Multi-Disease Detection and Classification in Paddy Using Deep Convolutional Neural Networks

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Keywords: Convolutional Neural Networks, Paddy Leaf Disease, Multi Label Classification, Computer Vision

Abstract: The world is expecting an exponential growth in food production in the recent future. Rice, a staple food for a large part of the world's population, faces the threat of various diseases that can seriously affect the crop. The proposed solution uses advanced deep learning algorithms on images of paddy leaves to predict leaf diseases. Using data containing high-resolution images of healthy and diseased leaves, convolutional neural network (CNN) model was implemented to accurately identify the disease. Preprocessing is used to improve the quality of the image and remove features that hinder accurate classification. The system has been shown to be useful in diagnosing many types of foliar diseases, providing good results for early disease detection and good agronomic management. The Resnet-50, efficient net B3 architectures of Convolutional Neural Networks (CNNs), a specialized deep learning architecture, has been trained on diverse datasets containing images of healthy and diseased rice leaves for the diseases bacterial leaf blight, Hispa and brown spot. Once trained, these models can accurately classify diseases with up to 90% accuracy thereby supporting timely interventions, ultimately preventing extensive crop losses and fostering sustainable practices. In addition to this, deep learning's image recognition capabilities is also used in sorting and grading rice leaves based on various parameters such as size, color, and ripeness. A user interface using Streamlit is developed for uploading test images and the system would identify the diseases.

1 INTRODUCTION

Rice is the first staple food crop in South India. The demand for rice is increasing due to the population growth. It is a crop chosen by many small scale and marginal farmers. It is cultivated in diverse climatic and soil bases, across south India. In contrast to the demand for rice, the production of paddy is facing many challenges. One of the major challenges faced in paddy cultivation are the bacterial diseases like foot rot, grain rot, sheath brown rot, fungal diseases like blast, brown spot, narrow brown leaf spot, sheath blight, false smut and viral diseases like Rice Tungro, Rice Grassy Stunt, Rice Yellow Dwarf (TamilNadu Agricultural University, 2024). These diseases when identified at early stages can be prevented from spreading and affecting other crops. Crop phenotyping is gaining popularity in precision agriculture recently. In phenotyping different classes of images such as RGB, multi-spectral and remote sensing are used for disease identification and different vegetative indices calculation. Such early interventions increases productivity, sustainability, and quality of the paddy crops.

The traditional machine learning models had several challenges like manual image feature extraction, multiple phases for feature engineering, sub set identification and ranking before classification. Deep learning, a subset of artificial intelligence, utilizes powerful deep neural networks to enhance various aspects of image classification. Deep learning's capacity to analyze and understand complex data, particularly images and time-series data, has demonstrated proficiency in image analysis and recognition tasks. However, challenges remain in implementing this technology, including the lack of comprehensive datasets and the interpretability of deep learning models. Additionally, concerns about

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K., S., Reddy, V. P. and Deepthi, R.
Multi-Disease Detection and Classification in Paddy Using Deep Convolutional Neural Networks.
DOI: 10.5220/0012881000004519

In *Proceedings of the 1st International Conference on Emerging Innovations for Sustainable Agriculture (ICEISA 2024)*, pages 32-39
ISBN: 978-989-758-714-6

scalability, adaptability, and computational resource limitations are essential to address.

In this paper, we deploy a Convolution Neural Network (CNN) ResNet 50 architecture and Visual Transformer Model (ViT) that classifies 3 paddy diseases namely Brown Spot , Hispa and LeafBlast. CNN is a type of deep neural network, employing supervised learning, which automatically extracts features from the training images and classifies the images. CNNs, a specialized deep learning architecture, can be trained on diverse datasets containing images of healthy and diseased paddy leaves. Once trained, these models can accurately diagnose potential issues and support timely interventions, ultimately preventing extensive crop losses and fostering sustainable practices. Furthermore, deep learning's image recognition capabilities can aid in sorting and grading Rice leaves based on various parameters such as size, color, and ripeness.

2 RELATED WORK

In (Batchuluun et al., 2022) the authors use thermal images for image classification using CNN and explainable AI on open paddy and self-collected rose leaves data sets. The proposed CNN 16 architecture used Class Activation Map XAI layer followed by a GAN discriminator in the custom architecture. The authors (Singh et al., 2022)propose a custom developed CNN architecture which is evaluated by two optimizers Adam and Stochastic Gradient Descent with Momentum. The dataset was custom collected in the fields of Orissa and later augmented. The work compares the performance of both the optimizers with different kernel sizes. Most of the erroneous classification occurred in healthy images because of the background noise and the Adam optimizer performed better. Eight diseases that are more predominant in Bangladesh are identified (Ahad et al., 2023). The best performing CNN architectures were used in the classification of the eight diseases. Six original individual architectures, three transfer learning architectures and one ensemble architecture were analyzed. The architectures using transfer learning performed better than individual models. The proposed ensemble model DEX provided consistent accuracy across diseases. The VGG 19 model is used for detecting brown spot diseases in paddy leaves(Dogra et al., 2023). The model employs transfer learning which provides improvement in accuracy.

The other type of work integrates sequencing models like Bi-GRU (Bi directional gated recurrent unit) with the CNN architectures(Lu et al., 2023). The outputs of the two models are concatenated and passed to the classification layer. The original block attention module in the inception layer also was improvised to use convolution block attention mechanism to generate the feature map. The work in a hierarchical model for detecting Rice Blast from UAV images of different types of rice with noise(Shaodan et al., 2023). The initial phase had a Swin transformer for the fine-grained recognition of features. The following phases used trinomial tree structures to capture detailed local information, finally predicting the output label. The authors developed a mobile application to detect multiple rice diseases and nutritional deficiencies (Nayak et al., 2023). The work combined open data sets and field collected data set for training the model. The images were resized, and the background was removed, along with using stochastic depth cut optimization made the models to converge faster in training phase. The comparison of models on mobile and cloud-based platforms are also discussed. The real time detection using phone image capture on field without the requirement of internet connection made the mobile app more usable by farmers on field. The work in (Stephen et al., 2023) have used a fine tuned ResNet architecture that enhances the feature extraction capability of the model. Some authors extract the features using different convolutional layers and then the features are classified using Machine Learning Algorithms (Aggarwal et al., 2023). The authors in (Simhadri et al., 2023) compared the performance of 15 CNN architectures with transfer learning included, and observed that the Inception v3 model performed better. The work in (Abasi et al., 2023) proposed a customized CNN architecture tailored for paddy leaf diseases. This work employed using transfer learning with EfficientNet and Inception v3 architectures. When a single plant is suffering from multiple diseases, the work proposed in (Yang et al., 2023)delivers a solution to find the affected area and classify diseases. The authors of (Bouacida et al., 2024) develop a small inception architecture to test how a model trained on one crop classifies the diseases on other crops. The work in (Trinh et al., 2024) uses both CNN and YOLO v8 as a multi step identification and classification of paddy leaf diseases. The summary of the different paddy leaf disease classification is given in Table 1.

Table 1: Comparison of computer vision based leaf disease classification

Reference	Data Set	Algorithm Used	Diseases Classified	GPU	Accuracy (%)	Image Type	Image Count	Augmentation	Pixel Size
(Batchuluun et al., 2022)	Custom (Rose) and Open (Paddy)	PlantXDAI (Custom)	Blast, Bacterial leaf blight, Hispa, Leaf fodder, Leaf Spot	Yes (NVIDIA Titan X)	90.04	Thermal	636 augmented to 3576	Yes	220x220
(Singh et al., 2022)	Custom	Custom CNN	Bactreial blight, Blast, Brown spot, Tungro	No	99	RGB	7332 augmented to 35190	Yes	256x256
(Ahad et al., 2023)	Bangladesh Rice Research institute, Custom	Inception V3, DenseNet, Mobile Net, ResNet, SeresNet, EfficientNet, Xception	Bactreial blight, Blast, Brown spot, Tungro, Leaf Scald, Leaf Smut, Hispa, Shath Blight	Yes. Google Colab Tesla	97.62 (DEX)	RGB	1800 augmented to 85752	Yes	132x132
(Lu et al., 2023)	Custom	CNN+BiGRU	Rice blast, Sheath blight, Brown Spot, Leaf Blight	Yes RTX3050	98.21	RGB	2414 augmented to 6000	Yes	224x224
(Shaodan et al., 2023)	Custom	Custom	Rice Blast	Yes Three Tesla V100	92.5	UAV	1702	No	5742x3648

(Nayak et al., 2023)	PlantVillage + Custom	DenseNet, ResNet 50, Xception, MobileNet	12 diseases	Yes, NVidia P100, Mali G52 MC2 in mobile	98	RGB	2259	No	300x300
(Stephen et al., 2023)	Kaggle	Improvised ResNet	Hispa, Brown Spot, Leaf Blast	Yes NVIDIA P5000	98	RGB	3355	Yes	256x256
(Aggarwal et al., 2023)	Custom	Multiple Convolution layers for feature extraction,	Bacterial leaf blight, Brown Spot, Blast	No	94	RGB	551	None	224x224

3 PROPOSED METHODOLOGY

3.1 Data Set

The data set we used was from Kaggle(Kaggle, n.d.) which had a total of 3355 images with 779 for Leaf blast, 565 for Hispa, 523 for Brown spot, 1488 for Healthy images. We converted the images to 448x448, The experiments were performed on a system with Intel i5 processor, 64 bit OS and 16GB RAM.

3.1.1 Leaf Blast *(Magnaporthe oryzae)*

Leaf blast is a fungal disease occurring at all stages of growth. It occurs in regions of frequent rainfalls or cool temperature. Green or grey or white lesions start to appear on the leaves as shown in Figure 1. The lesions are broad in the central parts of the leaf and pointed at the end. The lesions in due course of growth cycles might enlarge and kill the leaves.

3.1.2 Brown Spot (Helminthosporium oryzae):

Brown spot disease are result of infected seeds, After blast it is the second most occurring disease in paddy. It affects the quality and quantity of rice produced. This mainly occurs between seedling to milky stage. The disease starts as small brown spots and later spreads a big dark brown oval spot with a yellow halo as shown in Figure 2.

Figure 1: Leaf Blast.

Figure 2: Brown Spot.

3.1.3 Hispa (Dicladispa armigera, Olivier)

Hispa is a damage done due to the Rice Hispa insect. The insect grows a lot in monsoon and in pre monsoon seasons. Proximal weed will cause this insect to grow fast. The insect scrapes the upper part of the leaf leaving only the lower epidermis part of the leaf as shown in Figure 3.

Figure 3: Hispa.

Hispa effect can cause up to 20% loss in production. Care must be takes to identify the infestation at an early stage. Effort and experience help identify the streaks and lower epidermis in parallel leaves along with identification of accurate feeding marks left by the insect.

3.2 Disease Classification Process

In our work, we have chosen two fungal diseases and one insect-based damage. All three of these have to be identified at an early stage and should be classified correctly. Few symptoms between fungal diseases is common and high precision analysis is required to classify them from images. Similarly, Rice Hispa also requires more accurate model for classification.

We apply two different Convolutional Neural Network (CNN) architectures to classify the paddy leaf diseases. CNNs are a type of deep learning networks with different architectures which are extremely good in learning the features from images automatically. A CNN network has many layers which are useful in applying features extracted to the tasks like image classification.

1. The convolutional layer is the cornerstone of CNNs, serving as the fundamental building block. By sliding specialized filters (known as kernels) across the input image, it carries out convolutions to capture important local features such as edges, color depth, curvatures, textures, and patterns. These resulting feature maps represent the various spatial locations of the extracted features in the images.

2. At the conclusion of each convolutional operation, an activation function is employed to add a non-linear element, thereby boosting the model's ability to comprehend intricate connections within the dataset. This strengthens the model's capability to learn intricate relationships within the data.

3. Pooling layers are crucial components that reduce the spatial dimensions of the output feature maps from the convolution layer and alleviate the computational burden, while preserving the most relevant information. Among the popular techniques commonly used in pooling layers are max-pooling and average-pooling, which extract the highest or average values from within specific regions of the feature map.

4. Fully Connected Layer: This is one of the final layers in a CNN that takes the output of the previous layers which is a flattened matrix, representing the extracted features. This is present just before the output layer that uses this feature matrix to classify the output class.

5. Flattening: It prepares the feature maps for traditional neural network processing by converting them into a one-dimensional vector before passing them onto the fully connected layers. This allows for a smooth and streamlined flow of data.

6. Dropping Out for Better Results: When it comes to preventing overfitting, one effective approach is using dropout. This handy technique involves randomly omitting neurons during training, with a specified chance of setting their output to zero. By forcing the network to rely on alternate options for making predictions, dropout can greatly enhance overall accuracy.

7. Normalization:

Batch normalization is applied between layers in CNN in order to standardize data instead of only on the raw input image. It can help using larger learning rates and faster convergence possibilities.

8. Output Layer: The last layer that converts the activation functions and classifies producing the classification probabilities of the different classes.

All the above layers with different configuration comprise of various architectures of CNN. The layers should be able to learn the features efficiently without over fitting or missing any vital information.

By training on diverse datasets, these models can identify subtle variations and defects that might be imperceptible to the human eyes.

We apply ResNet50 and ViT architecture to the dataset and compare the performance of the models. The general process flow of ResNet 50 architecture and the ViT models are represented in Figure 4 and Figure 5 respectively.

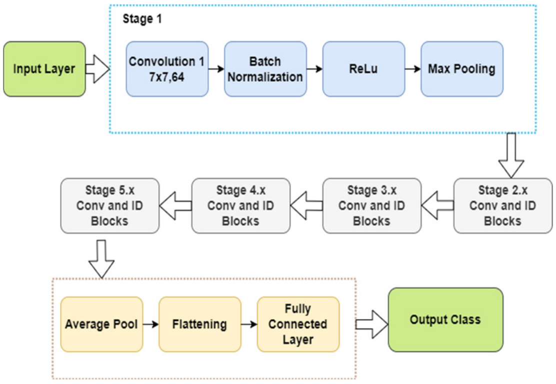

Figure 4: ResNet 50 process flow.

The ResNet 50 version of CNN is 50 layers deep. This architecture learns residual connections that helps to map input to output.

The Vision Transformers uses attention mechanism to differentially weigh different parts of the input data. The ViT model converts the images to patches without overlaps, converted into vectors and then processed using transformer architectures. This is the process used in text by Large Language Models and is now significantly producing results for image classification tasks.

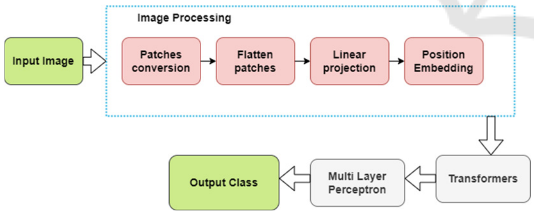

Figure 5: Vision Transformers process flow.

4 RESULTS AND DISCUSSION

4.1 ResNet 50 CNN Model

The training and validation loss, accuracy for epochs of 10, 20 and 50 are given in Figure 6a,6b and 6c.

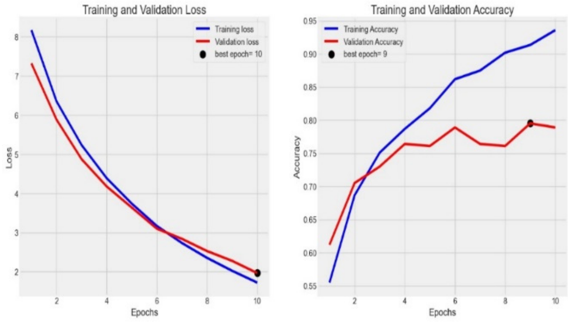

Figure 6a: Training and Validation Loss, Accuracy for 10 epochs.

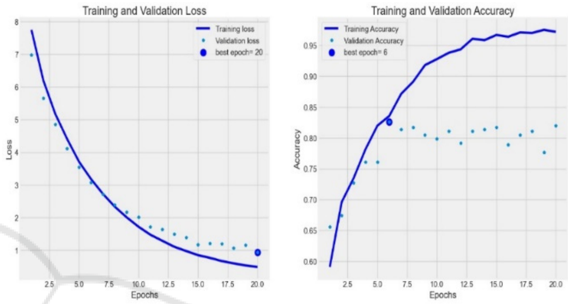

Figure 6b: Training and Validation Loss, Accuracy for 20 epochs.

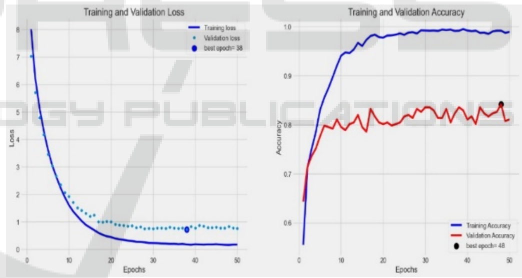

Figure 6c: Training and Validation Loss, Accuracy for 50 epochs.

Similarly, the confusion matrix for 10, 20 and 50 epochs are presented in Figure 7a, 7b and 7c respectively.

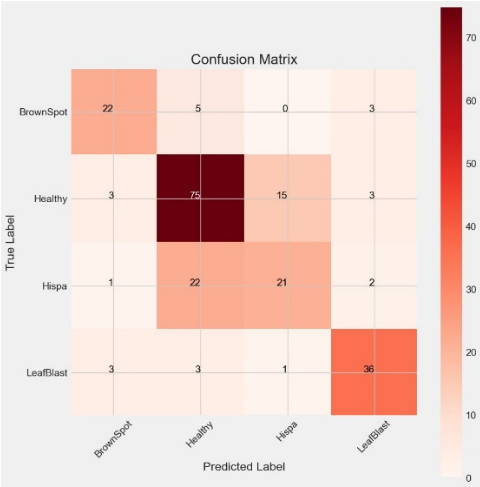

Figure 7a: Confusion Matrix for 10 epochs.

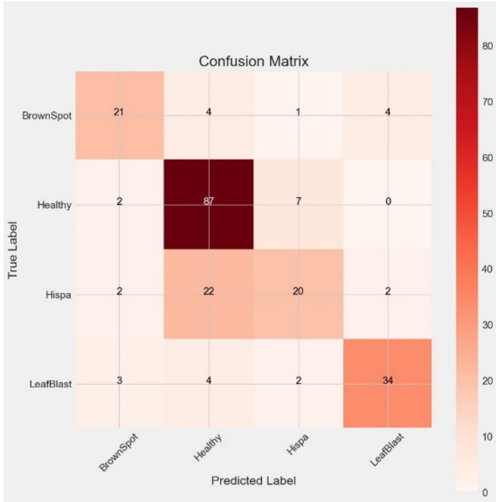

Figure 7c: Confusion Matrix for 50 epochs.

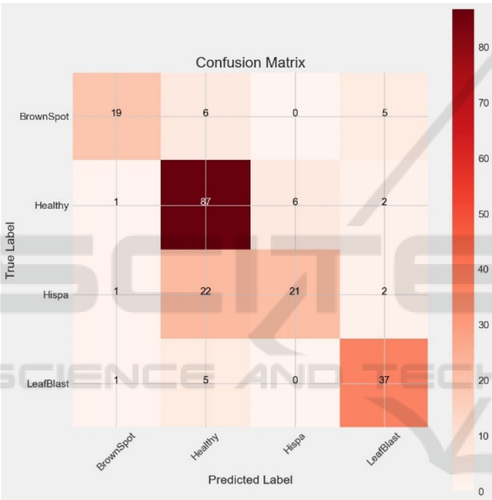

Figure 7b: Confusion Matrix for 20 epochs.

We developed a user interface using Streamlit where an image can be uploaded and the classification result can be viewed. The below Figures 8a and 8b are the sample images for Brown Spot and Healthy classes.

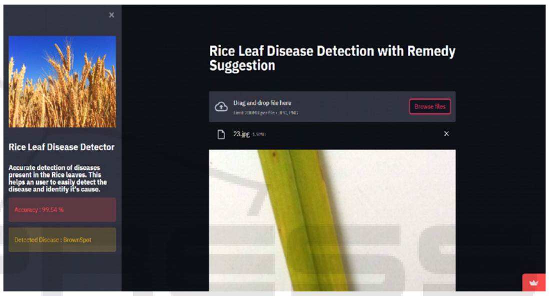

Figure 8a: Brown spot classification.

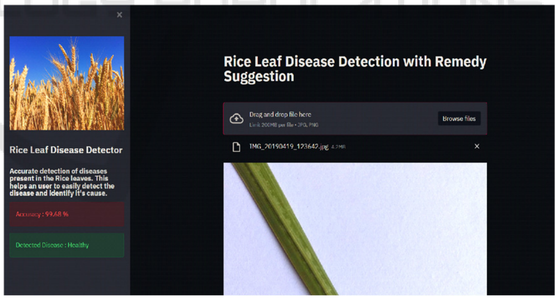

Figure 8b: Healthy leaf classification.

4.2 Vision Transformer Model

The training and validation accuracy of the Vision Transformer model is given in Figure 9 for 15 epochs.

Figure 9: Training and Validation Loss, Accuracy for 15 epochs.

5 CONCLUSIONS

Paddy leaf disease identification and classification at earlier stages could be very useful to farmers in treating the crops. In this work we have taken two fungal diseases and an insect base disease which have similar patterns when viewed with normal eyes. The image classifiers we used are ResNet 50 architecture of CNN and the Vision Transformer model. We got close to 90% accuracy in ResNet50, whereas we got upto 45% accuracy with 15 epochs in the ViT model. The ViT model is more promising in classifying generic images and could be improved for better accuracy in our task of paddy leaf disease classification by providing better runtime resources and more images in class.

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