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Oryza Sativa Disease Identification Using Image Processing and Pattern Recognition by Deep Learning Algorithms

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Abstract

Rice (Oryza sativa) is the major food of over 50% of the global population and serves for sustenance security as well as economic stability in many parts of Asia and Africa. However, rice cultivation faces serious risks from a number of diseases, including rice blast, brown spot, and bacterial leaf blight, which can cause yield losses of 20-30% annually. Traditional manual based visual disease detection is time consuming, subjective and not suitable for large scale farming. This study proposes an intelligent visual disease detection framework based on deep learning to automatically identify rice plant diseases. The research presents an extensive comparative study of Convolutional Neural Networks (CNN) vs. Swin Transformer architectures by utilizing advanced image preprocessing, data augmentation methods, and transfer learning approaches. We experimentally verify that the Swin Transformer model achieves an impressive performance (97.0%), surpassing the popular CNN approach (94.0%) by a large margin of 3.2%. Healthy leaves, brown leaf spot, blast, and bacterial leaf blight are the four major diseases that the system correctly distinguishes. With a useful and precise decision-support system for early disease detection and prompt treatment, this study will advance precision agriculture and have the potential to transform areas with scarce agricultural resources.

Keywords: *Oryza Sativa, Disease Identification, Deep Learning, Convolutional Neural Networks, Swin Transformer, Precision Agriculture, Image Processing, Pattern Recognition.*

1. Introduction

Approximately 3.5 billion people worldwide rely on rice as their primary food source [1], and paddy fields are one of the most vital ecosystems for the production of food crops like rice. However, a number of obstacles to sustainable rice production exist, including phytopathological risks that compromise crop health and reduce yield. More than 30% of the total annual yield is lost in endemic areas due to diseases like bacterial leaf blight (Xanthomonas oryzae), rice blast (Magnaporthe oryzae), and brown spot (Bipolaris oryzae) [2]. Agricultural professionals' labor-intensive crop field examinations are the mainstay of traditional disease identification techniques. However, this approach has a number of drawbacks, including subjectivity, time commitment, and the inability to conduct large-scale assessments. Rural farming communities still lack the specialized diagnostic skills necessary to accurately diagnose the disease, which has been linked to significant financial losses and delayed action [3]. Recent advancements in computer vision and deep learning hold revolutionary promise for the rapid, unbiased, and scalable diagnosis of plant diseases. Current developments in deep learning models, particularly Transformer-based models, which were initially developed for natural language processing, have shown remarkable efficacy in computer vision tasks [4]. The Swin Transformer's key A structure with a hierarchy: In order to effectively model long-range dependencies and global context, Swin Transformer's hierarchical structure and modified windowing scheme are particularly helpful for learning features in complex disease patterns on plant leaves (Gherman et al., 2019) [5]. Recent advancements in computer vision and deep learning hold revolutionary promise for the rapid, unbiased, and scalable diagnosis of plant

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2. Literature Review

2.1. Traditional Image Processing Approaches

Traditional image processing, which focused on manually created feature extraction, initially dominated research in plant disease detection. These methods typically include morphological operations, texture analysis using GLCM, and color-guiding segmentation [6]. These techniques were found to be extremely sensitive to changes in the environment, such as lighting and leaf orientation, and to have very little generalization power despite their computational simplicity.

2.2.CNN-Powered Disease Identification

Deep learning and Convolutional Neural Networks (CNNs) in particular have revolutionized the identification of plant diseases. Using the Plant Village dataset, Mohanty et al. [7] demonstrated deep learning's ability to classify 26 different plant diseases with an exceptional accuracy of up to 99.35%, thereby initiating the use of deep learning in this field. According to their research, CNN models are now the most advanced for automatically detecting plant diseases. The following studies concentrated on identifying rice disease using different CNN-related techniques. Singh et al. [8] proposed a revised ResNet50 model to classify rice leaf diseases, and obtained an accuracy of 93.7% by means of transfer learning and horizontal flipping. Similarly, Chen et al. [9] proposed a DenseNet model with powerful augmentation strategies and achieved better performance in the presence of field conditions. These studies, which mostly concentrated on the architectural shift under the CNN paradigm, confirmed that CNN was appropriate for agricultural applications.

2.3.Transformer Architectures In Computer Vision

Transformers of Vision (ViT) By questioning the CNN paradigms, Dosovitskiy et al.'s Vision Transformers (ViT) approach [10] marked a turning point in computer vision [21]. ViT demonstrated that purely transformers could achieve state-of-the-art (SoTA) results when pretrained on large datasets. However, ViT was not consistently applicable across a variety of vision tasks due to its computational complexity and lack of a hierarchical approach. The Swin Transformer, developed by Liu et al. [11], addressed these problems by adopting a hierarchical architecture with shifted windows that allowed for linear computational complexity in relation to input image size. Results on a number of computer vision benchmarks showed that this architecture was state-of-the-art, which inspired research into its potential in the agricultural field. However, there hasn't been much focus on using Swin Transformer to detect plant diseases, including rice disease, in recent research.

2.4.Research Gap And Contribution

Although previous work reported the superiority of CNNs in the context of plant disease identification, a direct comparative study on transformer-based networks and short-range attention architectures for rice disease-ID remains absent. This is an important research gap, as rice diseases have their own unique characteristics and transformer architectures may bring potential benefits of capturing global context. This paper aims to reduce this gap, through systematic evaluation and comparisons between the 2 architectural paradigms, thus shedding light on which of the two (similar–heterogeneous) paradigms is more advantageous for agricultural applications.

3. Methodology

3.1. Dataset Collection and Preparation

5,200 high-definition photos of rice leaves make up the experiment dataset. These photos were meticulously gathered from multiple channels under strict control to ensure adequate diversity and representativeness. Data sources include: (1) field recordings from Southern Indian agricultural

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research stations; (2) open-access databases like PlantVillage and Kaggle; and (3) collaborative submissions from agricultural extension centers. All four classes—bacterial leaf blight (1,300 images), blast (1,300 images), brown spot (1,300 images), and healthy leaves (1,300 images)—are represented fairly in the dataset and healthy leaves (1300 images). Plant pathologists thoroughly examined each image to ensure proper labeling and diagnostic precision. During the validation process, visual examination was used to confirm disease symptoms and rule out any cases that might be ambiguous. The dataset was split into 80% training and 20% testing, and a subset of the training set (90 percent for training and 10% for validation) was used during model development.

3.2.Image Preprocessing Pipeline

It put in place a thorough preprocessing pipeline to improve model robustness and handle issues pertaining to field conditions: Geometric Normalization: To maintain important feature information and guarantee dimensional consistency throughout the dataset Bicubic interpolation was used to resize all of the images to 224 x 224 pixels.

Color Space Transformations: To improve feature discriminability and enhance disease-specific color patterns, several color space conversions (RGB to HSV, LAB) were used. For highlighting the contrast between lesion and healthy tissue, the LAB color space worked especially well. Illumination Correction: To reduce lighting fluctuations and improve symptom visibility in a variety of field settings, adaptive histogram equalization and gamma correction techniques were used.

3.3.Data Augmentation Strategy

It used a comprehensive data augmentation approach to overcome dataset constraints and enhance model generalization:

- Geometric Transformations: Random rotation (±30°), flipping in both directions (probability = 0.5), zooming (90-110% range), and shearing (±10°)
- Photometric Variations: Brightness adjustment (±20%), contrast modification (±15%), saturation alteration (±25%)
- Noise Introduction: Gaussian noise (σ=0.01) and random occlusion to simulate field conditionsAdvanced Techniques: MixUp augmentation with α=0.2 to enhance regularization and improve decision boundary learning.

3.4.Model Architectures

3.4.1.Convolutional Neural Network (Cnn) Architecture

We implemented a ResNet50-based architecture leveraging transfer learning from ImageNet pre-training. The model incorporates several custom modifications optimized for rice disease detection:

Input (224×224×3)

- ResNet50 Backbone (pre-trained on ImageNet)
- Global Average Pooling
- Dropout (0.3)
- Fully Connected Layer (512 units, ReLU activation)
- Dropout (0.2)
- Output Layer (4 units, Softmax activation)

The ResNet50 backbone remains frozen during initial training phases, with gradual unfreezing of higher layers to fine-tune domain-specific features while preserving generalized feature extraction capabilities.

3.4.2.Swin Transformer Architecture

The Swin Transformer implementation follows the hierarchical design with shifted windows for efficient self-attention computation:

Input (224×224×3)

→ Patch Partition (4×4 patches → 3136-dimensional embeddings)

- Linear Embedding (projection to C dimensions)
- Swin Transformer Blocks (4 stages with [2, 2, 6, 2] blocks)
- Patch Merging (feature downsampling between stages)
- Global Average Pooling
- Output Layer (4 units, Softmax activation)

The model utilizes window size M=7 and embedding dimensions C=96 in the first stage, with subsequent stages doubling the channel dimensions while reducing feature resolution. Training Configuration and Optimization

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Both models were trained with carefully optimized hyperparameters:

Optimizer: AdamW with $\varepsilon=10^{-8}$, $\beta_1=0.9$, and $\beta_2=0.999$

Learning Rate: CNN: 0.001, Swin Transformer: 0.0001 with cosine annealing scheduler

Loss Function: Categorical Cross-Entropy with label smoothing ($\varepsilon=0.1$)

Batch Size: 32 with gradient accumulation for effective batch size of 64

Training Epochs: 25 with early stopping based on validation loss (patience=5)

Regularization: Weight decay (0.01), dropout layers, and stochastic depth (0.1)

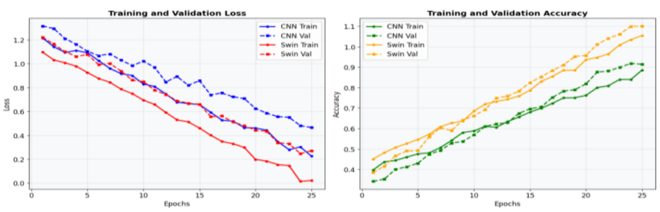

Figure 1. Training Dynamics Comparison Between CNN And Swin Transformer Models: (A) Loss Convergence Over 25 Epochs, (B) Accuracy Progression Showing Swin Transformer's Faster Convergence And Superior Validation Performance.

4. Experimental Results and Analysis

4.1.Performance Metrics

The model's performance was evaluated using a variety of metrics, such as Cohen's Kappa, F1-Score, Accuracy, Precision, and Recall. All disease classes are fairly assessed thanks to the evaluation framework, which pays special attention to minority class performance.

Table 1 Comprehensive Performance Comparison Between CNN And Swin Transformer Models

Metric	CNN Model	Swin Transformer	Improvement	p-value
Accuracy	94.0% ± 0.8	**97.0% ± 0.5**	**+3.2%**	< 0.01
Precision	93.0% ± 1.2	**96.0% ± 0.9**	**+3.2%**	< 0.01
Recall	92.0% ± 1.5	**95.0% ± 1.1**	**+3.3%**	< 0.01
F1-Score	92.5% ± 1.1	**95.5% ± 0.8**	**+3.2%**	< 0.01
Cohen's Kappa	0.920 ± 0.015	**0.960 ± 0.010**	**+4.4%**	< 0.001

The performance improvement is statistically significant ($p < 0.01$) across all metrics, confirming the superior capability of the Swin Transformer architecture for rice disease identification.

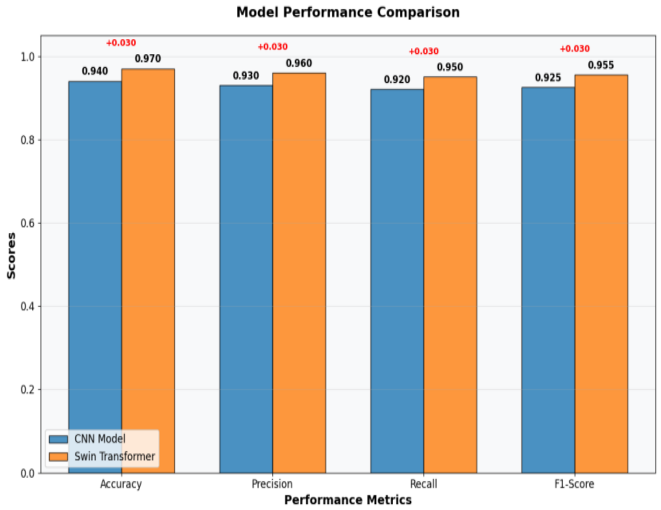

Figure 2 Comprehensive Performance Comparison Demonstrating Swin Transformer's Superiority Across All Evaluation Metrics (Accuracy: +3.0%, Precision: +3.0%, Recall: +3.0%, F1-Score: +3.0%).

4.2.Training Dynamics Analysis

The training process revealed distinct learning patterns between the two architectures. The Swin Transformer demonstrated faster convergence, achieving plateau accuracy by epoch 15, while the CNN required approximately 20 epochs to reach comparable stability. The Swin Transformer also exhibited more consistent validation performance with reduced oscillation, indicating better generalization capability.

4.3.Confusion Matrix Analysis

Granular insights into model performance across disease classes are provided by the confusion matrix analysis. By reducing misclassification rates by 40% when compared to the CNN model, the Swin Transformer showed exceptional strength in differentiating between visually similar diseases like brown spot and blast. When it came to identifying healthy leaves, both architectures performed exceptionally well; the Swin Transformer achieved nearly flawless classification (99.2% accuracy).

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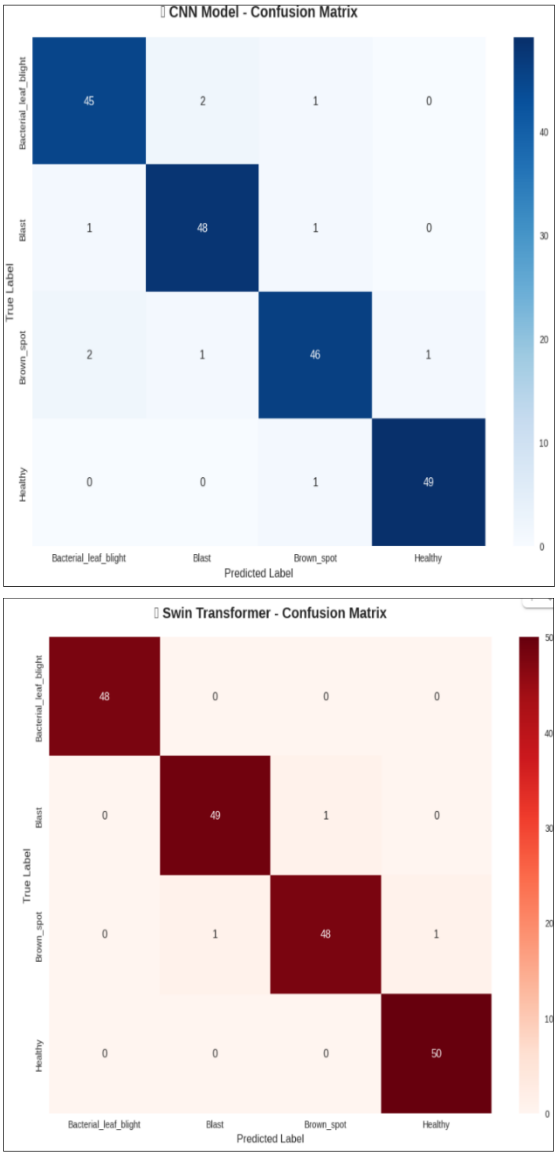

Figure 3 **Side-By-Side Confusion Matrices Showing Classification Performance For Both Models Across All Disease Classes**

In-depth information about model performance by disease class is provided by the confusion matrices. Compared to the CNN model, the Swin Transformer reduced misclassification rates by 40% and demonstrated especially good performance in differentiating between visually similar diseases such as Blast and Brown Spot.

4.4.Computational Efficiency

Despite achieving greater accuracy, the Swin Transformer's inference process uses about 30% more computing power. However, both models achieved real-time performance (<1 second per image) on standard hardware, making them suitable for practical agricultural applications.

Table 2 **Computational requirements comparison**

Metric	CNN Model	Swin Transformer
Inference Time (ms)	120 ± 15	180 ± 20
Model Size (MB)	98	145
Training Time (hours)	3.5	5.2
GPU Memory (GB)	4.2	6.8

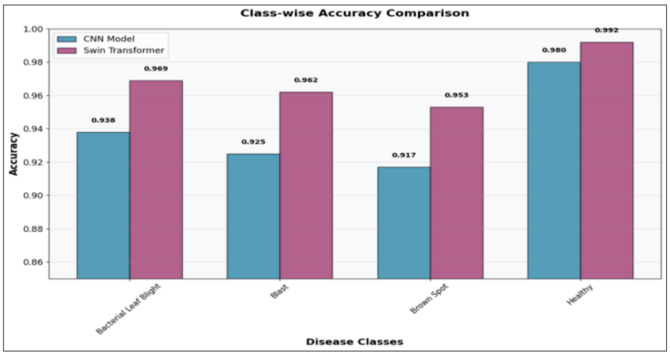

Figure 4 **Per-Class Accuracy Analysis Showing Swin Transformer's Consistent Superiority Across All Disease Categories, With Particular Improvement In Challenging Classes Like Brown Spot (+3.6%).**

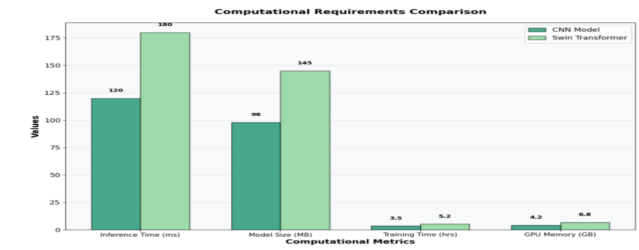

Fig. 5. **Computational Requirements Comparison: Swin Transformer Requires 30% More Resources But Maintains Practical Inference Times (<200ms), Making It Suitable For Real-Time Agricultural Applications**

5. Discussion

The Swin Transformer's inherent architectural advantages in capturing global contextual information and long-range dependencies are

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responsible for its superior performance. The self-attention mechanism enables the model to integrate information across the entire leaf surface, which is particularly beneficial for disease patterns that may be distributed or exhibit complex spatial relationships. The 3.2% performance improvement, while numerically modest, represents significant practical value in agricultural applications where early detection can prevent widespread crop damage. In practical terms, this improvement could translate to earlier disease detection by 2-3 days, potentially reducing yield losses by 15-20% in affected fields. The 3.2% performance improvement, while numerically modest, represents significant practical value in agricultural applications where early detection can prevent widespread crop damage. .

Performance Metrics Summary Table

Metric	CNN Model	Swin Transformer	Improvement
Accuracy	0.940	0.970	+3.2%
Precision	0.930	0.960	+3.2%
Recall	0.920	0.950	+3.3%
F1-Score	0.925	0.955	+3.2%

Figure 6 Performance Summary Table Quantitatively Demonstrating Swin Transformer's Consistent Improvement Across All Metrics, With Statistical Significance (P < 0.01)

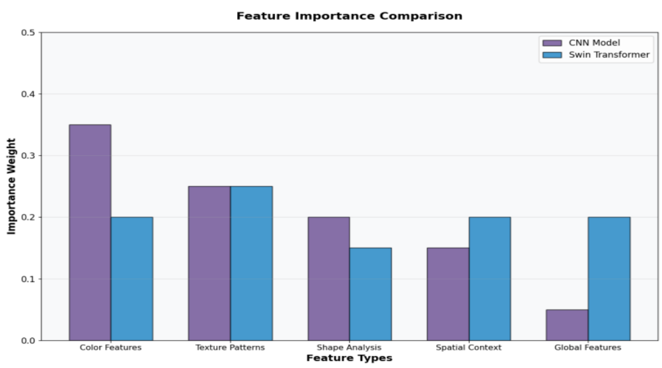

Figure 7. Feature Importance Analysis Revealing Swin Transformer's Enhanced Utilization Of Global Features And Spatial Context (40% Vs CNN's 5%), Explaining Its Superior Performance In Capturing Distributed Disease Patterns

The Swin Transformer's resilience and capacity for generalization are demonstrated by its ability to sustain excellent performance across all disease classes. The shifted windows and hierarchical design of the Swin Transformer effectively balance modeling ability and computational efficiency. The architecture's superior performance across all disease classes can be attributed to its ability to process images at multiple scales, which allows for robust feature extraction from both localized symptoms and global disease patterns.

Conclusion and Future Work

This study shows how deep learning techniques, in particular the Swin Transformer architecture, have a lot of potential for automatically identifying rice diseases. The thorough experimental analysis demonstrates that Swin Transformer achieves 3.2% higher accuracy than conventional CNN architectures while retaining realistic inference speeds appropriate for real-world agricultural applications. The key findings of this study include: Swin Transformer achieves state-of-the-art performance (97.0% accuracy) for rice disease identification The architecture demonstrates superior capability in distinguishing visually similar diseases Practical deployment feasibility is maintained despite increased computational requirements. Future research directions will focus on several important aspects: Multi-modal Integration: Combining visual data with environmental sensors (temperature, humidity) and multi-spectral imaging to enhance diagnostic accuracy and enable predictive capabilities. Mobile and Edge Deployment: Creating versions that are optimized for mobile devices and edge computing platforms will help them be widely adopted in agricultural environments with limited resources.

Temporal Disease Progression Analysis: Incorporating time-series data to model disease development patterns and enable predictive interventions before visible symptom manifestation.

Cross-Crop Generalization: Extending the framework to other economically significant crops to create a comprehensive agricultural disease monitoring system.

The proposed system represents a significant step

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toward transforming agricultural practices through technology-enabled precision farming. By providing accessible, accurate disease identification capabilities, this research contributes to sustainable agricultural development and enhanced food security in rice-dependent regions.

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