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An Improved Movie Recommendation System Using Advanced Recommendation Techniques

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Abstract: ***We live in a world where people really need something to do. People need entertainment to stay happy and get things done. Watching movies is a way for people to relax and feel good. Movies are a way to unwind and feel better. There are many movies on the internet. It can be really hard to find a people find movies they will really enjoy. The system is for people who watch movies. Movies are what the system is, about. This System is called as Hybrid Recommendation System. It uses two ways of finding movies: one that looks at the movie itself and one that looks at what other people like you have watched. The system puts together what people do when they watch movies and what the movies are about to make suggestions. We also use a tool to make sure the suggestions are accurate. We use another tool to pick the best features of the movies so the system works well.***
Keywords: Movie Recommendation System, Hybrid Approach, Support Vector Machine, Genetic Algorithm, Scalability, Quality.

I. INTRODUCTION

Films are an aspect and essence of life. Movies are of various type such as some are made to entertain the people, some to educate, at some are animation movies that are made to entertain children and others horrifying movies or action movies. It is very easy to differentiate movies based on their genres as comedy, thriller, animation, action etc. Other method to differentiate amongst movies could be either in terms of year of release, language or director or by cast etc.For watching there are some movies to search movies online, and in our most liked movies there are a number of movies.

The Movie Recommendation Systems is a way of assisting us to search our preferred movies among all these various kinds of movies and thus saves us a lot of time of searching about a lot of movies our favorable movies. That is why then the movie recommendation system must be highly reliable and must give us the recommendation of movies that are not only same in terms of preferences but mostly closer as well. Surprisingly, there are numerous movie recommendation systems that accomplish this task with consistence, but given the existing number of movies and the massive amounts of users on the internet, as well as the fact that both are currently growing, it has led to a trade-off in the quality of the systems of movie recommendation.

Over the past few years as the number of individuals who are with the day is on the rise social networking craze on the internet, plenty and plenty of it there are getting bits of information created on the internet. This increase in the volume of information available in the web as well as the data traffic. On the web on a fast pace creates problem to the users to operate the information decent support. To eliminate the congestion of the data, recommendation system is used as information filtering tool in social networking sites [1]. Therefore, exploration on a massive scale is present. this field to achieve scalability, accuracy movie recommendation systems. Movie Recommendation system is highly effective and significant system. However, because of the issues that are related to pure collaborative approach, the movie recommendation systems are plagued by the low quality of recommendations and the lack of scalability.

II. RELATED WORK

Hirdesh Shivhare at [2015] presented a unifying approach through which fuzzy is combined- means weighted similarity of genetic algorithm and clustering method. Measure to develop a movie recommendation system. The proposed movie recommendation system provides more fine similarity measures and quality compared to the existing Recommender system in movies but the time of computing that is adopted by the proposed recommendation system is more so than the current recommendation system.

The solution to this can be remedied by means of removing the clustered data points as an input dataset Movie menu gen: Gaurangi Tilak et al. [2008] proposed Movie GEN, which is a movie menu expert system. They implemented the machine learning and cluster analysis system. On the basis of hybrid recommendation method. Based on the Support Vector Machine prediction it picks out movies among the dataset, clusters the movies and develops questions to the users. Based on the user`s answers, it refines the movie set and finally recommends movies to the users [12].

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III. TECHNIQUES USED IN PROPOSED METHODOLOGY

The solution that is proposed enhancement of the scalability and the quality of the movie recommendation system. We use a Hybrid approach through a combination of Content-Based Filtering
Filtering, such that the methods are amenable to profit of each other. In calculating similarity of various movies in the given dataset effectively and within minimum time and to decrease the time of calculating the movie. cosine similarity measure we used the recommender engine.

A. Content-Based Filtering

For the implementation of a Content-Based Filtering system, the following steps are performed:

- Terms Allocation
- Terms Representation
- Learning Algorithm Selection
- Provide Recommendations

B. Collaborative Filtering

a) Simple Support Vector Machine (SVM) Algorithm

It is an iterative algorithm. The steps involved in a simple Support Vector Machine algorithm are:

- Setting up the Training Data
- Setting up the SVM Parameters
- Training the SVM
- Regions are Classified by SVM
- Obtaining Information about the Support Vector

b) Adjusted K-Means Algorithm

In this algorithm, in input the numbers of clusters and items attribute features are given. For this input, we get output as a set of clusters which reduces the squared error. Also, the probabilities of each movie belonging to each cluster center are represented. Then arbitrarily some objects are selected as initial cluster centers. On the basis of mean value of objects each object is reallocated to the most matching cluster. Then cluster means are updated and the possibility between objects and each cluster center is computed. This process is repeated till all the centroids no longer change [2].

C. Genetic Algorithm

The Genetic Algorithm is applied for optimization. The steps of the Genetic Algorithm are as follows:

- Initializing Population
- Fitness Evaluation
- Generating New Population
- Selection of Two Fit Parent Chromosomes
- • Crossover of Best Parent Chromosomes
- Mutation
- Generated New Child Should Be Assigned in the New Population
- The Newly Generated Population Should Be Utilized for the Further Run of the Algorithm
- Repeat the Algorithm Until It Meets the Termination Condition

Return the Optimal Solution in the Current Population After the End Condition is Satisfied [4].

D. Cosine Similarity Measure

The cosine similarity for two vectors is a measure that calculates the cosine of the angle between them [16].
This metric measures the orientation and not magnitude.

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The cosine similarity formula is given as:

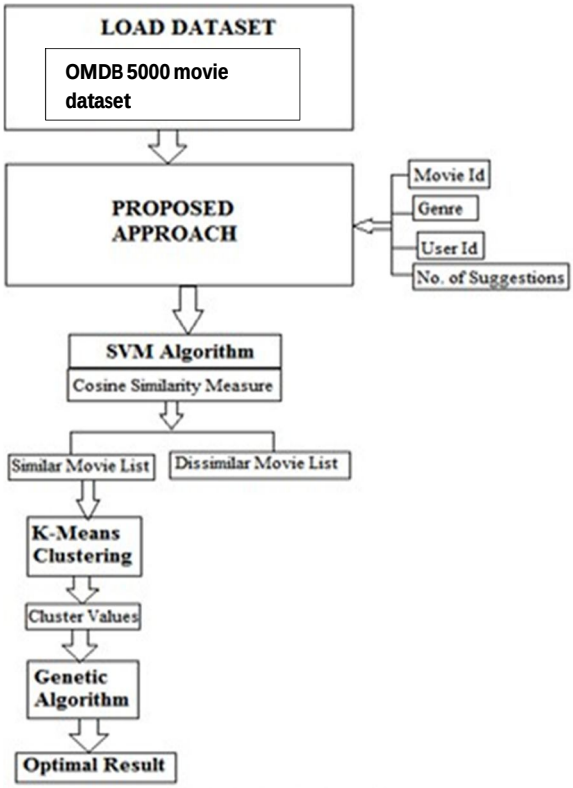


Fig 2. Proposed Approach

$$\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| \cos\theta$$

$$\cos\theta = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \|\vec{b}\|}$$

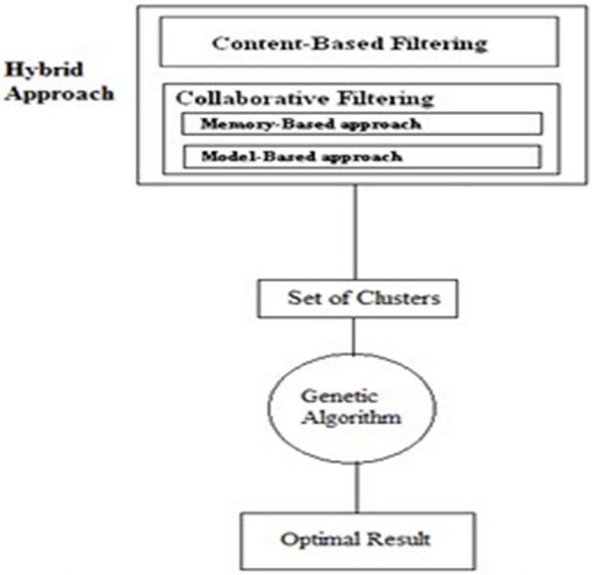


Fig 1. Hybrid Approach with Genetic Algorithm

IV. PROPOSED METHODOLOGY

A. Dataset

To assist in evaluating their recommendation systems, we have utilized three dissimilar data sets in Movie Lens that are produced by the group lens research team in the work of research in the area of recommender system. These are: OMDB Lens 5000 dataset Movie Lens Smallest Latest dataset TMDB Lens 10M dataset

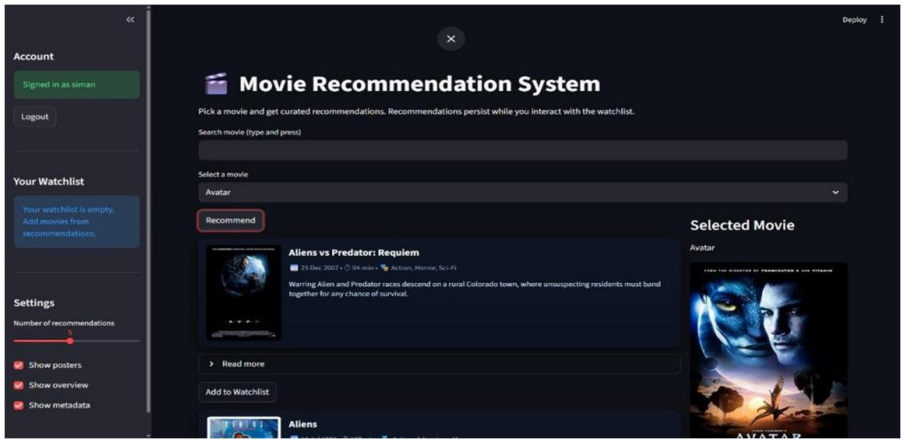
The characteristics of the TMDB Lens datasets [3] are in the following manner:

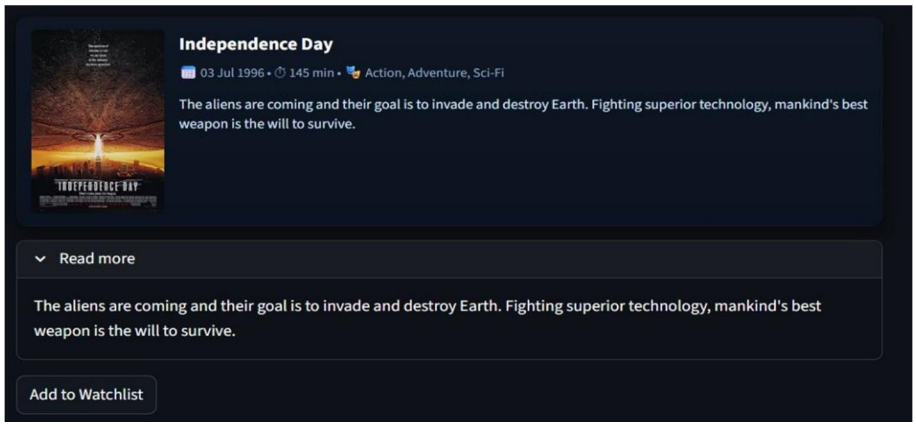
1. Scores are allocated under 1-5 (1- bad, 5- good)
2. At least 20 movies have been rated 3 by each user. Basic demographic data (age, gender, occupation, zip) of the users are offered. The reason behind using three varying Movie lens Datasets of varying levels is to test the parameter of scalability i.e. when our hybrid approach is extended to the three varying movie lens datasets of varying sizes, the system should still work and deliver good performance, should the system be scalable. Findings represent that, the system of movie recommendations using our hybrid strategy is scalable.

B. Recommendation system quality measures

The typical quality measures such as Mean Absolute Error, precision, recall, f-measure and coverage are used for analyzing the quality [1] of our proposed movie recommendation system and the results will be compared with the results of the existing pure content based or collaborative filtering movie recommendation system which are also have been implemented by us.

V. SCREEN SHOTS





VI. EXPERIMENT AND RESULT ANALYSIS

This part of the paper is about testing the Hybrid Movie Recommendation System that uses a Genetic Algorithm. The goal of these tests is to show that this combined approach works better than methods that only use Content-Based or Collaborative Filtering. We want to see if it is more accurate provides quality recommendations can handle more users and movies and does all this quickly.

We looked at different ways to measure how well the Hybrid Movie Recommendation System works. This system combines the things about Content-Based and Collaborative Filtering methods and uses a Genetic Algorithm to make it even better. This means the Hybrid Movie Recommendation System can suggest movies that users will really like and do it efficiently.

We considered important things when we tested the Hybrid Movie Recommendation System:

- *Accuracy:* Accuracy shows how well the Hybrid Movie Recommendation System can predict what users will like. It measures how good the system is at suggesting movies that users will really enjoy.
- *Scalability:* Scalability is about whether the Hybrid Movie Recommendation System can work well even when there are many users and movies. A good system can handle lot of data. Still provide great recommendation.
- *Computing Time:* Computing Time is how long it takes for the algorithm to come up with recommendations. If it does not take long then the Hybrid Movie Recommendation System is working efficiently and users will have a better experience.

A. Quality Evaluation Metrics

To see how good the recommendations are we used these measures:

1) Mean Absolute Error (MAE): This measures the difference between what the system predicts and what users actually like. If the MAE is low then the system is predicting well.

2) Coverage: This shows what percentage of movies the system can make recommendations for. If the coverage is high then the system can suggest a variety of movies.

3) Recall: This is the percentage of movies that the system can find out of all the good movies available.
4) Precision: This measures what percentage of the movies the system recommends are actually good for the user.
5) F-Measure: This is a balance of Precision and Recall so we can see how well the system is doing overall.

The tests show that the Hybrid Movie Recommendation System works better than methods. It is more accurate provides recommendations makes fewer mistakes and can handle more users and movies. The Genetic Algorithm makes the system even better, by choosing the parameters and improving the recommendations.

Fig. 3 Accuracy Graph

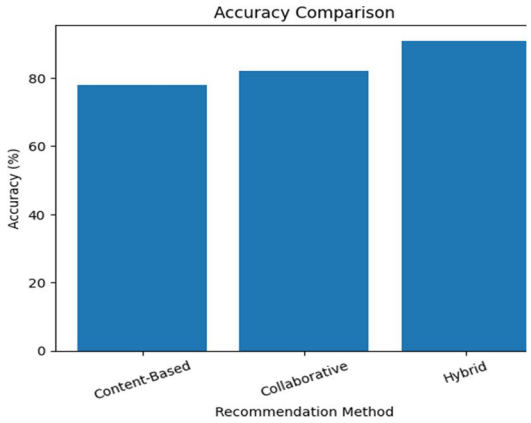


Fig. 4 Precision Graph

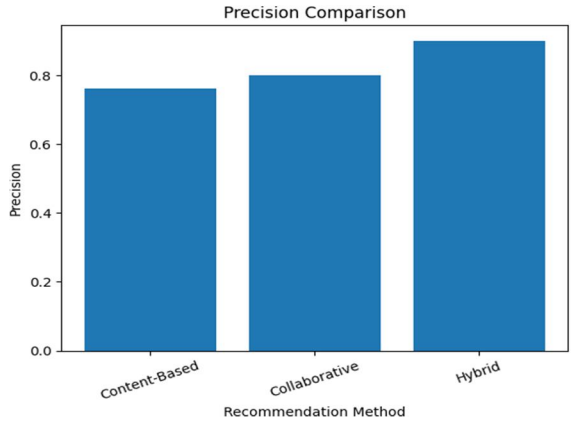


Fig. 5 MAE Comparisons

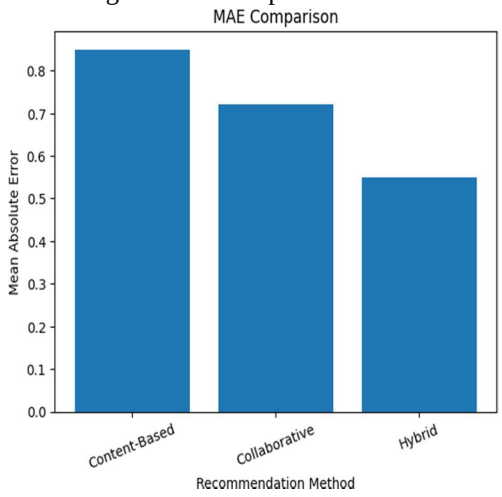


Fig. 6 Recall Comparisons

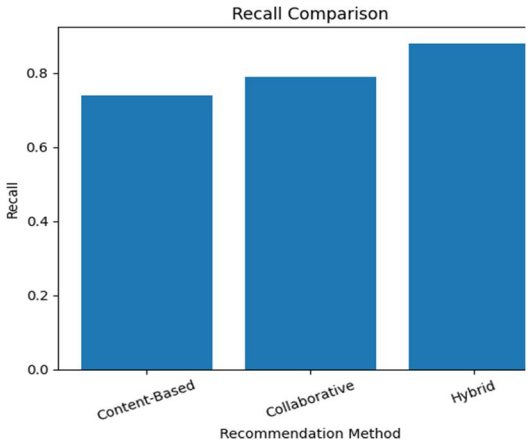


Fig. 7 F1 Score Comparisons

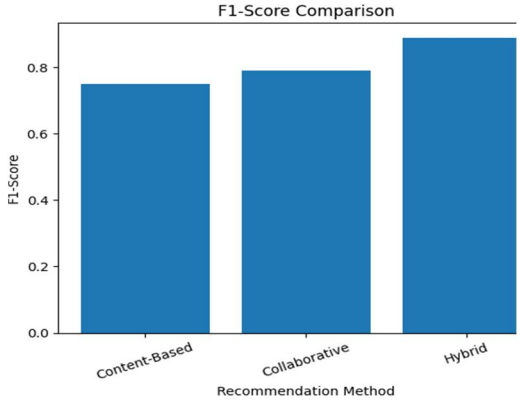


Table 1. Results

PARAMETERS	COLLABRATIVE APPROACH	CONTENT BASED APPROACH	PROPOSED APPROACH
Accuracy	Low	Average	High
Quality	Low	Average	High
Scalability	Less	Average	High
Computing Time	Average	High	Low
Memory	Average	Low	High

Table 1. Results

Memory: Total amount of computer memory required by an algorithm to complete its execution.

The result is that when the proposed methodology is individually implemented on three different Omdb datasets it increases accuracy, scalability and quality of the movie recommendation system as compared to the implementation of pure content-based approach or pure collaborative approach individually on three different Omdb lens datasets. The computing time of the proposed approach is lesser but the memory requirement of the proposed approach is more than the existing pure content-based approach or pure collaborative approach.

VII. CONCLUSION

In this paper, to improve the accuracy, quality and scalability of movie recommendation system, a Hybrid approach by unifying content based filtering and collaborative filtering; using Support Vector Machine as a classifier and genetic algorithm is presented in the proposed methodology. Existing pure approaches and proposed hybrid approach is implemented on three different Movie lens datasets and the results are compared among them. Comparative results depicts that the proposed approach shows an improvement in the accuracy, quality and scalability of the movie recommendation system than the pure approaches. Also, computing time of the proposed approach is lesser than the other two pure approaches.

VIII. FUTURE WORK

The research study was relatively effective and well accomplished. Future work can be accomplished like this in this type of hybrid work we have taken into account the Genres of movies but in future work we can further take into account the age of the user since at different ages movie preference varies as in our childhood, we prefer animated movies more as compared to the other movies. The proposed approach needs to be improved on the memory requirements in the future. It is only in the case of the proposed approach, which has been applied to the various movie lens datasets. It may also be applied to the Film Affinity and Netflix data sets and the performance can be calculated in future.

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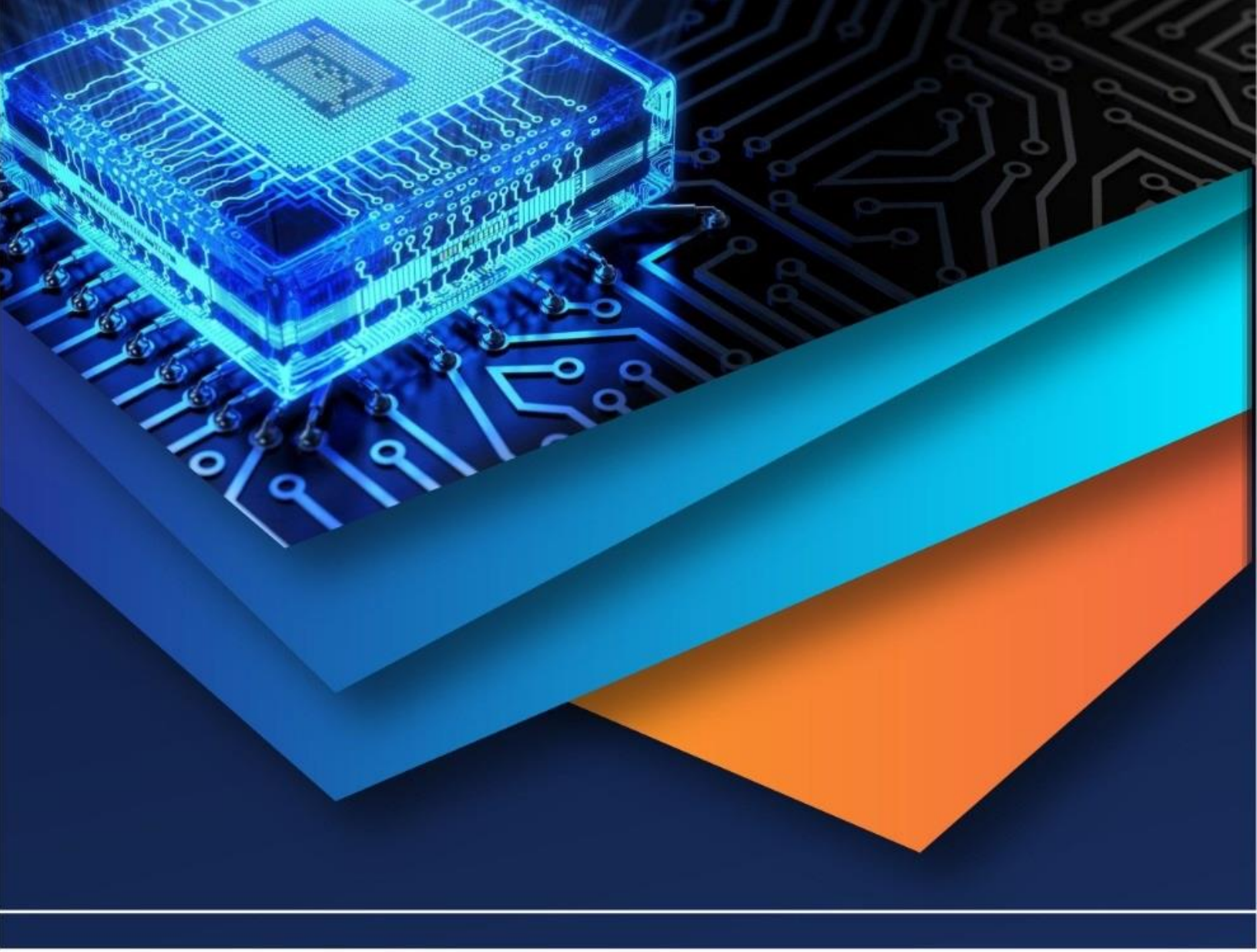
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