Software Tool for Plant Pathometry & Estimation of Nutrient Content

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I. Motivation

Agriculture plays a critical role in providing food supply to the growing population of the world. It is estimated that, on average, annual global food supply loss due to plant diseases stands at 40%. In developing countries, smallholder farmers generate more than 80% of the agricultural production. Farmers are unaware of which disease is harming their crops and what preventive measures need to be taken. This makes crop diseases a significant threat to food security around the world.

II. Problem Statement

Reliable, accurate assessments of nutrient content & disease intensity are critical for farmers & also for many research areas in plant pathology. We aim to employ deep learning tools to estimate the nutrient content & identify the intensity & type of disease in a plant by scanning its leaves & helping our fellow farmers by providing treatment options for the plant.

III. Methodology

We tried to understand what types of diseases occur in plants, mainly crops and tried to learn how to determine the plants' nutrient content by examining the leaf of that particular plant. We used the Plant Village Dataset collected by Penn State University's research and development team. The dataset contains more than 54,000 images of 14 different crop species for example Apple, Tomato, Orange, Blueberry Corn, etc. The images include plants affected by 21 different kinds of diseases with 25% healthy leaves images.

A. BASE MODELS FOR DISEASE DETECTION

We use two model frameworks: SE-ResNext 50 & T ResNet as base models. In the SE-ResNext 50 model, the prefix se is the process of squeeze and excitation. The principle of this process is to enhance the important features and weaken the unimportant features by controlling the size of the scale. It is the same as the attention principle. It is to make the extracted features more directional, so as to better recognize the fine features in the FGVC (Fine-Grained Visual Categorization) task.

TResNet provides a very good speed-accuracy - batch size trade-off for GPUs. We were able to train on input resolution 600x600 with a batch size of 64 and a training rate of 90 image/sec, which enabled us to experiment fast and efficiently.

B. NUTRIENT ESTIMATION

Pre-processing of all images was done to enhance their visual quality, further to achieve the various features of color images, and to transform color (RGB) images into normalized r, g, and b chromaticity coordinates. The composite color images were decomposed into red spectrum image (R), green spectrum image (G), and blue spectrum image (B) components. Subsequently, the images were also converted into hue, saturation, and intensity (HIS) coordinates to extract the intensity component. In order to extract the color information and to obtain different features, the entire image features were segmented from its background using an automatic segmentation technique based on a modification of Otsu's algorithm. Four image features (mean, variance, average energy, and entropy) from each normalized 'r' and 'g' segmented image histogram of leaves were calculated.

IV. Results

We achieved F-scores of 93.53, 87.12 and 94.13 using the SE-ResNext 50, T ResNet and Ensemble models respectively. We also compared the nitrogen estimated by our model with the results achieved by the Kjeldahl Method. The error was within the experimental range.

V. Task Remaining for ETE

Creation of a Web/Mobile application for farmers using Django as a backend with python framework and React for the frontend. The user would just need to click the photo of the Leaf and upload it there. After processing, the details about the health of the leaf and the nutrient content of the plant would be presented with the corrective measures that can be taken.

References

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