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Recommender Systems: A Review

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Abstract:The way in which the growth in the available digital information and the number of users on the Internet have created a challenge of data overload causes timely access to item of interest on the Internet. Many of the information retrieval systems try to solve this problem but prioritization of item and user were absent in most of the systems. The purpose of this paper is to develop a recommender system using collaborative filtering technique and Fuzzy C-mean (FCM). Collaborative filtering is the most successful algorithm in the recommender system's field. Recommender systems are the systems for filtering the information that handle with the problem of overloaded information by filtering important information fragment out of huge amount of dynamically generated information according to user's interest, preferences or observed behaviour about them. . This paper considers m users, n number of items and present an approach based on FCM clustering to produce a recommendation for the active user by a new approach. Here FCM clustering algorithm to categorize users based on their interests.
Keywords:Recommender system, item based collaborative filtering, user based collaborative filtering content based filtering, Knowledge based recommendation,

I. INTRODUCTION

Recommender system (sometimes replacing "system" with platform or engine) is a subclass of information filtering system that deal with the problem of information overload by filtering vital information out of large amount of dynamically generated information and to predict the "rating" or "preference" that a user would give to an item[1].

Recommender systems are most accepted in these eras, and are also used in a various fields available online including books, movies, music, news, mobile phones, research articles, home products, electronic products etc. There are also recommender systems for restaurants, jokes, ethnic wares, bangles etc.

Most of the recommender systems aim in an information filtering, which deals with the delivery of items selected from a large collection that the user is likely to find interesting or useful. Recommender systems are also called as special types of information filtering systems that predicts items and suggest to users[4]. To efficiently identify the invalid signatures in bad batches, instead of verifying each signature individually, divide-and-conquer techniques have been proposed [6]. Those methods can dramatically reduce the identification time at different levels. However, there are two limitations in existing works. One is that many methods are designed only for some particular batch types, such as RSA-type batches [7], and pairing-based batches [8]. Though these works are state-of-the-art, it is challenging to apply them with the various batch verification algorithms. Thei

rrr performance may heavily degrade if the ratio of invalid signatures varies when adversaries change attack frequencies and locations. In 2012,Akinyele et al. first proposed an automated tool for selecting the most

An engine, in software point of view, is a special-purpose program that performs a task through a variable algorithm, often as a feature of some larger program. A search engine is a kind of engine that provide recommendation, responding to search queries with a set of results that are theoretically the search engine's best suggestions for websites that satisfy the user's query, based on the search term plus other data, such as location and trending topics[2].

Recommender system is a software that analyzes the huge amount of data available from online to make suggestions for products that a website user might be interested in, such as a movies, music, books, a video or a job.

A. Data:

Recommender system works on input data and applies some recommendation algorithm and produces output data as a recommendation. But the question is what is that input data and output data? In recommender system the

Inputs: U, u, I, i

Where U = set of online users whose preferences are known.

u = users for whom the recommendations need to be generated.

I = set of items over which recommendations might be made.

i = item for which we would like to predicts u's preferences.

Output: u likes i?

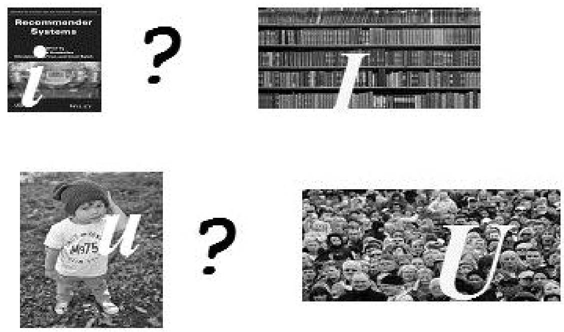

Fig. 1Input data

Fig. 2Output data

II. PHASES OF RECOMMENDATION SYSTEM

Recommendation system consists of three phases as in Fig. 3 below.

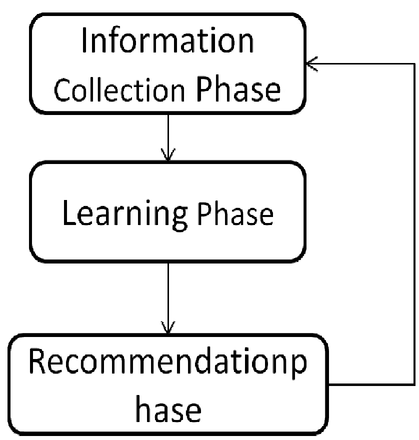

Fig.3 recommendation phases

A. Information collection phase

The information collection phase collects relevant information of users to generate a user profile for the recommendation including user's attribute, behaviours or content of the resources, the user accesses. A recommendation algorithm cannot function correctly until the user profile has been well constructed [3].

Information of a user can be collected in 3 ways.

1) *Explicit feedback:* The system normally prompts the user through the system interface to provide ratings for items in order to construct and improve his model. The accuracy of recommendation depends on the quantity of ratings provided by the user. The only shortcoming of this method is, it requires effort from the users and also, users are not always ready to supply enough information [11].

2) Implicit feedback

The system automatically inherits the user's choices by monitoring the different actions of users such as the history of purchases, navigation history, and time spent on some web pages, links followed by the user, content of e-mail and button clicks among others [15].Implicit feedback reduces the burden on users by inferring their user's preferences from their behaviour with the system. The method though does not require effort from the user.

3) *Hybrid feedback:* The strengths of both implicit and explicit feedback can be combined in a hybrid system in order to minimize their weaknesses and get a best performing system. This can be achieved by using an implicit data as a check on explicit rating or allowing user to give explicit feedback only when he chooses to express explicit interest[6].

B. Learning phase

It applies any one learning algorithms to filter and extract the user's features from the feedback collected in information collection phase.

C. Prediction/recommendation phase

It recommends or predicts what kind of items the user may like. This can be made either directly based on the data set collected in information collection phase which could be memory based or model based.

III.RECOMMENDATION TECHNIQUES

Recommendation techniques are the agents that attempt to forecast which items out of a large pool, a user may be motivated in and recommend the best ones to the user [8].

A. The techniques Can Be Classified based On The Information Sources They Use. The Available Sources Are

1) The user features (demographics)(Example age, gender, location, income).
2) The item features (Example keywords, category).
3) The user item rating (transaction data, explicit rating).
4) Knowledge (about user an item).

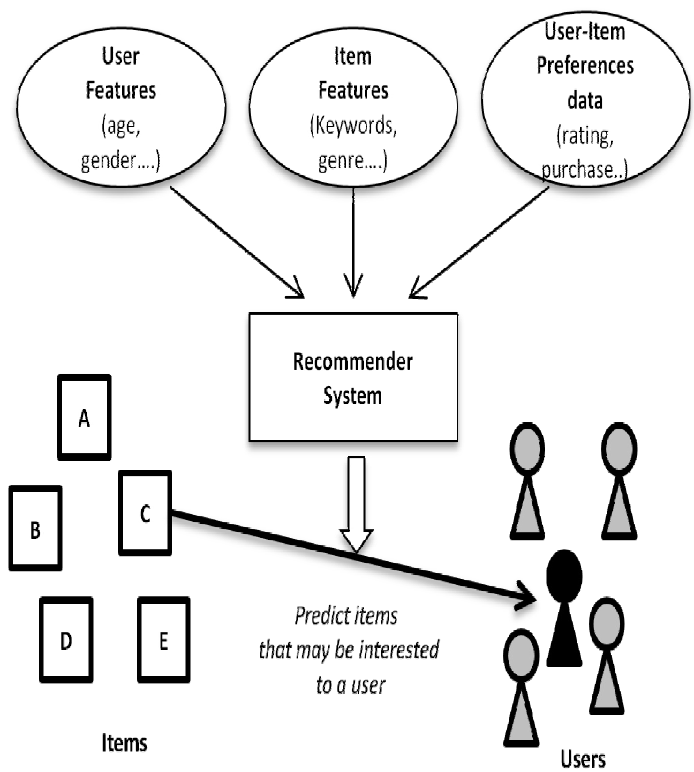

Fig. 4 Recommendation phases

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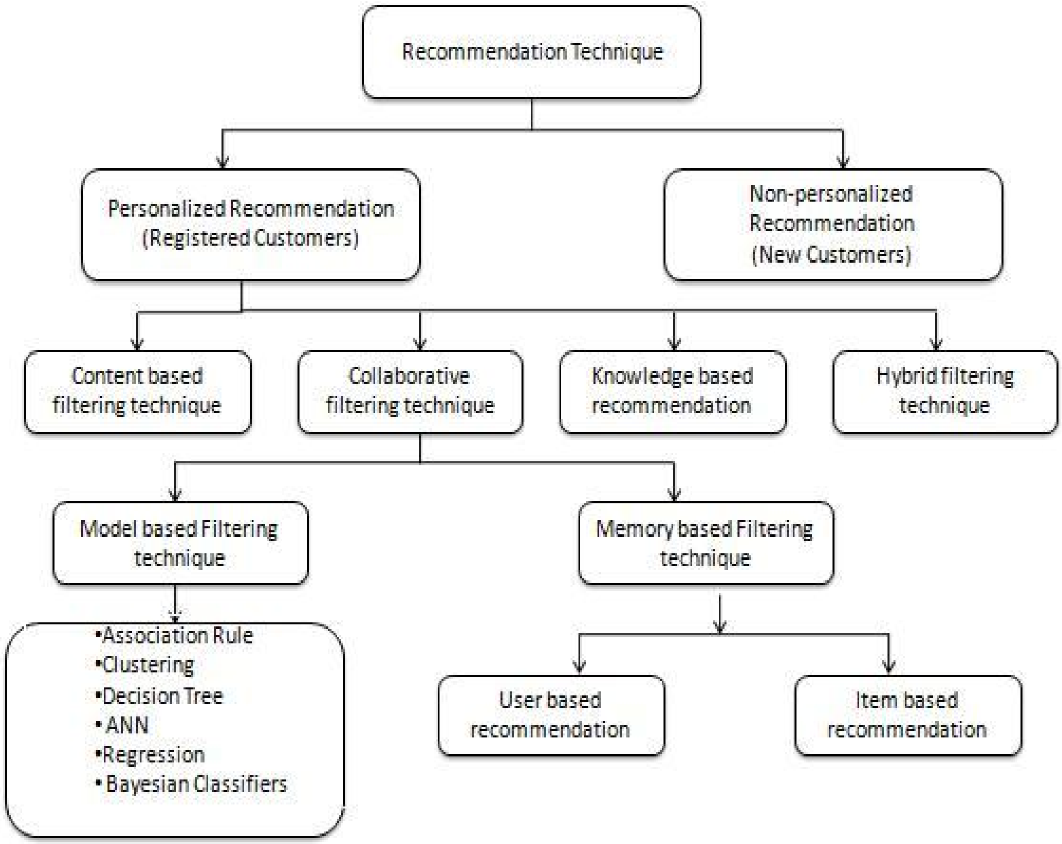

Fig.5 Recommendation techniques

For good and useful recommendation an efficient and accurate recommendation technique is very important. Figure 5 shows the different recommendation filtering techniques.

B. Content-based filtering

Content based recommendation method use information about item features and rating a user has given to items. The technique combines rating to the profile of user's interest based on features of rated items. Content-based technique is a domain-dependent algorithm. It emphasizes more on the analysis of the items in order to generate recommendations. When documents such as web pages, publications and news are to be recommended, content-based filtering technique is the most successful [17].

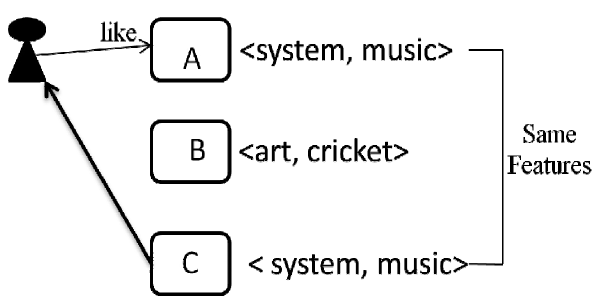

Fig. 5 Recommendation techniques

For example when you go for buying a saree may be a sales girl advises you to buy some saree according To your style and preferences.

Content-based recommender systems work with profiles of users that are created at the beginning [21].

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Table i
Movie the user has watched

Movies	Golmal	Bahubali	Shhhhhh	Dilwale
Ratings	3	5	4	2

Table ii
Movie the user has watched

Movies	Comedy	Violence	Horror	Drama
Shhhhh	2	3	2	1
Judwa	1	1	1	3
13B	3	3	5	4
……	……..	…….	………	……..

C. Advantages
1) No cold start and sparsity problem.
2) It can provide explanation for recommendation.
3) It is able to recommend users with unique taste.
4) No data is required on other users.

D. Disadvantages
1) Data must be structured.
2) Quality judgement cannot be made.

E. Collaborative filtering
Collaborative filtering is a technique which recommends items preferred by similar users. Collaborative filtering is a domain-independent prediction technique for content that cannot easily and adequately be described by metadata such as movies and music. Collaborative filtering technique works by building a database of preferences for items by users. It then matches users with relevant interest and preferences by calculating similarities between their profiles to make recommendation [23].
1) *Memory based techniques:* Memory-based Collaborative Filtering can be achieved in two ways through user-based and item-based techniques.

User based collaborative filtering technique calculates similarity between users by comparing their ratings on the same item, and it then computes the predicted rating for an item by the active user as a weighted average of the ratings of the item by users similar to the active user where weights are the similarities of these users with the target item [24].

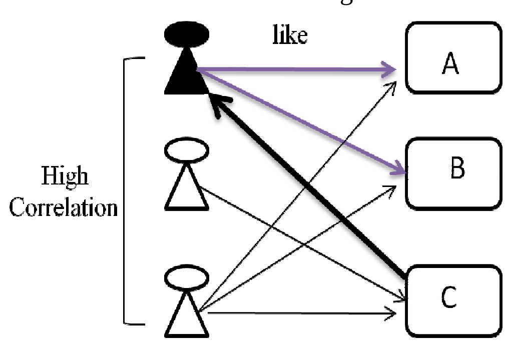

Fig. 6: User based collaborative filtering

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User Correlation:

$$userSim(u,n) = \frac{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)(r_{ni} - \bar{r}_n)}{\sqrt{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \subset CR_{u,n}} (r_{ni} - \bar{r}_n)^2}}$$

Where

User Sim (u, n) = similarity between two users u and n.

r_{ui} = Rating given to the item i by the user u.

$\bar{r}_u$ = mean rating given by the user u.

ur_{ni} = Rating given to the item i by the user n.

$\bar{r}_n$ = mean rating given by the user n

Prediction function

$$pred(u,i) = \bar{r}_u + \frac{\sum_{n \subset neighbors(u)} userSim(u,n) \cdot (r_{ni} - \bar{r}_n)}{\sum_{n \subset neighbors(u)} userSim(u,n)}$$

Item based filtering technique the taste of user remains constant or change very little. Similar items build neighbour-hoods based on users. After that system generates recommendations with items in the neighbour-hood that a user would prefer.

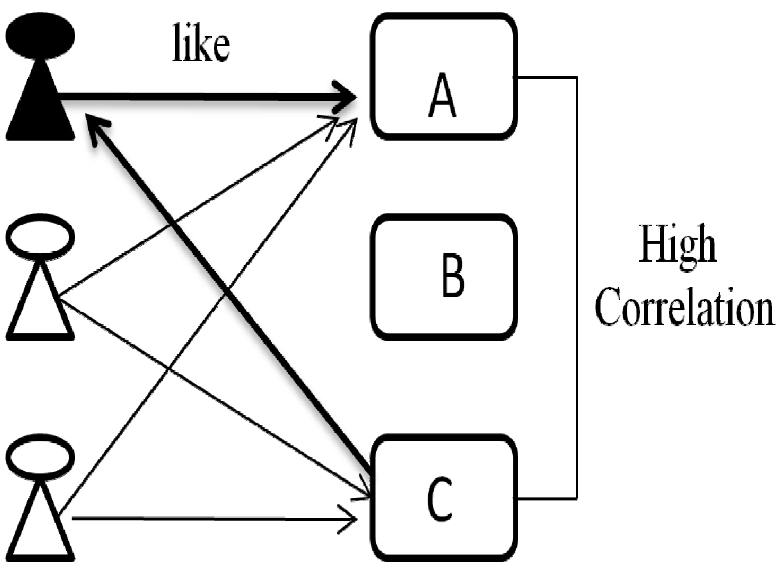

Fig. 6: Item based collaborative filtering

Item similarity

Where

Item Sim= similarity between two items i and j.

r_{ui} = rating given to item i by the user u.

r_{uj} = rating given to item j by the user u.

$\bar{r}_u$ = mean rating given by user u.

Prediction Function

$$pred(u,i) = \frac{\sum_{j \in ratedItems(u)} itemSim(i,j) \cdot r_{ui}}{\sum_{j \in ratedItems(u)} itemSim(i,j)}$$

User based VS Item Based:

Table iii
User based vs item based

	User Based	Item Based
Scalability	Bad when user size is large	Bad when item size is large
Explanation	Bad	Good
Novelty	Bad	Good
Coverage	Bad	Good
Cold Start	Bad for new users	Bad for new items
Performance	Need to get many user's history	Only need to get current user's history

2) *Model based techniques:* Model based filtering technique uses the previous rating to learn a model to improve performance of collaborative filtering technique. It can be done using data mining or machine learning techniques. Other learning algorithms, which are used in the above technique includes:
3) *Association Rule:* Association rule extracts rules predicting occurrence of items based on the presence of other items in a transaction.
4) *Clustering:* Clustering partitions a set of data into sub clusters to discover meaningful groups
5) *Decision Tree*: Decision tree is based method of tree graph constructed by analyzing a set of training examples.
6) *ANN:* Artificial neural network is a structure of many connected neurons (nodes) arranged in layers in systematic ways.
7) *Regression:* Regression analysis is used when two or more variables are thought to be systematically connected by a linear relationship.
8) Bayesian Classifiers: It considers each attribute and class level as random variable. The most commonly used Bayesian classifier is Naïve Bayes classifier.

C. Knowledge Based Recommendation

Considering the users' specific tasks, Knowledge-based recommendation can address this problem by using a model of knowledge [19].

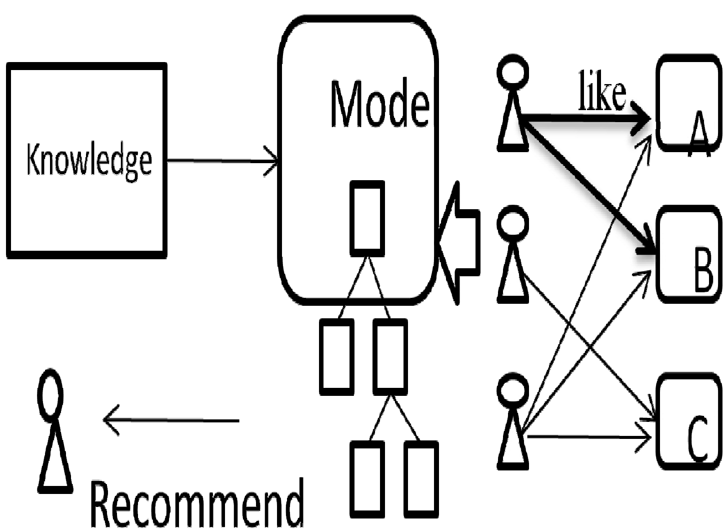

Fig. 7 Knowledge based recommendation

Table iv
Comparative study

Technique	Background	Input	Process
Collaborative	Rating from user of items in a set of items I	Rating from user of items in a set of items I	Identify users in U similar to u and estimate from their rating of item i.
Content- based	Features of items in a set of items I	User u's ratings of item in a set of items I	Generate a classifier that fits u's rating and use it on item i.
Knowledge- based	Features of items in a set of items I Knowledge of how these items meet user's needs.	Description of user u's need or interest	Imply a match among a set of items I and user u's need.

IV. CONCLUSIONS

Recommender systems provide new opportunities for researchers to retrieve personal information on the Internet. Based on that personal information , the recommender system predicts the similar items or similar users and recommend the products to the online users. This paper discussed the three recommendation techniques and highlighted their strengths and challenges.

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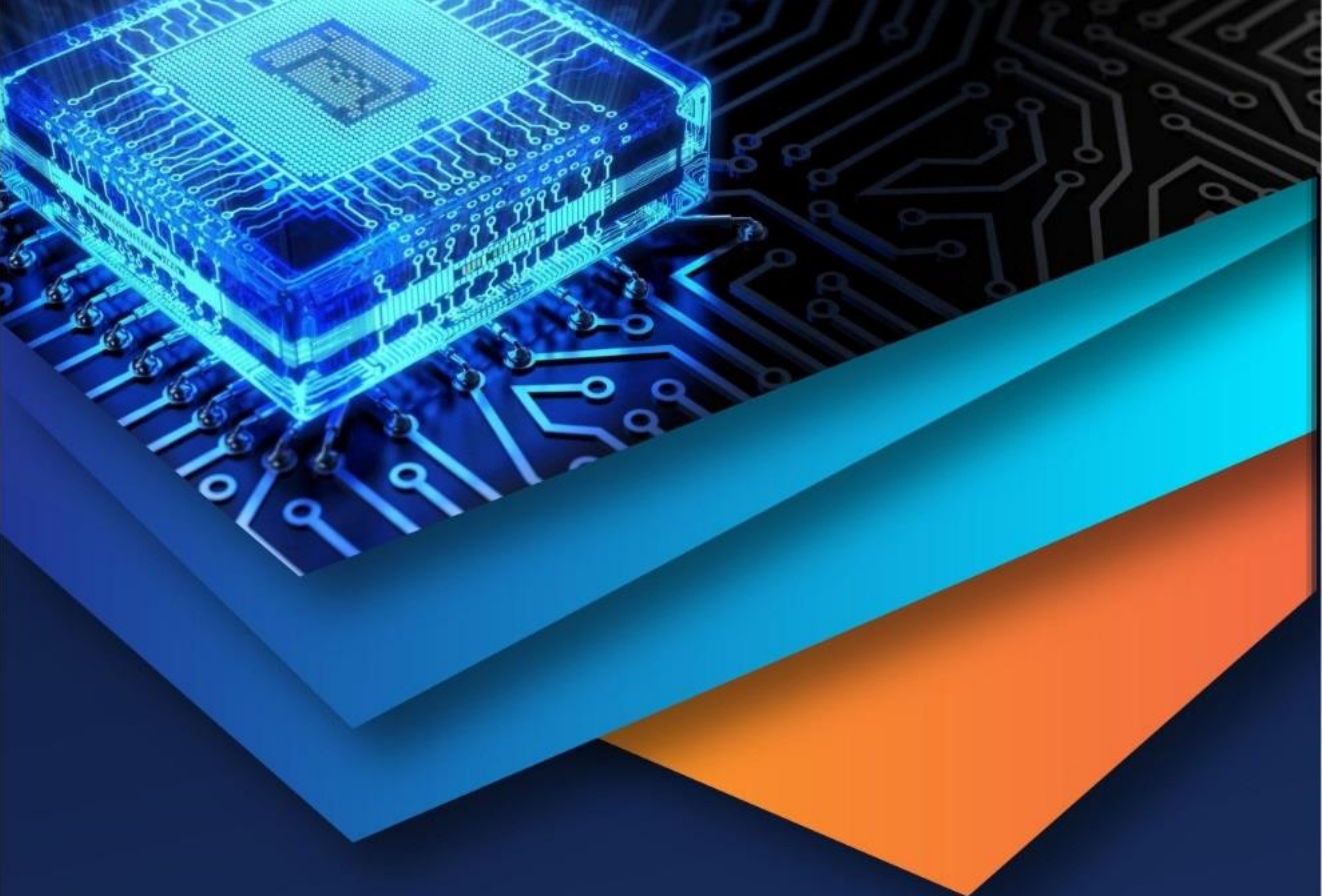

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