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YOLOv8-Based Road Defect Detection and Tracking Using Video Analysis

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Abstract: Road surface defects, including cracks, potholes, and edge breaks, pose serious challenges to transportation safety and infrastructure maintenance. Conventional inspection methods are labour-intensive, time-consuming, and often fail to provide timely assessment of road conditions. This paper presents an automated road defect detection and tracking system based on the YOLOv8 object detection model for efficient road surface monitoring. The model was trained on a road defect dataset containing nine defect categories representing different severity levels of cracks, potholes, and edge breaks. OpenCV was employed for video processing, while a centroid-based tracking algorithm was integrated to assign unique IDs to detected defects across consecutive video frames. The proposed system processes road videos by extracting frames, detecting and classifying defects, tracking identified objects, and generating an annotated output video. Performance evaluation was conducted using manually annotated video frames as ground truth and standard object detection metrics, including Precision, Recall, F1-Score, mAP@0.5, mAP@0.5:0.95, and Frames per Second (FPS). Experimental results demonstrated high detection accuracy, reliable localization, and efficient processing speed, highlighting the effectiveness of the proposed approach for automated road inspection. The developed system reduces dependence on manual surveys and provides a scalable solution that can be extended for intelligent transportation systems and smart road maintenance applications.
Keywords: Road Defect Detection, YOLOv8, Object Detection, Deep Learning, Computer Vision, Object Tracking.

I. INTRODUCTION

Road transportation is a critical component of modern infrastructure, and maintaining road quality is essential for ensuring safe and efficient travel. Over time, road surfaces develop defects such as cracks, potholes, and edge breaks due to heavy traffic, environmental conditions, and continuous wear. If these defects are not detected and repaired promptly, they can lead to vehicle damage, traffic disruptions, increased maintenance costs, and potential safety hazards. Consequently, accurate and timely road defect detection has become an important area of research.

Traditional road inspection methods rely heavily on manual surveys, which are time-consuming, labour-intensive, and prone to human error. Recent advances in deep learning and computer vision have enabled automated road inspection using object detection models such as Faster R-CNN, SSD, and the YOLO family. Among these, YOLOv8 has demonstrated superior performance in terms of detection accuracy, localization capability, and inference speed. However, many existing approaches are limited to image-based detection, support only a small number of defect categories, or do not provide continuous tracking of detected defects in video sequences. To overcome these limitations, this paper proposes a YOLOv8-based road defect detection and tracking system for automated road monitoring. The proposed approach processes road videos by extracting frames, detecting and classifying road defects, and assigning unique IDs to detected objects using a centroid-based tracking algorithm. The model is trained to recognize nine categories of road defects, including different severity levels of cracks, potholes, and edge breaks. Performance evaluation is carried out using manually annotated video frames and standard object detection metrics.

Experimental results demonstrate that the proposed system accurately detects and localizes road defects while maintaining consistent object tracking across consecutive video frames. The combination of efficient object detection, reliable tracking, and quantitative performance evaluation makes the proposed approach suitable for automated road inspection and provides a practical solution for future intelligent transportation and road maintenance systems.

II. RELATED WORK

Recent advances in deep learning have significantly improved the performance of automated road defect detection systems. Object detection models such as Faster R-CNN, SSD, and the YOLO family have been widely adopted because of their ability to accurately identify road surface defects from images and videos. Among these approaches, YOLO-based models have gained considerable attention due to their balance between detection accuracy and real-time processing speed.

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Several researchers have proposed enhanced versions of YOLO for road defect detection. HE-YOLOv5s improved feature extraction by integrating an enhanced Spatial Pyramid Pooling Fast (SPPF) module, a Normalization-based Attention Module (NAM), and model pruning techniques, resulting in improved inference speed and reduced model complexity. Similarly, RDD-YOLO introduced improvements to YOLOv8 through SimAM attention, GhostConv, and bilinear interpolation, achieving better detection accuracy while lowering computational cost.

More recent studies have focused on improving localization accuracy and feature representation. Optimized YOLOv8 models incorporating Deformable Attention Transformers (DAT), GSConv, MPDIoU loss, CBAM attention, and deformable convolution have demonstrated superior performance compared to conventional object detection methods. These enhancements have contributed to more accurate detection of cracks, potholes, and other road defects under controlled conditions.

Despite these developments, existing methods often rely on limited benchmark datasets, detect only a small number of defect categories, or focus primarily on image-based detection without continuous object tracking. Motivated by these limitations, the proposed work combines YOLOv8-based object detection with centroid-based tracking to identify and monitor multiple categories of road defects in video sequences while evaluating performance using standard object detection metrics.

III. PROPOSED METHODOLOGY

A. Overview of the Proposed System

The proposed system is designed to automatically detect and track road surface defects from recorded road videos using the YOLOv8 object detection framework. The overall workflow consists of video acquisition, frame extraction, defect detection, defect classification, object tracking, and visualization of the final output. Figure 1 illustrates the architecture of the proposed system.

Initially, the input road video is processed using OpenCV, where individual frames are extracted for analysis. Each frame is then passed to the trained YOLOv8 model, which identifies road defects by predicting their locations and assigning the corresponding class labels. The model is trained to recognize nine defect categories representing different severity levels of cracks, potholes, and edge breaks.

Following detection, a centroid-based tracking algorithm assigns a unique identification number to each detected defect and maintains its identity across consecutive frames. This enables continuous monitoring of road defects while minimizing duplicate detections. Finally, the processed frames are combined to generate an annotated output video displaying bounding boxes, class labels, confidence scores, and tracking IDs.

To assess the effectiveness of the proposed approach, the model is evaluated using manually annotated video frames and standard object detection metrics, including Precision, Recall, F1-Score, mAP@0.5, mAP@0.5:0.95, and FPS.

B. System Architecture

Figure 1 illustrates the complete workflow of the proposed road defect detection system. The architecture consists of several interconnected modules that process the input video sequentially. The system begins by receiving a road video, from which individual frames are extracted for analysis. These frames are processed by the trained YOLOv8 model to detect road defects and classify them into their respective categories.

The detected objects are subsequently forwarded to the defect identification module, where the predicted classes and confidence scores are verified before being passed to the centroid tracking module. The tracking algorithm assigns unique IDs to each detected object, allowing the same road defect to be monitored across multiple frames. Finally, the visualization module overlays bounding boxes, confidence scores, class labels, and tracking IDs onto the processed frames to generate the annotated output video.

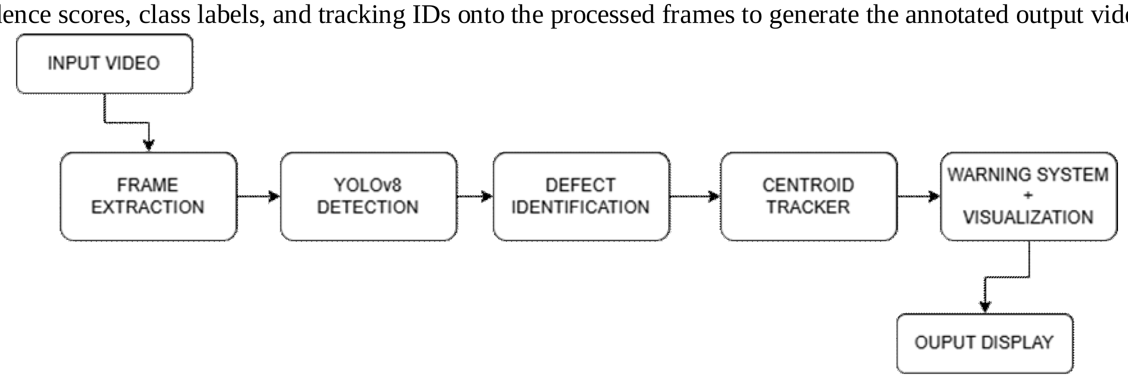

Fig.1. Architecture of the proposed road defect detection system.

C. YOLOv8-Based Road Defect Detection

The proposed system employs the YOLOv8 object detection model to identify and classify road defects from video frames. YOLOv8 was selected because of its high detection accuracy, efficient feature extraction, and real-time inference capability, making it well suited for intelligent road inspection applications. Compared with earlier object detection models, YOLOv8 offers improved localization performance while maintaining a lightweight architecture that supports faster processing.

The model was trained using a road defect dataset containing nine defect categories representing different severity levels of cracks, potholes, and edge breaks. All images were annotated using the YOLO annotation format, where each object was assigned a class label and corresponding bounding box coordinates. During training, the model learned the visual characteristics of each defect category, enabling it to distinguish between different types and severity levels of road damage.

During inference, the input video is first divided into individual frames using OpenCV. Each frame is then processed by the trained YOLOv8 model to detect road defects. For every detected object, the model predicts the bounding box location, class label, and confidence score. These predictions are forwarded to the subsequent tracking module for continuous monitoring throughout the video sequence.

The use of YOLOv8 enables accurate localization of multiple road defects within a single frame while maintaining efficient processing speed. This makes the proposed system suitable for analysing road inspection videos and provides a reliable foundation for automated road condition monitoring.

D. Object Tracking

Object tracking plays an important role in maintaining the identity of detected road defects across consecutive video frames. Instead of treating every detection as a new object, the proposed system incorporates a centroid-based tracking algorithm that assigns a unique identification number to each detected defect. This approach enables continuous monitoring of road defects throughout the video and minimizes duplicate detections.

The tracking process begins after the YOLOv8 model produces the detection results for each frame. The centroid of every detected bounding box is calculated and compared with the centroids of objects detected in the previous frame. Based on the minimum Euclidean distance between centroids, the tracker associates existing objects with newly detected ones and preserves their unique IDs. If a new object appears, a new tracking ID is assigned, whereas objects that disappear for several consecutive frames are removed from the tracking list.

By combining object detection with centroid-based tracking, the system provides consistent monitoring of road defects across the entire video sequence. The assigned tracking IDs also improve the interpretability of the detection results by allowing users to distinguish individual defects as the video progresses.

Fig. 2. Detection and tracking of road defects using the trained YOLOv8 model.

E. Performance Evaluation

The performance of the proposed system was evaluated using manually annotated video frames as ground truth. Standard object detection metrics, including Precision, Recall, F1-Score, mAP@0.5, mAP@0.5:0.95, and Frames per Second (FPS), were used to measure the effectiveness of the model. These metrics assess the system's ability to accurately classify road defects, localize bounding boxes, and process video efficiently.

To obtain reliable evaluation results, representative frames were extracted from the test videos and manually annotated using LabelImg. The annotated labels were compared with the model predictions to compute the evaluation metrics. This evaluation methodology provides a comprehensive assessment of both the detection accuracy and the real-time performance of the proposed road defect detection system.

IV. RESULTS AND DISCUSSION

The proposed road defect detection system was evaluated using manually annotated video frames to assess its detection and tracking performance. The trained YOLOv8 model was tested on road videos containing multiple categories of road defects, and the predicted results were compared with the ground truth annotations. Performance was measured using standard object detection metrics.

The experimental results indicate that the proposed model achieves reliable detection accuracy across different road defect categories. High Precision and Recall values demonstrate the model's ability to correctly identify road defects while minimizing false detections. Similarly, the obtained F1-Score reflects a balanced trade-off between Precision and Recall, confirming the robustness of the proposed approach. The high mAP values further indicate accurate localization of defects, while the measured FPS demonstrates the system's capability to process video efficiently.

TABLE I
PERFORMANCE EVALUATION OF THE PROPOSED SYSTEM

METRIC	VALUE
PRECISION	93.05%
RECALL	94.87%
F1-SCORE	93.95%
mAP@0.5	96.20%
mAP@0.5:0.95	83.82%
FPS	51.94

Figure 3 illustrates the confusion matrix generated during evaluation. The matrix shows that the majority of road defects were correctly classified into their respective categories, with only a small number of misclassifications occurring between visually similar defect classes. The results confirm that the model effectively distinguishes between different severity levels of cracks, potholes, and edge breaks.

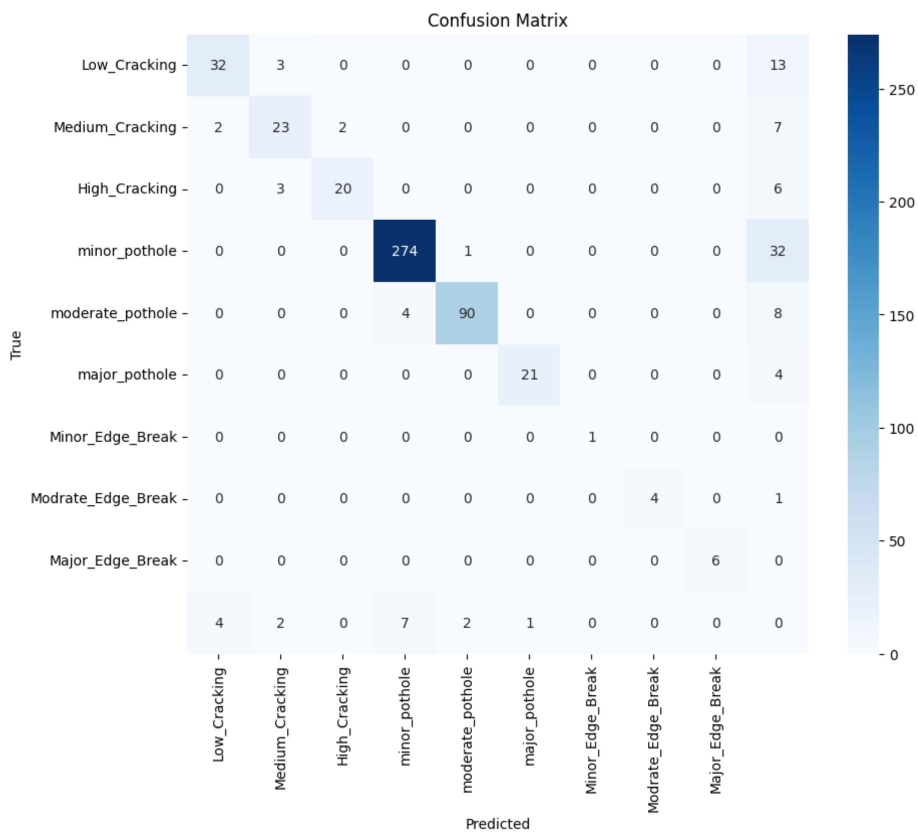

Fig. 3. Confusion matrix illustrating classification performance.

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Figure 4 presents the Precision–Recall (PR) curve obtained during model evaluation. The curves for most defect categories remain close to the upper-right region of the graph, indicating high precision across a wide range of recall values. This demonstrates that the trained YOLOv8 model is capable of accurately detecting multiple road defect classes while maintaining a low false positive rate. Minor variations are observed for certain crack categories, which are comparatively more difficult to identify because of their fine structure and lower visual contrast.

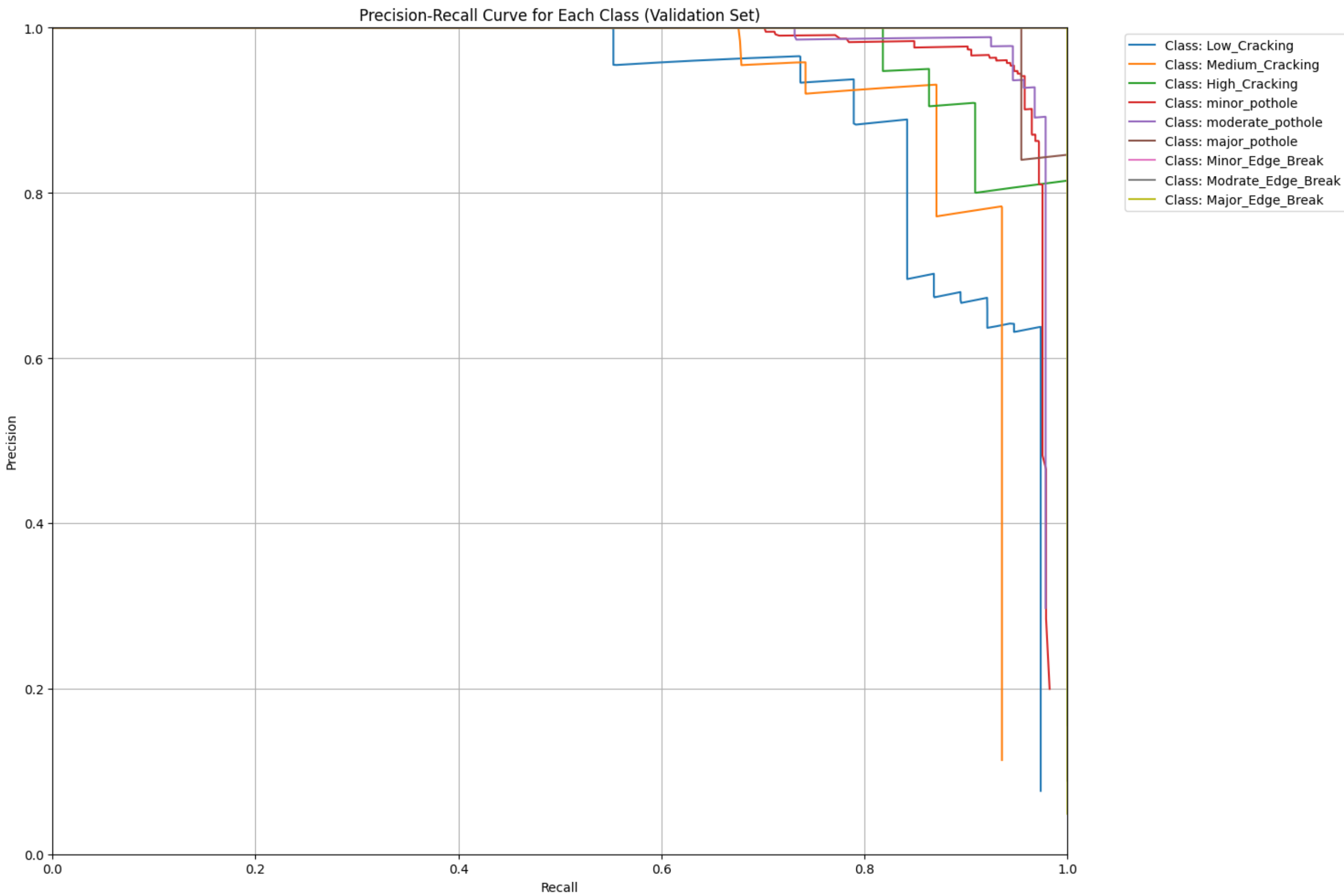

Fig. 4. Precision–Recall curves for the nine road defect categories.

Figure 5 presents sample detection results obtained from the test videos. The proposed system successfully detects road defects, assigns confidence scores and class labels, and maintains unique tracking IDs across consecutive frames. The integration of centroid-based tracking enables continuous monitoring of detected defects while reducing duplicate detections. Overall, the experimental results demonstrate that the proposed system provides accurate, efficient, and reliable road defect detection suitable for automated road inspection applications

Fig. 5. Qualitative detection and tracking results from video frames.

V. CONCLUSION

This paper presented a YOLOv8-based road defect detection and tracking system for automated road condition monitoring using video analysis. The proposed framework integrates YOLOv8 object detection with a centroid-based tracking algorithm to accurately detect, classify, and track road defects across consecutive video frames. The system was trained to recognize nine categories of road defects, including different severity levels of cracks, potholes, and edge breaks, and was evaluated using manually annotated video frames.

Experimental results demonstrated that the proposed approach achieved high detection accuracy and reliable localization, as reflected by strong Precision, Recall, F1-Score, and mAP values. The integration of object tracking enabled consistent identification of detected defects throughout the video sequence, improving the interpretability of the results while minimizing duplicate detections. These findings indicate that the proposed system provides an efficient and practical solution for automated road inspection and infrastructure monitoring.

Future work will focus on extending the system to real-time deployment using live camera feeds, incorporating GPS-based defect localization, and optimizing the model for edge devices. Further improvements can also be achieved by training on larger and more diverse datasets to enhance robustness under varying environmental and road conditions.

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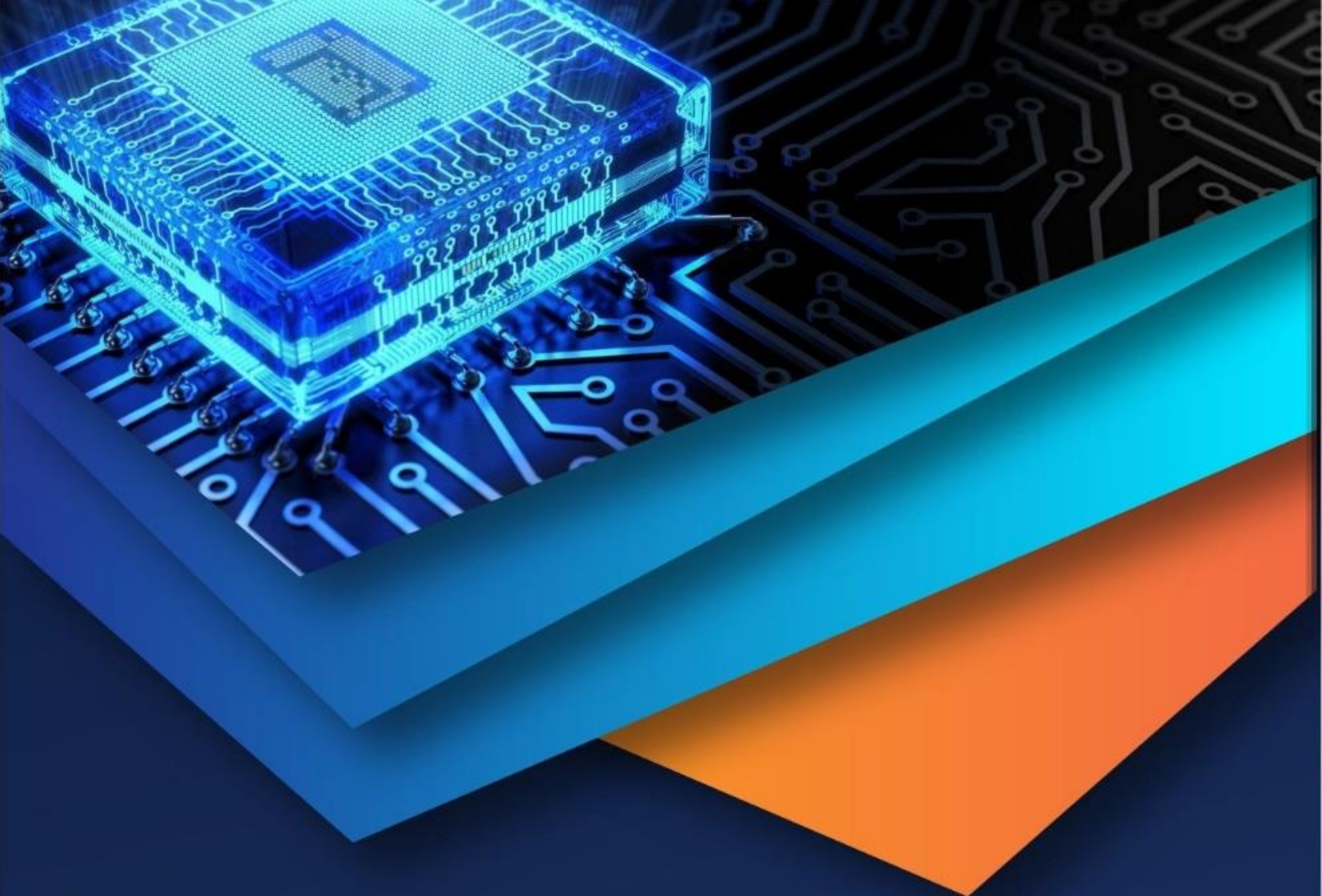

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