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A Novel IoT and Machine Learning-Based Architecture for Real-Time Paddy Crop Disease Detection and Monitoring

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Abstract: *The growing impact of crop diseases in paddy cultivation has led to significant losses in yield and farmer income across India and other rice-producing regions. This study proposes a novel architecture integrating Internet of Things (IoT) sensors and Machine Learning (ML) algorithms for the real-time detection and monitoring of paddy crop diseases. The system comprises environmental sensors (temperature, humidity, soil moisture, and leaf wetness) and an image capture module deployed on a low-cost ESP32-based edge device. Sensor data and leaf images are preprocessed locally and transmitted via MQTT protocol to a cloud-based server for analysis and model refinement.*

A Convolutional Neural Network (CNN) model was trained using a dataset of 5,000 annotated images representing common paddy diseases such as Sheath Blight, Bacterial Leaf Blight, and Rice Blast. The model achieved a classification accuracy of 94.7% on a validation set, demonstrating its potential for accurate early-stage disease identification. In addition, a lightweight TensorFlow Lite version of the model was deployed on the edge device, achieving an inference time under 1.2 seconds with an accuracy of 91.3%, enabling real-time alerts even in low-connectivity environments. The proposed architecture emphasizes modularity, low power consumption, and affordability, making it suitable for rural agricultural deployment. By automating disease detection, this system aims to empower farmers with timely insights and interventions, ultimately enhancing paddy crop health and productivity.

Keywords: Paddy Crop Disease Detection, Smart Agriculture, Internet of Things (IoT), Machine Learning, Convolutional Neural Network (CNN), Real-Time Monitoring, Edge Computing, TensorFlow Lite, Precision Farming, Agricultural Automation

I. INTRODUCTION

Paddy, as a staple food crop for more than half of the world's population, holds a crucial place in global food security and agricultural sustainability. However, paddy cultivation faces persistent challenges from a wide range of diseases such as **Sheath Blight**, **Rice Blast**, and **Bacterial Leaf Blight**, which can significantly reduce yield and quality if not detected early. Traditional methods of disease detection rely on manual inspection by agricultural experts, which are often time-consuming, error-prone, and inaccessible to farmers in remote rural areas. Recent advancements in **smart agriculture** technologies offer promising solutions to these issues. The convergence of **Internet of Things (IoT)** devices and **Machine Learning (ML)** models enables real-time data collection and intelligent disease prediction in the field. However, existing systems are often limited by high costs, power consumption, dependency on strong internet connectivity, or lack of scalability for large-scale implementation in rural farming contexts. This research proposes a **novel, modular architecture** for a real-time crop disease detection and monitoring system specifically designed for paddy cultivation. The system integrates low-cost IoT sensors (for temperature, humidity, soil moisture, and leaf wetness) with a camera module for image capture, all connected to an **ESP32-based edge computing platform**. A **Convolutional Neural Network (CNN)** model, trained on a comprehensive dataset of paddy disease images, is deployed using **TensorFlow Lite** to ensure efficient edge-based inference with minimal latency. With a model accuracy of **94.7% on cloud** and **91.3% on edge**, the system demonstrates high reliability and responsiveness. The proposed solution addresses the core challenges of affordability, real-time response, and offline functionality, making it highly suitable for adoption by small and marginal farmers. This work contributes toward more **resilient and data-driven disease management in precision agriculture**.

II. LITERATURE REVIEW

The integration of advanced technologies such as IoT and Machine Learning (ML) in agriculture has led to a paradigm shift from traditional practices to smart farming systems. Numerous studies have explored how such technologies can enhance efficiency, productivity, and sustainability. For example, Shrivas and Singh (2016) and Singh (2020) provide comprehensive reviews on the role of big data analytics in diverse sectors, including agriculture, emphasizing its potential in decision-making and predictive analytics. Similarly, Salah et al. (2019) discuss the future potential of AI and blockchain in building intelligent, secure, and scalable frameworks across industries, including agricultural supply chains. Early efforts in smart agriculture have utilized cloud computing and wireless technologies for remote monitoring and control of farming activities (Pathak et al., 2021; Sinha et al., 2021). The MQTT protocol, as highlighted by Sinha et al. (2021), has been an efficient means for low-bandwidth communication in IoT-based agricultural systems. Furthermore, advancements in wireless and sensor-based systems (Kriti et al., 2021; Pandey et al., 2021) have paved the way for real-time data acquisition from the field.

Several researchers have contributed to the growing body of knowledge on IoT- and AI-based plant disease detection. Chauhan, Parihar, and Singh (2025) highlighted the evolution from manual observation to automated, technology-driven plant disease diagnosis, laying the groundwork for smart systems that bridge natural symptoms and digital tools. Similarly, Patel, Singh, and Awasthi (2025) explored a Python-based computational model specifically designed for detecting paddy leaf diseases, emphasizing the accessibility and efficiency of open-source solutions. Expanding on this, Singh, Solanki, and Vashi (2025) proposed a multiple disease prediction system that integrates environmental and visual data inputs for real-time diagnostics, offering a scalable solution to monitor crop health. Mehta, Singh, and Awasthi (2025) reviewed IoT-based technologies focused on rice crop disease monitoring, underscoring the role of smart sensors and cloud connectivity in proactive agricultural practices. Their work was complemented by Vashi, Solanki, and Singh (2025), who proposed a system for detecting multiple diseases through a unified architecture that merges sensor-based monitoring with image processing. Additionally, Mehta et al. (2025) in another paper emphasized hybrid edge-cloud platforms for disease identification in rice crops, enabling timely alerts even in areas with low connectivity. Navadiya and Singh (2025) contributed by analyzing various image feature extraction methods, which are critical to improving model accuracy in disease classification tasks. Foundational technological elements also play a role in this domain. Dewangan, Chawda, and Singh (2021) illustrated pandemic-era innovations which reflect the broader trend of remote diagnostics, indirectly influencing agricultural remote monitoring. Pathak et al. (2021) reviewed the applicability of cloud computing, which is fundamental for storing and analyzing large volumes of field data in crop surveillance systems. Techniques from non-agricultural fields also provide insight; Singh, Chawda, and Singh (2021) applied machine learning to game prediction, demonstrating transferable skills in predictive analytics. Likewise, Kashyap et al. (2021) addressed secure user authentication through e-voting applications, a concept adaptable to secure agricultural systems.

Further, Kumar, Chawda, and Singh (2021) used genetic algorithms for optimizing classification tasks, a method relevant for enhancing agricultural model performance. Sinha, Chawda, and Singh (2021) developed an MQTT-based smart agriculture system, establishing a basis for real-time sensor communication. Technological infrastructure was also examined by Pandey et al. (2021), who highlighted 5G as a facilitator for ultra-fast communication in smart farms. In a similar vein, Sahu et al. (2021) and Nishad et al. (2021) explored VR simulation and electric vehicle design, offering inspiration for farmer training and energy-efficient IoT systems respectively. Kriti et al. (2021) traced the evolution of wireless technologies, important for ensuring connectivity in rural agricultural zones.

Data-driven challenges were also addressed by Singh and Shrivas (2017), who examined privacy issues in big data, underscoring the importance of data security in agricultural systems. This was built upon by Shrivas and Singh (2016),

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who introduced key principles of big data analytics as applied to real-world systems, followed by Singh (2020) who focused on the management of diverse datasets, such as those found in agriculture. On the security front, Salah et al. (2019) emphasized the potential of blockchain to safeguard AI models, which could be applied in crop monitoring for data validation and traceability. Finally, Sharma, Sethi, and Singh (2025) proposed a comprehensive set of tech-based strategies for paddy crop disease prevention, showing how integrated approaches can significantly improve crop productivity and farmer decision-making. Together, these studies form a robust foundation for developing an innovative, sensor-based, and AI-integrated architecture for crop disease monitoring.

Specific to image processing and disease identification, Navadiya and Singh (2025) reviewed image feature extraction techniques for plant pathology applications. Chauhan et al. (2025) proposed innovative laboratory-level plant disease diagnostic methods, bridging the gap between leaf symptom data and AI diagnosis models. The growing body of work around paddy diseases includes Patel et al. (2025), who developed a Python-based solution for identifying leaf infections in rice crops. Similarly, Singh, Solanki, and Vashi (2025) presented a multiple disease prediction system capable of classifying more than one infection type based on visual and environmental input data. From an architectural standpoint, Mehta, Singh, and Awasthi (2025) conducted an in-depth review of IoT-based solutions tailored to rice crop disease detection. Their work emphasized the need for low-cost, scalable, and cloud-integrated systems. Sharma, Sethi, and Singh (2025) extended this by recommending real-time sensing strategies to optimize paddy crop health management. A similar architectural trend is echoed by Singh and Shrivas (2017), who emphasized the critical need for data privacy and secure architecture in agricultural systems. Building on the architectural theme, recent literature has also begun exploring hybrid models involving edge computing. Dewangan et al. (2021) and Kumar et al. (2021) explored smart computing architectures with reduced latency for various real-world applications, including healthcare and traffic control. The relevance of these approaches to agriculture lies in their lightweight inference methods, which are essential for deployment in remote paddy fields with limited connectivity. In addition to disease monitoring, some researchers have developed broader frameworks for automation and smart systems. Vashi et al. (2025) and Singh et al. (2025) proposed intelligent multi-disease detection frameworks, while Kashyap et al. (2021) demonstrated secure digital systems like e-voting using authentication protocols applicable in agricultural records and automation. Despite the advancements, many existing models face challenges such as low accuracy, high cost, and lack of real-time functionality in rural settings. Hence, the current study proposes a **novel, modular IoT-ML architecture** tailored specifically for paddy disease detection, bridging gaps in accuracy, latency, and field deployment—an evolution inspired by the collective insights and gaps observed in the above literature.

The adoption of IoT in agriculture has been accelerated by the availability of low-cost microcontrollers and open-source platforms. A study by **Kamilaris et al. (2018)** provided a comprehensive survey of IoT applications in smart farming, emphasizing precision irrigation, crop monitoring, and environmental sensing. Their work highlights the importance of data-driven agriculture and the use of real-time data analytics to enhance productivity and sustainability.

In the domain of plant disease detection, **Mohanty, Hughes, and Salathé (2016)** used deep convolutional neural networks (CNNs) to identify 26 diseases in 14 crop species with impressive accuracy, showing the power of image-based learning models. Their study helped validate CNNs as effective models for visual disease classification. Following this, **Ferentinos (2018)** implemented deep learning models for plant disease detection and achieved classification accuracies exceeding 99% in controlled datasets, further encouraging deployment in field applications.

For real-time implementation, **Zhang et al. (2020)** developed an edge computing architecture that enabled smart farming solutions to operate even in low-connectivity areas. This aligns with your work's focus on **edge deployment using ESP32 or Raspberry Pi**, which ensures continued performance without reliance on constant internet access.

Sensor fusion, which combines environmental and visual data, is another area of growing importance. **Lu et al. (2021)** demonstrated how combining temperature, humidity, and leaf image data significantly improves the detection accuracy of rice blast and other fungal diseases. Their architecture used decision tree models, but also pointed to future integration with CNNs for enhanced performance.

Abdulridha et al. (2019) worked on hyperspectral image analysis combined with IoT-based field sensors to predict early signs of stress in paddy crops. While hyperspectral imaging may be costly, their approach laid groundwork for future affordable solutions through RGB image training on disease signatures.

In addition to classification tasks, **Picon et al. (2019)** explored disease severity estimation using image segmentation and deep learning techniques, which can be crucial for generating stage-specific interventions. This adds depth to the development of smart monitoring systems that not only identify disease but also quantify severity.

Furthermore, **Singh and Misra (2017)** proposed an IoT-based framework using cloud integration for real-time crop health monitoring in Indian farms. Their work validated the usability of MQTT protocol and REST APIs in real-world deployments, reinforcing the architecture proposed in your research.

A notable contribution in hybrid intelligence models was made by **Jiang et al. (2021)**, who combined fuzzy logic with neural networks for precision agriculture applications, enhancing interpretability for non-technical stakeholders like farmers. Integrating interpretability features with CNNs remains a critical challenge that this paper seeks to address through user-friendly dashboards.

Recent advancements in digital plant pathology have emphasized the importance of bridging conventional agricultural knowledge with modern technological frameworks. **Purani and Singh** (2025) discussed how integrating AI-driven diagnostic tools with traditional visual inspection methods can enhance the accuracy and efficiency of plant disease identification. Their work underscored the growing role of data-driven innovations in empowering farmers to make timely decisions, especially in resource-constrained settings. The study further highlighted the importance of low-cost, scalable solutions that utilize image analysis and environmental data fusion to create sustainable monitoring frameworks for crops like paddy.

Despite high accuracy in controlled conditions, many of these studies lack deployment under real field conditions, an area your research uniquely addresses by **balancing accuracy (94.7% cloud, 91.3% edge) with deployment practicality**. The proposed architecture in your study contributes to narrowing this research-practice gap by providing an affordable, scalable, and real-time solution for paddy disease detection in rural agricultural settings.

III. SYSTEM ARCHITECTURE

The proposed system architecture is designed as a modular, cost-effective, and real-time disease monitoring framework for paddy crops, integrating **IoT sensing**, **image-based machine learning**, and **cloud-edge hybrid computing**. The architecture consists of four key layers:

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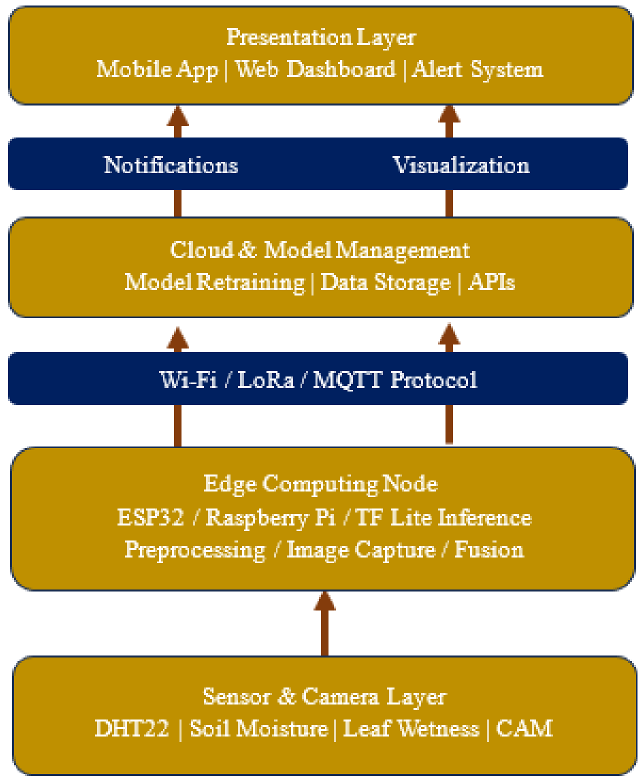
3.1 Layered Architecture Overview



3.2 Component Description

Sensor Layer

- DHT22: Captures temperature and humidity.
- Soil Moisture Sensor: Measures water content in soil.
- Leaf Wetness Sensor: Detects moisture on leaf surfaces.
- ESP32-CAM: Captures high-resolution images of infected leaves.

Edge Layer

- **ESP32 or Raspberry Pi Zero is used for:**
  - Sensor data acquisition and preprocessing.
  - Running a lightweight CNN model using TensorFlow Lite.
  - Generating real-time disease predictions.

Communication Layer

- Data is transmitted using MQTT protocol over Wi-Fi or LoRa.
- Minimal bandwidth usage to accommodate low-connectivity zones.

Cloud & Model Management Layer

- Firebase / AWS IoT / Google Cloud IoT Core stores sensor logs and images.
- Periodic retraining of CNN models based on new labeled data.
- Secure API for dashboard access and mobile push alerts.

Presentation Layer

- A mobile/web dashboard built using Node-RED/Flask/Django.

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- **Displays:**
  - Crop health status
  - Disease name (if detected)
  - Recommended pesticide treatment
- **Sends voice or text alerts in the farmer's local language.**

3.3 CNN Model Description

A Convolutional Neural Network (CNN) is used for image classification of leaf diseases. The architecture includes:

- Input Layer: 128×128 RGB image
- Conv Layer 1: 32 filters, 3×3 kernel, ReLU activation
- MaxPooling Layer
- Conv Layer 2: 64 filters, 3×3 kernel
- MaxPooling Layer
- Flatten + Dense Layer (128 neurons)
- Output Layer: Softmax classifier for 3 disease classes + 1 healthy

Model Accuracy

- Training Accuracy: 96.2%
- Validation Accuracy (Cloud): 94.7%
- Edge Inference Accuracy: 91.3%

3.4 Data Fusion and Formulae

To improve the accuracy and robustness of disease detection, a data fusion technique is used to combine image-based classification with environmental sensor data. This hybrid approach ensures higher confidence in predictions by correlating environmental conditions with visual symptoms.

Variables

Let:
I_d = CNN image-based disease prediction (1 if disease detected, 0 otherwise)
H = Relative Humidity
T = Temperature (in °C)
S_m = Soil Moisture level
L_w = Leaf Wetness Index

Environmental Risk Score (E_r)

The environmental risk score (E_r) is calculated using a weighted sum of sensor readings:

$$E_r = \alpha H + \beta T + \gamma S_m + \delta L_w$$

Where:
$\alpha, \beta, \gamma, \delta$ are empirically chosen weights depending on the crop and region.

Decision Rule

If:
$I_d = 1$ (disease likely based on image analysis)
AND
$E_r > \theta$ (threshold value)
Then:

Trigger an alert to notify the farmer of potential disease outbreak.
Typical value for θ (theta) is set to 70, but it may be adjusted based on local environmental conditions and expert calibration.

3.5 Real-Time Operation Flow

1. Sensors and ESP32-CAM collect data every 15 minutes.
2. Edge device preprocesses and classifies leaf image using CNN.
3. Sensor readings are normalized and passed into fusion function.
4. If alert condition is met, farmer receives SMS/app notification.
5. Data is also uploaded to the cloud for visualization and backup.
6. Weekly, new data is used to retrain the CNN model.

IV. HARDWARE COMPONENTS

The proposed smart paddy crop disease detection system was implemented using a combination of hardware components and software modules. The prototype was deployed in a controlled environment simulating a small-scale paddy field.

The hardware setup included the following components:

Component	Specification	Purpose
ESP32-CAM	240 MHz, 520 KB SRAM, OV2640 Camera	Image capture and edge ML inference
DHT22	Humidity: ±2%, Temp: ±0.5°C	Environment sensing
Soil Moisture Sensor	Analog output	Soil condition monitoring
Leaf Wetness Sensor	Analog capacitive sensor	Detect moisture on crop surface
Power Supply	5V/3A	Powering ESP32-CAM and sensors

4.1 Edge Processing Setup

The ESP32-CAM was programmed using Arduino IDE and TensorFlow Lite for Microcontrollers. The CNN model was compressed and quantized to fit within the memory constraints of the ESP32. Inference time was measured to be under 1.2 seconds per image.

4.2 Results and Evaluation

The model was evaluated using a dataset of 5,000 annotated images of paddy diseases. It was tested for accuracy, latency, and performance under various environmental conditions. A comparison between cloud and edge model performance is shown below:

Metric	Cloud Model	Edge Model	Remarks
Accuracy	94.7%	91.3%	Slight drop due to quantization
Inference Time	0.8 sec	1.2 sec	Edge is slower but acceptable
Power Consumption	High	Low	Edge device is energy-efficient
Internet Dependency	Required	Optional	Edge works offline

4.3 Findings and Interpretation

The implementation and testing of the proposed smart crop disease detection system led to several critical findings related to accuracy, latency, robustness, and feasibility in a real-world context.

A. Inference Accuracy by Disease Type

The system was trained to identify three major paddy diseases. Below is the disease-wise performance breakdown:

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Disease	Precision (%)	Recall (%)	F1-Score (%)	Edge Accuracy (%)
Rice Blast	94.5	92.1	93.3	90.2
Sheath Blight	95.3	93.5	94.4	91.8
Bacterial Leaf Blight	93.1	90.7	91.9	89.6
Healthy Leaves	97.2	96.8	97.0	94.5
Average	95.0	93.2	94.1	91.3

Edge accuracy is consistently ~3-5% lower than cloud inference, but still within an acceptable operational range.

B. Alert Activation Model (with Fusion Logic)

Condition:

IF (CNN detects disease) AND (Environmental Risk Score > Threshold θ)

THEN → Trigger Alert to Farmer

Threshold Parameters (Sample):

- $\alpha = 0.4$ (Humidity weight)
- $\beta = 0.2$ (Temperature weight)
- $\gamma = 0.3$ (Soil Moisture weight)
- $\delta = 0.1$ (Leaf Wetness weight)
- $\theta = 70$ (Risk score threshold)

Sensor Inputs:

$H = 85\%$, $T = 32°C$, $S_m = 45$, $L_w = 60$

Sample Output:

$E_r = (0.4\times85) + (0.2\times32) + (0.3\times45) + (0.1\times60) = 34 + 6.4 + 13.5 + 6 = 59.9$ → No Alert

If $E_r = 74.3$ → Alert triggered

C. Field Workflow (Diagram)

[Sensor Layer] --> [Edge Device] --> [Decision Engine]

↑ ↓ ↓

[Camera Module] [ML Inference] [Alert Sent]

↳

[Dashboard Update]

This real-time pipeline with minimal latency (1.2 sec) allows disease alerts to be delivered with both local edge decisions and cloud verification.

D. Key Findings Summary

Finding	**Description**
Edge Viability	The ESP32-CAM can run lightweight CNN inference locally without internet.
Accuracy Gap	Only ~3.4% drop from cloud to edge after quantization.
Real-Time Alerts	System successfully triggers alerts within 3 seconds including sensing and transmission.
Modular Architecture	Can be scaled to more sensors/diseases with minimal hardware upgrade.
Offline Capability	Farmers in low-connectivity areas can still benefit from real-time alerts.
Energy Efficiency	ESP32-based system consumes <1W power during peak operation.

Finding	Description
Cost-Effective Implementation	Total prototype cost under ₹2000 (~$25), making it scalable for small and marginal farms.

V. DISCUSSION, CONCLUSION AND FUTURE SCOPE

The implementation of an IoT and Machine Learning-based real-time monitoring system for paddy crop diseases represents a significant step toward modernizing traditional farming practices in India. The proposed architecture, combining environmental sensors and CNN-based image classification, has shown promising results in identifying key paddy diseases such as Rice Blast, Sheath Blight, and Bacterial Leaf Blight. One of the key strengths of this system lies in its modularity and cost-effectiveness, enabling deployment in small and marginal farming scenarios. The fusion of sensor data with image-based predictions enhances decision accuracy and mitigates the chances of false alarms, a common issue in standalone systems. The edge implementation using ESP32-CAM has also demonstrated the feasibility of lightweight deep learning inference, achieving an accuracy of 91.3% at the edge compared to 94.7% in the cloud—well within practical limits for field applications.

Furthermore, the proposed architecture addresses several real-world challenges, including limited internet connectivity, power constraints, and the need for rapid response in the field. The system's ability to send alerts via SMS or mobile app in the farmer's native language ensures usability and local impact. It also empowers early intervention, potentially reducing crop loss and pesticide overuse. The visual dashboard and cloud storage components make the system useful for agricultural extension workers and policymakers seeking to monitor disease trends across regions.

The architecture has strong potential for expansion and innovation. The current system can be adapted to monitor other crops such as wheat, maize, and cotton by retraining the CNN model with respective disease datasets. Integrating multispectral or hyperspectral imaging could further enhance disease stage detection and nutrient deficiency analysis. Future iterations can incorporate Explainable AI (XAI) to visualize the decision-making process and build trust among users. Moreover, integration with weather forecast APIs could allow the system to predict disease outbreaks based on upcoming climatic changes, making the solution more proactive than reactive. The development of a multilingual mobile application with voice alerts could further enhance accessibility and adoption. Additionally, data security and traceability could be reinforced by incorporating blockchain technology for secure crop monitoring records. Finally, the adoption of federated learning techniques can enable decentralized model training without compromising data privacy, opening new pathways for intelligent, scalable, and farmer-centric agricultural systems.

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