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# Plant Disease Detection using Advanced Deep Learning Algorithm

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**Abstract:** The early detection of plant diseases is crucial for maintaining healthy crop yields and minimizing economic losses in agriculture. Traditional methods of disease detection rely heavily on manual inspection, which is time-consuming, labor-intensive, and prone to human error. Recent advancements in deep learning (DL) have revolutionized the field of plant pathology, providing more efficient, accurate, and scalable solutions for plant disease detection. In this work, we review the application of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), for the automatic detection and classification of plant diseases from images. The use of CNN-based models has demonstrated remarkable success due to their ability to automatically extract relevant features from plant images. We also explore advancements in techniques such as transfer learning, Generative Adversarial Networks (GANs), and attention mechanisms to improve detection accuracy in scenarios with limited data. The integration of these deep learning approaches with IoT-enabled systems for real-time monitoring in agriculture is discussed, highlighting the potential for autonomous disease management. Our study concludes that deep learning-based plant disease detection systems offer significant improvements over traditional methods in terms of speed, accuracy, and scalability, paving the way for sustainable agriculture practices.

Keywords: Deep Learning (DL), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs).

## 1. Introduction

Plant diseases threaten worldwide food production and sustainable farming. For efficient crop management and loss prevention, prompt and precise detection of these diseases is essential [1] [2]. In recent years, deep learning methods have become very effective tools for automated and effective plant disease identification. Artificial neural networks (ANN) are the foundation of DL, a branch of ML that aims to replicate the structure and operations of the human brain. These networks are ideal for image analysis tasks because they can learn and extract relevant characteristics from complex datasets in real time. Deep learning for plant disease detection entails training DNN on large datasets of plant images, with each image labeled with its corresponding disease or healthy status [3] [4]. The trained models can then analyze new images and accurately classify them into healthy or diseased categories based on learned patterns and features. The key factors of DL in plant disease detection is its ability to handle high-dimensional and heterogeneous data, such as images captured under different lighting conditions, scales, and perspectives. Deep learning models can learn intricate patterns and subtle variations in plant images that may be indicative of diseases, even when human experts find it challenging to discern. Moreover, deep learning-based approaches can provide fast and automated disease detection, enabling early intervention and appropriate management strategies. This can significantly reduce crop losses, minimize the use of chemical treatments, and promote sustainable agriculture practices [5] [6].

Plant diseases are a significant issue in farming, leading to essential crop yield and quality losses. Conventional detection of plant illnesses methods, such as skilled observation, are time-consuming and labor-intensive—deep learning models trained using large healthy and diseased plant image datasets. These models can correctly identify new photos of plants as healthy or unhealthy once they have been trained. Without the assistance of human specialists, this can be completed swiftly. Plant disease detection has been applied to a variety of deep-learning architectures. The requirement for massive image databases of healthy and sick plants presents one difficulty. These datasets can be expensive and time-consuming to collect. Another challenge is the need to develop deep learning models that are robust to variations in lighting, background, and other factors. This is because plant diseases can appear differently in different conditions [9] [10]. Despite these challenges, deep learning has more strength to detect plant diseases. As the model continued to develop by adding a new approach, more accurate and reliable DL models were introduced.

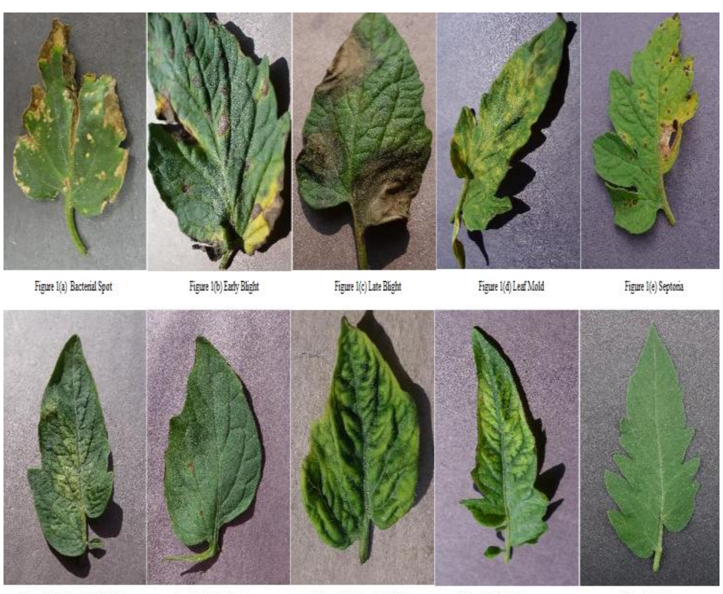


Figure 1Types of Tomato Plant Diseases

## 2. Literature Survey

Gao et al. [15] discussed various deep learning (DL) models that can detect crop leaf disease from the given crop leaf images. The proposed approach mainly focused on plant diseases detection and insect pests. Also discussed were various advantages and issues that required to be solved. Azimi et al. [16] introduced a hybrid model, such as CNN-LSTM, to find the water stress classification between the chickpea plant dataset. It is very significant to identify the plant health and status of diseases by using existing models. These models mainly failed to detect the water stress level at the plants. To overcome this, the proposed model CNN-LSTM focused on water stress among the two datasets, such as chickpea models JG-62 and Pusa-372. Finally, the classification model achieved an accuracy of 98.12% on Pusa-372 and 98.34% on JG-62.

B. Liu et al. [17] developed Leaf GAN, a novel approach for creating four different types of grape leaf diseases. The training model deep regret gradient approach is used to find accurate dataset features to identify genuine and fake disease images. Additionally, it takes elements out of the photos of grape leaves, which aids in precisely identifying the diseases. Ultimately, the accuracy of the suggested model was 98.67%, which is high compared to other currently used models, such as WGAN and DCGAN. Citrus leaf pictures gathered from the plant village and crowd were found to be impacted by Huanglongbing (HLB) using a hybrid model established by Q. Zeng et al. [18] in conjunction with Inceptionv3 and DCGANs. The main aim of this model is to find the seriousness of the HLB diseases among the given leaf images. The training model Inceptionv3 was mainly used to train the citrus images, which obtained high accuracy. The Inceptionv3 combined with DCGANs gives an accuracy of 93.23%, which is very high compared with existing models.

E. Ozbılge et al. [19] proposed a technique to find the tomato plant diseases from the given dataset. The training model ImageNet has used a transfer learning approach that helps transfer the deep network models. The accuracy is 99.78% for the testing set from the plant village dataset. K. Roy et al. [20] proposed the PCA-based DNN model that finds the diseases among the tomato leaves. It also adopted the GAN model to get better results. It achieves the accuracy of 99.45% and a precision of 98.45%.

Y. Wu et al. [21] proposed a fine-tuned classification model that mainly focused on solving the issues in classification. Finally, the classification model was utilized to improve the finding potentiality of disease detection. Two real-time datasets, such as peach and tomato leaf diseases, are used for the performance evaluation. The accuracy improved based on the features such as the redesigned model, and Discrimination Model helps find the conditions. N. Ullah et al. [22] proposed the unique end-to-end DeepPestNet system that finds the pests and classification. It contains 11 layers with eight conv and three FC layers. The size of the image dataset achieved better augmentations to get better results. The classification focused on classifying several pests among the given "Pest dataset." The proposed approach gives the accuracy of 98.34%.

S. Ahmed et al. [23] proposed a LTBA diagnosis the tomato plant leaf diseases. An efficient preprocessing method removes the noise and lighting modification in the given leaf images. An effective and efficient feature extracted by using the pre-trained MobileNetV2 architecture that classifies the diseased and non-diseased plant images. Existing models obtained several issues, such as data leakage, and found the imbalanced problem. The accuracy is 99.32% for the proposed model, which is high.

## 3. Pre-processing Techniques

One common data augmentation technique for image classification tasks, including the detection of tomato plant diseases, is rotation. The image is rotated to certain angle that creates new training samples. The rotation can be performed clockwise or counterclockwise.

The basic equation for rotating an image around its center is as follows:

$$x' = \cos(\theta) * (\chi - \chi_c) - \sin(\theta) * (Y - Y_c) + \chi_c \quad (1)$$

$$y' = \sin(\theta) * (\chi - \chi_c) - \cos(\theta) * (Y - Y_c) + Y_c \quad (2)$$

In this equation:
$(x, y)$ Coordinates of actual image.
(x', y') coordinated of rotated image.
$x_c, y_c$ represents the coordinates of the center point around which the rotation is performed.
$\theta$ represents the rotation angle.
By applying this rotation equation to each pixel in the original image, you can create a new image that is rotated by a specific angle.

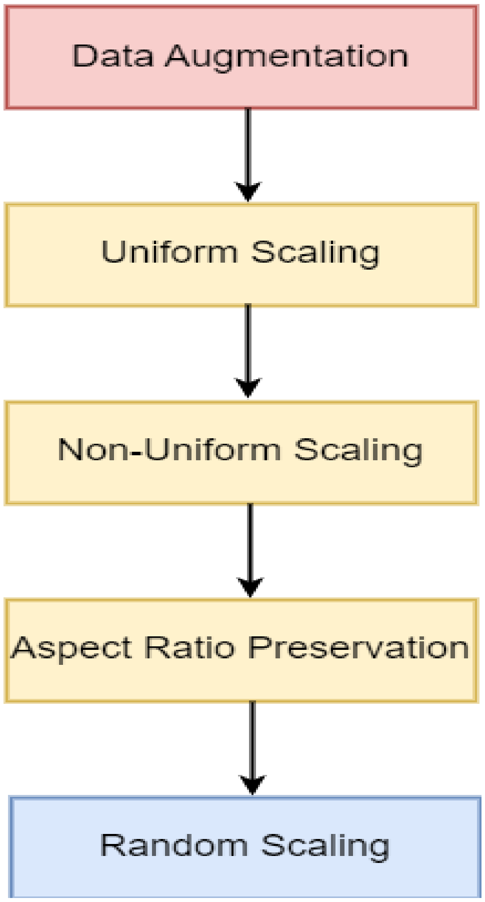


Figure 2 Data Augmentation Techniques

For instance, if you want to rotate an image by 45 degrees counterclockwise, you would use θ = -45 degrees in the equation. If you want to rotate it clockwise, you would use θ = 45 degrees.

**3.1 Uniform Scaling:**

This equation scales the image uniformly in both dimensions by a factor of "s."

$$\text{New width} = \text{original width} * x \qquad (3)$$

$$\text{New height} = \text{original height} * y \qquad (4)$$

**3.2 Non-Uniform Scaling:**

This equation scales the image by different factors for width and height. Use "$s_x$" to scale the width and "$s_y$" to scale the height.

$$\text{New width} = \text{original width} * s_x \qquad (5)$$

$$\text{New height} = \text{original height} * s_y \qquad (6)$$

**3.3 Aspect Ratio Preservation:**

This equation scales the image while preserving the aspect ratio. You can define the target width ($t_w$) or target height (th) and calculate the scaling factors (sx and sy) accordingly.

$$s_x - s_y = \min\left(\frac{t_w}{\text{original width}}, \frac{\text{th}}{\text{original height}}\right) \qquad (7)$$

**3.4 Random Scaling:**

Random scaling introduces a random factor to the scaling equation to add variability. You can define a range of scaling factors $\min_{scale}$ and $\max_{scale}$ and randomly select a scaling factor for each image.

A scaling factor "s" selected between $\min_{scale}$ and $\max_{8scale}$

## 4. Deep Reinforcement Learning with Transfer Learning (DRL-TL)

**A. Fine-tuning:**

Add a new fully connected layer on top of the feature extractor with a softmax activation function, representing the disease classes.

- Initialize the weights of the new layer randomly.
- Unfreeze the weights of the feature extractor layers and the newly added layer.
- The following shows the network training on labeled dataset

a. Convert the input images into feature vectors using the feature extractor.

b. Pass the feature vectors through the fully connected layer to obtain class probabilities.

c. Calculate the loss using a suitable loss function, such as categorical cross-entropy, comparing the predicted probabilities with the true labels.

d. Update the weights of the network using back propagation and gradient descent, minimizing the loss.

**B. Reinforcement Learning:**

- Use the fine-tuned network as a policy network in a reinforcement learning framework.
- Define the state representation, action space, reward function, and environment dynamics suitable for the plant leaf disease classification problem.
- Initialize the DRL agent's parameters and hyperparameters

- for episode in range(total_episodes)
- Initialize the environment and get the initial stat.
-

## 5. Performance Metrics

The performance metrics mainly focused on estimating the labels over the original labels by showing the attributes. The model's performance in each class and identifying any specific misclassification patterns. When evaluating the performance of Deep Reinforcement Learning for Transfer Learning (DRL-TL) classification models, several metrics can be used to assess their effectiveness. All the experiments conducted by using python programming language by using several libraries such as keras, pandas etc.
In the context of binary classification, the terms "TP," "TN," "FP," and "FN" are used to describe the outcomes of a prediction or classification.
***True Positive (TP):*** Labeled value correct estimated value also correct.
***True Negative (TN):*** Labeled value correct and estimated value wrong.
***False Positive (FP):*** Labeled value wrong and estimated value right.
***False Negative (FN):*** Labeled value right and estimated value wrong.
The following are some commonly used performance metrics:

$$\text{Accuracy (ACC)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Specificity (Spc)} = \frac{\text{No of TN}}{\text{No of TN} + \text{No of FP}}$$

$$\text{Recall (Re)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1} - \text{Score (F1S)} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

$$\text{Precision (Pre)} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Table 1 List of Existing and Proposed Models to Detect the Tomato Plant Diseases

| | ACC | Spc | Re | F1S | Pre |
|---|---|---|---|---|---|
| VGG19 | 95.56 | 96.12 | 94.23 | 95.45 | 95.23 |
| DoubleGAN Expansion | 98.98 | 97.78 | 97.23 | 98.11 | 98.02 |
| DRL-TL | 99.23 | 98.89 | 98.98 | 99.12 | 99.23 |

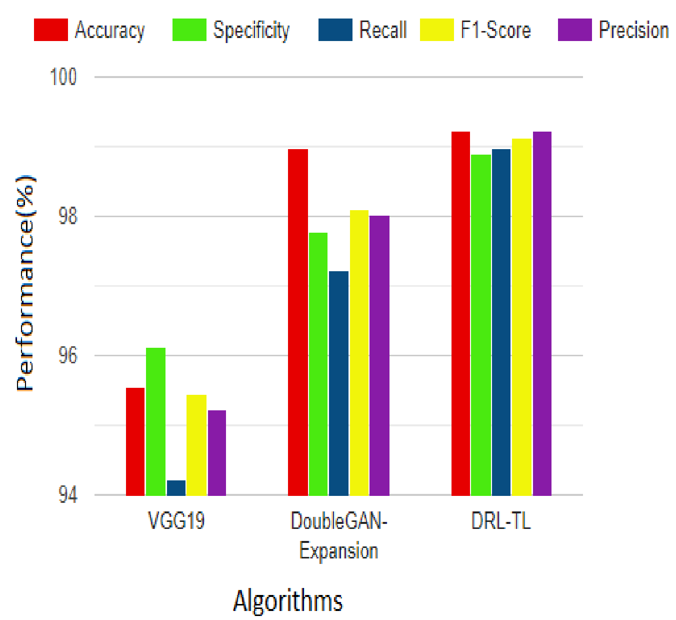

Figure 4 Existing and Proposed Models to Detect the Tomato Plant Diseases

## 6. Conclusion

In this research work, the Deep Reinforcement Learning with Transfer Learning (DRL-TL) for tomato plant disease detection shows promising results. Through the integration of transfer learning methods with the capacity of deep reinforcement learning algorithms, this strategy provides multiple benefits for precisely diagnosing and categorizing tomato plant illnesses. By utilizing deep reinforcement learning models' ability to learn from interactions with the environment, DRL-TL enables the system to enhance its performance gradually. This dynamic learning process allows the model to adapt and adjust its detection capabilities based on the specific characteristics of tomato plant diseases. Furthermore, transfer learning plays a crucial role in enhancing the efficiency and effectiveness of the DRL-TL approach. By leveraging pre-trained models on large-scale datasets, the system can benefit from the generalization capabilities of these models, enabling faster convergence and reducing the need for extensive training on limited data. The combination of DRL and transfer learning in tomato plant disease detection has demonstrated promising results in terms of accuracy and efficiency. The model shows high accuracy in correctly identifying and classifying various diseases affecting tomato plants, including early detection of symptoms that may be challenging to detect with the naked eye. The implementation of DRL-TL in tomato plant disease detection also offers practical advantages. It provides a non-invasive and cost-effective solution for farmers and plant pathologists, allowing for early intervention and preventive measures to be taken, which can significantly reduce crop losses and improve overall agricultural productivity. However, it is important to note that while DRL-TL shows promise, there are still some challenges that need to be addressed. One of the main challenges is the availability of labeled training data, as collecting a diverse and comprehensive dataset for training can be time-consuming and labor-intensive. Additionally, the interpretability of deep reinforcement learning models remains a concern, as understanding the decision-making process of these models is crucial for building trust and acceptance among end-users.

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