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AI-Based Bird Deterrent System for Crop Protection in Agricultural Fields

Dr. Sathyapriya J[1], Mrs. Priyadharshini[2], Hemalatha G[3], Karthika V[4]
[1]*Assistant Professor, Department of Information Systems, Velammal Engineering College, Chennai*
[2, 3, 4]*Student, Department of Information Technology, Velammal Engineering College, Chennai*

Abstract: Crop damage caused by birds is a major challenge in agriculture, leading to significant economic losses worldwide. Birds such as crows, pigeons, and sparrows feed on seeds, grains, and fruits, reducing both yield and quality of crops. Traditional deterrent methods such as scarecrows, reflective materials, and manual monitoring are widely used but become ineffective over time due to the adaptive behavior of birds. Studies have shown that birds can quickly learn and ignore repetitive deterrent mechanisms, leading to continuous crop damage [10].

To overcome these limitations, this paper proposes an AI-based bird deterrent system that provides automated, real-time, and adaptive crop protection. The system integrates computer vision, deep learning, and IoT technologies to detect and classify birds efficiently. A camera captures real-time images, and deep learning models such as YOLO and CNN are used for detection and classification [1], [4].

Based on the detected species, the system generates adaptive acoustic signals, including predator calls and distress sounds, to effectively scare birds. The system is implemented using embedded platforms such as ESP32 or Arduino, ensuring low power consumption and scalability. Experimental results indicate high detection accuracy and reduced bird activity in agricultural fields. This system offers a sustainable and intelligent solution for crop protection.

I. INTRODUCTION

Agriculture is one of the most important sectors globally, playing a crucial role in food production and economic development. In countries like India, agriculture supports a large population and contributes significantly to the economy. However, agricultural productivity is affected by various factors, including pests, diseases, and environmental conditions. Among these, bird-induced crop damage is a major concern that leads to considerable losses for farmers. Birds such as crows, pigeons, sparrows, and parrots are commonly found in agricultural fields. These birds feed on seeds, grains, and fruits, causing damage at different stages of crop growth. During the sowing stage, birds consume seeds directly from the soil, reducing germination rates. At later stages, they damage crops by feeding on grains and fruits, leading to reduced yield and poor quality produce. Studies indicate that bird damage can significantly affect agricultural productivity and farmer income [9]. Traditional bird deterrent methods, such as scarecrows and reflective materials, are widely used but have several limitations. These methods are static and lack intelligence, making them ineffective over time. Birds are highly intelligent and can quickly adapt to repetitive patterns. This phenomenon, known as habitual adaptation, reduces the effectiveness of traditional deterrent systems [10]. With the advancement of Artificial Intelligence, new solutions have emerged for agricultural challenges. AI enables systems to analyze visual data, detect objects, and make decisions automatically. Computer vision techniques allow real-time monitoring of agricultural fields, while deep learning models provide accurate detection and classification of objects [5].The integration of AI with IoT further enhances system capabilities by enabling remote monitoring and automation. This paper proposes an AI-based bird deterrent system that combines these technologies to provide an efficient and adaptive solution for crop protection.

II. LITERATURE REVIEW

The problem of bird-induced crop damage has been widely studied, and various methods have been proposed to address it. Traditional methods such as scarecrows, netting, and noise-making devices have been used for many years. However, these methods are not effective in the long term due to the adaptive behavior of birds. Birds can learn and ignore repetitive deterrent mechanisms, making these methods unreliable [10].

Recent research has focused on the use of Artificial Intelligence and deep learning for object detection and classification. Models such as YOLO, CNN, and Faster R-CNN have been widely used in various applications, including agriculture. YOLO is particularly effective for real-time object detection due to its speed and efficiency [1], [2]. CNN models are commonly used for image classification tasks and provide high accuracy when trained with sufficient data [4].

The integration of AI with IoT, known as AIoT, has further improved the performance of agricultural systems. IoT enables real-time data collection, remote monitoring, and automated control, making systems more efficient and user-friendly [12]. Several studies have proposed IoT-based systems for crop monitoring and pest control, highlighting the potential of these technologies in agriculture [9], [14].

Existing bird deterrent systems include laser-based devices, ultrasonic sound emitters, and motion-triggered alarms. While these systems provide some level of protection, they lack adaptability and intelligence. Most of them rely on fixed patterns, which leads to reduced effectiveness over time. This creates a need for an intelligent system that can detect birds in real time and respond dynamically.

The literature clearly indicates a gap in developing systems that combine real-time detection, species classification, and adaptive deterrent mechanisms. The proposed system aims to address these limitations by integrating AI, IoT, and adaptive acoustic technologies.

III. METHODOLOGY

The proposed AI-based bird deterrent system follows a systematic approach to detect, classify, and deter birds in real time. The system operates continuously and consists of multiple stages, including image acquisition, preprocessing, detection, classification, and deterrence.

In the first stage, a camera captures real-time images or video frames from the agricultural field. These images are then passed to the preprocessing stage, where noise is reduced, and the image is resized and normalized. Preprocessing improves the quality of the image and enhances the performance of the detection model.

Table 1: Adaptive Sound Response Based on Bird Species

Bird Species	Detected Sound Type	Frequency Range	Effectiveness
Crow	Predator Call	2–4 kHz	High
Sparrow	Distress Signal	3–5 kHz	Medium
Pigeon	Random Tone	1–3 kHz	High

The next stage involves bird detection using a deep learning model such as YOLO. The model analyzes the image and identifies the presence of birds by generating bounding boxes and confidence scores. YOLO is preferred due to its ability to perform real-time detection with high accuracy [1], [2].

Once a bird is detected, the system proceeds to the classification stage. A CNN model is used to classify the detected bird into specific categories such as crow, pigeon, or sparrow. This classification helps in selecting the appropriate deterrent mechanism [4].

After classification, the system generates adaptive acoustic signals based on the detected species. These signals include predator calls, distress sounds, and random frequency tones. The adaptive nature of the sound prevents birds from becoming habituated to the deterrent mechanism [10].

The final stage involves emitting the sound through a speaker system to scare the birds away. The entire process is automated and repeats continuously, ensuring effective crop protection.

Table 2: Adaptive Sound Response Based on Bird Species

Image ID	Bird Species	Number of Birds	Bounding Box (x,y,w,h)	Environment	Label
IMG001	Crow	2	(120,80,50,60)	Field	Bird
IMG002	Sparrow	5	(200,150,40,30)	Farm	Bird
IMG003	Pigeon	3	(90,60,70,80)	Open Area	Bird
IMG004	None	0	-	Field	No Bird
IMG005	Crow	1	(300,200,60,70)	Crop Area	Bird

IV. SYSTEM ARCHITECTURE

The system architecture consists of hardware and software components that work together to achieve real-time bird detection and deterrence. The main components include a camera module, AI processing unit, microcontroller, and speaker system.

The camera captures images from the agricultural field and sends them to the processing unit. The processing unit runs the AI model, which performs detection and classification of birds. Deep learning models such as YOLO and CNN are used to analyze the images and generate outputs [1], [4].

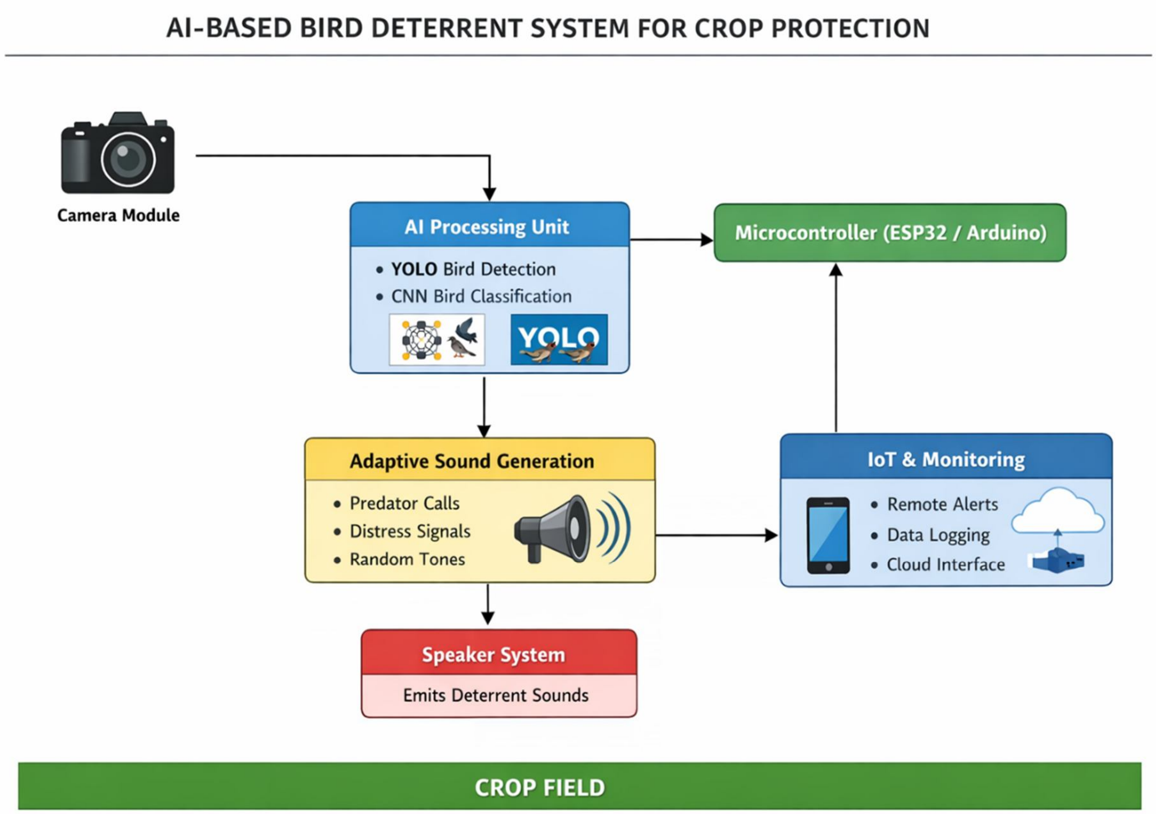
The output from the AI model is sent to the microcontroller, such as ESP32 or Arduino. The microcontroller processes the input and controls the speaker system. Based on the detected bird species, the system generates adaptive sound signals to deter birds.

IoT integration allows the system to connect to the internet, enabling remote monitoring and control. Farmers can receive real-time alerts and monitor bird activity through mobile devices. This enhances the usability and efficiency of the system [12].

The data flow in the system follows a sequence:

camera → AI processing → microcontroller → speaker. This architecture ensures smooth and efficient operation of the system.

Figure 1: System Architecture of AI-Based Bird Deterrent System



V. IMPLEMENTATION

The implementation of the system involves both hardware and software components. The hardware includes a camera module, ESP32 or Arduino microcontroller, and a speaker system. These components are integrated to form a complete system.

The software implementation is carried out using Python, OpenCV, and TensorFlow. The YOLO model is used for real-time detection, while CNN is used for classification [1], [4]. The system is trained using a dataset of bird images to improve accuracy.

The camera captures images and sends them to the processing unit, where the AI model processes the data. The output is then transmitted to the microcontroller, which activates the speaker system.

The system is tested under different conditions to ensure reliability and performance. Proper calibration is done to optimize detection accuracy and sound effectiveness.

Table 3: Dataset Distribution for Training and Testing

Bird Species	Training Images	Testing Images	Total Images
Crow	500	100	600
Sparrow	450	90	540
Pigeon	400	80	480
No Bird	300	60	360
Total	1650	330	1980

VI. RESULTS AND EVALUATION

The system is evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics help measure the performance of the detection and classification models.

The results show that the system achieves high accuracy, ranging from 90% to 95%. The precision and recall values are also high, indicating reliable detection of birds [11]. The F1-score shows a balanced performance of the system.

Field tests indicate a significant reduction in bird activity after the deployment of the system. The adaptive sound mechanism effectively deters birds and prevents them from returning.

Overall, the system demonstrates strong performance and reliability in real-world conditions.

Table 4: Performance Metrics of the Proposed System

Metric	Value (%)
Accuracy	93%
Precision	91%
Recall	92%
F1-Score	91.5%

Table 5: Reduction in Bird Activity After System Deployment

Day	Bird Count Before	Bird Count After	Reduction (%)
Day 1	50	20	60%
Day 2	45	15	66%
Day 3	60	18	70%
Day 4	55	17	69%

VII. DISCUSSION

The proposed system provides significant improvements over traditional bird deterrent methods. The use of AI enables real-time detection and accurate classification of birds. The adaptive sound mechanism prevents habituation, making the system effective in the long term [10].

The integration of IoT enhances the usability of the system by enabling remote monitoring and control. This reduces the need for manual intervention and improves efficiency.

However, the system has some limitations. Environmental conditions such as rain and poor lighting can affect performance. The initial setup cost may also be higher compared to traditional methods.

Despite these limitations, the system offers a reliable and intelligent solution for crop protection.

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VIII. OUTPUT

Figure 2: bird detection

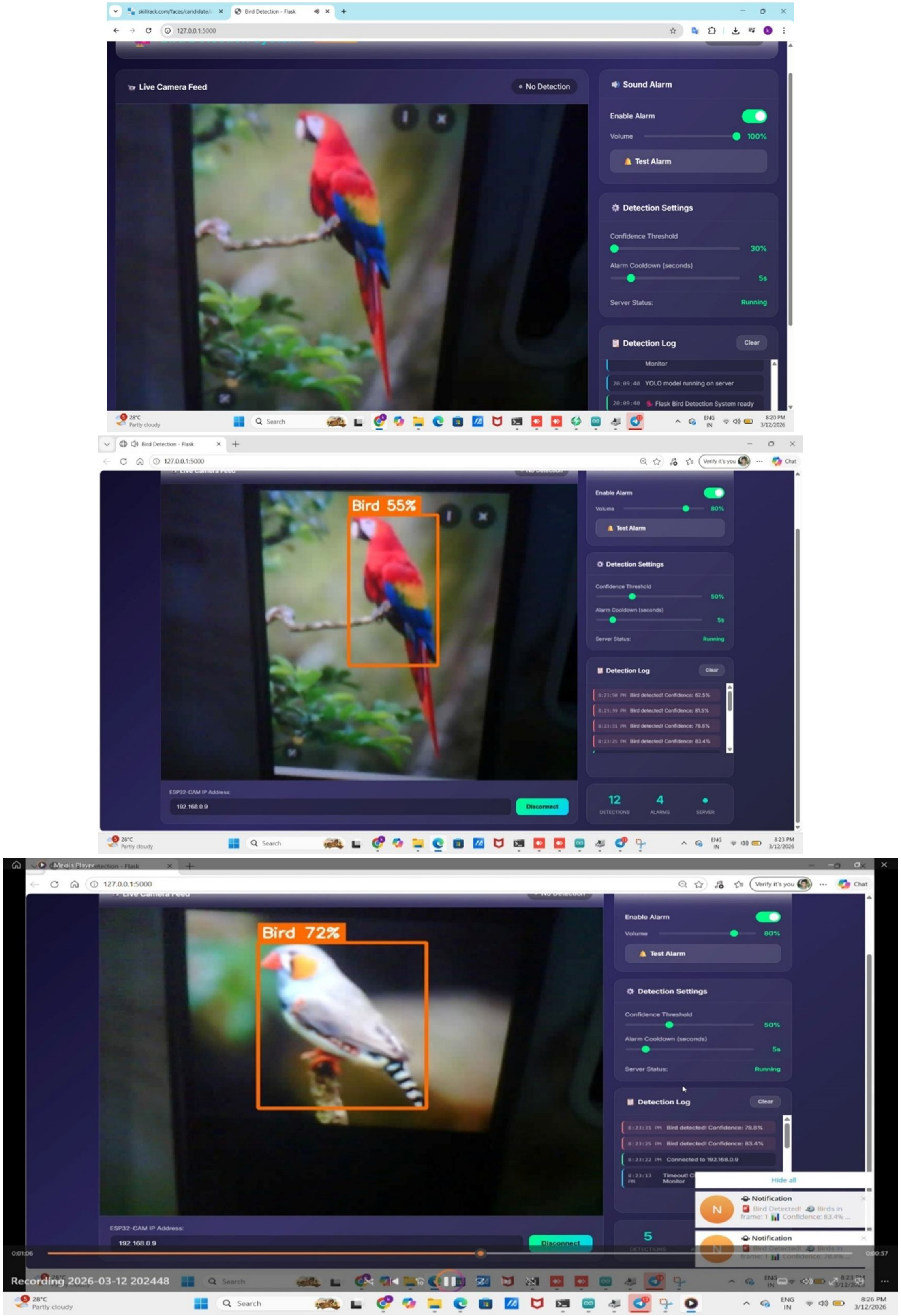
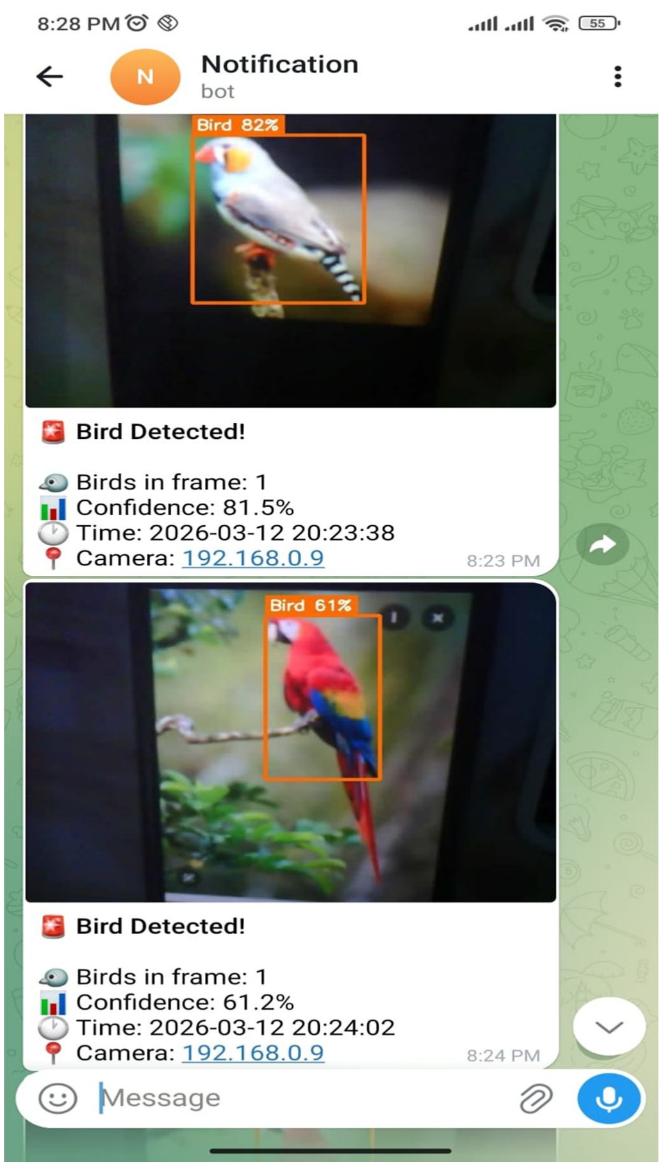


Figure 3: Notification alert



IX. CONCLUSION

The AI-based bird deterrent system provides an effective solution for reducing crop damage caused by birds. By integrating AI, computer vision, and IoT, the system achieves real-time detection and adaptive response.

The use of deep learning models ensures high accuracy, while adaptive sound generation prevents habituation. This makes the system more effective than traditional methods.

The system is automated, eco-friendly, and suitable for modern agriculture. It helps improve crop yield and reduces losses, supporting sustainable farming practices.

Future improvements can include drone integration, solar power, and mobile applications for enhanced functionality.

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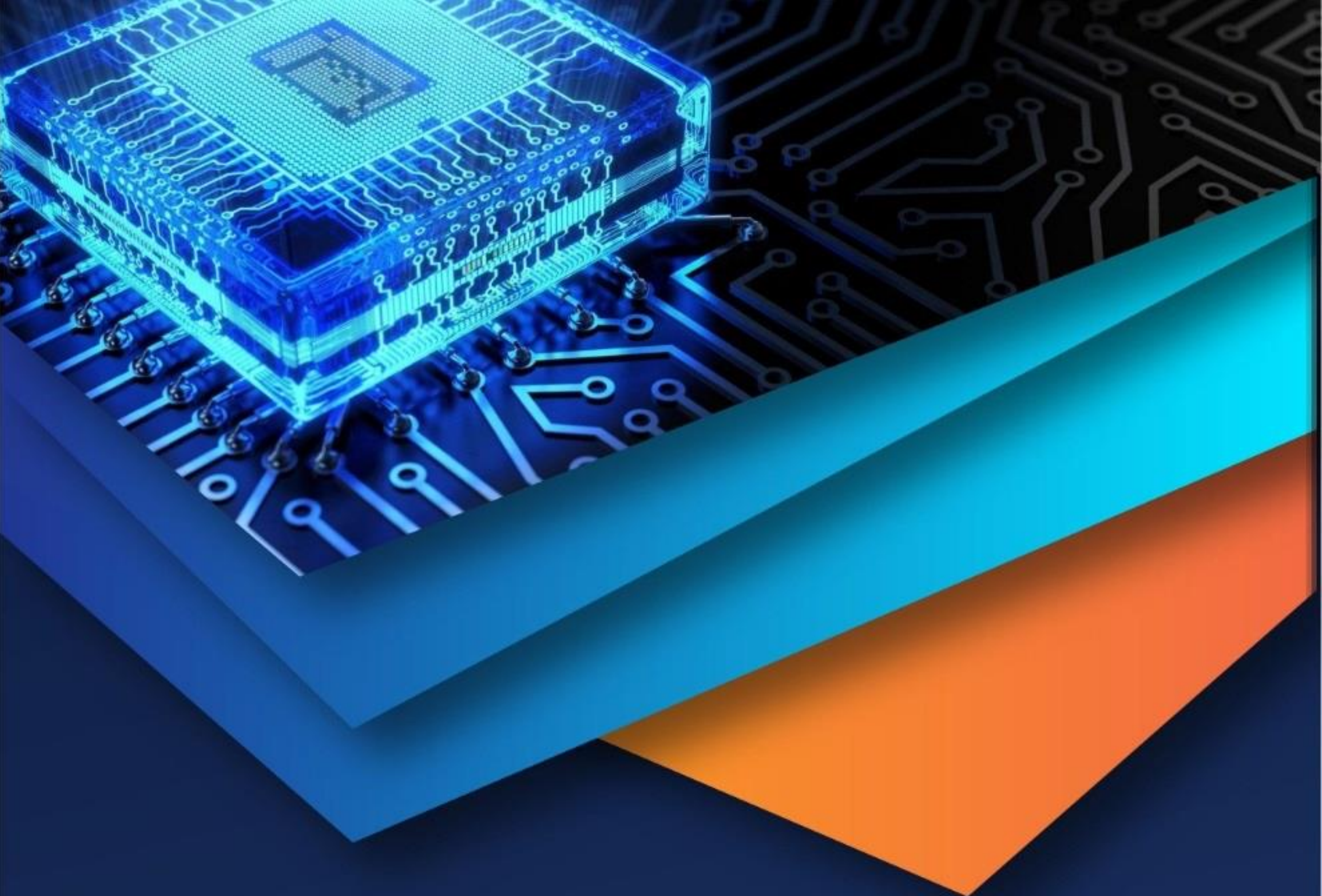

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