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RiceGuard: A Lightweight PSO-Optimized MobileNetV2 Framework for Stable Rice Leaf Disease Classification

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Abstrak

Penyakit daun padi seperti blast, bercak coklat, layu bakteri, dan tungro menjadi ancaman serius bagi produktivitas pertanian, dengan potensi kerugian hasil panen melebihi 50% dalam kondisi wabah. Oleh karena itu, deteksi dini yang cepat dan akurat sangat penting untuk mendukung ketahanan pangan yang berkelanjutan dan pertanian presisi. Penelitian ini mengusulkan sistem klasifikasi penyakit daun padi berbasis arsitektur MobileNetV2 yang dioptimalkan menggunakan Particle Swarm Optimization (PSO). Sebuah dataset yang terdiri dari empat kelas penyakit daun padi yang dikumpulkan dari repositori publik dan sumber yang mewakili kondisi lapangan digunakan untuk mengevaluasi pendekatan yang diusulkan. Pembelajaran transfer digunakan untuk meningkatkan efisiensi pelatihan, sementara PSO diterapkan untuk mengoptimalkan hiperparameter kunci guna meningkatkan stabilitas dan konvergensi model. Hasil eksperimen menunjukkan bahwa MobileNetV2 yang dioptimalkan dengan PSO mencapai kinerja klasifikasi yang optimal secara konsisten dan stabilitas pelatihan yang lebih baik dibandingkan dengan baseline MobileNetV2 standar. MobileNetV2 baseline menghasilkan akurasi 92% dengan F1-score tertinggi 0.99 pada kelas tungro dan performa terendah 0.88 pada kelas blast. Sebaliknya, MobileNetV2–PSO mencapai peningkatan signifikan hingga akurasi 99%, dengan F1-score meningkat menjadi 0.98 pada bacterial blight, 0.98 pada blast, 0.99 pada brown spot, dan 1.00 pada tungro. Peningkatan terbesar terjadi pada kelas blast dengan selisih 10 poin F1-score, yang menunjukkan bahwa optimasi PSO memberikan sensitivitas lebih baik terhadap variasi pola penyakit yang sebelumnya sulit diklasifikasikan. Temuan ini menunjukkan bahwa kerangka kerja yang diusulkan menyediakan solusi yang akurat dan ringan dengan potensi kuat untuk diterapkan pada platform seluler dan platform dengan sumber daya terbatas guna mendukung diagnosis penyakit padi yang cerdas.

Kata Kunci: Deep Learning; Klasifikasi Gambar; MobileNetV2; Particle Swarm Optimization; Penyakit daun padi;

Abstract

Rice leaf diseases such as blast, brown spot, bacterial blight, and tungro pose a serious threat to agricultural productivity, with potential yield losses exceeding 50% under epidemic conditions. Therefore, rapid and accurate early detection is essential to support sustainable food security and precision agriculture. This study proposes a rice leaf disease classification system based on the MobileNetV2 architecture optimized using Particle Swarm Optimization (PSO). A dataset consisting of four rice leaf disease classes, collected from public repositories and sources representing real field conditions, is used to evaluate the proposed approach. Transfer learning is employed to improve training efficiency, while PSO is applied to optimize key hyperparameters to enhance model stability and convergence. Experimental results show that MobileNetV2 optimized with PSO consistently achieves superior classification performance and improved training stability compared to the standard MobileNetV2 baseline. The baseline MobileNetV2 achieves 92% accuracy, with the highest F1-score of 0.99 on the tungro class and the lowest performance of 0.88 on the blast class. In contrast, MobileNetV2–PSO demonstrates a significant improvement, reaching 99% accuracy, with F1-scores of 0.98 for bacterial blight, 0.98 for blast, 0.99 for brown spot, and 1.00 for tungro. The largest improvement occurs in the blast class, with a 10-point increase in F1-score, indicating that PSO optimization provides greater sensitivity to complex disease patterns that were previously difficult to classify.These findings indicate that the proposed framework provides an accurate and lightweight solution with strong potential for deployment on mobile and resource-constrained platforms to support intelligent rice disease diagnosis.

Keywords: Deep Learning; Image Classification; MobileNetV2; Particle Swarm Optimization; Rice leaf disease;

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INTRODUCTION

Rice is a major food commodity in Asia, including Indonesia, and serves as a primary source of carbohydrates for a large proportion of the population (Saputra et al., 2021), (Daniya et al., 2022). However, rice productivity is frequently threatened by leaf diseases such as leaf blast, brown spot, bacterial leaf blight, and tungro, which can cause yield losses exceeding 50% under epidemic conditions (Patil & Kumar, 2022a), (Vasantha et al., 2022). Consequently, the development of rapid and accurate disease detection systems is essential to support food security and sustainable agricultural practices (Mathulaprangsan et al., 2021).

Conventional rice disease identification is typically performed through visual inspection by farmers or agricultural experts. This approach is inherently limited, as it requires specialized expertise, is prone to subjective bias, and becomes impractical when applied to large cultivation areas (Sethy et al., 2020), (Hawari et al., 2022). Similarly, traditional machine learning methods based on handcrafted features—such as Gray Level Co-occurrence Matrix (GLCM) combined with classifiers like K-Nearest Neighbor (KNN) or Support Vector Machine (SVM)—often achieve relatively low accuracy, frequently below 70%, which restricts their reliability for large-scale deployment (Shidik et al., 2024), (Anamisa et al., 2021).

Recent advances in machine learning and deep learning have significantly improved plant disease diagnosis. Convolutional Neural Network (CNN) architectures such as VGG16, ResNet, and Inception have demonstrated classification accuracies exceeding 90% for various plant disease datasets (Ahad et al., 2023), (Singh et al., 2022). Despite their effectiveness, these deeper architectures typically require substantial computational resources and specialized hardware, making them less suitable for field-level deployment on smartphones or edge devices commonly used by farmers (Richter et al., 2025), (Wang et al., 2022). This limitation highlights the need for models that balance accuracy and computational efficiency (Putra et al., 2023).

Lightweight CNN architectures—particularly MobileNet and MobileNetV2—have emerged as promising solutions to this challenge. By employing depthwise separable convolutions, these models significantly reduce the number of parameters and computational cost while maintaining competitive performance (Chen et al., 2024). Previous studies have successfully applied MobileNet-based models to various crops, including cassava, legumes, and shallots, demonstrating improved efficiency compared to conventional CNN architectures (Fathy et al., 2025), (Arafat et al., 2025). Furthermore, MobileNetV2 has been shown to perform robustly on relatively small datasets and under varying illumination conditions commonly found in agricultural environments (Annur et al., 2023).

Although MobileNetV2 is efficient, its performance is highly sensitive to hyperparameter selection—including learning rate, dropout rate, optimizer type, and dense layer configuration. Prior studies typically rely on manual tuning, Grid Search, or Random Search, which are limited in exploring complex, high-dimensional search spaces. Bayesian Optimization offers improvements but may converge prematurely when applied to lightweight architectures with non-smooth loss surfaces. Genetic Algorithms (GA) provide powerful global search capabilities but tend to require longer computation times and heavier parameter encoding. These limitations create a research gap in identifying an optimization approach that is both computationally efficient and capable of finding stable configurations for MobileNetV2 in resource-constrained environments.

Particle Swarm Optimization (PSO) provides a suitable alternative because of its fast convergence, simplicity, and ability to balance exploration and exploitation. PSO has been shown to be effective in optimizing non-convex and irregular loss landscapes, making it particularly relevant for training lightweight CNNs (Pan et al., 2020), (Shalehah et al., 2023). However, despite the growing use of MobileNetV2 in agricultural image classification, there is still a lack of studies integrating PSO-based hyperparameter optimization specifically for rice leaf disease detection. Most existing work focuses either on MobileNetV2 without metaheuristic optimization or on PSO applied only to feature selection in traditional ML pipelines. This gap indicates the need to investigate whether MobileNetV2 optimized with PSO can offer higher stability and accuracy while maintaining low computational cost.

Beyond architectural and optimization strategies, transfer learning plays a critical role in accelerating convergence and mitigating data scarcity. Leveraging pretrained weights from large-scale

datasets such as ImageNet allows the model to learn relevant patterns even with limited agricultural images (Chen et al., 2020), (Akay et al., 2021). Meanwhile, recent studies have explored multimodal detection systems that combine image-based CNNs with IoT sensor data, demonstrating improved diagnostic accuracy and resilience under field conditions (Hasan et al., 2023), (Patil & Kumar, 2022b).

Based on these considerations, this study focuses on applying the MobileNetV2 architecture with transfer learning and PSO-based hyperparameter optimization. Using a publicly available rice leaf image dataset from Kaggle, a classification model is developed to identify four major rice leaf diseases. Rather than emphasizing architectural complexity, this research prioritizes training stability, computational efficiency, and deployment feasibility. The proposed approach aims to contribute to the development of an accurate and efficient rice disease diagnostic system that can be implemented on mobile and resource-constrained devices, thereby supporting precision agriculture and sustainable food production (Ferdinand & Al Maki, 2022).

The main contributions of this study are summarized as follows:

1. This paper proposes RiceGuard, a lightweight rice leaf disease classification framework that integrates MobileNetV2 with Particle Swarm Optimization (PSO), specifically designed for deployment on mobile and resource-constrained agricultural devices.
2. An empirical analysis is conducted to demonstrate that PSO-based hyperparameter optimization improves training stability, convergence behavior, and class-level consistency without increasing model complexity or computational overhead.
3. A comprehensive comparative evaluation is performed against standard MobileNetV2 and larger convolutional architectures, highlighting the trade-off between accuracy, efficiency, and deployment feasibility in precision agriculture applications.

In summary, the challenges associated with accurate and efficient rice leaf disease detection highlight the need for lightweight and reliable deep learning solutions that can be deployed in real agricultural environments. By integrating MobileNetV2 with transfer learning and Particle Swarm Optimization, this study addresses the trade-offs between classification performance, computational efficiency, and deployment feasibility. The proposed RiceGuard framework is evaluated through comprehensive experiments and comparative analyses to demonstrate its effectiveness and practicality. The following section describes the dataset, preprocessing steps, model architecture, and optimization strategy employed in this study.

METHOD

This research methodology is designed to produce an accurate, efficient deep learning-based rice leaf disease classification system that is capable of working on devices with limited computing power. Broadly speaking, this research went through several main stages, starting from dataset selection and processing, applying preprocessing techniques to improve data quality, designing a lightweight MobileNetV2-based Convolutional Neural Network (CNN) model architecture, optimizing hyperparameters using Particle Swarm Optimization (PSO), training and validation processes, to evaluating model performance with various classification metrics.

Each stage is systematically designed to address the main problems in rice disease diagnosis, namely limited field data, potential overfitting, and the need for an efficient model that still has a high level of accuracy. The initial stage begins with the collection of rice leaf image datasets from open repositories that have been widely used by other researchers, thus ensuring data quality and validity standards. Next, data preprocessing is carried out in the form of normalization, resizing, and augmentation to improve the model's generalization to diverse real-world conditions in the field, such as lighting and background variations.

The next stage is the design of a deep learning architecture using the well-known lightweight and efficient MobileNetV2. To optimize its performance, hyperparameter optimization is carried out using the Particle Swarm Optimization (PSO) algorithm, which is capable of adaptively finding the best configuration. After the model was formed, the training process was carried out with a strict validation strategy to prevent overfitting. The training results were then evaluated using multiparameter classification metrics, including accuracy, precision, recall, F1-score, confusion matrix, and AUC, thus providing a more comprehensive picture of performance.

Overall, this research methodology focuses not only on achieving high accuracy, but also on efficiency and potential implementation in the field. Therefore, the standard MobileNetV2 baseline is used

as a comparison, so that the real contribution of PSO integration can be demonstrated empirically. The stages of this research methodology are shown in Figure 1.

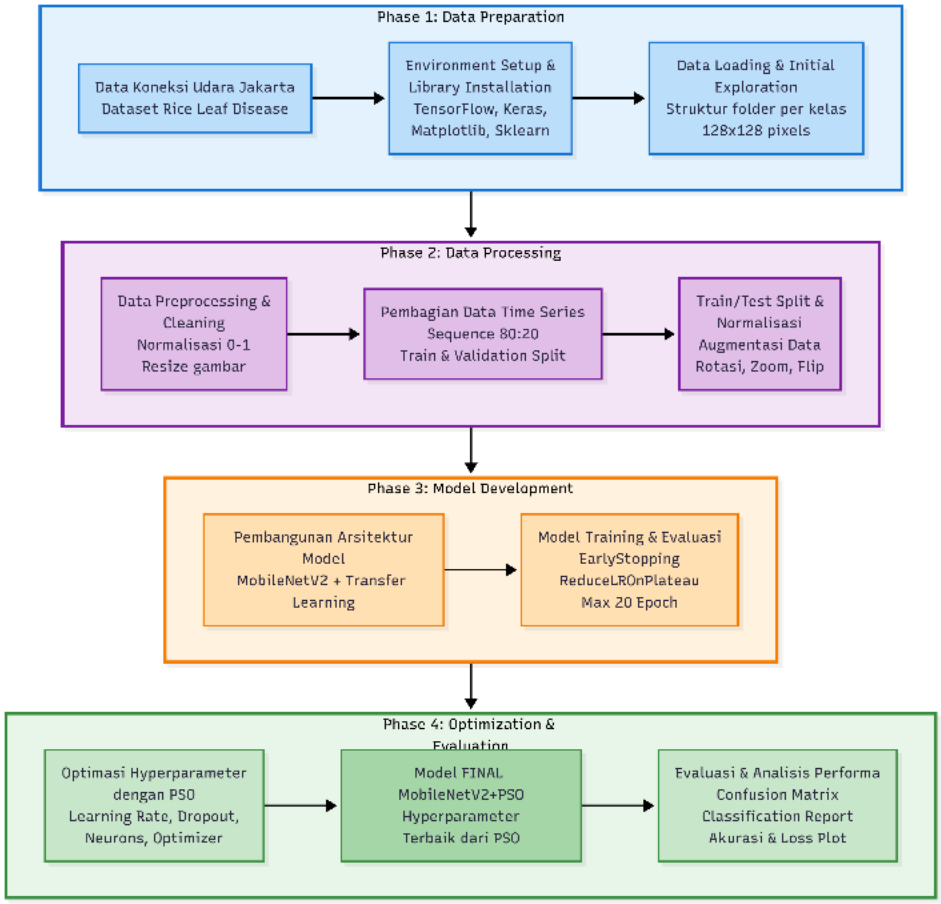


Figure 1. Flowchart Purpose Model

Dataset

This study uses Rice Leaf Disease Images that are publicly available on the Kaggle platform (Nirmalsankalana, 2021), (Joseph et al., 2024). This dataset contains 5932 images of rice leaves with four main disease categories, namely Bacterial Blight, Blast, Brown Spot, and Tungro. These four diseases are among the most damaging to rice cultivation in Asia and have the potential to reduce productivity by more than 50% if not treated properly (Daniya et al., 2022). The dataset can be accessed at: https://www.kaggle.com/datasets/nirmalsankalana/rice-leaf-disease-image.

Each image in the dataset has been annotated by experts so that the labels are reliable. The total number of images is 5932, with a relatively balanced class distribution to avoid classification bias (Hasan et al., 2023). The images were obtained under various lighting conditions, viewing angles, and backgrounds, representing real-world conditions in the field when farmers use mobile phones with varying image quality (Mathulaprangsan et al., 2021).

The dataset is divided into 80% training data and 20% test data, following common practice in machine learning. This separation ensures that the model can learn patterns from the training data and test its generalization on data it has never seen before. Several studies, such as Hasan et al. (2023) and Joseph et al. (2024), emphasize that good dataset representation is a key factor in the success of models in accurately detecting rice diseases.

Preprocessing

The preprocessing stage is performed to ensure image consistency and improve model performance. All images are resized to 128 × 128 pixels, as recommended by Chen et al. (2024), who show that resolution normalization improves training speed without reducing prediction quality. Additionally, each pixel value is normalized to the range [0,1] to stabilize the input distribution, using the formula:

$$x' = \frac{x}{x_{max}} \quad (1)$$

with the variables defined as follows:

x : The original pixel intensity value before normalization. For 8-bit images, this value ranges from 0 to 255.
x' : NThe normalized pixel intensity value, which falls within the range 0 to 1. This normalized value is used as model input because it provides greater numerical stability during training.
$Xmax$: The maximum pixel intensity value for the image format used. For 8-bit RGB images, this value is 255, meaning normalization is performed by dividing each pixel value by 255.

Ghosal et al. (2018) emphasize that variations in lighting conditions can affect disease detection, so data augmentation is applied. Augmentation includes rotation, flipping, zooming, and shifting, which aim to expand the distribution of synthetic data without the need to add expensive real images (Tejaswini et al., 2022). This strategy has been proven to improve model robustness in uncontrolled environmental conditions, as demonstrated in the study by Putra et al. (2022). With a combination of resizing, normalization, and augmentation, the dataset becomes more representative of real conditions and reduces the risk of *overfitting*, which commonly occurs in limited-sized datasets (Ahad et al., 2023).

Model Architecture

The core architecture of this research is MobileNetV2, a lightweight CNN with fewer parameters than conventional models such as VGG16 or ResNet. MobileNetV2 uses a depthwise separable convolution mechanism to improve computational efficiency without sacrificing accuracy (Elfatimi et al., 2022). The separable convolution formula is written as:

$$Y = (X *_{dw} K_{dw}) *_{pw} K_{pw} \quad (2)$$

The MobileNetV2 model in this study was initialized using weights from ImageNet, as suggested by Joseph et al. (2024) and Chen et al. (2020), because transfer learning has been proven to accelerate model convergence on limited datasets. Furthermore, the final classification layer was modified to accommodate the number of rice leaf disease classes, namely four categories.

Several studies have demonstrated the effectiveness of MobileNetV2 in agricultural image classification with an accuracy above 90% and high memory efficiency (Annur et al., 2023), (Babu et al., 2022). This makes it highly suitable for mobile deployment applications, which is the practical direction of this research.

Optimization with Particle Swarm Optimization (PSO)

To obtain the optimal hyperparameter configuration, this study applied the Particle Swarm Optimization (PSO) algorithm. PSO mimics the social behavior of animal groups such as birds or fish in finding the optimal position in the search space. Tejaswini et al. (2022) and Shidik et al. (2024) emphasize that PSO is capable of balancing exploration and exploitation, making it more efficient than random search or grid search.

Formula for updating particle velocity and position:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

In its implementation, PSO is run until convergence is achieved in the configuration with the highest validation accuracy. Related studies by Fathy et al. (2025) and Hartojo et al. (2024) prove that PSO can significantly improve model performance in the domains of medical and agricultural imaging.

Training and Validation

The model training process is an important step to ensure that the artificial neural network is able to recognize rice leaf disease patterns properly. At this stage, preprocessed images are fed into the MobileNetV2 architecture, and then the network weights are iteratively updated using an optimization algorithm. The selection of activation functions, loss functions, and optimization strategies plays an important role in determining model performance. Previous studies have shown that a combination of non-linear activation functions, entropy-based loss functions, and adaptive optimizers such as Adam can accelerate convergence while maintaining training stability (Wang et al., 2022).
ReLU activation function**:**

$$f(x) = (0, x) \tag{5}$$

Softmax activation function:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}, \quad j = 1,2, \dots, K \tag{6}$$

Categorical cross-entropy loss function:

$$L = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \, log \, log \left(\widehat{y_{ij}}\right) \tag{7}$$

The main optimizer is Adam, with early stopping support to prevent overfitting. Model evaluation is performed in stages using accuracy, precision, recall, and F1-score metrics as recommended by Sethy et al. (2020), Mekha & Teeyasuksaet (2021), and Ahad et al. (2023).

Performance Evaluation
Model performance evaluation was conducted using a confusion matrix to identify classification errors between classes in detail (Patil & Kumar, 2022b). In addition, the Area Under Curve (AUC) value was calculated as an additional measure of the model's sensitivity to minority classes.
Evaluation metrics:
Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

Precision:

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

Recall:

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

F1-score:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \tag{11}$$

Patil & Kumar (2022b) emphasize that integrating the confusion matrix with AUC results in stronger validation, especially for artificial intelligence-based diagnostic systems in agriculture..

Comparative Baselines
To assess the superiority of the proposed method, the results of MobileNetV2 optimized with PSO were compared with several reference models. First, standard MobileNetV2 was selected as the main baseline, because this model is known to be efficient but its performance is often not optimal without hyperparameter optimization. Next, a comparison was made with the VGG16 and ResNet50 architectures, two larger

convolutional models that have been proven to achieve high accuracy in many image classification tasks, despite requiring greater computational resources (Singh et al., 2022). In addition, this study also included the classic K-Nearest Neighbor (KNN) method with Gray Level Co-occurrence Matrix (GLCM) feature extraction as a comparison. Although this approach is relatively simple, the resulting accuracy is usually lower than that of modern CNNs, but it is still relevant to show the leap in performance offered by deep learning-based approaches (Sethy et al., 2020). Thus, this cross-approach comparison provides a more comprehensive picture of the effectiveness of MobileNetV2 + PSO in rice leaf disease classification.

Implementation Details

The implementation was carried out using TensorFlow with the Python programming language. The training process was run on an NVIDIA RTX GPU with 16GB of RAM. Pan et al. (2020) emphasized the importance of presenting details of the hardware, software, and training parameters so that the research could be replicated consistently.

To ensure reproducibility, all code and configurations are stored in a public repository. Studies by Joseph et al. (2024) and Putra et al. (2023) confirm that good experiments should not only pursue accuracy, but also pay attention to computation time, memory consumption, and resource efficiency. Therefore, this study explicitly reports the model complexity and average inference time per image.

RESULT AND DISCUSSION

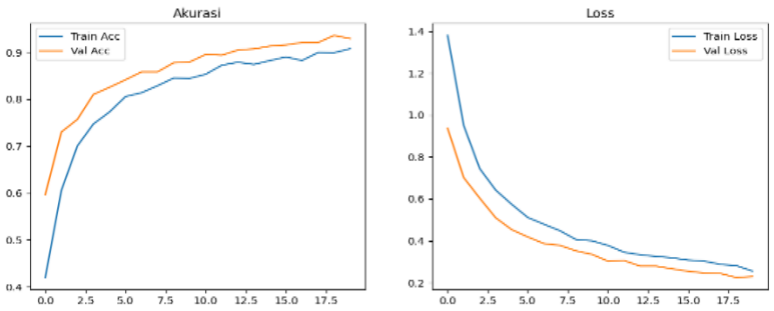
This section presents the experimental results obtained from evaluating the proposed RiceGuard framework for rice leaf disease classification. The evaluation is conducted by comparing the performance of the standard MobileNetV2 baseline model with the MobileNetV2 model optimized using Particle Swarm Optimization (PSO). The analysis focuses on three main aspects: (1) training and validation behavior observed through accuracy and loss curves, (2) class-level performance assessed using precision, recall, and F1-score metrics, and (3) error distribution analysis based on confusion matrices. This evaluation strategy provides a comprehensive assessment of both overall classification performance and per-class prediction behavior, enabling an objective examination of the impact of PSO-based optimization on the effectiveness of the lightweight MobileNetV2 architecture.

Table 1 Hyperparameter Comparison Between Baseline MobileNetV2 and PSO-Optimized MobileNetV2

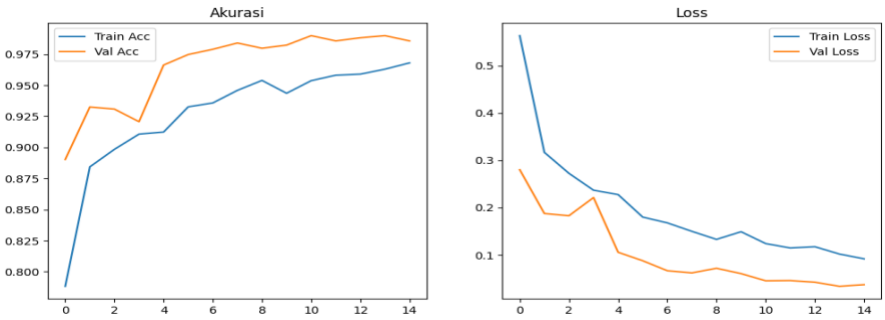
Hyperparameter	Baseline	PSO-Optimized (Best Value)
Learning Rate	0.001	1e-5 → 1e-3
Dropout Rate	0.20	0.20 → 0.50
Dense Units	128	64 → 256
Optimizer	Adam	{"adam","sgd","rmsprop"}
Training Epochs	20 (early stopping)	15 (early stopping)
Model Size	14 MB	14 MB
Parameter Count	3.40 M	3.40 M

The comparison in Table 1 shows that PSO explores a wider and more flexible hyperparameter search space, including ranges for learning rate, dropout probability, dense-layer width, and optimizer selection. These parameters influence the model's training dynamics, convergence behavior, and regularization strength, but they do not alter the underlying MobileNetV2 architecture. As a result, the parameter count remains fixed at 3.40 million. Since PSO does not modify convolutional layers or the overall model topology, the resulting model size is expected to remain similar to the baseline (approximately 14 MB), confirming that the performance improvement originates from more optimal training hyperparameters rather than increased model complexity.

Comparison of Accuracy and Loss Curves



(a) MobileNetV2 Standard



(b) MobileNetV2 + PSO

Figure 2. Accuracy and Loss Graph

Figure 2 illustrates the accuracy and loss curves during the training and validation processes for the MobileNetV2 baseline model and the proposed MobileNetV2 model optimized with PSO. For the baseline MobileNetV2 model, validation accuracy increases gradually and stabilizes at approximately 92%. However, the corresponding validation loss exhibits noticeable fluctuations and does not fully converge, indicating sensitivity to hyperparameter configuration during training.

In contrast, the MobileNetV2 + PSO model demonstrates a more stable training behavior. The validation accuracy increases rapidly and converges at a higher level, while the validation loss shows a consistent downward trend throughout the training process. This behavior indicates improved convergence characteristics and reduced instability during learning. The observed differences between the two models suggest that PSO effectively identifies hyperparameter configurations that promote smoother convergence and more stable training dynamics.

Classification Report

Classification Report:

	precision	recall	f1-score	support
Bacterialblight	0.92	0.91	0.91	316
Blast	0.87	0.89	0.88	288
Brownspot	0.93	0.92	0.92	320
Tungro	0.98	1.00	0.99	261
accuracy			0.92	1185
macro avg	0.93	0.93	0.93	1185
weighted avg	0.93	0.92	0.92	1185

(a) MobileNetV2 Standard

Classification Report:

	precision	recall	f1-score	support
Bacterialblight	0.98	0.99	0.98	316
Blast	0.98	0.97	0.98	288
Brownspot	0.99	0.99	0.99	320
Tungro	1.00	1.00	1.00	261
accuracy			0.99	1185
macro avg	0.99	0.99	0.99	1185
weighted avg	0.99	0.99	0.99	1185

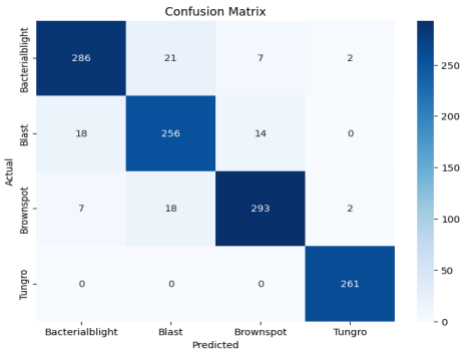
(b) MobileNetV2 + PSO

Figure 3. Classification Report

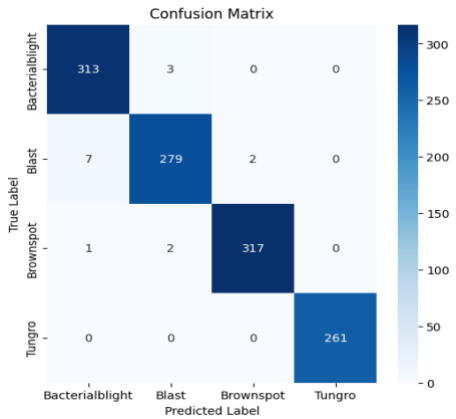
Figure 3 presents the classification report comparing the standard MobileNetV2 model and the PSO-optimized MobileNetV2 model in terms of precision, recall, and F1-score for each rice leaf disease class. The baseline model achieves average precision, recall, and F1-score values in the range of 0.91–0.93. The lowest performance is observed in the Blast class, which records an F1-score of approximately 0.88, likely due to visual similarities with the Bacterial Blight class.

After applying PSO-based optimization, the classification performance improves consistently across all classes. The optimized model achieves higher precision, recall, and F1-score values, reaching approximately 0.98–0.99 for each disease category. The most notable improvement is observed in the Blast class, where the F1-score increases substantially, indicating enhanced discrimination between visually similar disease patterns. These results demonstrate that PSO optimization contributes to more consistent and balanced class-level performance.

Confusion Matrix



(a) MobileNetV2 Standard



(b) MobileNetV2 + PSO

Figure 4. Classification Report

Further Figure 4 shows the confusion matrices for both the baseline MobileNetV2 model and the PSO-optimized model. In the baseline model, several misclassifications are observed, particularly between the Blast and Bacterial Blight classes, as well as occasional confusion between Brown Spot and Blast. These

misclassifications highlight the limitations of the baseline model in distinguishing diseases with overlapping visual characteristics. In contrast, the confusion matrix of the MobileNetV2 + PSO model shows a strong concentration of predictions along the diagonal, indicating a high proportion of correct classifications for each class. Misclassification rates are significantly reduced across all disease categories, and class prediction distributions become more balanced. This result confirms that PSO optimization enhances the reliability and consistency of the classification outcomes.

Discussion

This section discusses the implications of the experimental results presented in the previous section, with a focus on model stability, efficiency, and deployment feasibility for precision agriculture applications. The results demonstrate that integrating Particle Swarm Optimization into the MobileNetV2 training process primarily improves training stability and convergence behavior, rather than merely increasing peak accuracy. Similar findings have been reported in the literature, where metaheuristic-based optimization has been shown to enhance deep learning robustness without modifying the underlying architecture (Shalehah et al., 2023; Fathy et al., 2025). The smoother loss curves and faster convergence observed in the optimized model indicate that PSO effectively explores the hyperparameter search space to identify configurations that balance learning speed and generalization. This trend aligns with recent studies suggesting that MobileNet-based models benefit significantly from hyperparameter tuning when deployed in agricultural settings (Chen et al., 2024).

At the class level, the optimized model shows improved consistency in distinguishing rice leaf diseases with similar visual characteristics, particularly between Blast and Bacterial Blight. Prior research confirms that these diseases often share overlapping texture and color patterns, which pose challenges for lightweight convolutional networks (Ahad et al., 2023; Hasan et al., 2023). The improved precision and recall observed across all classes suggest that PSO optimization enables the model to learn more discriminative and stable feature representations—consistent with earlier findings that optimization-guided training can reduce inter-class confusion in plant disease classification tasks (Mathulaprangsan et al., 2021).

From an efficiency perspective, RiceGuard preserves the lightweight nature of MobileNetV2, making it well-suited for deployment on mobile and resource-constrained devices commonly used in agricultural environments. Studies such as Elfatimi et al. (2022), Pan et al. (2020), and Arafat et al. (2025) similarly highlight the suitability of MobileNet architectures for edge deployment due to their low parameter count and fast inference times. Compared to larger models like VGG16 or ResNet50—frequently used in previous rice leaf disease research (Sethy et al., 2020)—MobileNetV2 achieves competitive classification performance at a fraction of the computational cost. This balance between accuracy and efficiency is critical for real-time field applications, where limitations in hardware, connectivity, and energy availability must be considered (Patil & Kumar, 2022a; Vasantha et al., 2022).

Although high classification performance is achieved on the evaluated dataset, this study intentionally emphasizes model reliability and deployment feasibility rather than peak accuracy alone. The use of a publicly available dataset supports reproducibility and fair comparison with previous studies on rice disease classification (Saputra et al., 2021). Data augmentation techniques contribute to robustness under varying environmental conditions, consistent with observations from earlier work on deep learning–based plant disease detection (Joseph et al., 2024; Singh et al., 2022). However, the reliance on a single dataset remains a limitation of this study. Future work may involve cross-dataset validation , real-time testing on mobile or edge devices (Patil & Kumar, 2022b), and integration with explainability techniques to enhance transparency and user trus.

CONCLUSION

This study presents RiceGuard, a lightweight rice leaf disease classification framework based on MobileNetV2 optimized using Particle Swarm Optimization (PSO). The experimental results show that PSO-based hyperparameter optimization improves training stability, convergence behavior, and class-level classification consistency compared to the standard MobileNetV2 baseline, while preserving the computational efficiency of the original architecture. Rather than increasing model complexity, the proposed optimization strategy enhances performance through more effective parameter configuration during training. The findings indicate that RiceGuard achieves reliable classification performance while maintaining a low computational footprint, which is essential for real-time deployment on mobile and resource-constrained platforms commonly used in agricultural environments. By balancing accuracy,

efficiency, and deployment feasibility, this study demonstrates that lightweight deep learning models combined with metaheuristic optimization can provide practical solutions for automated rice leaf disease detection. Despite the promising results, this work is limited by the use of a single image dataset and evaluation under controlled experimental conditions. Practical deployment in the field may involve integration with mobile-based agricultural advisory apps, embedding the model into edge devices such as low-cost Raspberry Pi–based monitoring units, or implementing drone-assisted scanning to cover larger plantation areas. Additional considerations include illumination normalization modules to handle varying sunlight conditions, offline inference capability for regions with limited connectivity, and a farmer-friendly user interface for rapid on-site diagnosis. Future research may explore cross-dataset validation, real-world field deployment, and the integration of explainability techniques to further enhance model robustness and user trust. Overall, RiceGuard contributes to the development of deployable artificial intelligence systems that support precision agriculture and sustainable food production.

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