iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: II Month of publication: February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77499

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

Deep Learning Framework for Early Detection of Sugarcane Pathogens via Image Processing on Embedded Hardware

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Abstract: Precision Agriculture has become a revolutionary model on how crop productivity and sustainability can be improved. The crop organs that are most prone to diseases include red rot, red rust, mosaic virus and yellow leaf disease in sugar cane crops.
This study suggests a synthesized artificial-intelligence system, which is a convolutional neural network (CNN) integrated with the MATLAB ResNet-50 architecture, deployed in the Simulink hardware, and edge processing in the Raspberry Pi. The system classifies sugarcane leaf disease real-time by image processing and deep learning. The suggested framework allows disease identification using the automated system, minimizes human control of monitoring, and aids in the implementation of early intervention measures. The experimental outcomes show a high classification accuracy and an efficient ability to operate in a real-time situation.
Keywords: Precision Agriculture, Sugarcane Disease Detection, ResNet -50, MATLAB, Raspberry Pi, Simulink, Deep Learning.

I. INTRODUCTION

Sugarcane is one of the pillars of the agricultural economy of the whole world as it is the source of raw material to produce sugar and the bioenergy industry.
Even though sugarcane is an important crop economically, it is being seriously affected by Phyto pathological agents, such as red rot, red rust, mosaic virus, and yellow leaf disease. Such pathologies have a destructive effect on the yield and lower the content of sucrose, which threatens livelihoods of millions of farmers.
Historically the basis of managing diseases has been by manual scouting and eye inspection by agricultural professionals, but this method proves labour-intensive, subjective and human error is a common occurrence especially in large plantations where it is logistically impractical to inspect every plant.
This, in turn, creates an immediate necessity of automated scalable solutions that can be used to identify early symptoms with high specificity.
The Internet of Things (IoT) and artificial intelligence (AI) can be used to create precision agriculture, which provides a paradigm shift in crop management. According to the modern literature, modern agricultural systems are becoming more dependent on uncooked and semi-cooked information gathered through sensors and other related devices to make decision-making processes [1].
The solutions that are in place, however, have two major drawbacks. To start with, large numbers of deep-learning designs are optimized to work in high-performance computing platforms and are not optimized to run on low-cost, resource-constrained edge computing platforms like the Raspberry [2]. Second, there are no existing frameworks that focus on bridging the divide between training models in high-level environments (e.g., MATLAB) and executing them in real-time on hardware without much manual recoding [3].
This paper will offer a unified system of AI to combat these challenges in sugarcane disease detection. The results of this work are twofold:

1) An end-to-end deep-learning pipeline using the ResNet-50 model in MATLAB to handle five different sugarcane leaf conditions (healthy, red rot, red rust, mosaic, yellow leaf) with the help of transfer learning to make sure that the results are generalized in spite of the small data sets.
2) Smooth hardware implementation plan with Simulink to run the model trained on a Raspberry Pi, and thus to achieve real-time, offline inference at the network edge and address the connectivity problems prevalent in rural agriculture.

II. RELATED WORK

A. Agricultural IoT Sensing and Precision Agriculture.

Information technology in agriculture has created large volumes of data commonly referred to as the Big Data because of its size and diversity. Studies have shown that the agricultural data warehouses are critical in handling inputs by sensors, robots and weather stations to make predictions about crop yield effectively [1]. Even though remote-sensing systems like hyperspectral imaging can provide comprehensive plant-stress response signals, they often need costly and cumbersome electronics which can disturb the growth of crops [4]. Conversely, this work concentrates on the conventional RGB imaging that involves much less expenditure and complexity in the hardware. The computer-vision method used here is not invasive as opposed to complex robotic monitoring systems which can physically touch the leaf surface [4], and the camera modules used are inexpensive and can be employed at a vast scale by smallholder farmers.

B. Deep Learning Baselines and Deep Learning Generalisation.

Deep learning has been shown to be successful in visual recognition tasks and the theoretical reasons behind the effectiveness of such models generalising well are still an ongoing research topic [5]. Deep hypothesis spaces have been found to have an exponential capability compared to shallow networks to represent natural target functions, with such ability introducing overfitting risks [5, 6]. Besides, it is essential to build strong baselines and strict experimental guidelines since even small gaps in validation could be inflated in terms of performance claims [7]. Based on these observations, the framework uses ResNet -50 which is an established architecture that employs residual connections to address the vanishing-gradient problem as a robust baseline to extract features in complicated biological images.

C. Resource-Efficient Deep Learning.

One of the most challenging obstacles to the implementation of AI in agriculture is the problem of the limited resources of edge devices. The metric proposed in recent research to encourage small-scale deep learning is the performance per resource unit (PePR), which states that specialised models may be more suitable than massive models that are trained with large compute clusters [2]. It especially applies to the Global South and rural regions where high-end hardware is not available [2]. Also, embedded systems need multitask learning and effective model design due to limited memory and power [3]. This philosophy is consistent with the present work in its attempt to optimise a pre-trained network (transfer learning) on the Raspberry environment, trading the accuracy of the classification with the inference time taken by the computer.

III.METHODOLOGY

A. System Architecture

The suggested framework is a closed-loop system that offers edge computing. It consists of the hardware layer, which includes a Raspberry Pi 3 Model B+ with a high-definition camera module. This design is chosen because of its equilibrium between processing capability and energy consumption that makes it suitable in the field. The software ecosystem is based on model development with MATLAB and hardware support/deployment with Simulink. The process starts by acquiring images, which is then followed by the use of preprocessing, deep neural-network classification and finally visualisation of results or creation of alerts. The system architecture is shown in Fig 1.

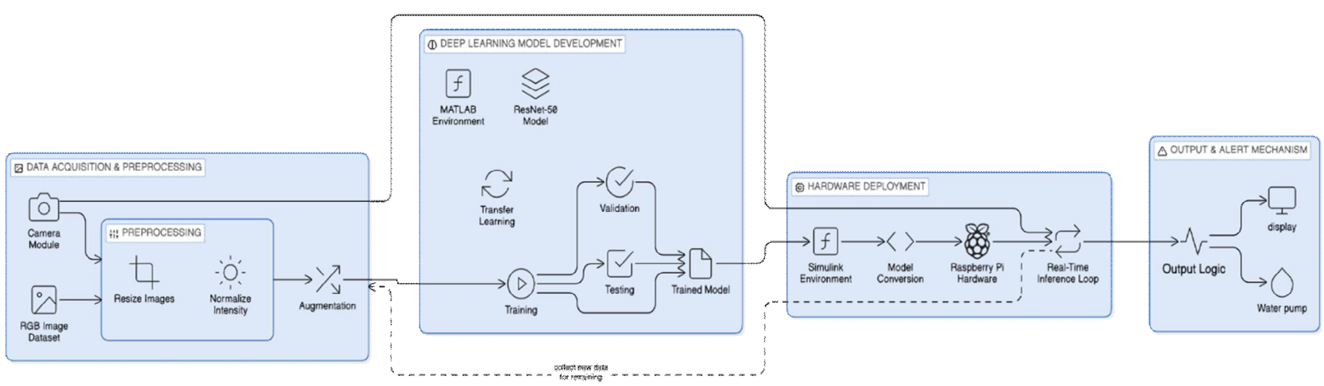

Fig. 1 Proposed System Architecture

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B. Data Acquisition and Preprocessing

A dataset of sugarcane leaf images in five classes Healthy, Red Rot, Red Rust, Mosaic Virus and Yellow Leaf disease is used to train the model.

1) Image Preprocessing: The background noise and light conditions vary among the raw images. The preprocessing measures are downsizing to 224x224 pixels so that images can fit the input of the ResNet50 network and pixel intensity normalisation.
2) Augmentation: To improve the generalisation of the model and reduce overfitting [5], data-augmentation methods including random rotation, reflection, and scaling are used. This artificially scales the training set, allowing the model to acquire strong features that are rotationally-invariant.

Healthy leaf | Mosaic leaf | Red Rot leaf | Red Rust leaf | Yellow leaf

Fig. 2 Dataset Images

C. Deep Learning Model (ResNet-50)

The ResNet50 architecture is used, which has 50 layers of the convolutional neural network. Its residual learning architecture enables the training of more complex networks re-expressing layers as residual functions with respect to their inputs. Confusion Matrix of Training Data, Testing Data, Training Graphs are shown in Fig 3-5.

1) *Transfer Learning:* Transfer learning instead of starting the network with random values (as randomization requires large datasets and memory) is adopted. The network, which has been trained on ImageNet, still has its original feature-extraction layers (which detect edges, textures, and shapes). We replace the last, fully-connected layer, and the following classification layer to match the model with our five different classes of sugarcane disease.
2) *Training Set-ups:* The training process is implemented in MATLAB as Stochastic Gradient Descent with Momentum (SGDM) optimizer. As dictated by conventional benchmarks [7], we set the number of epochs fixed and divide the information strictly into training (70%), validation (15%), and testing (15%) sets.

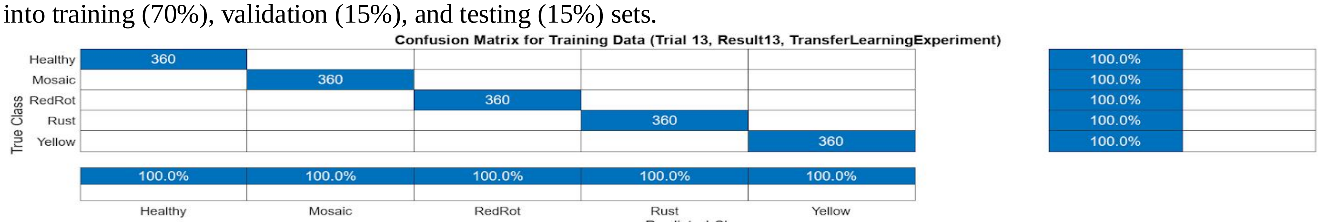

Fig. 3 Confusion Matrix for Training Data

Confusion Matrix for Validation Data (Trial 13, Result13, TransferLearningExperiment)

True Class \ Predicted Class	Healthy	Mosaic	RedRot	Rust	Yellow		
Healthy	40					100.0%	
Mosaic	1	38		1		95.0%	5.0%
RedRot			37		3	92.5%	7.5%
Rust			1	39		97.5%	2.5%
Yellow			2		38	95.0%	5.0%
	97.6%	100.0%	92.5%	97.5%	92.7%		
	2.4%		7.5%	2.5%	7.3%		

Fig. 4 Confusion Matrix for Validation Data

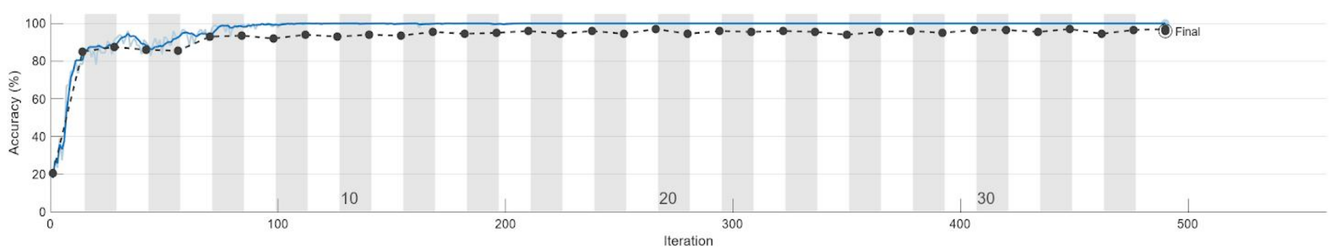

Fig. 5 Training Graph

D. Simulink and Hardware Deployment.

One of the main innovations of the proposed framework is to use Simulink in deploying devices. The Simulink Program Shown in Fig 6-7.

1) *Model loading:* The trained MATLAB network object is loaded into a Simulink block.

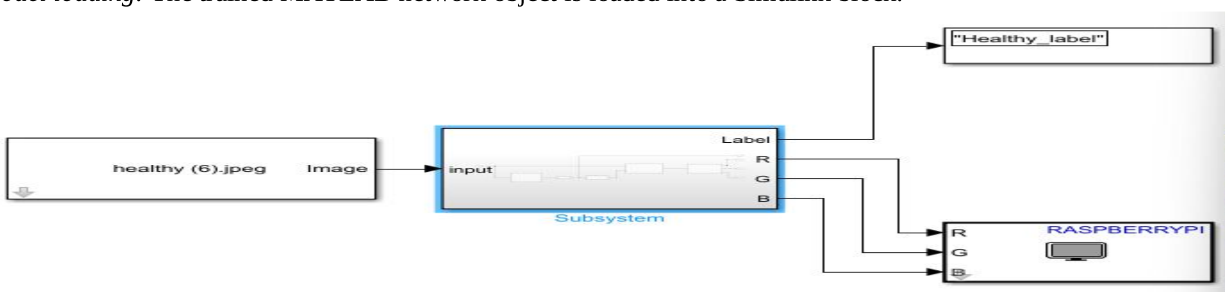

Fig. 6 Simulink Main Program

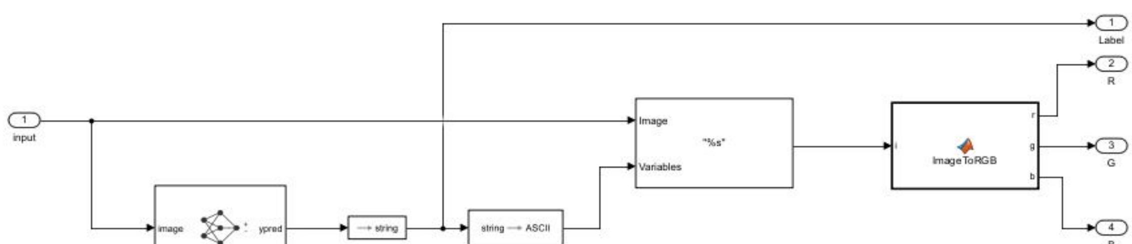

Fig. 7 Simulink Sub-System

2) *Hardware setup in the Simulink Support Package*: The Simulink Support Package is a hardware configuration platform to support the Raspberry PI Hardware, and the model is translated to C++ code to be optimally executed on the ARM processor of the Raspberry Pi. The Simulink Result is shown in Fig 8.

3) *Real -Time Loop:* This is an action that takes a frame and real time Resizes it. This frame is fed to the deep-learning block and the results are the probabilities, which are sent to a logic block that picks the most confident class. When the disease is detected, the system runs a digital output (e.g. Monitor and LED indicator).

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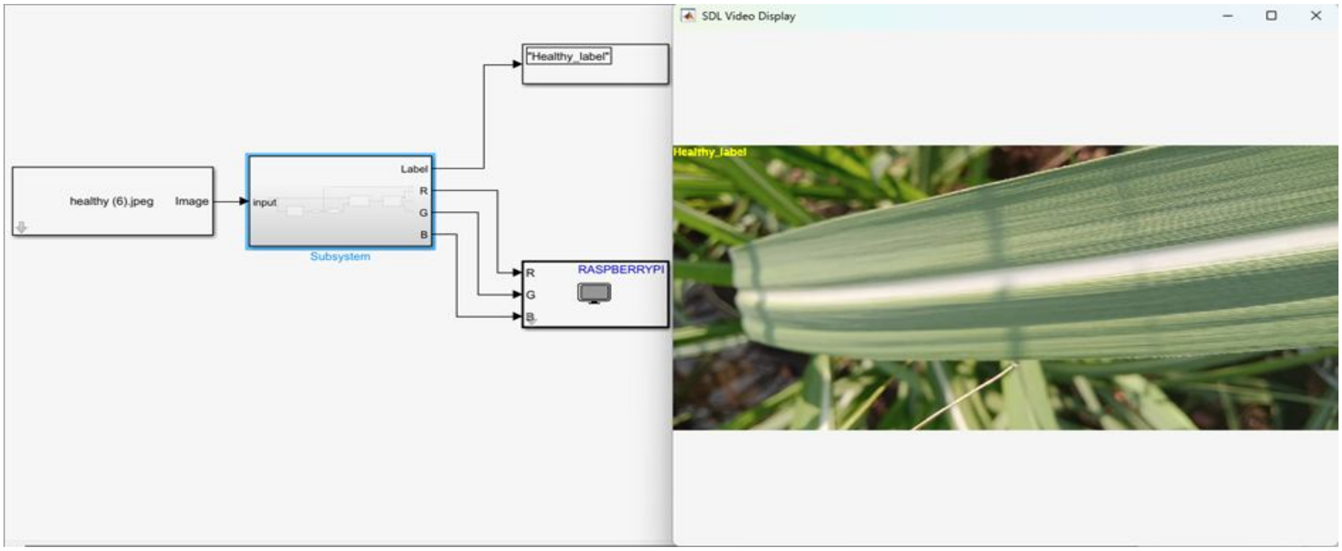

Fig. 8 Simulink Result

IV. DISCUSSION

A. *Real-world Applications and Implementation.*

The suggested system democratizes the usage of sophisticated agronomic devices by implementing the model on a Raspberry, which will support offline and without the continuous internet connection, which is often one of the main sources of limitations in remote sugarcane fields. The strategy is in line with the growing need of resource-efficient AI that reduces barriers to entry by practitioners in developing regions [2]. The MATLAB/Simulink integration eases the workflow enabling agricultural researchers who may lack embedded code knowledge to modify and redeploy models when a new disease strain arises.

B. *Limitations and Challenges.*

The system has a number of limitations in spite of its potential.

1) *Environmental Variability:* Although the model has proven to have strong performance on a validation data, its performance in a real-life scenario can be poor due to extreme changes in light, shadows or leaf occlusions, an inherent problem in remote sensing because indirect measurements require robustness [4].
2) *Interpretability:* Deep-learning models have been called black boxes. Even though their efficiency is clear, it is hard to understand why a lesion should be classified as Red Rot instead of Red Rust, which will lead to the loss of trust in farmers [8].
3) *Resource Constraints:* Despite optimization, the Raspberry Pi has significantly less computing capability than desktop GPUs. Higher frame rate processing can cause thermal throttling or battery wastage. The literature that has been released in recent times records the trade-off between model depth and resource consumption [2].

C. *Ethical Concerns and Future Employment.*

Using automated monitoring brings up the issue of data ownership and dependence on technology. Farming data often contains sensitive data on the agricultural operations [1], which requires edge-side data protection. Further, over-reliance on automated systems may undermine human capability of disease-identification in the labour force.

Future studies will focus on two major fronts. First, we will adopt multitask learning which will help detect diseases along with estimating the severity of an illness and this has the potential to be more efficient than independent models [3]. Second, we will explore the possibility of combining low-cost spectral sensors with RGB data because spectral resonance can commonly find stress before symptoms of visual effects occur [4].

V. CONCLUSIONS

The paper includes a combined approach to precision agriculture that is centred on the sugarcane disease detection. Utilizing the advanced feature-extraction powers of ResNet-50 and the affordable Raspberry hardware and the Model-Based Design platform of MATLAB/Simulink, we can find the much-needed automated, real-time crop-monitoring.

This strategy will reduce the inefficiencies of hand-inspections and will bypass the connectivity constraint of cloud-based solutions. Despite the existing issues related to environmental soundness and the interpretability of the models, the system is a step forward to scalable, resource-efficient, and affordable smart-farming technologies. This framework validation has a role to play in the greater aim of guaranteeing crop harvests and the economic sustainability of the sugarcane industry.

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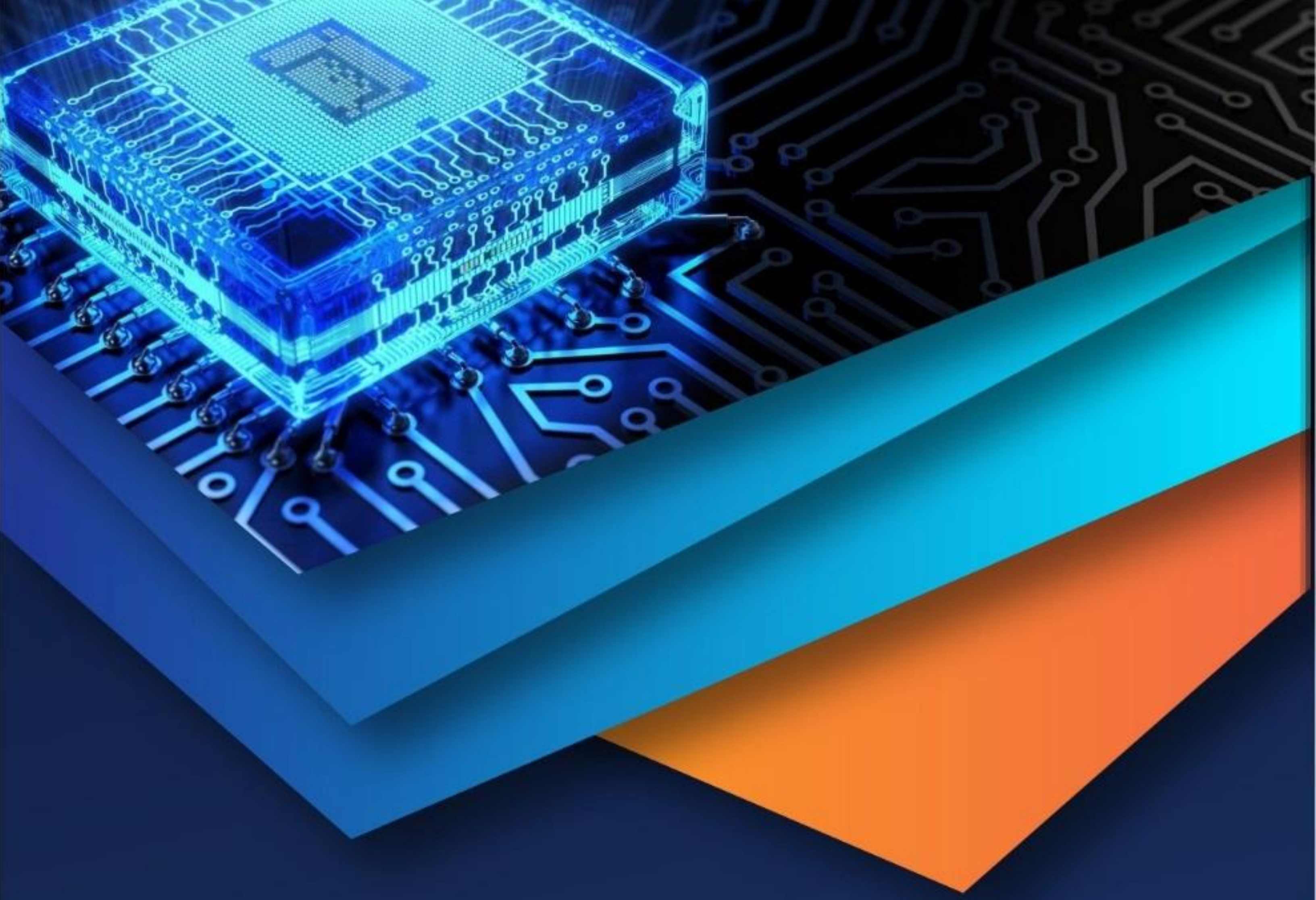

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