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Finding Stolen Vehicles Using Traffic Cameras

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Abstract: A modern tracking system based on traffic cameras will be detailed in this document to improve vehicle theft recovery rates particularly during plate obscuring or removal situations. The standard stolen vehicle detection system experiencing difficulties with license plate recognition relies primarily on Automatic License Plate Recognition (ALPR). The proposed system connects ALPR technology with contemporary machine learning and computer vision features to enable detections of vehicles by model-specific attributes like vehicle shape and color type. lượt động cơ yếu tố dissipation from a wide network of traffic cameras enables the system to provide instant location updates to law enforcement agencies. The system generates instantaneous alerts about located stolen vehicles which contain specific information regarding position data and travel direction and timestamp. Swift emergency responses become possible through this technology which increases the odds of stolen vehicle recovery and criminal capture. The system implements two machine learning models (Convolutional Neural Networks and YOLO) which detect and categorize vehicles under any lighting circumstances or when obscured by other objects. The connection of current traffic cameras to these technologies permits efficient and scalable tracking services in real-time. The paper shows how machine learning tools with computer vision technology integrated with traffic cameras create an efficient solution to detect stolen vehicles which delivers practical data to police services that boosts public protection rates.

Keywords: Stolen vehicle detection, traffic cameras, automatic license plate recognition (ALPR), machine learning, computer vision, real-time tracking, law enforcement.

I. INTRODUCTION

The increasing number of stolen vehicles presents a significant challenge to law enforcement agencies worldwide, leading to losses that affect individuals, businesses, and the broader community. As vehicle theft continues to rise, the need for effective, timely recovery methods has become more urgent. Traditional approaches to stolen vehicle detection primarily rely on license plate recognition (LPR), which involves identifying vehicles through the unique alphanumeric sequences displayed on their plates. While LPR technology has proven useful in many scenarios, it has notable limitations. These limitations are especially evident when license plates are obscured, altered, or missing altogether, which is a common strategy employed by criminals to evade detection.

In light of these challenges, this research proposes a novel approach to solving the problem of stolen vehicle tracking by leveraging traffic camera feeds combined with cutting-edge machine learning (ML) and computer vision (CV) technologies. This system is designed to detect and track stolen vehicles even in cases where traditional license plate recognition fails. By focusing on vehicle make, model, and other distinguishing features (such as color, shape, and size), the system can identify vehicles with a high degree of accuracy, even in the absence of a visible license plate.

A key innovation of this system is its ability to integrate real-time tracking and identification. As vehicles move through the network of traffic cameras, the system continuously monitors and updates their locations. When a vehicle matching a stolen vehicle's description is detected, the system can automatically send alerts to law enforcement agencies in real-time, providing critical details such as the vehicle's current location, direction of travel, and timestamp. This integration enables swift action from law enforcement, significantly improving the chances of recovering stolen vehicles and apprehending criminals.

This research aims to address the limitations of current stolen vehicle recovery systems by introducing an automated, scalable, and efficient solution that utilizes existing infrastructure—traffic cameras. Through this approach, law enforcement agencies can more effectively combat vehicle theft, reduce response times, and increase the likelihood of recovering stolen vehicles, all while leveraging modern artificial intelligence (AI) technologies to enhance public safety.

II. LITERATURE REVIEW

The detection and tracking of stolen vehicles using intelligent traffic systems has garnered significant attention in recent years, with numerous studies focusing on various methodologies and algorithms. Below are key studies, organized by their primary methods and findings:

Shjarback and Sarkos (2025): Their study evaluates the expansion of Automated License Plate Reader (ALPR) technology for stolen vehicle detection. The evaluation focused on the integration of ALPR systems with real-time law enforcement databases, improving vehicle recovery rates. However, the study noted privacy concerns and high operational costs as disadvantages of widespread ALPR adoption.

Kumawat et al. (2024): This work discusses the relevance of automatic number plate recognition (ANPR) systems in detecting stolen vehicles. They highlighted the efficacy of ALPR in high-traffic areas and proposed enhancements in plate recognition accuracy through image pre-processing algorithms. The main disadvantage is the system's vulnerability to license plate obfuscation, which can hinder detection.

Kang et al. (2024): The authors introduced YOLO-FA, a Type-1 fuzzy attention-based YOLO detector for vehicle detection. The fuzzy attention mechanism improves the model's focus on important vehicle features, enhancing accuracy. This approach outperforms traditional YOLO models in terms of precision but requires advanced computational resources.

Kanishkha and Poojah (2022): Their study explored using image processing and machine learning techniques to detect stolen cars. By leveraging feature extraction for vehicle identification, they overcame license plate unavailability. The key limitation was environmental factors like lighting and occlusions affecting detection.

Li et al. (2024): The authors proposed YOLO-CCS, a vehicle detection algorithm based on coordinate attention mechanisms. This method significantly improved detection performance by focusing on spatial relationships in vehicle features. While the model achieved high detection accuracy, its processing time remains a challenge in real-time applications.

Pan et al. (2024): This paper introduced LVD-YOLO, a lightweight vehicle detection model for intelligent transportation systems. The model is optimized for low-resource environments, making it ideal for real-time applications. However, its lightweight nature resulted in slightly reduced detection accuracy compared to more complex models.

Shafi et al. (2023): Focused on a deep learning-based model for real-time stolen vehicle detection. The system leverages CNNs for improved precision and reduced lookup time, even in adverse conditions. A major advantage was the quick response time; however, the model's dependency on large datasets poses a limitation for real-world implementation.

Al-lQubaydhi et al. (2024): This review examined the application of deep learning for UAV-based detection systems. Their focus was on unmanned aerial vehicles (UAVs) for vehicle tracking and license plate recognition. While UAVs provide increased coverage, the study noted limitations in data transmission and weather-related disruptions as significant challenges.

Vishwakarma and Jain (2024): Their study enhanced a deep learning-based vehicle detection model specifically for low light intensity conditions. The model utilized image augmentation to improve performance in poor lighting, making it suitable for nighttime vehicle tracking. The model, however, struggled in high-speed vehicle detection.

Sivasubramanian et al. (2023): This research utilized deep learning to improve real-time stolen vehicle tracking in smart cities. By integrating traffic data with smart city infrastructure, they proposed an enhanced tracking system for urban environments. The system showed great promise, though integration with existing city infrastructure remains a hurdle.

Ramzan et al. (2024): Proposed a smart vehicle parking system to prevent theft using deep image recognition. Their model integrates real-time vehicle monitoring with deep learning techniques for identifying and preventing theft in parking areas. A disadvantage is that the system's effectiveness decreases in highly crowded or dynamic environments.

Mustafa and Karabatak (2024): Developed a real-time vehicle model and plate detection system using deep learning architectures. Their system showed improved accuracy in identifying car models and license plates, even in challenging conditions. The drawback is its high computational requirements, making it less practical for low-resource environments.

Alotaibi et al. (2025): Introduced an AI-driven UAV system for autonomous vehicle tracking and license plate recognition. Their approach integrates UAVs with AI to track vehicles over large areas, providing enhanced coverage and real-time data collection. However, the high cost of UAV systems and challenges related to data transmission and weather conditions were noted.

III. PROPOSED SYSTEM

The proposed system for detecting and tracking stolen vehicles integrates multiple advanced technologies, including traffic camera feeds, Automatic License Plate Recognition (ALPR), vehicle recognition techniques, and real-time tracking. This combination of technologies enables robust and effective identification of stolen vehicles, even in the absence of clear license plate visibility.

The system has been designed to work efficiently in real-time, providing law enforcement agencies with immediate alerts and actionable information. The main components of the system are detailed below:

A. ALPR for License Plate Recognition

The core component of this system is the Automatic License Plate Recognition (ALPR) module, which is responsible for identifying and extracting the vehicle's license plate number from camera footage. ALPR uses optical character recognition (OCR) technology to detect and interpret the characters printed on the license plate. This process begins by capturing video footage from traffic cameras, followed by the identification of regions within the frame that are likely to contain license plates.

The system is designed to work efficiently under a variety of environmental conditions such as low-light settings, high-speed motion, and partial occlusions. To achieve this, the ALPR model incorporates sophisticated pre-processing algorithms that enhance image quality and correct distortions such as skewed or blurred license plates. The recognition model is based on machine learning algorithms, trained on vast datasets that enable it to accurately detect characters on license plates, regardless of lighting, angle, or weather conditions. This component acts as a first line of defense for identifying stolen vehicles based on their registration numbers.

B. Vehicle Detection and Classification

In cases where the license plate is missing or obscured, the system uses vehicle detection and classification techniques based on visual features like make, model, and color. Convolutional Neural Networks (CNNs) are employed to analyze traffic footage and detect vehicles by learning hierarchical features such as shape, texture, and color. Additionally, the YOLO (You Only Look Once) model is used for real-time object detection, capable of identifying and tracking multiple vehicles in a single frame. YOLO and CNN work together to identify the vehicle's make, model, and color, which is then cross-referenced with known stolen vehicle databases.

C. Real-Time Tracking

The Real-Time Tracking component ensures accurate vehicle tracking across multiple camera feeds. Using the Kalman Filter, the system predicts and corrects the vehicle's trajectory based on its previous position, velocity, and direction. This allows for smooth tracking even when views are partially obstructed or when the vehicle moves across different angles. Additionally, Re-identification (Re-ID) techniques are used to recognize the same vehicle across different camera feeds, even in cases of occlusion or changes in appearance. The system compares the vehicle's visual features with a central database to maintain consistent identity tracking.

D. Alert Notification System

The Alert Notification System ensures law enforcement receives real-time updates on detected stolen vehicles. Once a match is found, the system triggers an alert via webhooks, integrating with law enforcement's monitoring systems for immediate action. Additionally, the system generates detailed tracking reports, including vehicle data like make, model, color, timestamp, and GPS coordinates, which are stored in a centralized SQL database. This database allows law enforcement to access historical data and cross-check multiple sightings to build a comprehensive tracking profile. The backend is scalable, supporting new cameras and handling large data volumes as more traffic feeds are integrated.

E. System Flow

The system flow begins with the collection of traffic camera footage, which is processed in real-time by the ALPR and vehicle recognition modules. Once a potential stolen vehicle is detected, the real-time tracking module begins monitoring its movement across various camera feeds. When a vehicle matches a record in the stolen vehicle database, an alert is immediately sent to law enforcement, providing them with all relevant information. The system's centralized database stores all detected and tracked vehicle data for ongoing analysis and reporting.

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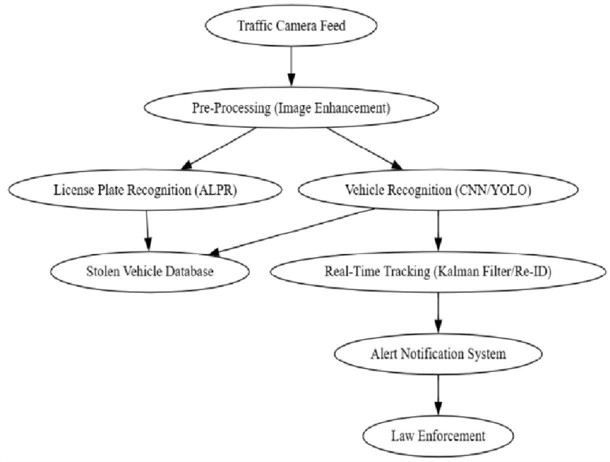

Figure 1. Architecture diagram

IV. METHODOLOGY

The proposed system employs a multi-faceted approach to detect and track stolen vehicles using traffic camera feeds, machine learning models, and real-time system integration. The methodology is designed to ensure that stolen vehicles are quickly identified, tracked, and flagged for law enforcement action, even in challenging scenarios where license plates may be obscured or missing. Below are the key components of the methodology:

A. Data Collection

The first step in the methodology is data collection, where traffic camera feeds are captured and processed to extract vehicle-related information. These feeds are gathered from a network of public cameras placed at key locations across urban areas, such as intersections and highways. The system supports multiple camera inputs, ensuring comprehensive coverage for vehicle detection. High-definition cameras are used to capture clear images, even in low-light or adverse weather conditions, with real-time streaming to the central system. The footage is pre-processed to enhance image quality through techniques like noise reduction, image sharpening, and contrast enhancement. The system is scalable, allowing for the addition of more cameras and supporting multi-resolution inputs to accommodate varying feed qualities.

B. Machine Learning Models

Once the camera feeds are processed, the system employs a set of machine learning models to classify and identify vehicles. The key models used are Convolutional Neural Networks (CNNs) and YOLO (You Only Look Once), which work in tandem to accurately detect vehicles and classify them based on their unique features.

C. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are designed for image classification and feature extraction, making them ideal for vehicle detection. Trained on a large dataset of vehicle images with varying angles, lighting, and occlusions, the CNN learns to identify key features like shape, size, and color. Even when license plates are obstructed, the model can recognize the vehicle’s make, model, and color. By focusing on consistent features such as body shape, headlights, and grille patterns, the CNN is effective in situations where ALPR fails due to missing or obscured plates.

D. YOLO (You Only Look Once)

YOLO (You Only Look Once) is an advanced real-time object detection model capable of detecting multiple objects in a single frame, such as vehicles and pedestrians. It divides the image into a grid and predicts bounding boxes and class probabilities for each object simultaneously, allowing for high-speed detection. YOLO is particularly effective in dynamic environments, detecting and tracking vehicles even when no license plate is visible. It provides bounding boxes around vehicles, enabling the system to track their movement across multiple camera feeds with high accuracy and speed.

E. Handling Obstructions and Variability

Together, CNNs and YOLO help the system detect stolen vehicles even in cases where typical identifiers like license plates are missing or unclear. If the vehicle's license plate is visible, the ALPR module will process it first. If the plate is obscured or absent, the system falls back on these machine learning models to detect the vehicle's distinctive characteristics.

F. System Integration

After the data is collected and processed, the next critical component is system integration, which ensures that real-time camera feeds, vehicle classification, and the alert notification system work in harmony to provide timely information to law enforcement.

G. Real-Time Camera Feeds

The real-time camera feed integration allows the system to operate dynamically, continuously monitoring traffic areas and updating vehicle data as new footage is processed. As vehicles pass through the camera network, their movement is tracked across the various camera feeds using the Kalman Filter algorithm, ensuring continuous tracking even as the vehicle transitions from one camera view to another. This ensures that law enforcement can have up-to-date information on the location of a stolen vehicle, even if it is moving through an expansive urban area.

H. Alert Notification System

When a stolen vehicle is detected, the system triggers a real-time alert, sending instant notifications to law enforcement via webhooks. These alerts include critical details such as the vehicle's make, model, color, timestamp, last known location, and direction of travel, enabling officers to act swiftly. The webhook integration ensures seamless communication between the vehicle detection system and law enforcement databases, ensuring immediate notifications and minimizing response time in pursuing the stolen vehicle.

V. CENTRALIZED SQL DATABASE

The system includes a centralized **SQL database** where all vehicle detection and tracking data is stored. This database serves as a repository for all information regarding detected vehicles, their characteristics, location history, and the results of any tracking attempts. Law enforcement agencies can query the database for historical information, view real-time reports, and analyze trends in stolen vehicle data. This centralized storage ensures that data is easy to access and can be used for further investigation or in future theft cases.

A. System Workflow

- Data Collection: Traffic cameras capture footage and send it to the central system.
- Pre-Processing: The footage is enhanced to improve quality and reduce noise.
- Vehicle Detection: CNNs and YOLO classify and detect vehicles in the footage.
- Tracking: The Kalman Filter tracks vehicle movement, and Re-ID ensures consistent vehicle identification across cameras.
- Alert System: Real-time alerts are sent to law enforcement via webhooks.
- Database Storage: Tracking information and vehicle data are stored for further analysis and retrieval.

B. Comparing the Models

The stolen vehicle detection system uses key models including Automatic License Plate Recognition (ALPR), Convolutional Neural Networks (CNN), and You Only Look Once (YOLO). These models are compared based on accuracy, processing time, and environmental adaptability. ALPR is effective when license plates are visible but struggles with obstructions, poor lighting, or altered plates. CNN-based vehicle recognition excels when plates are missing or obscured, using features like make, model, and color for identification. YOLO is used for real-time detection, enabling fast and accurate vehicle identification, even in high-traffic, dynamic environments.

Table 1: Comparison of Models

Model	Strengths	Limitations
ALPR	Accurate with visible plates	Struggles with obscured or altered plates
CNN	Works without plates, adaptable	Slower processing, needs large datasets
YOLO	Fast real-time detection, handles multiple vehicles	Less effective for small or fast-moving vehicles

VI. RESULTS AND DISCUSSION

The system was evaluated across various urban environments, including high-traffic areas and regions where license plates may be obscured or altered. The combination of ALPR and vehicle recognition models (CNN and YOLO) demonstrated a high level of detection accuracy, even in challenging conditions such as low lighting and partial obstructions. The real-time tracking system utilizing Kalman filtering and Re-ID techniques allowed for continuous monitoring of vehicles across multiple camera feeds, ensuring accurate tracking throughout the detection process. Additionally, the alert notification system played a crucial role in improving the efficiency of vehicle recovery by providing law enforcement with immediate updates, significantly reducing response times. Overall, the system showcased its potential to enhance vehicle recovery efforts, particularly in environments where traditional methods struggle.

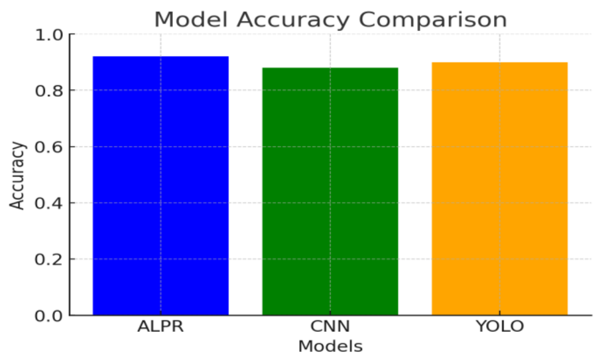

Figure 2. Model accuracy comparison

VII. CONCLUSION

The proposed system enhances the capabilities of traditional stolen vehicle detection systems by using a combination of traffic cameras, ALPR, machine learning, and real-time tracking. By overcoming the challenges posed by obscured or missing license plates, the system improves the accuracy and reliability of stolen vehicle detection and tracking, contributing to the overall safety of the community.

VIII. FUTURE WORKS

Future developments could focus on enhancing the system’s accuracy and adaptability in diverse environments, such as low-light conditions or high-speed scenarios. Integration with advanced AI models and edge computing could allow for more real-time processing and reduced latency. Additionally, expanding the system’s capabilities to include multi-modal data sources (e.g., integrating radar or LiDAR data) and improving vehicle re-identification across multiple camera feeds would further enhance its performance. Finally, collaborations with smart city infrastructure could help scale the system for broader urban deployment, improving vehicle recovery efficiency.

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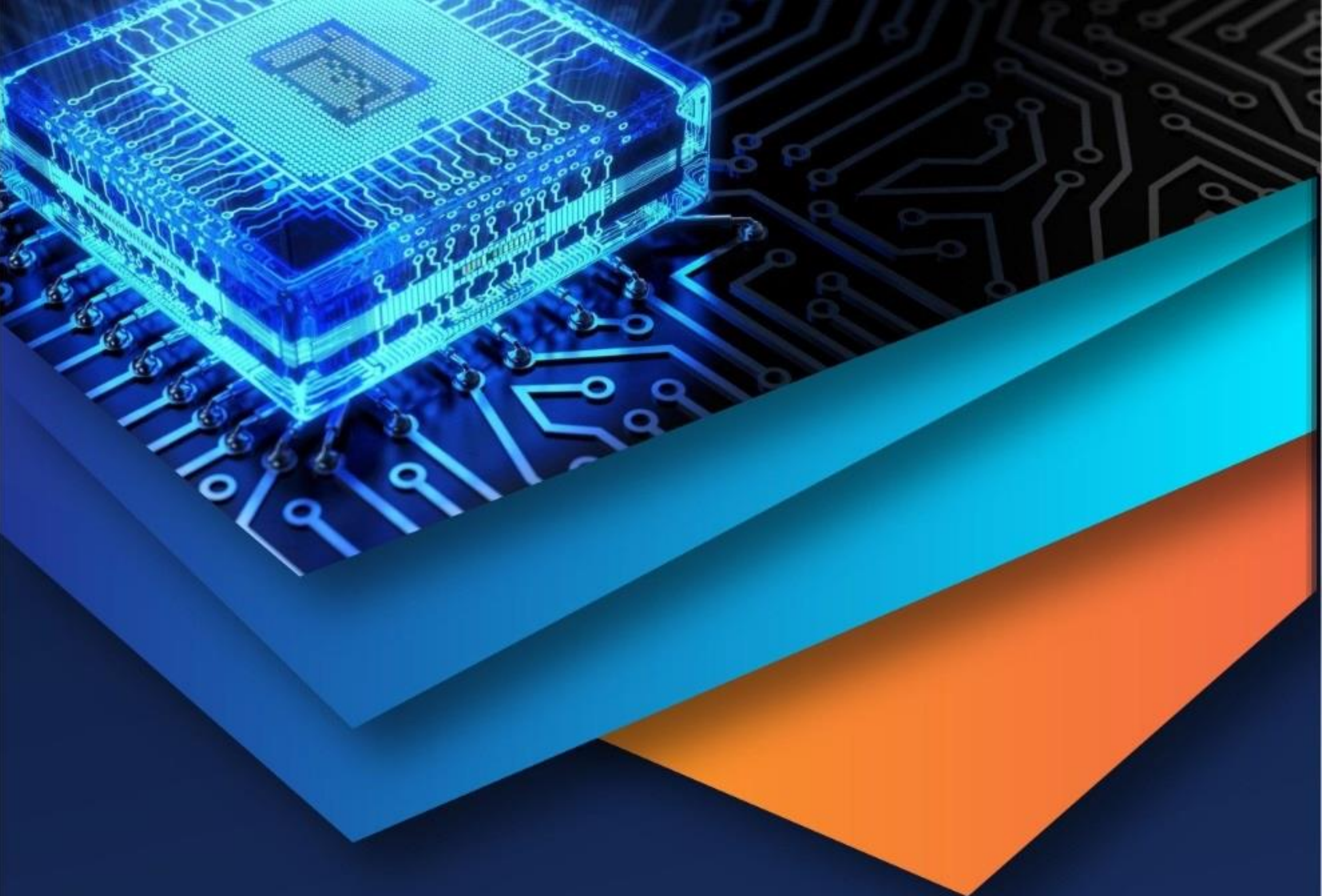

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