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# SEC-ToLeD: A Super-Efficient and Compact CNN for Tomato Leaves Diseases Detection for Resource-Constrained Devices

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**Abstract** Tomato leaf diseases significantly affect agricultural productivity and require accurate yet lightweight detection models suitable for real-world deployment. In this study, a super-efficient and compact convolutional neural network, named SEC-ToLeD, is proposed for tomato leaf disease classification using the PlantVillage dataset. The model integrates depthwise separable convolutions with squeeze-and-excitation blocks to enhance feature representation while maintaining low computational complexity. SEC-ToLeD contains only 219,651 trainable parameters with a compact size of 0.84 MB. Experimental results demonstrate 99.75% testing accuracy, 99% precision, recall, and F1-score. SEC-ToLeD is highly computationally efficient, as indicated by its compact size and low number of parameters. The average inference time of 1.105 ms per image is reported as a reference, which may vary depending on hardware. Compared to existing lightweight models, SEC-ToLeD achieves superior performance while being significantly smaller in size, making it highly suitable for real-time deployment on resource-constrained and edge devices.

**Keywords** Convolutional neural networks, soft attention, deep learning, tomato, plant disease detection, squeeze-and-excitation (SE) blocks

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## 1. Introduction

Tomatoes (Solanum lycopersicum) are among the most widely cultivated crops worldwide and represent a major source of nutrition and economic value. In Egypt, the fourth-largest tomato producer globally, production reached 7.1 million tons in the 2022–2023 season, marking an 11.7% increase compared to the previous year [1]. However, tomato crops are threatened by various diseases, particularly leaf mold, late blight, and early blight. Early blight, caused by the fungus Alternaria solani, can lead to severe defoliation and yield losses of up to 79% in some cases [2].

Timely detection of plant diseases is essential for maintaining crop health and ensuring sustainable agricultural production. Traditional methods rely on manual inspection or chemical treatments [3], which are time-consuming, labor-intensive, and require expert knowledge.

Recent advances in Artificial Intelligence (AI) and deep learning provide efficient alternatives for automatic plant disease detection, offering faster, more accurate, and cost-effective solutions suitable

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for precision agriculture [4]. Convolutional Neural Networks (CNNs) have shown remarkable performance in automatically extracting discriminative features from plant images without manual preprocessing [5]. Despite these advancements, AI models for agricultural applications often face challenges related to deployment of resource-constrained devices. Lightweight models are desirable for real-time inference, but reducing model size can negatively impact accuracy [6].
address this gap, we propose SEC-ToLeD, a CNN-based model designed to balance accuracy, efficiency, and practical deployment. Our contributions include:

- The main novelty of SEC-ToLeD lies in the effective integration of Depthwise Separable Convolutions and Squeeze-and-Excitation (SE) blocks, enabling high classification accuracy with extremely compact model size.
- Clearly addressing the deployment context, SEC-ToLeD is suitable for resource-constrained environments, such as embedded systems and mobile platforms, commonly used in real-time agricultural applications.
- Emphasizing the optimal trade-off between accuracy and computational efficiency, which is essential for real-time plant disease detection.
- Designing SEC-ToLeD, a lightweight CNN achieving 99.75% test accuracy with a model size of only 0.84 MB.
- Balancing high accuracy with low computational cost for real-time use on low-power devices.
- Integrating depthwise separable convolutions and squeeze-and-excitation (SE) blocks for efficient feature extraction.
- Applying strong data augmentation (CutMix, MixUp, RandAugment) to improve model generalization.
- Employing mixed precision training and adaptive learning rate scheduling for stable and fast convergence.

These contributions provide a practical and high-performance solution for real-time tomato disease diagnosis, aligning with the goals of general scientific journals to present innovative, applicable, and reproducible research.
remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 presents the SEC-ToLeD architecture and optimization methods. Section 4 shows experimental results. Section 5 provides discussion and interpretation of the experimental findings. Section 6 concludes the paper and outlines future work.

## 2. Literature Survey

Several review articles have discussed recent progress in plant disease detection based on deep learning approaches, highlighting the growing adoption of Convolutional Neural Network (CNN) architectures for automated feature extraction from plant leaf images. These studies also emphasize the role of attention mechanisms in enhancing feature representation, as well as the effectiveness of data augmentation strategies in improving model generalization and robustness.
Moreover, different experimental settings, evaluation protocols, and benchmark datasets have been analyzed to provide comprehensive insights into the strengths and limitations of existing deep learning-based plant disease detection approaches [7]. A hierarchical deep learning model leveraging the combination of the InceptionV3 model and a CNN was proposed for classifying sixteen different classes of diseases in tomatoes, apples, and peaches [8]. The model was trained on the PlantVillage dataset that comprised 24,000 images of healthy and diseased leaves. The hierarchical approach achieved 97.74% classification accuracy. However, the complexity and the need for many training samples might make it inappropriate for low-spec hardware or real-time mobile devices.

A smart mobile application using a deep convolutional neural network inspired by MobileNet for detecting ten prevalent tomato leaf diseases was proposed [9]. Colored images of 224 × 224 pixels were used as input, with a sequence of 3 × 3 depthwise separable convolution layers to reduce computation. These were followed by batch normalization, ReLU activation, average pooling, and a fully connected SoftMax layer. Trained in 7,176 PlantVillage images, the model achieved 90.3% accuracy. Although efficient, accuracy was lower than other state-of-the-art methods.

Two deep learning models for classifying three tomato leaf diseases—early blight, late blight, and leaf mold—were developed [10]. A residual learning-based CNN with an attention mechanism highlighted informative features. Trained on 95,999 augmented PlantVillage images with random crops and central zoom, the network achieved 98% validation accuracy with five-fold cross-validation. Large model size and sophisticated mechanisms may render it unsuitable for low-power devices.

Three CNN architectures—SqueezeNet, InceptionV3, and AlexNet—were utilized to assess the severity of late blight in tomatoes [11]. Images were categorized by disease progression stages (355 early, 347 middle, 382 late). Using transfer learning and a multi-class SVM classifier, AlexNet achieved 89.69–93.4% accuracy. With sixty-one million trainable parameters and 227 MB storage, the model is impractical for low-end devices.

A hybrid model combining a convolutional auto-encoder and CNN for tomato, potato, and maize disease detection was proposed [12]. Dimensionality reduction was applied via the auto-encoder. Trained in nine hundred images of six classes, the model achieved 97.50% overall accuracy but required 3.3 million trainable parameters and was computationally expensive.

A CNN classifier for tomato disease classification with three convolutions, three max pooling, and two fully connected layers was described [13]. Data augmentation addressed class imbalance. Trained on 17,500 PlantVillage images, the model achieved 91.2% test accuracy with 208,802 trainable parameters and a size of 1.5 MB. Accuracy was lower than some state-of-the-art methods.

A deep learning-based method using Conditional Generative Adversarial Networks (C-GANs) for synthetic image generation and DenseNet121 transfer learning was applied for tomato disease detection [14]. Across five, seven, and ten classes, accuracies of 99.51%, 98.65%, and 97.11% were achieved, respectively, with approximately 1.73 million trainable parameters.
learning with InceptionV3 was used to classify tomato leaf diseases, achieving 99.8% accuracy [15]. The model was deployed as a cloud-based application. Details on model size or computational complexity were not provided.
A CNN-based disease classification system with image preprocessing and segmentation was designed [16]. Trained on 3,000 tomato leaf images, it achieved 98.49% accuracy with 1.42 million trainable parameters, but storage requirements make it unsuitable for embedded devices.
A transfer learning-based approach using MobileNetV2 with runtime augmentation achieved 99.30% accuracy on PlantVillage images [17]. The model had 2.4 million trainable parameters and a size of 9.60 MB. Overfitting and negative transfer were noted.
A soft attention mechanism combined with depthwise separable convolutions for resource-limited devices achieved 99.04% test accuracy and 99.90% ROC-AUC [18]. The model size was 2.5 MB with 221,594 trainable parameters. Limitations include shallow architecture and limited data augmentation.

## 3. The Proposed Model

Achieving a balance between model precision and computational performance is one of the key challenges in plant disease detection based on deep learning. Detection precision is improved as finer-grained image features are encoded, which translates to higher computational complexity and reduced inference speed. To counteract this, we propose the Super-Efficient and Compact Tomato Leaves Diseases Detection (SEC-ToLeD) Model, a compact convolutional neural network for the classification of tomato leaf diseases.

SEC-ToLeD enhances computational efficiency without sacrificing high classification accuracy by combining Depthwise Separable Convolutions and Squeeze-and-Excitation Blocks to improve feature selection and adaptability. This approach renders the model particularly well-suited for deployment on low-power and edge devices [17].

SEC-ToLeD model consists of four structured feature extraction blocks, as illustrated in the architecture diagram of the SEC-ToLeD model in Figure 1:

- Blocks 1 and 2 employ Depthwise Separable Convolutions with batch normalization and pooling layers to efficiently extract low- and mid-level disease-related features. The output of Block 1 is fed as input to Block 2, illustrating the progressive refinement of features. Input/output dimensions and kernel sizes are clearly labeled in Figure 1.
- Block 3 merges depthwise separable convolutions with batch normalization layers to stabilize the training process and enhance mid-to-high-level feature learning capability. The data flow from Block 2 to Block 3 ensures that important hierarchical features are retained and emphasized.
- Block 4 utilizes a Squeeze-and-Excitation (SE) attention mechanism to dynamically enhance feature representations, enabling the network to focus on disease-relevant patterns and improve classification performance. GlobalAveragePooling2D replaces conventional fully connected layers to reduce model complexity, while the Softmax layer allocates class probabilities, and the final classification is determined using an argmax function. Arrows in Figure 1 illustrate the flow of features through all four blocks.

To enhance generalization and robustness, advanced data augmentation techniques are implemented, including RandAugment, MixUp, CutMix, random rotation and flip, brightness adjustment, and contrast adjustment. Pixel normalization is also applied by rescaling intensity values into the range [0,1] to ensure stable model convergence and improved efficiency [21].

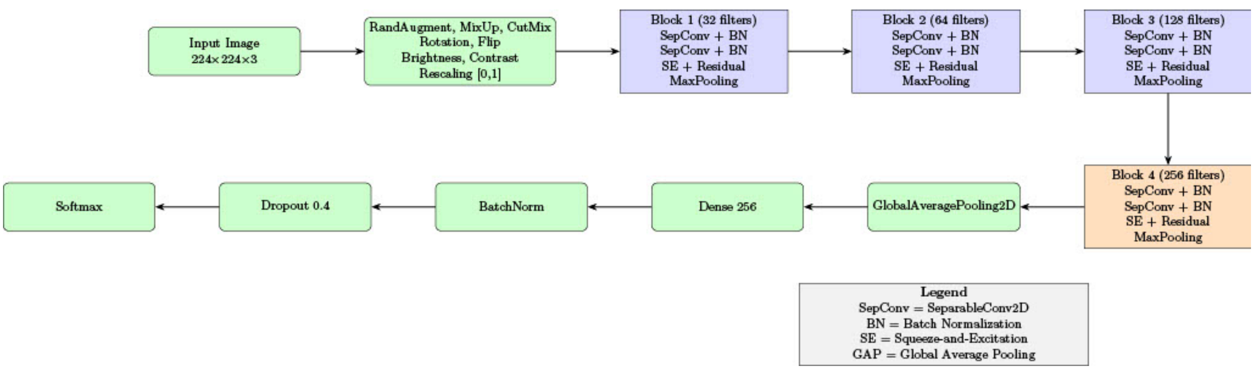


Figure 1. Architecture of the SEC-ToLeD model, showing the four structured feature extraction blocks. Each block consists of Depthwise Separable Convolutions followed by a Squeeze-and-Excitation (SE) module. Arrows indicate data flow, and labels illustrate input/output dimensions and operations applied in each block.

### 3.1. *Lightweight Feature Extraction Module with Separable Convolutions and Normalization-Pooling Layers (Block 1 and Block 2)*

In image processing, input images are of three dimensions—two spatial (width and height) and one channel—where convolutional calculations play a critical role in extracting hierarchical features. Standard convolutional kernels extract spatial relationships and cross-channel correlations to enable efficient feature representation, as shown in Equation (1) [22].

SEC-ToLeD's Block 1 consists of two depthwise separable convolutional layers, each preceded by batch normalization and succeeded by ReLU activation. The first convolutional layer uses $32 \times 32$ learnable filters with "same" padding, which keeps spatial dimensions intact while learning basic features. These filters traverse the input image, computing the dot product between filter weights $W$ and matching input patches $x$, learning basic texture patterns. The ReLU activation function enhances non-linearity, minimizes vanishing gradient issues, and improves stability during training [23].

The second convolutional layer increases feature extraction capacity with $64 \times 64$ filters, followed by a $2 \times 2$ max-pooling layer for spatial dimensionality reduction while retaining essential features [22]. Block 2 is structurally identical but with larger filters to extract deeper representations.

$$\mathrm{Conv}(W,x)_{(i,j)} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K} W_{(m,n,k)} \cdot x_{(i-m+1,j-n+1,k)} \tag{1}$$

in the paper: as shown in Equation (1), the convolution operation is computed over all input channels.

### 3.2. *Stabilized Depthwise Separable Convolutional Block with Batch Normalization (Block 3)*

Depthwise separable convolution divides convolution into two phases [24]:

- Depthwise convolution: Performs spatial filtering independently on each channel.
- Pointwise convolution: Combines features across channels using $1 \times 1$ convolutions.

This factorization significantly reduces computational complexity without sacrificing feature extraction capability, as shown in Equations (2) and (3). Block 3 of SEC-ToLeD employs depthwise separable convolutions followed by batch normalization to stabilize training, increase convergence rate, and avoid internal covariate shift [25]. Depthwise convolutions apply distinct filters per channel to preserve spatial information [26].

$$\mathrm{DConv}(W,x)_{(i,j)} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W_{(m,n)} \cdot x_{(i+m,j+n)} \tag{2}$$

$$\mathrm{PConv}(W,x)_{(i,j)} = \sum_{k=0}^{K-1} W_k \cdot x_{(i+k,j)} \tag{3}$$

: For a $10 \times 10 \times 3$ input and a $7 \times 7 \times 3$ convolution producing 256 output channels:

- Standard convolution: $10 \times 10 \times 7 \times 7 \times 3 \times 256 = 3{,}763{,}200$ multiplications.
- Depthwise convolution: $10 \times 10 \times (7 \times 7 \times 1 \times 3 + 1 \times 1 \times 3 \times 256) = 91{,}500$ multiplications.

results in $41\times$ fewer computations with similar classification performance [27]. With batch normalization, SEC-ToLeD achieves faster convergence and better generalization [28].

### *3.3. Squeeze-and-Excitation (SE) Attention Block (Block 4)*

Soft attention mechanisms help models dynamically emphasize relevant patterns while suppressing redundancy and noise. SEC-ToLeD integrates an SE Attention Block after depthwise convolutions to enhance feature selection and classification accuracy.
leaf lesions often involve subtle textures, requiring adaptive mechanisms to prioritize significant regions. SE Blocks compute global statistics using:

- Squeeze operation: Global average pooling captures channel dependencies.
- Excitation operation: Utilizes a light-weight gating mechanism with sigmoid activation to obtain channel-wise attention weights and selectively emphasize disease-related features.

This approach improves the model's robustness to light changes, ambient noise, and occlusions, and increases SEC-ToLeD's performance on fine-grained classification.
attention has been applied successfully in medical image analysis, writer verification, and histopathological analysis and has demonstrated its ability in capturing subtle but important patterns [29].

## 4. Results Analysis and Discussion

In this section, we will discuss an overall analysis of the experimental results achieved by the proposed SEC-ToLeD model. The discussion will be initiated by explaining the dataset used in the experiment for the training and testing of the proposed approach. Then, an overview of the experimental setup will be provided. In the subsequent subsections, an overall performance analysis of the proposed SEC-ToLeD approach will be carried out in terms of precision, recall, F1-score, and accuracy for various disease classes. In addition, comparative analysis of the proposed approach with some of the state-of-the-art approaches will be provided. Ablation analysis will be performed to evaluate the contribution of Depthwise Separable Convolutions and Squeeze-and-Excitation Blocks in the overall performance of the proposed approach. In the final subsection of this section, the overall generalization ability of the proposed approach will be evaluated in terms of its computational efficiency and trade-off between accuracy and time.

### *4.1. Dataset*

Tomato leaf disease images from the PlantVillage dataset are utilized to train and test SEC-ToLeD. PlantVillage is a widely used benchmark dataset in the plant disease detection literature, ensuring fair comparison with prior work and supporting reproducibility. The dataset contains 54,309 images of healthy and diseased leaves across 14 crop species, including tomato, potato, apple, soybean, grape, and maize [30].

To improve generalization and reduce potential overfitting to controlled conditions, extensive data augmentation techniques were applied during training, including rotation, flipping, brightness variation, scaling, CutMix, and MixUp. These techniques simulate real-world variability, such as illumination changes, partial occlusion, and viewpoint variation.

We acknowledge the limitations of controlled datasets and clarify that future work will include evaluation on real-world field images to further validate robustness under natural conditions.

In this study, we extracted tomato leaf images and categorized them into one healthy class and nine disease classes. These disease classes include Bacterial Spot (BS), Early Blight (EB), Late Blight (LB), Leaf Mold (LM), Septoria Leaf Spot (SLS), Target Spot (TS), Spider Mites (specifically Two-spotted Spider Mite, TSSM), Yellow Leaf Curl Virus (YLCV), and Mosaic Virus (MV), as shown in Figure 2. However, PlantVillage has present biases which can affect deep learning models:

- **Class Imbalance:** The data is not balanced across different disease classes. Models trained on such imbalanced data will be biased towards the majority class and degrade generalization to minority classes [31].

- **Controlled Laboratory Environment:** Photos used in PlantVillage were taken in controlled conditions, and thus they lack the variability that happens in real life, such as changing lighting and backgrounds, which will impact the model's robustness [32].

To overcome these issues, SEC-ToLeD employs advanced augmentation techniques and efficient feature selection processes, which are described in the following sections.

### *4.2. Experiments*

SEC-ToLeD was developed on a Python environment with TensorFlow, Keras, and other fundamental libraries on JupyterLab on Windows 10, 64-bit operating system. Training was carried out until 50 epochs, with a Cosine Annealing Learning Rate Scheduler, which dynamically adjusts the learning rate during training, with an initial warmup period for enhanced stability. The system had 8 GB RAM with GPU acceleration enabled for optimum computing. The remaining hyperparameters are listed in Table 1.

Our dataset initially contained 18,160 images, which were divided as described in Table 2. For a balanced and unbiased division between classes, all images were merged into a single list with their corresponding labels and randomly shuffled with random state = 42. The dataset was then split into 12,712 training samples (70%), 1,816 validation samples (10%), and 3,632 test samples (20%), with a good balance for testing. To comprehensively evaluate the performance of our SEC-ToLeD model, we conducted multiple experiments using this dataset. Each experiment followed the same data preprocessing and augmentation techniques to ensure consistency and reliability in performance assessment.

Table 1. Hyperparameters used for training the SEC-ToLeD model.

| **Hyper Parameters** | **Description** |
|---|---|
| No. of convolution layers | 8 |
| No. of Separable convolution layers | 8 |
| No. of max pooling layers | 4 |
| Initial Learning rate | 7.088656275030309e-06 |
| Max no. of epochs (Early Stopping) | 50 |
| Dropout rate | 0.4 |
| Batch Size | 64 |
| Optimizer | AdamW |
| Activation function | sigmoid & relu & softmax |
| Loss function | CategoricalCrossentropy |

Table 2. Dataset division for training, validation, and testing.

| **Set** | **Samples** | **Percentage** |
|---|---|---|
| Training | 12,712 | 70% |
| Validation | 1,816 | 10% |
| Test | 3,632 | 20% |

Each experiment followed the same data preprocessing and augmentation techniques to ensure consistency and reliability in performance assessment.

To ensure reproducibility and optimal performance, all hyperparameters were determined through controlled experimental tuning. The learning rate was set to 0.001, providing gradual convergence while preventing instability during training. Batch size and number of epochs were similarly chosen to balance convergence speed and model generalization.

Advanced data augmentation techniques, including CutMix and MixUp, were applied to enhance model generalization by exposing the network to more diverse feature combinations. These methods help reduce overfitting and improve robustness, which are widely adopted strategies in recent deep learning research.

All training configurations, including hyperparameters and augmentation strategies, are fully specified to allow other researchers to reproduce the results.

**Experiment 1:** In this experiment, SEC-ToLeD was trained using Depthwise Separable Convolutions alone, following the conventional dataset split protocol. The dataset contained 12,712 training images (70%), 1,816 validation images (10%), and 3,632 test images (20%). The training was conducted under the hyperparameters set prior to this as given in Table 1. The highest validation accuracy of 99.61% was achieved at epoch thirty-eight, and the lowest validation loss of 0.0400 at epoch forty-five. On the final performance test, the training accuracy was 100%, with the training loss being 0.0215. On the validation set, the model had an accuracy of 99.61% and a validation loss of 0.0408. When it was tested on the hidden test dataset, SEC-ToLeD scored 99.67% in testing accuracy and 0.0321 in testing loss. The model also exhibited good generalization with Precision, Recall, and F1-score all being 0.99, while its AUC-ROC score was 0.9998. Regarding model size, the total parameters to be trained were 208,261, resulting in a model size of 0.79 MB. The training time for the entire process took approximately 2,231 seconds (37 minutes), and the average time per image during inference was 0.813 milliseconds.
The training and validation accuracy/loss curves are plotted in Figure 3, the ROC curve is given in Figure 4, and the best classification performance is represented by the confusion matrix in Figure 5.

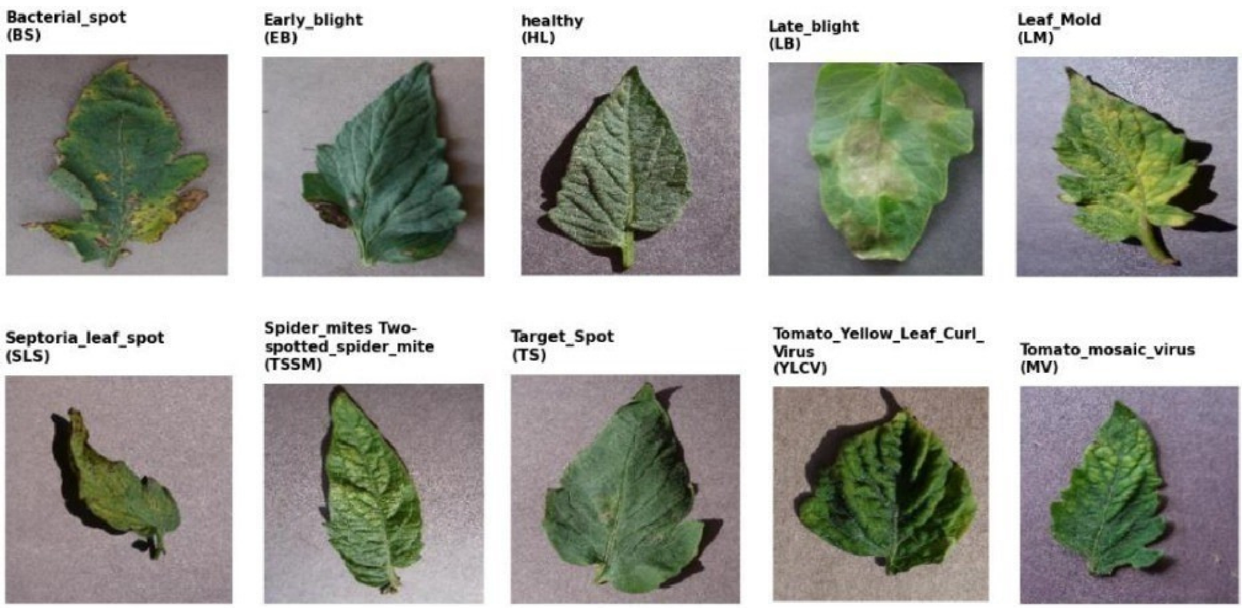


Figure 2. The ten classes of tomato leaf diseases.

**Experiment 2:** In the second experiment, SEC-ToLeD was trained using Squeeze- and-Excitation (SE) Blocks only, with the same dataset split as in the first experiment. Within the same training setting, the model attained its highest validation accuracy of 99.17% at epoch 49 and its lowest validation loss of 0.0522 at epoch 47. The final test indicated that SEC-ToLeD achieved a training accuracy of 100% and a training loss of 0.0214. On the validation set, the model was 99.12% accurate with a loss of 0.0522. On the hidden dataset, the accuracy was 99.28% with a test loss of 0.0420. Model classification performance was lower compared to Experiment 1 since Precision, Recall, and F1-score were 0.98, while the AUC-ROC value was 0.9995. The experiment generated a larger model complexity compared to Experiment 1, with trainable parameters of 1,254,440, resulting in a model size of 4.79 MB. Despite this, the training

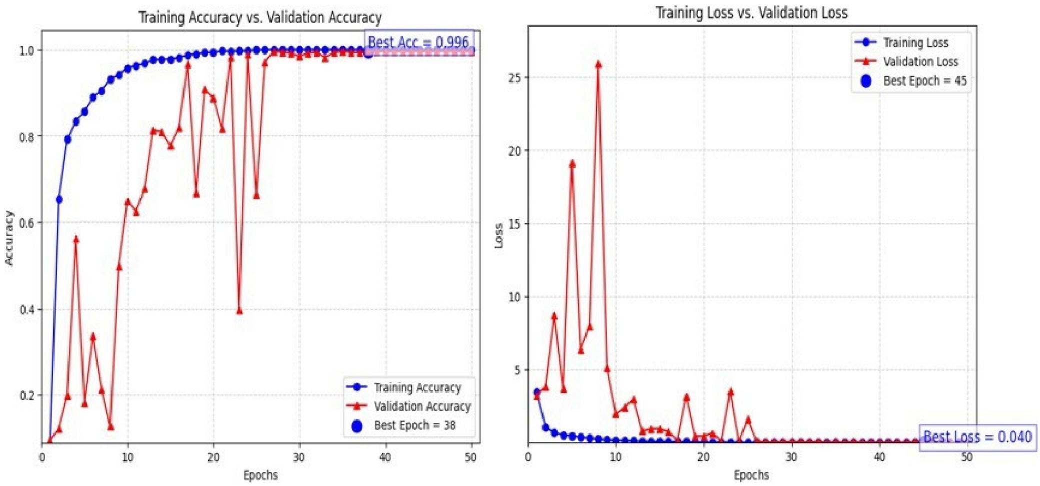


Figure 3. Training and validation accuracy/loss curves of SEC-ToLeD.

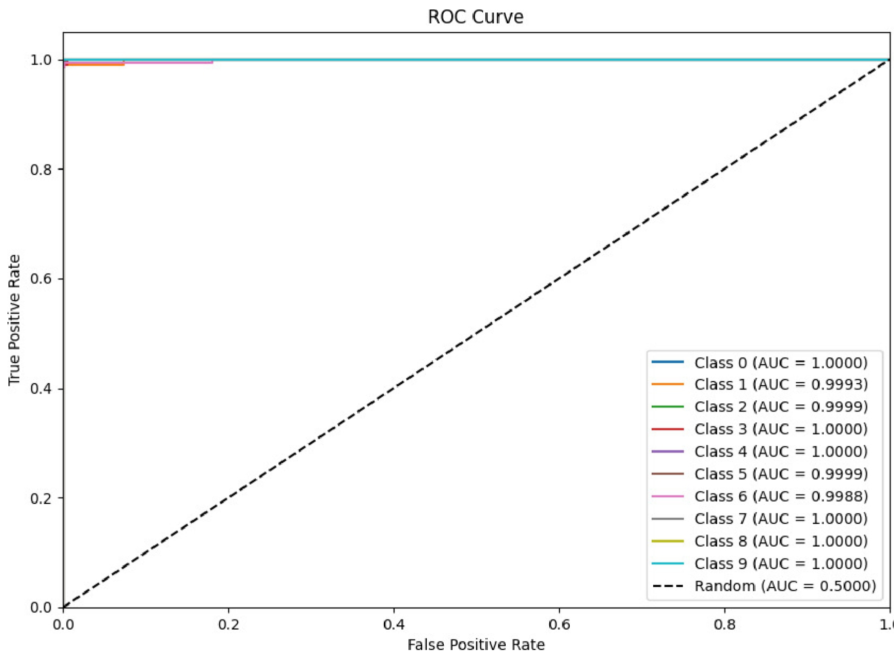


Figure 4. ROC curve of SEC-ToLeD.

duration was reduced to 1,850 seconds (∼30 minutes), with an average inference time per image of 1.263 milliseconds. The training versus validation accuracy and loss curves are illustrated in Figure 6, the ROC Curve is presented in Figure 7, and the Confusion Matrix is shown in Figure 8.

**Experiment 3:** In the previous experiment, SEC-ToLeD was trained using the combination of Depthwise Separable Convolutions and Squeeze-and-Excitation (SE) Blocks with the same dataset distribution and training configuration of the previous experiments. The highest validation accuracy of 99.67% at epoch 32 and the lowest validation loss of 0.0276 at epoch 43 were observed.

The total training outcome was 100% accuracy during training and 0.0198 training loss. Validation accuracy was 99.50% and validation loss was 0.0283. When tested on the test set, the model had a maximum test accuracy in all experiments at 99.75%, and testing loss of 0.0293. The model performed

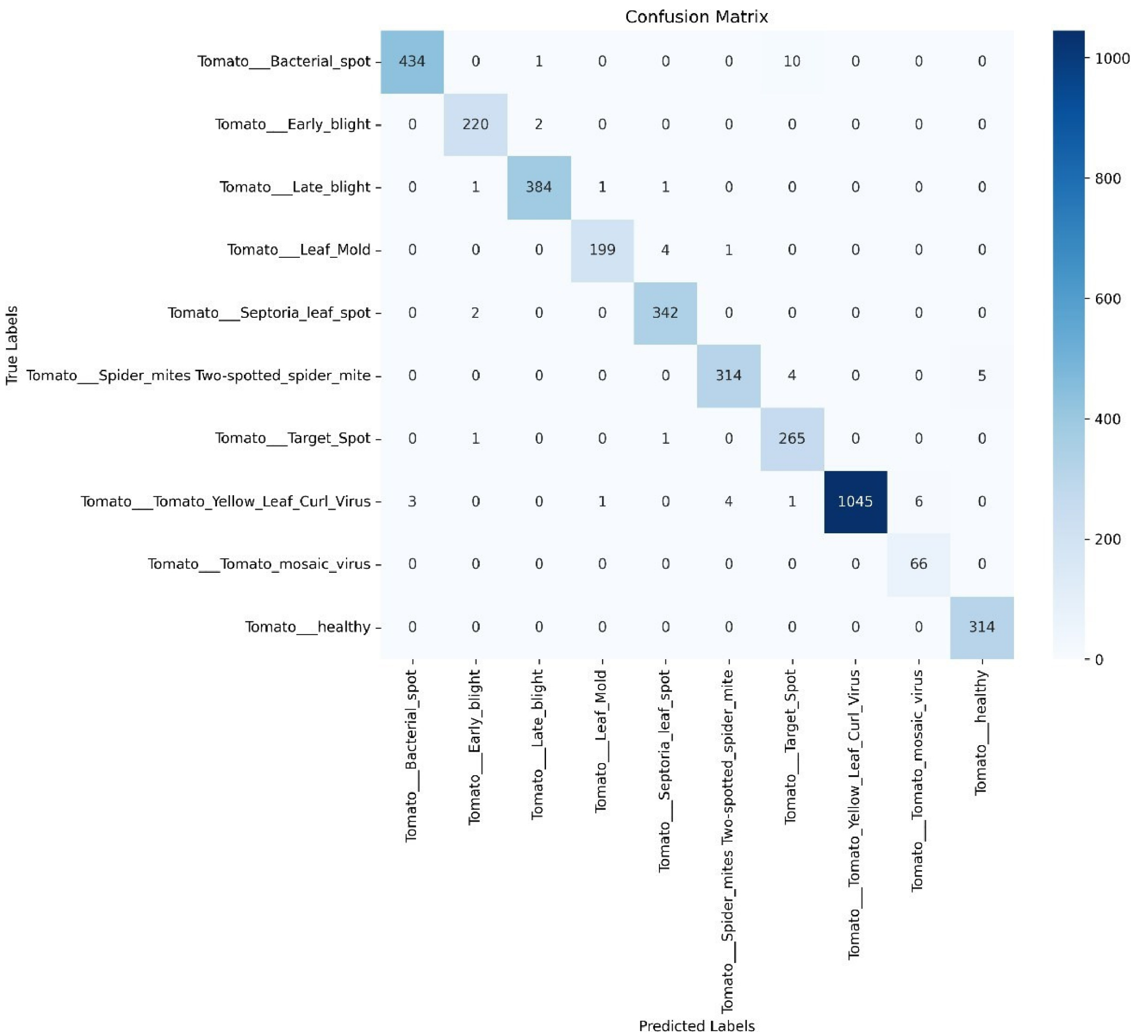


Figure 5. Confusion Matrix of Experiment 1.

similarly in classification as in Experiment 1 with Precision, Recall, and F1-score values of 0.99 and AUC-ROC value of 0.9999. In model complexity, there were 219,651 trainable parameters and a small model size of 0.84 MB. Training was 2,287 seconds ($\sim$38 minutes) and the average inference time per image was 1.105 milliseconds.

Training and validation accuracy/loss curve is provided in Figure 9, ROC Curve is given in Figure 10, and the Confusion Matrix is illustrated in Figure 14. A summary of the results in all experiments is presented in Table 3.

**Experiment 4:** In this experiment, SEC-ToLeD was evaluated using a 5-fold cross-validation strategy to ensure robust and reliable estimation of the model performance and generalization ability. The dataset contains 18,160 images belonging to 10 tomato disease classes. For each fold, the dataset was split into 80% for training and 20% for validation, resulting in approximately 14,528 training images and 3,632 validation images per fold. The same hyper-parameters listed in Table 1 were used to ensure fair comparison with the previous experiments. The obtained results demonstrate stable and consistent performance across the five folds. The best performance was achieved on fold no. 4, where the model obtained training accuracy (TRA) of 0.9860, validation accuracy (VA) of 0.9876, validation loss (VL) of 0.0304, and testing accuracy (TA) of

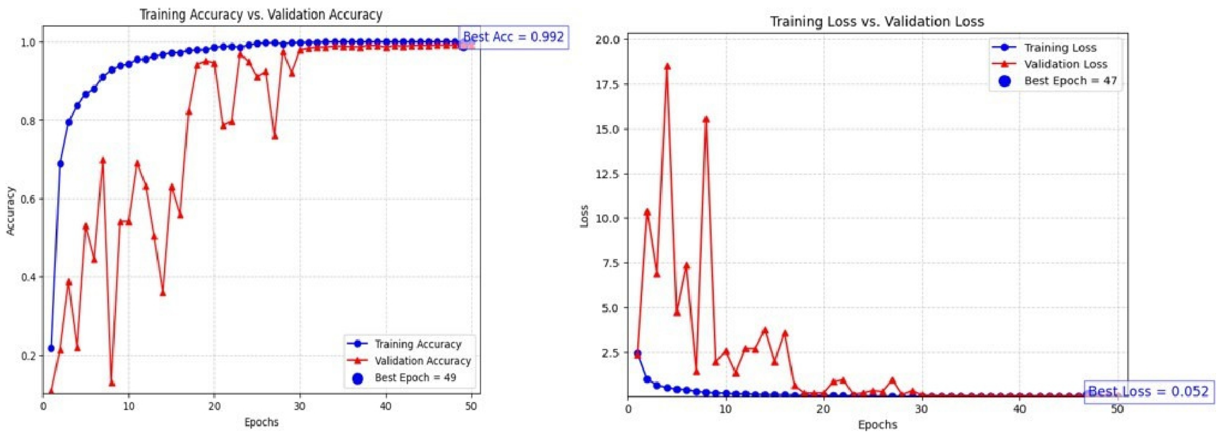


Figure 6. Training vs. validation accuracy and loss curves of Experiment 2.

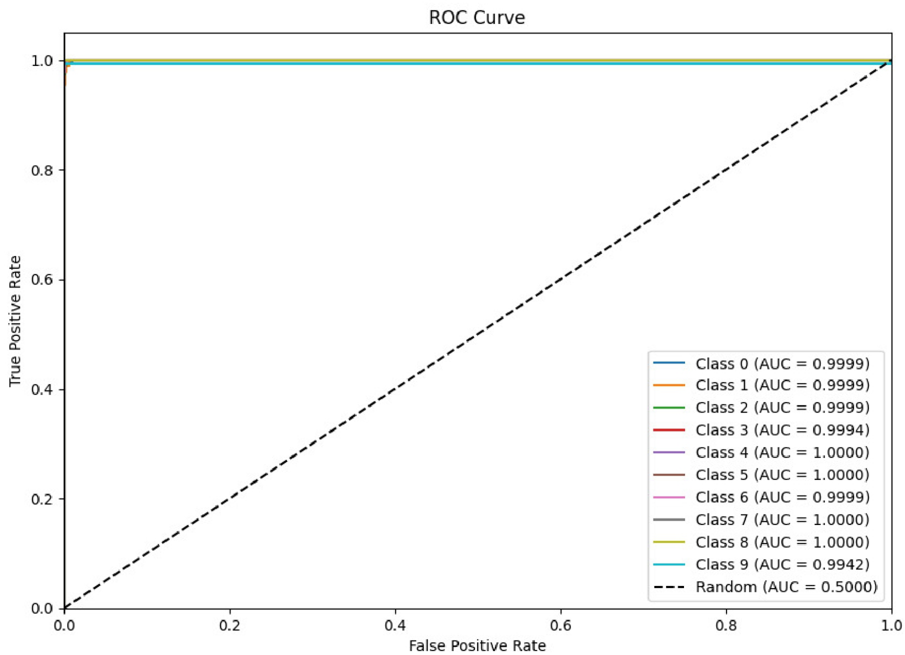


Figure 7. ROC Curve of Experiment 2.

0.9876. Furthermore, the precision (PRE), recall (REC), and F1-score (F1S) reached 0.9878, 0.9876, and 0.9876 respectively at epoch 50. The required training time for this fold was 24.92 minutes. The detailed performance results for all folds are presented in Table 4, which reports the evaluation metrics including training accuracy (TRA), validation accuracy (VA), validation loss (VL), testing accuracy (TA), precision (PRE), recall (REC), and F1-score (F1S). In Table 4, the Mean represents the average performance across the five folds, while Std refers to the standard deviation, which measures the amount of variation or dispersion of the results across different folds. The low standard deviation values indicate that the model performance is stable and consistent regardless of the data split. Across the five folds, the model achieved

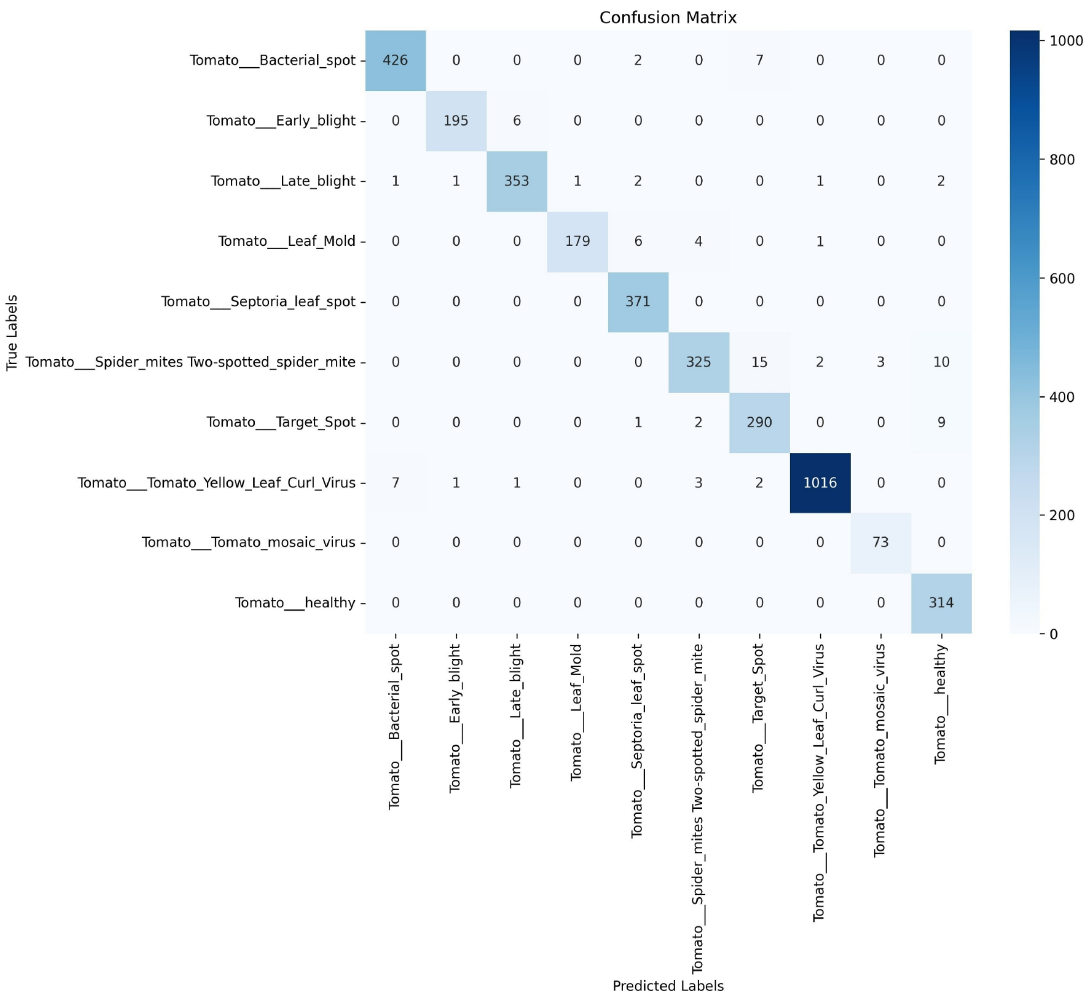


Figure 8. Confusion Matrix of Experiment 2.

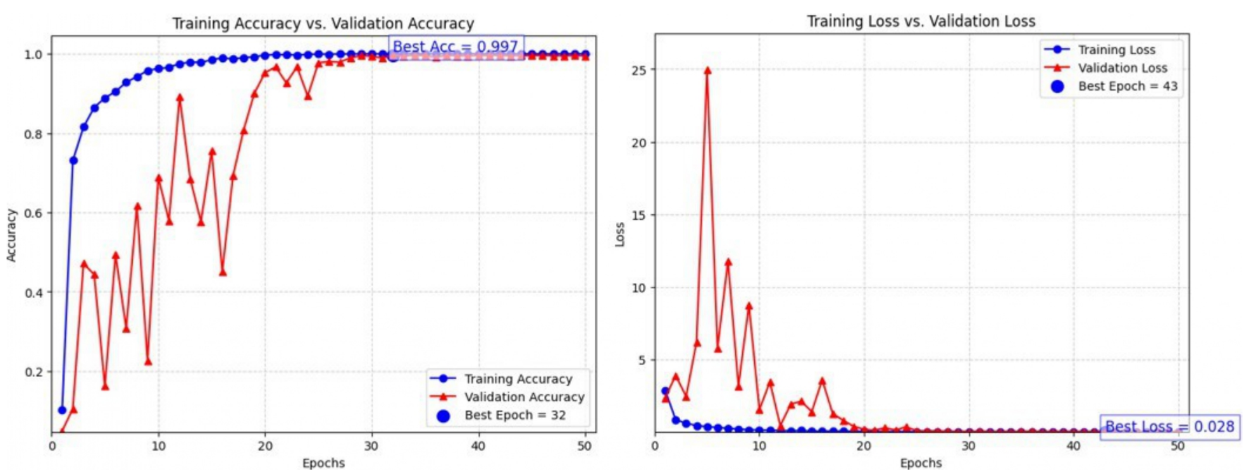


Figure 9. Training vs. validation accuracy and loss curves of Experiment 3.

Table 3. Comparative performance of SEC-ToLeD model across three experiments.

| **Metric** | **Experiment 1** | **Experiment 2** | **Experiment 3** |
|---|---|---|---|
| Best Validation Accuracy | 0.9961 | 0.9917 | 0.9967 |
| Best Epoch (Accuracy) | 38.0 | 49.0 | 32.0 |
| Best Validation Loss | 0.0400 | 0.0522 | 0.0276 |
| Best Epoch (Loss) | 45.0 | 47.0 | 43.0 |
| Training Accuracy | 1.0 | 1.0 | 1.0 |
| Training Loss | 0.0215 | 0.0214 | 0.0198 |
| Validation Accuracy | 0.9961 | 0.9912 | 0.9950 |
| Validation Loss | 0.0408 | 0.0522 | 0.0283 |
| Testing Accuracy | 0.9967 | 0.9928 | 0.9975 |
| Testing Loss | 0.0321 | 0.0420 | 0.0293 |
| Precision | 0.99 | 0.98 | 0.99 |
| Recall | 0.99 | 0.98 | 0.99 |
| F1-score | 0.99 | 0.98 | 0.99 |
| AUC-ROC | 0.9998 | 0.9995 | 0.9999 |
| Trainable Parameters | 208,261 | 1,254,440 | 219,651 |
| Model Size (MB) | 0.79 | 4.79 | 0.84 |
| Training Time (s) | 2,231 | 1,850 | 2,287 |
| Inference Time (ms) | 0.813 | 1.263 | 1.105 |

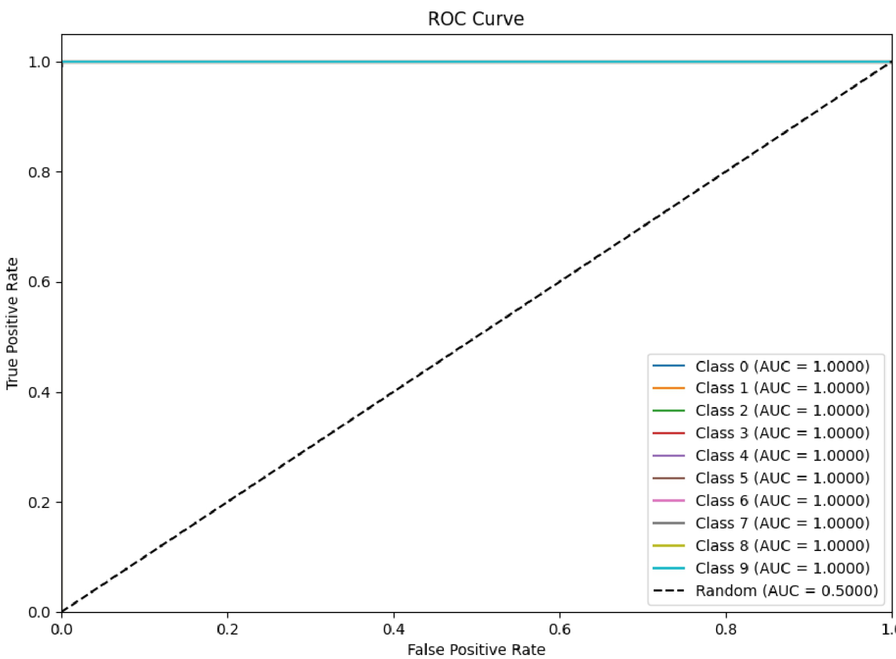


Figure 10. ROC Curve of Experiment 3.

an average training accuracy of $0.9866 \pm 0.0008$, validation accuracy of $0.9859 \pm 0.0012$, validation loss of $0.0258 \pm 0.0033$, and testing accuracy of $0.9859 \pm 0.0012$. The average precision, recall, and F1-score were $0.9863 \pm 0.0011$, $0.9859 \pm 0.0012$, and $0.9859 \pm 0.0012$ respectively. The average training time per fold was approximately 24.98 minutes, with a total training time of 125.41 minutes for the complete 5-fold cross-validation procedure. The classification report for all tomato disease classes is presented in

Table 5, which shows high precision, recall, and F1-score values across all classes, demonstrating the strong classification capability of SEC-ToLeD and its ability to distinguish between visually similar plant disease categories. To further evaluate the robustness of the proposed model, the best model obtained from fold no. 4 was selected and evaluated on a hold-out test set. The final evaluation results achieved an overall test accuracy of 0.9909, precision of 0.9911, recall of 0.9909, and F1-score of 0.9909, confirming the strong generalization capability of the proposed model. Figure 11 presents the confusion matrix for fold no. 4, showing the classification performance across all classes and indicating that most samples were correctly classified with very limited misclassification cases. Figure 12 illustrates the validation and test accuracy values across the five folds, demonstrating consistent performance and stability of the model during cross-validation. Figure 13 shows the validation loss across the five folds, confirming smooth convergence behavior and absence of significant overfitting. Overall, the results of Experiment 4 confirm that SEC-ToLeD achieves high classification accuracy with stable and reliable performance across different folds, demonstrating its effectiveness for plant disease detection using cross-validation evaluation strategy.

Table 4. Per-Fold Results (5 Folds) with Mean and Standard Deviation.

| **Fold** | **TRA** | **VA** | **VL** | **TA** | **PRE** | **REC** | **F1S** |
|---|---|---|---|---|---|---|---|
| 1 | 0.9863 | 0.9846 | 0.0267 | 0.9846 | 0.9852 | 0.9846 | 0.9846 |
| 2 | 0.9862 | 0.9846 | 0.0220 | 0.9846 | 0.9850 | 0.9846 | 0.9846 |
| 3 | 0.9882 | 0.9857 | 0.0222 | 0.9857 | 0.9860 | 0.9857 | 0.9857 |
| 4 | 0.9860 | 0.9876 | 0.0304 | 0.9876 | 0.9878 | 0.9876 | 0.9876 |
| 5 | 0.9864 | 0.9871 | 0.0277 | 0.9871 | 0.9873 | 0.9871 | 0.9871 |
| **Mean** | 0.9866 | 0.9859 | 0.0258 | 0.9859 | 0.9863 | 0.9859 | 0.9859 |
| **Std** | 0.0008 | 0.0012 | 0.0033 | 0.0012 | 0.0011 | 0.0012 | 0.0012 |

Table 5. Classification report of SEC-ToLeD model in Experiment 4.

| **Class** | **Precision** | **Recall** | **F1-score** | **Support** |
|---|---|---|---|---|
| Tomato___Bacterial_spot | 0.98 | 1.00 | 0.99 | 425 |
| Tomato___Early_blight | 0.96 | 0.99 | 0.98 | 260 |
| Tomato___Late_blight | 1.00 | 0.98 | 0.99 | 382 |
| Tomato___Leaf_Mold | 1.00 | 0.96 | 0.98 | 191 |
| Tomato___Septoria_leaf_spot | 0.98 | 1.00 | 0.99 | 354 |
| Tomato___Spider_mites Two-spotted_spider_mite | 0.98 | 1.00 | 0.99 | 335 |
| Tomato___Target_Spot | 1.00 | 0.99 | 0.99 | 281 |
| Tomato___Tomato_Yellow_Leaf_Curl_Virus | 1.00 | 0.99 | 0.99 | 1071 |
| Tomato___Tomato_mosaic_virus | 1.00 | 1.00 | 1.00 | 75 |
| Tomato___healthy | 1.00 | 1.00 | 1.00 | 318 |
| **Accuracy** | | 0.99 | | 3632 |
| **Macro avg** | 0.99 | 0.99 | 0.99 | 3632 |
| **Weighted avg** | 0.99 | 0.99 | 0.99 | 3632 |

### *4.3. Analysis of Performance*

Here, we present the best classification performance of SEC-ToLeD based on the utilized dataset split. Table 6 reports the precision, recall, and F1-score for each class separately. Furthermore, we conducted a comparative analysis of SEC-ToLeD against other state-of-the-art models considering multiple factors such as model architecture (MARCH), number of training images (NI), image size (IS), dataset distribution (DS), test accuracy (ACC), F1-score (F1S), precision (PRE), recall (REC), number of trainable parameters (NTP), model size (MS), and training time (TRT), as shown in Tables 7, 8, and 9.


Figure 11. Confusion Matrix – Fold 4 (Test Set, Experiment 4).

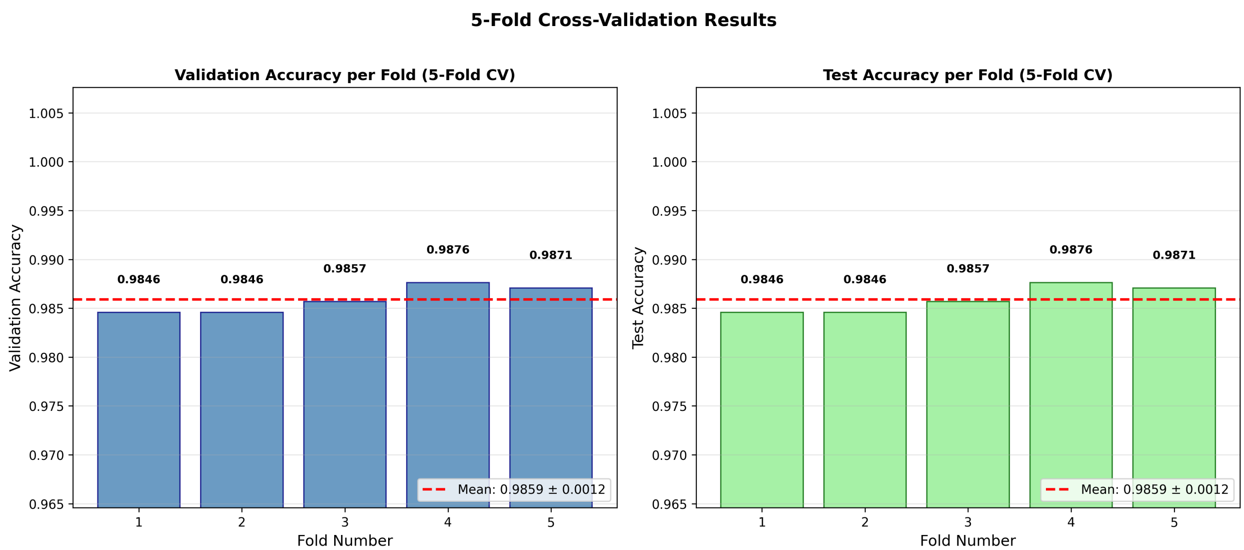


Figure 12. Validation and Test Accuracy per Fold (5-Fold Cross-Validation, Experiment 4).

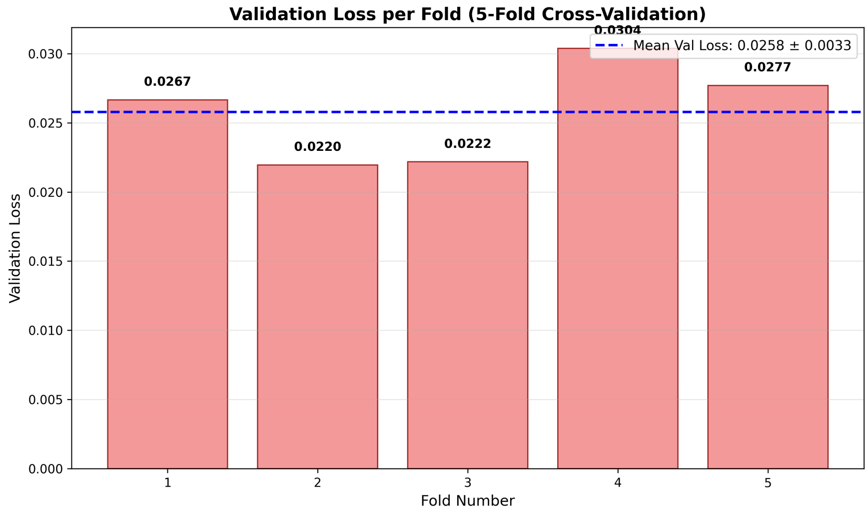


Figure 13. Validation Loss per Fold (5-Fold Cross-Validation, Experiment 4).

Several pre-trained models for plant disease detection have been explored in the literature. Table 7 provides a summary of notable examples, including Abbas et al. [14], Trivedi et al. [16], Ahmed et al. [17], Kumar and Singh [33], Tan and Xu [34], Wang and Zhang [35], Javed and Doermann [36], Bhandari et al. [37], Bhuiyan et al. [38], and Kaur et al. [39].

In addition, enhanced or modified deep learning models have been proposed to improve plant disease detection performance. Table 8 summarizes these approaches, covering studies by Sakkarvarthi et al. [40], Uluta¸s and Aslanta¸s [41], Zhang and Liu [42], Park and Lee [43], Peyal et al. [44], Chen and Zhang [45], Wang and Li [46], Kumar and Singh [47], Joshi and Bhatnagar [48], Bedi and Gole [49], and Schuler et al. [50].

Furthermore, hybrid and cascaded models have been widely investigated to enhance both accuracy and computational efficiency in plant leaf disease detection. Table 9 highlights representative works, including contributions by Agarwal et al. [13], Alnamoly et al. [18], Mohameth et al. [51], Ksibi et al. [52], Rashid et al. [53], Liu et al. [54], Zhang et al. [55], Tang et al. [56], Gomez et al. [57], Lee et al. [58].
For clarity, we have categorized the models into three groups based on their design features:

1. Pre-trained architectures (e.g., AlexNet, MobileNetV2, EfficientNet).
2. Enhanced/Altered CNNs (e.g., attention-based CNNs, convolutional autoencoders).
3. Cascaded/Hybrid models combining multiple architectures.

Among the models under comparison, SEC-ToLeD demonstrates a unique trade-off between high classification accuracy and low computational complexity. It achieves competitive performance with a compact model size and reduced computation cost, positioning it among the most efficient models.

Figures 15, 16, and 17 present a comparative analysis based on Accuracy, Model Size, and Training Time. Our dataset selection and preprocessing follow previous studies, using 18,160 tomato leaf images from the PlantVillage dataset with a 70:20:10 split. This uniform setting ensures fair comparison and highlights the efficiency and generalizability of the SEC-ToLeD model.

### *4.4. Ablation Study*

To understand the contribution of each architecture to SEC-ToLeD, ablation tests were carried out. The process of ablation testing involves methodical testing of the performance of the SEC-ToLeD architecture by excluding the important architecture used in the design. These architectures include the Depthwise Separable Convolutions and the Squeeze Excitation Blocks. The upcoming subsections will highlight

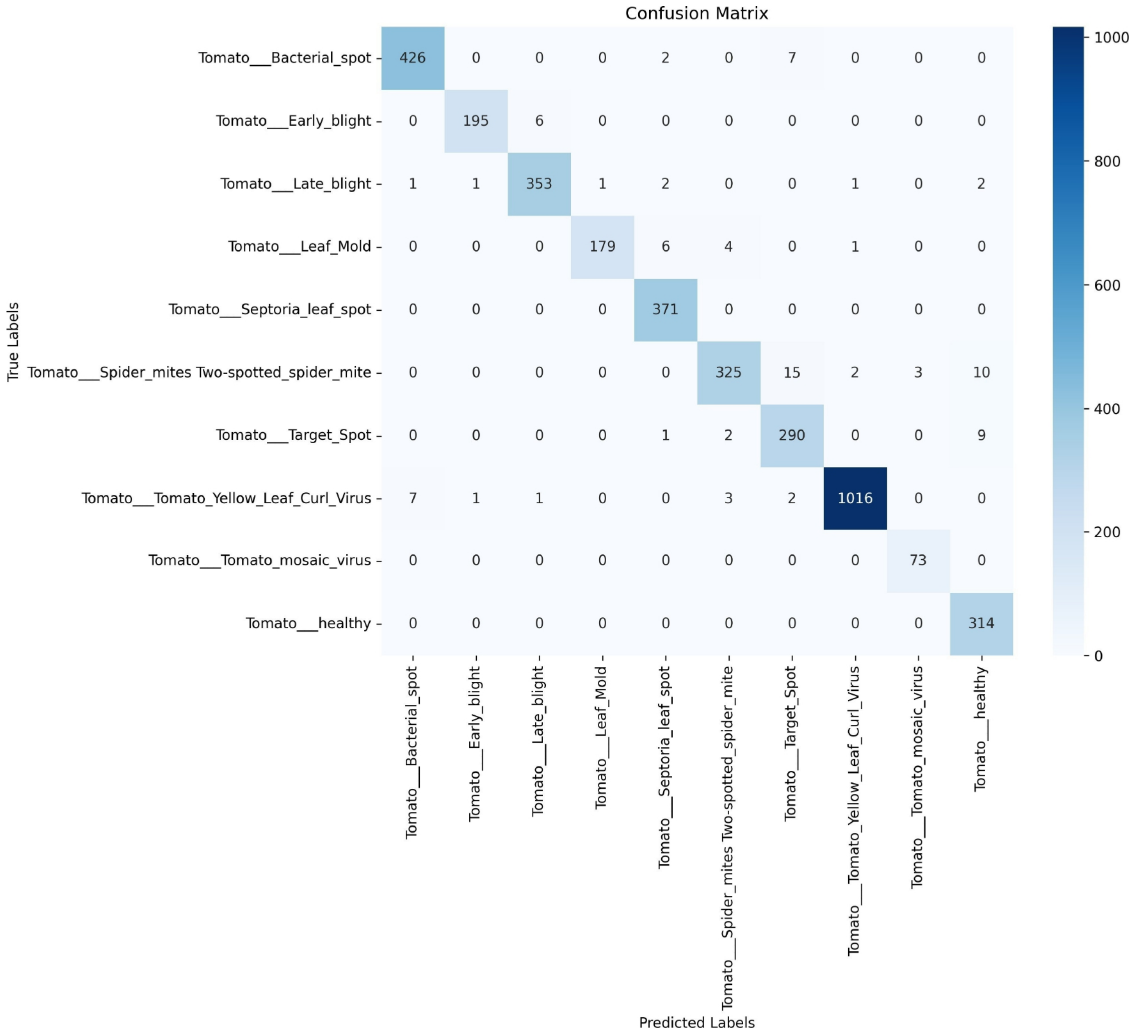


Figure 14. Confusion Matrix of Experiment 3.

Table 6. Class-wise precision, recall, and F1-score of SEC-ToLeD.

| **Class** | **Precision** | **Recall** | **F1-score** | **Support** |
|---|---|---|---|---|
| Tomato Bacterial spot | 0.99 | 0.98 | 0.98 | 403 |
| Tomato Early blight | 0.99 | 0.97 | 0.98 | 201 |
| Tomato Late blight | 0.99 | 0.98 | 0.98 | 309 |
| Tomato Leaf Mold | 0.99 | 0.98 | 0.98 | 396 |
| Tomato Septoria leaf spot | 0.98 | 1.00 | 0.99 | 386 |
| Tomato Spider mites Two-spotted | 0.99 | 0.98 | 0.98 | 380 |
| Tomato Target Spot | 0.96 | 0.98 | 0.97 | 354 |
| Tomato Yellow Leaf Curl Virus | 1.00 | 1.00 | 1.00 | 1096 |
| Tomato Mosaic Virus | 0.97 | 1.00 | 0.98 | 373 |
| Tomato Healthy | 0.96 | 1.00 | 0.98 | 321 |
| Macro avg | 0.98 | 0.99 | 0.99 | 3632 |
| Weighted avg | 0.99 | 0.99 | 0.99 | 3632 |

Table 7. Comparative analysis of pre-trained models for plant leaves diseases detection.

| Ref. No. | MARCH | Plant | NI | IS | DS | Acc | F1S | Pre | Rec | NTP | MS | TRT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [14] | DenseNet121 | Tomato | 16012 | 224 | 60:10:30 | 97.11 | 97.00 | 97.00 | 97.00 | 1.74 | – | – |
| [16] | AlexNet | Tomato | 1909 | 227 | 80:20 | 93.40 | 93.00 | 92.99 | 93.02 | 61 | 227 | – |
| [17] | MobileNetV2 | Tomato | 18160 | 256 | 60:20:20 | 99.30 | 99.12 | 99.18 | 99.70 | – | 9.60 | – |
| [33] | ResNet50 | Apple | 12000 | 224 | 80:20 | 97.20 | 97.10 | 97.50 | 97.00 | 25.6 | 48 | 7 hours |
| [34] | VGG16 | Rice | 5000 | 224 | 70:30 | 94.80 | 94.20 | 94.00 | 94.50 | 132 | 145 | 5 hours |
| [35] | InceptionV3 | Grapevine | 8000 | 299 | 70:30 | 98.50 | 98.20 | 98.30 | 98.30 | 23.1 | 100 | 10 hours |
| [36] | VGG-ICNN | Tomato | 3000 | 128 | 70:30 | 88.17 | 99.00 | 99.00 | 99.00 | 1.06 million | – | – |
| [37] | EfficientNet5 | Tomato | 11000 | 200 | 10 K-Fold | 99.07 | 99.50 | 99.50 | 99.50 | 28.80 | – | – |
| [38] | SqueezeNet | Banana | 937 | – | – | 96.25 | 96.17 | 96.53 | 96.25 | 0.737 | 4.78 | – |
| [39] | EfficientNet B7 | Grape | 9027 | 224 | 80:20 | 98.70 | 94.00 | 95.00 | 22.00 | 66 | – | – |

Table 8. Comparative analysis of enhanced/altered models for plant leaves diseases detection.

| Ref. No. | MARCH | Plant | NI | IS | DS | Acc | F1S | Pre | Rec | NTP | MS | TRT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [40] | CNN | Tomato | 3000 | 128 | 70:30 | 88.17 | 99.00 | 99.00 | 99.00 | 1.06 | – | – |
| [41] | CNN | Tomato | 18160 | 224 | 5 K-Fold | 96.87 | 97.00 | 97.00 | 96.80 | 0.494 | 6 | 82 minutes |
| [42] | CNN with Attention | Tomato | 3000 | 256 | 80:10:10 | 98.49 | – | – | – | 1.42 | 22.5 | – |
| [43] | CNN with Modified Loss Function | Tomato | 3000 | 128 | 70:30 | 88.17 | 99.00 | 99.00 | 99.00 | 1.06 | – | – |
| [44] | CNN | Tomato | 12693 | 150 | 90:10 | 97.36 | 97.00 | 97.00 | 97.00 | 9.50 | 108 | 114 minutes |
| [45] | CNN with Transfer Learning | Apple | 5000 | 224 | 70:15:15 | 95.50 | 95.00 | 95.20 | 95.80 | 0.15 | 2 | 10 hours |
| [46] | Ensemble CNN Model | Potato | 6000 | 128 | 60:20:20 | 94.80 | 94.50 | 94.70 | 95.00 | 0.20 | 2.50 | 12 hours |
| [47] | CNN with Data Augmentation | Strawberry | 4500 | 224 | 75:15:10 | 96.00 | 95.80 | 96.20 | 95.50 | 0.18 | 2 | 10 hours |
| [48] | CNN with Feature Fusion | Mango | 7000 | 256 | 80:10:10 | 97.50 | 97.20 | 97.80 | 97.00 | 0.22 | 3 | 14 hours |
| [49] | Convolutional Autoencoder network | Peach | 4457 | 256 | – | 98.38 | 98.36 | 98.00 | 98.72 | 0.009 | – | – |
| [50] | Modified MCNN based on Inception V3 | Vary species of crops | – | 224 | 60:20:20 | 99.48 | 0.992 | – | – | 5 | – | – |

the ablation tests carried out on the SEC-ToLeD architecture, followed by the comparative analysis to understand the contribution of the architectures to the optimization of the SEC-ToLeD architecture.

*4.4.1. Impact of Removing Depthwise Separable Convolutions* To evaluate the role of Depthwise Separable Convolutions in SEC-ToLeD, an experiment was conducted in which these layers were removed while

Table 9. Comparative analysis of cascaded/hybrid models for plant leaves diseases detection.

| **Ref. No.** | **MARCH** | **Plant** | **NI** | **IS** | **DS** | **Acc** | **F1S** | **Pre** | **Rec** | **NTP** | **MS** | **TRT** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [13] | Hybrid CNN-RNN Model | Grape | 8000 | 256 | 80:10:30 | 97.20 | 97.00 | 97.50 | 96.80 | 0.25 | 3.5 | 15 hours |
| [18] | CNN with Depth-wise Separable Convolution & Soft Attention | Tomato | 25127 | 224 | 5 SK-Fold | 99.04 | 99.00 | 99.00 | 99.00 | 0.221 | 2.5 | 70 minutes |
| [51] | VGG16 with SVM | 14 Crops | – | – | – | – | – | – | – | – | – | – |
| [52] | ResNet50 with MobileNet | Olive | 25127 | 224 | 75:15:10 | 98.72 | 99.00 | 99.00 | 99.00 | 0.221 | 2.5 | 51 minutes |
| [53] | MobileNetV2 with U-Net | Guava | 54000 | – | – | 97.82 | 96.42 | – | – | 138 | – | – |
| [54] | Deep Learning CNN with Random Forest Classifier | Apple | 5400 | 224 | 80:20 | 97.08 | 96.86 | 97.61 | 97.11 | – | – | 18.97 hours |
| [55] | Hybrid CNN and KNN-based Approach | Rice | 1316 | 416 | 73:18:9 | 83.40 | – | 73.30 | 73.10 | – | – | – |
| [56] | VGG16+LSTM Model for plant disease detection | Tomato | 5000 | 224 | 70:15:15 | 94.50 | 94.20 | 93.60 | 95.00 | 7.40 | 12 | 2 hours |
| [57] | Hybrid ResNet101 and SVM | Grapevine | 8500 | 256 | 80:10:10 | 97.20 | 97.40 | 97.10 | 97.30 | 5.80 | 15 | 4 hours |
| [58] | DesNet with BiLSTM for disease detection | Banana | 6000 | 224 | 70:20:10 | 96.90 | 96.70 | 97.20 | 96.50 | 6.50 | 11 | 3 hours |
| Ours | CNN with Depth-wise Separable Convolutions & Squeeze Excitation Attention | Tomato | 18160 | 128 | 70:20:10 | 99.75 | 99.00 | 99.00 | 99.00 | 0.2196 | 0.84 | 38 minutes |
| | | Tomato | 18160 | 128 | 5-Fold Cross Validation | 98.59 | 98.59 | 98.63 | 98.59 | 0.2196 | 0.84 | 24.98 minutes |

retaining only Squeeze-and- Excitation Blocks. Under this configuration, the model achieved its highest validation accuracy at epoch 49 (0.9917), while the best validation loss was recorded at epoch 47 (0.0522).

The final trained model exhibited a test accuracy of 0.9928, a test loss of 0.0420, and an AUC-ROC score of 0.9995. In terms of computational efficiency, training took 30 minutes, and the average inference time per image was 1.263 milliseconds.

*4.4.2. Effect of Deleting SE Blocks* A second experiment was conducted by removing SE Blocks while keeping only Depthwise Separable Convolutions. This configuration showed improved overall performance, with the highest validation accuracy at epoch 38 (0.9961) and the best validation loss at epoch 45 (0.0400). The final model under this configuration achieved a test accuracy of 0.9967, a test loss of 0.0321, and an AUC-ROC value of 0.9998. However, this improvement came at the cost of longer training time, which reached 37 minutes. The average inference time per image was reduced to 0.813 milliseconds, indicating improved computational efficiency during inference.

*4.4.3. Comparison and Analysis* A comparison of the two architectures highlights the trade-offs between accuracy and efficiency. Depthwise Separable Convolutions contributed to improved validation and test accuracy but required longer training time. In contrast, using only SE Blocks resulted in faster training but led to a slight degradation in accuracy and loss performance.

These results emphasize the complementary roles of both components in optimizing the SEC-ToLeD architecture. Depthwise Separable Convolutions enhance accuracy and stability, whereas SE Blocks contribute to training acceleration and computational efficiency. A detailed comparison of their performance differences is presented in Table 10.

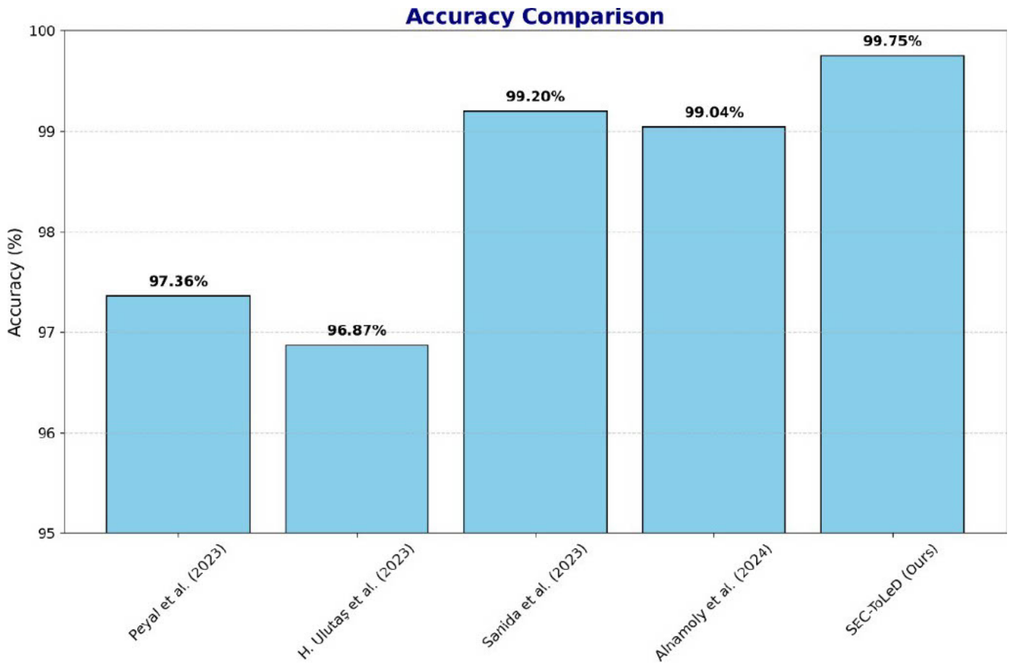


Figure 15. Accuracy comparison of SEC-ToLeD with selected CNN models.

Table 10. Performance Comparison of SEC-ToLeD Variants with Depthwise vs. SE Blocks.

| **Metric** | **Experiment 1 (Depthwise only)** | **Experiment 2 (SE Blocks only)** |
|---|---|---|
| Best Epoch (Validation Accuracy) | 38.0 | 49.0 |
| Validation Accuracy | 0.9961 | 0.9917 |
| Validation Loss | 0.0408 | 0.0522 |
| Testing Accuracy | 0.9967 | 0.9928 |
| Testing Loss | 0.0321 | 0.0420 |
| AUC-ROC | 0.9998 | 0.9995 |
| Training Time (minutes) | 37.0 | 30.0 |
| Inference Time (milliseconds) | 0.813 | 1.263 |

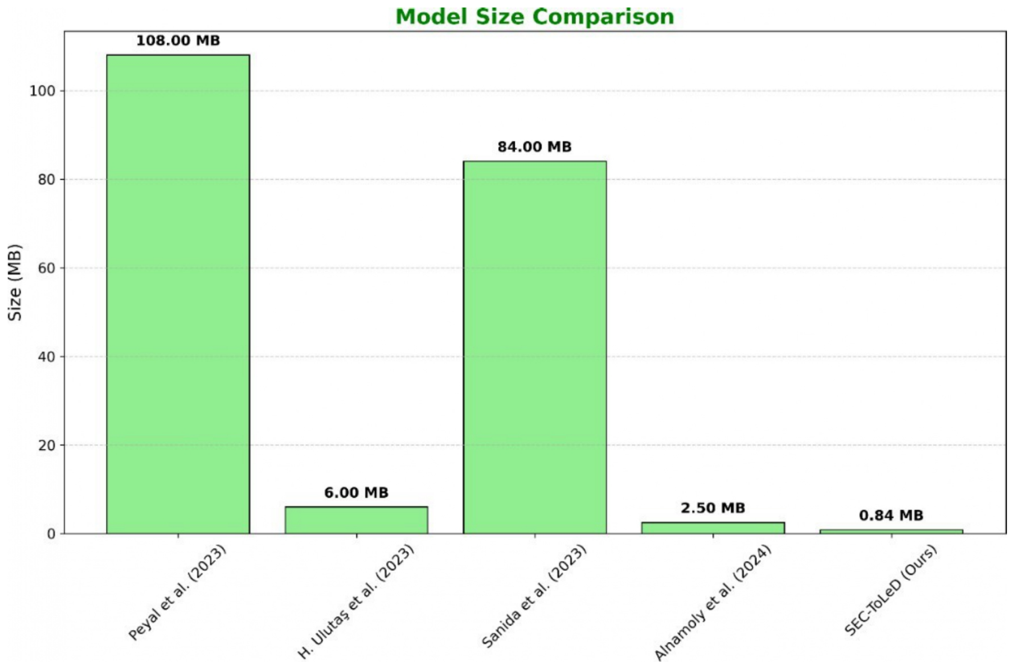


Figure 16. Model size comparison of SEC-ToLeD with selected CNN models.


Figure 17. Training time comparison of SEC-ToLeD with selected CNN models.

### *4.5. Analysis of Qualitative Data*

To analyze the decision-making process of the proposed SEC-ToLeD model, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed. Grad-CAM generates visual explanations by highlighting the most salient regions in an input image that contributes significantly to the model's predictions. By leveraging spatial feature maps extracted from the last convolutional layer, Grad-CAM produces coarse localization maps that reveal the regions on which the model focuses when classifying different disease categories. The Grad-CAM visualizations obtained from SEC-ToLeD demonstrate that the model effectively identifies disease-specific regions in tomato leaf images, resulting in accurate and interpretable classification outcomes[59].

As illustrated in Figure 18, the highlighted regions clearly correspond to the infected or symptomatic areas of the leaves. From left to right, these regions indicate the most influential features guiding the model's decision-making process, confirming that SEC-ToLeD learns meaningful visual representations rather than relying on background or irrelevant patterns.

Generalization remains one of the most significant challenges for deep learning models, referring to their ability to maintain robust performance on unseen data. SEC-ToLeD enhances generalization through advanced data augmentation techniques, including rotation, flipping, and contrast adjustment, which improve robustness against real-world variations in plant disease appearance.

In addition, Batch Normalization (BN) is utilized to normalize mini-batch feature activations, contributing to more stable dynamics and reduced overfitting. This mechanism accelerates convergence while preserving classification accuracy. Through the integration of these strategies, SEC-ToLeD achieves a balance between efficiency and performance, making it a suitable and reliable solution for real-time plant disease detection in agricultural applications.

### *4.6. Analysis of Quantitative Data*

When we tested the model with different splits on the dataset, we discovered that the model using the standard 70:20:10 train–validation–test split outperformed the model using other split configurations. Hence, this split was selected for conducting all experiments. These results indicate that the adopted split setup is optimal for SEC-ToLeD performance, as it achieves a suitable balance between training time, model accuracy, and generalization capability.

The proposed SEC-ToLeD model was compared with several state-of-the-art models for tomato leaf disease classification on the PlantVillage dataset. The results obtained confirmed the superiority of SEC-ToLeD over the compared models. Specifically, SEC-ToLeD achieved an accurate improvement of 0.71% compared to Alnamoly et al.[18].

Moreover, it outperformed Agarwal et al.[13] by 8.55% in terms of accuracy and achieved an improvement of approximately 8% in precision, recall, and F1-score. Furthermore, SEC-ToLeD surpassed the model proposed by Sakkarvarthi et al.[40] by 11.58% in accuracy, while maintaining identical precision, recall, and F1-score values of 99%. In comparison with the work of Ulutaş et al.[41], the proposed model achieved a 2.88% improvement in accuracy, along with gains of 2% and 2.2% in precision/F1-score and recall, respectively.

The ablation study reveals that SEC-ToLeD experiences a degradation in performance when either Depthwise Separable Convolutions or Squeeze-and-Excitation Blocks are removed. Specifically, eliminating Depthwise Separable Convolutions while retaining SE Blocks resulted in a test accuracy of 99.28%, whereas removing SE Blocks while retaining Depthwise Separable Convolutions achieved a higher test accuracy of 99.67%. This observation highlights that Depthwise Separable Convolutions contribute more significantly to the overall performance of the model. In terms of model complexity, SEC-ToLeD maintains a compact size of only 0.84 MB while achieving state-of-the-art test accuracy of 99.75%. Experimental results demonstrate that SEC-ToLeD outperforms baseline models by delivering higher accuracy with a smaller model size, underscoring the efficiency and practicality of the proposed approach.

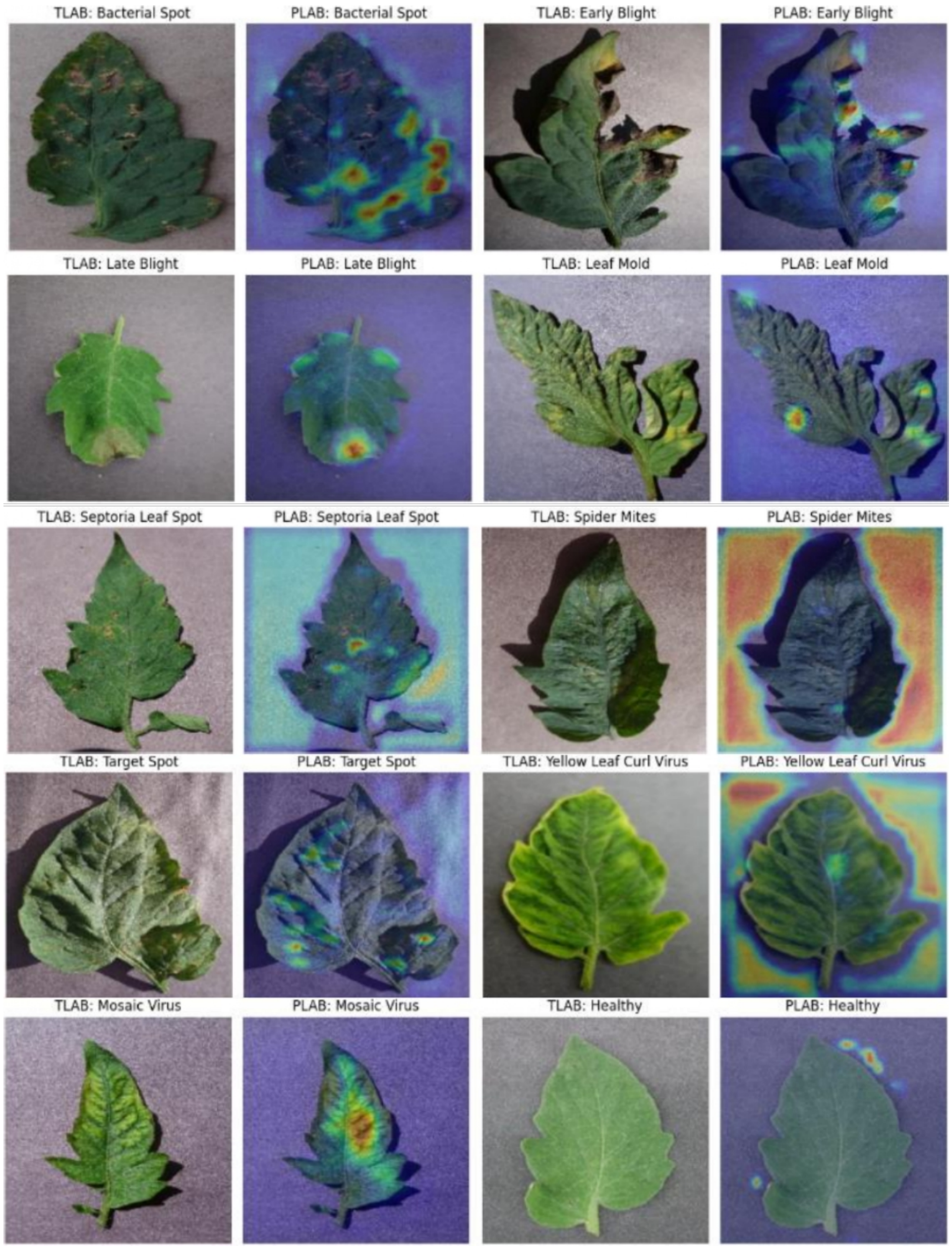


Figure 18. Visualization of Grad-CAM heatmaps for the proposed SEC-ToLeD Model.

## 5. Discussion

The experimental results of SEC-ToLeD demonstrate its superior performance compared to existing lightweight and state-of-the-art models for tomato leaf disease classification. The quantitative analysis shows that the standard 70:20:10 train–validation–test split provides the optimal balance between training time, model accuracy, and generalization capability. This choice ensures stable convergence and reliable evaluation of the model.

SEC-ToLeD achieves a test accuracy of 99.75%, with 99% precision, recall, and F1-score, outperforming models by Alnamoly et al., Agarwal et al., Sakkarvarthi et al., and Ulutaş et al. The improvements range from approximately 0.7% to 11.58% in accuracy, highlighting the effectiveness of combining Depthwise Separable Convolutions with Squeeze-and-Excitation blocks. These results indicate that the model can extract hierarchical features efficiently while maintaining a compact size of only 0.84 MB and 219,651 trainable parameters.

The favorable trade-off between accuracy and computational efficiency is a key advantage of SEC-ToLeD. With an average inference time of 1.105 ms per image, the model is highly suitable for deployment on resource-constrained devices, including mobile and embedded platforms. The integration of advanced data augmentation techniques, such as CutMix, MixUp, and RandAugment, along with Batch Normalization, further improves generalization and model stability, reducing the risk of overfitting.

Overall, the Discussion highlights that SEC-ToLeD not only achieves high classification performance but also provides a practical solution for real-time plant disease detection in precision agriculture. The model's lightweight architecture and computational efficiency make it adaptable for various deployment scenarios, including edge devices, IoT systems, and autonomous farming equipment. These findings reinforce the novelty and significance of the proposed approach in addressing the challenges of high-performance deep learning on resource-limited platforms.

## 6. Conclusion

In this paper, we developed SEC-ToLeD, a lightweight convolutional neural network that combines Depthwise Separable Convolutions and Squeeze-and-Excitation Blocks to achieve both high accuracy and computational efficiency for tomato plant disease classification. Experimental results show that SEC-ToLeD outperforms existing approaches on the PlantVillage dataset, achieving a test accuracy of 99.75% while maintaining a compact model size of only 0.84 MB.

The proposed model demonstrates a favorable trade-off between performance and model complexity, enabling real-time deployment on resource-constrained devices such as mobile phones or embedded systems. The integration of advanced data augmentation techniques and Batch Normalization further enhances the model's generalization and stability. Compared to other state-of-the-art methods, SEC-ToLeD achieves higher accuracy with reduced computational cost, confirming the effectiveness of the combined Depthwise Separable Convolutions and SE Blocks.

Future work may explore the application of SEC-ToLeD in broader agricultural scenarios, including deployment on autonomous farming equipment, adaptation to IoT devices, and extension to detect diseases on different plant organs. Additionally, techniques such as quantization or pruning could further optimize the model for ultra-low-power devices.

Overall, SEC-ToLeD provides a practical and efficient solution for real-time plant disease detection, offering both high performance and a lightweight architecture suitable for precision agriculture applications.

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