Plant Disease Detection Using CNN

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Abstract. Plants constitute one of the major sources of human foodstuffs. Farmers in countries across the globe are struggling to repel an array of destructive organisms. In this work, we propose a Convolutional Neural Network (CNN) architecture for image-based plant leaf disease detection based on deep learning with a total of 20 layers including convolutional layers, max pooling layers, dropout layers, flatten layer, and dense layers. The CNN classifier model was trained with a dataset of nearly 87,000 images of different healthy and disease crop leaves and background images. The spatial patterns were discovered by feature extraction mechanisms. The model displayed 95-98% accuracy on the test set and proved to be a promising tool in plant disease detection.

Keywords: Convolutional Neural Network, Data Augmentation, Disease Detection, Deep learning, Feature extraction.

1 Introduction

In the majority of economies Farming is the #1 job and feeds most of the people in the world. However, there are a host of obstacles farmers everywhere face when it comes to achieving the crop yields they desire from mercurial weather and sunless soils to sometimes suspect generational practices [1]. The most perilous killer among them is crop disease that can wipe out the entire food crops and cause a huge loss to the grower. Plant Disease and Pests by the Numbers the FAO estimates that diseases and pests in plants cause a 20–40% reduction in yield of the four major world crops, while plant diseases alone cause 13% losses to agricultural production as a whole. Traditional plant disease diagnosis depends on visual checking by experts, a time-consuming and labor and human-being fatiguing work [2]. These constraints, however, render traditional methods unsuitable for the scope of modern precision agriculture that includes the rapid and accurate identification of diseases. Hence, many researchers have resorted to AI based and image processing for the automatic identification of diseases. Round 2 (2018): Primary utilization of Convolutional Neural Networks (CNNs) has enabled end-to-end classification pipeline [3] for plant and disease identification over leaf image without any supervision. With the emerging deep learning models such as CNNs, architectures are designed to learn task-specific discriminative representations which coupled with distributed computing capabilities enables seamless transfer learning for big scale analysis on novel data sets. [3]. The CNN models gave always a better performance in plant disease classification with regards to conventional machine learning methods (SVM and KNN) showing that they can achieve high accuracy using less error rates making them also robust enough for testing on different datasets. [4].

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This study aims to enhance early plant disease detection methods by integrating advanced AI driven techniques while broadening the scope to identify a wider range of diseases. By improving accuracy and efficiency, these innovations can play a crucial role in better disease management, ultimately supporting more sustainable and productive agricultural practices.

2 Related Works

[5] proposed a SVM Classification Model on basis of High Dimensional Hyperspectral Data for the detection of Sugar Leaves diseases. With the hyperspectral data, the authors used a radial basis function to obtain an approximate accuracy of 86%

Different methods for image processing and feature extraction to detect the plant diseases in their leaf images are discussed and compared with each other [6].

The authors of [7], likewise introduced a machine learning model for ALS disease identification using apple, with the help of these 4 techniques in machine learning algorithm which are LR, FLDA, SVM and KNN. In [8] the authors considered two deep learning architectures, AlexNet and VGG16 net to classify the tomato crop diseases with images as the input.

A simplified CNN, with multiple attention modules, that increases the model performance in identifying tomato leaf diseases is developed to classify tomato disease. Numbers in [9] are better than the original ResNet50+, but there is more than 16 times fewer parameters and 23 times less computational cost. On the other hand, Xiangyu et al. [9] found that their model with the attention module had a slightly deeper and wider network with more parameters but achieved better detection performance than the corresponding model without attention modules. The authors in [10] designed a 13-layer convolutional neural network (CNN) for image-based fruit classification.

In Ref. [11], the authors discussed of the performance of the model can be improved by data augmentation techniques.

The authors in [12] demonstrated augmentation methods such as GANs and NST for detecting plant leaf diseases. From the result, the performance of the proposed augmentation method was better than those of each of the methods in [12].

In [13] the author has presented a Deep CNN classifier to classify various plants based on the leaf vein morphological patterns. The authors set the legume classification of four legumes; the white bean, the red bean, and soybean, in [13].

The authors in [14] proposed a SVM model with different kernel functions that classifies images and identifies the tomato leaves that are infected with Tomato yellow leaf curl virus (TYLCV).

In Ref. [15], the authors proposed a 9- layer deep convolutional neural network (DCNN) to identify leaf diseases. They used six different types of image augmentation methods, it resulted in the average accuracy of 94.46%.

CNN based models have been widely used for leaf image classification, outperforming conventional techniques Pandian et al. (2022) proposed a 14- layered Deep CNN (14-DCNN) trained on 147,500 images across 58 classes. They utilized data augmentation (BIM, DCGAN, NST) and hyperparameter optimization, achieving 99.96% accuracy, surpassing models like AlexNet, VGG16, and ResNet-50. Despite advancements, challenges remain in real-world deployment, leading to ongoing research on lightweight CNNs and real-time applications [16].

3 Methodology

3.1 Theoretical Structure

Convolutional neural network architecture: Convolutional Neural Network has three layers which are convolutional layer, pooling layer and fully connect layers. Fig 1 Combination of all Layers. (18)

Convolution Layer-

Convolutional layer– This layer is responsible for producing an activation map by convolving the images pixel by pixel. The working inside convolution layer is shown in Fig 2. [18]

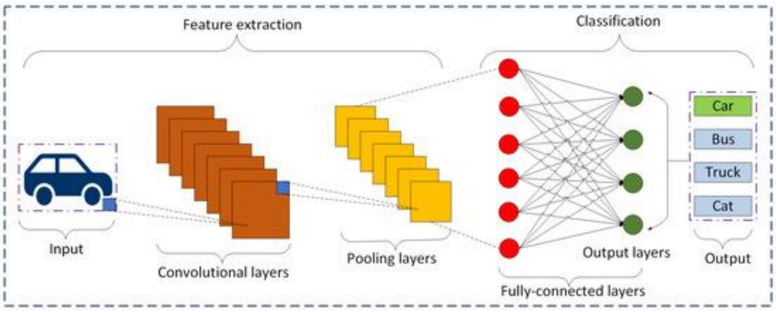

Fig. 1. CNN Architecture.[18]

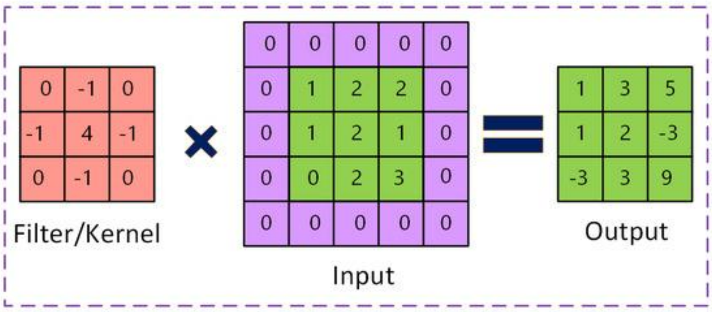

Fig. 2. Convolution Layer.[18]

Pooling Layer - Pooling layer: minimizes the data generated by the convolutional layer so that it is more efficiently stored. Fig 3 illustrates the inner operation of the pooling layer. [18]

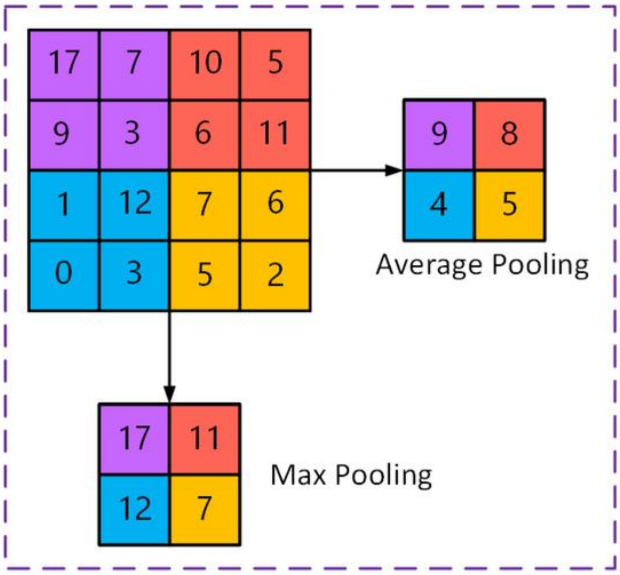

Fig. 3. Pooling Layer.[18]

Fully connected input layer (the outputs of the previous layers are "flattened" to form a one-dimensional vector that is fed into this step) — Fully Connected Layer Fully connected layer 1: It maps the input from feature analysis part to output as label, its output is of size n x c where n is number if samples and c class labels. [17] Fully connected Layer at the output (with 17 outputs i.e. each label) the network will give probability of each class for a given input [17]. VGG19: Deep Convolutional Neural Network (Fully connected Layer) VGG19 is a layer deep Convent with pretrained layers which have learned convolution filters for images, i.e., it has learnt the parameters of these filters to recognize images. We fine-tuned a deeply-trained neural network VGG19 on millions of images and hard classification problems. [17]

3.2 Methods

3.2.1 Data Processing

This image data set has been generated using Plant Village data, by combining images from seven different plant-disease pairs + the healthy class known as 21 common insect -deduced plant-disease categories created using a subset of New York State Ag experiment-station images & containing according to initial data ~108098 images and which is divided into based on diseases distributions (no. of recordings per disease), in such classes count: It will split data into a training set (80%) and validating set(20%) with the same directory structure. Creating after kind of new directory 33test images for the prediction. Bacterial Wilt (Tomato), Maize Streak Virus (Corn), Citrus Canker (Citrus Plants) and Anthracnose (Mango, Beans) are the diseases now available in this latest version. Fig 4: Sample images of one class Since these are the model input size those images have been scaled to 128 × 128. All the above steps is done to make it normalize between 0 and 1 (We Technically called it as feature scaling/ transformation) Will optimize and make the learning for model faster.

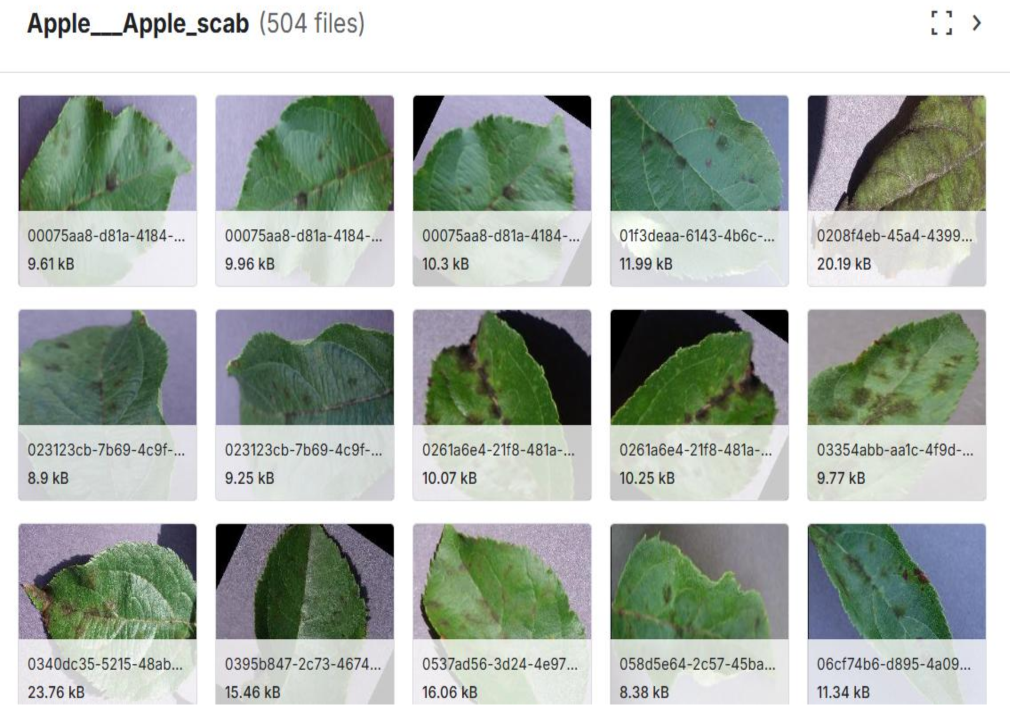

Fig. 4. Sample Image of Apple Scab Disease.

3.2.2 Proposed CNN Architecture

The CNN consists of 6 major feature extraction stages (9), by each stage has two layers for image pattern detection. After every 2 index and 5 index the pooling process will be done to pool the image so that unnecessary pixel values get eliminated. This one-dimensional vector of the extracted features is then used to a two fully connected layers. The last layer shows 38 output (so, the model prepares with a capacity of predicting if plants has one of 38disease categories).

Stage 1 contains a sequence of 2 Conv2D layer with basic features extracted via 32 filters (3×3 kernel) followed by MalPooling2D (2 x 2), as pooling might help reduce dimensions, in stage 2 we have consecutive two convoluted (Conv2d layers) and then comes a max pooling 2d (of size 22). Adding Two Conv2D layers (128 filters) brings out more feature extraction and achieved MaxPooling2D as 2×2 in the last stage. Stage 4: Two Conv2D with 256 filters + Conv2D with 256 filters → MaxPooling2(2×2) → The 5th layer: (512,) (cv)(2x2) → Conv2D (512 gimicks) & (pool size = 2x2).

In the same way, for the last layer we have a model including Dropout (to avoid overfitting), Flatten (features to convert into 1D) follow by Fully Connected with 1500 neurons and activation ReLU, followed by another dropout and final layer has another Dropout fully connected with 38 units and SoftMax used for classification. Train — The model was trained in order to diminish the Categorical Cross-Entropy loss, using Adam optimizer with a learning rate of 0.0001. Data was divided into a 80–20 training and validation set split. This model was trained with 10 epochs (fine-tuned to get maximum accuracy.)

3.2.3 Model Deployment

The trained Convolutional Neural Network (CNN) model is deployed for practical agricultural applications, ensuring farmers and agricultural experts can efficiently diagnose plant diseases in real time. Deployment is implemented on multiple platforms to maximize accessibility, ease of use, and scalability, allowing integration with both online and offline systems. Web-Based Application (Flask + TensorFlow): A user-friendly web application is developed using Flask as the backend framework, integrated with TensorFlow for real-time disease classification. Users can upload leaf images through an interactive interface, and the trained model processes the images to generate disease predictions. The system is designed with a simple and intuitive User Interface (UI), ensuring ease of use for individuals with minimal technical expertise.

3.2.4 Pseudo Code

- Load the dataset of training, validation, and test images.
- Preprocess images (resize, normalize pixel values).
- Use ReLU-activated convolutional layers, max-pooling down sampling layers, and softmax activated fully connected layers to define the architecture of the CNN.
- Train the model using categorical cross-entropy loss and the Adam optimizer.
- After the model has been trained on the training dataset, validate on the validation set.
- Monitor performance metrics (loss, recall, accuracy, and precision).
- Save the learned model for deployment.
- Use the test dataset to evaluate the model's performance.

4 Results and Evaluation

Dataset: Kaggle This comprises of (approximately) 87,000 RGB crop leaf images corresponding to 38 classes belonging either to sick or remaining appertaining the healthy leaves. Plant disease classification using CNN model was a major success which showed 95–98% accuracy on the test set. Fig. 5 The training and validation accuracy.

The performance evaluation of other measures such as precision, recall, and F1-score were used to confirm the strength of the model, showed that it had a great predictive ability in all classes. The trends of accuracy on training and validation reflect smooth convergence and minimal overfitting.

When compared to other plant disease classification models, our approach's improved training data and CNN architecture enabled it to achieve better generalization and higher accuracy. The model was trained on a GPU-enabled system over several epochs, taking computational efficiency into consideration as well, to guarantee practical viability for real-time applications. The model may be integrated into automated agricultural systems to assist farmers in early disease detection.

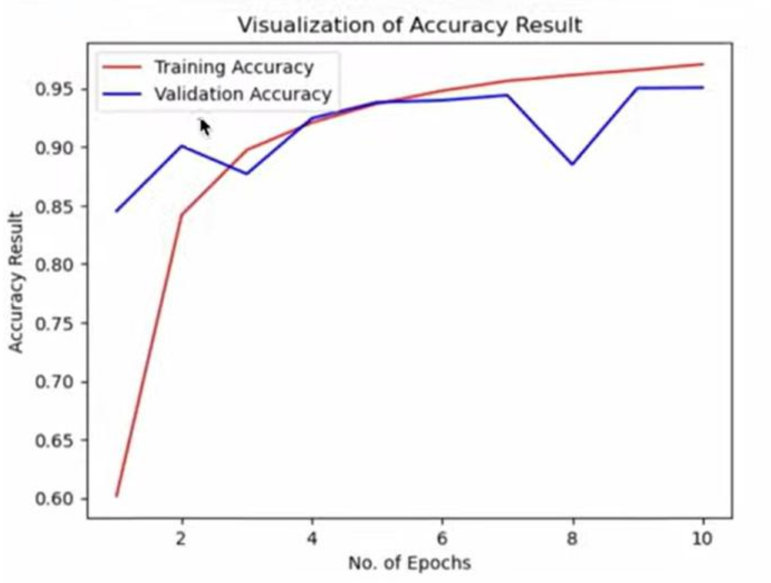

Fig. 5. Accuracy result.

They are much better in terms of accuracy but by using variety datasets (different and diverse) to train the model, testing them on real-world circumstances, and implementing explainable AI to make them interpretable instead of a black box. The next step is to deploy the proposed model in practical scenarios, and to explore some of the possible lightweight architectures for edge computing applications. This work focused on developing the a fully integrated system combination of server-side component (trained model for an application) and client side running on smart mobile devices that allows to diagnose diseases of fruits, vegetables or any crops using an image captured by the camera of phone as input.

5 Conclusion

Plant disease is a curtain raiser on food security and economic stability from the agriculture, where productive crops are source of people livelihood. Looking very cool and all, new technologies and advancements in the field of agriculture have been made a long while ago; however, these diseases continue to cause reduction in crop yield, quality of fruit and plant death. Deep alphabet also known as deep plantation identification in the image pattern recognition specialization, is quite at home with issues like plant problems. All in all, curing plant diseases on time through a robust plant disease detection system can tremendously improve the agriculture sector and enable farmers to identify the causes before it is too late. These are more of the computer vision-based images processing system which are evolving with Machine Learning, deep learning etc. to detect or classify image data into various plant diseases. Supported by field-deployed sensors communicating data-feed over the Internet of Things (IoT), and scrutinized in a real-time mode, they are overly precise enabling an even more tightly managed agriculture practice. Of course, there are still many challenges that remain to be addressed with deficient datasets, cumbersome workflow or under dynamic environments but looking at the answers already rendered it is unmistakable what a boon these tools can provide to smarter farming. To really make a dent in world food production, it would be necessary to do the following: Build an algorithm many times faster on this data; create even larger databases with disease data and prove its effectiveness over thousands of farmers.

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