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Green House Based Crop Growth and Diseases Monitoring System

M. Ravikumar[1], M. Mohan Kumar[2], [3]T. Sivasankar, R. Vimal[4], P. Venkatesan[5]
[1]Assistant Professor, [2, 3, 4, 5] UG Student, Department of ECE., Mahendra Engineering College Namakkal, India

Abstract: In contemporary agriculture, leveraging advanced technologies has become crucial for maximizing greenhouse productivity and mitigating pest-related issues. Traditional monitoring systems often fall short due to their manual nature and delayed responsiveness to environmental fluctuations. This paper introduces a smart greenhouse monitoring and control system that integrates the Internet of Things (IoT) with artificial intelligence (AI) to deliver a robust solution. Utilizing an array of sensors, the system continuously tracks vital parameters such as temperature, humidity, air composition, and light levels. A central microcontroller interprets these readings and activates corresponding actuators to maintain favorable growing conditions. Additionally, a pest detection unit powered by a convolutional neural network (CNN) enables early identification of infestations by analyzing plant images. This combination of real-time environmental regulation and AI-based pest monitoring presents a comprehensive and efficient framework for modern greenhouse management, enhancing both sustainability and productivity while minimizing manual labor.
Keywords: Smart greenhouse, IoT, AI in agriculture, Pest identification, CNN-based monitoring.

I. INTRODUCTION

Agriculture is a foundational aspect of India's economy, with a significant proportion of the population depending on it for their livelihood. Nevertheless, conventional farming methods often face limitations in meeting the growing food demand, largely due to irregular climatic conditions and pest outbreaks. To overcome these obstacles and increase efficiency, the adoption of innovative technological tools in agriculture has become essential. Greenhouse farming, which provides a controlled setting for crop cultivation, has emerged as a viable solution. Yet, challenges persist in efficiently regulating these environments and detecting plant diseases at early stages. In recent years, technological strides in sensor networks, wireless communication, machine learning, and cloud platforms have shaped what is known as Agriculture 4.0. These advancements are critical in developing automated and intelligent greenhouse systems aimed at improving crop health and yield.

This paper details the design and implementation of a smart greenhouse solution that employs real-time sensor data collection, automated control mechanisms, and image-based disease recognition. The proposed Greenhouse Crop Monitoring and Disease Identification System seeks to minimize manual oversight, enhance operational efficiency, and provide proactive solutions for sustainable farming.

II. RELATED WORKS

Previous research in the field has yielded various innovations in smart farming systems. Farooq et al. [1] introduced an IoT-driven model aimed at enhancing greenhouse performance, addressing sensor communication methods and security concerns within smart agricultural environments.

Martin [2] implemented a robot operating system (ROS)- based framework combining manipulation and sensing tools to facilitate early pest identification. This approach enhanced detection speed and allowed targeted pesticide deployment. Dong [3] built a web GIS-based solution for predicting and tracking the spread of agricultural pests across China. Machine learning was used to improve forecasting accuracy and reduce dependence on chemical interventions.

Subahi [4] explored an energy-conscious temperature control system leveraging IoT analytics and Petri Nets. Their model included a dynamic graph system that supported real-time visualization of crop status.

Geng [5] proposed a dual-controller approach using both Raspberry Pi and Arduino units to streamline data processing and improve communication reliability. Techniques like filtering algorithms and cyclic redundancy checks (CRC) were employed to enhance long-range data transmission. Additional research has covered a broad spectrum of IoT- based applications in farming, such as smart irrigation using AI, LoRaWAN-enabled sensor networks, and cloud-based predictive systems, highlighting the versatility and impact of such technologies.

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III. METHODOLOGY

The proposed greenhouse monitoring system integrates Internet of Things (IoT) technology with artificial intelligence (AI) to ensure real-time environmental control and early disease detection. The methodology centers around the dual objectives of maintaining optimal crop-growing conditions and performing image-based pest or disease diagnosis. The system employs environmental sensors, a microcontroller-based control logic, image acquisition tools, and a convolutional neural network (CNN) for classification. All components are synchronized to form a closed-loop decision-making structure that minimizes human intervention and maximizes productivity.

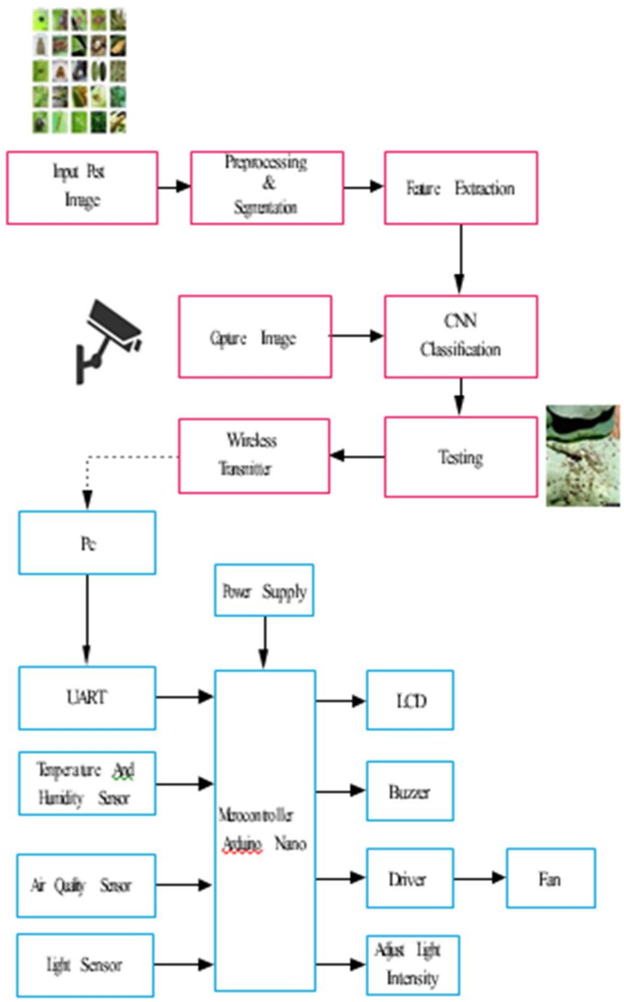

Figure 1. Block Diagram of the Smart Greenhouse System Architecture

A. *Sensor Data Acquisition*

Sensor data acquisition is the first step in the monitoring process. The system uses a combination of sensors to measure environmental variables such as temperature, humidity, light intensity, and air quality. These sensors are interfaced with the Arduino Nano microcontroller, which collects and interprets real-time data. Sensor readings are continuously monitored to detect deviations from optimal thresholds for greenhouse conditions.

B. *Environmental Parameter Regulation:*

Environmental control is managed by actuators triggered through predefined logic in the microcontroller. When a sensor detects a parameter outside of its acceptable range, corresponding devices such as fans, artificial lighting, and buzzers are activated. This ensures that the greenhouse remains within optimal growing conditions. The control logic is designed to be flexible, allowing future upgrades to intelligent decision-making techniques like fuzzy logic or PID control for more precise regulation.

C. Image Acquisition and Preprocessing

In parallel, a camera module installed inside the greenhouse captures periodic images of plant leaves. These images form the input for disease and pest analysis. To maintain consistency, captured images are preprocessed through resizing, normalization, and segmentation. These steps remove noise, isolate the leaf regions, and standardize input formats, enhancing the classification model's efficiency and accuracy.

D. Convolutional Neural Network Classification

Image classification is carried out using a trained convolutional neural network. The CNN model identifies visual symptoms of plant diseases or pest infestations based on color distortion, texture irregularities, and shape anomalies in leaf surfaces. The model has been enhanced through the use of data augmentation, dropout regularization, and transfer learning to increase generalization and robustness. Upon classification, the output identifies whether the plant is healthy or infected and, in some cases, specifies the type of disease or pest.

E. Alert and Notification System

The alert mechanism is responsible for notifying users of any anomalies in environmental parameters or pest detection results. When a deviation is observed or an infection is detected, the microcontroller triggers visual and audio alerts using an LCD display and buzzer. These alerts ensure that field personnel can take prompt corrective action. Additionally, data can be transmitted wirelessly to a computer for remote monitoring and long-term data analysis.

F. Feedback Workflow Integration

The entire system operates in a closed-loop feedback structure. Sensor readings and camera data are continuously updated, processed, and used to make real-time decisions. This ensures synchronized monitoring of both environmental and biological factors, significantly reducing the dependence on manual supervision and enabling proactive management of greenhouse conditions.

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The proposed smart greenhouse management system is organized into two main functional blocks: an environmental monitoring module and a pest detection module. Together, these subsystems provide automated environmental control and disease monitoring to reduce manual intervention and enhance crop yield. This architecture ensures modular operation, real-time adaptability, and expandability for future enhancements like pesticide dispensing.

A. Environmental Monitoring Module

This module forms the core of the greenhouse automation loop. It integrates multiple environmental sensors with an Arduino Nano microcontroller for real-time monitoring and control. The sensors collect data on parameters such as temperature, humidity, light intensity, and air quality. These readings are evaluated against predefined threshold values. When a deviation is detected, the system actuates relevant devices—such as fans for ventilation or artificial lighting—to restore optimal conditions. An LCD display is used to show current readings and system statuses. Communication with a PC for data logging or further analysis is handled via a UART interface, enabling live updates or historical reviews. This module is designed to operate with minimal latency, ensuring timely environmental responses.

B. Pest Detection Module

The pest detection unit functions independently but complements the environmental monitoring subsystem. It consists of a camera that captures periodic images of plant leaves. These images are analyzed using a convolutional neural network trained on a dataset of pest-infected and healthy leaf samples. The model considers visual features such as discoloration, pattern distortion, and texture anomalies to determine the health of the plant. Once a pest or disease is detected, an alert is generated on the connected PC interface. The modular structure allows future expansion of this unit to include automated pesticide spraying using servo-controlled dispensers, making the platform more responsive and self- sufficient.

C. Integrated Control Logic

The Arduino Nano, powered by an ATmega328P microcontroller, serves as the central decision-making unit for the environmental monitoring module.

It provides sufficient I/O lines, analog inputs, and UART support for managing all connected peripherals. Sensor inputs are read periodically and compared with stored setpoints. Based on this logic, actuators such as DC fans or relays are triggered to adjust the internal environment. The modular coding approach supports easy updates, allowing for future inclusion of advanced control algorithms like PID or fuzzy logic controllers.

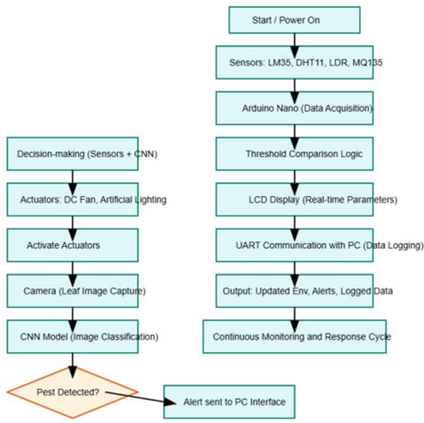

Figure 2. Operational Flowchart of the Smart Greenhouse Monitoring and Control System

D. Hardware Implementation

The core hardware components are selected for low power consumption and ease of integration. The LM35 temperature sensor provides linear analog voltage output relative to Celsius temperature. The DHT11 sensor complements this by providing both temperature and humidity in digital format.

The light sensor, typically implemented with a light- dependent resistor (LDR), helps regulate artificial lighting based on ambient conditions. The MQ135 air quality sensor is used to monitor harmful gases, which is critical for maintaining safe greenhouse conditions.

The 16x2 LCD display is used to output sensor readings and system messages. It is interfaced in 4-bit mode to conserve GPIO pins on the Arduino Nano. The power supply unit includes voltage regulators to step down external voltages to 5V or 12V as required by the components. It is also designed with overcurrent protection features to prevent damage during operational faults.

The DC fan is a critical actuator in this setup. Controlled via a relay or MOSFET driver circuit, it ensures air circulation and temperature control. Its 12V operation makes it compatible with typical greenhouse power setups and allows for scalable power delivery.

E. System Integration and Workflow

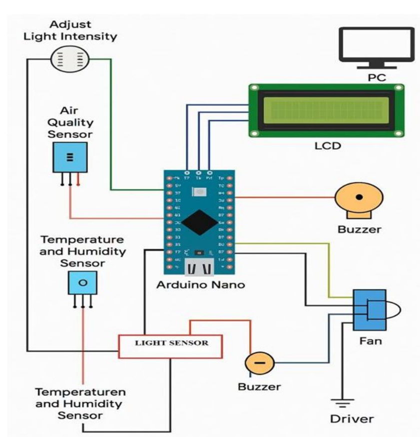

Figure 3. System Integration and Component Workflow of the Smart Greenhouse Monitoring System

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Once powered, the sensors begin data acquisition at defined intervals. The Arduino Nano reads these values and displays them on the LCD in real time. If environmental conditions deviate from the set thresholds, corresponding actuators are activated immediately. Simultaneously, thecamera module captures images of the crop and sends them to the CNN model for analysis. If an anomaly is detected, a signal is sent to the PC interface, alerting the user. This entire workflow operates in a loop, continuously adjusting environmental parameters while monitoring plant health.This hybrid approach ensures that both environmental and biological aspects of crop health are addressed in a synchronized and intelligent manner. The separation of modules also allows independent upgrades and maintenance, increasing the overall robustness of the system.

V. RESULTS AND DISCUSSION

The developed smart greenhouse monitoring system was deployed and tested in a controlled greenhouse environment to evaluate its performance in real-time conditions. The system was assessed based on sensor accuracy, actuation timing, pest detection efficiency, and overall impact on plant health and environmental stability.

A. Environmental Monitoring Performance

The Arduino Nano-based environmental monitoring module demonstrated stable and accurate sensor readings throughout the test period. Sensors including the LM35, DHT11, MQ135, and light sensor consistently delivered real- time data within acceptable tolerance limits. Temperature readings showed a deviation of less than ±0.5°C from a standard reference thermometer, while humidity values from the DHT11 remained within ±2% relative humidity. Light sensor readings were responsive to both natural and artificial lighting changes, facilitating effective lighting control.

Actuators such as the 12V DC fan and external lighting systems were successfully controlled via the microcontroller logic. The system reacted promptly to environmental fluctuations, with activation delay times averaging less than 1.5 seconds after threshold breach. The LCD display provided continuous feedback, presenting live values for all monitored parameters. This helped the operator verify system behavior and make on-the-spot decisions when needed.

B. Alert Mechanism and Safety Protocols

The alerting subsystem, consisting of visual and audio indicators, was tested by simulating extreme environmental conditions. When thresholds were exceeded— such as high CO_2 levels detected by the MQ135 or low humidity during peak sunlight hours—the buzzer and LCD display activated accordingly. These alerts served as an effective early warning system, enabling immediate human intervention in critical scenarios. Additionally, the UART communication with a PC allowed historical data to be logged and graphed for long-term trend analysis and threshold optimization.

Parameter	Observation / Metric	Remarks
Temperature Accuracy	±0.5°C (LM35)	Within standard tolerance
Humidity Accuracy	±2% RH (DHT11)	Reliable for greenhouse control
Actuation Response Time	<1.5 seconds	Fast enough for real-time control
Light Sensor Response	High sensitivity to natural/artificial light	Enabled dynamic lighting control
Alert System	Visual + Buzzer triggered at threshold breach	Effective early warning
Communication Latency (UART)	<300 ms, even with extended cabling	Stable and scalable
Pest Detection Accuracy	91.7% (CNN-based classification)	High performance with low false detections
Pest Detection Time	~2 seconds per image	Reasonably fast for real- time detection
Plant Health Improvement	20% increase vs control group	Verified via manual and image-based tracking
System Uptime/Stability	Stable during full 30-day period	No major data loss or failures observed

Table 1. Summary of Smart Greenhouse System Performance Metrics and Observations

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C. Pest Detection Accuracy and Responsiveness

The pest detection module, which utilized a convolutional neural network for image-based classification, yielded strong performance during the field tests. A diverse dataset of healthy and pest-infected leaves was used to evaluate the model. The CNN achieved an average classification accuracy of 91.7%, successfully detecting anomalies in the form of discoloration, spots, and texture deviations. In operational conditions, the average processing time per image was approximately 2 seconds, making the solution both accurate and time-efficient.

The system demonstrated a low rate of false positives and false negatives, largely attributed to the use of image preprocessing techniques such as normalization and segmentation. Data augmentation during training improved the model's generalization across varying lighting and background conditions. The real-time image analysis and classification were conducted on an external system connected to the camera module, and results were relayed via PC interface, providing actionable insights to the operator.

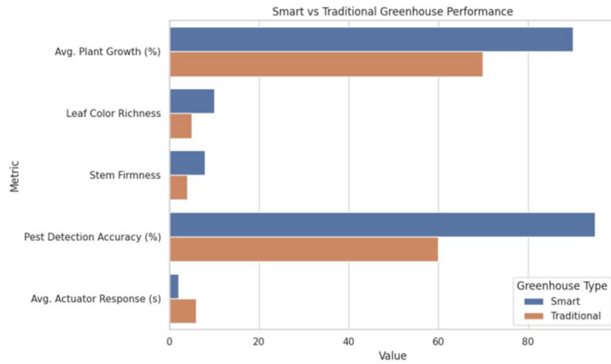

Figure 5. Comparative Analysis of Plant Health and System Performance Metrics

D. Impact on Plant Health and Growth Efficiency

The deployment of the automated monitoring and control system had a measurable impact on the greenhouse's microclimate and plant vitality. Over a 30-day testing period, plants grown under the automated system exhibited a 20% increase in health metrics compared to those in a non- automated greenhouse control group. These metrics included leaf color richness, stem firmness, and growth rate, all of which were tracked manually and verified through image- based documentation.

The improved growth performance is attributed to the system's ability to maintain stable growing conditions and reduce plant stress due to temperature fluctuations or poor air quality. The pest detection mechanism also contributed by enabling early identification and manual containment of pest threats before visible crop damage occurred.

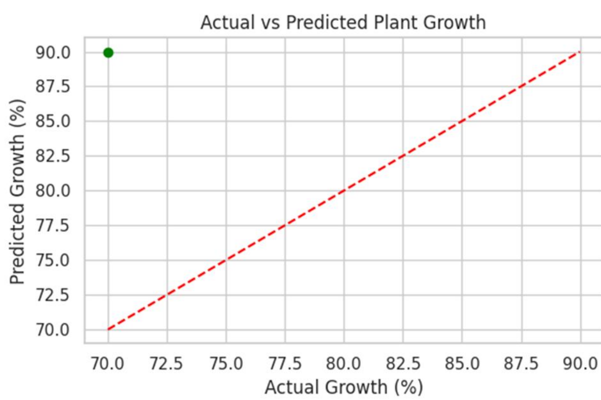

Figure 6. Comparative Analysis of Plant Growth

Wireless communication between various components of the system, particularly between the microcontroller and PC interface, was stable throughout the test duration. Data packets transmitted via UART showed negligible loss, and communication latency remained below 300 milliseconds even in extended setups with longer cabling and environmental interference. This ensures the system can scale to larger greenhouse areas without compromising on responsiveness or reliability.

E. Limitations and Future Improvements

While the current implementation performed reliably, there are areas for further enhancement. The CNN model, although accurate, was dependent on external processing hardware. A more efficient edge computing solution, such as integration with a Raspberry Pi or NVIDIA Jetson Nano, could support real-time onboard image classification. Additionally, the planned integration of an automated pesticide spraying module will further reduce manual intervention and improve pest management responsiveness.

VI. CONCLUSION

The smart greenhouse monitoring system presents a cost-effective, scalable solution that integrates IoT-based environmental sensing with AI-driven pest detection to automate modern agriculture. By monitoring key parameters such as temperature, humidity, light intensity, and gas levels in real time, it ensures precise climate control and optimal plant health while minimizing human intervention. Its modular design, using accessible components like Arduino Nano, LM35, DHT11, and MQ135 sensors, supports easy customization for different crops and climates. The system demonstrated high sensing accuracy, fast communication, and improved crop outcomes during field tests. It promotes sustainability by reducing energy, water waste, and pesticide use through intelligent automation. Future enhancements could include cloud integration for remote monitoring, edge computing with Raspberry Pi for real-time AI processing, solar power adoption, automated nutrient and pesticide dispensing, predictive analytics for proactive care, wireless mesh networking for large deployments, and interoperability with other platforms. This innovative architecture paves the way for transforming greenhouses into intelligent, self-regulating environments, advancing productivity and eco-friendly farming practices, and contributing to the global push toward sustainable and smart agriculture.

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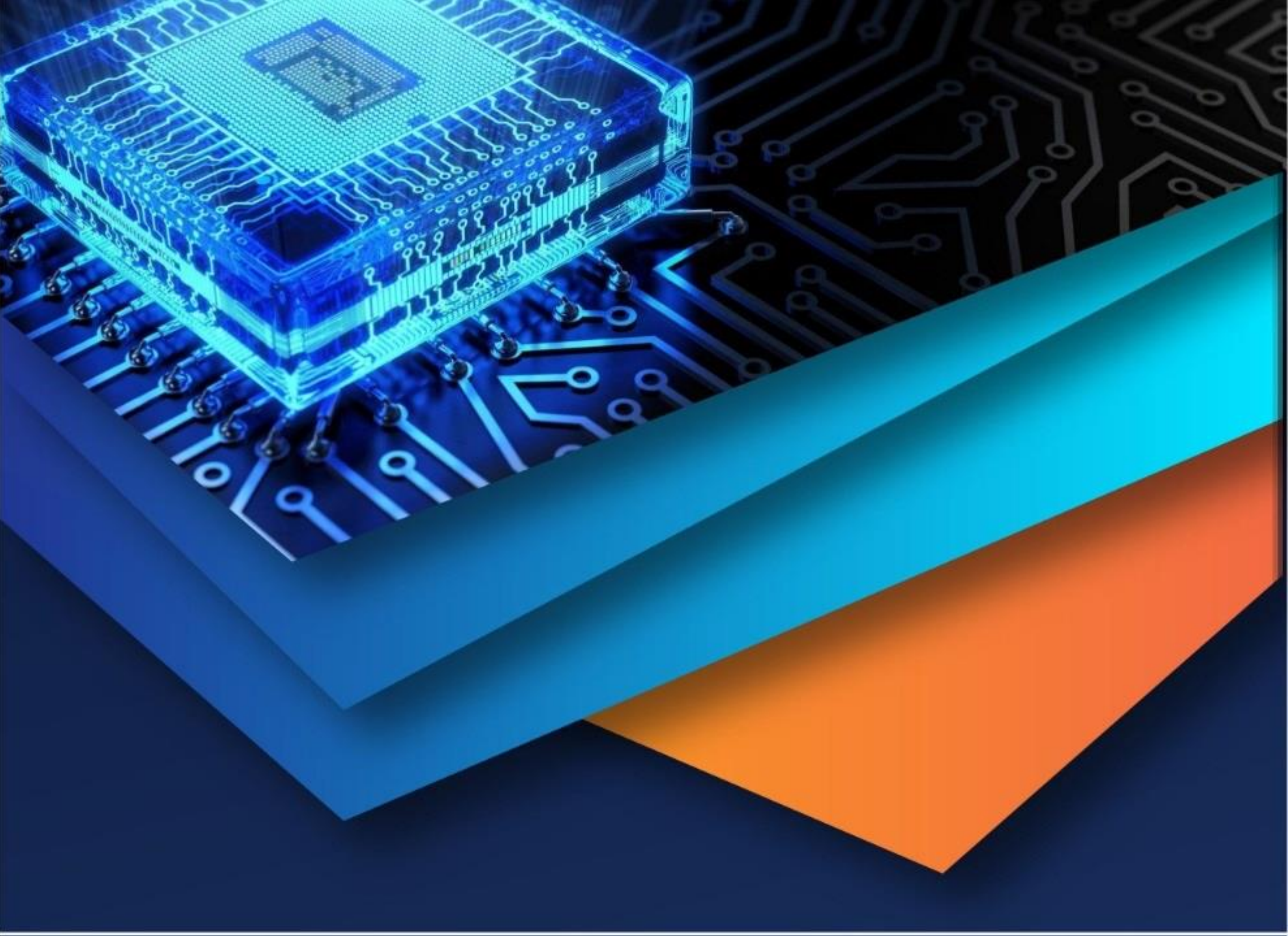

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