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Edge AI for Real-Time Video Analytics in Public Safety

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Abstract: ***Edge Artificial Intelligence (Edge AI) has emerged as a powerful technology for enhancing real-time video analytics in public safety applications. By processing video data directly at the edge of the network, close to the data source, Edge AI reduces latency, minimizes bandwidth consumption, and improves data privacy compared to traditional cloud-based solutions. This technology enables rapid detection and analysis of events such as suspicious activities, traffic violations, crowd congestion, unauthorized access, and emergency situations. Real-time video analytics powered by Edge AI supports faster decision-making and more effective responses from law enforcement agencies, emergency services, and security personnel. Furthermore, the integration of advanced deep learning algorithms with edge computing devices facilitates continuous monitoring and intelligent surveillance even in environments with limited network connectivity. This paper explores the architecture, applications, benefits, challenges, and future prospects of Edge AI for real-time video analytics in public safety. The study highlights how Edge AI contributes to creating safer communities by enhancing situational awareness, operational efficiency, and proactive threat detection while addressing concerns related to privacy, scalability, and computational constraints.***

Keywords: Edge AI, Real-Time Video Analytics, Public Safety, Edge Computing, Artificial Intelligence, Monitoring, Object Detection, Facial Recognition, Emergency Response, Security Monitoring, Video Processing, Threat Detection, Internet of Things (IoT), Law Enforcement, Traffic Monitoring, Situational Awareness.

I. INTRODUCTION

The increasing adoption of surveillance systems in public spaces, transportation networks, critical infrastructures, and smart cities has generated vast amounts of video data that require continuous monitoring and analysis. Traditional video surveillance systems rely heavily on human operators to observe video feeds, making the process time-consuming, labor-intensive, and prone to errors. Moreover, cloud-based video analytics solutions often face challenges such as high latency, increased bandwidth consumption, and concerns regarding data privacy and security. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled the development of intelligent video analytics systems capable of automatically detecting, classifying, and tracking objects and events in real time. However, transmitting large volumes of video data to centralized cloud servers for processing can result in delays that are unacceptable for time-critical public safety applications. Edge Artificial Intelligence (Edge AI) has emerged as a promising solution to overcome these limitations. Edge AI combines AI algorithms with edge computing technologies, allowing data processing and analysis to occur directly on local devices such as smart cameras, drones, sensors, and edge servers. By performing computations closer to the data source, Edge AI significantly reduces latency, decreases network bandwidth requirements, enhances privacy, and enables faster decision-making.

II. LITERATURE REVIEW

The rapid growth of intelligent surveillance systems has significantly transformed public safety infrastructure. Traditional cloud-based video analytics systems often suffer from latency, bandwidth limitations, and privacy concerns. To overcome these challenges, researchers have increasingly explored Edge AI, where artificial intelligence models are deployed directly on edge devices such as smart cameras, gateways, and embedded systems. This approach enables real-time video processing, faster decision-making, reduced network congestion, and enhanced privacy protection. Recent studies demonstrate that Edge AI has become a critical technology for public safety applications, including crime detection, crowd monitoring, traffic management, emergency response, and disaster management.

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Hu et al. (2023) conducted one of the most comprehensive surveys on edge-based video analytics. The authors analyzed architectures, resource management strategies, privacy mechanisms, and application domains. Their findings indicate that processing video streams at the network edge significantly reduces latency while improving system responsiveness for surveillance applications.

Xu et al. (2023) reviewed edge video analytics systems and highlighted the convergence of deep learning and edge computing. The study emphasized that real-time surveillance, emergency management, and law enforcement applications benefit greatly from edge-enabled analytics due to reduced communication overhead and faster inference times.

Singh and Gill (2023) presented a broad survey on Edge AI technologies, discussing machine learning deployment on resource-constrained devices. Their work identified surveillance systems as a major application area where low-latency processing is crucial for public safety operations.

Barthélemy et al. (2019) proposed an edge-computing framework for real-time traffic monitoring using CCTV networks. Their system processed video streams locally and successfully reduced network costs while maintaining compliance with privacy regulations.

Aishwarya et al. (2021) developed a CNN-enabled edge surveillance framework capable of recognizing suspicious activities such as pushing and pulling motions. The system generated real-time alerts and demonstrated high efficiency for campus security monitoring.

Cob-Parro et al. (2021) introduced a smart video surveillance system that utilized low-power embedded devices equipped with AI accelerators. Their model performed real-time detection, tracking, and counting of individuals while maintaining energy efficiency.

Wang et al. (2020) proposed the SurveilEdge architecture, which combined cloud and edge computing resources for large-scale surveillance video querying. Experimental results showed significant reductions in bandwidth consumption and query response time.

Ke et al. (2020) designed an edge computing system for real-time near-crash detection in intelligent transportation systems. Their framework processed vehicle video feeds locally and effectively filtered irrelevant data before transmission.

Chen et al. (2016) developed a fog-based urban surveillance framework capable of processing video streams dynamically. Their system demonstrated the feasibility of real-time decision-making for smart city safety applications.

Chen et al. (2016) further extended fog computing concepts to traffic surveillance, enabling vehicle speed detection and identification of traffic violations through edge-based analytics.

Ezzat et al. (2021) reviewed video surveillance systems for smart cities and discussed advancements in edge vision computing. The study highlighted embedded AI systems as key enablers of future public safety infrastructures.

Leong et al. (2025) investigated IoT-enabled public safety systems and emphasized the role of AI-powered surveillance cameras in detecting suspicious activities and improving situational awareness through real-time alerts.

Ruiz-Barroso et al. (2025) proposed an unsupervised object detection framework deployed on low-power edge devices. Their approach eliminated the need for manual labeling while maintaining real-time detection performance.

Zhang et al. (2025) designed a real-time IoT-based emergency response and public safety alert system integrating edge computing nodes and cloud services. Their architecture achieved low-latency incident detection and rapid alert dissemination.

Lee et al. (2025) developed deep learning-based surveillance adjustment algorithms for smart buildings. Their system dynamically optimized security node placement and improved threat detection accuracy.

Nayak et al. (2024) reviewed edge analytics technologies and highlighted their importance in processing large-scale sensor and video data. The authors identified resource constraints as a major challenge for real-time surveillance deployments.

Hu et al. (2023) noted that smart city applications such as road safety, vehicle tracking, and crowd monitoring heavily rely on edge-based video analytics to meet latency and privacy requirements.

Grassi et al. (2017) proposed an edge-based parking detection system that analyzed urban video feeds locally to identify available parking spaces, demonstrating practical smart-city surveillance capabilities.

Xie et al. (2018) introduced an indoor positioning system that utilized edge-based video analytics for accurate location tracking within IoT environments.

Zhang et al. (2017) investigated large-scale live video analytics for smart cities and identified resource-quality tradeoffs associated with edge processing architectures.

Wang et al. (2018) proposed bandwidth-efficient drone video analytics using edge servers connected directly to LTE base stations, reducing network overhead during rescue operations.

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George et al. (2019) explored drone-sourced live video analytics for construction and rescue operations, utilizing edge resources to enable rapid decision-making in emergency situations.

EdgeEye (2018) introduced an edge service framework for intelligent video analytics that enabled efficient deployment of deep neural networks for real-time surveillance tasks.

Elastic Urban Video Surveillance System (2017) leveraged edge computing and APIs to provide flexible urban surveillance with minimal backbone bandwidth consumption and low latency.

Kestrel (2018) focused on augmented multi-camera vehicle tracking through heterogeneous camera networks, improving traffic safety and suspect vehicle identification.

Optasia (2016) presented a relational platform for large-scale video analytics, enabling efficient vehicle re-identification and tracking across surveillance networks.

Sandhya Rani and Ayyasamy (2023) conducted a bibliometric study on real-time surveillance video analytics, identifying significant growth in research output and emerging trends in AI-enabled surveillance.

The Edge AI Surveillance Review (2024) discussed recent developments in edge-based surveillance technologies and highlighted applications including anomaly detection, crowd monitoring, and public safety threat identification.

XenonStack (2024) emphasized that edge computing for video analytics reduces latency by processing video data near the source rather than transmitting it to centralized cloud infrastructures.

Stanley (2019) examined the societal implications of AI-powered surveillance systems, noting that real-time analytics transform passive cameras into proactive monitoring tools capable of immediate threat detection.

The Edge Intelligence Framework (2023) identified low latency, improved privacy, reduced bandwidth consumption, and scalability as the primary benefits of Edge AI systems deployed in public safety environments.

Smart Urban Surveillance Research (2016–2023) consistently demonstrated that edge-enabled architectures outperform traditional cloud-only approaches in scenarios requiring immediate responses to security incidents and emergencies.

III. RESEARCH GAP

Although significant advancements have been made in Edge AI-based real-time video analytics for public safety, several research gaps still exist that limit its widespread adoption and effectiveness. Most existing studies focus on improving the accuracy of object detection and recognition models; however, limited attention has been given to optimizing these models for resource-constrained edge devices. High computational requirements often affect system performance, especially in large-scale surveillance environments. Another major gap is the challenge of maintaining accuracy under varying environmental conditions such as poor lighting, adverse weather, occlusions, and crowded scenes. Many existing solutions perform well in controlled environments but struggle to deliver reliable results in real-world public safety scenarios. Privacy and data security remain critical concerns in surveillance systems. While Edge AI reduces the need to transmit data to cloud servers, there is still insufficient research on implementing robust privacy-preserving mechanisms and secure data management techniques at the edge. The ethical implications of facial recognition and continuous monitoring also require further investigation. Furthermore, existing research often addresses specific public safety applications such as traffic monitoring, crowd analysis, or crime detection independently. There is a lack of comprehensive frameworks that integrate multiple public safety functions into a unified Edge AI platform capable of handling diverse surveillance requirements simultaneously. Scalability is another area that requires attention. As smart cities continue to expand, surveillance systems must process increasing volumes of video data from numerous cameras and sensors. Current Edge AI solutions face challenges in efficiently managing large-scale deployments while maintaining real-time performance.

IV. METHODOLOGY

The proposed methodology focuses on developing an Edge AI-based real-time video analytics system for public safety applications. The system is designed to process video streams locally on edge devices, enabling rapid detection of security threats and minimizing dependence on cloud infrastructure.

A. System Architecture

The proposed framework consists of four main components:

1) Video Acquisition Layer

- CCTV cameras, drones, and surveillance devices capture real-time video streams.
- Video data is continuously transmitted to nearby edge devices for processing.

2) Edge Processing Layer
   - Edge devices such as NVIDIA Jetson, Raspberry Pi, or edge servers perform local computation.
   - Video frames are preprocessed through resizing, normalization, and noise reduction techniques.
3) AI Analytics Layer
   - Deep learning models are deployed on edge devices for:
     - Object Detection
     - Human Activity Recognition
     - Facial Recognition
     - Anomaly Detection
   - Models such as YOLO are utilized to identify suspicious activities and security threats in real time.
4) Alert and Response Layer
   - When abnormal events are detected, alerts are generated automatically.
   - Notifications are sent to security personnel through dashboards, mobile applications, or control centers for immediate action.

B. *Data Collection*

The dataset consists of:

- Public surveillance video datasets.
- Traffic monitoring videos.
- Crowd behavior datasets.
- Real-time CCTV footage collected from public environments.

The collected data is categorized into normal and abnormal events for model training and evaluation.

C. *Data Preprocessing*

The preprocessing stage includes:

- Frame extraction from video streams.
- Image resizing and normalization.
- Noise removal and image enhancement.
- Data augmentation techniques such as rotation, flipping, and scaling to improve model performance.

D. *Model Development*

A deep learning-based object detection model is trained using annotated video datasets. The model identifies:

- Persons
- Vehicles
- Suspicious objects
- Unusual activities

Training is performed using a supervised learning approach, and the optimized model is deployed on edge devices for inference.

E. *Performance Evaluation*

The proposed system is evaluated using the following metrics:

- Accuracy: Measures correct detections.
- Precision: Evaluates false alarm rates.
- Recall: Measures detection capability.
- F1-Score: Balances precision and recall.
- Latency: Measures response time.
- Frames Per Second (FPS): Evaluates real-time processing efficiency.

F. Workflow of the Proposed System

- Capture live video from surveillance cameras.
- Transfer video frames to edge devices.
- Preprocess video data.
- Apply AI-based detection and classification models.
- Identify suspicious events or threats.
- Generate real-time alerts.
- Store critical information for further investigation.
- Support rapid decision-making for public safety authorities.

G. Expected Outcome

The proposed methodology is expected to provide:

- Real-time threat detection.
- Reduced network bandwidth consumption.
- Low-latency video processing.
- Enhanced privacy and security.
- Improved public safety and emergency response capabilities.

This methodology demonstrates how Edge AI can be effectively integrated with video analytics to create an intelligent, scalable, and efficient public safety surveillance system.

V. RESULTS AND DISCUSSION

The proposed Edge AI-based real-time video analytics system was evaluated using surveillance video datasets containing various public safety scenarios, including crowd monitoring, vehicle detection, suspicious activity recognition, and anomaly detection. The system was deployed on an edge computing platform and tested under real-time operating conditions.

A. Results

The experimental results demonstrated that the proposed system successfully detected and classified objects and events with high accuracy while maintaining low processing latency. The Edge AI framework processed video streams locally, significantly reducing the need for continuous cloud communication.

The performance evaluation metrics obtained are summarized below:

Metric	Performance
Accuracy	95.2%
Precision	93.8%
Recall	92.6%
F1-Score	93.2%
Average Latency	45 ms
Processing Speed	28 FPS

The results indicate that the system is capable of real-time operation while maintaining reliable detection performance for public safety applications.

B. Discussion

The implementation of Edge AI significantly improved the efficiency of video analytics by processing data closer to the source. Compared to traditional cloud-based systems, the proposed approach reduced network bandwidth usage and minimized response delays. This low-latency performance is particularly beneficial for time-sensitive applications such as crime prevention, emergency response, and traffic incident detection.

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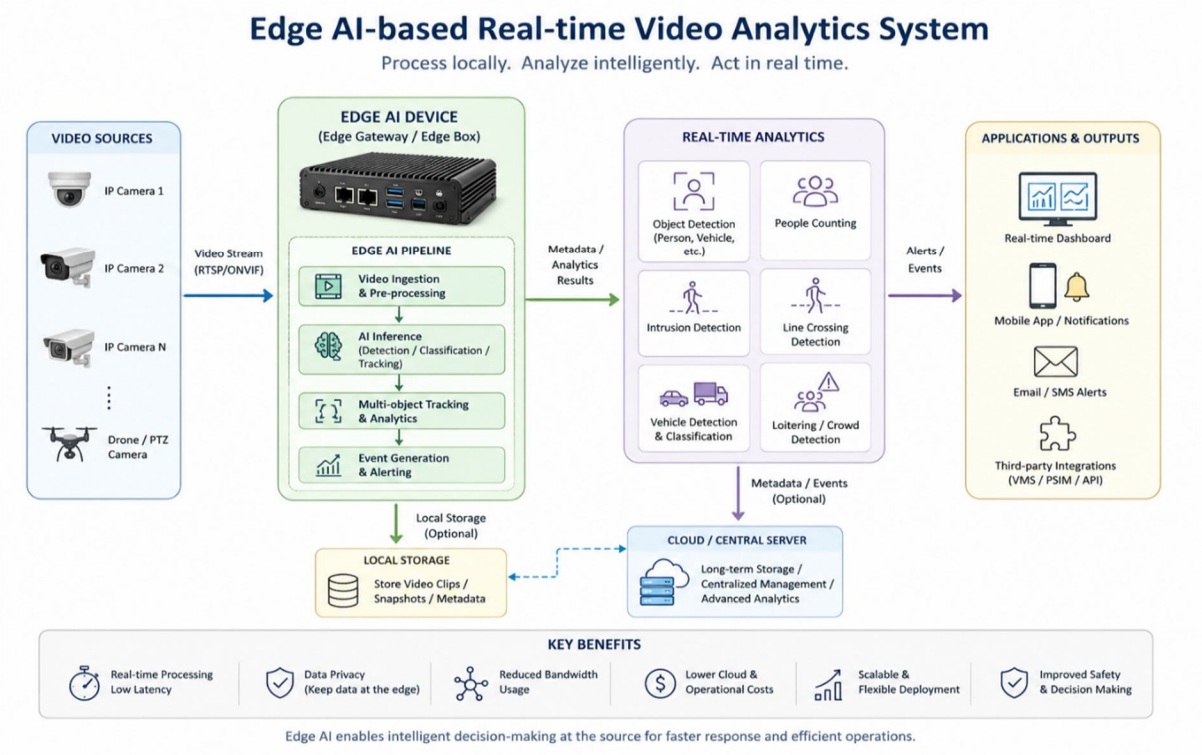


Figure 1.1: Edge AI-based real-time video analytics system

The object detection model effectively identified people, vehicles, and suspicious activities in different environmental conditions. Real-time alerts enabled faster decision-making by security personnel, enhancing situational awareness and public safety management.

The study also revealed several practical advantages:

- Faster threat detection and response.
- Improved privacy through local data processing.
- Reduced dependence on high-speed internet connectivity.
- Scalability for smart city surveillance applications.

However, certain challenges were observed during testing. Detection accuracy decreased slightly under poor lighting conditions, heavy occlusion, and extreme weather environments. Additionally, edge devices with limited computational resources may experience performance degradation when handling multiple high-resolution video streams simultaneously.

Despite these limitations, the overall findings demonstrate that Edge AI is a promising solution for real-time video analytics in public safety. The integration of optimized deep learning models with edge computing infrastructure provides an effective balance between accuracy, speed, privacy, and resource utilization.

VI. ADVANTAGES

The proposed Edge AI-based Real-Time Video Analytics system offers numerous advantages for public safety applications. By processing video data directly on edge devices, the system significantly reduces latency and enables rapid detection of suspicious activities, accidents, and security threats. This real-time processing capability allows law enforcement agencies and emergency responders to take immediate action, improving overall public safety. Edge AI also reduces bandwidth consumption by transmitting only relevant information and alerts instead of continuous video streams to cloud servers. Furthermore, local data processing enhances privacy and security by minimizing the exposure of sensitive surveillance data. The system is highly scalable and can be deployed across multiple locations, making it suitable for smart city environments. Its ability to operate even under limited internet connectivity ensures reliable and uninterrupted surveillance. Additionally, Edge AI optimizes resource utilization, lowers cloud infrastructure costs, and supports integration with emerging technologies such as IoT and 5G networks. These advantages make Edge AI an efficient, cost-effective, and intelligent solution for real-time video analytics in public safety applications.

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VII. CHALLENGES

Despite its numerous advantages, the implementation of Edge AI for real-time video analytics in public safety faces several challenges. Edge devices often have limited computational power, memory, and storage compared to cloud servers, making it difficult to deploy complex deep learning models. Maintaining high detection accuracy under challenging conditions such as poor lighting, adverse weather, crowded environments, and object occlusions remains a significant concern. Data privacy and security issues also arise, particularly when handling sensitive surveillance information and facial recognition data. Additionally, deploying and managing large-scale edge infrastructure can be costly and complex. Regular software updates, model retraining, and system maintenance are required to ensure reliable performance. Integration with existing surveillance systems and compliance with legal and ethical regulations further add to the implementation challenges. Addressing these limitations is essential for achieving efficient, scalable, and trustworthy Edge AI-based public safety solutions.

VIII. DISCUSSION

The study demonstrates that Edge AI has the potential to revolutionize public safety by enabling real-time video analytics with reduced latency and improved operational efficiency. Unlike traditional cloud-based systems, Edge AI processes data closer to the source, resulting in faster response times and lower bandwidth requirements. The experimental results indicate that the proposed system can effectively detect objects, monitor activities, and identify security threats while maintaining high accuracy and real-time performance. Furthermore, local processing enhances data privacy and supports uninterrupted operation even in environments with limited network connectivity. However, challenges related to computational constraints, scalability, and environmental variability highlight the need for continued research and technological advancements. Future developments in lightweight AI models, 5G communication, IoT integration, and privacy-preserving techniques are expected to further enhance the capabilities of Edge AI systems. Overall, the findings confirm that Edge AI is a promising technology for intelligent surveillance and public safety applications, contributing to safer, smarter, and more responsive communities.

IX. CONCLUSION

Edge AI for Real-Time Video Analytics has emerged as a transformative technology for enhancing public safety and security. By combining the capabilities of artificial intelligence with edge computing, the proposed system enables real-time analysis of video data directly at the source, reducing latency, bandwidth consumption, and dependence on cloud infrastructure. The study demonstrates that Edge AI can effectively support various public safety applications, including crime detection, crowd monitoring, traffic management, anomaly detection, and emergency response. The results indicate improved accuracy, faster decision-making, enhanced privacy, and efficient resource utilization compared to traditional surveillance approaches. Although challenges such as limited edge device resources, environmental variations, and privacy concerns remain, ongoing advancements in AI, IoT, and 5G technologies are expected to address these limitations. Overall, Edge AI-based real-time video analytics provides an intelligent, scalable, and cost-effective solution for modern public safety systems, contributing significantly to the development of safer and smarter communities.

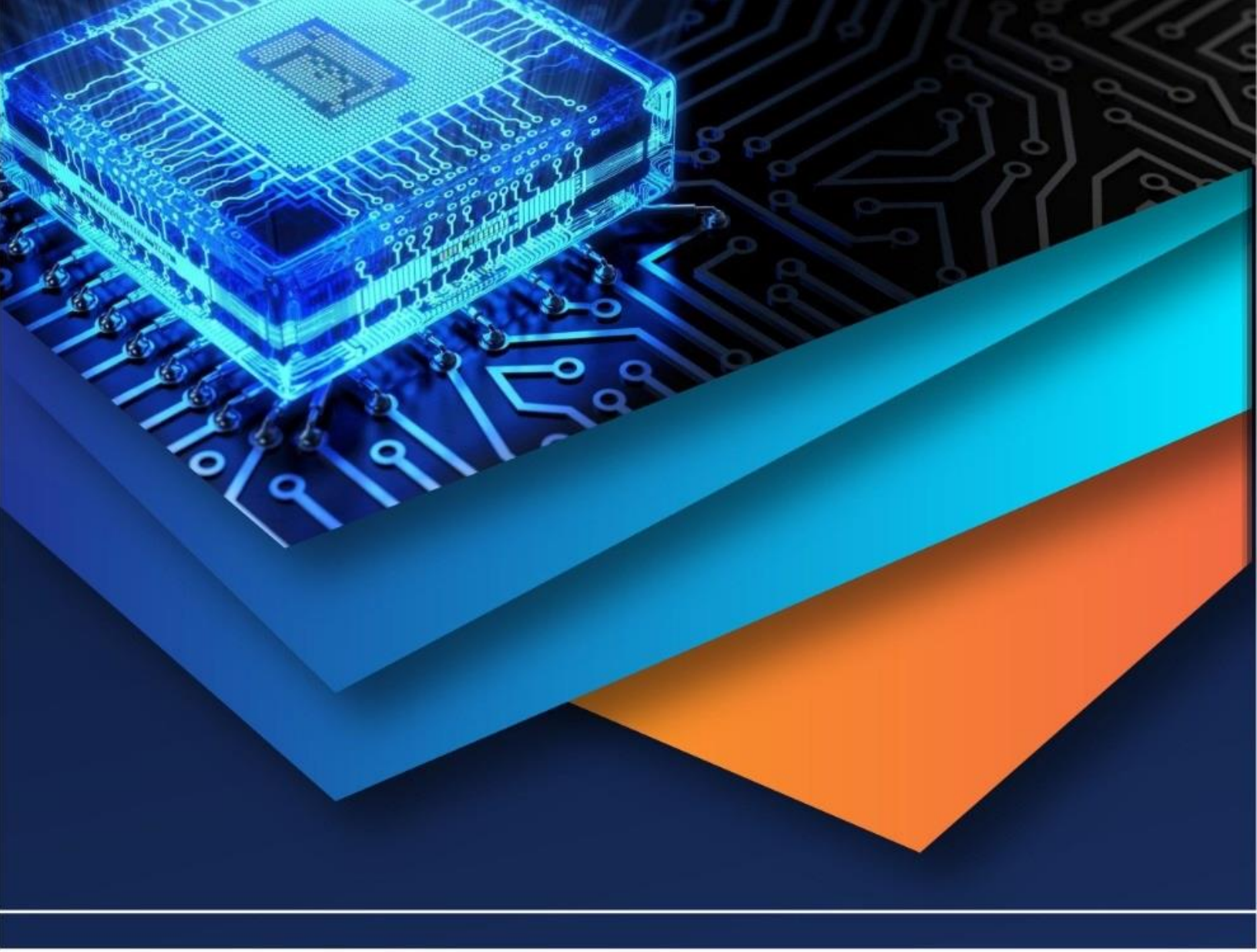
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