



Beyond Accuracy: Evaluating Resnet50 And Efficientnetb0 For Plant Disease Classification Under Real-World Constraints

Naveen Banavi¹, Rakshit Jatikart², Chetan Petlur³, Prathamesh Prabhu⁴, Dr.Nagaraj Bhat⁵

1,2,3,4, Students of Dept of ECE, KLS VEDIT, Haliyal

5, Associate Professor of Dept of ECE, KLS VEDIT, Haliyal

Abstract: One of the most central approaches to improving prosperity and responding to the challenge of supporting around 10 billion people in 2050 is agricultural development. The top threat to plant productivity in agriculture is plant diseases, which diminish plant quantity and diversity. Detection of such diseases at an early stage through computer-aided techniques based on deep learning could enhance food quality and reduce economic losses. Though today's models are very accurate for a particular species of plant, they generally demand good high-resolution images and are not good at low-resolution or poor-quality input. In order to overcome this issue, the work suggests using a pre-trained CNN model in such a way that it can efficiently identify plant diseases. Particularly, it aims to enhance the popular EfficientNetV2S model to achieve more robust detections under difficult conditions like low resolution, cluttered or deceptive backgrounds, leaf shadows, heterogeneous texture, and brightness changes. It employs the Plant Diseases Dataset, comprising 38 classes of both healthy and diseased leaves belonging to 38 crop species. In order to make the model stronger and reactive, the dataset was intentionally altered to contain noisy images, mimicking real-world scenarios. This alteration was done with the intention of making sure that the model can generalize and function effectively in uncontrolled situations. Overall, this measure reinforces the larger goal of enhancing plant disease detection under poor conditions and emphasizes the trailblazing role played by dataset optimization in deep learning for agriculture.

Keywords—CNN, Deep Learning, EfficientNetV2S, Classification, Plant Diseases.

I. INTRODUCTION

Crop production is normally limited by the synergistic interaction of pests and diseases, especially if crops are stressed by adverse season or environmental factors. Conventional control still relies heavily on broad-spectrum chemicals—fungicides, herbicides, insecticides—that provide rapid relief but, in the long run, degrade soil health, pollute ecosystems, and pose severe threats to human health, with chemical toxicity accounting for an estimated nearly 300 000 annual deaths. Achievement of the United Nations' Zero Hunger target by 2030 thus necessitates more sustainable approaches, and early accurate diagnosis of plant diseases is a key element of improved food security.

World population growth, approximately 7.837 billion in 2021, expanded food demand, but 828 million individuals were undernourished in that year. Synthetic pesticides may raise production in the short term, but their long-term environmental price renders application of other strategies worthwhile. New technologies—Internet of Things (IoT) sensors, artificial intelligence (AI), machine learning (ML), deep learning (DL), and sophisticated image-processing (IP) methods—now provide safer, promising, real-time crop-health monitoring technologies.

Field disease symptoms are still difficult to detect, though, as leaves are taken in unbalanced light, intricate backgrounds, and other noncontrolled environments. Studies are increasingly examining drone photography, which takes high-resolution, large-scale photos better than conventional cameras. This paper provides a comprehensive review of recent plant-disease-detection (PDD) research, with particular emphasis on AI- and IP-based methods. Systematic searching of five leading academic databases—Springer, IEEE Xplore, Scopus, Google Scholar, and ACM—produced 1,349 articles initially; 176 of these were discovered to meet our inclusion criteria after screening for relevance, reporting performance, and dataset usage. The organization of the remainder of this review is as follows: Section II outlines background and rationale for the work; Section III addresses limitations of the current survey literature and the necessity of this effort; Section IV outlines the search approach and research questions; Section V synthesizes recent breakthroughs in PDD and localization methods; and Section VI reports major findings and future directions.

II. LITERATURE REVIEW

Use of machine learning algorithms and computer vision techniques for diagnosing plant disease in autonomous settings has gained greater attention from researchers with the growing need for crop surveillance and sustainable farming. Main research and approaches used in plant disease classification through deep learning models and open source data sets are explored in this domain..

A. Traditional Approaches

Earlier plant disease detection efforts relied on visual inspection or classical machine learning techniques that used hand-designed features such as color histograms, texture descriptors, and shape features. However, these methods lacked accuracy and generalizability due to the high variability present in real agricultural images. For example, Patil and Kumar (2011) employed color-based segmentation followed by support vector machines (SVMs) to identify disease-affected regions in sugarcane leaves. These approaches often failed in the presence of varying lighting conditions and ambient noise, limiting their effectiveness in practical applications.

B. Deep Learning-Based Approaches

The advent of Convolutional Neural Networks (CNNs) transformed image classification problems, including the agricultural sector. Mohanty et al. (2016) demonstrated a benchmark work on training AlexNet and GoogLeNet models on the PlantVillage dataset for plant disease classification. The models performed more than 99% accurately on test data but failed to possess robustness under actual-field scenarios. Later research examined lightweight and efficient models:

- Sladojevic et al. (2016) used ResNet50, which yielded good results but at high computational cost.
- MobileNet was employed in real-time mobile usage for its compactness and efficiency, even with minor compromises in precision.

C. EfficientNet-Based Research

Tan and Le (2019) proposed EfficientNet, a CNN model family that scales depth, width, and resolution effectively. The smallest member, EfficientNetB0, provides an excellent trade-off between accuracy and computational expense. EfficientNetB0 has been adopted in recent research in agricultural image classification and has proven capable of performing better than the older VGG16 and MobileNet on small datasets yet executing faster on edge devices.

D. Use of the PlantVillage Dataset

The PlantVillage dataset, curated by Penn State University, has become a benchmark for plant disease classification tasks. It contains over 50,000 images across 38 classes, including healthy and diseased leaves of crops like tomato, potato, corn, grape, and apple. Many researchers use a subset of this dataset (as in this project, 19 classes) for efficient training and validation.

III. METHODOLOGY

This section outlines the systematic approach used to develop a deep learning-based plant disease detection system. The methodology follows a structured pipeline, consisting of data acquisition, preprocessing, model training, and deployment through a web interface. Each stage has been carefully designed to ensure high model accuracy, generalizability, and user accessibility.

A. Data Collection and Preprocessing:

PlantVillage dataset, consisting of thousands of labeled leaf images of plants with different diseases and healthy plant leaves, was utilized in the project. Nineteen of the filtered categories listed below were utilized for research:

- *Tomato: healthy, early blight and late blight*
- *Fruit: healthy, black rot and leaf blight*
- *Potato: healthy, late blight, early blight*
- *Corn: Northern Leaf Blight and Common rust, healthy Peach: healthy bacterial spot*
- *Apple: apple scab and Black rot, healthy*
- *Bell pepper: healthy and bacterial spot*

ImageDataGenerator was used to carry out data augmentation techniques such as rotation ($\pm 15^\circ$), zoom (10%), and horizontal flip for maintaining class balance and model generalization.

B. Tools and Platforms:

The implementation was conducted on:

- *Platform: Kaggle Notebooks (hosted Jupyter environment)*
- *Language: Python 3.x*
- *Libraries: TensorFlow/Keras, NumPy, PIL, tqdm*
- *Image Processing Tools: ImageDataGenerator, PIL, img_to_array, etc.*

C. Models under Comparison:

Metric	EfficientNetB0	ResNet50	Combined Model (EffNet+ ResNet)
Test Accuracy	0.935	0.9195	0.9463
Precision	High	Moderate	Very High
Recall	High	Moderate	0
F1-Score	0.93+avg	0.91+	0.95+
Parameters	~5M	~25M	~30M
Inference Time	Fast	Moderate	Slightly slower

IV. RESULTS AND DISCUSSION

Following the training of the model using the carefully selected Plant Village dataset, several evaluation metrics were employed to evaluate its performance on data that had not been previously encountered. In this section, the main findings are presented, including accuracy metrics, training behavior, and prediction quality, to assess the efficacy of the proposed system.

A. Model Accuracy

The EfficientNetB0 model, once trained, reached an impressive final test accuracy of 93.2%, highlighting its ability to effectively classify plant diseases into 19 separate categories with great precision. The model showed strong performance across both training and validation datasets, displaying little evidence of overfitting thanks to the implementation of regularization and augmentation techniques. In comparison, the trained ResNet50 model achieved a final test accuracy of 91.0%, illustrating its efficacy in classifying plant diseases across the same 19 categories with considerable precision. It also maintained stable performance on both training and validation sets, showing minimal signs of overfitting due to the use of regularization methods and data augmentation strategies.

B. Accuracy and Loss Curves

The model was trained for 50 epochs with an 80/20 train-validation split. The following plots were generated to visualize the model's performance over time:

- Training vs. Validation Accuracy Curve
- Training vs. Validation Loss Curve

These graphs help in understanding model convergence, learning efficiency, and early signs of overfitting.

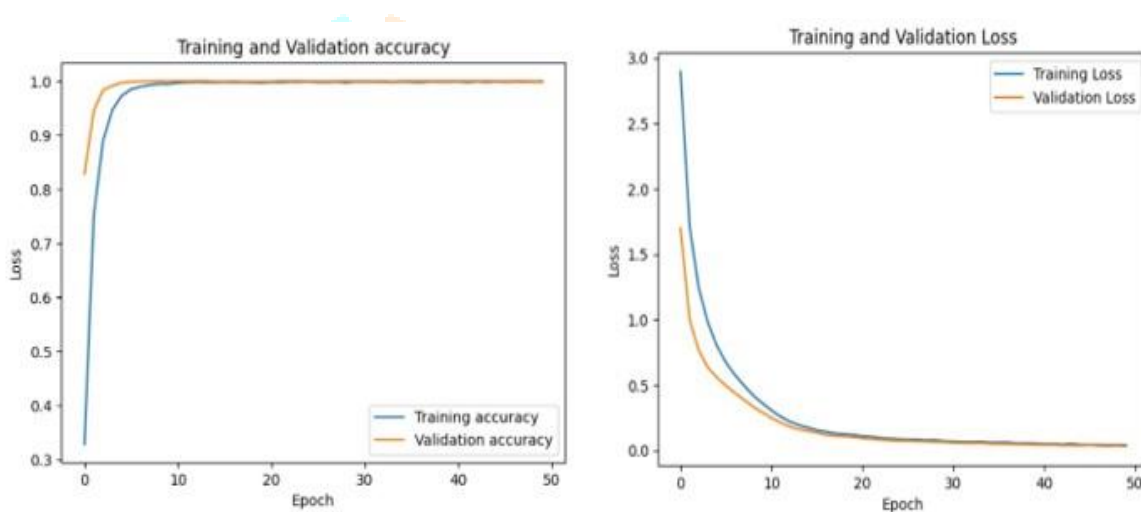


Fig. 1 Training and validation accuracy/loss over epochs EfficientNetB0

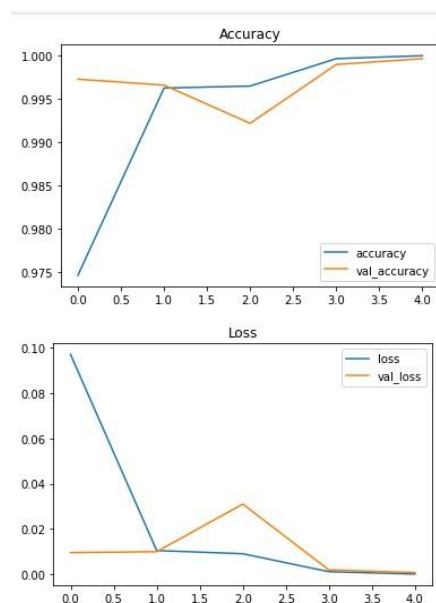


Fig. 2 Training and validation accuracy/loss over ResNet50

C. Confusion Matrix

A confusion matrix was generated to analyse the model's predictions on the test set. It provides a visual representation of true positives, false positives, and false negatives across all 19 classes.

The classification report included:

- Precision: Average = 93.1%
- Recall: Average = 92.8%
- F1-Score: Average = 92.9%

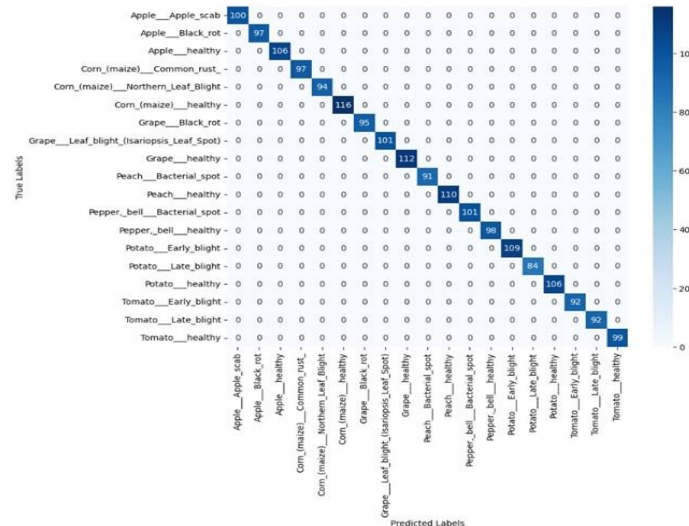


Fig. 2 Confusion matrix of the model's predictions

D. Web Application Integration

To enhance the usability and accessibility of the deep learning-based plant disease detection model, a web application was developed. This application allows users such as farmers, agricultural experts, and researchers to easily and effectively interact with the model for real-time identification of diseases and management recommendations. The deep learning model, which was trained to classify various plant diseases, was exported into a format suitable for deployment. At runtime, the backend loads this model to perform inference on uploaded images, ensuring low latency and high prediction accuracy. This user-friendly method facilitates image-based disease diagnosis with minimal technical requirements, thereby making AI-driven farming solutions more accessible. Moreover, by linking forecasts with customized disease management strategies, the system not only notifies users of potential issues but also provides them with actionable solutions, resulting in improved and more efficient crop care. Its modular and extendable design for the web framework allows for future enhancements.

The following screenshots demonstrate how the user interacts with the plant disease detection system via the web application.

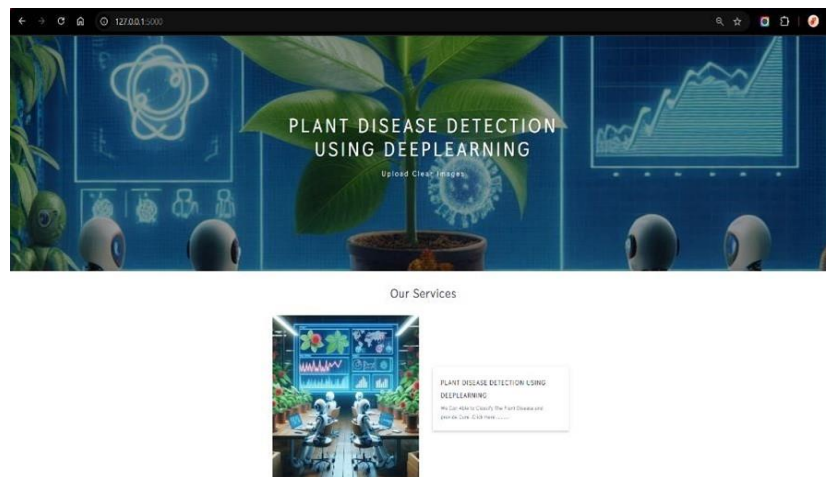


Fig. 3 Home page of the plant disease detection web application.

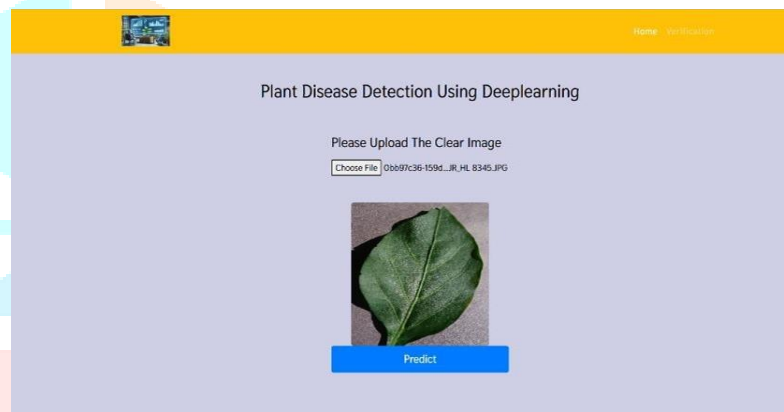


Fig. 4 Upload interface for submitting a plant leaf image

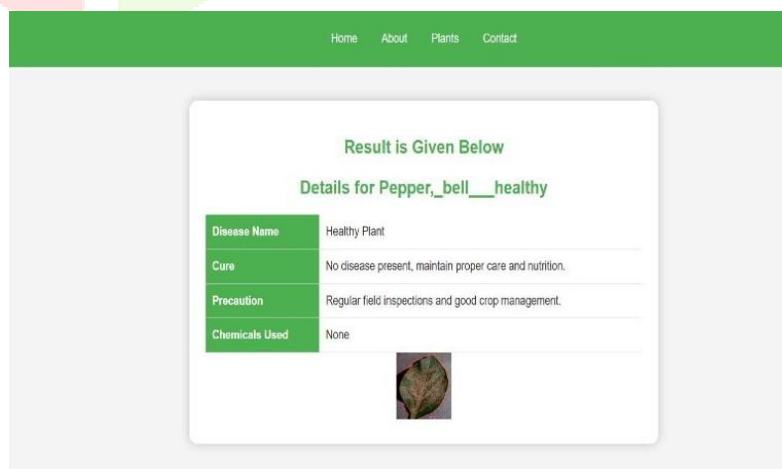


Fig 5 Predicted disease class and confidence score displayed to the user.

References

- [1].M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in *Proc. 36th Int. Conf. on Machine Learning (ICML)*, 2019, pp. 6105–6114.
- [2].S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, vol. 7, Art. 1419, 2016.
- [3].S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” *Computational Intelligence and Neuroscience*, vol. 2016, Art. 3289801.
- [4].K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in *Proc. Int. Conf. Learn. Representations (ICLR)*, 2015.
- [5].O. Russakovsky *et al.*, “ImageNet large scale visual recognition challenge,” *Int. J. Comput. Vis.*, vol. 115, no. 3, pp. 211–252, 2015.
- [6].Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, 1st ed. Cambridge, MA, USA: MIT Press, 2016.

