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Fracturespot: YOLO-Powered X-Ray Detection System

Mr. Ch. Sunil[1], Thottempudi Harsha Vardhini[2], Shaik Afsha Shireen[3], Abdul Sattar[4], Gadila Surya Revanth[5]
Department of Computer Scince & Engineering, Dhanekula Institute of Engineering and Technology, Andhra Pradesh, India

Abstract: Bone fracture detection is a crucial aspect of early cancer diagnosis, and deep learning-based object detection models have shown promising results in medical imaging. This study explores the application of YOLO (You Only Look Once) models for fast and reliable bone fracture detection. The dataset used in this research is the Bone Fracture Detection dataset from Roboflow, which includes annotated medical images to train and evaluate the models. Four YOLO variants—YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n—are implemented and compared based on their efficiency and ability to detect fractures accurately. Performance evaluation metrics such as precision, recall, and mean Average Precision (mAP) are used to assess model effectiveness. Among the tested models, YOLOv8n achieved the highest precision of 90.9%, demonstrating its superior capability in detecting bone fractures accurately. These models are optimized for real-time medical image analysis, ensuring quick and precise fracture identification. The study aims to identify the most effective YOLO variant for detecting bone fractures, balancing speed and reliability. The results demonstrate that advanced YOLO architectures significantly improve early fracture detection, aiding in timely diagnosis and treatment planning. This research contributes to the biomedical field by enhancing automated fracture detection methods, potentially reducing human error and improving healthcare outcomes.

Index Terms: Bone Cancer, Fracture Detection, Machine Learning, Yolo, Deep Learning, Bone Facture Detection, Precision.

I. INTRODUCTION

Bone fractures are abnormal growths of cells within the bone, which can be classified as benign or malignant. Malignant bone fractures, commonly referred to as bone cancers, include sarcomas that originate in the bone, muscle, or connective tissues and have the potential to metastasize to distant organs [1]. Early detection of bone fractures plays a critical role in effective treatment and improving patient survival rates. Delayed diagnosis or misinterpretation of imaging results can significantly impact treatment outcomes, leading to disease progression and reduced chances of successful intervention [2]. Traditional diagnostic techniques, such as X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI), rely on expert interpretation by radiologists and oncologists. While these imaging modalities provide valuable insights into fracture morphology and structure, they are often time-consuming and susceptible to human errors [3].

Recent advancements in artificial intelligence (AI) and deep learning have revolutionized the field of medical imaging, enabling automated and highly accurate disease detection. Convolutional Neural Networks (CNNs), a specialized type of deep learning architecture, have demonstrated remarkable efficiency in image classification and object detection tasks [4]. Among the various deep learning-based object detection models, You Only Look Once (YOLO) has gained significant attention due to its ability to perform real-time detection with high precision. YOLO is a single-stage detector that processes entire images in one pass, making it considerably faster than traditional region-based convolutional networks (R-CNNs) and other multi-stage detection methods [5]. This capability is particularly valuable in medical imaging, where timely diagnosis is essential for initiating prompt treatment plans.

The application of YOLO in bone fracture detection presents several advantages over conventional diagnostic techniques. By leveraging CNN-based feature extraction, YOLO can efficiently detect and classify bone abnormalities with minimal preprocessing [6]. Unlike traditional machine learning models that require handcrafted feature extraction, YOLO learns hierarchical features directly from raw medical images, improving accuracy and generalization. Furthermore, the ability of YOLO to localize fractures with bounding boxes enhances interpretability, allowing medical professionals to focus on specific regions of interest without manually analyzing entire scans [7]. This automation reduces diagnostic workload, minimizes observer variability, and enhances consistency in fracture detection.

In addition to its diagnostic efficiency, YOLO-based bone fracture detection systems can be integrated into real-time medical workflows, providing instant feedback to healthcare providers. Studies have demonstrated that deep learning models trained on large medical imaging datasets can achieve performance levels comparable to or even exceeding those of human experts [8].

Implementing YOLO for bone fracture detection can significantly reduce diagnostic errors, improve detection speed, and support early intervention strategies. As deep learning continues to evolve, the integration of AI-driven models into medical imaging holds great promise for transforming cancer diagnosis and treatment planning.

This study explores the application of YOLO models for automated bone fracture detection, comparing multiple YOLO variants to assess their effectiveness in medical imaging. By addressing key challenges in fracture classification and localization, this research aims to enhance diagnostic accuracy and streamline the medical imaging process. The findings of this study contribute to the growing field of AI-assisted healthcare, offering a potential solution to the limitations of conventional diagnostic methods.

II. LITERATURE REVIEW

Recent advancements in artificial intelligence (AI) and deep learning have significantly contributed to medical imaging, particularly in detecting bone fractures and fractures. Several studies have proposed various techniques, including object detection and segmentation models, to improve accuracy and efficiency in medical diagnosis. Ahmed et al. [9] introduced an enhanced YOLO-based wrist fracture detection model, demonstrating the effectiveness of deep learning in medical imaging applications. Their study highlighted the importance of real-time object detection models in automating diagnostic processes, reducing reliance on manual interpretation. Similarly, Likitha and Shidaganti [10] explored image segmentation techniques for bone cancer identification using X-ray and MRI imagery, emphasizing the role of deep learning in precise fracture localization. Their research demonstrated that segmentation-based models could enhance diagnostic accuracy by isolating cancerous regions more effectively.

Pattabiraman et al. [11] proposed a region-based convolutional neural network (R-CNN) for bone fracture detection, which significantly improved fracture localization accuracy. Their study compared R-CNN with other object detection models, concluding that region-based approaches offered superior detection in complex medical images. Erdem et al. [12] conducted a systematic review on automated bone lesion detection using CT and MRI, evaluating various deep learning methodologies and their performance.

Their findings emphasized the need for optimized feature extraction techniques to improve lesion detection accuracy. Alhussainan et al. [13] explored multiple YOLO versions, from YOLOv3 to YOLOv7, in detecting brain fracture firmness. Their comparative analysis demonstrated that the latest YOLO architectures provided higher precision and computational efficiency, reinforcing the adaptability of YOLO-based models in medical diagnostics.

Das et al. [14] introduced an enhanced YOLO11 model for detecting bone fractures and other abnormalities in wrist X-ray images, showcasing improvements in both sensitivity and specificity. Their study underscored the importance of refining YOLO architectures to meet the unique challenges of medical image analysis. Yao et al. [15] developed a radiograph dataset for classifying, localizing, and segmenting primary bone fractures, offering a comprehensive resource for training and evaluating deep learning models.

Their dataset contributed to the standardization of AI-driven bone fracture detection methodologies, facilitating further research in the field. Lastly, Parvin and Rahman [16] proposed a real-time deep learning technique for detecting and classifying bone fractures from multi-modal images, demonstrating the effectiveness of AI in processing diverse imaging formats. Their study highlighted the advantages of integrating deep learning with multi-modal imaging for improved diagnostic accuracy.

III. MATERIALS AND METHODS

The proposed system utilizes deep learning-based object detection models to develop a fast and reliable bone fracture detection framework. It leverages the Bone Fracture Detection dataset from Roboflow, which contains annotated medical images to train and evaluate the models. The system implements four YOLO (You Only Look Once) variants—YOLOv5x6 [17], YOLOv5s6 [18], YOLOv8n [19], and YOLOv9n [20]—to detect and localize bone fractures efficiently.

The dataset undergoes preprocessing, including image augmentation and normalization, to enhance model performance. Each YOLO variant is trained separately, and their outputs are analyzed to determine the most effective model based on detection speed and accuracy.

The system is designed to work in real-time, making it suitable for clinical applications where quick diagnosis is crucial. By automating fracture detection, this approach minimizes human error, improves diagnostic efficiency, and assists medical professionals in early cancer detection, ultimately contributing to better patient outcomes and enhanced healthcare decision-making.

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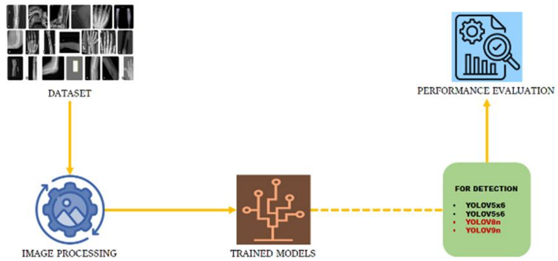

Fig.1 Proposed Architecture

The system architecture (fig.1) for bone fracture detection using YOLO models consists of four main stages. The process begins with a dataset of medical images, which undergo image processing to enhance quality and extract relevant features. These processed images are then used to train various YOLO models, including YOLOv5x6 [17], YOLOv5s6 [18], YOLOv8n [19], and YOLOv9n [20]. Finally, the trained models are evaluated for performance based on detection accuracy and efficiency.

A. Dataset

The Bone Fracture Detection dataset from Roboflow is utilized for training and evaluating YOLO models for bone fracture detection [15]. It comprises annotated medical images, primarily X-rays, capturing various bone conditions. The dataset is explored by reading and visualizing images to understand their distribution and quality. Image plotting helps analyze features, ensuring proper preprocessing. This dataset aids in developing deep learning models for accurate fracture detection by providing diverse bone abnormalities, improving detection performance, and enhancing automated medical imaging analysis.

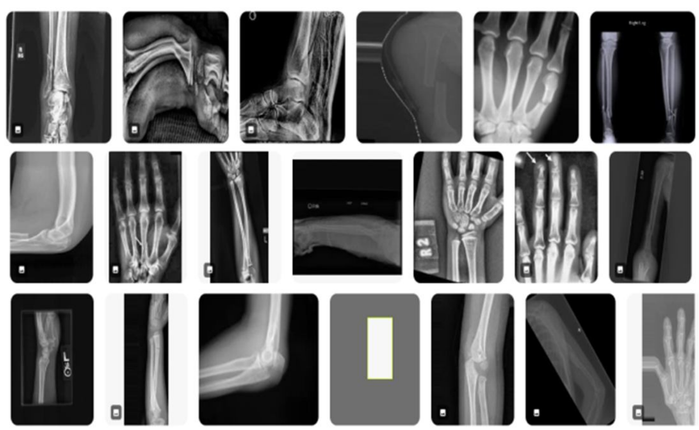

Fig.2 Dataset

B. Image Processing

The image processing pipeline begins by converting images into blob objects for efficient neural network input. Classes are defined, and bounding boxes are declared for precise fracture localization. The image array is converted into a NumPy array for seamless processing. A pre-trained model is loaded by reading network layers and extracting output layers. Further processing involves appending annotation files to images, converting BGR to RGB, creating segmentation masks, and resizing images, ensuring consistency and enhancing model performance in fracture detection.

C. Data Augmentation

Data augmentation enhances model generalization by applying transformations to the dataset. Randomizing images introduces variations in brightness, contrast, and noise, making the model robust to different conditions. Rotating images at various angles ensures the model learns orientation-invariant features, improving detection accuracy. Transforming images, such as scaling, flipping, or shifting, increases diversity, reducing overfitting. These augmentation techniques help create a more comprehensive dataset, allowing deep learning models to detect bone fractures effectively across varied medical imaging scenarios.

D. Algorithms

1) YOLOv5x6: YOLOv5x6, a high-accuracy variant, detects and classifies bone fractures with enhanced precision. Its larger architecture improves feature extraction from medical images, ensuring detailed anomaly identification. By leveraging deep learning capabilities, it enhances diagnostic reliability, reducing false positives and enabling early fracture detection for improved clinical decision-making [17].
2) YOLOv5s6: YOLOv5s6, a lightweight and fast variant, processes medical images efficiently, providing real-time fracture detection. Its optimized architecture balances speed and accuracy, making it suitable for rapid screening. With lower computational requirements, it ensures smooth integration with automated detection systems, facilitating quick and reliable bone fracture identification [18].
3) YOLOv8n: YOLOv8n, an advanced neural network, enhances detection accuracy with optimized feature extraction and improved localization techniques. It efficiently analyzes medical images, identifying fractures with minimal computational overhead. Its refined architecture ensures robust performance, supporting real-time analysis while minimizing false detections, crucial for early and accurate fracture diagnosis [19].
4) YOLOv9n: YOLOv9n, the latest evolution, integrates advanced deep learning optimizations for superior object detection. It improves fracture localization by refining bounding box accuracy and feature representation. Its enhanced efficiency and reduced latency contribute to precise anomaly identification, supporting early intervention and streamlining medical diagnostic workflows for optimal patient care [20].

IV. EXPERIMENTAL RESULTS

1) *Precision:* Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{ False Positive}} \quad (2)$$

2) *Recall:* Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} \quad (3)$$

3) *MAP:* Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

MODEL	Precision	Recall	mAP
Yolov5x6	0.860	0.775	0.832
Yolov5s6	0.893	0.794	0.843
Yolov8n	0.909	0.761	0.828
Yolov9n	0.900	0.764	0.840

Table.1compares YOLO models using precision, recall, and mAP, highlighting YOLOv5s6's highest mAP and YOLOv8n's best precision.

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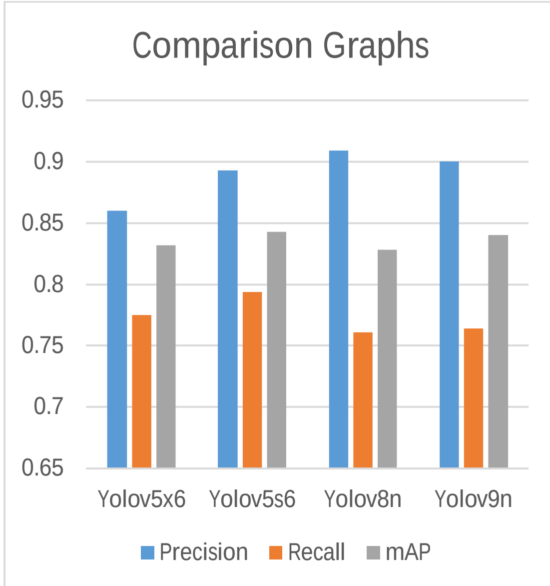

Graph.1 visualizes precision in blue, recall in orange, and mAP in grey for YOLO models, showing YOLOv8n with the highest precision and YOLOv5s6 excelling in mAP.

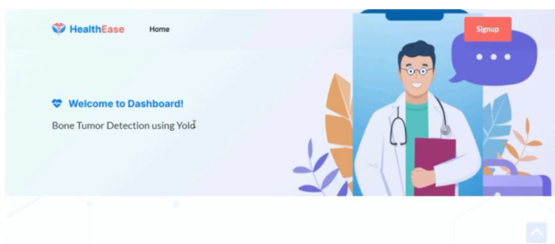

Fig.3 Home page

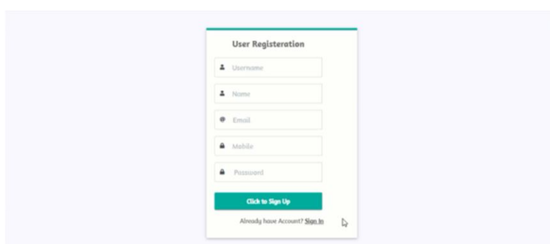

Fig.4 Registration page

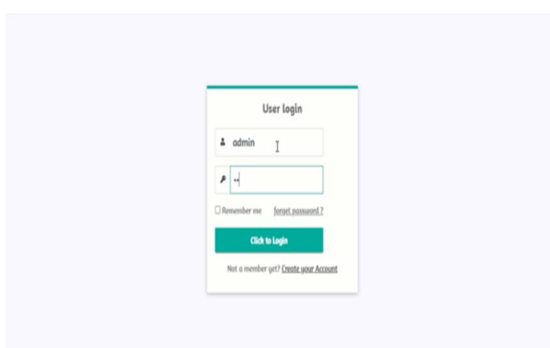

Fig.5 Login page

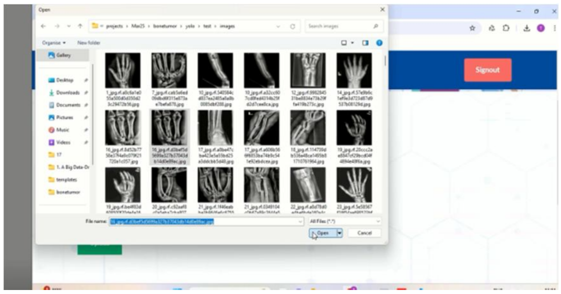

Fig.6 Upload Input Image

Fig.7 Predicted Result

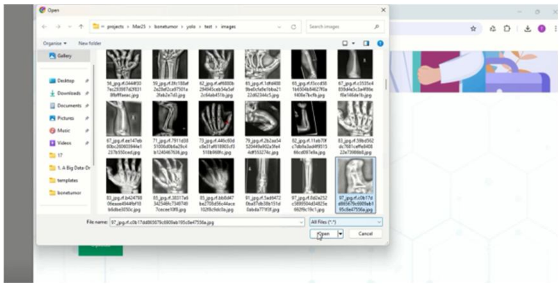

Fig.8 Upload another Input Image

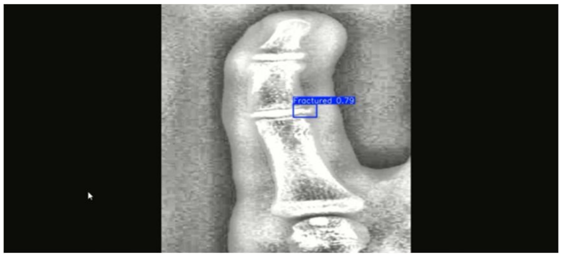

Fig.9 Final Outcome

V. CONCLUSION

Bone fracture detection plays a critical role in early cancer diagnosis, where timely identification can significantly improve treatment outcomes. Deep learning-based object detection models, particularly YOLO (You Only Look Once), have demonstrated their effectiveness in medical imaging for rapid and precise fracture identification. This study explores the application of YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n to develop an efficient bone fracture detection system. The Bone Fracture Detection dataset from Roboflow is used to train and evaluate these models, ensuring robust learning and accurate predictions. The dataset undergoes preprocessing techniques like augmentation and normalization to enhance detection performance. Each YOLO variant is assessed for its efficiency, detection speed, and reliability in fracture localization. The results indicate that advanced YOLO architectures significantly improve the accuracy and speed of bone fracture detection, making them suitable for real-time medical applications.

Performance metrics such as precision, recall, and mean Average Precision (mAP) were used for evaluation, with YOLOv8n achieving the highest precision of 90.9%. By automating the detection process, this system reduces dependency on manual diagnosis, minimizing human errors and assisting healthcare professionals in early cancer identification. The study highlights the potential of deep learning in revolutionizing medical diagnostics, offering a practical and effective solution for fracture detection.
Future work can focus on integrating this system with clinical workflows, further refining model accuracy and real-world applicability. Expanding the dataset with diverse medical images and optimizing model architectures can enhance system robustness. This research contributes to the advancement of AI-driven healthcare solutions, improving diagnostic reliability and patient outcomes.

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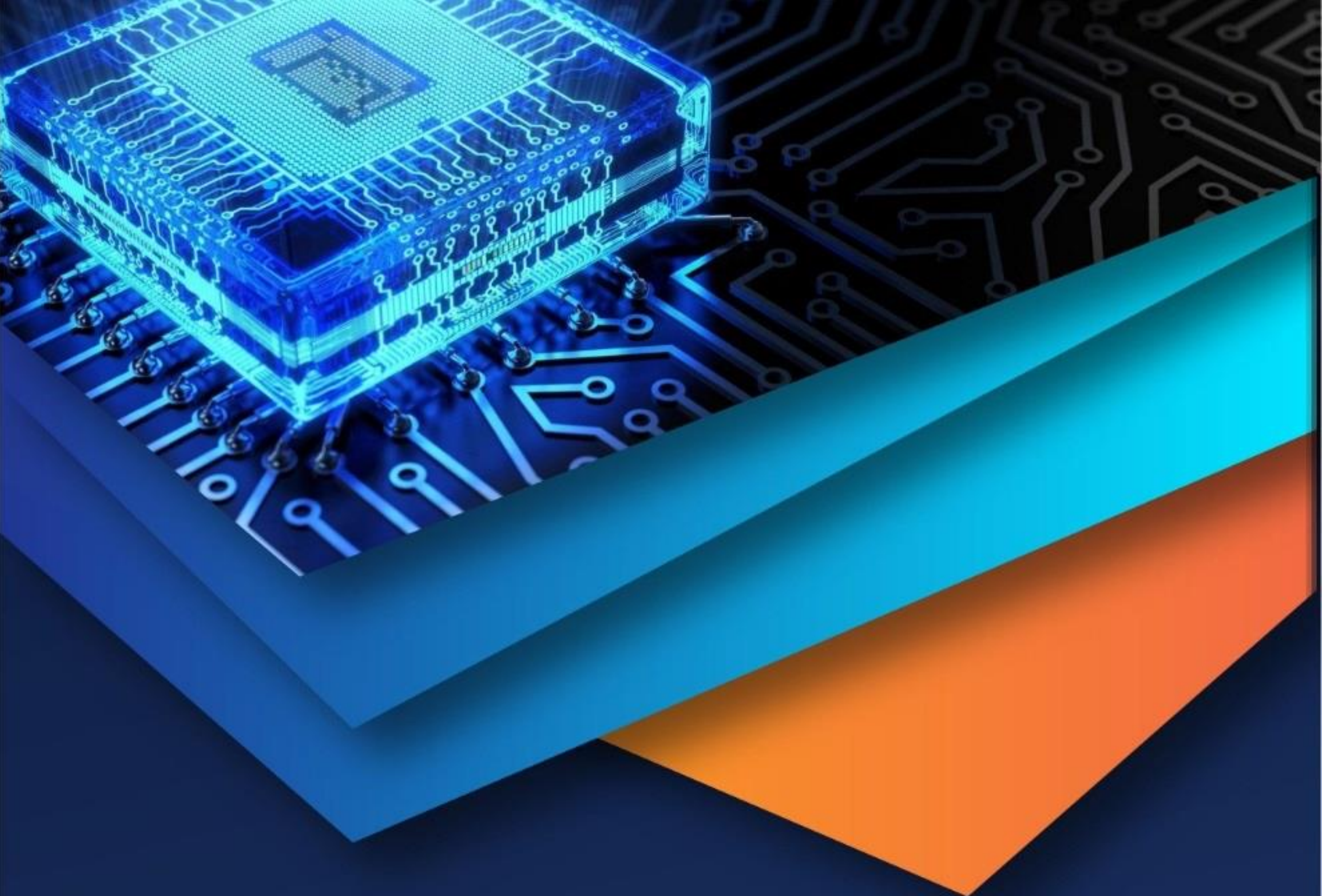

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