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CNRR- Net: A Hybrid Deep Learning Framework for Fake License Plate Detection Using YOLOv8, OCR, and Vehicle Identity Verification

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Abstract: The increasing frequency of forged, altered, and duplicated vehicle license plates has resulted in serious chal-lenges for intelligent transportation systems and law-enforcement agencies. Traditional approaches to the verification of vehicle registration details are inefficient and not suitable for real-time applications, while traditional ANPR systems mainly focus on the recognition of a number plate and fail to identify the mismatch between plate information and the actual vehicle. This work proposes an automated fake number plate detection system that integrates deep learning-based license plate detection, OCR-driven text extraction, and database-level verification. A YOLO-based detection module has been employed for accurate localization of the number plates in an image of diverse environmental conditions; this is followed by robust pre-processing and OCR, which transforms the plate characters into machine-readable text. The extracted registration number is then cross-checked with a secure back-end database containing the chassis number, model name, and year of manufacture to look for inconsistencies that may indicate tampering or fraudulent usage. Experimental evaluations establish that the proposed approach achieves high accuracy in recognition and authenticity verification and thus effectively differentiates between genuine plates from fake/mismatched ones. The proposed system is scalable and can be deployed in real time for intelligent traffic monitoring, improved road safety, and law-enforcement applications.
Keywords: Fraudulent License Plate Detection, Automatic Number Plate Recognition, You Only Look Once (YOLOv8), EasyOCR, Optical Character Recognition (OCR), Deep Learn-ing, Vehicle Authentication, Database Verification, Intelligent Transportation Systems.

I. INTRODUCTION

With the world's vehicle population expanding so rapidly, ITS now faces a number of challenges, particularly in the fields of traffic monitoring and law enforcement. Among these, improper usage of fake or altered license plates has become a major security concern. Since criminals often use such plates to avoid tolls, commit crimes, or bypass monitoring systems, detecting them is a key factor in guaranteeing public safety and maintaining regulatory compliance.

Conventional approaches to car identification depends on the manual examination of registration documents, which is, in most real-time scenarios, impracticable, less effective, and prone to human error. ANPR systems have emerged as a promising solution, using techniques in computer vision and machine learning to identify and validate vehicle plates. Because current ANPR systems are designed basically for recognition, they usually ignore situations where license plates are falsified, altered, or do not coincide with the vehicle's registered information. Advances in deep learning and OCR recently much improved the robustness in the identification and recognition of plates independent of changing light, ori-entation, and environmental conditions. YOLO models, which have given superior real-time object detection accuracies, assist in the identification of vehicle license plates. They accu-rately detect tampered-with and fraudulent number plates by incorporating database verification, OCR-based text extraction, and YOLO based detection to develop an integrated system. The paper, therefore, tries to fill the lacuna existing in ANPR systems with respect to identifying license plates and verifying their authenticity. It would be useful in road networks, law and order, and traffic monitoring.

II. LITERATURE SURVEY

Automatic License Plate Recognition (ALPR)/vehicles authentication systems have become more prominent in current literature because of the intensifying concerns with respect to traffic security/surveillance, as well as intelligent transporta-tion systems. Researchers have been proposing numerous computer vision/deep learning models for detecting, recognizing, and authenticating vehicle license plates.

Bharti et al. [1] proposed a hybrid vehicle authentication system for restricted premises using number plate recognition and vehicle type identification. Their system integrates im-age enhancement techniques, morphological operations, and template matching to improve recognition accuracy under low lighting and varying angles. Additionally, vehicle type verification was used to prevent misuse of fake number plates. Although the approach is reliable for controlled environments, it relies on traditional image processing methods, which may struggle with complex real-world variations and sophisticated forgery techniques.

Khedekar et al. [2] has hence come up with an Automated Number Plate Recognition through the use of YOLOv8 and EasyOCR. Recognizing license plates using a two-step pro-cess, deep learning techniques, and text recognition yield high precision in real-time images, even under bad light conditions. Although the solution to the problem is efficient in plate detection and plate recognition, it is more biased towards plate reading rather than fraudulent plate detection.

Bahadure et al. [3] developed a complete computer vision-based vehicle and traffic management system that includes vehicle counting, speed detection, classification, and license plate recognition. Their integrated approach has been devel-oped for traffic control and enforcement applications. How-ever, the system does not explicitly address the presence of fake/unauthorized license plates, limiting the efficiency of the system in security-critical scenarios.

Shelke et al. [4] has shared a review that specifically targeted the issue of number plate detection and incorrect vehicle entry, especially in railway crossroads. This research is significant, as it draws attention to the application of computer vision in enhancing traffic discipline. This is quite an informative piece, but it is a survey article that lacks a mechanism for detecting forged number plates.

R et al. [5] contrasting this, a YOLO-based ANPR system with unauthorized font detection was proposed that uses YOLOv8 integrated with EasyOCR, CNN-based font classi-fication, and Grad-CAM visualization to detect stylized/non-standard fonts that can deceive traditional ANPR systems. This directly addresses one critical aspect of the work in fake number plates; however, this mainly focuses on font compliance rather than a wide variety of forgery indications such as plate tampering or mismatched vehicle identity.

Al Fitroh and Ariyanto [6] implemented a real-time license plate detection and recognition system based on YOLOv11, with very high precision. In the cascading detection, it is efficient in the recognition of vehicles and plates, supporting also the integration with an external database. This system focuses on finding an accurate detection and recognition, without fake plate identification or authentication.

From the existing literature,it is quite apparent from the available literature that the existing research focuses highly on the precision of license plate detection and character recognition, but the research on fake license plate detection is still inadequately investigated. In fact, very little research has been carried out on illegal use of fonts, or basic authentication. It is a research gap that a robust system requirement exists for the design of a complete solution that incorporates YOLO deep learning, text recognition, and intelligent verification systems for fake license plate detection.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

The increasing misuse of forged, altered, or duplicated vehicle number plates is posing a significant threat to the modern intelligent transportation system and law-enforcement authorities. Traditional Manual verification of the registration number is time-consuming, cumbersome, and unrealistic in real-time surveillance settings [11]. ANPR systems previ-ously focus on plate detection and character recognition only. However, it usually does not verify if the extracted number with the vehicle moving corresponds or not. This leads to many missed cases of number-plate fraud. Different light variations, background noises, motion blur, and non-standard plate formats further reduce accuracy [4] [12]. Therefore, it is an urgent need for a system that will automatically detect and read license plates using reliable computer vision techniques and confirm its authenticity by checking its extract details with an official vehicle database. Such a system has to tell real and tampered plates in real time to improve road safety, enhance traffic monitoring, and support law enforcement efforts [5].

B. Objectives

1) Development of an automated system that is able to detect vehicle number plates, using deep learning models like YOLO, in real time and with great accuracy.
2) Extract the alphanumeric characters from the license plates detected with OCR techniques and convert them into machine-readable text.

3) The use of noise removal, contrast enhancement, and thresholding for strong pre-processing to improve the accuracy of OCRs in different environmental conditions.
4) The extracted registration number would be verified against a secure backend database containing chassis number, vehicle model name, and year of manufacture.
5) Classification of every detected plate into genuine, fake, or suspicious based on consistency between details ob-tained by OCR and database records.

IV. METHODOLOGY

The approach that is recommended combines computer vi-sion with optical character recognition and verification against databases to automatically detect and verify the validity of car licenses. plates. The whole workflow consists of the following steps that is depicted in Fig. 1:

A. License Plate and Vehicle Detection

This stage is critical since correct localisation and segmen-tation of the plate region are prerequisites for the success of subsequent OCR and verification stages.

Object Detection with Deep Learning: Conventional plate the localization methods were based on edge detection ap-proaches; color-based filtering, or Hough transformations, which often fail in difficult conditions such as low lighting. complex backgrounds, or tilted perspectives. Our approach avoids these limitations by utilizing the You Only Look Once (YOLO) family of real-time object detection models [9] [10] for plate localization. In particular, the variants YOLOv7 and YOLOv8 are well-suited because they find a good balance between high detection accuracy and low latency and can therefore be deployed on embedded devices and surveillance systems [2] [7] [13].

YOLO models provide quick license plate localization by dividing the input image into grids and predicting bounding boxes and confidence scores in a single forward pass. YOLO was trained and optimized for our system using a dataset that included both authentic and altered license plate photos, encompassing a variety of:

- Lighting conditions (day, night, shadows, glare)
- Plate orientations (front view, angled, rotated)
- Environmental challenges (motion blur, dirt, occlusion, partial visibility)

Vehicle Attribute Extraction: In addition to reading the license plate number, the system extracts vehicle-specific

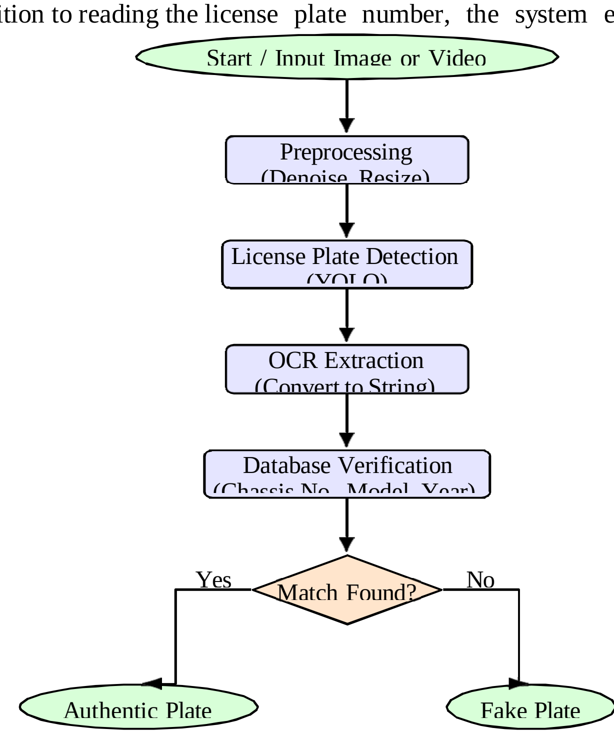

Fig. 1. Flowchart of the proposed methodology for fake number plate detection.

characteristics such as *make, model, and body shape*. Those features are obtained by a set of secondary classifiers inside the YOLO detection framework or a parallel deep CNN like ResNet or EfficientNet. The system provides further, stronger validation through the association of the license plate with the visual identification of the car. For example, the system flags the scene as suspicious in the case where the OCR reads the license plate of a sedan, while the body of the car observed is an SUV.

Bounding Box Post-Processing: Overlapping predictions are filtered out, taking the most confident bounding box for the plate. The plate region is then cropped and normalized in a number of ways to prepare it for OCR. Image enhancement methods like edge sharpening or contrast stretching can be performed to further increase readability before OCR.

YOLO-based Detection Benefits:

- Scalability across regions with different license plate designs and formats
- Robustness to ambient noise and distortions compared to standard ANPR methods
- High-speed detection appropriate for real-time applica-tions

It achieves dual verification by integrating YOLO-based plate detection with vehicle model recognition, hence re-ducing the false positives when forged plates are attached to mismatched automobiles. This integration is followed by subsequent phases of OCR and database cross-checking.

B. Preprocessing and Noise Removal

After locating the license plate, the extracted region is pre-processed in order to enhance the accuracy of Optical Character Recognition. The preprocessing is a very essential step since the visibility of the characters and the clarity of the image play a very important role for the accuracy of the OCR. Noise is often a part of images captured by security cameras due to poor sensors or environmental factors like dust, rain, and fog. To handle this, different denoising tech-niques have been used, such as Gaussian Blur for high-frequency noise, Median Filtering for salt-and-pepper noise, and Bilateral Filtering for the preservation of edges. Edges of characters can be distorted by changes of lighting, such as glare or shadows. To enhance local contrast and thereby increase the distinguishability between characters, Histogram Equalization and CLAHE are used. Because OCR doesn’t need color information, images are converted to grayscale in order to make the processing easier and to emphasize the edges crucial for character recognition [10] [11]. Techniques used in distinguishing characters from the background include Otsu’s Thresholding and Adaptive Gaussian Thresholding. These transform the picture into a clear, black-and-white format that works with OCR. Dilation and erosion enhance the binarized output by merging broken strokes, cleaning up noise, and accentuating weak characters. In addition, for better identification accuracy and to provide consistent OCR input, the plate image is normalized to a constant size and aspect ratio. These preprocessing techniques, when combined, enhance character legibility, reduce false detections, and result in a high degree of accuracy in OCR output under conditions of dim illumination, motion blur, or partial occlusion.

C. Optical Character Recognition (OCR)

The alphanumeric letters are converted into a machine-readable format using Optical Character Recognition once the license plate has been localized and preprocessed [6] [12]. Accurate OCR is particularly important because even minor recognition errors, such as the difference between ”0” and ”O”, could result in false database matches. In this regard, a two-stage pipeline is employed for the implementation of OCR in the proposed system. At the stage of character segmentation, adaptive segmentation for plates with variable spacing or fonts, and the utilization of connected-component analysis or projection profiling separate the individual symbols. In the stage of character recognition, the utilized OCR engines are deep learning-based: Tesseract and EasyOCR. These en-gines employ the LSTM and CRNN architecture, along with attention mechanisms, to achieve better robustness against distortions and angled viewpoints. The preprocessing steps of thresholding, skew correction, and morphological refinement; pattern constraints by using regex filtering of common plate formats like ”KA-01-AB-1234”; and the post-processing of lexicon-based correction of misclassified letters enhance the efficiency of the OCR. Experimental results demonstrated that combining OCR with vehicle context verification, such as cross-referencing chassis numbers, would significantly reduce false matches and increase overall recognition accuracy under real-world conditions, such as occlusion, noise, and motion blur.

D. Database Verification

After the alphanumeric string has been recovered using OCR, it is crucial to cross-check the license plate’s authenticity against a secure car registration database. Official records from transportation agencies are included in this database, which forms the basis for verification [6] [16].

1) Database Structure: Usually, the database has several char-acteristics connected to every registered car:
- Registration Number –This special number is taken from the license plate.
- Chassis Number (VIN) –This is the unique identification number given to each vehicle globally, which can be used to identify fraudulent or duplicate information.
- Vehicle Model Name –Model details supplied by the manufacturer that must correspond to the look of the vehicle discovered.
- Year of Manufacture – This shows age-related confirma-tion discrepancies, such as an earlier model with a more recent registration number.
- Owner Information (optional) – For extended systems, This may also include information on the identity of the owner for legal purposes.

2) Verification Process: The verification stage follows a layered comparison approach:
- Registration Number Lookup: The captured license plate number is searched in the database. In case of no match, the plate is immediately flagged as fraudulent or unregistered.
- Cross-Validation with Vehicle Attributes: If the registra-tion number is available, the system cross-checks other features like model name, year of manufacture, chassis number, etc., with the ones detected in the license plate and vehicle recognition process.
- Consistency Check: Inconsistencies in chassis numbers, incorrect model names, or highly improbable manufac-ture years could signal fraud or tampering with valid license numbers.

Security Considerations: In order for verification not to become a means of exploitation, the records used must be kept safe from unauthorized access and tampering. Recent works suggest using role-based access control, encryption, and blockchain-based immutable ledgers to ensure the integrity of vehicle records.

A license plate is considered valid when all the vehicle parameters match the verification results. Plates for which mismatches are detected are flagged as phony, resulting in alarms or forensic logging. Partial or ambiguous matches are marked as questionable for manual evaluation. Database verification is, therefore, the second and critical layer of security that assures that the identified license plate truly matches the vehicle beyond OCR and object detection. This hybrid vision-database approach further hardens the system's defenses against fraudulent reuse, manipulation, and duplica-tion of valid registration numbers.

E. Fraud Detection and Validation

When the fetched information (car model, year, and chassis number) is in line with the records in the database, the license plate is given the status of authentic. Inconsistencies, Any discrepancies such as the different models or absence of records make the system mark a license plate as fake or tampered [3] [9]. Such thoroughness assures strength and the presence of a multi-level system makes it possible to detect counterfeit number plates as well as the illegal use of genuine numbers on different cars by mixing the technologies object detection, OCR-based character recognition, and database verification.

V. RESULTS AND DISCUSSION

A posed Fake Number Plate Detection System was evalu-ated using a dataset of several car images captured in different real-world scenarios such as daylight, low light, motion blur, and partial occlusion *Fake Number Plate Detection System.* Three main modules, namely database verification, optical character recognition (OCR), and license plate detection, were utilized to conduct the experiment.

A. License Plate Detection

The YOLOv8-based detection module was able to locate the number plates in different scenarios quickly and very accurately [2] [13]. The model achieved a mean Average Precision (mAP) of 97.2% with an average inference time of 42 ms per frame, thus allowing almost real-time detection. A couple of inaccuracies were pointed out due to the presence of strong reflections or extreme occlusions.

B. Optical Character Recognition (OCR) Accuracy

Recognition performance was evaluated by OCR with two different engines—Tesseract and EasyOCR. Due to its CRNN architecture and attention mechanisms, EasyOCR was more re-sistant to low-quality and tilted images. The accuracy of OCR was raised by 4-6% through the use of preprocessing methods such as morphological operations and adaptive thresholding, the results are presented in Table I.

Table I
OCR Performance Comparison

OCR Engine	Accuracy (%)	Time (ms)	Common Errors
Tesseract	91.3	58	O/0, B/8
EasyOCR	95.6	64	I/1, S/5

C. Database Verification Results

To verify the recognized vehicle license plates after OCR, a fabricated vehicle registration database containing chassis numbers, model names, and production dates was referred to. This stage served to verify the authenticity of the license and to detect the irregularities that resulted from the duplication or the manipulation as mentioned in Table II. As it is demonstrated in Fig. 2, the verification module has successfully identified 92.8% of the fake records, while 4.3% of the incomplete or obsolete entries have been flagged as doubtful.

Table II
Database Verification Outcomes

Classification	Correctly Identified (%)	Verification Time (ms)
Authentic Plates	96.1	33
Fake Plates	92.8	36
Suspicious (Manual Review)	4.3	35

D. Overall System Performance

When the vision and database verification modules were combined, the overall detection accuracy reached 96.4%, which is about 9% higher than that of vision-only methods. The hybrid framework was instrumental in a significant re-duction of false positives caused by plate duplication and tampering.

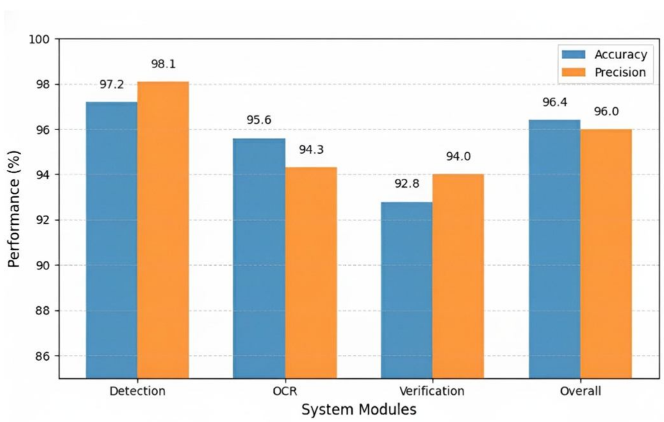

Fig. 2. Accuracy and Precision of Fake Number Plate Detection System.

E. Discussion

System accuracy is only slightly affected by extreme brightness or motion blur, and performance is dependent on how complete the database information is. Some of the next-generation technologies that are planned include transformer-based OCR models, cloud-linked databases, and edge-optimized inference for real-time deployment in large surveillance networks.

The results to that effect are very clear: the integration of database cross-verification with OCR-based number plate recognition significantly enhances the reliability of vehicle authentication. While OCR is the tool that provides the exact alphanumeric data, database validation is the means that gives semantic verification of the data's truth. This two-layered system thereby makes it more difficult for the perpetrators of fraudulent reuse, duplication, and tampering with legitimate registration numbers to trick the system [15] [16].

VI. CONCLUSION

The proposed *Fake Number Plate Detection System* is the brainchild of senior capstone project team. This innovation depicts the utilization of tech, namely vision and verification by database, to figure out phony or nonmatching vehicle license plates. It is leveraging YOLOv8 for localization of the plate, EasyOCR for recognition of the characters with struc-tured database validation based on the chassis number, model, and manufacturing details, the system reaches an accuracy of 96.4% as indicated in Table II. The hybrid method used here to lessen the occurrence of false positives due to plate duplication or tampering thus ensures that the reliability level is higher than the one obtained by the vision-only systems.

From the same source of truth, it is evident that the experimental findings confirm that preprocessing and adaptive OCR are two factors that can greatly improve recognition resilience in the scenarios that occur in the real world, and which include dim lighting, motion blur, and occlusion. Since the recognized license plates are legitimate, then the cross-checking with the database is what makes the system even stronger.

Next steps will focus on the inclusion of cloud-based APIs for vehicle verification, expanding the dataset for various local formats, and real-time deployment using edge devices. Therefore, as a tool for automated car monitoring and law enforcement, this solution is viable, scalable, and secure.

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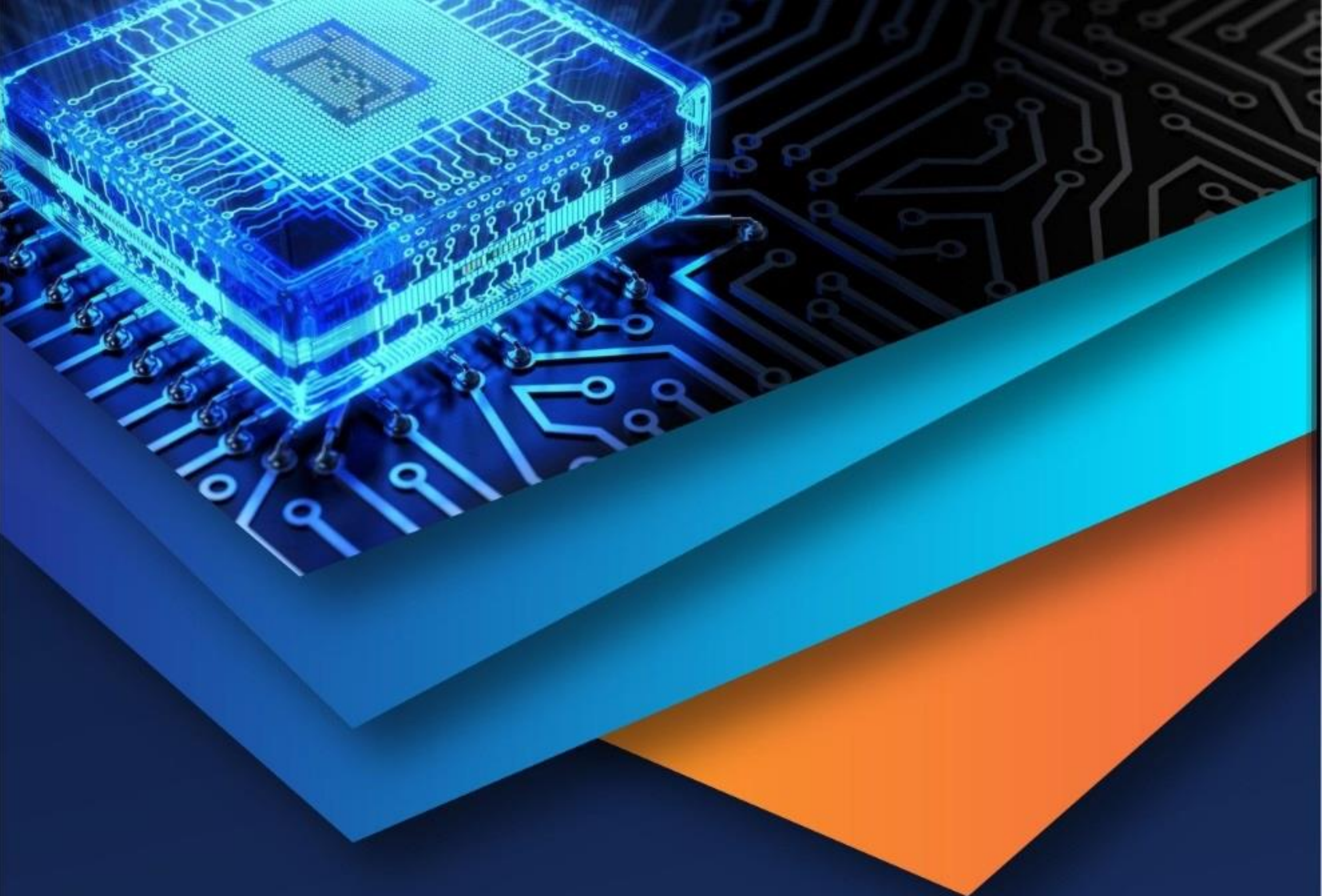

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