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AI and IoT-Based Crowd Capacity Prediction and Event Safety Management System Using Historical Event Analysis

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Abstract: Large-scale gatherings in public places often face significant safety risks due to overcrowding, inadequate planning, and the lack of automated decision support. Traditional approval processes depend heavily on manual judgment, leading to frequent errors in capacity estimation and insufficient emergency preparedness. Tragic situations (e.g., Karur Temple stampede, 2024; Morbi Bridge collapse, 2022) highlight the urgent need for predictive and system-level safeguards.

This paper introduces an integrated AI+IoT framework for pre-event capacity prediction and live-event risk enforcement. The AI module evaluates venue geometry, historical incidents, and event metadata to determine safe occupancy and classify risk. The IoT module combines live counts (people counters, CV- based density maps) with the predicted capacity to trigger alerts and auto-generated SOPs, including evacuation routing, steward allocation, and Public Address (PA) messaging. We describe the data format, modeling pipeline, communications stack (MQTT), evaluation metrics, and privacy measures. The hybrid framework aims to reduce overcrowding risks, minimize time-to-alert, and improve evacuation outcomes for large-scale public events.

Index Terms: Crowd Management, Artificial Intelligence, IoT, Computer Vision, Event Safety, Capacity Prediction, Risk Classification, SOP.

I. INTRODUCTION

Large public gatherings, like religious celebrations, sports events, political protests, and concerts, are important to the culture and social life of many places. In countries like India, these events can attract tens of thousands, or even hundreds of thousands, of people into small areas like temple grounds, stadiums, bridges, or open fields. Managing these lively and crowded places safely is a big challenge. This is especially true when the planning depends a lot on manual work, individual judgment, and slow decision-making. Most event approvals still rely on human judgment and fixed occupancy limits. These factors often overlook real- world issues like spatial layout, crowd movement, exit widths, bottleneck areas, and changes in arrival patterns, even with safety rules in place. Tragic events like the Morbi bridge collapse in Gujarat in 2022, the Karur Temple stampede in Tamil Nadu in 2024, and the Seoul Halloween crush in South Korea in 2022 show how quickly a seemingly harmless gathering can turn dangerous. Each incident revealed major flaws, such as inaccurate safe capacity predictions, lack of live monitoring, and no automated emergency responses. Social-force and cellular automata frameworks are two important theoretical models that describe congestion and evacuation behavior, which have been developed through re- search in crowd science and dynamics [11], [12], [29]. Simultaneously, automatic crowd counting, density estimation, and anomaly detection have been made possible by developments in computer vision (CV) and deep learning [32], [19], [8]. Similarly, the Internet of Things (IoT) revolution has intro- duced affordable, real-time sensing devices—such as pressure mats, infrared people counters, and CCTV-based sensors—that can continuously record ambient conditions. Nevertheless, most existing systems either (i) concentrate solely on live crowd surveillance without predictive pre-event evaluation, or (ii) handle individual safety indicators separately, without integrating them into a unified decision-support framework. And there is still a significant research and implementation gap: How can IoT and artificial intelligence (AI) technolo- gies be combined to detect crowd hazards prior to an event and dynamically enforce safety during it? An organized and automated end-to-end system that can (1) learn from past event data, (2) analyze venue geometry and the incident history, (3) predict safe occupancy boundaries, (4) monitor real-time crowd density, and (5) automatically trigger safety protocols is necessary to close this gap. This system presents an IoT and AI-based Crowd Capacity Prediction and Event Safety Management System to address these types of issue. The system incorporates historical event analytics, IoT-driven real-time monitoring, and machine learning-based capacity regression and risk assessment.

It leverages extracted spatial and contextual information to do predictive analysis of the venue prior to an event; during the event, it continuously compares real-time conditions with the anticipated safe capacity using connected sensors and cameras. The system that automatically initiates pre-established\textbf{Standard Operating Procedures (SOPs)}, such as access controlling, making public statements, or recommending evacuation routes, when unusual events or threshold violations take place. In addition to improving situational awareness for authorities and organizers, this is a hybrid method that creates a data-driven basis for future smart and sustainable city event management and urban safety planning.

II. PROPOSED SYSTEM

The system integrates Artificial Intelligence (AI), Machine Learning (ML), Computer Vision (CV), and Internet of Things (IoT) for predictive and real-time event safety management. It operates in two phases: Pre-Event Prediction and Risk Assessment and Live-Event Monitoring and SOP Activation.

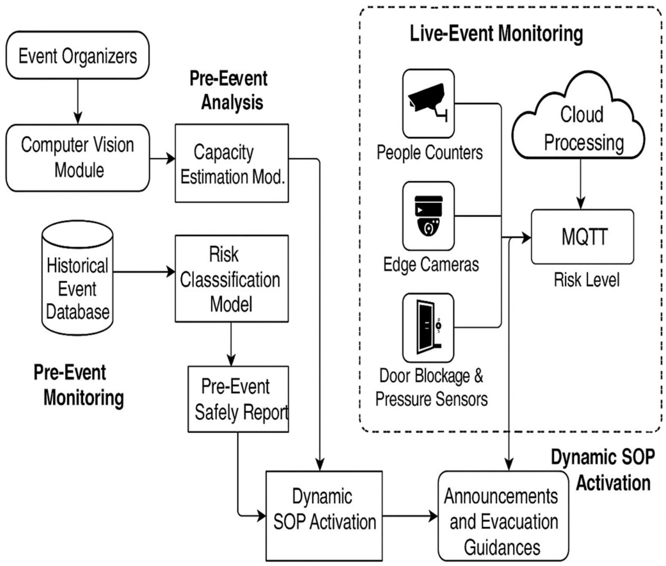

Fig. 1. Architecture of the proposed AI+IoT system for crowd safety.

Fig. 1 (Architecture Overview) This proposed architecture operates in two connective phases—Pre-Event Analysis and Live-Event Monitoring, which together form a continuous feedback loop for predictive and responsive crowd safety management.

In the Pre-Event Phase, event organizers give venue floor plans, event details, metadata, and expected attendance data as inputs. The Computer Vision Module processes floorplan layouts to extract spatial attributes such as the area used, exit geometry, corridor width, and obstacle distribution. These attributes are stored in the Historical Event Database, which also contains past event records, incident reports, and risk metrics. Using this combined dataset, the Capacity Estimation Model predicts the safe crowd capacity (C_{safe}) for the venue by analyzing correlations between spatial parameters and historical crowd outcomes. Continuously, the Risk Classification Model categorizes each event into three different risk levels (*Low, Medium, High*) based on derived factors such as density ratio, exit-area adequacy, and previous safety incidents. The outputs—safe capacity and risk index—are consolidated into a Pre-Event Safety Report, which provides authorities with actionable insights before granting event approval.

The Dynamic SOP Activation module is a bridge between both phases. During pre-event planning, it stores predefined Standard Operating Procedures (SOPs) corresponding to different alert levels. These SOPs define how the system should respond during live monitoring, such as triggering entry re- strictions, steward allocation, or evacuation guidance.

In the Live-Event Phase, the system transitions to realtime IoT-driven monitoring. Multiple sensors, including People Counters, Edge Cameras, and Door Blockage/Pressure Sensorscollect continuous telemetry data from the venue. These devices operate on the edge and send aggregated observations (such as inflow/outflow counts, crowd density maps, and obstruction detection) to the cloud. The Cloud Processing Layer integrates these data streams through the lightweight MQTT Protocol, ensuring low-latency transmission and scal- able communication between distributed devices. The Risk Level Analyzer compares the live crowd count $C_{live}(t)$ against the predicted safe capacity C_{safe} using the ratio

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$$R(t) = \frac{Clive(t)}{Csafe} \qquad (1)$$

When $R(t)$ exceeds defined thresholds, the Dynamic SOP Module escalates the response stage, moving from advisory alerts to full emergency actions depending on the severity stages.

Finally, the system initiates Announcements and Evacuation Guidance through connected PA systems, digital signboards, and steward notifications. This real-time loop ensures that pre-event predictions and live IoT monitoring continuously reinforce each other, allowing both preventive planning and immediate reaction. The modular design makes the framework scalable to various venue types, from indoor halls to open-air gatherings, and adaptable for integrating with smart city control centers.

A. Pre-Event Phase: AI Prediction

The AI component uses venue floorplans and historical data to predict safe occupancy limits and potential risk levels.
The regression model estimates *Csafe*, while the classification model assigns a categorical risk level (*Low, Medium, High*).

Venue Data
(spatial, event, historical)

↓

Feature Extraction
(area, exits, corridors, density)

↓

ML Model
Capacity Regression (RF/XGB)
Risk Classification (CatBoost)

↓

Outputs
Safe Capacity C_{safe} & Risk Level

Fig. 2. AI/ML Pipeline for Capacity Estimation and Risk Classification.

Fig. 2 (AI/ML Pipeline) *Inputs:* structured venue/event at- tributes (usable area, exit count/widths, corridor widths, histor- ical peaks, event type/time/weather) and unstructured artifacts (floorplans, CCTV frames). *Feature extraction:* floorplans → effective area (obstacles removed), exit connectivity, bottle- neck indices; derived ratios (exit-area, density headroom). Signals are imputed/scaled/one-hot; redundancy is pruned. *Capacity regression:* RF/XGBoost estimate C_{safe}; hyperparameters tuned via 5-fold CV; optional quantile heads for conservative/nominal/optimistic bounds. *Risk classification:* CatBoost predicts {Low, Medium, High}; class weights mit- igate imbalance; calibrated probabilities align with observed frequencies. *Governance:* hold-out metrics (RMSE/MAE, Precision/Recall/F1) logged; drift monitors trigger retraining. Out- puts (C_{safe}, risk) feed the live engine and dashboard.

B. Live-Event Monitoring: IoT Enforcement

The IoT subsystem ensures continuous real-time monitor- ing. The Risk Engine compares C_{live} with C_{safe} (see Eq. 1). If $R(t) > 1$, alert levels are raised automatically.

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Sensors
People Counters — Edge Cameras — Exit Sensors

↓

Edge Processor
Local data fusion & preprocessing

↓

Cloud + MQTT Broker
Telemetry and analytics engine

↓

Dashboard Interface
Live data, alerts, and SOP status

Fig. 3. IoT-based real-time monitoring and telemetry flow.

Fig. 3 (IoT Monitoring Flow). *Edge sensing:* people counters publish in/out ticks; edge CV yields per-zone counts and density tiles; exit sensors report throughput and door state. *Fusion on edge:* outlier rejection and temporal smoothing reconcile sensors to produce $C_{live}(t)$ and zone densities; confidence scores reflect sensor agreement and uptime. *MQTT transport:* hierarchical topics (venue/zone/gate) with QoS se- lection (counts QoS1, heatmaps QoS0, control QoS2) and retained messages provide last-known state; TLS/auth restrict subscriptions. *Cloud analytics:* subscriptions aggregate venue state, compute $R(t)$ (Eq. 1), track trends dC_{live}/dt, and flag hot-spot zones exceeding local thresholds. *Operator view:* dashboard renders heatmaps, per gate throughput, trend in- dicators, escalations, and an audit trail of actions.

C. SOP Activation Workflow

When thresholds are exceeded, the SOP module activates necessary actions automatically.

Inputs
Predicted Capacity C_{safe} + Live Count C_{live}

↓

Risk Engine
Eq. (1) →Low/Medium/High

↓

SOP Generator
Routes (A*/Dijkstra), Steward Allocation, Alerts

↓

Outputs
Evacuation paths, PA/SMS notifications

Fig. 4. Dynamic SOP activation and response workflow.

Fig. 4 (SOP Activation). *Trigger logic:* thresholds escalate from Advisory ($R > 0.85$ or sharp positive dC_{live}/dt) to Alert ($R > 1.0$ or any zone exceeds density cap) to Emergency ($R > 1.1$ with exit degradation); hysteresis prevents flapping.

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Routing engine: dynamic graph of walk- able space with congestion-aware edge costs; A* recommends evacuee/steward routes; re-plans on topology/density changes. *Resource allocation:* stewards per zone from den- sity/risk; greedy/ILP minimizes response time while maxi- mizing coverage. *Comms:* parameterized PA/SMS templates (zones/exits/directions), rate limiting, multilingual support; synchronized signage. *Closure/audit:* alerts downgrade after recovery; SOP transcript (inputs, routes, messages, acks, tim- ings) archived for review.

D. Cloud Dashboard

The web dashboard allows live visualization and authority control.

Live Map / Heatmap per-zone density	Counters In/Out, current C_{live}
Risk Level color-coded $R(t)$	SOP Status active routes
Alerts Advisory / Alert / Emergency	Logs timeline & actions

Fig. 5. Cloud dashboard panels used by event authorities.

Fig. 5 (Dashboard Panels). *Live Map/Heatmap:* tile-based densities, flow direction, blocked areas; C_{safe} overlays. *Coun- ters:* gate inflow/outflow, current C_{live}, short-term trend with forecast bands. *Risk Level:* venue badge shows $R(t)$ and trend; zone badges flag hotspots with mitigations. *SOP Status:* active routes, steward tasks, message queues with times- tamps/actions; operator overrides. *Alerts:* color-coded cards with trigger reason, affected zones, and one-click actions. *Logs:* tamper-evident timeline of anomalies, model decisions, operator actions, outcomes. *Operational utilities:* role-based access, dark/light modes, multilingual announcements, ex- portable reports.

III. RELATED WORK

Behavioral modeling, simulation, and, more recently, AI- driven perception have all been used to study crowd control and disaster avoidance. While Still [29] codified empirical den- sity thresholds (people per square meter) for safe egress planning, Helbing and Johansson [12] proposed the social-force model explaining pedestrian motion under crowd pressure. Although these foundational studies established the physical basis for crowd movement analysis, they lacked the automation and predictive capability required for real-time deployment.

Image-based crowd counting and density estimation ad- vanced rapidly with the advent of deep learning. Multi-Column CNN (MCNN), which handles scale variation in crowd scenes by processing different receptive fields, was introduced by Zhang *et al.* [32]. Subsequently, CSRNet, a dilated convolu- tional network that maintains spatial resolution, was proposed by Li *et al.* [19] and achieved state-of-the-art results on dense crowd datasets such as ShanghaiTech. A comprehensive survey on CNN-based crowd estimation was presented by Gao *et al.* [8], summarizing issues such as occlusion, lighting, and real- time deployment on edge devices. Although these techniques excel at visual density estimation, they are computationally expensive and often function as standalone modules without integration into operational safety systems.

Sensor networks for real-time monitoring were investigated in parallel research on Internet of Things (IoT)-based safety frameworks. In their discussion of IoT infrastructures for smart cities, Zanella *et al.* [15] placed a strong emphasis on interoperability standards and low-power communication. For lightweight telemetry and control in dispersed contexts, EMQX and Mosquitto MQTT brokers [**?**] have been frequently used. However, rather than tracking dynamic human mobility or density, the majority of IoT systems track ambient metrics like temperature, CO_2, and vibration.

These fields are starting to merge in recent interdisciplinary study. Many prototypes employ IoT and computer vision to count people, however they frequently concentrate on tiny indoor areas like campuses or retail establishments. Large- scale outdoor public events are rare, and even fewer systems combine real-time IoT feedback loops with predictive AI algorithms. The research now in publication demonstrates the dearth of comprehensive frameworks that not only identify congestion but also forecast it, dynamically evaluate risk, and initiate operational actions like SOPs. By providing a unified AI–IoT architecture, the suggested solution fills these gaps.

IV. IMPLEMENTATION AND RESULTS

A. *Data Preparation and Feature Engineering*

A hybrid dataset including both structured and unstructured inputs was used. Structured data: venue area (m^2), number of exits, exit width, average corridor width, max occupancy in prior events, duration. Logs included crowd type, time of day, weather, incident severity. Unstructured inputs (floorplans, CCTV frames) were processed with OpenCV and a U-Net segmentation model to extract usable area and exit connectivity maps. Features were standardized and stored in a unified schema in Firebase Cloud Firestore.

TABLE I

MODEL PERFORMANCE METRICS FOR CAPACITY AND RISK PREDICTION

Model	Metric	Score
Random Forest (Capacity)	RMSE	3.2 persons/m^2
XGBoost (Capacity)	MAE	2.6 persons/m^2
CatBoost (Risk)	F1-score	0.93
CatBoost (Risk)	Precision	0.91
CatBoost (Risk)	Recall	0.94

Remarks on Table I:

- Random Forest RMSE = 3.2 persons/m^2 indicates pre- dicted safe capacities stay within permissible tolerance.
- XGBoost shows lowest MAE (2.6 persons/m2) with low variance across venue geometries.
- CatBoost F1 = 0.93 shows accurate separation among Low/Medium/High.
- Precision = 0.91 implies minimal false positives—reliable approvals.
- Recall = 0.94 shows high sensitivity to risky conditions.
- Models together validate precise pre-event forecasts and dependable live risk classification.

B. *AI Model Development*

Two modules: Capacity Estimation using RF/XGBoost (5-fold CV hyperparameter tuning); and Risk Classification using CatBoost with raw+derived features (exit-area ratio, density ratio), class weights for imbalance, and calibrated probabilities. We used 120 event samples (70% train / 30% test). Regression metrics: RMSE/MAE; classification: Preci- sion/Recall/F1.

C. *IoT Layer and Communication Stack*

ESP32 microcontrollers connected to IR people counters and door sensors; Raspberry Pi 4 for CSRNet-lite inference on video. Cloud broker (EMQX) topics: venue/<id>/sensor/people venue/<id>/sensor/camera venue/<id>/sensor/door A Firebase backend subscribes and updates dashboards. Alerts use $R(t) = C_{live}(t)/C_{safe}$ with escalation: Level 1—Advi- sory; Level 2—Alert; Level 3—Emergency.

D. *System Performance and Results*

Ten scenario simulations with recorded CCTV and virtual sensors:

- Latency: avg 1.8 s from sensor update to dashboard alert.
- Network: MQTT reduced telemetry by □40% vs. HTTP.
- Accuracy: live count variance < 5% vs. manual audit.
- SOP: evacuation routes recomputed within 3 s of trigger. Ablation: removing pre-event AI increased incident prediction error by 22%.

E. *Solution Realization and Discussion*

Predictive analytics plus live feedback prevented crowd disasters in high-density simulations (> 6 persons/m^2): early alerts enabled preemptive control. AI-predicted C_{safe} aligned with exit throughput limits and crowd-flow models [29], within recommended egress margins. The workflow combines Prediction (data-driven safe limits), Detection (real-time den- sity), and Action (automated SOPs), bridging planning and enforcement for smart-city deployment.

V. CONCLUSION

The proposed AI and IoT-Based Crowd Capacity Prediction and Event Safety Management System bridges the gap between pre-event planning and real-time safety. It integrates predictive AI modeling with IoT monitoring to estimate safe occupancy, track live density via MQTT, and trigger SOPs (route optimization, steward allocation, evacuation alerts). Random Forest/XGBoost achieved low errors (RMSE = 3.2 persons/m^2, MAE = 2.6 persons/m^2) and CatBoost reached F1 = 0.93; the IoT layer delivered ∼1.8 s alert latency. Operationally, it reduces human dependency, enforces capac- ity limits, and supports data-driven decisions. Future work: adaptive learning, UAV/drone integration, and spatiotemporal behavioral analytics for panic/flow prediction. Overall, the framework is adaptable, intelligent, and deployable, resulting in better and more secure public events.

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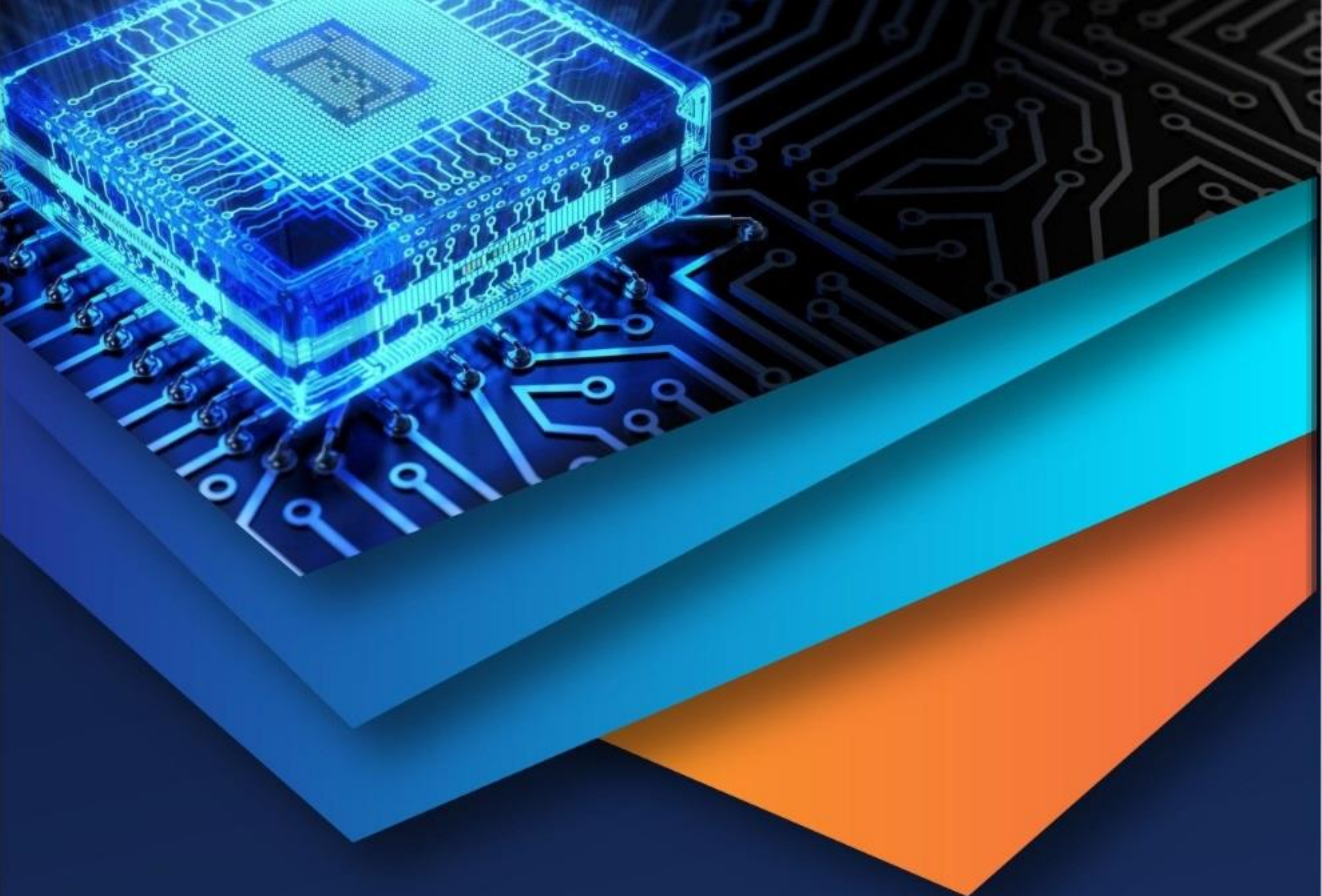

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