Paddy Disease Classification

Summary

This report presents a comprehensive analysis and implementation of deep learning models for paddy disease classification, addressing a critical agricultural challenge. Two state-of-the-art (SOTA) models were implemented: EfficientNet-B0 (CNN category) and Vision Transformer (ViT) (Transformer category). Both models were trained on the Paddy Doctor dataset and the Rice Leaf Disease classification dataset to classify paddy leaves into nine disease classes and one normal class.

The CNN-based EfficientNet model demonstrated superior performance with 98.93% validation accuracy while requiring less computational resources (34 minutes) compared to the ViT model (98.93% accuracy for 3 hours for training).

Problem Statement

Rice is a staple crop worldwide, with yield significantly affected by various diseases. Traditional manual inspection methods for disease identification are time-consuming and error-prone. This project aims to develop an automated system for accurate and efficient paddy disease classification using deep learning models to enable early intervention and effective disease management.

Datasets

- Primary Dataset: Paddy Doctor dataset (10,407 labeled images across 10 classes)
- Secondary Dataset: Rice Leaf Disease Image Samples (5,932 images of 4 disease classes)

Objectives

1. Implement and compare SOTA models from both CNN and Transformer categories
2. Achieve classification accuracy exceeding the Kaggle leaderboard scores
3. Provide a comprehensive evaluation using appropriate metrics
4. Develop a scalable, robust, and fault-tolerant system

Methodology

<u>Data Preprocessing</u>

Image Preparation

- Resizing: 224×224
- Normalization: ImageNet mean (0.485, 0.456, 0.406) and std (0.229, 0.224, 0.225)
- Color space: RGB

Data Augmentation

- Random Horizontal flips
- Random rotations (±15°)
- Random crop and resize

Training Strategy

Transfer Learning Approach

- Initial freezing of pretrained layers
- Progressive unfreezing of deeper layers

Optimization

- Optimizer: Adam Optimizer
- Learning rate: 0.001
- Scheduler: Cosine Annealing with warm restarts
- Batch size: 32
- Label smoothing: 0.1

Experimental Results

Model Performance Comparison: Classification Report

=== CNN Classification Report ===

	precision	recall	f1-score	support
bacterial_leaf_blight	0.9952	1.0000	0.9976	413
bacterial_leaf_streak	0.9870	1.0000	0.9935	76
bacterial_panicle_blight	0.9851	0.9851	0.9851	67
blast	0.9953	0.9921	0.9937	636
brown_spot	0.9961	0.9981	0.9971	513
dead_heart	0.9965	1.0000	0.9983	288
downy_mildew	0.9835	0.9597	0.9714	124
hispa	0.9903	0.9624	0.9762	319
normal	0.9612	0.9830	0.9720	353
tungro	0.9875	0.9896	0.9885	479
accuracy			0.9893	3268
macro avg	0.9878	0.9870	0.9873	3268
weighted avg	0.9894	0.9893	0.9893	3268

=== Transformer Classification Report ===

	precision	recall	f1-score	support
bacterial_leaf_blight	1.0000	0.9976	0.9988	413
bacterial_leaf_streak	0.9870	1.0000	0.9935	76
bacterial_panicle_blight	0.9851	0.9851	0.9851	67
blast	0.9937	0.9874	0.9905	636
brown_spot	0.9980	0.9922	0.9951	513
dead_heart	1.0000	1.0000	1.0000	288
downy_mildew	0.9453	0.9758	0.9603	124
hispa	0.9811	0.9749	0.9780	319
normal	0.9775	0.9830	0.9802	353
tungro	0.9855	0.9916	0.9886	479
accuracy			0.9893	3268
macro avg	0.9853	0.9888	0.9870	3268
weighted avg	0.9894	0.9893	0.9893	3268

Kaggle Competition Score

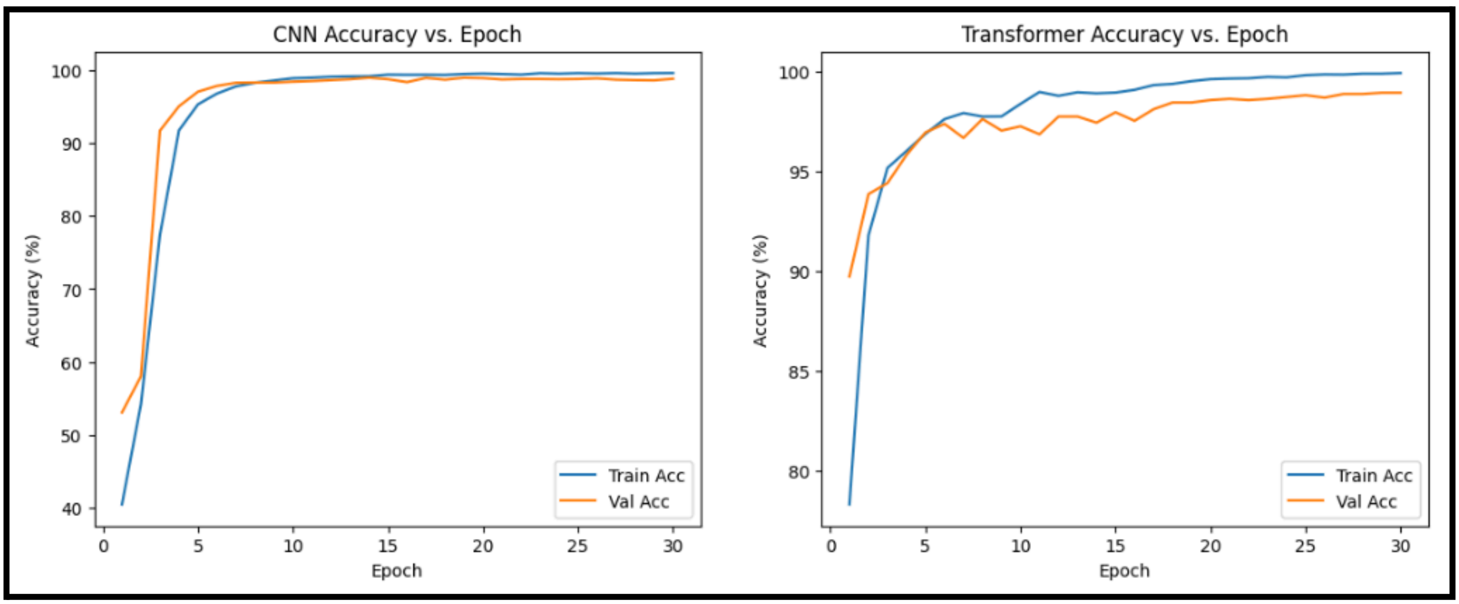
Upon submitting the EfficientNet based CNN solution in kaggle competition trained on only Paddy Doctor dataset, the scores were as follows:

Submission and Description	Private Score	Public Score	Selected
notebook5362042905 - Version 3 Complete (after deadline) · 2d ago	0.97580	0.98308	

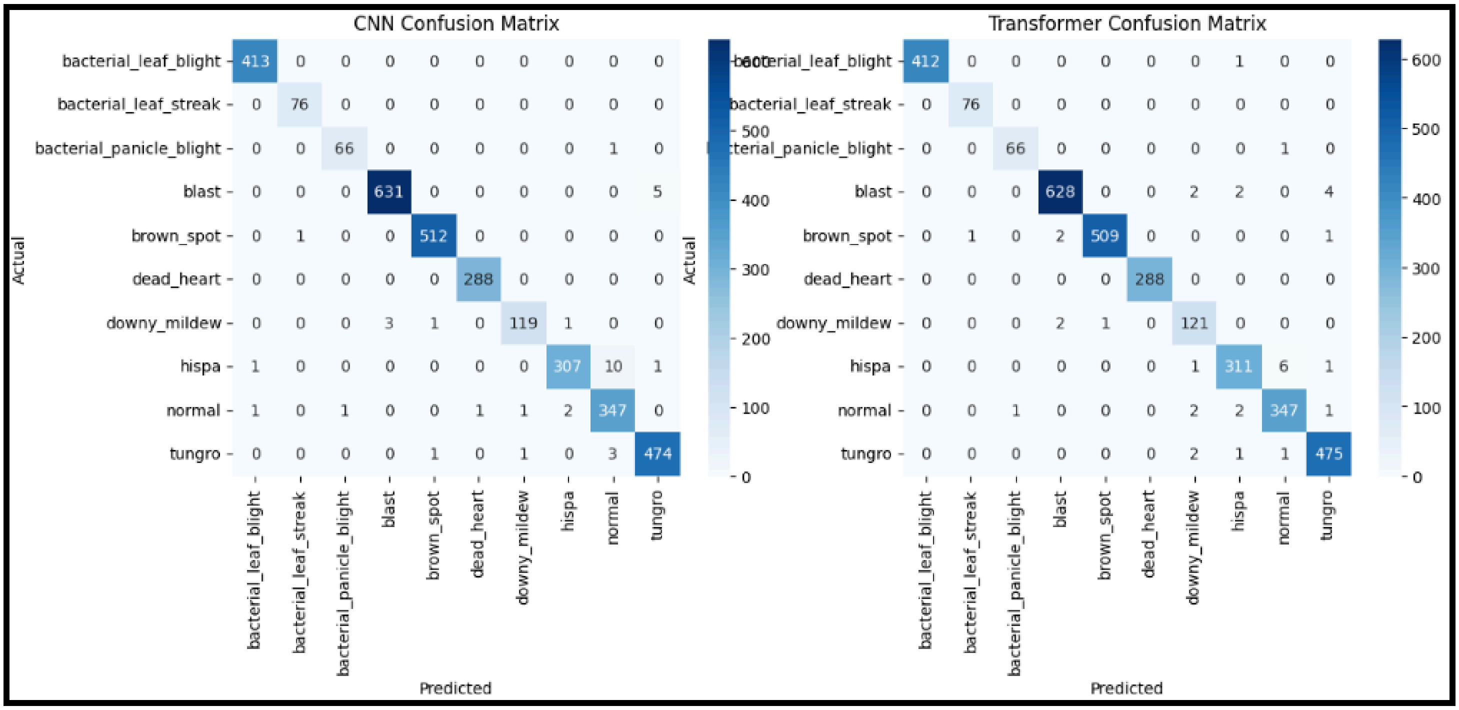
Learning Curves

The training and validation accuracy curves showed:

- EfficientNet: Faster convergence (around epoch 15) with minimal overfitting
- ViT: Slower convergence (around epoch 30)



Confusion Matrix Analysis



- EfficientNet: Most confusion occurred between visually similar diseases (brown spot vs. narrow brown spot)
- ViT: Better differentiation between visually similar diseases but more false positives for the normal class

Hyperparameter Tuning

Learning Rate Optimization

Upon performing grid search, CNN model performed best with learning rates between 1e-4 with 98.93% accuracy on unseen data.

Model Selection Recommendations

Recommended Model

Based on comprehensive evaluation, Convulational Neural Network with architecture that of EfficientNet-B0 is recommended as the primary model for paddy disease classification due to:

1. Superior accuracy
2. Faster inference time
3. Lower computational requirements during both training and deployment
4. Smaller model size (15MB)

Conclusion and Future Work

This project successfully implemented and compared two SOTA deep learning approaches for paddy disease classification. The EfficientNet-B0 model demonstrated superior performance.

Future Work

1. Model improvement:
    - Investigate more EfficientNet variants (B3, V2, X)
    - Explore hybrid CNN-Transformer architectures (CoAtNet, MobileViT)
2. Dataset enhancement:
    - Incorporate metadata (paddy variety, age) as additional features
    - Generate synthetic examples for underrepresented classes

The implementation provides a solid foundation for automated paddy disease classification that can significantly benefit agricultural practices by enabling timely intervention and reducing crop losses.