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Wheat Disease Severity Estimation: A Deep Learning Approach

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Abstract. In the agriculture domain, automatic and accurate estimation of disease severity in plants is a very challenging research field and most crucial for disease management, crop yield loss prediction and world food security. Deep learning, the latest breakthrough in artificial intelligence era, is promising for fine-grained plant disease severity classification, as it avoids manual feature extraction and labor-intensive segmentation. In this work, the authors have developed a deep learning model for evaluating the image-based stem rust disease severity in wheat crop. Real-life experimental field conditions were considered by the authors for the image dataset collection. The stem rust severity is further classified into four different severity stages named as healthy stage, early stage, middle stage, and end-stage. A deep learning model based on convolutional neural network architecture is developed to estimate the severity of the disease from the images. The training and testing accuracy of the model reached 98.41% and 96.42% respectively. This proposed model may have a great potential in stem rust severity estimation with higher accuracy and much less computational cost. The experimental results demonstrate the utility and efficiency of the network.

Keywords: Deep learning · Image classification · Plant disease severity · Wheat rust

1 Introduction

Plant diseases pose a significant threat to agricultural production losses. Disease identification and severity is a major concern for farmers in terms of reduced crop production as well as the crop yield loss. This leads to economic loss and food insecurity in many areas. Plant disease severity is a critical parameter for determining the disease level and as a result, can be used to forecast yield and recommend control measures. Hence, preventive action is required for the disease identification in plants at an early stage. The ability to

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diagnose disease severity quickly and accurately would aid in reducing yield losses [1]. Plant disease severity is traditionally determined by domain experts visually inspecting the plant tissues. Modern agriculture's rapid growth is stymied by the high cost and low efficiency of human disease evaluation [2]. Precision farming, high-throughput plant phenotype, and other fields are striving for automated disease diagnosis models, due to the advent of digital cameras and advances in computer vision. To overcome this concern, automated systems and techniques for detecting plant diseases are needed that will take less time and effort with much higher accuracy as compared to other conventional ways [3, 4].

[5] reviewed and studied the comparison of Deep Learning (DL) techniques which has gain momentum in recent years. Deep learning is when a neural network learns hierarchical data representations with several abstraction layers [6, 7]. Their results show that deep learning outperforms commonly used image processing techniques in terms of accuracy [8, 9]. While existing plant disease detection and diagnosis procedures are reliable, they are inadequate when it comes to assessing disease severity. [10] annotated the healthy and black rot images of apple in the Plant Village dataset with various severity categories. The Leaf Doctor app [11], an interactive smartphone app, may be used on colour images to distinguish lesion areas from healthy tissues and calculate disease severity percentages. This application even outperformed the Assess in terms of accuracy. A novel deep learning architecture named PD2SE-Net was constructed with accuracies of 91%, 98%, and 9%, respectively, for evaluating plant disease intensity and categorization, as well as plant species identification, using ResNet50 as the basic model [12]. There is considerable intraclass similarity and modest inter-class variation, fine-grained disease severity classification is substantially more challenging than classification among distinct diseases [10, 13]. Deep learning is ideal approach for fine-grained disease severity classification because it avoids time-consuming feature extraction and threshold-based segmentation [14].

This research was motivated by a breakthrough in deep learning for image-based plant disease recognition [15, 16]. It proposes a deep learning model for automated image-based diagnosis of plant disease severity in wheat caused by stem rust disease. Wheat rusts have been the most important biotic stresses responsible for unstable crop production. The wheat crop has three types of rusts named yellow rust, leaf rust, and stem rust. If not properly managed, these diseases can infect and cause significant yield losses. Rusts are known for spreading quickly and reducing wheat yield and quality. [17] identified the wheat yellow rust from the healthy leaves using deep learning. However, this research, on the other hand, is solely focused on stem rust and its severity estimation based on the different severity levels, such as Healthy Stage, Early Stage, Middle Stage, and End Stage. Therefore, the aim of this study is to develop a deep learning model for wheat stem rust disease severity estimation that will have the caliber to correctly predict the disease severity stage from the input image.

2 Methodology

The complete methodology for the experiment is summarized in Fig. 1. The images were collected from the experimental field according to the four different disease severity stages. In second step, the images were preprocessed. The detailed image preprocessing done is mentioned in Sect. 2.2. After the image preprocessing, the images were fed into the Convolution neural network (CNN) as an input for feature extraction and classification.

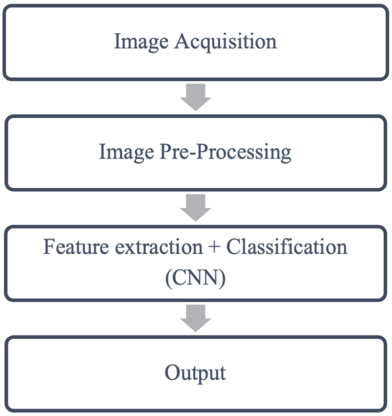


Fig. 1. Methodology for image-based classification

Convolution neural network architecture is one of the most promising deep learning architectures for image-based classification (CNN). The three layers that make up a CNN architecture are the convolution layer, pooling layer, and fully connected layer. Convolution Layer automatically extracts features from each input image. It is made up of a set of learnable filters that train the relationship between features and use kernel or filters to build a feature map. During training, CNN employs the Rectified Linear Unit (ReLU), which has an output of $(x) = \max(0, x)$ and introduces non-linearity into the network. The pooling layer downsamples convolution maps, decreasing training time and preventing overfitting by keeping just the most useful information for future processing. The final pooling layer output (3D matrix) is flattened into a one-dimensional vector, which is then used as the input in a fully connected layer. The features are then combined to form a model. Finally, the SoftMax or sigmoid activation function computes the predefined class scores and assigns the image to one of them. This study's Convolution neural network architecture (CNN) is shown below (Fig. 2).

The stem rust infected image is given input to the model. In the first phase of feature extraction, the features are automatically extracted from the images in convolution layers and down sampled in pooling layers. In the second phase of classification, the layers are first flattened and fully connected layers further classify the input image into four different classes as mentioned above.

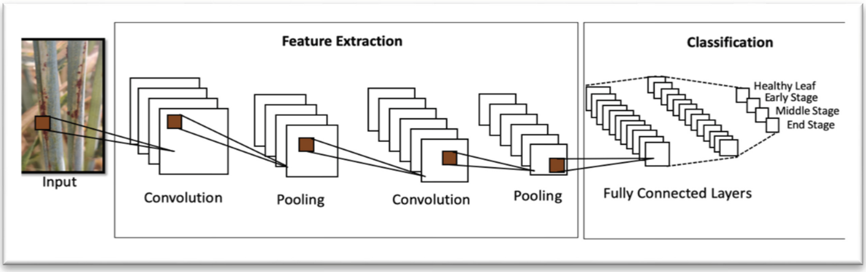


Fig. 2. CNN architecture for image-based plant severity estimation

2.1 Dataset

The author has created the dataset from the real-life conditions. The dataset consists of stem rust images collected from the experimental fields of ICAR-Indian Agricultural Research Institute Regional Station, Indore from January 2021 to March 2021. The pustules in stem rust are much larger, orange-red, oval to elongated, and appear on the stem, leaf blade, and sheath, as well as parts of the spike (Fig. 3). The images were collected keeping in mind the four levels of severity.

Healthy Stage Early Stage Middle Stage End-Stage

Fig. 3. The different four severity stages of Stem Rust disease

The author has divided these stages into four classes 0, 1, 2, and 3. These classes can also be referred to as the Severity scale for the stem rust disease. Table 1 provides a detailed description of the data.

Table 1 shows that there were a total of 2587 images collected, which were classified into four categories. The dataset is further split into a training set, testing set, and validation set into 80: 20:10 for the network input.

Table 1. The number of images in each severity stage.

Classes (severity scale)	Severity stage	Total no. of images (Train set + Test set)	Severity range (%)
0	Healthy stage	580 + 145 = 725	0
1	Early stage	624 + 156 = 780	0–25
2	Middle stage	564 + 142 = 706	25–50
3	End-stage	278 + 98 = 376	>50

2.2 Image Pre-processing

The author-created dataset mentioned in the previous section consists of arbitrarily sized RGB images. In deep learning models with effective end-to-end learning, only basic steps for image pre-processing are required. Images are processed in this stage according to these steps. For our network, firstly, all of the images to 256 * 256 pixels were resized. On these rescaled images, both model optimization and prediction were performed. Second, all pixel values are divided by 255 in order to match the network's initial values. In the third step, the training images are subjected to a variety of random augmentations such as rotation, shearing, and flipping. The augmentation helps the model generalize better by preventing over-fitting.

2.3 Implementation

The experiment for this study is performed on an Ubuntu workstation having Intel Xeon (R) Silver 4214 CPU (125.6 GB), accelerated by Quadro RTX 4000 graphics card. The Anaconda environment, with the Keras framework and the Tensorflow at the backend, is used to implement the model (Table 2).

Table 2. Software and hardware specifications used for the experiment

S. no.	Software and hardware specifications	
1	Operating system	Ubuntu
2	Workstation configuration	Intel Xeon (R) Silver 4214 CPU (125.6 GB)
3	Graphics card	Quadro RTX 4000
4	Environment	Anaconda
5	Framework	Keras with TensorFlow at the backend

2.4 Model Developed

Six convolutional layers, five Max Pooling layers, and two fully linked layers make up the neural network architecture. Previously, we downsized all of the photos for our network to 256 * 256 pixels, and rescaled images with a dimension of 256 * 256 were sent to the network. The size of the filter utilised is 3 * 3. To achieve non-linearity, we employed a rectified linear unit (ReLU) after the convolution layer.The first convolutional layer has 16 filters, the second has 20, and so on, with the number of filters increasing layer by layer. There are no paddings in any of the convolutional layers. We employed 128 neurons in the first completely linked layer. Before being supplied to a fully linked layer, the data is flattened. After each convolutional layer, a max-pooling layer decreases the dimensionality, and a 20% drop-out prevents the model from over-fitting. A sigmoid activation function is used in the last fully connected layer to generate probability distributions for each of the four classes. The batch size for training data is set to 20 and the epoch count was set to 40. The model compilation consists of the Adamax optimizer and Sparse Categorical Crossentropy loss, to handle the imbalanced number of pixels for each class. The learning rate was set to 0.001. The total number of trained parameters is 631,228. All the hyperparameters are mentioned in Table 3.

Table 3. Hyperparameters used in the experiment

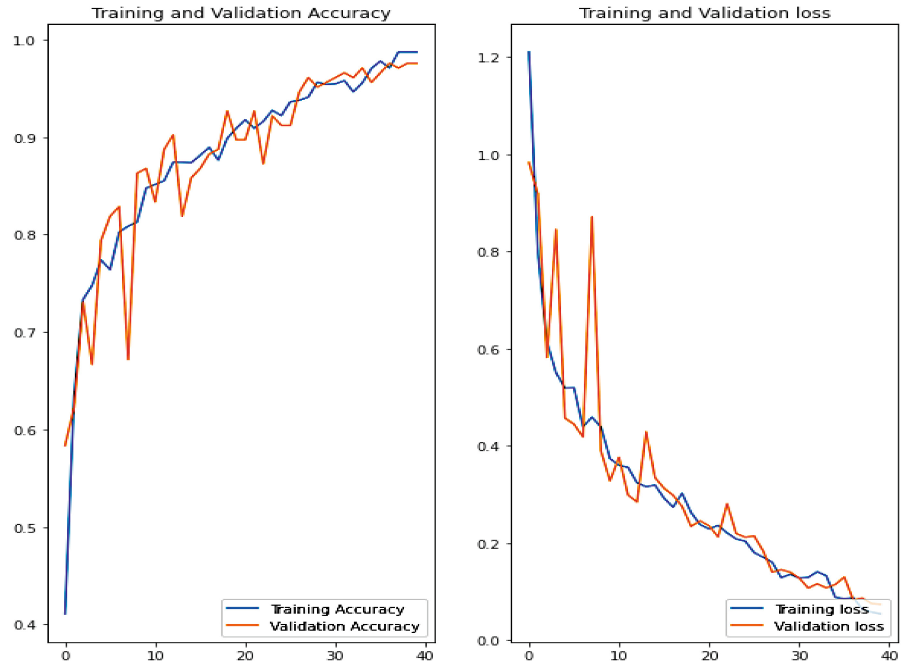
S. no.	Hyperparameters	Value
1	Filter size	3 * 3
2	Batch size	20
3	Epochs	40
4	Optimizer	Adamax
5	Loss	Sparse categorical crossentropy
6	Learning rate	0.001
7	Dropout	20%
8	Padding	0

3 Results and Discussion

A batch size of 20 was set for the model, which was trained on 40 epochs. The training accuracy at 40 epochs is 98.41% and validation accuracy is 97.55%. The number of iterations per epoch is 93. We trained our model from scratch. The test data consist of 541 images from the different classes. In model testing, we observed that the overall average model testing accuracy was 96.42%. Therefore, it can conclude that model has the potential for performing real-time diagnosis for plant disease severity based on these four stages.

Therefore, in Fig. 4(a) and Fig. 4(b), it is clear to see from the above curves that the model has been well trained. It can conclude that it is a good fit model because training loss decreases to a point of stability and a slight difference between the train and validation loss learning curves is observed.

The confusion Matrix for four different classes is shown in Fig. 5. It can be observed that 5 healthy stage images out of 145 were misclassified as early-stage disease. Similarly,



(a) *(b)*

Fig. 4. (a) Training accuracy vs. validation accuracy. (b) Training loss vs. validation loss

9 images of early-stage disease out of 156 were misclassified as middle stage and healthy stage. It can be noticed further that 4 middle stage out of 142 and two end stage images out of 98 were not correctly classified as the true class.

True Class \ Predicted Class	Healthy Stage	Early Stage	Middle Stage	End Stage
Healthy Stage	140	1		
Early Stage	5	147	3	
Middle Stage		8	138	2
End Stage			1	96

Fig. 5. Confusion matrix for four classes

4 Conclusion

This study proposes a novel network for diagnosing plant diseases and estimating severity of wheat stem rust. It creates an end-to-end pipeline for diagnosing the severity of plant disease by automatically discovering discriminative characteristics for fine-grained categorization. The developed model outperforms, with a test set accuracy of 96.42%, proving that deep learning is a promising new technology for fully automatic classification of plant disease severity. Therefore, the presented framework is a viable candidate for use in a portable device that can diagnose crop diseases in real time. In the future, more images of various diseases at different severity levels can be collected to increase model accuracy. Additionally, after the model has been trained, it must be evaluated on images from a variety of sources in order to gain a better understanding of the model's actual utility. A precise estimation of disease severity could lead to the proper application of pesticides in the fields. Hyperspectral imaging combined with deep learning may be a promising method for early prediction, reducing the use of pesticides on crops significantly. The deep learning model can be used to forecast yields, make treatment recommendations, and so on. Moreover, the development of a mobile application for plant disease severity estimation could profit the farmers to overcome the technology barrier present and crop loss. The authors anticipate that the proposed framework would be enhanced to make a remarkable contribution to agricultural sciences.

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