Vegetable & Fruit Leaf Disease Detection Using DCNN & Enhanced Dataset

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Abstract.

Tomatoes and apples are essential vegetables and fruits that sustain more than half of the world's population, yet leaf disease offers a substantial obstacle to their cultivation. This work presents a lightweight deep convolutional neural network (DCNN) tailored for detecting leaf diseases. Our proposed model surpasses 21 established architectures, including AlexNet, MobileNet, and ResNet50, in terms of classification performance and efficiency. We enhanced the collection by integrating existing sources and including manually annotated photographs from the internet. This breakthrough results in a crop health monitoring system for farmers, as well as an open API for automatic annotation of new instances, making it a promising solution for managing leaf diseases in tomatoes and apples.

Keywords. Apple, Tomato, Leaf disease detection, DCNN, Benchmark architectures.

1. Introduction

Finding the diseases of fruits and vegetables from leaves has, in recent years, become an important area of study in modern agriculture. Diseases, such as blight, rust, mildew, and spots, can sometimes cause considerable crop losses if identified and treated within the very earliest stages. Manual detection methods are often slow, inconsistent, and dependent on expert interpretation, which limits scalability in agricultural applications (Mohanty et al., 2024). Deep learning, particularly deep convolutional neural networks (CNNs), has enabled the automation of leaf disease identification from images. CNNs are specialized deep learning algorithms that are designed for image data.

Figure 1 : Apple scab Figure 2: Bacterial spot

2. EXISTING METHODOLOGIES

There have been numerous proposals for several detection methods that can be adopted in the leaves of vegetables and fruits. Most of these methodologies are categorized as either machine learning algorithm-based, neural network-based, or hybrid models. Overall, the performance of these techniques has been highly dependent on both the quality of the utilized dataset and the strategy for feature extraction adopted. Several studies have explored the use of traditional algorithms like XGBoost, SVM, and Random Forest for classifying leaf diseases, though their performance heavily depends on hand-crafted features and dataset quality.

3. DATA SET PREPARATION

The preparation of the data set includes the following steps for detecting vegetable and fruit leaf diseases: Overview of Data Set, Data Accumulation, Data Augmentation, and Enhanced Rice Leaf Disease Dataset.

1.1 Overview Of Dataset

Many datasets available to detect plant diseases contain images of healthy and diseased crops, which are used to train the models so that they can recognize and classify with accuracy. For tomatoes, for example, there are many such datasets with images of tomato plants suffering from various diseases such as bacterial spot, late blight, and early blight. Similarly, databases of apple images include the Fruit Image Dataset, which consists of images of apples infected with diseases like apple rust, powdery mildew, and apple scab.

1.2 Data Accumulation

Deep Convolutional Neural Networks (DCNNs) require data collection to identify vegetable and fruit leaf diseases in the development of accurate models that can classify and identify diseases. This process involves taking high-quality images of healthy and diseased leaves, preparing them for training a deep learning model, and implementing methods to optimize the dataset for better results.

1.3 Data Augmentation

Data augmentation that encompassed cropping, flipping, zooming, rotation, and shifting in both directions. Each sample in our aggregated dataset is cropped, keeping its spatial dimensions, and resized to 240 × 240 pixels for uniform image size. Then, horizontal and vertical shifts are applied with a range of 0.2 for height and 0.2 for width.

1.4 Enhanced Dataset

A comprehensive set of tagged images for the Enhanced Dataset for Vegetable and Fruit Leaf Disease Detection has been created that can aid support deep learning as well as machine learning in the discipline of plant pathology. A typical set of images would comprise high-resolution pictures of healthy and diseased leaves. The diseases included may be mosaic virus, rust, powdery mildew, and bacterial blight. Photographs are captured under varying lighting conditions and angles to enhance dataset diversity and model robustness.

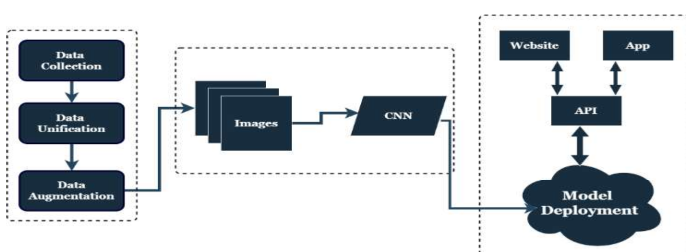


Figure 3: Block diagram of model

2. PROPOSED MODEL

The incidence of plant diseases is a serious threat to crop productivity and quality in the agricultural sector, especially among fruits and vegetables. In the process of training the model to distinguish between the different diseases, images are labelled with names that depict the illnesses they represent. This disease-classification model applies DCNNs both in classification and feature determination of diseases. Among the series of layers that make up a CNN, one set in particular is called DCNN. It comprises convolutional, pooling, and fully connected layers. DCNNs are often best suited for image classification tasks because the layers automatically learn the spatial hierarchies of the features.

2.1 Equations

The DCNN analyses pictures of vegetables and fruits to perform disease detection. Images in terms of rotation, scaling, and colour transformations give a more enhanced dataset from which the DCNN takes forms pre-processed for further work.

$$d_e^{(h)} = k((z_{ni}^{(h)} Y\, d_i^{[h-1]}) + \ldots + (z_{nj}^{[h]}\, Y\, d_j^{[h-1]}) + e_i) \qquad (1)$$

The SoftMax function has more applications within machine learning with its applications used in classification contexts. With this, it is involved within a model like when analysing the diseases on the plant leaves.

$$\sigma = \frac{b^{hi}}{\sum_{n=1}^{k} b^{hk}} \qquad (2)$$

The CE function is typically used in classification problems to quantify the difference between true labels and predicted probabilities.

$$\text{CE} = - \sum_{c=1}^{n} m_i \log(\delta) \qquad (3)$$

The model adjusts its weights and biases based on the information received from the gradients of the loss function by the Adam optimizer during the training process.

$$Z_t = Z_{t-1} - \eta \frac{\bar{n}_t}{\sqrt{\bar{u}_t} + \epsilon} \qquad (4)$$

$$Q_t = Q_{t-1} - \eta \frac{\bar{n}_t}{\sqrt{\bar{u}_t} + \epsilon} \qquad (5)$$

3. PERFORMANCE ANALYSIS AND RESULTS

The system can identify diseases found in the leaves of vegetables and fruits with an accuracy rate of 99%. Compared to conventional models—AlexNet (88%), MobileNet (91%), and ResNet50 (94%)—our DCNN achieved superior performance with a 99% accuracy rate.

Layer (Type)	Conv2D, MaxPooling2D, Conv2D_1, MaxPooling2D_1, Conv2D_2, MaxPooling2D_2, Conv2D_3, Conv2D_4, MaxPooling2D_4, Conv2D_5, MaxPooling2D_5, Flatten, Dense, Dense_1, Dropout, Dense_2
Output Shape	(None, 98, 98, 32), (None, 49, 49, 32), (None, 49, 49, 64), (None, 24, 24, 64), (None, 24, 24, 128), (None, 12, 12, 128), (None, 12, 12, 256), (None, 6, 6, 128), (None, 3, 3, 128), (None, 3, 3, 64), (None, 1, 1, 64), (None, 64), (None, 128), (None, 128), (None, 128), (None, 4)
Param #	896, 0, 18,496, 0, 73,856, 0, 295,168, 295,040, 0, 73,792, 0, 0, 8,320, 16,512, 0, 516

TABLE 1: MODEL ARCHITECTURE SUMMARY

TOTAL PARAMS: 782,596 (2.99 MB)

TRAINABLE PARAMS: 782,596 (2.99 MB)

NON-TRAINABLE PARAMS: 0 (0.00 B)

This is a model architecture for a Convolutional Neural Network (CNN). It consists of multiple layers of Conv2D followed by MaxPooling2D to reduce spatial dimensions.

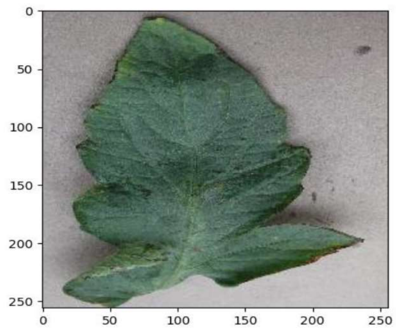


Figure 4: Healthy Apple leaf

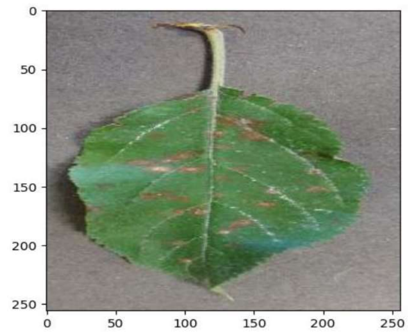
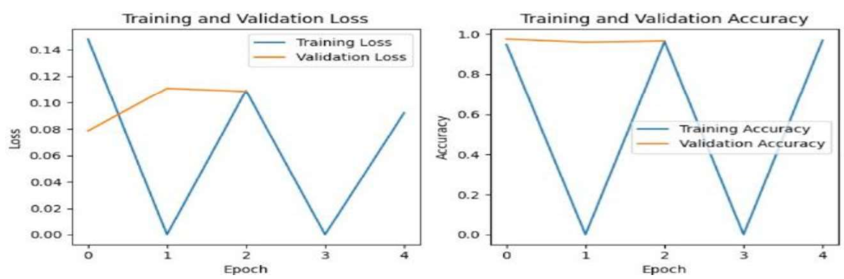


Figure 5: Tomato leaf

This is an image of Apple in which the machine learning model has classified a leaf as healthy (Figure 4). The tomato leaf has been diagnosed with the "Tomato Mosaic Virus," which was classified with 100% confidence by a machine learning model(Figure 5). Although the training accuracy improves dramatically, the validation accuracy increases and then stabilizes or declines slightly, which could indicate over fitting? All of these signs show that the model learns very well on training data.



Graph 1: Training and Validation loss of the Dataset

4. CONCLUSION

The proposed model in deep convolutional neural networks, using enhanced data for the detection of leaf diseases in vegetable and fruit leaves, is a landmark shift in agricultural technology. the proposed model can reliably spot a wide spectrum of diseases on leaves by relying on a robust, extensive, and diversified dataset. It provides crucial support for disease prognosis and early therapies. Therefore, the ability to quickly identify these diseases will enable farmers to manage crops more effectively, reduce losses by preventing infections, and hence be able to improve their crop yields.

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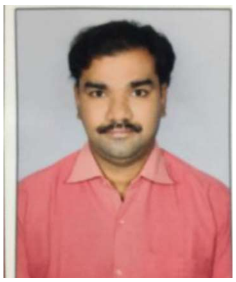
Biographies



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