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Multi-Level Multiple Learning-Based Recommendation (Mmlr) Model For Youtube Recommendation And Security Enhancement

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ABSTRACT

As many entertaining social media factors are evolving around online and YouTube is the topmost entertainer. In YouTube, the anchors' list increases day-by-day making the selection tough for the viewers to select their favorite anchors and follow them. To avoid these confusing circumstances and to effectively choose the right anchor an efficient recommendation system is required. The main aim of the paper is to produce an effective, secured data transaction over streaming platforms. Generally, the user's preference and creator's preference changes over time. In the previous system, there were algorithms to study only viewer's choices and prefer contents according to them. In the proposed system a deep learning and preference matching on both the anchors' preference and user's preference is made manually and automatically. A novel 'Multi-level Multiple learning-based recommendation (MMLR)' model for YouTube recommendation is proposed. Further, the system concentrates on the data transaction and its security. Several optimized techniques such as cuckoo hashing, elliptic curve cryptographic algorithm (ECC), fault tolerance, and anonymity maintenance to provide secure data transaction on cloud streaming platforms. To evaluate the performance of the proposed model, the paper initializes experiments on real datasets, and the result proves that the system outperforms all other recommendation models.

Keyword- Recommendation system, elliptic curve cryptographic algorithm (ECC), cuckoo hashing, cloud streaming plat

I. INTRODUCTION

Cloud live Streaming (YouTube) has shown immense growth recently where millions of users are active as followers. YouTube is the world's largest platform for creating and sharing content-based videos providing opportunities for real creators. Every efficient content creator can succeed as an anchor by delivering their specialty in this YouTube platform. The viewers not only watch the content they participate in the live streaming with some personal details, involve in advertisement display, price sending mechanism by trusting and following them. With the increasing anchors' list, it is tough for the users' to choose the best broadcasting anchor over the net. But the issue can be solved by emphasizing a deep learning recommendation system for live streaming paths[1].

A deep study of modeling the users' and anchor's behavior over every live streaming is monitored. The recommendations are deliberated according to the priority from low to high [2]. A 'Multi-level Multiple learning-based recommendations (MMLR)' model was proposed for an effective recommendation in YouTube. The main contributions of the proposed paper are reminded as follows.

The system proposes deep learning of the user and content creators' preferences. A deep learning model for creators' live streaming recommendations on YouTube considering the preferences of both is made.

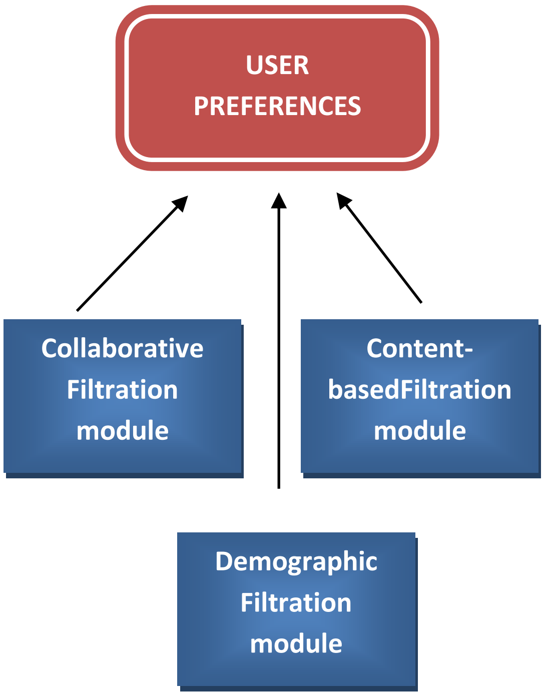


Figure 1. User Preference-Based Recommendation (Filtration Process)

In figure 1.According to the user preferences, the recommendation is validated and implemented. Some filtration process is done before the recommendation is preferred. The three basic **User Preference-Based** filtration process are listed below:

1. **Content-Based Filtration Process**: This process describes and collects the past search of the user. And delivers anchors content according to the user requirements. The keyword search is extracted and using the referral keyword the recommendations are made.

1. **Collaborative Filtration Process:** This process keeps a record of ratings and suggests according to the highest and most searched rated items or information.

1. **Demographic modules**: This process retains a collection of users' attributes. The attributes are filled by the user himself or collected while social sign up.

The main theory is called the Multi-level Multiple learning-based recommendation (MMLR) model ensured in the proposed model that undergoes multiple recommendations. Through, this model the matching preferences of anchors and viewers are captured for a better recommendation.

Further, the system emerges several algorithmic techniques such as cuckoo hashing, elliptic curve cryptographic algorithm (ECC), fault tolerance, and anonymity maintenance to enhance the security in the live streaming platform.

Experimental analysis on comparing with the previous recommendation systems is conducted. The experimental analysis is proved best comparatively.

The paper's remainder is summarized as follows. Section 2 deliberates the related work of the paper. Section 3 represents the methodologies involved in the proposed model. Section 4 represents the techniques used in the system. The experimental analysis and results are discussed in section 5. At last, the conclusion of the paper is formatted in Section 6.

I. RELATED WORK

As there are evolving anchors' in YouTube the preferences of the user change constantly. To overcome the data overload and security problems a mechanism named socially constrained recommendations is found. This method provides a proper diffusion of contents analyzing the user constraints online [3].

The security issue is being a big concern as the security threats are increasing immensely, that many organizations have faced at present. Many encrypting techniques and splitting techniques were used. There are several methods to provide security over data transactions. Some of the security-related algorithms are the elliptic curve cryptographic algorithm (ECC), RSA public-key cryptosystem, Cuckoo Hashing [4], and fault tolerance. The proposal uses the Multi-level Multiple learning-based recommendation (MMLR) model for YouTube recommendation. The other technique for encryption and decryption uses various algorithms. Deep-learning techniques used in recommendation systems are also compiled in research [6]. The research presented by Batmaz et al., briefly represents the development techniques, that emphasis on the problems and challenges that can be faced by deep learning in recommendation [7]. Li et al. evaluated deep learning of user's preference on recent behavior and behavioral history by RNN method. P. Lops et al., in [8] reviews Recommender system (RS) **accounting** for the content-based recommendation history on the latest trend [9]. The survey expands the usage of Link Open Data (LOD) and user-generated data and projects e-learning. The systematic approach in [9] flows on user preferences (UP) or their efficiency has been improved using UP [10].

II. SYSTEMATIC METHOD MMLR

The systematic theory of recommendation system defines a detailed discussion about various methodologies. The system proposes a deep learning and a novel theory named as Multi-level Multiple learning-based recommendation (MMLR)' model to enhance the recommendation theory. In this recommendation scheme, multiple key generation algorithms and multiple learning are executed.The below figure 2. Shows the methods used in the proposed system and architecture of the proposed system.

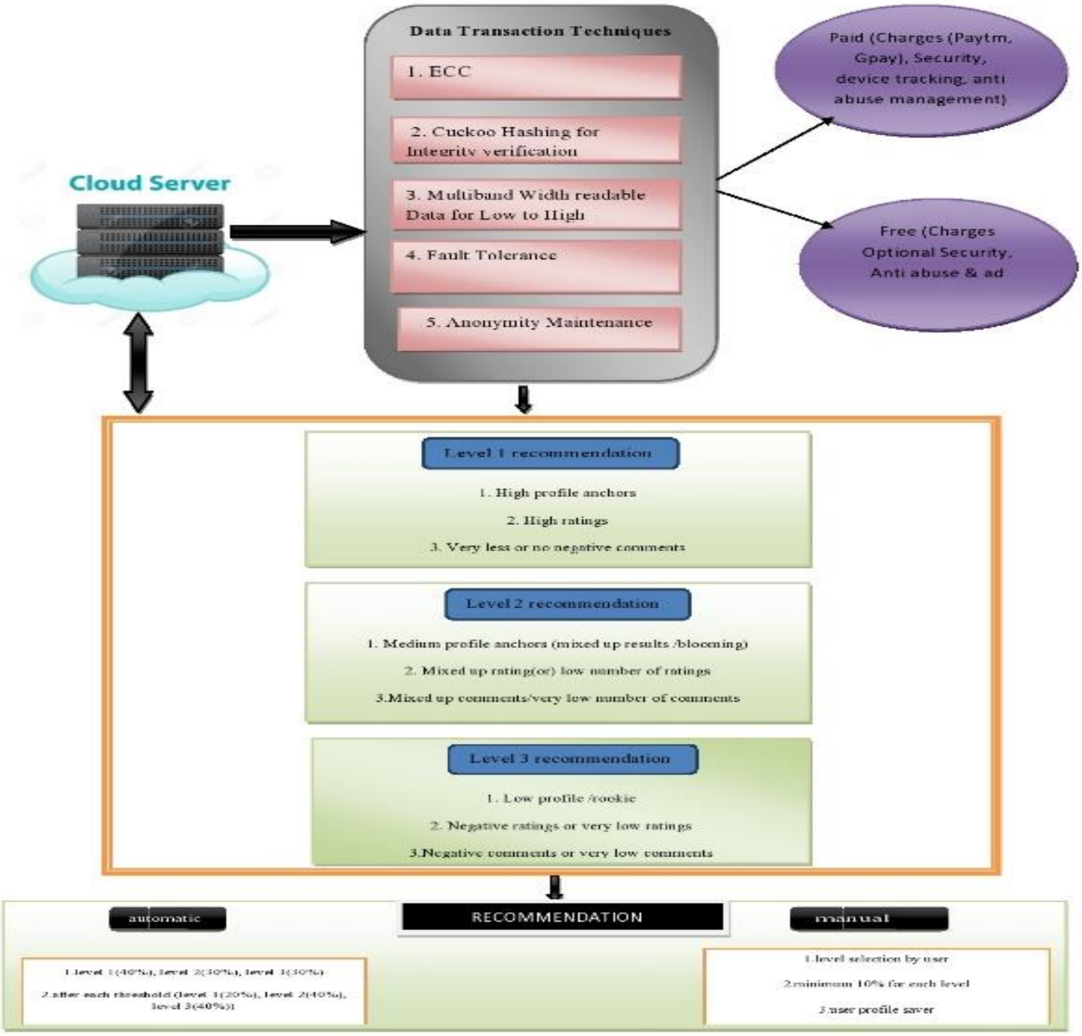


Figure 2. Architecture of Proposed Model

A cloud server is created permitting two suggestions in YouTube one is free and the next is paid.

i. **Free Version:** Free in free track the charges are optional and the choice is allowed to user preference supporting (Paytm, Gpay, etc...). the scheme concentrates on the security of the data-sharing duplicate copies among the platform and on another platform. In case of any unusual activity of sharing is found immediately, a copyright strike is given. The platform has allocated some primitive measures to stop repetition and multi-user track. Further, the authorities ensure anti-abuse comments management and advertisement management to stop negative comments and misuse of ads.

ii. **Paid Version:** the paid version is built in a way that permits charges on anchors' request. If any security measures are exceeded immediately copyright claim/strike is given after 3 strikes then the account gets terminated. For a classic representation, the user device tracking is done with the permission of the user and the personal data are kept confidential without any data leak. When the data usage is done the data is deleted at once it is completed. The negative or abusive comments management is triggered when an abusive comment is posted. The negative comments are deleted considering the reputation of the concerned anchor.

ALGORITHM 1

The below algorithm provides input data and occurs achor recommendation. CSP provides anchor recommendation for users. Some of the data transaction techniques are usednamelyECC_{ds}elliptic curve cryptography for data streaming, C_h Cuckoo hashing and fault tolerance. The transaction undergoes free and paid methods with optional charges Oc, Security Duplication Ds, Multi-user Tracking Mut, Anti abuse management ACm and advertisement Management Am. Further the syste, Performs Automatic recommendation with Level 1 ($L1_{10}$,$L2_{30}$,$L3_{30}$and varies $L1_{10}$,$L2_{40}$,$L3_{40)s}$ time. User level selection is offered and user can choose there level. As the ouputa accurate anchor recommendation is made.

Algorithm1. MMLR: Multi-Level Multiple Learning-Based Recommendation Algorithm

Input: D_s // streaming data
Output: A_r //anchor recommendation
Initialization: cloud service provider provides anchor recommendation for users
While (D_s) //data streaming(providing data security)
$ECC_{ds} \longleftarrow$ elliptic curve cryptography for data streaming
$C_h \longleftarrow$ cuckoo hashing for data integrity verification
$F_t \longleftarrow$ fault tolerance for data recovery
$A_m \longleftarrow$ annonimity maintainance
If (D_{sf}) **then** // free data streaming
$O_c \longleftarrow$ optional charges
$D_s \longleftarrow$ security for duplication
$M_{ut} \longleftarrow$ multi user tracking
$AC_m \longleftarrow$ anti abuse comments management
$A_m \longleftarrow$ advertisement management
End if
If (D_{sp}) **then** // paid data streaming
$D_c \longleftarrow$ data copyrights
$UD_t \longleftarrow$ user device tracking
$AC_m \longleftarrow$ anti abuse comments management
$A_m \longleftarrow$ advertisement management
End if
If (A_r) **then** // automatic recommendation
If (D_s>T) **then** // data stream greater than threshold(level assignment)
$L1_{40} \longleftarrow$ level 1 40 percent
$L2_{30} \longleftarrow$ level 2 30 percent
$L3_{30} \longleftarrow$ level 3 30 percent
Else
$L1_{10} \longleftarrow$ level 1 10 percent
$L2_{40} \longleftarrow$ level 2 40 percent
$L3_{40} \longleftarrow$ level 3 40 percent
End if
If (M_r) **then** // manual recommendation
$M_{10} \longleftarrow$ minimum 10 percent
$U_l \longleftarrow$ user level selection
End if
End while

2.1 DATA TRANSACTION TECHNIQUES

Cloud ensures some major security-related algorithms in live streaming data transactions. The algorithmic method used in the proposed method is cuckoo hashing, elliptic curve cryptographic (ECC), fault tolerance, and anonymity maintenance.

3.1.1 Elliptic curve cryptographic (ECC)

Generally in live streaming or any other social network security is a challenging task. To provide secure communication among the content creators and users a high-level security algorithm is required [10-12]. The system deliberates a public key cryptographic algorithm named 'Elliptic Curve Cryptography (ECC)' to process encryption and decryption of data. ECC is an algebraic form of an elliptical curve that emphasizes finite field cryptography that requires lesser bit keys managing with an equal security level.

3.1.2 Cuckoo hashing Technique

Cuckoo is a dictionary-type hashing technique that involves 2 or more hashing attributes resolving hash collisions. The cuckoo hash technique intrudes a load balancing and supports effective queries that utilize constant time even in bad cases. In the proposal, the cuckoo hash technique is used for data occupation the available positions are suggested, and the user data.

3.1.3 Multi Bandwidth Readability:

A multi-level bandwidth readability scheme is maintained that reads data from low to high range. The bandwidth ranges are noted and the variations are validated and maintained sequentially.

3.1.4 Fault Tolerance

The technique involves the recovery of data lost and proposes a fault tolerating mechanism algorithm processed for tolerating the data corruption, data loss, or even abusive comments.

3.1.5 Anonymity Maintenance:

This level scheme maintains all the personal details of the user and the anchors'. Proper data maintenance is initiated where all the records, transactions/data sharing are handled securely.

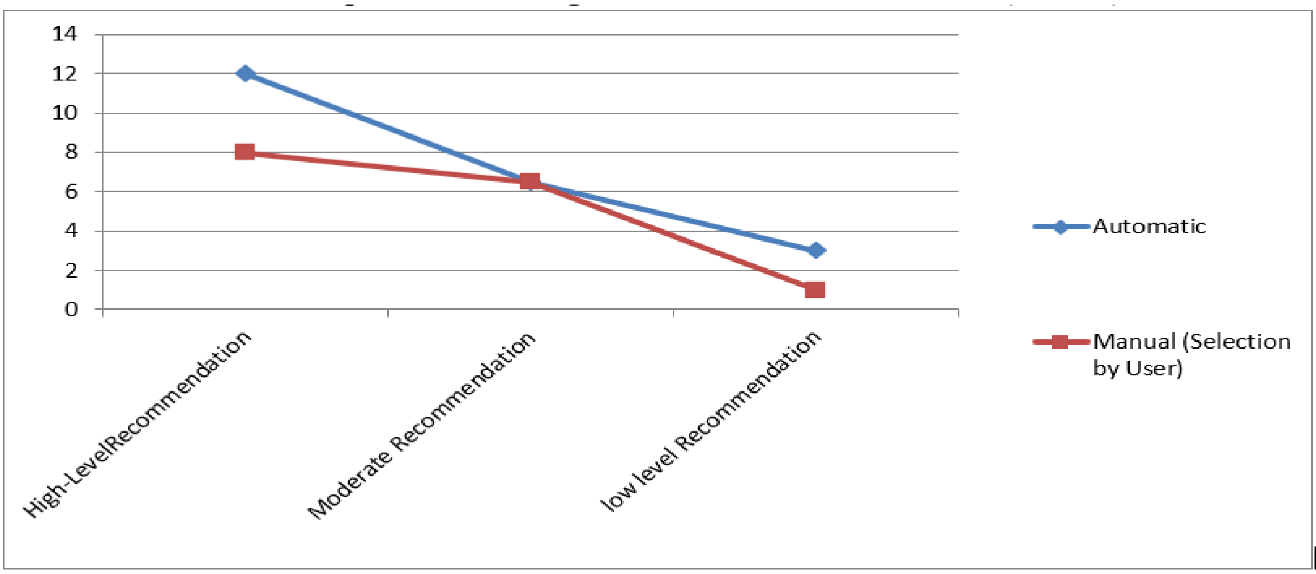
2.2 RECOMMENDATION PROCESS

The recommendation process in the prosed system undergoes three major categorizations level 1, level 2, and level 3 recommendation. The live streaming suggestion is classified as High-level, middle-level, and low-level.

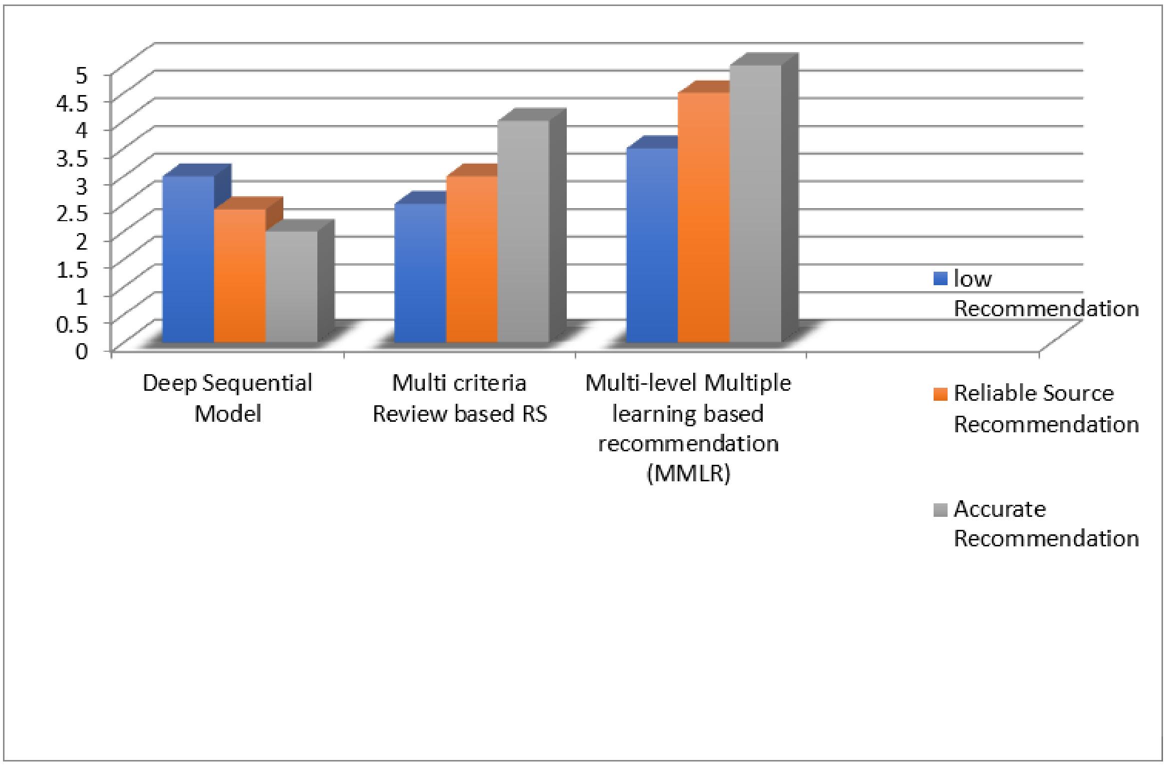
- Level 1 Recommendation: Level 1 recommendation is the high-level category in this category the system categorizes all the successful YouTubers and top content creators in the first level.
- Level 2 Recommendation: level 2 recommendation is middle-level categorization which indulges all the moderate level creators are focussed that privilege both negative comments and positive comments in common. The general system concentrates and focuses on a rating basis.
- Level 3 Recommendation: the last level is level 3 which is the Low-level categorization that involves the low profile start-up channels and initial stage creators who have not reached an extent.

IV. RESULT ANALYSIS

In the result analysis, a comparison of all the preceding algorithms is done. The experiments are done both manually and automatically. In automatic consideration the validation is done via level optimization (level 1(40%), level 2(30%), level 3(30%)). After each threshold measurement, the level varies according to the rating prediction. According to the threshold changes, the values get differed (level 1(10%), level 2(40%), level 3 (60%) all the variations are noted and recommendations implemented automatically. Whereas, in manual consideration, the level selection is done manually according to the users' preferences. In Graph 2 a comparative analysis with existing algorithms such as Deep Sequential Model, Multi-criteria Review based RS with proposed Multi-



Graph 1. Recommendation Automatic Vs Manual



Graph 2 . COMPARITIVE ANALYSIS OF VARIOUS EXISTING ALGORITHM

V. CONCLUSION

Inthis paper, a deep study of challenges faced by recommendations on live streaming is discussed. The previous system used a deep sequential method which is not that efficient in providing security towards the user and anchor. The system proposes 'Multi-level Multiple learning-based recommendations (MMLR)' that indulge multiple security-related algorithms such as ECC, Cuckoo hashing and fault tolerance mechanism, etc. The system further emphasizes a three-level recommendation category that delivers a clear vision on recommendations from high to low on users' preference manually and automatically. The proposed model can also be operated on other recommendation scenarios. the result analysis conducted on a live streaming dataset is discussed and a comparative analysis is provided for better analysis. As multiple level and deep learning is implemented the quality, effectiveness, and accuracy of the recommendation performance is improvised to a stage.

FUTURE ENHANCEMENT

In a future study, the video content improvisation muststudiedin detail and an algorithm to improve the quality of the video is outperformed. Also, in the future, a higher level of online broadcasting should be done.

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