Paddy Leaf Disease Detection Using Ensemble Stacking

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***Abstract*—Paddy leaves, fundamental components of rice plants (Oryza sativa), play a critical role in global food production, particularly in countries like India, where paddy production is notably high. Beyond their role as photosynthetic powerhouses, these leaves serve as crucial indicators of plant health. Detecting diseases affecting paddy leaves is imperative for sustaining crop yields and global food security, especially in regions where rice cultivation is a cornerstone of agricultural practices. In our paper, ensemble technique utilizes pre-trained models which are ResNet50, InceptionV3, and MobileNetV2, to address disease detection on our dataset, which encompasses four distinct classes. Trained on a real-world dataset capturing diverse disease features, the models leverage deep training proficiency, multi-scale feature extraction, and efficiency. Experimental results, exhibit reduced false positives and negatives, emphasizing the methodology's accessibility and effectiveness in early disease detection. The InceptionV3 model attains a precision of 82.79%, the ResNet model achieves 91.89%, and the MobileNetV2 model reaches 73.02%. The Stacking Classifier attains the highest accuracy of 96.09%.**

***Index Terms*—ResNet50,InceptionV3,MobileNetV2,Ensemble technique,Stacking .**

I. INTRODUCTION

Paddy cultivation plays a pivotal role in global agriculture, serving as a staple food source for millions of people. However, the thriving paddy fields are susceptible to various diseases that can adversely impact crop yield and quality. Diseases such as tungro, bacterial blight, blast, and brown spot are common threats to paddy leaves, requiring prompt identification and intervention for effective crop management.

Traditional methods [1] of manually identifying diseases in paddy leaves, pose significant challenges for farmers. The labor-intensive nature of these approaches, coupled with the potential for errors, necessitates a more efficient solution. This research addresses the need for automated disease detection in paddy fields by leveraging advanced machine learning models [8]. Our approach focuses on enhancing the accuracy and early detection of diseases, providing farmers with a reliable tool to safeguard their crops and improve overall agricultural productivity.

Our approach underscores the critical role that early disease detection plays in sustaining global food security. Paddy crops, being a staple food source, are susceptible to various diseases that can lead to significant yield losses if not promptly addressed. By automating the early detection process using pretrained models [4] like ResNet50, InceptionV3 [3], and MobileNetV2, we aim to empower farmers with a proactive means of managing and mitigating disease outbreaks. This not only preserves crop health but also contributes to the broader goal of ensuring a stable and sufficient food supply for the growing global population.

The primary goal is to push the boundaries of automated paddy leaf disease detection. We plan to assess how well three powerful pretrained models—ResNet50, InceptionV3, and MobileNetV2—perform individually. Taking it a step further, we aim to blend their strengths using a stacking ensemble technique [23]. This approach should amplify our overall disease detection capabilities. The ultimate objective involves training and validating our ensemble model with a diverse dataset featuring four distinct disease classes: tungro, bacterial blight, blast, and brown spot. Through these steps, our aim is to provide practical insights and solutions that directly address the challenges faced by farmers in managing and securing their paddy crops. We particularly emphasize the importance of early disease detection as a key focus of our efforts.

In our paper, we employed state-of-the-art deep learning models to tackle the classification task. Notably, the InceptionV3 model demonstrated a precision of 82.79%, showcasing its effectiveness in the given context, the ResNet model gave the accuracy of 91.89%, while the MobileNetV2 model achieved 73.02% precision. Remarkably, our Stacking Classifier emerged as the top performer, achieving the highest accuracy among all models at 96.09%.

The following sections are organized as: Section II details traditional challenges and reviews to related work. Section III outlines our methodology, covering dataset organization, preprocessing, and training of base models (ResNet50, InceptionV3, and MobileNetV2). Section IV presents results, demonstrating the efficacy of stacking ensembles.The conclusion in Section V emphasizes insights gained, including the impact of class imbalance, the role of supplementary dense layers, and the overall contribution to accurate deep learning models for paddy leaf disease detection.

II. Background Study

Deep Neural Networks (DNNs) are complex models adept at hierarchical learning. Transitioning to Convolutional Neural Networks (CNNs), these models enhance spatial pattern capture. In CNNs, Global Average Pooling compresses features, and padding preserves spatial information during convolutions.

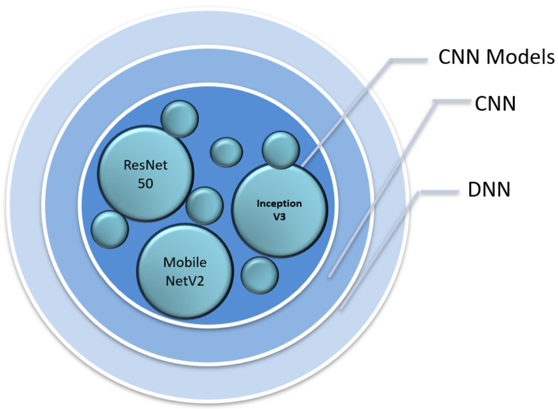

Fig. 1. Visualizing the diversity of CNN models under DNN.

The crucial need for early detection of paddy leaf diseases to mitigate crop yield losses is emphasized by the authors [5]. They employ various CNN architectures, including GoogLeNet, ResNet, ShuffleNet, ResNext, and wide ResNet, forming an ensemble model with distinct weightings. Through comprehensive training and testing, the ensemble model achieves an impressive accuracy score of 0.9554, specifically targeting the detection of blast, bacterial leaf blight, and brown spot diseases.

Focusing on effective disease detection, [7] employs Convolutional Neural Networks (CNN) and Thermal Imaging techniques. The study evaluates various algorithms, such as SVM, VGG19, ResNet152V2, InceptionV3, and MobileNetV2. Notably, the InceptionV3 model stands out with an impressive accuracy of 0.9234, showcasing its efficacy in real-time disease identification from pictures.

Centered on enhancing disease detection accuracy in paddy crops through thermal images, the study in [8] introduces an adapted lemurs optimization algorithm for filter-based feature transformation. The authors leverage this method in conjunction with machine learning techniques, resulting in a significant improvement. Notably, the k-nearest neighbor classifier attains a balanced accuracy of 90%, showcasing the effectiveness of the proposed approach in identifying specific paddy diseases.

Considering the above works, we leverage the capabilities of three pretrained models—ResNet50, InceptionV3, and MobileNetV2. Additionally, we employ a stacking ensemble approach, combining the strengths of three models for improved Paddy leaf disease detection accuracy.

A. *ResNet50*

ResNet50 [3] stands out for its innovative approach to deep learning with the introduction of residual blocks. With 48 layers, ResNet50 utilizes skip connections to address the vanishing gradient problem, allowing for effective training of extremely deep neural networks. The concept of identity mapping ensures a smooth flow of information through the network, and the parameter efficiency of the model is enhanced by reusing learned features through these skip connections. Pre-trained on datasets like ImageNet, ResNet50 brings the advantages of transfer learning to tasks such as paddy leaf disease detection, making it proficient in capturing intricate patterns and features.The architecture is shown in (Fig. 2).

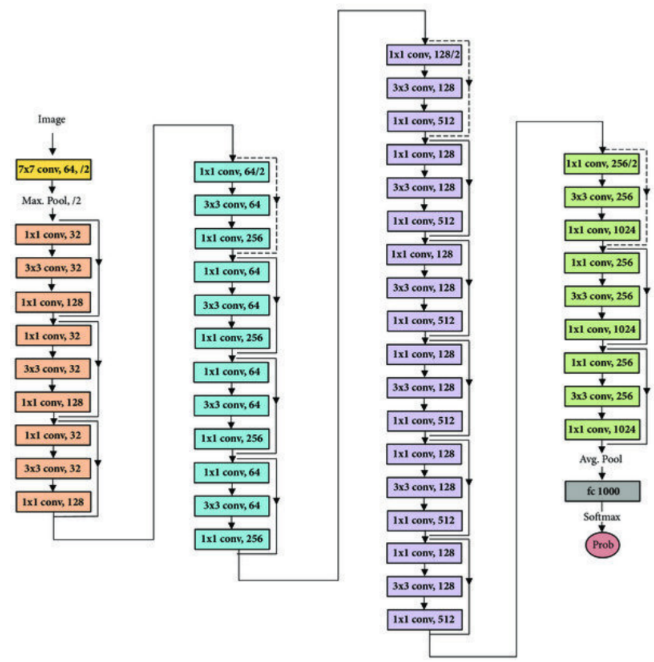

Fig. 2. Architecture of ResNet50.

B. *Inceptionv3*

InceptionV3 [3], known for its intricate design, focuses on multi-scale feature extraction through its Inception modules. These modules employ filters of varying sizes simultaneously, enabling the network to capture both fine and coarse-grained features. Efficiency is a key aspect of InceptionV3, achieved by using 1x1 convolutions to reduce dimensionality before larger convolutions. The model strikes a balance between depth and width, avoiding the need for excessively deep networks while still capturing complex hierarchical features. The introduction of auxiliary classifiers during training enhances the learning process, providing additional supervision for better convergence.The architecture is shown in (Fig. 3).

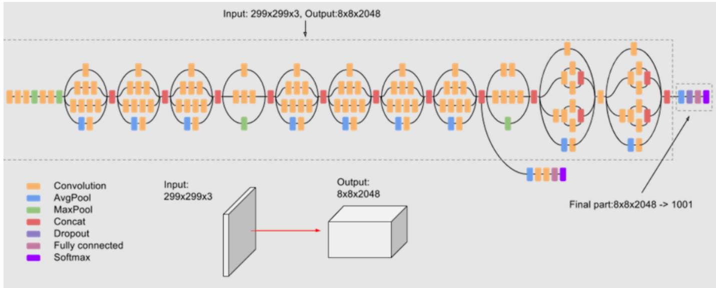

Fig. 3. Architecture of InceptionV3.

C. MobileNetV2

MobileNetV2 [18], [19], designed for resource-constrained environments, adopts depthwise separable convolutions to achieve efficiency. This approach factorizes standard convolutions into depthwise and pointwise convolutions, significantly reducing computation and parameter count. The linear bottleneck design of inverted residual blocks facilitates a linear path through the network, promoting better information flow. MobileNetV2's adaptability to limited computational resources makes it suitable for real-time applications on mobile and edge devices, contributing to its effectiveness in paddy leaf disease detection.The architecture is shown in (Fig. 4).

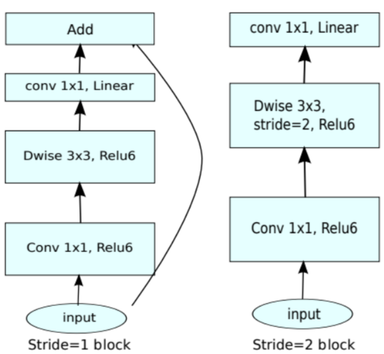

Fig. 4. Architecture of MobileNetV2.

D. Stacking ensemble

In the realm of ensemble learning, the stacking ensemble [23] technique is a powerful strategy for combining predictions from diverse base models. The ensemble benefits from the diversity of these models, each contributing unique perspectives to the task at hand. The meta-model within the stacking ensemble is trained to generalize well to different types of predictions, ensuring adaptability to various model architectures. This diversity not only enhances the robustness of the ensemble by mitigating individual model weaknesses but also leads to improved accuracy and generalization performance, making it a compelling approach for precise and reliable paddy leaf disease detection.The architecture is shown in (Fig. 5).

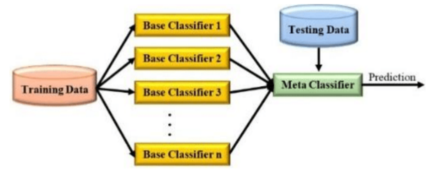

Fig. 5. Architecture of Stacking Ensemble Model.

III. Methodology

The initial step involves selecting Keras, TensorFlow implementations of ResNet50, MobileNetV3, and InceptionV2 as baseline models. We present our stacked ensemble model Fig. 5.

Section-A covers the dataset, Section-B discusses preprocessing and augmentation, Section-C details the train-test-validation set split, Section-D delves into baseline model training, and Section-E outlines our stacking ensemble model. In this section, we introduce our proposed methodology shown in Fig. 6.

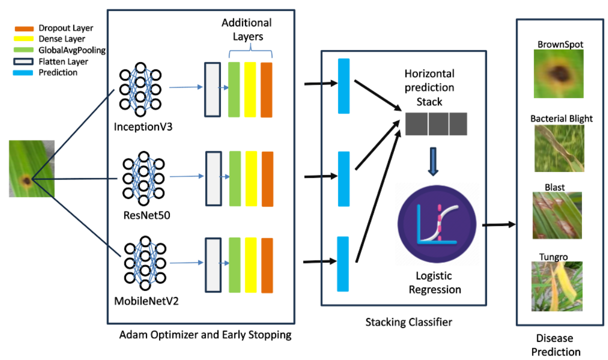

Fig. 6. Proposed Methodology for Paddy Leaf Disease Detection.

A. Data set

The dataset [24] employed in this study is meticulously organized into four distinct subfolders, each representing a distinct group of illnesses that impact paddy leaves. The "Tungro" subfolder encompasses 1308 pictures pertaining to the Tungro disease, while the "BacterialBlight" disease subfolder comprises 1584 images associated with bacterial blight. The "Blast" class is represented by 1440 images stored in its designated subfolder, and the "Brown Spot" subfolder contains 1600 images pertaining to brown spot disease. This structured arrangement facilitates a methodical investigation of various illness categories, making it possible to train and assess models for machine learning on a sizable and representative dataset. The careful categorization and abundance of photos in each class contribute to the dataset's richness, providing a robust foundation for the investigation into the paddy leaf disease detection method based on ensembles that is presented in this paper.A sample images from each class are shown in (Fig. 7).

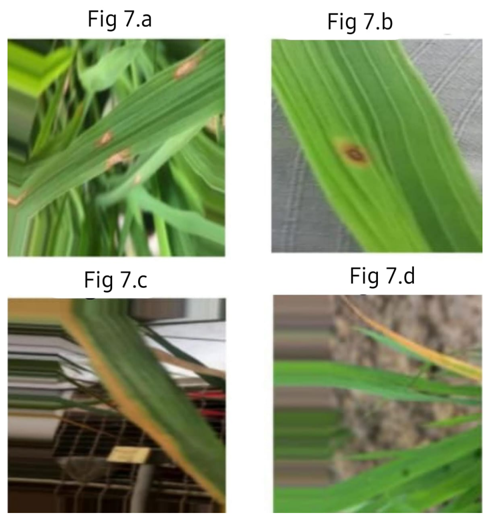

Fig. 7.

Fig. 7(a): Image of Blast disease, (b): Brown Spot, (c): Bacterial Blight, (d): Tungro.

B. Preprocessing and Augmentation

After collecting data, our focus shifts to preprocessing and augmenting [20] images using Keras' ImageDataGenerator. We aim for class balance [20], setting a threshold of 1600 images per class for categories like tungro, brownspot, blast, and bacterial blight. Excess images are removed, and augmentation techniques such as rotation and flips are applied iteratively until each class reaches the specified threshold. Transparency issues are addressed by converting rgba to rgb [6] format, and potentially corrupted images are identified and removed to ensure dataset integrity. Additionally, image rescaling is performed to normalize pixel values. The final dataset, with balanced classes and enhanced diversity, along with normalized pixel values, forms the basis for optimal model training. This meticulous preparation ensures that subsequent training occurs on a robust and representative dataset, contributing to improved classification performance.

C. Train-Test Split

Upon resolving the issue of class imbalance, the next step is to divide the augmented dataset into train test and valid sets as shown in TABLE III-C. To accomplish this a custom function called move or copyimage is used which copies or moves images to the appropriate subfolders while providing error-handling capabilities. 10% are set aside for validation, 10% are for testing and 80% of the images are carefully distributed for training. Furthermore copying too many images is inhibited by a max-images parameter that sets a limit on the number of images per set. This meticulous procedure not only guarantees a structured dataset but also establishes the foundation for the later stages of training and assessing the models.

TABLE I
IMAGES IN EACH SET

Classes	Train	Test	Validation
Tungro	1279	160	160
BacterialBlight	1280	160	160
Brownspot	1280	160	160
Blast	1280	160	160

D. Training of Base Models

Three well-established architectures—InceptionV3, ResNet50, and MobileNetV2—are systematically employed in an intricately designed training regimen to cultivate more proficient image classification models. Each model undergoes meticulous construction, incorporating distinctive layers such as dropout (1) which is used for regularization.

$$Dropout(X,p) = \frac{1}{1-p}.Bernoulli(1-p).X \tag{1}$$

p is the droupout rate

Dense layers(2) for feature extraction.

$$Dense(X,W) = ReLU(X.W + b) \tag{2}$$

The global average pooling(3) for dimension reduction. The dimensions have been reduced from the original image size of (224, 224, 3) to a one-dimensional vector.

$$GAP(X) = \frac{1}{HxW}\sum_{i=1}^{H}\sum_{j=1}^{W} X_{i,j} Dense(X,W) = ReLU(X.W{+}b) \tag{3}$$

Our guiding benchmarks encompass accuracy, categorical crossentropy loss (4) which was used because the task involved multi-class classification, where each input belongs to one of multiple exclusive classes.

$$L(\hat{y}, y) = -\sum_i y_i \log(\hat{y}_i) \tag{4}$$

The Adam optimizer(9) during the compilation of these models because of its adaptive learning rate and momentum properties, providing effective and efficient optimization for training deep neural networks. Throughout the training process, pixel values are dynamically scaled to optimize model convergence.

$$m \leftarrow \beta_1.m + (1-\beta_1).g \tag{5}$$

$$v \leftarrow \beta_2.v + (1-\beta_2).g^2 \tag{6}$$

$$\hat{m} = \frac{m}{1-\beta_1^t} \tag{7}$$

$$\hat{v} = \frac{v}{1-\beta_2^t} \tag{8}$$

$$W \leftarrow W - \alpha\frac{\hat{m}}{\sqrt{\hat{v}}+\epsilon} \tag{9}$$

To ensure judicious training, we introduce the strategic implementation of early stopping and model checkpoint callbacks, enhancing training efficiency and preventing potential overfitting. The models are rigorously monitored through accuracy and loss graphs, serving as insightful guides to visualize their performance in real-time. These visualizations (Fig. 8,Fig. 9) offer apt snapshot of the models learning trajectory and convergence during the training phase, encapsulating a comprehensive understanding of their training dynamics. In essence, the utilization of these well-established architectures, combined with meticulous construction and strategic training methodologies, underscores our commitment to crafting robust and effective image classification models.

E. Stacking Ensemble

After training each base model, including InceptionV3, ResNet50, and MobileNetV2, on a comprehensive dataset of paddy leaves, we implemented a Stacking Classifier approach to refine the accuracy of disease detection. Predictions from each base model were generated, and these predictions were horizontally stacked to create a feature matrix(10).

$$D_{\text{meta}} = \begin{bmatrix} P_1^{(1)} & P_2^{(1)} & \dots & P_n^{(1)} \\ P_1^{(2)} & P_2^{(2)} & \dots & P_n^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ P_1^{(m)} & P_2^{(m)} & \dots & P_n^{(m)} \end{bmatrix} \tag{10}$$

Following this, the true labels for the validation set were extracted, and the dataset was appropriately split for training the meta-model. Notably, in constructing the Stacking Classifier, logistic regression was chosen as the final estimator, even though the dataset encompassed four classes, showcasing the adaptability of logistic regression in handling multi-class classification tasks. Additionally, it's important to highlight that logistic regression within the Stacking Classifier inherently performs binary classification(11) for each class (one-vs-rest strategy)

$$f(x) = \frac{1}{1+\exp(-x)} \tag{11}$$

Range:(0,1)

while collectively contributing to the multi-class prediction. This binary classification approach within the Stacking Classifier enables it to handle multi-class scenarios seamlessly. The Stacking Classifier was trained on the stacked features of the base models, and subsequent predictions were made on the validation set. The introduction of Rectified Linear Unit (ReLU)(12) activation in the hidden layers of the base models further enhanced the model's ability to capture nonlinear patterns, contributing to improved overall performance.

$$f(x) = \max(0, x) \tag{12}$$

Range:[0,∞)

TABLE II
TRAINING MODEL ACCURACY

Model	Accuracy (in %)	Epochs
ResNet50	91.89	5
InceptionV3	82.79	5
MobileNetV2	73.02	1

IV. RESULTS

The method of stacking ensembles demonstrates an astounding degree of accuracy of 96.09%, showcasing substantial enhancement in comparison to distinct models as shown in TABLE II. After 5 epochs, the InceptionV3 model attains a precision of 82.79%, the ResNet model achieves 91.89%, and the MobileNetV2 model reaches 73.02% after just 1 epoch.

Notably, a shift from 5 to 1 epoch for MobileNetV2 was prompted by its sensitivity to overfitting on the original 5-epoch setting, attributed to its optimal performance on lighter datasets. In contrast, the initial accuracy without class balancing and optimization was 69%, highlighting the significant progress achieved through utilizing an ensemble approach and optimizing the models' parameters as mentioned in TABLE III.

TABLE III
PARAMETERS FOR MODEL TRAINING

Parameter	**Value**
Batch Size	5
Number of Batches	1280
Learning Rate	0.001
Epochs	5
MobileNetV2 Epochs	1
Dropout Ratio	0.5
Patience Parameter	5

The accuracy graphs for ResNet50 (Fig. 8) and InceptionV3 (Fig. 9) demonstrate consistent improvement over epochs, ultimately reaching high values. In contrast, MobileNetV2, trained for fewer epochs, achieves comparatively lower accuracy. The loss graphs for all models exhibit a decreasing trend, indicating effective optimization during training. The implementation of early stopping helps prevent overfitting, while the use of checkpoints ensures that optimal models are saved throughout the training process.

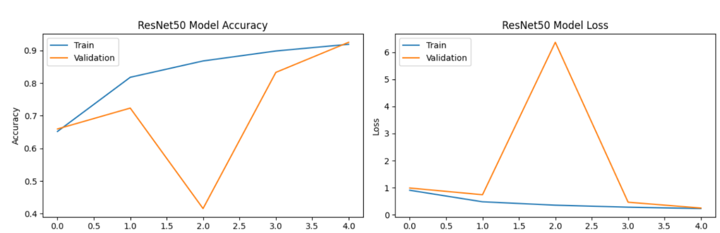

Fig. 8. Training graph for ResNet50.

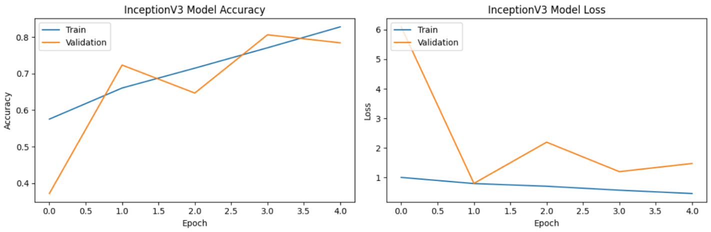

Fig. 9. Training graph for InceptionV3.

V. Conclusion

In this study, we have observed that addressing class imbalance significantly impacts the efficacy of training base models. Enhancing models like ResNet50, InceptionV3, and MobileNetV2 with additional dense layers enhances their capacity to capture intricate patterns. The implementation of early stopping proves crucial in preventing overfitting and promoting model generalization. Furthermore, the utilization of the ADAM optimization technique is essential for ensuring efficient model convergence through adaptive adjustments of learning rates for each parameter. The stacking ensemble technique excels in integrating diverse models, showcasing superior predictive capabilities. By emphasizing class distribution, customizing architectures, and incorporating ensemble strategies, our methodology establishes a comprehensive framework for developing robust and accurate deep learning models. These insights contribute to a holistic understanding of model advancement, presenting practical solutions for overcoming challenges in image classification tasks.

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