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Towards Intelligent Government Grievance Redressal Systems: A Survey of Computational Methods and System Architectures

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Abstract: Citizen grievance redressal has long suffered from systemicinefficienciesrootedinmanualtriage,opaquerout-ing, and delayed resolution cycles. Citizens routinely encounter portals where complaints go unacknowledged, routing decisions remain invisible, and resolution timelines stretch indefinitely, erodingpublictrustingovernanceitself.Asgovernmentsincreas-ingly deal with large volumes of structured and unstructured complaint data, the demand for intelligent automated processing has become hard to ignore.

This survey examines 20 research papers from 2017 to 2026, tracing the full arc of AI-driven grievance management, from early Naive Bayes and SVM classifiers to transformer-based architectures, zero-shot LLM pipelines, Graph Neural Networks (GNNs) and blockchain-integrated multimodal frameworks. The analysis reveals a clear technological progression: statistical models established baseline classification capability but ran into scalability and generalization limits; deep learning methods like CNNsandLSTMsimprovedaccuracyatthecostofinterpretabil-ity; transformer models such as BERT and RoBERTa brought complaintunderstandingfarclosertohuman-levelperformance; and the latest graph-based and multimodal systems have further strengthened civic complaint analysis by capturing relational, spatial, and contextual signals that text-only approaches tend to miss.

Key findings include the persistent challenge of multilingual support, the absence of standardized public benchmarks, the ongoing tension between interpretability and performance, and thelargelyuntappedpotentialofLLMsinzero-shotcivic NLP. This survey identifies critical research gaps and outlines directions for building grievance intelligence systems that are scalable, transparent, and grounded in fairness and inclusivity.

Index Terms—Grievance Redressal, Natural Language Pro-cessing, Graph Neural Networks, Large Language Models, Com-plaint Classification, E-Governance

I. INTRODUCTION

Citizengrievancesystemssitatthecoreofhowthepub-lic interacts with governing institutions. Whether embeddedin municipal portals, national e-governance platforms like CPGRAMS, or institutional complaint cells, these systems share a common bottleneck: the manual effort required toread, categorize, route, and track thousands of heterogeneous complaints. The fallout — delayed resolutions, misrouted complaints,missedescalationsignals,andweakenedpublic trust — has made the case for AI-augmented grievance re-dressal increasingly difficult to ignore.

Over the past decade, the AI methods applied to thisdomain have shifted considerably. What started with key-word matching and Na¨ıve Bayes classifiers has grown to include BERT fine-tuning, zero-shot LLM prompting, Graph Attention Networks that model entire complaint ecosystems, and blockchain-integrated multimodal platforms capable of processing text, images, and video evidence together. Each technologicalwavehasbroughtrealgainsalongsidenewtrade-offs,yet the fieldstill lacksa consolidatedsynthesis thatmaps this progression in any analytical depth.

This survey addresses that gap by examining 20 papers published between 2017 and 2026, spanning civic complaint portals,educationalgrievancesystems,socialmediacomplaint detection, legal redressal chatbots, and threat-language anal-ysis tools — domains where grievance intelligence directly bears on the effectiveness of government systems. Our contri-butions are:

- Astructuredanalysisofmethodologicalevolutionin AI-driven complaint processing, ranging from classical machinelearningtograph-basedandmultimodalsystems.
- Ataxonomyofapproachesorganizedbyarchitecturaland functional distinctions.
- A comparative analysis of techniques, datasets, and per-formance metrics across the reviewed literature.

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- Identification of concrete, literature-grounded research gaps and actionable directions for future work.

Theremainderofthispaperisorganizedasfollows.Section II describes the review methodology; Section III presents the core literature review; Section IV provides the taxonomy; Section V offers comparative analysis; Sections VI and VII address research gaps and future directions; Section VIII concludes.

II. REVIEW METHODOLOGY

This survey employs a systematic literature review frame-work. Primary sources were aggregated from IEEE Xplore, Google Scholar, Scopus, the ACM Digital Library, arXiv,andNatureScientificReportsusingtargetedsearchstrings such as grievance redressal, complaint classification, civic NLP, e-governance AI, and escalation detection. Studies were includedifthey(a)proposedautomatedsystemsforcomplaint routing or classification in civic and social contexts; (b) uti-lizedmachinelearningmethodologies; and(c)werepublished between 2017 and 2026. We excluded papers focusing on general NLP without a specific grievance application or those lacking technical depth. The final corpus of 20 papers was curated based on relevance, methodological rigor, and domain diversity.

III. LITERATURE REVIEW

A. Early Machine Learning and Rule-Based Grievance Sys-tems

The early AI-driven grievance systems were built using classical machine learning models applied to preprocessed complainttext.ModelslikeNaiveBayes,LogisticRegression and Support Vector Machines showed the automatic routingof complains. However, they did struggle with two major issues such as they depended heavily on small, carefully prepareddatasetsandtheydidn’tgeneralizewelltoreal-world scenarios.

Forinstance,onesystemtrainedonaround170recordswith the accuracy of 92%. While that sounds impressive, such a small dataset makes the result unreliable and highly sensitive tohowthedatawassplit[11].Duringthisphase,mostsystems relied on manually labeled and domain-specific data, which worked fine in controlled environments but often failed in practical use.

At the same time, early mobile grievance application such asthefirstversionsofAllIndiagrievanceappsfocused more on digitizing workflows rather than adding intelligence. Complaints were stored using Firebase real-time databasesand submitted through simple category-based forms without any automated classification. Although these systems lacked AI capabilities to understand the urgency of the complaint, they played an important role in building an initial digital infrastructure for citizen services. [16].

Some systems have also tackled the problem of multi-department routing, where a single complaint needs to reach the right authority without the citizen having to figure out which department handles what [3].

B. Deep Learning Era: CNNs, LSTMs, and the Race forAccuracy

As deep learning approaches have became more prevalent, CNN and LSTM hybrid architectures and GloVe/Word2Vec embeddings are gradually replacing traditional bag-of-words representations.Word2Vec-based approaches paired with recur-rent models also picked up during this period, showing that oral and text complaints could be sorted into categories with-outmuchmanualfeatureengineering[5].Whenappliedtothe PuneMunicipalCorporationcomplaintdataset,aCNN–LSTM model achieved an accuracy of 81.61%, which is relatively modest for a four-class problem.This can be partly explained bythefactthatonly2,983outoftheavailable100,000 records were used for training [15]. This example persistant problem in grievance AI research: the mismatch between dataset scale and model capacity.In contrast, experiments on government railway complaint data used a much larger and more balanced dataset, with 186,940 complaints across 14 categories. Here, LSTM and CNN models achieved over 95% accuracy [12]. Although these results appear strong, the dataset does not reflect real world class imbalance, where common issues such as main tenance dominate while sensitive complaints like bribery are rare. As a result, actual deployment performance may be lower than reported. Overall, this phase demonstrated that deep learning can outperform classical methods when sufficient data is available, but also showed that data quality and representativeness are often more important than model complexity. Social media complaint detection introduced an additional challenge: identifying complaints within informal andnoisytext.AnearlyTwitter-basedclassifiertrainedonjust 100tweets[8]reportedhighaccuracy(95.8%)withinthesam-ple, but did not establish whether the model could generalize beyond this limited dataset. This highlights a broader concern in the literature—the gap between controlled experimental results and real-world applicability—which later approaches attempt to address more systematically.

C. TheTransformerInflectionPoint

The introduction of the Transformer architecture [18] marked a turning point in natural language processing, and complaint intelligence systems were no exception. Pre-trained contextual representations from models like BERT and its variantsprovedtotransferwelltodownstreamcomplaintclas-sificationtasks.AsystematiccomparisonofBERT,RoBERTa, ALBERT, and XLNet on multi-domain social media com-plaints [13] reported an 8% improvement in macro F1 overthe previous LR-BOW baseline, with BERT reaching 88.0% accuracy and a macro F1 of 87.0. Notably, the study also demonstrated cross-domain transfer capability — something earlier statistical and LSTM-based systems consistently strug-gled with.

The rise of transformer models coincided with a broader shift toward more integrated complaint routing architectures. Systems began combining NLP with rule-based routing en-gines,SLA-drivenescalationmechanisms,andsentimentanal-ysistosupportend-to-endcomplaintlifecyclemanagement.A university grievance system [20] that brings together NLP-based categorization, Random Forest-based resolution time prediction, and SLA-aware escalation reported 89% cate-gorization accuracy alongside a 40% reduction in average resolution time — a clear indication that pairing classification with workflow automation can produce tangible operational gains.Educational institutions have seen similar efforts, with automated categorization and department-level routing being applied to student grievance management to cut down on manual handling [4].Similar hybrid approaches combining NLP with standard ML classifiers have shown that complaint routing across departments is achievable without deep learn-ing, provided the pipeline is well designed [7].

The Retrieval-Augmented Generation (RAG) paradigm pushed transformer capabilities further into domain-specific legal applications. A system built for Indian consumer rights query handling [9] assembled a curated legal knowledge base and introduced the HAB (Helpfulness, Accuracy, Brevity) evaluation framework as a domain-specific metric set forlegalconversationalAI.Despitestronghelpfulnessscores,the system managed only 3.61/5 on accuracy — a telling limita-tion. In high-stakes legal contexts, where imprecise responses can carry real consequences, large language models still fall noticeably short.

D. TowardStructuralIntelligence:Graph-BasedandMulti-Model system

The latest developments point to a clear shift in how grievance systems are being designed. Rather than treating complaints as isolated text, they are increasingly understoodas part of larger relational, spatial, and temporal networks. Two GNN-based systems — one focused on civic escalation detection[1]andanotherongrievancenetworkanalysis— reflect this shift well. They show that escalation risk [1] is betterpredictedbylookingatacomplaint'spositionwithin a network — geographic proximity to other complaints, de-partmentaloverlap,userbehaviorpatterns—thanbyrelying on text alone. A Graph Convolutional Network with attention mechanisms achieved 91.2–92.2% accuracy for escalation prediction, roughly 9 percentage points ahead of LSTM-based models.

Thezero-shotLLMframework[2]representsaparallelline of development. Instead of training task-specific classifiers, it prompts a pre-trained multimodal LLM to handle grievance classification, urgency scoring, and abuse detection without anydomain-specificfine-tuning.Sinceitprocessesbothtext andimageinputsthroughasinglepromptinterface,itremoves thedependencyonlabeleddatasets—ameaningfuladvantage in real-world deployments where annotated data is hard to come by.

BlockchainintegrationenteredthepicturewithCitizenCon-nect [19], which brings together NLP classification, computer vision-based evidence analysis, cryptographic complaint log-ging, and geospatial heatmap visualization within a Flutter mobile platform. Its evaluation is qualitative only, whichlimits direct performance comparison, but the architectural contribution stands on its own — blockchain-backed com-plaint immutability with optional citizen anonymity tackles accountability gaps that purely ML-based systems are notbuilt to handle.Efforts toward fully autonomous redressal for government services have also emerged, attempting to handle the entire complaint lifecycle from intake to resolution with minimal human involvement [6].

A more recent direction involves unsupervised topic mod-eling on large-scale government portal data [10]. Rather than slotting complaints into predefined categories, BERTopic and NMF applied to 91,866 SewaSetu grievance records surface latent thematic structures that administrators may not have anticipated.Thisisparticularlyusefulforpolicydiscovery and proactive governance, where the goal is understanding complaint landscapes broadly rather than routing individual tickets.

IV. TAXONOMY OF APPROACHES

Based on the reviewed literature, we derive a five-tier tax-onomy that captures the architectural and functional evolution of grievance AI systems, as summarized in Table I.

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TABLEI
TAXONOMYOFAIAPPROACHESINGRIEVANCEREDRESSAL

Tier	Category	KeyCharacteristics
T1	Rule-Based&ClassicalML	Keyword routing, Na¨ıveBayes, SVM, LogisticRegression; low scalability;high interpretability
T2	DeepNeuralNetworks	CNN, LSTM, GloVe/Word2Vec; improvedaccuracy; limited cross-domain transfer
T3	Transformer-Based	BERT, RoBERTa, RAG; contextualembeddings;strongtransfer learning; moderateinterpretability
T4	Structural& Graph-Based	GCN,GAT;modelsrelational complaint networks; capturesescalation patterns; computa-tionally intensive
T5	Multimodal &LLM-Integrated	Zero-shot LLMs,Vision–Language Models,Blockchain; multimodal input;minimallabeleddata; increased architecturalcomplexity

Each tier reflects not just a performance jump but a conceptual expansion in what aspects of a complaint are actuallybeingmodeled.T1systemsworkwithlexicalfeatures of complaint text; T2 brings in sequential context; T3 tapsintotransferlearningfrompre-trainedcorpora;T4factors in inter-complaint relational structure; and T5 adds modality richness alongside institutional accountability mechanisms. This progression is not strictly linear — recent systems often blendmultipletiers,suchasGNNsbuiltonBERT-basednode embeddings — but the taxonomy helps clarify what each generation of approaches is actually contributing.

V. COMPARATIVE ANALYSIS

Table II summarizes representative systems across the re-viewedliteraturealongkeycomparativedimensions.Forspace efficiency, we present one to two systems per methodological tier.

A. DiscussionofTrade-offs

Several cross-cutting trade-offs emerge from this analysis. First, there is a persistent tension between *accuracy and in-terpretability*:GNNandtransformer-basedmodelsachievethe highestreportedaccuraciesbutgeneratepredictionsthatare

TABLEII
COMPARATIVEANALYSISOFREPRESENTATIVEGRIEVANCEAISYSTEMS

System/Reference	MethodType	CoreTechnique	DatasetType	BestMetric	Strengths	Limitations
NBClassifier[11]	ClassicalML	Na¨ıveBayes	Organic(170 records)	Acc:92%	Simple; interpretable	Tinydataset;no gen-eralization
CNN–LSTM[15]	Deep Learning	CNN+LSTM, GloVe	Municipal (2,983of 100K)	Acc:81.61%	Realgovt.data	Underutilized dataset; modest accuracy
RailwayLSTM[12]	Deep Learning	LSTM,CNN	Govt.(186,940 balanced)	Acc:95%+	Largerealdataset	Artificial class balance; low interpretability
BERT/Transformer	Transformer	BERT,	Twitter(1,971	F1:87.0	Cross-domain	Smalldataset;social

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[13]		RoBERTa, M-BERT	tweets)		transfer	mediabias
RAGChatbot[9]	Transformer +RAG	RAG,LLM, BERTScore	LegalQA(4 novelsets)	HABAcc: 3.61/5	Novelevaluation framework	Legalprecisiongaps; English-only
GNNEscalation[1]	Graph-Based	GCN+Attention, BERT	Civic (10,000+)	Acc:91.3%; F1:0.88	Capturesrelational context	Computationallyin-tensive;black-box
Zero-ShotLLM[2]	LLM (Zero-Shot)	MultimodalLLM, prompting	Civic(text+ images)	Qualitative	Nolabeleddata required	Limitedevaluation; hallucinationrisk
CampusCare[20]	Transformer +Rules	NLP,Random Forest,SLA	Institutional (2,500+)	Acc:89%; -40%ART	SLAescalation; sentiment	Slangsensitivity;no multimedia
CitizenConnect[19]	Multimodal+ Blockchain	NLP,CV, Blockchain	Prototype(9 complaints)	Qualitative only	Immutability; anonymity	Noquantitativeeval-uation
BERTopic/ NMF [10]	Unsupervised	LDA,NMF, BERTopic	Govt.(91,866 records)	Cv coherence: BERTopic best	Largestreal dataset; privacy-aware	Nocomplaintrout-ingoutput
Grievance Dictionary[14]	Lexicon-Based	Psycholinguistic lexicon,NLP	Multi-corpus (novels,Reddit, manifestos)	Precision: high	Threat-language analysis	Narrowscope;no routing

difficult for administrators and policy-makers to meaningfully interpret. Classical ML systems, while less accurate, offer considerablymoretransparency—apropertythatstillmatters ingovernancecontextswherealgorithmicdecisionsneedtobe auditable.

Second, *dataset scale and realism* heavily shape reported performance, often overstating confidence in otherwise lim-ited systems. Several studies claiming 92–96% accuracy are built on datasets with fewer than 200 samples or artificially balanced class distributions — conditions far removed from real-world deployment. Meanwhile, the largest dataset in this survey (91,866 grievances from the SewaSetu portal) is used for unsupervised topic discovery, where supervised accuracy cannot be reported at all. This points to a fundamental gap: there is no large, publicly available, labeled benchmark for civic complaint classification.

Third, *modality richness versus computational overhead*marks the current frontier. Zero-shot LLMs and multimodal architectures reduce or eliminate the need for labeled data,but they bring inference latency, hallucination risk, and in-frastructuredemandsthatmaybeimpracticalforlow-resource municipal environments.

Finally,*evaluationmethodology*remainsinconsistentacross the literature. Some systems are assessed using standard met-rics like accuracy and F1, while others lean on operational indicators such as resolution time reduction or user satisfac-tion scores. Recent LLM-based systems introduce their own evaluationframeworks—HABmetricsbeingoneexample making direct comparison harder still. This inconsistency weakens cross-study comparability and complicates evidence-based system selection for practitioners.

VI. RESEARCH GAPS AND CHALLENGES

Lack of Transparency and Trust Mechanisms. Despite advancesinautomatedgrievanceprocessing,veryfewsystems incorporate meaningful mechanisms for verifying complaint authenticity or ensuring transparency in resolution workflows. Most reviewed platforms rely on internal administrative pro-cesses, offering citizens no verifiable proof of action, no audit trails, and no tamper-resistant records. This erodes publictrust — especially when complaints are delayed, misrouted,or closed without clear justification. Blockchain-integrated systems [19] make a start on immutability and optional anonymity,buttheabsenceofstandardizedverificationand accountabilityframeworksremainsarealbarriertotrustworthy large-scale deployment.

AbsenceofStandardizedBenchmarks.Themoststruc-turallydamaginggapinthereviewedliteratureisthelackof a publicly available, large-scale, labeled benchmark for civic grievanceclassification.Studiesbuildingorganicdatasetsof 100–170records[11],ortrainingonjust2,983of100,000 availablerecords[15],produceaccuracyfiguresthatcannot bemeaningfullycomparedorreproduced.Withoutashared benchmark,thefieldhasnoreliablewaytomeasureactual progress.Duplicatecomplaintdetectionandsmartescalation remain largely separate from classification pipelines, yet both arenecessaryinpractice—withoutthem,systemsgetflooded withrepeatsubmissionsandmissgenuinelyurgentcases[17].

MultilingualLimitations.EverysysteminthissurveyisEnglish-onlyorEnglish-dominant—despitetargetde-ployment contexts like India, civic municipalities, and multi-districtportalsbeinginherentlymultilingual.Systemsde-scribed as having “rural applicability” consistently push mul-tilingualsupporttofuturework.Thisisnotaminorgap: code-switchingininformalcomplainttext—mixingHindi, Kannada,orTeluguwithEnglish—degradeseventransformer models that individually perform well on monolingual inputs.
Interpretability Deficit. GNN-based escalation models de-liverthestrongestperformanceonrelationalcomplainttasks butoffernohuman-interpretableexplanationfortheirrisk scores.IngovernancecontextswhereAI-drivendecisions must be defensible to citizens and oversight bodies, black-box outputsareinstitutionallyunworkable.XAItechniquessuchas GNNExplainerorattentionvisualizationhavenotbeenapplied togrievanceescalationinanyreviewedpaper.

Real-Time Deployment Constraints. Transformers and GNNs require inference infrastructure that sits well beyondthe resource constraints of district-level governments or small institutions. Edge deployment optimization, model quantiza-tion, and distillation for grievance classifiers remain entirely unexploredinthereviewedliterature—despitebeingpractical prerequisites for deployment at any meaningful scale.

Dataset Bias and Class Imbalance. Several systems trained on artificially balanced datasets [12] or small curated corpora [11] are prone to performance degradation under real complaint distributions, where common categories vastly out-number rare ones — maintenance complaints versus briberyor emergency reports, for instance. No paper in this corpus treats class imbalance as an explicit design constraint.

Evaluation Framework Fragmentation. The absence of a shared evaluation framework — one that spans classification metrics,operationalimpact,andusertrust—makesevidence-based comparison between systems practically impossible.TheHABframeworkintroducedby[9]isastepforward for conversational systems, but nothing equivalent exists for routing, escalation, or end-to-end redressal platforms.

VII. FUTURE WORK

The gaps identified above point to several concrete and practicalresearchdirections.Inparticular,thelackoftrans- parency and verifiable trust mechanisms in existing systems highlightstheneedforgrievanceplatformsthatnotonlymake accurate predictions but also provide auditable workflows, clear resolution trails, and mechanisms for complaint verifi-cation. Addressing this alongside technical improvements will be critical for real-world adoption.

Oneofthemostimpactfulnear-termcontributionswouldbe thecreationandpublicreleaseofamultilingual,multi-domain, large-scale civic grievance benchmark—analogous to GLUE forgeneralNLP—thatenablesreproduciblecross-systemcom-parison.SuchadatasetshouldspanmultipleIndianlanguages, include metadata (e.g., location, timestamp, department), and capture both resolved and escalated complaint labels.

On the modeling side, combining the relational capabilities of GNNs with the contextual understanding of transformer encoders in an end-to-end architecture represents a promising butunderexploreddirection.HybridGraph–BERTapproaches, which have shown success in domains such as citation net-works and fraud detection, could be effectively adapted for complaint escalation prediction.

Improving explainability in graph-based grievance systems remains both a technical and institutional priority. Techniques such as GNNExplainer or Integrated Gradients can be ex-tended to generate complaint-level justifications, ideally ex-pressed in natural language, enabling non-technical adminis-trators to better understand and trust model outputs.

For deployment in low-resource settings, lightweight trans-formermodelssuchasDistilBERTorMobileBERT,fine-tuned on civic complaint data and optimized through quantization, offer a practical path toward achieving high accuracy without reliance on centralized infrastructure.

Finally,federatedlearningacrossmultiplemunicipalbodies presents an opportunity to improve model performance col-laboratively while preserving data privacy. Such an approach allows systems to learn from diverse complaint distributions without requiring centralized storage of sensitive citizen data, addressingbothprivacyconcernsanddatascarcity challenges.

VIII. CONCLUSION

ThissurveytracesthearcofAI-drivengrievanceredressal from early rule-based and statistical classifiers through deep learning and transformer models, to the current frontier of graph-based, zero-shot LLM, and blockchain-integrated multimodal architectures. Each stage has pushed both the per-formanceceilingandtheconceptualscopeofwhatautomation can do: early systems focused on categorizing complaints, while modern ones can predict escalation risk from relational complaintnetworks,processimageevidence,andhandletasks without any labeled data through zero-shot prompting.

Three themes run consistently through this progression. First, data quality and scale tend to matter more than model complexity — systems that pair strong models with large, realisticdatasetsholdupreliably,whilethosetrainedonsmall curated corpora often overfit. Second, the tension between performance and interpretability does not go away: the most accuratemodels,GNNsandtransformersinparticular,offer limited transparency for institutional decision-making. Third, multilingual support stays largely unaddressed across the lit-erature, despite being a basic requirement for equitable and inclusive civic AI.

The field is at something of an inflection point. Method-ological capabilities have matured considerably, but the sup-porting empirical infrastructure — standardized benchmarks, unifiedevaluationframeworks,real-worlddeploymentstudies has not kept pace. Closing that gap is both the central challengeandthemostconsequentialdirectionforfuturework in grievance intelligence.

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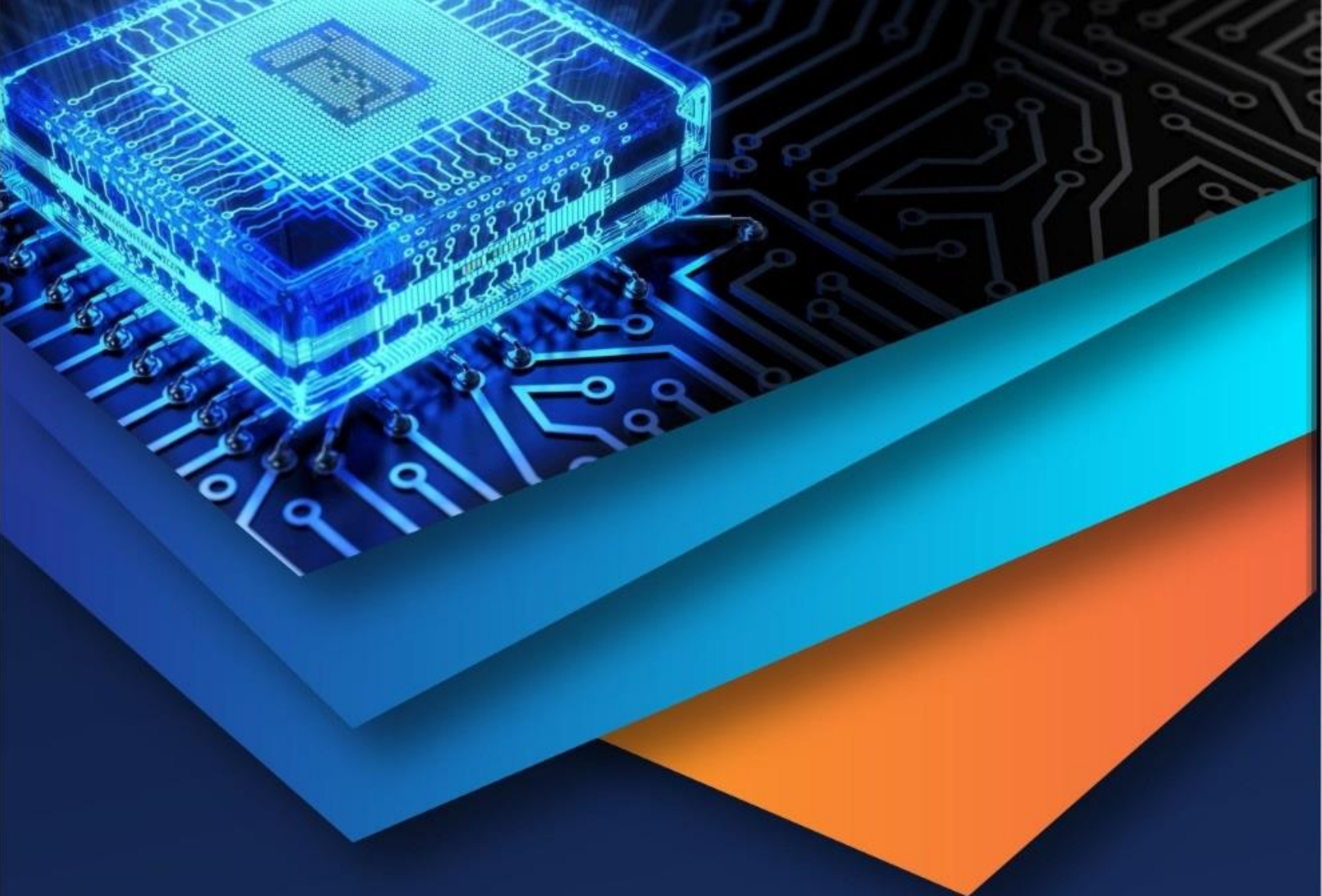

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