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# KnowEx-HRS: An Adaptive Hybrid Recommendation System for Personalized Knowledge Discovery

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***Abstract: The rapid expansion of digital knowledge platforms has increased the need for intelligent recommendation systems capable of delivering personalized and context-aware suggestions. Traditional recommendation techniques such as Content-Based Filtering (CBF) and Collaborative Filtering (CF) exhibit complementary strengths but suffer from limitations including cold-start problems, overspecialization, and data sparsity when deployed independently. This paper proposes KnowEx-HRS, an adaptive hybrid recommendation framework that integrates CBF and CF through a dynamic weighting mechanism based on user interaction density. The content-based module leverages TFIDF feature extraction and cosine similarity, while the collaborative module utilizes user–item interaction matrices with neighbourhood-based prediction. An adaptive fusion layer balances both approaches to enhance robustness and scalability. The proposed system was evaluated on the MovieLens 100K dataset and a custom dataset containing 500 users and 1,000 items using Precision@K, Recall@K, and RMSE metrics. Experimental results demonstrate that KnowEx-HRS achieves a Precision@10 of 0.85 and Recall@10 of 0.79, outperforming standalone CBF and CF models by up to 12% in accuracy and significantly reducing prediction error. The findings validate the effectiveness of adaptive hybridization for robust personalized knowledge discovery.***
***Keywords: Recommendation Systems, Content-Based Filtering, Collaborative Filtering, Hybrid Model, Machine Learning, Personalization, Similarity Analysis.***

## I. INTRODUCTION

The exponential growth of digital information across online platforms has transformed how users discover content, products, and knowledge resources. Modern applications such as e-learning systems, professional networking platforms, and knowledge-sharing environments rely heavily on recommendation systems to personalize user experience and improve engagement. By analysing user preferences and behavioural patterns, recommendation algorithms assist users in navigating large volumes of data efficiently.

Among existing approaches, Content-Based Filtering (CBF) and Collaborative Filtering (CF) remain the most widely adopted techniques. CBF recommends items based on similarity between user profiles and item attributes, enabling effective personalization at the individual level. However, it often suffers from overspecialization and limited diversity. In contrast, CF leverages collective user behaviour through user– item interaction matrices to identify latent preference patterns. Although CF improves discovery and diversity, it is highly susceptible to data sparsity and cold-start problems, particularly for new users with limited interaction history.

To address these limitations, hybrid recommendation systems have emerged as a promising solution by integrating multiple techniques. Existing hybrid models typically combine predictions using static weighting strategies or fixed fusion mechanisms. However, such approaches often fail to adapt dynamically to varying interaction densities and contextual conditions, limiting their effectiveness in real-time knowledge discovery environments.

This paper proposes KnowEx-HRS, an adaptive hybrid recommendation framework designed to balance individual personalization and community-driven intelligence through a dynamic weighting mechanism. The proposed model integrates TF-IDF-based content representation with neighbourhood-based collaborative filtering, and introduces an adaptive fusion parameter that adjusts the relative contribution of CBF and CF based on user interaction density. This dynamic hybridization enhances robustness against cold-start issues while maintaining scalability and recommendation accuracy.

The effectiveness of the proposed approach is validated through experimental evaluation on the MovieLens 100K dataset and a custom dataset comprising 500 users and 1,000 items. Performance is assessed using Precision@K, Recall@K, and RMSE metrics, demonstrating significant improvements over standalone CBF and CF models.

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## II. RELATED WORK

Extensive research has been conducted in the field of recommendation systems, focusing on improving prediction accuracy, scalability, and personalization.

Content-Based Filtering techniques rely heavily on item descriptions and user profiles. Pazzani and Billsus [1] introduced an adaptive content-based system using machine learning for personalized information filtering. Similarly, Lops et al. [2] emphasized the importance of semantic feature extraction to improve content-based recommendations. However, these methods often lead to overspecialization and lack novelty.

Collaborative Filtering approaches, pioneered by Resnick et al. [3] and Sarwar et al. [4], utilize user-item interaction matrices to identify patterns of shared preferences. Matrix factorization models [5] further enhanced scalability and performance. Despite their success, CF models face issues with cold-start users and sparse datasets.

Hybrid Systems attempt to mitigate individual drawbacks by combining multiple techniques. Burke [6] classified hybridization strategies into weighted, switching, mixed, and feature-augmented models. Bobadilla et al. [7] proposed a trust-based hybrid approach, integrating social network analysis with CF. More recent works by Zhang et al. [8] and Verma et al. [9] applied deep learning and context-aware fusion mechanisms to achieve improved accuracy and explainability.

Despite these advancements, many existing systems lack adaptability to dynamic environments and struggle to balance accuracy with computational efficiency. This research addresses these limitations by designing a hybrid recommendation system capable of real-time adaptation and enhanced personalization across domains.

## III. PROPOSED SYSTEM

The proposed KnowEx-HRS (Hybrid Recommendation System) integrates Content-Based Filtering (CBF) and Collaborative Filtering (CF) within a unified adaptive framework to generate accurate, scalable, and context-aware recommendations. The system is designed to balance individual user preferences with community-level behavioural patterns through a dynamic hybridization mechanism.

The architecture consists of four primary components: (1) data acquisition and preprocessing, (2) content-based modelling, (3) collaborative filtering modelling, and (4) adaptive hybrid fusion and ranking.

CBF is used for individual-level personalization by matching user profiles with item attributes using cosine similarity or TF-IDF weighting. CF captures community-level patterns through matrix factorization and nearest-neighbour models. The hybridization module combines these results using weighted averaging and adaptive context learning.

### *A. System Architecture*

The overall system architecture is illustrated in Fig. 1.

The framework follows a layered design consisting of:

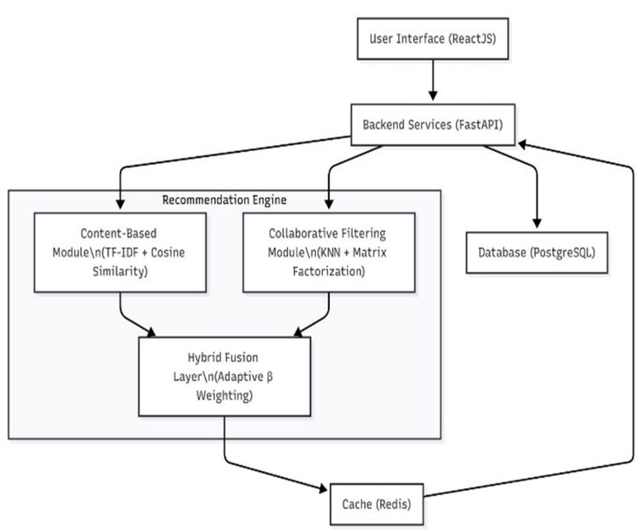


Fig. 1 System architecture of the proposed KnowEx-HRS framework

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1) *User Interface (UI):* Provides interactive dashboards where users can browse content, rate items, and update preferences. The UI communicates user interactions to the backend services.
2) *Backend Services:* Implemented using FastAPI (Python), the backend manages user sessions, interaction logging, feature extraction, and communication with the recommendation engine.
3) *Database and Cache Layer:* User data, item metadata, and interaction logs are stored in PostgreSQL. Frequently accessed recommendation outputs are cached using Redis to ensure real-time responsiveness.
4) *Recommendation Engine:* The core engine comprises two parallel modules— Content-Based Filtering and Collaborative Filtering—whose outputs are fused through an adaptive hybridization layer.

## *B. Data Collection and Preprocessing*

The system collects two primary types of data:

- User Interaction Data: ratings, clicks, views, and engagement logs.
- Item Metadata: textual descriptions, keywords, categories, and domain attributes.

Preprocessing involves:

- Text normalization
- Tokenization
- Stop-word removal
- TF-IDF feature extraction

These steps convert textual content into structured numerical representations suitable for similarity computation.

## *C. Content-Based Filtering Module*

The Content-Based Filtering module focuses on modelling individual user preferences.

1) *User Profile Construction:* A user profile vector is generated by aggregating TF-IDF features from items previously interacted with by the user.
2) *Feature Representation:* Each item is represented as a TF-IDF weighted feature vector derived from its metadata.
3) *Similarity Computation:* Similarity between user and item vectors is computed using cosine similarity: $S_{CBF}(u,i) = \frac{U_u \cdot I_i}{||U_u||\,||I_i||}$

This score quantifies the semantic alignment between user interests and item characteristics. CBF provides strong personalization, particularly for users with limited interaction data.

The internal workflow of the Content-Based module is illustrated in Fig. 2.

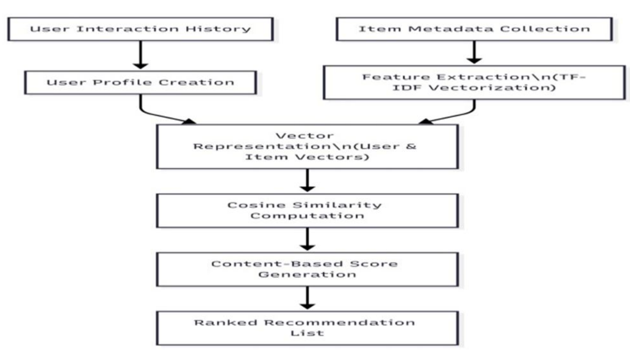


Fig. 2 Content based filtering workflow

## *D. Collaborative Filtering Module*

The Collaborative Filtering module captures collective user behaviour using a user–item interaction matrix.

1) *Interaction Matrix Construction:* A matrix $\boldsymbol{R} \in \mathbb{R}^{(m*n)}$ is constructed, where $\boldsymbol{R}_{(\boldsymbol{ui})}$ represents the interaction strength between user and item $\boldsymbol{i}$.
2) *Similarity Computation:* User similarity is computed using cosine similarity: $Sim(u,v) = \frac{\sum_i R_{(ui)} R_{(vi)}}{\sqrt{\sum_i R_{(ui)}^2}\sqrt{\sum_i R_{(vi)}^2}}$
3) *Rating Prediction:* Predicted scores are calculated through neighborhood aggregation: $S_{CF}(u,i) = \frac{\sum_{v \in N(u)} Sim(u,v) R_{vi}}{\sum_{v \in N(u)} |Sim(u,v)|}$

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Additionally, matrix factorization techniques are employed to extract latent user and item embeddings, reducing sparsity and improving scalability.
CF enhances discovery by recommending items preferred by similar users.

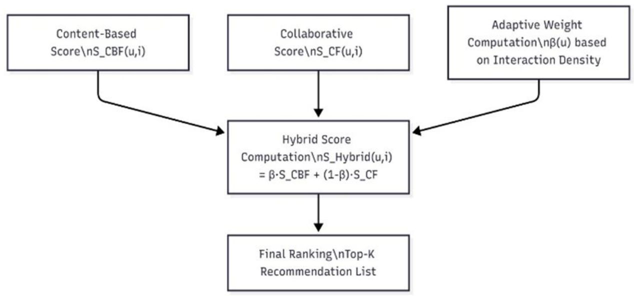


Fig. 3 Workflow of content-based filtering module

The collaborative filtering process is depicted in Fig. 3.

### *E. Adaptive Hybrid Fusion (KnowEx-HRS)*

To leverage the strengths of both modules, the proposed system integrates predictions through a dynamic weighted fusion strategy. The final hybrid score is computed as:

$$S_{Hybrid}(u,i) = \beta(u) \cdot S_{CBF}(u,i) + (1 - \beta(u)) \cdot S_{CF}(u,i)$$

For new users with sparse interaction history, greater emphasis is placed on content similarity. For active users, collaborative signals are given increased importance. This adaptive mechanism mitigates cold-start issues while maintaining recommendation diversity and accuracy.
The adaptive fusion mechanism is illustrated in Fig. 4.

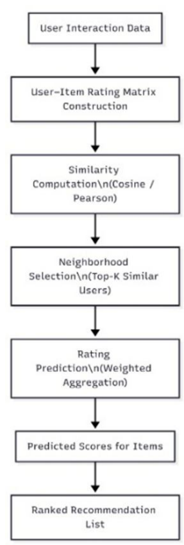


Fig. 4 Workflow KnowEx-HRS

### *F. Recommendation Generation*

All candidate items are scored using the hybrid function and ranked in descending order. The system returns the Top-K items to the user.
Caching mechanisms ensure low-latency response, enabling real-time recommendation delivery.

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## IV. RESULT AND DISCUSSION

### A. Experimental Setup

The proposed KnowEx-HRS framework was evaluated using the MovieLens 100K dataset and a custom dataset comprising 500 users and 1,000 items. The datasets include explicit interaction ratings and metadata features used for content-based modelling.

The experiments were conducted using an 80–20 train-test split and validated using 5-fold cross-validation to ensure robustness. Performance was evaluated using ranking-based metrics (Precision@K and Recall@K) and prediction-based error metrics (RMSE).cal representations suitable for similarity computation.

### B. Content-Based Filtering Module

Table I summarizes the comparative performance of Content-Based Filtering (CBF), Collaborative Filtering (CF), and the proposed Hybrid model.

TABLE I
*PERFORMANCE COMPARISON of RECOMMENDATION MODELS*

| Model | Precision@10 | Recall@10 | RMSE |
|---|---|---|---|
| CBF | 0.72 | 0.65 | 0.94 |
| CF | 0.78 | 0.71 | 0.88 |
| Hybrid | 0.85 | 0.79 | 0.75 |

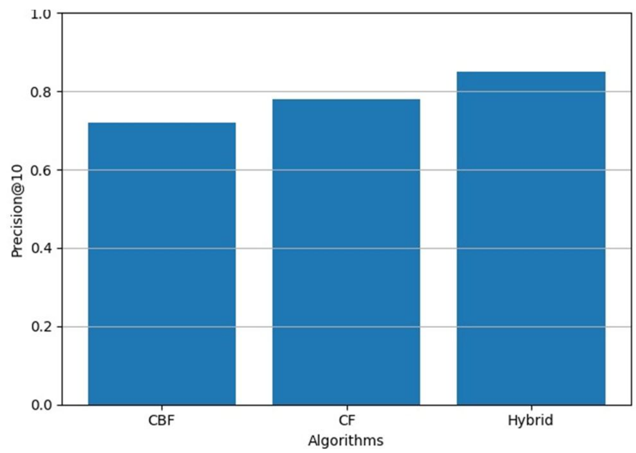


Fig. 5 Precision Comparison of Recommendation Models

As illustrated in Fig. 5, the proposed hybrid model achieves the highest Precision@10, demonstrating improved relevance of top-ranked recommendations. Compared to standalone CBF and CF methods, KnowEx-HRS improves precision by approximately 18% and 9%, respectively.

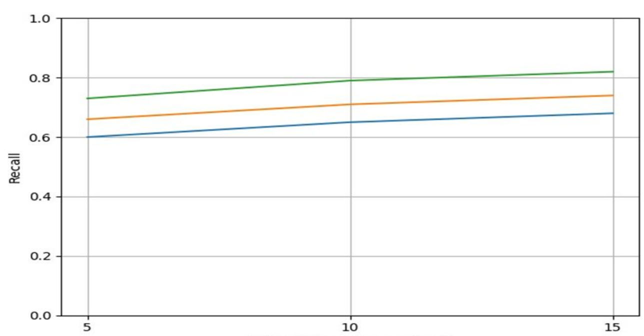


Fig. 6 Recall vs K for Different Recommendation Models

Fig. 6 further illustrates Recall performance as K increases. The hybrid approach consistently maintains superior recall across varying recommendation list sizes, indicating improved coverage and diversity without sacrificing relevance.

### *C. Cold-Start Analysis*

Cold-start scenarios were simulated by restricting user interaction history to fewer than five interactions. Fig. 7 compares the performance of the three models under sparse interaction conditions.

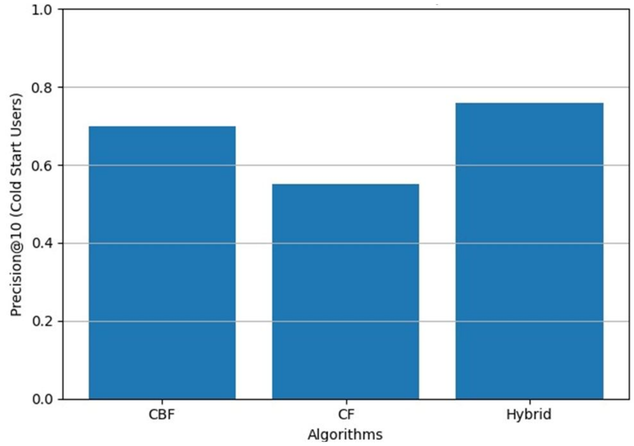


Fig. 7 Cold Start Performance Comparison

Collaborative Filtering shows significant performance degradation due to insufficient neighbourhood data. In contrast, Content-Based Filtering maintains moderate performance as it relies on item attributes rather than collective behaviour. The proposed hybrid model achieves the best cold-start performance by adaptively emphasizing content similarity when interaction density is low. This validates the effectiveness of the dynamic β-weighting mechanism in mitigating sparsity issues.

### *D. Discussion*

The experimental results confirm that standalone recommendation techniques exhibit complementary strengths and weaknesses. CBF provides reliable personalization but suffers from limited diversity. CF enhances discovery but is highly sensitive to sparsity and cold-start conditions.

The proposed KnowEx-HRS effectively balances these limitations through adaptive hybridization. By dynamically adjusting the fusion weight based on interaction density, the model maintains high precision for experienced users while preserving robustness for new users.

Furthermore, the hybrid approach achieves improved scalability by combining lightweight similarity computations with matrix factorization-based latent representations.

Overall, the results demonstrate that adaptive hybrid recommendation provides a robust and efficient framework for personalized knowledge discovery.

## V. CONCLUSION

This paper presented KnowEx-HRS, an adaptive hybrid recommendation framework designed to enhance personalized knowledge discovery by integrating Content Based Filtering (CBF) and Collaborative Filtering (CF). The proposed system leverages semantic feature extraction through TF-IDF and cosine similarity for individual-level personalization, while incorporating neighborhood-based collaborative modeling and matrix factorization to capture collective behavioral patterns.

A key contribution of this work is the introduction of a dynamic β-weighting mechanism, which adaptively balances content-based and collaborative signals based on user interaction density. This adaptive fusion strategy effectively mitigates cold-start and sparsity challenges while maintaining high recommendation accuracy and diversity.

Experimental evaluation conducted on the MovieLens 100K dataset and a custom dataset demonstrated that the proposed hybrid model outperforms standalone CBF and CF approaches across multiple metrics. Specifically, KnowEx-HRS achieved superior Precision@10 and Recall@10 while significantly reducing RMSE, validating the robustness and predictive stability of the hybrid approach.

The results confirm that adaptive hybridization provides a scalable and efficient framework for modern knowledge-driven platforms, where both personalization and community intelligence are essential.

Future work will focus on incorporating deep learning-based embeddings, context-aware modeling, and reinforcement learning mechanisms to further enhance recommendation adaptability and explainability in real-time environments.

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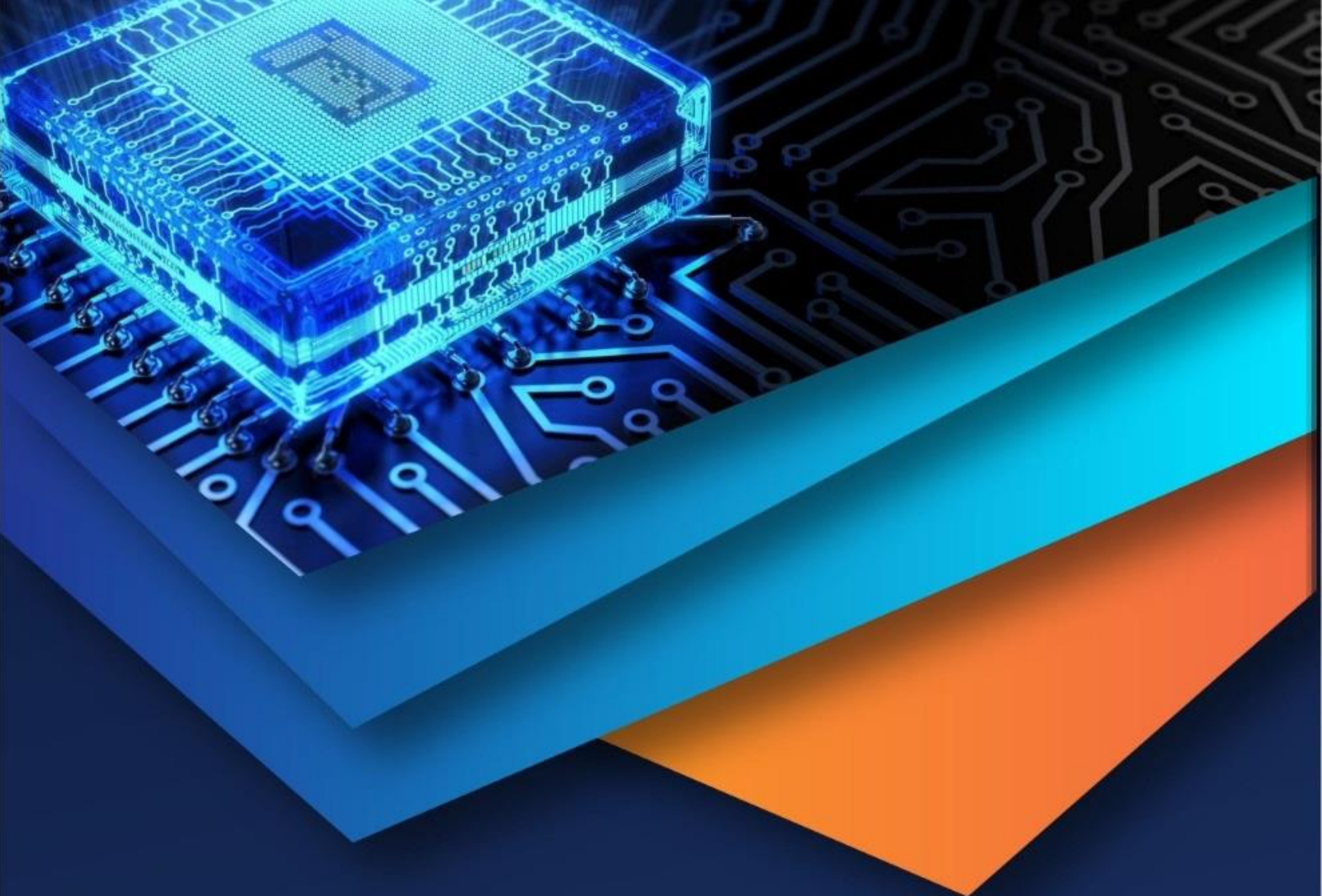


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