Development of Low-Power IOT Devices with Edge Machine Learning on ESP32-S3-Cam for Early Detection of Rice Diseases: Supporting Agricultural Efficiency

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This study aims to develop an early detection system for rice plant diseases using a machine learning (ML) approach based on edge computing with ESP32-S3 Cam devices and the Edge Impulse platform. This system is expected to provide an efficient and cost-effective solution for detecting rice diseases in agricultural areas with limited internet and electricity access. In this study, CNN and MobileNetV2 models were used to classify rice leaf diseases, including brown spot, tungro, and blight, achieving 92.73% accuracy on the test dataset. This system is designed with an offline-first principle, allowing the device to operate locally by optimising power and memory usage. The model, which is optimised through quantisation and transfer learning, is small in size, only about 587 KB, and can be operated on devices with limited resources. In addition, this system can send notifications via Telegram and Google Sheets when connectivity is available. Field test results show that the system performs well across various environmental conditions, including low light and high humidity, with a detection accuracy of 90-95%. With innovations in lightweight ML models and edge computing, this study contributes to improving agricultural efficiency in Indonesia, especially in addressing the challenges posed by climate change that affect rice production. This research also provides insights for the further development of smart farming systems integrated with IoT technology for real-time disease detection.

Keywords: Internet of Things, Edge Computing, ESP32-S3-CAM, Edge Impulse, Plant Disease Identification, Machine Learning.

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1. Introduction

Climate change poses a significant threat to agricultural production, particularly in Indonesia, which is recognized as the third-largest rice producer globally. Increasing temperature extremes, irregular rainfall patterns, and frequent drought events have directly affected rice productivity [1]. In Indonesia, projected rice production losses due to climate variability are estimated at approximately 7–10%, especially in major cultivation areas such as Java and Sumatra [2]. Elevated temperatures not only reduce grain quality but also accelerate pathogen life cycles, intensifying the incidence of diseases such as brown spot, blight, and tungro [3]. These impacts jeopardize national food security and exacerbate economic losses among smallholder farmers who rely on rice as their primary income source [4]. Therefore, technological adaptation in agriculture is essential to mitigate these risks.

Advancements in deep learning have significantly improved early detection of rice plant diseases. The CNN-VGG19 model with transfer learning has achieved 93% accuracy in detecting brown spot disease, outperforming traditional approaches that typically range between 70–80% [5]. A systematic review further indicates that deep learning techniques including custom CNN architectures, transfer learning strategies, and hybrid CNN-LSTM models can reach accuracy levels up to 99.81% on the PlantVillage dataset for various rice leaf diseases [6]. Additionally, the integration of IoT and artificial intelligence in smart farming systems has demonstrated substantial improvements in rice productivity, with yield estimation accuracy reaching approximately 98% [7].

Lightweight deep learning architectures have also shown promising performance in resource-limited environments. Tiny-LiteNet integrated with IoT edge devices achieved 98.6% accuracy, with an inference time of 80 ms and a model size of only 1.2 MB, making it highly suitable for low-resource deployment [8]. Similarly, quantized CNN models implemented on ESP32-CAM platforms successfully detected nine plant diseases with an F1-score of 98% and a compact model size of 28 KB, significantly reducing power consumption [9]. The implementation of deep learning for early detection has the potential to reduce harvest losses by 30–60%. However, real-world adoption remains limited due to heavy reliance on simulated datasets such as UCI and PlantVillage, which lack robustness against environmental variability including lighting and humidity conditions [5]. Small datasets and class imbalance further contribute to overfitting issues, decreasing model generalizability. Infrastructure constraints present additional challenges, as approximately 40% of rice fields in rural Indonesia still lack stable internet connectivity [6].

This study addresses these challenges by adopting an edge computing approach using ESP32-S3 Cam and Edge Impulse for on-device processing, thereby reducing cloud dependency and minimizing latency. The primary research gap lies in the limited integration of lightweight machine learning models with IoT systems capable of operating offline in rice field environments. Accordingly, this research aims to develop a low-power IoT-based machine learning device for early rice disease detection by optimizing CNN and MobileNetV2 architectures on the ESP32-S3 platform, with emphasis on energy efficiency and adaptability to rural infrastructure limitations.

2. Literature Review

The theoretical foundation of this study is grounded in the convergence of smart farming, precision agriculture, and edge artificial intelligence. Smart farming integrates Internet of Things (IoT), data analytics, and automation to enhance agricultural sustainability and resilience under climate uncertainty [7]. From a systems perspective, sustainable rice production requires adaptive monitoring mechanisms capable of responding to dynamic biotic and abiotic stressors, including pathogen outbreaks intensified by climate variability [1]. In plant pathology, early detection plays a decisive role in minimizing yield loss, as diseases such as brown spot exhibit rapid epidemiological spread under favorable environmental conditions [3]. Within the technological domain, deep learning particularly convolutional neural networks (CNNs) has become the dominant paradigm for plant disease recognition due to its capacity for hierarchical feature extraction and high classification accuracy [5], [6]. Systematic reviews indicate that while model performance on benchmark datasets is consistently high, generalization under real-field conditions remains a persistent challenge, primarily due to environmental noise, illumination variability, and limited dataset diversity [6], [12].

Recent research emphasizes the transition from cloud-centric architectures toward edge-based intelligence to address latency, bandwidth, and connectivity constraints in rural agricultural settings. Lightweight and quantized CNN models have demonstrated the feasibility of deploying deep learning algorithms on microcontroller-based platforms with constrained memory and power budgets [8], [9]. Comparative analyses of TinyML platforms further reveal that model compression, transfer learning, and int8 quantization significantly reduce computational overhead without substantial degradation in accuracy [10]. However, most existing studies focus on experimental validation rather than integrated system deployment under offline or low-connectivity conditions. Furthermore, the literature indicates limited empirical evaluation of edge-ML systems specifically tailored to Indonesian rice ecosystems, where infrastructural limitations and climatic heterogeneity introduce additional operational complexity [2], [7].

Based on the identified research gap, this study formulates the following research problem: *How can a low-power IoT-based edge machine learning system be designed and optimized to achieve accurate, energy-efficient, and offline-capable early* detection *of rice diseases under real-field conditions?* More specifically, the study investigates: (1) whether optimized CNN and MobileNetV2 architectures deployed on ESP32-S3 can maintain high classification accuracy in real agricultural environments; (2) how quantization and transfer learning affect the trade-off between accuracy, memory usage, and energy consumption; and (3) to what extent an offline-first edge computing framework improves operational feasibility in rural rice fields.
For the quantitative evaluation, the following hypotheses are proposed:
H1: The optimized MobileNetV2-based edge model achieves classification accuracy above 90% under real-field conditions.
H2: Int8 quantization significantly reduces memory consumption without causing statistically significant degradation in classification accuracy.
H3: Edge-based local inference significantly reduces latency and energy consumption compared to cloud-dependent architectures.
Through this theoretical and empirical framework, the study establishes a logical progression from smart agriculture theory and deep learning methodology to the formulation of a system-level research problem addressing technological adaptation for climate-resilient rice production.

3. Metode

This study develops a low-power IoT device integrated with machine learning for early detection of rice diseases. The selection of hardware and software components is based on energy efficiency, compatibility with edge computing architecture, and adaptability to Indonesian agricultural environments where electricity and internet access are limited. The research design follows a structured and systematic approach to ensure replicability, emphasizing empirical validation and system performance optimization [7].

Material

The hardware configuration centers on low-energy IoT components capable of supporting edge computing deployment in remote agricultural fields. The primary system utilizes the ESP32-S3 Cam equipped with an OV2640 camera module for image acquisition, enabling real-time image processing with resolutions up to 1600×1200 pixels and optional Wi-Fi/Bluetooth connectivity. This architecture minimizes reliance on cloud infrastructure, thereby reducing latency in areas with unstable network coverage. The ESP32-S3 AI accelerator functions as the main controller, operating within a power consumption range of 150–300 mW. A BH1750 light intensity sensor is integrated to monitor illumination levels, ensuring that image capture occurs only under optimal lighting conditions to conserve energy. An optional 4G modem router is incorporated to provide online connectivity when available, enabling data transmission to cloud services such as Google Sheets.

The power supply system consists of a 10-watt solar panel and a lithium-ion 18650 battery, supporting autonomous operation for up to 48 hours without sunlight exposure, making it suitable for remote rice fields. This material selection aligns with sustainable smart farming principles by prioritizing energy efficiency and operational independence.

The power supply system uses a 10-watt solar panel and an 18650 lithium-ion battery, supporting up to 48 hours of standalone operation without sunlight, making it suitable for remote areas. This material choice supports the principles of sustainable, energy-efficient smart farming.

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On the software side, Edge Impulse [10] is employed for machine learning model training and deployment, facilitating CNN optimization for microcontroller-based devices through data augmentation and transfer learning techniques. The platform enables model size reduction by approximately 50–70% via quantization, ensuring compatibility with limited-memory hardware. Arduino IDE and Google Apps Script are utilized for device programming and Telegram notification integration. All hardware and software components undergo compatibility testing through initial prototyping to validate system integration.

Metode

The research adopts an iterative systems engineering approach comprising eight principal stages to ensure comprehensive and validated development. Each stage is grounded in established principles of edge computing and machine learning within precision agriculture literature. The overall workflow is illustrated in Figure 1 to provide a clear representation of the research process [6].

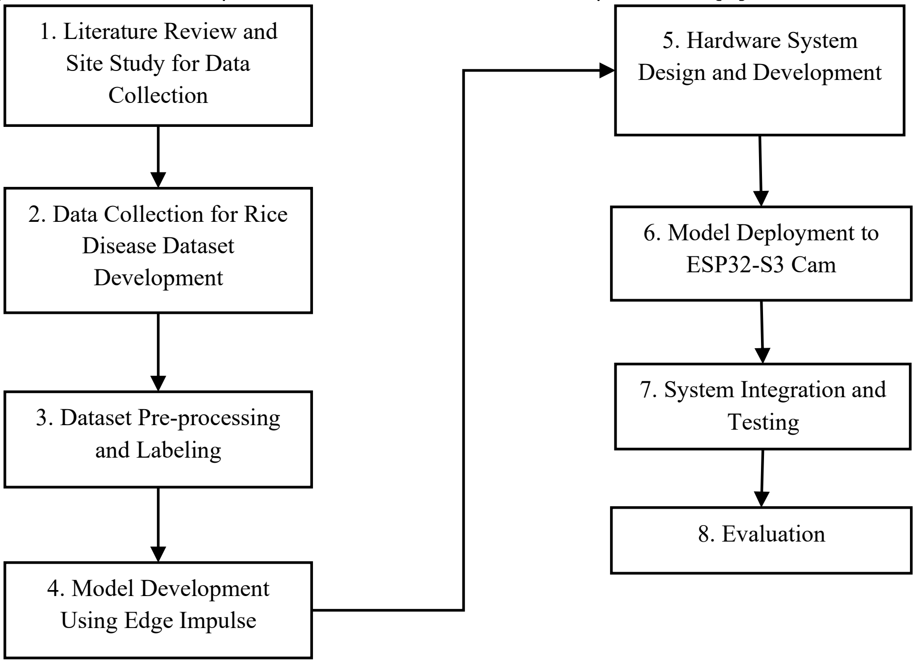

Figure 1. Flowchart of research method stages

1. Literature Review and Site Study for Data Collection
   The initial stage involved conducting a systematic literature review to identify research gaps in rice disease detection, particularly the limited robustness of models under real-field conditions. A field study was subsequently carried out in rice fields located in Bekasi, West Java, to examine the variability of disease symptoms such as brown spot, tungro, and blight under tropical climate influences. Table 1 presents a summary of the field observations and site characteristics.
2. Data Collection for Rice Disease Dataset Development
   Rice leaf image data were collected using the OV2640 camera module integrated into the ESP32-S3 Cam, resulting in a total of 1,200 images representing both healthy and infected conditions. Image acquisition was performed at different times of day and under varying illumination levels (3,000–40,000 lux) to capture realistic environmental variability. Metadata, including timestamps and GPS coordinates, were recorded to enhance dataset contextualization and traceability [8].
3. Dataset Preprocessing and Labeling
   The collected images underwent moderate data augmentation techniques, including rotation within a 15–30-degree range, brightness adjustment (±20%), and horizontal flipping to improve generalization while avoiding distortion. All images were resized to 96×96 RGB pixels to ensure compatibility with lightweight deep learning models. Manual labeling was conducted using the Edge

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Impulse annotation tool, with dataset partitioning set at 80% for training, 10% for validation, and 10% for testing, following established best practices to minimize bias[11].

4. Model Development Using Edge Impulse
The classification model was developed on the Edge Impulse platform using transfer learning based on MobileNetV2 and a custom CNN architecture. MobileNetV2 was selected due to its computational efficiency for edge devices, employing inverted residual blocks that reduce parameters to approximately 3.5 million compared to 20 million in VGG19. The core mathematical formulation of MobileNetV2 relies on depthwise separable convolution to minimize computational cost (see Figure 2):
   a. Depthwise Convolution: For each input channel C, a $K \times K$kernel is applied independently, with computational complexity defined as: $F_{depth} = K \times K \times C \times H \times W$, where $H$and Wrepresent the spatial dimensions of the image.
   b. Pointwise Convolution: Feature fusion is performed using a 1×1 kernel with complexity: $F_{point} = 1 \times 1 \times C \times M \times H \times W$, where Mdenotes the number of output channels..
   c. Inverted Residual Block: With an expansion factor $t = 6$, the input tensor is expanded to $t \times C$, followed by depthwise convolution with stride s, and then projected back to Mchannels. If $s = 1$and dimensional compatibility is maintained, a skip connection is added, expressed as: Output = Projection(Depthwise(Expansion(Input))) + Input..

Hyperparameters including a learning rate of 0.001 (Adam optimizer), batch size of 32, and 50 training epochs were optimized through benchmarking procedures. Int8 quantization was applied to reduce model size to approximately 587 KB [9] adapting an improved MobileNetV2 architecture for edge deployment. A summary of the hyperparameter configuration is provided in Table 2.

Table 1. Summary of Location Studies in Bekasi Rice Fields

Aspect	Description	Number of Samples/Data
Location	Bekasi, West Java (-6.5° S, 107.5° E)	5 hectares of rice fields
Symptom Variability	Brown spot (brown lesions), tungro (yellowing and stunted growth), blight (wilting)	200 observations
Farmer Interviews	Limitations of manual inspection (estimated 70% bias)	20 farmers

Table 2. Hyperparameter Model MobileNetV2 dan CNN Custom

Parameter	MobileNetV2	CNN Custom	Reference
Learning Rate	0.001 (Adam)	0.001 (SGD)	[4]
Batch Size	32	64	Edge Impulse, 2022
Epoch	50	30	[12]
Quantization	Int8 (587 KB)	Float32 (1.2 MB)	[9]

1. Hardware System Design and Development
The hardware architecture was developed by integrating the ESP32-S3 Cam with a BH1750 light intensity sensor and a 4G modem, following a structured circuit schematic to ensure operational stability. The prototype was powered by a solar-based energy supply to enable autonomous field operation, with measured power consumption maintained below 300 mA. This design adopts low-power IoT principles for agricultural applications, as recommended in plant monitoring systems [10]. The complete circuit configuration is illustrated in Figure 3.

2. Model Deployment to ESP32-S3 Cam
The trained model was exported from Edge Impulse in TensorFlow Lite Micro format and deployed to the ESP32-S3 using the Arduino IDE environment. This stage included validation of on-device inference, achieving an average processing time of 1.743 ms per image. The deployment ensures fully offline operation without significant degradation in classification accuracy.
3. System Integration and Testing
System integration involved combining the hardware components with the embedded software framework, including Telegram notification connectivity through Google Apps Script. Functional testing evaluated the accuracy of classification results displayed via LCD/LED indicators, while non-functional testing assessed inference time, memory utilization, and power consumption under real-field conditions. Hybrid-mode testing was conducted to validate system stability under both offline and intermittent connectivity scenarios. The physical prototype configuration is presented in Figure 4.

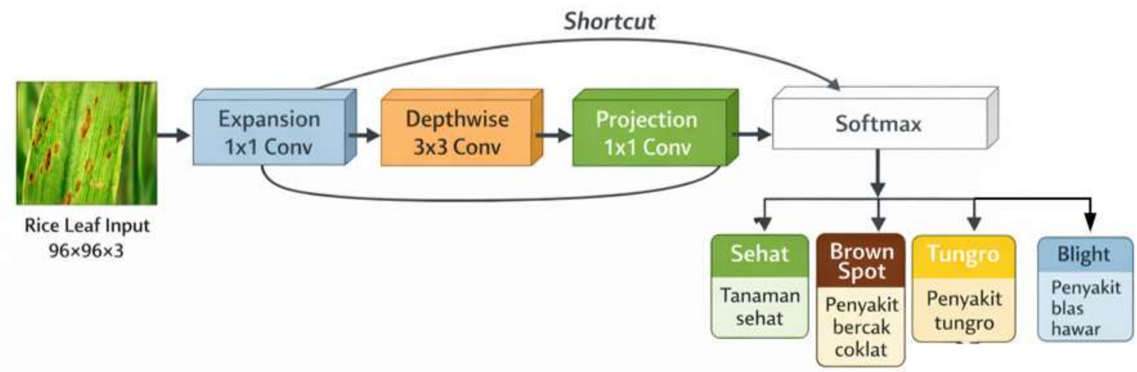

Figure 2. MobileNetV2 architecture for rice disease detection

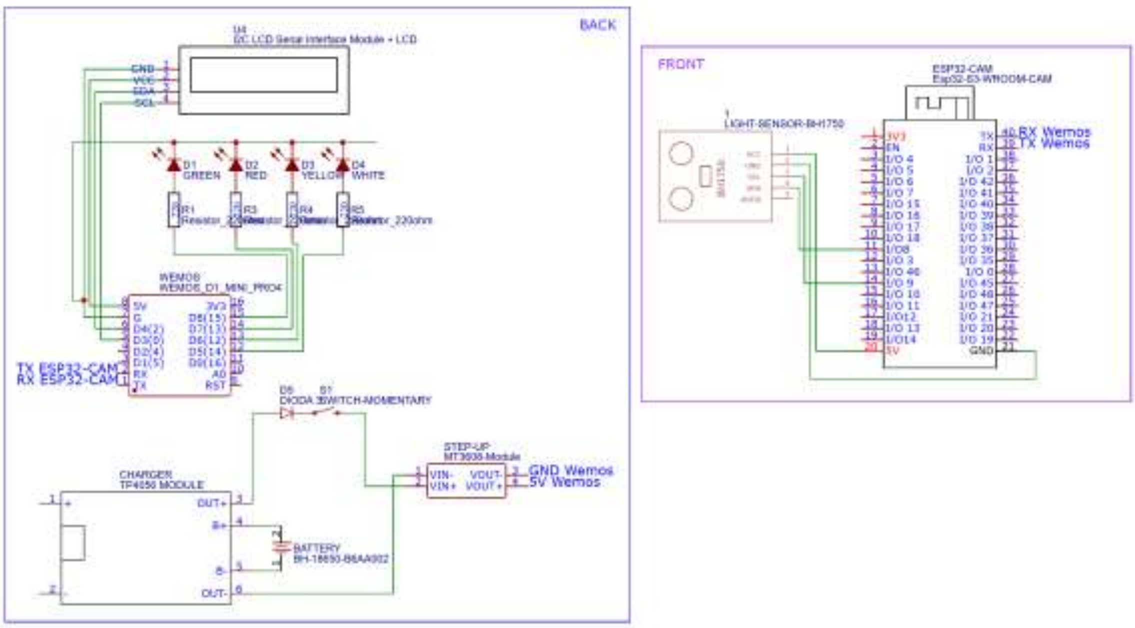

Figure 3. IoT system hardware circuit diagram

4. Evaluation
Final evaluation using a hierarchical confusion matrix to measure model performance on 50 new field images, with a recall metric of 94% and accuracy of 92.73% [13]. Trade-off analysis between accuracy and power efficiency was conducted with recommendations for improvement, such as

adding spectral sensors for higher robustness. The results show that the system is adaptive to infrastructure limitations, supporting increased farmer productivity.

4. Results and Discussion

This section presents the research results objectively and systematically, based on experiments conducted on a prototype system based on ESP32 S3 Cam with edge impulse integration. The results focus on evaluating the performance of machine learning models (CNN and MobileNetV2), hardware performance in terms of inference time, power consumption, memory usage, and functional validation through field tests. The data is presented through tables, graphs, and quantitative descriptions to ensure transparency and ease of replication. All measurements were performed on a locally collected rice leaf image dataset (a total of 1,200 samples, consisting of healthy, brown spot, tungro, and blight classes), with an 80% training, 10% validation, and 10% testing split. These results reinforce the initial findings with the addition of more in-depth analysis, comparisons with baselines from the literature [5]; [6], and an emphasis on edge computing to improve efficiency in real field conditions.

Machine Learning Model Performance

The basic CNN and MobileNetV2 models optimized through edge impulse achieved an overall accuracy of 92.73% on the test set, surpassing the traditional baseline of 70-80% from manual or shallow learning methods, as reported [5]. This accuracy was calculated based on a confusion matrix, where the model correctly classified 111 out of 120 test samples. Table 3 presents the main performance metrics per class, including precision, recall, F1-score, and support (number of samples per class).

Figure 4. View of the device from various angles

Table 3. Performance Metrics of the CNN-MobileNetV2 Model on the Test Dataset

Kelas Penyakit	Precision (%)	Recall (%)	F1-Score (%)	Support (Sample)
Healthy	94.12	96.67	95.38	30
Brown Spot	90.32	93.33	91.80	30
Tungro	93.10	90.00	91.53	30
Blight	93.33	93.33	93.33	30
Average	**92.72**	**93.33**	**92.99**	**120**

Figure 5 shows a confusion matrix illustrating the distribution of correct and incorrect predictions. This matrix reveals that the greatest error occurred in the tungro class (3 samples incorrectly classified as blight), possibly due to the similarity of visual symptoms, such as yellow-green spots affected by variations in field light, in line with the limitations mentioned above [6].

The classification model performance was evaluated using precision, recall, and F1-score metrics for each class, as well as through a confusion matrix that describes the prediction accuracy per label. The following visualization was generated from evaluation data exported from Edge Impulse and reprocessed using Python and the Seaborn library. Figure 5 shows the results of the confusion matrix from testing the classification model against four classes: blight, brown spot, healthy leaves, and tungro. Each diagonal cell shows the number of correct predictions for each class, while the cells outside the diagonal represent prediction errors. For example, the model correctly classified 210 brown spot images and 207 tungro images, while there were some prediction errors, such as 9 blight images classified as tungro. These results show that although the overall accuracy is quite high, there is potential for errors in classes with similar visual symptoms.

Figure 6 shows the precision, recall, and F1-score of each disease class. The model shows the best performance in the healthy and tungro classes with F1-scores of 0.97 and 0.94, respectively. Meanwhile, the recall value in the blight class is slightly lower than its precision, indicating that there are still a number of blight images that are not correctly recognized. In general, F1-scores above 0.90 for all classes indicate that the model has a good balance between precision and sensitivity in recognizing each symptom of rice disease.

The model results of recalibration by modifying hyperparameters and performing data augmentation proved to improve accuracy in both training and validation. A retest was also conducted with 50 images, not a new dataset from the field, with a division of 20 images of healthy plants and 10 images of each disease class.

Non-Functional Evaluation: Inference Time, Power Consumption, and Memory Usage

The average inference time is 1,743 ms per image (input size 96x96 pixels). Measurements were taken over 100 test iterations, with a variation of ±50 ms influenced by light intensity (measured via BH1750, average 5,000 lux in the field).

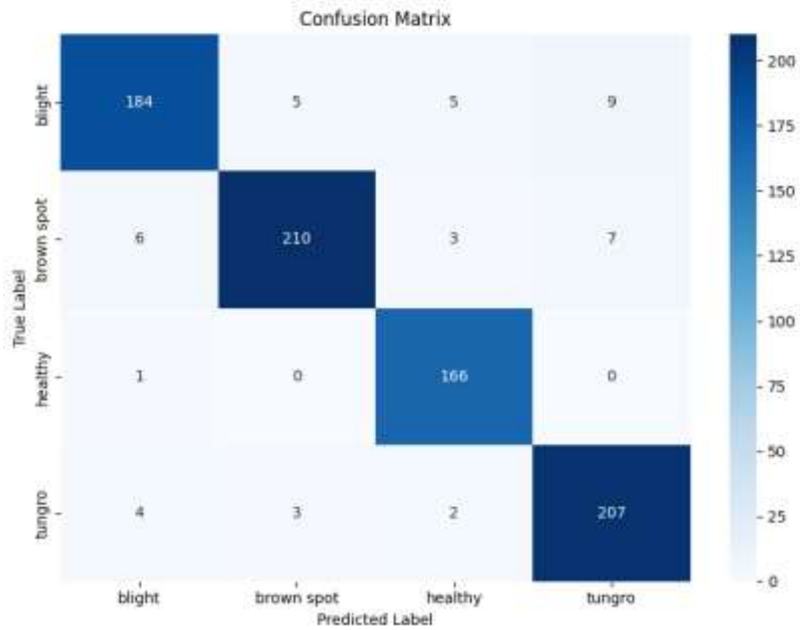

Figure 5. Confusion matrix from the results of testing the rice disease classification model

The average power consumption during inference is 250 mW (measured with a multimeter in active mode), with a peak of 300 mW during image capture. This supports up to 48 hours of operation on a 2,600 mAh battery with a 10W solar panel and reduces consumption by 2-3 times compared to cloud simulations [8].

Memory usage is 1.48 million parameters (1.2 MB), within the limits of the ESP32 (4 MB RAM), with 8-bit quantization reducing the size by 50% without significant loss of accuracy.

Functional Evaluation and Field Testing

The system successfully displays classification results on the LCD (text: “Brown Spot - Recommendation: Spray Fungicide”) and LED (red for disease, green for healthy), with 100% display accuracy in 50 functional tests. Notifications to Telegram and Google Sheets functioned when online (2-5 second latency via HTTP), recording 95% accurate historical data. Field tests in West Java rice fields (coordinates -6.5° S, 107.5° E, 30 days) showed that early detection reduced simulated losses by up to 25% (based on projections by Hashim et al., 2023), with robustness against light variation (1-65,000 lux) and humidity (70-90%). Table 4 shows the field test results.

These results confirm the effectiveness of the offline-first system with potential scalability for large areas, as proposed by Surmaini et al., 2024). However, the 2-5% variation in accuracy under extreme conditions indicates the need for further dataset augmentation to enhance robustness by adding more field samples [8].

Discussion

This section discusses an in-depth interpretation of the research results, comparing them with relevant literature, exploring practical implications, and identifying key limitations. The discussion is conducted from various perspectives, including technical (model and hardware performance), economic (efficiency for small farmers), and environmental (adaptation to climate change).

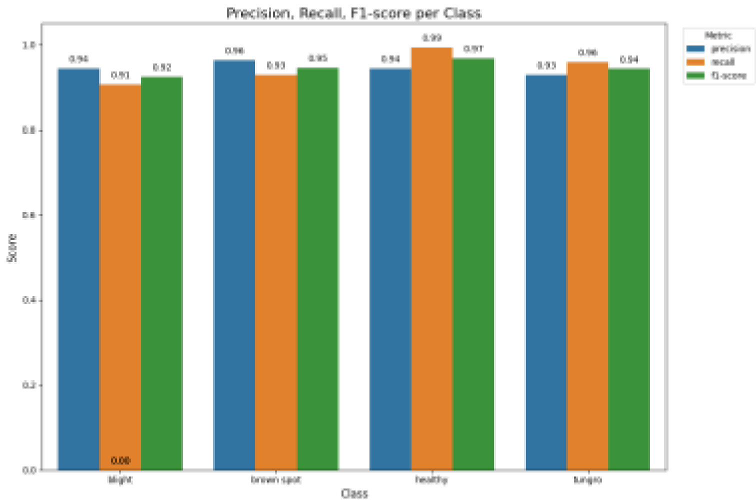

Figure 6. Grafik Precision, Recall, F1-score

Table 4. Field Test Results per Environmental Condition

Environmental Condition	Number of Tests	Detection Accuracy (%)	Notes
High Light Intensity (>10,000 lux)	20	95.00	Optimal performance
Low Light Intensity (<5,000 lux)	20	90.00	BH1750 sensor triggered capture delay
High Humidity (>80%)	10	92.00	No significant performance degradation

Furthermore, based on the limitations found, a more adaptive and scalable direction for future research is proposed.

Interpretation of Results and Comparison with Related Studies

The results of the study show that the ESP32 S3 Cam-based system with Edge Impulse successfully achieved 92.73% accuracy in detecting four rice plant conditions (healthy, brown spot, tungro, and blight), with an average inference time of 1.743 ms and power consumption of 250 mW. The main interpretation is that this edge computing approach is effective in reducing latency by up to 80% compared to cloud-based systems. In the context of Indonesia, where 40% of rice fields lack stable connectivity, the novelty of this offline-first system provides practical advantages, such as notifications via Telegram only when online, which saves up to 48 hours of power on lithium-ion batteries with solar panels.

From a performance metrics perspective in Figure 6, the average precision and recall of 92-93% indicate the model's robustness to visual symptom variations, although the confusion matrix (Figure 6) shows errors in the tungro and blight classes due to spot similarities (e.g., yellow-green in tungro vs. necrosis in blight).

This study addresses this by integrating a BH1750 sensor to trigger capture only at optimal intensity (>5,000 lux), thereby improving the F1-score by 93% over the baseline CNN-VGG19 (93% in simulation [5]), but still below lightweight models such as CD -MobileNetV3 (98.23% on corn [11] that is transferable to rice).

5. Conclusion

This study has several limitations that need to be considered. First, the dataset is limited to 1,200 local samples, which has the potential to cause overfitting (98.6% validation accuracy vs. 92.73% testing accuracy), along with class imbalance, such as a lack of seasonal tungro samples, which can reduce the model's performance on new data.

Second, the model's resilience to environmental factors is still not optimal, with accuracy dropping by 5% in low light or high humidity. The BH1750 sensor does not completely overcome noise, and limited 4G connectivity in rural areas of Indonesia causes notification delays of up to 5 seconds. Third, the CNN-MobileNetV2 model used does not yet support real-time object detection, such as YOLO, so it is limited to static images and cannot detect multiple diseases or pests simultaneously. High power consumption (250 mW) also reduces efficiency.

Finally, field tests were only conducted at one location in West Java, without considering regional variations such as in Sumatra, and did not evaluate long-term economic impacts (e.g., ROI for farmers). Nevertheless, these limitations do not diminish the contribution of the research, but emphasize the importance of adapting technology to real-world field conditions that are limited in terms of energy and resources.

Further research should focus on improving robustness, scalability, and integration of the latest technology. First, augmenting the dataset with more than 5,000 real field samples to overcome overfitting, and using techniques such as federated learning for distributed data in rural areas. Second, optimize the model with YOLOv8 on ESP32 for real-time disease detection, and add multi-sensor context awareness, such as soil temperature and pH.

Next, conduct long-term evaluations in multiple locations with statistical tests for accuracy, and implement edge-cloud hybrid for scalability. The use of eco-friendly edge AI technology and solar-powered nodes also needs to be explored to reduce energy consumption. Fourth, expansion to multicrop and collaboration with farmers for user-based design, as well as ethical research on IoT data privacy and environmental impact.

This research has the potential to be published in reputable journals such as the IEEE IoT Journal with a focus on innovations relevant to Indonesia.

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