Severity Based Rice Leaf Disease Classification using Convolutional Neural Networks

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Abstract*—A significant proportion of the global populace depends on rice as a fundamental dietary component, thereby rendering rice crucial for ensuring food security. Nevertheless, the cultivation of rice is in grave jeopardy due to afflictions such as bacterial blight, blast, brown spot, and tungro. Our endeavor is centered around the creation of a dependable framework that possesses the capacity to accurately identify and categorize these ailments by harnessing the capabilities of state-of-the-art technology, specifically advanced machine learning algorithms. We were able to achieve a decent Validation Accuracy of 100% and Test Accuracy of 98%. We progressively extract features through convolutional and max-pooling layers, flatten the output, and then classify the features using densely connected layers. Dropout is employed to enhance generalization by reducing overfitting during training . The optimization is performed using the RMSprop algorithm, adapting learning rates based on recent gradients for improved convergence. Batch normalization is applied to stabilize training by normalizing layer inputs. This combination of convolutional operations, dropout, RMSprop optimization, and batch normalization contributes to the network's ability to learn discriminative features and generalize effectively on diverse datasets.

Keywords*—deep learning, convolutional neural network, image classification

I. Introduction

Rice production appears as a key in maintaining food security for enormous populations in the global agricultural domain. However, this critical crop faces ongoing challenges from a variety of diseases, which can significantly reduce yields and damage grain quality. The diagnosis and mitigation of these diseases are critical problems in the quest of sustainable agriculture methods. Among the several approaches available, utilizing sophisticated technologies, particularly deep learning and image classification holds enormous promise for changing illness treatment. This study delves into the complex world of rice leaf diseases, with the goal of developing a Severity-Based Rice Leaf Diseases Classification system to improve disease assessment and intervention tactics.

The main goal of this study is to present a novel method of classifying rice leaf diseases by including severity as an important factor. Conventional disease categorization schemes frequently classify illnesses according to their kind, ignoring smaller variations in symptom intensity that can have a big impact on crop health. Our suggested solution uses image analysis to identify minute variations in illness severity by utilizing machine learning. This increased level of classification granularity not only makes it possible to diagnose patients with more accuracy, but it also makes it easier to respond specifically to address the unique problems that different disease impacts present. We hope that this method will help develop a more sophisticated and successful plan for controlling rice leaf diseases.

This study's significance extends beyond the immediate sphere of rice farming. As the world's population grows, so does the demand for food, necessitating agricultural technologies that optimize agricultural techniques. The suggested Severity-Based Rice Leaf Diseases Classification system addresses a fundamental part of rice cultivation while also serving as a model for improving disease management in other crops. By incorporating modern technology into precision agriculture, we hope to usher in a new era of efficient, data-driven approaches to crop disease mitigation, ultimately contributing to better yields, decreased environmental impact, and improved global food security.

II. Equations

Eq1 subtracts each pixel value from 255 to accomplish pixel-wise inversion. It successfully projects a negative image.

Eq1 : 255 - image_array = n_image_array

`image_array`: This presumably represents the pixel values of an image. Each element in `image_array` likely corresponds to the intensity or color value of a pixel in the image.

`255`: This is a constant value representing the maximum intensity or color value for each channel in an 8-bit image. In many image processing contexts, pixel values range from 0 (minimum intensity or color) to 255 (maximum intensity or color) for each channel.

`n_image_array`: This seems to be the result of the pixel-wise inversion. Each pixel value in `image_array` is subtracted from 255, and the result is stored in `n_image_array`. As a result, the intensity or color values are inverted for each pixel.

Data Augmentation: The input photos undergo a number of changes, including rotation, shearing, zooming, horizontal flipping, and width and height shifting. The ImageDataGenerator class's formulas are used to apply these changes.

Batch Normalization: Following each convolutional layer, batch normalization is conducted. It entails normalizing each layer's inputs so that the mean and standard deviation are almost equal to 0.

Learning Rate Scheduler: During training, a scheduler is used to modify the learning rate. The learning rate is exponentially decreased over epochs using the particular formula, which is 0.001 * pow(0.9, epoch).

Convolutional layers, batch normalization, activation functions (ReLU), max-pooling layers, a flatten layer, thick layers, and dropout for regularization are all included in the model architecture. Filter size, input shape, and unit count are among the characteristics that are included in the specialized formulas for convolution and dense layers.

III. Literature review

Plant diseases pose a significant threat to global agriculture, affecting crop yield and food security. Early and accurate detection of plant diseases is crucial for implementing timely interventions and minimizing economic losses. In recent years, researchers have increasingly turned to deep learning (DL) techniques, particularly convolutional neural networks (CNNs), to enhance the accuracy and efficiency of plant disease identification. This literature review discusses key studies that contribute to the growing body of knowledge in this field.

Yousef Methkal Abd Algani et al. [1] proposed method, Ant Colony Optimization with Convolution Neural Network (ACO-CNN), combines ant colony optimization for feature extraction and Convolutional Neural Network (CNN) for classification.addresses the critical issue of plant leaf disease identification in agriculture, emphasizing the importance of early and accurate diagnosis. The authors contend that existing methods suffer from drawbacks such as time consumption and lack of flexibility, motivating the need for a more effective approach. Evaluation metrics demonstrate the superior performance of ACO-CNN compared to other models, showcasing its potential as an innovative and efficient method for plant leaf disease detection in agriculture.The results highlight the accuracy, precision, recall, and F1-score, with ACO-CNN outperforming other models in all aspects.

Focusing on the challenge of differentiating diseases with similar symptoms, especially in small areas, Sudhesh K.M., Sowmya V., Sainamole Kurian P., and Sikha O.K. [2] presented an innovative approach to improving AI-based rice leaf disease identification by incorporating Dynamic Mode Decomposition (DMD)-based attention-driven preprocessing method. This addresses the limitations of global image-based CNN models, which may be affected by irrelevant noisy regions. The study evaluates ten transfer-learned Deep CNN (DCNN) models, with DenseNet121 identified as the most effective. Additionally, the combination of XceptionNet with SVM on DMD preprocessed images achieves outstanding accuracy of 100%. The proposed DMD-based preprocessing is further validated on on-field rice leaf images, demonstrating a classification accuracy of 94.33%.

In the research conducted by Guosheng Zhang et al. , hyperspectral imaging [3] proved to be a robust tool for assessing rice leaf blast severity across multiple growth stages. Their study introduces a spectral reflectance ratio (SRR) data analysis method and support vector machine (SVM) models, demonstrating impressive accuracy in disease severity classification. The full-spectrum-based SVM model yields high accuracy rates, with 94.75% in 2019, 92.92% in 2021, and 88.09% in the 2019–2021 combined model. The SRR–SVM model, designed to evaluate disease severity over diverse growth stages, exhibits good generalizability. Overall, their findings underscore the potential of hyperspectral imaging as a valuable tool for monitoring and managing rice blasts, offering insights that can contribute to more effective disease control strategies in agriculture.

Archana K.S. and Sahayadhas A. introduce the Rice Disease Detection System (RDDS), which is a comprehensive solution that seamlessly integrates the innovative RDD_CNN model and an Infection Intensity Estimation (IIE) module.the RDD_CNN model achieves a remarkable 98.47% test accuracy in classifying eight major rice diseases. The authors meticulously provide a detailed performance analysis, emphasizing precision, recall, F1-Score, sensitivity, and specificity across diverse disease classes. Notably, the IIE module, specifically designed for Brown Spot (BS) disease, accurately estimates infection intensity and disease stage. These results highlight the potential of RDDS for early and precise disease diagnosis, offering farmers a crucial tool for timely crop protection. The comparative analysis with contemporary CNN models, coupled with insightful suggestions for future extensions, underscores the authors' significant contributions to advancing agricultural technology.

The research presented by Sk Mahmudul Hassan and Arnab Kumar Maji [11] in which a CNN model is used for the identification of plant diseases, addressing the challenges posed by existing deep learning models such as parameter volume and training time. The model integrates inception and residual connection architectures, incorporating depthwise separable convolution to significantly reduce parameters. Evaluated on three diverse plant disease datasets, including PlantVillage, rice, and cassava, the model achieves impressive accuracy rates of 99.39%, 99.66%, and 76.59%, respectively. The paper emphasizes the robustness of the model across varied conditions, showcasing its effectiveness in real-time field scenarios. Comparative analyses demonstrate superior performance, lower parameter usage, and reduced training time compared to pre-trained networks and existing literature. The study provides a valuable contribution to the field of plant disease identification using deep learning techniques.

The study, authored by Prabira Kumar et al. focuses on automated rice leaf disease identification using deep features and support vector machines (SVM)[13]. Introducing 5932 on-field images of four rice leaf diseases, the research evaluates the performance of 11 deep Convolutional Neural Network (CNN) models through transfer learning and deep feature plus SVM. Results indicate that the deep feature plus SVM outperforms transfer learning, with ResNet50 plus SVM achieving a notable F1 score of 0.9838. The study explores small CNN models like MobileNetv2 and Shufflenet and compares their performance in both transfer learning and deep feature plus SVM approaches. This research, conducted in the rice-rich region of Sambalpur and Bargarh districts in Odisha, India, contributes insights into effective disease identification, emphasizing the practical implications of using on-field images. The authors highlight the limitations of traditional methods and advocate for the superiority of deep learning techniques in agricultural disease classification, showcasing the potential of their proposed approach.

IV. Dataset

Our dataset focuses on the classification of severity-based rice leaf diseases, aiming to revolutionize the protection of rice crops from lethal illnesses. As rice is a staple diet for a significant portion of the world's population, ensuring food security is paramount.

Threats such as bacterial blight, blast, brown spot, and tungro seriously jeopardize rice production. Our project employs cutting-edge technology, particularly sophisticated machine learning algorithms, to develop a reliable system capable of accurately recognizing and categorizing these diseases.

The objective is to distinguish between healthy and diseased rice leaves through the analysis of leaf photographs. Early detection is crucial for prompt intervention, safeguarding crop output and food availability. Recognizing the value of early disease identification, our initiative aims to empower farmers and agricultural professionals with a robust tool. Utilizing specifically selected datasets containing images of healthy leaves and those affected by diseases, our machine learning models are trained to precisely identify and classify various disease types and their severity levels.

Central to our project is the application of Convolutional Neural Networks (CNNs), specialized in extracting intricate information from images, enabling the detection of subtle signs of illness. Once trained and validated, our models will be integrated into a user-friendly application. Users can input rice leaf photos, and the application will swiftly classify whether the leaf is healthy or infected, providing detailed information on the severity of the condition for targeted interventions.

The initiative's motivation is rooted in enhancing farming methods and ensuring food security. By contributing to increased rice crop production and a more robust food supply chain, we provide farmers and agricultural professionals with a potent tool for disease diagnosis. Ultimately, our project aims to make meaningful contributions to global food security and the protection of farmers' livelihoods.

V. Proposed Model

Classifying leaf diseases is an essential activity in agriculture for plant disease control and early detection. Our study suggests using a Convolutional Neural Network (CNN) architecture to effectively classify leaf diseases according to their visual symptoms.

1. Data Preprocessing :

(i) Image Augmentation: We used Tensorflow's ImageDataGenerator along with data augmentation approaches to improve the model's generalization capabilities. Rotation, shifts in width and height, shear, zoom, and horizontal flips are all included in the augmentation. By diversifying the training set, overfitting is avoided and the resilience of the model is enhanced.

Model Architecture :
Multiple convolutional layers interspersed with Batch Normalization and ReLU activation functions make up the suggested CNN architecture. The latter layers consist of fully connected layers with a softmax activation layer for multi-class classification, Batch Normalization, ReLU activation, and dropout regularization.

Convolutional Layers:

Layer 1:
32 filters of size (3, 3)
Batch Normalization
ReLU activation
MaxPooling (2, 2)
Layer 2:
64 filters of size (3, 3)
Batch Normalization
ReLU activation
MaxPooling (2, 2)
Layer 3:
128 filters of size (3, 3)
Batch Normalization
ReLU activation
MaxPooling (2, 2)
Layer 4:
256 filters of size (3, 3)
Batch Normalization
ReLU activation
MaxPooling (2, 2)
Fully Connected Layers

Dense Layer 1:
256 units
Batch Normalization
ReLU activation
Dropout (0.5)
Output Layer:
Dense layer with a softmax activation function for multi-class classification.

Model Compilation and Training :
Categorical crossentropy is used as the loss function and the RMSProp optimizer is used to construct the model. A learning rate scheduler with an initial learning rate of 0.001 that decays by a factor of 0.9 after each epoch is used to prevent overfitting.

Table.I: Comparison of algorithms used.

SNO	**Paper Title**	**Algorithm**	**Precision**	**Accuracy**
1	Leaf disease identification and classification using optimized deep learning	ACO-NN	99.6%	99.98%
2	AI based rice leaf disease identification enhanced by Dynamic Mode Decomposition	DCNN	— —	93.87%
3	Hyperspectral imaging-based classification of rice leaf blast severity over multiple growth stages	CNN	— —	94.75%
4	Enhancing Rice Crop Management: Disease Classification Using Convolutional Neural Networks and Mobile Application Integration	CNN	96.2%	97.9%

5	Rice Leaf Disease Detection Via Deep Neural Networks With Transfer Learning For Early Identification	InceptionV3	97%	95.41%
6	Rice Plant Disease Classification using Transfer Learning of Deep Convolution Neural Network RICE PLANT DISEASE CLASSIFICATION USING TRANSFER LEARNING OF DEEP CONVOL UTION NEURAL NETWOR K	deep CNN	— —	91.37%
7	Rice Disease Diagnosis System (RDDS)	CNN	95.67%	98.47%
8	Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications	DenseNet-12 1	— —-	99.81%
9	A Copy Paste and Semantic Segmentation-Based Approach for the Classification and Assessment of Significant Rice Disease	RLDCP	-	85.38%
11	Plant Disease Identification using a Novel Convolutional Neural Network	Deep Learning Model	-	91.88%
12	A novel Hybrid Severity Prediction Model for Blast Paddy Disease using Machine Learning	Convoluti onal Neural Network, Support Vector Machine	-	97%
13	Deep feature based rice leaf disease identification using support vector machine	Tran sfer Lear ning, SV M	99.46%	98.38%
14	Application of machine learning techniques in rice leaf disease detection	SVM	_ _	96.2%
15	An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection	Inceptionvesn et -V2	93.71%	92.86%
16	An Efficient Disease Detection Technique of Rice Leaf Using AlexNet	AlexNet	_ _	99.42%
17	Techniques for Rice Leaf Disease Detection using Machine LearningAlgorith ms	AlexNet	_ _	99%
18	Idea Explored 1	CNN with global average pooling and inversion layer		98.0%
19	Idea Explored 2	CNN with Learning Rate Scheduling		98.0%

VI. Results

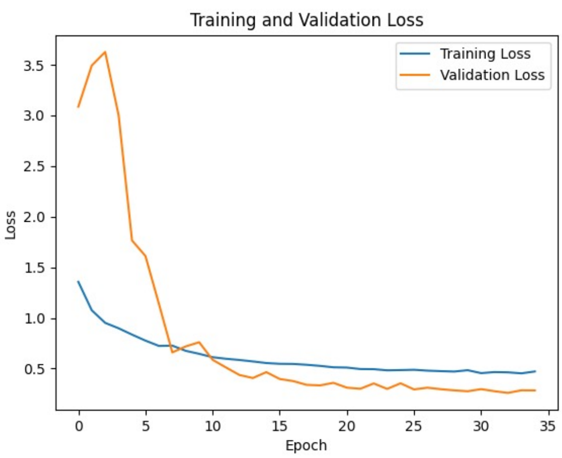

Fig: 1 Training and Validation loss graph.

Table II: Classification Report

	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	20

Mild Bacterial blight	1.00	1.00	1.00	20
Mild Blast	1.00	0.90	0.95	20
Mild Brownspot	1.00	1.00	1.00	20
Mild Tungro	0.95	1.00	0.98	20
Severe Bacterial blight	1.00	1.00	1.00	20
Severe Blast	0.95	1.00	0.98	20
Severe Brownspot	1.00	1.00	1.00	20
Severe Tungro	1.00	0.95	0.97	20
accuracy			0.98	180
macro avg	0.98	0.98	0.98	180
weighted avg	0.98	0.98	0.98	180

VII. Conclusion

Convolutional Neural Networks (CNNs) have been developed and trained for the purpose of classifying leaf diseases. The results are extremely promising, as seen by their astonishing 98% accuracy rate. This accomplishment highlights how well the suggested methodology identified and categorized leaf diseases in the provided dataset. Utilizing cutting-edge methods, such as batch normalization, data augmentation, and an optimal CNN architecture, has shown to be effective in improving the model's performance. By incorporating these tactics, the model was able to generalize well to data that had not yet been observed, in addition to facilitating strong learning.The model's great accuracy has important ramifications for the agricultural industry since it provides a precise and early means of identifying leaf diseases in crops. In order to implement focused management methods and timely interventions that will ultimately improve crop output and health, accuracy is essential.

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