Chapter

Rust Disease Classification Using Deep Learning Based Algorithm: The Case of Wheat

Shivani Sood, Harjeet Singh and Suruchi Jindal

Abstract

Rusts are plant diseases caused by obligate fungi parasites. They are usually host-specific and cause greater losses of yields in crops, trees, and ornamental plants. Wheat is a staple food crop bearing losses specifically due to three species of rust fungi namely leaf rust (*Puccinia triticina*), stem rust (*Puccinia graminis*), and yellow rust (*Puccinia striiformis*). These diseases are usually inspected manually by a human being but at a large scale, this process is labor-intensive, time-consuming, and prone to human errors. Therefore, there is a need for an effective and efficient system that helps in the identification and classification of these diseases at early stages. In the present study, a deep learning-based CNN (i.e., VGG16) transfer learning model has been utilized for wheat disease classification on the CGIAR image dataset, containing two classes of wheat rust disease (leaf rust and stem rust), and one class of healthy wheat images. The deep learning models produced the best results by tuning the various hyper-parameters such as batch size, number of epochs, and learning rate. The proposed model has reported the best classification accuracy rate of 99.54% on 80 epochs using an initial learning rate from 0.01 and decayed to 0.0001.

Keywords: food security, plant disease detection, wheat rust disease, deep learning, convolutional neural networks

1. Introduction

Rust diseases are the fungal diseases of plants, mainly grasses, caused by fungi. They affect the aerial plant parts especially leaves but can also attack stems and even flowers and fruits. They bear complex life cycles that require two alternative unrelated hosts. Rusts produce spore pustules which vary in color according to the rust species. About 7000 rust species are known to affect a variety of host plants globally. They can cause a wide range of symptoms depending upon the host species like the formation of Galls or swellings on the branches, formation of Canker on the trunks, and formation of Spores on the surface of the leaf. Leaf rust is also known as bown rust due to the brown color of circular urediniospores on the surfaces of the leaf of the crop. Yellow rust or stripe rust is characterized by the yellow color of stripes on the surfaces of the leaf. Stem rust is also brown and characterized by the patches of brown color on the surface of stems. Many approaches are being deployed to combat the problem of these diseases which involves accurate phenotyping which means characterization of the diseases at field level followed by genotyping to find out the genes responsible for its cause. Many germplasm resources are being explored and screened by scientists worldwide to find new sources of resistance. Precision phenotyping is the key requirement to achieve the goals. So far there are manual interventions involved to screen these diseases. But manual scoring of these diseases is a cumbersome job in large pre-breeding and breeding programs. Therefore, there is a strong need for high precision phenomics which involves imaging using high-quality cameras or equipment followed by image analysis using newly developed software and tools. In today's era of artificial intelligence, it is possible to explore high-end phenomics to achieve better yields of important crops like wheat. Many machine learning and deep learning models have been tested and tried to analyze and characterize wheat fungal diseases [1–4]. One of the main reasons for the popularity of these techniques is the use of GPUs (graphics processing units). The classification tools, computer vision, and GPUs are combined in a single framework called deep learning [5]. Deep learning-based models have been used in the various applications of agriculture for end-to-end learning. With the use of GPUs, deep learning can give a better solution to the given problem in a shorter time [6]. The process of building such models is computationally challenging but using GPU power becomes very easy [7, 8]. Fungal diseases have been identified using image processing techniques on different horticulture and agriculture crops. Various feature extraction and classification algorithm have been used to detect the different types of fruits, vegetables, and cereal crops.

Among the various rust diseases, soybean-, coffee-, and wheat-rusts are the most damaging diseases. Therefore, the constant efforts are being done worldwide, to combat this problem. Wheat is one of the staple food crops in addition to rice and maize. The total area under wheat in the world is around 220 million hectares with a production of 772.64 million metric tons (2020–2021). Wheat rusts especially leaf rust, stem rust, and yellow rusts are major fungal diseases that affect the production of the wheat crop throughout the world particularly in South Asian countries [9]. As per the prediction of the Food and Agricultural Organization (FAO) of the United Nations, wheat production might not be fulfilled the requirement in near future due to rapid population growth [10, 11]. In this chapter we discuss the usefulness of deep learning-based algorithms to identify rust using wheat as a case study.

2. Computer vision approaches for plant disease identification

Human perception is based on the interaction between the brain and the eye. On the other hand, computer vision system (CVS) is used to emulate human vision for gathering information without physical interaction [12, 13].

It is also defined as the process of automatic acquisition, and analysis from image data. CVS emulates the dynamic vision system whose operation is very transparent and natural. The data is processed in various stages such as capturing, processing, and analysis of images. **Figure 1** depicts the steps involved during image processing. In the first stage, image acquisition and pre-processing are involved. The images can be acquired using high-resolution cameras and sensors. Further, the images are pre-processed through data cleaning, background removing, adding/removing noise, and also enhancing the quality of images. In the second stage, the images are segmented. The segmentation process involves extracting only important and useful information from the whole image that further helps in the discrimination of classes. In the third stage, the high-level analysis is performed in which direct emphasis is done on the recognition (objects) and interpretation (making results). In a CVS, the following attributes contribute to decision-making: shape, color, texture, and also size. **Figure 2** depicts the utilization of various

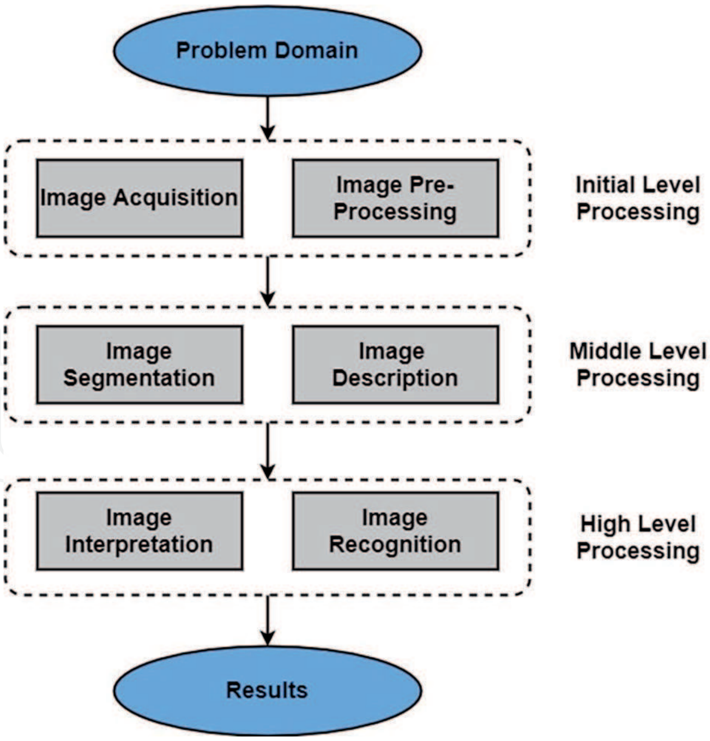

Figure 1.
Steps of image processing techniques.

artificial intelligence algorithms in plant disease detection. These algorithms are further divided into machine learning and deep learning-based classifiers. The description of these algorithms is illustrated in the coming subsections.

2.1 Machine learning based approaches

Classification is the process of dividing the dataset into different categories or groups by adding labels. Nowadays, the machine learning and deep learning approaches are performing well for classifying the algorithm images based on their category. Following are the machine learning algorithms which are used to classify plant disease and are based on supervised learning. Supervised learning is a type of learning where labels (category of images) are given along with input images.

2.1.1 k-Nearest neighbor

It is the machine learning algorithm used for classification and calculated by k-neighbors. It is mostly used in image processing, machine learning, and also for statistical estimation. This algorithm worked on the principle of calculating the distance between different data points using Euclidean distance and Manhattan distance [14, 15]. It works with the following steps: (a) getting data, (b) define k neighbors, (c) calculate the neighbor distance using Euclidean distance or Manhattan distance and (d) assign new instances to the majority of the neighbors.

2.1.2 Decision tree

It is the algorithm of machine learning which comes under supervised learning to solve regression and classification-based problems. The decision tree is the graphical representation of pre-defined rules along with the solution. The graph of the decision tree has two types of nodes: one is decision nodes and another is leaf nodes. Additionally, the edges store the information of the answers to the questions,

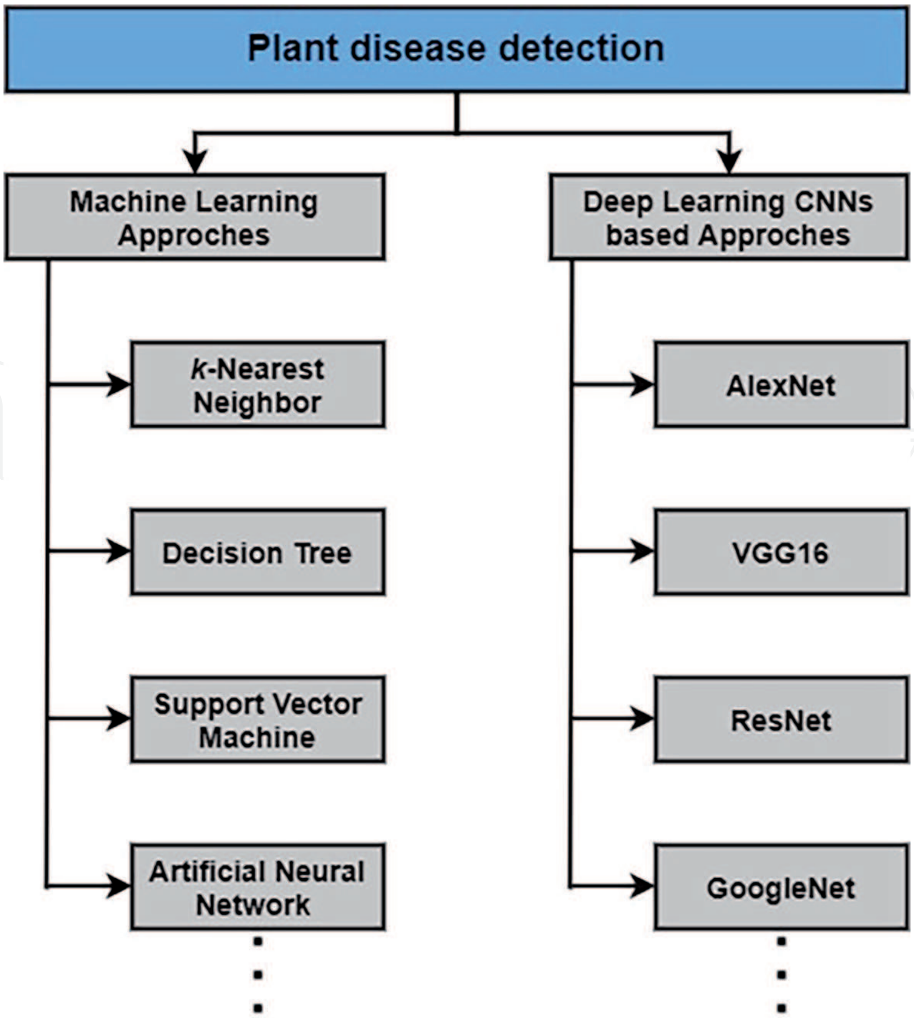

Figure 2.
Description of machine learning and deep learning algorithm used for plant disease detection.

and leaf nodes store the actual output. In Sabrol and Kumar [16], Chopda et al. [17] and Rajesh et al. [18], the authors reported appreciable results in plant disease classification and recognition.

2.1.3 Support vector machine

Support vector machine (SVM) is a very popular classifier used in statistical learning. The classifier aims to discriminate the classes from each other. In SVM, a hyperplane is used to discriminate one class from another. Those points which are close to the hyperplane are referred to as support vectors. The task of the SVM is to classify the different categories based on some features. Additionally, this algorithm performs well in extreme classes. Let us consider, color, texture, shape are some features of a particular plant. If we consider two features such as color and texture to classify diseased and healthy leaves. To classify them, the optimal decision boundary is required. Optimal decision boundaries could result in greater misclassification for the new instance. Therefore, the boundary support vectors are very important than all the training examples. This algorithm works well for linearly separating data points whereas in some cases if the data points are not linearly separable then 2-dimensional (2D) feature spaces are converted into 3-dimensional feature spaces. But the only problem is that it is computationally very expensive. In addition to that, it provides kernel function which can reduce the computational cost to convert 2D feature space to 3-dimensional feature space. Using kernel function the dot product is performed between two vectors. Especially, this is used to transform non-linear to linear transformation space. Various popular kernel functions are polynomial, radial basis, sigmoid kernels used to change 2D data to high dimensional feature space. Choosing the best kernel is a non-trivial task and is a hyper-parameter that can be selected by performing various experiments on the data. The main benefit of using SVM is that it is memory efficient and effective for high-dimensional feature space data.

2.1.4 Artificial neural networks

It is the special type of machine learning algorithm used for classification. The researchers have been working on artificial neural networks (ANNs) since the beginning of the 1980s [19]. ANNs are a special type of classification algorithm and their structure is inspired by the human brain. ANNs takes input from the external world in the form of feature vector or patterns. Each input value is multiplied by their corresponding weights that are summing with the bias value. Further, the result is mapped to the activation function (binary, sigmoid) and produced the output. Other than these algorithms, there are various algorithms available that reported appreciable results in image recognition such as Random Forest, Naive Bayes, many more. Initially, we started with the study of traditional computer vision approaches used for plant disease detection. Plant disease can be caused by fungi, bacteria, and viruses from which fungi are the common disease organism. It is the type of disease that can be formed by taking energy from plants. The fungal disease has been identified using image processing techniques on different horticulture/agriculture crops [20]. To detect the different types of fruits, vegetable, commercial, and cereal crops that have been utilized using various feature extraction and classification algorithms. They achieved appreciable classification accuracy to identify the disease from horticulture/agriculture crops. Han et al. proposed a novel technique for feature extraction using super-pixel and marker-controlled segmentation methods for the classification of yellow rust and septoria diseases. They have used SVM and ANN for these disease classifications. Their experimentation concludes that SVM classifiers outperformed well than ANN classifiers for the classification of disease [21]. Su et al. experimented with the detection of fungal yellow rust disease on wheat crops. The author collected RGB images with a high-resolution camera and there are a total of three different classes present in region of interest (RoI) as rust, healthy, and background. To monitor the yellow rust, they used the U-Net deep learning architecture and the results were compared with the Random Forest algorithm. They found that U-Net-based segmentation outperformed spectral images. In their work, the average precision of 81.06%, recall of 90.10%, and F1-score of 84.00% have been achieved to segment the disease from spectral images [22]. An application of Fuzzy C-Means clustering has been proposed as the model to identify the wheat leaf disease [23]. In their work, they extracted inter- and intra-class features and further combined them to build a model for identifying the different wheat plant diseases. Although the traditional machine learning-based techniques are performing well for image classification, still there are certain limitations such as it requires manual feature extraction and is only suitable for small datasets, which may lead to the over-fitting problem [23, 24].

2.2 Deep learning-based approaches

Convolutional neural network (CNN) is a popular neural network, designed for solving computer vision problems. The architecture of CNNs is shown in **Figure 3**.

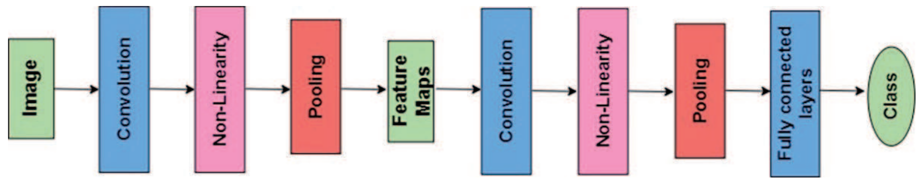

Figure 3.
The basic architecture of CNNs.

The images are represented in the form of pixel values. In the convolution layers, the operation of convolution is performed i.e., the kernel is slide over the input image after choosing the padding and stride values at each layer. Thereafter, the power of non-linearity is to give the non-linear mapping with the input images in such a way that after the non-linear mapping it becomes linearly separable. ReLU activation function is used to change all the negative values to positive values. With this, the pooling layer is used to down sample the different feature maps for getting the most prominent features i.e., the convolution layer performs these triplet operations like convolution followed by ReLU and ReLU followed by pooling one after another. These triplets operations are typically stacked one after another and also based on these triplets, the depth of the neural network has been defined. After these layers, the network is followed by one or more fully connected layers which are responsible for classification.

To build the CNN model, all the above-mentioned parameters play a very important role. To build the custom CNN model, the numbers of convolution layers, max-pool layer, number of filter values, filter size, stride, padding, number of fully connected layers need to be specified. Increasing the number of convolution layers will produce different feature maps and also increasing the fully-connected layers increase the training time of the model. Although, the custom CNN model reported appreciable accuracy. The process of creating a custom CNN model takes more time. Therefore, the concept of transfer learning comes into the picture. Transfer learning is a concept of deep learning where the weights of pre-trained models are reused for a new problem. Every year, there is a competition held on the ImageNet dataset. Many researchers developed new models to classify the different objects of the ImageNet dataset and reported good classification accuracy and reduced error rate. There are variants of transfer learning models such as ResNet, GoogleNet, and EfficientNet varied in terms of the number of layers, filter size, number of filters used, stride, padding, and so on. Some of the few models are elaborated as given below:

AlexNet: AlexNet model is a transfer learning model which is based on CNN's and is proposed by Alex Krizhevsky for classifying the different objects of ImageNet Large Scale Visual Recognition Challenge (ILSVRV). Training can be performed on hundreds of epochs. GPUs are the game-changer in deep learning. Using GPUs, the model will train in very little time and with less effort. AlexNet is the eight-layer network that has a further five convolution layers, and three fully-connected layers including the output layer. It used the ReLU activation function instead of the sigmoid function. In this model, the initial layers used variant sizes of kernels i.e., 11×11, 5×5, and 3×3 to get different features maps as an output. Thereafter, fully-connected layers are used to train the model based on the extracted features.

VGG16: Visual geometry group (VGG) model is the first runner-up of the ImageNet dataset in 2014. It has 13 convolution layers, 5 max-pool layers, and 3 FC layers. The output layer used the softmax activation to classify the 1000 different objects. VGG16 model is different from the AlexNet model in terms of kernel size and the number of layers. VGG16 model used the same kernel size whereas the AlexNet model used the different kernel size. Additionally, the VGG16 model is 16-layered but the AlexNet model is 8-layered architecture. In the present study, the VGG16 model has been utilized to classify the wheat rust diseases and the elaboration is given in Section 3.2.

Modern deep learning architectures are significantly popular to solve agriculture-related problems. Sladojevic et al. developed a CNNs based model for plant disease classification. The model recognized 13 different types of plants. In their work, they used 30,880 images in the training and 2589 images for validation and reported a classification accuracy of 96.30% [25]. Zhang et al. proposed a deep learning model for the detection of rust disease of wheat crop from hyperspectral images. In their work, they automate the process of detecting yellow rust-captured images from unmanned aerial vehicle (UAV). Yellow rust is a fungal disease that can cause 100% loss for the wheat crop. The author used the Inception-ResNet model for feature extraction and reported the highest accuracy of 85.00% when compared with the random forest that was 77.00% [26]. A deep learning model has been built for grading wheat stripe rust disease [27]. In their work, they used different mobile devices to capture images and build their dataset, referred WSRgrading. It contained 5242 wheat leaf images at six different levels. They build and proposed the model by adding an attention layer in the pre-trained DenseNet model and build a new model named as C-DenseNet which has been reported a good classification accuracy of 97.99%. Genaev et al. classify the rust disease from the wheat crop. In their work, they used the CGIAR dataset, containing three classes (healthy wheat, leaf rust, and stem rust). They implemented the DenseNet transfer learning model and reported the F1-score and AUC of 0.90 and 0.98, respectively [28]. Jia et al. in proposed the model for detection and segmentation of fruit features for optimal harvesting of apples using Mask R-CNN. ResNet model was used as the backbone of this network. The model was tested on 120 images and reported precision and recall rates of 97.31% and 95.70%, respectively [29]. The shortage of the wheat disease dataset motivated the researchers to create the dataset which should be publicly available for all [30]. They are motivated to collect more data that will help the research community for conducting the research competitions on wheat diseases classification. Finally, they attempted to prepare their WFD2020 dataset which contains 2414 images. They performed their experiments using the EfficientNet CNN-based model and reported 94.20% classification accuracy.

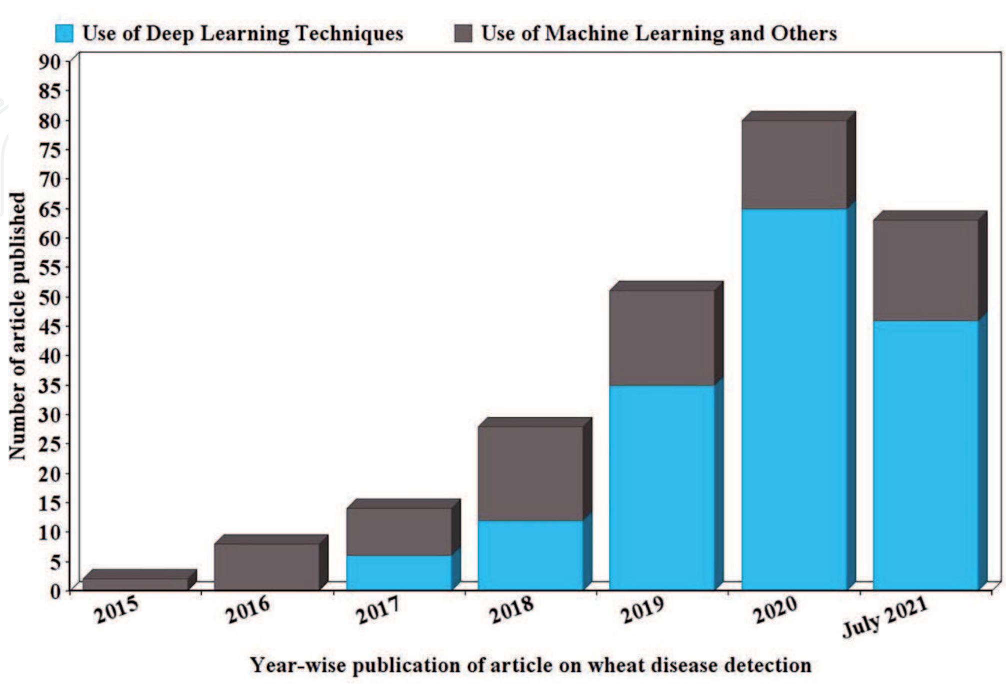

Figure 4.
Year-wise statistics publication of wheat disease detection.

In the recent decade, deep learning techniques are highly utilized for image processing. Deep learning models are producing appreciable results than machine learning methods [31]. **Figure 4** depicts the utilization of computer vision approaches (i.e., old machine learning methods and modern deep learning approaches) for the wheat crop. These statistics have been built based on work done from the period (2015 to July 2021) for classifying most of the wheat crop diseases. Deep learning approaches include CNN-based architecture such as VGG16, ResNet, Faster R-CNN, and so on. In different circumstances, the traditional machine learning approaches include SVM, Random Forest, and so on. The analysis concludes that the modern deep learning architectures have been utilized more for classifying most of the wheat crops diseases as compared to traditional machine learning approaches.

3. Classification of wheat rust disease

3.1 Dataset description

There are standard datasets that are publicly available for research experimentation in the computer vision and image processing domain, such as PASCAL VOC [32], ImageNet [33], IMDB-Wiki [34], CIFAR [35], and PlantVillage [36]. CGIAR dataset is one of the dataset publicly available on https://www.kaggle.com/shadabhussain/cgiar-computer-vision-for-crop-disease [37]. This dataset was further distributed in three different classes of wheat rust i.e., healthy wheat, leaf rust, and stem rust. A sample of each class is shown in **Figure 5**. Most of the images in this dataset were collected by CIMMYT and its partners from Ethiopia and Tanzania. Additionally, a few images were sourced from the Google image database. The images in this dataset have the specific characteristics like (i) all are colored (ii) mixed format, (iii) different orientation, (iv) variable quality, and captured with different resolutions. The datasets are already classified into two categories i.e., 876 images and 610 images for training and testing, respectively. From the training dataset (i.e., 876 images) a total of 863 images have been filtered and considered for training the model. In the present study, the 863 images dataset was further split for training and validation in the ratio of 3:1 (i.e., 75% data in training and 25% into validation). **Table 1** describes the class-wise distribution of this dataset. It is a challenging task to build an efficient model that is capable to classify all three classes of images accurately.

3.2 Methodologies used for training the model

Deep learning is a popular methodology used for image processing. In deep learning models, features are extracted automatically and little human intervention is required to train the model. Deep learning models are quite efficient to discover the internal structure or patterns of high-dimensional data. However, directly

Figure 5.
Sampled images of (a) healthy wheat plant, (b) leaf rust, and (c) stem rust.

Class label	Images	Training set	Validation set
Healthy wheat	142	105	36
Leaf rust	345	258	86
Stem rust	376	283	95
Total images	863	646	217

Table 1.
Class-wise distribution of image dataset.

processing the original images leads to inappropriate recognition results, therefore, it is necessary to pre-process the images before feeding them to the model. Pre-processing involves e.g. resizing, enhancing, or removing noise of the input images. It is worth mentioning that CNNs perform better for image recognition and classification. There are various transfer learning models which are based on CNNs like AlexNet, VGG16, GoogleNet, and Inception V3, that are pre-trained on the ImageNet dataset. ImageNet is the standard dataset that contains 1000 different categories of objects. CNN's based transfer learning models reported appreciable results to classify 1000 different objects present in the ImageNet dataset. In the present study, the VGG16 model has been utilized and the architecture is depicted in **Figure 6**. This model is the composition of 16-layers (13 convolution layers, and 3 fully connected layers). In this model, the images are processed in standard size i.e., 224 × 224. The reason for resizing the fixed image size is to extract the uniform or equal feature maps at the end of the convolution process. This model used a fixed size of kernel i.e., 3 × 3. Sometimes, the kernel is referred to as a filter that is responsible for extracting features from the given images. These extracted patterns or features might be horizontal edges, vertical edges, and a combination of both. Initially, a convolution process has been performed to extract the features, and thereafter the classification is done. In the convolution operation, the kernel/filter is sliding over the image starting from the top left to the bottom right corner to extract the features.

The movement of the kernel is either pixel-wise or by skipping some pixels using stride values. If the stride value is 1 then the movement of the kernel is shifted by one pixel after another and if the stride value is 2, then the movement of the kernel is shifted by two-pixel values during the operation of convolution. The convolution layers are used to identify the pattern or features from the images which further help in discriminating the classes. The initial layers extract the general features like edges and the subsequent layers extract the domain-specific features. Each convolution block is followed by the max-pool layer which is used for down-sampling the feature maps. In this process, the dimensionality of the image is reduced by

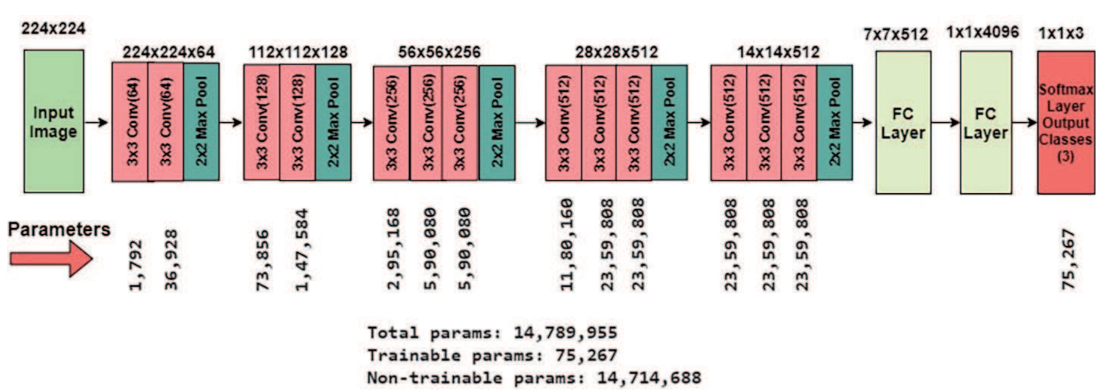

Figure 6.
The architecture of VGG16 for wheat rust disease detection.

retaining the most prominent feature. At the end of the convolution layers, different feature maps are generated as an output. These feature maps are further flattened and mapped with a fully connected layer in the classification module. Here, the model has a feature vector of size 4096 neurons also referred to as dense layer. This feature vector is further passed to the next dense layer of the same size. Finally, the last layer neurons are fully connected to the output neurons by using the soft-max activation function. However, in the current study, we considered the three classes classification problem. Therefore, the output layer changed to three classes using the soft-max probability function. The actual learning starts from data using forward and backward passes. In the forward pass, input neurons are multiplied with the weight values and also apply the activation function as ReLU. ReLU activation function adds non-linearity to the model i.e., all the negative pixel-values become positive after passing through it. On the other hand, in backward pass back-propagation is used to minimize the loss value. In this process, weights and biases are getting updated from the last to the initial layer by calculating the gradients at each layer using a convolution operator.

To summarize this model, the important and noticeable point is that this model has a total of 14,789,955 parameters but 75,267 are trainable parameters and the rest are non-trainable, the reason is that using transfer learning, the already trained weights have been used during building the model. Therefore, the model is trained in less time with fewer number parameters.

3.3 Hyper-parameter tuning

Hyper-parameter tuning is the backbone of any deep learning model. Finding the best parameters is a very tedious task, it needs many experiments to be performed while building the model. Hyper-parameters include learning rate, batch size, loss function, number of epochs, and optimizer is usually considered for tuning the model. To build the classification model for three classes each hyper-parameter is considered within a specific range. In this way, several experiments have been performed to build an efficient model. After performing some experiments with the variation in the given hyper-parameters, it was concluded that model accuracy is highly dependent on the batch size, learning rate, number of epochs, and size of the dataset. In the present study, the following hyper-parameters has been utilized: *batch size = 10*, *optimizer = Adam*, *loss function = categorical cross-entropy*, *initial learning rate = 0.01*, *decay learning rate = 0.0001*, *epochs = 80*. Using these parameters, the model produced good classification accuracy.

4. Experimental results

4.1 Accuracy and loss results

As discussed in Section 3.1 image dataset of wheat disease classification has been utilized to train the model. We used the online google colab platform with GPU support. Among the performed experiments, we discuss the best one, which produces the highest training accuracy. **Table 2** illustrates the training and validation accuracies obtained at different epochs (varied from 10 to 90) along with their loss values. Here, the training accuracy starts with 81.42% on 10 epochs and ends up with 99.54% on 80 epochs. We continued to compute the accuracy for the 90 epochs also but did not get any significant improvement in training accuracy. Although more experiments could be performed by increasing the number of epochs, the accuracy obtained at epoch 80 was quite promising. On the other hand, the validation

Epochs	Training accuracy (in %)	Validation accuracy (in %)	Training loss	Validation loss
10	81.42	74.76	0.50	0.65
20	91.02	79.05	0.33	0.61
30	95.05	77.14	0.22	0.61
40	96.59	78.10	0.18	0.61
50	97.06	76.67	0.15	0.56
60	97.99	78.10	0.12	0.56
70	98.61	74.29	0.09	0.66
80	99.54	77.14	0.07	0.74
90	99.23	74.76	0.08	0.82

Table 2.
Comparison of training accuracy, validation accuracy, and training loss, and validation loss at different epochs.

accuracy fluctuating between 74.76% and 79.05% at different epochs, as shown in **Figure 7**. Similarly, it was observed that the training loss decreases at every increasing step of the epoch (from 10 to 80). Beyond that, the loss has started to increase. In contrast, the validation loss is fluctuating between 0.60 and 0.65 up to 40 epochs. Then, after 70 epochs it starts increasing rapidly (**Figure 8**).

4.2 Model evaluation

To test the performance of the trained model, we performed the test experiments on the validation data (i.e., 25% of the total dataset). In this way, a total of 36 sample images of healthy leaf, 87 sample images of leaf rust, and 94 sample images of stem rust have been considered. The evaluation of the testing results was done

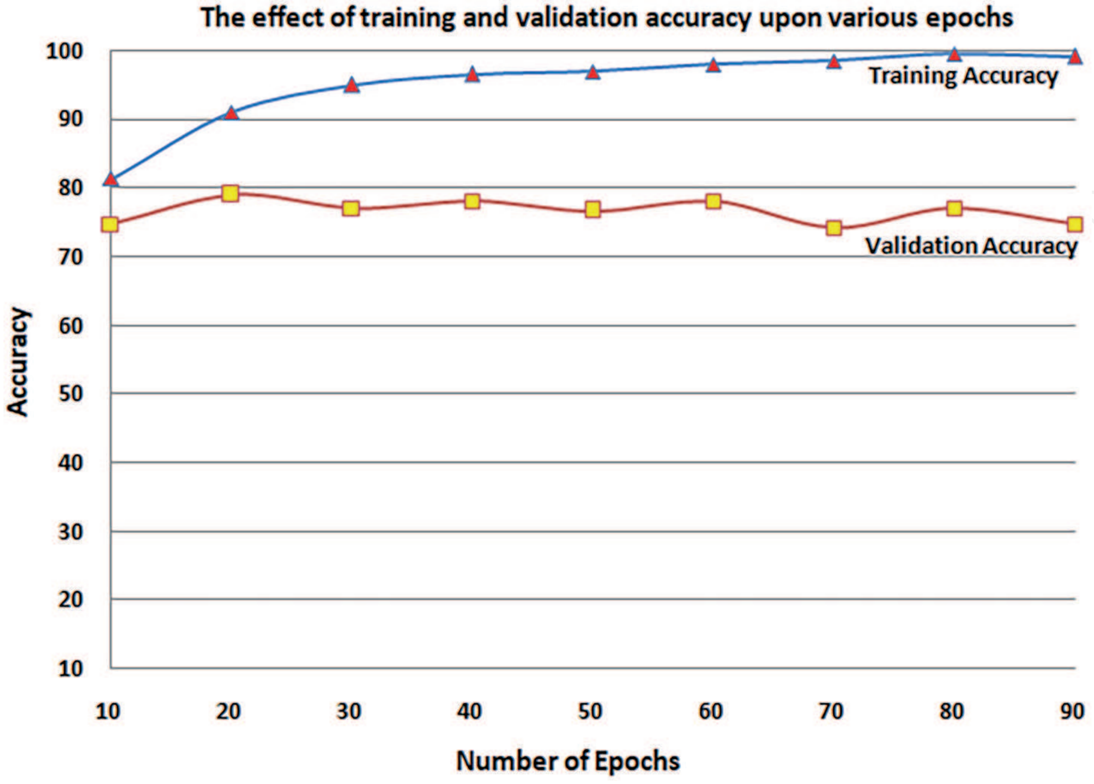

Figure 7.
Representation of the comparison of training and validation accuracy.

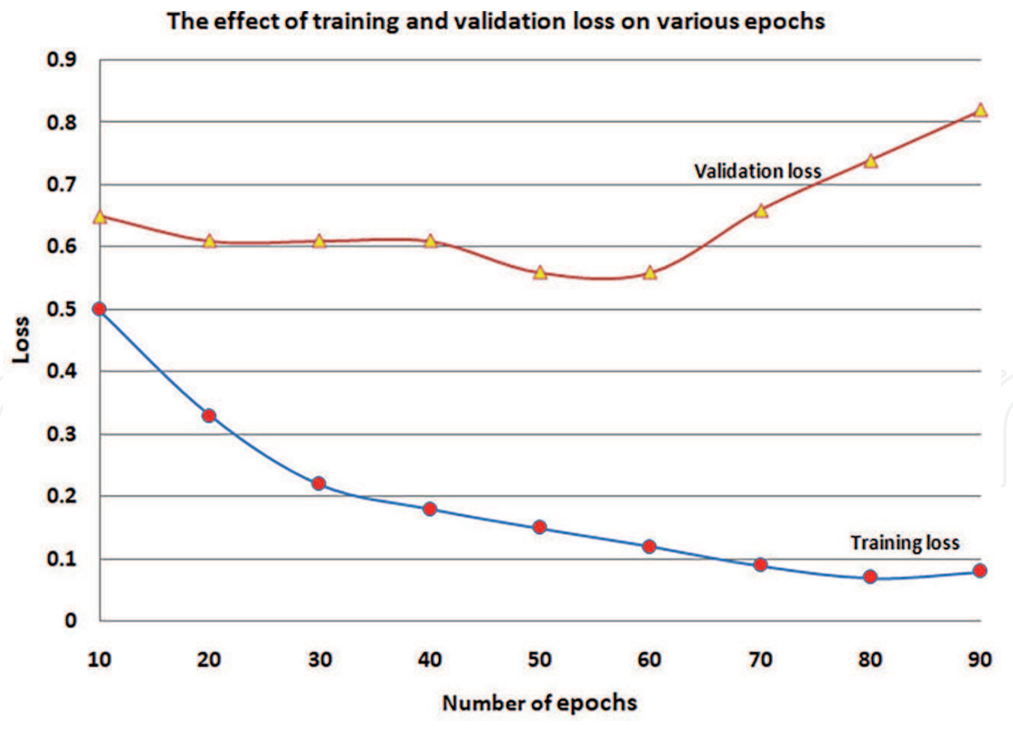

Figure 8.
Representation of the comparison of training and validation loss.

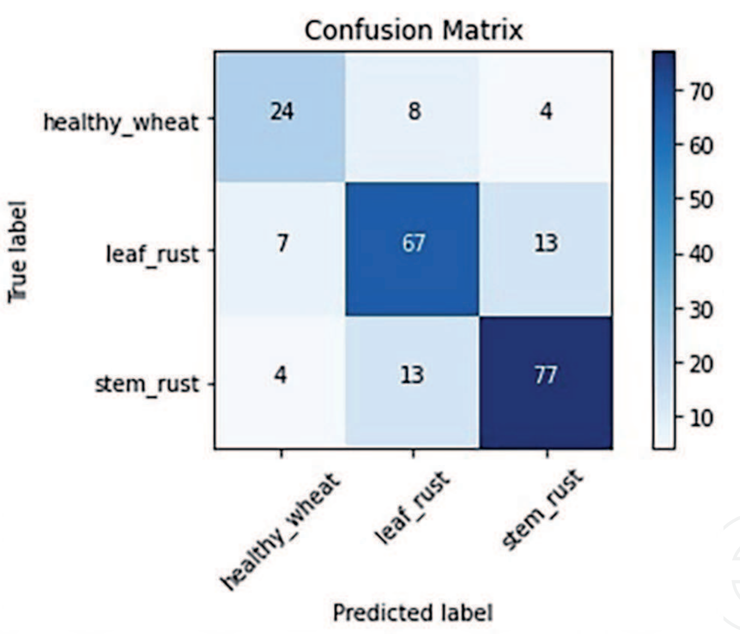

Figure 9.
Confusion matrix at epoch = 80.

using a confusion matrix. **Figure 9** illustrates the accuracy and confusion with other intra-classes, wherein, it is shown that leaf rust class samples are confused with stem rust class samples due to less variation between classes.

5. Conclusions

To summarize this book chapter, different machine learning and deep learning-based models have been discussed to solve plant disease classification and detection problems. Considering a case study of wheat rust diseases, a deep learning-based model is proposed to classify the different wheat rust diseases using a pre-trained

VGG16 model. Based on the CGIAR dataset with three classes (stem rust, leaf rust, and healthy wheat), the proposed model has been optimized and produced the classification accuracy of 99.54%, and when evaluated on unseen data it gave a validation accuracy of 77.14%. This model will further help farmers or experts to diagnose disease in the early stages. Although these models give good training accuracy, they were not appropriate to classify stem- and leaf rust when result plot on confusion metrics. This is due to the fact that some images in this dataset contained multiple diseases, meaning that one image contained the features of both leaf- and stem rust. Detection and classification of the wheat rust disease in the early stages lead to high yield at the production level [38]. In the future, we will extend this work by collecting real-time images of wheat rust disease and also incorporating object detection-based algorithms such as Yolov3, Faster R-CNN, and Mask R-CNN [39] to exactly localize the location of the disease in the image.

Author details

Shivani Sood[1], Harjeet Singh[1*] and Suruchi Jindal[2]

1 Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India

2 School of Agricultural Biotechnology, Punjab Agricultural University, Ludhiana, Punjab, India

*Address all correspondence to: harjeet.singh@chitkara.edu.in

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