Volume 11, Issue 3, March – 2026 International Journal of Innovative Science and Research Technology
ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar496

Rice Disease Detection and Classification Using Deep Learning with Regularization Technique

Abdulmalik Abdulsalam[1]; Dr. Ayoade Akintayo Michael[2]; Grace Ojochenemi Emmanuelanorue[3]; Umar Muhammad Bello[4]; Paul Joseph Agada[5]; Harisu Aliyu[6]; Abdullahi Lawal Rukuna[7]; Alabi Abdultoyyib Adebayo[8]; Muhammad Sirajo[9]; Muhammad Buhari Suleiman[10]

[1]Department of Information Technology, National Open University of Nigeria
[2]Department of Computer Science, Lead City University, Ibadan
[3]Department of Computer Science, Federal College of Education (Technical) Gombe
[4]Directorate of ICT, Federal University Gusau
[5]Department of Computer Science, Plateau State University
[6]Department of Artificial Intelligence, Abubakar Tafawa Balewa University, Bauchi
[7]Department of Artificial Intelligence, Abubakar Tafawa Balewa University, Bauchi
[8]Department of Technical Education, Federal College of Education Gidan Madi
[9]ICT Division, Nigerian Content Development and Monitoring
[10]Department of Computer Science, Federal University Wukari

Publication Date: 2026/03/21

Abstract: Rice production plays a critical role in global food security, particularly in Asia and Africa, where it serves as a staple food for billions of people. However, rice cultivation is highly susceptible to foliar diseases such as bacterial leaf blight, leaf blast, brown spot, and tungro, which significantly reduce crop yield and grain quality. Traditional disease diagnosis relies on manual visual inspection, which is time-consuming, subjective, and often inaccurate, particularly in resource-constrained farming environments. To address these limitations, this study proposes RiceNet-D169, a deep learning-based rice leaf disease detection system built on a modified DenseNet-169 convolutional neural network architecture. An experimental research design was adopted to develop and evaluate the proposed model. A publicly available Kaggle dataset consisting of 5,932 rice leaf images across four disease classes was utilized. The images were preprocessed through resizing and normalization, followed by systematic data augmentation techniques, including rotation, flipping, zooming, and brightness adjustment, to enhance dataset diversity and improve model generalization. Transfer learning was employed by fine-tuning a pre-trained DenseNet-169 model, while regularization techniques dropout, L2 weight decay, and batch normalization were incorporated to reduce overfitting. The dataset was split into training, testing and validation, and the model was trained. Experimental results demonstrate that the DenseNet-169 achieved an overall test accuracy of 99.83. The model was compared with state-of-the-art approaches, a fine-tuned CNN and ResNet50 transfer learning model implemented under the same experimental conditions. The results show that DenseNet-169 outperformed the comparison models in terms of accuracy, and stability.

Keywords: *DenseNet-169, Transfer learning, Deep learning, Data augmentation, Regularization.*

How to Cite: Abdulmalik Abdulsalam; Dr. Ayoade Akintayo Michael; Grace Ojochenemi Emmanuelanorue; Umar Muhammad Bello; Paul Joseph Agada; Harisu Aliyu; Abdullahi Lawal Rukuna; Alabi Abdultoyyib Adebayo; Muhammad Sirajo; Muhammad Buhari Suleiman (2026) Rice Disease Detection and Classification Using Deep Learning with Regularization Technique. *International Journal of Innovative Science and Research Technology*, 11(3), 1704-1714. https://doi.org/10.38124/ijisrt/26mar496

I. INTRODUCTION

Rice (Oryza sativa) is among the most important staple crops, serving as a major source of calories and livelihood for billions of people, particularly across Asia and parts of Africa(Seelwal et al., 2024). Stable rice production is therefore central to world food security and rural economies. However, rice cultivation is highly vulnerable to a range of biotic stresses especially foliar diseases like bacterial leaf blight, blast, brown spot, and leaf smut which can cause substantial yield loss, reduce grain quality, and increase the cost of production (Andargie et al., 2024). In many smallholder farming systems, limited access to extension services and plant pathology expertise means disease outbreaks are often detected late, after irreversible damage has occurred (Omuse et al., 2025).

Conventional disease diagnosis commonly depends on visual inspection by farmers or agronomists, using observable symptoms on leaves and stems. This manual process requires a significant amount of time, subjective, and error-prone: symptom appearance can vary with disease stage, cultivar, environmental conditions, and co-occurring abiotic stresses (K. Li et al., 2023). Moreover, expert diagnosis is scarce in remote areas, making timely and accurate detection of early infections difficult. These limitations motivate development of automated, scalable tools that can support fast, accurate disease identification in the field.

Recent advances in AI and computer vision most notably deep learning offer promising solutions for plant disease classification. Deep learning architectures have demonstrated leading performance in image classification tasks by learning multi-level feature representations directly from raw images (Rukuna et al., 2025). In the context of crop pathology, deep models can be trained to recognize disease-specific patterns on leaves, enabling rapid, objective screening from photographs taken by smartphones or drones. Such systems can potentially enable early intervention, targeted treatment, and more efficient use of inputs, thereby improving yields and reducing environmental impact (S.Venkatramulu et al., 2025).

Despite their potential, deep learning models face practical challenges when applied to agricultural imagery. A major challenge is overfitting, where models achieve excellent performance on the training dataset but struggle to generalize to unseen images from different farms, lighting conditions, leaf orientations, or varieties (Jiang et al., 2025). Overfitting is especially likely when datasets are small, imbalanced, or lack variability common situations for specialized disease datasets. Another challenge is that real-world field images often include complex backgrounds, partial occlusions, and mixed infections, which increase classification difficulty compared to clean, lab-collected images (Ying, 2019).

➢ *Contributions*

This study provides significant contributions to the advancement of automated plant disease detection. The key contributions of this research are outlined below:

- A framework leveraging transfer learning with DenseNet-169 was developed for rice disease detection.
- Dropout, L2 weight decay, and batch normalization were systematically integrated to reduce overfitting and improve generalization performance.
- A comparative performance evaluation was conducted against selected advanced rice disease detection models

II. SUMMARY OF REVIEWED LITERATURE

The use of deep learning techniques for rice disease detection has significantly advanced automated disease diagnosis, due to its strong performance in handling large, complex image datasets. Numerous studies have explored various architectures, datasets, and training strategies to enhance the accuracy and robustness of disease classification systems. These studies collectively highlight the growing role of AI in modern agriculture, especially in automating disease diagnosis and supporting precision farming.

Table 1 Summary of Reviewed Literature on Rice Leaf Disease Detection

Author	Method	Accuracy (%)
(Pai et al., 2025)	Ensemble CNN fuse with GoogLeNet, ResNet-34, DenseNet-121, , and VGG-16	96.81
(Y. Li et al., 2024)	Modified CNN with hyperparameter optimization	96.80
(Haridasan et al., 2023)	CNN with data augmentation	91.45
(Noorishta Hashmi, 2025)	CNN + SVM hybrid model	98.50
(Ayyappan et al., 2025)	CNN-based classifier	97.50 for DenseNet121, 96.32 for Xception, 96.25 for EfficientNet-B4, 96.25 for MobileNetV3 Large
(Venkatesh et al., 2023)	CNN with attention mechanism (CNN-AM)	99.80
(Latif et al., 2022)	Improved CNN with feature enhancement	96.08
(Daniya & Vigneshwari, 2023)	Optimized CNN using Adam optimizer	93.04
(Deng et al., 2021)	Transfer learning with CNN architectures	91.00
(K. K. Kumar et al., 2025)	CNN trained on Indian rice datasets	96.50
(Kaur et al., 2024)	Ensemble model (SqueezeNet + NN classifier)	93.30
(Gogoi et al., 2023)	3-stage CNN with transfer learning	94.00
(Mandwariya & Jotwani, 2024)	Fine-tuned CNN	93.30
(Chen et al., 2020)	Transfer learning (ResNet50, VGG16)	94.07
(Rai & Pahuja, 2023)	Deep CNN with segmentation	94.11
(Jain et al., 2022)	CNN + Chatbot integration	97.36
(Dewi et al., 2024)	YOLOv8 object detection model	97.00

(Kokila et al., 2025)	CNN trained with diverse rice leaf dataset	ResNet101 82.35, DenseNet201 85.23, YOLOv5 89.95
(Rahman et al., 2024)	CNN and ResNet50 with image preprocessing	CNN 88.00, ResNet50 97
(Jayaraju et al., 2025)	Transfer learning (ResNet-50, VGG16)	ResNet50 97.57 VGG16 91.63

➢ *Rice Leaf Diseases*

Rice cultivation is highly vulnerable to a range of diseases that affect different parts of the plant, including the roots, stems, leaves, and grains. Among these, leaf diseases are particularly critical because they directly interfere with photosynthesis, leading to reduced plant vigor, lower grain yield, and poor quality (Lu et al., 2025). These diseases are affected by factors including temperature, humidity, and rainfall, along with farming practices, the susceptibility of rice varieties, and the amount of pathogen inoculum present in the field. In regions with warm and humid climates, disease outbreaks can occur rapidly, causing severe epidemics that threaten food security and farmer livelihoods (Khadka et al., 2025).

Leaf diseases not only reduce yields but also increase production costs through the need for frequent pesticide applications and other control measures. In smallholder systems, limited access to timely disease diagnosis and control technologies often exacerbates their impact, resulting in significant economic losses. Effective management therefore depends on the early detection and precise identification of the causative pathogens, which is essential for guiding appropriate interventions (Das et al., 2025).Several foliar diseases affect rice globally, but this study focuses on four of the most economically important: Bacterial Leaf Blight, Leaf Blast, Brown Spot, and Tungro.

- *Bacterial Leaf Blight*

Bacterial leaf blight is a highly damaging rice disease caused by the bacterium *Xanthomonas oryzae* pv. *oryzae*. This pathogen attacks the leaf tissues and, when conditions are favorable, can greatly reduce rice production. Under severe outbreaks, losses in grain yield often fall within the range of about 20–50 %, and in extreme situations they may exceed this level. The disease is common in both tropical and subtropical rice-growing regions, particularly where warm temperatures and high humidity prevail (Teja et al., 2025).

Fig 1 Bacterial Leaf Blight Disease Caused by Xanthomonas oryzae pv
Source: (Faizal Azizi & Lau, 2022)

- *Leaf Blast*

Leaf Blast is a highly destructive fungal infection affecting rice, caused by *Magnaporthe oryzae*. It is recognized as one of the most serious threats to global rice production, with the potential to cause yield reductions ranging from 30% up to complete crop failure under favorable conditions. The disease thrives in warm, humid environments, particularly in areas with frequent rainfall and dense crop canopies, which create conditions ideal for spore germination and spread (Devanna et al., 2022).

Fig 2 Bacterial Leaf Blight Disease Caused by Magnaporthe oryzae
Source:(Neupane & Bhusal, 2021)

- *Brown Spot*

Brown Spot is a common and economically important fungal disease of rice, caused by *Bipolaris oryzae* (previously *Helminthosporium oryzae*). It is present in nearly all rice-growing regions and can lead to yield losses from 10% to more than 50% during severe outbreaks. The disease is more prevalent in rain-fed and upland ecosystems, where nutrient deficiencies and water stress make plants more susceptible to infection (Bhutia et al., 2025).

Figure 3: Brown Spot Disease Caused by Bipolaris oryzae
Source: (Bhutia et al., 2025)

- *Tungro*

Tungro is a significant viral disease of rice caused by the simultaneous infection of Rice Tungro Bacilliform Virus (RTBV) and Rice Tungro Spherical Virus (RTSV). It is mainly transmitted in a persistent manner by green leafhoppers of the *Nephotettix* genus. The disease is widespread in South and Southeast Asia and can cause yield losses ranging from 5% to 100%, depending on the infection stage and environmental conditions. Outbreaks are often associated with high vector populations, continuous rice cultivation, and overlapping cropping seasons, which allow the virus to persist and spread rapidly (Dey et al., 2024).

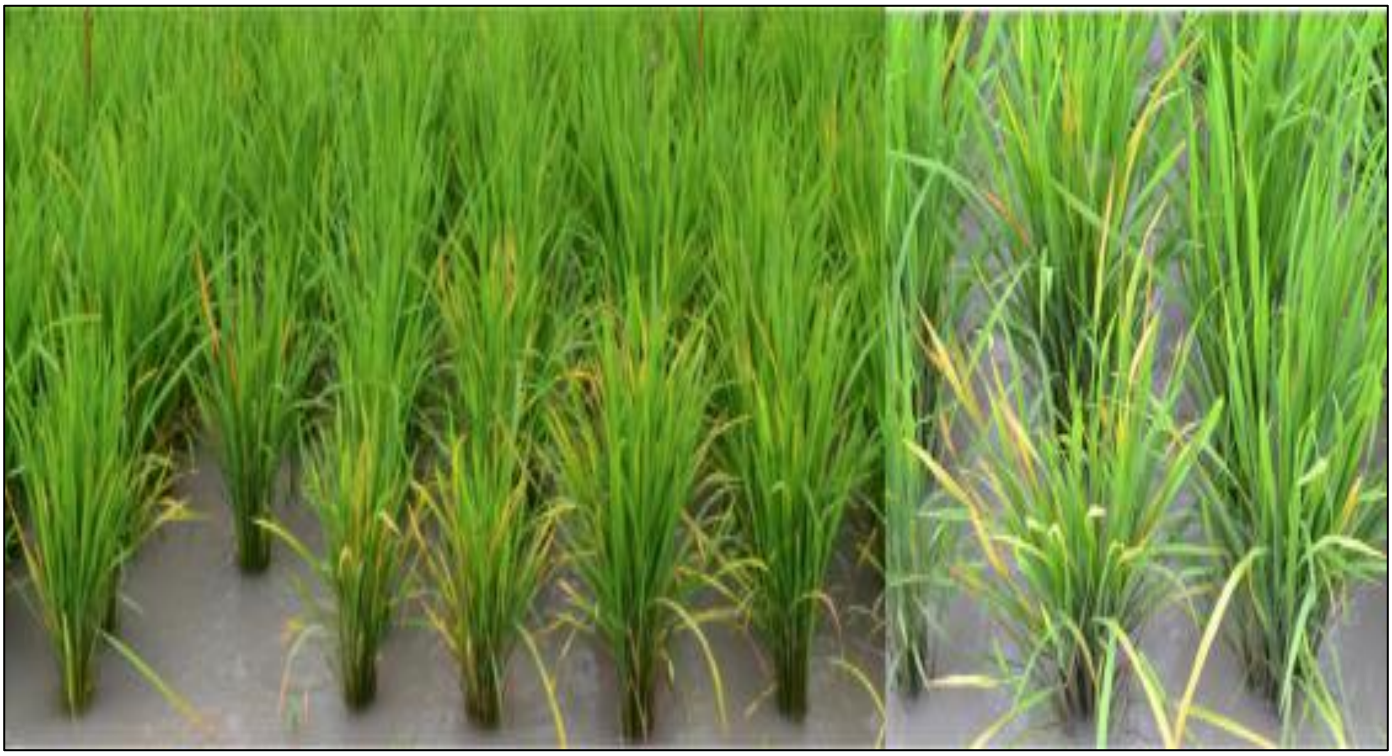


Fig 4 Tungro Disease Caused by the Combined Infection of Bacilliform and Spherical Virus.
Source: (G. Kumar et al., 2021)

III. MATERIALS AND METHODS

This section describes the dataset used in this study, the preprocessing and augmentation techniques applied, the deep learning architecture adopted, and the experimental setup employed for model training and evaluation. The overall framework integrates transfer learning using DenseNet-169 with systematic regularization strategies to enhance classification performance and generalization capability.

- *Dataset Description*

The dataset for this research was sourced from a publicly accessible repository on Kaggle: https://www.kaggle.com/datasets/nirmalsankalana/rice-leaf-disease-image, consisting comprising rice leaf images classified into four disease categories: Bacterial Leaf Blight, Leaf Blast, Brown Spot, and Tungro. The dataset contains 5,932 rice leaf images.

Table 2 Distribution of Classes in the Rice Disease Dataset

Classes	**Number of Images**
Bacteria Blight	1584
Leaf Blast	1440
Brown Spot	1600
Tungro	1308
Total	5932

- *RiceNet-D169 System Architecture*

The overall framework of the RiceNet-D169 system is illustrated in figure 5. The process begins with image acquisition from rice plants, followed by image preprocessing, which includes resizing and normalization. To increase dataset diversity and strengthen model robustness, data augmentation techniques were employed.

The augmented dataset was then split into training and testing. The training data were fed into the DenseNet-169 model for feature extraction and classification. Regularization techniques, including dropout and L2 weight decay, were integrated into the training process to reduce overfitting and enhance generalization capability. The model's performance was assessed using standard classification metrics prior to generating the final disease classification results.

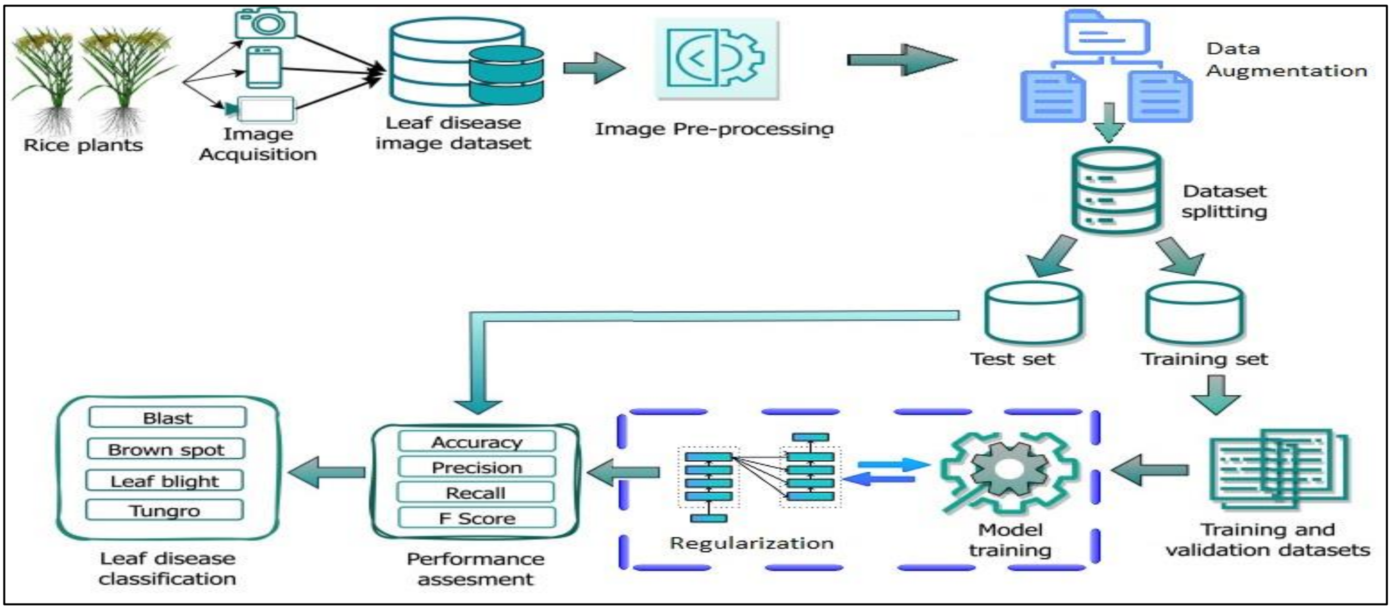


Fig 5 Architecture of the RiceNet-D169 System

➢ *Model Architecture and Training*

The RiceNet-D169 system introduces a modified deep learning workflow for rice leaf disease detection and classification using the DenseNet-169 architecture. The system incorporates systematic data augmentation and regularization techniques to enhance model robustness and reduce overfitting. DenseNet-169 was chosen as the backbone architecture because its dense connectivity facilitates better feature propagation and helps alleviate the vanishing gradient issue. Transfer learning was applied by initializing the network with pre-trained weights, and the final classification layer was adapted to predict four output classes. To improve generalization, dropout, L2 regularization, and batch normalization were incorporated during training. The model was trained over 30 epochs using a suitable optimizer and learning rate setup, with hyperparameters chosen according to validation performance.

➢ *Performance Evaluation Metrics*

The performance of the model was evaluated using four widely used classification metrics: accuracy, precision, recall, and F1-score. In addition, a confusion matrix was employed to examine class-level predictions and identify possible misclassification patterns.

- *Accuracy*

Accuracy represents the proportion of correctly predicted samples among all predictions made by the model. It reflects the overall effectiveness of the classifier in identifying both positive and negative instances correctly.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

- *Precision*

Precision indicates the reliability of positive predictions. It measures the fraction of correctly predicted positive samples relative to all samples predicted as positive. A higher precision value means that the model produces fewer false positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

- *Recall*

Recall, also referred to as sensitivity or true positive rate, measures the proportion of actual positive instances that are correctly identified by the model. It evaluates the model's ability to capture all relevant positive samples.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

- *F1-score*

The F1-score combines precision and recall into a single metric by computing their harmonic mean. It provides a balanced evaluation of the model, particularly when dealing with imbalanced datasets.

$$F1 - Score = 2 \times \frac{Precision\ \times Recall}{Precision\ + Recall}$$

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained using the DenseNet-169 model and provides a detailed discussion of its classification performance. The model was evaluated using standard performance metrics and compared with baseline architectures to determine its effectiveness.

➢ *Training Performance Analysis*

Figure 6 illustrates the training and validation accuracy and loss curves across 30 epochs. The model demonstrated rapid convergence during the early training phase, with training accuracy increasing from approximately 78% to nearly 99.9% within the first ten epochs. Validation accuracy followed a similar trend, stabilizing around 99% with minimal fluctuations.

The loss curves show a rapid decline during the early epochs, with training loss decreasing from about 0.70 to nearly zero and validation loss dropping from approximately 0.22 to 0.01. The close alignment of both curves indicates stable learning.

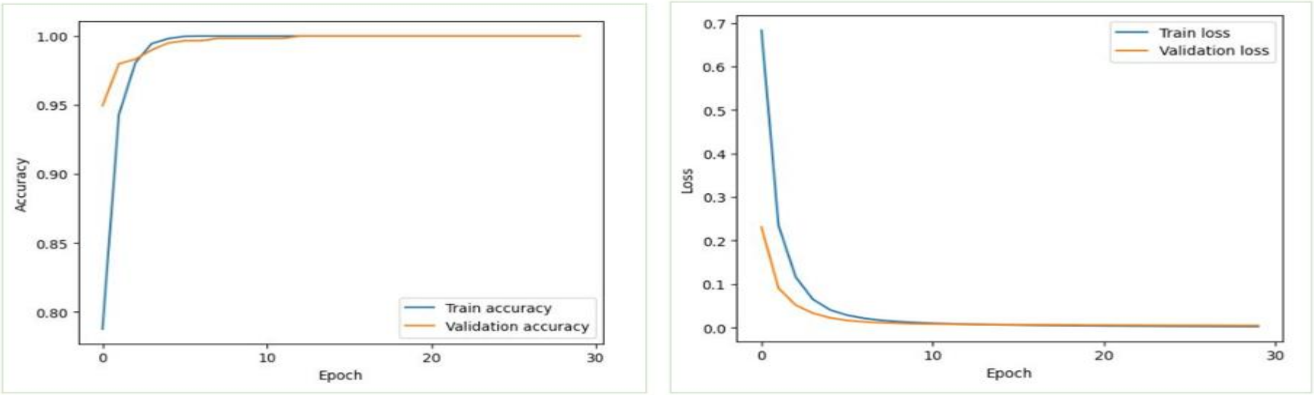


Fig 6 Training and validation accuracy and loss curve

- *Classification Performance Evaluation*

The classification performance of the DenseNet-169 model on the test set is presented in table 3. DenseNet-169 achieved an overall accuracy of 99.83%, indicating excellent discriminative capability across the four rice leaf disease classes.

Table 3: Classification Report of DenseNet-169 on test dataset

	Precision	**Recall**	**F1-score**	**Support**
Bacterial blight	1.000000	1.000000	1.000000	159.000000
Blast	0.992754	1.000000	0.996364	137.000000
Brown spot	1.000000	0.994125	0.997067	171.000000
Tungro	1.000000	1.000000	1.000000	126.000000
Accuracy	0.998314	0.998314	0.998314	0.998314
Macro avg	0.998188	0.998538	0.998358	593.000000
Weighted avg	0.998326	0.998314	0.998314	593.000000

The classification report shows near-perfect precision, recall, and F1-score for all classes. Bacterial Blight and Tungro achieved perfect detection performance with precision, recall, and F1-score values of 1.000. Brown Spot recorded a precision of 1.000 and recall of 0.994, while Blast achieved a precision of 0.993 and recall of 1.000. The macro-average and weighted-average F1-scores of 0.9984 and 0.9983 further confirm the balanced and consistent performance of the model across all classes.

To further analyze prediction behavior, the confusion matrix is illustrated in figure 7.

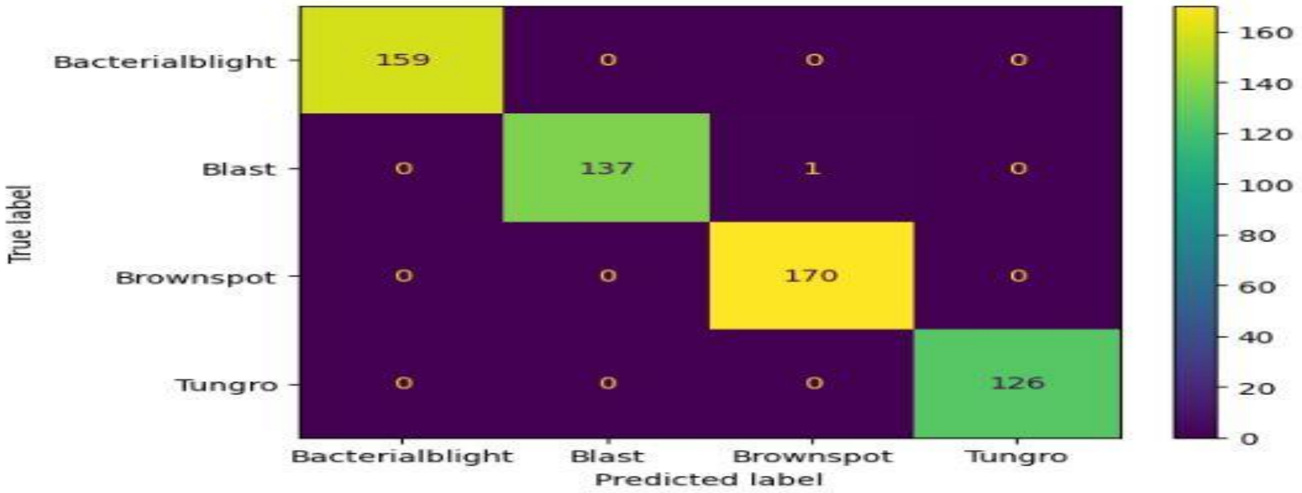


Fig 7 Confusion Matrix on Test Data

The confusion matrix demonstrates that all 159 Bacterial Blight samples, 170 Brown Spot samples, and 126 Tungro samples were correctly classified. For the Blast class, 137 out of 138 samples were correctly predicted, with only one instance misclassified as Brown Spot. This single misclassification represents the only error in the entire test set, highlighting the model's strong ability to distinguish between visually similar disease patterns.

The pronounced diagonal in the confusion matrix indicates the robustness and generalization ability of the proposed framework. The minimal misclassification further validates the effectiveness of transfer learning combined with systematic regularization and data augmentation strategies.

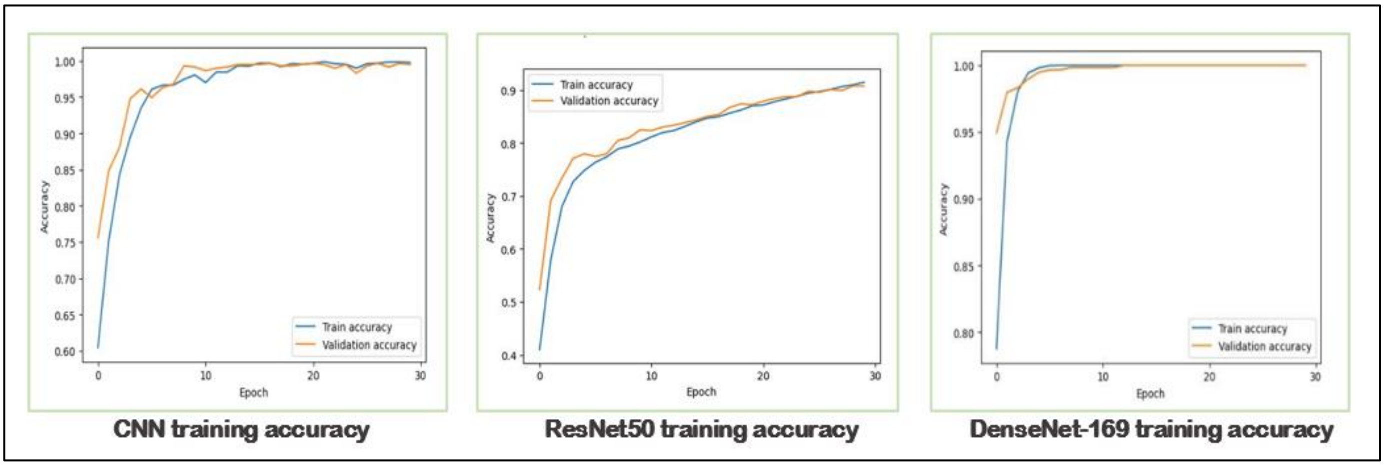
- *Performance Comparison with State-of-the-Art Models*

To ensure a fair evaluation, two state-of-the-art models a fine-tuned CNN and a ResNet50 transfer-learning model were re-implemented and trained using the same rice leaf disease dataset and experimental settings as the proposed DenseNet-169 model.

The CNN achieved 99.34% accuracy, showing strong performance but minor instability and occasional misclassification. ResNet50 obtained 93.09% accuracy, demonstrating moderate stability but more classification errors. In contrast, DenseNet-169 achieved the highest accuracy of 99.83%, exhibiting superior generalization and overall classification performance.

Figure 8 illustrate training and validation accuracy curves of CNN, ResNet50, and DenseNet-169 over 30 epochs.

The CNN model demonstrates rapid initial learning but exhibits slight fluctuations, indicating mild instability and limited robustness. ResNet50 presents smoother learning behaviour but achieves lower overall accuracy compared to DenseNet-169. The proposed DenseNet-169 converges faster and maintains minimal gap between training and validation accuracy, reflecting strong generalization and stable learning throughout the training process.

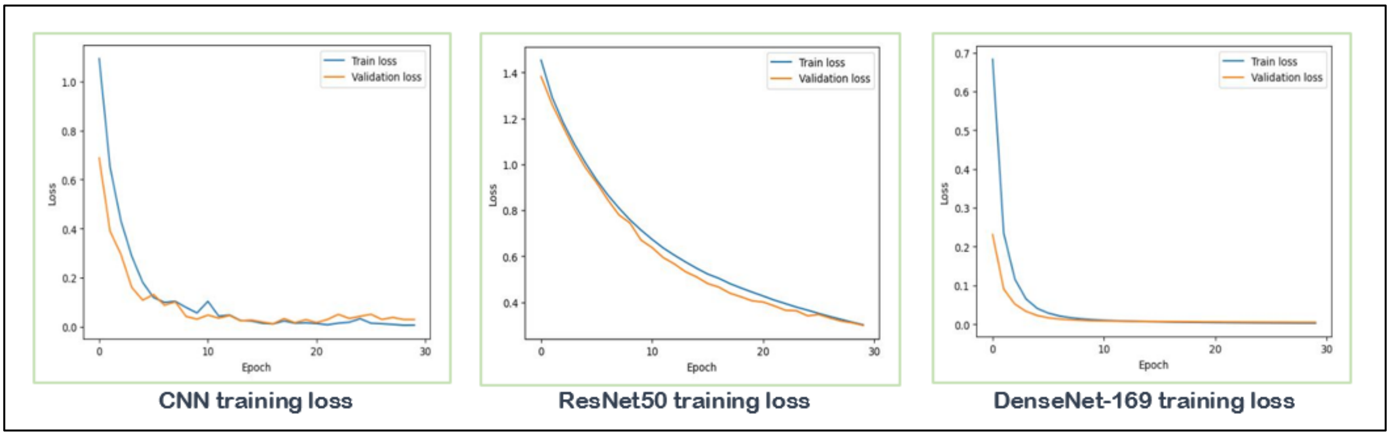


CNN training accuracy ResNet50 training accuracy DenseNet-169 training accuracy

Fig 8 Training Accuracy Comparison of CNN, ResNet50 and DenseNet-169

Figure 9 illustrates the training and validation loss curves for the three architectures.

The CNN loss curve shows noticeable mid-training fluctuations, suggesting optimization instability and mild overfitting. ResNet50 demonstrates smoother and more stable loss reduction but converges more slowly and at higher loss values. DenseNet-169 exhibits the most efficient convergence, with both training and validation loss rapidly decreasing and stabilizing near zero, indicating robust feature learning and excellent generalization capability.



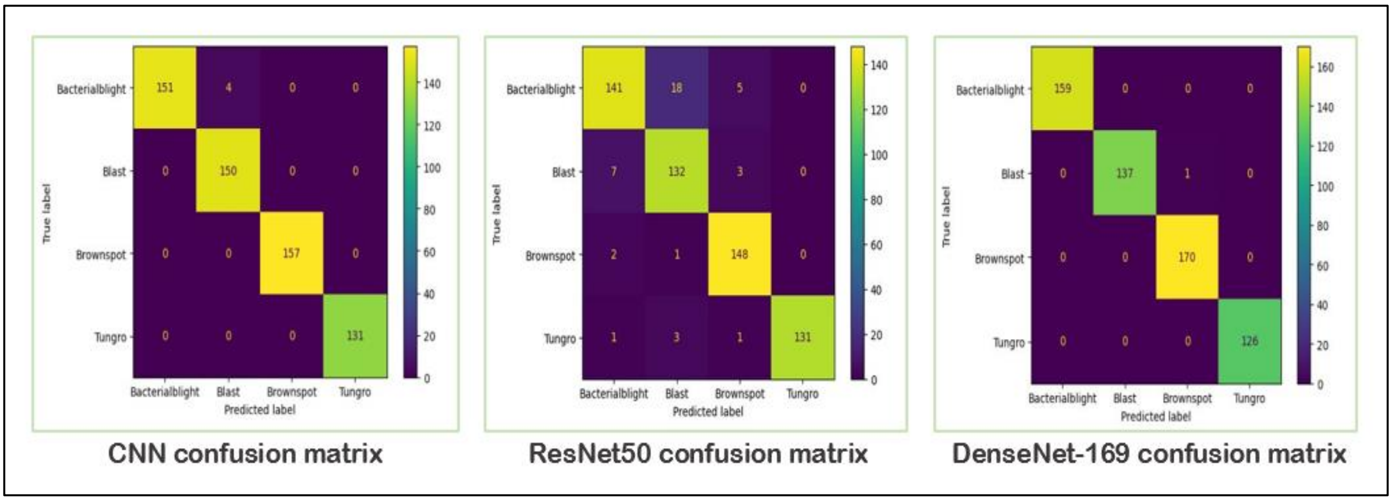
CNN training loss ResNet50 training loss DenseNet-169 training loss

Fig 9 Training Accuracy Comparison of CNN, ResNet50 and DenseNet-169

Figure 10 compares the confusion matrices of CNN, ResNet50, and DenseNet-169 on the test dataset.

The CNN model achieved high classification performance but showed a few misclassifications, particularly between Bacterial Blight and Blast. ResNet50 produced more distributed errors across multiple classes, indicating difficulty in distinguishing visually similar disease patterns.

In contrast, DenseNet-169 demonstrated near-perfect performance, with only one misclassification in the Blast category. This result confirms its superior generalization ability and stronger class discrimination compared to the other models.



CNN confusion matrix ResNet50 confusion matrix DenseNet-169 confusion matrix

Fig 10 Confusion Matrix Comparison of CNN, ResNet50 and DenseNet-169

Table 4 Summary of Model Performance Based on Test Accuracy

Class	**Model**	**Accuracy**
Proposed	DenseNet-169	99.83%
(Mandwariya & Jotwani, 2024)	Fine-tuned CNN	99.34%
(Jayaraju et al., 2025)	Resnet50	93.09%

The results show that DenseNet-169 outperforms other models, achieving the highest accuracy and demonstrating better feature learning and generalization, making it a more reliable and robust choice for rice leaf disease detection than traditional CNNs and ResNet50.

- *Discussion*

The study demonstrates that DenseNet-169 successfully achieved all research objectives, including accurate detection of four major rice leaf diseases, improved generalization through regularization, enhanced dataset diversity via augmentation, and strong benchmarking against state-of-the-art models. The model showed rapid, stable learning without overfitting, aided by dropout, weight decay, and batch normalization. Data augmentation improved robustness to real-world variations, contributing to a high test accuracy of 99.83%. Evaluation metrics confirmed near-perfect precision, recall, and F1-scores, with only one misclassification, highlighting DenseNet-169's ability to distinguish subtle disease features. Compared to a fine-tuned CNN (99.34% accuracy) and ResNet50 (93.09% accuracy), DenseNet-169 exhibited smoother convergence, superior feature reuse, and stronger gradient propagation, making it a more reliable and effective architecture for rice leaf disease classification.

V. CONCLUSION

The study successfully developed a DenseNet-169-based deep learning model for classifying four major rice leaf diseases, demonstrating exceptional accuracy (99.83%) and robust performance. The model leveraged extensive data augmentation and regularization techniques, ensuring strong generalization, stable convergence, and effective learning of fine-grained visual features. Compared to state-of-the-art alternatives, including a fine-tuned CNN and ResNet50, DenseNet-169 outperformed in accuracy, stability, and its ability to differentiate diseases with overlapping symptoms. The results confirm its reliability as an automated diagnostic tool, capable of supporting early disease detection, enhancing decision-making in rice farming, and contributing to precision agriculture practices. Furthermore, the model's adaptability suggests potential deployment in mobile apps, real-time field monitoring, and integration into broader crop management systems, offering practical value for farmers and agricultural stakeholders.

REFERENCES

[1]. Andargie, M., Abera, M., Tesfaye, A., & Demis, E. (2024). Occurrence, distribution, and management experiences of rice (Oryza sativa L.) major diseases and pests in Ethiopia: a review. Cogent Food &

Agriculture, 10(1). https://doi.org/10.1080/23311932.2023.2300558

[2]. Ayyappan, A. B., Gobinath, T., Kumar, M., & Sivaramakrishnan, A. (2025). Rice Plant Disease Detection using Convolutional Neural Networks. Discover Artificial Intelligence, 5(1), 50. https://doi.org/10.1007/s44163-025-00277-x

[3]. Bhutia, T. P., Rao, Y. D., Kharel, P., Rai, P., Rana, M., & Srivastava, S. (2025). A comprehensive review on brown spot disease of rice: etiology, epidemiology, management strategies and future directions. Plant Science Today. https://doi.org/10.14719/pst.4657

[4]. Chen, J., Zhang, D., Nanehkaran, Y. A., & Li, D. (2020). Detection of rice plant diseases based on deep transfer learning. Journal of the Science of Food and Agriculture, 100(7), 3246–3256. https://doi.org/10.1002/jsfa.10365

[5]. Daniya, T., & Vigneshwari, S. (2023). Rice Plant Leaf Disease Detection and Classification Using Optimization Enabled Deep Learning. Journal of Environmental Informatics. https://doi.org/10.3808/jei.202300492

[6]. Das, A., Pathan, F., Jim, J. R., Kabir, M. M., & Mridha, M. F. (2025). Deep learning-based classification, detection, and segmentation of tomato leaf diseases: A state-of-the-art review. Artificial Intelligence in Agriculture, 15(2), 192–220. https://doi.org/10.1016/j.aiia.2025.02.006

[7]. Deng, R., Tao, M., Xing, H., Yang, X., Liu, C., Liao, K., & Qi, L. (2021). Automatic Diagnosis of Rice Diseases Using Deep Learning. Frontiers in Plant Science, 12. https://doi.org/10.3389/fpls.2021.701038

[8]. Devanna, B. N., Jain, P., Solanke, A. U., Das, A., Thakur, S., Singh, P. K., Kumari, M., Dubey, H., Jaswal, R., Pawar, D., Kapoor, R., Singh, J., Arora, K., Saklani, B. K., AnilKumar, C., Maganti, S. M., Sonah, H., Deshmukh, R., Rathour, R., & Sharma, T. R. (2022). Understanding the Dynamics of Blast Resistance in Rice-Magnaporthe oryzae Interactions. Journal of Fungi, 8(6), 584. https://doi.org/10.3390/jof8060584

[9]. Dewi, C., Bilaut, F. Y., Christanto, H. J., & Dai, G. (2024). Deep Learning for the Classification of Rice Leaf Diseases Using YOLOv8. Mathematical Modelling of Engineering Problems, 11(11), 3025–3034. https://doi.org/10.18280/mmep.111115

[10]. Dey, S. R., Das, R., & De, M. (2024). A Brief Review on Present Status of Rice Tungro Disease: Types of Viruses, Vectors, Occurrence, Symptoms, Control and Resistant Rice Varieties. International Journal of Advancement in Life Sciences Research, 07(03), 15–23. https://doi.org/10.31632/ijalsr.2024.v07i03.002

[11]. Faizal Azizi, M. M., & Lau, H. Y. (2022). Advanced diagnostic approaches developed for the global menace of rice diseases: a review. Canadian Journal of Plant Pathology, 44(5), 627–651. https://doi.org/10.1080/07060661.2022.2053588

[12]. Gogoi, M., Kumar, V., Begum, S., Sharma, N., & Kant, S. (2023). Classification and Detection of Rice Diseases Using a 3-Stage CNN Architecture with Transfer Learning Approach. Agriculture, 13(8), 1505. https://doi.org/10.3390/agriculture13081505

[13]. Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. Environmental Monitoring and Assessment, 195(1), 120. https://doi.org/10.1007/s10661-022-10656-x

[14]. Jain, S., Sahni, R., Khargonkar, T., Gupta, H., Verma, O. P., Sharma, T. K., Bhardwaj, T., Agarwal, S., & Kim, H. (2022). Automatic Rice Disease Detection and Assistance Framework Using Deep Learning and a Chatbot. Electronics, 11(14), 2110. https://doi.org/10.3390/electronics11142110

[15]. Jayaraju, P., Hussan, M. I. T., Shekar, G., Krishna, T. R., & Kanagaraj, A. (2025). Empowering Precision Agriculture: A Deep Learning Comparison for Rice Disease Detection (pp. 236–249). https://doi.org/10.2991/978-94-6463-716-8_20

[16]. Jiang, C., Miao, K., Hu, Z., Gu, F., & Yi, K. (2025). Image Recognition Technology in Smart Agriculture: A Review of Current Applications Challenges and Future Prospects. Processes, 13(5), 1402. https://doi.org/10.3390/pr13051402

[17]. Kaur, A., Guleria, K., & Trivedi, N. K. (2024). A deep learning-based model for biotic rice leaf disease detection. Multimedia Tools and Applications, 83(36), 83583–83609. https://doi.org/10.1007/s11042-024-18730-x

[18]. Khadka, R. B., Manandhar, H. K., Shrestha, S., Acharya, B., Sharma, P., Baidya, S., Luu, V. S., & Joshi, K. D. (2025). Defending rice crop from blast disease in the context of climate change for food security in Nepal. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1511945

[19]. Kokila, S., Abirami, S., & Nagaraju, D. (2025). www.etasr.com Kokila et al.: Image-Based Deep Learning Method for Detecting Diseases in Rice Plants. Technology & Applied Science Research, 15(6), 28943–28949. https://doi.org/10.48084/etasr.11930

[20]. Kumar, G., Zarreen, F., & Dasgupta, I. (2021). Rice Tungro Disease (Secoviridae, Caulimoviridae). In Encyclopedia of Virology (pp. 667–674). Elsevier. https://doi.org/10.1016/B978-0-12-809633-8.21243-0

[21]. Kumar, K. K., Sasikala, S., Maheswari, G., Kumar B. Suthar, M., Sridevi, P., Kavitha, D., & Vengatesh, T. (2025). A Convolutional Neural Network Approach for Rice Leaf Disease Detection in India Using Deep Learning. Journal of Neonatal Surgery, 14(4S), 1024–1028. https://doi.org/10.52783/jns.v14.1909

[22]. Latif, G., Abdelhamid, S. E., Mallouhy, R. E., Alghazo, J., & Kazimi, Z. A. (2022). Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. Plants, 11(17), 2230. https://doi.org/10.3390/plants11172230

[23]. Li, K., Li, X., Liu, B., Ge, C., Zhang, Y., & Chen, L. (2023). Diagnosis and application of rice diseases based on deep learning. PeerJ Computer Science, 9, e1384. https://doi.org/10.7717/peerj-cs.1384

[24]. Li, Y., Chen, X., Yin, L., & Hu, Y. (2024). Deep Learning-Based Methods for Multi-Class Rice Disease Detection Using Plant Images. Agronomy, 14(9), 1879. https://doi.org/10.3390/agronomy14091879

[25]. Lu, C., Yue, Y., Liu, B., Jiang, Y., Li, Z., Latif, M. Z., Zhang, X., Chen, D., Dai, L., Kong, L., Du, Q., Yin, Z., Li, Y., Dong, H., & Ding, X. (2025). A Multi-omics Approach Reveals the Effects of Bio- and Chemical- Pesticides on Rice Yield and Quality under Disease Stress. Rice, 18(1), 63. https://doi.org/10.1186/s12284-025-00822-3

[26]. Mandwariya, D., & Jotwani, Dr. V. (2024). A Deep Learning Approach For Automated Rice Disease Detection And Classification. Journal of Advanced Zoology. https://doi.org/10.53555/jaz.v45i3.4313

[27]. Neupane, N., & Bhusal, K. (2021). A Review of Blast Disease of Rice in Nepal. Article in Journal of Plant Pathology & Microbiology, 12(1), 528. https://doi.org/10.35248/2157-7471.20.12.528

[28]. Noorishta Hashmi. (2025). A Hybrid Deep Learning Approach for Rice Plant Disease Detection. Journal of Information Systems Engineering and Management, 10(25s), 128–141. https://doi.org/10.52783/jisem.v10i25s.3956

[29]. Omuse, E. R., Machekano, H., Sokame, B. M., Mutyambai, D. M., Dubois, T., Subramanian, S., & Chidawanyika, F. (2025). One Health interventions and challenges under rural African smallholder farmer settings: A scoping review. One Health, 20, 100959. https://doi.org/10.1016/j.onehlt.2024.100959

[30]. Pai, P., Amutha, S., Patil, S., Shobha, T., Basthikodi, M., Shafeeq, B. M. A., & Gurpur, A. P. (2025). Deep learning-based automatic diagnosis of rice leaf diseases using ensemble CNN models. Scientific Reports, 15(1), 27690. https://doi.org/10.1038/s41598-025-13079-z

[31]. Rahman, Md. M., Hosen, Md. H., Chowdhury, R., Tasnia, N., Nawar, S., & Nazim Uddin, M. (2024). Automated Paddy Disease Detection: A Deep Learning Approach. Proceedings of the 3rd International Conference on Computing Advancements, 1026–1033. https://doi.org/10.1145/3723178.3723314

[32]. Rai, C. K., & Pahuja, R. (2023). Detection and Segmentation of Rice Diseases Using Deep Convolutional Neural Networks. SN Computer Science, 4(5), 499. https://doi.org/10.1007/s42979-023-02014-6

[33]. Rukuna, A. L., Zambuk, F. U., Gital, A. Y., & Bello, U. M. (2025). Citrus diseases detection and classification based on efficientnet-B5. Systems and Soft Computing, 7, 200199. https://doi.org/10.1016/j.sasc.2025.200199

[34]. Seelwal, P., Dhiman, P., Gulzar, Y., Kaur, A., Wadhwa, S., & Onn, C. W. (2024). A systematic review of deep learning applications for rice disease diagnosis: current trends and future directions. Frontiers in Computer Science, 6. https://doi.org/10.3389/fcomp.2024.1452961

[35]. S.Venkatramulu, Dr., Srinivas, V., Sadala, T. M., Rajoju, R., & Kamalakar, R. (2025). Deep Learning-Based Early Detection of Crop Diseases Using Leaf Image Analysis in Smart Agricultural Systems. International Journal of Environmental Sciences, 11(5s), 294–303. https://doi.org/10.64252/xhbme341

[36]. Teja, B. S., Jamwal, G., Gupta, V., Verma, M., Sharma, A., Sharma, A., & Pandit, V. (2025). Biological control of bacterial leaf blight (BLB) in rice–A sustainable approach. Heliyon, 11(2), e41769. https://doi.org/10.1016/j.heliyon.2025.e41769

[37]. Venkatesh, N., Sarkar, S., Sunil, A., Priya, T. G., Aarthi, R., & Devi, K. M. (2023). Deep Learning-based Identification and Classification of Rice Plant Diseases for Precision Agriculture. 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS), 1027–1032. https://doi.org/10.1109/ICACRS58579.2023.10404154

[38]. Ying, X. (2019). An Overview of Overfitting and its Solutions. Journal of Physics: Conference Series, 1168, 022022. https://doi.org/10.1088/1742-6596/1168/2/022022