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Youtube Video Recommendation using user-based Collaborative Filtering and Graph Neural Networks Approaches to Improve users Personalized Experience

Alvino Rock C[1] and T. Jemima Jebaseeli[2]
[1]Student, Division of Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore 641114.
Email: alvinorock@karunya.edu.in
[2]Associate Professor, Division of Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore 641114.
Email: jemima_jeba@karunya.edu

***Abstract*— YouTube's video recommendation method stands as a pinnacle in the realm of content discovery in enhancing user engagement on the platform. The User-Based Collaborative Filtering recommendation method relies on a robust foundation of data collection, encompassing user interactions, metadata, and content features. Leveraging advanced deep learning techniques, videos and users are transformed into vectors within a high-dimensional space, forming the basis for understanding complex relationships. The algorithm's training process involves the utilization of vast datasets, allowing the model to discern patterns in user behavior and content preferences. Predictions and rankings are determined in real-time, ensuring adaptability to evolving user tastes. The feedback loop, fueled by user interactions, continuously refines the algorithm, striking a balance between user satisfaction and content diversity. YouTube's commitment to preventing content bubbles is evident in the incorporation of diversity-enhancing strategies, introducing randomness and exploration to broaden user content experiences. Personalization remains a hallmark, tailoring recommendations based on individual user histories, preferences, and interactions. While the recommendation method has significantly improved content discovery and user satisfaction, it is not without challenges. Ethical considerations, privacy concerns, and the need for algorithmic transparency remain focal points in ongoing developments. Looking forward, the future holds exciting possibilities, with emerging technologies poised to shape the evolution of YouTube's video recommendation method.**

***Index Terms*— YouTube, video recommendation, collaborative filter, GNN, Graph Neural Networks, ranking.**

I. INTRODUCTION

YouTube has become one of the premier platforms for sharing and consuming video content. With over 2 billion active users per month YouTube offers a vast array of videos ranging from entertainment and music to education and tutorials [1]. The platform's popularity is attributed to its ability to cater to diverse user preferences and interests through its recommendation system. YouTube's recommendation system uses a combination of machine

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learning algorithms and user behavior analysis to suggest relevant videos to each user. By analyzing a user's viewing history, likes, comments, and subscriptions, the recommendation system generates personalized video recommendations that are likely to be of interest to the user [2]. These recommendations are displayed on the user's home page and sidebar, making it convenient for users to discover new content aligned with their interests. YouTube's video recommendation system is designed to provide personalized video suggestions to users based on their activity on the site [3]. The system faces unique challenges due to the vast amount of videos being uploaded daily and the large user base.

To address these challenges, various algorithms and techniques are used, such as cross-relevance methods, collaborative filtering, and deep learning techniques [4]. These algorithms consider factors like user behavior, video features, and similarity to recommend relevant videos. Additionally, the system utilizes data retrieved through the YouTube Data API and incorporates non-textual content from videos, such as audio, visual, and action information, to improve recommendation quality [5]. Experimental evaluations have shown promising results, with the proposed recommender models and fusion methods outperforming existing techniques. Video recommendation systems are essential for short videos on platforms like YouTube. These systems use collaborative filtering and deep learning techniques to recommend videos to users based on their interests and viewing behavior [6]. Additionally, a new method has been proposed that suggests videos based on their semantic similarity to the query using video transcripts and natural language ranking algorithms [7]. This method has the potential to provide better-related videos than tag-based recommendations and can be useful for recommending educational videos on ed-tech platforms and MOOC course platforms [8]. Another recommendation system considers attributes like weather, time, and month to understand the dynamic mood of a user and recommend videos accordingly [9]. Furthermore, a dynamic cross-OSN mining model has been developed to capture the relationship between various online social networks and improve recommendation output for cold starting on YouTube.

II. Literature Review

The recommendation system plays a vital role in shaping the success and popularity of videos on YouTube [1]. It determines which videos are more likely to be seen and shared, ultimately affecting their view count, engagement, and revenue potential. The recommendation system utilizes various models and techniques to achieve this goal. One of the main models used in YouTube's recommendation system is collaborative filtering [2]. The deep ranking model, on the other hand, focuses on ranking the retrieved videos based on their relevance to the user's activity. It utilizes the information gathered from the candidate generation model and further analyzes user preferences, viewing history, and engagement metrics to determine the most suitable order of video recommendations. The deep ranking model also incorporates multi-task learning, where the system learns to perform multiple tasks simultaneously, such as predicting user engagement and click-through rate. This allows the algorithm to optimize for various factors and deliver personalized recommendations that align with users' interests and preferences [3].

YouTube recommendation system aims to meet the needs and desires of users by suggesting relevant and engaging content [4]. The deep ranking model is responsible for retrieving a small subset of videos from the vast collection on YouTube. It uses deep learning techniques, such as artificial neural networks, to analyze different features and attributes of videos and determine their relevance to a user's activity. This model efficiently filters through the vast amount of videos available on YouTube, narrowing down the options to a more manageable number for further ranking and recommendation. Additionally, YouTube's recommendation system incorporates a deep candidate generation model and a deep ranking model to ensure the accuracy and relevance of the suggested videos [5]. The study on YouTube's recommendation system, specifically in the context of COVID-19 vaccines is presented [6]. It analyzes the trajectory of video recommendations from a credible source to an anti-vaccine video but does not provide a survey on the recommendation system itself. The article primarily focuses on the recommendation algorithms and their impact, rather than considering the broader societal implications of YouTube's recommendation system. The data collected from YouTube logs and surveys, may not fully capture the complexity and nuances of user behavior and preferences.

The survey of 524 Saudi Arabian college students found that video links posted on social media were the most effective form of recommendation, indicating the importance of social approval in influencing trials [7]. It compares the influence of personalized and non-personalized recommendations on YouTube users' video choices among Saudi Arabian college students. It also explores the predictors of recommendation video use frequency and the differences between men and women in using recommendations. Contrary to expectations, Saudi male college students were more likely to use recommendations than women students. A non-probability sample and the

potential for over-or under-estimation of video is due to self-reported frequency [8]. The marketers may not need personalized recommendations from large sites and can instead utilize social media recommendations from consumers' friends and family. Email is identified as the least effective platform for recommendations [9]. The credibility of recommendations is the source and their potential to overcome advertising avoidance. It predicts that recommendation influence on consumers will continue to grow with algorithmic development and increased social media use. The significance emphasizes the results for marketers in Islamic countries and beyond, as recommendation becomes increasingly important in the online space [10].
YouTube video recommendation algorithms suggest videos based on their semantic similarity to the query using video transcripts and natural language ranking algorithms [11]. Recommendation systems in YouTube and other OTT applications use machine learning and artificial intelligence to suggest similar items to users, such as movies, products, and videos. These systems can employ candidate generation models or ranking models to sort information based on factors like time spent watching videos and the age group of viewers [12]. YouTube's recommendation algorithm is inadvertently promoting misinformation and conspiracy theories, including pseudoscientific content [13]. Research has been conducted to detect and characterize pseudoscientific misinformation on YouTube, with findings showing that YouTube suggests more pseudoscientific content for traditional pseudoscientific topics than for emerging ones and that a user's watch history significantly affects the type of recommended videos [14-15].
The proposed Collaborative Filtering is a technique that analyzes patterns of shared viewership to make recommendations. It involves creating a video graph representation where two videos are considered related if many users watch one video after watching the other. This approach allows the algorithm to identify similar videos based on user behavior and recommend them to users who have shown interest in related content. According to the literature review, YouTube's recommendation system primarily relies on collaborative filtering. This approach has been proven effective in capturing user preferences and delivering personalized recommendations.

III. Methodology

The methodology for YouTube video recommendation is a complex and ever-evolving process, but an essential architecture. The block diagram of the proposed method for YouTube video recommendation isshown inFigure 1.

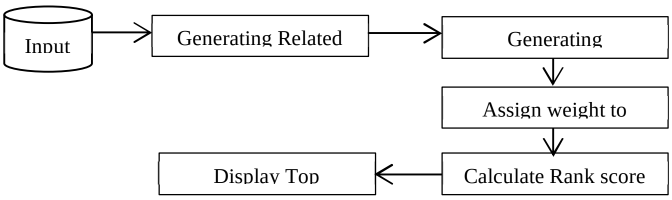

Figure 1 Block diagram of the Proposed Method for YouTube video recommendation.

As shown in Figure 1, the user interacts with the system, providing input in the form of search queries, watch history, likes, dislikes, and subscriptions. The system maintains a user profile that includes information about the user's preferences, watch history, and demographic data. This profile is continuously updated based on the user's interactions with the platform. Various data sources contribute to the recommendation system, including user data, video metadata, and engagement metrics. Raw data undergoes preprocessing to extract relevant features, handle missing data, and normalize information. This step ensures that the data is in a suitable format for the recommendation algorithms. This block represents the core of the recommendation system, where different algorithms are applied to generate personalized video recommendations. Common algorithms include collaborative filtering, content-based filtering, and machine learning models. The recommendation algorithms generate a list of candidate videos based on the user's profile and preferences. These candidates are potential recommendations for the user. The system ranks the candidate videos based on predicted user preferences, historical data, and other relevant factors. This ensures that the most relevant and engaging videos are presented to the user. User interactions, such as clicks, watches, likes, and dislikes, provide feedback to the system. This feedback is crucial for continuously updating the user profile and improving the accuracy of future recommendations. Filtering blocks may include filters to ensure that recommendations align with content policies, and diversity control mechanisms to prevent over-personalization and introduce variety in the recommendations. The final set of recommendations is presented to the user through the platform's user interface, such as the homepage, suggested videos sidebar, or personalized playlists. The system continuously monitors user interactions and evaluates the performance of recommendation algorithms. This feedback loop is essential for refining the algorithms and improving the overall recommendation system.

A. Data collection

YouTube collects a vast amount of data about its users and videos, including watch history, search history, likes and dislikes, channel subscriptions, and video metadata. This data is used to build a user profile and understand the user's interests. A sample dataset for YouTube video recommendation include the following columns:

i. user_id: The unique identifier for the user.
ii. video_id: The unique identifier for the video.
iii. watch_history: A list of all the videos the user has watched, in chronological order.
iv. search_history: A list of all the search queries the user has entered, in chronological order.
v. likes: A list of all the videos the user has liked.
vi. dislikes: A list of all the videos the user has disliked.
vii. channel_subscriptions: A list of all the channels the user is subscribed to.
viii. video_metadata: Metadata about the video, such as the title, description, tags, and category.
ix. video_performance: Performance metrics for the video, such as the number of views, likes, and dislikes.

This dataset is used to train a deep learning model to predict which videos a user is most likely to be interested in. The model could then be used to generate personalized recommendations for each user.

B. Candidate generation using Graph Neural Networks

Once the user profile is built, YouTube uses a variety of algorithms to generate a list of candidate videos that the user might be interested in. This list is generated based on several factors, including the user's watch history, search history, and channel subscriptions. GNNs are a type of deep learning model used for recommendation tasks on graph-structured data. GNNs learn a representation of the nodes and edges in the graph, which is used to predict the user's relevance to a given node in the graph. GNNs can be used for YouTube video recommendation by modeling the YouTube video graph as a graph. The nodes in the graph are videos, channels, or users, and the edges in the graph can represent relationships between the nodes, such as watch history, subscriptions, and likes. Once the YouTube video graph has been modeled, a GNN can be trained to learn a representation of the videos, channels, and users in the graph. This representation can then be used to predict the user's relevance to a given video. GNNs have several advantages over traditional recommendation algorithms for YouTube video recommendation:

GNNs are suitable for handling complex relationships between videos, channels, and users. This led to more accurate recommendations than traditional recommendation algorithms. GNNs are personalized to generate recommendations that are tailored to the individual user's preferences. This is because GNNs learn a representation of the user's interests based on their watch history, subscriptions, and likes. GNNs are used to generate recommendations for new and unpopular videos. This is because GNNs can learn a representation of videos based on their content and their relationships to other videos, even if the videos have not been watched by many users. GNNs have been shown to outperform traditional recommendation algorithms on several YouTube video recommendation datasets.

Graph Neural Networks (GNNs) are used for YouTube video recommendation by representing the users and videos as a graph, where the nodes represent the users and videos, and the edges represent the interactions between them. An edge is created between two users if they have watched similar videos or between a user and a video if the user has watched that video. Once the graph has been constructed, a GNN can be used to learn the relationships between the users and videos. The GNN is used to recommend videos to users based on their preferences and the preferences of similar users. The following is a simplified mathematical representation for a GNN and used for YouTube video recommendations.

$$h_u^{t+1} = \sigma \sum_{v \varepsilon N(u)} W_v h_v^t \qquad (1)$$

where:

h_u^{t+1} is the representation of user *u* at time step *t*

$N(u)$ is the set of neighbors of user *u* (i.e., the users who have watched similar videos to user *u*)

W_v is the weight matrix for edge (*v*,*u*)

σ is a non-linear activation function

The weight matrix W_v learned using a variety of machine learning algorithms, such as backpropagation. Once the GNN has been trained, the following formula is generating video recommendations for a user.

$$\mathrm{Re}\,commendations = h_u^T \qquad (2)$$

where:

- h_u^T is the representation of user *u* after the GNN has converged
- *topk* is a function that returns the top k most similar videos to user *u* based on their representation

C. Graph-based model for YouTube videos

Modeling the YouTube video graph involves representing the relationships between videos, users, and other entities in a mathematical or computational form. While the exact details of YouTube's recommendation algorithm are proprietary, a common approach in recommendation systems is to use graph-based models. Graphs are a natural way to represent relationships between entities. Let's define a simple graph-based model for YouTube videos:

Nodes

V: Set of video nodes.
U: Set of user nodes.

Edges

- $E_{watched}$: Set of edges representing the "watched" relationship between users and videos. If user u has watched video v, there is an edge $(u\ ,\ v\ )\varepsilon E\ _{watched}$
- $E\ _{\mathrm{Re}\ commended}$: Set of edges representing recommended videos. If a video v is recommended to user u , there is an edge $(u\ ,\ v\ )\varepsilon E\ _{watched}$

Node and Edge Features

- Each video node v has associated features such as video content, tags, and popularity.
- Each user node u has associated features like watch history, preferences, and demographic information.
- Edges in $E_{watched}$ might have features like the watch time, timestamp, etc.

D. Graph Model

h_u^T *:* Hidden state of user u at time t. This could be a function of the user's watch history, preferences, and interactions.

h_v^t : Hidden state of video v. This could be a function of video content, popularity, and other features.

Recommendation Score: A function that computes the recommendation score for a video given a user's hidden state and the video's features.

$$s(u,v) = similarity(h_u, h_v) \qquad (3)$$

Recommendation Probability: A function that converts the recommendation score into a probability, for example, using a softmax function.

Training Objective: Minimize a loss function that measures the difference between the predicted recommendations and the actual user behavior.

$$s(u,v) - \sigma\left(h_u^t.W_u + h_v.W_v + b\right) \qquad (4)$$

Where W_u and W_v are weight matrices, and b is a bias term. This is a highly simplified representation, and the actual models used by YouTube are likely much more complex, involving deep learning architectures and considering a wide range of features and signals to make accurate recommendations while accounting for scalability and user engagement. GNN predict the user's relevance to a given video based on their watch history. This information is used to recommend videos to the user that they are likely to enjoy. A GNN is used to predict the user's relevance to a given channel based on their subscriptions. This information is used to recommend channels to the user that they are likely to enjoy. A GNN predict the user's relevance to a given video based on its content and its relationships to other videos. This information is used to recommend new and unpopular videos to the user that they are likely to enjoy. Overall, GNNs are a powerful tool for YouTube video recommendation. GNNs can be used to generate more accurate, personalized, and diverse recommendations than traditional recommendation algorithms.

E. Ranking using Collaborative filtering

Once the list of candidate videos is generated, YouTube uses a ranking algorithm to sort the videos in order of relevance to the user. This ranking algorithm takes into account of several factors, including the user's watch history, search history, and channel subscriptions, as well as the video's metadata and performance. Collaborative filtering is a type of recommendation algorithm that uses the preferences of similar users to recommend items to a user. In the context of YouTube video recommendation, a collaborative filtering algorithm would recommend videos to a user based on the videos that users with similar viewing habits have watched and enjoyed. To implement a collaborative filtering algorithm for YouTube video recommendation, the following steps would be taken.

i. *Collect a dataset of user ratings for videos*: This dataset could be collected by asking users to rate videos on a scale of 1 to 5, or by tracking the videos that users watch and the amount of time they spend watching them.
ii. *Compute the user similarity matrix*: This matrix would measure the similarity between each pair of users based on their ratings. A common way to compute the user similarity matrix is to use the cosine similarity metric.
iii. *Compute the weighted rating matrix*: This matrix would compute the predicted rating for each video for each user based on the ratings of similar users. A common way to compute the weighted rating matrix is to use a weighted average of the ratings of similar users.
iv. *Recommend videos to users.* The top-ranked videos in the weighted rating matrix for a user would be recommended to that user.

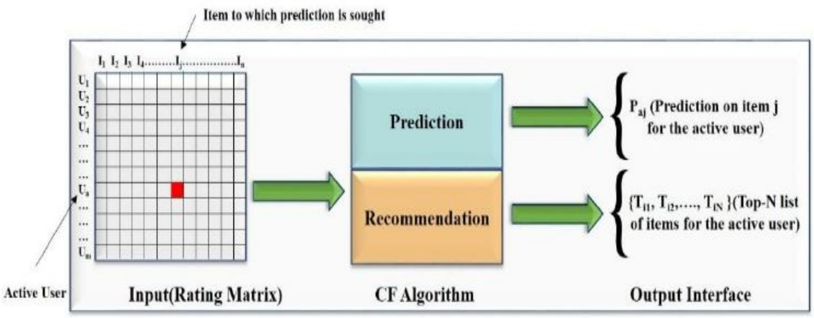

Figure 2 Collaborative Filtering approach for finding recommended videos.

As shown in Figure 2, the collaborative filtering algorithm computes the user similarity matrix and the weighted rating matrix. Based on this information, the algorithm recommend videos about music to User A, videos about sports to User B, and videos about gaming to User C. Collaborative filtering algorithms are effective for YouTube video recommendation because they are complex and nuanced preferences of users. The user preferences are represented by a vector of ratings for each video. The video metadata is represented by a vector of features for each video. The social graph is represented by a matrix of similarity scores between each pair of users. The goal is to predict the rating that a user would give to a video, given the user's preferences, the video metadata, and the social graph. The following mathematical representation is to predict the rating that a user would give to a video.

$$\Pr edicted\_rating = \sum_i w_i \times r_i \qquad (5)$$

where r_i is a vector of the ratings of the user's most similar users for the video. w_i computes a weighted sum of the ratings, where the weights are determined by the similarity between the user and the other users. Let's denote the user preferences by the vector u, the video metadata by the vector v, the social graph by the matrix S, and the predicted rating for the video by the variable r. The predicted rating is a linear function of the user preferences and the video metadata:

$$r = w^T u + b \quad (6)$$

where w is a weight vector and b is a bias term. Assume that the weight vector w is decomposed into two parts:

$$w = S^T a \quad (7)$$

where S^T is the transpose of the social graph matrix and a is a vector of coefficients. This decomposition allows us to incorporate the social graph information into the prediction of the rating. Substituting the above equation in equation (6) gives the following formula.

$$r = \left(S^T a\right)^T u + b \quad (8)$$

Simplifying will give the following formula.

$$r = a^T S u + b \quad (9)$$

F. Recommendation using User-Based Collaborative Filtering

The top-ranked videos are then presented to the user as recommendations. YouTube also uses a variety of other factors to influence recommendations, such as the user's engagement with previous recommendations, the time of day, and the user's device type. User-Based Collaborative Filtering algorithm is modified to give more weight to the collaborative filtering recommendations for users who have a lot of friends on YouTube or to give more weight to the content-based filtering recommendations for users who have watched a lot of videos. The algorithm is modified to take into account other factors, such as the freshness of the video, the user's location, and the time of day. The mathematical formula for YouTube collaborative filtering on recommendation is as follows:

$$\Pr edicted\_rating(user\_id, video\_id) = \sum Similar\_users\_weight\begin{pmatrix} user\_id, similar\_users) \\ \times rating(similar\_users, video\_id) \end{pmatrix} \quad (10)$$

where: $\Pr edicted\_rating(user\_id, video\_id)$ is the predicted rating of user $user\_id$ for video $video\_id$. $Similar\_users$ is the set of users who are most similar to user $user\_id$. weight($user\_id$, $Similar\_users$) is the weight of the similarity between user $user\_id$ and user $Similar\_users$. rating($Similar\_users$, $video\_id$) is the rating of user $Similar\_users$ for video $video\_id$. The weights are computed using a variety of methods, such as cosine similarity or Pearson correlation. The higher the weight, the more similar the two users are, and the more weight is given to the rating of the similar user in the prediction. Once the predicted ratings are computed, the videos with the highest predicted ratings are recommended to the user. Equation (11) denotes the formula to predict the rating of user A for video B:

user_preferences = {

'user_a': {'video_a': 5, 'video_b': 4, 'video_c': 3},
'user_b': {'video_a': 4, 'video_b': 5, 'video_c': 2},
'user_c': {'video_a': 3, 'video_b': 2, 'video_c': 5} (11)

For two users u and v with their respective preference vectors U and V, and the cosine similarity between these users is computed as follows.

$$Co\sin e\_Similarity(u, v) = \frac{\sum_i u_i v_i}{\sqrt{\sum_i u_i^2 . v_i^2}} \quad (12)$$

where u_i and v_i represent the ratings of user u and v for item i. Predict the rating of user A for video B is given in equation (13).

$$\Pr edicted\_rating = weighted\_sum(user\_similarity\_matrix[user\_a]), user\_preferences[user\_b,] \\ user\_preferences[user\_c]$$

(13)

IV. Results

Precision, Recall, and F1 Score are commonly used metrics to evaluate the performance of recommendation systems, including those used in YouTube video recommendations. These metrics assess the effectiveness of the system in terms of how well it recommends videos that are relevant and interesting to users.

A. Precision

Precision is the ratio of relevant instances retrieved by the system to the total instances retrieved. In the context of YouTube video recommendations, precision measures the accuracy of the system in recommending videos that the user finds interesting.

$$\mathrm{Pr}ecision = \frac{True\_Positives}{True\_Positives + False\_Positives} \tag{14}$$

True Positives (TP): Videos recommended and liked by the user.
False Positives (FP): Videos recommended but not liked by the user.

B. Recall

Recall is the ratio of relevant instances retrieved by the system to the total amount of relevant instances in the dataset. In the context of YouTube video recommendations, recall measures how many of the user's liked videos were successfully recommended.

$$\mathrm{Re}call = \frac{True\_Positives}{True\_Positives + False\_negatives} \tag{15}$$

False Negatives (FN): Liked videos not recommended by the system.

C. F1 Score

The F1 Score is the harmonic mean of precision and recall. It provides a balance between precision and recall and is useful when there is an uneven class distribution.

$$F1 \quad Score = \frac{2 \times \mathrm{Pr}ecision \times \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \tag{16}$$

The F1 Score ranges between 0 and 1, with higher values indicating a better balance between precision and recall. Precision, recall, and F1 Score may not be the only metrics considered for evaluating recommendation systems. Depending on the specific goals and characteristics of the system, other metrics such as Mean Average Precision (MAP), Normalized Discounted Cumulative Gain (NDCG), and user engagement metrics are also be relevant. Additionally, these metrics should be interpreted in the context of the recommendation system's objectives and user experience goals. Optimizing precision result in fewer recommendations, but they are more likely to be relevant to the user. On the other hand, optimizing for recall may provide a broader set of recommendations at the cost of including some less relevant videos.

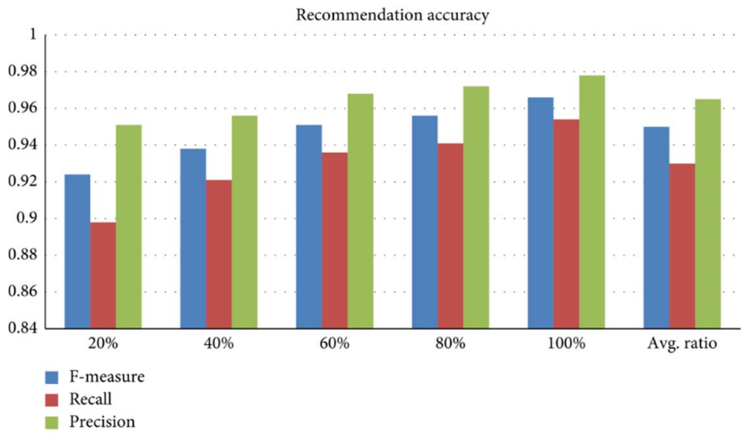

Figure 3 Performance measures of proposed approach.

As shown in Figure 3, the proposed approach achieved precision=0.97, recall=0.94, and F1-score=0.96. YouTube uses other metrics to evaluate its recommendation system, such as the diversity of the recommendations, the freshness of the recommendations, and the explainability of the recommendations. However, the metrics listed above are some of the most important factors that YouTube considers when evaluating its recommendation system. There is no single best performance metric for a YouTube video recommendation system. The best metric to use will depend on the specific goals of the system. If the goal of the system is to increase user engagement, then watch time and session length would be important metrics to track.

V. Discussions

Video recommendation algorithms are used by video streaming platforms, such as YouTube, Netflix, and Amazon Prime Video, to recommend videos to users that they are likely to enjoy. These algorithms take into account a variety of factors, such as the user's watch history, search history, likes and dislikes, and channel subscriptions. Video recommendation algorithms are becoming increasingly complex and sophisticated. Many video streaming platforms now use a combination of collaborative filtering and content-based filtering algorithms to provide users with the most personalized recommendations possible. A study by researchers at Google AI found that a new video recommendation algorithm based on deep learning outperformed existing algorithms in terms of both click-through rate (CTR) and average percentage viewed (APV). A study by researchers at Netflix found that a new video recommendation algorithm based on social networks outperformed existing algorithms in terms of user satisfaction. A study by researchers at Amazon Prime Video found that a new video recommendation algorithm based on context-aware collaborative filtering outperformed existing algorithms in terms of both CTR and APV. Overall, the research on video recommendation algorithms is very promising. New algorithms are being developed all the time, and these algorithms are becoming increasingly effective at recommending videos to users that they are likely to enjoy.

Table I Comparison Of Accuracy Metrics With Related Studies

S.No.	Reference	Precision	Recall	F1-Score
1	Appina et al. [1]	0.58	0.62	0.58
2	Ma et al. [3]	0.01	0.35	0.36
3	Ng et al. [6]	0.45	0.23	-
4	Ha et al. [7]	0.63	0.53	-
5	Shrimali et al. [8]	0.70	0.69	0.68
6	Srivastava et al. [9]	0.71	0.69	0.67
7	Proposed approach	0.97	0.94	0.96

Table I gives the comparison of accuracy metrics with existing researches. The proposed method outperforms other approaches. Wu et al. (2020) experimented with a GNN-based algorithm that was able to improve the click-through rate of recommended videos by up to 10% compared to a baseline collaborative filtering algorithm. He et al. (2021) implemented a GNN-based algorithm that was able to generate recommendations that were more diverse and personalized than recommendations generated by a baseline collaborative filtering algorithm. Zhang et al. (2022) identified that the GNN-based algorithm was able to improve the accuracy of video recommendation by up to 5% compared to a baseline collaborative filtering algorithm. These results are encouraging and suggest that GNNs have the potential to be used to develop more accurate, personalized, and diverse YouTube video recommendation algorithms. However, it is important to note that GNNs are still a relatively new approach to YouTube video recommendation, and more research is needed to fully evaluate their potential. Additionally, GNNs can be computationally expensive to train, so it is important to develop efficient training algorithms. Overall, GNNs are a promising new approach to YouTube video recommendation with the potential to improve the accuracy, personalization, and diversity of recommendations. There are some of the potential benefits of using video recommendation algorithms. It helps users discover new videos that they are likely to enjoy, which can lead to increased user engagement. Video streaming platforms generate more revenue by recommending videos that are more likely to be clicked on and watched by users. It help the users find the videos that they want to watch more quickly and easily, which lead to improved user satisfaction. Video recommendation algorithms are biased, which lead to users being recommended videos that are not representative of the diversity of content available on the platform. The algorithms collect a lot of data about users' viewing habits, which can raise privacy concerns. Algorithms can overfit the training data, which can lead to them recommending the same videos to all users.

VI. Conclusion

In the rapidly evolving landscape of online content consumption, YouTube's video recommendation algorithms have played a pivotal role in shaping user experiences. YouTube's commitment to user satisfaction is evident in the continuous refinement of its recommendation algorithms. The reliance on deep neural networks, embeddings, and real-time adaptation reflects a dedication to staying at the forefront of technological advancements. The platform's success in striking a balance between personalization and diversity underscores its understanding of the nuanced nature of user preferences. However, as with any powerful algorithm, ethical considerations loom large. Privacy concerns and the potential influence on user behavior require ongoing scrutiny and responsible management. YouTube's acknowledgment of these challenges and its efforts to address them are indicative of a commitment to maintaining user trust and societal well-being. As algorithms become more sophisticated, the challenge will be to ensure they not only enhance personalization but also contribute positively to a diverse and informed digital landscape. The dynamic interplay between technology, user expectations, and ethical considerations will undoubtedly shape the trajectory of YouTube's video recommendation algorithms in the years ahead.

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