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AI-Driven Autonomous Precision Agriculture System for Smart Crop Management

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Abstract: The rapid growth of global food demand, coupled with the challenges posed by plant diseases and weed infestation, necessitates the development of intelligent and autonomous agricultural systems. This paper presents a survey of an AI-Driven Autonomous Precision Agriculture System for Smart Crop Management that integrates two core functionalities: (1) an autonomous field robot capable of navigating crop rows, detecting and removing weeds, and recording the entire process in real time, and (2) a deep learning-based crop disease detection system targeting Rice, Onion, Cotton, and Tomato crops with integrated soil temperature and humidity sensing. The proposed system employs a Raspberry Pi-based low-budget rover equipped with a camera module and IoT sensors for real-time data acquisition. Deep learning models including Convolutional Neural Networks (CNN) and transfer learning architectures are used for weed identification and disease classification. The survey reviews existing approaches, identifies critical research gaps such as the absence of multimodal sensor fusion and closed-loop autonomous action, and proposes an integrated framework that addresses these limitations. The system aims to reduce chemical usage, improve crop yield, and support sustainable precision agriculture practices.
Keywords: Precision Agriculture, Weed Detection, Crop Disease Detection, Autonomous Robot, Deep Learning, IoT, CNN, Raspberry Pi, Soil Sensing.

I. INTRODUCTION

Agriculture remains the backbone of global food security, yet it faces mounting pressures from a rapidly growing population, climate change, and increasing incidences of plant diseases and weed infestations. Traditional farming practices rely heavily on manual labor for field monitoring, disease identification, and weed removal, which are not only time-consuming and expensive but also prone to human error. The excessive and indiscriminateuse of chemical pesticides and herbicides has further led to soil degradation, environmental pollution, and health hazards. The integration of Artificial Intelligence (AI), the Internet of Things (IoT), and robotics into agriculture has opened new avenues for addressing these challenges through automation and data-driven decision-making. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in image-based classification tasks such as plant disease identification and weed detection. Simultaneously, low-cost microcontrollers like the Raspberry Pi have enabled the development of affordable autonomous robotic platforms suitable for field deployment.

Despite these advances, existing systems often address only one aspect of crop management — either disease detection or field robotics — but rarely both in an integrated manner. Furthermore, most disease detection systems rely solely on image data and do not incorporate environmental sensor data such as soil temperature and humidity, which are critical indicators of plant health and disease susceptibility. This gap motivates the development of a comprehensive system that combines autonomous robotic field scouting, AI-based weed and disease detection, and multimodal sensor fusion into a unified precision agriculture framework. This survey focuses on two primary research areas: (1) autonomous field robots for weed detection, removal, and process recording, and (2) deep learning-based disease detection for Rice, Onion, Cotton, and Tomato crops with integrated soil sensing. The study reviews existing literature, identifies research gaps, and presents the proposed methodology along with complete system requirements for practical implementation.

II. LITERATURE SURVEY

A. IoT Assisted Plant Disease Detection Using Deep Learning

Author and Year: Al-Shahari et al. (2025)

Methodology: This work developed an automated Plant Disease Detection and Crop Management system (APDDCM-SHODL) for sustainable agriculture. The system employs Vector Median Filter (VMF) for preprocessing, DenseNet201 for feature extraction, Spotted Hyena Optimizer (SHO) for hyperparameter tuning, and a Recurrent Spiking Neural Network (RSNN) for classification.

Tested on Fruit Disease Image (FDI) and Leaf Disease Image (LDI) datasets of 250 samples each, the system achieved a peak accuracy of 98.60%.
Limitation: The system relies solely on image data collected from pre-existing datasets and does not integrate environmental sensors such as soil temperature or humidity. Furthermore, the system lacks a real IoT deployment and any robotic mechanism for autonomous field action. Future work was identified to include environmental factor integration and larger field deployments.

B. A Real and Novel Smart Agriculture Implementation with IoT Technology
Author and Year: Cheng et al. (2021)
Methodology: The authors implemented the TIAGA (Tano Intelligent Agriculture GACP Cloud Management System) in a real cantaloupe greenhouse in Yilan, Taiwan. The system uses a TEENSY USB 3.3 EVB (ARM Cortex-M4) host connected to a micro-weather station, crop growth environment sensors (soil pH, EC, temperature, humidity), pest traps, and an automation control subsystem via RS-485/ModBus protocol. An Agricultural Expert System (AES) sends farming suggestions via LINE app. Post-deployment results showed manpower reduced from 3 workers to 0.5, water usage reduced to 60%, and fertilizer usage reduced to 65%.
Limitation: Despite this practical deployment, the system explicitly acknowledged that AI-based image recognition for disease and pest identification was not implemented and was planned as future work. No autonomous robotic movement or weed removal capability was present.

C. Smart Agriculture: Current State, Opportunities, and Challenges
Author and Year: Ahmed et al. (2024)
Methodology: This comprehensive IEEE Access survey reviewed key technologies in smart agriculture including IoT devices, robots and drones, sensors, AI/ML, data analytics, and blockchain. The paper catalogued 33 publicly available plant disease datasets including PlantVillage (54,303 images), PlantifyDr (125,000 images, 37 diseases), Tomato Leaf Disease (100,000 images), and Corn Leaf Diseases NLB (4,000 images created specifically for drone-based disease mapping).
Limitation: The survey explicitly identified that seamless integration of ground sensors with autonomous robotic platforms, cost-effective adaptable robots for precision spraying, and multimodal sensor fusion remain open research problems. The paper called for continued research on autonomous navigation with AI and affordable robotic systems across different farm environments.

D. Autonomous Cloud Robotic System for Smart Agriculture
Author and Year: Dharmasena et al. (2019)
Methodology: This work introduced an automated cloud-connected mobile robot for greenhouse management. The robot monitors humidity, soil moisture, temperature, and pH levels while navigating a pre-drawn greenhouse layout. A camera mounted on the robot captures plant images to detect unhealthy plants through leaf color and texture analysis. A fuzzy controller manages irrigation, humidifiers, and cooling/heating systems based on sensor data.
Limitation: The system is confined to greenhouse environments and does not support open-field navigation. Weed detection and removal mechanisms are absent. Disease detection relied on simple color/texture analysis rather than deep learning, limiting its accuracy and generalizability across crop types.

E. Automatic Agriculture Spraying Robot with Smart Decision Making
Author and Year: Sharma and Borse (2016)
Methodology: The authors designed an autonomous mobile robot for agriculture and plant nursery applications encompassing plant disease detection, growth monitoring, and spraying functions for pesticides, fertilizers, and water. The platform offered a compact, portable, and robust solution capable of autonomously surveying farmland. The robot could identify diseases, monitor plant growth, and administer spraying as needed.
Limitation: The disease detection component was basic and lacked deep learning integration. Weed-specific detection and selective removal were not addressed. Soil environmental sensors were not incorporated into the decision-making pipeline, and the system did not record or log field operations for traceability.

F. IoT-Based Intelligent Farming Using CNN for Early Disease Detection

Author and Year: Debnath and Saha (2022)

Methodology: This work introduced an IoT-integrated CNN system for early detection of brown-spot disease in rice paddies. The system utilized a custom image-processing tool for preprocessing and feature extraction, and a mobile application was developed to give farmers access to detection results. The CNN model demonstrated early detection capability specifically for rice brown-spot disease.

Limitation: The system was crop-specific and did not generalize to multiple crop types. Soil sensor data was not fused with image data for decision support. No robotic or autonomous field mechanism was present, limiting the system to a passive detection tool requiring human intervention for action.

G. Application of Drone Surveillance for Advance Agriculture Monitoring

Author and Year: Shah et al. (2023)

Methodology: This study proposed an automated method for plant identification using EfficientNet-B3 trained to recognize specific combinations of plants and diseases from drone-captured images. Both an Android application and a website were developed for farmer accessibility. The system demonstrated impressive disease identification accuracy from aerial images.

Limitation: Drone-based systems incur high operational costs and require skilled operators, making them less accessible to smallholder farmers. The system lacked ground-level soil sensing integration and provided no mechanism for physical intervention such as weed removal or targeted spraying based on detection results.

H. IoT and Interpretable Machine Learning for Disease Prediction in Pearl Millet

Author and Year: Kundu et al. (2021)

Methodology: This paper presented an IoT and interpretable ML-based framework for disease prediction in pearl millet. The system used SHAP values for model interpretability alongside CNN-based detection. IoT devices collected environmental data to support prediction. While the integration of IoT data with ML showed promise, the system demonstrated effective decision support for disease management.

Limitation: The system was limited to a single crop type and did not demonstrate autonomous action based on predictions. Weed detection and robotic field operations were outside the scope of this work. The system served as a decision support tool for farmers rather than an autonomous intervention system.

III. METHODOLOGY

The proposed AI-Driven Autonomous Precision Agriculture System is designed around two integrated modules: the Autonomous Field Robot Module and the Crop Disease Detection Module. Together, these modules form a closed-loop precision agriculture system capable of real-time field monitoring, weed management, and disease diagnosis with environmental sensor support.

A. Module 1: Autonomous Field Robot for Weed Detection and Removal

The robotic platform is built on a low-cost Raspberry Pi 4 Model B-based rover chassis. The robot autonomously navigates crop rows using a pre-mapped path or line-following sensors. A Pi Camera Module mounted on the robot captures real-time images of the field as it moves. These images are processed on-device using a lightweight CNN model (MobileNetV2 or YOLOv5-nano) to distinguish between crop plants and weed species.

Upon weed detection, the robot triggers a servo-actuated mechanical arm for physical weed removal. The entire process — including navigation path, detection events, timestamps, GPS coordinates, and annotated images — is recorded to a local SD card and optionally synced to a cloud dashboard. A dual-camera setup (front-facing for navigation, downward-facing for plant scanning) ensures comprehensive field coverage. Motor control is handled through an L298N motor driver interfaced with the Raspberry Pi.

B. Module 2: Crop Disease Detection with Multimodal Sensor Fusion

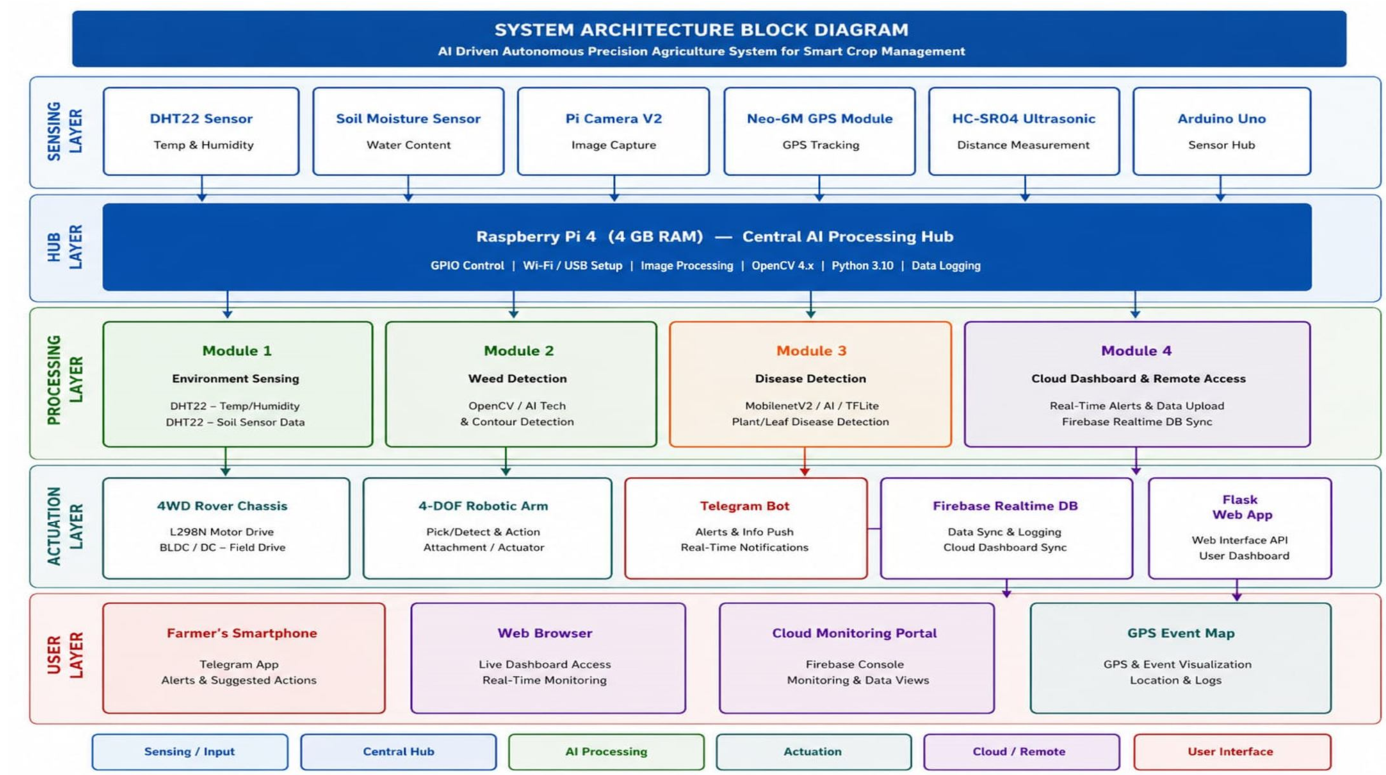
The disease detection module targets four crops: Rice, Onion, Cotton, and Tomato. Image data from the camera module is preprocessed using resizing, normalization, and data augmentation techniques. A DenseNet201 or EfficientNet-B3 transfer learning model is fine-tuned on publicly available datasets including PlantVillage (54,303 images) and PlantifyDr (125,000 images).

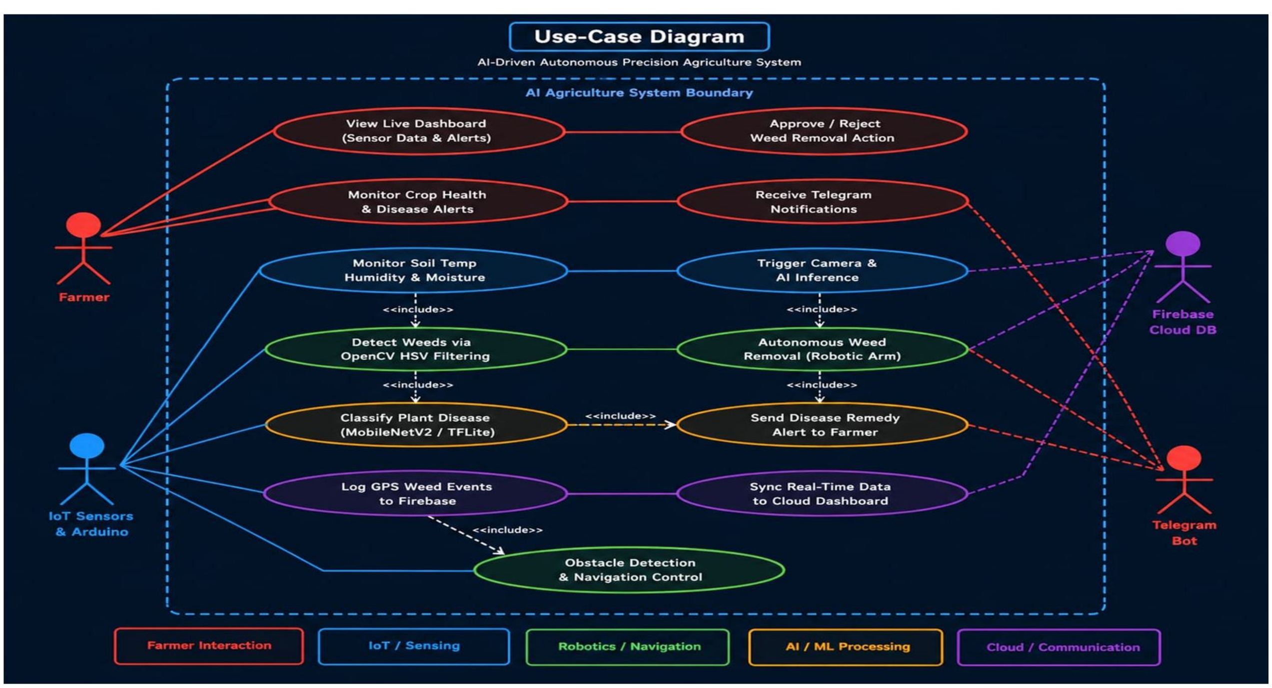
The key innovation over existing systems is the fusion of image-based predictions with real-time soil sensor data. A DHT22 sensor provides soil temperature and humidity readings, while a soil moisture sensor measures water content.

These sensor values are passed as auxiliary inputs to the classification pipeline, enabling the model to correlate environmental conditions with disease likelihood — a feature absent in all reviewed prior works. Classification outputs are displayed on a mobile dashboard with disease name, confidence score, sensor readings, and recommended action.

C. System Workflow

Field Entry → Robot Navigation → Camera Capture → Weed/Disease Detection (CNN) → Sensor Data Fusion → Classification Output → Weed Removal Action / Disease Alert → Process Recording → Cloud Sync / Dashboard Display





D. Advantages of the Proposed System

- Integrates autonomous robotic action with AI-based detection — closing the gap identified in all reviewed works
- Fuses image data with soil temperature and humidity sensors — a novel multimodal approach not present in existing models
- Covers four crop types (Rice, Onion, Cotton, Tomato) enabling broader agricultural applicability
- Low-budget Raspberry Pi platform makes the system accessible to smallholder farmers
- Real-time process recording provides field traceability and operational logs
- Eliminates the need for constant human presence through autonomous navigation and intervention
- Reduces chemical usage through targeted weed removal and precision disease management

IV. DISCUSSION

The review of existing systems reveals a consistent pattern: most approaches address either disease detection or field robotics in isolation, and none integrate soil environmental sensing into the disease classification pipeline. Al-Shahari et al. [1] achieved high accuracy in disease detection but operated entirely on offline datasets without any real-world IoT deployment or robotic action component. Cheng et al. [2] successfully deployed a comprehensive IoT sensor network in a real farm but explicitly noted the absence of AI-based image recognition as a limitation for future work.

The broader survey by Ahmed et al. [3] confirmed that seamless integration of autonomous robots with disease detection and multimodal sensor fusion remains an open and critical research gap. Robotic systems reviewed by Dharmasena et al. [4] and Sharma and Borse [5] demonstrated autonomous navigation in controlled environments but lacked deep learning-based detection and open-field weed removal capability. Crop-specific systems like that of Debnath and Saha [6] showed promise for CNN-based early detection but were limited to single crops and passive monitoring roles. Drone-based approaches such as Shah et al. [7] offered aerial surveillance but at prohibitive costs unsuitable for smallholder farmers and without ground-level sensor integration.

The proposed system addresses all these identified gaps by combining autonomous low-cost robotic navigation, real-time weed detection and removal, multi-crop disease detection using transfer learning, and soil temperature and humidity sensor fusion — delivering a complete, end-to-end precision agriculture solution. The process recording capability further adds an audit trail dimension absent in all reviewed works, which is valuable for farm management traceability.

Certain challenges remain for future consideration. Weed species diversity across different geographical regions may require region-specific model training. Open-field navigation in unstructured environments presents greater complexity than greenhouse settings. Real-time processing on edge devices requires model optimization through quantization or pruning to maintain inference speed within acceptable limits.

V. CONCLUSION

This paper presented a survey and proposed methodology for an AI-Driven Autonomous Precision Agriculture System for Smart Crop Management. The review of existing literature revealed that while individual components such as disease detection models, IoT sensor networks, and agricultural robots have been developed independently, no existing system integrates all three into a unified closed-loop precision agriculture framework.

The proposed system uniquely combines a Raspberry Pi-based low-cost autonomous rover for weed detection and removal, a multi-crop disease classification model covering Rice, Onion, Cotton, and Tomato, and a multimodal sensor fusion pipeline incorporating soil temperature and humidity data — directly addressing the limitations identified across all reviewed works. The complete hardware requirements estimated at approximately INR 12,380 and the open-source software stack make this system practically implementable at low cost, ensuring accessibility for smallholder farmers.

Future enhancements may include GPS-based field mapping for autonomous multi-row navigation, integration of weather forecast APIs for predictive disease risk assessment, and federated learning for collaborative model improvement across multiple farms. This work contributes to the growing body of research in autonomous precision agriculture and lays a practical foundation for a fully autonomous, affordable, and intelligent crop management system.

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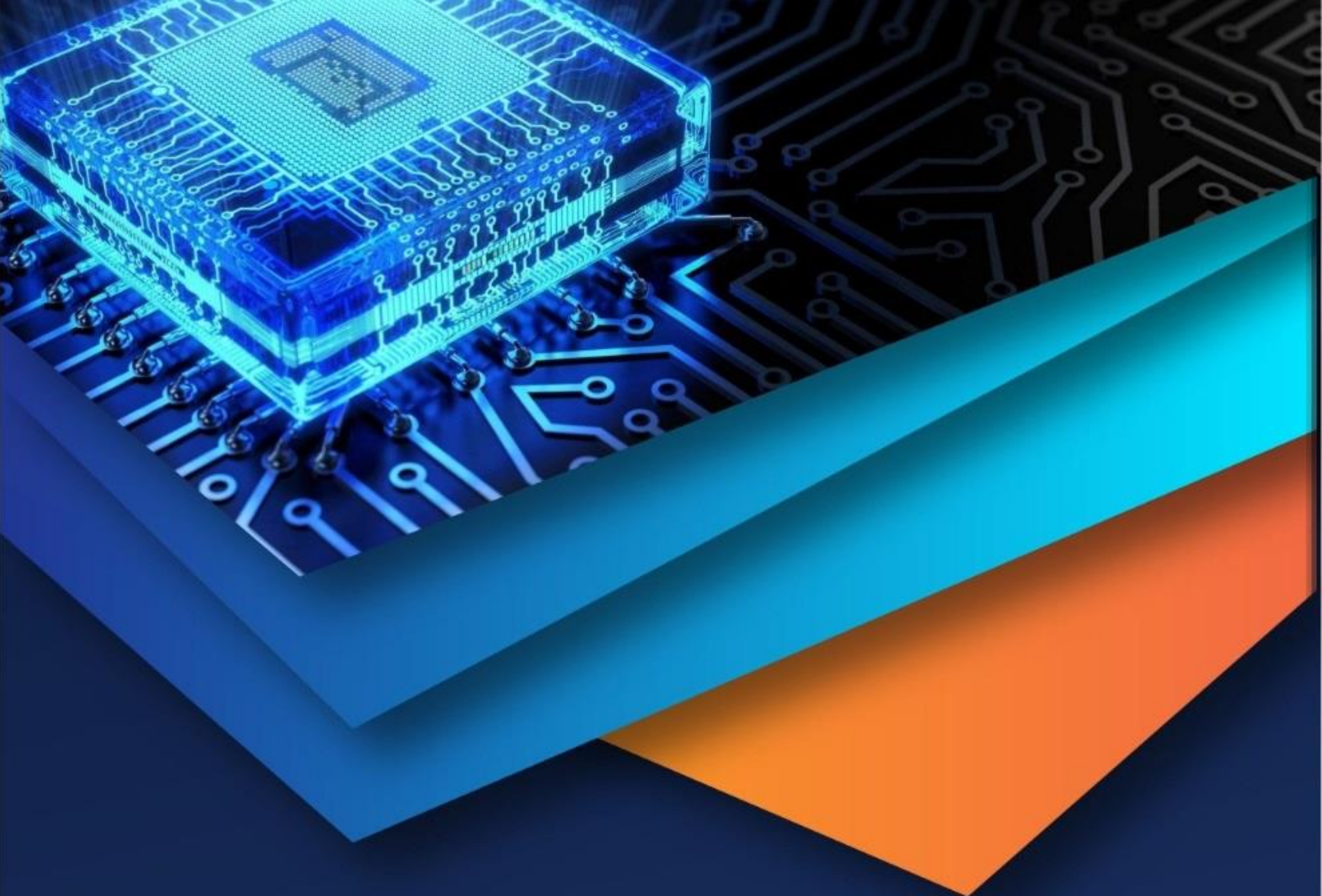

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