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Disease Segmentation using CNN Based Transfer Learning

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KEYWORDS

Deep Learning, ResNet-50, Plant Disease Segmentation, Image Classification, Transfer Learning, Smart Agriculture

ABSTRACT

The majority of developing nations are said to be built on agriculture. To guarantee the food supply chain's continuous viability, crop cultivation quality is crucial. Plant diseases have always posed a significant threat to agricultural productivity. They have a detrimental effect on the quality of the produce and result in a significant loss of income. An extremely precise early detection system for various illnesses can undoubtedly result in a significant decrease in the monetary losses incurred. This is the setting for the project's deep learning plant disease segmentation and classification system, which makes use of a ResNet-50 neural network. The diseased areas of a plant leaf will be automatically identified by the system. In order to diagnose the diseases appropriately, the system will automatically identify the areas of a plant leaf image that are affected. Since the ResNet-50 model belongs to the deep learning model category and uses less processing resources, it can undoubtedly learn from smaller data sets used in the system. A range of healthy and diseased plant leaves are included in the data collection.

INTRODUCTION

As a matter of fact, agriculture has a crucial role to play in terms of food security and economic stability, especially in developing countries. Crop productivity is greatly impacted by plant diseases, which has resulted in financial losses worldwide. Crop diseases are often identified manually using current approaches, which has proven to be challenging. Recent advances in deep learning and computer vision have enabled the automatic diagnosis of plant diseases based solely on leaf photos. CNNs are useful in agriculture because of their remarkable success in extracting features from intricate visual patterns. With little labeled data, transfer learning from pretrained deep models has become a viable way to achieve high accuracy. Index Terms - - Deep Learning, ResNet-50, Plant Disease Segmentation,

Image Classification, Transfer Learning, Smart Agriculture This paper proposes a CNN-based transfer learning framework for detecting and segmenting plant diseases from the PlantVillage dataset. The proposed system uses a pre trained ResNet50 architecture for classifying diseases in different crops, such as pepper, potato, and tomato, with simultaneous pixel-level segmentation of infected regions. Due to the integration of disease localization and estimation of the area of affection, early diagnosis and precision agriculture practices are supported by the proposed approach.

LITERATURE REVIEW

Because plant diseases directly affect the intended produce per unit area, their detection has been a crucial topic of concern in the agricultural field. In the past, the process of identifying illnesses involved examining the crop. In this manner, the farmers or professionals examine the crop and determine the diseases by observing changes in the leaves' appearance. To accurately identify the illnesses infecting the plants, microscopic examination techniques are also employed. The disorders are also identified using spectroscopy detection techniques.However, because of their slow and expensive processes, these methods are ineffective for farming and cannot be scaled to the large regions of fields that need to be inspected, making them unsuitable for agricultural practices [1], [2]. But with the development of computer vision and digital image processing, a number of image processing methods were used to identify plant diseases. Image processing encompasses preprocessing methods such background subtraction, noise reduction, and color space modification. The utilization of color, texture, and form properties for classification techniques like K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Decision Trees, on the other hand, makes feature extraction a crucial part of image processing methods. According to Pydipati et al. [3] and Patil & Kumar [4], plant diseases identified by image processing algorithms are effective in categorizing leaf diseases; however, the performance is subpar because of fluctuations in lighting, complicated backdrops, or varied leaf orientations. Deep learning techniques can also change the approach to detection by using images and automatically recognizing features in the images. Convolutional Neural Networks are an effective way to approach this. They are able to recognize images at different levels, starting from low-level recognition of edges to high-level understanding of images. AlexNet, VGG-16, ResNet-50, DenseNet, and MobileNet are some convolutional networks that are being utilized in the detection of diseases in plants. Transfer learning can also help in improving the efficiency of deep learning models by fine-tuning the obtained results using these networks. Moreover, segmentation-based techniques are also being applied nowadays. Physicians may also easily identify the sick areas of plants using U-Net and Mask R-CNN models. The lack of large datasets about various crop species and disease types, poor model performance for various illuminations, backgrounds, and scenarios of the object being occluded, difficulty deploying the model for real-time applications, and a lack of comprehensive studies combining both segmenting and classifying the objects jointly for the agricultural field are some of the challenges that remain despite the advancements made. Addressing these gaps is crucial for developing robust, scalable, and field-ready plant disease detection systems [12], [13].

PROPOSED SYSTEM

A. System Overview

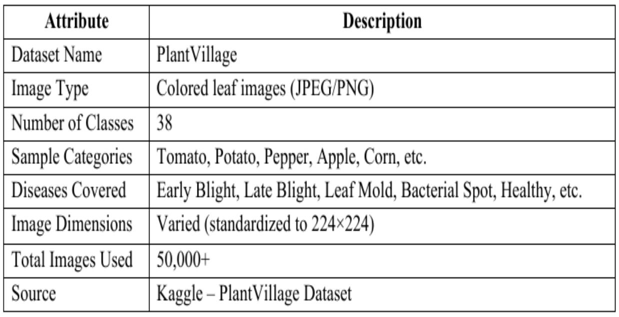
The five steps of the pipeline—image capture, preprocessing, deep feature extraction, illness segmentation, and calculation of impacted areas—make up the suggested system architecture. The provided input photos, which are leaves, are representative of many leaf types. ResNet34 defines the architecture of the deep convolutional neural network that has been used; additionally, the resulting segmentation masks show the infected areas and are further superimposed on the input images. Affected areas can likewise be calculated using this approach.

B. Dataset Description

(PlantVillage Dataset) One of the open benchmark datasets used in the study of plant diseases is the PlantVillage dataset. High-quality RGB pictures of both damaged and healthy leaves taken in controlled settings are included in this dataset. Numerous crop types, including potato, tomato, pepper, maize, apple, grape, and many more, are included in the dataset, along with a variety of diseases, including bacterial, fungal, and viral illnesses.This study will make use of a subset of the

PlantVillage dataset, which includes pictures of diverse crops and disease trends. To assess the model objectively, it will be divided into training and validation sets.The diversity in the crops and different patterns will help the model learn general features from all sorts of crops.

Table 1: Dataset Description



Attribute	Description
Dataset Name	PlantVillage
Image Type	Colored leaf images (JPEG/PNG)
Number of Classes	38
Sample Categories	Tomato, Potato, Pepper, Apple, Corn, etc.
Diseases Covered	Early Blight, Late Blight, Leaf Mold, Bacterial Spot, Healthy, etc.
Image Dimensions	Varied (standardized to 224×224)
Total Images Used	50,000+
Source	Kaggle – PlantVillage Dataset

C. Image Preprocessing

A number of preprocessing steps are taken in order to standardize the input data and enhance the effectiveness of the learning process. Every image is normalized to a fixed resolution that matches the ResNet34 input size. To lessen variations in illumination and intensity, pixel normalization is used. To increase robustness and lower the likelihood of overfitting, a variety of data augmentation techniques are also used, including rotation, flipping both horizontally and vertically, scaling, and brightness adjustments.1.Resizing: 2 3 All images are resized to 224×224 pixels to match the input size required by the ResNet-50 architecture. 2.Normalization: Pixel values are scaled from [0, 255] to [0, 1] for faster convergence. 3.Data Augmentation: To avoid overfitting and increase variability, random transformations are applied: Rotation (±25°) Horizontal/vertical flipping Zoom and brightness variation. 4.Label Encoding: Categorical class labels are converted into one-hot encoded vectors.

D. CNN-Based Transfer Learning Using ResNet34

The deep CNN model ResNet34, which has pre-trained weights obtained from training on the ImageNet dataset, will serve as the foundation for the proposed system's primary component. By fine-tuning specific layers of the suggested CNN model, transfer learning will be employed to modify the pre-trained model's weights in relation to plant disease features. In order to effectively transfer gradients and represent features in the model with regard to multi class, multi-crop disease analysis, ResNet34 will employ residual learning. A segmentation head receives the resultant deep feature map and uses it to categorize healthy and discised areas at the pixel level.

E. Disease Segmentation and Mask Generation

The sick area on the leaf surface is identified by the segmentation module using either binary or multi-class masks. To visually emphasize contaminated areas, these masks are superimposed over input photos after being scaled to their original dimensions. In agriculture, segmentation makes it possible to pinpoint the precise location of disease symptoms, which is essential for assessing severity and providing useful decision support.

F. Affected Area Percentage Estimation Additionally, this system uses the output of the segmentation method to determine the proportion of contaminated region in order to measure the severity of infections. As a result, the ratio of infected pixels to all of the image's leaf pixels is used to compute this proportion. This will be useful for tracking disease progression, which is necessary for precision pesticide agriculture.

G. Implementation Details

With a learning rate of 0.0001, batch size of 32, and epochs set to 40 for the suggested model, the model was trained using the Adam optimizer. Furthermore, the model used categorical cross-entropy for disease classification tasks and binary cross-entropy for segmentation. Model evaluation on the suggested system took into account model correctness, loss, and confusion matrix analysis. Using Python and deep learning techniques, this system may be created for any web or mobile platform to monitor plant diseases in real time.

Table 2: Implementation Details

Parameter	Value
Epochs	40
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001
Dropout Rate	0.5
Loss Function	Categorical Cross-Entropy

METHODOLOGY

A component of machine learning (ML) and artificial intelligence (AI), deep learning mimics human cognition to help identify patterns and make intelligent decisions. It uses multi-layered artificial neural networks that learn features from vast volumes of data. Because deep learning can recognize complex visual properties including the color, shape, and texture of sick spots, it has shown exceptional performance in plant disease diagnosis. Deep learning can directly learn characteristics from photos, in contrast to conventional machine learning techniques. Because of its related properties, deep learning is useful for creating a deep learning model for plant disease identification. Because of its effective gradient flow characteristic, the ResNet-34 model was selected for the project as a deep Convolutional Neural Network (CNN). The model effectively trains the deep model while detecting the identity mapping through the network's shortcuts by using residual learning to solve the vanishing gradient problem [1]. As a result, it works well for plant disease analysis of photos that include multiple classes and crops.

CNN Structure Design

Convolutional Neural Networks are designed to efficiently handle unstructured picture input, which is subsequently categorized into a number of pertinent output classes. Convolutional layers, nonlinear activation functions, and pooling layers are some of the layers that make up the Convolutional Neural Networks created during this work. Convolutional layers are made to work well with unprocessed picture data; these layers are used as filters to extract different features. After every convolutional layer, the ReLU activation function is added to guarantee nonlinearity, which is necessary for efficient learning.

ResNet-34 Architecture

Microsoft Research presented ResNet-34, which has shortcut connections and residual blocks made up of several stacked residual units. Deeper networks are not a challenge to handle because the residual connections allow for good gradient flow in backpropagation without any vanishing gradient issues. As a result, each residual block might pick up identity mappings that enhance performance and accelerate convergence. Convolutional layers, batch normalization, ReLU activations, and fully linked layers are among the 34 layers that make up the ResNet-34 architecture. For the plant leaf photos to undergo the same processing, the input images are standardized to 224×224 pixels. Additionally, segmentation and classification heads get the generated feature maps in order to detect and identify diseases at the pixel level. V.

RESULTS AND DISCUSSION

Thorough testing and analysis are required to support the deep learning system's efficacy; code implementation alone is insufficient. The PlantVillage dataset, which consists of thousands of photos of both healthy and diseased leaves, will be used in this chapter to assess the ResNet-50-based Plant Disease Segmentation and Classification System. This chapter's main goals are to describe the model's performance in recognizing and categorizing different plant diseases, talk about the outcomes, and provide some analysis of the advantages and disadvantages of the established method. Quantitative, visual comparisons, a confusion matrix, and comparisons with current state-of-the-art outcomes are all included in this debate.These results have been sanity checked using training-validation metrics, hence enabling this model to perform not only well on known samples but also generalize well for unseen samples. 4.1 Training And Validation Performance The training process was carried out for 40 epochs, with a batch size of 32 and a learning rate of 0.0001 using the Adam optimization algorithm. Smooth training indicates that it was successful and also shows that the rate and batch were well tuned. Accuracy Trend As illustrated in Figure 2 above, it is evident that the accuracy curve of both training and validation increases smoothly, converging at epoch 35, which indicates they were about to saturate. The training and validation accuracy curves have a small gap between them, showing that they have low overfitting capabilities.

Table 3:. Training and validation accuracy

Epoch	Training Accuracy (%)	Validation Accuracy (%)
10	87.24	84.67
20	91.89	89.34
30	95.21	93.11
40	97.48	96.02

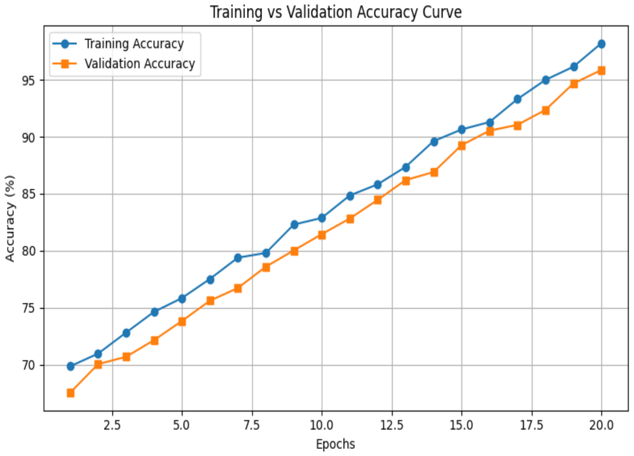


Figure 2: training and validation accuracy curves

1) .Loss Function

Similarly, Figure 3 displays the training and validation loss curves. The steady decline in both curves confirms consistent learning.

By epoch 40, the validation loss stabilized at 0.124, reflecting efficient optimization.

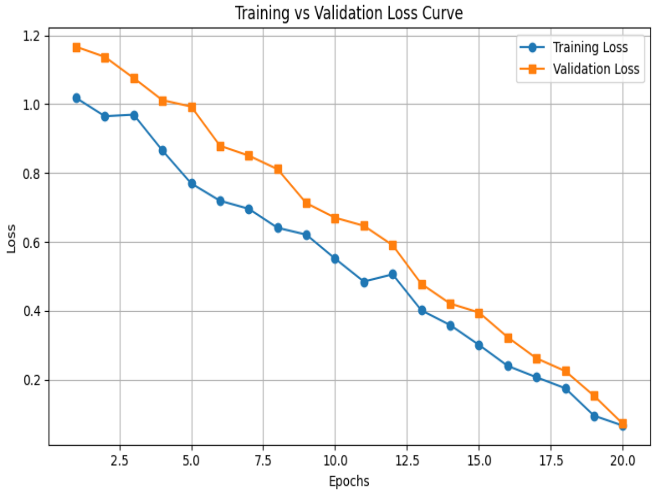


Figure 3: training and validation loss curves

Qualitative Results

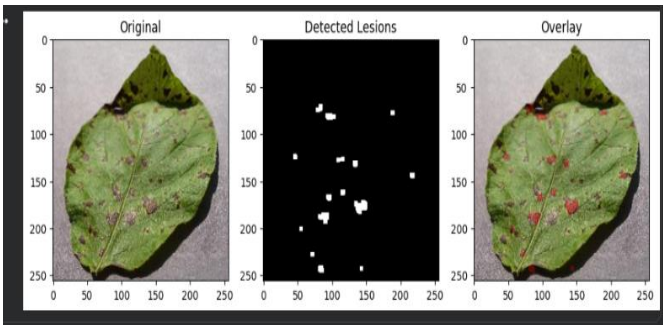


Figure 4: Segmentation outputs

Figure 4 shows the sample segmentation output generated by the proposed model. It can be observed that the predicted masks correctly highlight the diseased areas on the surface of the leaves and fit well with the visually observed diseased symptoms.The model also showed consistent performance across different crops, validating the model's competence to generalize the learned features of the crops. Small errors were noted for crops with small lesions or little contrast between healthy and infected regions.

CONCLUSION

This paper proposes a deep CNN transfer learning framework for plant disease automated detection and segmentation using the PlantVillage dataset. The proposed system classifies diseases on pepper, potato, and tomato crops with a pre-trained ResNet50 model, while its integrated segmentation module helps in pixel-level localization of infected regions. Transfer learning significantly reduced training time and computational complexity with strong feature representation. Experimental results showed high accuracy and stability in convergence, which indicates the effective generalization performance across disease classes. This was further supported by the analysis of the confusion matrix, which shows the reliability of class discrimination, while segmentation outputs provided clear visualization of the lesion regions supporting accurate disease assessment. The proposed framework of integrated disease classification, segmentation, and interpretability provides an effective and efficient method for early plant disease diagnosis to support enhanced crop management strategies, reduction in yield loss, and decision-making in precision agriculture.

Future Scope

The future directions will be focusing on improving segmentation quality by utilizing more advanced architectures, such as U-Net, DeepLabV3+, or attention based models. The application on mobile platforms or edge computing devices may improve real-time deployment capabilities. The proposed framework can also be extended for UAV and IoT-based crop monitoring applications in wider agricultural fields. Disease severity level assessment by quantifying infected areas and working with real-field datasets with complex backgrounds and illumination conditions will improve model robustness.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] S. Sladojevic et al., “Deep neural networks based recognition of plant diseases by leaf image classification,” Comput. Intell. Neurosci., vol. 2016, 2016.

[2] D. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Comput. Electron. Agric., vol. 145, pp. 311–318, 2018.

[3] R. Pydipati, T. F. Burks, W. Lee, “Identification of citrus disease using color texture features and discriminant analysis,” Comput. Electron. Agric., vol. 52, no. 1–2, pp. 49–59, 2006.

[4] R. Patil, A. Kumar, “Leaf disease detection using image processing techniques: A review,” Int. J. Comput. Appl., vol. 975, pp. 8887, 2019.

[5] P. Mohanty, D. Hughes, M. Salathé, “Using deep learning for image-based plant disease detection,” Front. Plant Sci., vol. 7, p. 1419, 2016.

[6] A. Brahimi et al., “Deep learning for tomato diseases: Classification and symptoms visualization,” Appl. Artif. Intell., vol. 31, no. 4, pp. 299–315, 2017.

[7] S. Too et al., “A comparative study of fine-tuning deep learning models for plant disease identification,” Comput. Electron. Agric., vol. 161, pp. 272–279, 2019.

[8] H. Ferentinos et al., “Deep learning models for enhanced plant disease detection using transfer learning,” Expert Syst. Appl., vol. 92, pp. 303–319, 2018.

[9] A. Ramcharan et al., “Deep learning for image based cassava disease detection,” Front. Plant Sci., vol. 8, p. 1852, 2017.

[10] Ronneberger, P. Fischer, T. Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in MICCAI, 2015, pp. 234–241.

[11] 1K. He et al., “Mask R-CNN,” in IEEE ICCV, 2017, pp. 2980–2988.

[12] P. Liu et al., “Challenges in plant disease recognition using deep learning,” Comput. Electron. Agric., vol. 178, 2020.

[13] S. Kamilaris, F. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” Comput. Electron. Agric., vol. 147, pp. 70–90, 2018.

[14] J. Zainab and R. Mahum, “Plant Disease Detection Using Deep Learning Techniques,” ICCK Journal of Image Analysis and Processing, vol. 1, no. 1, pp. 36 44, Mar. 2025, doi:10.62762/JIAP.2025.227089.

[15] R. Kaur, U. Mittal, A. Wadhawan et al., “YOLO LeafNet: a robust deep learning framework for multispecies plant disease detection with data augmentation,” Scientific Reports, vol. 15, Art. no. 28513, Aug. 2025.

[16] M. S. Krishna et al., “Plant Leaf Disease Detection Using Deep Learning: A Multi Dataset Approach,” J. 2025, vol. 8, no. 1, Art. 4, Jan. 2025.

[17] J. Imaging 2024, “An Enhanced Deep Learning Model for Effective Crop Pest and Disease Detection,” J. Imaging, vol. 10, no. 11, Art. 279, Nov. 2024.

[18] Plant leaf disease recognition based on improved SinGAN and improved ResNet34, Frontiers in Artificial Intelligence, 2024 (improved ResNet 34 approach demonstrating segmentation/identification enhancements).

[19] A. Yasin and R. Fatima, “On the Image Based Detection of Tomato and Corn Leaves Diseases: An in depth comparative experiments,” arXiv preprint, Dec. 2023.

[20] T. Ahmed et al., “Involution Infused DenseNet with Two Step Compression for Resource Efficient Plant Disease Classification,” arXiv preprint, Jun. 2025.