iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VI **Month of publication:** June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72117

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

Session Based Recommender System Using Gated Graph Neural Network

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Abstract:** This study explores a new approach using Graph Neural Networks for session-based recommendation systems. These systems focus on forecasting user preferences by examining recent interactions instead of depending on past user profiles. Conventional approaches like collaborativefilteringandrecurrentneuralnetworksoftenfacechallengesinidentifyingcomplex sequential patterns and relationships between items within session data. Graph Neural Networks offer a promising alternative by representing session data as graphs, allowing them to efficiently capturebothlocalandglobaldependencies. This study seekstoevaluatetheeffectivenessofGNNs in improving session-based recommendation systems by enhancing prediction accuracy, scalability, and adaptability across diverse domains, including e-commerce, streaming services, andonlineeducation. ByharnessingthecapabilitiesofGraphNeuralNetworks,thesesystemscan gain deeper insights into item relationships, user behaviors, and contextual interactions, resulting in more precise recommendations. This paper examines the development of session-based recommendation systems, focusing on the transition from heuristic models to deep learning techniques. It also highlights the role of Graph Neural Networks in enhancing recommendation accuracy, scalability, and adaptability across various domains, including streaming services, e- commerce, and online education. Future innovations, such as hybrid models, self-supervised learning, and fairness-aware algorithms, offer promising opportunities to further improve performance and reduce biases in recommendation systems.

Several real-world case studies highlight the effectiveness of Graph Neural Networks in session- based recommendation systems. In the e-commerce industry, platforms such as Alibaba have leveraged GNN-based models to analyze complex user-item interaction graphs, resulting in notable improvements in click-through and conversion rates. In the streaming sector, companies likeSpotifyandNetflixemployGNNstobettercapturedynamicuserpreferenceswithinsessions, enablingthedeliveryofmoreaccurateandtimelycontentrecommendations.Likewise,inthefieldofonlineeducation,platformssuchasCourseraandedXutilizeGNNstorecommendpersonalized learning paths by modeling learners' interactions with courses and materials as graphs.

***Keywords:** Session based recommendation, Graph Neural Networks, Collaborative filtering, Recurrent Neural Networks, Sequential patterns, Prediction accuracy, Contextual interaction, Scalability, User preferences, Hybrid models*

I. INTRODUCTION

Session-basedrecommendationsystemsplayacrucialroleinpredictinguserpreferencesinonline platforms by leveraging short-term interactions rather than long-term user profiles. Traditional recommendation approaches such as collaborative filtering and content-based methods have shown limitations in effectively capturing sequential dependencies and item relationships in session data. To address these challenges, recent research has explored deep learning techniques, including recurrent neural networks, convolutional neural networks, and more recently, Graph Neural Networks, for session-based recommendations.

Graph-basedmodelshavegainedpopularityduetotheirabilitytorepresentsessioninteractionsas structured graphs, enabling more effective modeling of user behavior. Graph Neural Networks provideaframeworkforlearningitem relationships byleveraging message-passingmechanisms, allowing for better contextual understanding of user sessions. Unlike traditional deep learning models, which often struggle with long-range dependencies and data sparsity, Graph Neural Networks dynamically aggregate information from neighboring nodes, capturing both short-term and long-term patterns.

With the rapid growth of e-commerce, entertainment, and personalized content platforms, the demandforefficientand scalablerecommendationsystemshasneverbeenhigher.Theintegration of Graph Neural Networks into session-based recommendation models not only enhances recommendation accuracy but also opens new avenues for adaptive learning, real-time updates, and cross-domain recommendations. By leveraging the inherent graph structure of session data, Graph Neural Network-based models have the potential to redefine user engagement and satisfaction in digital ecosystems.

This paper aims to provide a comprehensive literature review of session-based recommendation systems, focusing on the evolution from heuristic methods to deep learning-based approaches. It explores key advancements in Graph Neural Network-powered recommendations, highlighting their advantages over conventional models. Additionally, it discusses challenges, research gaps, ethical considerations, and future directions in the field, offering insights into how Graph Neural Networks can further improve session-based recommendations across various online platforms.

A. Architecture of Transformer Based GNN:

Adiagramshowing:ATransformer-basedGNNcombinesthegraphstructureofaGNNwiththe attention mechanism from a Transformer. The graph structure is used to model relationships between nodes (e.g., items in a session), while the attention mechanism enables the model to capture dependencies and assign importance to neighbors.

Multi-HeadAttentionMechanism(SimplifiedtoSingle-Head):

- TheattentionmechanismreplacestraditionalGNNaggregationbyassigningimportanceweights to neighbors.
- Forasinglehead, theattentionscorefornodei attendingto node j is computed as

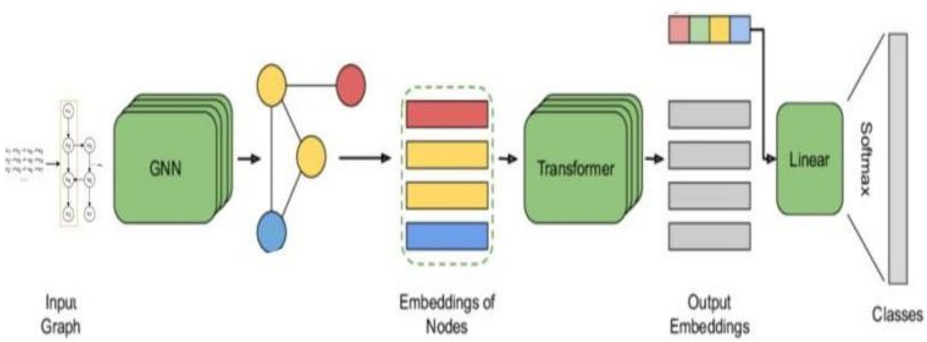
$$\text{Attention}(i,j) = \text{softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right)$$

- $Q_i = W_Q h_i$: Query vector for node i.
- $K_j = W_K h_j$: Key vector for node j.
- d_k: Dimensionality of the query and key vectors.

- The updated embedding for node i is computed as:

$$h_i' = \sum_{j \in \text{Neighbors}(i)} \text{Attention}(i,j) \cdot V_j$$

- $V_j = W_V h_j$: Value vector for node j.



II. OBJECTIVE OF THE STUDY

To assess the effectiveness of Graph Neural Networks (GNNs) in enhancing session-based recommendationsystems,focusingonimprovedpredictionaccuracy,scalability,andadaptability across various domains such as e-commerce, online education, and streaming services.

Specifically,thestudy isintendedto pursuethefollowing objectives:

1) Tounderstandhowrecommendationsystemshaveevolvedovertime.We'll start by looking at the journey of session-based recommenders—from simple rule- based and heuristic approaches to more complex deep learning models. This helps us appreciate why newer techniques like GNNs are gaining attention.
2) To explore how Gated Graph Neural Networks (GGNNs) work in real recommendation scenarios. GGNNsareaspecialtypeofGNNthatusegatingmechanismstomodelsequences.We'll examine how they represent sessions as graphs and how they manage to keep track of the order and context of user interactions.
3) To tackle common challenges like cold-start issues, sparse data, and long-term dependencies.

Manysystemsstrugglewhenthere'snotenoughuserdataorwhentryingtomakesenseoflongerusersessions.We'llseehowGNNsmightprovidesolutionsbymakingbetteruseof available data and capturing more complex item relationships.

4) TocompareGNN-basedmodelswithotherpopularapproaches. GNNsaren'ttheonlyoption—sowe'llbenchmarkthemagainstmodels like Collaborative Filtering (CF), Recurrent Neural Networks (RNNs), and even Transformer-based models. The goal is to see where GNNs truly shine, and where they might fall short.
5) Toconsiderethicalandfairnessaspectsinrecommendations. As recommendation systems become more powerful, it's crucial to ensure they are also fair and responsible. We'll look at how GNN-based systems handle issues like bias, transparency, and user privacy, and how they can be made more ethical in real-world deployments.

III. LITERATURE REVIEW

1) The linear modeling ability of matrix factorization makes it unable to effectively express the complex preferences of users, so the recommendation results are not good enough. Withtheriseofdeeplearning,neuralmatrixfactorization(Heetal.,2017) Anditsvariants have achieved good results in recommendation tasks by virtue of the powerful ability of neural networks to fit any function.
2) Gated GNN was proposed to deal with sequential input, which has a similar mechanism likeGatedRecurrentUnit(GRU), whichissimilartoLongShort-TermMemory.Theuser interaction history in sequential recommendation system is believed to have a sequential relation that reveals his/her short-term interest, which makes it a suitable scenario for GGNN.Threedifferentmodelsareproposedandinvestigatedin TrendyRecommenderto modeltheitemtrendrepresentation.Leveraginguponthepowerofgraphneuralnetwork, our model is able to aggregate the information from the item's latest activity history. Trendy Recommender learns the item's trend representation and the item's long-term representation, then our proposed model combines them together and feeds into the prediction layer alongside with the user's short-term and long-term preferences as well. (Tao, Ye, 2019).
3) Recommender systems often face data sparsity and cold start problems. Data sparseness referstothelimitedinteractionbetweenusersanditems,whilecoldstartreferstoproviding recommendations for users and items that have no historical interaction records. To alleviate these two problems, researchers have designed various collaborative filteringalgorithms that integrate auxiliary information. Auxiliary information is mainly divided into two categories: structured auxiliary information and unstructured auxiliary information (Sun et al., 2019). Structured auxiliary information mainly refers to social networks, knowledge graphs, item catalogs, etc., while non-structured auxiliary information includes item text, item pictures, item videos, etc.
4) Besides,recentpretrainingmodelshaveshowntheireffectivenessintransferringexternalknowledgetospecificscenarios,andhavebeenusedinrecommendersystems(Zengetal.,2021). However, few works are suitable for heterogeneous graphs (Jiang et al., 2021). Compared to homogeneous graphs, heterogeneous graphs have richer and more differentiated semantic and structural properties, which pose additional challenges for the design of pre-training models and for fine-tuning them on downstream tasks.
5) To well apply graph neural networks into recommender systems, there are some critical challenges required to be addressed. First, the data input of recommender system should be carefully and properly constructed into graph, with nodes representing elements and edgesrepresentingrelations.Second,forthespecifictask,thecomponentsingraphneural networks should be adaptively designed, including how to propagate and aggregate, in which existing works have explored various choices with different advantages and disadvantages. Third, the optimization of the GNN-based model, including the optimization goal, loss function, data sampling, and so on (Yang et al., 2022), should be consistentwiththetaskrequirement. Last,sincerecommendersystemshavestrict limitations on the computation cost, and also due to GNNs' embedding propagation operationsintroducinganumber ofcomputations, theefficientdeploymentofgraphneural networks in recommender systems is another critical challenge.
6) Existing graph-based approaches capture collaborative information by constructing a globalgraph[17] orahypergraph[21]containingallitemnodes.However,boththeglobalgraphandthehypergraphcontainrelevantorirrelevantitemstothecurrentusersincethey considerallneighborsofeachnode.Whenitconsidersitemsirrelevanttothecurrentuser in the modeling process, the accuracy of recommendations will be compromised. To address this problem, we propose collaborative attention to capture collaborative informationthatisusefulforthecurrentsession.Specifically,westatisticallymeasurethe collaborative similarity between items based on the training sessions and normalize it as collaborative attention. (Xiaoyan Zhu, Yu Zhang, 2024).

IV.RESEARCH METHODOLOGY

A. *Data Collection Method sand Sources*

To assess the efficacy of GNN-based recommendation models, both qualitative and quantitative data collection approaches were utilized.

Qualitative Data Collection

- Acomprehensiveliteraturereviewwasconducted,examiningresearchpapers,conferenceproceedings,andtechnicalreports related to session- basedrecommendationsystems,cold start mitigation techniques, and graph neural networks.
- Theoretical insights were drawn from studies on hybrid recommendation models, meta- learning, and memory-augmented neural networks, which provide essential context for addressing long-term dependencies.

B. *InvestigativeApproachforAssessingModelEffectiveness*

AmultifacetedapproachwasemployedtoevaluatetheimpactandefficiencyofGNN-based recommendation systems in tackling cold start challenges and long-term user engagement.

1) *Theoretical Frameworks*

- Core concepts from graph neural networks (GNNs), deep learning, and recommendation system design were explored to establish a strong theoretical foundation.
- A focus was placed on hybrid recommendation strategies that integrate collaborative filtering (CF), content-based filtering (CBF), and graph-based learning.
- Memory-enhanced architectures, such as memory-augmented neural networks, were analyzed to assess their potential in improving long-term dependency modeling.

2) *CaseStudies andBenchmarking*

- Real-worldapplicationsofGNN-basedrecommendationmodelswerestudiedinindustries such as e-commerce, media streaming, and online education.
- EmpiricalcomparisonsweremadebetweenGNN-basedmodelsandalternativetechniques to assess performance differences in handling cold start users/items and sustaining user engagement over time.

3) *ComparativePerformanceAnalysis*

To establish the advantages of GNN-based models, their performance was benchmarked against traditional recommendation approaches, including:

- Collaborative Filtering (CF): A widely used technique based on past user-item interactions.
- RecurrentNeuralNetwork(RNN)-BasedMethods(e.g.,GRU4Rec,LSTM):Designed to capture sequential patterns in session data.
- Transformer-BasedModels:Utilizingself-attentionmechanismstolearnlong-termuser preferences.

V. DISCUSSION

A. *Superior Sequential Modelling:*

GNN-based models demonstrate a strong capacity to capture complex user behavior patterns through sequential and contextual modelling. This leads to more accurate and dynamic recommendations compared to traditional approaches. They excel at learning item transition probabilitiesandlatentconnectionsbetweenactionswithinsessions.Thisenablesmorenuanced tracking of evolving user interests during a browsing session.

B. *ImprovedColdStart Handling:*

By leveraging graph structures, GNNs can infer meaningful relationships even in sparse data environments, showingsignificantimprovementsincold-startscenariosforbothusersanditems. They utilize neighborhood aggregation to relate new items or users with similar nodes in the graph.Thisalleviatesdependencyonhistoricalinteractions andenhancesinitial recommendation quality.

C. *EnhancedPersonalizationthroughHybridModels:*

Combining GNNs with other techniques, such as collaborative filtering, content-based filtering, and memory-augmented neural networks, enables the system to tailor recommendations more preciselybycapturingbothshort-terminterestsandlong-termpreferences.Thesehybridmodels balance session-level signals with persistent user traits for greater personalization.

GNNs enhance the learning of complex, multi-modal patterns that single-method systems may overlook.

D. Context-AwareRecommendations:

GNNsfacilitatereal-time,context-sensitiverecommendationsbymodellingcurrentsession dynamics effectively. This adaptability enhances user satisfaction and engagement across applications.

Incorporatingtemporalandcontextualinformationdirectlyintographstructuresrefinesthe recommendation flow. Users benefit from more relevant suggestions that align with their immediate intent.

E. *Ethical AI Deployment:*

Thestudyunderscorestheimportanceofintegratingfairnessawaretrainingmethodstomitigatebiasesandpromoteresponsible AIusage.Fairnessmetricsandexplainabilitytoolsarecriticalto ensuring trust and transparency.

Byincorporatingdebiasingmechanismsinto GNNpipelines,systemscanavoidreinforcing societal or demographic inequalities. Transparency in how recommendations are generated builds user confidence and accountability.

VI.FUTURE WORK

The continued evolution of Graph Neural Network (GNN)-based session-based recommendation systems is expected to bring significant advancements in the field of personalized recommendations. A forward-looking analysis of this domain reveals numerous opportunities, challenges, and transformative possibilities.

A. EmergingTrendsandTechnologies

- Advancements in Graph Neural Networks (GNNs):Thedevelopmentofmoreefficientandscalable GNNarchitectureswill enhancetheability of recommendation models to handle large-scale session data while improving accuracy andcomputationalefficiency.Innovationssuchasself-supervisedlearningandcontrastive learning in GNNs will further refine session-based recommendations.
- Hybrid Recommendation Models: Future systems will integrate GNNs with other deep learning techniques, such as transformers and reinforcement learning, to capture long-term user preferences while maintaining real-time adaptability. These hybrid models will provide more personalized and dynamic recommendations.
- FederatedLearningforPrivacyPreservingRecommendations:Withgrowingconcernsoveruserdataprivacy,federatedlearningwillenablemodelstobe trainedacrossdecentralizeddeviceswithoutdirectlysharinguserdata.Thisapproachwill help organizations comply with data regulations while still benefiting from GNN-based personalization.

B. PotentialChallengesand Opportunities

- Ethical and Bias Mitigation Challenges: AsGNN-basedrecommendationsystemscontinueto evolve ,biasin recommendationswillremain a significant concern. Ensuring fairness, diversity, and bias mitigation in AI-driven recommendations will require new algorithmic techniques and regulatory oversight to prevent unintentional discrimination.
- Regulatory Compliance and Data Privacy:Withtheintroductionofstricterdataprivacylaws (e.g.,GDPR,CCPA), companies usingsession- based recommendations will need to implement privacy-preserving mechanisms, such as differential privacy and secure multiparty computation, to protect user information while maintaining effective recommendation performance.

VII.CONCLUSION

To sum up, this study has provided a comprehensive analysis of the effectiveness and transformative potential of Graph Neural Network (GNN)-based session-based recommendation systems. A systematic exploration of past developments, current implementations, and future directionshasrevealedseveralkeyinsights.First,GNN-basedmodelshavesignificantlyenhanced the accuracy, efficiency, and adaptability of session-based recommendation systems.

Byleveraginggraphstructurestomodelcomplexuseriteminteractions,thesesystemsoutperformtraditionalapproachessuchascollaborative filteringandrecurrentneuralnetworks(RNNs).Their ability to capture sequential dependencies and contextual relationships has led to improved recommendation quality across various domains, including e-commerce, media streaming, and online learning.

Additionally, the integration of graph neural networks into recommendation systems highlights the convergence of AI-driven innovation and real-world applications. The dynamic interaction between deep learning techniques and user behavior modeling has reshaped conventional recommendation frameworks, enabling personalized experiences and adaptive learning capabilities.

The findings of this study have broad implications for researchers, practitioners, and industry leaders. Organizations adopting GNN-based recommendation models can enhance user engagement,optimizecontentdelivery, anddrivebusinessgrowth. Atthesametime,dataprivacy, fairness, and ethical considerations remain crucial aspects of responsible AI deployment. Addressing bias mitigation, interpretability, and regulatory compliance will be essential to ensuring that AI-driven recommendation systems benefit users equitably and transparently.

Policymakers must take proactive steps to regulate the ethical deployment of AI-powered recommendations, ensuringthatuserprivacy,fairness,andaccountabilityaremaintained.Industry collaboration, multidisciplinary research, and regulatory frameworks will play a key role in balancing technological innovation with ethical responsibility.

In conclusion, Graph NeuralNetwork-based recommendationsystemshaveimmensepotentialto revolutionizesession-based recommendationsacrossmultiplesectors.Byfosteringcollaboration,continuouslearning,andethicalAIpractices,stakeholderscanharnesst hefullpotentialofGNNs to drive innovation, enhance user experiences, and shape the future of personalized recommendation technologies.

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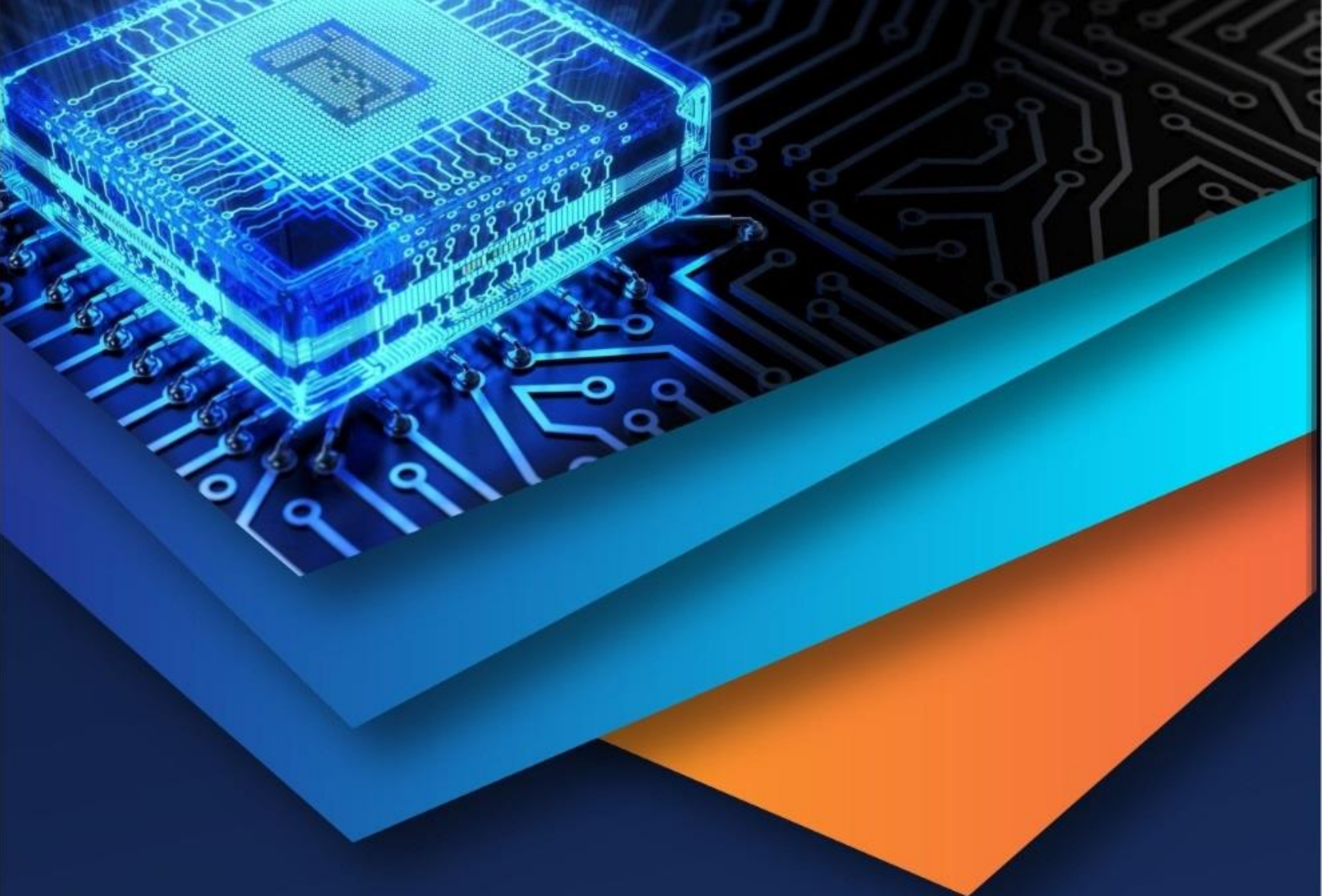

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