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Tomato Fruit Diseases Classification using Mobilenetv2

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ABSTRACT: The production of tomatoes is an integral part of global food system, which provides essential nutritional value and enjoyment for economic activity in many parts of the world. However, the crop itself is very susceptible to several fruit diseases that threaten both rate and quality. Such diseases often escape notice until they have developed into advanced stages causing great loss to farmers. Manual inspections are time-consuming, error-prone and ineffective for large-scale farming. Consequently, there is an increasing demand for automated, intelligent systems capable of accurately identifying, classifying and diagnosing tomato fruit diseases early on. In this research paper, a deep learning-based solution was proposed that adopts the MobileNetV2 architecture, a lightweight convolutional neural network (CNN) optimized for speed and performance. The model was trained on a curated dataset of tomato fruit images representing four common disease categories. The image data had labels such as Blossom End Rot, Sunscald, Cracking and Splitting. Data preprocessing techniques such as resizing, normalization and augmentation were employed to improve the robustness and generalization of the model. The system under discussion achieved a training accuracy of 98% and a test accuracy of 91%, indicating it is very effective in classifying tomato fruit diseases with high precision. The lightweight architecture makes it suitable for real-time agricultural applications under conditions of limited computing resources. This study proves the potential of MobileNetV2 as a scalable, easily accessible tool for detecting diseases which is conducive to smarter farming practices and better crop management.

KEYWORDS: MobileNetV2, Deep Learning, Tomato fruit diseases, CNN

INTRODUCTION

Tomatoes are one of the most widely cultivated and consumed crops worldwide, with others existing in massive numbers as well. They are highly valued not only for their nutritional benefits, but also economically being in demand all over the world. As a major farming product and staple ingredient used in many kinds of cuisine, it is essential that tomatoes grow consistently well. Not only does this help food supply chains function smoothly but it also determines how much money fresh tomatoes can bring in for farmers every year. However, tomato cultivation is often infected by a variety of diseases which have a direct impact on quality and yield. Some of the most serious disorders in terms of fruit quality are often found on tomato fruit: blossom end rot, sunscald, cracking, and splitting. These diseases not only devalue produce but also lead to substantial economic losses due to reduced crop worth and higher management charges. Blossom end rot is characterized by sunken, dark spots at the blossom end of the tomato, primarily caused by calcium deficiency and irregular watering. Sunscald appears on fruit as pale or yellowish blotches formed in the skin. Cracking and splitting are generally caused by environmental conditions (such as overwatering) that cause the fruit skin not to grow quickly enough alongside expanding internal plant tissue. These diseases not only damage the visual appearance of tomatoes, but also provide entry points for secondary infections, resulting in large postharvest losses and greatly reducing marketable quality [1]. Traditional means of identifying and managing these diseases involve manual inspection and intervention; in addition, this often requires experienced labor and constant supervision. But these approaches are time-consuming as well as error prone, they are especially difficult to adapt for large-scale agricultural production. As a result, there is an urgent need for automated, intelligent systems with the ability to detect diseases early and accurately. Recent advances in computer vision and artificial intelligence, particularly deep learning, provide promising approaches to meet this challenge by enabling automatic image-based classification of plant diseases [2].

Under these circumstances, our study proposes a deep learning model which uses MobileNetV2. This is a lightweight convolutional neural network (CNN) architecture specifically for image classification tasks, and it provides an efficient alternative to not only MobileNets but traditional CNNs as well. MobileNetV2 has become famous for performing well even on resource-constrained devices and maintaining a high level of accuracy. It achieves this through its unique use of depth wise separable convolutions, making it much more practical for real-time applications needing fast answers such as mobile or embedded systems used in agricultural applications [3].

The aim of this study is to use MobileNetV2 to classify four specific diseases of the tomato fruit: blossom-end rot, sunscald, cracking, and splitting. To this end a curated image dataset representing these disease classes was employed for both training and evaluation of the model. The system sets up an accurate, fast and cheap tool for difficulty detection in tomatoes field: This will meet the needs of farmers, scholars and agriculture practitioners. Deploying such systems in actual agricultural practice will more powerfully enable us to monitor the growth process of crops, cut wasted pesticide chemicals with certainty, or only help people grow more tomatoes for less cost. It is hoped that this study will point out the feasibility, as well as merits and drawbacks, when one uses MobileNetV2 to detect diseases on tomato fruits. The immediacy of MobileNetV2 means it will be an asset to link into mobile applications and smart farming networks. This study represents a small link in the burgeoning chain of precision agriculture and shows what deep learning can offer in solving real agricultural problems.

Related Work

Agricultural applications have been significantly improved by recent developments in deep learning, and this is particularly true for applications in plant disease detection. Original research work employed handcrafted feature extraction with traditional classifiers such as SVM, decision trees and k-NN. But these methods were limited by their susceptibility to environmental changes, such as lighting, occlusions and image noises [4]. Because the advent of Convolutional Neural Networks (CNNs) completely transformed the field. In 2016, Mohanty et al were among the first to show CNNs' effectiveness in agriculture by training their model on PlantVillage dataset and achieving over 99% accuracy for disease classification among 14 kinds of crops and 26 total diseases [5]. Although their work had high accuracy it was confined to environments with controlled lighting and lacked practical strength which is essential for users living in real situations with spontaneous backgrounds To achieve generalization, researchers began to use transfer learning. Too et al. (2019), were first to compare VGG, DenseNet, ResNet and MobileNet by training models for plant disease recognition. Lightweight networks like MobileNets can provide a better tradeoff between accuracy and efficiency [6]. Proposed by Sandler et al. (2018), MobileNetV2 introduces inverted residuals and linear bottlenecks to improve performance on mobile and embedded systems. It's well suited for real-time agricultural diagnostics [7]. Parmar and Mehta (2020) tested its application on rice leaf disease recognition, finding high accuracy whilst still maintaining low inference times using basic equipment [8]. In 2017, Fuentes et al developed a tomato-specific detection system using Faster R-CNN, accurately localising diseases and pests. However, it was computationally expensive and therefore not suited to wider deployments [9]. Similarly, Ferentinos (2018) trained five deep CNNs on a dataset of 87 co plant images drawn from 58 course s although found good results in general still had problems with overfitting especially when datasets were smaller [10]. In order to combat limited real data, Zhang et al. (2019) used Generative Adversarial Networks (GANs) to artificially expand the plant disease dataset. The mean loss function for CNNs without GANs is reduced by GANs especially for underrepresented categories [11]. There are also new approaches that combine deep learning with edge AI. Ma et al. MobileNet (2021) show how to merge their innovations in disease detection with Raspberry Pi on the edge, enabling practical use of efficient architectures by ordinary farmers to monitor their crops [12] Although much progress is made in this area, most previous work is concentrated on leaf diseases. On the other hand, our research uses MobileNetV2 to classify tomato fruit diseases like blossom-end rot, sunscald, cracking, and so on areas not previously focused upon. This addresses a crucial gap in the diagnosis of plant diseases occurring at the post-flowering stage.

METHODOLOGY

The process of identifying the diseases that affect tomato fruits using the MobileNetV2 deep learning model is a sequence that includes data collection, preprocessing, model building, training and evaluation. To begin with, assorted photos of tomatoes afflicted by actual diseases of the field were chosen, and the data set was manually categorized into four basic types: blossom-end rot, sunscald, splits and cracks. Image resizing and data augmentation are used to increase the variety of examples using in training models. This can enhance the model’s capacity for generalizing or recognizing images that look very different but actually contain similar structures. Then MobileNetV2 was trained, employing transfer learning from the ImageNet weights followed by fine-tuning of the deeper layers. This two-stage approach is selected due to the balance struck by MobileNetV2 in delivering high accuracy at no significant computational cost, which is appropriate for use in agricultural settings with limited resources. Finally, when evaluating the system in a real-life situation, we assessed its performance employing four traditional metrics: precision, recall, and F1-score as well as overall accuracy. This methodology aims to construct a lightweight and reliable deep learning framework for diagnosing tomato diseases.

Figure-1: Sample of dataset images

This flowchart clearly illustrates the steps involved in the methodology for detecting tomato fruit diseases using the MobileNetV2 algorithm.

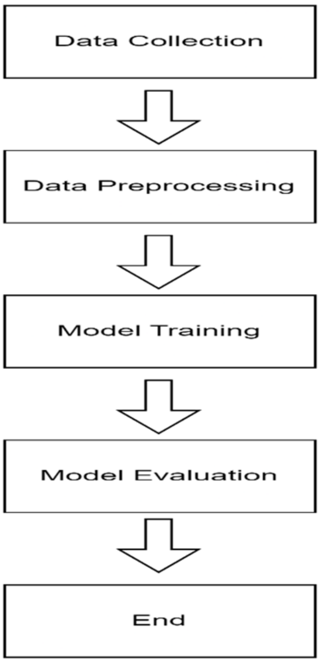

Figure-2: Methodology Flowchart

Initially, the dataset for tomato fruit detection and diseases [13] contained 2,158 images, with 1,878 allocated for training, 92 for testing, and 188 for validation. After applying data augmentation techniques, the total number of images increased to 4722, including 3108 for training, 269 for testing, and 1,345 for validation. The dataset includes images of tomato fruits affected by four specific diseases: its common damages include blossom end rot, sunscald, splitting and cracking. In each image, regions of the disease were not only labeled but the outline of the diseased portion also marked precisely using bounding boxes. In order to make the model even more invariant and to improve its generalization, data augmentation was performed using rotation and flipping, as well as other transformations. With a large number of images and detailed annotations, this diverse dataset can help effectively train and test the MobileNetV2. This paper aims to evaluate the efficiency of the algorithm in identifying and categorizing tomato fruit diseases.

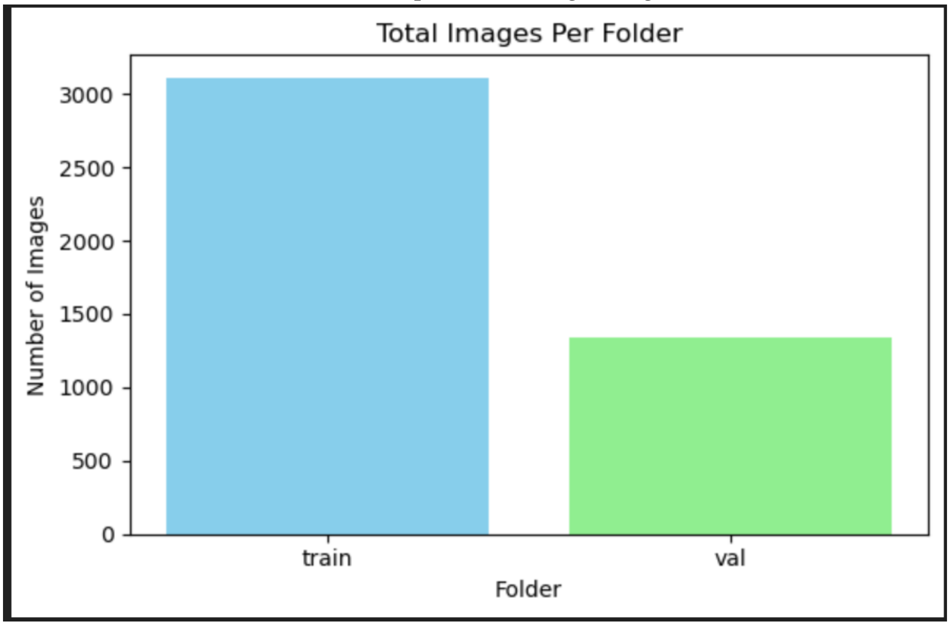

Figure-3: Data Description

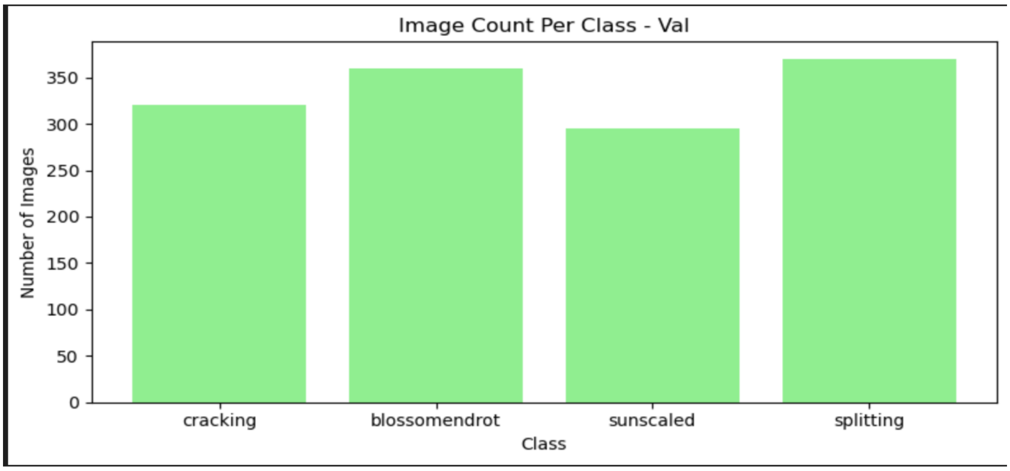

Figure-4: Distribution of Tomato Disease Classes in the Validation Dataset

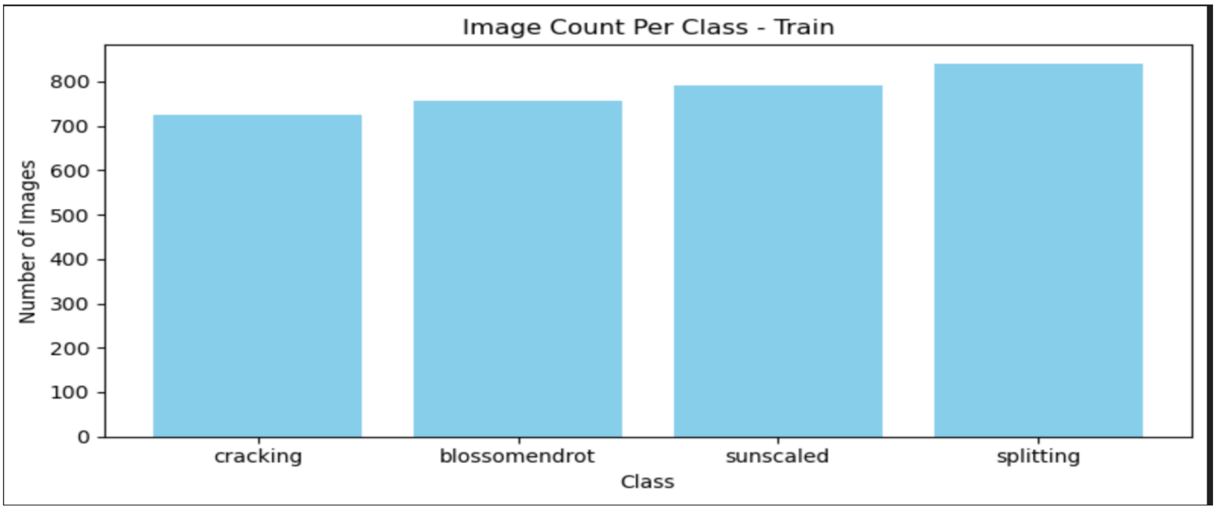

Figure 5: Distribution of Tomato Disease Classes in the Training Dataset

To improve generalization and reduce overfitting, data augmentation was applied to the training set. This included a variety of transformations such as random rotation (up to 30 degrees), horizontal flipping, width and height shifting (up to 20%), zooming, shearing, and fill mode adjustment using nearest. These augmentations simulated different real-world variations in tomato fruit images, making the model more robust to changes in orientation, scale, and position. Together, these preprocessing and augmentation steps enhanced the quality and diversity of the training data, enabling the model to perform more reliably in practical agricultural scenarios (Figure-8).

Figure-6: Applying Data Augmentation on the data

Architecture of MobileNetV2

The MobileNetV2 architecture is a lightweight deep learning model designed for efficient computation, particularly on mobile and embedded devices [14]. Due to its lightweight and high accuracy, it was chosen to train the model.

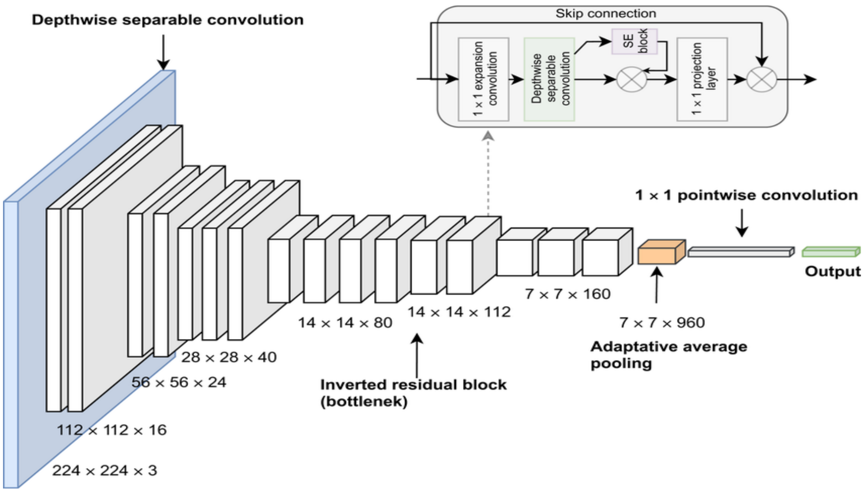

Figure 7: MobileNet Architecture [15]

https://www.researchgate.net/figure/The-MobileNetV3-architecture-and-its-core- components_fig4_375462137

Model Evaluation:

The generalization capability of the trained model has been evaluated in the test data set. Apart from that, several performance metrics, such as precision, recall, F1-score, and overall accuracy are computed to present an all-around understanding of model effectiveness. Beyond that, an estimation of a loss function indicates how well one's model will predict values relative to the truth. Further insight was sought into the behavior of the model by analyzing the confusion matrix for patterns of misclassifications. This identified some areas where the model has struggled, thus pointing out potential biases or weaknesses that can be worked on in future improvements.

Accuracy	Predictions/ Classifications	$\frac{\text{Correct}}{\text{Correct + Incorrect}}$
Precision	Predictions/ Classifications	$\frac{\text{True Positive}}{\text{True Positive + False Positive}}$
Recall	Predictions/ Classifications	$\frac{\text{True Positive}}{\text{True Positive + False Negative}}$
F1	Predictions/ Classifications	$\frac{\text{2 * True Positive}}{\text{True Positive + 0.5 (False Positive + False Negative)}}$

Figure 8: Definitions of accuracy metrics

https://www.researchgate.net/figure/Evaluation-metrics-accuracy-precision-recall-F-score-and-Intersection-over-Union_fig2_358029719

RESULTS

All experiments in this project were conducted using a locally installed Jupyter Notebook with Visual Studio Code as the development environment, thus giving us a flexible and efficient workflow in three respects: coding, debugging and visualizing results. Configuration for both training and evaluating our neural net saw that the model was trained for 30 epochs, using a batch size of 32 images. This combination provides efficient learning without loss of predictive accuracy. A custom evaluation script was implemented in addition to training the model so predictions can be visualized and verified for new tomato image data: this clarifies the meaning behind our classification results much better. Figure 9(a) shows an example output being analyzed. This graph highlights how well the model recognizes where areas with disease attack appear in images.

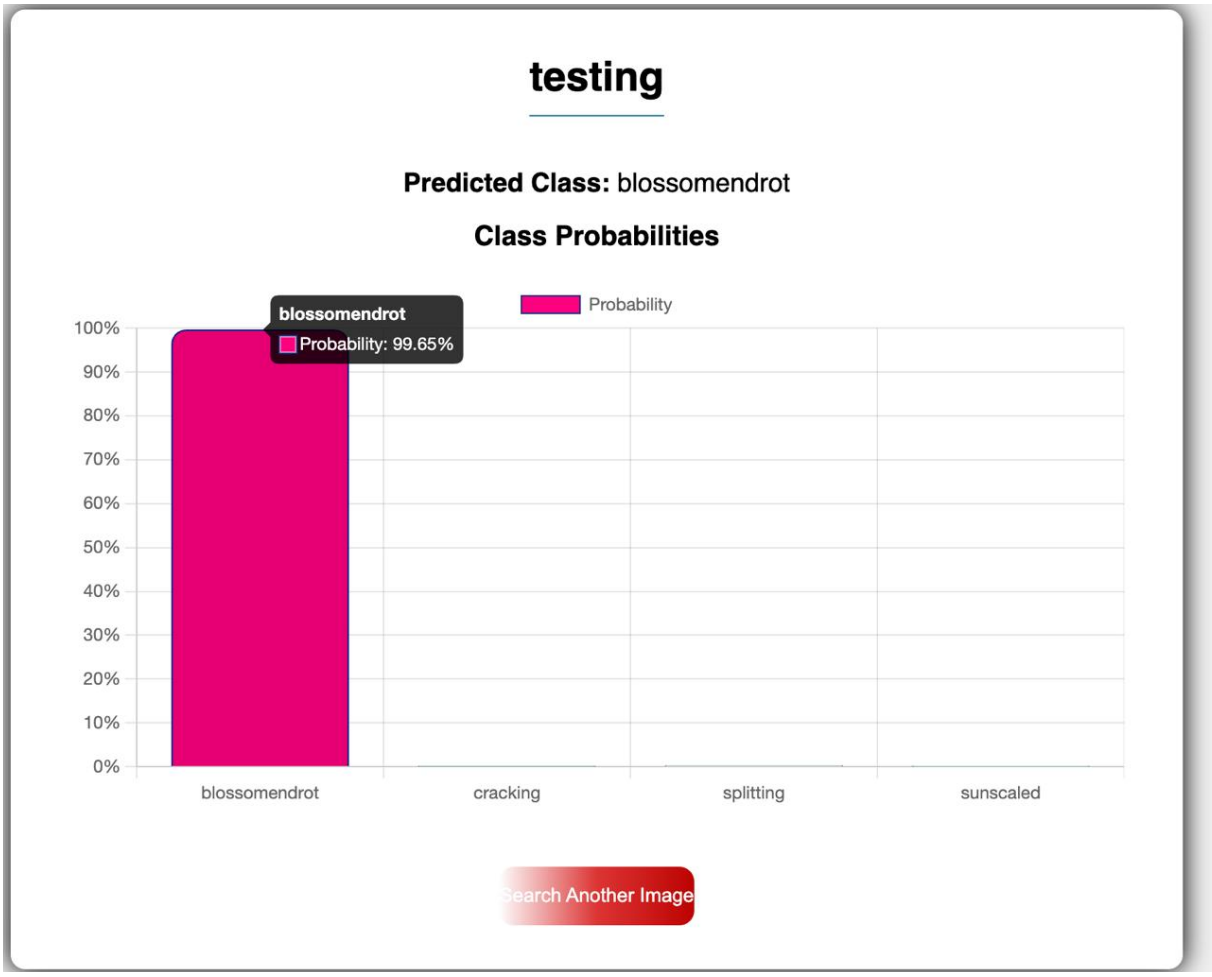

Figure 9(a): Sample from Experimental Results

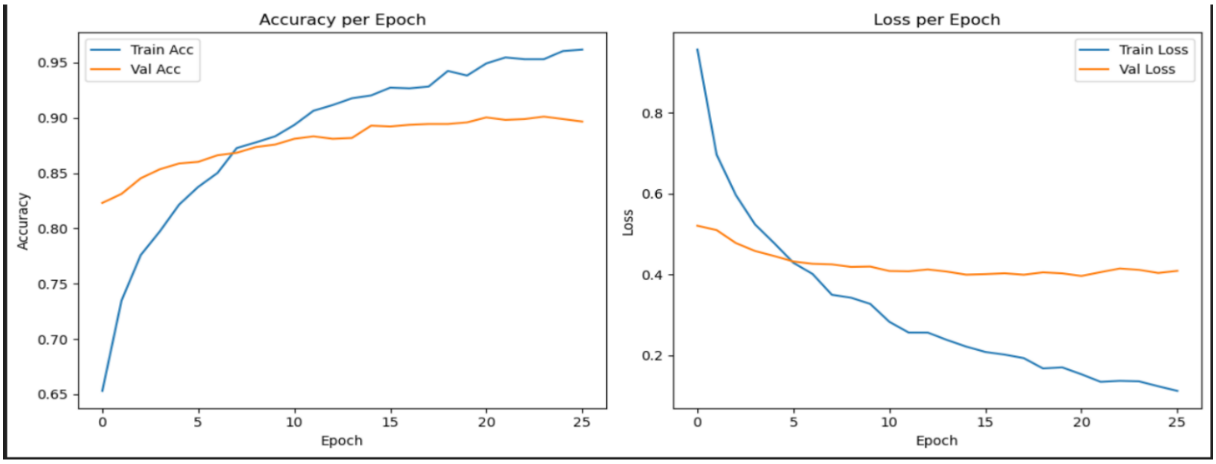

Figure 9(b): Accuracy and Loss per Epoch

Figure 9(c): Precision, Recall, and F1-Score (Bar Plot)

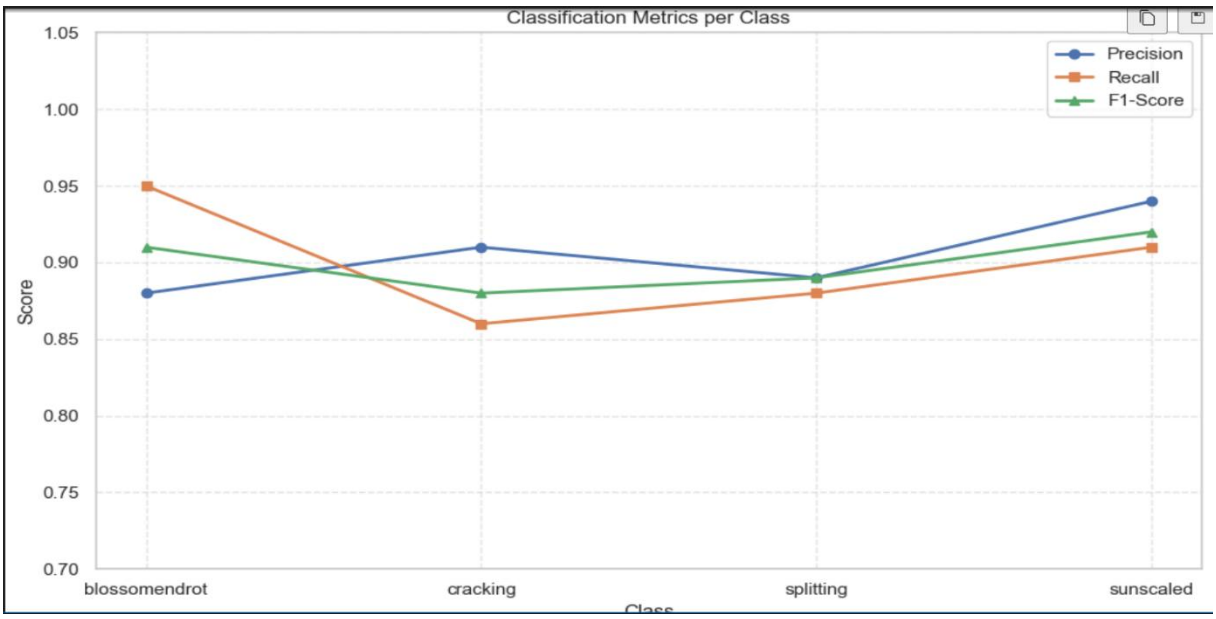

Figure 9(d): Precision, Recall, and F1-Score (Line Plot)

We can see from the 30 epochs across training and validation accuracy for MobileNetV2 model curve, Figure 9(b). As the left panel shows, the training accuracy increases steadily from around 65% to 96%, while the validation accuracy remains roughly 90%, indicating that our model fits general. The right panel shows a sharp drop in training loss coupled with an extended period of stable validation loss, an indication that optimization is proceeding successfully with minimal risk of overfitting. A Figure 9(c) bar chart cross-comparison of precision, recall and F1 score for each tomato disease class. All indicators show excellent performance across the board, with just cracking having a slight drop in recall -suggesting that there may be a small number of cases missed among false negatives for that class. Despite this the F1-scores overall for all classes are equally balanced and above 0.89, evidence that our method has strong categorization power. Figure 9(d) No matter how blossom-end rot has slightly higher recall than precision, of the histogram cracking class is lower in recall than any others. Sunscald and splitting maintain a good balance in all three metrics, thereby showing their consistent positions as tree stainings. Using a line graph for the same classification metrics in Figure 9(d) facilitates the visualization of inter-class performance trends. On the one hand, because blossom-end rot has slightly higher recall than precision, and on the other because cracking has the lowest recall for any kind of tree stain; while Sunscald and splitting both retain a strong balance between all three measures, confirming their constant classification. This graph makes it easy to see subtle metric changes from class to class, reaffirming the bar chart results and giving even more insight into the stability of trends of consistency in categorization.

A confusion matrix has been provided in Figure-10 depicting the various types of diseases identified by this model. Each cell contains the probability of the model making an accurate prognostication or misdiagnosing a particular disease for another. Summing up, it should be pointed out that in the case of the discussed model of scoring the tester’s performance, the obtained accuracy rate was as high as 90.1% across all diseases. However, these statistics merely reflect average performance which does not give information about variations of performance in the case of each separate disease.

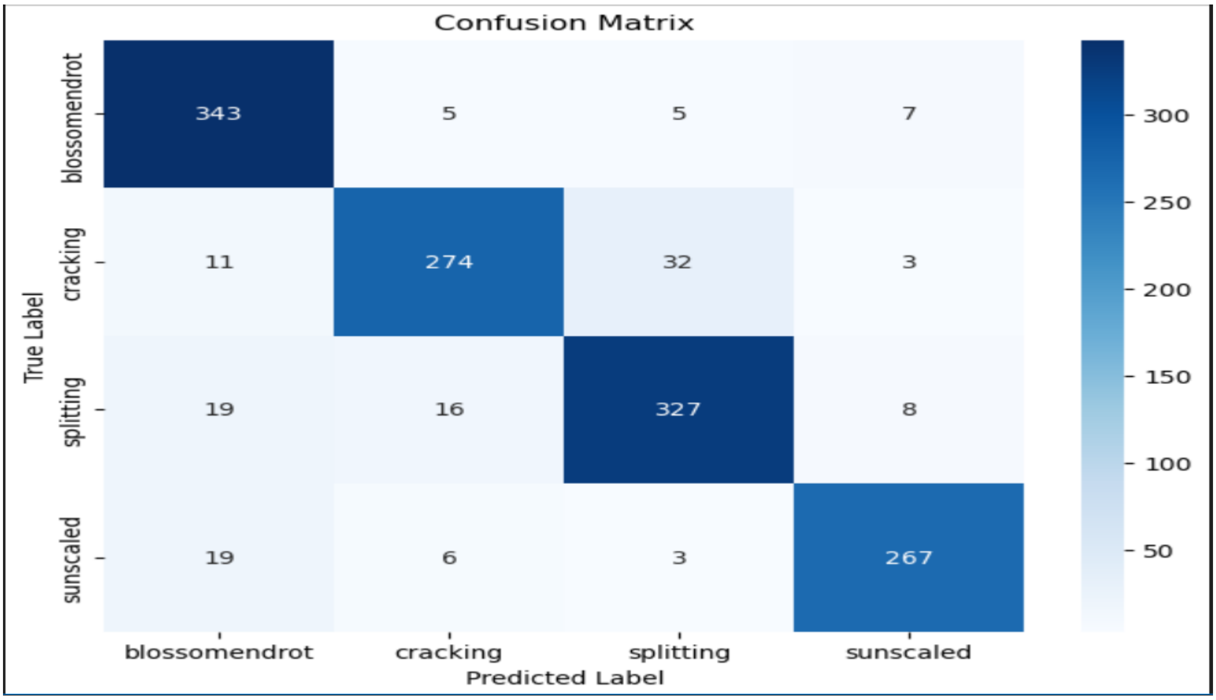

Figure-10: Normalized Confusion Matrix

The following table (Table-1) presents a comparison between our proposed model and two recent studies, focusing on aspects such as the algorithms used and dataset specifications.

Table-1: Comparison Table Between the Proposed Model and Other Recent Studies

Aspect	**Recent Study [16]**	**Recent Study [17]**	**Our Model**
Algorithm	YOLOv8	ResNet152V2, ResNet50, VGG19, Inception V2	MobileNetV2
Dataset	Balanceddata Computer Vision Project		balanceddata - Tomato Disease Images

		20,000 tomato leaf images (768x768, 10 classes)	
Annotation	Bounding boxes for various plant diseases	One-hot label encoding	Image-level class labels
Data augmentation	Applied (rotation, flipping, color adjustments, image resizing)	Rotation, translation, scaling, flipping, shearing	Applied (rotation, flipping, zoom, shearing)
Preprocessing	Resized images to 640 pixels (By default)	Normalization (0–1), resizing (interpolation), label encoding	Resized to 224×224 pixels (MobileNetV2 input requirement)
Training Duration	50 Epochs	Until convergence (early stopping)	30 Epochs
Batch Size	3	Not specified	32
Performance Metrics	Precision, Recall, F1-Score	Precision, Recall, F1-Score	Precision, Recall, F1-Score
Accuracy	67%	Best Model (Inception V2): Train 93.7%, Val 93.7%; Worst Model (ResNet50): Train 71.86%, Val 55.30%	Training Accuracy: 98%, Test Accuracy: 91%

Comparative analysis of our proposed tomato fruit disease classification system based on MobileNetV2 as a reference, we used two recent deep learning studies. The first is YOLOv8 [16], which uses object detection to identify tomato fruit diseases by using bounding box annotations. Although it was efficient in real time application, results were 67 % less accurate than those made with the elaborately annotated ImageNet. The study had to support several heavy loads. The second study, Innovative Approaches in Tomato Leaf Disease Recognition using Deep Learning [17] studied different architecture models such as ResNet152V2, VGG19 and Inception v2 on a large-scale tomato leaf dataset. Although its results are strong, Inception v2 even reaches 93.7 % accuracy, the paper primarily examines leaf related diseases and uses more heavy and long training methods, as well as complicated data enhancement. Our model, on the other hand, worked exclusively with fruit diseases. It used the lightweight MobileNetV2 architecture to reach a training accuracy of 98% and test accuracy of 91 %. In addition, our implementation only took 30 training epochs and used simple augmentation techniques (e.g., rotation, flipping, zoom), making it more practicable for deployment in low resource agricultural environments. These results suggest that our model best balances between power, efficiency and practical usability.

Table-2: Comparing each tomato diseases with respect to performance metrics

Disease Type	Precision	Recall	F1-Score
Blossom End Rot	88%	95%	91%
Cracking	91%	86%	88%
Sunscald	94%	91%	92%
Splitting	89%	88%	89%
Overall	90.5%	90%	90%

CONCLUSION

Tomato fruit diseases represent a serious threat to agricultural productivity, a typical case in which the output of both crop quality and quantity is reduced. This presents a significant challenge to growers because it lifts production costs and reduces the market value for their produce. It is therefore important that these diseases be identified as well as possible as early on as possible so as not only to reduce losses but also to maintain high yields.

This paper develops a deep learning-based solution for classifying four types of tomato fruit diseases using the MobileNetV2 model. With its streamlined framework and high efficiency, the model achieved strong performance, reaching 98% training accuracy and 91% validation accuracy. The system is thus highly efficient, and by this it can be used as a practical tool for identifying diseases under real-world conditions-without much demand from the computer side. Integrating techniques such as preprocessing and data augmentation, the model was able to generalize well over different forms of image, suitable for diverse agricultural situations. This approach also greatly reduces the need for manual inspection, giving faster and more consistent diagnosis.

The next step in research could build up the dataset with more diverse samples to further improve the accuracy of the model. Other deep learning architectures or hybrid models could be tried out too to help improve detection performance. Moreover, laboratory testing in the artificial intelligence model will provide valuable experience into how it works and its practical applicability. With continuous improvements, these AI-adaptations of traditional practices have the potential to support smarter farming practices in respective environments and more sustainable agriculture across different productions.

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