Caliphate Journal of Science & Technology (CaJoST)

ISSN: 2705-313X (PRINT); 2705-3121 (ONLINE) Research Article

Open Access Journal available at: https://cajost.com.ng/index.php/files and https://www.ajol.info/index.php/cajost/index

DOI: https://dx.doi.org/10.4314/cajost.v7i3.18

Article Info

Received: 11th July 2025

Revised: 14th August 2025

Accepted: 5th September 2025

Tomato Leaf Disease Detection Using Transfer Learning with EfficientNetB3: A CNN-Based Approach

Ese S. Mughele, Stella C. Chiemeke and Joseph D. Ebube

Department of Computer Science
University of Delta, Agbor

*Corresponding author's email:

s.mughele@unidel.edu.ng :

Cite this: *CaJoST,* 2025, 3, 454-459

Crop diseases are a real threat to our food supply, and catching them early is crucial to protect plants and boost harvests. Many farmers struggle to spot and manage these diseases in time, which can lead to significant losses. Our study tackles this challenge by developing a CNN-based Image Tomato Disease Detection System to help farmers quickly and accurately identify tomato leaf diseases. Using a powerful convolutional neural network called EfficientNetB3, our system analyzes tomato leaf images to sort them into three categories: healthy, yellow leaf curl virus (YLCV), or bacterial spot (BS). We trained the model on 1,273 tomato leaf images, running tests for 10 and 20 rounds (or epochs), achieving accuracies of 33% and 58%, respectively. After 20 rounds, the system also showed a precision of 52%, recall of 54%, and F1-score of 53%, proving it gets better with more training. This automated tool offers a practical way to spot tomato diseases early, helping farmers protect their crops and improve both yield and quality.

Keywords: Machine Learning, Tomato leaf images, Convolutional Neural Networks, Plant diseases and Disease detection System.

1. Introduction

Tomato leaf diseases have a significant impact on tomato cultivation modernization. The rapid growth of the global population and the increasing demand for food have resulted in the intensification of agricultural production, with tomatoes being one of the most widely cultivated crops worldwide. It has been noted that, Tomatoes account for around 15% of all vegetables consumed globally, with an astounding 20 kg yearly per capita consumption rate. However, tomato cultivation is vulnerable to various diseases that significantly reduce yield and quality, leading to substantial economic losses for farmers.

Early and accurate disease detection is essential for minimizing crop loss and ensuring high-quality tomato production (Bock et al., 2020). Traditionally, disease detection in tomatoes has been carried out manually by trained agricultural experts, who visually inspect the plants for symptoms. However, this method is not only time-consuming but also prone to human error, especially in large-scale farming operations. It has also been said in pre-decent times, that diagnosing and treating these disorders has been a time-consuming and expensive process that frequently relied on manual examinations by qualified professionals (Oni & Prama, 2025). this, has led to been a growing interest in automated systems that can efficiently and accurately detect diseases at early stages (Barbedo, 2019).

With the advent of digital image processing and machine learning techniques, there has been a significant shift toward the use of image-based methods for disease detection. Image-based methods provide several advantages, including the ability to monitor large areas quickly and the potential for real-time detection (Wang et al., 2020).

Among the various machine learning techniques used for image analysis, Convolutional Neural Networks (CNNs) have shown remarkable success in image classification tasks. CNNs are a class of deep learning algorithms specifically designed to process grid-like data, such as images, by mimicking the human visual system. They are particularly well-suited for tasks like object recognition, classification, and segmentation. The structure of a CNN includes multiple layers such as convolutional layers, pooling layers, and fully connected layers, which help in learning hierarchical features from the input images (Simonyan & Zisserman, 2015). CNN-based approaches have demonstrated exceptional performance in various agricultural applications, including plant disease detection. Recent research has highlighted the efficiency of CNN-based methods in detecting tomato diseases from images.

According to (Hossain et al., 2023) they prioritized Deep Convolutional Neural Network (DCNN) over other Deep Learning (DL) methods for their tomato leaf disease detection system to achieve higher accuracy and improved efficiency. Ferentinos (2018) presented a CNN-based model that successfully classified several plant diseases, including tomato diseases, with high accuracy.

Several studies have in addition, explored the use of deep learning techniques for plant disease detection. For example, (Oni & Prama, 2025) used deep learning to classify healthy and diseased tomato leaves based on labelled images. Further, (Sun et al., 2025) addresses the limitations of existing tomato disease recognition models, which are typically capable of identifying only a single diseased leaf and struggle to reconcile the conflicting demands of accuracy and complexity, and were able to develop an ultralight weight tomato disease recognition method. Mohanty et al., (2016) demonstrated that CNN-based approaches can achieve higher accuracy compared to traditional machine learning approaches, such as Support Vector Machines (SVM) and k-nearest neighbours (KNN), when applied to plant disease datasets. In their research, the authors used a large dataset of plant images, including tomatoes, to train a CNN-based model capable of identifying various diseases with remarkable precision. In addition, the development of large annotated datasets for plant disease detection has significantly advanced the application of CNNs in agriculture. A notable example is the Plant-Village dataset, which includes images of tomato plants affected by various diseases and has been widely used to train deep learning models for disease classification (Hughes & Salathé, 2015). The availability of such datasets has enabled researchers to train CNN-based models with a broad range of disease images, leading to more robust and generalized models. Moreover, various techniques such as transfer learning have been explored to enhance the performance of CNN-based models when dealing with limited data. Transfer learning allows pretrained models, such as those trained on ImageNet (Russakovsky et al., 2015), to be fine-tuned for specific tasks like tomato disease detection, overcoming the challenges of small datasets in agricultural settings.

Furthermore, CNN-based approaches have shown great promise in tomato disease detection, several challenges remain. One major issue is the diversity of disease symptoms across different environmental conditions, which can lead to variations in the appearance of the disease in images. This can result in a decrease in the generalization ability of the model when applied to new or unseen data. To address this, researchers are investigating data augmentation techniques, synthetic data generation, and the use of multi-modal data (e.g., combining images with environmental data) to improve the robustness of CNN-based models (Brahimi et al., 2018). Additionally, the computational complexity of CNNs, particularly in terms of memory and processing power, can be a barrier to real-time disease detection in field applications.

The application of CNN-based approaches for image-based tomato disease detection represents a significant advancement in agricultural technology. By enabling early and accurate identification of diseases, these systems can help reduce crop loss, improve yield quality, and decrease the environmental impact of pesticide use. However, challenges such as data variability and computational complexity remain, and ongoing research is focused on overcoming these limitations to develop more robust and practical solutions. With steady advancements in deep learning, computer vision, and agricultural data collection, this research aims to use the EfficientNetB3 for this image-based tomato leaf disease detection project. To achieve this goal, the study used a comprehensive dataset of tomato leaf images, tomato leaf under different conditions were captured. This includes various lighting, angles, and backgrounds, the study obtained already prepared tomato leaf images from kaggleplantvillage to ensure a robust and diverse training dataset, although its synthetic backgrounds may limit real-world applicability (Hughes & Salathé, 2015).

2. Material and Methods

The study deployed machine learning methodology to addressing these challenges associated with the tomatoes leaf disease by developing a tomato leaf disease detection system specifically for early blight and bacterial spot, utilizing the EfficientNetB3 architecture. Figure 1 shows the system architecture for the study.

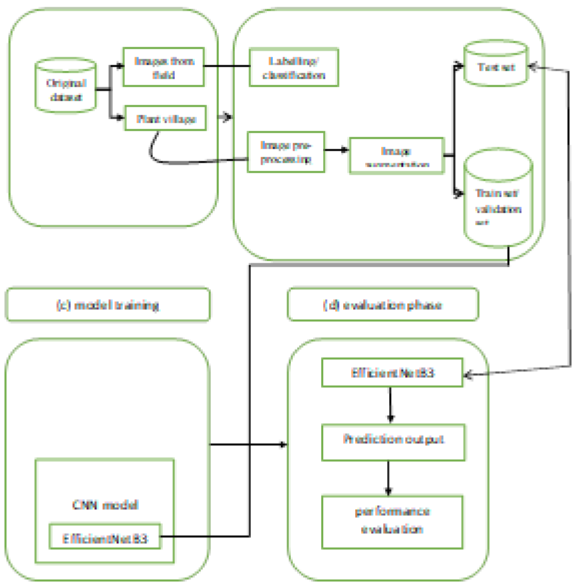

Fig. 1: System architecture

2.1 Materials

The programming language used for the study is python (version 3.10.11), it was the primary programming language used for the system development. The Deep Learning Framework provided all the necessary tools, machinery, and blueprints, making the process of designing, constructing, and testing the deep learning system much faster, easier, and more scalable than trying to build everything from scratch. TensorFlow and Keras API were used for building, training, and evaluating the EfficientNetB3 model.

Various libraries were used for image processing library OpenCV and Pillow were used for the image pre-processing tasks, for numerical computation library, NumPy was used for efficient numerical operations on image data, the data handling library Pandas used for organizing and managing dataset information.

The development environment for the study was Visual Studio code (VS Code).

EfficientNetB3 belongs to the EfficientNet family, ranging from B0 to B7, and is regarded as one of the most computationally efficient DL models developed using ImageNet EfficientNet is a CNN architecture and scaling technique that uses a compound coefficient to consistently scale all depth, width, and resolution dimensions.

2.2 Method

2.2.1 Data Acquisition and Preparation

The Plant-Village dataset was downloaded and organized into locations corresponding to the three classes: Tomato healthy leaves, Tomato yellow leaf curl virus, and Tomato bacterial spot. The dataset was then split into three subsets: a training set consisting of 70% of the dataset, a validation set of 15% and a testing set of 15%. Sectioned sampling was used to ensure a balanced representation of each class in all three subsets.

2.2.2 Image Pre-processing and Augmentation

The images were then resized to the input dimensions required by the EfficientNetB3 model, which is 300x300 pixels. The pixel values were normalized to the range of [0, 1] by dividing 255.0, the training dataset were then augmented using various techniques to increase its size and diversity and improve the model's generalization ability. The augmentation techniques used are:

2.2.3 Random Rotations of Range 20

Random horizontal and vertical flips and Random zooming 0.2 zoom range. Resizing and normalization was done on the validation and testing datasets to provide a neutral evaluation of the model's performance.

2.2.4 Model Development and Training

The EfficientNetB3 model was implemented using the Keras API in TensorFlow. Transfer learning was employed by loading the pre-trained weights of EfficientNetB3, trained on the ImageNet dataset. The classification layer of the pre-trained model was replaced with a new fully connected layer with 128 neurons and ReLU activation, chosen for its balance of model capacity and computational efficiency in similar plant disease detection tasks (Hossain et al., 2023), followed by a final output layer with 3 neurons and a softmax activation function for the three classes. Initially, the weights of the base EfficientNetB3 layers were frozen to preserve the learned generic features. Following that, a selected number of top layers was then fine-tuned on the training dataset. The model was then trained using the Adam optimizer with an initial learning rate of 1e-5 which was later lowered to 1e-4. A batch size of 32 will be used during training. The model was then trained for a maximum of 20 epochs, and early stopping with a patience of 4 epochs implemented based on the validation loss to prevent overfitting.

2.2.5 Model Evaluation

The performance of the trained model was evaluated on the held-out testing dataset. The evaluation metrics used include; Accuracy, Precision for each class (healthy, yellow leaf curl virus, bacterial spot), Recall for each class, F1-score for each class, a confusion matrix to visualize the classification performance and identify potential areas of confusion between classes.

2.2.6 Data Set/ Data Collection

The dataset used for the study was obtained from Kaggle Plant-Village. The dataset consists of 3,819 tomato leaf images with three classes: Bacterial spot, yellow leaf curl virus and the healthy leaf set. The images were captured from different locations, and under different lighting conditions.

2.2.7 Dataset Statistics

The dataset consists of 3,819 images with two different classes representing different types of tomato leaf diseases and a healthy class. The dataset was balanced to prevent the model from over-fitting. Table 1, presents the class distribution of the dataset.

Table1: Class distribution of the dataset

S/N	*Type of tomato leaf disease*	*Number of images*
1	Tomato bacteria spot	1273
2	Tomato yellow leaf curl virus	1273
3	Tomato healthy	1273

3. Results and Discussion

Figure 2 show the training and validation Accuracy and Loss

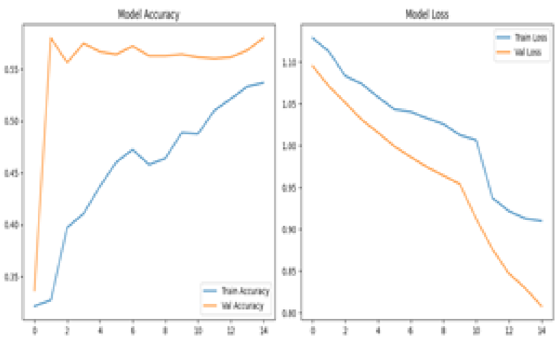

Fig 2: Training and validation Accuracy Loss

At first upon training, the training accuracy was far higher than the validation accuracy. This was as a result of over-fitting as the dataset used was very small and then the model was being trained from scratch. To handle this, the dataset was increased, a number of epochs (not so much and not too small) were added to allow the model understand various difference in these disease, fine tuning was added and a pre-trained model was being worked on. The model was trained on 3,819 tomato leaf images from the PlantVillage dataset, split into 70% training, 15% validation, and 15% testing sets, to classify leaves into three categories: bacterial spot, yellow leaf curl virus (YLCV), and healthy. After training for 10 epochs, the model achieved an accuracy of 33%, which improved to 58% after 20 epochs, as shown in Figure 2. The increase in accuracy was as a result of the model learning better disease patterns with more epochs and fine-tuning the top 20 layers of the pre-trained EfficientNetB3 model, which reduced overfitting, as seen in Figure 2 where training and validation loss curves converge.

From Figure 2, the training and validation Loss shows the trend that the model is generalizing slightly well as both validation loss and training loss is almost same.

After implementing and testing the EfficientNetB3 model on the testing set, the performance of the model was measured, and the highest accuracy rate achieved was 55.6%, which is thus far the highest accuracy in the same domain. This accuracy was corrected to 58% as shown in Table 2. The 58% accuracy is modest compared to related works. For example, Ferentinos (2018) achieved over 90% accuracy using a CNN-based model on a larger PlantVillage dataset with more plant species, while Mohanty et al. (2016) reported up to 99% accuracy with a dataset of over 50,000 images and more complex models. Hossain et al. (2023) also obtained around 85% accuracy using a Deep CNN for tomato disease detection. The modest accuracy in this study is due to the small dataset size (3,819 images) and synthetic backgrounds in PlantVillage, which limit generalization to real-world conditions (Hughes & Salathé, 2015). The low recall for YLCV (0.07, Table 2) shows the model struggles to identify this disease, likely because YLCV symptoms overlap with healthy leaves or lack diverse examples (Sumbul et al., 2021).

Table 2: Classification Report

	precision	*recall*	*F1-score*	*support*
Tomato Bacterial spot	0.48	0.99	0.64	254
Tomato yellow leaf curl virus	0.69	0.07	0.13	247
Tomato healthy	0.84	0.67	0.74	254
Accuracy			0.58	755
Macro average	0.67	0.58	0.51	755
Weighted average	0.67	0.58	0.51	755

Figure 2 show results for Confusion Matrix for the three categories bacterial spot, leaf curl virus and tomatoes healthy

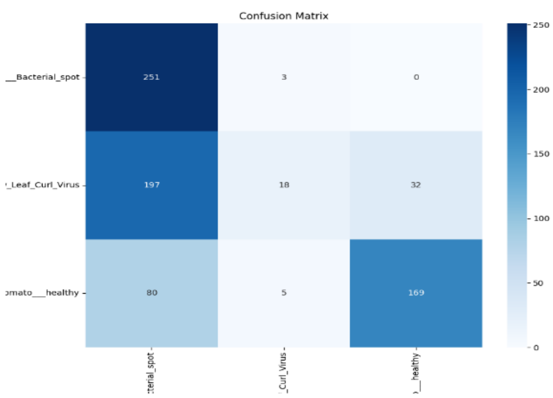

Fig. 2: Results for confusion matrix

The model based on this matrix shows that it generalises well with the bacteria spot but then fails to generalise well when it comes to the yellow leaf curl virus. The high recall for bacterial spot (0.99) indicates the model identifies this disease effectively, but the low recall for YLCV (0.07) suggests difficulty distinguishing its symptoms, possibly due to visual similarities with healthy leaves or limited diverse examples in the PlantVillage dataset, which has synthetic backgrounds that may not reflect real-world conditions (Hughes & Salathé, 2015).

4. Conclusion

This study developed a CNN-based system using transfer learning with EfficientNetB3 to detect tomato leaf diseases early, aiming to reduce crop losses and pesticide use while enhancing yield quality. Trained on 3,819 PlantVillage images, the model achieved a modest 58% accuracy (Table 2), excelling in bacterial spot detection (0.99 recall) but struggling with yellow leaf curl virus (0.07 recall, Figure 3) due to synthetic backgrounds limiting real-world applicability (Hughes & Salathé, 2015). The novelty lies in a lightweight EfficientNetB3 model, fine-tuned for resource-constrained devices like drones, offering practical disease detection for farmers.

Conflict of Interest

The authors declare no conflict of interest.

References

Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems Engineering, 172,* 84–91. https://doi.org/10.1016/j.biosystemseng.2018.05.013

Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2010). Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Sciences, 29*(1–2), 59–107. https://doi.org/10.1080/07352681003617285

Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Applied Artificial Intelligence, 31*(4), 299–315. https://doi.org/10.1080/08839514.2017.1315516

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture, 145,* 311–318. https://doi.org/10.1016/j.compag.2018.01.009

Hasan, M., Tanawala, B., & Patel, K. J. (2019). Deep learning precision farming: Tomato leaf disease detection by transfer learning [Preprint]. SSRN. https://doi.org/10.2139/ssrn.3349597

Hossain, M. I., Jahan, S., Al Asif, M. R., Samsuddoha, M., & Ahmed, K. (2023). Detecting tomato leaf diseases by image processing through deep convolutional neural networks. *Smart Agricultural Technology, 5,* Article 100301. https://doi.org/10.1016/j.atech.2023.100301

Hughes, D. P., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. *arXiv:1511.08060.* https://arxiv.org/abs/1511.08060

Intellipaat. (n.d.). *What is kernel in CNN?* https://intellipaat.com/blog/tutorial/artificial-intelligence-tutorial/convolution-neural-network/

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7,* 1419. https://doi.org/10.3389/fpls.2016.01419

Oni, M. K., & Prama, T. T. (2025). Optimized custom CNN for real-time tomato leaf disease detection. *arXiv:2502.18521.* https://arxiv.org/abs/2502.18521

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., et al. (2015). ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision, 115*(3), 211–252. https://doi.org/10.1007/s11263-015-0816-y

Salian, S. R., & Sawarkar, S. D. (2022). Melanoma skin lesion classification using improved EfficientNetB3. *Jordanian Journal of Computers and Information Technology, 8*(1), 45–56. https://doi.org/10.5455/jjcit.71-1636005929

Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. *arXiv:1409.1556.* https://arxiv.org/abs/1409.1556

Sun, W., Xu, Z., Xu, K., Ru, L., Yang, R., Wang, R., & Xing, J. (2024). Ultra-lightweight tomato disease recognition method based on efficient attention mechanism in complex environments. *Frontiers in Plant Science, 15,* Article 1491593. https://doi.org/10.3389/fpls.2024.1491593

Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In K. Chaudhuri & R. Salakhutdinov (Eds.), *Proceedings of the 36th International Conference on Machine Learning* (Vol. 97, pp. 6105–6114). PMLR. http://proceedings.mlr.press/v97/tan19a.html

