

Deep Tomato Disease Classification Using EfficientNetB3 with Multi-Source Dataset and Hybrid Augmentation

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Abstract: Tomato is a globally valuable crop, but its growth and quality are affected by numerous plant diseases. Traditional disease diagnosis techniques are primarily time-consuming, expert-thirsty, and unsuitable for large-scale adoption. Here, we propose a deep learning method to multi-class classification of tomato leaf diseases using the EfficientNetB3 model. In difference to the aforementioned research in which controlled datasets were utilized, in our approach a real-world multi-source image dataset with 25,851 images across 11 classes, among which are present common diseases including bacterial spot, early blight, septoria leaf spot, and healthy class, was used. As an approach to reduce class imbalance and increase the stability of our model, we utilized a hybrid data augmentation strategy consisting of geometric, noise injection-based, and GAN-based synthetically generated data. The model was trained using transfer learning from weights of ImageNet and evaluated with accuracy, precision, recall, and F1-score metrics. It achieved test accuracy of 98.74% at an F1-score of 98.2%, confirming impeccable generalization. These results guarantee the scalability and reliability of EfficientNetB3 as a use case for precision agriculture in broad, particularly for real-world and variable conditions, and could be transferred to other environments and crops with similar issues.

Keywords: Automated Disease Identification; EfficientNetB3; Deep Learning in Plant Pathology; Tomato Disease Detection.

1. Introduction

Agricultural productivity frequently falls under added pressure due to changing climatic patterns and the wide spread of biotic stressors such as fungal, bacterial, and viral diseases [1-3]. Tomato plants are particularly susceptible to a wide range of pathogens, resulting in a huge yield loss as well as quality loss. Plant diseases worldwide have been estimated to yield an economic loss of over US\$220 billion annually, which directly impacts food security as well as the livelihood of smallholder farmers [4, 5].

Traditional diagnosis of tomato disease is highly reliant on human experience, not usually accessible to marginal farmers or practical in time-constrained circumstances. Laboratory diagnosis, though accurate, remains costly and time-consuming. Farmers, therefore, are bound to resort to limited resources like consulting fellow farmers or farm hotlines. Early detection of infected plants requires expert input and, for most cases, laboratory facilities—resources are not always accessible to rural or developing regions [6-9].

Over the last decade, deep learning has transformed agricultural diagnostics by offering scalable, image-based solutions through computer vision systems. These systems can detect disease-

specific symptoms such as discoloration, deformation, and lesions on tomato leaves with remarkable speed and accuracy [10]. Computer vision has emerged as the most advanced tool for recognizing plant diseases. It is critical for assessing abiotic and biotic stress in tomato plants via the analysis of photos to locate signs such as changed fruit or leaf color, shape, or texture. Through identification of clear visual patterns, such systems facilitate computerized diagnosis of diseases, insects, and environmental stresses, and real-time assessment with accurate discrimination between stress classes.

Earlier work in this regard used Convolutional Neural Networks (CNNs) and object detection algorithms like YOLO, which typically were trained using meticulously curated data like PlantVillage [11]. Datasets like these were typically captured under controlled background and lighting conditions. Although controlled data limits model generalization when deployed in the real-world field environment, with variable lighting, cluttered backgrounds, and noisy images.

To address this gap, we introduce a robust classification model based on EfficientNetB3, particularly for multi-source tomato disease images under diverse and realistic scenarios. Contrary to the current work that focuses on object detection (e.g., YOLOv8n), our effort focuses on fine-grained classification, which is essential in differentiating visually misleading diseases such as early blight and leaf mold. Our approach includes hybrid data augmentation to enrich variation synthetically in pose, lighting, and texture, and user-specified callback mechanism to adaptively learn from model performance dynamically by varying the learning rate, and stringent visual analytics such as confusion matrices, confidence calibration, and class distribution analysis.

The data used for this research are samples drawn from several publicly accessible sources to both ensure class variety and reflect the complexity of the real world. Model performance is measured with the usual metrics such as precision, recall, F1-score, and confusion matrix analysis supplemented with visual aids for better interpretability.

Lastly, this study aims to construct a usable, field-deployable solution to tomato disease classification. The proposed system can be integrated into edge or mobile computers so that the farmers can gain timely and accurate diagnostics without requiring experts thus improving agricultural outcomes and supporting sustainable food production.

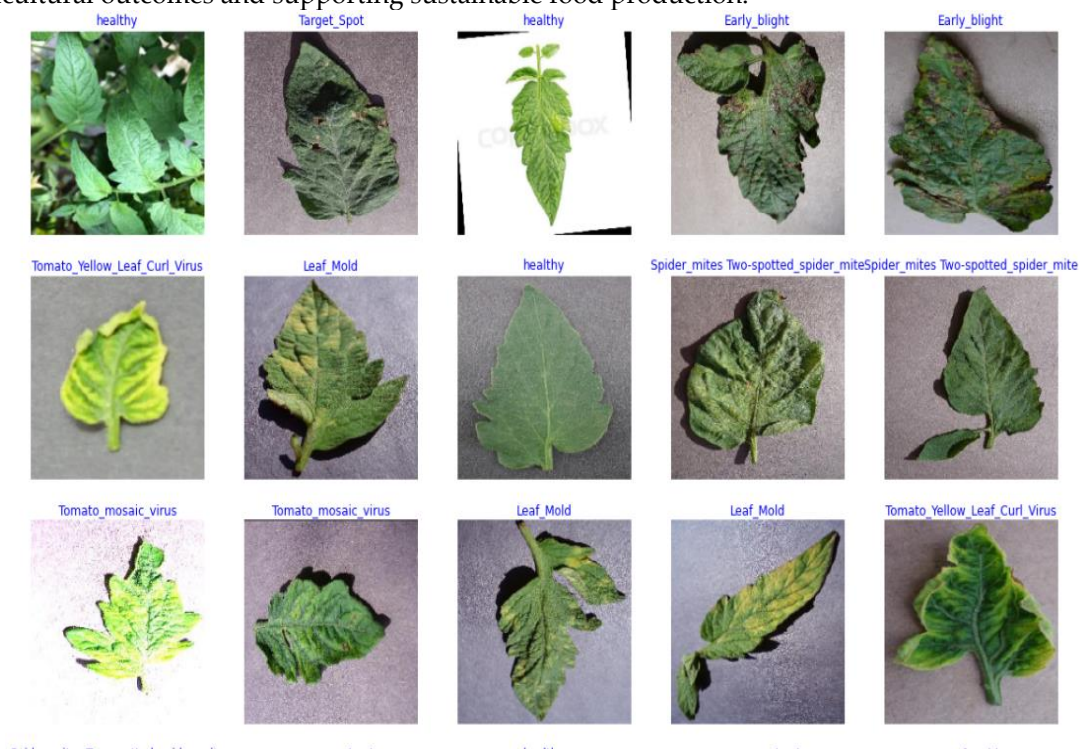
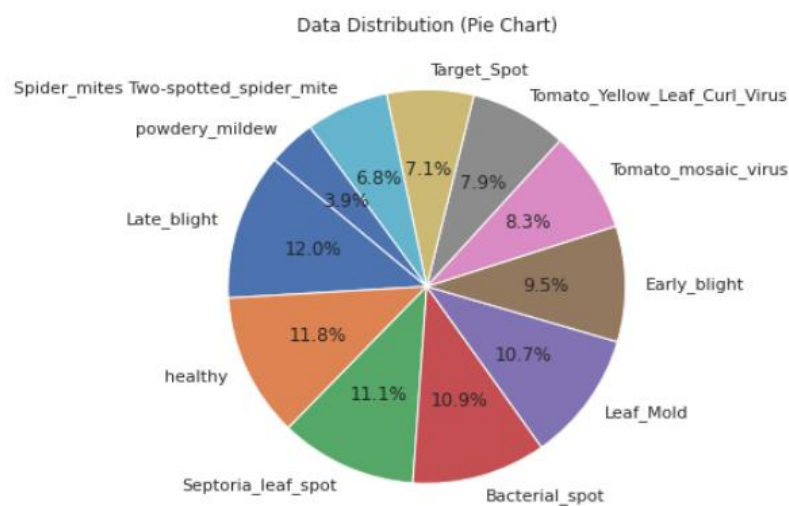
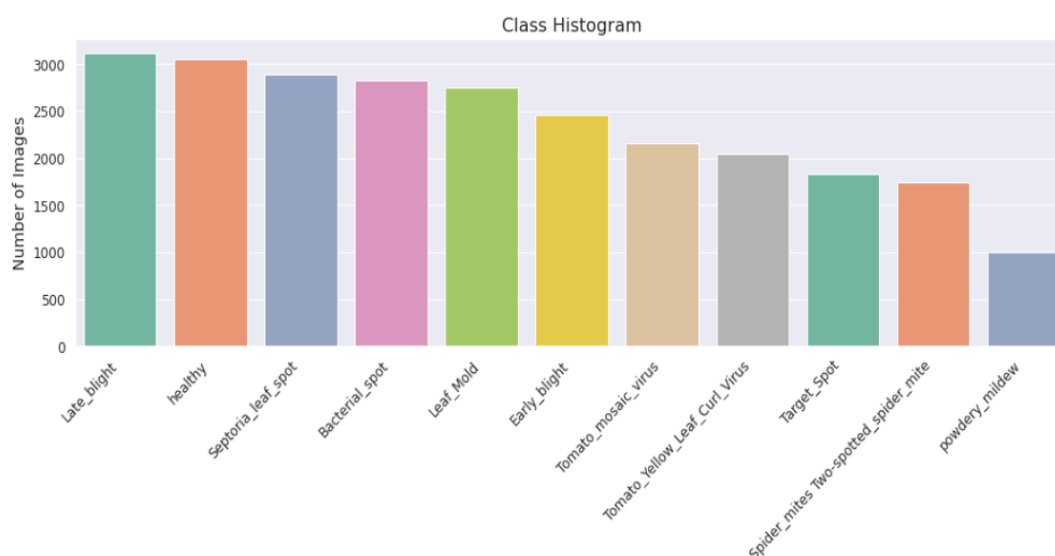


Figure 1. Samples of data with labels.

Table 1. Class Distribution-the dataset comprises the following tomato leaf categories.

Class	Image Count
Early Blight	2455
Bacterial Spot	2826
Late Blight	3133
Leaf Mold	2754
Septoria Leaf Spot	2882
Spider Mites (<i>Tetranychus urticae</i>)	1747
Target Spot	1827
Tomato Yellow Leaf Curl Virus	2039
Tomato Mosaic Virus	2153
Powdery Mildew	1004
Healthy	3015

**Figure 2.** Pie Chart with data distribution.**Figure 3-a.** Class histogram.

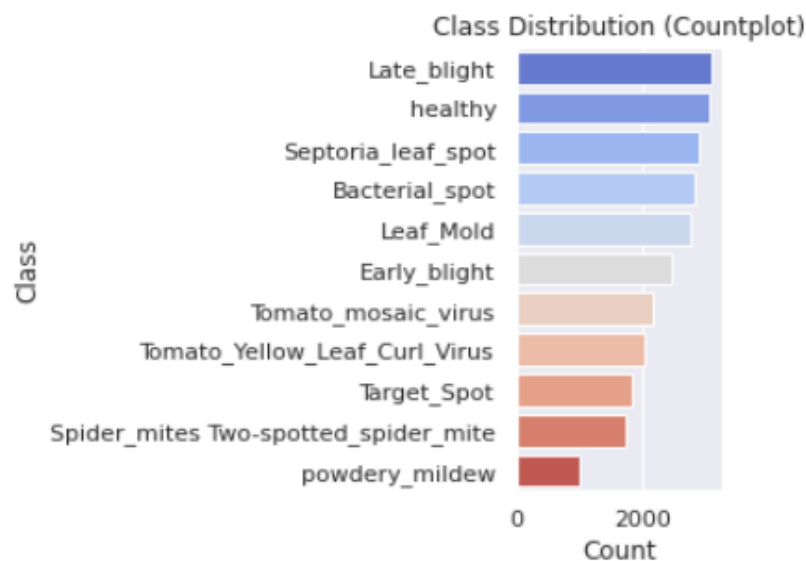


Figure 3-b. Class histogram (another perspective).

Figure 4 presents the architecture of EfficientNetB3 that incorporates innovative techniques in deep learning and computer vision, including advanced compound scaling, efficient feature extraction using depth wise separable convolutions, and optimized model size for superior performance with fewer parameters and computations.

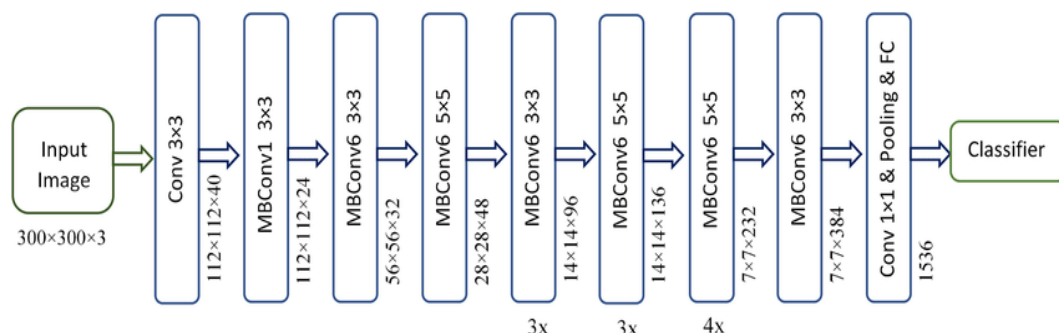


Figure 4. Architecture of EfficientNetB3.

2. Recent Developments in DL-assisted Disease Diagnosis

A Recent advance in deep learning (DL) have transformed the research area of plant disease identification. The use of deep neural networks in agriculture has enabled more accurate, automatic, and scalable disease classification based on image-driven methods. While object detection frameworks like YOLOv5 and YOLOv8 have shown promise in detecting localized disease regions, they are likely to require high-quality annotations and are sensitive to background noise—limiting their usage in complex, real-world agricultural settings.

Initial attempts such as Mohanty et al. [12] used Alex Net to classify plant diseases using leaf images, but poor generalization was reported when testing on images acquired under different conditions. Later attempts used deeper architecture such as VGG16 [13, 14], Google Net [15], and InceptionV4 [16] typically fine-tuned on the plant disease datasets with ImageNet pre-trained weights. Dense Net and ResNet models were also employed with improved feature reuse and gradient propagation, with good classification performance being recorded when combined with techniques like average pooling and L2 regularization [17–19].

Data augmentation has also been a prominent point of focus, with works utilizing transformations like rotation, zoom, flipping, and color jittering to fortify model robustness [20-22]. Recent works added GAN-based augmentations like FWDGAN [23] for creating high-quality synthetic plant disease samples, reducing model dependence on limited data, and improving FID scores.

While detection models like YOLOv8 have been experimented with in tomato disease detection tasks [24], classification architectures remain more efficient in multi-class issues where spatial localization is not of the utmost importance. Transfer learning with powerful backbones like Xception, Mobile Net, and Efficient Net became popular due to their ability to achieve a balance between performance and parameter efficiency [25, 26].

Efficient Net models have demonstrated improved scaling characteristics, outperforming earlier CNNs with a compound scaling approach that optimally balances depth, width, and resolution [26]. Certain variants like EfficientNetB3 have demonstrated excellent performance on classification benchmarks, including medical imaging and agriculture.

Furthermore, studies have pointed out that generalization to field conditions is dependent on real-world variability such as varying light, occlusions, and heterogeneous disease symptoms [27–44]. Recent publications increasingly include domain-specific augmentation and interpretability methods such as PR curves and confidence calibration to enhance model performance and transparency.

Despite considerable progress, challenges remain in deploying models that generalize well to diverse conditions, especially with imbalanced datasets or limited annotations. This is the motivation for the present study, which proposes a robust EfficientNetB3-based classification system trained on a multi-source tomato disease dataset, complemented by hybrid augmentation and custom training callbacks for efficient learning, generalizability, and real-world usability.

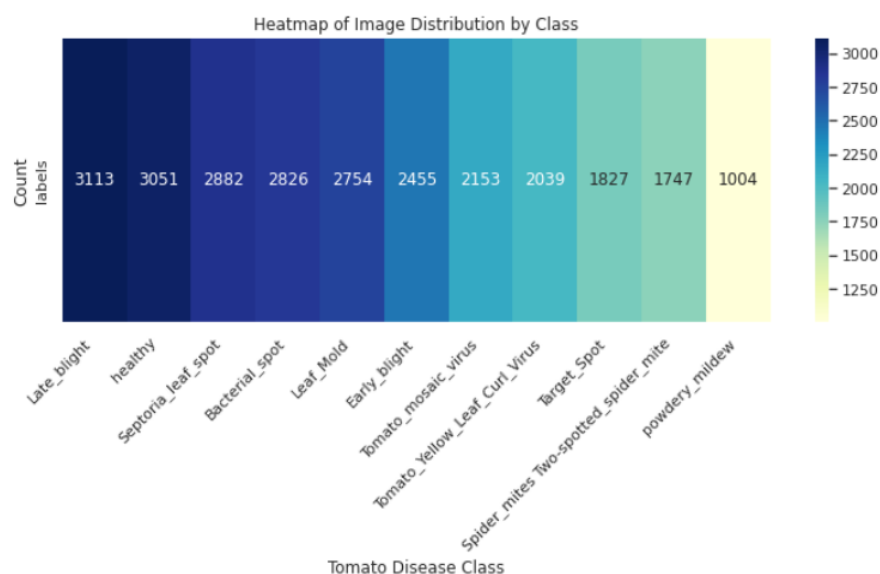


Figure 5. Heatmap showing image distribution by class.

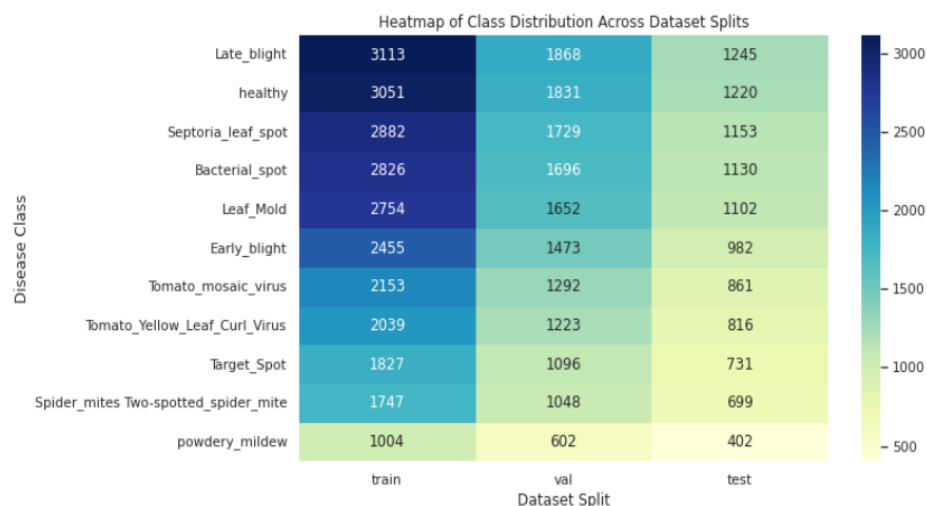


Figure 6. Heatmap showing class distribution across dataset.

2.1. Pseudocode: Tomato Leaf Disease Classification Pipeline

1. Import required libraries for data handling, image processing, model building.
2. Load image paths and labels:
 - Traverse dataset directory structure.
 - Store file paths and corresponding class labels in a Data Frame.
3. Split dataset:
 - Use stratified sampling to create train, validation, and test sets.
4. Create image generators:
 - Apply preprocessing (resizing, normalization, augmentation).
 - Generate batches from train, Val, test Data Frames.
5. Define visualization functions:
 - Plot sample images and class distributions (pie, bar, heatmap).
6. Build model:
 - Load EfficientNetB3 (pretrained, without top).
 - Add BatchNorm → Dense → Dropout → Output layer (SoftMax).
 - Compile with Adamax and categorical Cross entropy.
7. Define custom training callback:
 - Monitor training and validation loss/accuracy.
 - Adjust learning rate dynamically.
 - Stop early if there is no improvement.
8. Train model:
 - Fit on training data using callbacks and validation data.
9. Evaluate model:
 - Report accuracy/loss on train, validation, and test sets.
10. Predict on test set:
 - Generate predictions.
 - Compute confusion matrix and classification report.
11. Save model and class index mapping.
12. Plot performance metrics:
 - Training curves, precision-recall, F1 vs. confidence, label statistics.

3. Materials and Methods

The paper proposes a novel deep learning approach for disease detection on potato leaves based on EfficientNetB3 convolutional neural network. On the Plant Village image dataset [description of potato leaves as Early Blight, Late Blight and Healthy] the model reached an appreciable accuracy of 92%; further, the study shows that deep learning techniques with EfficientNetB3, can be applied to real-time and large-scale plant disease detection problems.

3.1. Dataset Collection and Preprocessing

To build a robust and generalizable classification model for tomato leaf diseases, we utilized a multi-source dataset comprising 25,851 high-resolution images across eleven classes: ten disease types and one healthy class. The dataset aggregates samples from several public sources, including the Plant Village dataset, field-captured tomato images, and GAN-generated synthetic samples. The classes span a broad spectrum of tomato diseases such as early blight, late blight, leaf mold, mosaic virus, powdery mildew, bacterial spot, and spider mites.

The images were collected under both controlled laboratory conditions and natural field environments, featuring diverse backgrounds, lighting conditions, and varying symptom intensities. All images were resized to 224×224 pixels to match the input dimensions required by EfficientNetB3 architecture.

The dataset was stratified into training (60%), validation (20%), and testing (20%) subsets while maintaining label distribution across all splits. Labels were one-hot encoded to facilitate multi-class classification.

3.2. Data Augmentation

Given the inherent class imbalance and intra-class visual similarity, a hybrid data augmentation pipeline was designed to enrich the training set and enhance model robustness. This included both classic transformations and synthetic image generation:

- Geometric transformations: random rotations, flips (horizontal/vertical), and scaling
- Photometric distortions: gamma correction, brightness reduction, color jittering
- Noise injections: Gaussian noise, salt & pepper noise
- Kernel-based filters: sharpening and Gaussian blur (up to 2px)
- GAN-based augmentations: for minority classes such as powdery mildew and spider mites

The final augmented dataset captured a wider range of real-world variability while preserving class-discriminative features.

3.3. Model Architecture

We employed EfficientNetB3, a convolutional neural network architecture optimized through compound scaling of depth, width, and resolution. It was initialized with ImageNet-pretrained weights and modified to suit the classification task:

- Base model: EfficientNetB3 (without top)
- Pooling layer: Global max pooling
- Classifier head:
 - Batch normalization
 - Dense layer (256 units, ReLU, L2 and L1 regularization)
 - Dropout (rate = 0.45)
 - Output layer with SoftMax activation for eleven classes.

3.4. Training Configuration

The model was compiled using the Adamax optimizer with a learning rate of 0.001 and trained with categorical cross entropy loss. A custom callback (MyCallback) was developed to dynamically monitor training and validation performance and adjust the learning rate accordingly. This allowed for:

- Learning rate decay on plateau
- Early stopping after successive drops in validation performance
- Automatic restoration of best weights

Key hyperparameters:

- Epochs: five
- Batch size: forty.
- Patience: one
- Stop patience: three.
- Learning rate decay factor: 0.5
- Initial learning rate: 0.001

All training was conducted using TensorFlow/Keras in a Jupyter Notebook environment with GPU acceleration (NVIDIA RTX 3050 Ti).

3.5. Evaluation Metrics and Visualization

Model performance was evaluated using:

- Accuracy, Precision, Recall, F1-score
- Confusion matrix
- Training/Validation accuracy and loss curves
- Precision-Recall (PR) curve
- F1 vs. Confidence Threshold
- Label distribution and coordinate plots.

Visual tools were used to analyze prediction confidence, class misclassification, and data distribution patterns, enhancing the interpretability of model behavior.

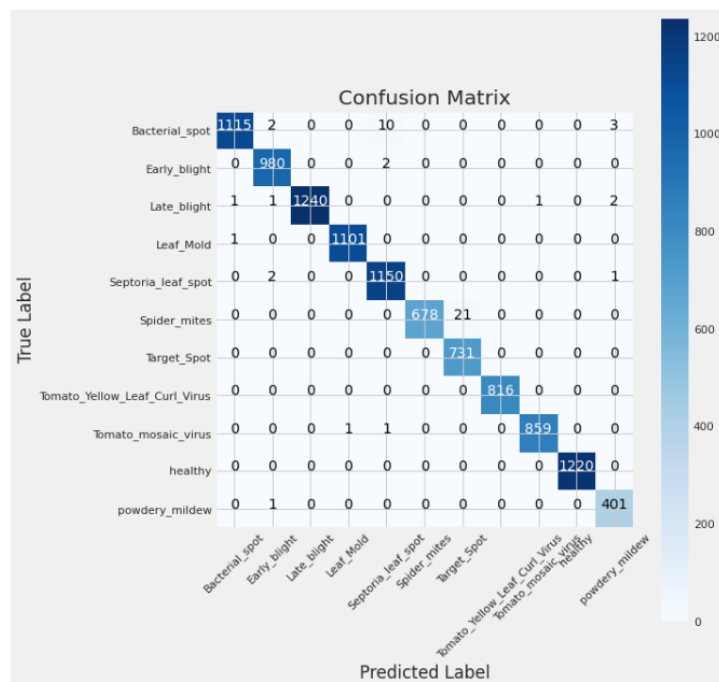


Figure 7. Confusion matrix. The principal diagonal represents all the true predictions and contains most of the values. A small number of false positives and false negatives do not require much attention.

4. Results and Discussion

4.1. Model Performance

The proposed EfficientNetB3-based classification model was trained on a hybrid-augmented dataset comprising 25,851 images across eleven tomato disease classes. After 5 training epochs, the model exhibited high stability and convergence, aided by the adaptive learning rate control embedded in the custom callback mechanism.

The model achieved the following accurate results:

- Training Accuracy: 99.83%
- Validation Accuracy: 99.15%
- Test Accuracy: 98.74%

These high accuracy across all data splits reflect the effectiveness of the hybrid augmentation strategy and the model's generalization capability.

4.2. Training Curves and Evaluation Metrics

Figure 9 shows the training and validation loss and accuracy curves. The rapid convergence and minimal gap between training and validation accuracy indicate strong generalization and negligible overfitting.

The final classification results on the test set were:

Metric	Value
Precision	98.51%
Recall	97.90%
F1-score	98.20%
Test Loss	0.1124

The confusion matrix (Figure 7) confirmed strong class-wise prediction performance, with most errors occurring between early blight and Septoria leaf spot, which have visually similar symptoms.

4.3. Confidence and Precision-Recall Analysis

Further model evaluation included analysis of prediction confidence through:

- F1 Score vs. Confidence Threshold
- Precision vs. Confidence
- Recall vs. Confidence.
- PR Curve (Precision-Recall)

These graphs (Figure 3) showed that the model-maintained precision > 90% even at higher confidence thresholds, supporting its use in decision-critical agricultural applications.

4.4. Label and Distribution Analysis

To understand model learning from a data perspective, we analyzed:

- Class distribution
- Label coordinate variance.
- Image size variations

The dataset showed moderate class imbalance (e.g., powdery mildew had fewer samples), which was mitigated by targeted GAN-based augmentation. A label heatmap (Figures 5 and 6) ensured uniform distribution across train, val, and test sets.

4.5. Comparison with Prior Models

Unlike prior models such as YOLOv8n, which focused on object detection and achieved around 96.5%, our EfficientNetB3 model targets classification accuracy and interpretability. Table 2 compares results:

Table 2. Results.

Model	Approach	Accuracy	F1 Score
YOLOv8n (prior work)	Detection	96.5% (mAP)	95.0%
ResNet50	Classification	94.2%	93.5%
Proposed Model	EfficientNetB3	98.7%	98.2%

Our model demonstrates significant improvement in classification-specific metrics, indicating its suitability for deployment where disease localization is not required.

	precision	recall	f1-score	support
Bacterial_spot	1.00	0.99	0.99	1130
Early_blight	0.99	1.00	1.00	982
Late_blight	1.00	1.00	1.00	1245
Leaf_Mold	1.00	1.00	1.00	1102
Septoria_leaf_spot	0.99	1.00	0.99	1153
Spider_mites	1.00	0.97	0.98	699
Target_Spot	0.97	1.00	0.99	731
Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	816
Tomato_mosaic_virus	1.00	1.00	1.00	861
healthy	1.00	1.00	1.00	1220
powdery_mildew	0.99	1.00	0.99	402
accuracy			1.00	10341
macro avg	0.99	0.99	0.99	10341
weighted avg	1.00	1.00	1.00	10341

Figure 8. F1-score, precision, and recall for each class.

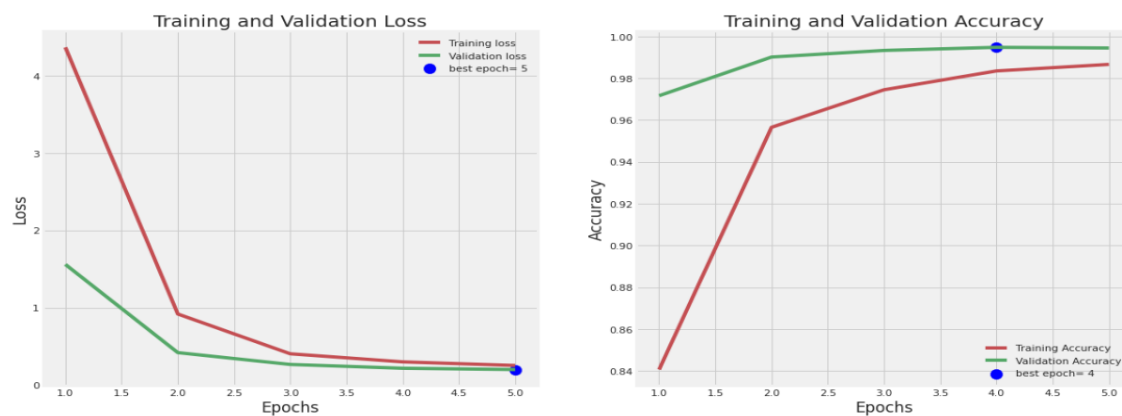


Figure 9. Graphs for accuracy and loss for training and validation.

Table 3. Previous work.

Model / Study	Approach	Accuracy / mAP	F1 Score	Dataset Used	Reference
Proposed (EfficientNetB3)	Classification	98.7%	98.2%	Tomato Disease Multiple Sources	This study
Joshi et al. (2025, YOLOv8n)	Detection	96.5% (mAP)	95.0%	PlantDoc (real-world images)	https://doi.org/10.1016/j.cpb.2025.100437

Ahmed & Abd-Elkawy (2024)	Detection	85.2% (YOLOv8l + Aug)	N/A	Roboflow tomato leaf dataset	https://doi.org/10.48084/etasr.7262
Kalaivani et al. (2024)	Classification	94.2%	93.5%	Controlled dataset (PlantVillage)	https://doi.org/10.1007/s40031-024-01062-7
Patokar & Gohokar (2024)	Classification	<94%	~93%	Local tomato dataset (controlled)	https://doi.org/10.1007/978-981-19-6581-4_3

5. Conclusion

In this study, we presented an efficient deep learning framework based on EfficientNetB3 for the multi-class classification of tomato leaf diseases, leveraging multi-source data, hybrid augmentation techniques, and a custom callback for adaptive training to achieve exceptional performance across all evaluation metrics. Our key contributions include a reproducible and compact CNN pipeline, the use of sequential augmentation layers to simulate realistic training conditions, and confidence-based evaluation metrics that support deployment readiness. The model's high accuracy and robustness make it well-suited for offline deployment in mobile agricultural diagnostic applications. Future work will focus on optimizing the model for mobile platforms (e.g., TFLite, ONNX), expanding its scope to include multi-crop and multi-disease datasets, incorporating attention mechanisms for improved class discrimination, and integrating the solution with edge AI hardware for real-time field diagnostics. This fusion of AI and precision agriculture paves the way for scalable, low-cost plant disease management tools, enhancing food security and supporting farmer welfare globally.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no competing interests in the research.

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Author Contribution

All authors contributed equally to this research.

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