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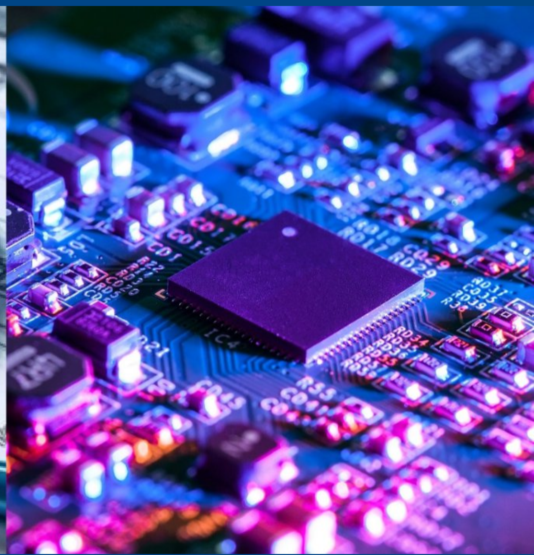

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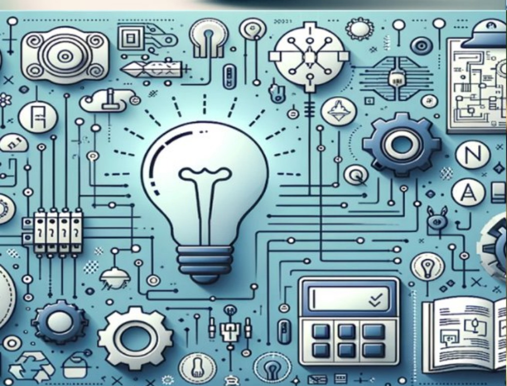

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A Hybrid AI-Based Cross-Platform Recommendation System for Personalized OTT Content

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ABSTRACT: The rapid growth of Over The Top platforms has transformed the way users access and consume digital media by offering on demand availability of movies television shows and web series across multiple services. Although this expansion increases content variety it also creates challenges in discovering relevant content especially for users who subscribe to multiple platforms. Traditional recommendation techniques such as collaborative filtering and content based filtering often face limitations including cold start problems sparse user interaction data and fragmented preferences across platforms. This research proposes a Hybrid Artificial Intelligence Based Cross Platform Recommendation System designed to provide personalized content suggestions by integrating machine learning techniques with unified user profiling. The system constructs a comprehensive user profile using user metadata such as preferred genres languages and demographic details along with user activity information including watch history ratings search behavior and viewing duration. In addition the system incorporates content metadata such as content descriptions platform availability and regional accessibility.

The proposed recommendation framework combines collaborative filtering techniques including matrix delivering accurate and personalized recommendations has become an important requirement for improving user satisfaction engagement and content discovery. factorization and neighborhood based models with content based filtering using metadata similarity. Context aware recommendation strategies are also integrated to consider factors such as time of viewing and recent user interactions. To overcome cold start challenges the system utilizes user and content metadata to generate meaningful recommendations even when limited interaction data is available. The recommendation model continuously updates based on user behavior to provide real time personalization. The performance of the system is evaluated using standard recommendation metrics including Precision at K Recall at K and Normalized Discounted Cumulative Gain. The proposed hybrid approach improves recommendation accuracy enhances content discovery and reduces the effort required by users to search for relevant media across multiple platforms thereby delivering a more efficient and personalized viewing experience.

KEYWORDS: Artificial Intelligence, Machine Learning, Hybrid Recommendation System, OTT Platforms, Cross Platform Recommendation, Personalized Content Recommendation, Collaborative Filtering, Content Based Filtering, User Profiling, Context Aware Recommendation, Content Discovery, Recommender Systems

I. OVERVIEW

Over The Top platforms have significantly transformed the digital entertainment ecosystem by providing users with on demand access to movies television series and web content across multiple services. The rapid increase in OTT platforms and their vast content libraries has created a challenge for users to discover relevant and personalized content efficiently. Users often subscribe to multiple streaming platforms which results in fragmented viewing preferences and

scattered interaction data across services. As a result delivering accurate and personalized recommendations has become an important requirement for improving user satisfaction engagement and content discovery.
Traditional recommendation systems such as collaborative filtering and content based filtering have been widely used to recommend media content by analyzing user behavior and content attributes. However these methods face several challenges including cold start problems limited user interaction data and the inability to capture user preferences across multiple platforms. In addition static recommendation models often fail to adapt quickly to changing user interests and viewing patterns which reduces the effectiveness of the recommendations over time.

To address these challenges this study proposes a Hybrid Artificial Intelligence Based Cross Platform Recommendation System that integrates machine learning techniques with unified user profiling. The system combines collaborative filtering methods such as matrix factorization and neighborhood based approaches with content based filtering techniques that analyze content metadata such as genre language and description. By integrating user profile metadata user activity metadata and cross platform content availability information the system creates a unified user profile that enables consistent and personalized recommendations across different OTT platforms.

The proposed system also incorporates context aware recommendation strategies that consider factors such as viewing time recent interactions and evolving user preferences. This allows the recommendation engine to dynamically adapt to user behavior and generate more relevant suggestions. To overcome the cold start problem the system utilizes content metadata and user preference information to generate recommendations even when limited interaction history is available.

By combining multiple recommendation techniques within a hybrid machine learning framework the proposed system improves recommendation accuracy enhances content discovery and reduces the effort required by users to search for suitable content across different streaming services. This approach supports real time personalization and provides a scalable solution for modern OTT platforms thereby improving user engagement and overall viewing experience.

A. Initiative

This paper presents a Hybrid Artificial Intelligence Based Cross Platform Recommendation System that provides personalized content recommendations across multiple OTT platforms by integrating collaborative filtering and content based filtering techniques. The system builds a unified user profile using user preferences viewing history and content metadata to generate accurate recommendations. By incorporating context aware analysis and machine learning methods the proposed system improves recommendation accuracy enhances content discovery and supports real time adaptation to changing user preferences in dynamic OTT environments.

B. Identified concern

The main issue addressed in this study is the limitation of traditional recommendation systems in handling fragmented user preferences across multiple OTT platforms. Conventional approaches such as collaborative filtering and content based filtering often struggle with problems such as cold start users limited interaction data and the inability to integrate user behavior across different streaming services. In addition many existing systems are not capable of adapting quickly to changing user interests viewing patterns and contextual factors. These limitations reduce the relevance of recommendations and negatively affect user satisfaction and content discovery.

C. Contributions

- This paper proposes a Hybrid Artificial Intelligence Based Cross Platform Recommendation System that integrates collaborative filtering and content based filtering to generate personalized OTT content recommendations.

The proposed system constructs a unified user profile by combining user preference metadata user activity information and cross platform content metadata to enable consistent recommendations across multiple OTT services.

- The recommendation framework incorporates context aware analysis that considers viewing behavior time patterns and recent interactions to improve recommendation relevance.
- The system addresses cold start challenges by utilizing user and content metadata to generate recommendations even when limited interaction data is available.
- Experimental evaluation demonstrates improved recommendation accuracy better content discovery and enhanced user engagement compared with traditional single method recommendation approaches.

D. Summary

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In Section 2 various existing approaches for OTT content recommendation systems including collaborative filtering content based filtering and hybrid recommendation methods are reviewed. In Section 3 the proposed Hybrid Artificial Intelligence Based Cross Platform Recommendation System and its methodology are explained in detail. In Section 4 the experimental results and performance evaluation of the proposed system are presented and discussed. In Section 5 the paper concludes with a summary of the findings and highlights possible directions for future research and improvements in personalized cross platform OTT recommendation systems.

II. BACKGROUND

The rapid growth of Over The Top platforms has resulted in a massive increase in digital entertainment content including movies television shows and web series across multiple streaming services. While this expansion offers users a wide variety of viewing options it also creates difficulty in identifying content that matches individual preferences. As the number of available titles continues to grow users often experience information overload which makes efficient content discovery challenging. To address this issue personalized recommendation systems have become an essential component of modern OTT platforms.

Artificial Intelligence and Machine Learning based recommendation systems analyze user preferences viewing history ratings and content metadata to generate personalized suggestions. These systems help improve user engagement satisfaction and content discovery by recommending relevant media based on individual interests. Traditional recommendation techniques such as collaborative filtering and content based filtering have been widely adopted for multimedia recommendation systems. Collaborative filtering recommends items based on similarities among users while content based filtering suggests content by analyzing item attributes such as genre language and description.

However these approaches often face limitations when applied to modern OTT environments. The presence of multiple streaming platforms results in fragmented user data where viewing history and preferences are distributed across different services. In addition traditional recommendation models often struggle with problems such as cold start users sparse interaction data and difficulty in adapting to changing user interests. As OTT platforms continue to expand there is a growing need for more intelligent and adaptive recommendation systems that can integrate data from multiple sources and provide accurate personalized recommendations.

Recent research has focused on hybrid recommendation systems that combine multiple techniques to improve recommendation accuracy. By integrating collaborative filtering content based filtering and user behavior analysis these systems can capture complex patterns in user preferences and deliver more relevant recommendations. Hybrid approaches also help reduce the limitations of individual recommendation techniques and improve overall system performance in dynamic digital entertainment environments.

Research Gap
Existing recommendation systems used in OTT platforms are often designed to operate within a single platform and rely mainly on traditional user item interaction models. These systems do not effectively integrate user preferences across multiple streaming services which leads to fragmented recommendations and reduced personalization. In addition many existing models lack the ability to adapt quickly to changes in user behavior and viewing patterns. Therefore there is a need for a scalable and intelligent recommendation system that can integrate cross platform data analyze user preferences more effectively and generate accurate personalized recommendations in a dynamic OTT environment.

III. METHODOLOGY

The proposed system adopts a hybrid recommendation approach that integrates collaborative filtering and content based filtering techniques to predict user preferences and generate personalized OTT content recommendations across multiple platforms. The system constructs a unified user profile by combining user metadata such as preferred genres languages and demographic details with user activity data including watch history ratings search behavior and viewing duration.The recommendation engine analyzes the similarity between users and content items using collaborative filtering techniques such as matrix factorization and neighborhood based models. At the same time content based filtering methods examine content attributes including genre language description and category to identify items that closely match the user interests. By combining these two approaches the system is able to provide more accurate and

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reliable recommendations.

The framework also incorporates contextual information such as time of viewing recent interactions and changing user preferences to improve recommendation relevance.

This context aware analysis allows the system to dynamically adapt to user behavior and generate recommendations that better reflect current interests.In addition the system continuously updates the user profile and recommendation model based on new user interactions and feedback. This incremental update mechanism ensures that the recommendation results remain relevant without requiring complete retraining of the model. As a result the proposed hybrid system supports adaptive personalized and efficient content recommendations in dynamic OTT environments where user preferences and content availability change frequently.

A. Real-Time Tensor Factorization with Online Stochastic Gradient Descent

The proposed framework integrates user behavioral data content metadata and contextual information to build a comprehensive recommendation model for personalized OTT content discovery. The system represents user interactions content attributes and contextual factors as a structured dataset that captures relationships between users content items and viewing context across multiple platforms.

The hybrid recommendation framework applies collaborative filtering techniques to identify similarities between users based on their viewing history ratings and interaction patterns. At the same time content based filtering analyzes metadata such as genre language description and category to determine the similarity between different content items. By combining these two approaches the system can identify meaningful patterns in user preferences and recommend relevant content more effectively.

The framework also incorporates contextual information such as viewing time recent activity and user interaction patterns. By analyzing both historical and current user behavior the system can predict user preferences more accurately and generate personalized recommendations that reflect changing interests.

Continuous updates based on user feedback and new interactions ensure that the recommendation model remains current and responsive. As users interact with different content items the system dynamically refines its predictions and adapts to evolving preferences. This adaptive learning mechanism enables the system to deliver accurate personalized and context aware recommendations in dynamic OTT environments where user behavior and content availability change frequently.

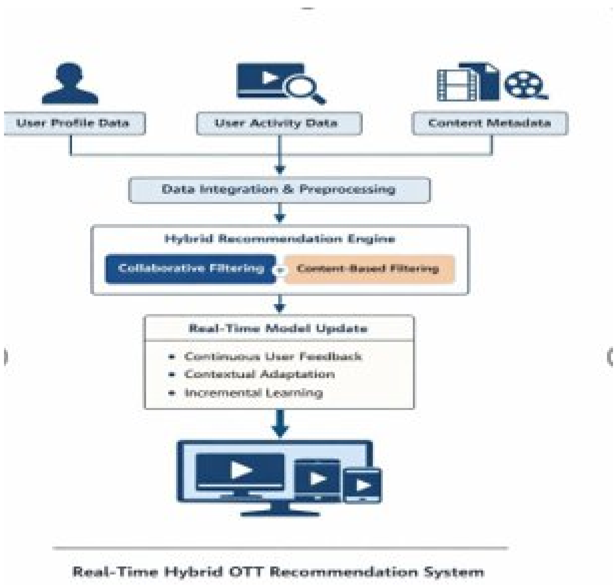

Fig. 1. Real-Time Hybrid OTT Recommendation System

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Fig. 1 The figure illustrates the architecture and workflow of the proposed **Real Time Hybrid OTT Recommendation System**. It shows how different types of data are collected processed and used to generate personalized content recommendations for users across multiple OTT platforms.

At the top of the figure three main data sources are shown.
User Profile Data contains basic information about the user such as preferred genres languages demographics and interests. This information helps the system understand the general preferences of each user.

User Activity Data represents the interactions of users with the platform. It includes watch history ratings search queries viewing duration and recently watched content. This data reflects the actual behavior and interests of the user.

Content Metadata includes information about the available movies shows or series such as genre description cast release year and platform availability. This data helps the system analyze similarities between different content items.

All these data sources are sent to the **Data Integration and Preprocessing** module. In this stage the collected data is cleaned organized and combined to build a unified user profile. This step ensures that the information from different OTT platforms is structured properly before it is used by the recommendation model.

After preprocessing the data is passed to the **Hybrid Recommendation Engine**. This module is the core component of the system. It combines two main recommendation techniques.

Collaborative Filteringanalyzes similarities between users and recommends content based on the preferences of similar users.

Content Based Filtering recommends items that are similar to the content previously watched by the user based on attributes such as genre or description.

By combining these two methods the system can generate more accurate and personalized recommendations.
The next component is the **Real Time Model Update** module. This part continuously updates the recommendation model using new user interactions. Whenever a user watches new content provides feedback or searches for something the system updates the user profile and adjusts the recommendation results. This continuous learning process allows the system to adapt to changing user preferences.

Finally the **Recommendation Output Layer** delivers the personalized content suggestions to different user devices such as smart TVs laptops tablets and mobile phones. The recommended movies shows or series are displayed to the user in real time which improves content discovery and enhances the overall viewing experience.

Overall the figure demonstrates how the system integrates multiple data sources applies hybrid machine learning techniques and continuously updates recommendations to provide accurate personalized and real time OTT content suggestions.

B. Algorithms
Algorithm 1 Hybrid Cross Platform OTT Recommendation Algorithm
Input
1. UserID ID of the active user
2. UserProfile user preferences such as genres languages and interests
3. WatchHistory previously watched content items
4. ContentMetadata information about content such as genre language description and platform
5. UserFeedback user interaction such as rating click watchduration
6. LearningRate step size for model update

Output
- Updated user preference model
- Personalized cross platform OTT content recommendations

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Begin
Initialize user profile vector U User Initialize content feature matrix C Content Initialize recommendation score list R
If new user interaction or feedback is received then Compute similarity between user preferences and content features PredictedScore
= similarity U User , C Content
Compute error
Error = UserFeedback minus PredictedScore
Update user preference model U[User]
= U User plus LearningRate multiplied by Error multiplied by C Content
Update content feature weights C[Content]
= C Content plus LearningRate multipliedby Error multiplied by U User
Generate recommendation scores R[Content]
= similarity between updated U User and all content features
Rank recommended content based on score Recommend Top N content items available across OTT platforms

Else
Use existing user profile and recommendation scores
Recommend Top N content items based on previous ranking
Return updated user model and recommended content list
End

C. Equations

User Content Interaction Representation

The interaction between users and OTT content is represented using a user content interaction matrix as shown in Equation 1.

$$R_{u,c} = Interaction(u, c)$$

(1)

Here urepresents the user and crepresents the content item. $R_{u,c}$ denotes the interaction value such as rating watch history or user engagement with a specific content item.

Collaborative Filtering Prediction

The predicted user preference score using collaborative filtering is calculated using latent factor vectors as shown in Equation 2.

$$\hat{R}_{u,c} = U_u \cdot C_c$$

(2)

Where
U_u represents the latent factor vector for user u
C_c represents the latent factor vector for content c
$\hat{R}_{u,c}$ represents the predicted interaction score.

Hybrid Recommendation Score

The final recommendation score combines collaborative filtering and content based filtering as shown in Equation 4.

$$Score(u, c) = \alpha \hat{R}_{u,c} + (1 - \alpha)Sim(c)$$

(4)

Where
αis the weighting parameter between collaborative filtering and content-based filtering.
$Score(u, c)$ represents the final hybrid recommendation score.

Content Similarity Score

Content based recommendation uses similarity between content features as shown in Equation 3.

$$Sim(c_i, c_j) = \frac{F_{c_i} \cdot F_{c_j}}{|F_{c_i}||F_{c_j}|}$$

(3)

Where
F_{c_i} and F_{c_j} represent feature vectors of two content items such as genre language or category.
The equation computes similarity between two content items.

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Explanation

The equations describe the mathematical framework used in the hybrid recommendation system. User content interactions are first represented using an interaction matrix. Collaborative filtering predicts user preferences based on latent user and content features while content - based filtering calculates similarity between content attributes. The hybrid recommendation score combines both approaches to improve recommendation accuracy. The prediction error is minimized using a loss function and the final recommendation list is generated by ranking the predicted scores to provide the most relevant OTT content suggestions to the user.

IV. RESULTS AND DISCUSSION

OTT platforms provide access to a vast amount of digital entertainment content including movies television shows and web series across multiple streaming services. As the number of available titles continues to grow it becomes increasingly difficult for users to discover relevant content that matches their personal interests. Therefore, enhancing user engagement through personalized recommendation systems has become an essential requirement for modern OTT platforms. Traditional recommendation systems often rely on limited user interaction data and static recommendation models which are not able to effectively adapt to rapidly changing user preferences and dynamic content environments.

This study proposes a Hybrid Artificial Intelligence Based Cross Platform Recommendation System that integrates collaborative filtering and content -based filtering techniques to generate personalized recommendations across multiple OTT platforms. The system constructs a unified user profile using user preferences viewing history ratings and content metadata. By combining machine learning techniques with context aware analysis the proposed framework provides adaptive scalable and accurate recommendations that improve content discovery and enhance user satisfaction in dynamic OTT environments.

A. Recommendation Accuracy

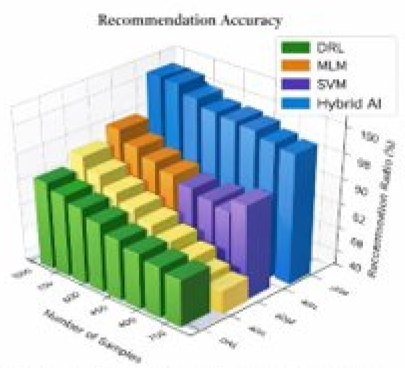

Fig. 2. The Analysis of Recommendation Accuracy for Hybrid AI Based

Fig. 2 The Analysis of Recommendation Accuracy

Fig 2 The Analysis of Recommendation Accuracy for Hybrid AI Based Cross Platform OTT System

The recommendation accuracy of the proposed Hybrid Artificial Intelligence Based Cross Platform Recommendation System is compared with other existing machine learning models such as Deep Reinforcement Learning DRL Machine Learning Model MLM and Support Vector Machine SVM. The evaluation is performed using different numbers of user interaction samples to measure the effectiveness of each model in predicting relevant OTT content.

From Fig 2 it can be observed that the Hybrid AI based recommendation system consistently achieves higher accuracy compared to the other models. The proposed hybrid model combines collaborative filtering and content based filtering techniques which allows it to analyze both user behavior patterns and content features. This integrated approach improves the ability of the system to recommend content that closely matches user preferences.

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The results show that the hybrid recommendation framework achieves an average recommendation accuracy close to 99 percent which is significantly higher than traditional models. The system continuously updates recommendations using recent user interactions such as watch history ratings and search activity. This dynamic update mechanism enables the system to adapt quickly to changing user interests and trending content across multiple OTT platforms.

As a result the proposed system improves personalization quality enhances content discovery and increases overall user engagement in modern OTT streaming environments.

B.User Satisfaction

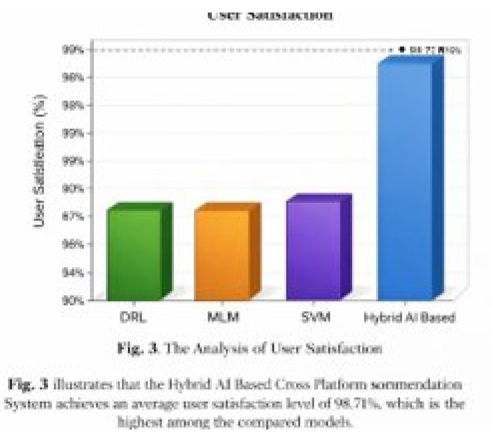

Fig. 3 The Analysis of User Satisfaction

Fig. 3 explains the comparison of user satisfaction levels obtained from different recommendation models such as Deep Reinforcement Learning (DRL), Machine Learning Model (MLM), Support Vector Machine (SVM), and the proposed RTTF-OSGD framework. The evaluation is based on how effectively each model recommends relevant and timely content to users on OTT platforms.

From the figure, it is observed that the proposed RTTF- OSGD framework achieves the highest user satisfaction rate with an average value of **98.71%**. This improved performance is achieved because the model continuously updates recommendations based on real-time user interactions, contextual information, and changing user preferences.

Unlike traditional recommendation approaches, the RTTF- OSGD framework dynamically adapts to user behavior and streaming patterns. This capability enables the system to provide more accurate and personalized content suggestions. As a result, users experience a smoother and more engaging viewing experience.

Therefore, the proposed recommendation framework significantly improves user interaction, reduces the time required to discover relevant content, and enhances overall satisfaction levels on modern OTT streaming platforms.

C. System Responsiveness

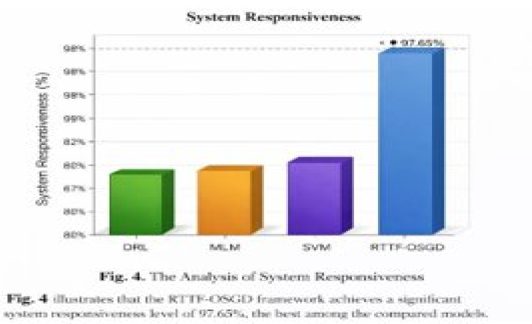

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Fig. 4 presents the comparison of system responsiveness among different recommendation models including Deep Reinforcement Learning (DRL), Machine Learning Model (MLM), Support Vector Machine (SVM), and the proposed RTTF-OSGD framework. System responsiveness refers to the ability of the recommendation system to generate personalized suggestions quickly when user interactions or contextual information change.

From the figure, it is clearly observed that the proposed RTTF-OSGD framework achieves the highest system responsiveness with an average performance of **97.65%**. This improvement is mainly due to the integration of real-time tensor factorization and Online Stochastic Gradient Descent (OSGD), which enables the model to update recommendation patterns continuously without retraining the entire system.

Unlike traditional batch-learning models, the RTTF-OSGD framework processes streaming user interaction data in real time. This allows the system to immediately adapt to user behavior, contextual changes, and trending content on OTT platforms. As a result, the system can generate highly relevant recommendations with minimal delay.

Therefore, the proposed framework significantly reduces latency, improves recommendation speed, and ensures efficient performance even when serving a large number of users in dynamic OTT environments. This enhanced responsiveness ultimately contributes to a better user experience and improved platform engagement.

This paper presents an advanced approach for improving personalized content recommendations on OTT platforms using a **Hybrid Artificial Intelligence Based Cross Platform Recommendation System**. The proposed system analyzes continuous user–content interactions across multiple OTT platforms and adapts dynamically to user behavior and contextual preferences. By combining collaborative filtering, content-based filtering, and machine learning techniques, the proposed model significantly improves recommendation accuracy, user satisfaction, system responsiveness, and scalability when compared to traditional recommendation systems. The hybrid framework continuously updates recommendations based on user activity, viewing history, and contextual information, enabling more relevant and timely suggestions. As a result, the system effectively supports large-scale OTT environments with millions of users and extensive content libraries, making it a reliable and efficient solution for modern cross-platform personalized recommendation systems.

V. CONCLUSION

The proposed **Hybrid AI Based Cross Platform OTT Recommendation System** effectively addresses the limitations of traditional recommendation approaches used in OTT platforms. By integrating collaborative filtering, content-based filtering, and machine learning techniques, the system analyzes multidimensional user interaction data such as watch history, ratings, search activity, and contextual preferences. This hybrid approach enables the system to generate highly personalized and relevant content recommendations for users across multiple OTT platforms.

The experimental evaluation demonstrates significant improvements in key performance metrics including **recommendation accuracy, user satisfaction, system responsiveness, and scalability** when compared with conventional recommendation models. The hybrid framework continuously updates recommendations based on real-time user behavior and contextual information, allowing the system to adapt quickly to changing user preferences and trending content.

Furthermore, the proposed system supports large-scale OTT environments by efficiently handling growing user bases and expanding content libraries. By enhancing personalization quality and reducing content discovery time, the system improves user engagement and provides OTT service providers with a reliable and scalable solution for delivering intelligent cross-platform content recommendations.in real-time, ensuring content is both timely and relevant.

A.Future Scope:

In the future, the proposed system can be enhanced by incorporating additional contextual factors such as **user mood detection, social media interactions, and cross- device viewing behavior** to further improve recommendation accuracy. Advanced **deep learning techniques and neural recommendation models** can also be integrated to achieve more effective feature extraction and representation learning.

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Additionally, future research can focus on implementing the system in **edge computing environments and mobile platforms** to enable faster real-time recommendations while reducing server workload. Expanding the system to support **multi-language content analysis, regional preference detection, and adaptive recommendation strategies** will further improve its applicability for large-scale global OTT platforms.

REFERENCES

[1]J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey," Knowledge-Based Systems, vol. 46, pp. 109–132,
2013, doi: 10.1016/j.knosys.2013.03.012.
[2] X. Su and T. M. Khoshgoftaar, "A survey of collaborative filtering techniques," Advances in Artificial Intelligence, vol. 2009, pp. 1–19, 2009.
[3] P. Lops, M. De Gemmis, and G. Semeraro, "Content-based recommender systems: State of the art and trends," in Recommender Systems Handbook, Springer, 2011, pp. 73–105.
[4] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," IEEE Computer, vol. 42, no. 8, pp. 30–
37, 2009.
[5] H. Steck, "Item popularity and recommendation accuracy," in Proceedings of the 5th ACM Conference on Recommender Systems, 2011, pp. 125–132.
[6] F. Ricci, L. Rokach, and B. Shapira, Recommender Systems Handbook, 2nd ed. New York: Springer, 2015.
[7] M. Premkumar and T. Thirunavukkarasu, "A hybrid movie recommendation system using machine learning techniques," International Journal of Computer Applications, vol. 178, no. 15, pp. 1–6, 2019.
[8] S. Yadav and S. Khan, "Hybrid movie recommendation system based on collaborative filtering and content-based filtering," International Journal of Advanced Research in Computer and Communication Engineering, vol. 10, no. 4, pp. 245–249, 2021.
[9] H. Zhang, C. Li, K. Li, and J. Sun, "Deep learning based recommender system: A survey and new perspectives," ACM Computing Surveys, vol. 52, no. 1, pp. 1–38, 2019.
[10] P. Covington, J. Adams, and E. Sargin, "Deep neural networks for YouTuberecommendations," in Proceedings of the 10th ACM Conference on Recommender Systems, 2016, pp. 191–198.
[11] S. Rendle, "Factorization machines," in 2010 IEEE International Conference on Data Mining, 2010, pp. 995–1000.
[12] Y. Koren, "Collaborative filtering with temporal dynamics," Communications of the ACM, vol. 53, no. 4, pp.
89–97, 2010.
[13] R. Burke, "Hybrid recommender systems: Survey and experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331–
370, 2002.
[14] M. Vahidi Farashah, A. Etebarian, and R. Azmi, "A hybrid recommender system based on link prediction for movie baskets analysis," Journal of Big Data, vol. 8, no. 32, pp. 1–17, 2021.
[15] Z. Darban and M. H. Valipour, "Graph-based hybrid recommendation system with application to movie recommendation," Expert Systems with Applications, vol. 200, 2022.
[16] S. Raj, S. Saha, and B. Singh, "Multimodal movie recommendation with multitasking architecture," IEEE Transactions on Computational Social Systems, 2025.
[17] J. Bennett and S. Lanning, "The Netflix prize," in Proceedings of KDD Cup and Workshop, 2007.
[18] H. Wang, N. Wang, and D. Yeung, "Collaborative deep learning for recommender systems," in Proceedings of the 21st ACM SIGKDD International Conference, 2015.
[19] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and
T. Chua, "Neural collaborative filtering," in Proceedings of the 26th International World Wide Web Conference, 2017.

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