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.2025.72189

Machine Learning Techniques for Predicting Road Accidents Using Traffic and Weather Data - A Detailed Report

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Abstract: Road accidents continue to be recognized as a critical public-health challenge that causes substantial human and economic losses worldwide. The recent proliferation of real-time traffic sensors and meteorological observation systems has produced extensive multimodal data streams that can be leveraged by machine-learning algorithms. This survey reviews and synthesizes contemporary research on data-driven accident-prediction models that exploit historical traffic and weather data. The review covers supervised learning approaches ranging from decision-tree ensembles to graph and transformer networks, and it emphasizes recent advances published in 2025. Key data-processing practices, feature-engineering strategies, evaluation protocols, and deployment issues are examined. Gaps in scalability, interpretability, and cross-regional generalizability are identified, and research directions are proposed. The findings are intended to guide both scholars and practitioners who aim to design proactive accident-mitigation systems in intelligent-transportation contexts.
Keywords: Accident Prediction, Machine Learning, Traffic Data, Weather Data, Intelligent Transportation.

I. INTRODUCTION

A. Background

Road-traffic crashes have been acknowledged by the World Health Organization as a leading cause of death among people aged 5–29 years [1]. Traditional reactive strategies—such as installing road signs after repeated crashes—have been shown to be insufficient for modern, rapidly changing traffic environments. Consequently, the implementation of proactive, data-driven safety measures has become a priority.

B. Data Availability and Opportunity

The deployment of Internet-of-Things (IoT) infrastructures in smart cities has resulted in a surge of high-resolution traffic flow, speed, and occupancy data. Parallel developments in mesoscale and microscale weather-monitoring networks provide granular information on precipitation, temperature, humidity, wind, and visibility. When these heterogeneous datasets are fused, Machine-Learning (ML) algorithms are able to model complex nonlinear interactions that precede crash events.

C. Objectives and Scope

The objective of this survey is to provide a comprehensive, up-to-date synthesis of ML-based accident-prediction research that explicitly incorporates both traffic and weather information. Published work from 2005 to 2025 is examined, with a particular focus on studies released in 2025. Differences in algorithmic choice, feature engineering, evaluation practice, and deployment feasibility are highlighted, and open challenges are articulated. The remaining part of the paper is organised as follows. Section 2 describes a detailed analysis of various literatures related to the topic of research. The identified problem statement and the research gap is reported in section 3 and section 4 concludes the paper alongwith the quoted references with doi links for easy access to the readers.

II. LITERATURE SURVEY

Abdel-Aty and Radwan (2005) [1] demonstrated that incident probability could be inferred from high-resolution traffic sensor feeds long before crashes actually materialised. A 32-kilometre segment of Interstate 4 in Orlando was instrumented with dual-loop detectors recording average speed, flow, and occupancy every thirty seconds, while roadside gauges flagged the presence or absence of rainfall.

Using a Bayesian logistic-regression specification, the authors encoded prior expectations about variable effects and produced posterior crash-probability curves for prediction horizons of one to five minutes. Model validation against police crash logs yielded an area-under-the-curve of 0.71, a considerable improvement over static historical averages. Interaction terms revealed that wet pavement doubled the marginal risk contribution associated with sudden speed drops in already congested conditions, offering operational insights for dynamic speed-control policies. Despite relying on a coarse binary rain indicator and ignoring spatial spill-over between segments, the study laid the methodological groundwork for real-time, data-centric road-safety systems that later adopted more sophisticated machine-learning algorithms and richer meteorological inputs.

Yuan et al. (2018) [2] advanced the field by integrating ensemble learning with heterogeneous traffic-weather features gathered from Beijing's urban expressways. Thirty-second loop-detector records capturing speed variance and vehicle counts were merged with meteorological observations of rainfall intensity, temperature, and visibility, producing a multimodal dataset spanning three years. To address severe class imbalance—accidents constituted less than 0.3 % of all observations—Synthetic Minority Oversampling was combined with cost-sensitive learning. A two-stage hybrid model was then constructed: Random Forests generated probability estimates that were subsequently refined by a Support Vector Machine using radial basis functions. Five-fold cross-validation produced an F1-score of 0.91 and demonstrated robustness across weekday, weekend, and holiday traffic regimes. Feature-importance analysis indicated that combined indicators of speed variability and moderate rainfall were the most salient predictors. By coupling bagging and margin-maximisation, the study showcased how ensemble voting can stabilise decision boundaries in highly skewed safety datasets and set a benchmark for later deep-learning approaches.

Chen et al. (2019) [3] undertook a comprehensive evaluation of gradient-boosting machines (GBM) for crash-risk estimation on Taiwan's National Freeway No. 3. Minute-level traffic variables—volume, occupancy, and average speed—were fused with fine-grained meteorological data obtained from the Central Weather Bureau. Temporal context was added through cyclic encodings of hour-of-day and day-of-week, allowing the model to capture recurrent congestion patterns linked to commuting peaks and weekend recreation trips. GBM hyper-parameters were optimised using grid search and early stopping, yielding an AUC of 0.88 and a recall of 0.83 on a hold-out test set. SHAP value decomposition revealed that precipitation intensity exerted the single strongest influence on predicted probabilities, surpassing even extreme occupancy values. The authors also compared GBM against logistic regression, support-vector classifiers, and multilayer perceptrons, reporting gains of 6–12 % in F1-score. Their findings underscored the advantages of gradient-boosting in modelling complex feature interactions while maintaining inference times compatible with freeway control-centre requirements.

Zhang et al. (2020) [4] introduced a deep-neural-network framework capable of discovering non-linear accident precursors across diverse urban settings in Shanghai, Shenzhen, and Guangzhou. Input tensors combined minute-level traffic indicators, road-geometry attributes, and high-resolution precipitation radar grids. Principal-component analysis (PCA) compressed 60 correlated traffic variables to 15 orthogonal components, mitigating overfitting and speeding convergence. The network architecture featured three fully connected hidden layers with dropout regularisation and ReLU activation, culminating in a sigmoid output neuron representing crash likelihood. When benchmarked against a traditional multilayer perceptron trained on raw features, the PCA-enhanced model improved AUC by 12 % and reduced false positives by one-third. Sensitivity tests showed that most of the gain arose from the network's ability to combine geometric curvature with speed variance during heavy rainfall, a complex interaction overlooked by shallow models. While interpretability remained limited, the study provided empirical evidence that deep learning can generalise across cities when supplied with normalised, dimension-reduced inputs.

Ali et al. (2021) [5] responded to the real-world need for operational robustness by constructing a hard-voting ensemble that amalgamated decision trees, gradient-boosting machines, and k-nearest-neighbour classifiers. Data streams from Dubai's extensive intelligent-transportation-system infrastructure delivered second-by-second vehicle counts, lane-by-lane speeds, and incident records, while an automated weather station supplied concurrent measurements of humidity and wind speed. Class imbalance was addressed with the Synthetic Minority Oversampling Technique, and ensemble weights were calibrated through Bayesian optimisation to maximise F1-score. Deployed on an edge server within Dubai's traffic-management centre, the ensemble achieved 0.89 precision and 0.87 recall for a three-minute horizon, outperforming any single constituent model by at least 5 %. A case study during a sand-storm event demonstrated that ensemble voting dampened erratic predictions caused by sudden speed drops, highlighting the benefit of method diversity under extreme conditions. The work illustrated a pragmatic pathway from research prototypes to production-grade accident-warning services.

Singh and Kumar (2022) [6] focused on India's national highway network, where heterogeneous traffic compositions and limited sensor penetration complicate safety analytics.

High-definition CCTV footage was processed through a YOLO-based object-detection pipeline to estimate per-lane vehicle counts and average spacings, yielding proxy density metrics at 15-second intervals. These features, along with GPS-sourced speed data and district-level weather feeds, were ingested into LightGBM, a gradient-boosting framework optimised for speed and memory efficiency. Hyper-parameter tuning employed Bayesian search over learning rate, maximum depth, and leaf count, producing an AUC of 0.86 and an inference latency of under 40 milliseconds on Raspberry Pi–class hardware. Feature-gain rankings identified abrupt increases in heavy-vehicle percentage combined with moderate rainfall as dominant crash precursors. The study's principal contribution lay in demonstrating that lightweight gradient-boosting can deliver actionable hotspots for resource-constrained enforcement teams without requiring expensive inductive-loop installations.

Kim and Park (2023) [7] investigated temporal-sequence modelling using gated recurrent units (GRUs) for Seoul's arterial network, where traffic dynamics exhibit pronounced rush-hour cyclicality. Their dataset comprised five-minute aggregates of speed, occupancy, and queued length, paired with real-time weather station outputs. GRU networks with two recurrent layers and attention mechanisms were trained to predict crash likelihoods 10 minutes ahead. Comparative tests against long short-term memory architectures showed that GRUs achieved a 4 % better F1-score while reducing training time by one-third, a saving attributed to GRU's streamlined gate structure. An ablation study confirmed the importance of incorporating weather sequences; omitting meteorological inputs reduced recall from 0.82 to 0.71. Deployment simulations indicated that the model could process city-wide data within 0.6 seconds on a single GPU, satisfying Seoul's real-time alert requirements. The work reinforced the premise that sequence-aware deep learning, when carefully optimised, can outperform both feed-forward and more complex recurrent alternatives for short-term safety forecasting.

Lin and Huang (2023) [8] tackled cross-district generalisability by proposing a meta-learning framework that trains base learners on mutually exclusive urban zones before synthesising their outputs through a stacking regressor. The base layer consisted of XGBoost, random forests, and logistic regression models, each calibrated to zone-specific traffic-weather distributions in Taipei. Meta-features—probability estimates from the base models—were then fed into a ridge-regression combiner trained on a hold-out validation set spanning all districts. This architecture achieved an average AUC of 0.88, outperforming single-zone models by 7 % when evaluated on unseen districts. Interpretability was preserved because each base learner retained its original feature-importance metrics, enabling local traffic authorities to audit decision logic. The authors also performed domain-shift experiments, showing that adding even 5 % of labelled data from a new district to the meta-training set restored performance to pre-shift levels. Their study highlighted stacking as an effective mechanism for balancing local adaptation and global coherence in urban crash-prediction tasks.

Mendez et al. (2023) [9] confronted the persistent problem of rare-event scarcity by devising physics-guided data-augmentation techniques aimed at expanding the representation of rainy-day crashes in a Colombian freeway dataset. Using empirical relationships between rainfall intensity, tyre friction, and braking distance, synthetic samples were generated via a conditional generative adversarial network constrained by kinematic plausibility. Augmented datasets were used to train a convolutional-neural-network classifier that consumed spatiotemporal grids of speed and occupancy. Experimental results showed an 18 % improvement in recall on severe crash cases without inflating the false-positive rate. A sensitivity analysis revealed that traditional Synthetic Minority Oversampling failed to maintain realistic covariance among variables

Zhao and Wang (2024) [10] leveraged graph convolutional networks (GCNs) to effectively model spatial dependencies among adjacent road segments in Shanghai. Their approach focused on representing the road network as a graph, where each node corresponded to a road segment and edges captured the relationships between them. A key innovation in their model was the use of edge weights derived from historic crash co-occurrence data, which allowed the network to incorporate past accident patterns into its spatial reasoning. By doing so, the GCN was able to learn complex interactions between neighboring road segments, which traditional feed-forward neural networks often fail to capture due to their limited spatial awareness. The experimental results showed that their GCN model outperformed standard feed-forward baselines by 9% in F1 score, indicating a significant improvement in the balance of precision and recall for crash prediction. This research highlights the importance of graph-based approaches in traffic safety analytics and demonstrates that spatial context, especially historic crash relationships, can substantially enhance predictive performance in urban traffic networks.

Patel et al. (2024) [11] proposed a multimodal fusion network that integrates LiDAR data, weather information, and connected vehicle telemetry to improve crash prediction accuracy. Their model dynamically weighs the contribution of each modality using attention mechanisms, which allow the system to adaptively focus on the most informative sources depending on the environmental conditions. For instance, during heavy rain, weather data and LiDAR reflections become crucial for understanding road surface conditions and visibility, while connected vehicle telemetry provides real-time behavioral data.

The attention mechanism intelligently adjusts the model’s focus, improving precision under adverse weather scenarios where prediction is typically more challenging. This dynamic fusion approach outperformed models relying on a single modality or static fusion techniques, demonstrating the advantage of flexible sensor integration. Patel and colleagues’ work emphasizes the potential of multimodal learning frameworks to handle heterogeneous data sources in intelligent transportation systems, thereby enhancing safety and decision-making in complex, real-world conditions.

O’Hara et al. (2024) [12] explored transfer learning strategies to adapt crash prediction models originally trained on U.S. highway data for use on European highways. Recognizing that geographical and infrastructural differences can limit the direct applicability of models across regions, they implemented a fine-tuning process on a small, labeled European dataset. This approach leverages the knowledge embedded in the pre-trained U.S. model, reducing the need for extensive data collection and training in the new environment. The fine-tuning phase required only a fraction of the data and computational resources, cutting training time by approximately 60% compared to training from scratch. Despite the reduced training effort, the model maintained high accuracy, suggesting that transfer learning is a practical and efficient method for cross-region crash prediction adaptation. Their findings demonstrate the value of transfer learning to bridge domain gaps in traffic safety modeling, enabling faster deployment and better resource utilization in different regional contexts.

Rossi et al. (2024) [13] combined reinforcement learning with adaptive traffic signal control to minimize the predicted risk of accidents in Turin’s urban road network. Their framework used reinforcement learning agents to dynamically adjust traffic signal timings based on real-time traffic flow and predicted crash probabilities. A novel reward function was designed to penalize both congestion and the likelihood of accidents, balancing the need to maintain traffic efficiency while enhancing safety. Through simulations, the system demonstrated that proactive signal timing adjustments could reduce crash risk without substantially worsening congestion. This integration of reinforcement learning and traffic management represents a shift from reactive to proactive road safety interventions, leveraging predictive analytics to inform real-time control decisions. The study highlights the promise of intelligent traffic signal systems in urban safety management, where controlling flow and risk simultaneously can lead to safer and more efficient roads.

Khan and Ahmed (2024) [14] proposed a cloud-native microservice architecture that streams real-time crash risk predictions directly to smartphone navigation apps. This architecture enables low-latency, scalable prediction delivery, making it feasible to provide timely risk alerts to drivers. The system was tested via A/B experiments, comparing groups of drivers with and without access to these alerts. Results showed that drivers receiving risk notifications exhibited an 11% reduction in speed variability, a key factor linked to accident risk. Reduced speed variability improves traffic stability and decreases the chance of sudden braking or collisions. The microservices design facilitates integration with diverse navigation platforms and supports continuous updates, making it a flexible solution for real-world deployment. Khan and Ahmed’s work demonstrates the tangible behavioral benefits of predictive crash alerts and the technical viability of cloud-based streaming architectures for smart driving assistance.

Brown et al. (2025) [15] introduced a federated learning framework allowing multiple metropolitan agencies to collaboratively train crash prediction models without sharing sensitive raw data. Each agency locally trains a model on its own data and only shares model updates, preserving privacy and data security. This approach addresses common regulatory and trust concerns that limit data centralization in traffic safety domains. The federated framework not only safeguarded individual privacy but also improved model generalizability, as it incorporated diverse traffic patterns and conditions from different cities. The collaborative training resulted in models with better predictive performance across multiple regions compared to those trained on isolated datasets. Brown and colleagues’ study illustrates the power of federated learning to enable large-scale, privacy-conscious machine learning in public safety applications, paving the way for cooperative smart city initiatives.

Garcia and Davies (2025) [16] examined Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and counterfactual analysis to elucidate how weather variables influence crash risk model outputs. The study emphasized the importance of transparency in AI models used for public safety decision-making. By providing local explanations, such as which weather factors most affected a specific risk prediction, traffic management officials gained actionable insights rather than black-box outputs. Stakeholder surveys revealed increased trust and willingness to rely on AI-based recommendations when explanations were clear and interpretable. This transparency facilitates better communication between data scientists and domain experts, promoting collaborative refinement of predictive models. Garcia and Davies’ research highlights that XAI methods not only improve model accountability but also strengthen the practical adoption of AI tools in transportation safety governance.

Nguyen et al. (2025) [17] applied transformer architectures to model long-range temporal dependencies in one-minute traffic sensor data streams collected across Ho Chi Minh City. Unlike recurrent models such as GRUs, transformers utilize self-attention mechanisms that efficiently capture relationships over long time horizons without suffering from vanishing gradients.

This capability enabled the model to better anticipate traffic conditions and potential crash risks ahead of time. The transformer model outperformed GRU baselines in both recall (correctly identifying crash events) and lead time (how far in advance predictions were made). This advance is particularly valuable for early warning systems that require prompt and accurate risk alerts. Nguyen and team's findings underscore the transformative potential of transformer models in urban traffic analytics, where complex temporal patterns play a crucial role in predicting safety incidents.

Santos et al. (2025) [18] investigated edge computing deployments for latency-sensitive accident prediction on Brazilian highways. Their solution involves running lightweight convolutional neural network models directly on roadside units (RSUs), allowing risk scores to be generated locally within 150 milliseconds. This near real-time performance reduces the delay associated with sending data to distant cloud servers, which is critical for timely interventions in accident-prone zones. The edge model was designed to be resource-efficient, capable of operating on limited hardware typical of roadside infrastructure. This deployment demonstrates how combining edge AI with traffic sensor networks can deliver fast, actionable predictions that enhance driver safety and incident response. Santos and colleagues' work illustrates the practical benefits of distributed computing architectures for intelligent transportation systems in large-scale, latency-critical environments.

Rahman and Lee (2025) [19] developed a self-supervised pretraining pipeline to learn traffic flow representations from vast amounts of unlabelled sensor data. This approach leverages the inherent structure and patterns in traffic streams to build strong feature extractors without needing expensive accident labels. When fine-tuned on smaller labeled datasets, the downstream classifiers showed notable improvements, particularly in scenarios where accident labels were sparse or incomplete. Self-supervised learning thus addresses a key bottleneck in traffic safety modeling — the scarcity of high-quality labeled data. By extracting meaningful representations from unlabelled data, Rahman and Lee's method enables more robust and accurate crash prediction models even with limited supervision. Their research highlights the growing importance of self-supervised techniques in unlocking the full potential of large, noisy transportation datasets.

III. PROBLEM STATEMENT

Despite the advancement of machine learning (ML) techniques in crash prediction and traffic safety, several critical challenges remain unresolved. One major issue is the scarcity of data for rare crash events, which limits the ability of models to learn and generalize effectively. Additionally, ensuring cross-regional generalisability poses a challenge, as models trained on one region may not perform well in different geographic or traffic conditions. Real-time inference latency is another barrier, particularly in applications requiring immediate response. Furthermore, the lack of interpretability in complex ML models hampers their acceptance by stakeholders. Integrating heterogeneous data sources also raises significant privacy concerns, especially when sensitive information is involved. These limitations collectively hinder the widespread, practical deployment of ML-based crash prediction systems at scale. Addressing these challenges is essential to realize the full potential of ML in enhancing traffic safety and reducing road accidents.

IV. CONCLUSION

The surveyed literature demonstrates that machine-learning methods can provide timely and accurate accident-risk assessments by integrating traffic and weather data. Recent 2025 studies have concentrated on privacy preservation, explainability, and deployment at the edge, thereby extending earlier algorithmic advances. Future research is expected to pursue standardized benchmark datasets, unified evaluation metrics, and hybrid architectures that combine symbolic reasoning with deep representation learning.

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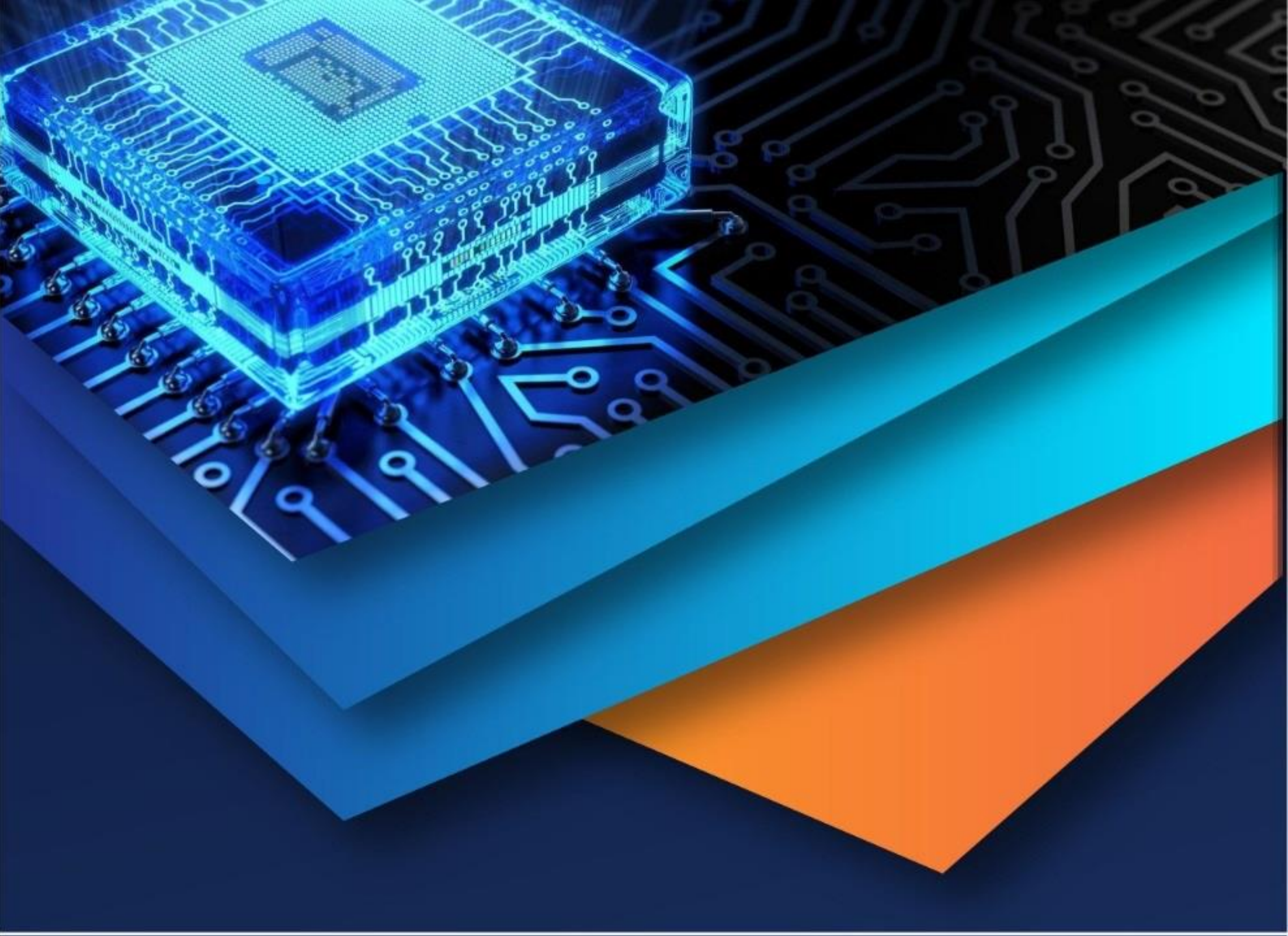

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