A custom CNN model for detection of rice disease under complex environment

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***Abstract*—The work in this paper designs an image-based rice disease detection framework that takes rice plant image as input and identifies the presence of BrownSpot disease in the image fed into the system. A CNN-based disease detection scheme performs the binary classification task on our custom dataset containing 2223 images of healthy and unhealthy classes under complex environments. Experimental results show that our system is able to achieve consistently satisfactory results in performing disease detection tasks. Furthermore, the CNN disease detection model compares with state-of-the-art works and procures an accuracy of 96.8%.**

***Index Terms*—Rice disease, CNN model, Crop segmentation, Image processing**

I. Introduction

For identifying or categorizing diseases in plant images, a number of traditional machine learning-based approaches have been cited [Guo et al.(2020)Guo, Zhang, Yin, Hu, Zou, Xue, and Wang] that include support vector machine (SVM) [Jiang et al.(2020)Jiang, Lu, Chen, Cai, and Li], Artificial Neural Network (ANN) [Orillo et al.(2014)Orillo, Cruz, Agapito, Satimbre, and Valenzuela], and so one. The drawback of those approaches is that they require manual hand-crafted features. Recently, the Deep learning approach, particularly Convolution Neural Networks (CNN), eliminated this problem by automatically learning the relevant features needed to classify or detect the objects of interest. For example, a novel automatic rice disease detection approach based on CNN model is introduced in [Liang et al.(2019)Liang, Zhang, Zhang, and Cao]. This model presents a comparison and accuracy analysis between traditional low-level features produced by local binary pattern histograms (LBPH) and Haar-WT with high-level features produced by the CNN model. The system realizes two classifier models; CNN merged with Softmax and CNN merged with SVM. The former model with high-level features shows higher accuracy than the latter. Another work on an automatic wheat disease detection system based on four different CNN models has been presented in [Lu et al.(2017a)Lu, Hu, Zhao, Mei, and Zhang]. The method takes 50,000 pictures of unhealthy and healthy wheat crops into consideration. Among the four types of model, VGG-16 model provides the maximum average accuracy of 97.95%. The models in [Liang et al.(2019)Liang, Zhang, Zhang, and Cao] and [Lu et al.(2017a)Lu, Hu, Zhao, Mei, and Zhang] perform the task of disease detection by increasing the processing speed and robustness of the system at work. However, these models can detect only a limited number of diseases of the paddy plant. The model [Lu et al.(2017b)Lu, Yi, Zeng, Liu, and Zhang] overcomes this issue by increasing the number of recognizable diseases to ten. To train the model inspired by Alexnet and LeNet-5, 500 images are used. Although the experimental results have attained an average detection accuracy of 95.48%, the number of images for ten classes is very small when considering the deep learning model. The work in [Aukkapinyo et al.(2020)Aukkapinyo, Sawangwong, Pooyoi, and Kusakunniran] presents another system model called Stack CNN on the detection of the infected area of rice plants and pests. The work finds six different diseases: Neck Blast, Sheath Rot, Brown Spot, Bacterial Leaf Blight, False Smut, Sheath and, Blight, and three pest varieties: Stem Borer, Hispa, and Brown Plant Hopper. The novelty of the study lies in its ease and applicability. Methods in [Liang et al.(2019)Liang, Zhang, Zhang, and Cao], [Lu et al.(2017a)Lu, Hu, Zhao, Mei, and Zhang], and [Lu et al.(2017b)Lu, Yi, Zeng, Liu, and Zhang] could only accept paddy leaf images for disease classification. However, the model can identify plant disease in any portion of the rice plant. Moreover, it can correctly predict the disease when it infects the non-leaf parts of the plant body. The study also recognizes five existing CNN models and compares their performance with the help of transfer learning and without learning. Out of the five models, the VGG16 outperforms in terms of accuracy. The stacked CNN is able to classify the

This research work is designed and developed as part of project work sponsored by the Ministry of Electronics and Information Technology (MeitY), Govt. of India.

Proceedings of the Workshop on NLP in Agriculture and Livestock Management, pages 5 - 8
December 15, 2022 ©2022 Association for Computational Linguistics

diseases and pests with 95% accuracy.

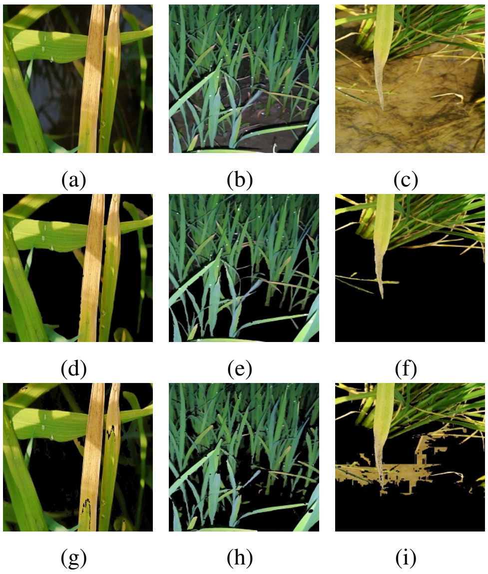


Fig. 1: Visual-based description of the paddy field dataset: Fig. (a)-(c) depict the images under various background conditions; (a) Shadows image on an unclouded day; (b) The scene of the crop field taken in the evening time; (c) Soil and disease color near to each other; Fig. (d)-(f) present the images done by manual segmentation; Fig. (g)-(i) depict output images by the automated segmentation approach.

The current work has the following contributions:

1) A custom dataset of 2223 rice plant images is taken directly from the rice field using an ordinary mobile handset camera.
2) A custom CNN architecture is designed to distinguish between healthy and unhealthy rice plants. Experimental results show that the crop segmentation technique enhances the performance of the CNN model by extracting only the regions of interest parts from the images of the given custom dataset.

II. Materials and Methods

A. Data Acquisition

A total of 2223 RGB images containing healthy and BrowSpot disease are captured from the paddy field in Durgapur, West Bengal under different lighting conditions. We have considered RGB images that are captured during the early and middle harvesting season as presented in Fig. 1. The description of the dataset is presented in Table I.

TABLE I: Dataset split description

Name of the Class	Train	Test
Diseased	1000	400
Healthy	556	267

B. Data Pre-processing

To remove the unwanted part from the image, we have applied a crop segmentation approach [Pal et al.(2022)Pal, Pratihar, Chatterji, and Mukherjee] in the current work such that it becomes easy for the classifier to identify the diseased portions in the image. Furthermore, the crop extraction algorithm uses the features from the edges of the object of interest parts and color indices of an image to segregate the plant part from the background of the image. The resultant image produced by the crop segmentation approach consists of plant parts (both diseased and healthy), as shown in Fig. 1. These processed images will be used to process the disease detection model further.

C. Custom CNN Model

The CNN model has gained so much popularity in the computer vision domain [Sharma et al.(2020)Sharma, Berwal, and Ghai], [Koklu et al.(2021)Koklu, Cinar, and Taspinar]. For this reason, we have deployed a custom CNN model for our problem. In the proposed CNN model binary cross entropy function is deployed as the work is defined for the two-class classification problem. The system is designed using three convolution layers and two Max- pooling layers. Each of the intermediate layers is attached to the ReLU activation function, and the last layer, called the output layer, is attached to Softmax as an activation function. For parameter adjustment, the learning rate is fixed at 0.001. The epochs are set to 10. The weight decay for the model is 0.0001, and the train batch size is 32. The detailed architecture of the custom CNN model is demonstrated in Fig.2.

D. Pretrained CNN Models

The ResNet50 [Qiang et al.(2019)Qiang, He, and Dai] and Inception V3 [Chen et al.(2020)Chen, Chen, Zhang, Sun, and Nanehkaran] are applied in the experiment, which detects paddy leaf diseases from the custom dataset. The considered models: ResNet50 and Inception V3 comprise of 50 and 48 layers, respectively. The ResNet50 is trained with 23 million trainable parameters. The model consists of five stages of convolution and identity blocks, whereas the architecture of Inception V3 is inherited from the Inception family. It is the modified version as it includes Factorized 7×7 convolutions, label Smoothing, and the application of a secondary classifier to forward class information downward the network.

III. Result and Analysis

A. Experiments on Classifiers using Custom Dataset:

In our experimental setup, a custom dataset of 2223 images is split into two parts; one part contains 1556 training images and another part contains 667 testing images. To verify the model's validity, test images unknown to the model are applied to it. In many cases model suffers from the over fitting problem. To overcome this over fitting problem, a data augmentation technique has been deployed. Data augmentation includes rotation, translation, flipping, cropping, and scaling. The model has gained an accuracy of 98.6% during the training phase and

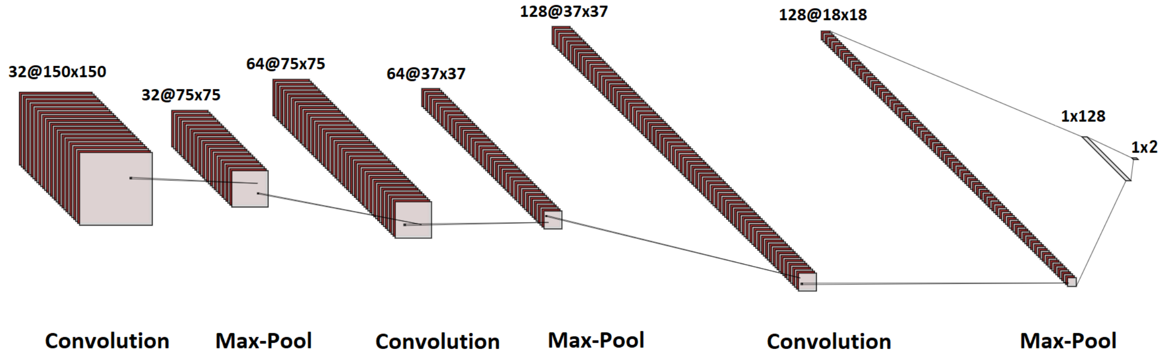


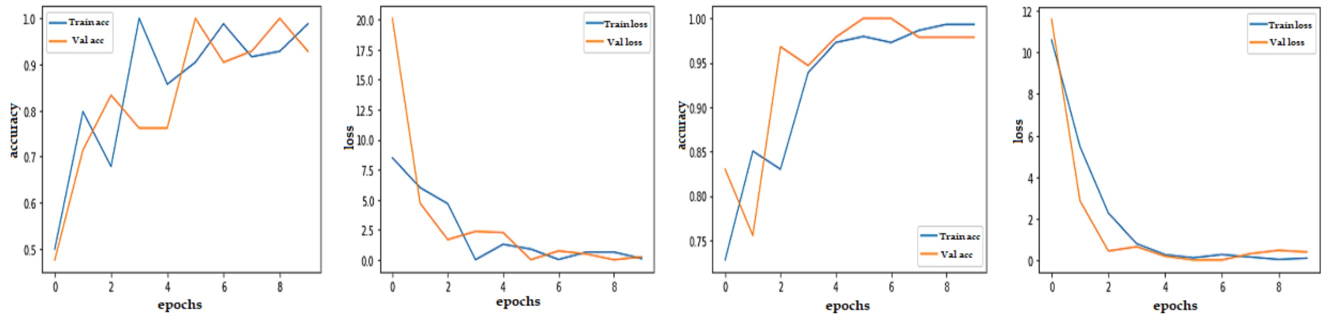
Fig. 2: Architecture of the proposed CNN model.

TABLE II: Accuracy and loss of considered models with 10 epochs.The models are deployed on images without segmentation

Model Name	Train Accuracy	Train Loss	Test Accuracy	Test Loss
ResNet50	0.961	0.125	0.875	0.400
Inception V3	0.976	0.233	0.928	0.238
Proposed CNN	0.960	0.130	0.928	0.182

TABLE III: Accuracy and loss of considered models with 10 epochs.The models are deployed on images with segmentation

Model Name	Train Accuracy	Train Loss	Test Accuracy	Test Loss
ResNet50	0.988	0.034	0.973	0.039
Inception V3	0.993	0.159	0.989	0.162
Proposed CNN	0.986	0.014	0.968	0.136



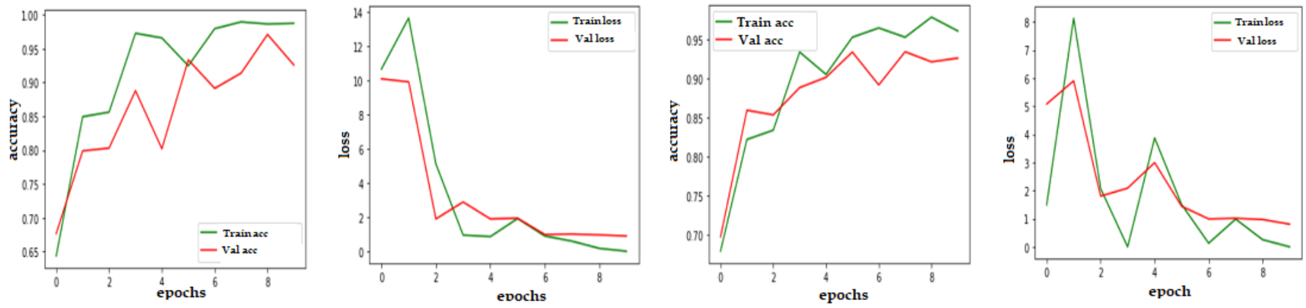
(a) (b) (c) (d)

Fig. 3: Inception V3 model performance metrics after 10 epochs; (a) and (b) depict accuracy and loss of the considered model without segmentation; (c) and (d) represent the accuracy and loss of the considered model with segmentation.

96.8% accuracy during the testing phase on the custom dataset without segmentation. To compare the accomplishment of the proposed model, the same dataset is applied to other state-of-the-art works. Table III and Table II show that the proposed model has provided consistent accuracy during the training and testing images. To ensure that the crop segmentation will help in enhancing the performance of disease recognizer models, the processed images are passed to Inception V3, Resnet50, and our proposed model. Table III shows that the accuracy of the model is increased with the segmented images. Hence, the experimental outcomes conclude that the proposed CNN model can enhance the accuracy when combined with the image segmentation approach. The pictorial representations of accuracy and loss curves of Inception V3, custom CNN, and Resnet50 are shown in Fig. 3, Fig. 4, and Fig. 5 respectively.

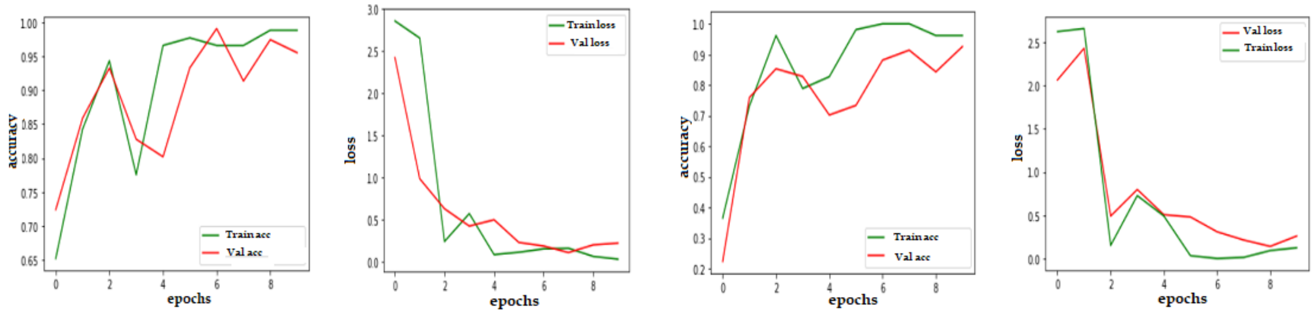
IV. Conclusion

The main task of the current work was to implement an automated BrownSpot disease detection system that works on images captured from the paddy field. The proposed model can detect the presence of BrownSpot disease in a rice plant



(a) (b) (c) (d)

Fig. 4: Proposed CNN model performance metrics after 10 epochs; (a) and (b) depict the accuracy and loss of the considered model with segmentation; (c) and (d) represent the accuracy and loss of the considered model without segmentation.



(a) (b) (c) (d)

Fig. 5: Resnet50 model performance metrics after 10 epochs: (a) and (b) depict the accuracy and loss of the considered model with segmentation; (c) and (d) represent the accuracy and loss of the considered model without segmentation.

leaf with reliable accuracy. In the future, we wish to build a mobile-based application that will help farmers to recognize the category and severity of rice disease without help of human expertise.

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