Vol.no 1, Issue no 2, Sep - Dec, 2025

PUXplore Multidisciplinary Journal of Engineering

Parul® University NAAC GRADE A++

# Plant Disease Detection Using Transfer Learning

[1]Mohammad Arif, [2]Arun Kumar Marandi
[1,2]*Department of Computer Science and Engg (AIDS)*
*Parul University, Vadodra, India*
[1]arif_mohd2k@yahoo.com
[2]arun.marandi41293@paruluniversity.ac.in

***Abstract*— Agriculture plays a crucial role in human lives, with around 70% of the population directly or indirectly involved in it. However, traditional approaches lack tools to identify diseases in crops and increase agricultural output. Early detection of crop diseases is vital as they impact plant growth and pose a significant threat to food security. Machine Learning (ML) models have been used to identify and categorize agricultural diseases, but recent advancements in Deep Learning show promise for improved accuracy. This proposed method utilizes convolutional neural networks and deep neural networks to effectively and accurately identify and recognize crop disease symptoms. By training deep learning models using large publicly available datasets, it becomes possible to detect plant diseases on a large scale.**

**Keywords: Plant Disease Detection, ResNet50, Machine learning, Deep Neural Network, Transfer Learning**

## I. Introduction

Plant diseases pose a threat to global agriculture, leading to significant crop losses and impacting food security. Early and accurate detection of plant diseases is crucial for effective management and minimizing output losses. Traditional methods relying on manual inspection are time-consuming and subjective.

To overcome these limitations, automated systems utilizing computer vision and deep learning have gained interest. Deep learning, particularly Convolutional Neural Networks (CNNs) like ResNet50, has revolutionized computer vision, delivering impressive results in tasks such as segmentation, object detection, and image classification.

ResNet50 is a 50-layer deep neural network model that includes residual blocks to make deep network training easier. The introduction of skip connections, often referred to as residual connections, which enable the network to skip specific layers and learn residual mappings, is the main novelty of ResNet50. These skip connections solve the vanishing gradient issue and make it possible to train extremely deep neural networks. ResNet50 has been effectively used in a number of fields, including object identification and picture recognition.

## II. Relevance of the Project

ResNet50's use in plant disease detection has a lot of potential to advance the science. The model's remarkable feature extraction abilities and capacity to use deep learning techniques can help to construct reliable, automated illness detection systems. These tools can help farmers, agronomists, and plant disease specialists recognize and control crop diseases with accuracy.

We investigate the application of ResNet50 for plant disease detection in this research article. In our methodology, ResNet50 is trained using a sizable dataset of labelled plant photos that depict various plant illnesses. A second validation set is used to test the trained model's performance in terms of recall, accuracy, and other pertinent metrics. To improve the model's ability to generalize to new data, we also investigate strategies for data augmentation. We also examine the effects of transfer learning, where pre-trained ResNet50 weights are adjusted using our dataset on plant diseases.

### *A. Problem Statement*

Agriculture is India's primary industry, and the rural economy heavily depends on it. The country faces challenges such as monsoon dependency and crop damage caused by insects. Identifying the pests responsible for crop damage and implementing preventive measures is a key concern. Pest-induced crop damage leads to reduced food production, food insecurity, and lack of knowledge about pest management. Plant diseases can often be identified by examining diseased leaves, but in underdeveloped regions, conventional diagnostic techniques and the need to consult specialists can be time-consuming and inconvenient. Computer programs can provide a rapid and accurate method to diagnose plant diseases, offering a solution to these challenges.

### *B. Objectives*

We can use image processing to identify the plant, leaf, fruits, roots and as well PEST. PEST affects crops in two ways direct (eg. insect stings and bites) and indirect (eg.bacterial, viral, or fungal infection). Image processing algorithm is used to analysis the plants, leaf, fruits, roots and other machine leaning algorithm for image classification that include a high dimension training dataset and convolutional neural network (CNN) model is used for image recognition or identify the leaf spot through which machine generate accurate prediction and use insect pest detection algorithm to analysis insect through crops get affected.

## III. Literature Survey

The proposed system using the method of sorting is helpful in identifying the infection with up to 93% accuracy. It pre-scans the image and divides the leaf area using Gaussian size, limit, and filter. The suggested system gives farmers access to weather forecasting data that might assist them in daily decisions like deciding which fertilizer is best for a certain weather scenario [1].

This study offers a practical method for quickly identifying various diseases in a range of plant species. Apples, corn, grapes, potatoes, tomatoes, sugarcane, and other plant kinds were especially targeted for detection and recognition by the system. The technology can also identify a number of plant illnesses [2].

This study discusses various challenging problems that must be tackled in density, as well as a concept about deep learning technology, utilized for plant disease detection. Deep learning, an instance of machine learning, has a few layers in higher information transformation and categorization and is often utilized for agricultural purposes [3].
This article explores challenging problems that can be addressed through density learning and highlights the potential applications of deep learning, a subfield of machine learning, in identifying plant diseases for agricultural purposes. [4].
Data augmentation is essential to enhance the training sample size and improve classification accuracy. Thus, the Resnet model is used in this study to classify the enhanced rice-leaf picture data set. The trained model's 98.10% accuracy on the test dataset demonstrates the efficacy of this methodology. The goal of this research project was to improve the model's performance with as well as without data augmentation [5].
The Enhanced Vision Transform Classification (EVTC) neural network approach for accurate plant disease identification was introduced by the author in this research. Deep learning has significantly increased the precision of recognizing objects and picture categorization systems in recent years. The studies used the renowned Plant Village data set, which includes 54,305 pictures of different plant disease types divided into 38 classification [6].
In order to understand the number of independent variables that influence the correctness of the CNN algorithm, the study has used linear regression analysis. Early blight and late blight on potato leaf photos from two plant diseases were used to teach CNN. The accuracy of CNN increased as the dataset's image count rose, according to the results. However, accuracy did not much improve as image resolution increased. The algorithm displayed higher accuracy when there were fewer image features and categories, and lower accuracy when there were more features. The accuracy of CNN's overall regression analysis using linear regression was 85%; this accuracy can be raised by expanding the dataset [7].
The authors suggest changing the Inception V3 architecture to classify plant diseases using CIE Lab color space rather than RGB. The number of parameters that can be trained and computational load are decreased by splitting the architecture into two branches: one for chromatic data (AB channels) and one for achromatic data (L channel). On the Plant Village dataset, they achieve a cutting-edge classification accuracy of 99.48%, and on the Cropped-Plant Doc dataset, 76.91% [8].

## IV. PROPOSED SOLUTION

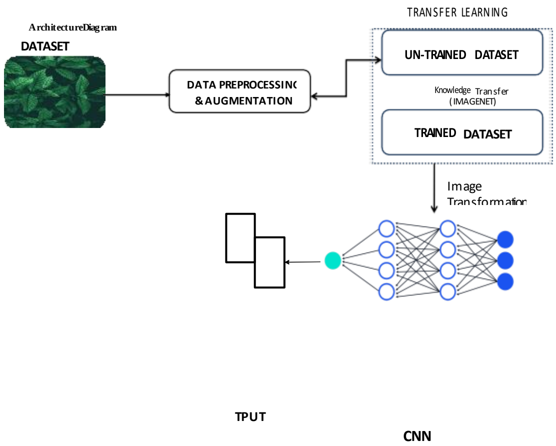


Fig. 1. Proposed System for Plant Disease Detection

## V. METHODOLOGY

A thorough explanation of the full process for utilising a CNN model to find plant diseases is provided. The model's process is shown in Figure 1 and is composed of multiple subsequent steps. It begins with training photos and includes image preprocessing, the use of augmentation techniques, the use of weights that have been trained obtained from the ResNet50 model, and parameter optimisation. Then, comprehensive testing is carried out, and the outcomes are carefully examined.

### A. *Dataset*

The leaf photos from 38 distinct plant types make up the set of images used in our investigation. The plant disease dataset, which features pictures of both healthy and afflicted plants, was collected from a GitHub repository. For the objective of detection, the suggested model had been trained using a variety of leaf classes.

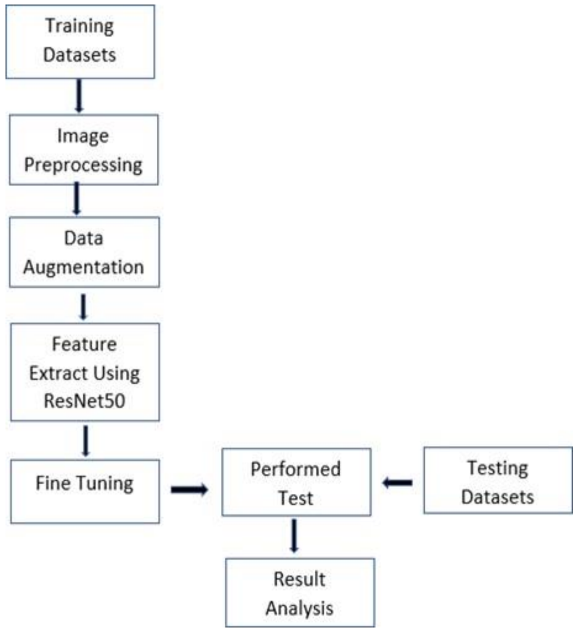


Fig. 2. Flow Diagram for Plant Disease Detection

### B. *Image Preprocessing and Labelling*

Image preprocessing enhances the image data required to perform the process of image classification. Preprocessing approaches employ geometric adjustments of images, such as rotation of images, image scaling, and image translation. All of the photographs were scaled down to 224*224 pixels throughout the preprocessing steps. All of the photographs must have the same resolution, according to the rule. For straightforward picture searching, labels or groups of related photographs must be created.

### C. *Augmentation Process*

By including additional pictures, this technique expands the training dataset. During the training process, it helps to avoid the problem of overfitting. Overfitting occurs when the artificial neural network adapts form data in question instead of from the broad pattern of the dataset. Images augmentations have been carried out by making particular adjustments to the photos, such as a rotation, wide shift, height shift, shearing range, and perpendicular flip.

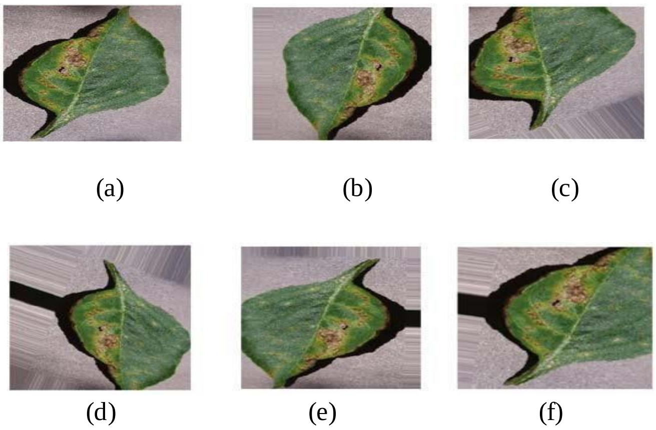

Fig. 3, 4. Some augmentation of pepper bel bacterial spot leaf image: (a) Original image, (b) Rotating, (c) shifting right, (d) shifting vertical, (e) right shifting and rotation (f) shifting left..

### D. *ResNet50*

In order to overcome saturation and accuracy loss in deep CNN training, ResNet50 is an advanced convolutional neural network architecture. There are fifty layers total, which are grouped into distinct groups and each group is represented by a different colour. The main characteristic of ResNet50, which is the incorporation of identity blocks, which link earlier layers, to address problems with degradation and vanishing or bursting gradients in the training of very deep networks. The architecture consists of a layer with a kernel size of 7x7, a layer of max pooling, and a set of blocks with different amounts of similar or similar blocks connected by curves.

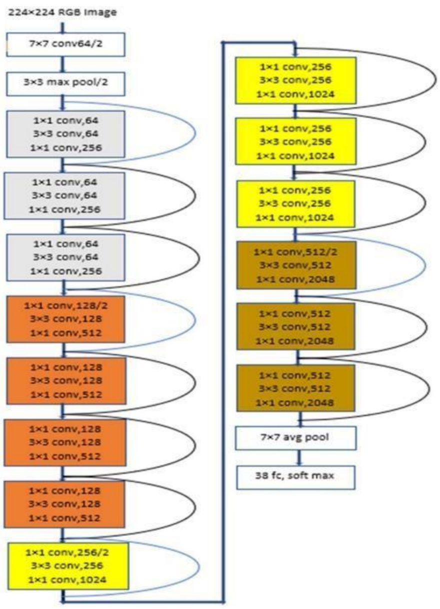


Fig. 5. ResNet50 Model Architecture.

### E. *Fine-Tuning*

The method for adapting becomes so essential that a single modification may have an important effect in the amount of time operations use, the speed at which converge happens, as well as how a lot units of processing are utilised during training. To raise the efficiency of a function, we continually executed this fine-tuning process to improve the result.

## VI. EXPERIMENT AND RESULT

In order to start training, our model was instructed to use a training dataset that contained both the original photos and the enhanced versions. Since then, the model has been validated to increase its applicability. The suggested network displays good convergence in the training and validation phases. Although possessing a single low peak, the validation curve shows 98.76% precision over validating across the vast majority of the curve.


Fig. 6. Results of Plant Disease Detection.

## VII. CONCLUSION AND FUTURE WORK

In this study, a convolutional neural network was constructed to automatically identify plant diseases. Our suggested method can distinguish between 38 different varieties of healthy and disease-ridden leaves. The entire procedure has been thoroughly laid out. Through examination of several other models of transfer learning and pertinent graphs, the model's efficacy has been assessed. The CNN model's increasing depth necessitates more picture data for the greatest generalization. As a result, we preprocessed the information and then grew the dataset throughout the augmentation phase. The renowned pre-trained model ResNet50 was then used in the application of Transfer Learning. The proposed model's overall accuracy was 98.76%.

## ACKNOWLEDGMENT

We remain grateful to Prof. Mohammad Arif for providing us a spark for this field of study, for his substantial help in finding resources for me via computers or information, and for his advice and supervision, which allowed this Project to be completed. we would want to state that working on this project has in fact been a fulfilling experience.

## REFERENCES

1. S. Pawar, S. Shedge, N. Panigrahi, A. P. Jyoti, P. Thorave and S. Sayyad, "Leaf Disease Detection of Multiple Plants Using Deep Learning," 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), Faridabad, India, 2022, pp. 241-245, doi: 10.1109/COM-IT-CON54601.2022.9850899.
2. S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," in 2020 IEEE 8th International Conference on

3. Smart Instrumentation, Measurement and Applications (ICSIMA), 2020, pp. 200-205.
4. https://doi.org/10.1109/ICSIMA50843.2020.9308612
5. Haveri and K. Shashi Raj, "Review on Plant Disease Detection using Deep Learning," 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2022, pp. 359-365, doi: 10.1109/ICAIS53314.2022.9742921.
6. Leung, "Plant Disease Detection Mobile Application Development using Deep Learning," 2021 International Conference on Computer & Information Sciences (ICCOINS), Kuching, Malaysia, 2021, pp. 34-38, doi: 10.1109/ICCOINS49721.2021.9497190.
7. T. Bhargavi and D. Sumathi, "Significance of Data Augmentation in Identifying Plant Diseases using Deep Learning," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp.1099-1103, doi: 10.1109/ICSSIT55814.2023.10061007.
8. R. Dhivya and N. Shanmugapriya, "Multi-class Plant Leaf Image Disease Prediction Using Deep Learning Algorithm," 2022 International Conference on Knowledge Engineering and Communication Systems (ICKES), Chickballapur, India, 2022, pp. 1-6, doi: 10.1109/ICKECS56523.2022.10059590.
9. S. N, S. Nema, B. K. R, P. Seethapathy and K. Pant, "The Plant Disease Detection Using CNN and Deep Learning Techniques Merged with the Concepts of Machine Learning," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 1547-1551, doi: 10.1109/ICACITE53722.2022.9823921.
10. Schwarz Schuler, J. P., Romani, S., Abdel-Nasser, M., Rashwan, H. and Puig, D. (2022) “Color-Aware Two-Branch DCNN for Efficient Plant Disease Classification”, MENDEL, 28(1), pp.55-62. doi: 10.13164/mendel.2022.1.055.