Wheat Rust Disease Detection Using Convolutional Neural Network

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Abstract*: Wheat is a vital crop globally, playing a crucial role in ensuring food security. Any damage to wheat crops, particularly from diseases like wheat rust, can exacerbate the global food crisis. Wheat rust, along with other crop diseases, poses a serious threat to agricultural sustainability and food supply. Technological approaches to detect crop health can significantly enhance disease prevention compared to traditional manual methods. This study focuses on detecting wheat rust diseases, specifically wheat leaf rust, stem rust, and yellow rust, all of which vary in their impact on crops. By employing image analysis of wheat plants, the research aims to accurately distinguish between healthy crops and those affected by rust diseases. The experiments consider multiple variables, such as learning rate, dropout, and train-test split ratio, reflecting a comprehensive research approach. The model achieved an impressive 99.64% accuracy in detecting wheat rust, highlighting its potential for early disease detection and prevention.*

Keywords: *Deep Learning, Convolutional Neural Networks, Color Code, Segmentation, Classification, Detection, Wheat*

I.INTRODUCTION

Wheat rust disease has become a major concern in India's wheat-producing regions, especially in light of recent food security challenges. This crop-damaging fungus has spread across various states, causing stunted plant growth and pre-harvest losses ranging from 50% to 100%. The disease has impacted many communities and vast agricultural lands, leading to significant economic and food production setbacks

In recent years, the use of machine learning, particularly deep learning, in agriculture has shown great promise. Deep learning, a branch of machine learning, focuses on statistical models known as deep neural networks. Its origins date back to the 1940s and 1960s, with key advancements like the backpropagation algorithm emerging in the 1960s-1980s period. One notable achievement in deep learning is the development of convolutional neural networks (ConvNets), specialized for image detection and recognition tasks. These networks use specific processing layers in the extractor module to learn and extract meaningful features from input images.

By applying deep learning techniques, models can be developed to detect and recognize plant diseases, such as wheat rust. These models can automatically extract features from plant images, enabling efficient and accurate disease identification. Implementing such systems empowers farmers and agricultural authorities to take timely actions to prevent disease spread, minimize its impact, and protect crop yields. Ultimately, integrating deep learning and other advanced technologies into agriculture offers significant potential to tackle the challenges posed by plant diseases and bolster global food security efforts.

II.LITERATURE REVIEW

Wheat rusts are fungal diseases that can cause significant yield losses. In Ethiopia, where wheat is a crucial staple and a key part of the economy, poor crop performance can have a profound impact. However, relying solely on fungicides is not a complete solution. Spraying at the wrong time or place may leave the crop vulnerable, while incurring unnecessary costs. Wheat rust is currently the most common and damaging fungal disease challenging Ethiopia's agricultural sector. The three major types of wheat rusts—leaf rust, yellow rust, and stem rust—can cause crop losses of up to 100% if not controlled promptly. Among these, stem rust and yellow rust pose the greatest threat to Ethiopian wheat farmers, as both can cause extensive damage.

Leaf rust, also known as brown rust, is caused by the fungus Puccinia triticina, affecting the leaves of wheat, barley, and other cereals. The disease manifests as reddish-brown, dusty lesions on the leaf surface. Yellow rust (Puccinia striiformis), also called stripe rust, predominantly affects wheat in cooler environments, typically when temperatures range between 2 and 15 °C (36-59 °F). While both leaf rust and yellow rust belong to the same family, they are distinct races that often require laboratory testing for accurate identification due to their visual similarities.

Stem rust, caused by the fungus Puccinia graminis, is another serious wheat disease affecting crops like bread wheat, durum wheat, barley, and triticale. Throughout history, stem rust has been a persistent challenge in cereal farming.
Machine learning, including both traditional and deep learning approaches, has been applied to address agricultural problems through image processing techniques. While machine learning applications have shown advancements in this area, challenges

related to efficiency remain. For instance, Amanda Ramcharan et al. [5] used 15,000 manually cropped RGB images of single leaves to detect infected areas in cassava crops. They employed various training, validation, and test split configurations, such as 10% validation and 10/80, 20/70, 40/50, and 50/40 for training and testing. Their study used the Google InceptionV3 model, achieving 98% accuracy. However, the model struggled with real-world conditions where random images, captured under varying circumstances, were used.

Similarly, David Hughes et al. [6] used GoogleNet and AlexNet to train on 54,306 images from the PlantVillage website. GoogleNet showed better and more consistent results, with a training accuracy of 99.35%. However, when tested on images taken under different conditions, accuracy dropped to 31.4%. This highlights the challenge of applying these models in real-world scenarios. In our study, we experimented with three train-test split configurations: 75/25, 60/40, and 70/30, using RGB color images, grayscale images, and segmented images.

Konstantinos Ferentinos et al. [7] employed CNN-based automated pattern recognition to detect plant diseases using simple leaf images. The study utilized five pre-trained CNN models and trained on 70,300 images, with 17,458 images reserved for testing. The image size was standardized at 256x256 pixels. Fine-tuned models, including AlexNet, GoogleNet, and VGG, achieved impressive accuracies—up to 100% on the training set and 99.48% on the test set using the VGG model. Other researchers, such as Alvarez Gila et al. [9], have explored the use of X-ray images and machine learning for human disease detection [10-14].

The integration of advanced machine learning techniques holds great potential for improving the detection of wheat rust and other plant diseases, helping to protect crops and ensure food security.

Table 1: Some selected work relevant to this Study

Ref No.	Technique	Accuracy	Gaps
[12]	Fine-tuned pre-trained deep learning models	99.35%	Limited to single leaf images with a uniform background
[13]	Trained using various pre-trained networks on lab images	99.48%	Accuracy declines when tested with images from real cultivation fields
[14]	Fine-tuned ResNet50 model	87%	Images were manually segmented by expert technicians
[11]	Transfer learning using InceptionV3	96%	Images were manually cropped to single leaflets

III.PROPOSED MODEL

This CNN model is designed using a dataset of 2,113 images, which includes both healthy and infected crop samples. The dataset is divided into training and testing sets in an 80%-20% ratio. Figure 1 illustrates the architecture of the model. The training process is conducted using the training set, and the model's accuracy is then evaluated on the 20% test set. This model serves as a binary classification model, where the dataset is labeled with two classes. The output layer utilizes a sigmoid activation function to handle binary classification. The learning rate is fine-tuned within a range of 0.001 to 0.0001, using the Adam gradient descent algorithm to optimize the weights.
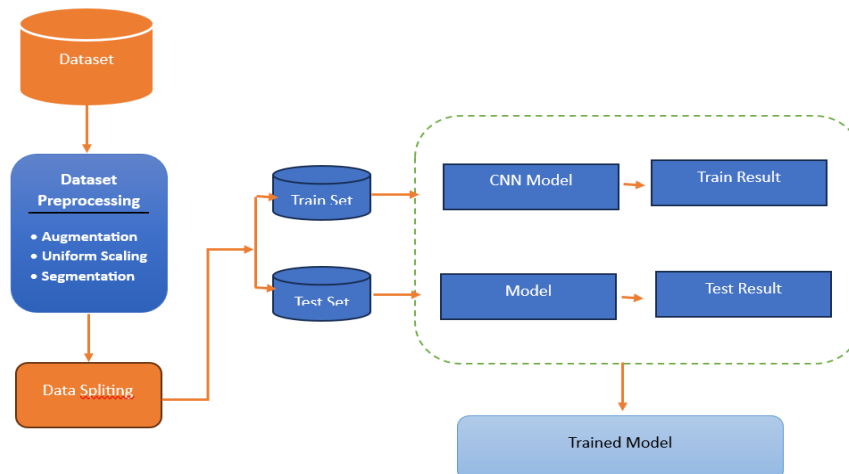
Figure 1: The proposed model

The structure of the CNN model is detailed in Figure 2. It begins with a preprocessed image as input. The first layer is a Conv2D layer with 32 feature maps of size 3x3, using the ReLU activation function. This is followed by a MaxPooling2D layer with a pool size of 2x2. In total, the model includes three convolutional layers, all utilizing the ReLU activation function. The final output layer has 2 neurons corresponding to the two classes, with a sigmoid activation function that produces probability-like predictions for each class.
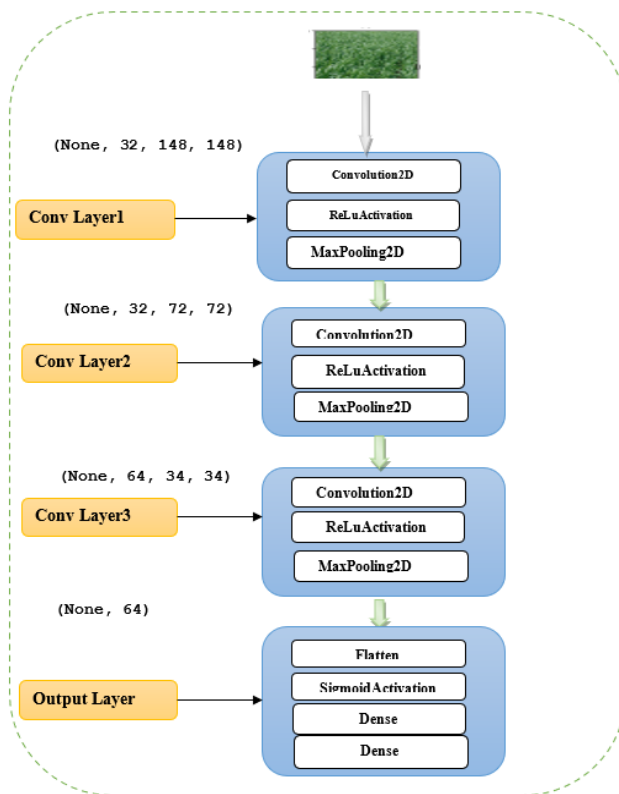

Figure 2: Details of CNN Layer

IV.DATA PREPARATION

The dataset collected from OUAT, Bhubaneswar consists of 213 images, which is insufficient for training a machine learning model effectively. To address this, data augmentation was applied, using 10 different augmentation techniques: rotation, width shift, height shift, rescaling, shear, zoom, horizontal flip, fill mode, data format adjustments, and brightness enhancement. After augmentation, the dataset increased to 2,113 images, though the sizes of the images were non-uniform.
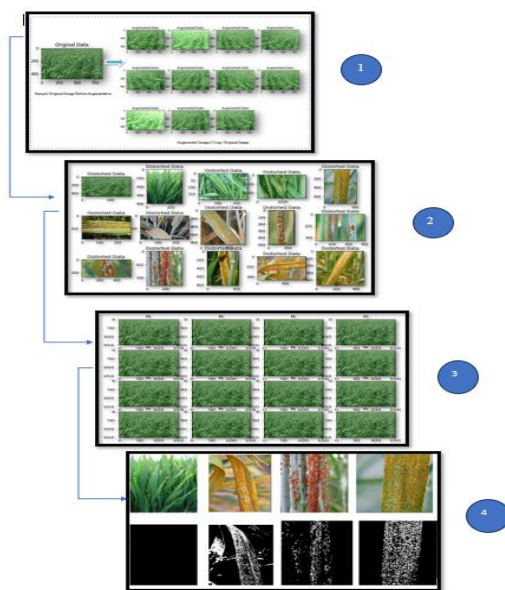

Figure 3: Data preprocessing

To standardize the dataset, each image was normalized to a uniform size of 150x150 pixels, correcting the sparse nature of the original dataset. Segmentation was then applied as a crucial step in the dataset preparation process, allowing the images to be divided into meaningful patterns. The entire image preprocessing pipeline, including augmentation, normalization, and segmentation, is illustrated in Figure 3.

The first image illustrates how a single image is augmented using 10 different features. The second image displays the sparse nature of the dataset, which has been converted to a uniform size of 150x150 pixels, as shown in the third image. The lower half of the fourth image contains the segmented images.

V.EXPERIMENT AND RESULTS

The model's performance is evaluated using various hyper parameters, which are tuned within specified ranges to assess accuracy and effectiveness. Our proposed model is tested with hyper parameters such as learning rate, dropout rate, different train-test split ratios, and the number of epochs. Three different datasets are utilized:
the first is a grayscale image dataset, which contains a single color channel; the second is an RGB image dataset; and the third input consists of RGB segmented images.

Table 1 presents the results of the model on the grayscale images. The number of epochs executed by the model ranges from 100 to 300. With a train-test ratio of 75%-25%, the model achieves an accuracy of 89.62% at 200 epochs, with a learning rate of 0.001 and a dropout rate of 50%.

Table 1: Performance of model in Grayscale images

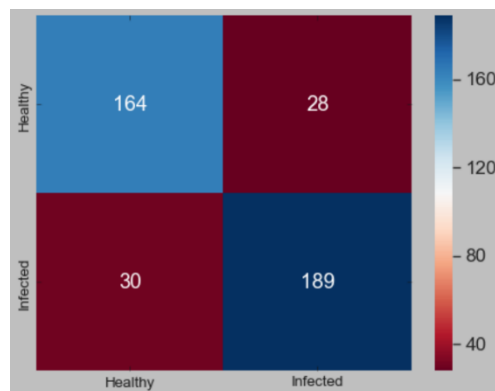| Sl. No	Generation	LR	Dropout	Train time in minutes	Accuracy
1	100	0.001	0.5	58.49	87.89%
2	100	0.00001	0.5	59.95	82.63%
3	200	0.001	0.3	121.77	83.78%
4	200	0.001	0.5	176.25	89.62%
5	300	0.001	0.5	123.43	81.08%

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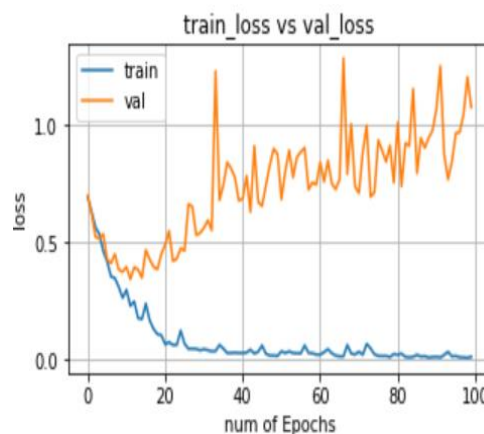
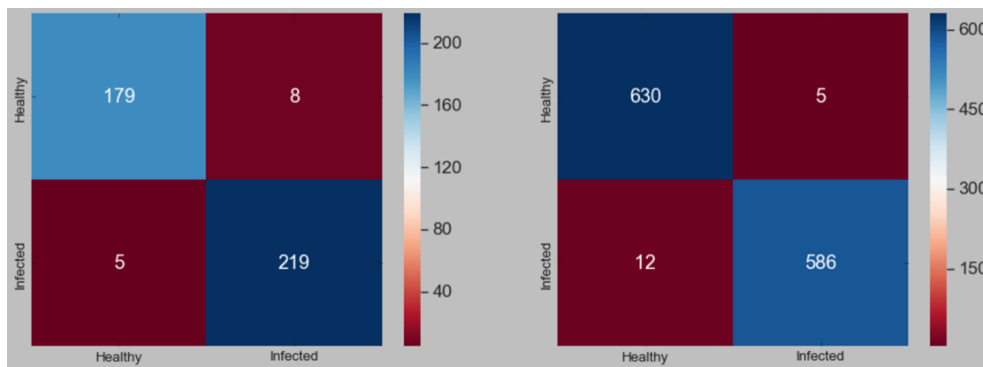*Figure 5: Training loss and validation loss comparison*

After evaluating the model on grayscale images, which consist of only one channel, we found a substantial amount of misclassification in both the training and validation datasets. Consequently, it is imperative to seek alternative solutions to enhance the model's performance

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%

Next, the model was trained and tested using RGB images, yielding significantly better performance compared to the grayscale images. As shown in Table 2, row 3, the highest accuracy score achieved was 99.58%, obtained with 300 epochs and a learning rate of 0.001. The accuracy for the RGB images consistently remained above 95% across all tested hyper parameter values.

A) For validation data   B) For training data

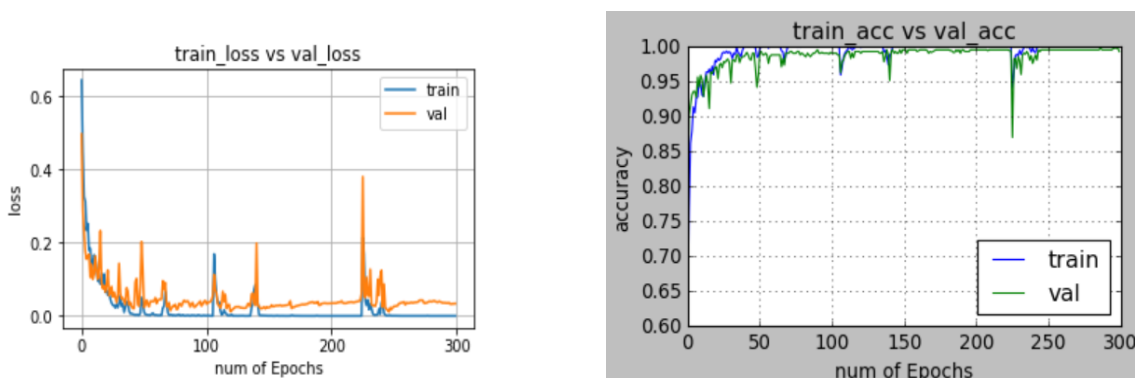*Figure 6: Confusion matrix of result in Table 4, row 6*

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 Ingra 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%

VI.CONCLUSION

This article presents a CNN-based model for detecting wheat rust disease, trained and tested using a dataset sourced from OUAT, Bhubaneswar. Three types of datasets were utilized: grayscale, colored, and colored segmented images. The training and testing ratio employed for the model was 75%-25%. The highest accuracy of 99.64% was achieved with the segmented images at 300 epochs. In contrast, the model demonstrated lower performance with the grayscale image dataset, where accuracy remained around 90% across different epochs. For normal RGB images, the model reached a maximum accuracy of 99.58% at300 epochs. Overall, it can be concluded that the model performs better with colored images compared to grayscale images, while the grayscale images outperformed colored images in some aspects.

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