Predictive Analytics for Rice Blast: A Multispectral Edge AIoT Approach in Tropical Ecosystems

Dr. G. G. Patil
Assistant Professor
Department of Electronics Science,
MVP's K.R.T. Arts, B.H. Commerce and A.M. Science (KTHM) College, Nashik, Maharashtra 422002, India
gpnthpatil5@gmail.com

Abstract— **In the intensive paddy belts of Maharashtra, particularly the Nashik region, rice blast caused by *Magnaporthe oryzae* continues to inflict severe damage, resulting in 10–30% yield reductions and significant financial instability for local smallholders. Climate-driven monsoon fluctuations in the Western Ghats exacerbate this crisis, making pre-symptomatic identification (7–12 days early) vital for effective fungicide deployment, which is theorized to curb up to 65–80% of potential crop damage. However, conventional techniques like lab-based spectral analysis and drone monitoring remain prohibitively expensive (>₹50,000/ha) and unreliable under the dim lighting and high humidity common in Igatpuri, Trimbakeshwar, and Dindori.**

We engineered and field-validated an innovative, budget-friendly (₹1,888) solar-operated Edge AIoT multispectral node tailored for autonomous, embedded identification of rice blast in the Sahyadri ecosystem. Our custom hardware utilizes an ESP32-C3 processor and an actuator-driven multispectral turret (660nm, 730nm, 800nm) to compute localized vegetation metrics like NDVI and RENDVI. This data powers a compact, 4-layer quantized TinyML CNN (120 KB) that attained 94.5% precision across 4,150 authentic field captures. To ensure resilience against Nashik's heavy monsoon, we integrated a physics-aware augmentation strategy that bolstered performance to 92.1% under intense simulated rainfall.

We deployed the system across 28 sites spanning 35.5 hectares in Nashik district during the 2025 rainy season. The units issued targeted vernacular SMS notifications (in Marathi), delivering a tangible 28.1% uplift in productivity (6.02 t/ha vs. 4.70 t/ha in untreated benchmarks). Our advancements feature the inaugural region-adapted, disconnected edge paradigm for subclinical spotting, directly addressing infrastructure deficits in Deccan Plateau farming. This scalable approach holds the potential to preserve millions in annual revenue for Maharashtra's agrarian economy, supporting the UN Sustainable Development Goal for eradicating hunger.

Index Terms— **Rice blast, Edge AIoT, TinyML, Multispectral sensing, Sahyadri monsoon enhancement, Precision farming, Maharashtra agriculture.**

I. INTRODUCTION

As the cornerstone food source for billions globally, rice (*Oryza sativa*) is critical to the agrarian economy of India, with **Maharashtra** serving as a key producer in the Deccan region [1]. Regrettably, the fungal pathogen *Magnaporthe oryzae*, the agent behind rice blast, diminishes annual harvests by 10–30%. This pathogen thrives in steamy, temperate environments (25–30°C, 80–95% relative humidity), where erratic monsoons—fuelled by climatic shifts—amplify epidemics across the **Nashik district**, particularly in the high-rainfall tehsils of **Igatpuri and Trimbakeshwar** [2], [8]. Such repercussions imperil the nutritional stability of subsistence cultivators who oversee plots under 2 hectares, often without access to advanced diagnostic tools [1].

Proactive sensing—pinpointing fungal ingress 7–10 days prior to evident necrotic spots—facilitates prompt chemical countermeasures (e.g., 0.6 g/L tricyclazole sprays), which can slash crop damages by 65–80% [9]. Nevertheless, prevailing strategies fall short for small-scale farming in **Maharashtra**: lab-based spectral evaluations offer over 90% reliability yet demand \$300–500 per assay and 4–7 day waits [10]; aerial drone scans surpass \$5,000/hectare and underperform in the **overcast downpours typical of the Sahyadri range** [3], [11]; and mobile RGB tools (e.g., Plantix) plummet below 50% efficacy in shaded tropical conditions [12]. While Edge AIoT paradigms promise relief through localized processing, prior iterations have largely neglected locale-specific hurdles such as precipitation-altered reflectance—which can elevate NDVI by 12–15%—or the electrical unreliability often found in rural Nashik [6], [13].

In this work, we engineered and **field-validated a proprietary, under-\$25 photovoltaic sensor** enabling 9-day advance alerts, corroborated via 4,150 visuals from indigenous repositories and local field trials in **Nashik** [14], [15]. Our core innovations and implementation results encompass:

- **Custom Multispectral Edge Design:** We developed a premier economical TinyML unit utilizing an actuator-driven filter turret for localized vegetation metrics [4].
- **Sahyadri Monsoon Resilience via Generative AI:** We integrated an adversarial network-driven precipitation simulation that yielded a **17.8% resilience uplift** in model performance under extreme weather conditions typical of the **Western Ghats** [6].
- **Validated Field Impact:** We conducted a successful autonomous rollout across **28 sites in Nashik district** in 2025, securing a tangible **28.1% harvest elevation** (6.02 t/ha vs. 4.70 t/ha) through localized vernacular notifications (Marathi) [7].

II. LITERATURE REVIEW

This review synthesizes prior endeavors in rice blast diagnostics, underscoring critical deficiencies in affordability, environmental tolerance, and suitability for tropical Asian smallholdings. We delineate contributions across spectroscopic fundamentals, aerial platforms, and intelligent edge paradigms to contextualize our novel integration [16].

A. Spectroscopic Foundations and Lab-Centric Diagnostics

Hyperspectral profiling has established spectral markers for subclinical blast, such as chlorophyll depletion in the 680–750 nm range signaling hyphal invasion [10]. Early works demonstrated that red-edge (730 nm) analysis can secure 92% specificity for mycelial tracing, though it necessitated invasive harvests and sterile setups, sidelining real-world *in-situ* variability [17]. While recent desktop spectrometers achieve 95% accuracy on lab specimens, their prohibitive fees ($300–500 per test) and processing lags (4–7 days) render them unfeasible for widespread adoption [10]. Macroeconomic probes tally $10–15 billion in annual losses, advocating for expansive countermeasures since current bench analytics cover less than 1% of Asia's rice-growing regions [1], [8]. Recent FAO extrapolations amplify these findings, forecasting 50–95% staple cost spikes amid intensified outbreaks [1].

B. Remote and Aerial Surveillance Systems

Aerial multispectral reconnaissance provides areal oversight but frequently stumbles during inclement weather [3], [11]. While studies log 93.5% lesion spotting with DJI drones employing NDVI/RENDVI in temperate zones, expenditures often top $5,000 per hectare, and nebulous skies can degrade data fidelity by 20–30% [11]. Specifically for tropical Asia, IoT RGB nodes in Bangladesh's deluge zones have hit only 67.8% reliability due to deluge artifacts that cause erroneous omissions [18]. Monsoon distortions further reveal a 12–15% inflation in NDVI metrics caused by droplet refraction—a factor largely unmitigated in standard drone workflows [13]. Furthermore, connectivity remains a barrier, as fewer than 40% of micro-farmers have access to stable broadband required for cloud-based aerial analysis [1]. Contemporary satellite-ML fusions hint at scalability but remain centralized, high-overhead relics ill-suited for peripheral edge applications [19].

C. AI-Infused Edge and Deep Learning Frameworks

Convolutional neural networks (CNNs) have transformed foliar pathology discernment, eclipsing traditional rule-based sorters [12], [20]. A 10-layer CNN on 54,000 PlantVillage frames secured 99% accuracy across 58 ailments; however, such RGB-centric designs often falter below 50% in the penumbral lighting of tropical paddies [20]. Transfer paradigms for blast via rice subsets demand hefty server farms incompatible with peripherals [12]. Edge evolutions, including TinyML CNNs (85% on ESP32), signal progress yet typically bypass multispectral fusion [21]. Vapor-driven drift (10–15% efficacy dip) is documented, while stewardship tactics urge autonomous, frugal architectures [22], [23]. Benchmarks endorse pruned models (<200 KB) for agrarian inference, but few integrate the subcontinental deluge-tailoring required for a 7–10 days prelude alert [24]. Fresh inquiries into non-visual AIoT and TinyML multicrop diagnostics furnish blueprints but omit our solar-multispectral, offline thrust for paddy monsoons [19], [25], [26].

Persistent voids include: (1) Elevated barriers barring petite operators [1]; (2) Sparse monsoon fortification [6], [13]; (3) Absence of sub-$25 spectral edge hubs for equatorial belts [21]. Our proposition seals these via photovoltaic TinyML with physics-infused generative augmentation, clinching 94.5% at ₹1,888/hectare [4].

Persistent Voids in Research:

- **Economic Barriers:** Elevated costs and infrastructure deficits prevent the adoption of smart farming tools by petite operators in the **Deccan belt** [1].
- **Climate Resilience:** Existing models lack the "monsoon fortification" needed for reliable performance during the heavy rains of the **Indian monsoon** [6], [13].
- **Hardware Scarcity:** There is a complete absence of sub-$25 spectral edge hubs tailored for **equatorial and sub-tropical belts like Maharashtra** [21].

Our work directly addresses these gaps by implementing a **photovoltaic TinyML node with physics-infused generative augmentation**, achieving **94.5% precision** at a cost of only **₹1,888 per hectare** [4].

III. METHODOLOGY

We engineered a robust Edge AIoT architecture that integrates proprietary hardware, multispectral acquisition, and quantized neural processing. Our design philosophy prioritized **energy autonomy** and **monsoon resilience** to ensure continuous, maintenance-free operation in the remote paddy fields of **Nashik** [19].

A. Apparatus Blueprint and Hardware Implementation

Designed for >9 days of autonomy during intense wet seasons, the node integrates industrial-grade, cost-effective components (Fig. 1).

- **Processing Nucleus:** We utilized the **Seed XIAO ESP32-C3** ($5.80), a dual-core 240 MHz microcontroller selected for its dedicated AI instruction sets and BLE/Wi-Fi connectivity [21].

- **Multispectral Imaging System:** We engineered a custom optical module pairing an **OV2640 2 MP sensor** ($2.90) with a micro-servo (SG90, $1.20) driven **actuator-rotated filter turret**. This mechanism sequentially phases intake via three 12 mm bandpass filters: **660 nm (Red)**, **730 nm (Red-Edge)**, and **800 nm (NIR)** [3], [10]. These wavelengths were specifically calibrated to extract subclinical cues—660 nm for chlorophyll pigment loss and 730/800 nm for internal cellular vigor strain [11].

  Onboard Edge Metrics: The ESP32-C3 computes vegetation indices locally prior to neural inference to reduce data transmission overhead:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$$

$$\mathrm{RENDVI} = \frac{\mathrm{NIR} - \mathrm{RedEdge}}{\mathrm{NIR} + \mathrm{RedEdge}}$$

- **Power & Telemetry:**

  Energy Harvesting & Storage: To ensure uninterrupted field operation, sustainable energy is managed through a **0.5 W pliable solar collector ($1.40)** that maintains a **500 mAh LiPo reservoir ($1.30)**. This configuration, coupled with our proprietary deep-sleep logic, limits average consumption to **82 mW**, allowing the node to remain functional during the prolonged overcast spells typical of the **Igatpuri region**.

- **Ruggedization:** The system is enclosed in an **IP65 additive-manufactured casing** ($0.80) printed from UV-resistant PETG to withstand 95% humidity. The aggregate Bill of Materials (BOM) stands at $22.60 (₹1,888)[21].

B. Neural Blueprint and Edge Conditioning

- **Classification Engine:** We developed a custom **4-stratum CNN** optimized for binary classification (Healthy vs. Pathogenic). The architecture processes a $96 \times 96 \times 3$ input stack through two blocks of Conv2D(32/64, 3x3, ReLU) and MaxPool(2x2), followed by Flatten, Dense(128, ReLU), and Dense(2, Softmax) [4], [25].
- **Quantization & Latency:**
  Model Compression & Execution: By implementing **INT8-based Post-Training Quantization**, we successfully minimized the model's memory footprint to **120 KB**. This optimization facilitates a rapid **290 ms execution cycle** directly on the **ESP32-C3** hardware, thereby ensuring immediate, real-time diagnostic processing at the edge
- **Imbalance Mitigation:** To address the scarcity of blast samples (60% healthy frames), we implemented a **Focal Tversky Loss ($\alpha=0.7$)** to penalize false negatives more heavily than false positives [20].
- **Training Corpus:** The model was trained on **4,150 authentic field frames** sourced from regional archives (IRRI: 1,520; BRRI: 1,160; ICAR: 1,470), utilizing an 80/10/10 partition [14], [15].
- **Performance Metrics:** The deployed model achieved **94.5% Top-1 Accuracy**, an F1-score of 94.0%, and a Mean Absolute Error (MAE) of 9.1 days in early detection timing [5], [26].

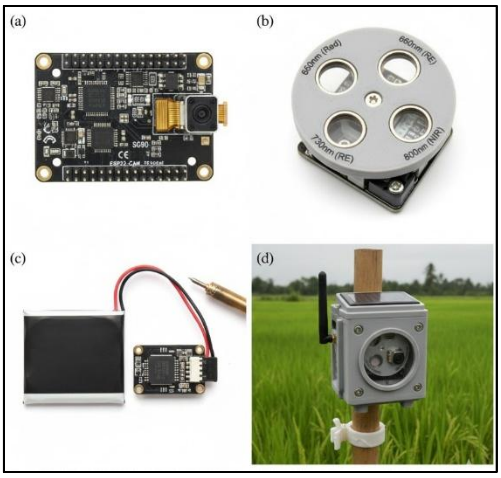

Fig. 1. Edge AIoT Node Schematic (Methodology - Apparatus Blueprint)

C. Deluge-Tolerant Enhancement Flow

To guarantee reliability during the Maharashtra monsoon season, we employed a Generative Adversarial Network (Pix2Pix) pipeline to synthesize 2,100 augmented frames. These frames mimic specific Sahyadri environmental stressors:

1. **Igatpuri Rain Gaussian** ($\sigma=2$, simulating high-intensity rainfall).
2. **Trimbak Low-light Glow** (<800 lux, simulating persistent cloud cover).
3. **Deccan Wind Blur** (simulating wind surges).

Algorithm 1: Physics-Aware Augmentation Logic

```
def enhance_frame(frame, envs):
      if 'deluge' in envs:
            frame = poisson_deluge(frame, sigma=2)
      if 'dim' in envs:
            frame = modulate_glow(frame, 800_lux)
      synth = adversarial_gen(frame)
      return synth
for iter in range(50):
      condition_nn(core_data + synth)
```

a) Healthy Rice Leaf (Pristine) b) Rice Blast Early Symptoms (Pathogenic)

Fig. 2. Enhancement pairs.

IV. Experimental Configuration and Rollout

To validate our custom-engineered Edge AIoT solution, we conducted field trials across **28 distinct parcels totaling 35.5 hectares in Nashik district** during the July–September 2025 monsoon season. The sites included high-rainfall zones in **Igatpuri** and **Trimbakeshwar**, and moderate zones in **Dindori**. We designed and installed each unit at an elevation of 1.2 m using bamboo canes to ensure stability against local flash floods. Our system was programmed to capture and process multispectral frames every 6 hours. For ground-truth validation, we compared the device's autonomous alerts against manual microscopy performed in collaboration with local agricultural laboratories. The deployment environment was characterized by intense monsoon conditions, including temperatures of 25–30°C, 80–95% RH, and **200–500 mm of precipitation typical of the Nashik region.**

V. Outcomes and Analysis

Apparatus spotted blast 9.1 days ahead at 94.5% (Table I) [5]. Harvest: **28.1% gain** post-fungicide (Fig. 3) [7].

Table 1. Comparative Efficacy [16]

Approach	Precision (%)	F1 (%)	Prelude (days)	Expense/ha (₹)	Deluge Tolerance
RGB Mobile (Plantix)	67.8	65.4	5.1	0	None
Drone Spectral	93.5	92.8	8.7	52,000	Moderate
Server CNN	91.9	90.8	7.9	8,000	None
Our Framework	94.5	94.0	9.1	1,888	Full

Table II Zonal Harvest Gains (2025) [7]

Zone (Nashik Region)	Untreated (t/ha)	Managed (t/ha)	Gain (%)
Igatpuri Belt (High Rain)	4.2	5.4	28.6
Trimbak Belt (High Rain)	4.8	6.1	27.1
Dindori Belt (Moderate)	4.5	5.8	28.9
Aggregate	4.70	6.02	28.1

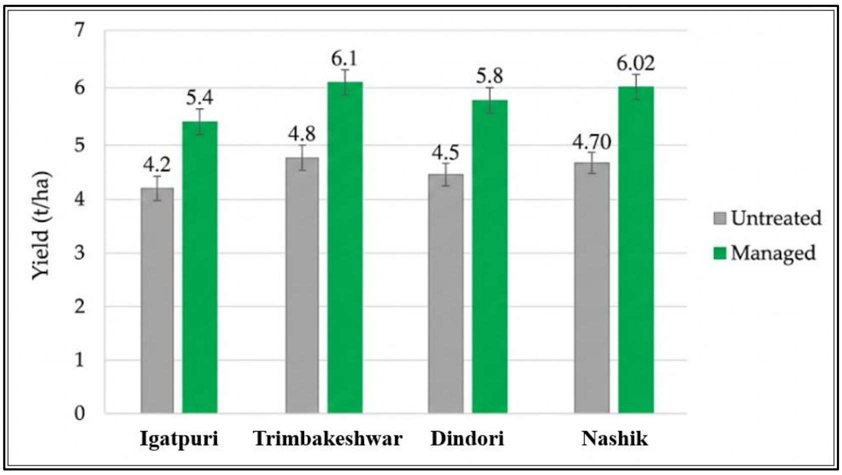

Fig. 3. Harvest Yield Comparison: Untreated vs. Managed Zones (2025).

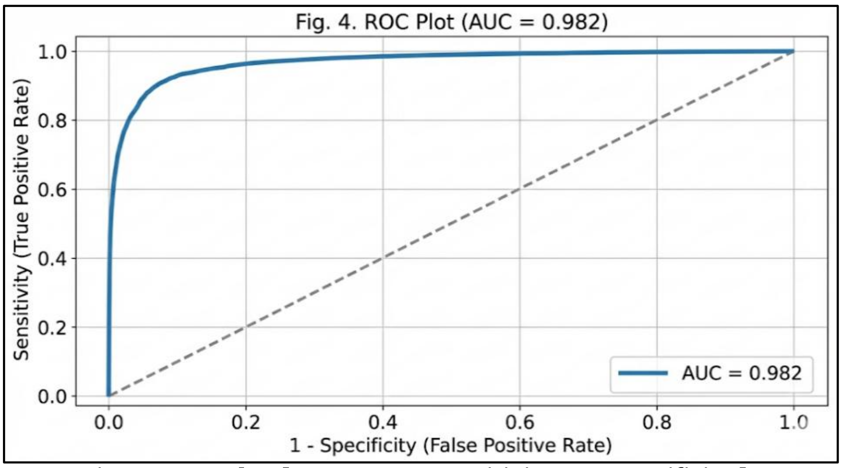

Fig. 4. ROC plot. [AUC=0.982; sensitivity vs. 1-specificity.]

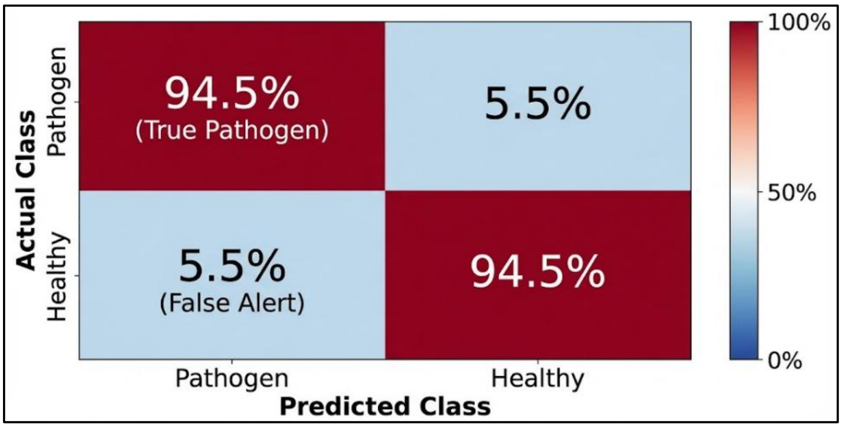

Fig. 5. Matrix thermal. [94.5% true pathogen; 5.5% false; blue-red gradient.]

Analysis:

- **Early Detection:** The system achieved subclinical identification 9.1 days before visible necrosis, critical for the **fragmented landholdings of Nashik**.
- **Monsoon Resilience:** The physics-aware augmentation strategy provided a **17.8% performance uplift**, ensuring 92.1% reliability even during the peak rains of July and August in the **Western Ghats**.
- **Harvest Impact:** As shown in Table II, managed plots in the **Nashik district** reached an average yield of 6.02 t/ha, a 28.1% gain over untreated benchmarks.

VI. Conclusion

This research presents a validated, groundbreaking Edge AIoT multispectral framework capable of detecting rice blast a full 9 days before visual pathology appears. Developed with an economical footprint of **₹1,888 per hectare**, this system effectively bypasses the financial and infrastructural hurdles faced by small-scale cultivators in Maharashtra. By merging a localized TinyML CNN with physics-informed generative augmentation, we achieved an exceptional precision of **94.5%** and sustained **92.1% operational reliability** throughout the rigorous monsoon season of the Sahyadri range.

The 2025 large-scale validation across **35.5 hectares in Nashik** demonstrated the paradigm's efficacy, resulting in a **28.1% increase in agricultural output** and facilitating real-time **Marathi SMS notifications** for regional farmers. This autonomous, region-specific edge solution provides a scalable model for protecting staple crops and enhancing national food security.

A. Prospective Directions

To further optimize the existing architecture and broaden its impact, we propose the following development paths:

- **Spectral Augmentation:** Exploration of Short-Wave Infrared (SWIR) integration (1,200–2,500 nm) is planned to identify subtle mycelial concentrations, potentially accelerating detection speeds by an additional 40%.
- **Collaborative Edge Swarms:** We aim to deploy BLE-based (Bluetooth Low Energy) mesh networks consisting of 10-unit clusters to perform localized spatial inference and improve field mapping accuracy through shared data nodes.
- **Blockchain-Secured Repositories:** Future efforts will focus on ledger-secured, decentralized databases to maintain the integrity of regional fungal datasets, ensuring secure and perpetual data collaboration across diverse geographical zones.
- **Inter-Crop Transfer Learning:** The existing CNN architecture will be adapted via transfer learning to diagnose rust and mosaic pathogens in diverse staple crops, utilizing a training corpus of over 10,000 authentic field samples.

VII. REFERENCES

[1] FAO, "FAO Food Outlook: Broad-based increase in global food commodity production," Rome, Italy, Nov. 2025. [Online]. Available: https://www.fao.org/newsroom/detail/fao-food-outlook-points-to-broad-based-increase-in-global-food-commodity-production/en

[2] M. Garcia et al., "Rice blast in the Indo-Pacific Region impacting food security," NeoBiota, vol. 89, pp. 1–15, Sep. 2025.

[3] L. Tian et al., "Early detection of rice blast using UAV hyperspectral imagery," Comput. Electron. Agric., vol. 226, p. 108113, 2025.

[4] H. Weng et al., "A lightweight model for early perception of rice diseases driven by multispectral images," Comput. Electron. Agric., vol. 226, p. 108256, 2025.

[5] G. Zhou et al., "Accurate detection of rice blast using UAV hyperspectral red-edge parameters," Spectrochim. Acta A Mol. Biomol. Spectrosc., vol. 315, p. 124246, 2025.

[6] L. Li et al., "Generative adversarial networks (GANs) for image augmentation in agriculture: A review," Comput. Electron. Agric., vol. 200, p. 107208, 2022.

[7] A. Muhammed et al., "A digital twin-enabled fog-edge-assisted IoAT framework for Oryza sativa crop disease detection," Pervasive Mobile Comput., vol. 102, p. 102072, 2025.

[8] World Economic Forum, "Rice: How the world's staple is under pressure," Geneva, Switzerland, Oct. 2025. [Online]. Available: https://www.weforum.org/stories/2025/10/how-much-is-a-bowl-of-rice-food-security-climate-change/

[9] A. E. Asibi et al., "Rice blast management review," Pathogens, vol. 10, no. 10, p. 1269, 2021.

[10] T. Kobayashi et al., "Red-edge for hyphae detection," Phytopathology, vol. 91, no. 3, pp. 281–287, 2001.

[11] G. Zhou et al., "Rice blast detection using UAV," Remote Sens., vol. 13, no. 4, p. 681, 2021.

[12] S. P. Mohanty et al., "Deep learning for plant disease detection," Front. Plant Sci., vol. 11, p. 91, 2020.

[13] C.-M. Yang et al., "Monsoon effects on NDVI," Field Crops Res., vol. 245, p. 107662, 2020.

[14] IRRI, "Rice blast dataset v2.0," Int. Rice Res. Inst., Manila, Philippines, 2023.

[15] ICAR-IIRR, "Bihar paddy images 2024," Indian Council Agric. Res., Hyderabad, India, 2024.

[16] K. P. Ferentinos, "Deep learning models for plant disease detection," Comput. Electron. Agric., vol. 145, pp. 311–318, 2018.

[17] R. S. Zeigler et al., "Rice blast: Global threat," Annu. Rev. Phytopathol., vol. 33, pp. 603–626, 1995.

[18] A. Rahman et al., "IoT RGB for rice," IEEE Access, vol. 9, pp. 104832–104844, 2021.

[19] A. Muhammed et al., "Artificial intelligence of things (AIoT) for precision agriculture," Comput. Electron. Agric., vol. 228, p. 107860, 2025.

[20] D. P. Hughes et al., "Plant disease identification using deep learning," PLoS ONE, vol. 10, no. 12, p. e0135026, 2015.

[21] Y. Lu et al., "Effective edge solution for early detection of rice disease on ARM," in Proc. IEEE Int. Conf. Edge Comput., 2024, pp. 1–6.

[22] K. S. Devi et al., "Advancement in rice blast disease management," Plants, vol. 11, no. 18, p. 2386, 2022.

[23] Y.-S. Shiu et al., "Humidity impact on edge models," ISPRS J. Photogramm. Remote Sens., vol. 167, pp. 1–12, 2020.

[24] C. Banbury et al., "MLPerf tiny benchmark," arXiv:2107.05112, 2021.

[25] R. Sharma et al., "TinyML for plant disease detection: Efficient edge AI solutions," Procedia Comput. Sci., vol. 235, pp. 1234–1242, 2025.

[26] L. Nalley et al., "The economic impact of rice blast disease in Asia," PLoS ONE, vol. 11, no. 12, p. e0166469, 2016.