PLANTPATHOVISION: IMAGE-BASED DISEASE RECOGNITION

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Abstract

According to the Food and Agriculture Organization of the United Nations, each year between 20% to 40% of global crop production is lost due to plant diseases & costs the global economy around $220 billion. Crop loss is one of the major concerns in food security across countries. 4 Traditionally plant diseases are detected by plant pathologists by examining the plants visually However, by the time these diseases were spotted, significant damage had often already occurred, rendering treatments ineffective. In this modern era, due to the rapid growth in the usage of smartphones & technical advancements, farmers and agriculturists have advanced in capturing the image of the plants and diagnosing the plant based on images captured with the help of deep learning techniques. The usage of deep learning in the early diagnosis and treatment of plants not only adds immense value in the field of agriculture but also prevents crop-based food & economic losses. This project aims to build a plant disease identification tool based on Convolutional Neural Network.

1. Introduction

In contemporary agriculture, the timely detection and mitigation of plant diseases are critical factors influencing crop yield, food security, and economic stability. According to the Food and Agriculture Organization of the United Nations, global crop production suffers significant losses each year, ranging from 20% to 40%, due to plant diseases, amounting to approximately $220 billion in economic losses. Traditional methods of disease detection relying solely on visual inspection by plant pathologists often result in delayed diagnoses, leading to ineffective treatments and substantial crop damage. However, with the widespread adoption of smartphones and advancements in deep learning technologies, there has been a paradigm shift in disease detection approaches. Farmers and agriculturists now have access to powerful tools capable of capturing images of plants and diagnosing diseases with remarkable accuracy. Leveraging deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized the early diagnosis and treatment of plant diseases. By analyzing images of plant leaves, these models can identify diseases with near accuracy, thereby preventing crop losses and ensuring food security.

Our project, titled "PLANTPATHOVISION: IMAGE-BASED DISEASE RECOGNITION," aims to contribute to this growing field by developing a robust plant disease identification tool based on CNNs. By harnessing the capabilities of deep learning, our objective is to empower farmers and agriculturists with a reliable and efficient solution for detecting and combating plant diseases, thereby enhancing crop productivity and sustainability.

2. Related Work

[1] Murk Chohan et al. (2020) primary objective was the identification of plant diseases, and they proposed a deep learning model known as the "Plant Disease Detector." This model recognizes different diseases based on images of plant leaves. To increase the size of the dataset, the authors used data augmentation techniques. By implementing modifications like rotation, scaling, and flipping, these methods produce variations of pre-existing images. The augmented dataset enhances the robustness and generalization of the model. The Convolutional Neural Network (CNN) architecture, which consists of many convolutional layers followed by pooling layers, is the brains behind the suggested plant disease detection model. The PlantVillage dataset is used by the authors to train their model and achieved around 98% accuracy when tested. This dataset includes a wide range of images of both healthy and diseased leaves from numerous plant variants.

[2] Sultana et al.'s (2018) study focuses on advancements made with convolutional neural networks (CNNs) for image classification. It covers several CNN architectures for image categorization and offers insights into the various CNN components. Notably, the study comprises from the classic foundation LeNet-5 model to the cutting-edge SENet model. Each architecture is meticulously designed to meet the challenges of picture classification. Layer combinations with convolutional, pooling, and fully linked layer arrangements are included in the architecture. The activation functions chosen by the authors are tanh, sigmoid, or ReLU. The authors conduct a comparative analysis of the various CNN models, taking into consideration parameters such as accuracy, precision, recall, and F1 score.

[3] Khirade et al. (2015) offer a founding approach for addressing the challenging task of automating plant disease detection through a combination of computer vision and machine learning methodologies. The need for automated methods is highlighted by the labour- and time-intensive nature of the traditional manual observation of plant diseases. The exact goal of Khirade et al.'s proposed architecture was to use leaf images as input data for disease identification using the fusion methodology. Sophisticated approaches are used in the image processing pipeline to extract important information from these images, such as colour analysis, illness stage evaluation, damaged region identification, and texture pattern characterization. When taken as a whole, these characteristics offer a thorough picture of the plant's condition and make precise disease diagnosis possible.

[4] Poornam et al. (2021) delivered an innovative research effort exhibiting the potential of deep learning in plant leaf disease detection, illustrating the significance of prompt identification and classification. Their study includes a carefully selected dataset of 54,306 photos showing healthy and damaged plant leaves from 14 different crop types and 26 distinct diseases. The use of a deep Convolutional Neural Network (CNN), an established architecture known for its skill in extracting hierarchical features from raw pixel data and especially suitable for complex picture classification tasks, lies at the heart of their methodology. Convolutional layers, fully connected layers, and ReLU activation functions are all integrated into the CNN architecture used by Poornam et al. synergistically to identify and learn relevant features inherent in leaf pictures. On the test set, the trained model had an exceptional accuracy of 99.35%. This model can adapt to smartphone-assisted disease diagnosis thanks to the growing global smartphone penetration and advancements in computer vision.

3. Dataset

We will use the Plant Village Dataset for our experimentations. The dataset consists of 20.6K healthy and unhealthy leaf images divided into 15 categories by species and disease (Tomato Healthy, Tomato Bacterial Spot, Potato Healthy, Potato Early Blight etc.,).

4. Experiments

Our experimentation commenced with image augmentation using the ImageDataGenerator. We applied a range of augmentation techniques, including rescaling, horizontal and vertical flips, rotation, zoom, brightness adjustment, shifting, shearing, and filling mode modification to the images. Subsequently, the generator was employed to retrieve images from directories, and the resulting augmented images were saved for future utilization in model training.

For preliminary testing, we initiated the construction of a Convolutional Neural Network (CNN) by working with a subset of the dataset. Specifically, we focused on images of pepper plants, which encompass two distinct classes: 'Pepper__bell___Bacterial_spot' and 'Pepper__bell___healthy'. Below, we present the summary of the model developed in Figure 1. The model is constructed using hyperparameters mentioned in the table below

Hyper Parameter	**Value**
Batch Size	32
Epochs	3
Optimizer	Adam
Learning Rate	0.01

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 32)      896

 max_pooling2d (MaxPooling2  (None, 127, 127, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 64)        36928

 max_pooling2d_2 (MaxPoolin  (None, 30, 30, 64)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 28, 28, 64)        36928

 max_pooling2d_3 (MaxPoolin  (None, 14, 14, 64)        0
 g2D)

 conv2d_4 (Conv2D)           (None, 12, 12, 64)        36928

 max_pooling2d_4 (MaxPoolin  (None, 6, 6, 64)          0
 g2D)

 conv2d_5 (Conv2D)           (None, 4, 4, 64)          36928

 max_pooling2d_5 (MaxPoolin  (None, 2, 2, 64)          0
 g2D)

 flatten (Flatten)           (None, 256)               0

 dense (Dense)               (None, 64)                16448

 dense_1 (Dense)             (None, 2)                 130

=================================================================
Total params: 183682 (717.51 KB)
Trainable params: 183682 (717.51 KB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 1. Summary of CNN Model

To facilitate training and testing, we utilized the computational resources available through Google Collaboratory, which offers access to a T4 GPU equipped with 16GB of GDDR6 memory.

5. Results

The generalization accuracy on the test images came out to be around 85%. Figure 2 demonstrates train loss vs validation loss and Figure 3 demonstrates training accuracy vs validation accuracy. Figure 4 depicts the sample predictions along with the prediction accuracies.

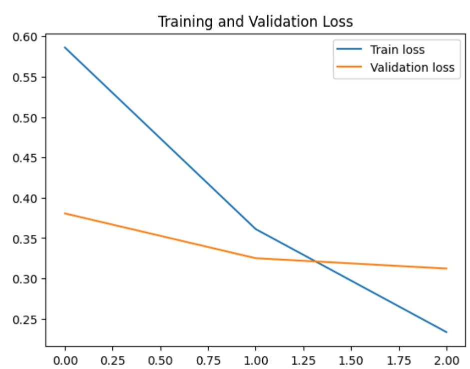

Figure 2. Training Loss vs Validation Loss

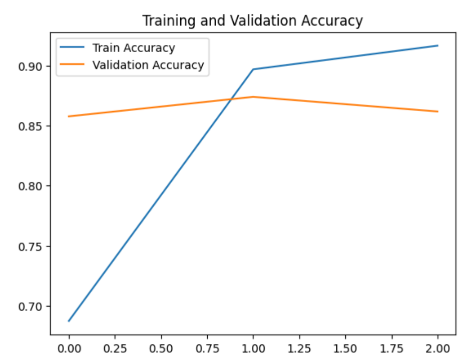

Figure 3. Training Accuracy vs Validation Accuracy

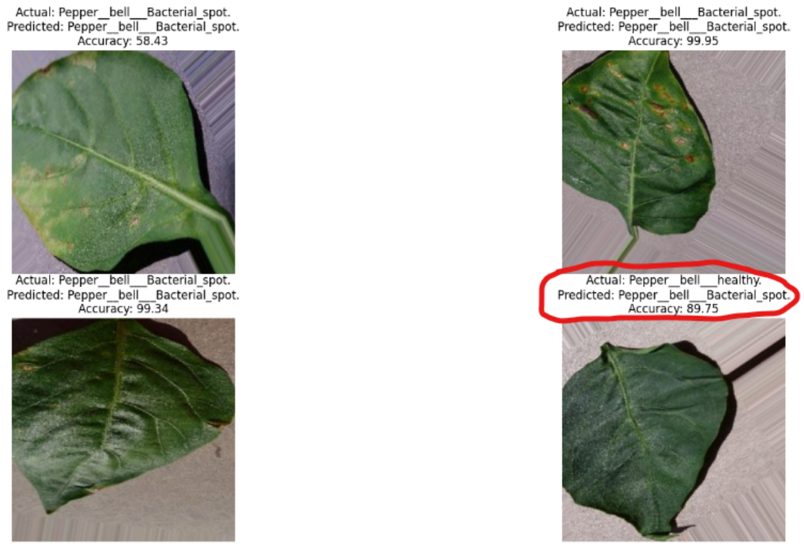

Figure 3. Sample Predictions along with prediction accuracies.

6. Acknowledgement

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References

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