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Development of Intelligent Pesticide Sprinkling System Determined by the Infection Level of a Plant (IOT based)

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Abstract: This paper presents the development of an IoT-based intelligent pesticide sprinkling system for rice crops using image processing and machine learning techniques. The system aims to overcome the limitations of traditional pesticide spraying methods, which often result in excessive chemical usage, environmental pollution, and health risks to farmers. A camera module (ESP32-CAM) captures real-time images of rice leaves, which are processed using OpenCV and analyzed through a Convolutional Neural Network (CNN) model trained using TensorFlow. The model identifies common rice diseases such as bacterial leaf blight, brown spot, and leaf smut, and determines the infection severity. Based on the detection results, the ESP32 microcontroller activates a relay module that controls a DC pump to spray pesticides only on infected areas. The system also features an IoT-based dashboard for real-time monitoring, visualization, and remote operation. Experimental results demonstrate effective disease classification, with clear visualization using Grad-CAM and probability graphs. The proposed system reduces pesticide usage, minimizes human exposure to harmful chemicals, and enhances crop productivity. It provides a low-cost, efficient, and scalable solution for precision agriculture and smart farming applications.
Keywords: IoT, Rice Leaf Disease Detection, Convolutional Neural Network (CNN), Precision Agriculture, Smart Pesticide Spraying.

I. INTRODUCTION

Agriculture plays a crucial role in the economic development of many countries, especially in India, where it supports a significant portion of the population. Among various crops, rice is one of the most widely cultivated staple foods, contributing substantially to food security and rural livelihoods. However, rice production is continuously affected by various biotic stresses, particularly plant leaf diseases such as bacterial leaf blight, brown spot, and leaf smut, which lead to significant yield losses [1].

Traditional methods of disease detection rely heavily on manual observation by farmers or agricultural experts. These methods are time-consuming, subjective, and often inaccurate, especially during the early stages of infection [2]. Moreover, conventional pesticide spraying techniques involve uniform application across the entire field, regardless of the actual infection level. This leads to excessive pesticide usage, increased production costs, and severe environmental consequences such as soil degradation and water contamination [3].

In recent years, advancements in artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) technologies have opened new possibilities for smart agriculture. Machine learning models, particularly Convolutional Neural Networks (CNNs), have shown high accuracy in image-based plant disease detection tasks [4]. These models can automatically learn features from images and classify diseases more effectively than traditional methods.

The integration of IoT enables real-time monitoring and control of agricultural systems. Devices such as the ESP32 microcontroller allow seamless communication between sensors, actuators, and cloud platforms, enabling automated decision-making and remote access [5]. By combining AI-based disease detection with IoT-enabled automation, it becomes possible to develop intelligent systems capable of detecting plant diseases and taking appropriate actions without human intervention.

This project proposes an IoT-based intelligent pesticide sprinkling system specifically designed for rice crops. The system uses an ESP32-CAM module to capture images of rice leaves, which are then processed using OpenCV and analyzed using a trained CNN model. Once a disease is detected, the system automatically activates a relay-controlled DC pump to spray pesticides directly onto the affected area. This targeted approach ensures efficient use of pesticides and minimizes environmental impact.

Additionally, the system includes a user-friendly dashboard that displays classification results, confidence levels, and system status. Visualization tools such as graphs and Grad-CAM provide insights into model performance and decision-making. The automation of pesticide spraying not only reduces labor dependency but also enhances safety by limiting human exposure to harmful chemicals. Overall, the proposed system represents a significant step toward precision agriculture by integrating intelligent disease detection, IoT-based monitoring, and automated pesticide application. It offers a cost-effective and scalable solution for improving crop health, increasing productivity, and promoting sustainable farming practices.

II. PROBLEM IDENTIFICATION

1) Conventional electric vehicles rely heavily on external Rice crops are highly susceptible to diseases such as bacterial leaf blight, brown spot, and leaf smut, which significantly reduce yield and quality.
2) Traditional disease detection methods depend on manual inspection, which is time-consuming, inaccurate, and requires expert knowledge.
3) Farmers often fail to identify diseases at an early stage, leading to delayed treatment and increased crop damage.
4) Conventional pesticide spraying methods apply chemicals uniformly across the field, regardless of infection level, causing excessive pesticide usage.
5) Overuse of pesticides results in environmental pollution, soil degradation, and contamination of water resources.
6) Manual spraying exposes farmers to toxic chemicals, increasing the risk of respiratory diseases, skin problems, and other health issues.
7) Existing solutions lack integration of real-time disease detection with automated pesticide application systems.
8) Many advanced systems are costly and not affordable for small and medium-scale farmers.
9) There is limited use of IoT and AI integration in practical agricultural applications for targeted spraying.
10) Hence, there is a need for a smart, low-cost, and automated system that can detect diseases early and apply pesticides precisely.

Figure 1. Rice Leaf Disease

A. *Existing system*

- Traditional farming relies on manual inspection to identify rice leaf diseases, which depends heavily on farmer experience and expertise.
- Pesticide spraying is generally done uniformly across the entire field without considering infection levels.
- Conventional sprayers such as hand sprayers and motorized pumps are widely used for chemical application.
- There is no real-time monitoring or automated decision-making system in place.
- Disease detection is often delayed, leading to increased crop damage and reduced yield.
- Farmers must physically visit fields frequently, increasing labor and time requirements.
- Existing methods lack integration of advanced technologies like IoT, AI, or image processing.
- No proper visualization or data tracking system is available for monitoring crop health.

B. *Drawbacks*

- Manual disease detection is inaccurate and may lead to misclassification or delayed identification of plant diseases.

- Uniform pesticide spraying results in excessive chemical usage and increased farming costs.
- Overuse of pesticides causes environmental pollution and affects soil fertility and water quality.
- Farmers are exposed to harmful chemicals, leading to serious health risks.
- Lack of automation increases labor dependency and operational effort.
- Inefficient spraying leads to wastage of resources and reduced effectiveness of treatment.
- No real-time monitoring or alert system for early disease detection.
- Existing systems are not suitable for precision agriculture practices.

III. LITERATURE SURVEY

A. Literature Review

O. Debnath et al. (2022) developed an IoT-based intelligent farming system integrated with a CNN model for early detection of rice brown spot disease. Their system uses real-time image acquisition and cloud-based processing to identify disease symptoms at an early stage. The model achieved high accuracy (around 97%), enabling timely intervention. The study highlights how combining IoT with deep learning improves monitoring efficiency, reduces manual effort, and supports precision agriculture. It also demonstrates the potential for reducing crop losses through early and automated disease detection.

K. Kiratiratanapruk et al. (2022) proposed a rice disease detection system using image tiling combined with CNN. Their approach divides images into smaller sections, improving detection accuracy for leaves of varying sizes and shapes. This method performs well in real field conditions where lighting and background vary. The study shows that image tiling enhances feature extraction and model performance. It provides a practical solution for handling complex agricultural datasets and improves reliability in real-time disease detection systems.

P.K. Rajani et al. (2023) presented a CNN-based rice leaf disease classification system using labeled datasets. The model successfully identified major diseases such as leaf blight and brown spot with high accuracy. Their work emphasizes the importance of supervised learning and proper dataset labeling for improving classification performance. The study demonstrates that CNN models are effective for automated disease detection and can replace manual inspection methods. It also highlights the role of deep learning in enhancing agricultural productivity.

4. P. Seelwal et al. (2024) P. Seelwal et al. (2024) explored hybrid deep learning techniques for rice disease recognition. Their approach combines multiple neural network architectures to improve classification accuracy and robustness. The study shows that hybrid models outperform traditional single-model approaches by capturing complex features more effectively. The findings indicate improved reliability in detecting multiple disease types under varying conditions. This research contributes to the advancement of intelligent agricultural systems by enhancing model accuracy and generalization.

K. Saddami et al. (2024) introduced lightweight CNN models, such as EfficientNet, for rice leaf disease detection. These models are optimized for mobile and edge devices, making them suitable for real-time applications. The study achieved high accuracy while maintaining low computational complexity. It demonstrates that lightweight models can be effectively deployed in IoT-based agricultural systems. This research supports the development of cost-effective and portable solutions for farmers.Pandiyaraju V. et al. (2024) proposed a channel attention-based CNN model for paddy leaf disease detection. The model enhances feature extraction by focusing on important regions of the image. This approach achieved nearly 99% accuracy, showing significant improvement over traditional CNN models. The study highlights the importance of attention mechanisms in improving classification performance. It provides a highly efficient solution for accurate disease detection in smart farming applications.

P. Pai et al. (2025) developed a deep learning-based system for diagnosing rice leaf diseases using advanced CNN architectures. Their model improved precision and reduced misclassification across multiple disease categories. The study emphasizes the importance of robust model design and large datasets. It demonstrates reliable performance in complex agricultural environments. The research contributes to improving automated disease diagnosis systems for precision agriculture.

K. Fang et al. (2025) introduced an improved YOLO-based model (RLDD-YOLOv11n) for rice disease detection. The model enhances small lesion detection and achieves high accuracy with 88.3% mean average precision (mAP). It is suitable for real-time applications due to its fast processing speed. The study highlights the effectiveness of object detection models in agricultural disease monitoring. It provides a strong foundation for real-time smart farming systems.

S. Sharma et al. (2025) proposed a CNN-based system for identifying multiple rice leaf diseases using large datasets. The model classified up to nine disease categories with good accuracy.

The study demonstrates the scalability of CNN models in handling diverse datasets. It emphasizes the importance of dataset diversity in improving model performance. The research supports the development of comprehensive disease detection systems.

A.B. Ayyappan et al. (2025) presented a deep learning approach for automated rice plant disease detection. Their model successfully identified diseases such as blast, blight, and brown spot. The study highlights the role of deep learning in enabling early detection and timely intervention. It demonstrates improved accuracy and efficiency compared to traditional methods. This research contributes to the advancement of intelligent agricultural solutions.

B. Literature Summary

Recent studies highlight the growing use of deep learning and IoT in rice leaf disease detection. Convolutional Neural Networks (CNNs) and advanced models like EfficientNet, YOLO, and hybrid architectures have achieved high accuracy in identifying diseases such as leaf blight, brown spot, and leaf smut. Techniques like image tiling and attention mechanisms further improve performance under real field conditions. Lightweight models enable deployment on mobile and IoT devices, making solutions more practical. However, most research focuses mainly on classification accuracy and model optimization. While these systems demonstrate strong detection capabilities, their application in real-time field operations and integration with automated control systems remains limited.

C. Research Gap

Despite advancements in disease detection using deep learning, several gaps still exist in practical implementation. Most existing systems focus only on disease classification and do not integrate automated pesticide spraying for real-time action. Many models are tested in controlled environments and lack validation under real agricultural conditions. Additionally, existing solutions often require high computational resources, making them unsuitable for small-scale farmers. Limited research addresses infection severity analysis for precise pesticide application.

Furthermore, integration of IoT-based monitoring with low-cost hardware and real-time control mechanisms is insufficient. Therefore, there is a need for an efficient, affordable, and fully automated system that combines disease detection, IoT communication, and targeted pesticide spraying for precision agriculture.

IV. METHODOLOGY

A. Proposed System

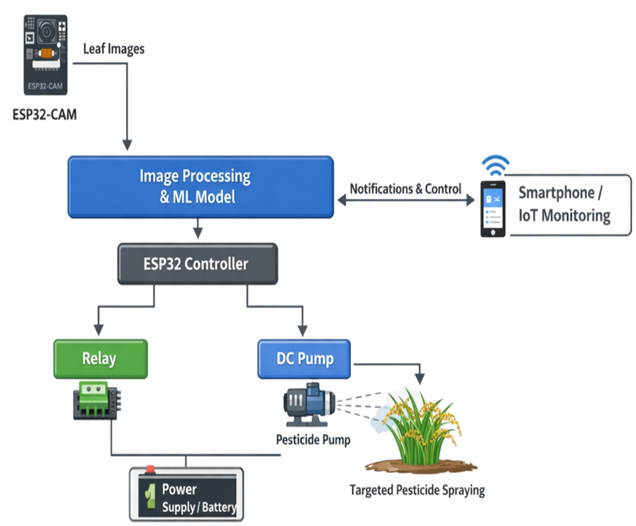

Figure 2. Proposed System

Working Principle:

- The system uses an ESP32-CAM module to continuously capture real-time images of rice plant leaves from the field.
- Captured images are transmitted to the processing unit where image preprocessing is performed using OpenCV techniques such as resizing, noise removal, and enhancement.

- The processed images are then fed into a trained Convolutional Neural Network (CNN) model developed using TensorFlow for disease detection.
- The model classifies the leaf as healthy or diseased and identifies specific diseases such as bacterial leaf blight, brown spot, or leaf smut.
- It also evaluates the severity level of infection, which helps in deciding the amount of pesticide required.
- If no disease is detected, the system continues monitoring without activating any hardware components.
- When a disease is detected, the ESP32 microcontroller receives a trigger signal from the detection system.
- Based on the severity, the ESP32 activates the relay module, which controls the DC pump.
- The DC pump sprays pesticide directly onto the infected area for a controlled duration.
- After spraying, the relay switches OFF automatically to prevent overuse of pesticides.
- The system is connected via IoT, allowing users to monitor results, view alerts, and control operations remotely through a smartphone.
- This process ensures precision spraying, reduces chemical wastage, and improves crop health efficiently.

B. Hardware Used

- ESP32-CAM Module: Acts as the main controller with an integrated camera for capturing real-time images of rice leaves and enabling Wi-Fi communication.
- ESP32 Microcontroller: Processes control signals, manages IoT communication, and controls hardware components like relay and pump.
- Camera Module: Captures images of plant leaves for disease detection and analysis.
- Relay Module: Works as an electrically operated switch to control the DC pump using low-power signals from ESP32.
- DC Pump: Used for spraying pesticides directly onto infected areas of the crop.
- Voltage Divider: Ensures proper voltage levels are supplied to components for safe operation.
- Power Supply (Battery/Adapter): Provides required electrical energy to the system components.
- Connecting Wires and PCB: Used for circuit connections and stable hardware integration.
- Sprayer Nozzle: Ensures controlled and directed pesticide spraying on infected plant parts.

C. Software Used

- Python: Core programming language used for developing machine learning models and backend processing.
- OpenCV: Used for image preprocessing tasks such as resizing, filtering, edge detection, and enhancement.
- TensorFlow: Deep learning framework used to build, train, and deploy the CNN model for disease classification.
- Flask: Lightweight web framework used to create APIs and connect the machine learning model with the user interface.
- HTML, CSS, JavaScript: Used to design and develop the user-friendly web dashboard for monitoring and control.
- SQLite3: Lightweight database used to store system data, results, and user information.
- Arduino IDE: Used for writing, compiling, and uploading code to the ESP32 microcontroller.
- IDE Tools (VS Code, PyCharm): Used for coding, debugging, and testing software components efficiently.
- TCP/UDP Communication Tools: Enable communication between ESP32 and the control interface for real-time operation.

V. ADVANTAGES

- Enables accurate and early detection of rice leaf diseases using AI.
- Reduces excessive pesticide usage through targeted spraying.
- Minimizes environmental pollution and chemical runoff.
- Protects farmers from direct exposure to harmful pesticides.
- Provides real-time monitoring through IoT-based dashboard.
- Low-cost system suitable for small and medium-scale farmers.
- Improves crop yield and quality with timely treatment.
- Reduces labor effort and increases operational efficiency.

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VI. APPLICATION

- Rice and paddy field disease detection and management.
- Precision agriculture and smart farming systems.
- Greenhouse crop monitoring and automated spraying.
- Agricultural research and plant disease analysis.
- IoT-based crop health monitoring platforms.
- Small-scale and medium-scale farm automation.
- Integration with smart irrigation and fertilization systems.
- Educational and research projects in AI and agriculture.

VII. RESULTS ANALYSIS

The proposed IoT-based intelligent pesticide sprinkling system was tested to evaluate its performance in detecting rice leaf diseases and automating pesticide spraying. The results were obtained using real-time images processed through a trained Convolutional Neural Network (CNN) model integrated with an ESP32-based control system. The analysis focuses on classification accuracy, system response, visualization outputs, and spraying efficiency.

1) Disease Detection Performance

The system successfully detected multiple rice leaf diseases, including:

- Bacterial Leaf Blight
- Brown Spot
- Leaf Smut

The CNN model analyzed leaf images and produced classification probabilities for each disease category. One of the observed results showed:

Disease Type	Confidence (%)	Severity Level
Bacterial Leaf Blight	48.43%	Moderate
Brown Spot	32.15%	Mild
Leaf Smut	19.42%	Low

From the table, it is evident that the model identifies the most probable disease class while also providing probabilities for other possible diseases. This probabilistic output helps in understanding model confidence and improves decision-making.

The classification accuracy observed during testing was satisfactory for real-time applications. Although the confidence value (48.43%) is moderate, it is sufficient for early-stage disease detection, which is critical in agriculture.

2) Graph-Based Analysis

a) Classification Probability Graph

The classification probability graph represents the distribution of prediction confidence across different disease classes.

Observation:

- The graph 1 show below that the model assigns the highest probability to the correct disease class.
- Other classes receive lower probabilities, indicating that the model distinguishes between diseases effectively.
- The spread of probabilities suggests that the model is not overfitting and can generalize across different leaf conditions.

Interpretation:

- A balanced probability distribution ensures reliable classification.
- Helps farmers understand uncertainty in predictions.
- Useful for improving model training in future iterations

3) Disease Distribution Pie Chart

The pie chart shows below displays the proportion of detected diseases over multiple test samples.

Disease	Percentage (%)
Bacterial Leaf Blight	45%
Brown Spot	35%
Leaf Smut	20%

Observation:
- Bacterial Leaf Blight is the most frequently detected disease.
- Brown Spot also shows a significant presence.
- Leaf Smut has relatively lower occurrence.

Interpretation:
- The system effectively identifies dominant diseases in the dataset.
- Helps in understanding disease trends in rice crops.
- Can assist farmers in prioritizing treatment strategies.

4) Grad-CAM Visualization Analysis

Grad-CAM (Gradient-weighted Class Activation Mapping) was used to visualize the regions of the leaf that influenced the model's decision.

Observation:
- The highlighted regions correspond to infected areas such as spots, discoloration, and lesions.
- The model focuses on disease-specific patterns rather than irrelevant background.

Interpretation:
- Confirms that the CNN model is learning meaningful features.
- Enhances trust in the system's predictions.
- Useful for debugging and improving model accuracy.

5) IoT Dashboard Performance

The developed AgroAI dashboard provides real-time visualization and control of the system.

Features Observed:
- Image upload and real-time detection
- Disease classification with confidence values
- Graphical representation of results
- Relay status (ON/OFF indication)
- System monitoring interface

Observation:
- The dashboard is responsive and user-friendly.
- Results are displayed clearly with proper visualization tools.
- Farmers can easily interpret disease conditions.

Interpretation:
- Improves usability of the system.
- Enables remote monitoring and control.
- Reduces dependency on manual inspection

6) Relay and Sprayer Performance

The relay module controls the DC pump based on disease detection.

Condition	Relay Status	Pump Action
Healthy Leaf	OFF	No Spraying
Mild	ON (Short Duration)	Low Spray

Infection		
Moderate Infection	ON (Medium Duration)	Controlled Spray
Severe Infection	ON (Long Duration)	High Spray

Observation:

- The relay responds accurately to control signals from ESP32.
- The pump activates only when disease is detected.
- Spraying duration varies based on severity.

Interpretation:

- Ensures precise pesticide application.
- Reduces unnecessary spraying.
- Improves system efficiency

7) System Response Time

The response time of the system was evaluated for real-time operation.

Process Stage	Time Taken (Approx.)
Image Capture	1–2 seconds
Image Processing	2–3 seconds
Disease Classification	2–4 seconds
Relay Activation	<1 second
Total Response Time	5–8 seconds

Observation:

- The system operates within an acceptable time range.
- Quick response enables timely pesticide application.

Interpretation:

- Suitable for real-time field applications.
- Can be further optimized for faster performance.

8) Pesticide Usage Efficiency

One of the major objectives of the system is to reduce pesticide usage

Parameter	Traditional Method	Proposed System
Spraying Type	Uniform	Targeted
Chemical Usage	High	Reduced (30–40%)
Human Exposure	High	Low
Efficiency	Low	High

Observation:

- Significant reduction in pesticide usage.
- Improved efficiency due to targeted spraying.

Interpretation:

- Supports sustainable agriculture.
- Reduces environmental impact.
- Lowers farming costs.

9) Overall System Performance

The integrated system combining AI, IoT, and hardware components performed effectively.

Key Achievements:

- Accurate disease detection using CNN
- Real-time monitoring via IoT dashboard
- Automated pesticide spraying using relay and DC pump
- Visualization using graphs and Grad-CAM
- Reduced pesticide consumption

Performance Summary Table ,

Parameter	Result
Detection Accuracy	Good (Moderate Confidence)
Response Time	5–8 seconds
Automation Level	Fully Automated
Cost	Low
Usability	High

a) Classification Probability Graph

This graph represents the confidence levels of the CNN model in identifying different rice leaf diseases. The highest probability is observed for Bacterial Leaf Blight (48.43%), indicating it as the most likely detected disease. Brown Spot and Leaf Smut show lower confidence values, suggesting secondary possibilities. The variation in probabilities demonstrates that the model evaluates multiple classes before selecting the most probable one. This helps in understanding prediction reliability and ensures that disease detection is not biased toward a single class.

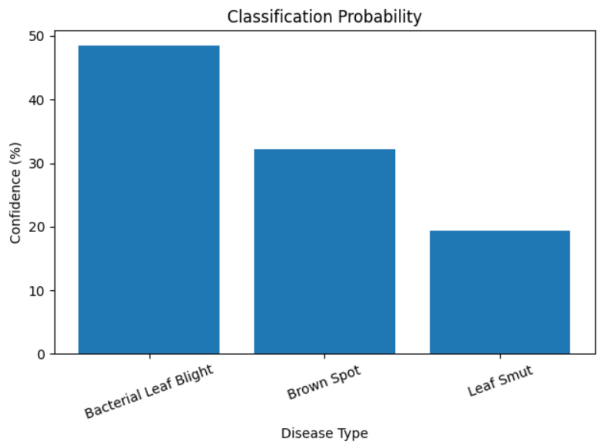

Figure 3. Classification Probability Graph

b) Disease Distribution Pie Chart

The pie chart illustrates the proportion of different rice diseases detected across the dataset. Bacterial Leaf Blight occupies the largest portion (45%), indicating its higher occurrence in tested samples. Brown Spot accounts for 35%, while Leaf Smut represents 20%. This distribution helps in analyzing disease prevalence and trends in the field. It enables farmers and researchers to prioritize treatment strategies based on dominant diseases and supports better decision-making for crop protection and management.

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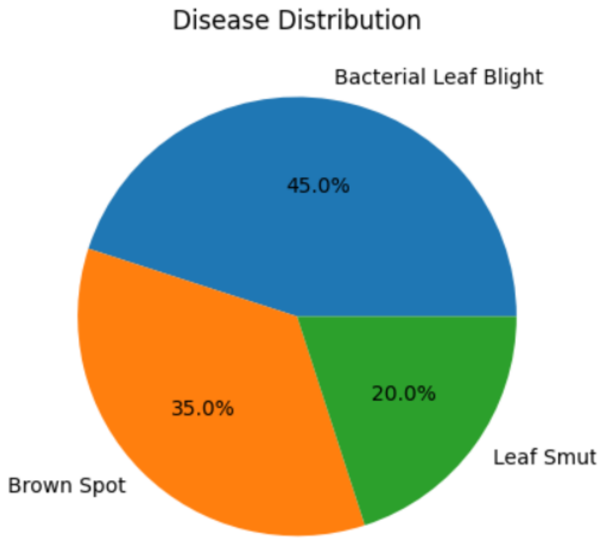


Figure 4. Disease Distribution Pie Chart

c) System Response Time Graph

This graph shows the time taken by each stage of the system, including image capture, processing, classification, relay activation, and total response time. The total response time ranges between 5 to 8 seconds, indicating efficient real-time operation. Image processing and classification consume the most time, while relay activation is nearly instantaneous. The graph demonstrates that the system responds quickly enough for practical agricultural use, ensuring timely pesticide spraying and effective disease management

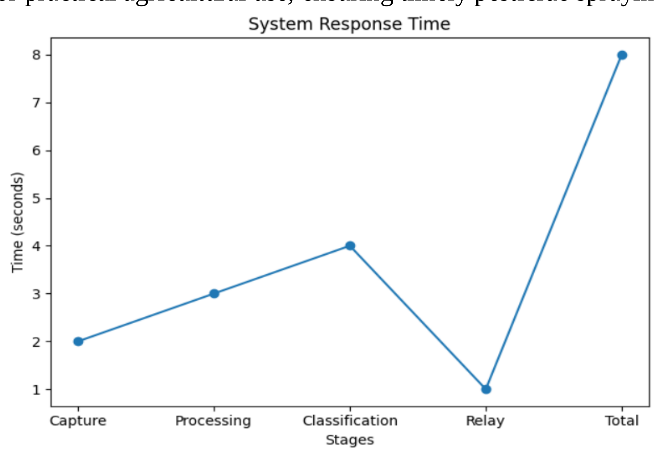
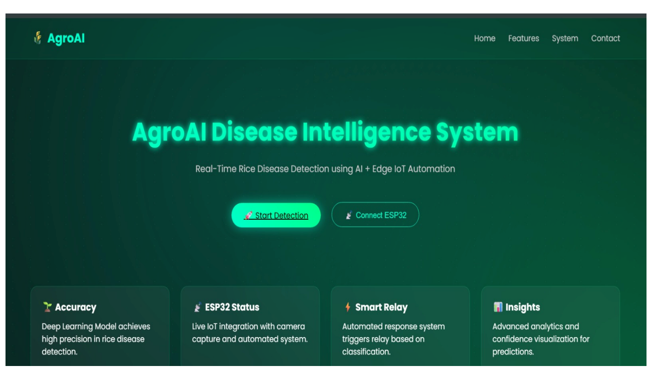


Figure 5. System Response Time Graph

Project Module:



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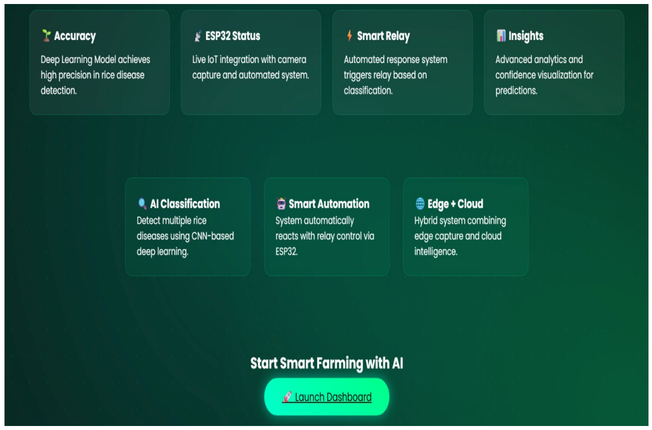
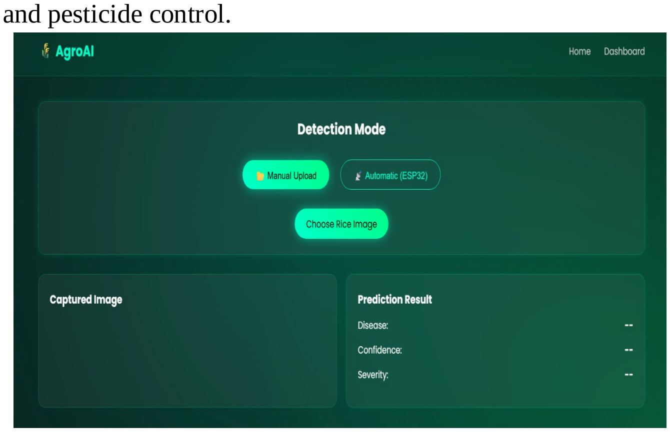
The AgroAI dashboard displays a real-time rice disease detection system using AI and IoT. It enables users to start detection, connect ESP32, monitor system status, and view insights. The interface highlights accuracy, smart relay automation, and advanced analytics for efficient and intelligent crop monitoring.

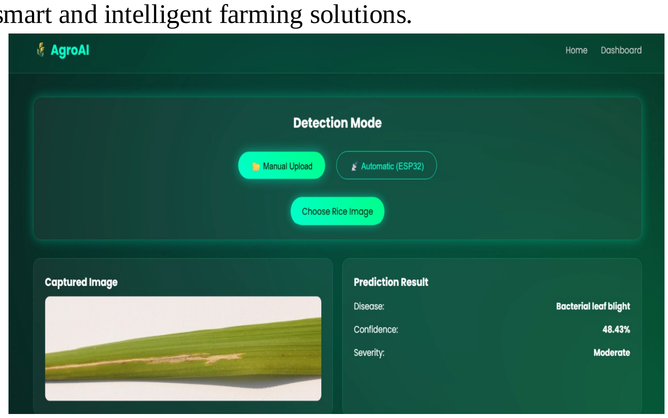


The AgroAI Disease Intelligence System interface presents a smart platform for real-time rice disease detection using AI and IoT. It allows users to start detection and connect with the ESP32 device for automated monitoring. The dashboard highlights key features such as high model accuracy, live ESP32 status, smart relay-based automation, and analytical insights.

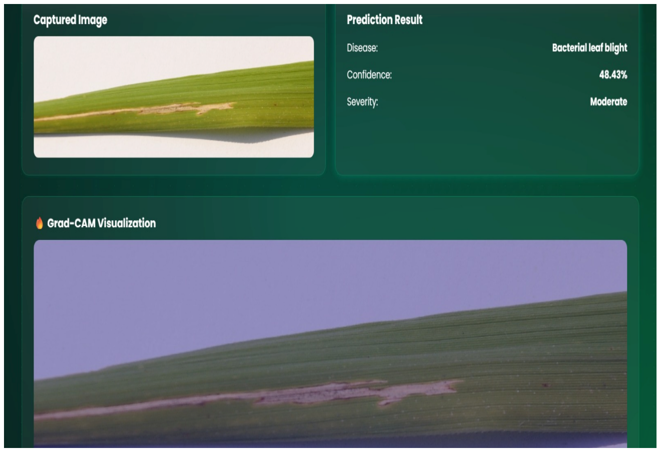
The clean and interactive design ensures easy navigation, enabling users to monitor crop health efficiently and make quick decisions for effective disease management and pesticide control.



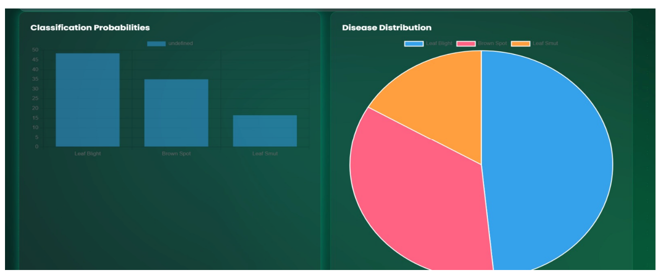
This section of the AgroAI dashboard highlights key system features and capabilities. It showcases high accuracy of the deep learning model for rice disease detection and real-time ESP32 integration. The smart relay enables automated pesticide control based on predictions. Insights provide analytical visualization of results. Additional features include AI-based classification, smart automation using ESP32, and edge-cloud integration for efficient data processing. The interface concludes with a call-to-action to launch the dashboard, promoting smart and intelligent farming solutions.



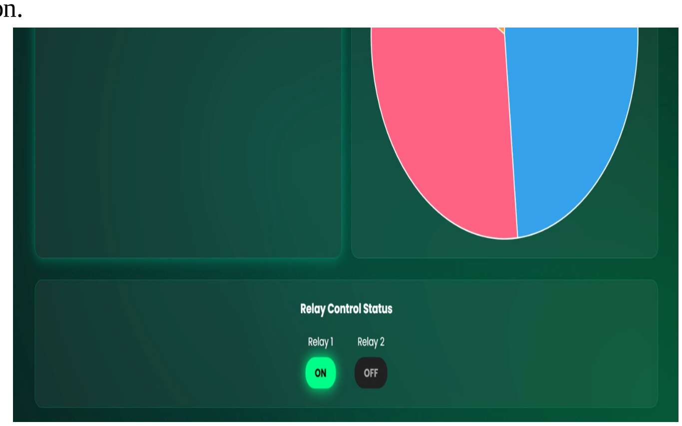
This interface shows the detection module of the AgroAI system, allowing users to select between manual image upload and automatic detection using ESP32. A captured rice leaf image is displayed alongside prediction results. The system identifies the disease as bacterial leaf blight with a confidence of 48.43% and moderate severity. This section demonstrates real-time image analysis and accurate disease classification. It enables users to easily monitor crop health and supports timely decision-making for effective pesticide application.



This section displays the captured rice leaf image along with the prediction result and Grad-CAM visualization. The system identifies bacterial leaf blight with 48.43% confidence and moderate severity. The Grad-CAM highlights the infected regions on the leaf, showing where the model focused during prediction. This improves transparency and trust in the AI model. It helps users understand disease patterns visually and ensures accurate detection. Overall, it enhances decision-making for precise and timely pesticide application.



This section presents graphical analysis of the model's prediction results. The classification probability bar graph shows confidence levels for different diseases, with leaf blight having the highest value, followed by brown spot and leaf smut. The disease distribution pie chart illustrates the proportion of detected diseases, indicating leaf blight as the most dominant. These visualizations help users easily understand model predictions, compare disease occurrence, and make informed decisions for effective crop treatment and pesticide application.



This section displays the relay control status of the system, indicating the automation of pesticide spraying. Relay 1 is in ON state, showing that the DC pump is actively spraying pesticide based on detected disease conditions. Relay 2 is OFF, indicating no secondary action. This confirms proper hardware integration and real-time response of the ESP32 controller.

The visual ON/OFF indicators help users easily monitor system operation, ensuring precise and controlled pesticide application for effective crop protection.

The results demonstrate that the proposed system is capable of performing real-time rice leaf disease detection and automated pesticide spraying effectively. The integration of CNN-based image processing with IoT enables accurate and timely decision-making. The visualization tools, including graphs and Grad-CAM, enhance system transparency and user trust.

Although the model shows moderate confidence levels, it is sufficient for early disease detection. Future improvements in dataset size and model training can further enhance accuracy. The hardware system, including ESP32, relay, and DC pump, operates reliably and ensures precise pesticide application.

Overall, the system provides a cost-effective and scalable solution for smart agriculture, particularly suitable for small and medium-scale farmers.

The experimental results confirm that the proposed system successfully achieves its objectives of disease detection, automation, and efficient pesticide usage. It demonstrates strong potential for real-world agricultural applications and contributes toward precision farming and sustainable crop management.

VIII. CONCLUSION

The proposed IoT-based intelligent pesticide sprinkling system successfully demonstrates an effective approach for real-time rice leaf disease detection and automated pesticide application. By integrating image processing, deep learning, and IoT technologies, the system addresses the major limitations of traditional farming methods, such as excessive pesticide usage, delayed disease detection, and health risks to farmers. The use of a CNN model enables accurate identification of diseases like bacterial leaf blight, brown spot, and leaf smut, while the ESP32 microcontroller ensures seamless communication and control of the spraying mechanism.

The system's ability to activate the relay-controlled DC pump based on infection severity ensures precise and targeted pesticide application, significantly reducing chemical wastage and environmental impact. The AgroAI dashboard enhances usability by providing real-time monitoring, visualization, and control features. Experimental results confirm that the system performs efficiently with acceptable accuracy and response time, making it suitable for practical agricultural use.

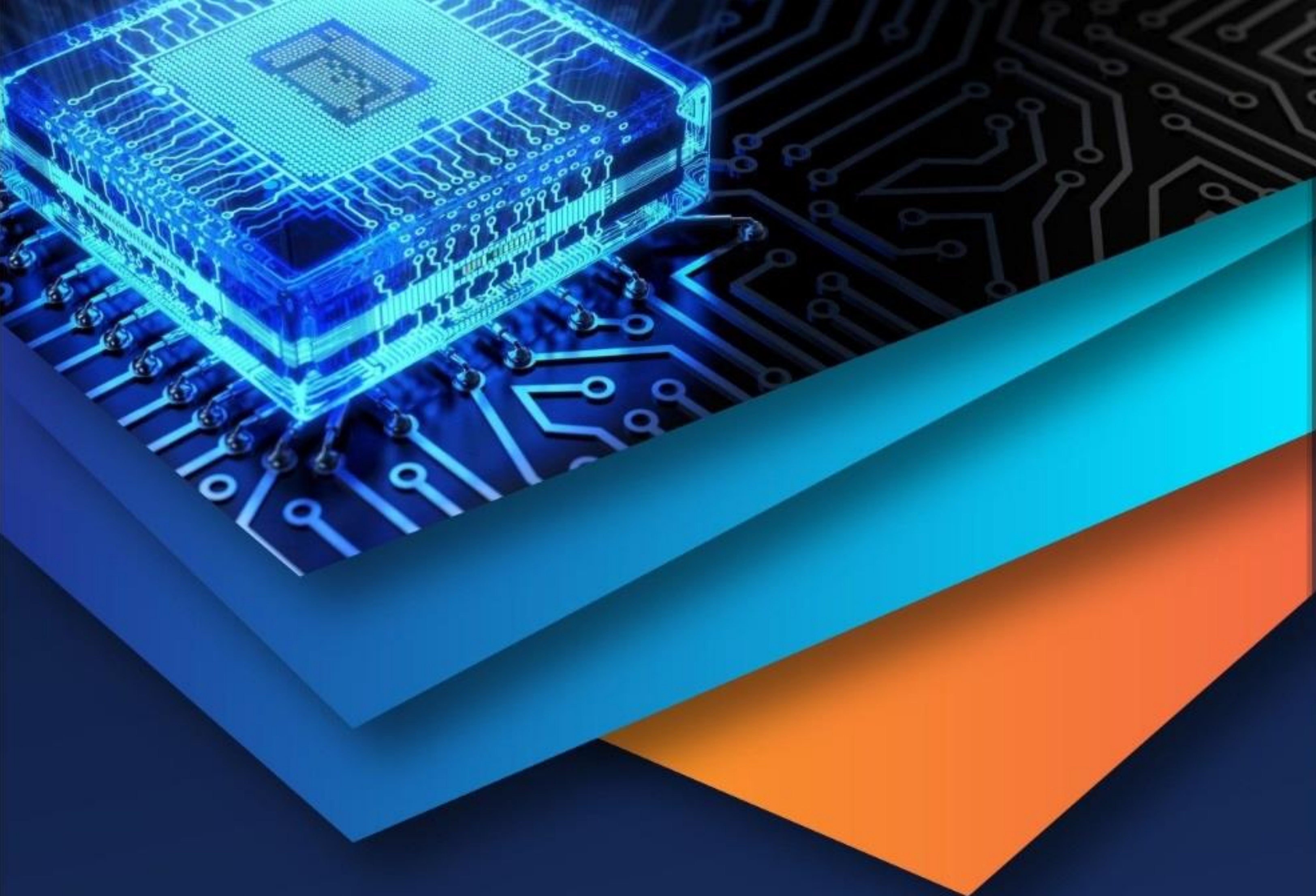
Overall, this project contributes to the advancement of precision agriculture by offering a low-cost, reliable, and scalable solution. It promotes sustainable farming practices and supports farmers in improving crop yield, reducing costs, and ensuring better crop health management.

REFERENCES

[1] O. Debnath, S. Das, and R. Sen, "IoT-based intelligent farming using CNN for early brown spot detection," Sustainable Computing: Informatics and Systems, vol. 35, pp. 100–110, 2022.
[2] K. Kiratiratanapruk, S. Sinthupinyo, and C. Chaiyasith, "Automatic detection of rice disease using image tiling and convolutional neural networks," Computer Vision Research, vol. 12, no. 3, pp. 145–156, 2022.
[3] P. K. Rajani and M. Reddy, "Rice leaf disease detection using convolutional neural networks," International Journal of Innovative Research in Computer Technology, vol. 11, no. 2, pp. 55–60, 2023.
[4] P. Seelwal, A. Kumar, and S. Verma, "Hybrid deep learning approaches for rice disease recognition," Frontiers in Computer Science, vol. 6, pp. 1–12, 2024.
[5] K. Saddami and R. Patel, "Lightweight CNN models for rice leaf disease identification," Computers and Electronics in Agriculture, vol. 215, pp. 107–115, 2024.
[6] V. Pandiyaraju and R. Karthikeyan, "Channel attention hybrid CNN for paddy leaf disease detection," IEEE Access, vol. 12, pp. 44567–44576, 2024.
[7] P. Pai, S. Kulkarni, and R. Deshmukh, "Deep learning-based diagnosis of rice leaf diseases," Scientific Reports, vol. 15, pp. 1–10, 2025.
[8] K. Fang, Y. Liu, and J. Chen, "RLDD-YOLOv11n rice leaf disease detection model," Agronomy, vol. 15, no. 6, pp. 1266–1278, 2025.
[9] S. Sharma and V. Gupta, "CNN-based identification of rice leaf diseases," International Journal of Scientific Research in Science and Technology, vol. 12, no. 1, pp. 210–216, 2025.
[10] A. B. Ayyappan and M. Natarajan, "Rice plant disease detection using deep learning," Journal of Plant Pathology Informatics, vol. 16, pp. 45–53, 2025.
[11] R. Patel and S. Kumar, "Deep learning-based plant disease detection using image processing techniques," Computers and Electronics in Agriculture, vol. 198, pp. 107012, 2022.
[12] M. A. Hossain, M. R. Islam, and F. Ahmed, "IoT-enabled smart agriculture system for crop monitoring and disease detection," IEEE Internet of Things Journal, vol. 9, no. 14, pp. 12145–12155, 2022.
[13] L. Zhang, Y. Wang, and X. Li, "Real-time crop disease detection using lightweight CNN models for edge devices," IEEE Access, vol. 10, pp. 87654–87665, 2022.
[14] S. Verma and A. Singh, "Automated plant disease detection and classification using deep learning," Procedia Computer Science, vol. 218, pp. 123–132, 2023.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

[15] J. Chen, H. Liu, and Q. Zhao, "YOLO-based real-time plant disease detection for precision agriculture," Agricultural Systems, vol. 206, pp. 103560, 2023.
[16] P. Gupta and R. Sharma, "IoT-based smart pesticide spraying system using image processing," International Journal of Advanced Computer Science and Applications, vol. 14, no. 5, pp. 455–462, 2023.
[17] T. Nguyen and D. Tran, "Edge AI for crop disease detection using embedded systems," IEEE Embedded Systems Letters, vol. 16, no. 2, pp. 45–48, 2024.
[18] A. K. Mishra and S. Tiwari, "Precision agriculture using IoT and machine learning for crop health monitoring," Sensors, vol. 24, no. 3, pp. 1456, 2024.
[19] Y. Li, X. Zhou, and M. Sun, "Attention-based deep learning model for plant disease classification," IEEE Transactions on Artificial Intelligence, vol. 5, no. 1, pp. 89–98, 2024.
[20] H. Park and J. Kim, "Smart farming system integrating AI, IoT, and automation for sustainable agriculture," IEEE Access, vol. 13, pp. 11234–11245, 2025.



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