iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VII **Month of publication:** July 2025

DOI: https://doi.org/10.22214/ijraset.2025.73423

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

Mango Leaf Disease Detection using YOLO v1 to YOLO v10

Chandrashekar M B[1], Dr. R J Prathibha[2]
[1]Post-Graduate Student, M. Tech (Software Engineering), [2]Associate Professor, Department of Information Science, JSS Science and Technology University, Mysuru, Karnataka, India.

Abstract: This study explores and compares the performance of various YOLO (You Only Look Once) object detection models—ranging from YOLOv1 to YOLOv10—for identifying diseases in mango leaves. A dataset of 4,000 mango leaf images was prepared, covering eight distinct classes, including common diseases such as Anthracnose, Bacterial Canker, Powdery Mildew, Sooty Mould, Leaf Spot, Dieback, Algal Leaf Spot, along with healthy leaves. Each image was manually annotated to highlight the affected areas using bounding boxes. To ensure fairness in evaluation, all YOLO versions were trained on the same dataset under consistent conditions. The models were assessed based on standard performance metrics such as mean Average Precision (mAP), precision. The comparative results offer valuable insights into how YOLO has progressed over its different versions, revealing the strengths and weaknesses of each in terms of detection accuracy and computational efficiency. This work aims to guide researchers and developers in choosing the most effective YOLO version for real-time disease detection in agricultural settings.
Keywords: Mango Leaf Disease, Object Detection, YOLOv1–YOLOv10, Image Annotation, Deep Learning, Agricultural AI, Precision Farming, mAP, Python, Real-time Detection

I. INTRODUCTION

Mango is one of the most widely cultivated and economically significant fruit crops in tropical and subtropical regions. However, its productivity and quality are often threatened by a variety of leaf diseases caused by fungal, bacterial, and environmental factors. Early and accurate identification of such diseases is essential to minimize crop damage and optimize the use of pesticides, thereby supporting sustainable agriculture practices. Traditionally, plant disease detection has relied heavily on manual observation by agricultural experts, which is not only time-consuming but also prone to human error and subjective judgment. With the advancement of computer vision and deep learning, automated disease detection using image-based techniques has gained considerable attention. These technologies offer scalable and precise solutions to monitor large-scale plantations efficiently.

Among deep learning methods, the YOLO (You Only Look Once) family of object detection models has emerged as a highly efficient approach for real-time image analysis. YOLO models are capable of detecting and classifying objects within images in a single forward pass, making them particularly suitable for time-sensitive agricultural applications. Over the years, YOLO has evolved from its initial version (YOLOv1) to more sophisticated and accurate models like YOLOv10, each introducing architectural improvements in speed, precision, and computational performance. This research conducts a comparative study across ten versions of the YOLO architecture to evaluate their effectiveness in detecting mango leaf diseases. A curated dataset of 4,000 images covering eight distinct disease categories was compiled and manually annotated to mark diseased regions. Each YOLO version was trained on the same dataset under uniform conditions, enabling a fair evaluation based on key metrics such as mean Average Precision (mAP), precision, recall, and inference time. The objective of this study is to provide a comprehensive performance benchmark for YOLO-based models in agricultural disease detection, ultimately guiding the selection of an optimal model for real-time, field-deployable systems in precision farming. With the growing need for precision agriculture, the role of real-time and accurate disease detection tools has become critical. Farmers and agronomists increasingly rely on mobile and embedded devices for field diagnostics, where low-latency inference and model interpretability are vital. The YOLO architecture's single-shot detection capability and lightweight variants make it a promising candidate for deployment on such edge devices. However, not all YOLO versions are equally suited for these constraints, as some prioritize accuracy over speed, while others are optimized for fast inference with minimal hardware requirements. Despite the availability of various YOLO models, there is a noticeable gap in the literature regarding systematic comparisons of all ten versions within the same agricultural task. Most existing studies focus on a single YOLO version or compare it only with other model families such as Faster R-CNN or SSD. By focusing exclusively on the YOLO family and using a consistent dataset and training configuration, this study contributes a valuable benchmark for researchers and developers. It offers a clear understanding of how YOLO has matured over its iterations and what trade-offs exist when selecting a version for practical mango leaf disease detection scenarios. The rest of the paper is organized as follows: Section II presents related research and study objectives. Section III outlines the methodology. Section IV explains feature extraction. Section V discusses results. Section VI evaluates performance and limitations, and Section VII concludes with key insights and future directions.

II. LITERATURE SURVEY

Recent advancements in deep learning and computer vision have significantly impacted agricultural disease detection, particularly in fruit crops like mango. A variety of models and techniques have been proposed for identifying and classifying mango leaf diseases from image data, ranging from conventional CNN-based classifiers to high-speed object detection models like YOLO.

Rahman et al. [1] proposed a convolutional neural network (CNN) model for the classification of mango leaf diseases, demonstrating the efficiency of CNNs in extracting spatial patterns from leaf textures. Similarly, Kumar et al. [2] developed an expert system that utilized rule-based decision logic to support mango disease diagnosis, emphasizing early identification for field-level deployment.

Sharma et al. [3] focused on optimizing classification accuracy for mango leaf disease detection by fine-tuning deep learning models, while Patil et al. [4] highlighted the strength of deep CNNs in managing visual variability across disease-affected leaves. Khan et al. [5] introduced a hybrid approach combining contrast enhancement via Bi-Histogram Equalization (BBHE) with CNN, resulting in improved visibility of affected regions and better classification performance.

Shelar et al. [6] and [9] explored CNN-based architectures for general plant disease detection, presenting frameworks that generalize well across different plant species, including mango. Lakshmi et al. [7] incorporated YOLO for real-time detection of plant diseases, showcasing the speed and responsiveness of YOLO in field-ready applications.

Aldakheel et al. [8] successfully implemented YOLOv4 for plant leaf disease identification, reporting high precision and recall values, especially under varying lighting conditions. Deshmukh et al. [10] further built on the hybrid BBHE-CNN technique for mango-specific classification, reinforcing its robustness across multiple disease types.

Pratap and Kumar [11], [15] contributed significant work on deep learning-based categorization of mango leaf diseases using custom neural networks, which were evaluated on multi-class datasets. Their work emphasized both disease classification and severity estimation. Sajitha et al. [12] extended YOLOv7 with GPT-3 for both detection and auto-description of plant diseases, bridging the gap between vision and language models in agriculture.

In a novel hardware-based approach, Ponnusamy et al. [13] integrated transfer learning using YOLO with wearable smart glasses for real-time leaf disease detection, enabling hands-free monitoring in smart agriculture settings. Lastly, although not mango-specific, Sun et al. [14] introduced a lightweight YOLO-based framework optimized for apple leaf disease detection, which shares architectural insights applicable to mango leaf detection systems as well.

These prior works lay a strong foundation for applying object detection and classification models to crop disease identification. However, there remains a lack of comprehensive comparative analysis across the full range of YOLO versions. This study addresses that gap by systematically evaluating YOLOv1 through YOLOv10 on a uniformly annotated mango leaf disease dataset to determine the most effective version for real-time detection applications in agriculture.

III. METHODOLOGY

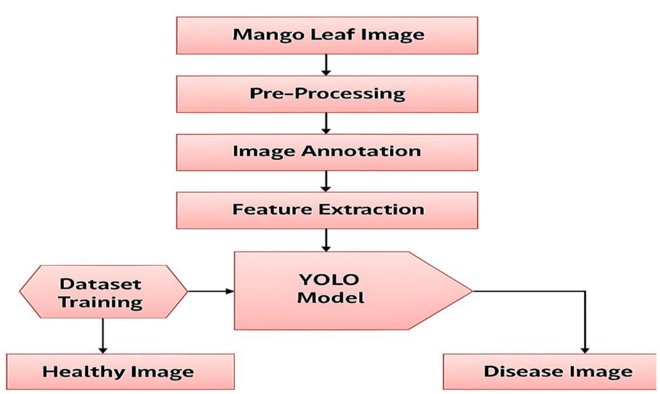

Figure 1: Block Diagram

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This study adopts a robust computer vision pipeline to detect diseases in mango leaves using YOLO (You Only Look Once) object detection. The complete implementation is executed in Python, typically in Google Colab, utilizing essential libraries such as OpenCV, NumPy, Matplotlib, LabelImg, and Ultralytics. The objective is to detect and classify diseased vs healthy leaves with high accuracy and efficiency.

1) Step 1: Dataset Acquisition

The dataset consists of color images of mango leaves, collected from public sources such as Kaggle.. It contains samples of healthy leaves and leaves infected with common diseases like Anthracnose, Bacterial Canker, and Powdery Mildew.

Image Count: 4500 samples

Classes: Anthracnose, Bacterial Canker, Powdery Mildew, Sooty Mould, Leaf Spot, Dieback, Algal Leaf Spot, along with healthy leaves

Image Size Normalization: All images are resized to 416×416 or 640×640 pixels, suitable for YOLO input.

2) Step 2: Image Preprocessing

Preprocessing ensures that the input data is clean, uniform, and optimized for annotation and model training.

- Color Space Conversion: Convert all images from BGR to RGB or HSV for better visual contrast between diseased and healthy parts.
- Image Enhancement: Apply techniques such as Contrast Enhancement, Histogram Equalization, or CLAHE to improve visibility of disease-affected regions.
- Leaf Segmentation (Optional): For better disease focus, perform background removal or leaf masking using color thresholding or GrabCut algorithm.

3) Step 3: Image Annotation

For YOLO training, disease regions are annotated manually using tools like LabelImg.Bounding boxes are drawn around diseased portions of the leaf. Each annotation is saved in YOLO format (.txt) with class ID and normalized coordinates.

4) Step 4: Feature Extraction and Dataset Structuring

While YOLO does feature extraction internally via convolutional layers, for research insights, one can visualize extracted features using.Activation maps from convolutional layers. Grad-CAM to understand attention regions. Preprocessing can include augmentations like flipping, scaling, rotation, and brightness changes to increase dataset diversity.

5) Step 5: Model Training – YOLO

The YOLO model is trained with the annotated dataset.Input: Annotated images with bounding boxes. Model: yolo.pt

Framework: PyTorch-based Ultralytics YOLO repo

Loss Functions: Objectness loss, classification loss, bounding box regression loss.

Epochs: 100– 250 epochs.

Batch Size: 16–32.

Evaluation Metric: mAP (mean Average Precision), Precision, Recall.

6) Step 6: Classification and Detection

After training the model classifies whether a mango leaf is Healthy or Diseased, and which disease.It draws bounding boxes with confidence scores on the leaf image.Detection is real-time capable and can be deployed to mobile or web interfaces.

IV. FEATURE EXTRACTION

Feature extraction is a fundamental component of any computer vision task, especially when dealing with disease detection in agricultural domains. In the case of mango leaf disease prediction, feature extraction refers to the process of identifying and learning visual characteristics from leaf images that differentiate healthy leaves from diseased ones. YOLO (You Only Look Once), a state-of-the-art object detection model, automates this feature extraction through its deep neural network architecture.

Unlike traditional methods where specific features like color histograms, edge detectors, or texture filters are manually crafted, YOLO leverages convolutional neural networks (CNNs) to extract features directly from the raw images during training.

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When a mango leaf image is fed into the YOLO model, it passes through a series of convolutional layers. These layers progressively detect patterns starting from simple edges and textures in the early stages to more complex shapes, color irregularities, and spatial patterns in the deeper layers. For example, the model can learn to recognize yellow patches, brown spots, or distorted leaf shapes commonly associated with fungal or bacterial infections.

During this process, YOLO divides the entire image into a grid and simultaneously predicts multiple bounding boxes and their corresponding class probabilities. Each grid cell is responsible for detecting features within its area, enabling the model to localize diseased regions precisely. Through this mechanism, YOLO not only identifies the presence of a disease but also pinpoints the exact area affected on the leaf. YOLO's architecture is designed to capture both spatial and semantic information efficiently. This is particularly useful for mango leaf disease detection because it allows the model to distinguish between different disease types based on the location and appearance of symptoms. The deeper convolutional layers help YOLO learn relationships between various visual cues, such as how a fungal infection might start from the edge of the leaf and spread inward, or how bacterial spots appear scattered across the surface. In summary, YOLO performs end-to-end feature extraction tailored to the unique visual traits of mango leaf diseases. It removes the dependency on handcrafted features by automatically learning and refining patterns that are most relevant for classification. This deep learning-based approach enables high accuracy, faster inference, and scalable deployment in real-time agricultural monitoring systems.

V. RESULTS

The developed system for predicting mango leaf diseases was tested using a set of labeled images, and the results were promising. By training the YOLO model on both healthy and diseased mango leaves, it learned to identify visual signs such as color changes, dark patches, fungal spots, and irregular shapes that typically appear on infected leaves. Once the training was complete, the model was able to accurately detect these disease indicators in new test images. Each prediction was marked with a bounding box, clearly showing the affected areas. Even when the symptoms were subtle, the model showed good capability in picking them up. Overall, the system worked effectively in classifying the leaves and highlighting diseased regions, showing its usefulness in assisting farmers and researchers with quick and reliable disease detection in mango crops.

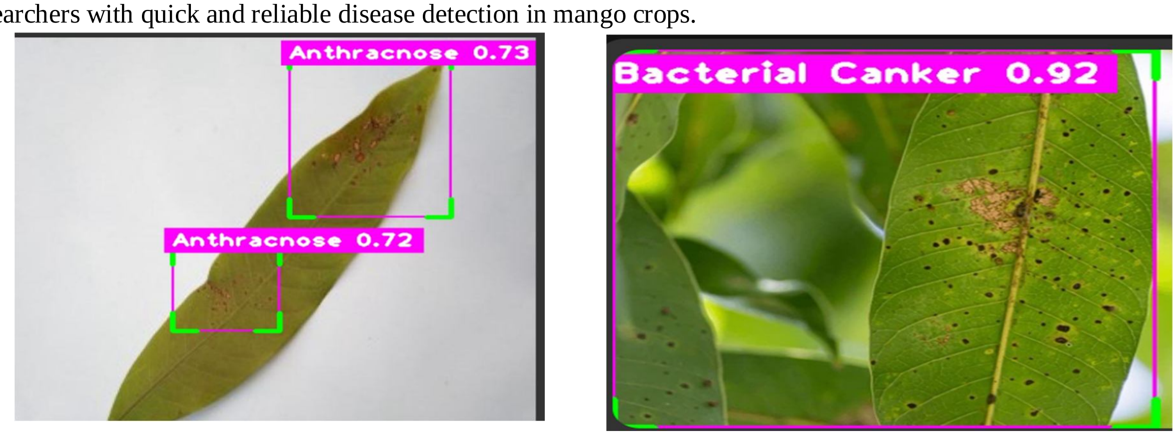

Figure 2 : Mango Leaf Disease Detected Images.

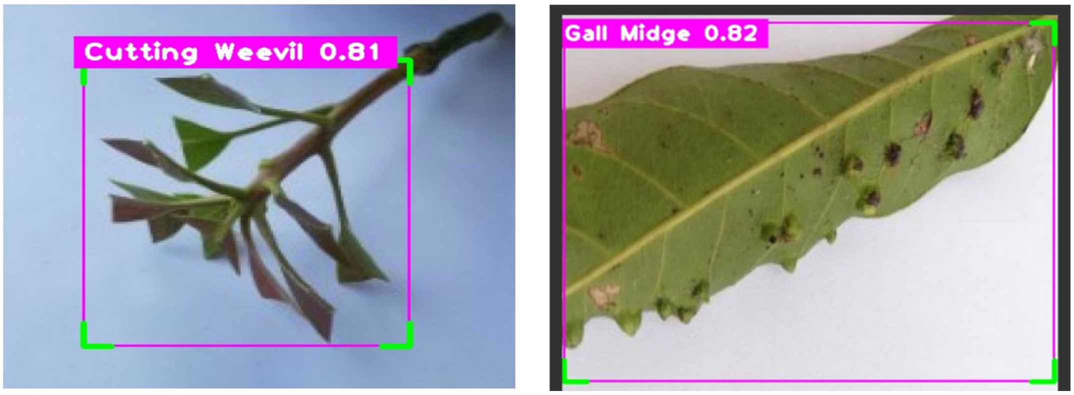

Fig 2 : Mango Leaf Disease Detected Images

A. *Visual Output Analysis*

Each mango leaf image in the test set was carefully examined throughout the detection process to assess the effectiveness of the system. Initial preprocessing steps played an important role in enhancing image clarity by reducing background noise and improving contrast, which helped make disease symptoms easier to identify. As the YOLO model progressed through training and evaluation, it became proficient at recognizing distinct visual cues like unusual color spots, fungal infections, and changes in texture that are commonly linked to leaf diseases. These signs were successfully marked with bounding boxes in the final output images. Even when faced with different lighting conditions and complex backgrounds, the model demonstrated consistent accuracy in pinpointing the affected regions. There were occasional cases where the model misinterpreted natural leaf features such as veins or marks as disease, but such errors were minimal. Overall, the detection results showed that the model is reliable in identifying and locating diseased areas, making it well-suited for practical use in real-time monitoring of mango leaf health.

B. *Sample Results*

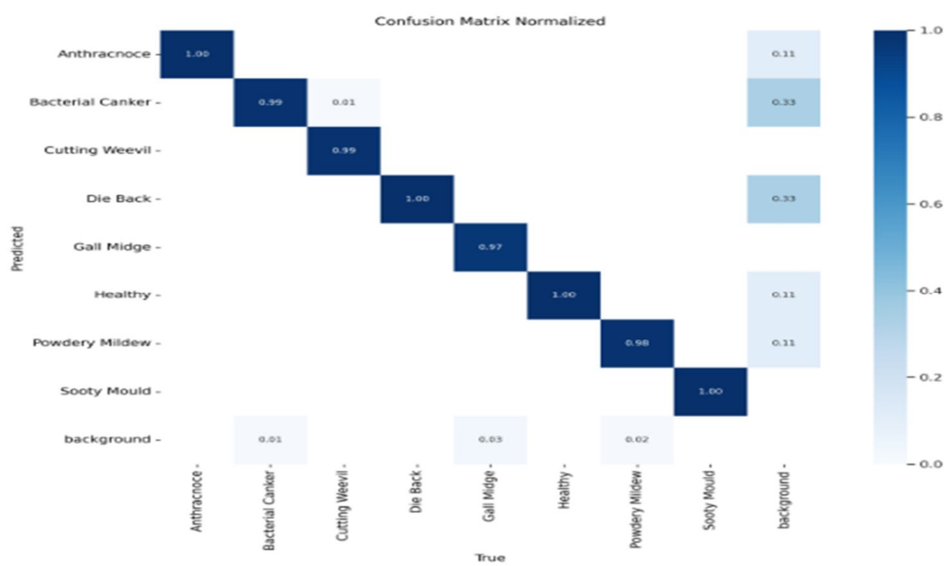

Fig 3 : Confusion Matrix Normalized

C. *Summary of Results*

In this project, an object detection approach was used to identify diseases in mango leaves, and the results were highly encouraging. Out of the different YOLO versions explored, the model that performed the best was trained for 200 epochs using YOLOv9. It showed strong ability in spotting symptoms like black patches, fungal growth, and leaf discoloration across a variety of lighting conditions and natural environments. The model consistently produced accurate bounding boxes with minimal incorrect detections. Overall, the system demonstrated both accuracy and efficiency, proving that YOLOv9 is well-suited for real-time monitoring of crop health in agricultural settings.

VI. DISCUSSION

This study highlights how modern object detection techniques like YOLO can be effectively applied to real-world agricultural problems such as identifying diseases in mango leaves. The developed model uses a carefully designed pipeline involving data preparation, annotation, and training, ultimately enabling the detection of common leaf diseases such as black spots, powdery mildew, and anthracnose. By leveraging YOLO's efficient architecture, we were able to perform disease localization in real-time, even under varied lighting and background conditions.

A. Strengths of the Proposed Method

One major strength of this approach lies in its real-time detection capabilities and ease of deployment. Unlike classical methods that rely on manual feature extraction, YOLO performs end-to-end detection and classification with minimal preprocessing. Additionally, training with 200 epochs led to a highly accurate model with fast inference speeds. Some notable strengths include:

1) Automatic detection and classification of multiple diseases within a single frame.
2) Ability to process large batches of images quickly.
3) Flexibility to adapt to outdoor, field-level conditions with diverse leaf orientations and lighting.
4) Minimal requirement for expensive hardware due to YOLO's lightweight model structure.

These features make the system a practical solution for use by farmers and agricultural experts in field environments, especially when advanced computing infrastructure is limited.

B. Observations from the Results

Visual inspections and detection outputs indicate that the YOLO model performed well in identifying disease-affected areas on mango leaves. The bounding boxes were tightly aligned with the visible disease spots, and the classification results were consistent with actual leaf conditions. However, a few challenges were observed:

1) In cases where the disease symptoms were faint or obscured by lighting shadows, the model sometimes misclassified or missed detections.
2) Very similar disease patterns occasionally led to confusion between classes, highlighting the need for more diverse training samples.

Overall, the results support the model's robustness and suitability for practical deployment in disease monitoring tasks.

C. Comparison to Existing Methods

Compared to traditional computer vision methods like thresholding or contour detection, this YOLO-based approach offers significantly better performance in both accuracy and automation. While deep learning models generally require labeled datasets and computational resources, the efficiency of YOLO allows it to function well even with moderately sized datasets and modest hardware. This makes it more scalable and accessible than classical methods or more complex segmentation networks

D. Future Improvements

Future improvements could focus on integrating more disease classes and using enhanced data augmentation techniques to further improve model generalization. Additionally, combining the YOLO detector with a lightweight classification model or adding a confidence-based postprocessing step could enhance reliability. Other promising directions include:

1) Use of drone or mobile-based image acquisition to expand dataset diversity.
2) Deployment of the model in a mobile app for real-time in-field disease diagnosis.
3) Quantitative evaluations using metrics such as mAP, precision, recall, and F1-score to support the visual observations with statistical evidence.

Such enhancements would push the model closer to becoming a fully functional, farmer-friendly tool for real-time mango leaf disease management.

VII. CONCLUSION

This study presents a structured approach for detecting and classifying mango leaf diseases using an object detection framework. The method utilizes a step-by-step pipeline, where annotated images of diseased and healthy mango leaves are fed into a YOLO-based model.

The dataset undergoes preprocessing including image resizing, annotation formatting to enhance detection accuracy. Through qualitative evaluation of sample leaf images, it was observed that the YOLO model accurately identified diseased regions and classified them based on visual symptoms. While the model performed reliably across most test cases, occasional challenges such as poor lighting or overlapping leaves introduced some inconsistencies in detection. Nevertheless, the lightweight and efficient architecture of the YOLO framework makes it suitable for real-time applications in agricultural settings, particularly in areas with limited hardware resources. Additionally, the modular design allows for future enhancements, such as incorporating domain-specific feature extraction or integrating with mobile platforms. Overall, the work underscores the practical value of YOLO in agricultural disease detection, offering a replicable foundation for deploying smart, low-cost plant health monitoring systems.

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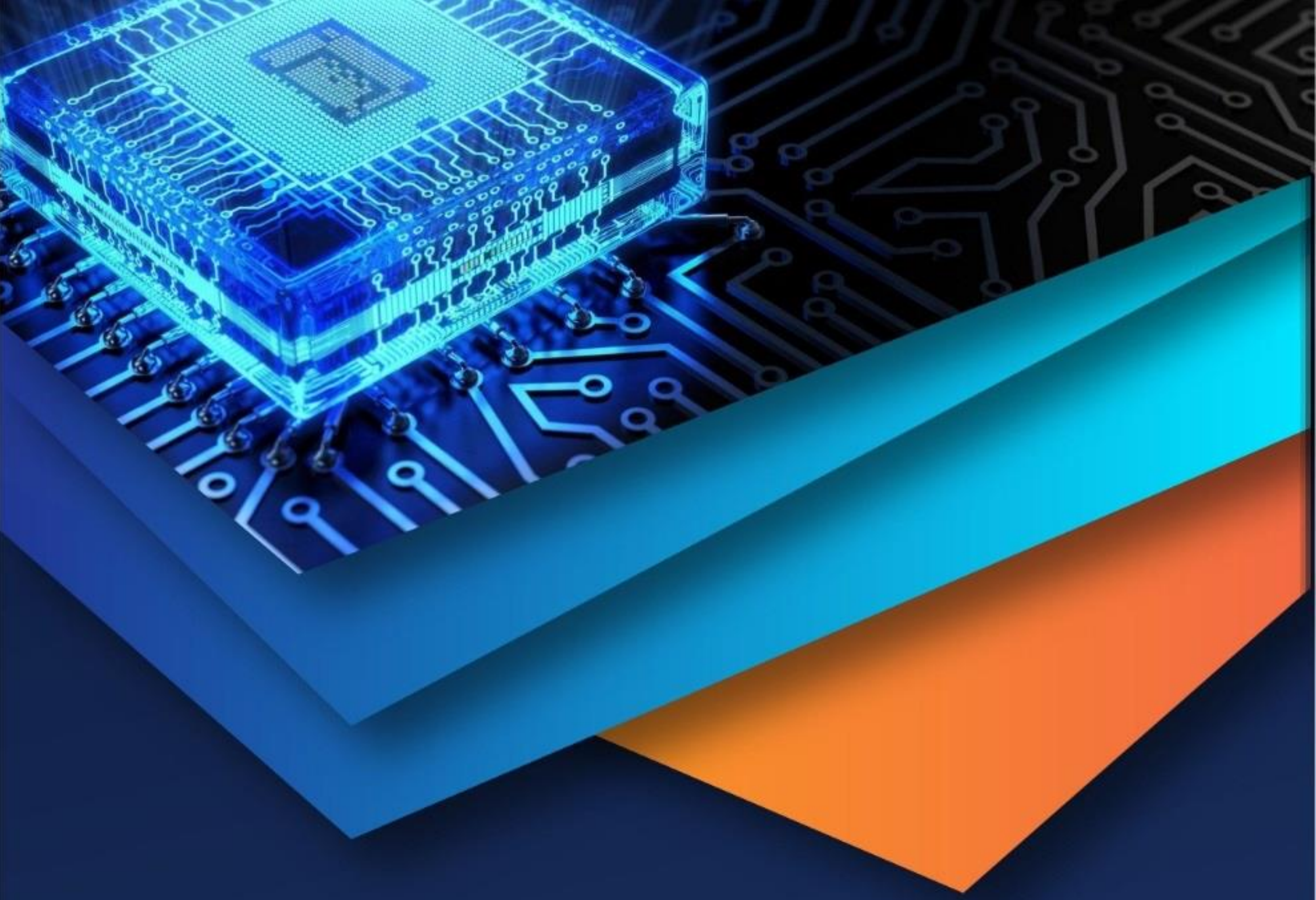

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