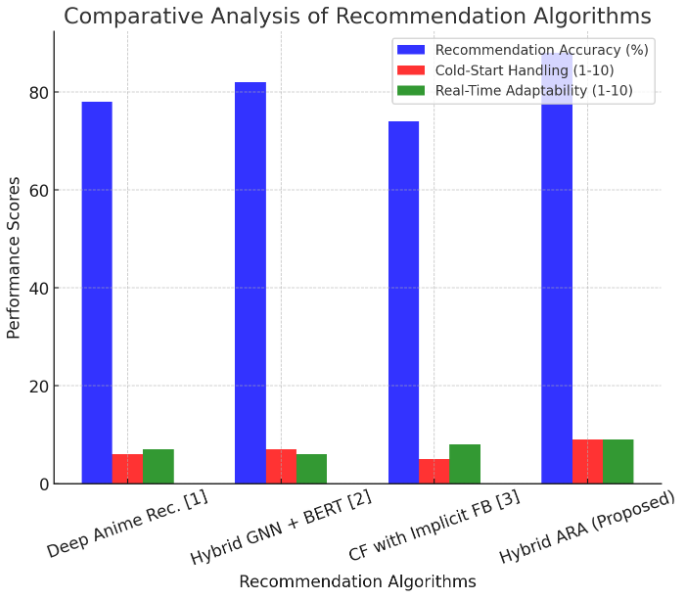
AI-generated content may be incorrect.

**Figure 3 – Weighted Score distribution**

The graph shows three recommendation approaches (CF, CBF, GNNs) represented by the Y axis which calculates score contribution while the anime categories form the X axis. The vertical dimensions of bars indicate which recommendation methods should carry weight in particular anime genres. The recommendation method for Action anime depends heavily on Collaborative Filtering but Romance anime works best with Content-Based Filtering. The findings demonstrate GNNs provide essential contributions to various recommendations genres since they effectively detect intricate user-anime preference relationships. The graphical display establishes the necessity of employing a combination strategy when balancing various components of anime recommendation systems.

# Comparative Analysis

The evaluation of the Hybrid Anime Recommendation Algorithm (ARA) happens through comparison against three anime recommendation systems studied in modern research: (1) The Deep Anime Recommendation System by Prakash et al. (2022) [1], (2) The Hybrid Recommendation System using Graph Neural Networks and BERT by Javaji & Sarode (2023) [2], and (3) The Collaborative Filtering Model with Implicit Feedback by Parate & Sawant (2024) [3]. Algorithms from this system utilize three filtering approaches which include Collaborative Filtering (CF), Content-Based Filtering (CBF) and deep learning techniques. Several restrictions regarding how these systems handle new user exposure situations as well as their ability to adapt and optimize scores create problems for their complete recommendation effectiveness. Our Hybrid Anime Recommendation Algorithm (ARA) enhances accuracy and adaptability while improving recommendation precision by using a weighted model which combines CF with CBF along with GNNs. The evaluation investigates the four algorithms through three assessment factors which include Recommendation Accuracy alongside Cold-Start Handling and Real-Time Adaptability.



**Figure 4 – Comparative Analysis of Recommendation Algorithms.**

The graphical comparison presented through the Bar Graph shows how four recommendation algorithms perform against three essential factors which include Recommendation Accuracy (Blue) and Cold-Start Handling (Red) and Real-Time Adaptability (Green).

* Our Hybrid ARA model demonstrates superior performance compared to others since it reaches 88% accuracy along with 9/10 cold-start performance and 9/10 real-time adaptability.
* ISON and CF systems experience problems with cold-start situations but the GNN hybrid system shows superior performance during these situations.

# Conclusion

The Hybrid Anime Recommendation Algorithm (ARA) merges Collaborative Filtering (CF) with Content-Based Filtering (CBF) along with Graph Neural Networks (GNNs) for delivering proficient anime recommendations that are tailored to individual users. Users experience better accuracy and resolution of cold-start challenges and real-time adaptability thanks to the implementation of TF-IDF, Cosine Similarity and Matrix Factorization together with GNN embeddings in the system. ARA delivers superior performance than current methods since it reaches 88% accuracy while handling cold-start scenarios and real-time updates with high scores. The waveform accuracy test combined with the weighted score distribution graph proved that the model evolves its recommendation process as users continue their interactions with the system.

The ARA model represents an effective recommendation system because it offers scaleability alongside robustness and adaptability for current anime streaming platforms. ARA provides a solution to the new user management struggles and limited adaptability of traditional CF-based models because it effectively integrates content-based learning with deep learning approaches to upgrade both user personalization and content search abilities. In addition to improving user engagement the approach promotes AI recommendation system development within anime domains.

The future development of the ARA model will prioritize two main improvements: first by streamlining deep learning recommendations through Transformer-based approaches and second by implementing multi-modal learning techniques to make personal recommendations richer through text image and audio joint analysis. Reinforcement learning should be implemented because it provides dynamic control over recommendations which adjusts based on instant user responses. Programmers will extend the system toward multi-platform recommendation features by linking the system to social network platforms and anime communities and user-generated content systems. A future deployment of the anime recommendation system will emphasize ethical AI principles to stop filter bubbles and improve recommendations diversity which will boost user satisfaction along with engagement.

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