



EFFICIENT AND ACCURATE DETECTION OF TOMATO LEAF DISEASES USING FINE-TUNED EFFICIENTNETV2 IN KERAS

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ABSTRACT

Tomato is a widely consumed vegetable both in Senegal and worldwide. However, it is frequently affected by insect pests and diseases, leading to a significant reduction in yield. Curative and preventive approaches have been implemented for disease detection, but some are costly, while others remain prone to human error. In this study, we employ a Convolutional Neural Network (CNN) to classify tomato leaf diseases using deep learning techniques. The proposed approach involves preprocessing tomato leaf images, training an EfficientNetV2B3 model pre-trained on the ImageNet dataset for feature extraction, fine-tuning it on the tomato leaf dataset, and evaluating the model's performance on a test set. Experimental results show that the model achieves an overall accuracy of 94%, demonstrating excellent capability in identifying two specific diseases, Tomato Yellow Leaf Curl (TYLC) and early blight, as well as healthy leaf conditions. The proposed method offers a reliable and efficient solution for tomato disease detection, which is essential for ensuring food security and reducing financial losses in agriculture. The model performs well even in cases of severe infections, highlighting the potential of deep learning methods for automated and accurate disease classification in tomato cultivation.

Keywords: deep learning, transfer learning, fine-tuning, Keras, TensorFlow, efficient net, tomato leaf disease, computer vision.

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1. INTRODUCTION

Tomato is one of the most widely produced vegetables worldwide, according to the FAO, second only to staple crops such as potatoes. Its high economic value and critical role in food security justify special attention to its protection. Diseases and pests pose a serious threat to yields; therefore, accurate classification of tomato leaf images can support early intervention by identifying diseased leaves promptly, helping to reduce losses and improve productivity.

Manual detection techniques, still widely used by farmers, are time-consuming and labor-intensive. Their reliability remains limited, with a significant risk of human error, which can lead to late or incorrect diagnoses and, consequently, reduce the effectiveness of interventions. Recent approaches combining multispectral or hyperspectral cameras with artificial intelligence models such as convolutional neural networks (CNNs) enable faster and more accurate disease detection. However, their high cost limits adoption among small-scale farmers, especially in rural or low-resource settings. With the rise of machine learning reshaping agricultural practices, numerous studies have highlighted the ability of CNNs to accurately classify plant health status from images, an approach that is being increasingly adopted. One of the most widely adopted techniques in recent years within computer vision is fine-tuning applied to the EfficientNetV2 architecture, a modern approach that has demonstrated remarkable performance across various image classification tasks. The objective of this work is to propose a cost-effective and efficient solution based on a

Convolutional Neural Network (CNN) implemented with Keras, Tensor Flow's high-level API, and optimized using the fine-tuning technique. The approach leverages RGB images captured by mobile phone cameras or standard drones, enabling fast and reliable detection of diseases in tomato plantations. To achieve this objective:

- we design a robust model based on the EfficientNetV2 architecture, initialized with weights pre-trained on ImageNet;
- we employ a dataset consisting of images collected in the Thiès region of Senegal, which is used for training and validation of the model.

The paper begins with a review of related works, followed by a presentation of the adopted methodology. The results are then analyzed and discussed, and the study concludes with final remarks.

2. RELATED WORK

Several studies focus on the early detection of plant diseases using imaging techniques combined with Convolutional Neural Networks (CNNs). For instance, the study conducted by Yohannes AgegnehuBezabh et al. (2024) on mango leaf image classification achieved an accuracy of 99.21% on the test dataset, suggesting that CNNs yield highly effective results [1]. Various approaches are implemented to further enhance performance, particularly through improved data quality and the use of transfer learning [8], which enables the reuse of pretrained models by fine-tuning only the



classification layers. This is illustrated by the study of Mingle Xu *et al.* (2022), which employed a pretrained Vision Transformer (ViT) model on the Plant CLEF 2022 dataset and achieved an accuracy above 86% [2]. Other techniques, such as fine-tuning [9], which involves carefully adjusting the internal layers of a model, also demonstrate their effectiveness. The study by Wasswa Shafik, Ali Tufail *et al.* (2024) is a notable example, reporting significant results in the early detection of plant leaf diseases [3].

Numerous studies have focused on the detection of plant diseases using various techniques. For example, Mohd Sharul Aikal Baharim *et al.* (2022) employed advanced geospatial techniques to detect palm oil diseases by leveraging satellite imagery and spatial data [5]. Moreover, detection through segmentation and feature extraction for image classification remains a widely used method. Sachin D. Khirade *et al.* (2015) demonstrated the effectiveness of these techniques by applying image segmentation to isolate affected areas and extract relevant features in order to accurately classify plant diseases [6]. In the context of research on tomato vegetable cultivation, several studies have focused on the early detection of diseases, notably through the use of spectral images that enable the prediction of plant health status. For example, the study conducted by Xuemei Zhang *et al.* (2024) utilizes hyperspectral data to improve diagnostic accuracy [4]. Additionally, other research has highlighted very high accuracy rates achieved with convolutional neural networks (CNNs), employing various pretrained model architectures, as demonstrated by the results of Nixon Jiménez *et al.* (2025).

While existing methods have proven effective and accurate, they often remain computationally expensive due to the use of hyperspectral data. In this work, we focus on applying convolutional neural networks to standard RGB images of tomato leaves, enabling disease detection with satisfactory accuracy at a lower computational and acquisition cost. The following section details the methodology adopted to achieve this objective.

3. PROPOSED METHODOLOGY

In this study, we propose a framework for tomato leaf disease detection based on pre-trained and fine-tuned deep learning models, specifically EfficientNetV2B3 with ImageNet weights, a state-of-the-art architecture in image classification. To achieve optimal detection accuracy, a rigorous training methodology with a relevant dataset is required. Our approach begins with the construction of a dataset consisting of both healthy and diseased tomato leaves. The raw images undergo a preprocessing phase to mitigate noise and imperfections that could negatively impact the learning process. The preprocessed images are subsequently used to fine-tune the EfficientNetV2B3 model. Model performance is then evaluated on an independent test set, using multiple evaluation metrics.

This section outlines the methodology adopted for developing the model aimed at detecting tomato leaf

diseases. The figure below provides a schematic representation of the proposed approach.

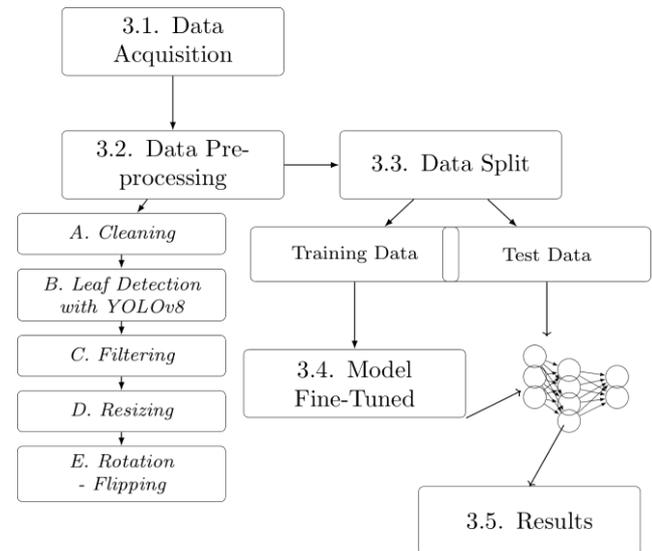


Figure-1. Methodology.

3.1 Data Acquisition

The first step of our approach involves the collection of essential data required to train any deep learning model. In this study, images of tomato leaves from the Roma variety were collected in Mboro, located in the Thiès region of Senegal, during the March-April 2025 season. These data consist of images of:

- healthy tomato leaves,
- leaves exhibiting Tomato Yellow Leaf Curl disease,
- as well as cases of Early Blight.



Figure-2. Early Blight.



Figure-3. TYLC.



Figure-6. TYLC.



Figure-4. Healthy Leaf.



Figure-7. Healthy Leaf.



Figure-5. Early Blight.

3.2 Data Preprocessing

The second step of our proposed approach focuses on data preprocessing. This phase encompasses several essential operations, such as the automatic detection of leaves using YOLOv8, followed by image quality filtering, resizing, rotation, and horizontal flipping. These transformations are crucial to optimizing the performance of the deep learning model for classification tasks.

After data processing and selection of high-quality samples to construct the dataset, we obtained the data distribution shown below:

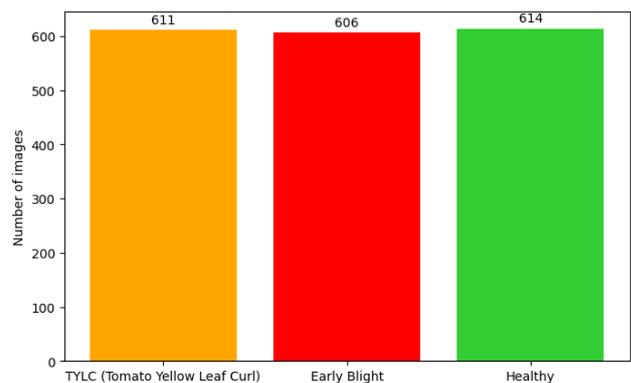


Figure-8. Total number of images per category.



3.3 Data Split

3.3.1 Model development and training

In this stage, we adapted the pretrained EfficientNetV2B3 architecture originally trained on ImageNet to suit our specific tomato leaf disease classification task. The fine-tuned model was subsequently trained on 90% of the total dataset after preprocessing. Within this portion, 80% was allocated for training and 10% for hyperparameter validation.

3.3.2 Model evaluation

The remaining 10% of the dataset was reserved for evaluating the model's performance. The model was assessed on its ability to accurately detect tomato diseases in unseen test samples.

The following subsection provides a detailed description of the proposed model architecture.

3.4 Model Fine-Tuned

Fine-tuning is a transfer learning approach that involves reusing a pretrained model trained on a large dataset, such as ImageNet, for a new, specific task by partially or fully adjusting its weights. Unlike feature extraction, this method requires unfreezing certain layers of the model and retraining them, thereby allowing the model to better adapt to the characteristics of the new dataset. This strategy offers a dual advantage:

- It leverages the general knowledge already acquired by the model, enabling the use of a pre-existing learning foundation;
- It adapts this knowledge to the specific task at hand, ensuring effective specialization.

This combination allows the model to achieve high performance even when the available dataset is limited.

In our experiment, the preprocessed images were used to train the pre-trained EfficientNetV2 CNN model, which is known for its fast training speed, lightweight architecture, and high efficiency, as demonstrated by the work of Mingxing Tan *et al.* (2021). Furthermore, EfficientNetV2 has shown superior performance in classification tasks such as waste recognition, outperforming several traditional architectures, according to WenxuanQiu *et al.* (2025). The choice of the EfficientNetV2-B3 architecture is based on several criteria, beyond the performance reported in previous studies [10, 11]. Unlike MobileNet or EfficientNet-B0, which are lighter but less effective on complex tasks, EfficientNetV2-B3 provides an optimal balance between accuracy, training speed, and computational efficiency. Compared to heavier architectures such as ResNet50 or Xception, EfficientNetV2-B3 achieves comparable or even superior performance while requiring fewer hardware resources. These characteristics make it particularly well-suited for tomato disease classification in contexts with

limited data and for mobile or drone-based applications, as envisioned in this study.

To enhance image quality for the models, the input images were first resized to 300x300x3, followed by several preprocessing operations in accordance with the EfficientNetV2 requirements. The pre-trained EfficientNetV2 models were then used as a base, with the last four layers made trainable to allow fine-tuning. Additional layers were subsequently added, including dense and dropout layers, to adapt the model for the classification of tomato leaf diseases. The classifier head was structured as follows:

- A dense layer with 512 units and ReLU activation, followed by a Dropout layer with a rate of 0.5;
- A second dense layer with 256 units and a Dropout of 0.3;
- A third dense layer with 128 units and a Dropout of 0.2;
- An output dense layer with 3 units (corresponding to the three classes) and Softmax activation.

The model was then trained using the training images, employing data augmentation to mitigate overfitting and enhance model robustness.

The model is subsequently retrained on the new tomato images with a very low learning rate of $1e-6$. This gradual adaptation of the pretrained weights enables optimal model performance and effectively improves the classification of tomato diseases.

To better illustrate the structural differences, the figure below clearly presents the original EfficientNetV2 architecture alongside the fine-tuned version employed in this study.

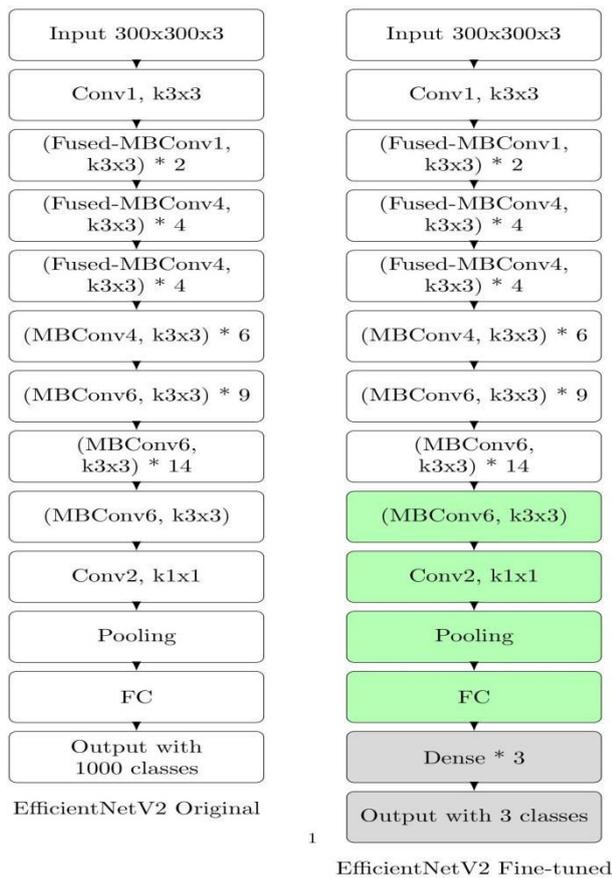


Figure-9. Comparison: Original EfficientNetV2 vs Fine-tuning.

4. RESULTS

The results were analyzed using various performance metrics such as training and validation loss, model accuracy, precision, recall, F1 scores, and the confusion matrix. The learning curves show how the model's performance evolves during training. As the number of epochs increases, the training accuracy indicates how well the model fits the training data, while the validation accuracy provides an estimate of the model's performance on unseen data, reflecting its generalization ability.

Figure-10 illustrates the training and validation accuracy over the course of the epochs. The validation accuracy improves as the number of epochs increases, reaching approximately 94%, which reflects the model's effective learning on our dataset.

Figure-11 depicts the loss curves for both training and validation. Both losses decrease progressively over time, with minor fluctuations observed during validation, indicating stable convergence of the model.

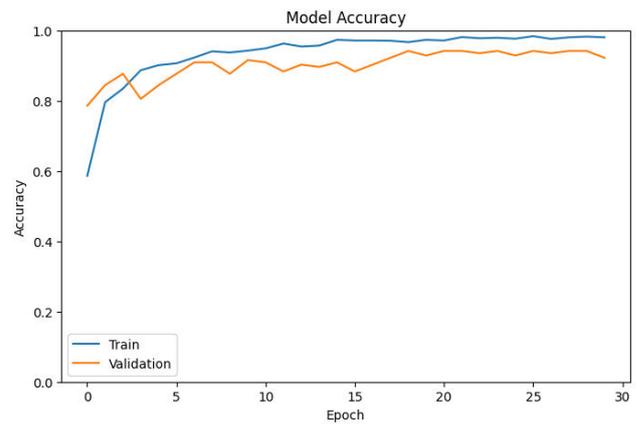


Figure-10. Accuracy vs Epoch.

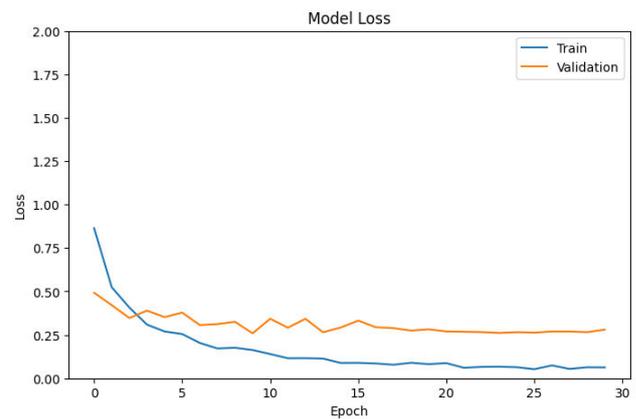


Figure-11. Loss vs Epoch.

Figure-12 presents the confusion matrix of the deep learning model for leaf disease detection. This matrix demonstrates that the model correctly classifies 144 out of 154 tomato leaf images, reflecting a high overall accuracy. Regarding precision, the model achieves 94% for healthy leaves, TYLC (Tomato Yellow Leaf Curl), and 92% for Early Blight leaves. For recall, the values vary between 86%, 96%, and 98% for TYLC, Early Blight, and healthy leaves, respectively. The F1 score further highlights the model's strong performance across individual classes, with values of 90%, 94%, and 96%, respectively. Overall, the confusion matrix confirms that the model is precise, balanced, and well generalized for the task. These results demonstrate the model's ability to achieve consistent and accurate classification across all target categories, reflecting both its robustness and effectiveness in handling the variability present within the dataset.

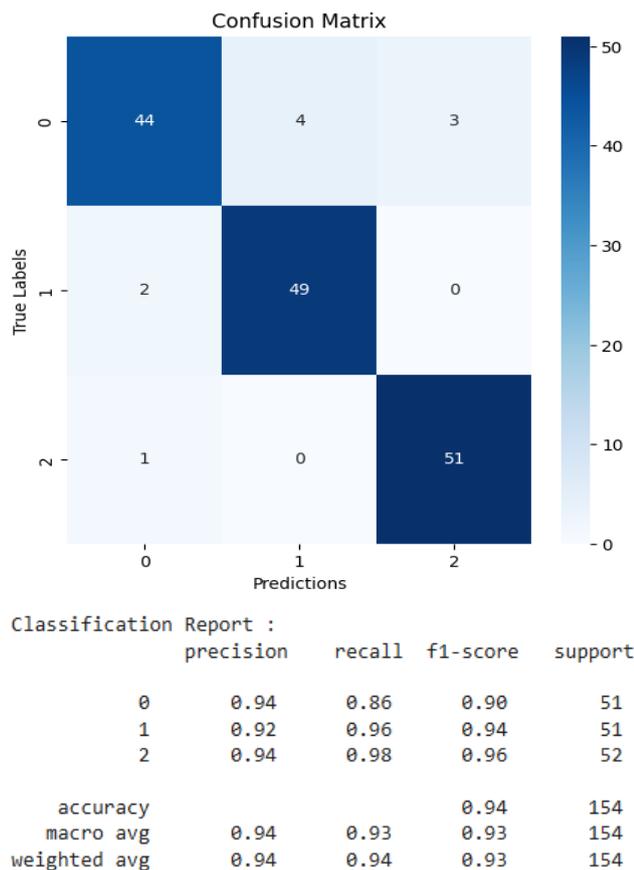


Figure-12. Confusion matrix.

5. DISCUSSIONS

The results demonstrate a high accuracy of 94%, confirming the CNN model's effectiveness in detecting leaf diseases. This performance aligns with findings reported in Yohannes Agegnehu Bezabh *et al.* (2024), which showed similar outcomes. This study highlights a lightweight and fast model achieving significant accuracy, paving the way for practical applications that enable farmers to quickly identify infected areas using a simple mobile phone. Furthermore, the use of drones equipped with standard cameras could facilitate large-scale assessment of the health status of entire plantations. However, several limitations of this work must be acknowledged:

- **Varietal specificity:** The image dataset is limited to tomato leaves of the Roma variety, which may reduce the model's performance when applied to other tomato varieties.
- **Geographic specificity:** The data were collected exclusively from the agricultural area of Mboro (Thiès, Senegal), thereby restricting the external validity of the model in other agro-climatic environments.
- **Infection variability:** The diversity of foliar infection types and their developmental stages constitutes a

factor that may limit the robustness and generalization capability of the model.

6. CONCLUSIONS

The tomato (*Solanum lycopersicum*, Roma variety) is one of the most widely consumed crops in Senegal and worldwide. It is marketed locally and exported to numerous countries, both as fresh produce and as processed products such as canned tomatoes. To support research on improving tomato health and yield, a dataset was collected using a digital camera in a tomato production area located in Mboro, in the Thiès region. The captured leaf images were preprocessed to improve dataset quality. Image processing combined with deep learning plays a crucial role in the classification of foliar diseases, helping to reduce the use of potentially harmful pesticides. In this study, we propose an optimized tomato disease detection system based on a combination of image processing techniques and deep neural networks. By fine-tuning the top layers of the EfficientNetV2B3 model and leveraging its extracted features, the approach achieved high accuracy while ensuring fast execution and low computational complexity. The proposed model achieved a training accuracy of 98.77% and a validation accuracy of 94% in experimental results. Overall, the system demonstrated excellent performance in correctly classifying healthy leaves as well as those affected by Tomato Yellow Leaf Curl (TYLC) and early blight. These results provide practical responses to real-world challenges and suggest concrete applications such as:

- integration into a mobile application for farmers,
- deployment on agricultural drones,
- coupling with an early warning system for producers.

These perspectives represent significant advances compared to the initial limitations outlined at the beginning of this work. To further improve and strengthen the proposed model, future research should rely on larger, multi-source, and more diverse datasets, including different types of foliar infections, in order to enhance the robustness and generalization capability of the model.

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