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Automating yellow rust disease identification in wheat using artificial intelligence

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ABSTRACT

Plant disease has long been one of the major threats to world food security due to reduction in the crop yield and quality. Accurate and precise diagnosis of plant diseases has been a significant challenge. Cost-effective automated computational systems for disease diagnosis would facilitate advancements in agriculture. The objective of this paper is to explore computer vision based Artificial Intelligence method for automating the identification of yellow rust disease and improve the accuracy of plant disease identification. The dataset of 2000 images of wheat leaf were collected in the real life experimental conditions of ICAR-Indian Agricultural Research Institute, New Delhi in the crop season during January-April, 2019. Based on our experiment, we propose a deep learning-based approach to detect healthy leaves and yellow rust infected leaves in the wheat crop. The experiments are implemented in python with PyCharm IDE, utilizing the Keras deep learning library backend with TensorFlow. The proposed model achieves 97.3% testing accuracy and 98.42% as the training accuracy. The accuracy of the developed model can be improved further by training it with larger size of the dataset in future. In future, accuracy of computer vision based AI models can be improved by using the larger size training datasets. Also, these models can be used for providing automatic advisory services to the farmers, thereby, adding much needed assistance to the overloaded extension experts.

Keywords: Artificial Intelligence, Automated plant disease identification, Computer vision, Deep learning, Image processing, Wheat rust

In India, wheat has a significant share in consumption of food basket with a share of 36% in the total food grains produced in India. Wheat rusts have been the most important biotic stresses responsible for unstable crop production. Wheat crop has three types of rusts named as yellow rust, leaf rust, and stem rust. Yellow rust has the higher abundance compared with the other two types, and responsible for significant yield reduction (Vaibhav *et al.* 2017). The preventive action is required for early detection of the plant diseases. Identification of plant diseases from experts is laborious task, challenging, time consuming, less accurate, and can be done only in limited areas. Thus, there is a need of automated models for identifying plant diseases that will take less time and efforts with higher accuracy (Mohanty *et al.* 2016, Yang and Guo 2017).

In the last decade, AI and ML technologies have attained a remarkable interest with the availability of high-performance computing processors and devices (Lee *et al.* 2015, Patricio and Rieder 2018, Hungilo *et al.* 2019). Yang and Guo (2017) highlighted that machine learning domain creates new opportunities in the agriculture with their improved sensitivity towards plant disease detection and forewarning of crop disease. For example, decision tree (Jain *et al.* 2009) artificial neural network (Bashish *et al.* 2010), support vector machine (Rumpf *et al.* 2010, Mokhtar *et al.* 2015) and, k-nearest neighbours (He *et al.* 2017). However, machine learning techniques and image-processing techniques are only successful under limited and constrained systems. Kamilaris and Boldu (2018) reviewed and studied the comparison of existing popular image processing and machine learning techniques with another subset of Artificial Intelligence that is Deep Learning (DL) which has gain momentum in recent years. The findings indicate that deep learning provides high accuracy and outperforms commonly used image processing techniques (Schmidhuber 2015, LeCun *et al.* 2015). Therefore, in this paper, authors emphasize on the potential of deep learning particularly on the Convolutional Neural Network (CNN), for developing a model for plant disease identification.

MATERIALS AND METHODS

In this study, 2000 images of wheat plant leaves were

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Table 1 Dataset and hardware/software specifications

Dataset		Hardware/Software Specifications	
Image dataset	Wheat rust	Operating system	Ubuntu
Location	ICAR-Indian Agricultural Research Institute, New Delhi	Processor	Intel Core i7-3930 CPU @ 3.60GHz
Time period	January to April, 2019	Memory	32 GB
Devices used	Canon digital camera, One Plus 6T phone	Graphics	NVIDIA GeForce GT 360
Images	2000	Environment	Anaconda With Keras
Classes	Two (Yellow rust, Healthy leaves)	IDE	Pycharm

collected to develop AI-based model for wheat disease classification. The authors have created a dataset of 2000 images that consist of healthy leaves (1000 images), yellow rust infected leaves (1000 images) (Table 1). The dataset is further divided into training (1600 images), testing (200 images) and validation set (200 images). The split ratio for these sets is 80:10:10. As a part of image pre-processing, images were resized into 256*256 pixels to maintain the homogeneity among the images with the python code. The dataset and Hardware specifications adopted for this study are presented in Table 1. These images were captured keeping in mind the different sizes, orientations, and backgrounds. In the case study, Keras and Tensorflow are used as open-source libraries for deep learning. The Graphical Processing Units facilitates the execution of the deep learning algorithms faster as compared to CPUs. Further, PyCharm is used as the python IDE for the programming interface. The main objective was to evaluate the model performance for unseen images of rust infected leaves.

AI methods for Plant Disease Identification: Most recent and advanced algorithm for plant disease identification is Deep learning. The basic steps involved in plant disease identification involves four phases namely image acquisition, image pre-processing, features extraction, and classification (Nigam and Jain 2020). In Image acquisition, the acquired images are converted to the preferred output format for further processing. The procedure of image pre-processing aims at highlighting the region of interest (disease infected area) in plant leaves (Picon *et al.* 2018). Image pre-processing commonly involves image segmentation, image enhancement and color space conversion (Lu *et al.* 2017). The last phase of plant disease identification is a classification where classification model is implemented to identify the existing plant disease in predefined classes (Cruz *et al.* 2017). Deep learning algorithms have shown their strength in automatic feature extraction from images (Sladojevic *et al.* 2016, Ferentinos 2018, Kamilaris and Boldu 2018, Ramcharan *et al.* 2019). Several authors experimented with the different implementation of deep learning in agriculture domain for identification of plant diseases and identified the convolution neural network (CNN)'s performance is better as compared to other algorithms for automatic identification of disease (Barbedo 2018, Too *et al.* 2019, Nigam and Jain 2020).

Convolutional Neural Networks (CNN): CNN involves a smaller number of parameters which does not require much human supervision. It consists of three layers: convolution layer, pooling layer, and fully connected layers with two components: feature extraction and classification (Jadhav *et al.* 2020). The convolution layer and pooling layers perform the feature extraction from the input images, whereas fully-connected layers have their role in classification of the images into pre-defined classes (Boulent *et al.* 2019). The different layers involved in CNN are explained below:

Convolution layer: This layer extracts features automatically from the each input image. It basically consists of a set of learnable filters and learns the relationship between features using kernel or filters to produce a feature map. Each learnable filter is applied to the raw pixel values of the image in a sliding window manner, computes the dot product between the filtered and input pixel. This results in a two-dimensional activation map known as a feature map. The values of these filters are learnt by the CNN during the process of training. Rectified Linear Unit (ReLU) is a

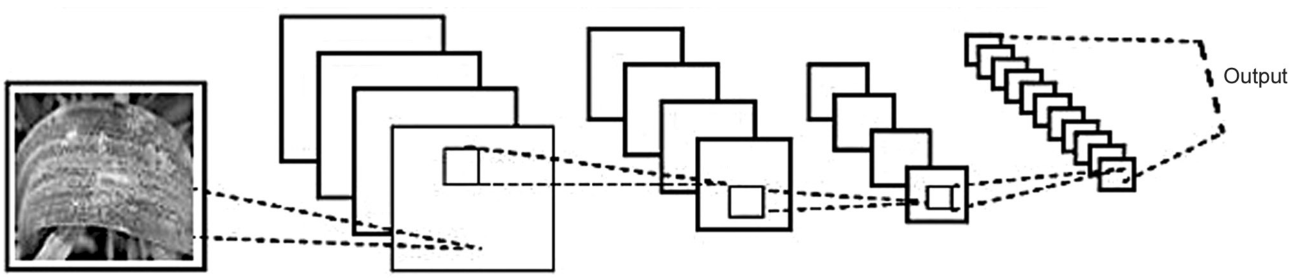

Fig 1 Convolution Neural Network Architecture.

activation function having output as $f(x) = \max(0, x)$ used to introduce the non-linearity in the CNN model.

Pooling layer: This layer reduces the size of convolution maps by down-sampling which decreases the training time and combats overfitting by retaining only the valuable information to process further. Max pooling is a commonly used pooling type, which takes the max value in the pooling window, whereas a mean value is taken in case of average and sum pooling. The output is given in the form of the maximum activation value and hence reduces the dimensionality of the feature.

Fully connected layer: Final Pooling layer output (3D matrix) is flattened into a one-dimensional vector and that becomes the input to the fully connected layer. These features are then combined to create a model. In the end, SoftMax or sigmoid activation function computes the pre-defined class scores and classifies image into a predefined class.

Parameters and hyperparameters in CNN Model: CNN parameters are the configuration variables whose value can be estimated from the data, whereas variables of hyperparameters determine the network structure of a model. These are decided before the training of the network. Hyperparameters related to a network structure are as follows.

Batch and batch size: It is the total amount of training examples present in a single set. Batch size is the number of subsamples given to the network for parameter updates. The optimum size is determined based on experiments (Fig 1).

Epochs: It refers to the times the training data is given to the network while training the model. Even though the training accuracy is increasing on increasing epochs, but at some point the validation accuracy starts decreasing. At that point, more epochs will lead to overfitting of model.

Hidden layers and units: Middle layers present between the input and the output layer. Layers can be added until the test error improves.

Activation function: It introduces the non-linearity in a model, which allows the learning of nonlinear prediction boundaries. SoftMax is used more often in the output layer while making multi-class predictions.

Learning rate: It defined as the speed of a network of updating its parameters while learning in a model. Usually, a decaying learning rate is mostly preferred.

Momentum: It gives the information about the next step direction with the help of prior knowledge about previous steps and prevents oscillations. A momentum of 0.5–0.9 is generally chooses while training a model.

RESULTS AND DISCUSSION

The hyperparameters are empirically determined as per the multiple experiments conducted on the author's own image dataset according to the best results obtained for wheat disease identification. Root Mean Square Propagation (RMSprop) optimizer was used as it learns the appropriate set of weights and biases of the network and minimizes the loss function, eg. Learning rate of 0.01 means weights in the network are updated (0.01* estimated error) each time. Here, binary cross-entropy loss function is used for training binary classifiers. Another concept of most important hyperparameters in networks is batch size and epochs. Larger batch size leads to faster training and develops a well-generalized model on the unseen data. However, larger batch size depends on the computational power of the machine that is machine would be able to process the large batch of input data without crashing. The smaller batch size makes the learning slower and not less accurate. As per our experimental setup, the optimal batch size selected is 20 according to our machine and data (Fig 2).

The sigmoid activation function performs the non-linear transformation to the input which makes it learn and perform more complex features efficiently. Next, the experiment was conducted by varying the images in a dataset. It is observed that accuracy improves and time is taken for the training also rises as number of images increases. With maximum available images in the dataset, the training accuracy was 98.42% (Table 2) and 97.3% as

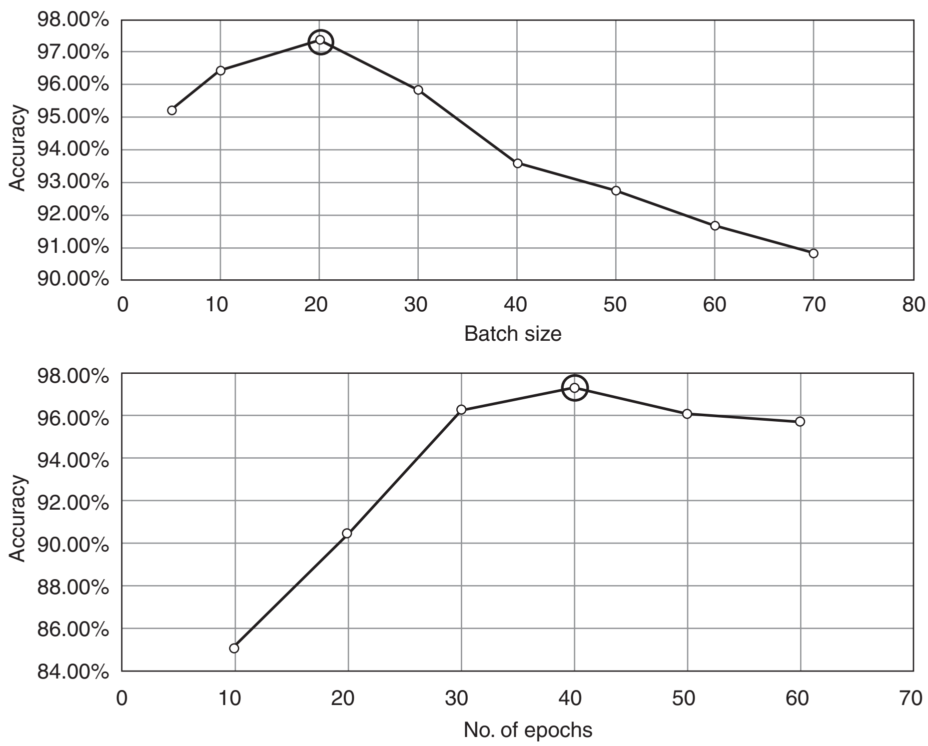

Fig 2 Variation of Accuracy with respect to batch size and epochs size.

Table 2 Training time and accuracy varies with number of images used for training

No. of images	Time (s/epochs)	Accuracy (%)
100	186	76.0
200	275	77.5
500	394	83.3
1000	498	90.2
1500	761	93.6
2000	1524	98.42

the testing accuracy was obtained. Figure 2 illustrates that a further increase in accuracy is not ruled out by increasing the number of images for training and using higher and better specifications of hardware.

As per the Kamilaris and Boldú (2018) and Nigam and Jain 2020 the performance for CNN in image classification and plant disease identification varies from 90–99% accuracy for different crops. Therefore, authors claim their model performance for wheat crop better because less work has been reported for wheat crop disease identification specifically.

Large datasets with advanced model can motivate more researchers to experiment with deep learning, applying it for solving various agricultural problems involving classification or prediction, related to image processing. The study of the presented works and the problems that they set out to solve together with the new advances in computer vision and artificial intelligence can lead to new solutions for agriculture bringing gains of production, quality, and food security. This paper presents an automated, low cost and easy to use end-to-end solution to one of the biggest challenges in the agricultural domain for farmers–precise, instant and early diagnosis of crop diseases and knowledge of disease outbreaks - which would be helpful in quick decision making for measures to be adopted for disease control.

A sophisticated Artificial Intelligence based technique for image processing is needed for plant disease identification. Among other state of art techniques, Deep Learning technique shows higher accuracy. The proposed model achieves training accuracy of 98.42% and testing accuracy as 97.3%. The experimental result also reflects that to improve the accuracy, expanding the dataset would help in improving the generalization ability of the developed model. The presented model is also computationally efficient and simple. The results presented could be further extended to the development of a mobile application-based on wheat rust disease identification. Authors are confident that present work will be an inspiration for the disease identification area for wheat crop. Moreover, the study can be implemented in the more diverse situations and conditions. The work has the scope to be implemented with portable mobile device so that farmers can easily identify the crop disease at the early stage.

In future work, number of crop diseases can be increased for model implementation. Further, the model can be associated with the mobile based advisories for farmers involving information about treatment recommendation, control measures and yield prediction.

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