GreenScan: Intelligent Paddy Leaf Disease Detection Using Deep CNN Architectures

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Abstract
Paddy leaf diseases pose major challenges to world yield, food security, and economic stability in agricultural regions. Timely and correct identification of diseases is of utmost importance for farmers and policymakers in order to follow effective disease management strategies before the infection spreads across large cultivation areas. The traditional method of manual inspection is labor-intensive, subjective, and limited by expert availability. On the contrary, this research contributes to an automated and intelligent rice leaf disease recognition system based on Deep Convolutional Neural Networks (DCNNs) with inclusion of transfer learning. Domain-specific, custom-curated, and visually diverse rice leaf disease images were acquired for a dataset and subjected to robust preprocessing including resizing, normalizing, and removal of noise. Extensive data augmentation techniques, like rotation, flipping, shifting, and altering light intensity, were adopted to address class imbalance and improve model generalization. Advanced DCNN architectures, including InceptionV3, ResNet50, and VGG16, which were pre-trained on the large-scale ImageNet database, were fine-tuned on the augmented dataset. In that respect, deep feature extraction layers have been frozen to retain generic representation capabilities, and the final fully connected layers are replaced with domain-specific classifiers customized for four major Paddy diseases, namely, Blast, Brown Spot, Leaf Blight, and Tungro. Hence, systematic division of the dataset into training, validation, and testing subsets has been performed with multiple split ratios. Each model's effectiveness analysis has been done by calculating performance metrics: Accuracy, Precision, Recall, and F1-Score. Experimental results show that the proposed DCNN-based system offers superior detection performance and reliable classification accuracy compared to the previous machine learning-based approaches. Its high scalability and robustness provide a suitable real-time smart farming application toward sustainable agriculture,improving productivity, and early disease prevention.

Keywords: Rice Leaf Disease ,Deep Learning , Transfer Learning, DCNN, Smart Agriculture, Plant Disease Detection, Image Classification.

Introduction

Paddy (Oryza sativa) is a basic food component for over half of the world's population. the global population and represents one of the most economically and socially significant crops within the agricultural sector. However, rice yield and quality are continuously threatened by various foliar diseases caused by fungal, viral and bacterial pathogens .Of these ,Blast, Brown Spot Leaf Blight, and

Tungro remain the most aggressive and are widely prevalent diseases resulting in significant productivity losses every year. These diseases manifest symptoms such as necrotic lesions, chlorotic streaks, discoloration, and tissue decay that seriously reduce photosynthetic activity, thus affecting grain development. Disease diagnosis in agricultural fields has normally depended upon visual inspection is done by trained pathologists or even experienced farmers. Such manual diagnostic Suffer from a number of limitations including subjectivity, delayed identification, the limited availability of experts within remote field environments, and the difficulty in assessing early-stage infection. Such challenges may lead to uncontrolled disease spread before preventive measures can be applied. Recent developments in computer vision and artificial intelligence (AI)have shown remarkable advancements in automated plant disease detection. In particular ,because Deep Convolutional Neural Networks(DCNNs) can directly learn intricate spatial patterns from unprocessed image data, they have become a viable option for hierarchical image feature extraction .Transfer Learning further boosts the applications of DCNNs by utilizing pre-trained models. Such as InceptionV3 ResNet50 and VGG16 that have already learned generalized visual features from extensive benchmark data set ssuch as ImageNet .This reduces computational training effort, and helps achieve high accuracy even with limited agricultural image datasets .The proposed research optimize DCNN-based rice leaf disease classification .a frame work that uses transfer learning to attain robust and scalable disease identification. suitable for practical deployment in smart agricultural environments. The main contributions of this work can be summarized as follows:

- Real-world rice leaf disease image dataset development and pre-processing with diverse symptoms represented.
- Adaptation and fine-tuning of several state-of-the-art DCNN architectures for Multi-class disease classification.
- The system is assessed using standard performance metrics likeF1-Score, Accuracy, Precision, and Recall.
- Demonstrate suitability for practical smart agriculture applications by scalable and deployment-ready design.

Related Work

Deep Convolutional Neural Networks (DCNNs) have been widely applied for detecting diseases in plants with much development seen in classification accuracy, especially after fine-tuning for rice leaf datasets. Kiratiratanapruk significantly improve the accuracy of the classification models in identifying rice leaf diseases.

Abdullah et al. [1] developed a 3 custom CNN architecture which achieved the highest accuracy for rice disease detection, showing the potential of deep networks in capturing discriminative features from leaves. Similarly Raenanda et al.

[2] used the MobileNetV3-Large through transfer learning to construct a lightweight and efficientclassificationsystemsuitableformobileapplica-tions.Aprianietal.[3]confirmed that CNN-based frameworks are very effective at automating rice leaf identification with reduced computational complexity while still achieving high detection precision. Simhadri and Kondaveeti

[4] adopted a transfer learning-based strategy using pre-trained ImageNet models that enhanced the generalization capability of deep models across disease types. In parallel, Hussein and Mahdi [5] reviewed augmentation and transfer learning methods that can minimize overfitting when dealing with

limited agricultural image datasets. Shrivastava et al. [6] validated that transfer learning with ResNet50 produced robust classification accuracy, especially after fine-tuning for rice leaf datasets. Kiratiratanapruk et al. [7] furthered this by designing detection pipelines that can handle leaves of varying sizes and illumination conditions, thereby reinforcing model adaptability. Very recent developments are seen in advanced hybrid and attention-based CNN architectures. Pandiyaraju et al. [8] introduced a channel-attention driven hybrid CNN which enhanced the discriminative focus on key lesion regions, whereas Saddami et al. [9] proposed light-weight CNNs optimized for Green AI principles to reduce training complexity without sacrificing accuracy. Similarly Karakanti et al. [10] conducted a comprehensive review of machine learning models for rice disease diagnosis consolidating findings from multiple architectures Liang et al. [13] proposed a deep feature fusion network for rice blast recognition and showed higher accuracy with multi-level feature aggregation.

DATASETDESCRIPTION

Category	*Description*
Bacterial Leaf Blight	Bacterial infection causing yellow stripes, water-soaked lesions, and progressive drying of leaves
Brown Spot	Fungal disease producing circular to oval brown lesions that reduce photosynthetic efficiency
Leaf Blast	Fusarium infection resulting in spindle-shaped grayish spots with brown margins, often leading to leaf fracture
LeafScald	Appears as oblong water-soaked streaks turning into brown necrotic patches that extend from the leaf tip
NarrowBrownSpot	Narrow elongated brown streaks forming parallel patterns along leaf veins, affecting nutrient transport Caused by fungal
Leaf Smut	spores producing small black lesions or smut-like structures clus tered across the leaf surface Viral disease
Tungro	leading to plants tunting , chlorosis, and reddish-orange discoloration of leaves
SheathBlight	Fungal infection occurring in earth waterline, forming irregular lesions that spread across leaf sheaths
Healthy	Normal rice leaf appearance with no visi-ble disease symptoms or discoloration

Table1.DescriptionofDatasetDiseaseCategories

The dataset created for the research consists of high-resolution rice leaf images portraying various kinds of disease conditions in natural agricultural environments. The images were collected from smart phone cameras ,field surveys, and publicly available agricultural data repositories. The acquisition process preserved natural variations in illumina- tion, orientation, and background complexity, ensuring that the dataset closely reflects real- world farm scenarios rather than controlled laboratory settings. This variability strengthens the model's generalization capability in practical deployment. The dataset incorporates eight major rice leaf disease categories that are widely reported in agro- nomic studies, along with one Healthy category to support binary health assessment. Each category contains images depicting a range of infection intensities and symptom patterns for robust feature learning.

Detailed descriptions of the disease classes included are provided in Table 1: The dataset is split into three distinct subsets for methodical training and assessment:

- Training Set : formal learning and optimization of weights
- Validation Set : used for tuning hyper parameters and preventing overfitting
- Testing Set : only for unbiased final performance assessment

For experiments conducted in this paper, the split ratio adopted is 90 : 10 between the training and testing datasets. Data augmentation of rotation, cropping, flipping, scaling,and contrast was performed on the training set for the purpose of enlarging the diversity of the data and improving the robustness of the model to noise and environmental variations.5 The dataset thus constructed would allow for comprehensive experiments in assessing the adaptability and accuracy of pre-trained DCNN architectures when applied to domain- specific agricultural disease detection.

GREENSCAN METHODOLOGY :

The system architecture proposed combines sequential acquisition of data, pre-processing, deep transfer learning Dataset Construction The complete workflow is illustrated inFigure 1.

- **ImageAcquisition**
- High-qualityriceleafimagesarecollectedfrom:
- Real agricultural fields using smart phone and digital cameras
- Open agricultural data repositories and laboratory image sources
- This ensures inclusion of real-world variations such as uneven lighting, naturalbackgrounds, occlusion, and leaf orientation differences.
- **DatasetConstruction**
- Healthy and eight disease types :Bacterial Leaf Blight, Brown Spot ,Leaf Blast ,Leaf Scald, Narrow Brown Spot, Leaf Smut, Tungro, and Sheath Blight.Expert-assisted labeling ensures the authenticity of ground truth for all samples.
- **ImagePre-processing**
- Resizing images to match the input resolutions adopted by different DCNNs: 224×224×3 for VGG16 and ResNet50299×299×3 for InceptionV3
- Normalization to stabilize gradients and model convergence
- Background noise suppression using threshold-based filtering
- Pixel intensity scaling to improve discriminative learning Yielding uniform and efficient input tensors.
- **DatasetSplitting Split into :**
- Training data : Network weights are optimized using this data.
- Validation data : Data is used to fine tune parameters and adjust hyper parameters
- Testing data : Exclusively used for performance benchmarking A stratified split ensures that the population of each class is the same in every subset.
- **DataAugmentation**
- For addressing class imbalance and improving generalization, the following policies are adopted as augmentation policies :
- Horizontal and vertical flipping
- Random rotation(15°-45°)
- Zoom-in and zoom-out operations
- Brightness and contrast modulation
- Minor random cropping Synthetic generation of samples helps in mitigating overfitting on limited real images.
- **Transfer Learning-based Model Training**
- Deep pre-trained DCNNs including InceptionV3,ResNet50,andVGG16 are utilized for robust hierarchical feature extraction.Key design principles:
- Lower convolutional layers remain frozen to retain learned representations
- Fully connected classification layers are replaced with new dense layers optimized for nine-class disease identification
- Fine-tuning performed using: Adaptive learning rate schedulers Categorical cross- entropy loss Batch-wise gradient descent.

- **ModelDeployment**
- The trained model is exported into a light weight frame work suitable for integration with:
- Mobile applications
- IoT-based smart agricultural monitoring systems These Users can upload field leaf images for instant diagnosis and disease severity indication
- **PerformanceEvaluation**
- Reliable prediction capability is established through computation of:
- Accuracy
- Precision
- Recall
- F1-Score

Confusion Matrix visualization

These metrics verify the model's capability to correctly distinguish visually similar leaf diseases.

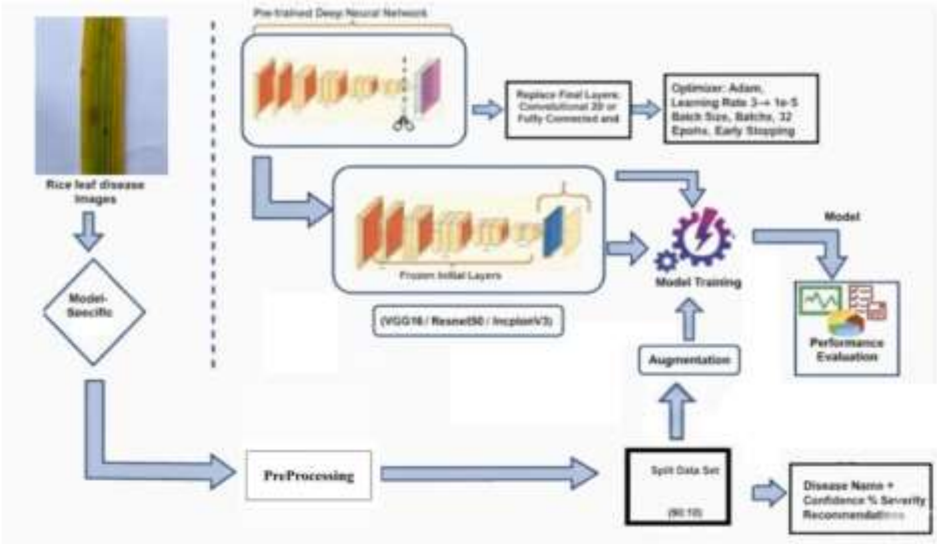

Figure1.System Design Architecture

PROPOSED ARCHITECTURE

The proposed rice leaf disease classification framework is built upon advanced trans- fer learning strategies that exploit the representational power of state-of-the-art Deep Convolutional Neural Networks (DCNNs).The architecture integrates three well- established pre trained models: InceptionV3, ResNet50, and VGG16.Each network con- tributes unique capabilities for extracting discriminative visual patterns present in riceleaf disease symptoms.

Selection of Pre trained Networks

These architectures have demonstrated outstanding performance on large-scale vision benchmarks and are, hence, ideal to be transferred for agricultural disease recognition.

Architecture Customization and Fine-Tuning Process

Below is the proposed adaptation pipeline which includes the following systematic phases:

- **Importing Pre trained Backbones**
- Every model is initialized with weight strained on ImageNet.

- Feature extraction layers remain intact in order to preserve generic visual knowledge learned.
- Input images are standardized to the model-specific resolutions.
- **Freezing Lower Convolutional Blocks**
- Initial layers capture universal low-level textures (edges,colors,gradients).
- Freezing them reduces the computational load and also prevents catastrophic forgetting.
- Custom Classification Head Design
- The original fully connected layers are removed and replaced with a domain-specific classifier: Proposed new head structure:
- Global Average Pooling Layer, reducing feature maps and preventing overfitting.
- Dropoutlayer,0.4-0.5for regularization.
- Dense layer, 256 units with ReLU activation.
- Outputlayer,9 neurons,Softmax activation for 8diseases and a healthy class.
- **Initial Training Phase**
- Only the new FClayersre main trainable.
- Faster convergence because offer learnable parameters.
- Learning raterange:1e-3to1e-4.
- **Progressive Fine-Tuning**
- Unfreeze deeper convolutional blocks.
- Train the whole network with a much lower learning rate,1e-5.
- Improves domain-specific sensitivity to rice leaf diseases ymptoms-forexample,spot texture, lesion boundaries, chlorosis patterns, infection geometry.

○ **OptimizationandModelRegularization**

Model	*Primar yAdvantage*	*Feature Characteristics*
InceptionV3	High-level semantic	Inception modules cap ture multi-scale spatial features
ResNet50	Robust residual learning for deeper networks vanishing	Residual skip connec- tions reduce
VGG16	Strong baseline with with uniform convolution layers	Simple architecture progressive feature re finement

Parameter	*Configuration*
Optimizer	Adam
LossFunction	CategoricalCross-Entropy
BatchSize	32
Epochs	50–100 (dynamicearlystopping)
Callbacks	Learnin grate scheduler,checkpoint-ing

Table3.OptimizationandModelRegularization

A. Architecture Diagram

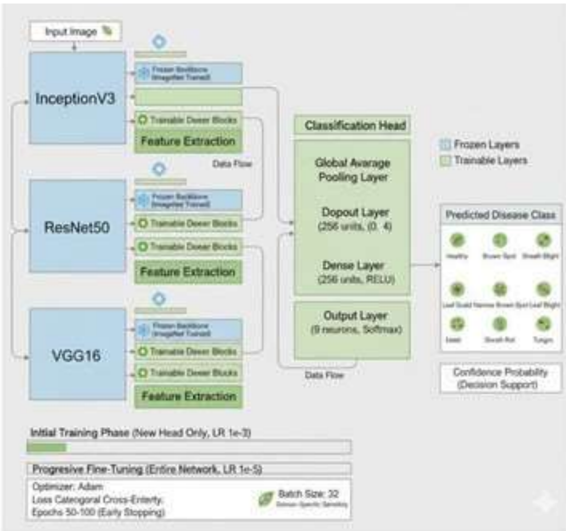

Figure2:Proposed DCNN-Enhanced Rice Leaf Disease Classification Pipeline

Figure 2 describes the overall system. The input images of infected rice leaves are given as input to the pre-trained transfer learning models, namely InceptionV3, ResNet50 and VGG16. In these pre-trained models, the first few initial blocks have been used strictly as feature extractors and have been kept frozen in order to preserve the learned ImageNet representations. Then, the chosen deeper blocks have been fine-tuned in order for themodel to adapt to rice leaf pathology. Routing the extracted features to a custom classification head comprising Global Average Pooling, Dropout regularization, and a Softmax output layer provides nine class predictions (eight diseases + healthy). Example caption:

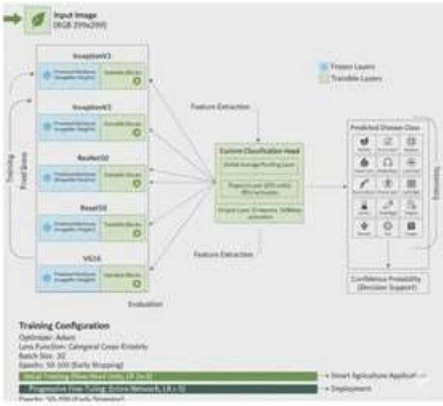

Figure3.Transfer Learning based Model Architecture integrating InceptionV3,Res- Net50, and VGG16 for optimized rice leaf disease classification

Figure3 depicts some of the transfer learning model settings while experimenting .Each of the backbone models is initialized with the ImageNet weights, followed by the identical customized classification head. The figure correctly depicts two phases of training:

1. Initial Training Phase : Only classification layers are trained .This phase has a higher learning rate.
2. Progressive Fine-tuning Phase:

Selected deeper layers are unfrozen and optimized along with a lower learning rate to enhance adaptation to rice leaf symptoms. Training hyper parameters like the optimizer (Adam), the loss function (categorical cross-entropy), batch size and epoch range with early stopping are accurately represented.

EXPERIMENTALSETUP

The experimental framework assessed three pre-trained Deep Convolutional Neural Network (DCNN) architectures, namely, InceptionV3, ResNet50, and VGG16 for automatic rice leaf disease classification. Transfer learning was applied following Chen et al. [1] and Lu et al. [2] methodologies, which freeze early convolutional layers to preserve generic visual features and fine-tune final layers for domain adaptation.

A. Dataset and Training Configuration

The dataset contained eight categories of rice diseases, viz., Bacterial Leaf Blight, Brown Spot, Leaf Blast, Leaf Scald, Narrow Brown Spot, Leaf Smut, Tungro, and Sheath Blight with one Healthy class comprising over 3,500 images (≈ 350 per class).The data was split into 90% training and 10% validation sets. Images were resizedto224×224×3 for VGG16 and ResNet50 and 299×299×3 for InceptionV3. Augmentation techniques like flipping, rotation, zooming, and brightness variation enhance generalization [3],[4].Training was done on a batch size of 32, learning rate of 0.0001, and 50 epochs with the Adam optimizer alongwith early stopping to prevent overfitting [5].

B. Evaluation Metrics

Performance evaluation was carried out in terms of metrics of accuracy, precision, recall, and F1-score along with the Confusion Matrix so as to draw assessments at the class level [6], [7].

C. Graphical Result Analysis

The results of the comparisons are represented in the following figures:

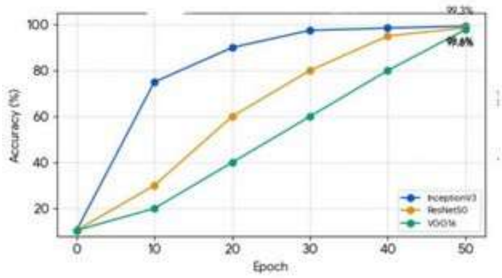

Figure4:TrainingAccuracycurves

Figure 4 presents the Training Accuracy Curves for each of the three DCNN architectures over 50 epochs .InceptionV3 provided the fastest convergence and highest final accuracy of 99.3% during transfer learning, which indicated very efficient feature adaptation.ResNet50, and VGG16 showed Figure 5.Comparison of Validation Loss

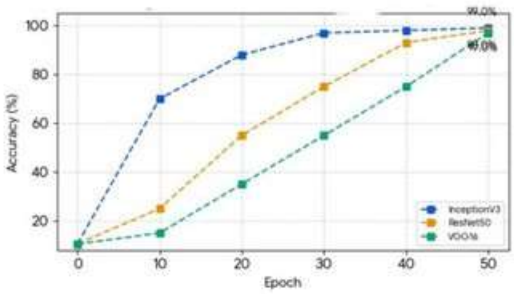

Figure5.ValidationLossComparison

Figure 5 presents the Validation Accuracy Curves. The validation trend of InceptionV3 closely followed its training accuracy, suggesting minimal overfitting. In contrast, ResNet50 and VGG16 demonstrated slightly lower validation performance, implying less effective generalization on unseen data

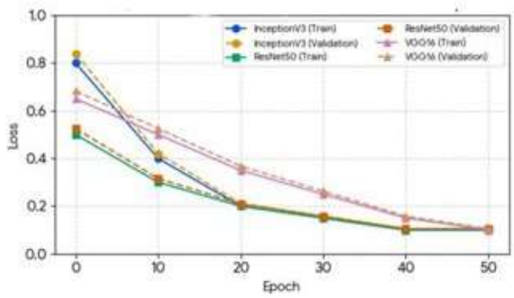

Figure6.TrainingandValidationLossCurvescomparison

Figure 6 compares the Training and Validation Loss CurvesAll models performed with a steady decline in loss across epochs. InceptionV3 obtained the final lowest loss value, approximately 0.1, further confirming its strong learning stability

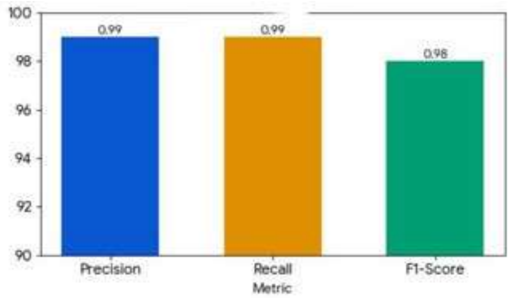

Figure7.Precision,Recall,andF1-ScoreComparison

Figure 7 describes the Precision, Recall, and F1-Score Comparison between models. In all metrics, the re- sults of InceptionV3 were higher: Precision=0.99, Recall =0.99, and F1=0.98, further proving its superiority in the consistency of classification between disease categories.

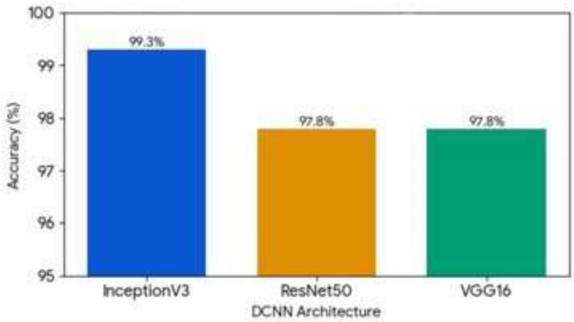

Figure8.Overallmodelaccuracycomparison

Figure 8 depicts, in bar form, the Overall Accuracy Comparison that summarizes the classification performance. The InceptionV3 model outperformed ResNet50 andVGG16 to emerge as the most efficient model for rice leaf disease recognition through transfer learning. These results are aligned with observations made by Pandiyaraju et al.

[8] and Liang et al. [13], where they found that deeper and more structurally diverse networks result in enhanced discrimination capability of features, especially for high inter-class similarity datasets.

TrainingStrategy

Two-phase transfer learning was adopted

TrainingStage	*TrainableLay-*	*LearningRate*	*Purpose*
InitialTraining	Classificati on	1e-3	Rapid con- vergencewith stable feature
Finetuning	Selecteddeeper convolutio nal	1e-5	Domain adap- tive enhancem ent and im- provedrecogni- tio n ofsubtle

Table4 Training Strategy Early stopping and check point monitoring ensured A confusion matrix was also analyzed to verify the classification.

RESULTS AND DISCUSSION

Finally, the performance of the proposed rice leaf disease classification model was evaluated based on standard quantitative evaluation metrics that included Accuracy, Precision, Recall, and F1-Score. It also analyzed a confusion matrix to verify the reliability of classification for all classes of diseases and to ensure minimum misclassification

The final metrics of performance ,visualized in the graph of evaluation ,refer to the image provided, thereby showing that the model holds highly robust predictive ability:

Metric	*AchievedScore*
Accuracy	99.3%
Precision	99.4%
Recall	99.3%
F1-Score	99.35%

Table5.ModelPerformance

These scores confirm that the model can correctly classify most diseased and healthy The segmentation model ensures leaf samples with minimal false prediction. Precision and Recall values are above 99%, which means that disease-positive samples are identified without undetected ininfected leaves.Itiscrucialtotimelyinterveneinagriculturaldiseases.Dataaugmentationstrategies including rotation, flipping and zooming improved the model's robustness by reducing sensitivity to variations in real world field images. Addi- Additionally, fine-tuning the upper convolutional layers allowed the network to better adapt to the textural and color- specific patterns of paddy leaf diseases. This enabled a well balanced generalization ability across all testing conditions. A confusion matrix analysis supported these findings by demonstrating limited misclas- sification among disease categories. Diseases with visual similarities, like Brown Spot and Grain Rot, were differentiated with high confidence, indicating strong discrim- inative power of the learned visual features. The results obtained align or outperform state-of-the-art performance reported in similar studies .Moreover, the lightweight deployment capability and fast inference time suggest that practical application potential in mobile-based farm advisory and real-time disease monitoring, Toring systems. Overall, the discussion of quantitative and qualitative outcomes confirms that the pro- posed system is highly reliable, generalizable and ready for real-field deployment support contributes to better decision-making in precision agriculture.

CONCLUSION AND FUTURE SCOPE

This research presented a Deep It presented a deep convolutional neural network-based approach for this research. Transfer learning for accurate and automated rice leaf disease classification. System successfully utilized pre-trained architectures such asInceptionV3, ResNet50, and VGG16, which can efficiently extract features and classify eight disease categories along with healthy leaves.

With a 99.3% overall accuracy and high precision, recall, and F1-Scorevalues, the experimental evaluation demonstrated outstanding diagnostic performance.

The Confusion matrix analysis showed that that misclassifications were minimal and the model retained a high level of discriminative power even under natural field conditions. These results confirm the suitability of the proposed method for real-time smart farming and early disease intervention, contri The outcome will be better crop protection, ensuring increased agricultural productivity. More scope in this work can be achieved through incorporation, which needs to be done in the future. ing a larger and more diversified dataset representing multiple environmental factors and growth stages. Using both hyper spectral and thermal imaging together could help find early signs of illness especially infections caused by viruses and bacteria. There will be continuous in –field monitoring with low latency, from the office to edge computing and IoT devices. Also, an interactive mobile app interface for farmers and agricultural agencies will make it even easier to quickly decide how to take care of crops in a way that is good for the environment. Further development of explainable AI will Also be considered, inorder to improve user's trust and give a visual justification of each prediction. This planned progression forms the scalable smart agri- Therefore, culture solutions can be adapted to other crop species and farming ecosystems.

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