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Wheat Rust Disease Detection Using Convolutional Neural Network

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Abstract:
Wheat is one of the major crops of almost all the countries of the world. It contributes a major portion of the world's food security. Any damage to these crops may impact adversely the food crises of the world. The damage can be because of some diseases like wheat rust. Crop diseases, including wheat rust, are indeed a significant problem affecting food security and agricultural sustainability worldwide. Detecting the health status of crops through technological means can help prevent the spread of diseases more effectively than relying solely on manual labor. The study's focus on wheat rust diseases, including wheat leaf rust, stem rust, and yellow rust, is crucial as these diseases can have varying impacts and levels of damage on crops. By utilizing image analysis of wheat crops, the study aims to differentiate between healthy and infected crops. The experimentation involving various factors such as learning rate, dropout, and train-test split ratio demonstrates the thoroughness of the research. The result shows a 99.64% accuracy rate in detecting wheat rust from healthy crops, which is an impressive outcome, indicating the potential of the developed model to aid in early detection and prevention of wheat rust diseases.
Keywords: Deep Learning, Convolutional Neural Networks, Color Code, Segmentation, Classification, Detection, Wheat Rust

Introduction

Wheat rust disease, in particular, has been a significant concern for India's wheat-producing regions, especially following a period of food security challange. This crop-damaging fungus has spread to various regional states, and has resulted in stunted plant growth and significant pre-harvest losses ranging from 50 to 100 percent. The disease has affected numerous communities and a substantial amount of agricultural land in the country. In recent years, the application of machine learning, specifically deep learning, in agriculture has shown promising results. Deep learning is a sub-field of machine learning that focuses on statistical models called deep neural networks. It has its roots in early work done in the 1940s and 1960s, with subsequent waves of development in the 1960-1980 period, such as the invention of the backpropagation algorithm. Deep learning has led to the creation of convolutional neural networks (ConvNets), which are specialized neural networks designed for image detection and recognition tasks. These networks employ specific processing layers in the extractor module to learn and extract relevant features from input images. By leveraging deep learning techniques, it is possible to develop models and systems that can aid in the detection and recognition of plant diseases, including wheat rust. These models can automatically extract features from images of plants, allowing for efficient and accurate identification of diseases. Implementing such systems can help farmers and agricultural authorities take timely actions to prevent the spread of diseases, mitigate their impact, and safeguard crop production. Overall, the integration of deep learning and other advanced technologies in agriculture holds significant potential to address the challenges posed by plant diseases and enhance food security efforts worldwide.

Literature Review

Wheat rusts are fungal diseases that can cause devastating losses[1][2] to yields of the crop. In Ethiopia, where wheat is a key part of the diet and of the economy, a poorly performing crop can have a huge impact. Yet fungicides are only half of the answer. Spray a field at the wrong time or in the wrong area, and not only will the crop still be at risk, but the cost of spray will also have been wasted. Wheat rust is the most common fungal disease that is challenging Ethiopia's agricultural economy currently. There are three most common wheat rusts, which are very severe and have the capability of damaging 50 to 100% of the crop unless it is controlled as soon as it occurs on the crop. These rusts are Leaf rust, Yellow rust, and Stem rust. From these rusts, Stem and Yellow rusts represent the greatest disease threat to Ethiopian wheat farmers; with both diseases capable of causing huge losses. Even though yellow and leaf rusts are both types of leaf rusts, they are treated as different kinds of rust races, but most of the time they are identified in laboratories, because of the similarities they make on the structure and color of the fungus on the crop.

Leaf rust, also known as brown rust, is caused by the fungus[2][3] (*Puccinia triticina).* This rust disease occurs wherever wheat, barley, and other cereal crops are grown. Leaf rust attacks foliage only. Symptoms are dusty, reddish-orange to reddish-brown fruiting bodies that appear on the leaf surface.

Yellow rust (Puccinia striiformis)[2], also known as wheat stripe rust, is one of the three wheat rust diseases principally found in wheat grown in cooler environments. Such locations are generally associated with northern latitudes or cooler seasons. The disease usually occurs early in the growing season, when temperature ranges between 2 and 15 °C (36 and 59 °F); but it may occur to a maximum of 23 °C (73 °F). Even though Leaf and Yellow rusts are types categorized under leaf rust family, they are in different races, but they are sometimes difficult to recognize[4] them easily by normal visual inspection and they need to be tested in Laboratory.

The stem, rust is caused by the fungus like other rust types, (Puccinia graminis)[2] and is a significant disease that affects wheat crops. Crop species that are affected by the disease include bread wheat, durum wheat, barley, and triticale. These diseases have affected cereal farming throughout history.

Previously, several machine learning applications are used including traditional machine learning and deep learning approaches in agricultural problem solving, using image processing techniques. Even though machine learning applications advance in such fields, efficiency from different angles still remains a question.

Amanda Ramcharan et al.[5] used 15000 manually cropped RGB images into a single leafs to detect only the infected area of the crop. These images used to classify three types of cassava leaf diseases, by applying a different set of a train, validate and test split ranges, in which 10 percent is used for validating the model, and other are used for train and test of 10/80, 20/70/, 40/50 and 50/40 percents respectively. They also used Google InceptionV3 and achieved 98% of accuracy, but at the same time, this study cannot achieve good performance when we have random images, which are captured under random conditions, which will not allow the model to be applied in real-world conditions.

David Hughes et al.[6], used GoogleNet and AlexNet models to train 54,306 images from the plant Village website, in which GoogleNet performs better and consistently with a training accuracy of 99.35%. But in this study, the accuracy degrades to 31.4% when it is tested using images taken under conditions different from images used for training the model. In this study, we have used three train test split distribution of 75/25, 60/40, and 70/30 in percent with three types of image types which are RGB color images, grayscale images, and segmented images.

Konstantinos Ferentinos et al. [7] used an automated pattern recognition using CNN is used in, to detect three types of plants and their diseases, based on simple leaves of the plants, using the 5 basic CNN models, from pre-trained models. The study uses 70,300 for training and other 17,458 images for testing, with a standard size of 256x256 pixel size. Models fine tuned[8] and Alvarez Gila et al. [9] in these studies are AlexNet, AlexNetOWTBN, GoogleNet, OverFeat, and VGG, with the highest accuracy on the training set with 100% and 99.48 percent on the testing set in VGG model. The other researcher use X-Ray images and machine learning for human disease detection[10][11][12][13][14].

Table 1: Some selected work relevant to this Study

Ref No.	Technique	Accuracy	Gaps
[12]	Applied fine-tuning using pre-trained deep learning models.	0.9935	The study constrained to single leaf images with homogenous background
[13]	Applied different pre-trained networks to train it on laboratory images	0.9948	Accuracy degrades when the model tested on images from real cultivation field
[14]	Fine-tuned Resnet50 model to	0.87	Images are segmented manually by expert technicians.
[11]	Transfer Learning using InceptionV3	0.96	Images are manually cropped to a single leaflets

1. Proposed Model

This is a CNN architecture with 2113 data set. The dataset contains healthy as well as infected images. The dataset are divided into training and testing sets into 80%-20% ration. The architecture of the model is given in figure 1. The model is trained using the training dataset. Nest the accuracy of the models are tested using the 20% test dataset. This developed model is a classification model. The dataset are labeled dataset, having binary labeling. The layers used sigmoied activation function in the output layers. The learning weights are adjusted in the range of 0.001 and 0.0001, using Adam gradient descent algorithm. The details of the CNN model is depicted in figure 2.

CNN model's takes a preprocessed image as input. Conv2D is the first layer in the model, with 32 feature map of size 3X 3. ReLu activation function is used in this layer. Next polling layer called as MaxPooling2D have 2 X 2 pool size. There are totally 3 convolutional layer, where ReLu activation function is used. The last output layer has 2 neurons for the 2 classes with a sigmoid activation function to output probability-like predictions for each class.

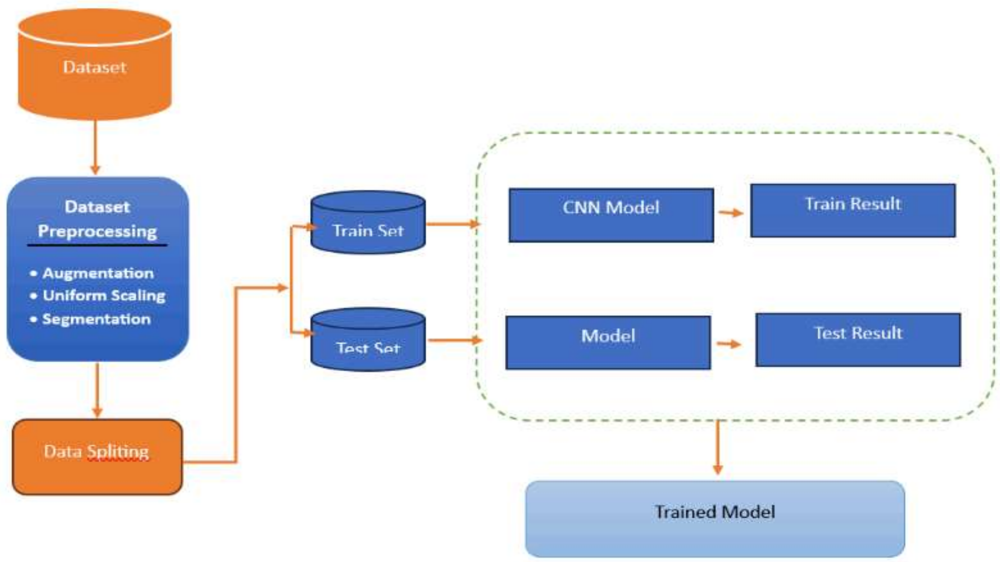


Figure 1: The proposed model

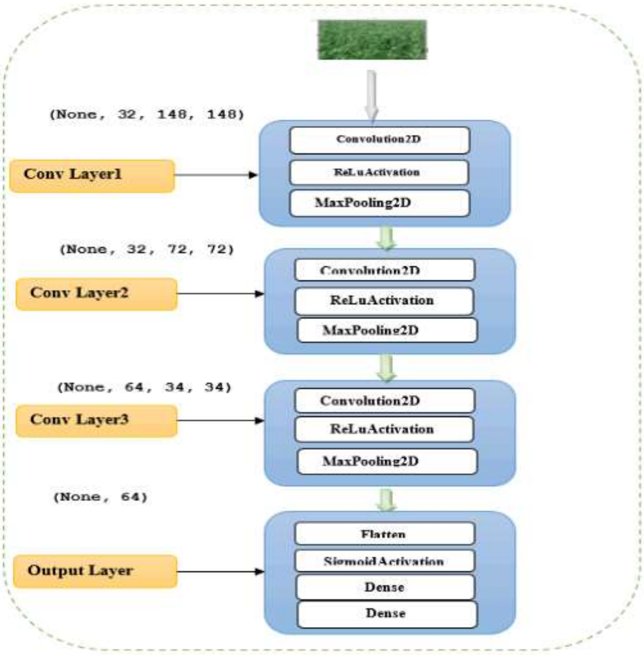


Figure 2: Details of CNN Layer

2. Data preparation

The total dataset collected from OUAT, Bhuabaneswar is 213. This number of image are very less for machine learning model. So augmentation was performed on the dataset. For image augmentation 10 feature factor like rotation, width shift, height shift, rescaling, shear, zoom, horizontal flip, fill mode, data format, brightness are used. Total 2113 augmented image of non uniform size are created after augmentation. The images in the dataset as well as the augmented dataset are of different size. The sparse nature of the dataset are corrected using normalizing the indivisual image to a uniform size. The size of the indivisual image for this research is 150 X 150. Segmentation is the next process of the dataset preparation. It is the most important part of the dataset preparation. The image are segmented to form a patern. Whole image preprocessing process is illustrated in figure 3.

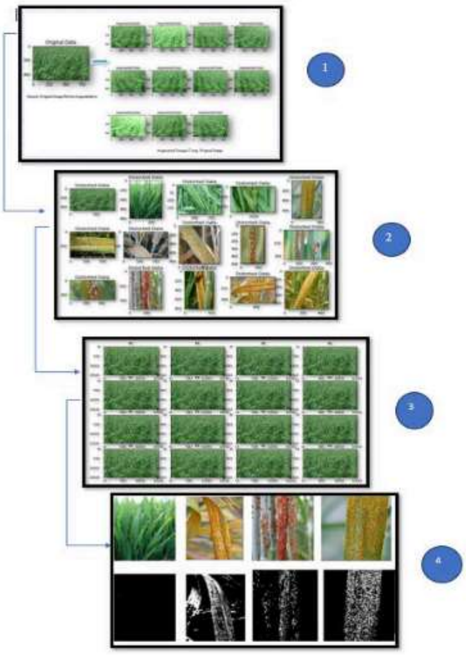


Figure 3: Data preprocessing

The 1st image show a single image is augmented using 10 features. 2nd image contains image of sparse nature, which are converted to uniform size(150 X 150) like in 3. Segmented images are on the lower half of the 4th image.

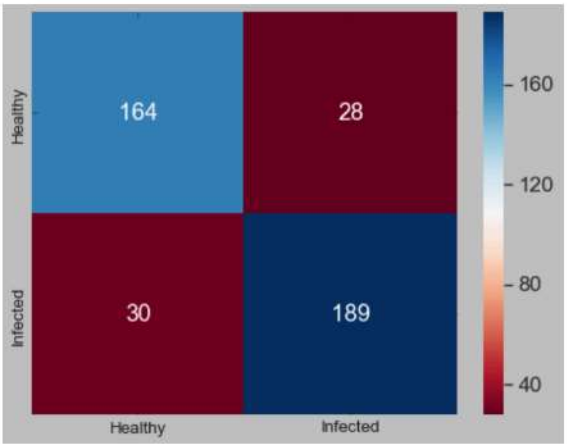
3. Experiment and Results:

The model is evaluated using different hyperparameters. Hyperparameters are tuned with range of value to check the model accuracy and performance. Our proposed model is evaluated with hyperparameter learning rete, dropout rate, different train and test split ration and number of epoch. Three different dataset are fed into the models. First is grayscale image which consist of one colour channel, second datatype is RGB image, and the last input to the model is RGB segmented.

Table 1 show the result of the model on grayscale image. No of epoch the model execute range from 100 to 300. With a train and test ratio of 75%- 25%, the accuracy of the model is 89.62% for 200 epoch, learning rate(LR) of 0.001 and dropout rate is 50%.

Table 1: Performance of model in Grayscale images

Sl. No	*Generation*	*LR*	*Dropout*	*Train time in minutes*	*Accuracy*
1	*100*	*0.001*	*0.5*	*58.49*	*87.89%*
2	*100*	*0.00001*	*0.5*	*59.95*	*82.63%*
3	*200*	*0.001*	*0.3*	*121.77*	*83.78%*
4	*200*	*0.001*	*0.5*	*176.25*	*89.62%*
5	*300*	*0.001*	*0.5*	*123.43*	*81.08%*



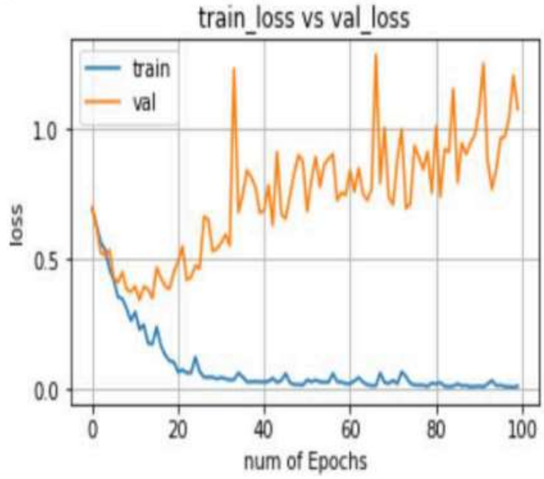


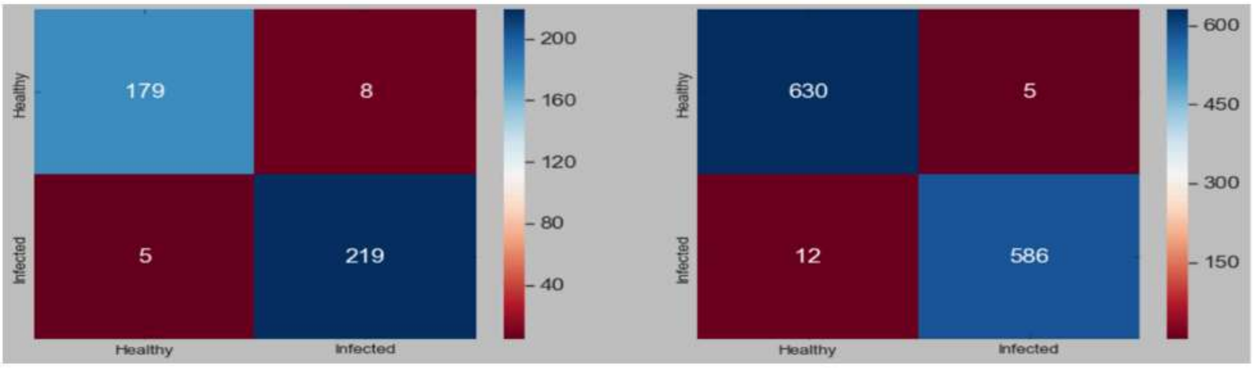
Figure 4: Confusion matrix for the training data of gry scale image Figure 5: Training loss and validation loss comparison

After evaluating the model on grayscale images, images with only one channel, which results in a model with a lot of misclassified data on both training and validation data, it is a must option to find a new solution to get a better model that can perform in a better way.

Table 2: performance of the model in RGB images

Sl. No	*Generation*	*LR*	*Dropout*	*Train time in minutes*	*Accuracy*
1	200	0.001	0.5	111.34	97.78%
2	200	0.001	0.5	116.65	97.48%
3	300	0.001	0.3	169.9	99.58%
4	300	0.001	0.5	192.24	99.12%
5	300	0.0001	0.5	167.19	98.57%
6	300	0.00001	0.5	171.61	96.84%

Secondly the model is trained and tested using RGB image. The performance of the RGB model is quite better as compared with grayscale image. Table 2, row 3 indicate a highest accuracy score of 99.58. This accuracy is achieved with 300 epoch and learning rate of 0.001. For RGB image the accuracy remains more than 95% in any hyperparameter value.



A) For validation data B) For training data

Figure 6: Confusion matrix of result in Table 4, row 6

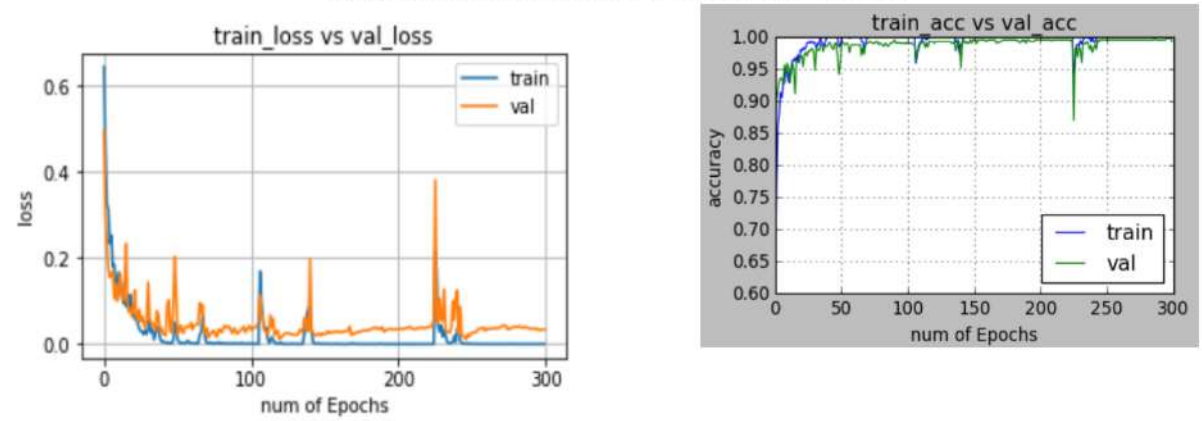


Figure 7: Training and validation loss and training testing accuracy of RGB images

Next the model is trained and tested using RGB segmented data. The results show more accuracy in RGB segmented image data.

Table 3: Result Summary of the model on RGB segmented images

Sl. No	*Generation*	*LR*	*Dropout*	*Train time in minutes*	*Accuracy*
1	300	0.001	0.3	173.9	99.64%
2	300	0.001	0.5	201.24	99.29%

4. Conclusion

This article proposed a CNN based model for wheat rust disease detection. Model is train and tested using dataset provided from OUAT, Bhubaneswar. Three type of dataset are used to train and test the model. These images are grayscale, coloured and coloured segmented. Training and testing ratio used for the model is 75%-25%. For segmented image the accuracy is highest i.e. 99.64% for 300 epoch. The performance of the model is low in case of grayscale image dataset. For different epoch the accuracy is within 90%. In case of normal RGB image the accuracy highest accuracy is 99.58 in 300 epoch. It can be concluded that the model performance is more in coloured image than grayscale image. In coloured image grayscale image performance is better.

References:

[1] ReliefWeb, "Ethiopia battles wheat rust disease outbreak in critical wheat-growing regions," 2016. [Online]. Available: https://reliefweb.int/report/ethiopia/ethiopia-battles-wheat-rust-disease-outbreak-critical-wheat-growing-regions.

[2] GreenLife, "Wheat Rust (1)." [Online]. Available: https://www.greenlife.co.ke/wheat-rust/.

[3] S. N. Wegulo, E. P. Pathologist, and E. Byamukama, "Rust Diseases of Wheat," 2000. [Online]. Available: https://ohioline.osu.edu/factsheet/plpath-cer-12.

[4] Kolomsa Agricultural Research Center, "No Title," 2019.

[5] Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, and D. P. Hughes, "Deep Learning for Image-Based Cassava Disease Detection," *Front. Plant Sci.*, vol. 8, no. 2002, pp. 1–10, 2017.

[6] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Front. Plant Sci.*, vol. 7, 2016.

[7] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Comput. Electron. Agric.*, vol. 145, no. January, pp. 311–318, 2018.

[8] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Comput. Electron. Agric.*, vol. 161, no. October 2017, pp. 272–279, 2019.

[9] Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild," *Comput. Electron. Agric.*, vol. 161, no. October 2017, pp. 280–290, 2019.

[10] Mohapatra, Sudhir Kumar, Srinivas Prasad, and Sarat Chandra Nayak. "Wheat Rust Disease Detection Using Deep Learning." Data Science and Data Analytics: Opportunities and Challenges (2021): 191.

[11] Sinshaw, Natnael Tilahun, et al. "Applications of Computer Vision on Automatic Potato Plant Disease Detection: A Systematic Literature Review." Computational Intelligence and Neuroscience 2022 (2022).

[12] Sinshaw, Natnael Tilahun, Beakal Gizachew Assefa, and Sudhir Kumar Mohapatra. "Transfer Learning and Data Augmentation Based CNN Model for Potato Late Blight Disease Detection." 2021 International Conference on Information and Communication Technology for Development for Africa (ICT4DA). IEEE, 2021.

[13] Mohapatra, Sudhir Kumar. "Automatic Lung Tuberculosis Detection Model Using Thorax Radiography Image." Deep Learning Applications in Medical Imaging. IGI Global, 2021. 223-242.

[14] Mekonnen, Adem Assfaw, et al. "Developing Brain Tumor Detection Model Using Deep Feature Extraction via Transfer Learning." Handbook of Research on Automated Feature Engineering and Advanced Applications in Data Science. IGI Global, 2021. 119-137.