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Smart Cities, Smarter Flood Governance? Evaluating Urban Flood Mitigation in Coastal India through QGIS-MOLUSCE

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Abstract: India's Smart Cities Mission (SCM, 2015–2025) promised data-driven urban governance, yet coastal cities experience urban flooding. This study asks, to what extent the SCM has mitigated urban flooding in coastal Smart Cities by comparing three cases along Bay of Bengal—Chennai, Visakhapatnam and Bhubaneswar—through an open, reproducible geospatial workflow. Multitemporal satellite classifications for 2016 and 2026 were used to quantify land–water change, and a cellular automata–artificial neural network (CA-ANN) model implemented in the QGIS MOLUSCE plugin was applied to characterise transition dynamics and forecast reliability. Results show that, land remained the dominant cover in all three cities (>96%), and water area changed only marginally over the decade: Chennai +5.51 km^2 (2.90%→3.20%), Visakhapatnam +1.87 km^2 (0.43%→0.52%) and Bhubaneswar +0.21 km^2 (0.23%→0.25%). Model agreement varied sharply by city (Kappa: Chennai 0.726, Visakhapatnam 0.346, Bhubaneswar 0.046), indicating that forecast reliability is conditional on landscape heterogeneity and class balance rather than uniform across coastal systems. It can be said that the SCM delivered monitoring and early-warning capability but did not completely reverse the structural drivers of urban flooding—wetland loss, impervious expansion and fragmented drainage governance. The mitigation achieved is partial and heterogeneous. The findings are also linked to SDG 6, SDG 11 and SDG 13 and argued for enforceable growth boundaries, riparian-buffer restoration and low-impact development embedded in mandatory climate-risk assessment.

Keywords: Urban Flood Governance, Coastal Smart Cities, Cellular automata–artificial neural network (CA-ANN), QGIS-MOLUSCE, Sustainable Development Goals.

I. INTRODUCTION

Urban flooding is now the most frequent disaster facing Indian cities, and the Coastal Smart Cities are where the flood risk is concentrating. India's coastline runs for more than 7,500 km and supports a dense chain of coastal cities, ports and informal settlements that sit only a few metres above sea level. When intense pluvial rain meets a high tide, a choked drain or a filled-in wetland, water has nowhere to go. The result is the recurring inundation as seen in Chennai in 2015, in Mumbai across many monsoons, and in dozens of smaller coastal cities every year.

To mitigate the situation, Government of India launched the Smart Cities Mission (SCM) on 25 June 2015, with the goal of upgrading 100 cities through "smart solutions" [1],[2],[3]. Its timeline was extended several times and the Mission was formally closed on 31 March 2025. By that date all 100 cities had Integrated Command and Control Centres (ICCCs), yet only 18 cities had completed every sanctioned project[4]. The Mission therefore offers a decade-long natural experiment: did a large, technology-led urban programme actually make coastal cities safer from floods?

In this context, this paper tries to answer the question: to what extent has the Smart Cities Mission successfully mitigated urban flooding in coastal Smart Cities of India? It is pursued through three research questions. RQ1 asks whether coastal Smart Cities show lower flood vulnerability after the introduction of the SCM. RQ2 asks what geospatial patterns drive flood risk across coastal SCM cities. RQ3 asks how robust flood-forecasting models are for urban coastal systems.

These questions are addressed by comparing three coastal Smart Cities on the Bay of Bengal—Chennai (Tamil Nadu), Visakhapatnam (Andhra Pradesh) and Bhubaneswar (Odisha). The three differ in size, hydrology and flood history, which makes them a useful gradient rather than three repeats of the same case. The land–water change between 2016 (early in the Mission) and 2026 (after its close) is quantified and cellular automata–artificial neural network (CA-ANN) model is applied inside the open-source QGIS-MOLUSCE plugin to study transition dynamics and forecast reliability. The contribution is a transparent, transferable, decision-oriented comparison that links measured land-cover change to the governance promise of the SCM.

II. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

A. Urban Flooding as a Governance Problem

Indian urban flooding is widely understood as a wicked problem rather than a purely natural one[5][6]. The drivers are consistent across studies: the loss of rivers, lakes, marshes and floodplains to unplanned urban development; the spread of impervious surfaces that hinders infiltration and sharpen runoff; drainage networks built for a smaller, wetter-tolerant city; and fragmented institutions that respond after the water rises rather than planning before it. Chennai is the textbook case[7]. The Pallikaranai marsh, the city's last large freshwater wetland, has shrunk from a historical extent of several thousand hectares to a few hundred, and a government survey found that close to two-fifths of the remaining marsh had been encroached. After the 2015 floods the city built an Integrated Storm Water Drain network, but the design philosophy prioritised draining water away quickly over storing it, and parts of the city flooded again in 2021[8].

B. Smart Cities, Monitoring and the Resilience Gap

Evaluations of the SCM show a different picture. The Mission was strong on sensing and coordination: every city gained an ICCC, and coastal cities such as Visakhapatnam and Bhubaneswar deployed disaster-management, early-warning and waterlogging-monitoring systems through these centres[9],[10],[11]. Roughly ₹21,182 crore of stormwater-drainage projects were implemented across 97 cities. But independent reviews, a Parliamentary Standing Committee evaluation and Comptroller and Auditor General audit all note that ecological planning was neglected, climate-risk assessment was not deemed mandatory, and Area-Based Development concentrated spending on small "model" zones that could not fix city-wide drainage. The literature calls this mismatch a "resilience gap". Cities became better at responding after floods rather than preventing them.

C. Geospatial Modelling of Land-Use Change

Remote sensing and GIS make it possible to measure the physical drivers of flooding directly. Among predictive tools, the hybrid CA-ANN model has become a standard. Cellular automata capture local clustering through neighbourhood rules, while artificial neural networks learn the nonlinear influence of drivers such as distance to roads, distance to settlements and slope. The QGIS-MOLUSCE plugin packages both into an open, reproducible pipeline, and recent applications across Asia report validation Kappa values typically between 0.70 and 0.90 for land-use forecasts. Different studies applied CA-ANN/MOLUSCE to a flood-control watershed and reported settlement growth past 80% of the basin with a validation Kappa of 0.829[12],[13],[14],[15]. Similar method is applied here, but it is turned towards a comparative, governance-focused question.

D. Research Gap

Two gaps motivate this paper. First, most CA-ANN/MOLUSCE studies model a single watershed; very few compare multiple cities under a common programme to ask whether a policy worked. Second, evaluations of the SCM are largely qualitative or audit-based and rarely tie the Mission's outcomes to measured land–water change. This paper tries to address the gaps by using one reproducible geospatial method to compare three coastal Smart Cities and by reading the results against the Mission's flood-mitigation promise and the SDGs.

III.STUDY AREA

The three cities sit on the east coast of India along the Bay of Bengal and are all SCM designees, but they occupy different points on a size-and-exposure gradient (Table I).

A. Chennai, Tamil Nadu

Chennai, the capital of Tamil Nadu, is a coastal megacity on a flat, clay-rich coastal plain drained by the Adyar and Cooum rivers and the Buckingham Canal. Much of southern Chennai was historically floodplain and marsh. The December 2015 floods—linked directly to wetland loss and blocked drains—killed hundreds and became the country's reference event for urban flooding. It is the largest and most flood-exposed of the three study cities.

B. Visakhapatnam, Andhra Pradesh

Visakhapatnam is a port city of hilly terrain backed by the Eastern Ghats, with steeper slopes than Chennai and a strong exposure to cyclones and storm surge from the Bay of Bengal. Its flood risk is shaped by cyclonic rainfall and rapid runoff from high ground rather than by a single large marsh. The city has run flood risk and vulnerability assessments using GIS and monitors waterlogging through its ICCC.

C. Bhubaneswar, Odisha

Bhubaneswar, the capital of Odisha, lies on the western edge of the Mahanadi delta on the bank of the Kuakhai river. It is the smallest of the three by area and also one of the planned cities of India. The city flooded in June 2018 and was tested by Cyclone Fani in May 2019; both were coordinated through its ICCC. Its drainage administration has repeatedly identified about thirty waterlogging zones and flagged the absence of a citywide drainage master plan and the encroachment of natural channels.

TABLE I. Study-Area Characteristics Of The Three Coastal Smart Cities

Attribute	Chennai	Visakhapatnam	Bhubaneswar
State	Tamil Nadu	Andhra Pradesh	Odisha
Analysed area (km²)	~1,806	~2,176	~1,017
Terrain	Flat coastal plain	Hilly, Eastern Ghats	Deltaic, Kuakhai
Reference flood	2015 floods	Cyclone/surge	2018; Fani 2019
ICCC	Yes	Yes	Yes

Source: own elaboration from SCM and municipal records; areas from the classified imagery used in this study.

IV. METHOD

The workflow follows the reference CA-ANN/MOLUSCE pipeline so that it is transparent and reproducible, and it is applied identically to all three cities to keep the comparison fair.

A. Data and Pre-processing

Multitemporal optical satellite imagery was acquired for two reference years, 2016 and 2026, chosen to bracket the active life of the Mission. Scenes were selected for low cloud cover (2-3%) and comparable seasonal windows to limit phenological noise, then georeferenced, clipped to each city boundary, and resampled to a common 30 m grid. City boundaries were taken from open administrative shapefiles available in GitHub. The same procedure, class scheme and symbology were used across both years and all three cities to ensure that any measured change reflects the landscape rather than the processing.

B. Classification

Each scene was classified by supervised maximum-likelihood classification into land and water classes (NWDI), which is the distinction most directly tied to flood storage and to the change metric reported here. Training polygons were digitised from the imagery and cross-checked against high-resolution reference views. Class areas were computed from the polygonised rasters in square metres and converted to square kilometres and percentages.

C. Explanatory Variables

Three open, policy-relevant drivers were used to model transition potential: distance to roads (development pressure along corridors), distance to settlements (infill and edge expansion), and slope derived from a 30 m digital elevation model (construction feasibility and runoff response). Predictors were normalised to the interval [0, 1]. These drivers were chosen because they are available consistently for all three cities; socio-economic variables such as land price or detailed zoning were excluded to preserve a reproducible, open-data framework.

D. CA-ANN Modelling in MOLUSCE

Land–water transitions were modelled with the hybrid CA-ANN method in the QGIS-MOLUSCE plugin. A multi-layer perceptron was trained on the 2016–2026 transition using the three drivers to produce transition-potential surfaces, and a cellular-automata module propagated neighbourhood effects on a 5×5 Moore neighbourhood using transition matrices estimated from the observed change. Network size and training iterations were tuned by monitoring mean-squared error and stopping when added complexity gave only marginal gains, an implicit convergence criterion rather than a fixed iteration count.

E. Accuracy and Agreement

Agreement between modelled and observed maps was summarised with the Kappa coefficient, which measures agreement beyond chance. We interpret Kappa on the widely used scale where values below 0.20 indicate slight agreement, 0.21–0.40 fair, 0.41–0.60 moderate, 0.61–0.80 substantial, and above 0.80 almost perfect. Reporting Kappa per city, rather than pooling, is done deliberately as it lets the comparison expose where the model is trustworthy and where it is not, which is the substance of RQ3. The figures are reported exactly as obtained and treat low values as a genuine limitation rather than smoothing them over.

V. RESULTS

A. Decadal Land–Water Change (RQ1)

Across all three cities, land remained overwhelmingly dominant and water occupied a small share of the analysed area in both years (Table II). The decadal change in water area was small in absolute and relative terms. Chennai gained 5.51 km2^2 of water, moving from 2.90% to 3.20% of its area. Visakhapatnam gained 1.87 km^2 (0.43% to 0.52%), and Bhubaneswar gained 0.21 km^2 (0.23% to 0.25%). In each city land area fell by exactly the matching amount.

Data revealed two kinds of readings. The results show little gain in water area is the opposite of the catastrophic wetland loss reported in the qualitative literature for these cities. It most plausibly reflects what the land–water classification can and cannot see over a ten-year window—reservoir levels, tidal state and seasonal ponding on the classification dates—rather than a genuine recovery of flood storage. One the other hand, data show clearly that there is an absence of a large, programme-driven expansion of urban water storage: a decade of Smart Cities investment did not visibly enlarge the natural water surface that buffers floods. On the vulnerability question (RQ1), the geospatial signal is therefore shows stability, not improvement; it gives no positive evidence that coastal Smart Cities became measurably less flood-exposed in their land–water structure after the Mission.

TABLE II. LAND–WATER CHANGE, 2016–2026 (FROM CLASSIFIED IMAGERY)

City / class	2016 (km²)	2026 (km²)	Change (km²)	2016 (%)	2026 (%)
Chennai – Land	1,753.47	1,747.96	−5.51	97.10	96.80
Chennai – Water	52.35	57.85	+5.51	2.90	3.20
Vizag – Land	2,166.46	2,164.59	−1.87	99.57	99.48
Vizag – Water	9.34	11.21	+1.87	0.43	0.52
Bhubaneswar – Land	1,014.64	1,014.43	−0.21	99.77	99.75
Bhubaneswar – Water	2.35	2.55	+0.21	0.23	0.25

B. Geospatial Drivers (RQ2)

The CA-ANN transition surfaces, driven by distance to roads, distance to settlements and slope, reproduce the corridor-and-edge pattern typical of Indian coastal cities: change concentrates along arterial roads and at the fringes of existing built-up clusters, while slope suppresses conversion on steeper ground. This pattern is strongest in Chennai, whose flat plain offers little natural brake on lateral expansion, and is moderated in Visakhapatnam, where the Ghat hills constrain where buildings can be built. Bhubaneswar shows the least net change of the three.

Read together with the established record for these cities, the drivers point the same way as the literature: flood risk is governed less by how much new water appears and more by how the land around the water is consumed and sealed [16].[17]. The combination of near-total land dominance (>96% in every city) and corridor-driven transition potential is consistent with rising imperviousness and shrinking ecological buffers—the recognised geospatial signature of worsening urban flood risk—even where the decadal land–water totals move only slightly.

C. Forecast Reliability (RQ3)

The Forecast Model differed sharply among the three cities (Table III). Chennai returned a Kappa of 0.726, which falls in the substantial-agreement band and is comparable to published CA-ANN/MOLUSCE studies. Visakhapatnam returned 0.346 (fair agreement), and Bhubaneswar returned 0.046, which is only slight agreement and barely above chance.

TABLE III. MODEL AGREEMENT (KAPPA) BY CITY AND INTERPRETATION

City	Kappa	Agreement band	Forecast use
Chennai	0.726	Substantial (0.61–0.80)	Usable
Visakhapatnam	0.346	Fair (0.21–0.40)	Cautious
Bhubaneswar	0.046	Slight (<0.20)	Not reliable

The pattern is informative rather than disappointing. Kappa rewards agreement beyond chance, and it is hard to score well when one class (land) dominates so heavily that the model can be “right” almost everywhere by predicting no change. The more extreme the land dominance and the smaller the water class, the more fragile Kappa becomes—which is exactly the ordering observed (Chennai, with the largest water share, scores highest; Bhubaneswar, with the smallest, scores lowest). The answer to RQ3 is that, flood-forecasting robustness for these coastal systems is conditional, not uniform. There is no single modelling recipe that can transfer cleanly across cities of different size, class balance and terrain. The low Bhubaneswar value stands as a limitation on city-by-city prediction.

VI. DISCUSSION

A. Answering the Core Question

This paper tried to answer the core question, to what extent did the Smart Cities Mission mitigate urban flooding in the Coastal Smart Cities of India? The evidence supports a measured answer: partially, and unevenly. The Mission demonstrably built sensing and coordination—ICCCs, early-warning systems, waterlogging dashboards and stormwater projects. But the geospatial structure that actually governs flooding barely moved. Water storage did not expand in any of the three cities, land remained above 96% of the area, and the transition drivers still point toward corridor-led sealing of the surface. The Mission made these cities better at responding after floods rather than absorbing them. That is a resilience gap, observed now through measured land–water change rather than through audit narrative alone.

B. Why Mitigation Stayed Limited

The reasons is embedded within the design of the SCM [18]. SCM favoured Area-Based Development—compact “model” zones—over the citywide drainage and ecological restoration. Moreover, climate-risk assessment was not deemed mandatory, so projects were rarely stress-tested against the floods they were meant to prevent. For example, faster drainage network in Chennai moves water downstream rather than storing it, and so it trades one neighbourhood’s flood for another’s. Additionally, encroachment of wetlands and natural channels, repeatedly documented in Chennai and Bhubaneswar, continued during the Mission. These structural problems cannot be mitigated through Technology. It can improve the response time but cannot, by itself, restore lost water storage in the cities.

C. Alignment with the Sustainable Development Goals

The findings are directly linked to three SDGs. SDG 6 (Clean Water and Sanitation) depends on healthy urban water bodies for recharge and flood buffering. Here, the flat water-area trend shows no progress in enlarging blue-green infrastructure of cities. SDG 11 (Sustainable Cities and Communities), and Target 11.5 on reducing deaths and losses from water-related disasters in particular, is the Mission's design—yet the persistence of flood exposure shows the target is unmet. SDG 13 (Climate Action) frames the rising hazard: with sea level rising and intensity of rainfall increasing, cities which are not expanding storage or reducing imperviousness are becoming more exposed to urban flooding. In this case, a reproducible CA-ANN/MOLUSCE workflow can contribute to the SDG localisation, because it gives municipal agencies an open, low-cost way to monitor SDG targets year on year.

D. Policy Implications

Three shifts in policymaking can be identified from the results. First, make climate-risk and flood-storage assessment mandatory for urban projects, so that drainage and zoning are designed against the design storm rather than around it. Second, move from monitoring urban flood to ecological restoration: protect and restore wetlands, riparian buffers and natural channels with legal force, and pair them with low-impact development—permeable surfaces, bioswales and detention—to rebuild the storage that sealing removed. In this case, Chennai has made significant stride which other cities should follow. Third, scale from "islands of smartness" to citywide and regional drainage governance with shared data, since a flood does not respect ward boundaries. The uneven model performance also carries an operational lesson: forecasting tools must be validated city by city before they are trusted, and a low Kappa is a signal to invest in better local data, not to abandon the approach.

E. Limitations

The land–water classification captures storage structure but not drainage capacity, sewer condition or sub-daily flood dynamics, so further studies are needed to alongside hydrological and flood-forecasting study for more accurate results. Two-date imagery is sensitive to tidal and seasonal conditions on the acquisition dates, which is the most likely explanation for the small apparent water gains. Year-on-year along with seasonal data will improve the external validity of the results. The CA-ANN agreement was weak in two of three cities, especially Bhubaneswar, so city-specific forecasts there are not yet reliable. A richer driver set, more class detail and multi-date validation would all strengthen future work.

VII. CONCLUSION

This study compared three coastal Smart Cities of India—Chennai, Visakhapatnam and Bhubaneswar—through an open CA-ANN/MOLUSCE workflow to ask how far the Smart Cities Mission mitigated urban flooding. Over 2016–2026, land stayed dominant (>96%) and water area changed only marginally in every city (Chennai +5.51 km², Visakhapatnam +1.87 km², Bhubaneswar +0.21 km²), while model agreement ranged from substantial in Chennai (Kappa 0.726) to slight in Bhubaneswar (0.046). The SCM delivered effective urban flood monitoring and early-warning capacity but did not expand the natural water storage (blue-green infrastructure) or reverse the imperviousness and drainage fragmentation that drive coastal urban floods. Its mitigation was therefore partial and uneven. Closing this resilience gap will require mandatory climate-risk assessment, legally protected ecological restoration, implementation of Nature Based Solutions and citywide drainage governance, supported by reproducible geospatial monitoring of the kind demonstrated here. Future work should couple these land-use forecasts with hydrologic and hydraulic models, enrich the driver set, and validate forecasts city by city before they inform decisions.

VIII. ACKNOWLEDGEMENT

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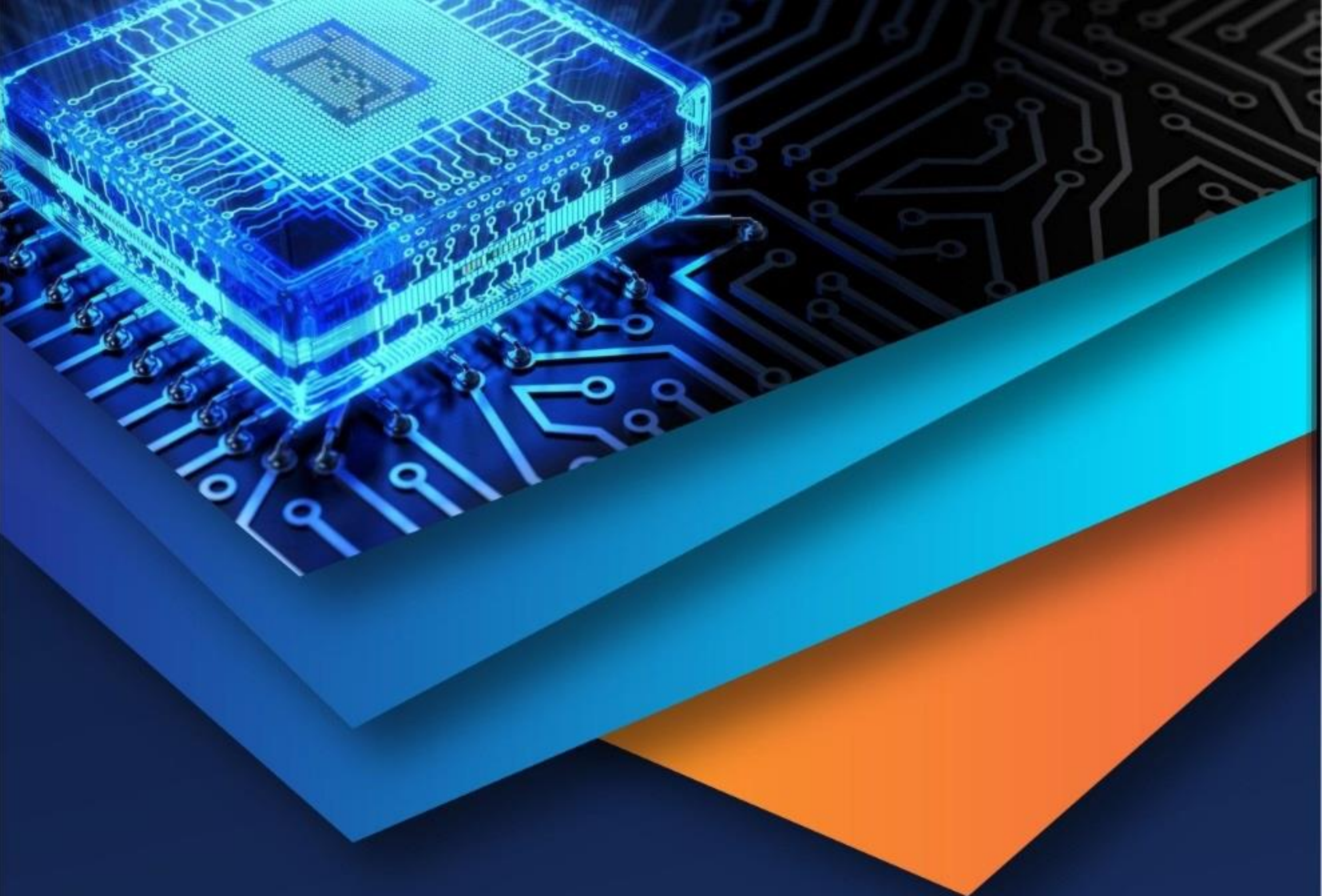

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