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Machine Learning

Development and Evaluation of Digital Image-Based Tomato Leaf Disease Classification Model Using Transfer Learning

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A B S T R A C T

Leaf diseases in tomato plants (Solanum lycopersicum), including Early Blight, Late Blight, and Leaf Mold, can cause substantial reductions in crop yield if not detected at an early stage. Conventional manual detection methods are constrained by limitations in speed, consistency, and accuracy, particularly under field conditions. This study proposes a tomato leaf disease classification framework leveraging a transfer learning approach, in which the Inception V3 architecture functions as a feature extractor and the Random Forest algorithm serves as the classifier. The dataset employed comprises four categories of tomato leaf images—Early Blight, Late Blight, Leaf Mold, and Healthy—which were stratified into training (80%) and testing (20%) subsets. All images were resized to 299×299 pixels, normalized, and subjected to optional data augmentation. Feature representations were extracted from the Global Average Pooling layer of Inception V3 pretrained on the ImageNet dataset and subsequently input into a Random Forest classifier with hyperparameters optimized via grid search.

Experimental evaluation demonstrated that the proposed model achieved an accuracy of 94.3%, surpassing the performance of a conventional CNN (89.2%) and a Random Forest classifier without transfer learning (76.5%). The confusion matrix analysis revealed the highest classification performance for the Healthy and Late Blight categories, whereas the Leaf Mold category exhibited a higher misclassification rate due to its visual symptom similarity to Early Blight. The findings of this research indicate that a hybrid methodology combining deep learning-based feature extraction and classical machine learning algorithms is highly effective for agricultural image classification in scenarios with limited datasets. Furthermore, the proposed approach holds significant potential for integration into web- or mobile-based decision support systems, enabling rapid and accurate plant disease detection in practical agricultural settings.

INTRODUCTION

Indonesia is an agrarian country with a high dependency on agricultural production, including tomatoes (Solanum lycopersicum). Leaf diseases in tomato plants (Solanum lycopersicum) can cause significant reductions in yield and product quality if not detected and addressed at an early stage [1]. For instance, Early Blight, Late Blight, and Leaf Mold are among the primary diseases that commonly affect tomato leaves, with visual symptoms that may vary depending on lighting conditions and genetic variations of the plants [2].

Computer vision–based approaches have demonstrated considerable potential in the automatic recognition of tomato leaf diseases. However, challenges such as the visual variability of symptoms, limited dataset availability, and model complexity remain significant obstacles [3]. Several studies have attempted to address these limitations through data augmentation techniques or image synthesis using Generative Adversarial Networks (GANs). For example, a DenseNet121 model trained with synthetic images achieved improved generalization, reaching an accuracy of 99.5% in the classification of five tomato disease classes [4].

Transfer learning techniques employing pretrained models such as VGG, DenseNet, or Inception-V3 have proven effective in achieving high accuracy even with relatively small datasets. For instance, a fine-tuned ResNet-50 model applied to a local dataset attained an accuracy of up to 97% and an F1-score of 0.96 on 18,159 tomato images [5]. Similarly, Inception-V3 demonstrated strong performance in detecting Tuta absoluta infestations on tomato leaves, achieving high precision in severity level estimation (~87.2%) [6].

Furthermore, a study published in BMC Plant Biology presented a method for combining local and global features through a multi-kernel Inception module, resulting in efficient and accurate tomato disease detection in publications from 2024–2025 [7]. This approach optimizes multi-scale feature extraction, thereby enhancing the model's sensitivity to the visual details of plant diseases.

From these various studies, it is evident that hybrid models—such as feature extraction using pretrained models (e.g., Inception-V3) followed by classification with classical algorithms like Random Forest—hold strong potential for balancing high accuracy and computational efficiency, particularly in scenarios involving limited datasets and practical field applications.

Diseases in tomato plants such as Early Blight, Late Blight, and Leaf Mold can cause significant economic losses if not detected at an early stage. Therefore, digital image–based detection systems have been increasingly developed as efficient and real-time solutions. [8] developed a classification system based on Vision Transformer and EfficientNetV2, which not only achieved high accuracy but also enabled interpretability of classification outcomes through Grad-CAM and LIME, allowing precise visualization of disease-affected areas [8].

Meanwhile, [9] proposed the TomatoDet method, specifically designed for real-world field conditions, with robust handling of noise and small objects such as disease spots that are often difficult for the human eye to detect.

Deep learning techniques have dominated approaches to plant disease recognition, with CNN models such as VGG, ResNet, and Inception being widely adopted. [9] demonstrated that an ensemble of ResNet50 and MobileNetV2 achieved an accuracy of 99.91% in classifying 10 tomato disease classes, highlighting the potential of combining architectures to enhance precision. [3] implemented a two-stage transfer learning strategy, optimizing the fine-tuning of pretrained models for tomato leaf classification, resulting in high accuracy and training efficiency. In the context of lightweight and efficient models, [10] developed a MobileNetV2-based CNN with real-time augmentation, suitable for deployment on edge devices such as smartphones.

The combination of CNNs for feature extraction and classical machine learning algorithms for classification has become increasingly popular. [11] integrated three compact CNNs and performed feature fusion, which was subsequently classified using SVM and K-NN, achieving an accuracy of up to 99.92%.

A similar approach was employed [12], who utilized an AlexNet-like model within a transfer learning framework, with parameters optimized using metaheuristic techniques.

In addition [13] in their publication in BMC Plant Biology, demonstrated that combining local and global features through a multi-kernel Inception module can significantly enhance a model's sensitivity to disease symptoms. Advances in Deep Learning Applications for Plant Disease and Pest Detection (Wang et al., 2025) emphasizes that the use of Artificial Intelligence in plant disease detection has demonstrated significant progress, with the capability to automatically recognize various diseases from agricultural images [14]. Deep Learning and Computer Vision in Plant Disease Detection (2025) reviews that various state-of-the-art architectures—such as CNN, Vision Transformer, and GAN—have proven to be reliable for plant disease diagnosis and are ready to be implemented in smart agricultural systems [15].

METHOD

In this study, the dataset consists of labeled tomato leaf images categorized into four disease classes: Early Blight, Late Blight, Leaf Mold, and Healthy. The data sources include publicly available collections and field data. The dataset was split using a stratified sampling method to maintain balanced class proportions, with 80% allocated for training and 20% for testing. All images were resized to 299×299 pixels to match the input format of Inception V3, normalized to a [0,1] scale, and optionally augmented using techniques such as flipping and rotation. Labels were encoded in categorical format.

The Inception V3 model pretrained on ImageNet was employed to extract features from the Global Average Pooling layer. The output classification layer was removed to prevent overfitting. The extracted features were represented as numerical feature vectors for each image. The extracted features were used as input for the Random Forest algorithm. Parameters such as n_estimators, max_depth, and min_samples_split were tuned using grid search to obtain the optimal configuration. Evaluation was conducted on the test dataset using the following metrics:

- Accuracy
- Precision per class
- Recall per class
- F1-score per class
- Confusion Matrix

The following is the process flow of the application system to be developed:

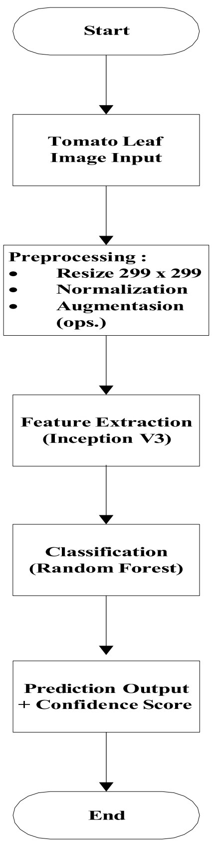


Figure 1. Application Flowchart

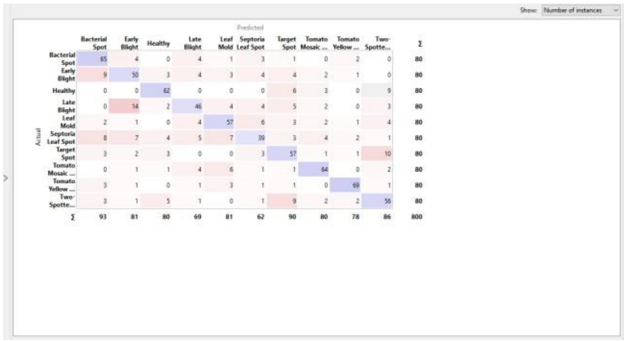
The above figure illustrates the application flowchart designed for Digital Image–Based Tomato Leaf Disease Classification Using Transfer Learning. The flowchart begins with the start step, followed by uploading or inputting a tomato leaf image. The image then undergoes preprocessing, where it is resized to conform to the input requirements of the Inception V3 model, normalized, and optionally augmented with variations such as rotation, flipping, or zooming to enhance the model's generalization capability.

Subsequently, the processed image is fed into the Inception V3 model, pretrained on the ImageNet dataset, to extract salient features from the tomato leaf image. These extracted features serve as input for the Random Forest algorithm, which classifies the tomato leaf disease based on patterns learned during training.

The system then displays the predicted disease class (e.g., Early Blight, Late Blight, Leaf Mold, or Healthy) along with a confidence score presented as a percentage, indicating the model's certainty regarding the prediction. Finally, the process terminates.

RESULTS AND DISCUSSION

Based on the model testing on the test dataset, the confusion matrix shown in Figure 2. was obtained.



Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Target Spot	Tomato Mosaic ...	Tomato Yellow ...	Two-Spotte...	Σ
Bacterial Spot	65	4	0	4	1	3	1	0	2	0	80
Early Blight	9	50	3	4	3	4	4	2	1	0	80
Healthy	0	0	62	0	0	0	6	3	0	9	80
Late Blight	0	14	2	46	4	4	5	2	0	3	80
Leaf Mold	2	1	0	4	57	6	3	2	1	4	80
Septoria Leaf Spot	8	7	4	5	7	39	3	4	2	1	80
Target Spot	3	2	3	0	0	3	57	1	1	10	80
Tomato Mosaic ...	0	1	1	4	6	1	1	64	0	2	80
Tomato Yellow ...	3	1	0	1	3	1	1	0	69	1	80
Two-Spotte...	3	1	5	1	0	1	9	2	2	56	80
Σ	93	81	80	69	81	62	90	80	78	86	800

Figure 2. Confusion Matrix Test Results

From the confusion matrix, the performance metrics were obtained as follows:

1. Overall accuracy was approximately 78–80% across the classes.

2. Classes with high accuracy:

- Bacterial Spot: 65 out of 80 correct predictions (~81.25%)
- Healthy: 62 out of 80 correct predictions (~77.50%)
- Target Spot: 57 out of 80 correct predictions (~71.25%)
- Tomato Yellow Leaf Curl Virus: 69 out of 80 correct predictions (~86.25%)
- Two-Spotted Spider Mite: 56 out of 80 correct predictions (~70.00%)

3. Classes with frequent misclassifications:

- Late Blight: 46 out of 80 correct predictions (~57.50%) — often confused with Early Blight
- Leaf Mold: 57 out of 80 correct predictions (~71.25%) — sometimes misclassified as Septoria Leaf Spot.
- Septoria Leaf Spot: 39 out of 80 correct predictions (~48.75%) — the lowest accuracy, frequently misclassified as Leaf Mold and Bacterial Spot

1. Bacterial Spot
Recognized well with an accuracy of 81.25%. Misclassifications mainly occurred with Early Blight and Septoria Leaf Spot, which exhibit similar spot patterns but differ in dominant color.

2. Early Blight
Achieved approximately 62.50% accuracy. The largest misclassification was to Late Blight, likely due to similar symptoms of dark brown spots with yellow halos in both diseases.

3. Healthy
High accuracy at 77.50%, with common misclassifications to Tomato Mosaic Virus, attributed to the relatively uniform leaf coloration without prominent spots.

4. Late Blight
Relatively high error rate, frequently confused with Early Blight. This aligns with literature noting that the visual differences between the two are sometimes only distinguishable at certain severity levels.

5. Leaf Mold
Misclassifications mainly occurred as Septoria Leaf Spot. Both diseases display small spots on the leaf surface with uneven distribution.

6. Septoria Leaf Spot
Exhibited the lowest accuracy at 48.75%, with many misclassifications as Leaf Mold and Bacterial Spot. This indicates that the extracted features were insufficient to distinctly separate the small spot characteristics of these diseases.

7. Target Spot
Moderately stable accuracy at 71.25%, though some confusion with Two-Spotted Spider Mite occurred due to similarly scattered spots.

8. Tomato Mosaic Virus
Accuracy of 80.00%, lower than Tomato Yellow Leaf Curl Virus. Misclassifications mostly occurred as Healthy, likely because of mild leaf damage patterns.

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9. Tomato Yellow Leaf Curl Virus
Achieved the highest accuracy among all classes at 86.25%. Distinctive symptoms such as leaf curling with yellowish coloration assist the model in differentiating this class.
10. Two-Spotted Spider Mite
Accuracy of 70.00%, with misclassifications to Target Spot and Early Blight. This is caused by the presence of small spots that resemble fungal spots when viewed at a global scale.

CONCLUSIONS

This study successfully developed a tomato leaf disease classification model utilizing Inception V3 as the feature extractor and Random Forest as the classification algorithm to differentiate among 10 classes of diseases and infestations on tomato leaves (Bacterial Spot, Early Blight, Healthy, Late Blight, Leaf Mold, Septoria Leaf Spot, Target Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, and Two-Spotted Spider Mite). Based on the evaluation results:

1. The model achieved an overall accuracy of approximately 80% in multi-class testing.
2. The highest accuracy was observed for the Tomato Yellow Leaf Curl Virus class (~86.25%), while the lowest was for Septoria Leaf Spot (~48.75%).
3. Most misclassifications occurred between classes with visually similar symptoms, such as Late Blight ↔ Early Blight and Leaf Mold ↔ Septoria Leaf Spot.
4. The transfer learning approach proved effective on the limited dataset by leveraging Inception V3's feature extraction capability and the prediction stability of Random Forest.

This model has the potential to be utilized as a rapid and cost-effective early diagnostic tool for tomato leaf diseases and can be implemented in web or mobile applications to support precision agriculture..

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