Tomato Leaf Disease Identification Using EfficientNetB3 Transfer Learning and Grad-CAM Explainable Analysis

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Method Article

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Abstract

Tomato leaf diseases (TLDs) such as Early Blight (EB), Late Blight (LB), and Leaf Mold (LM) have a negative impact on crop yield and quality, resulting in economic losses in agriculture. Traditional diagnosis methods depend on the visual recognition of a disease, which are time-consuming, subjective and may be difficult to reach in rural settings. Keeping these drawbacks in mind, the present work introduces a Transfer Learning model for tomato leaf disease classification based on EfficientNetB3 network. A pretrained EfficientNetB3 network, trained on ImageNet, is used to obtain discriminative features like lesion boundaries, discoloration, fungal textures, and infection spots. Images are cropped to 224×224 pixels and split into training, validation and test set. The proposed architecture employs Global Average Pooling, a dense layer with ReLU activation, drop out regularization and Softmax classifier for classification of tomato leaf images into four classes:

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Early Blight, Late Blight, Leaf Mold and Healthy. Experimental results show the high classification accuracy and low training, validation and testing losses. Inter-class misclassifications of the confusion matrix show very few, which supports good generalization. Moreover, Grad-CAM visualizations can generate interpretable heat maps that point to the regions of the image affected by the disease, and multi-class ROC analysis gives high AUC values, which means that it has excellent class separability. The proposed framework provides a precise, reliable, and interpretable approach for automated tomato leaf disease diagnosis, contributing to precision agriculture by assisting in early detection and prompt management of tomato diseases.

Keywords:
Tomato Leaf Disease, EfficientNetB3, Transfer Learning, Deep Learning, Explainable Artificial Intelligence, Grad-CAM, Precision Agriculture

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1. Introduction

Tomatoes (Solnum Lycopersicum) are crucial for agricultural production globally and are valued for the taste and nutritional value. Tomato plants exhibit high vulnerability to numerous diseases, leading to substantial losses in both production and quality.Expert manual inspection is an important part of traditional disease diagnosis methods, which suffers from several limitations including subjectivity, susceptibility to human error, fatigue, and inconsistency.While deep learning models have demonstrated remarkable outcomes for applications involving the categorization of images,they operate as "black boxes" that lack transparency in their reasoning and cause effect analysis. This opacity is particularly problematic in critical sectors like agriculture, where stakeholders including farmers, agronomists, and agricultural professionals need to understand why a particular diagnosis was made to make informed decisions about treatment and management strategies. Additionally, inaccurate disease diagnosis can lead to ineffective treatments that may harm plants and ecosystems. This gap between high performing but opaque models and the need for trustworthy, explainable solutions motivates this research[1].However, its production is deteriorating owing to the exposure of the crop to various diseases such as early blight, late blight, leaf mold and other diseases. For example, early blight is responsible for significant yield losses worldwide and accounts for up to 78% of the yield declines[2].Tomatoes are an economic crop widely cultivated in multiple countries and regions due

Figure 1: Tomato crop disease damage.

to their rich nutritional value. However, tomatoes are open to a variety of diseases during their growing season Figure 1.

The health of the tomato plants has a major effect on tomato growth. Tomato output will be restricted if tomato plant culture is decreased.Therefore, it needs to happen to maintain plant health.Many tomato plant diseases attack the fruit, leaves, stems, and roots.Tomato disease need to be managed by drugs or pesticides.This study focuses on tomato leaf diseases of the several diseases which impact tomato plants. Figure 2 illustrates various kinds of TLD as well as healthy. This can be a consideration for the comparison process with tomato leaves affected by the disease[3].

Figure 2: Healthy tomato plants .

Plant diseases are caused by a number plant reasons, such viruses, fungus, bacteria, and adverse environmental conditions.Plant diseases may damage the plant's vital procedures, such photosynthesis, pollination, fertilization, and germination. Therefore, for treatment, it is very important to detect diseases as early as possible[4].Since plant leaves are often the primary indicators of disease, their visual symptoms, such as discoloration, irregular textures, and stains, serve as critical clues for disease detection [5]. CNNs are particularly effective at image classification tasks, enabling automated systems to process large datasets of leaf images and detect disease symptoms without manual involvement. Explainable Artificial Intelligence (XAI) has emerged as an effective approach to address this challenge. By describing how models derive their conclusions, XAI methods aim at enhancing the understanding and transparency of AI models'decision making methods. XAI proved clear which elements of the leaf images impacted the model's predictions incorporation with CNN models may enhance system trust in identifying the presence of plant diseases.By improving transparency, XAI can not only help users better understand the underlying symptoms of the diseases but also foster collaboration between agronomists, farmers, and AI researchers to develop more reliable and context-aware disease detection technologies[6]. The explainable Artificial Intelligence (XAI) and DL algorithms that produce human readable explanations for AI judgments lay the groundwork for imaging based artificial intelligence applications [7] in various domains, such as health informatics [8], computer vision [9], and many more. In cases when the XAI can enhance the model's output, it is vital to explain it as without a demand for human feature engineering.A few studies have anticipated XAI with DL models for the prediction of different subtypes of TLD to include explanatory results [10].

2. Related Work

The capability of DL to learn intricate visual characteristics has become the primary one to use in leaf disease detection in tomatoes plants. A number of studies have established CNN based models to be far superior over traditional image processing and machine learning models in the classification of tomato leaf diseases, that includes early blight, late blight, septoria leaf spot and leaf mold[11,12]. Such models perform well especially when they are trained on test datasets such as Plant Village and also on field images.

Recent studies have been dedicated to efficient architectures to mitigate the drawbacks of deep CNNs in terms of computational complexity. Models that use a compound scaling of depth, width and resolution have found great acceptance in agricultural image analysis namely EfficientNet models. The reason why EfficientNet-B3 was so widely deployed is its balance between the accuracy and efficiency. EfficientNet-B3 has an excellent classification efficiency than VGG, ResNet, and MobileNet in the detection of tomato leaf diseases, particularly with the application of transfer learning [13].

The recent outputs focus on and lay emphasis on preprocessing methods like image resizing, image normalization, background suppression, and augmentation methods (rotation, flipping, and zooming) to enhance generalization and robustness to stay consistent with changes in environmental conditions [14, 15].These methods would be especially useful in overfitting reduction in case of limited or imbalanced training data.Simultaneously, explainable artificial intelligence (XAI) has been growing in popularity in the agricultural decision support. Grad-CAM is popular to gain an understanding of CNN predictions by highlighting area of disease on plant leaves. Articles on studies that occurred after 2020 indicate that Grad-CAM is a useful method to detect lesions, spots, and infected areas on tomato leaves, thus, improving the transparency and reliability of the models [16]. These methods ensure that the models address biologically significant regions as opposed to the background noise and as a consequence, is applicable in the field of agriculture[17]. Although the above improvements have been made, such issues like different levels of illumination, occlusion, and complicated backgrounds in the field still pose research problems.

Vijay et al., [18] used CNN and K-nearest neighbor (KNN) models in their classification of tomato leaf disorders using the Plant Village dataset, while LIME was used to provide explainability for the predictions made by each model. When it ultimately came to spotting leaf disease, the CNN model exceeded the KNN model. The accuracy, precision, recall, and F1-score of the CNN model were 98.5%, 93%, 93% and 93%—all greater than those of the KNN model, which only managed to reach values of 83.6%, 90%, 84%, and 86%, respectively.

Kaur et al., [19] used an EfficientNetB7 model to examine leaf diseases of grape plants from the PlantVillage dataset.This work focuses on proposing a DL-XAI framework for diagnosing TLD, addressing the need to explain model decisions despite the high accuracy achieved by deep learning techniques.

Atila et al., [20] The accuracy of the Efficient Net CNN based state of the art model was compared with different models in order to detect various diseases of a plant leaf. As compared with other architectures, this model gets 96.18% accuracy.The combined Convolutional Neural Network for grape plant disease identification.

Debnath et al.,[21] created a support system of tomato leaf disease detection with EfficientNetV2B2, transfer learning, and explainable AI such as Grad-CAM and LIME, which demonstrated very high classification accuracy on tomato leaf images with the use of web-deployed and smartphone versions. The system shows the possibility of real-time field deployment and diagnostics, which can be interpreted. Sun et al.,[22] have suggested E-Tomato Det, an advanced network of tomato leaf disease detection that improves global and local feature perception by employing a hybrid backbone made of CSWin Transformer and multi-kernel convolution fusion. Their model performed better in the detection of objects even when there was a complex background.

Bhandari M et al.,[23] provided a broad comparison among EfficientNetV2, ConvNeXt, Swin Transformer, ViT and hybrid Conv-Net/Vision Transformer on multiclass crop leaf disease datasets such as tomato leaves, with a primary focus on performance and visual interpretability through the use of Grad-CAM heatmaps to identify the location of the disease.

Chandel Kaur et al.,[24] combined Grad-CAM with deep learning models to detect plant diseases, emphasizing on visual symptom localization and model interpretation- these two forms of explainable disease classification which has a limited use in previous tomato leaf imaging studies

3. Materials and Methods

3.1. Dataset collection

The dataset in this study will be made of tomato leaf photographs of publicly available repositories of plant diseases like Plant Village of 4 different types(Early blight,Late Blight,leaf mold and healthy) were collected from the publicly available Kaggle dataset[25].Sample images are shown in Figure 3. 4000 images over total, divided evenly among 4 classes.To ensure fair evaluation, An 80:10:10 split was applied to allocate the dataset into training, testing, and validation subsets, respectively.

EB LB LM Healthy

Figure 3: Example images.

There are four classes in the dataset: *Tomato_EB* (Early Blight), *Tomato_LB* (Late Blight), *Tomato_LM* (Leaf Mold), and *Tomato_Healthy*. The training set contains approximately 880 images for each class, while the validation and test sets each contain approximately 200 images per class, as illustrated in Figure 4. The dataset is well-balanced, with nearly equal numbers of samples in each class across all data splits. This balanced distribution improves the model's learning capability, minimizes classification bias, and enhances its generalization performance. Consequently, the dataset is well suited for training and evaluating the proposed EfficientNetB3-based tomato leaf disease (TLD) classification model.

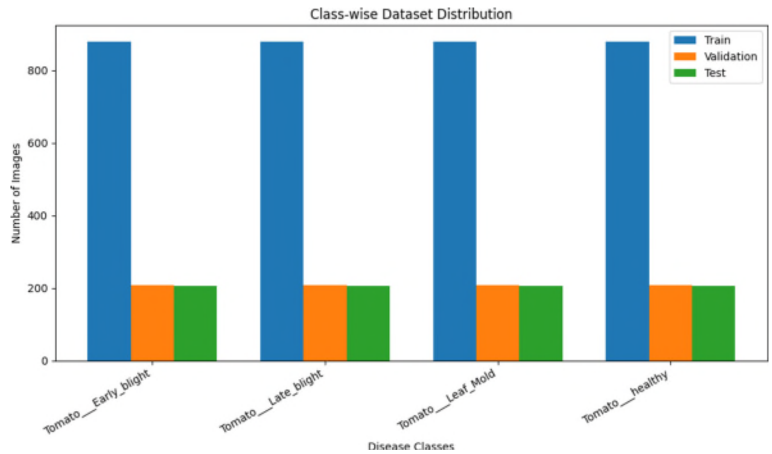


Figure 4: Class wise dataset distribution.

3.2. Proposed Method

This study presents a deep learning system that is an EfficientNetB3 model used in automatic TLD detection and classification. The system is expected to classify disease categories based on tomato leaves correctly using discriminative features that include the texture of the leaf, lesion arrangement, color changes, and the appearance of the infected spots.

3.2.1. Image Preparation

TensorFlow provides built in function image_dataset_from_directory(), which constructs image datasets directly from directory paths and automatically assigns class labels based on the corresponding folder names.Each image in the dataset was resized to 224×224 pixels before training to ensure uniformity and compatibility with the EfficientNetB3 architecture. The TensorFlow image_dataset_from_directory() function automatically constructs the dataset by reading images from directory paths and assigning class labels based on the corresponding folder names. The model was trained using a mini-batch size of 32 to improve computational efficiency and optimize GPU memory utilization. To enhance the model's generalization capability and reduce training bias, the training dataset was randomly shuffled before each epoch. In contrast, the test dataset was not shuffled to preserve the original ordering of samples, ensuring accurate performance evaluation and reproducible predictions. Finally, the dataset categories were retrieved using the class_names attribute to verify the class labels employed for tomato leaf disease classification.

3.2.2. *Data Augmentation*

It is used on training images in order to enhance dataset diversity and decrease overfitting.The techniques used in augmentation include rotation, flipping, zooming, shifting and adjustment of brightness. This allows the model to acquire the strong disease characteristics in various real life situations.

3.2.3. *EfficientNetB3*

The proposed model uses EfficientNetB3 as the backbone and adds new layers for TLD classification. EfficientNetB3 is the main feature extraction block of the suggested system. The EfficientNetB3 model (ImageNet weights) is a pre-trained model that produces high level deep features on tomato leaf images[26]. It trains patterns related to disease e.g.:lesion boundaries,color discoloration,fungal growth textures, and infected spot regions.The reason why EfficientNetB3 is selected is that its compound scaling method has high accuracy using fewer parameters and less computational cost[27]. The suggested solution uses EfficientNetB3 in transfer learning to predict and categorize tomato leaf diseases. The input images are initially normalized and reshaped to a dimension of 224 * 224 so that there is uniformity and also to enhance model stability. The model, EfficientNetB3, which is pre-trained on ImageNet, can be an extractor of features, and the classification head of the original model is substituted with a global average pooling, fully connected layers, dropout regularization, and a softmax output layer for multiclass classification.Proposed EfficientNetB3 based model provides an accurate and computationally efficient approach to identifying tomato leaf disease remotely. A compound scaled CNN architecture called EfficientNetB3 in parallel optimizes depth, width, and resolution for balanced performance. Figure 5 illustrates architecture of EfficientNetB3.

Architecture Details:

- **Baseline:** Derived from EfficientNetB0 via compound scaling coefficients.

- **Building Block:** Mobile inverted bottleneck convolution layers combined with squeeze-and-excitation optimization are employed.

- **Input Resolution:** Input size $300 \times 300 \times 3$, scaled up from EfficientNetB0.
- **Activation Function:** Swish (better gradient flow than ReLU).
- **Dropout:**Applied for regularization.

Highlights:

- High accuracy with efficient parameter usage (12M parameters).
- Strong generalization and robustness across datasets.
- State-of-the-art model among CNN architectures tested.

EfficientNetB3 employs a compound scaling strategy that uniformly scales the network depth, width, and input resolution using a compound coefficient ϕ. The scaling is defined as follows:

$$
\begin{aligned}
d &= \alpha^{\phi}, \\
w &= \beta^{\phi}, \\
r &= \gamma^{\phi},
\end{aligned}
\tag{1}
$$

The scaling coefficients satisfy the following constraint:

$$
\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \tag{2}
$$

The model is built upon Mobile Inverted Bottleneck Convolution (MBConv) blocks integrated with Squeeze-and-Excitation (SE) modules for channel-wise feature recalibration. The SE operation is defined as:

$$
\mathbf{s} = \sigma\left(W_2\, \delta\left(W_1 \mathbf{z}\right)\right) \tag{3}
$$

where $\mathbf{z}$ denotes the globally average-pooled feature vector, W_1 and W_2 are learnable weight matrices, $\delta(\cdot)$ represents the ReLU activation function, and $\sigma(\cdot)$ denotes the sigmoid activation function.

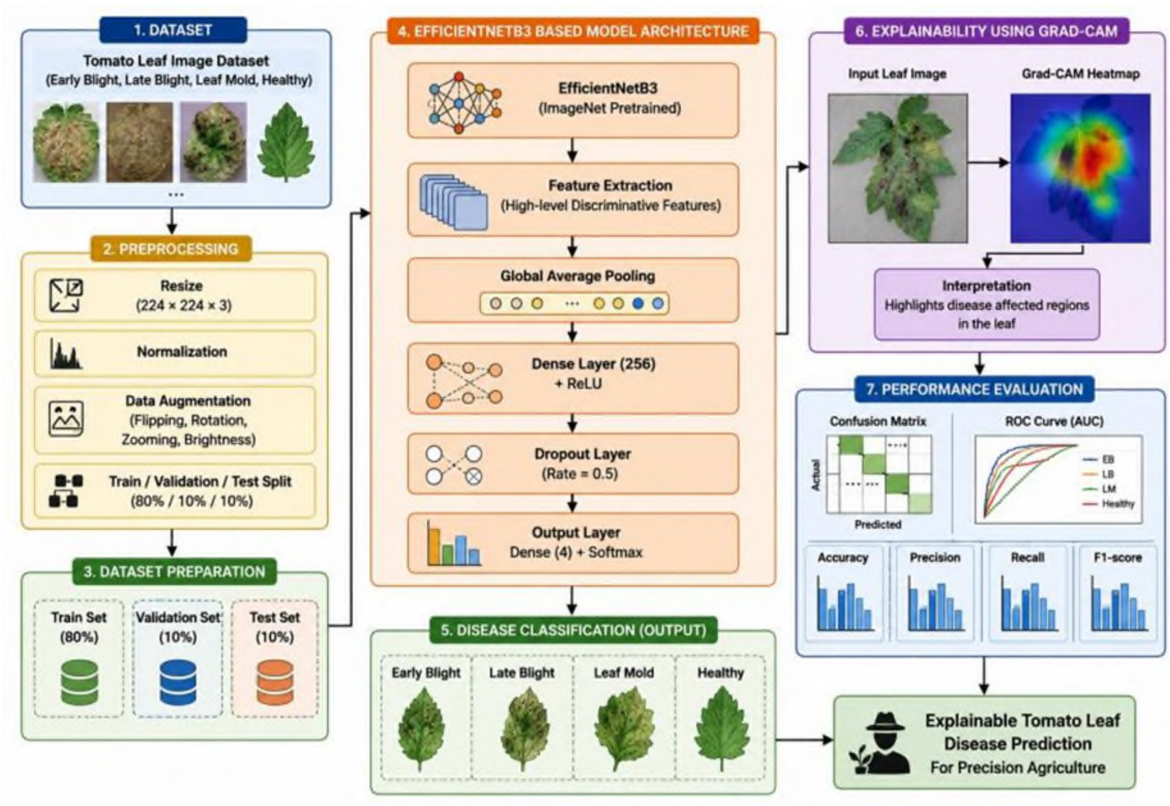


Figure 5: Architecture of the proposed EfficientNetB3-based tomato leaf disease classification model.

3.2.4. Explainability in AI systems

Traditional metrics for evaluation do not allow for the interpretation of the outcome and do not accurately represent the steps needed by the AI system to arrive at an output.An AI application must so accurately explain how it arrived at a decision.Particularly in domains involving high stake decision making, there has been an upsurge in demand for explainability of deep-learning-based systems [28]. For this, LIME, and GradCAM, two commonly used XAI algorithms are used GradCAM is used in this study.

3.3. Implementation Details

The identified TLD detection algorithm was coded in Python as the TensorFlowKeras deep learning environment. The tomato leaf data was arranged as training, validation and testing folders and loaded when using image dataset write-up through image dataset-from-directory. All the input images were down-sampled to $224 \times 224 \times 3$ and scaled to enhance the learning performance. The batch was set to 32 and training was shuffled to achieve improved generalization.

As the backbone network, the EfficientNetB3 model with ImageNet weights was trained in order to extract the features. To lower the cost of computation, all EfficientNetB3 convolutional layers were frozen to maintain the pre-trained knowledge. A Global Average Pooling layer was used to transform feature maps into 1536 dimensional feature vector. Classification learning was then performed in a Dense layer (256 neurons, ReLU activation) and the overfitting was prevented by dropping the neurons (Dropout layer, 0.5). Lastly, there was a Softmax output layer that categorized images into four categories. Visual explanation of disease regions was done using GradCAM.

4. Evaluation Metrics

The effectiveness of the model was measured using metrics like accuracy, precision, recall, and F1-score, which are calculated based on the confusion matrix components (TP=True Positive, TN=True Negative, FP=False Positive, FN=False Negative)[29].

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

5. Findings from Experiments and Discussion

5.1. Performance Assessment Relative to Existing DL Models

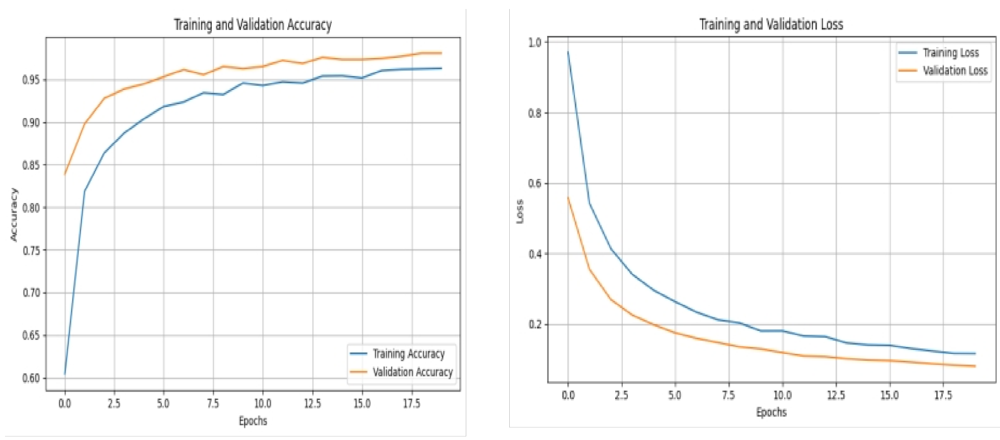
Table 1 reflects performance analysis of various pretrained DL algorithms, including MobileNet, VGG16, Exception, Hybrid CNN and DenseNet121 in identifying tomato leaf disease. According to the results, all models had good learning capabilities with training accuracy value of over 91%. Nevertheless, VGG16 had the worst performance of 88.75% validation accuracy and 87.90% test accuracy, and higher loss, demonstrating poor generalization capabilities. MobileNet was more efficient and had moderate performance, with a test accuracy of 92.60%. Exception also showed better test accuracy 94.85% than depthwise separable convolutions, which allows it to perform better classification. Competitive results were also achieved with the Hybrid CNN model of 91.75% test accuracy. All other models had lower overall performance and lower test accuracy 95.90%and lower test loss 0.245, which means that DenseNet121 reused the features better and exhibited better generalization. Thus, the best of the architectures assessed has been found to be DenseNet121, which is the best model in detecting tomato leaf disease.The proposed DL model with EfficientNetB3 outperformed the other models in terms of accuracy and loss.

Table 1: Performance analysis of various pretrained deep learning models.

DL Model	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss	Test Accuracy (%)	Test Loss
MobileNet	96.45	0.214	93.80	0.328	92.60	0.401
VGG16	91.20	0.682	88.75	0.794	87.90	0.821
Xception	97.10	0.183	95.60	0.271	94.85	0.312
Hybrid CNN	95.30	0.265	92.40	0.354	91.75	0.428
DenseNet121	97.85	0.152	96.40	0.220	95.90	0.245
Proposed Model	**99.09**	**0.118**	**99.06**	**0.080**	**99.20**	**0.126**

5.2. Model Explanation with EfficientNetB3

As can be seen in the Figure 6 training and validation accuracy graph, the proposed model has a good learning curve across epochs. First, the accuracy of training begins at approximately 60%, but it rises quickly in the initial few epochs, and it reaches over 90% which is an indication of quick learning of features. Validation accuracy is also steadily increasing and more than a little higher than training accuracy, and ultimately at approximately 99.06% in the end. This direction proves that the model is well generalized on unseen validation information and is not highly overfitted.The training and validation loss curve indicates that there is a constant reduction in the values of the loss over epochs. The loss in training becomes lower (approximately 1.0) to approximately 0.10, whereas the loss in validation becomes less (approximately 0.55) to approximately 0.08. The regular fall in the two losses represents convergent stability. The validation loss does not increase, so it can be stated that the model is optimized well with a good classification performance.



(a) (b)

Figure 6: Performance curves for training and validation: (a) accuracy, (b) loss.

The prediction matrix is used to show how the proposed model classifies tomato leaf into four classes, namely EB, LB, LM and Healthy. The off diagonal values represent misclassifications and the diagonal values represent correct predictions as shown in Figure 7 . The confusion table shows that the model is very good at all the four tomato leaf classes. EB and LB are slightly confusing with one another because of the similar appearance. LM and healthy leaves are further categorized with greater accuracy indicating the high power of the model to identify specific disease patterns and normal leaves. The precision,recall, and f1 score are shown in Table 2.

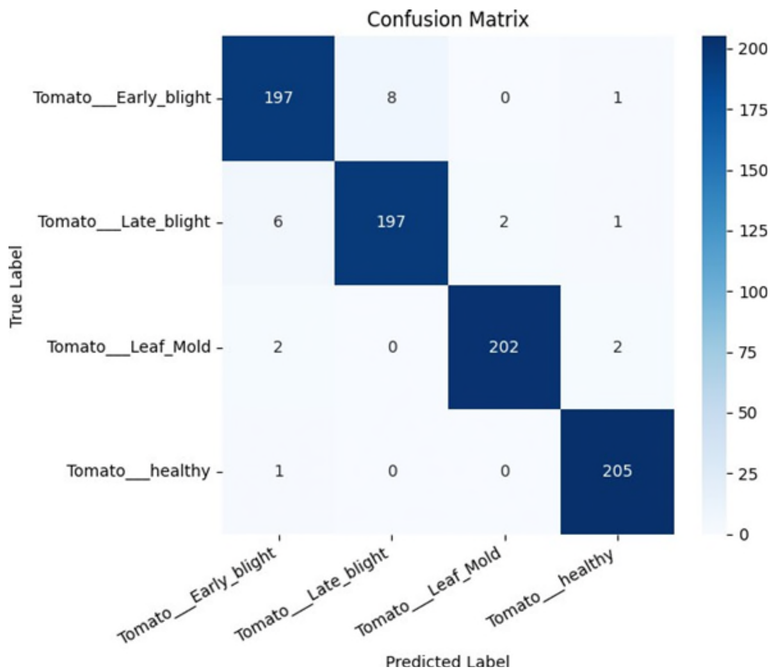


Figure 7: Confusion matrix

Table 2: Detailed performance metrics across individual tomato leaf disease (TLD) classes.

Class	**Precision**	**Recall**	**F1-score**
Early Blight	0.96	0.96	0.99
Late Blight	0.96	0.96	0.96
Leaf Mold	0.99	0.98	0.99
Healthy	0.98	1.00	0.99
Accuracy		**0.97**	
Macro Average	0.97	0.97	0.97
Weighted Average	0.97	0.97	0.97

Multi-class ROC curve is used to measure the performance of the proposed tomato leaf disease detection model in terms of classification. Every curve is a representation of one of the classes EB,LB,LM, and Healthy. The curves are placed close to the upper left section which means that the model is highly sensitive and very low false prediction is realized. The dotted straight line is random classification performance. All curves are far above this line, thus the model is much better than random guessing. The value of AUC of

1.00 of all classes is excellent is shown in Figure 8.

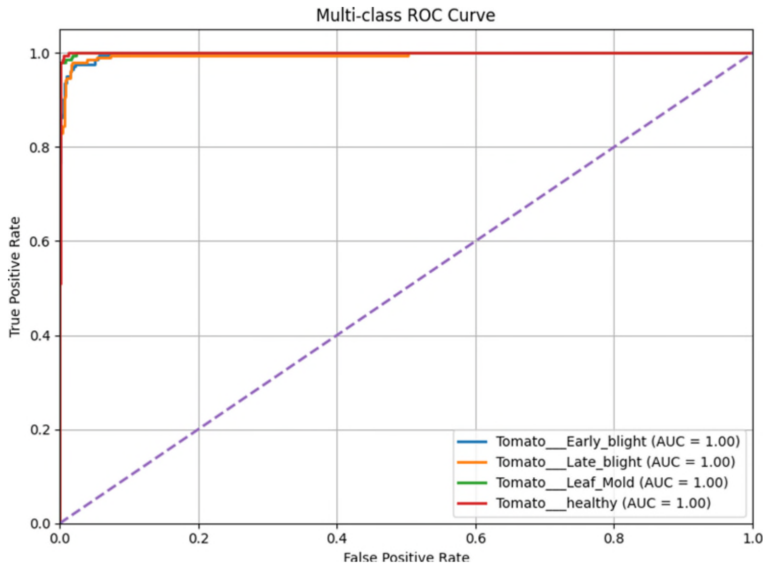


Figure 8: AUC–ROC evaluation results of the proposed model

5.3. Grad-CAM

Grad-CAM (Gradient-weighted Class Activation Mapping) is used to interpret deep learning model predictions for plant leaf disease detection for tomato leaves[30].By aligning visual cues with expert knowledge, Grad-CAM facilitates the deployment of deep learning-based models in plant disease warning systems[31]. Strictly speaking, GCAM computes the gradient of the target label concerning the activation map of a convolutional layer and multiplies the activation map by the average gradient in each channel across the spatial dimensions[31].The blue-to-red color-coded heatmaps show which parts of the leaf were the most influential for the classification. The Figure 9 presents the original tomato leaf images (left) and their respective Grad-CAM heatmap (right) of four classes: EB, LB, LM and Healthy. Grad-CAM draws attention to the parts of the leaf that give the most contribution to the prediction of the model. Red and yellow areas in the heatmaps mean high significance and blue areas mean low contribution. In the case of EB, model is highly geared towards the areas of infection of brown lesions with a confidence of 99.02. In the case of Late Blight, Grad-CAM identifies both dark necrotic spots on each side of the leaf with 99.99% accuracy and the disease is well localised. In the case of Leaf Mold, the model fully focuses on the central fungal-infested area with a confidence of 98.87%. The pattern of veins and the central leaf texture are the primary features addressed by the model in the Healthy class, with confidence of 99.25%. In general, these findings verify that the proposed model can learn the meaningful characteristics of diseases and the predictions can be explained.

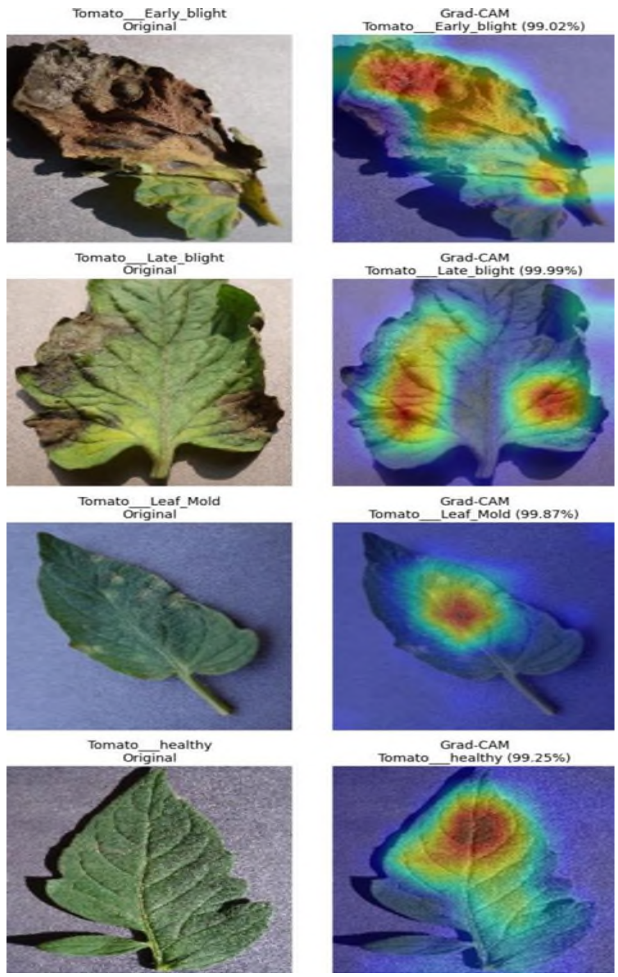


Figure 9: Grad-CAM-based visualization of tomato leaf disease (TLD) classification results

6. Conclusion and Future work

An EfficientNetB3 DL model for TLD detection was demonstrated in this work. The proposed algorithm was effective to categorize four classes which were EB, LB, LM and Healthy leaves. The findings showed high training, validation, and accuracy of test which showed the strength and validity of the model.Performance matrix proved that there was little misclassification and mostly one disease was confused with another disease which appeared similar in a visual perception like early blight v/s late blight. Also, the Grad-

CAM visualization demonstrated the areas of infection on the leaf images, which could be interpreted and proved that the model acquired meaningful disease-related features. In general, the suggested solution gives a proper and explainable solution to the issues of detecting tomato disease in real-time, which can be used in supporting precision agriculture and early disease control. The model can be enhanced in future work through addition of more categories of tomato diseases and also image testing on actual field with different lighting and background scenarios. The generalization can be enhanced by using advanced image augmentation and domain adaptation methods. Also, the segmentation-based disease localization coupled with classification can increase the accuracy of diagnosis. The suggested system can also be implemented as a mobile-based or IoT-based application to farmers to allow them to be aware of what is happening in real-time. Moreover, early disease prediction and decision-making can be enhanced by using deep learning with the multimodal data, including weather and soil conditions.

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Ethics Statement

This study does not involve human participants or animals.

Author Contributions

B. Bhagya Laxmi: Conceptualization, Methodology, Formal Analysis, Writing Original Draft.

Rupesh Kumar Mishra: Supervision, Validation, Reviewing and Editing.

Shree Harsh Attri: Software, Methodology Validation, Visualization, writing review & editing.

D. Gireesha: Data set collection and selection

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Dual publication

The results / data / figures are not previously published.

Authorship

Manuscript is submitted in accordance with the Journal policies.

Permission to use third-party material

Images or figures are never published previously and did not take from any internet resources.

Data Availability

The dataset used in this study is publicly available from the PlantVillage tomato leaf disease dataset on Kaggle's following link:

https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf

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