Image-Based Tea Leaves Diseases Detection Using Deep Learning

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*Abstract: Using a public dataset of **2**990 images of infected and healthy tea leaves, we trained deep convolutional neural network model to identify 4 types of tea leaf diseases. The model achieved an accuracy of 99.84%, on a held-out test set.*

Keywords: Deep Learning, Tea Leaves, Disease, Detection

1. INTRODUCTION

Since the earliest times, plants have been vital to human survival. From our ancestors' nomadic searches for food to the agricultural revolution that enabled civilization, crops have been essential. Today, despite agricultural technologies that feed over 7 billion people, plant diseases critically threaten global food security (Jones & Smith, 2003).

These diseases disproportionately affect smallholder farmers, who produce about 80% of the developing world's food (World Bank, 2012). For them, healthy crops are essential for their livelihoods.

Early and accurate disease identification is crucial. While traditional plant clinics are important, smartphones offer new opportunities. Billions of these devices have high-resolution cameras that can be used for rapid disease detection.

Recent advances in computer vision, especially convolutional neural networks (CNNs), have transformed image recognition. The "deep learning revolution," driven by innovations like Ciresan et al.'s work and Krizhevsky et al.'s 2012 ImageNet victory, has greatly improved image analysis. However, the successful deployment of these technologies hinges on addressing key challenges related to data quality and model generalization. Variations in lighting conditions, leaf maturity, and disease severity can significantly impact the accuracy of image-based diagnostic systems. Furthermore, the computational demands of deep learning models necessitate careful optimization for efficient execution on resource-constrained mobile devices.

To address these challenges, our study focuses on developing a robust and efficient smartphone-compatible model for identifying tea leaf diseases. We leverage a dataset of 2990 images and advanced deep learning techniques to achieve high accuracy while minimizing computational overhead. The ultimate goal is to provide a practical and accessible tool that empowers farmers to proactively manage plant diseases and safeguard their crops.

Building upon existing research, our work explores novel approaches to enhance the resilience of deep learning models against environmental variations. We investigate the use of data augmentation techniques to simulate diverse field conditions, thereby improving the model's ability to generalize to unseen scenarios. Additionally, we employ model compression strategies to reduce the computational footprint, enabling seamless integration into low-power smartphone platforms.

The significance of this research extends beyond the specific context of tea leaf diseases. The methodologies and insights gained from this study can be readily adapted to address similar challenges in other crop systems and geographical regions. By providing a blueprint for developing accessible and accurate disease detection tools, we aim to contribute to a more sustainable and resilient agricultural future.

In this study, we use these advances to create a smartphone-compatible model for identifying tea leaf diseases. Using a dataset of 2990 images, our model achieves up to 99.84% accuracy in detecting three types of tea leaf diseases, providing a valuable tool for farmers.

2. STUDY OBJECTIVES

1. To demonstrate the effectiveness of deep learning for automated plant disease diagnosis.
2. To develop a high-accuracy, mobile-friendly tool for on-site plant disease identification.

3. DATASET

Figure 1: Dataset Samples

We constructed our dataset using images from the Plant Village dataset, a widely recognized source of plant disease imagery that includes nearly 50,000 images across 14 crop species and 26 distinct diseases. We selected 2,990 images of tea leaves, representing both healthy leaves and three common tea leaf diseases. The dataset comprises the following four classes [16]:

- Class 0: Bird eye Spot
- Class 1: Red leaf spot
- Class 2: White spot
- Class 3: Healthy leaves

For efficient processing, all images were resized to a uniform resolution of 150x150 pixels, a size determined to balance computational speed and image detail.

4. THE ARTIFICIAL CONVOLUTIONAL NEURAL NETWORKS: AN INTRODUCTION

In the field of machine learning, a Convolutional Neural Network (CNN), also known as a ConvNet, represents a class of deep, feed-forward artificial neural networks. CNNs are most commonly used for analyzing visual imagery.

CNNs are a type of multilayer perceptron designed to minimize the need for extensive preprocessing. They are also referred to as Shift Invariant or Space Invariant Artificial Neural Networks (SIANNs) due to their shared-weights architecture and translation invariance.

Convolutional networks draw inspiration from biological processes, specifically the organization of the animal visual cortex. Individual cortical neurons respond to stimuli within a limited region of the visual field, known as the receptive field. The receptive fields of different neurons overlap, ensuring coverage of the entire visual field.

Compared to other image classification algorithms, CNNs require relatively little pre-processing. This is because the network learns the filters that were traditionally hand-engineered. This independence from prior knowledge and manual feature design is a significant advantage.

CNNs have a wide range of applications, including image and video recognition, recommender systems, and natural language processing.

- **Design**

A CNN consists of an input layer, an output layer, and multiple hidden layers. The hidden layers typically include convolutional layers, pooling layers, fully connected layers, and normalization layers [1-5]. The description of the process as a *convolution* in neural networks is conventional; mathematically, it is a *cross-correlation*. This distinction primarily affects the indices in the matrix and the placement of weights.

- **Convolutional Layers**

Convolutional layers apply a convolution operation to the input, passing the result to the subsequent layer. This convolution emulates the response of individual neurons to visual stimuli, with each neuron processing data only within its receptive field. While fully connected feedforward neural networks can learn features and classify data, applying this architecture to images is impractical due to the high number of neurons required, even in shallow architectures. For example, a fully connected layer for a small 100x100 image would have 10,000 weights per neuron in the next layer.

The convolution operation addresses this problem by reducing the number of free parameters, allowing for deeper networks with fewer parameters. For instance, tiling regions of size 5x5 with shared weights requires only 25 learnable parameters, regardless of image size. This approach also helps resolve the vanishing or exploding gradients problem in training traditional multi-layer neural networks with backpropagation [6-7].

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- **Pooling layers**

Convolutional networks may include local or global pooling, which combine the outputs of neuron clusters at one layer into a single neuron in the next layer. For example, max pooling uses the maximum value from each of a cluster of neurons at the prior layer. Another example is average pooling, which uses the average value from each of a cluster of neurons.

- **Fully Connected laers**

Fully connected layers connect every neuron in one layer to every neuron in another layer, similar to traditional multi-layer perceptron neural networks (MLPs).

13 Conv2D + 5 MaxPooling2D + 1 GlobalPooling + 2 Dense + 1 Dropout + 1 InputLayer = 23 layers.

- **Receptive Field**

In neural networks, each neuron receives input from a number of locations in the previous layer. In a fully connected layer, each neuron receives input from every element of the previous layer. In a convolutional layer, neurons receive input from only a restricted subarea of the previous layer, typically a square shape (e.g., 5x5). This input area is the neuron's receptive field. Thus, in a fully connected layer, the receptive field is the entire previous layer, while in a convolutional layer, it is smaller.

- **Weights**

Each neuron in a neural network computes an output value by applying a function to the input values from its receptive field. This function is defined by a vector of weights and a bias (typically real numbers). Learning in a neural network involves making incremental adjustments to these biases and weights.

The vector of weights and the bias are collectively called a filter, representing a specific feature of the input (e.g., a particular shape). A key characteristic of CNNs is that many neurons share the same filter. This reduces memory usage because a single bias and a single vector of weights are used across all receptive fields sharing that filter, rather than each receptive field having its own bias and vector of weights.

5. METHODS

We experimented with images to see how the model work and what exactly it learns,t we take the image as it is with 3 color channels. And as expected the model learns different patterns in each approach.

6.MODEL

Our model accepts raw images as input and utilizes Convolutional Neural Networks (CNNs) for feature extraction. The architecture consists of two main parts:

- **Feature Extraction:** This section comprises 13 convolutional layers, each followed by a ReLU activation function and a max pooling layer.
- **Classification:** Following the flattening layer, two dense layers are used. The first dense layer

contains 256 hidden units, and the final output layer uses a Softmax activation function with 3 output classes.

The total number of trainable parameters in the network is 14,978,883.

layer has Softmax as activation and 3 outputs representing the 3 classes.

Table 1: Model Summary

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 256, 256, 3)	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1,792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36,928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73,856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147,584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295,168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590,080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590,080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 8, 8, 512)	0
global_max_pooling2d (GlobalMaxPooling2D)	(None, 512)	0
dense (Dense)	(None, 512)	262,656
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 3)	1,539

Total params: 14,978,883 (57.14 MB)
Trainable params: 14,978,883 (57.14 MB)
Non-trainable params: 0 (0.00 B)

7. DATA VISUALISATION

To gain insight into the model's internal orkings, we visualized intermediate activations by examining the feature maps generated by convolutional and pooling layers in response to specific inputs. These feature maps, also known as activations, provide a visual representation of how the network decomposes the input image into its learned features [16].
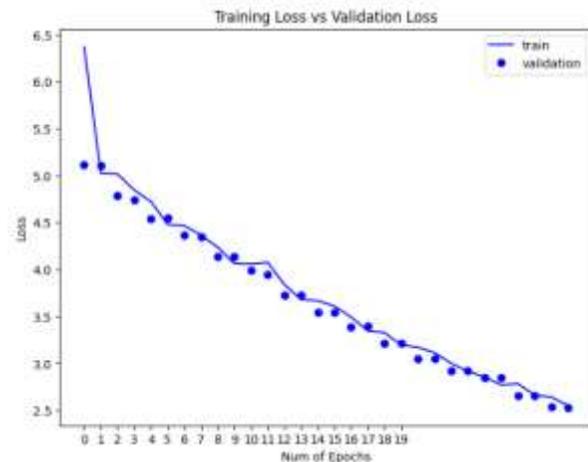

Figure 2: Training and Validation Accuracy

Figure 3: Training and Validation Loss

8. CONCLUSION

This research has successfully demonstrated the application of convolutional neural networks to the challenging task of plant disease identification. Our full-color model achieved a high level of accuracy (99.84%) on the held-out test set, clearly indicating its robustness and significant potential for real-world deployment. The training progress, as illustrated in Figures 3, further validates the effectiveness of our approach. These findings strongly suggest that color information plays a crucial role in achieving accurate disease detection, and that deep learning techniques offer a powerful tool for early disease diagnosis and timely intervention.

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