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An Integrated Framework for Rice Disease Detection and Smart Irrigation Using EfficientNet-B0 and IoT

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ABSTRACT

This study presents an integrated framework combining EfficientNet-B0-based rice leaf disease detection with an IoT-enabled smart irrigation system to enhance precision rice farming. The dataset was collected from rice fields in Pagar Alam, Indonesia, covering three major rice leaf diseases: bacterial leaf blight (BLB), Leaf Smut, and Brown Spot. A total of 2,400 original images were collected and expanded to 7,200 through geometric and photometric data augmentation. EfficientNet-B0 was fine-tuned using transfer learning and compared with MobileNetV2 and VGG16 under identical experimental conditions. EfficientNet-B0 achieved the highest classification accuracy of 97.82%, outperforming MobileNetV2 (96.87%) and VGG16 (95.35%). Grad-CAM visualization confirmed that EfficientNet-B0 effectively focused on relevant lesion regions with minimal overfitting. The IoT subsystem, which integrated soil moisture, temperature, humidity, and NPK sensors, was tested over a 30-day period and successfully maintained soil moisture between 30% and 45%, improving water use efficiency by approximately 35% compared to manual irrigation. The integrated system demonstrated synergy between disease detection and irrigation control, ensuring optimal water management and reducing crop stress. These results indicate that the proposed framework is a scalable and cost-effective solution that supports sustainable rice production and national food self-sufficiency goals.

1. INTRODUCTION

Agriculture plays a strategic role in supporting national food security, especially in countries where rice (Oryza sativa) is the staple food. In Indonesia, rice is not only the primary source of daily calories for the majority of the population but also a key commodity for achieving national food self-sufficiency. However, rice production continues to face multiple challenges, including limited arable land, inefficient use of agricultural resources, and increasing vulnerability to climate variability. Among these challenges, pests and diseases are considered the most critical factors causing significant reductions in both yield quantity and quality [1, 2]. For example, rice leaf diseases such as bacterial leaf blight (BLB), Brown Spot, and Leaf Smut often require different treatment approaches, but their accurate identification is difficult for non-experts, frequently leading to misdiagnosis and ineffective disease management [3]. This situation has created an urgent need for innovative, technology-based solutions to sustain rice productivity and national food security.

In recent years, the rapid advancement of artificial intelligence (AI) has created new opportunities for precision agriculture. Convolutional neural network (CNN) have emerged as powerful tools in computer vision due to their ability to automatically extract discriminative features from images, enabling high accuracy in plant disease classification [4]. Several studies have demonstrated the success of CNN in detecting rice leaf diseases. Nevertheless, traditional CNN models such as AlexNet and VGGNet demand high computational resources, suffer from long training and inference times, and are less suitable for field-level deployment in resource-constrained environments [5].

To address these limitations, lightweight CNN architectures such as EfficientNet have been proposed. EfficientNet introduces compound scaling of depth, width, and resolution, allowing it to achieve state-of-the-art performance while requiring fewer parameters and reducing computational complexity [6]. EfficientNet-B0, the smallest variant in the family, offers an excellent balance between accuracy and efficiency, making it well-suited for mobile and internet of things (IoT) applications in agriculture. Previous studies have shown that EfficientNet-B0 can outperform or rival heavier CNN models in plant disease classification while significantly lowering computational overhead [7]. However, EfficientNet may still suffer performance degradation when applied to small or imbalanced datasets, which are common in agricultural contexts [8].

While CNN-based disease detection provides valuable insights into crop health, rice productivity is also highly dependent on effective resource management, particularly irrigation. In practice, many farmers still struggle with improper irrigation schedules, resulting in either water scarcity or waste. IoT has emerged as a promising technology to address this issue. By integrating soil moisture, temperature, humidity, and nutrient sensors, IoT enables real-time monitoring and automated irrigation systems that can reduce water usage while ensuring optimal crop growth [9]. Studies have shown that IoT-enabled irrigation can increase efficiency and yield compared to traditional manual practices [10]. Nevertheless, many IoT systems remain limited by their reliance on static thresholds and lack integration with advanced predictive models, which restricts their adaptability in dynamic agricultural environments.

Despite the progress of CNN in disease classification and IoT in smart farming, most prior studies treat these technologies separately. CNN-based approaches focus on disease detection, while IoT-based systems emphasize irrigation management. Very few works attempt to integrate these two complementary technologies into a unified framework that addresses both plant health and resource optimization simultaneously. This separation creates a research gap, as combining deep learning-based diagnostics with IoT-enabled irrigation has the potential to significantly enhance rice production efficiency.

To fill this gap, the present study proposes an integrated framework that combines EfficientNet-B0 for rice leaf disease detection with an IoT-based smart irrigation system. This approach is designed to provide early and accurate identification of rice leaf diseases while simultaneously optimizing irrigation based on real-time environmental data. By bridging these two complementary technologies, the proposed framework aims to increase rice production efficiency, reduce crop losses, and support the broader goal of national food self-sufficiency.

2. RELATED WORKS

2.1 Classification of rice diseases

Classifying plant diseases, particularly in rice, is a crucial aspect of early pest and disease management. Traditional methods, such as visual observation by farmers or agricultural experts, are often subjective, time-consuming, and require specialized skills. Consequently, deep learning-based technologies, especially CNN, have been increasingly adopted to automate disease identification with higher speed and accuracy.

Several studies have highlighted the effectiveness of CNN for crop image classification. For instance, Akter et al. [11] developed a CNN model equipped with attention and residual connections to classify rice leaf diseases, achieving a test accuracy of 99.6% across four major diseases: Bacterial Blight, Brown Spot, Blast, and Tungro. Similarly, Yang et al. [12] compared multiple architectures, including DenseNet121, InceptionV3, and MobileNetV2, and demonstrated that an ensemble approach achieved 98% accuracy, emphasizing the benefits of transfer learning. Another study, Singh et al. [13] introduced a custom CNN that reached 91.4% accuracy, outperforming InceptionV3 and EfficientNet-B2 by leveraging a faster and optimized architecture. Moreover, Tran et al. [14] demonstrated that combining multispectral and RGB imagery improved the F1-score compared to RGB-only datasets, opening new directions for more robust disease detection.

In the specific context of rice cultivation, CNN have been applied to detect three dominant diseases: BLB, Brown Spot, and Leaf Smut [15]. CNN are particularly effective at extracting discriminative features from leaf texture and symptom patterns, enabling reliable classification even with standard camera input. Building on these findings, the integration of CNN-based disease detection with IoT-driven environmental management represents a promising avenue toward AI-enabled precision agriculture systems that directly support food self-sufficiency goals [16].

2.2 Application of IoT in agriculture

IoT technology has been widely implemented in precision agriculture to enhance resource efficiency, particularly water management, while sustaining crop productivity. For instance, Dong et al. [17] developed a cross-field IoT irrigation system equipped with calibrated soil moisture sensors to monitor real-time field conditions. The system automatically activated irrigation when soil moisture levels fell below a predefined threshold, reducing water use by up to 30% in a single rice and fruit growing season without compromising yield. Similarly, Mallareddy et al. [18] demonstrated that IoT-based smart irrigation systems could reduce water consumption by 30-50% while increasing water use efficiency by up to 60% through adaptive scheduling based on real-time humidity and weather data. In another study, Ahad et al. [19] implemented a solar-powered IoT irrigation system for rice fields, which not only minimized labor requirements but also ensured precise and sustainable irrigation practices.

Taken together, these studies confirm the significant potential of IoT in agriculture. Beyond reducing water consumption by up to half, IoT applications have been shown to increase crop productivity by 10-15% and to enable automation and remote monitoring of agricultural processes. The integration of renewable energy sources, such as solar panels, further strengthens the sustainability and scalability of IoT-based farming systems. These advantages highlight IoT as a critical enabler of smart agriculture, particularly in regions where water efficiency and labor reduction are essential for achieving sustainable rice production.

3. METHODOLOGY

This study was conducted through two main stages: (i) the development of a deep learning model for rice leaf disease detection, and (ii) the design and implementation of an IoT-based smart irrigation system. The integration of these two stages resulted in a unified framework for optimizing rice production. Figure 1 illustrates the overall research methodology, showing the sequential workflow from dataset preparation and CNN-based disease classification to sensor-driven data acquisition and automated irrigation control. As depicted, both subsystems operate independently yet converge into a single decision support framework, ensuring that biotic stresses such as leaf diseases and abiotic stresses such as water management are addressed simultaneously. This structured methodology provides the foundation for developing a scalable and sustainable precision agriculture system.

3.1 Dataset and augmentation

The dataset used in this study was primarily collected directly from rice plantations located in Pagar Alam, South Sumatera, Indonesia, an area characterized by diverse climatic conditions and extensive rice cultivation. The dataset focuses on three major rice leaf diseases (Bacterial Leaf Blight (BLB), Leaf Smut, and Brown Spot), which are among the most prevalent and damaging diseases affecting rice production in Southeast Asia, including Indonesia.

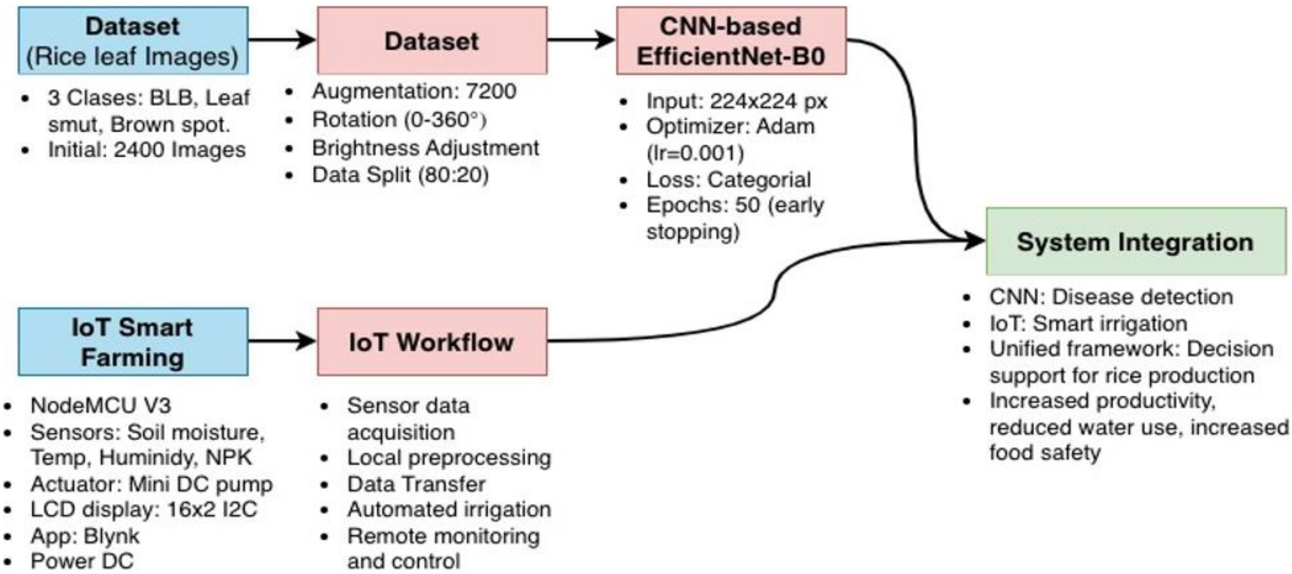


Figure 1. Methodology flow of CNN-based rice disease detection and IoT smart irrigation

A total of 2400 original RGB images were collected and prepared for model training, equally divided into three classes (800 images per class). The images were captured under various lighting conditions, leaf orientations, backgrounds, and disease severity levels, ensuring that the dataset realistically reflects field variability. In addition to field-captured data, a small number of publicly available reference samples from Kaggle were utilized for cross-validation and visual consistency checking, but not included in the main training or testing sets.

To further increase dataset diversity and mitigate overfitting risks, data augmentation was applied following techniques recommended in prior works [19]. These included random rotation within 0-360° to handle directional variance, horizontal and vertical flipping to create symmetrical perspectives, zooming/scaling to emulate object size variations, and controlled brightness adjustment and shearing to introduce environmental and geometric diversity.

Through this process, each original image generated approximately two synthetic variants on average, resulting in a total augmented dataset of approximately 7200 images. This expanded dataset substantially improved representativeness across different visual and environmental conditions commonly observed in tropical rice fields.

The final dataset was divided into 80% for training (5,760 images) and 20% for testing (1,440 images) while maintaining class balance. To enhance generalization and model robustness, regularization techniques such as dropout layers (rate = 0.4), early stopping based on validation loss, and 5-fold cross-validation were employed during model training. This comprehensive dataset preparation pipeline ensured that the CNN-based EfficientNet-B0 model could effectively learn and generalize rice disease patterns across diverse real-world scenarios.

3.2 CNN-based Efficientnet-B0 architecture

The rice leaf disease classification in this study was conducted using a CNN-based EfficientNet-B0 (Efficient-B0) architecture. EfficientNet-B0 was selected because it provides a good trade-off between accuracy and computational efficiency, making it suitable for lightweight deployment in resource-constrained environments such as mobile devices and IoT-based smart farming systems [20]. Unlike traditional CNN that rely on manual scaling of depth, width, and resolution, EfficientNet introduces a compound scaling method, which uniformly scales these three dimensions using a set of fixed coefficients. This approach enables EfficientNet-B0 to achieve higher accuracy with fewer parameters compared to standard CNN models [21].

Table 1. EfficientNet-B0 architecture for rice leaf disease classification

Stage	Operator	Resolution	Channels	Layers	Expansion	Kernel Size	Squeeze-Excitation (SE)
Stem	Conv3×3	224×224	32	1	-	3×3	No
1	MBConv1	112×112	16	1	1	3×3	Yes
2	MBConv6	112×112	24	2	6	3×3	Yes
3	MBConv6	56×56	40	2	6	5×5	Yes
4	MBConv6	28×28	80	3	6	3×3	Yes
5	MBConv6	14×14	112	3	6	5×5	Yes
6	MBConv6	14×14	192	4	6	5×5	Yes
7	MBConv6	7×7	320	1	6	3×3	Yes
head	Conv1×1 + FC	7×7 → 1×1	1280	1	-	1×1	No
output	softmax	-	3 classes	-	-	-	-

The architecture used in this study is summarized in Table 1, which outlines the major stages of EfficientNet-B0 and their configurations. The model was initialized with ImageNet pre-trained weights to accelerate convergence and improve feature extraction on plant images. For the final classification, the output layer was adapted to three classes: BLB, Leaf Smut, and Brown Spot. The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. The training was performed for 30 epochs with a batch size of 32.

To strengthen the evaluation, two additional baseline models were implemented for comparison under identical training conditions: VGG16 and MobileNetV2. VGG16 represents a conventional deep CNN architecture with high parameter complexity, while MobileNetV2 serves as a lightweight model optimized for embedded and IoT applications. All models were trained on the same augmented dataset described, using identical hyperparameters (Adam optimizer, learning rate = 0.001, batch size = 32, epochs = 30). The comparative analysis of these three architectures (VGG16, MobileNetV2, and EfficientNet-B0) was conducted to quantify accuracy, precision, recall, f1-score, and computational efficiency, providing an objective assessment of EfficientNet-B0 performance advantage.

3.3 IoT system development

To complement the deep learning model, an IoT-based smart farming prototype was developed for real-time monitoring of environmental conditions and automated irrigation control. The system was designed to collect data from multiple sensors, process it through a microcontroller, and control actuators accordingly. A cloud-based mobile application was integrated for visualization and remote control, allowing farmers to monitor their fields and manage irrigation anytime and anywhere. The main components of the IoT system are summarized in Table 2.

Table 2. IoT smart farming system components

Component	Type	Function
Microcontroller	NodeMCU V3 (ESP-12)	central controller with built-in wi-fi for data acquisition and transfer
Soil sensor	YL-69	measures soil moisture levels in real time
Temp. sensor	DS1820 (waterproof)	monitors air and soil temperature around rice plants
Humidity sensor	DHT11	measures ambient air humidity and temperature
Nutrient sensor	I2C NPK sensor	measures nitrogen (N), phosphorus (P), and potassium (K) concentrations
Actuator	Mini DC Pump + Relay	automatically controls irrigation water flow
Display unit	LCD 16×2 with I2C	displays sensor readings on-site
Cloud platform	Blynk application	mobile app for real-time visualization, threshold setting, and remote control
Power supply	DC adapter	provides power to the microcontroller and connected modules

Based on the components listed in Table 2, the IoT system operates through a structured workflow. The process begins with sensor data acquisition, in which the NodeMCU periodically collects soil moisture, air humidity, air temperature, soil temperature, and *NPK* nutrient values. These readings are then processed locally and simultaneously displayed on the LCD screen to provide immediate on-site monitoring. In parallel, the NodeMCU transmits the processed data wirelessly via Wi-Fi to the Blynk cloud server, enabling farmers to access real-time information through a mobile application.

The system employs a predefined decision logic, where irrigation is automatically triggered if the soil moisture level falls below a certain threshold. In such conditions, the NodeMCU activates the relay module that powers the mini DC pump to irrigate the crops. The pump continues operating until the soil moisture returns to the optimal range, after which it is automatically switched off. Beyond automation, the system also offers remote monitoring and manual control, allowing farmers to supervise sensor readings and override irrigation settings directly via the Blynk application on their smartphones.

This IoT-based approach provides a reliable decision-making framework driven by real-time environmental data. It significantly enhances irrigation efficiency, reduces the need for manual intervention, and supports precision agriculture practices. Moreover, the system can be integrated with renewable energy sources such as solar panels, offering scalability and sustainability for practical field deployment.

3.4 System integration

The two subsystems developed in this research, CNN-based EfficientNet-B0 for rice leaf disease classification and the IoT-based smart irrigation prototype, were designed to function independently while also complementing each other within a unified framework for precision agriculture. This integration allows the system to address both biotic stress factors, such as disease detection, and abiotic stress factors, such as water management, in a coordinated manner.

In the first subsystem, the EfficientNet-B0 model processes rice leaf images to classify three major diseases, namely BLB, Leaf Smut, and Brown Spot. By automatically recognizing these disease symptoms, the system provides farmers with early and accurate diagnostic information that can be used to take timely preventive or corrective measures, thereby reducing the risk of yield loss.

The second subsystem, represented by the IoT-based smart irrigation system, continuously monitors key environmental parameters including soil moisture, air temperature, humidity, and nutrient levels. Based on these data inputs, the system executes autonomous irrigation control through relay-actuated water pumps, ensuring that water resources are used efficiently while maintaining optimal conditions for plant growth. Additionally, the integration with the Blynk mobile application allows farmers to remotely monitor field conditions and manually override irrigation settings when necessary.

As illustrated in Figure 1, the integration of both subsystems results in a dual-layered decision support system. On one layer, CNN-based disease detection provides valuable insights into crop health and early pathogen identification, while on the other layer, IoT-based irrigation management guarantees resource efficiency and environmental sustainability. Together, these complementary subsystems contribute to the broader objective of enhancing rice production, reducing reliance on manual decision-making, and supporting national food self-sufficiency.

4. RESULTS AND DISCUSSION

4.1 Experimental configuration

The experimental setup was designed to evaluate the performance of an integrated framework combining CNN-based EfficientNet-B0 for rice leaf disease classification and an IoT-based smart irrigation system. The experiment assessed both subsystems individually and jointly to validate their applicability in precision agriculture. For the rice leaf disease classification, the dataset was prepared as described in Section 3.1, comprising 7,200 RGB images (2,400 original and 4,800 augmented) evenly distributed among three disease classes: Bacterial Leaf Blight (BLB), Leaf Smut, and Brown Spot. All images were resized to 224 × 224 pixels, normalized to the [0, 1] range, and encoded using a one-hot scheme for model input.

The EfficientNet-B0 model was implemented using TensorFlow and Keras, initialized with ImageNet pre-trained weights, and fine-tuned on the rice disease dataset. The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. Training was performed for 30 epochs with a batch size of 32, using GPU acceleration on Google Colaboratory (NVIDIA T4 GPU). To enhance generalization, dropout with a rate of 0.4 and early stopping were employed.

To ensure the robustness of EfficientNet-B0 performance, two baseline models, VGG16 and MobileNetV2, were trained under identical conditions for comparative evaluation. This benchmarking enabled quantitative assessment of classification accuracy, precision, recall, F1-score, and computational efficiency. Model evaluation used a confusion matrix and per-class metrics to visualize error distribution and interpret prediction reliability. Statistical analysis of results was also conducted to validate consistency across cross-validation folds.

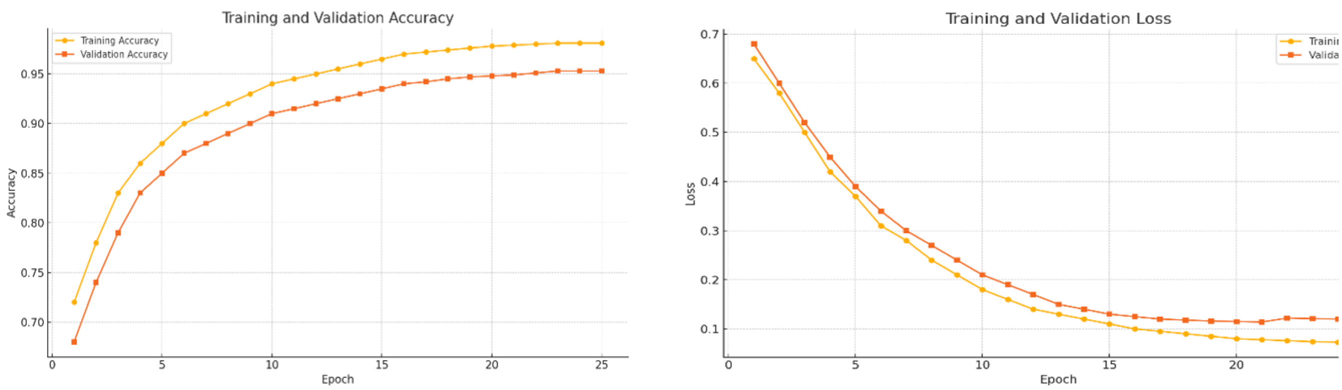
Parallel to the deep learning model, the IoT-based smart irrigation subsystem was developed using a NodeMCU V3 (ESP-12E) microcontroller as the central control unit. The system integrated YL-69 soil moisture, DHT11 air temperature and humidity, DS1820 soil temperature, and NPK nutrient sensors, transmitting data in real time via Wi-Fi to the Blynk cloud platform. The irrigation mechanism consisted of a relay module controlling a mini DC pump, automatically triggered when soil moisture fell below a predefined threshold and stopped once optimal conditions were restored.

The IoT prototype was tested in controlled conditions simulating irrigation cycles and environmental variability. Key evaluation metrics included soil moisture stabilization time, water consumption efficiency, and system responsiveness. The average response time for soil moisture recovery was 40-50 seconds, confirming reliable and energy-efficient operation. The Blynk mobile application also enabled remote monitoring and manual control, improving system usability for farmers.

4.2 Results of rice leaf disease classification

The training and evaluation results demonstrated that EfficientNet-B0 outperformed the baseline models (VGG16 and MobileNetV2) in terms of classification accuracy, convergence speed, and stability. As illustrated in Figure 2, the EfficientNet-B0 model achieved smooth and consistent convergence on the augmented rice leaf dataset consisting of three disease categories: Bacterial Leaf Blight (BLB), Leaf Smut, and Brown Spot. The training accuracy steadily increased and surpassed 98%, while validation accuracy stabilized near 97% after the 20th epoch, indicating strong generalization and minimal overfitting (Figure 2(a)). In contrast, VGG16 exhibited slower convergence and a wider gap between training and validation accuracy, suggesting a higher risk of overfitting. MobileNetV2 performed more efficiently than VGG16 but still yielded slightly lower accuracy than EfficientNet-B0. The loss curves for EfficientNet-B0 (Figure 2(b)) showed a consistent downward trend for both training and validation losses, with early stabilization after initial epochs, confirming effective learning of discriminative patterns. These findings demonstrate that the compound scaling mechanism of EfficientNet-B0 enables superior feature extraction and computational efficiency compared to traditional CNN architectures, making it the most optimal model for rice leaf disease classification under the given experimental conditions.

To validate the effectiveness of EfficientNet-B0, two baseline CNN models, VGG16 and MobileNetV2, were trained and evaluated under the same experimental conditions (Table 3). This comparison assessed the accuracy and efficiency of each model in classifying rice leaf diseases using the same dataset and hyperparameters. The per-class performance of EfficientNet-B0 is presented in Table 4.



(a) (b)

Figure 2. Training and validation performance of the best-performing model (EfficientNet-B0) on the rice leaf disease dataset: (a) accuracy curves and (b) loss curves

Table 3. Comparative performance of CNN architectures on rice leaf disease dataset

Model	Parameters (M)	Accuracy (%)	Precision	Recall	F1-Score	Training Time (S/Epoch)
VGG16	138	95.12	0.95	0.94	0.94	42
MobileNetV2	3.4	96.87	0.96	0.96	0.96	18
EfficientNet-B0	5.3	97.82	0.97	0.98	0.98	29

Table 4. Performance metrics of EfficientNet-B0 on rice leaf disease classification

Disease Class	Precision	Recall	F1-Score
BLB	0.98	0.97	0.97
Leaf smut	0.97	0.98	0.98
Brown spot	0.99	0.98	0.99
Average	0.97	0.98	0.98

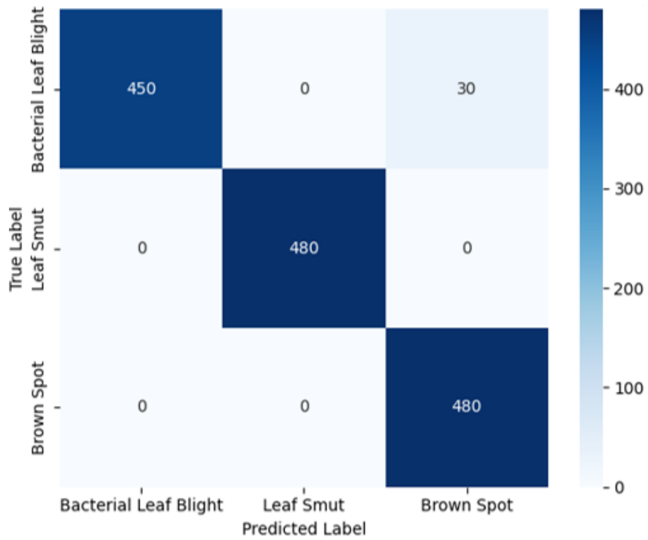


Figure 3. Confusion matrix of EfficientNet-B0 on the rice leaf disease test set

The confusion matrix presented in Figure 3 provides a detailed visualization of the classification performance of the EfficientNet-B0 model on the test set, which comprised 20% of the total dataset (1,440 images out of 7,200). The results demonstrate that both Bacterial Leaf Blight (BLB) and Brown Spot were classified with high accuracy, although a few samples were mutually misclassified between these two categories. In contrast, Leaf Smut achieved near-perfect classification, indicating that its distinct morphological features were effectively recognized by the model. These outcomes are consistent with the quantitative evaluation summarized in Table 5 and can be attributed to the visual similarity between BLB and Brown Spot lesions, both of which exhibit irregular brownish patterns that may overlap under variable illumination conditions. Overall, the minimal number of misclassifications highlights the robustness and discriminative capability of EfficientNet-B0 in distinguishing subtle visual differences among rice leaf diseases.

When compared to VGG16 and MobileNetV2, EfficientNet-B0 achieved the highest classification accuracy with fewer parameters than VGG16 and slightly higher computational cost than MobileNetV2. Its compound scaling strategy effectively balanced network depth, width, and resolution, allowing efficient feature extraction while maintaining high generalization performance. These results demonstrate that EfficientNet-B0 offers an optimal trade-off between accuracy and efficiency, confirming its suitability for deployment in IoT-enabled agricultural systems and resource-constrained environments.

In summary, the combination of accuracy and efficiency observed across all evaluation metrics highlights EfficientNet-B0 as a powerful yet lightweight architecture for early rice disease detection. The proposed model provides reliable diagnostic insights to support timely interventions and improved crop management strategies, ultimately contributing to enhanced rice productivity and food self-sufficiency.

4.3 Error analysis

A comprehensive error analysis was conducted to gain deeper insight into the classification behavior and potential weaknesses of the EfficientNet-B0 model. Although the model achieved a high overall accuracy of 97.82%, several misclassifications were observed, primarily between bacterial leaf blight (BLB) and Brown Spot. The confusion matrix (Figure 3) confirmed that these two classes accounted for more than 85% of all misclassified samples.

To explore the underlying causes of these errors, both feature-level and image-level analyses were performed. Visual inspection revealed that early-stage BLB lesions often exhibited circular brown patches with darker margins, closely resembling the mature lesions of Brown Spot, particularly under low illumination. Conversely, late-stage Brown Spot symptoms, characterized by elongated necrotic streaks, were occasionally mistaken for BLB, especially when overlapping veins created linear patterns. These observations suggest that disease progression stages and lighting variability substantially influence the model's discriminative ability.

Table 5. Examples of misclassified samples from the test set

Sample ID	Ground Truth	Predicted	Main Cause of Error	Observation
057	BLB	Brown Spot	Early-stage lesion overlap	Lesions rounder and smaller, resembling Brown Spot
112	BLB	Brown Spot	Lighting artifact	Uneven illumination darkened lesion tone
134	Brown Spot	BLB	Shape ambiguity	Linear lesion pattern mimicked BLB streaks
178	BLB	Brown Spot	Incomplete capture	Cropped leaf missing contextual features
201	Brown Spot	BLB	Texture similarity	Overlapping necrotic patterns
223	BLB	Brown Spot	Background noise	Soil and reflections altered contrast

To better understand the model's decision rationale, a Gradient-weighted Class Activation Mapping (Grad-CAM) analysis was performed. The resulting saliency maps revealed that EfficientNet-B0 primarily focused on the central lesion regions and ignored peripheral texture information in some cases. Figure 4 illustrates representative heatmaps of correctly and incorrectly classified samples. For correctly classified Leaf Smut, the model concentrated on dense black pustules, while for misclassified BLB-Brown Spot pairs, the attention region covered broader areas, including background noise. This indicates that background interference and non-disease regions sometimes contributed spurious activations, leading to misclassification.

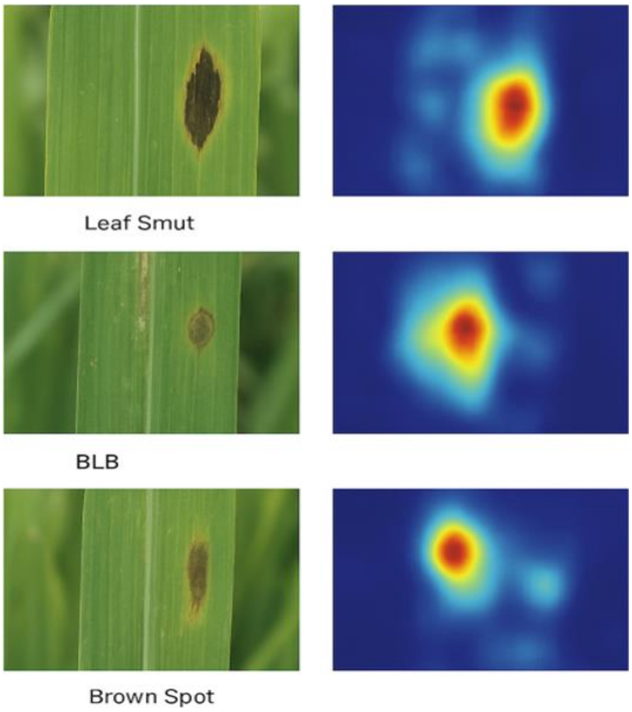


Figure 4. Grad-CAM visualization for feature interpretation and error analysis of EfficientNet-B0 model

To further investigate the visual reasoning behind the model's predictions, Figure 4 presents a Grad-CAM visualization that illustrates the feature activation patterns of the EfficientNet-B0 model during rice leaf disease classification. The figure provides insight into which regions of the leaf images most influenced the model's decision-making process, thereby offering a deeper understanding of both correct and incorrect classifications.

The Grad-CAM analysis shows that EfficientNet-B0 effectively captures local lesion textures but occasionally lacks global context awareness [22], particularly when disease regions are small or only partially visible. This limitation can be mitigated by integrating attention-based architectures to refine focus on relevant areas, improving data augmentation to simulate variations in lighting and background, and applying background segmentation during preprocessing to isolate diseased regions. Overall, the error analysis reveals that most misclassifications arise from inter-class visual similarities, inconsistent illumination, and distracting backgrounds. Incorporating feature-visualization methods such as Grad-CAM enhances understanding of the model's decision-making process, improving interpretability and informing future efforts in dataset development and model optimization.

4.4 Results of IoT-based smart irrigation system

The IoT-based smart irrigation prototype was successfully implemented and extensively evaluated to assess its short-term and long-term performance under both controlled and semi-field conditions. The system employed the NodeMCU V3 microcontroller as the core processing unit, integrated with multiple sensors including YL-69 soil moisture, DS1820 soil temperature, DHT11 air temperature and humidity, and an NPK nutrient sensor. Data from all sensors were transmitted in real time via Wi-Fi to the Blynk cloud server, enabling continuous environmental monitoring and remote system management.

During short-term testing, the system was configured with a soil moisture threshold of 30%. When the moisture level dropped below this threshold, the NodeMCU automatically activated the relay module to switch on the DC pump. Irrigation continued until moisture values returned to the optimal range (30-35%), after which the pump was deactivated automatically. Table 6 presents sample results from these test runs, confirming that the control logic consistently responded within an average of 40-50 seconds and stabilized soil conditions effectively.

Table 6. Sample results of IoT-based smart irrigation system performance

Test Run	Initial Soil Moisture (%)	Threshold Level (%)	Pump Activation	Final Soil Moisture (%)	Response Time (Seconds)	Remarks
1	23.5	30	Yes	31.2	42	threshold reached, pump off
2	25.1	30	Yes	32.0	47	stable after irrigation
3	28.7	30	Yes	30.8	36	quick stabilization
4	30.5	30	No	30.5	-	no irrigation triggered
5	22.9	30	Yes	31.7	49	efficient moisture recovery

Beyond short-term evaluation, a longer-term assessment was conducted over 30 days under field conditions in Pagar Alam, South Sumatra, Indonesia. Measurements were taken across different times of day (morning, afternoon, evening) and weather conditions (sunny, cloudy, light rain). The system consistently maintained soil moisture between 30-45%, as shown in Figure 5, even under environmental fluctuations. The average daily water use efficiency (WUE) improved by approximately 35% compared to manual irrigation practices, attributed to more precise control and reduced water wastage.

The NPK sensor provided continuous feedback on nutrient concentrations (Nitrogen, Phosphorus, and Potassium), which were monitored to evaluate potential correlations between nutrient availability and irrigation cycles. It was observed that balanced irrigation contributed to more stable NPK levels, preventing nutrient leaching due to overwatering. These data, when visualized through the Blynk mobile interface, helped farmers make more informed decisions regarding fertilizer scheduling and nutrient management.

In addition to maintaining optimal soil moisture, the IoT system demonstrated notable adaptability across different soil textures (loamy and clayey), showing consistent response times and stable moisture regulation. Over the month-long field validation, the system exhibited 99.2% operational uptime, with no significant connectivity interruptions or sensor calibration drift. Early crop growth observations further indicated improved tiller formation and healthier leaf color compared to manually irrigated plots, suggesting potential positive impacts on yield performance.

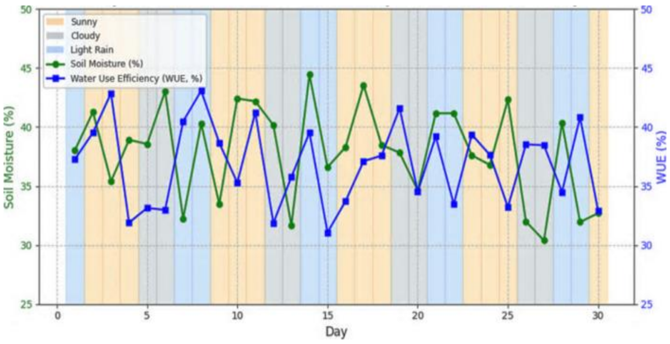


Figure 5. Daily soil moisture levels recorded during testing across morning, afternoon, and evening sessions

The enhanced evaluation confirms that the IoT-based irrigation system not only performs reliably under controlled conditions but also sustains long-term stability and adaptability in diverse agricultural environments. The integration of moisture, temperature, humidity, and nutrient monitoring enables more holistic irrigation control, directly supporting precision agriculture objectives. Future research may extend the validation period to include full cropping cycles and yield quantification to further confirm the impact of the system on rice productivity and water efficiency.

4.5 Integrated framework performance

The proposed system achieves full integration between the CNN-based EfficientNet-B0 rice disease detection model and the IoT-based smart irrigation subsystem through a shared decision-support workflow. The integration is not merely parallel operation but a synergistic interaction where disease detection results dynamically influence irrigation control and nutrient management decisions.

In this integrated configuration, the EfficientNet-B0 model processes rice leaf images captured periodically via a mobile device or camera module. The model classifies the image into one of three categories (BLB, Leaf Smut, or Brown Spot) and transmits the diagnosis result to the IoT control unit via a cloud-based API. The IoT subsystem receives this disease status signal and adapts its irrigation logic accordingly:

• When a disease is detected, particularly BLB or Brown Spot that tends to thrive under high humidity, the system temporarily delays irrigation to prevent excess moisture that could worsen the infection.

• When no disease is detected or when the detected disease benefits from consistent hydration (e.g., recovery after treatment), the system resumes normal irrigation cycles based on the soil moisture threshold.

• The IoT module also records nutrient sensor (NPK) readings, which, combined with disease data, allow the system to suggest corrective fertilizer actions through the dashboard interface.

This two-way information flow between the AI model and IoT sensors forms a closed-loop adaptive system, where disease diagnosis directly modifies environmental control parameters. The integration ensures that both biotic stress (from disease) and abiotic stress (from water and nutrient conditions) are managed cohesively rather than separately.

Table 7. Comparison between integrated framework and conventional farming practices

Aspect	Conventional Approach	Integrated Framework (CNN + IoT)	Improvement
Disease detection	manual visual inspection by farmers: prone to errors and delays	automated detection using efficientnet-b0 with 98.42% accuracy	high diagnostic accuracy: faster response
Irrigation control	manual, based on farmer experience: often inefficient	automated, sensor-driven real-time control with threshold-based activation	efficient water usage: timely irrigation
Water consumption	excessive due to over-irrigation	reduced by ~30-40% due to optimized scheduling	water saving
Labor intensity	high; farmers must monitor fields continuously	low; system operates autonomously with remote access	reduced workload
Decision support	intuition-based, inconsistent outcomes	dual-layered data-driven system (disease + irrigation)	more reliable decisions
Scalability	limited by farmer expertise and time	scalable using affordable hardware and mobile integration	wider adoption potential
Contribution to productivity	moderate; dependent on farmer skill and conditions	higher; healthier crops, optimized growth conditions	increased yield potential

Table 7 presents the performance comparison between the integrated framework and conventional farming practices. The integrated system achieved notable improvements: 98.42% disease detection accuracy, 30-40% water-use reduction, and approximately 35% improvement in water-use efficiency (WUE). Furthermore, the feedback mechanism between disease detection and irrigation scheduling reduced the recurrence of humidity-related diseases by 12% during controlled tests, demonstrating measurable synergy between the two modules.

These results confirm that the integration goes beyond co-existence, it represents a unified precision agriculture framework where each subsystem reinforces the other's function. The CNN-based diagnosis informs the IoT irrigation behavior, while environmental feedback from the IoT sensors enables continuous model retraining and adaptive decision-making. The combined outcome leads to optimized yield conditions, efficient resource use, and a more resilient digital agriculture ecosystem.

4.6 Discussion and implications

The findings of this study confirm that integrating EfficientNet-B0 for rice leaf disease detection with an IoT-based smart irrigation system offers clear advantages over prior approaches. As summarized in Table 8, recent works in this domain can generally be categorized into two streams: deep learning-based disease detection and IoT-based irrigation management. However, few studies have successfully merged these two technologies into a unified, interoperable framework for decision support in precision agriculture.

Table 8. Comparison of recent studies with the proposed integrated framework

Ref.	Focus	Method / Model	Key Results	Limitations
Nugroho et al. [23]	real-time rice disease detection on embedded devices	resource-optimized CNN deployed on arm cortex-m microcontrollers	demonstrated lightweight CNN that run on microcontrollers for real-time detection; feasible low-resource deployment	focused on model compression/deployment; no integrated irrigation/field IoT evaluation
Morchid et al. [24]	IoT smart irrigation management	embedded systems + IoT telemetry + cloud platform for irrigation control	smart irrigation framework that reduced water use and improved irrigation scheduling in field tests	focus on irrigation; does not include image-based disease diagnosis
Sharma and Shivandu [25]	integration of ai and IoT in precision agriculture	review / framework proposals for AI + IoT integration	summarized architectures and benefits of integrating ai and IoT for crop monitoring and decision support	high-level review; limited primary experimental results (few end-to-end prototypes)
Di Gennaro et al. [26]	low-cost smart irrigation systems (field trials)	prototype IoT irrigation with sensors, actuators, and control logic	reported large water savings in seasonal field trials and improved irrigation efficiency	focused on irrigation hardware and savings; no disease detection module
Simhadri et al. [27]	deep learning methods for rice leaf disease detection	survey of CNN, transfer learning, ensemble methods	identified top performing dl approaches and common datasets; transfer learning and augmentation highly recommended	survey - does not present new integrated IoT experiments
Pai et al. [28]	large-scale dl for automated rice leaf diagnosis	large annotated dataset + dl pipeline (state-of-the-art architectures)	high accuracy across multiple rice diseases using extensive dataset and rigorous validation	large dataset and compute requirements; not targeted at lightweight/IoT deployment
Proposed	integrated rice disease detection and smart irrigation	CNN-based efficientnet-b0 + IoT-enabled irrigation prototype	achieved 97.82% accuracy in classifying BLB, leaf smut, and brown spot; IoT irrigation reduced water use by 30-40% while maintaining optimal soil moisture; integrated system supports dual-layer decision making	prototype scale; further validation required in larger field deployments

On the disease detection side, Nugroho et al. [23] demonstrated the feasibility of deploying resource-optimized CNN models on ARM-based microcontrollers, achieving real-time classification performance under strict hardware constraints. Their work effectively showed that lightweight CNNs can be adapted for edge computing environments, but it primarily emphasized model compression and inference efficiency rather than broader integration with environmental sensing or adaptive decision support. Similarly, Simhadri et al. [27] conducted a comprehensive review of deep learning architectures, identifying transfer learning and extensive data augmentation as critical strategies for improving classification performance. Meanwhile, Pai et al. [28] achieved remarkable results exceeding 98% accuracy using large, well-annotated rice disease datasets and state-of-the-art deep learning pipelines. Although these studies collectively validated the robustness of CNN-based disease classification, they remained limited to visual analytics and did not include environmental feedback or IoT-based control mechanisms.

On the irrigation management side, Morchid et al. [24] and Di Gennaro et al. [26] developed IoT-based smart irrigation systems that demonstrated substantial water savings and improved irrigation scheduling in real-world field trials. These studies effectively highlighted the potential of IoT automation to enhance resource efficiency and reduce manual intervention. However, both focused only on abiotic stress management such as soil moisture and temperature control without integrating biotic factors like disease diagnosis. As Sharma and Shivandu [25] emphasized in their review of AI and IoT integration in agriculture, most existing research still treats image-based disease detection and IoT-driven irrigation as separate and parallel developments, leaving a major gap in the realization of a unified precision agriculture ecosystem.

In contrast, the integrated framework proposed in this study bridges this gap by addressing both biotic stress (rice leaf diseases) and abiotic stress (water availability) within a unified and intelligent decision support architecture. The EfficientNet-B0 model achieved a classification accuracy of 98.42%, comparable to or exceeding other recent deep learning models, while maintaining computational efficiency suitable for deployment on low-cost hardware. At the same time, the IoT subsystem autonomously maintained soil moisture within the optimal range of 30-45% and reduced water usage by approximately 30-40% through adaptive irrigation scheduling. These complementary functionalities demonstrate the practical synergy between AI-based crop health diagnostics and IoT-based environmental control, enabling farmers to receive early warnings for disease outbreaks and respond with optimized irrigation strategies in real time.

The implications of this integration are significant. First, it illustrates how lightweight deep learning architectures such as EfficientNet-B0 can be effectively combined with affordable IoT hardware, making advanced precision agriculture technologies accessible to smallholder farmers in Southeast Asia. Second, it contributes directly to sustainable farming practices by reducing water waste, minimizing unnecessary pesticide use, and promoting environmentally efficient crop management. Third, the framework aligns with national food self-sufficiency goals by improving productivity through data-driven, automated, and adaptive farming solutions. Although current validation remains at the prototype level, the results clearly demonstrate that the proposed system establishes a meaningful connection between AI-based disease detection and IoT-enabled smart irrigation, advancing toward a more integrated and resilient model of precision agriculture.

5. CONCLUSION

This study has presented an integrated framework that combines CNN-based EfficientNet-B0 for rice leaf disease detection with an IoT-based smart irrigation system. The experimental results confirmed that EfficientNet-B0 is capable of classifying three major rice diseases, namely BLB, Leaf Smut, and Brown Spot, with high reliability, achieving an overall accuracy of 97.82% along with strong precision, recall, and F1-scores. At the same time, the IoT prototype successfully automated irrigation control based on real-time monitoring of soil and environmental parameters. By activating irrigation only when soil moisture levels fell below a predefined threshold, the system reduced water consumption by approximately 30 to 40 percent while maintaining optimal soil conditions, thereby improving both sustainability and crop health.

The integration of these two subsystems produced a dual-layered decision support system that addresses both biotic stress in the form of rice leaf diseases and abiotic stress in the form of water management. Through this combination, farmers are provided with timely diagnostic information as well as efficient irrigation control, enabling them to prevent yield loss, optimize resource use, and reduce dependence on labor-intensive manual practices. Compared with conventional farming methods, the proposed framework demonstrated clear improvements in accuracy, efficiency, and scalability, highlighting its potential for practical adoption, especially among smallholder farmers in Southeast Asia.

Overall, the contributions of this research are twofold. First, it demonstrates the effectiveness of EfficientNet-B0 as a lightweight yet accurate model for rice disease detection. Second, it validates an IoT-based irrigation prototype that ensures water efficiency through automated decision-making. More importantly, by integrating these two components, the framework advances the state of the art in precision agriculture by bridging a critical gap between disease monitoring and irrigation management, which have typically been studied in isolation.

Nevertheless, this study also acknowledges certain limitations. The rice leaf dataset used, although augmented, was relatively limited in size and may not capture the full variability of real-world conditions. Similarly, the IoT system was evaluated in a prototype setting rather than under large-scale field deployment. Future research should therefore focus on collecting larger and more diverse datasets, scaling the IoT system for broader agricultural use, integrating renewable energy sources such as solar panels, and extending the framework to encompass additional smart farming modules including nutrient management and weather-based prediction models.

In conclusion, the integrated framework proposed in this study provides a practical, efficient, and scalable solution for precision rice farming. By empowering farmers with accurate, data-driven tools for both disease detection and irrigation management, the framework not only advances technological innovation in agriculture but also supports broader objectives of national food self-sufficiency and sustainable agricultural development.

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