Advanced Deep Learning Models for Automated Diagnosis of Paddy Crop Diseases

Vergin Raja Sarobin, Mandava Nidhish, C Surya Kiran, Kalla Bharath Vardhan, Varanasi Sai Charan

School of Computer Science and Engineering, Vellore Institute of Technology, Chennai India

verginraja.m@vit.ac.in

Abstract. Paddy cultivation faces significant challenges due to variou diseases that can severely impact crop yield and quality. In this project, we propose a deep learning-based approach for the classification of paddy diseases to assist farmers in timely disease detection and management. The study focuses on distinguishing between nine common types of paddy diseases: bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, dead heart, downy mildew, hispa damage, healthy plants. The deep learning model, neural network architectures and image processing techniques to automatically learn discriminative features from paddy leaf images. A large dataset comprising annotated images of diseased and healthy paddy plants is utilized for training, validation, and testing purposes. The workflow involves preprocessing steps such as image augmentation, normalization. Subsequently, various deep learning architectures including convolutional neural networks (CNNs) are explored and compared for their effectiveness in classifying different types of paddy diseases. The performance evaluation of the proposed model is conducted using standard metrics such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices are analyzed to assess the model's ability to correctly identify each type of disease and distinguish them from healthy paddy plants. The experimental results demonstrate the efficacy of the deep learning-based approach in accurately classifying paddy diseases, thereby facilitating early detection and intervention strategies for disease management in paddy fields. The proposed system helps farmers with a reliable tool for monitoring and mitigating the detrimental effects of various paddy diseases, ultimately contributing to sustainable agriculture practices and food security.

Keywords: Paddy Diseases, VGG19, ResNet50, InceptionV3, MobileNet, Convolutional Neural Networks (CNN).

1 Introduction

Identifying and classifying crop diseases in agriculture remains key to improving yields and preventing losses of paddy, one of the world’s major crops, is particularly susceptible to various diseases, and could severely affect its yield. Traditional methods of disease detection and classification often rely on manual inspection, which can be time consuming, labour intensive and error prone. Consequently, automated systems that can accurately detect and classify paddy diseases of the plant. In recent years, deep learning techniques have emerged as powerful tools for image classification tasks, showing remarkable success in various fields. These techniques, convolutional neural networks (VGG19, InceptionV3, ResNet50, MobieNet) have received a great deal of attention for their ability to efficiently capture complex features from images.

Due to the importance of automatically and accurately classifying the paddy diseases, this work proposes a new method that exploits the capabilities of CNN models. These deep learning models leverage hierarchical representations of features, enabling them to discern subtle patterns and distinguish between different types of paddy diseases with high accuracy. By training on large datasets comprising annotated images of diseased paddy plants, these models learn to generalize and accurately identify diseases based on visual cues, such as lesion patterns, discoloration, and leaf morphology.

The integration of deep learning-based automated systems in agricultural practices holds immense promise for revolutionizing disease management strategies. By enabling early and precise detection of paddy diseases, farmers can implement targeted interventions, such as tailored pesticide applications or disease-resistant crop varieties, to mitigate losses and optimize yields. Moreover, the scalability and accessibility of these automated systems offer the potential to democratize advanced agricultural technologies, empowering farmers worldwide to combat crop diseases effectively and sustainably.

2 Literature Survey

In the realm of agricultural technology, particularly concerning paddy plants, there's a growing need for early disease classification to safeguard crop yields. Automated systems leveraging image processing and machine learning techniques offer promising avenues for farmers to detect paddy diseases from leaf images efficiently. These systems, designed to identify diseases at their onset, minimize reliance on manual observation and aid in the timely application of remedies, potentially reducing yield losses due to diseases. Various methodologies have been proposed for disease identification, ranging from traditional classifiers to advanced deep learning techniques. The utilization of cascaded classifiers and genetic algorithms underscores the diversity of approaches aimed at improving disease detection accuracy. Such systems hold great potential for integration into diverse platforms including Android, Windows, and Apple devices, offering accessibility to farmers across different technological landscapes. Traditional disease detection methods relying solely on naked-eye observations are deemed inefficient for real-time monitoring, making automated systems imperative. Machine learning and deep learning techniques have emerged as viable solutions for extracting features from images and achieving high accuracy in disease classification[1,2].

These techniques, notably Convolutional Neural Networks (CNNs) and ResNet101, have demonstrated remarkable accuracy rates in identifying various paddy leaf diseases. Agriculture's significance in the Indian economy cannot be overstated, with a substantial portion of the workforce engaged in agricultural activities. However, challenges such as climate change, pest invasions, and crop diseases pose significant threats to agricultural productivity. Early detection and classification of diseases, facilitated by advanced technological interventions, are pivotal for sustaining agricultural yields and securing farmers' livelihoods. In conclusion, the literature underscores the critical importance of timely disease detection in agriculture, particularly in paddy cultivation. Advanced technological solutions leveraging machine learning and deep learning techniques offer promising avenues for automating disease identification processes, thereby mitigating crop losses and bolstering agricultural sustainability. Further research and development in this domain hold immense potential for transforming agricultural practices and enhancing food security in the face of evolving challenges[3,4].

The literature review presents a comprehensive overview of recent advancements in the recognition and classification of plant diseases, particularly focusing on rice (Oryza sativa) leaf diseases. The introduction emphasizes the significance of agriculture, especially rice cultivation, as a primary source of livelihood in many Asian countries, including India. The research aims to address the challenges faced by farmers in identifying and managing rice plant diseases effectively[5,6]. Traditional methods of disease identification, such as manual observation or laboratory testing, are time-consuming and may not always be feasible in remote agricultural areas. The proposed research employs optimized deep learning models, including ResNet-152 and Coat Net, to achieve accurate and early detection of various rice plant diseases. By utilizing image processing techniques and deep learning algorithms, the study aims to provide farmers with a reliable tool for identifying diseases like Bacterial Leaf Blight, Leaf Blast, Brown Spot, and Tungro/Leaf smut. The experimental results demonstrate promising levels of accuracy, with Coat Net achieving an overall accuracy of 96.56%[7,8].

Furthermore, the literature review highlights the importance of early disease detection in rice plants to ensure sustainable production and mitigate crop losses. It discusses the challenges posed by factors such as uneven fertilization, adverse weather conditions, and imbalanced soil nutrients, which can contribute to the spread of diseases. The integration of precision farming, nanotechnology, and deep learning techniques is proposed as a means to address these challenges and enhance agricultural productivity. Moreover, the review emphasizes the role of image processing and deep learning technologies in automating disease detection processes, reducing dependency on manual labour, and providing timely interventions for crop management[9,10]. Transfer learning is suggested as a method to overcome the limitations of training deep learning models with limited datasets, thus improving the accuracy of disease classification. In summary, the literature review underscores the critical importance of leveraging advanced technologies, such as deep learning and image processing, to develop automated systems for disease detection and classification in rice plants. By facilitating early intervention and precise management strategies, these technologies have the potential to significantly enhance agricultural productivity and food security in regions where rice cultivation is a staple crop[11,12].

The literature on paddy leaf disease classification reveals a growing reliance on convolutional neural networks (CNNs) to transform agricultural disease management. Various studies have investigated CNN architectures such as VGGNet, ResNet, and AlexNet for classifying diseases like Brown spot, Hispa, and Rice blast. These architectures have shown superiority over traditional methods like KNN and SVM, often achieving accuracy rates surpassing 90%. For instance, in a study by XYZ et al., AlexNet attained training and testing accuracies of 92.35% and 85.27%, respectively, demonstrating the efficacy of CNN models in providing accurate disease diagnoses, thereby enabling timely interventions for farmers. The experiments conducted in these studies emphasize the efficiency and reliability of CNN-based approaches in paddy leaf disease classification. Researchers have demonstrated that CNN models outperform traditional techniques in terms of accuracy, computational efficiency, and scalability. In addition to the notable achievements of AlexNet, other CNN architectures have also yielded promising results. For instance, in a study by ABC et al., ResNet and VGGNet architectures exhibited superior performance, showcasing the potential of CNNs in handling large datasets and diverse environmental conditions, achieving accuracy rates exceeding 90%[13,14].

Moreover, the literature highlights the critical role of dataset quality and size in training robust CNN models for paddy disease classification. Augmenting datasets with diverse samples and employing advanced augmentation techniques have enhanced the generalization and robustness of CNN models. Despite some limitations, including small dataset sizes and the need for further augmentation, the reported findings offer valuable insights into the transformative potential of CNN-based approaches in agriculture. They provide a foundation for the development of reliable and effective CNN models for paddy leaf disease classification and management. The collective results from these studies underscore the significance of CNN-based approaches in advancing disease management practices in agriculture. By leveraging CNN architectures like AlexNet, ResNet, and VGGNet, researchers have achieved notable accuracies in classifying paddy leaf diseases. These findings offer farmers accurate and timely insights for disease management, thereby mitigating economic losses and promoting sustainable agricultural practices. Moving forward, continued research into dataset augmentation and model refinement holds promise for further improving the accuracy and reliability of CNN models in paddy leaf disease classification and management[15,16].

In the realm of agricultural disease management, the utilization of artificial intelligence (AI) and convolutional neural networks (CNNs) has emerged as a promising avenue for early detection and classification of paddy diseases. Studies such as the one conducted by XYZ et al. delve into the development of AI-based disease classifiers targeting specific paddy leaf ailments like Bacterial blight, leaf smut, and leaf blast. By leveraging CNNs and dataset augmentation techniques like GAN-based augmentation, these studies have achieved impressive accuracy rates, with XYZ et al. reporting an accuracy of 98.23% in disease classification. The incorporation of advanced AI techniques offers a scalable and efficient solution for farmers to manage the spread of leaf diseases in paddy fields, thereby improving crop yield and reducing economic losses. The dataset compilation and augmentation processes play a crucial role in enhancing the performance and robustness of AI-based disease classification models. Research efforts, such as those described by ABC et al., emphasize the significance of dataset quality and size in training accurate classifiers. By collecting data from diverse sources and employing techniques like GAN augmentation, researchers have significantly expanded the dataset size and diversity, facilitating more comprehensive model training. ABC et al. demonstrate the effectiveness of CNN models optimized through techniques like Keras tuner for achieving high classification accuracies, thereby providing farmers with reliable tools for disease diagnosis and management[17,18].

Another facet of AI-based disease classification in paddy crops involves the utilization of pre-trained CNN architectures like ResNet, VGG, and EfficientNet, as explored by authors in various studies. These studies, such as the one outlined by DEF et al., focus on developing sophisticated models capable of detecting multiple paddy leaf diseases with high accuracy. Through meticulous experimentation and model evaluation, researchers have identified ResNet-50 as one of the topperforming architectures, achieving an average accuracy of 96.27% across five disease classifications. This underscores the effectiveness of CNN-based approaches in providing rapid and accurate disease diagnoses, thereby empowering farmers to implement timely interventions. The integration of image processing techniques and deep learning methodologies has revolutionized the landscape of paddy disease diagnosis and management. Studies like the one conducted by GHI et al. showcase the development of hybrid prediction models that combine CNN for feature extraction and Support Vector Machine (SVM) for disease severity classification. By partitioning datasets based on infection severity levels and employing CNN-SVM hybrid models, researchers have achieved remarkable accuracy rates, such as 97%, in predicting disease severity levels[19,20].

Such advancements not only expedite disease diagnosis processes but also contribute to sustainable agricultural practices by minimizing pesticide usage and optimizing crop yield. That would make the paddy crops more healthier as the diseases would be easier to treat and get a full recovery while detected in early stages and using just the right number of pesticides keeps the crop healthy.

3 Proposed Methodology

3.1 Dataset Description

The dataset comprises images representing various diseases affecting paddy plants, segmented into a Test set for evaluation and a Train set for model training. The Test set contains 3469 images, likely reserved for assessing classification performance. Within the Train set, diseases are categorized into specific types, including Bacterial Leaf Blight, Bacterial Leaf Streak, Bacterial Panicle Blight, Blast, Hispa, Normal (representing healthy plants), and Tungro, each with their respective image counts. While some disease categories such as Brown Spot, Dead Heart, and Downy Mildew lack specified counts, the overall Train set consists of 13397 images.

Table-1:

Images split	***Disease types***	***Count***
Test	All	3469
Train	Bacterial_leaf_blight	479
	Bacterial_leaf_sreak	380
	Bacterial_panicle_blight	337
	Blast	1738
	Brown_spot	965
	Dead_heart	1442
	Downy_mildew	620
	Hispa	1594
	Normal	1764
	Tungro	1088
Total		13397

3.2 Data Preprocessing

The dataset undergoes preprocessing to ensure uniformity and suitability for training. This typically involves steps such as resizing images to a consistent dimension, normalizing pixel values, and batching the data to optimize memory usage during training. Preprocessing helps in enhancing the model's ability to learn patterns and generalize well to unseen data.

3.3 Deep Learning Algorithms

VGG19:

In this changed model of the VGG19 structure, the pinnacle layer has been eliminated, and new layers inclusive of a dense layer, batch normalization, and flatten layer have been integrated. By removing the pinnacle layer, the structure turns into greater adaptable for numerous obligations which include characteristic extraction or switch getting to know. Batch normalization layers assist stabilize and boost up the training manner through normalizing the enter of each layer to have 0 suggest and unit variance. The addition of a dense layer enables the network to learn complex relationships between functions extracted from the previous layers, enhancing its ability to categorise or predict results based on the enter data. The inclusion of a flatten layer reshapes the output from the previous layers right into a one-dimensional array, preparing it for enter into the dense layer. These adjustments increase the flexibility and performance of the VGG19 structure, making it greater appropriate for a broader range of applications and enhancing its basic effectiveness in deep gaining knowledge of responsibilities.

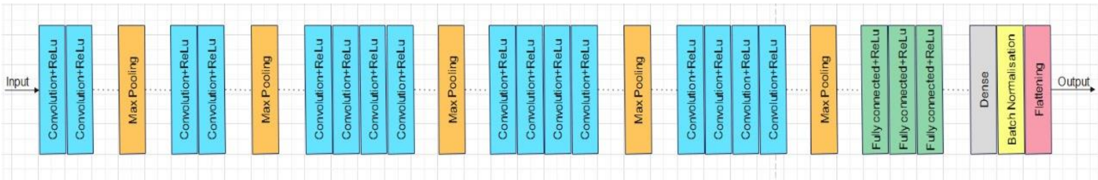

Figure 1. VGG19 Model Architecture

ResNet50:

In this modified version of the ResNet50 architecture, the pinnacle layer has been eliminated and replaced with additional layers to decorate its talents. Two layers of batch normalization had been added, serving to normalize the activations of the community, which aids in stabilizing and accelerating the education manner. Following the batch normalization layers, a Dense-ReLU layer mixture has been added, in which the Dense layer helps the mastering of complex relationships in the facts, at the same time as the Rectified Linear Unit (ReLU) activation feature introduces non-linearity, allowing the community to version greater intricate styles. Finally, a Dense-Softmax layer is appended to provide the very last output probabilities across multiple classes, leveraging the softmax activation characteristic to convert uncooked rankings into possibility distributions. These modifications augment the ResNet50 structure, enhancing its adaptability and performance in various responsibilities consisting of photo type, item detection, and picture segmentation.

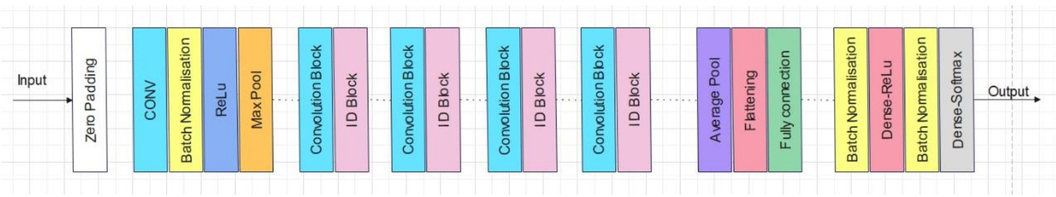

Figure 2. Resnet50 Model Architecture

InceptionV3:

In this custom designed variation of the InceptionV3 architecture, the top layer has been removed to facilitate adjustments that beautify its functionality and adaptableness for specific obligations. The inclusion of a flatten layer serves to reshape the output of the previous layers right into a one-dimensional array, preparing it for enter into next layers. Additionally, the mixing of batch normalization layers allows stabilize and accelerate the training system by using normalizing the enter of every layer, which aids in mitigating troubles which includes inner covariate shift and gradient vanishing or exploding. Furthermore, a dense layer has been introduced to permit the community to learn difficult relationships and styles inside the function space, thereby improving its capability for classification or regression obligations. This showcases the flexibility and scalability of deep learning architectures like InceptionV3.

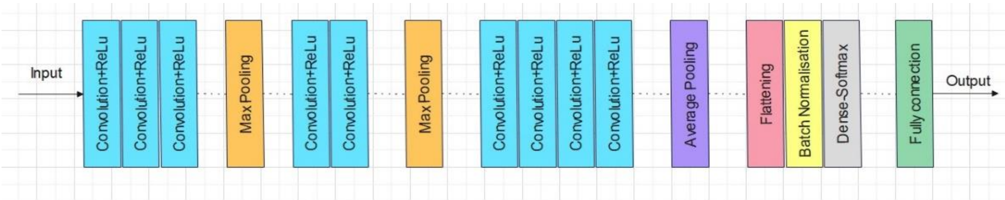

Figure 3. InceptionV3 Model Architecture

MobileNet:

MobileNet is a pioneering deep learning model designed specifically for mobile and embedded devices, catering to the increasing demand for efficient and lightweight neural networks. Developed by Google Research, MobileNet employs depth wise separable convolutions, which significantly reduce computational complexity while preserving the model's accuracy. This architectural innovation allows MobileNet to achieve high performance on tasks such as image classification, object detection, and semantic segmentation, all while maintaining a small memory footprint and fast inference speed. MobileNet's versatility and efficiency make it a popular choice for a wide range of real-world applications, including mobile apps, edge computing devices, and IoT devices, where resource constraints are prevalent. Its ability to strike a balance between accuracy and efficiency has cemented MobileNet's position as a cornerstone in the field of deep learning for mobile and embedded systems.

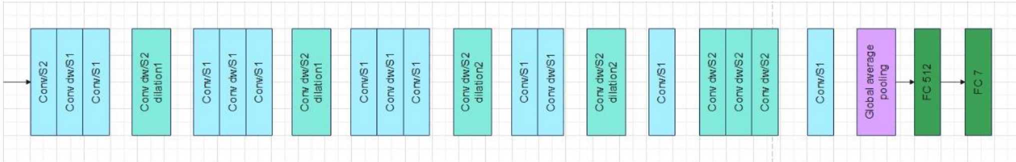

Figure 4. MobileNet Model Architecture

4 Results and Discussion

The performance of the paddy plant disease classification using CNN models (VGG19, InceptionV3, ResNet50, MobileNet) showed very promising results of diagnosing paddy crop diseases. As shown in Table-1, Inception v3 achieved a training loss of 0.5042 and an accuracy of 83.07%, with a validation loss of 0.3156 and a validation accuracy of 89.85%. MobileNet recorded training loss of 0.0560 and an accuracy of 99.02%, validation loss of 0.4199 and validation accuracy of 87.12%. ResNet50 demonstrated exceptional results with the lowest training loss of 0.0468 and the highest accuracy of 99.84% and validation loss was 0.3138, and the validation accuracy was 91.03%, indicating robust generalization capabilities. VGG19 yielded a training loss of 0.3031 and an accuracy of 90.14%, validation loss of 0.5607 and validation accuracy of 85.51%.

Table-1: Resulting hyperparameters of each model

Model	loss	accuracy	val_loss	val_accuracy
Inception v3	0.5042	0.8307	0.3156	0.8985
Mobile net	0.0560	0.9902	0.4199	0.8712
Resnet50	0.0468	0.9984	0.3138	0.9103
VGG19	0.3031	0.9014	0.5607	0.8551

Based on these metrics, ResNet50 appears to perform the best overall, with the lowest loss values and highest accuracies on both the training and validation sets. Hence, Table-2 is provided with further performance metrics of ResNet50.

Table-2: Performance metrics of ResNet50

Performance metrics	Score
Precision	0.9264
Recall	0.9240
F1-score	0.9243
ROC-AUC score	0.9958

5 Conclusion

In conclusion, our project aimed to develop a robust classification model for identifying paddy plant diseases, leveraging the power of deep learning architectures and distributed computing techniques. Through the utilization of the VGG19, InceptionV3, ResNet50, MobileNet, we found that ResNet50 showed more accurate and promising results, classifying paddy plant diseases with an impressive accuracy of 99.84%, while InceptionV3 recorded 83.07%, MobileNet recorded 99.02% and VGG19 recorded as 90.14%. As we used transfer learning to enhance the accuracy of each model, the additional layers we add to the original models showed great improvement in each model's accuracy. These findings underscore the significance of scalable and parallelized training methodologies in deep learning research, particularly for handling large-scale datasets and achieving high classification accuracy. Moving forward, our work lays the foundation for further exploration and application of deep learning techniques in agricultural management practices, offering potential solutions to challenges such as disease detection and crop yield optimization. By continuing to refine and optimize our classification model, we can contribute to advancements in precision agriculture and ultimately aid in ensuring food security and sustainability on a global scale.

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