Plant Disease Detection Using Machine Learning

Dibyansu Sharma, Madhav Bansal, Jeswin Mathew
Department of Computer Science & Engineering, Chandigarh University, Punjab, India
sharmadibyansu1501@gmail.com,

Abstract: Agriculture plays a crucial role in sustaining societies worldwide, and effective crop management is paramount for food security. Plant diseases pose significant threats to agricultural productivity, making timely detection imperative. Leveraging advancements in deep learning and machine vision, this research explores the application of Convolutional Neural Networks (CNNs) to detect tomato leaf diseases. A novel dataset comprising images of diseased and healthy tomato leaves is introduced and utilized for model training. By employing the Inception V3 architecture and data augmentation techniques, the proposed CNN model demonstrates promising results in disease classification. This study presents a framework for leveraging AI/ML techniques to enhance plant disease diagnosis and contribute to global food security efforts.

Keywords: Plant Disease Detection, Deep Learning, Convolutional Neural Networks, Inception V3, Agriculture, Tomato Leaf Diseases.

1. Introduction

Agriculture serves as the backbone of civilizations, providing sustenance and livelihoods. In regions like India, where diverse climatic conditions prevail, crops like tomatoes thrive but are susceptible to various diseases. Timely identification of plant diseases, such as Early Blight and Late Blight, is essential to mitigate their adverse effects on crop yield. Traditional methods of disease detection are time-consuming and often inadequate, necessitating innovative solutions. In recent years, the intersection of deep learning and computer vision has enabled the development of efficient disease detection systems. This research focuses on harnessing the power of AI/ML algorithms, particularly CNNs, to automate the identification of tomato leaf diseases, thereby facilitating proactive agricultural management.

Convolutional neural networks are image processing methods using jpg files to comprehend them [3]. Shift invariant is another name for them. Because of their weight-sharing architecture and translation invariance properties, this is the case. As a result, they've also been known as space-invariant neural networks. They're used in recommender systems, image and video recognition, medical image analysis, image detection, natural language processing (NLP) [5], brain-computer interfaces, and financial time series, among other items. They also rule a slew of different applications in a variety of fields. The paper is further classified into sections that discuss various viewpoints in analyzing tomato diseases' impact on Indian agriculture. Raw Dataset was used, and the detail extraction is discussed in section 3.1. The results, the accuracy, and their evaluation have been documented in section 4. The paper is finally concluded on a note with an evaluated conclusion and expectations of future scope in sections 5 and 6, respectively.

2. Related Work

The utilization of computer vision for agricultural disease detection has emerged as a prominent area of research. Early approaches predominantly relied on traditional machine learning methods and external networks within the agricultural domain.

Sannakki et al. proposed employing k-means clustering at the pixel level to pinpoint infected areas, demonstrating the utility of a grading system developed through machine vision and fuzzy logic in disease evaluation [6]. Samanta et al. introduced a histogram-based technique for identifying potato scab diseases, achieving remarkable classification accuracy of 97.5% [7]. Pedro et al. utilized fuzzy decision-making to classify marijuana forms with 92.9% accuracy [8]. Matson and Cheng utilized Support Vector Machine (SVM), Decision Tree, and Neural Network for rice and weed classification, with Decision Tree yielding the highest accuracy of 98.2% [9].

In their study, Tiwari et al. explored transfer learning and concluded that VGG 19 exhibited superior accuracy in detecting potato leaf diseases [10]. Sardogan et al. employed Convolutional Neural Networks (CNNs) with a Learning Vector Quantization algorithm for tomato leaf disease classification[11]. Pranathi et al. proposed a compact CNN model, LeNet, for tomato leaf disease diagnosis, emphasizing computational efficiency without compromising accuracy [12].

Chittaragi et al. advocated for automatic feature extraction in neural networks, achieving an average accuracy of 94-95% [13]. Mokhtar et al. proposed a method utilizing Gabor wavelet transform and Support Vector Machines (SVMs) with varying kernel functions for tomato disease diagnosis [14]. Hefny et al. employed support vector machine classifiers with different kernel functions to detect tomato leaves infected with Powdery mildew or early blight, attaining an accuracy rate of 99.5% [15].

These studies collectively underscore the potential of computer vision and machine learning in revolutionizing agricultural disease detection, fostering collaboration between agricultural experts and technology systems to deliver more reliable and effective results.

3. Materials and Methods

This study aims to utilize deep learning techniques for the detection of tomato leaf diseases. Deep neural networks are employed to identify disease presence by extracting features from Inception V3. Specifically, the photos depict instances of early blight and late blight. To expedite training and facilitate loss convergence, the Adam optimizer is utilized (Kingma & Ba, 2014). Adam, an extension of SGD, is widely adopted in computer vision tasks. Additionally, the softmax activation mechanism is employed for label classification (Srivastava et al., 2014) [16]. This function transforms a vector of real values into a probability distribution, allowing for the interpretation of input values as probabilities.

3.1 Raw Dataset

The initial step in developing a deep-learning framework involves acquiring a dataset, which serves as the foundation for model training and analysis. In this study, the dataset utilized originates from the Kaggle platform, specifically the PlantVillage dataset (Hughes & Salathé, 2015) [17]. Kaggle serves as an online hub for data scientists and machine learning practitioners, offering a diverse array of datasets and facilitating collaboration through competitions and shared notebooks. The PlantVillage dataset comprises approximately 20,000 images of

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leaves from various plant species, including tomatoes, bell peppers, and potatoes, among others. These images are provided in jpg/png format and encompass both healthy and diseased specimens. Diseased leaves are categorized into early blight and late blight, with a division of 80% of the dataset allocated for training and the remaining 20% for testing. This partitioning strategy ensures adequate representation for both healthy and diseased samples during model training and evaluation. Each plant species within the dataset is organized into its respective directory, with distinct folders for each associated disease. The Tomato plant subset of the dataset contains 1000 images each of early blight and late blight leaf specimens, along with 152 images specifically depicting late blight.

Fig. 1 Sample images of the Dataset

3.2 Data Preprocessing

In order to effectively harness the power of deep learning for disease detection in tomato plants, the data, initially comprising images, must undergo preprocessing to ensure compatibility with the computational framework. This preprocessing step is crucial as it lays the groundwork for subsequent analysis and model training. Through the utilization of Keras functions, the images are transformed into arrays, a format conducive to computational processing. This conversion process facilitates the extraction of meaningful features from the images, allowing the model to discern intricate patterns indicative of disease presence.

Furthermore, it is imperative that the color information within the images is preserved during the conversion process. The retention of color data is essential for accurate disease classification, as different ailments often manifest distinct visual characteristics. By representing each pixel in the image as a set of RGB values within a 3D NumPy array, the model gains access to crucial color information necessary for precise classification.

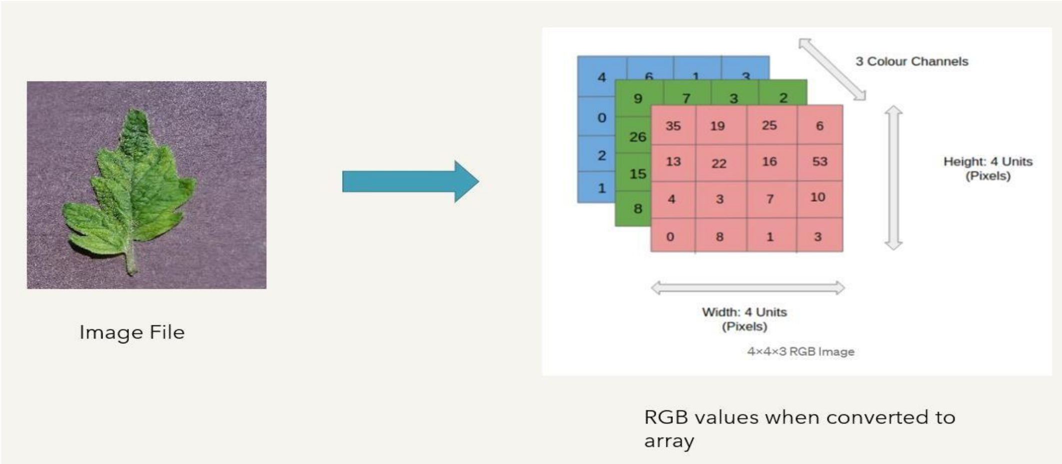

Fig. 2 Converting images to Numpy array

The Inception V3 model, renowned for its effectiveness in image recognition tasks, serves as the cornerstone of the disease detection framework. This model draws upon the vast knowledge accumulated from the ImageNet Dataset, a comprehensive repository containing millions of labeled images spanning diverse categories. By leveraging insights from ImageNet, the Inception V3 model is primed to excel in discerning subtle patterns and features within the PlantVillage dataset, thereby enhancing its diagnostic capabilities for tomato plant diseases.

In addition to feature extraction and model architecture, the process of labeling the data is pivotal in facilitating supervised learning. After the images have been converted into arrays, they must be assigned appropriate labels corresponding to the respective diseases they depict. This labeling process is essential for training the model to accurately associate visual cues with specific disease classes. Leveraging the Label Binarizer library streamlines this task, ensuring that the images are properly categorized prior to model training.

Fig. 3 Labeling Data

3.3 Data Augmentation

In our research endeavor, we employed Convolutional Neural Networks (CNNs) for the classification task. These deep neural networks were trained to discern the presence of early and late blight in the images by extracting relevant features from Inception V3 [16]. Additionally, we utilized the Adam optimizer during the classification process to expedite training and stabilize the loss function (Kingma & Ba, 2014) [1]. Adam, an extension of the Stochastic Gradient Descent (SGD) algorithm, is widely adopted in the field of computer vision due to its effectiveness in optimizing deep learning models.

For label classification, we employed the softmax activation function. This activation mechanism translates a vector of absolute values into a probability distribution, where each value represents the likelihood of a particular class. By ensuring that the probabilities sum up to one, softmax enables the model to make confident predictions based on the input data (Srivastava et al., 2014) [2].

3.4 Deep Learning Models

All images are fed into the CNN model's input layer at the start. The images are then provided in the inception v3 architecture [3] for feature extraction. There are Deep neural nets that identify the images based on pre-trained information using feature-extracted images. The images are finally sent to the output layer. The model comprises a few layers that are first generated and then compiled together using TensorFlow library functions [3].

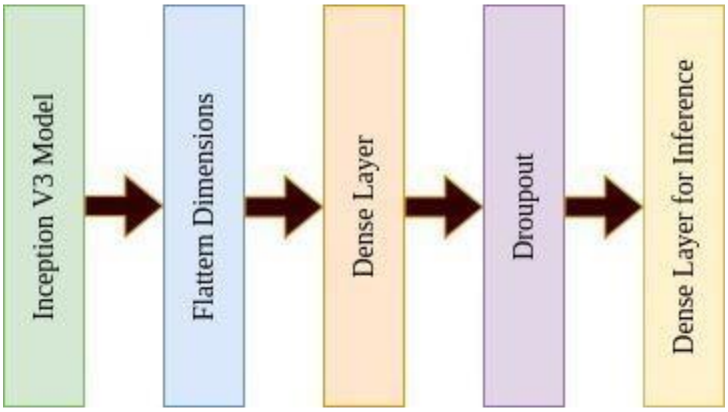

Fig. 4 Abstract form of Inception V3 model

4. Experimental Results and Discussions

The research utilized the PlantVillage dataset, comprising approximately 1000 images of early blight-infected tomato leaves and 152 images of healthy tomato plants, as the foundation for developing the proposed model. To facilitate model training and evaluation, the dataset was divided into two subsets: a training set, which constituted 80% of the total dataset, and a test set, which comprised the remaining 20%. The Inception V3 pre-trained model was employed to extract features from the dataset, leveraging its extensive knowledge acquired from ImageNet.

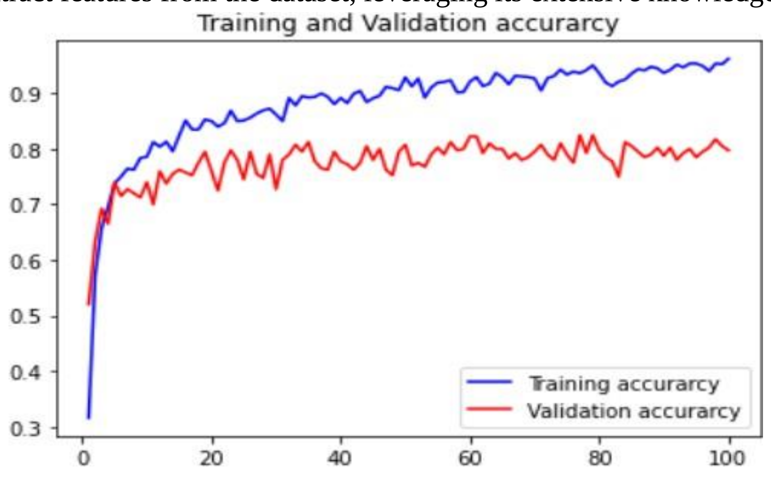

Fig. 5 Training and Validation Accuracy

Following training and testing procedures, the CNN model achieved a classification accuracy of approximately 84% [1]. However, it is noted that further improvements in accuracy could be attained with additional computational resources for running more complex machine learning models. The input images in the dataset were standardized to dimensions of 128 x 128 pixels, with RGB color channels and a density of 512. This standardization resulted in image data being represented as 3-dimensional matrices of size 128 x 128 x 3.

Labeling of the input image data was facilitated using the Label Binarizer library, ensuring proper categorization of images into disease classes. By converting the images into 3D NumPy arrays, the model was equipped to effectively differentiate between various diseases based on their visual characteristics. This process of array generation preserved the color information inherent in the images, thereby enabling accurate disease classification.

After conducting training with 70 epochs, the accuracy on the training set surpasses 90%, indicating significant improvement over successive iterations. However, the validation accuracy, which measures the model's performance on unseen data, reaches a plateau at around 80 to 85%. Despite this plateau, a thorough evaluation of the model reveals an overall mean accuracy of 84%.

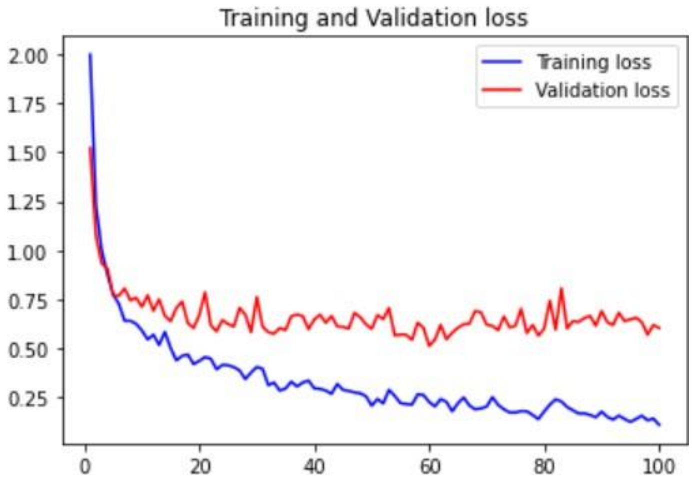

Fig. 6 Training and Validation Loss

Throughout the epochs, the model demonstrates continuous enhancement in its learning process, resulting in a notable reduction in training loss. Initially, the training loss decreases exponentially, ultimately stabilizing at a percentage between 10 to 15% [1]. Following evaluation, this reduction in training loss is quantified at 12%.

As the training loss (referred to as val_loss) starts decreasing, the training accuracy (referred to as val_acc) increases. This inversely proportional relationship confirms that our model is learning and working as expected.

5. Conclusion

In this research endeavor, the Inception V3 architecture combined with the Adam Optimizer was employed to develop a Convolutional Neural Network (CNN) model aimed at diagnosing and identifying diseases affecting tomato plants, including early and late blight. The model exhibited a classification accuracy of 90% when evaluated on the test dataset. Leveraging our model, farmers can establish a computer-based system to efficiently monitor plant health, enhance crop productivity, and promptly detect and diagnose diseases in their early stages.

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