Wheat Disease Detection Using Transfer Learning Techniques

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Abstract. Wheat stands as a crucial staple crop for a substantial portion of the global population, contributing significantly to food security. However, the productivity and expansion of wheat cultivation face substantial challenges due to the prevalence of diseases, resulting in considerable annual crop losses. Nowadays, deep learning methods have become major in the identification of leaf diseases. The study proposes the techniques that mainly concentrating on transfer learning (TL) architectures, to advance agricultural research. Various TL architectures, such as VGG16, ResNet50, Squeeze Net, and VGG19, are explored for disease detection in wheat plants. The methodology involves preprocessing of leaf images, utilizing TL architectures to extract the features of the leaf. Subsequently, TL architectures are fine-tuned using these segmented images, and the fully connected layers of the combined architecture of VGG19 and RESNET50 are employed for disease classification. The model focuses on all diseases caused by fungi and bacteria in wheat plants. The analysis confirms that the developed model outperforms existing counterparts, highlighting its efficacy in advancing wheat leaf disease detection. This project contributes to empowering farmers with innovative tools for accurate and early disease detection, ultimately safeguarding wheat crop yield and quality.

Keywords: *Transfer Learning, wheat leaf disease detection, Convolution Neural Networks (CNN), Deep Neural Networks (DNN), TL architectures* (ResNet50, VGG19).

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1 Introduction

Convolutional Neural Networks (CNNs) is the major algorithm used for image analysis, particularly for their proficiency in discerning patterns in visual data. By using the power of deep learning, this paper employs Transfer Learning (TL) techniques to take advantage of pre-trained models and adapt them to the particular task of wheat disease detection. This framework uses Transfer Learning approach, that is, these models that are made available are pre-trained utilizing immense image datasets, examples are InceptionV3, VGG16, ResNet, Squeeze Net, and VGG19. Pre-processing of wheat leaves takes normalization, resizing, data augmentation and stack of techniques with model enhancement for feature recognition as its approach. Semantic segmentation identifies which specific regions in an image that depict model training and hence allows the model to focus better. Fine-tuned transfer learning models are created via this optimization process, where the weights of the pre-trained model are adjusted and set up so it could amend to the wheat leaf disease dataset. The composition of these architectures into a DNN's final stage determines how well this power to discern and classify diseases from wheat leaves is.

2 Literature Review

Recent advancements in computer vision and deep learning techniques have made image segmentation, a critical component of numerous applications including disease detection. Early research efforts such as [1-5] A review of the Deep Learning approaches have been applied to both biotic and abiotic plant stress phenotyping to effect transformational changes in agricultural science. These mostly involve Convolutional Neural Networks for image classification, with some using self-created CNN architectures and some adapting popular architectures for solving the same. The applications of deep learning, specifically Convolutional Neural Networks (CNNs), has demonstrated successful outcomes in various domains, eliminating the necessity for manual feature extraction. Subsequently authors of papers [6-10], introduced the CNN method that is founded on the Efficient Net technique to restrict the increase of these diseases in the plants. Authors of [15-17] utilized CNNs' ability to automatically learn features from data, significantly enhancing segmentation accuracy. Also, challenges persisted in fine-tuning complex networks, prompting exploration into hybrid methods. Recent literature, such as [16], the development of algorithm for disease spot segmentation based on image processing approaches on plant leaves is introduced. This is the initial and the crucial step for automatic detection and imaging diagnoses of plant diseases. The lower accuracy than for horticultural crops is likely due to the lack of sufficient images for each type of the Wheat rust disease. [5] utilizes the deep learning classifiers and methods in differentiating the wheat rust and wheat fungi classes. The dataset has gone through the time consuming of collecting and preprocessing to have an important result and leveraging two deep learning models, ResNet50 and VGG16. Notably, as of our current knowledge, no other studies have explored the application of the Efficient Net architecture specifically for identifying Wheat rust diseases. Our proposed work seeks to address this gap by proposing Combined models for VGG19 and ResNet50 for the detection of disease in wheat plants.

3 Methodology

This section, briefs about the steps of Wheat leaf disease detection using transfer learning techniques. The steps for performing Wheat disease detection using Transfer learning Techniques like VGG19 and ResNet50 models have been specified in figure 1. Initial step is to gather dataset samples to perform image segmentation. Proposed work utilizes Wheat dataset for wheat disease detection from kaggle. The dataset is cleansed and then randomly partitioned into two dissimilar groups: training and testing, as well. To perform the evaluation on the target data and avoid overfitting, this type of division must essentially be adopted. The test set controls model generalized capabilities, while the training set source is the primary basis for its learning. We have factored in this consideration for easier access and collection in later stages of the model development and assessment by keeping separate repositories for these sets. By coupling with pre-processing methods, this dataset organization structure constitutes a considerable ground-work for the development of machine learning models which facilitate the discovery and precise categorization of particular diseases respective of the features which have been retrieved.

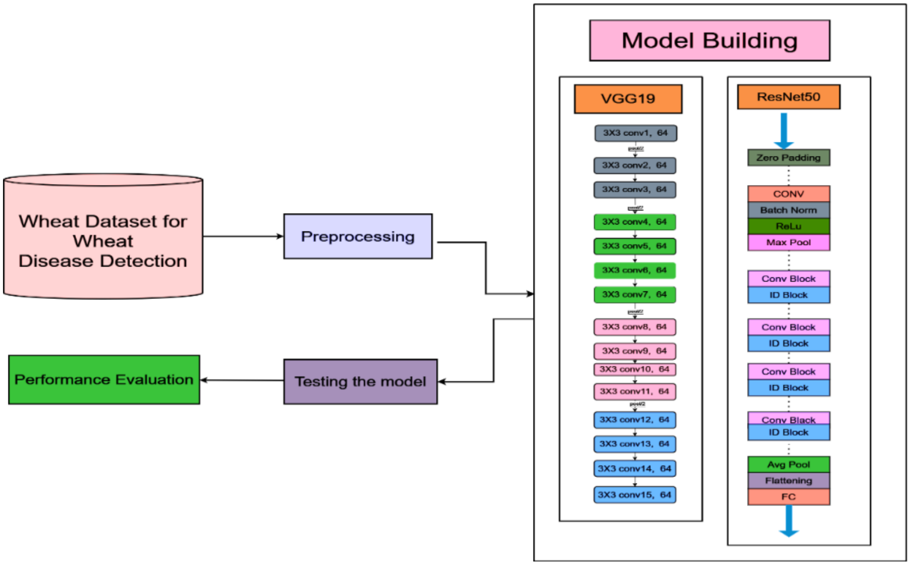

Fig. 1. Wheat disease detection using VGG19 and ResNet50 models

Figure 1 represents the combined architecture of VGG19 and ResNet50 models.First step involves scaling down all images with a standard size so that the model can handle them correctly. Augment the data to simulate a larger size of datasets and improve the robustness of your model add random rotation, flips, and brightness adjustments to your images.

There are several popular pre-trained models such as VGG19, ResNet50 which could use at the outset. These models are pre-trained on large data collections trained on ImageNet that generally learn already the low-level features like edges and textures. This is the knowledge that can be utilized for wheat disease detection by adjusting the last layers of the model on the wheat diseases images dataset which is yours.

Next step is Train the model through using a proper optimizer (Adam) and a loss function (categorical cross-entropy) which are relevant to multi-class classification (identifying different disease types). Watching over training and validation accuracy/loss curves helps to avoid overfitting.

Next, the models like VGG19 and ResNet50 predicts the output as follows: The VGG19,which is known neural network architecture has been used to classify the diseases in wheat by analyzing preprocessed wheat leaf images. Using the VGG19 architecture our implemented convolutional neural network (CNN) aims to identify patterns that indicate different diseases in wheat plant, in preprocessed wheat leaf images. The dataset is carefully organized into training, validation and testing subsets and undergoes preprocessing to ensure compatibility with the VGG19 model. We leverage trained weights from ResNet50 and incorporate the VGG19 as base model keeping the convolutional layers frozen to retain learned features.VGG19 is the most advanced variant within the VGG model framework and is characterized by its architecture which is comprising of 19 layers. These layers enclosed with 16 convolution layers, 3 fully connected layers, 5 max-pooling layers, and terminate in softmax layer for classification. There are some notable variants within the VGG family that includes VGG11 and VGG16, each with a distinct number of layers. VGG19 is known for its substantial computational load, amounting to 19.6 billion Floating Point Operations (FLOPs). ResNet stand for Residual Network and were developed to address challenges related to vanishing or exploding gradients in deep neural networks. The key principle underlying ResNet is the notion of enabling the network to fit the residual mapping rather than forcing layers to learn the underlying mapping directly. The concepts in the ResNet is introduced to implement the skip connections, which bypass certain intermediate layers to directly link the activations of one layer to subsequent layers. This arrangement gives rise to residual blocks, and these blocks are strategically stacked to form the ResNet architecture.

The steps of the proposed Wheat disease detection algorithm is specified below.

Algorithm: Wheat disease detection using Transfer Learning Techniques.

Step 1: Data Collection:

- The dataset compilation bounded with four distinct sets, each tailored to advance the understanding and detection of specific plant diseases.
- Firstly, the Leaf Rust dataset comprises a significant collection of 1566 images depicting instances of Leaf Rust disease. This dataset serves as a thorough resource for training machine learning models to accurately

identify and classify the characteristic symptoms of Leaf Rust, a prevalent fungal affliction affecting various plants, including wheat. The Crown and Root rot Dataset of 1033 images where wheat plants are susceptible to diseases that not only affect the crown and roots of the plant, but also have the potential to cause losses in agricultural production are current focus of the data.

Step 2: Data Preparation:

- Load and preprocess the image dataset, ensuring compatibility with the input format.

Step 3: Model Selection and Training:

- Choose pretrained models like VGG19 and ResNet50.
- Model is created by use of only required layers and after that the network is trained for feature extraction where the training set is sent to the network for helping it to train. Now further we specify the total number of epochs to train the model to which the loss gradient of the model eventually decreases.

Step 3: Optimization:

- The optimizer is defined to adapt the model's parameters.
- The optimizer adjusts the model parameters so that the loss function gets maximized and the model is compiled.

Step 4: Model testing:

- The model is tested using the test set to validate its performance.
- Each model is built in such a way that it is, trained, tested and saved individually.
- Evaluate the accuracy and other metrics for each trained Transformer.

Step 5: Select Best Solution:

- Choose the solution (VGG19 and ResNet50) that resulted in the highest accuracy.
- This solution represents the disease detected for the wheat leaf using Transfer Learning techniques like VGG19 and ResNet50.

Model performance is then assessed based on the optimal parameters selected for segmentation task. Final step is to perform model evaluation using performance metrics as specified in table 1.

4 Results and Discussions

The project's outcomes, which comprise single deep learning systems as well as Transfer Learning models and system architectures made from several deep learners, are described. Considering the aforementioned parameters, the predicted results of the suggested transfer learning model are more accurate than those of its individual learners. This indicates that it is more effective in categorizing photos of wheat illness.

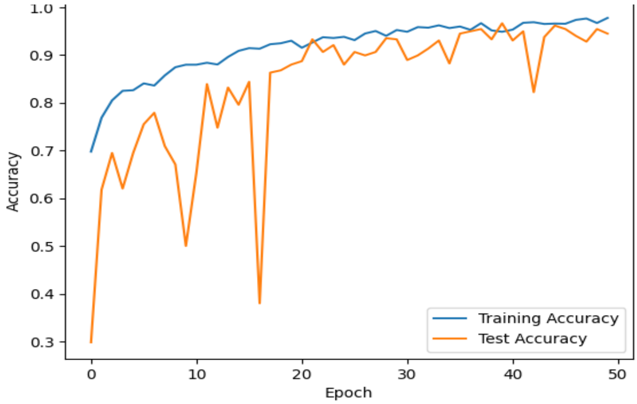

Fig. 2. Accuracy of VGG19

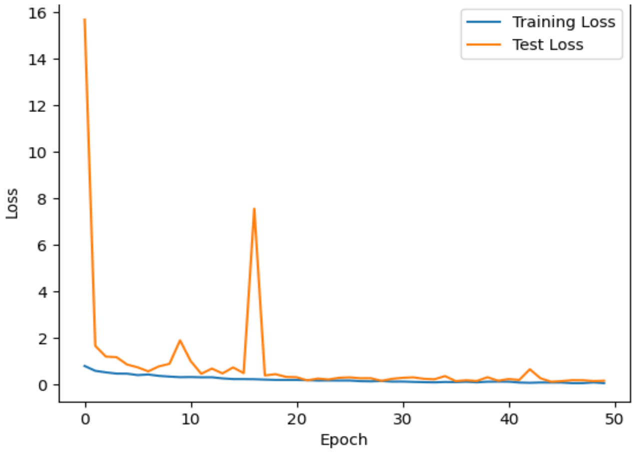

Fig. 3. Loss of VGG19

The graphs represented in figures 2 and 3 shows the lookout between the defined model against the existing models, and it indicates that the developed model is superior in terms of accuracy and performance than the other available models. It validates the existence of our creation and is suitable for real environment. The weighted average combined method that was benefited from both VGG19 and ResNet50 showed the better performance.Performance evaluation of VGG19 and ResNet50 with relevant metrics is specified in Table 1.

Table 1. Evaluation of VGG19 and ResNet50 Models for the detection of disease in Wheat leaf.

The details reveal that the combined VGG19 and ResNet50 models performs well compared to existing approaches in detection of disease in wheat leaf. The accuracy trends of a ResNet50 model during training and validation over epochs are depicted in

Model	Accuracy %	Weighted avg	Precision	Recall	F1-Score
ResNet50	92.73	38.33	24.25	24.25	24.00
VGG19	**95.05**	**95.0**	**70.25**	**48.75**	**52.57**

the graph in Figure 2. The accuracy values are displayed on the axis, and the number of training iterations is shown on the horizontal axis. The model's performance on the training dataset is indicated by the blue line, which illustrates how well it adapted to and learned from it. It steadily stabilizes at a 95% accuracy after first reaching 70%. On the other hand, the accuracy of the model is shown by the orange line on a validation dataset. Despite its noticeable fluctuations, it exhibits a trend with peaks at roughly 90% and 70%, respectively.

5 Conclusion

This paper focuses on classification of wheat diseases involving image data. The study conducts analysis of pre-trained models, specifically leveraging two widely recognized deep learning architectures: VGG19 and ResNet50. The aim is to achieving the best model for exactly determining wheat diseases by the features extracted from pictures. The models such as VGG19 and ResNet50 that are compared through do not depend on Convolutional Neural Networks, however they reveal their efficiency features. To address this task, the researchers expended on higher performing and widely used deep learning architectures like VGG19 and ResNet50 for the detection of wheat diseases. The capability of ResNet50, with its residual connectivity that enables network training of even deeper levels, and VGG19, which is known for its depth and the simplicity in design, to discriminately perceive and classify diseases in harvested wheat were analyzed.

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