Severity Estimation of Plant Leaf Diseases based on a CNN ensemble

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Abstract: The estimation of plant disease intensity is essential for various purposes, including monitoring epidemics, understanding yield loss, and evaluating treatment effects. Despite the availability of sensor technology to measure disease severity using the visible spectrum or other spectral range imaging, deep learning has emerged as a recent and advanced technique for image processing and data analysis. To enhance the severity estimation in diseased leaves, a CNN ensemble is proposed by fusing deep features extracted from outputs of fully connected layers of various CNN models. A SVM (Support Vector Machine) is utilized to achieve the classification stage. Experiments are carried out on wheat leaf images infected by the Yellow rust disease. Experiments conducted using three CNN models that are VGG16, MobileNetV2 and a customized CNN reveal that the CNN ensemble outperforms individual models.

Keywords: Convolutional Neural Networks, plant leaf disease, SVM, severity estimation

1. INTRODUCTION

Reliable and precise disease severity estimation is vital for understanding the biological aspects and has economic significance in predicting yield loss through epidemic monitoring and forecasting [1]. Pests and phytopathological complications pose a significant threat to global food security [2], driven by factors such as population growth, climate change, and industrial and economic expansion [3]. Artificial intelligence and deep learning have emerged as promising solutions for plant leaf severity estimation [4], in contrast to traditional determination by domain experts [5] with visual inspection of plant leaf changes, including color, texture, and morphology [6], which is an expensive and less efficient process. It is characterized by high human labor intensity, low speed, and a high misjudgment rate [7]. Plant leaf disease detection and severity classification systems, similar to many computer vision models, are typically composed of three main steps, preprocessing such as background removal, resizing and image filtering to facilitate information extraction, the feature generation and the classification. These steps aim to extract relevant information for estimating the severity level [8]. In this respect, several studies have explored color and texture features of plant leaves. For instance, in [9], the gray-level co-occurrence matrix (GLCM) was used as a textural feature descriptor with gray level images of wheat leaves. Similarly, [10] employed different color spaces, including LAB and HSV, as features for tea leaves. In [11], authors proposed, a CNN model based on Xception model named Yellow-Rust-Xception to determine the severity level in yellow-rust disease in wheat. In another research work, MobileNetV2 and VGG16 were adopted as feature generators for yellow-rust severity estimation in wheat leaves [12]. In [13], a customized CNN model was developed to classify four severity stages of stem rust disease in wheat crop. Furthermore, recent advances in image processing and analysis have introduced more accurate and plant leaf representative features. CNN (Convolutional neural networks), algorithms designed to learn from big data as generalization of mathematical models inspired from human cognition system [14,15], actually, they are at the forefront of this progress, as they have the ability to recognize patterns and show promising results for image classification through multiple abstraction layers [5,9]. CNN specialize in processing data structured as multiple arrays, such as color images. The feature verification is performed by convolutional layers using the mathematical operation of convolution between the image and a kernel filter. Fully connected layers handle the classification task through

backpropagation, which updates internal parameters based on computations and representations from the previous layer [10].

2. PROPOSED SYSTEM

The proposed framework for severity estimation based on CNN ensembles is exhibited in Fig. 1.

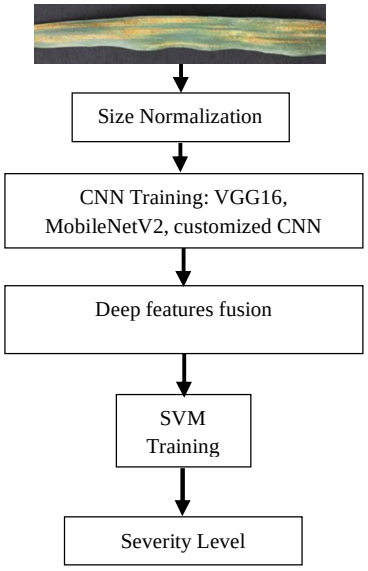

Fig. 1. Proposed CNN ensemble for plant leaf severity estimation

Initially, a size normalization is employed, to scale all images at 120×120 pixels to expedite system development. Then, three CNN models are trained to predict six severity levels of the Yellow Rust disease. The CNN combination is carried out by training concatenated deep features generated from outputs of fully connected layers. In this respect, we utilize the VGG16 and the MobileNetV2, in addition to our proposed CNN model. Its architecture comprises four convolutional layers with a 3×3 kernel size. Maxpooling operations are applied after each convolution. Additionally, a dropout of 20% of the network's parameters is applied at the input of This latter. The prediction block consists of three dense layers containing 256, 128 and 80 nodes respectively, culminating in the final SoftMax layer. Batch normalization is applied at the end of the convolution bloc and after the first and the second dense layers.

3. EXPERIMENTAL RESULTS

Experiments are carried out on images extracted from Yellow-Rust-19 dataset, which focuses on the severity level of Yellow Rust disease in wheat under field conditions. This dataset contains wheat leaf images of varying sizes, totaling 15,000 samples. The samples are classified into six severity levels, labeled as 0 (Healthy: No signs of infection), R (Resistant: Minor signs of infection), MR-MS (Moderately Resistant—Moderately Susceptible), MR (Moderately Resistant: Small and medium signs of infection), MS (Moderately Susceptible: Medium signs of infection), and S (Susceptible: Major signs of infection). Fig. 2 showcases a sample from each class of the experimental set.

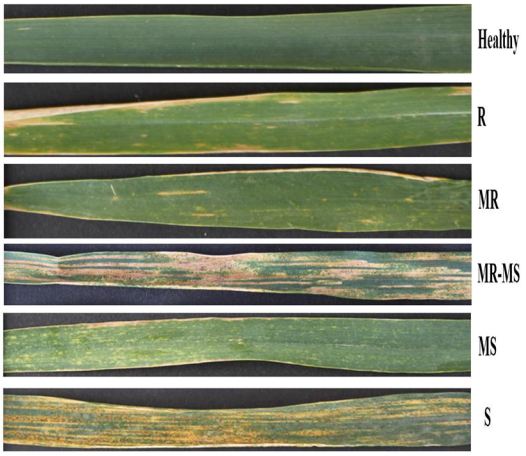

Fig. 2. Images from the experimental dataset

Results in terms of overall classification accuracy are reported in Table 1. It is easy to see, that individual CNN models provide approximately the same precision. Also, the CNN ensemble provides an improvement about 1.13% over the best individual CNN.

Table.1. Severity estimation accuracy obtained for the CNN ensemble versus individual CNN

Classification system	Overall Accuracy (%)
Customized CNN	82.13
VGG16	83.13
MobileNetV2	82.92
CNN ensemble	84.26

According to the confusion matrix depicted in Fig. 3, the CNN ensemble provides its best precisions in the healthy class (Index 0) where the severity level is small than 5%. On the contrary, there are

some confusions between other levels were several samples have quite similar severities.

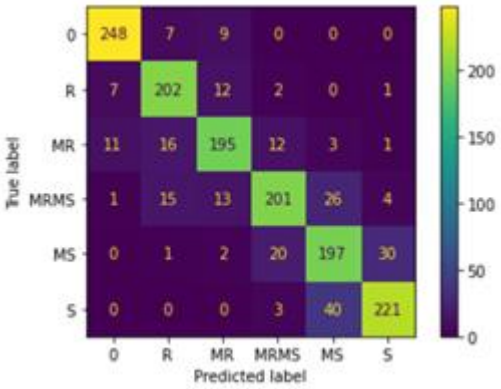

Fig. 3. Confusion Matrix obtained for the CNN ensemble

4. CONCLUSION

In the present work, an approach for combining CNN models is introduced to improve the Yellow Rust severity estimation in wheat crops. First, three CNN models that are VGG16, MobileNetV2 and a customized CNN were employed as end-to-end severity estimation systems. Then, a CNN ensemble was elaborated by combining deep features and output probabilities of CNN to get an improved classification. Combined features were trained by a SVM classifier was used to perform the severity classification task from combined CNN. Across all experiments, the results showed that end-to-end CNN provide medium performance with variable accuracies among different classes. Also, the customized CNN which is a lightweight architecture provides similar performance as the VGG16 while having a small computation cost. Meanwhile, the CNN ensemble based on a deep features combination which collects 1024 features of the VGG16 and the MobileNetV2 with the 80 features of the customized CNN provided better performance.

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