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Development of An Edge AI Powered Precision Pest Control Robot for Smart Agriculture Using Raspberry PI

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Abstract - **This paper proposes the design of an edge AI-based intelligent agricultural system that can help increase crop productivity through efficient pest control and monitoring of the condition of the soil. In the proposed system, there is a pest detection module based on deep learning that can detect pests from the image obtained from the leaves of the crops or the image obtained from the crops themselves. In addition, the system can monitor the condition of the soil through the measurement of the moisture level, pH value, and temperature of the soil using IoT sensors. An autonomous rover is used to move around the crops and take images from different points of the crops as well as measure the environmental conditions. This data is then used to provide efficient recommendations through the usage of a large language model. Additionally, it provides forecasts for the potential yield of crops depending on the soil or environmental factors. The proposed method has the potential to reduce manual labor and promote efficient farming practices by incorporating edge AI, mobile sensing, and data-driven decision support.**

Keywords - Edge Artificial Intelligence, Smart Agriculture, Pest Detection, Internet of Things (IoT), Autonomous Agricultural Rover, Raspberry Pi, Precision Farming

I. INTRODUCTION

Agriculture is an essential aspect that has substantial effects on the security and stability of the world's food supply and economic development. However, the conventional methods employed in the farming sector involve manual monitoring and experience-oriented decision-making, which has often resulted in inefficient usage of resources and low productivity in the cultivation of crops. In the recent past, the incorporation of the latest technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning has dramatically changed the way farming is carried out, leading to the emergence of the term precision agriculture [1].

Precision agriculture aims at optimizing agricultural practices through the acquisition of information regarding different environmental parameters, such as moisture, temperature, humidity, and nutrient content of the soil. IoT technology-based sensors and smart devices are used to monitor environmental parameters in agricultural fields, which helps farmers to react to changing environmental conditions. The incorporation of IoT technology into agricultural activities has helped optimize resources, reduce water consumption, and increase agricultural yields [2], [3].

Recent developments in cloud computing and wireless communication technologies have also improved IoT-based agricultural monitoring systems. Data collected by sensors in the field may be transmitted to clouds for storage, analysis, and visualization, which may be accessed by farmers in remote locations to obtain valuable insights about their fields and make proper decisions regarding irrigation, pest management, and crop selection [4].

Another significant challenge facing the agricultural sector is the detection and management of plant diseases, as they have the potential to affect the yield of crops. In the past, the detection of plant diseases was based on manual inspection by experts. However, the procedure was a tedious one that was sometimes subject to human mistake. In recent times, the detection of plant diseases has been widely implemented through using computer vision and deep learning techniques. Convolutional Neural Networks have been used to detect plant diseases from the images of leaves with remarkable accuracy [5], [6].

The combination of AI image analysis with IoT environmental monitoring systems may improve decision-making in the agricultural sector. By integrating sensor data and image crop analysis, smart agriculture systems may offer holistic information on crops and environmental status. These systems may enable farmers to take interventions in crops such as precision irrigation, nutrient management, and disease control, thus improving crop productivity and sustainability [7].

This study proposes a smart agriculture monitoring system with the concept of intelligent IoT technology and machine learning for plant diseases, inspired by the aforementioned developments. The suggested system is based on the NodeMCU microcontroller and a series of sensors, including the DHT11 sensor for temperature and humidity measurements, as well as the soil moisture sensor for water level measurements. The agricultural field is equipped with sensors that collect environmental data and transmit it to the cloud platform.

In addition to the above parameters, the proposed system includes an automated control mechanism for maintaining the optimal growing environment. If the sensor readings are below the threshold value, the system will be able to control the devices such as motors and fans for maintaining the optimal growing environment.

Furthermore, the system includes a camera module for the capture of images of the leaves of the plants in order to detect diseases. The captured images are then analyzed through Convolutional Neural Networks (CNN) in order to detect diseases such as fungi and nutrient deficiency in the plants. Early detection of diseases in the plants enables the farmer to take early precautions in order to prevent the damage and maintain the health of the plants.

Thus, the proposed system provides a comprehensive solution for modern agriculture through the integration of IoT-based monitoring systems, automated environmental control systems, and AI-based disease detection systems. The proposed system aims at improving the productivity of the farms and the efficient use of resources in order to develop a more efficient and sustainable agricultural system. In order to create a more sophisticated and intelligent agricultural monitoring system, future advancements in the suggested system could involve adding more sensors to track additional factors including light intensity, air quality, and soil nutrient content.

II. LITERATURE REVIEW

The rapid advancement in smart technology has led to a number of developments in precision agriculture systems. Various researchers have used IoT devices, artificial intelligence, and machine learning algorithms for efficient crop monitoring, disease prediction, and resource management in agriculture systems. In this section, a number of existing research studies on IoT-based crop monitoring systems, automated control systems, and artificial intelligence-based plant disease prediction systems are discussed.

IoT technology has been widely used in modern agriculture systems for monitoring environmental conditions and soil parameters in real-time. Various researchers have used sensor-based systems for efficient crop monitoring in agriculture systems. A study on a smart agriculture monitoring system was conducted by researchers in which a wireless sensor network was used for monitoring soil moisture, temperature, and humidity levels in real-time conditions. The sensor nodes send signals to a cloud platform where a farmer can monitor the conditions remotely for efficient irrigation practices. The results showed efficient water management practices in agriculture systems for crop productivity [8].

Some researchers have also emphasized the development of automatic irrigation systems using IoT technology. In this system, soil moisture sensors are utilized to detect the moisture requirements of the crops. Once the moisture level in the soil drops below a certain threshold, the system will automatically turn on the pumps for irrigation purposes. This system helps in reducing water wastage and ensures efficient irrigation management in regions where water scarcity is a major problem. [9].

Another technology that has further augmented the potential of IoT-based agricultural systems is cloud computing. Cloud computing has enabled the storage of a large amount of data, which can be used for analysis. Farmers can now access this data in real-time or in a historical format, which can be used for visualization or even prediction using cloud computing platforms. A study on cloud computing in agriculture monitoring systems showed that by integrating IoT sensors with cloud computing systems, decision-making processes can be augmented for farmers who can monitor their agricultural systems remotely through mobile applications or web interfaces. [10].

Another key challenge in agriculture is the early detection of diseases in plants, which can affect the overall yield of crops in terms of quantity and quality. Conventional methods for disease detection in plants heavily rely on manual inspection by experts in agriculture. However, this approach is often cumbersome and may not be feasible for large agricultural fields. In this regard, researchers have now started using computer vision for the automated detection of diseases in plants [11].

Deep learning approaches, such as Convolutional Neural Networks (CNN), have demonstrated promising results in plant disease classification problems. CNN-based approaches are capable of automatically extracting useful features from plant leaf images and effectively classifying diseases without any need for feature engineering. Researchers have demonstrated that CNN models, when applied to large datasets of plant diseases, are capable of achieving high classification accuracy in plant disease classification problems [12].

In addition to this, some studies have also focused on the concept of integrated smart farming systems, wherein the

Internet of Things technology, along with machine learning algorithms and control mechanisms, can be implemented for effective smart agriculture practices. In this regard, environmental sensors are used to collect data, and based on this data, the growth patterns can be analyzed using machine learning algorithms, thereby suggesting suitable agricultural practices. [13].

Research has also recently focused on the development of autonomous agricultural platforms such as drones and robotic systems that can be used in monitoring crops. These autonomous platforms can take images with high resolutions and can obtain environmental information from multiple locations in the field. The autonomous platforms can improve the spatial accuracy in monitoring the fields and can reduce the need to physically go into the fields [14].

However, despite these developments, many agricultural monitoring systems have been designed to focus on specific monitoring activities, such as environmental monitoring and plant diseases. Therefore, there is still the need to design an integrated system that can incorporate IoT technology, automated environmental control mechanisms, and image analysis using AI technology into a unified platform that can provide complete information about the state of the plants and the environmental conditions, which can be used to carry out precision farming. Based on the above challenges and problems, the proposed system has the objective of integrating IoT technology with automated environmental control mechanisms and plant diseases using CNN technology into a unified platform that can be used to carry out smart farming activities.

III. System Architecture

The smart agriculture monitoring system, as suggested, incorporates Internet of Things technology, cloud data processing, and artificial intelligence technology in the detection of diseases in plants into a single, efficient, and effective system. The purpose of the smart agriculture monitoring system is to improve agricultural monitoring activities through the real-time observation of environmental conditions. The smart agriculture monitoring system incorporates various advanced technologies, which are essential in precision agriculture activities. The smart agriculture monitoring system architecture allows farmers to monitor various critical environmental parameters, such as temperature, humidity, and moisture, through the incorporation of Internet of Things technology sensors in the agricultural field. The sensors are used to retrieve information, which is then sent to a cloud platform for processing, storing, and visualizing the information, thus enabling the farmer to observe the condition of the agricultural field at all times.

In addition to this, the system also includes an automatic control mechanism that may respond to unfavorable environmental conditions detected by the sensors. If any of the parameters detected by the sensors are beyond the threshold values, the system may automatically turn on motors or fans to regulate environmental conditions. This automation may also ensure proper growing conditions for crops.

Another vital component of the proposed system is the AI-based plant disease detection module. The camera module of the proposed system may be used to capture images of plant leaves directly from the field. These images may be analyzed by using machine learning algorithms, particularly Convolutional Neural Networks (CNN), which may detect patterns of plant diseases. Early detection of diseases may help farmers take preventive measures to avoid losses to crops and improve plant health.

The smart agriculture monitoring system is illustrated in **Fig. 1**, which highlights the interaction between different system components. The architecture demonstrates how environmental sensor data and plant leaf images are collected from the field, transmitted through IoT communication networks, processed using cloud-based platforms, and analyzed using machine learning models. This integrated approach enables intelligent decision-making and provides farmers with valuable insights for efficient farm management.

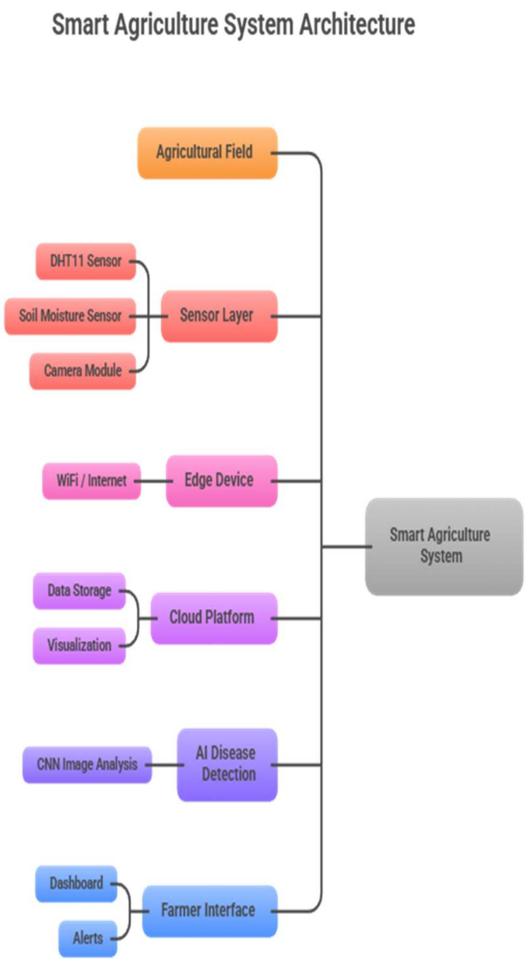

Fig. 1. Overall Architecture

A. IoT-Based Environmental Monitoring Module

The first component of the suggested architecture is the IoT-based environmental monitoring module. The module is in charge of gathering data from the agricultural field in real-time using different sensors. Environmental parameters such as temperature, humidity, and moisture are constantly monitored by using different sensors such as DHT11 temperature and humidity sensors and soil moisture sensors. These sensors are placed in different locations of the field to obtain accurate environmental parameters for crop growth.
The data collected from different sensors is communicated to the central controller by using wireless communication protocols. Constant monitoring of environmental parameters helps farmers to comprehend micro-climatic parameters of the field and make accurate decisions regarding crop management, fertilizer use, and irrigation. Recent studies have proven that IoT-based environmental monitoring systems improve precision farming by analyzing environmental parameters in real-time [15].

B. Edge Processing and Communication Layer

The second part of the system architecture is the edge processing and communication layer. In the proposed system, a microcontroller called NodeMCU is used as the main edge device for collecting sensor data and sending it to the cloud platform. NodeMCU is a microcontroller based on the ESP-12 platform and is capable of processing raw sensor data and sending it via Wi-Fi communication to remote servers for further analysis and processing. Edge devices are significant in reducing latency and increasing the efficiency of agricultural monitoring systems. Edge devices can process data collected from the field and send it to the cloud for further analysis and processing, and this is the main reason for using edge device architecture in smart agriculture applications [16].

C. Cloud-Based Data Storage and Monitoring Platform

The cloud platform is the central hub that is used for the storage, analysis, and visualization of the data. The sensor data sent from the NodeMCU is stored in the cloud database, which can be accessed remotely using the web and mobile application dashboards. The cloud platform will enable the farmer to analyze the environmental conditions in the fields in real-time and historical trends in environmental parameters using the cloud infrastructure. Cloud computing can be used to perform complex data analysis, which can be used to analyze patterns that can be related to the growth of the crops and environmental parameters. Visualization dashboards can be used to display the data to the farmers in an easily understandable format, which can be used to analyze the environmental parameters such as temperature, humidity, and soil moisture. IoT and cloud integration has been recognized as the key enabler of the precision farming movement [17].

D. Plant Disease Detection Module Powered By AI

The final part of the architecture is the AI-based plant disease detection module. This module uses the camera module that is embedded in the field to take images of the plant leaves. The images that have been obtained are then processed using the Convolutional Neural Network (CNN), which is able to analyze the images and detect the plant diseases that may be affecting the plants. Using photos of the plant's leaves, the deep learning method has shown remarkable success in identifying plant illnesses. The CNN approach is able to detect the diseases that affect the plants using the images that have been obtained from the leaves, such as discoloration and spots that may occur on the leaves due to the diseases [18].

IV. HARDWARE AND SOFTWARE IMPLEMENTATION

The proposed Edge-AI powered precision pest control robot is based on the integration of hardware and intelligent software modules that can automatically detect pests and control them in the agricultural environment. The suggested solution is based on the direct deployment of the mobile robotic platform with intelligent software modules/hardware in an agricultural environment. The hardware modules can collect environmental and visual information from the agricultural environment, and the intelligent software modules can process the information through the application of artificial intelligence algorithms.

The application of edge computing and AI can enable the proposed system to automatically detect pests in the agricultural environment without the application of cloud computing.

The overall implementation architecture of the proposed system is illustrated in Fig. 2.

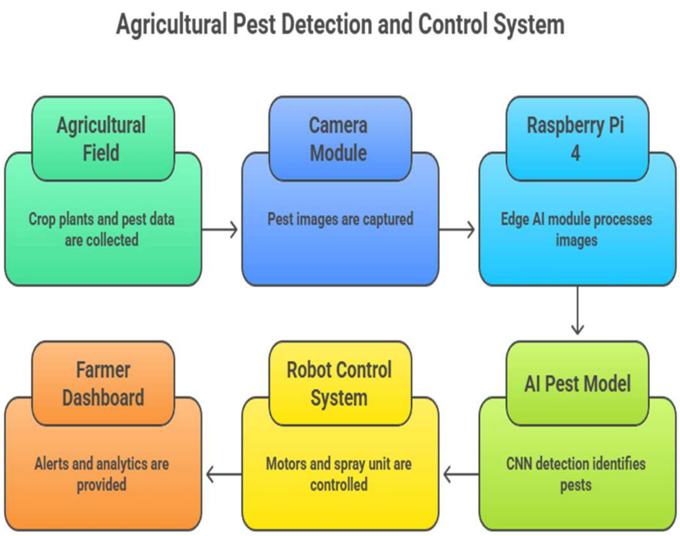

Fig. 2. Edge AI–Based Pest Control Robot System Architecture

A. Hardware Components

The hardware subsystem of the proposed robot consists of embedded computing units, environmental sensors, motor control modules, and imaging devices that enable the robot to navigate agricultural fields and collect data. The **Raspberry Pi** acts as the CPU, providing sufficient computational capability to execute edge AI models and control robotic movement.

A **camera module** is integrated into the robot to capture high-resolution images of crop leaves and surrounding areas. These images are used for pest detection using deep learning algorithms. Additionally, environmental sensors such as soil moisture sensors and temperature sensors can be integrated to monitor crop health conditions.

Motor drivers and DC motors are used to enable the rover to navigate across crop rows. A spraying mechanism is also integrated into the robot to apply pesticides precisely in locations where pests are detected.

Table 1. Hardware Components Used in the Proposed System

Component	Description	Purpose
Raspberry Pi 4	Edge computing device	Executes AI model and controls robot
Camera Module	High-resolution camera	Captures crop and pest images
Soil Moisture Sensor	Measures soil water level	Monitors soil conditions
Motor Driver (L298N)	Controls DC motors	Enables robot movement
DC Motors	Drive wheels of rover	Field navigation
Pesticide Spray Unit	Sprayer mechanism	Targeted pest control

Recent studies show that Raspberry-Pi-based edge computing systems are highly effective for deploying AI models in agricultural robotics due to their low cost, portability, and sufficient processing capabilities [19].

B. Edge AI Pest Detection Module

The intelligence of the proposed system lies in the Edge AI pest detection module, which uses deep learning algorithms to detect pests based on images taken through the camera mounted on the device. The system uses a CNN model to identify different types of pests and infected areas of the crops.

A pre-trained model of the Edge AI device is used, which runs directly on the device, a Raspberry Pi, allowing the system to perform inference at the edge, thus not relying on the cloud to perform this function, which allows the system to perform pest detection more quickly, a critical function of smart agriculture, as pest detection needs to be performed in a timely manner to allow for effective pest control.

Deep learning-based systems have been shown to perform effectively in detecting pests, as they are accurate in detecting different types of insect species [20].

Table 2. AI Model Configuration

Parameter	Value
Model Type	Convolutional Neural Network
Training Dataset	Agricultural pest image dataset
Image Resolution	224 × 224
Framework	TensorFlow / PyTorch
Deployment	Raspberry Pi Edge Device

I.

C. Robotic Navigation and Pest Control Mechanism

The robotic platform is essential in the movement and taking images from different angles in the agricultural fields. The rover is equipped with DC motors that are connected to the raspberry pi via the motor driver module. The movement is achieved through the control algorithm, which guides the robot through the rows of the crops. Once the AI algorithm has identified the pests, the robot is able to spray the pesticides using the precision pesticide spraying mechanism. This mechanism ensures that the pesticides reach the infected plants only, hence minimizing the environmental effects and the usage of the pesticides. The precision pesticide spraying mechanism has greatly enhanced the efficiency of the pesticides in the modern smart farming systems [21].

D. Software Framework and Data Processing

The software architecture of the proposed system has several layers, including data acquisition, AI processing, robotic control, and user interaction. In addition, the system software is implemented using Python as the programming language because it is compatible with AI libraries such as TensorFlow and OpenCV. Image processing is implemented using OpenCV libraries to process the acquired images before they are sent to the CNN model for image classification and determination of the presence of pests. The results from the AI model are then sent to the monitoring system for the farmer to monitor the system status. Edge AI systems with IoT connectivity enable efficient data processing and provide intelligent decision support for smart agricultural applications. [22].

V. Experimental Results and Discussion

The experimental evaluation of the proposed edge AI-powered precision pest control robot was performed to assess the efficacy of the system in detecting pests, monitoring crop conditions, and performing precision pest control operations. The edge AI system was tested using the dataset of pest images and real-time data collected from the sensors and the camera module of the system. The experiments performed aimed to test the effectiveness of the AI system, the response time of the edge computing system, and the reliability of the precision pest control robot.

The experiments were performed in a controlled agricultural environment where the precision pest control robot was used to navigate through the crops and take images of the leaves of the plants. The images taken by the precision pest control robot were used as input to the Convolutional Neural Network (CNN) model running on the edge computing platform based on the Raspberry Pi system. The images were classified as pest-infected and healthy plant leaves, allowing the precision pest control robot to spray the pests using the targeted spraying mechanism.

A. Dataset and Training Configuration

The pest detection dataset was used to train the model with labels, consisting of images of different crop pest species collected from publicly available datasets and images collected from the fields. Images were used in the dataset, showing the patterns of damage caused by pests to plants. Images were preprocessed before being used in the model training process.

Table 3. Training Dataset Configuration

Parameter	Value
Dataset Type	Agricultural Pest Image Dataset
Total Images	4,000
Exercise Set	60%
Mutation Set	20%
Test Set	20%

The CNN model was trained using the TensorFlow library with multiple epochs to improve the accuracy of the classification results. Various data augmentation techniques were used to improve the variety of the dataset. These include rotation, flipping, and brightness adjustment.

B. Pest Detection Performance Evaluation

The classification metrics like precision, recall, F1-score, and accuracy were used to determine the efficiency of the proposed module of AI-based pest detection. The results show the high accuracy of the suggested approach for distinguishing between healthy plants and those infected with pests.

Table 4. Performance Evaluation of the Pest Detection Model

Metric	Value
Accurate	94.2%
Precision	94.6%
Recall	93.8%
F1-Score	92.2%

From the results obtained, it is evident that the CNN-based model is effective in the detection of pest infestations in the crops. The usage of the proposed model on the Raspberry Pi edge device is effective since it does not involve the usage of cloud computing.

C. Edge AI Processing Performance

Another significant factor in the evaluation was the performance of the edge AI module in terms of processing performance. The inference time of the CNN model running on the Raspberry Pi device was measured to evaluate its real-time performance.

Table 5. Edge AI Processing Performance

Parameter	Result
Average Inference Time	0.85 seconds
CPU Usage	58%
Memory Usage	1.2 GB
Power Consumption	6.5 W

The findings demonstrate that the edge computing system based on the Raspberry Pi device efficiently runs the AI model with low power consumption, which enables the system to be deployed in a remote agricultural field where resources are scarce.

D. System Performance Analysis

The robotic platform was also assessed based on its capacity to move in agricultural fields and conduct specific pest control operations. During the experiments, the robot was able to identify the pest-affected plants and activate the pesticide spraying mechanism only in the affected areas.

Fig. 3. Training Accuracy of the Pest Detection Model

The experimental results show that the efficiency of the pest detection and control can be enhanced through the integration of edge AI and robotic platforms. Previous studies have proved that the application of agricultural robots based on AI technologies can improve the accuracy of pest detection and reduce the usage of chemical pesticides through the spraying method [23], [24]. Moreover, the application of edge computing technologies has achieved the effectiveness in the processing and response of smart agricultural data [25], [26].

VI. Conclusion and Future Enhancements

A. Conclusion

In this discourse, the design of an Edge AI-based precision pest control robot for smart agriculture using the Raspberry Pi has been discussed. In this system, edge computing, computer vision, and IoT technologies are utilized for real-time pest detection and management in the field of agriculture. In this system, a mobile robot and an AI-based pest control model are utilized for monitoring the crop condition and controlling the pest in the field of agriculture. The implementation is based on the Raspberry Pi edge computing platform, environmental sensors, and a camera module to collect the images and plant information from the fields. The images are then processed using the proposed CNN model to detect the presence of pests with high accuracy. The experiment results show that the proposed system can efficiently detect the infected plants with pests and perform the processing with efficient performance on the edge device. Moreover, the proposed robotic system can efficiently perform the navigation and spraying tasks in the fields, which minimizes the usage of chemical pesticides.
Overall, the proposed system based on edge AI, robotics, and IoT technologies can efficiently solve the problem with the advantages of the proposed system in terms of efficiency and cost-effectiveness for modern agricultural fields. The proposed system can efficiently improve the efficiency of the agricultural fields with the reduced usage of chemical pesticides and can confirm the importance of agricultural robots based on AI technologies in the fields.

B. Future Work

Though this proposed system shows encouraging results, certain aspects can be taken up in future work for further improvement in the system's efficiency. Some of these aspects include the incorporation of more advanced deep learning models for more precise pest detection.
Future versions of this system can be designed with autonomous navigation systems, including GPS or computer vision for row detection, which can help the robot move through fields more effectively without human intervention.
In addition, multi-spectral or hyperspectral cameras can be used for more in-depth analysis of plant health by recognizing early signs of stress or diseases that may not be visible through normal cameras.

Another area that needs to be explored in the future is the integration of predictive analytics and large language models, which can offer intelligent suggestions regarding pest management, fertilizers, and irrigation systems. This can be achieved by examining the historical patterns in crop cultivation and environmental factors, thereby assisting in better decision-making by farmers.
In the future, the structure can be enhanced to make it more energy-efficient by using solar-powered modules and wireless sensors, thereby enabling the system to be used in a wider area for agriculture.

In conclusion, the continued integration of edge AI, robotics, and smart sensing technologies has the potential for revolutionizing agricultural pest management while creating more efficient and sustainable farming systems.

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