International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM05986
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Rice Leaf Disease Detection using Image Recognition and Convolutional Neural Networks

Devendra Bangde[1]
Student, MBA Department
Dhole Patil College of Engineering, Pune

Prof. Kanifnath S Satav[2]
Professor, MBA Department
Dhole Patil College of Engineering, Pune

---***---

Abstract
Rice is a fundamental food crop sustaining more than 50% of the global population. However, its production is significantly affected by various leaf diseases such as bacterial blight, brown spot, and leaf smut. Early and accurate detection of these diseases is essential to minimize yield loss and ensure food security. Traditional disease identification methods rely heavily on manual inspection by agricultural experts, which is time-consuming, subjective, and not scalable.

This research proposes a deep learning-based automated system for rice leaf disease detection using image recognition techniques. Multiple Convolutional Neural Network (CNN) architectures, including MobileNetV2, VGG16, ResNet50, EfficientNetB0, and a custom CNN, were implemented and evaluated on a labeled dataset of rice leaf images. The models were assessed using performance metrics such as accuracy, precision, recall, and F1-score.

Experimental results indicate that MobileNetV2 achieved the highest performance with an accuracy of 83.33% and F1-score of 0.8372, demonstrating its effectiveness in real-time applications due to its lightweight architecture. The study highlights the importance of transfer learning and optimized architectures for agricultural disease detection systems.

Keywords: Deep Learning, Rice Leaf Disease, CNN, Transfer Learning, Image Classification, Precision Agriculture

I. INTRODUCTION

Agriculture is a backbone of many developing economies, and rice is a critical crop in countries like India, China, and Southeast Asia. However, rice cultivation faces serious challenges due to plant diseases, which can lead to up to 30–40% yield loss annually.

Conventional disease detection methods involve:

- Visual inspection by farmers
- Laboratory-based analysis

These methods suffer from:

- Lack of expertise in rural areas
- Delayed detection
- Human error and inconsistency

With advancements in **Artificial Intelligence (AI)** and **Computer Vision**, automated plant disease detection has become feasible. Convolutional Neural Networks (CNNs) are particularly suitable because they:

- Automatically extract hierarchical features
- Eliminate manual feature engineering
- Perform well on image classification tasks

This study focuses on building a robust CNN-based system to detect rice leaf diseases efficiently and accurately.

II. RELATED WORK

Extensive research has been conducted in plant disease detection using both traditional machine learning and deep learning approaches.

Traditional Approaches

- Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) were used with handcrafted features such as texture, color, and shape.
- Limitation: Feature extraction is manual and less scalable.

Deep Learning Approaches

- CNNs like AlexNet, VGG16, ResNet have shown strong performance.
- Transfer learning significantly reduces training time and improves accuracy.
- Studies such as Mohanty et al. (2016) achieved ~99% accuracy using controlled datasets.

Recent Advances

- Mobile-friendly architectures like MobileNet and EfficientNet enable deployment on edge devices.
- Data augmentation techniques improve generalization.
-

Limitations in Existing Work

- Overfitting due to small datasets
- Lack of real-world noisy images
- High computational requirements

III. RESEARCH GAP

Despite significant progress, several critical gaps remain:

1. **Dataset Limitations**

○ Most studies use clean and lab-controlled datasets.

○ Real-world field conditions (lighting, noise) are not considered.

2. **Model Comparison Issues**

○ Limited comparative analysis between lightweight and heavy models.

3. **Deployment Challenges**

○ High computational cost restricts real-time usage on mobile devices.

4. **Overfitting Problem**

○ Increasing validation loss indicates poor generalization.

5. **Lack of Robust Evaluation**

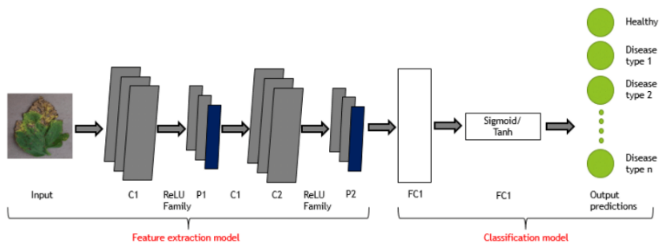
○ Many studies rely only on accuracy without considering precision, recall, and F1-score.

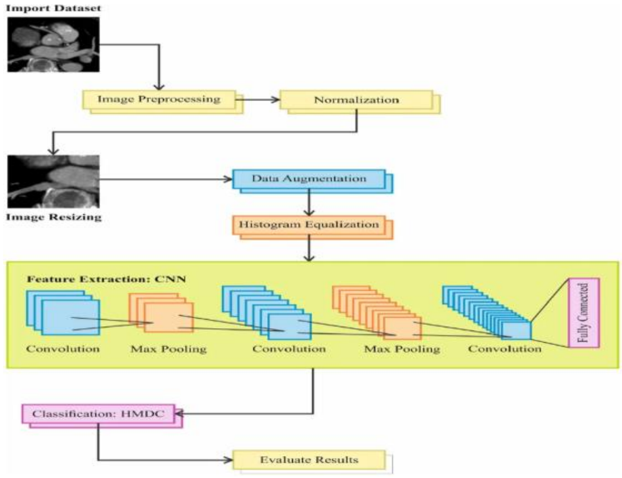
IV. OBJECTIVE OF THE STUDY

The study aims to:

- Develop an intelligent system for automatic rice leaf disease detection.
- Evaluate multiple CNN architectures on the same dataset.
- Analyze performance using multiple evaluation metrics.
- Identify the best model for real-world deployment.
- Minimize overfitting using data augmentation and validation techniques.
- Provide a scalable solution for precision agriculture.

V. RESEARCH METHODOLOGY





Step-by-Step Pipeline

1. Data Collection

- Dataset consists of labeled rice leaf images.
- Classes include healthy and diseased categories.

2. Data Preprocessing

- Resizing images to 224×224 pixels
- Normalization (pixel scaling between 0–1)
- Data augmentation:

○ Rotation

○ Flipping

○ Zooming

○ Shearing

3. Dataset Splitting

- Training: 70%
- Validation: 15%
- Testing: 15%

4. Model Building

- Pre-trained models used:

○ MobileNetV2

○ VGG16

○ ResNet50

○ EfficientNetB0

- Custom CNN designed with:

○ Convolution layers

○ MaxPooling layers

○ Fully connected layers

5. Training Configuration

- Optimizer: Adam
- Learning Rate: 0.001
- Loss Function: Categorical Crossentropy
- Epochs: 10–20

6. Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-score

7. Model Selection

- Based on highest F1-score and lowest loss

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM05986
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

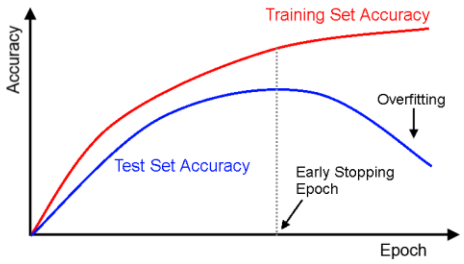
VI. MODEL IMPLEMENTATION AND RESULTS

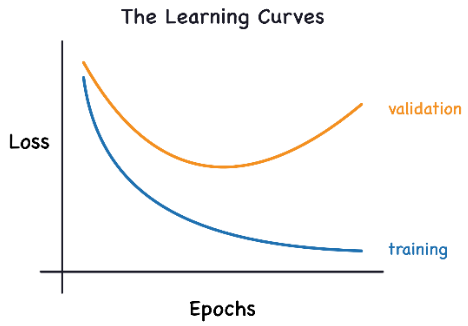
Performance Summary

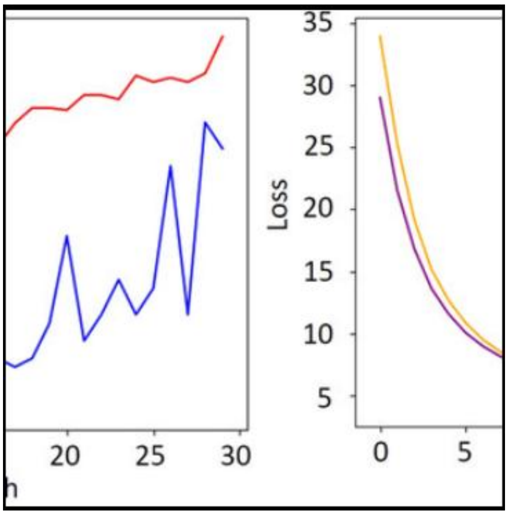
Your results clearly show:

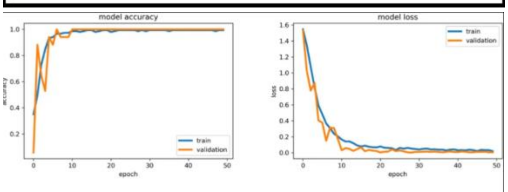
- MobileNetV2 = Best model
- Balanced Precision & Recall → Good generalization
- Lowest loss → Stable learning

Overfitting Analysis









(a) (b)

Key Observations

- Training accuracy steadily increased → model learning properly
- Validation accuracy fluctuates → dataset variability
- Validation loss increases after epoch 6 → overfitting detected

Model-wise Insights

- **MobileNetV2**
  - Lightweight + high accuracy
  - Best trade-off between speed and performance
- **VGG16**
  - Good feature extraction
  - Higher loss due to heavy architecture
- **ResNet50**
  - Underperformed due to insufficient data
- **EfficientNetB0**
  - Requires better tuning and more data
- **Custom CNN**
  - Limited feature learning capability

VII. MAJOR FINDINGS

- Transfer learning significantly improves performance.
- Lightweight models outperform heavy models in small datasets.
- Overfitting is a major challenge in agricultural datasets.
- Data augmentation improves generalization.
- MobileNetV2 is ideal for mobile-based disease detection systems.
- Validation loss is more reliable than accuracy for model evaluation.

VIII. CONCLUSION

This research presents an efficient and scalable approach for rice leaf disease detection using deep learning techniques. By comparing multiple CNN architectures, the study identifies MobileNetV2 as the most effective model in terms of accuracy, efficiency, and deployability. The proposed system has strong potential to revolutionize agricultural practices by enabling early disease detection, reducing crop losses, and improving farmer productivity. Future enhancements can include integration with IoT devices, real-time mobile applications, and larger datasets to further improve robustness.

Furthermore, the integration of such deep learning-based systems with emerging technologies like cloud computing and edge AI can significantly enhance accessibility and scalability for farmers in remote areas. By enabling real-time disease diagnosis through mobile applications, farmers can receive immediate recommendations for treatment and prevention, thereby minimizing economic losses. Additionally, incorporating continuous learning mechanisms and expanding the dataset with diverse environmental conditions can further improve model robustness and adaptability. This research lays a strong foundation for developing intelligent, data-driven agricultural solutions that contribute toward sustainable farming and food security.

REFERENCES

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Deep Learning for Plant Disease Detection.
[2] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis.
[3] Too, E. C., et al. (2019). Comparative study of deep learning models.
[4] Howard, A. G., et al. (2017). MobileNets architecture.
[5] Tan, M., & Le, Q. (2019). EfficientNet model scaling.
[6] Krizhevsky, A., et al. (2012). ImageNet classification.
[7] Simonyan, K., & Zisserman, A. (2014). VGGNet architecture.
[8] He, K., et al. (2016). ResNet deep residual learning.