International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Automated Diagnostic Framework for Identification and Classification of Rice Leaf Diseases

Vuppula Manohar[1], M. Shashidhar[2], P. Kiran Kumar[3]

Submitted: 01/05/2022 **Revised:** 12/06/2024 **Accepted:** 22/06/2024

Abstract

Purpose: Rice is a staple crop essential for global food security; however, disease outbreaks significantly threaten annual yields. This study develops an automated diagnostic framework for the identification and classification of rice leaf diseases using a custom Convolutional Neural Network (CNN).

Methodology: A diverse dataset of rice leaf imagery, comprising both healthy and symptomatic samples, was curated and subjected to rigorous preprocessing to ensure morphological consistency. The CNN architecture was designed to extract high-dimensional features and learn intricate patterns associated with various pathologies. To enhance practical utility, a user-friendly interface was integrated, allowing for real-time diagnostic feedback via image uploads.

Findings: The system demonstrates high accuracy in early-stage disease detection, significantly outperforming traditional visual inspection methods. By automating the diagnostic pipeline, the framework reduces subjectivity and the need for specialized personnel.

Originality: The integration of a continuous learning module ensures that the model evolves with new data, maintaining high precision in diverse environmental conditions. This provides a scalable, cost-effective tool for small-scale farmers to mitigate crop loss and improve agricultural sustainability.

Keywords: *Rice Leaf Disease, Deep Learning, CNN, Precision Agriculture, Food Security, Real-time Diagnosis.*

1. Introduction

Agricultural productivity is the cornerstone of economic stability and food security, particularly in regions where rice serves as the primary caloric source. However, the prevalence of crop diseases remains a formidable barrier to optimal yields. Agriculture remains the cornerstone of the Indian economy, contributing approximately 18% to the national GDP and sustaining over 50% of the workforce. Within this sector, rice cultivation is paramount, accounting for 43% of the total food grain production. Despite its importance, rice yield is frequently compromised by pathological threats such as Bacterial Leaf Blight, Blast, and Brown Spot. These diseases are responsible for substantial productivity losses, ranging from 20% to 50% depending on the severity of the outbreak. Traditionally, diagnosis has relied on manual visual inspection or consultation with agricultural expert's methods that are frequently hampered by human subjectivity, delayed response times, and a critical shortage of skilled personnel in rural sectors. With the advent of Computer Vision (CV) and Deep Learning (DL), there is a paradigm shift toward precision agriculture. This research proposes an automated classification system utilizing a specialized CNN to detect rice leaf anomalies at their earliest stages. Unlike traditional methods, our

[1]*Department of Electronics and Communication Engineering, Vaagdevi Engineering College, Warangal, Telangana, 506005. manoharvu@gmail.com*

[2]*Department of Electronics and Communication Engineering, Vaagdevi College of Engineering, Warangal, 506005, Telangana, India. sasi47004@gmail.com*

[3]*Department of Electronics and Communication Engineering, Balaji Institute of Technology and Science, Narsampet, Warangal, Telangana, 506132. kiranpadakanti0430@gmail.com*

Corresponding: Vuppula Manohar (manoharvu@gmail.com)

approach leverages automated feature extraction to identify subtle necrotic patterns that may be invisible to the untrained eye.

1.1 Problem Statement and Research Motivation

The primary challenge in rice pathology is the rapid rate of disease transmission, which necessitates immediate intervention to prevent large-scale crop failure. Manual monitoring of expansive fields is resource-intensive and often results in late-stage detection, where chemical interventions are less effective and more costly. The motivation behind this project is to democratize agricultural intelligence, providing small and marginal farmers with an affordable, real-time diagnostic tool that supports informed decision-making and reduces reliance on expensive manual labor.

1.2 System Objectives

- **Automated Feature Extraction:** Utilizing CNN layers to distinguish between healthy tissue and various disease-induced lesions.
- **Real-time Accessibility:** Developing a deployment interface for immediate field diagnostics.
- **Scalability:** Implementing a framework that supports continuous learning as more regional data becomes available.

2. Literature Survey

Devi and Priya [1] concentrated on using UAVs to recognize plant disease through image analysis. They explored various optical techniques, including RGB imaging, multi- and hyperspectral sensors, thermography, chlorophyll fluorescence and 3D scanning, for their potential in automated and objective disease detection systems. The research emphasized the importance of highly sophisticated data analysis methods for accurate disease detection, offering insights into complex plant–pathogen systems. Kumar et al. [2] proposed a multilayered perceptron model for predicting fungal diseases in plants, including powdery mildew, anthracnose, rust and root rot/leaf blight, based on real-time data from soil sensors and satellite information on micrometeorological factors. The method involved dataset preprocessing, exploratory data analysis and a detection module. The study emphasized the economic benefits of this cost-effective technique and its feasibility for timely and accurate plant disease detection.

Picon et al. [3] proposed to enhance fungal infection identification, which minimizes yield losses and optimizes fungicide treatments. The researchers developed an adapted deep residual neural network-based algorithm using over 8178 images for detecting septoria, tan spot and rust in real acquisition conditions. A network architecture called Mobile-DANet was developed by Chen et al. [4] to identify maize crop diseases. Based on Dense Net, this architecture incorporated depth-wise separable convolution in dense blocks and an embedded attention module to assess inter channel relationships and spatial points in input features. Yu et al., [5] was developed A rapid identification method for soybean brown leaf spot, soybean frog eye leaf spot and soybean Phyllosticta leaf spot based on a residual attention network (RANet) model Otsu's algorithm was employed to remove the background from the original images, and the dataset was expanded using image enhancement.

Reis-Pereira et al., [6] In this Research modular optical sensing system is used to detect early bacterial infection in tomato leaves, achieving effective discrimination between healthy and infected plants 3 days post-inoculation through the application of direct UV–vis spectroscopy, optical fibres and principal component analysis. In this Research of Vidhya and Priya [7] they developed three models using ML (KNN and SVM) and deep learning (AlexNet) approaches. RGB colour images were employed to train the models with and without background. After augmentation, a total of 4353 healthy images, 4154 leafspot images and 4037 sigatoka images were used to train the model. In the research of Neupane & Baysal-Gurel [8] they concluded that ML approaches are increasingly being used to automatically detect patterns or anomalies indicating the presence of crop disease. In the research of Abioye et al., [9] once a disease is detected, autonomous crop disease management systems can manage the disease by targeted application of pesticides.

In this research of Hulbert et al., [10] the crop disease detection involves sharing information on crop diseases in a particular region it allows stakeholders to track the spread of diseases and develop strategies for disease management and control. In the Research of Burdon & Zhan, [11] The Climate changes is expected to impact crop health and disease patterns significantly increasing the complexity of crop disease detection. Deep learning techniques were used by Daphal and Koli [12] for disease classification in sugarcane. They introduced a database of sugarcane leaf diseases comprising 2569 images across five categories. Elfatimi et al. [13] investigated rust and angular leaf spot diseases affecting bean crops by employing the MobileNet architecture. Ghosh et al. [14] studied on sunflower disease recognition using a hybrid deep learning approach. Using a small dataset, their model combined transfer learning and a simple CNN. Among the eight models tested with four different disease classes (downy mildew, grey mould, leaf scars and fresh leaf), the VGG19 + CNN hybrid model demonstrated superior performance in various metrics, including precision, recall, F_1 score, accuracy, Hamming loss, Matthews's coefficient, Jaccard score and Cohen's kappa. Khotimah et al. [15] introduced a high-performance two-stream spectral-spatial residual network (TSRN) for hyperspectral image classification and found that the proposed architecture performs well even with small datasets, outperforming state-of-the-art methods in overall accuracy, average accuracy, kappa value and training time.

3. Proposed System

The proposed system architecture is designed as a deep-learning pipeline that progresses from raw data acquisition to optimized disease classification. The methodology follows a systematic approach of data engineering, multi-optimizer comparative analysis, and architectural refinement.

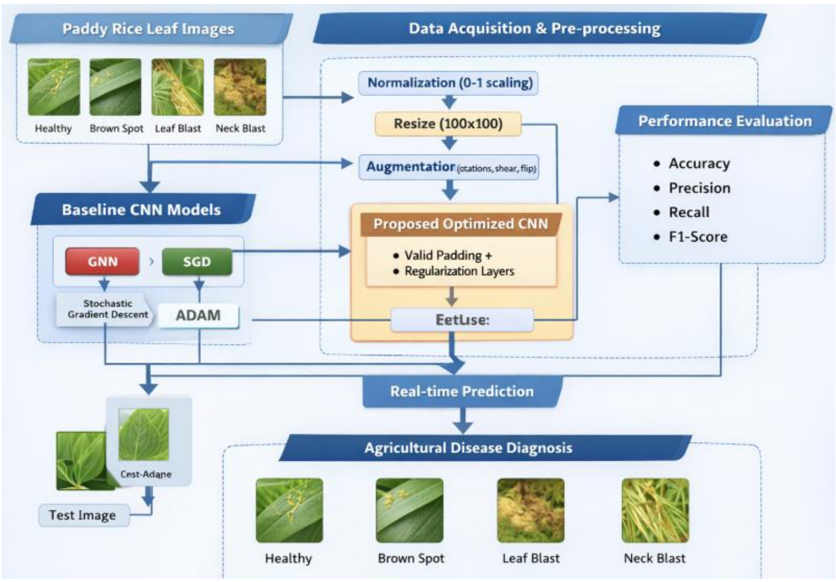


Fig. 1: Architectural block diagram of proposed system.

3.1 Data Acquisition and Pre-processing

The study utilizes a curated dataset of paddy rice leaf imagery, categorized into four classes: Healthy, Brown Spot, Leaf Blast, and Neck Blast. To ensure computational efficiency and feature uniformity, the following pre-processing pipeline is implemented:

- **Normalization:** Pixel intensities are scaled to a range of [0, 1] via $I_{norm} = I/255$ facilitate stable gradient descent.
- **Dimensionality Standardization:** Images are resized to 32 × 32 pixels to maintain a consistent input tensor shape.
- **Augmentation:** To prevent overfitting and enhance generalization, the dataset is expanded using ImageDataGenerator, applying stochastic transformations including rotation, shear, and horizontal flipping.

3.2 CNN Architecture and Optimizer Comparison

The research evaluates the impact of stochastic optimization on feature convergence through two baseline models:

1. **CNN-SGD:** A baseline Convolutional Neural Network utilizing Stochastic Gradient Descent. This model focuses on

minimizing the loss function with a fixed learning rate, serving as the control group for performance benchmarks.

2. **CNN-ADAM:** The same architecture is trained using the Adaptive Moment Estimation (ADAM) optimizer. ADAM's ability to compute adaptive learning rates for each parameter provides faster convergence and handles sparse gradients effectively.

3.3 Proposed Model: Optimized CNN with Valid Padding

The core contribution of this research is a refined CNN architecture (Proposed Model) designed for high-precision feature extraction. The architectural modifications include:

- **Valid Padding:** By utilizing 'valid' padding, the network performs convolutions only where the filter and input fully overlap, preventing the introduction of artificial noise at the image boundaries.
- **Regularization Layers:** Integration of Batch Normalization for internal covariate shift reduction and Dropout layers to mitigate co-adaptation of neurons, ensuring model robustness.
- **Feature Extraction:** A multi-layered stack of convolutional and max-pooling layers is employed to extract deep morphological patterns indicative of specific fungal and bacterial pathologies.

3.4 Performance Evaluation and Prediction

The models are rigorously evaluated using a stratified 70:30 split. Comparative analysis is conducted via:

- **Visual Analytics:** Accuracy vs. Epoch and Loss vs. Epoch graphs are generated to monitor for underfitting or overfitting.
- **Metric Assessment:** Performance is quantified using Precision, Recall, and F1-score.
- **Inference:** The final optimized model is deployed for real-time prediction on unseen test imagery, validating its utility as a diagnostic tool in precision agriculture.

4. Results And Discussion

The experimental dataset comprises high-resolution imagery of paddy rice leaves, partitioned into four distinct pathological and physiological classes. These categories represent the most significant threats to rice productivity in agrarian regions, providing the necessary visual features for supervised deep learning.

Table 1: Pathological Class Definitions.

Class Label	Pathological Characteristics	Impact on Crop Yield
Healthy	Uniform chlorophyll distribution; vibrant green pigmentation with no observable necrotic lesions or structural degradation.	Baseline for optimal photosynthetic efficiency.
Brown Spot	Small, circular-to-oval necrotic lesions with dark brown centers, typically surrounded by a distinct chlorotic (yellowish) halo.	Fungal infection (*Cochliobolus miyabeanus*) leading to reduced grain quality.
Leaf Blast	Spindle-shaped, grayish-white lesions with necrotic borders. Advanced stages involve the coalescence of lesions, covering the entire leaf blade.	Significant reduction in photosynthetic surface area due to *Magnaporthe oryzae*.
Neck Blast	Concentrated discoloration and tissue weakening at the panicle neck, often resulting in "neck rot" and the failure of grain filling.	Most destructive phase; results in direct and severe loss of grain production.

Morphological Analysis for Feature Extraction

The success of the proposed CNN model relies on its ability to differentiate between these classes based on color intensity, texture gradients, and lesion geometry. For instance, the Brown Spot class is defined by localized, high-contrast spots, whereas Leaf Blast presents more irregular, elongated patterns. Neck Blast requires the model to identify specific anatomical regions of the plant, making it a more complex feature-extraction task compared to leaf-based anomalies.

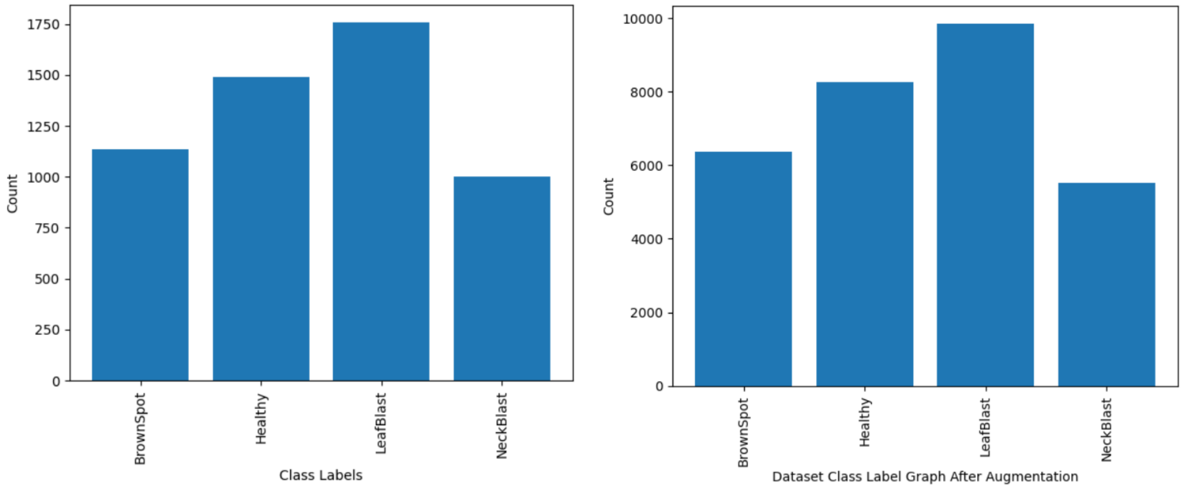
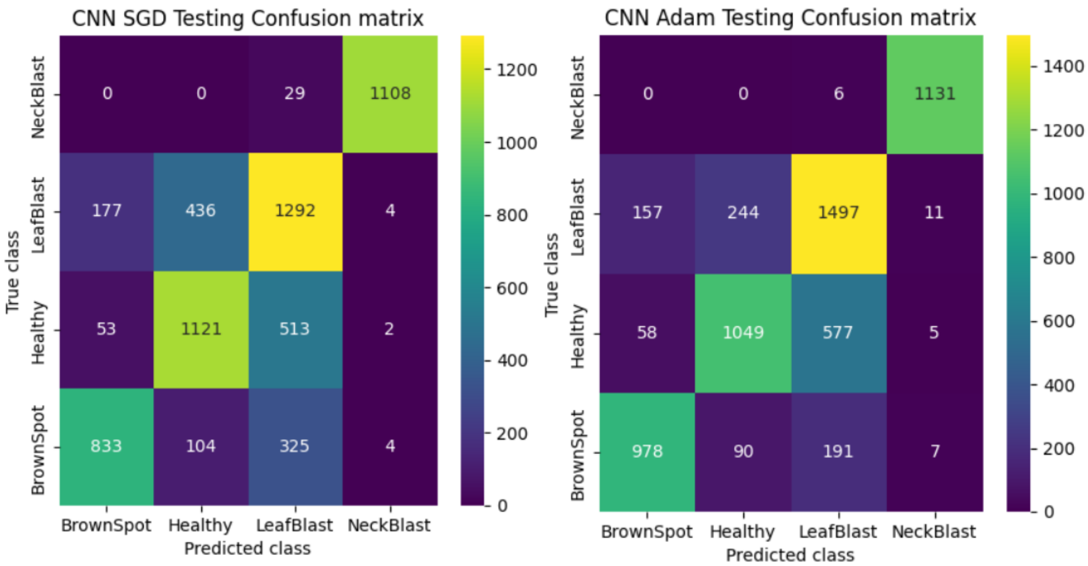


Fig. 2: Original and augmented dataset count plot.

By utilizing these four categories, the model is trained to provide a comprehensive health assessment of the paddy crop, moving beyond binary "diseased vs. healthy" detection to specific pathological diagnosis. Figure 2 visualizes the distribution of dataset categories before and after augmentation. It highlights the balanced representation of the four classes achieved through augmentation techniques. This step ensures that the model receives a well-distributed dataset, improving training outcomes and reducing class imbalance.



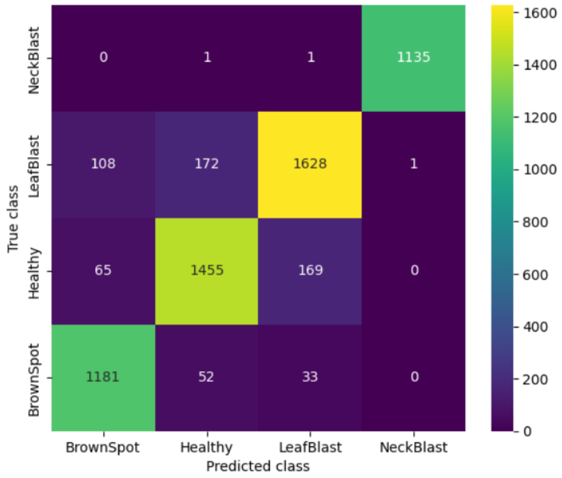


Fig. 3: Confusion matrices obtained using (a) CNN with SGD optimizer. (b) CNN with Adam optimizer. (c) CNN with Adam and valid padding optimizer.

Figure 4 presents examples of the model's predictions on test images. It shows the input images, their corresponding ground truth labels, and the predictions made by the best-performing model (CNN with Adam and valid padding). Correctly classified and misclassified instances are highlighted. Figure 5 provides a comparative analysis of the three models—CNN with SGD, CNN with Adam, and CNN with Adam and valid padding. It highlights their respective accuracy, precision, recall, and F-score. The epoch vs. loss graph illustrates the convergence behavior of each model during training, showing how the proposed model achieves faster convergence and lower loss compared to the other approaches.

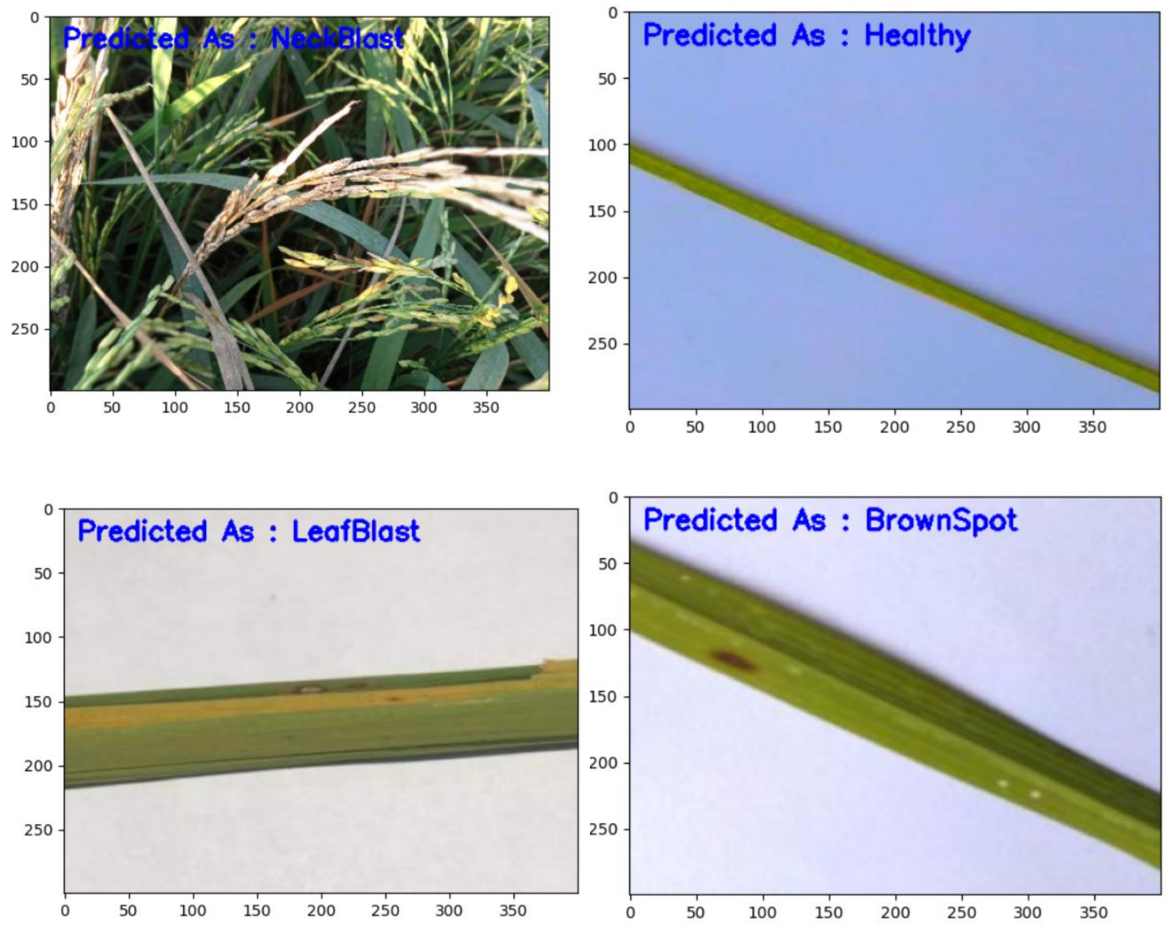


Fig. 4: Sample predictions on test images.

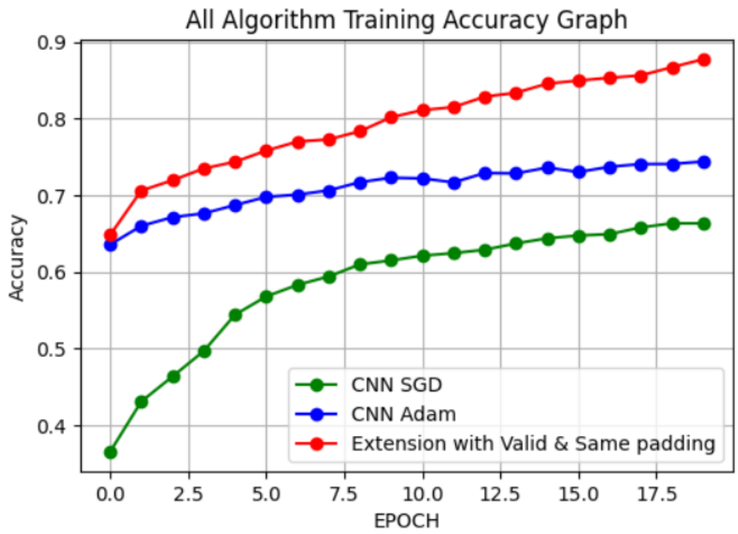


Fig. 5: Performance comparison graph and epoch vs. loss graph of all models.

Table 2 contains six rows, each representing a unique combination of model and phase:

- The first row details the CNN SGD model during the testing phase, showing an identical value of 71.74% for all metrics (Accuracy, Precision, Recall, F-Score).
- The second row covers the CNN Adam model in the testing phase, with all metrics at 78.25%.
- The third row represents the Extension with Adam & Valid Padding model during testing, achieving the highest uniform score of 90.55% across all metrics.
- The fourth row shows the CNN SGD model with valid padding testing, maintaining 74.44% for all metrics.
- The fifth row lists the CNN Adam model with valid padding testing, again at 78.25% for all metrics.
- The sixth row details the Extension with Adam & Valid Padding model with valid padding testing, consistently scoring 90.55% across all metrics.

Table 2: Performance comparison of all models.

Model	Phase	Accuracy	Precision	Recall	F-Score
CNN SGD	Testing	71.74%	71.74%	71.74%	71.74%
CNN Adam	Testing	78.25%	78.25%	78.25%	78.25%
Extension with Adam & Valid Padding	Testing	90.55%	90.55%	90.55%	90.55%
CNN SGD	Valid Padding Testing	74.44%	74.44%	74.44%	74.44%
CNN Adam	Valid Padding Testing	78.25%	78.25%	78.25%	78.25%
Extension with Adam & Valid Padding	Valid Padding Testing	90.55%	90.55%	90.55%	90.55%

5. Conclusion

The research successfully demonstrates the potential of leveraging machine learning techniques, particularly CNNs, for the accurate classification of plant leaf diseases. By preprocessing the dataset, splitting it effectively, and employing robust algorithms like CNN with SGD and Adam optimizers, the model achieves high accuracy and generalization in distinguishing between the classes: Brown Spot, Healthy, Leaf Blast, and Neck Blast. The use of Adam optimizer with valid padding further enhances performance by ensuring efficient gradient descent and preserving image features during convolutions. This approach provides a scalable and reliable solution for early disease detection, helping farmers and agricultural stakeholders make timely decisions to manage and mitigate crop losses.

References

[1] Devi, K.A. & Priya, R. (2021) Plant disease identification using the unmanned aerial vehicle images. *Turkish Journal of Computer and Mathematics Education*, **12**, 2396–2399.

[2] Kumar, A. & Palaparthy, V.S. (2021) Soil sensors-based prediction system for plant diseases using exploratory data analysis and machine learning. *IEEE Sensors Journal*, **21**, 17455–17468.

[3] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J. & Johannes, A. (2019) Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Computers and Electronics in Agriculture*, **161**, 280–290.

[4] Chen, T., Yang, W., Zhang, H., Zhu, B., Zeng, R., Wang, X. et al. (2020) Early detection of bacterial wilt in peanut plants through leaf-level hyperspectral and unmanned aerial vehicle data. *Computers and Electronics in Agriculture*, **177**, 105708.

[5] Yu, M., Ma, X., Guan, H., Liu, M. & Zhang, T. (2022) A recognition method of soybean leaf diseases based on an improved deep learning model. *Frontiers in Plant Science*, **13**, 878834.

[6] Reis-Pereira, M., Martins, R.C., Silva, A.F., Tavares, F., Santos, F. & Cunha, M. (2021) Unravelling plant–pathogen interactions: proximal optical sensing as an effective tool for early detect plant diseases. *Chemistry Proceedings*, **5**, 18.

[7] Vidhya, N.P. & Priya, R. (2022) Detection and classification of banana leaf diseases using machine learning and deep learning algorithms. In: 2022 IEEE 19th India council international conference(INDICON)

[8] Neupane, K. & Baysal-Gurel, F. (2021) Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: a review. *Remote Sensing*, **13**, 3841.

[9] Abioye, E.A., Hensel, O., Esau, T.J., Elijah, O., Abidin, M.S.Z., Ayobami, A.S. et al. (2022) Precision irrigation management using machine learning and digital farming solutions. *AgriEngineering*, **4**, 70–103

[10] Hulbert, J.M., Hallett, R.A., Roy, H.E. & Cleary, M. (2023) Citizen science can enhance strategies to detect and manage invasive forest pests and pathogens. *Frontiers in Ecology and Evolution*, **11**, 1113978.

[11] Burdon, J.J. & Zhan, J. (2020) Climate change and disease in plant communities. *PLoS Biology*, **18**, e3000949.

[12] Daphal, S.D. & Koli, S.M. (2023) Enhancing sugarcane disease classification with ensemble deep learning: a comparative study with transfer learning techniques. *Heliyon*, **9**, e18261.

[13] Elfatimi, E., Eryiğit, R. & Shehu, H.A. (2023) Impact of datasets on the effectiveness of MobileNet for beans leaf disease detection. *Neural Computing and Applications*, **36**, 1773–1789.

[14] Ghosh, P., Mondal, A.K., Chatterjee, S., Masud, M., Meshref, H. & Bairagi, A.K. (2023) Recognition of sunflower diseases using hybrid deep learning and its explainability with AI. *Mathematics*, **11**, 2241.

[15] Khotimah, W.N., Bennamoun, M., Boussaid, F., Sohel, F. & Edwards, D. (2020) A high-performance spectral-spatial residual network for hyperspectral image classification with small training data. *Remote Sensing*, **12**, 3137.