Deep Transfer Learning Models for Rust Disease Identification in Wheat Crop

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A R T I C L E I N F O

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A B S T R A C T

Wheat diseases are a major factor contributing to production losses and affecting agriculture-based industries. The Indian Grain Storage Management & Research Institute reports that wheat diseases have caused a 6.75% loss in wheat grain quality globally. Therefore, accurate identification of wheat diseases is crucial for ensuring production stability. Traditionally, wheat disease identification is performed by experienced evaluators; however, this method is time-consuming and expensive. To address these limitations, computer vision techniques have been increasingly used due to their ability to deliver high recognition accuracy. This paper focuses on classifying wheat yellow rust and healthy wheat plants using five transfer learning models: AlexNet, VGG16, GoogLeNet, ResNet-34, and ResNet-50. The effectiveness of each CNN transfer learning model was evaluated using the CGIAR dataset. The experimental results of the transfer learning-based pre-trained model show that ResNet-50 achieved the highest classification accuracy of 97.7%. This highlights its superior performance in the classification of wheat yellow rust disease.

1. INTRODUCTION

Crop diseases play a significant role in global food production [1]. The crop diseases have a great effect on a broad spectrum and may result in substantial loss of yield [3]. Wheat is grown worldwide, and it is the second-highest producer. Wheat is attacked by biographic fungi, microphytic species, and nematodes, as well as viruses [4]. Among the various threats to wheat production, fungal diseases like stripe rust, powdery mildew, leaf rust, and stripe rust are widespread and present significant challenges [5], [6], [7], [8]. Climate factors play an important role in rust and bacterial-based wheat diseases [9]. Many varieties of wheat in our country are affected due to fungus and bacteria microorganisms. These diseases are exposed due to bad weather and climate reasons. If it does, it will cause a great loss. These pathological diseases are the most important factors in limiting wheat production as well as wheat quality [10]. According to the Indian Council of Agricultural Sciences [11], every year, 50% of wheat loss is due to yellow rust. There can be more loss if fungicides are not applied at the proper time. To save the qualitative and quantitative losses, an accurate and detailed diagnosis of the wheat plant on time is important [6], [12], [9], [13], [14]. It is possible to diagnose wheat plants accurately using computer vision techniques that increase classification accuracy [15], [10]. In further advancement, deep learning models have been used for the classification of wheat healthy and diseased plants [16], [17], [18]. The images that are used during the classification of crop diseases are done through the usage of RGB/grey or hyperspectral/spectral/ multispectral sensed images [19], [20].

The main aim of this study is to detect the presence of yellow rust disease in wheat plants using several transfer learning DL models. Even the dataset is collected in terms of RGB images through primary and secondary sources. After the collection of the dataset, transfer learning DL models have been applied to the image's dataset. Wheat yellow rust disease recognition is a critical task in agriculture as it can significantly impact the yield and quality of wheat crops.

By using data augmentation, it is possible to create more diverse training data, which can improve the accuracy of deep learning models. In the case of wheat yellow rust disease recognition, transfer learning has been used to leverage the knowledge learned by a deep learning model on a large dataset.

The structure of this paper is organized as follows: The related work has been presented in Section 2. Even the detailed description of materials and methods, along with dataset details, has been described in Section 3. The results extracted by transfer learning models have been represented

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in Section 4. Lastly, the conclusion of this paper is defined in Section 5.

2. RELATED WORK

Several researchers have proposed in-depth study models, especially the convolutional neural networks (CNN) for wheat rust disease detection. For the classification or detection of wheat rust diseases, the images are taken with the help of either real-time images or from research institutes/drone/hyperspectral sensors. The authors [4], [5], [6], [7] used segmentation image processing which is achieved through K-means clustering. Through the segmentation technique, some important useful information can be extracted, which is very helpful during prediction. After segmentation, some features, namely colour, shape, and textures, can be extracted through principal component analysis (PCA). For example, Gaikwad and Musande [4] used the colour histogram technique for feature classification and achieved 89.23% classification accuracy through SVM.

Kumar et al. [5] used some feature techniques, namely colour occurrence metrics and classified the features using the PNN classifier. Hence, through the PNN classifier, 88.3% accuracy can be achieved. Raichaudhuri and Sharma [6] explained the PCA feature extraction technique, which helps classify wheat rust diseases. The authors [7] analyze the wheat image features through morphological features. Based on morphological features, the PCA feature selection model helps to reduce the stripe rust, powdery mildew, and wheat leaf rust features and achieves an 80.12% classification rate. The authors [8] classify the wheat disease, namely as powdery mildew, tan spot, yellow rust, snow molds, and features that can be extracted through image segmentation. Therefore, 84.8% classification accuracy was achieved.

Zhang et al. [10] compare the continuous wavelet analysis method with raw reflectance and derivative spectral vegetation indices through spectral sensors disease severity. Thus, wheat rust disease severity is achieved with the help of CWA and achieves 0.81% coefficient determination. The authors [14] extract colour and shape features and compare PCA, MaxRel, and mRMR feature selection methods. With the help of NN, wheat fungal diseases will be classified and achieve 83.8%, 91.9%, and 98.3% classification accuracy using feature selection methods. Additionally, other authors [18] classify wheat plant diseases using a fuzzy interference system and achieve a 95% diagnosis rate through Haralick texture features. The authors [12], [19], [9], [13] used different classifiers such as Bayesian network and decision trees (DT) for wheat rust disease recognition and achieved classification accuracy of 93.68%,88.89%, 85.68%,86.67% respectively. However, during classification, the classifier takes a lot of training time and achieves less performance. The deep learning techniques [20], [21], namely CNN, extract the features and classify features of wheat rust diseases automatically. Therefore, CNN achieves 84.8% prediction accuracy through the raw images dataset. Additionally, a new hybrid approach known as CNN-LSVM has been proposed [12] for wheat leaf rust diseases. This hybrid approach has a higher average identification accuracy (93.68%) than CNN-SoftMax (90.32%). During the spectral analysis of wheat plant images, ANN is mostly applied to material biology mechanisms. For example, Yang et al. [22] extract the hyperspectral image features through neural networks (NN). The experimental results show that SOFM has a higher disease severity rate than PCA during hyperspectral images.

With the development of agriculture applications in real-time, the family of NN models, such as deep neural networks (DNN), has been used to predict plant diseases through real-time device-captured images. For example, The authors [16] classify wheat rust, septoria, and tan spot wheat diseases through different mobile device applications using DCNN. The images are taken visually from Germany and Spain. For the classification of these wheat diseases, the DCNN achieves a higher AUC (0.78) than CNN. Many authors [15] and [16] use the same approach for classifying the wheat yellow rust through UAV hyperspectral images and comparing the DCNN with a random forest (RF) classifier. The results show that DCNN has a detection rate of AUC (0.85) compared to RF AUC (0.79). It is designed for their specific function-specific function for DCNN to differentiate plant species. Lin et al. [23] suggested a matrix-based CNN known as the MbCNN approach, which is used for fine-grained transfer learning. Also, the author has compared the proposed approach with CNN frameworks (AlexNet), and it achieves higher accuracy than CNN frameworks [23]. During experimentation, MbCNN has a higher validation accuracy (96.5%) than AlexNet (90.1%) through 83,260 augmented images.

Lu et al. [24] made the dataset, namely a wheat disease dataset (WDD2017) with 9230 wheat images and used two deep neural network frameworks (VGG-FCN-VD16, VGG-FCN-S) for image recognition. Therefore, VGG-CNN-VD16 achieves high accuracy (97.95%) in comparison to VGG-FCN-S (95.12%) during wheat yellow rust, leaf rust, and powdery mildew disease classification. However, the above in-depth study methods of plant disease diagnostics form their models of deep perception of pure images collected under controlled, non-functional conditions in the wild. Consequently, transfer learning models [25], [26] are already integrated into MATLAB’s deep learning toolboxes and are utilized for identifying various crop diseases. The training of the CNN model is difficult as wheat yellow rust classification due to the unavailability of wheat disease images [41], [42]. Even CNN is a class of neural networks that obtains visual patterns from images in the form of pixels. In CNN, the identification of visual patterns is achieved from raw pixels. In this study, five different transfer learning models, such as VGG16, AlexNet, ResNet34, ResNet50, and GoogleNet, have been used for the binary classification of wheat yellow rust and normal wheat plant.

For example, Singh et al. [25] compare the performance of two visual geometry groups transfer learning models (VGG16, VGG19) for wheat yellow rust classification. During experimentation, VGG16 (86.53%) has higher testing accuracy than VGG19 (83.97%).

3. MATERIALS AND METHODS

This section describes the dataset details along with a description of prediction models. The methodology for finding the wheat yellow rust disease and healthy plant prediction has been presented in Figure 1.

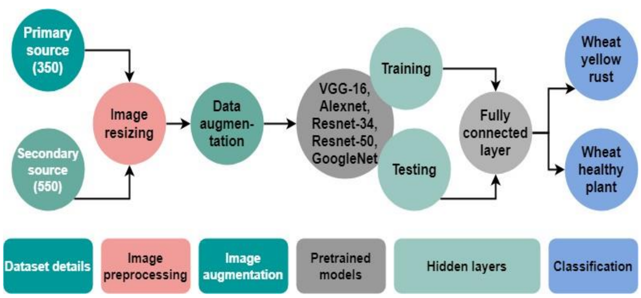

Fig. 1. Proposed model for yellow rust disease classification system.

3.1. Dataset Collection

For the classification of wheat healthy and diseased plants, a total number of 350 wheat plant images are obtained from the primary source. On the other hand, wheat plant images are collected from internet sources such as websites and web blogs in secondary source [36] form. As a result, 550 wheat plant images are gathered from a secondary source. An entire 900 wheat plant images were collected and used for recognition purposes. The dataset description has been presented in Table 1. The sample of wheat rust images is shown in Figure 2.

Table 1: Dataset collection

Source	Category	Count
Primary	Wheat yellow rust	1580
	Wheat healthy plant	670
Secondary	Wheat yellow rust	1850
	Wheat healthy plant	2100

3.2. Image pre-processing

Image processing techniques are typically used to enhance images and extract meaningful information. These methods take an input image and generate outputs that represent key features or characteristics of the image. In the context of classifying wheat yellow rust, it uses RGB images with the limited power of my computer; then the images are enlarged to a size of 224X224 RGB image. The image can be resized through the MATLAB toolbox. Figure 3 describes the image resizing technique applied to the input image respectively.

Fig. 2. Sample of wheat rust images.

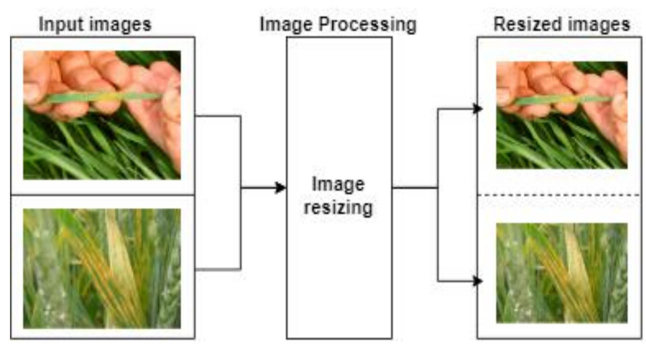

Fig. 3. Overview of Image resizing.

3.3. Data augmentation

To build a good recognizer model, validation errors should continue to decrease with training errors. Hence, the validation error from the training and testing side is reduced through the data augmentation technique. Therefore, the data available in the form of wheat plant images (6200 images) is much less. So, this dataset value is too short and decreases the performance of transfer learning models while predicting. The data augmentation involves several techniques, namely rotation, horizontal flipping, and noise booster; the wheat plant images were augmented. Through the rotation augmentation technique, an image is rotated with a 10-degree angle in a clockwise direction. Therefore, reversing the rows and columns of image pixels is done through horizontal flipping. The data augmentation procedure is carried out by fine-tuning the following parameters: rotation range with value= 10, width_shift_range with value = 0.4, height_shift_range with value= 0.4, shear_range with value = 0.4, zoom_range with value = 0.4, horizontal_flip with value = True, fill_mode = 'nearest'. In the end, a total of 24800 wheat rust images are generated.

3.4. Implementation details of pre-trained models

The main aim of retrained transfer learning models is to determine the effectiveness of wheat yellow rust disease binary classification. For a single convolutional layer, the weighted sum at all feature maps (i) at position F(x,y) is described in equation 1.

$$F(x,y)=\sum_{hg}^{hg-1}\sum_{wd}^{wd-1}\sum_{c}^{c-1} Wg(x+hg, y+wd)+bs(i) \quad (1)$$

The (hg, wd) is the height and width of filters used by convolutional layers. C is the number of strides for feature map extraction, and b is the bias of the I feature map. W is the set of convolutional layers corresponding to I feature maps.

- AlexNet: AlexNet is a deep learning model commonly applied in object recognition and transfer learning tasks, and it consists of five convolutional layers followed by three fully connected layers [20].
- VGG16: The VGG is a family of CNN models, and it is used during large-scale transfer learning [25], [28]. In this model, the image is passed through a convolution filter. The convolution filter converts the image into matrix form. Three FC layers have been used for visualization. In VGG16, there are three dense layers and 13 convolution layers.
- Googlenet: Generally, Googlenet is a CNN model that has 22 deep layers [17], [37]. The Googlenet is used for transfer learning and generates captions from an image. In the Googlenet model, each convolution layer is connected with other convolution layers.
- Resnet-34 and Resnet-50: The full form of ResNet is a residual network, and it is used for computer vision tasks, namely object detection, transfer learning, and prediction [38], [29]. The resnet-34 consists of two deep layers, and resnet-50 consists of three deep layers. In resnet-34 and resnet-50, there are 34 and 50 residual layers, respectively.

A layer-wise description of transfer learning models has been described in Table 2.

Table 2: Learning parameters of transfer learning models

Model	Input layer	Size of the input layer	Size of the output layer	Parameters (millions)
AlexNet	8	(224*224*3)	(2,1)	55
VGG16	16	(224*224*3)	(2,1)	167
GoogleNet	22	(224*224*3)	(2,1)	6.7
Resnet-34	34	(224*224*3)	(2,1)	20
Resnet-50	50	(224*224*3)	(2,1)	23

Each transfer learning, along with their parameter's capacity, is shown in Table 2. The Relu activation function increases the training speed.

3.5. Fine-tuning of hyperparameters

The performance of each CNN-based transfer learning model was evaluated by comparing different hyperparameters, including the number of epochs and batch sizes [11]. During the adjustment of hyperparameters, several experiments are repeated with varying sizes of batches and different epochs. After changing the hyperparameter values, the optimal state rapidly achieves the best accuracy for prediction. The description of each hyperparameter is described hereunder:

- Max Pooling: The image that has been converted into matrix form in the convolution layer, the pooling function [31] is used. Generally, the max-pooling function selects the maximum pixel value from the matrix region that is obtained by the convolutional layer.
- Network weight initialization: Most Glorot [31] initialization techniques have been used to initialize the weight of each neuron in a network. The Glorot initializes the weight of each neuron by its Gaussian value (0.0).
- Activation function: The activation function is added to an artificial neural network, and it helps in learning so that networks can easily learn complex data.
- Epochs: The total no of epochs confirms whether the data fits over in the training network or not [31]. In this study, several experiments have been performed on different epochs to compare the accuracy of each model.
- Batch size: The batch size refers to the number of training samples that are processed together in a single forward and backward pass during model training. Instead of updating the model after every individual sample, the training algorithm calculates the error and updates the weights after processing an entire batch [23]. Generally, a large batch size increases the performance of each model.

3.6. Performance parameters

The images with size 224*224 are input images of transfer learning models. Each transfer learning model has been compared with different epochs and batch sizes to achieve better accuracy. These performance parameters are calculated through different parameters of confusion matrices. The description of various parameters of confusion matrices is followed as:

- True positive: It defines when actual classification is true [22], and from your side, classification is true, which is denoted by Tp.
- True negative: Generally, when actual classification is true [22] but from your side, classification is false, which is denoted by Tn.
- False-positive: It is known as a type 1 error. This error occurs [22] when the actual classification is true, but from your side, the classification is false, which is denoted by Fp.
- False-negative: This type of error is known as a type 2 error [22]. This type of error occurs when the actual classification and your classification are false. Therefore, this type of error is denoted by Fn.

3. EXPERIMENTAL RESULTS

This part shows the performance results of transfer learning models. To identify wheat yellow/stripe rust diseases, five different types of transfer learning models are used. Every transfer learning model has special functions and extractable feature capabilities, which both help us see patterns and make predictions. The research data for wheat yellow rust detection was split into two groups at 70% training and 30% test. The program transforms all images into 224 pixels by 224 pixels through Python. The research utilized these system components for experimentation: Intel Core (TM) i5-8300H processor at 2.30 GHz speed, 8GB RAM, and an OS setup for 64-bit architecture with 64-bit processing. NVIDIA GTX1050 GPU contains 4GB of memory and a programming environment based on Anaconda Navigator and Python versions. By using Adam optimizer and evaluation of CNN, transfer learning models run effectively through MATLAB on Intel GPU servers. These issues can be fixed through drop-out, which sets network weights equal to zero before training begins. The network parameters, such as momentum, learning rate, and max batch size with max epochs, are described in Table 3.

Table 3: Network parameters for each model

Optimizer	**The momentum of each model**	**Learning rate**
ADAM	0.9	0.01
Max batch size	**Validation frequency**	**Max Epochs**
32	7	100
Activation function	**Network weight initialization**	**Size of pooling layer**
Relu	Glorot uniform	2*2

Table 4: Performance evaluation of transfer learning models

Transfer learning models	**No of epochs**	**Training loss**	**Validation loss**	**Estimated accuracy (%)**
AlexNet	1-100	0.856-0.0121	0.437-0.0021	83.61-95.5
VGG16	1-100	0.803-0.117	0.307-0.178	82.36-94.81
GoogleNet	1-100	0.489-0.0029	0.246-0.0435	81.56-94.07
ResNet-34	1-100	0.856-0.0015	0.453-0.026	76.82-96.66

4.1. Training/validation loss

The training performance shows how well the model learns through training loss, valid loss, and valid accuracy measurements done after each network training session. Trainers work through 1 to 100 epochs during each model's process. Table 4 shows the training performance of all transfer learning models.

4.2. Models' recognition rate and confusion metrics for classification

The classification results obtained by each transfer learning model in terms of their performance metrics have been represented in Table 5. Even the confusion metrics generated by each transfer learning model have been shown in Figure 4.

Table 5: Performance of each transfer learning model

Models	**Recall (%)**	**Precision (%)**	**F1-score (%)**	**Classification accuracy (%)**
AlexNet	94.8	96.2	95.5	95.5
Vgg-16	95.5	94.2	94.69	94.81
Googlenet	93.4	94.5	94.6	94.07
ResNet-34	97	96.3	96.5	96.66

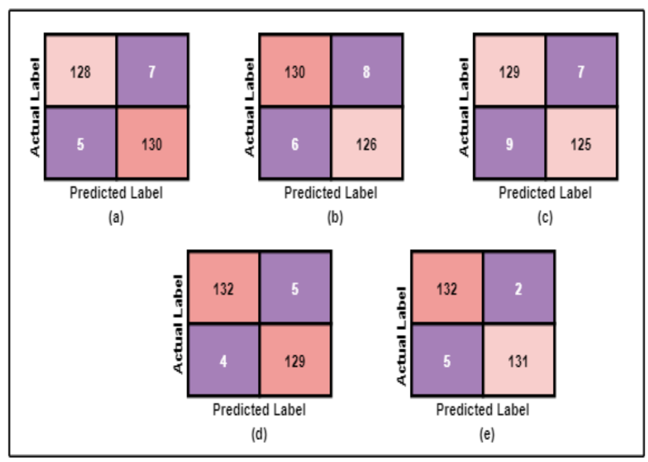

Fig. 4. Confusion matrices (a) AlexNet, (b) VGG16, (c) GoogleNet, (d) ResNet-34, (e) ResNet-50.

4.3. Performance comparison

The performance of each transfer learning model is measured through different network parameters.

- Model comparison: The ResNet-34 achieves 97%, and ResNet-50 achieves 96.5% classification accuracy. It can be noted that ResNet-50 achieves more classification accuracy than ResNet-34, as shown in Figure 5.

- Model comparison through different batch sizes: The batch size serves as a hyperparameter to determine how many samples to process before adjusting the model's internal properties. A batch size specifies how many samples will be processed together through the network. Before updating the model, the batch size needs to be determined first. Every network type shows strong and constant test performance when running samples in batches of size 32. Using batches of 32 samples provides the best performance in classifying wheat plants. Table 6 shows the testing accuracy of five different pre-trained transfer learning models with varying sizes of batches.

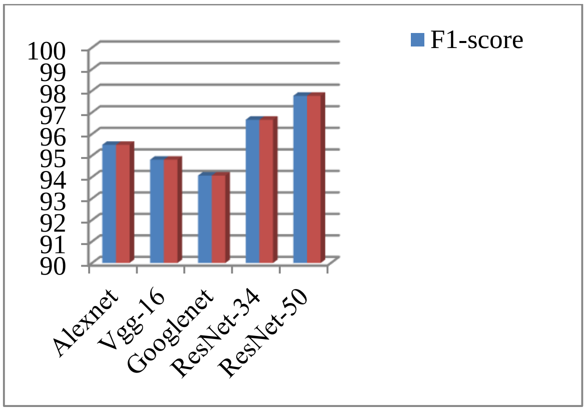

Fig. 5. Comparison of each transfer learning model through F1-score and Classification accuracy.

Table 6: Testing accuracy with different batch sizes

Models	Batch size (8)	Batch size (16)	Batch size (32)
AlexNet	94.62	95.23	95.5
VGG16	94.8	93.76	94.81
Googlenet	94.07	93.89	94.07
ResNet-34	96.6	96.4	96.6
ResNet-50	97.7	97.13	97.77

5. DISCUSSIONS

Analyzing images of wheat plants for the accurate detection of yellow rust has gained significant interest among both small-scale and large-scale farmers [22]. Numerous attempts have been made to develop effective models for detecting wheat yellow rust using various techniques; however, many have encountered performance limitations. The use of CNN-based transfer learning models has notably enhanced the performance of deep learning approaches for the automatic identification of wheat yellow rust. The key contributions of our study can be outlined as follows:

- Most of the studies [11], [23], [25], [27], [31] used neural network models namely CNN, DCNN, and ANN for wheat disease classification.
- For increasing the boosting speed of pre-trained transfer learning models and decreasing the training and testing error, Data augmentation techniques such as rotation, flipping, and noise models are commonly used.
- For classification, our method is fully automated and doesn't describe the involvement of feature extraction and classification steps.
- The performance of various transfer learning models, namely AlexNet, VGG-16, GoogLeNet, ResNet-34, and ResNet-50, has been compared during the rust diseases classification process. The transfer learning models are directly applied to other images via the transfer learning technique [12]; the resnet-50 has a high transfer rate in comparison to the resnet-34 model.

5.1. Comparison of pre-trained models with previous state-of-the-art approaches

There have been various studies that have compared the performance of different transfer learning models for wheat yellow rust disease identification. Here is a brief overview of some of the findings:

Z. Sarayloo et al. [14] evaluated and compared the effectiveness of several deep learning models, namely AlexNet, VGG16, GoogLeNet, and ResNet-50, for identifying wheat yellow rust. Their experimental results show that ResNet-50 achieved the highest accuracy at 95.38%, followed by GoogLeNet (93.29%), VGG16 (92.48%), and AlexNet (90.95%).

Similarly, Q. Pan et al. [26] assessed the performance of the same models in detecting various forms of wheat rust, including yellow rust. According to their results, ResNet-50 again outperformed the others with an accuracy of 96.72%, while GoogLeNet, VGG16, and AlexNet followed with accuracies of 95.33%, 93.53%, and 91.96%, respectively.

In the present study, we extended this comparison by incorporating additional models, such as ResNet-34, alongside AlexNet, VGG16, GoogLeNet, and ResNet-50, to classify wheat yellow rust and healthy plants. Our experimental results demonstrated that ResNet-50 achieved the highest classification accuracy of 97.77%, outperforming AlexNet (95.5%), VGG16 (94.81%), GoogLeNet (94.07%), and ResNet-34 (96.6%).

6. CONCLUSION AND FUTURE SCOPE

In this paper, several pre-trained transfer learning models, namely AlexNet, VGG16, GoogLeNet, ResNet-34, and ResNet-50, have been used effectively to classify wheat yellow rust and healthy wheat plants using RGB-scaled wheat images. A total of 900 wheat images are used for the wheat rust disease recognition. The collected dataset degrades the performance of CNN transfer learning models. Hence, with the help of data augmentation techniques, 3600 wheat plant data have been generated, which increases the performance of CNN models. The results showed that ResNet-50 has a high classification accuracy of 97.7% among four models. Therefore, it can be considered the best CNN transfer learning model for wheat yellow rust disease. After training and testing on wheat images, the transfer learning CNN models have been applied to the CGIAR dataset through transfer learning. In our study, the wheat yellow rust and healthy plant classification are performed through AlexNet, VGG16, Googlenet, Resnet-34, and

Resnet-50 transfer learning models. The experimental results showed that ResNet-50 obtained higher classification accuracy (97.77%) than AlexNet (95.5%), VGG16 (94.81%), Googlenet (94.07%) and Resnet-50 (96.6%) transfer learning models. In the future, the potential of these transfer learning models can be explored for solving multiclass classification tasks.

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