# An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset

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## ABSTRACT

**Deep learning has gained widespread adoption in various fields, including object recognition, classification, and precision agriculture. This study aimed to investigate the use of deep convolutional neural networks for the real-time identification of diseases in tomato plant leaves. A customized field dataset was constructed, consisting of several images of tomato leaves captured using a mobile phone from agricultural fields in the Kerala and Tamil Nadu regions and classified into two categories: healthy and diseased. A YOLO v5 deep learning model was trained to classify images of tomato leaves into the respective categories. This study aimed to determine the most effective hyperparameters for the classification and detection of healthy and sick leaves sections, using both proprietary and publicly available datasets. The YOLO v5 model demonstrated a notable accuracy rate of 93% when evaluated in the test dataset. This method can help farmers quickly recognize diseased leaves and prompt the implementation of preventive measures to curtail the spread of tomato plant diseases.**

***Keywords-convolutional neural networks; deep learning; object classification; plant disease detection; YOLO v5***

## I. INTRODUCTION

Deep Learning (DL) and computer vision are two examples of cutting-edge technologies that have seen tremendous expansion in the agriculture sector over the last few years. Using these technologies can increase agricultural productivity and reduce yield losses caused by plant diseases. Plant diseases have historically been a significant concern for farmers around the world due to the substantial effects they may have, both in terms of crop quality and quantity. Visual examination by experts is the traditional way to determine plant diseases, however, this method is laborious, expensive, and prone to mistakes. The advancement of DL techniques has facilitated the automated and precise identification of plant diseases through the analysis of leaf images. DL, which is sometimes referred to as supervised learning, is a specialized domain within the science of Machine Learning (ML) that encompasses the systematic extraction of patterns and representations from data using neural networks with many layers. DL has several advantages over more conventional ML methods, the most notable being the remarkable accuracy it achieves when applied to high-dimensional data sources, such as still photos, audio, and video.

The development of DL models for the diagnosis of plant diseases has the potential to increase crop production while simultaneously reducing the amount of crop yield lost [1]. The diagnosis of plant diseases has seen a significant improvement due to the incorporation of image-processing methods and ML [2-3]. This approach has the potential to alleviate problems that people and plants are experiencing. Artificial Intelligence (AI) gives humans the ability to communicate with computers and comprehend the requirements of such interactions. However, the reliability and performance of this technology are affected by a variety of challenges, making it difficult for ML approaches to recognize specific diseases [4]. A notable obstacle encountered in the use of ML and DL techniques to detect plant diseases is the considerable computing time required since some approaches depend on obsolete data sources [4]. Significant resources are necessary to develop and implement ML and DL applications, often supported by non-governmental organizations, which may impact their use and development. Image recognition can be used to identify diseased leaves by comparing images of infected and healthy leaves [5]. Traditional image processing techniques have been used, such as segmentation, feature retrieval, and categorization. In [6], an attribute image-based method was proposed to classify wheat plant diseases using a Support Vector Machine (SVM) [6]. DL has seen a surge in its application within agricultural research due to its superior ability to extract profound feature data and surpass conventional ML algorithms [7-8]. In [9], a rider neural network based on the sine-cosine algorithm provided enhanced classification performance. Deep learning has shown promising results in identifying plant diseases [10-13].

This study aims to investigate the field of plant disease detection and develop a DL method to detect tomato plant leaf diseases, on the following basis:

- Collect a diverse dataset consisting of various scenarios and sizes, featuring damaged leaves on sophisticated backdrops with varying lighting and perspectives, providing optimal information for the detection of tomato plant diseases using leaf images.
- Conduct a comprehensive review of current methods and datasets on plant disease identification, offering a comparative analysis of their advantages and disadvantages.
- Use various Convolutional Neural Networks (CNNs) to classify the health status of tomato leaves.
- Determine the hyperparameters of the EfficientDet, Faster R-CNN, and YOLO v5 methods, allowing for a comparison between them for classifying plant leaf diseases.
- Evaluate these methods using standard efficiency parameters, including accuracy, precision, recall, and F1-score.

This study investigated three different approaches for tomato plant leaf detection. The YOLO v5 approach obtained a mean Average Precision (mAP) of 93.1% on both customized and public datasets while maintaining a frame rate of 120 fps.

## II. PREVIOUS WORKS

Since the introduction of DL algorithms, there have been notable improvements in the identification and diagnosis of plant diseases. In [14], a detailed analysis of DL models demonstrated the impact of computer vision techniques and neural networks on the effective detection and diagnosis of plant diseases and the improvement of precision agriculture. In [15], the significant contributions of indoor plants to improving general well-being, reducing stress levels, and improving indoor air quality were examined. In [16], different techniques and tools were examined to identify and treat plant diseases, increase crop production, and ensure long-term viability. In [17], a review of plant-microbiome interactions and their effects on plant health was carried out, shedding light on the broader ecological difficulties associated with managing plant health. In [18], automated methods were investigated to capture optical and infrared (IR) images to determine the level of water stress experienced by a plant. This study examined the potential use of image registration techniques to monitor plant health, which can be used in disease identification efforts. In [19], thermal imaging techniques were examined to monitor and detect stress in tomato plants. Although the main objective of this study was not the diagnosis of diseases, it demonstrated the prospective use of imaging technologies in the realm of plant health monitoring. In [2], existing advances in DL techniques were investigated for the detection and diagnosis of plant diseases, offering valuable information on current challenges and advancements within the domain.

In [3], textural characteristics were analyzed to detect diseased areas in plant leaves and diagnose leaf-related issues, highlighting the importance of texture analysis in the detection and classification of diseases in a way that complements existing DL methods in the field. In [4], CNNs were used to provide a segmentation and quantification solution for cucumber powdery mildew. In [5], imaging chlorophyll fluorescence patterns was employed to investigate the application of supervised ML techniques, namely hidden Markov models, for the accurate identification and classification of plant stress levels and types. This study showcased the use of ML techniques in assessing plant stress levels, facilitating the assessment of disease severity. Although this study did not pertain to the diagnosis of diseases, it demonstrated the promising results of ML. Table I shows a summary of other related works.

TABLE I. SUMMARY OF SELECTED WORKS

| Reference | Year | Methodology used | Dataset Source |
|---|---|---|---|
| [20] | 2021 | CNN | Internet |
| [21] | 2021 | Inceptionv3 and googlenet | Dataset from field |
| [22] | 2022 | ResNet-152 | Internet |
| [23] | 2019 | Image Processing | Dataset from field |
| [24] | 2020 | MobileNet, Faster R-CNN | Dataset from field |
| [25] | 2022 | YOLO v5 | Dataset from field |
| [26] | 2018 | YOLO v3, YOLO v4 | Internet |
| [27] | 2021 | CNN | Internet |
| [28] | 2018 | Residual Network | Internet |
| [29] | 2018 | ANN | Internet |
| [30] | 2007 | IoT | Dataset from field |
| [31] | 2018 | 3D CNN | Internet |
| [32] | 2019 | HSI | Internet |
| [33] | 2019 | Remote sensing | Internet |
| [34] | 2019 | Satellite images | Internet |
| [35] | 2016 | Machine learning | Internet |
| [36] | 2019 | AlexNet | Internet |
| [37] | 2018 | AlexNet | Internet |
| [38] | 2019 | SSD and CNN | Internet |
| [39] | 2023 | Machine learning | Internet |
| [40] | 2022 | DCNN | Internet |
| [41] | 2021 | Segmentation | Dataset from field |

## III. MATERIALS AND METHODS

This study focused on the use of DL techniques for the identification and categorization of tomato plant diseases. This approach involved acquiring data, pre-processing it, and choosing models to train and evaluate. This study also compared YOLO v5 with conventional DL methods and underlined the importance of employing CNNs for efficient photo classification. Figure 1 illustrates the approach followed.

### A. Dataset Collection

Tomato leaf images were collected from the farm of the Department of Agriculture, Karunya Institute of Technology and Sciences (Deemed to be University) in Coimbatore, TamilNadu and Deesan Farm in Palakkad, Kerala, India. The dataset was collected in a real-world environment using an Apple iPhone X mobile camera, capturing images with a resolution of 812×375 pixels. Figure 2 shows examples of images collected in the field. Obtaining and labeling the dataset was a significant challenge. This study also used a publicly available dataset from PlantVillage that contains a total of

54,309 images. During the study, 1,000 images were collected and preprocessed to normalize their proportions, reduce noise levels, and remove background and unwanted distortions. All pictures, even those with several leaves or a mix of good and unhealthy leaves, were able to have bounding boxes created around them with the use of the Roboflow tool. Each leaf was marked with a label indicating whether it was healthy or diseased. A YOLO file was saved with the resulting coordinates of the boxes and the corresponding values for each class. These images were then used as input in the next phase of the study.

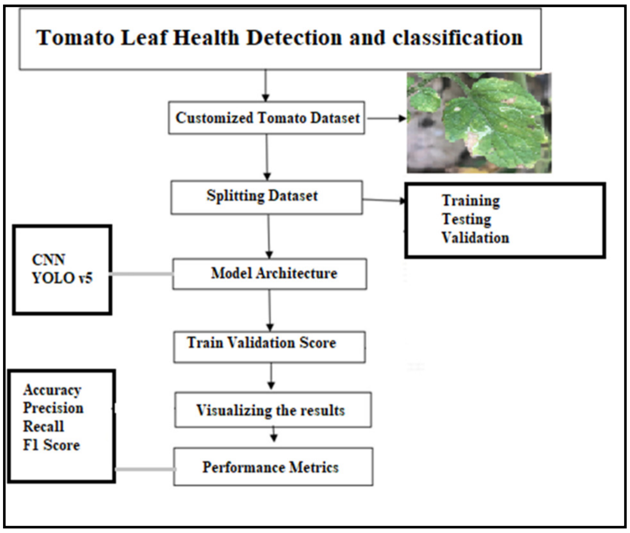


Fig. 1. Proposed tomato leaf health detection process.

Fig. 2. Sample tomato diseased leaf images collected in the field.

### *B. Preprocessing*

Image preprocessing involved various techniques used to improve their quality before feeding them to an ML model. Labeling and annotation are important preprocessing steps for supervised learning tasks, particularly for object detection and recognition in images. In this process, a label was assigned to each image indicating the object of interest, and the corresponding Region of Interest (RoI) was annotated using bounding boxes or masks. This information was used to train the ML model to recognize and classify objects accurately. Annotating and labeling large datasets manually can be a tedious and time-consuming process, but various software tools automate this process to some extent, such as Roboflow. The labeling process was initiated using the Roboflow web application, which involved identifying RoIs by creating bounding boxes. Table III displays the exact number of pictures that were included in each collection. The images in the dataset were labeled as either healthy or diseased, and all subsequent tasks were carried out using Google Colab.

TABLE II. DATASET SIZES

| Type | Number of images |
|---|---|
| Training dataset | 2000 |
| Testing dataset | 206 |
| Validation dataset | 105 |
| Total Number of Dataset | 2311 |

### *C. Training Models Using EfficientDet*

EfficientDet is a modern object detection model that is effective in determining the nature of plant diseases. The object recognition models that belong to this family were developed by Google. These models use a compound scaling approach that enables them to improve accuracy while retaining efficiency. EfficientDet has been used in many research projects to identify plant diseases, such as those that are detrimental to tomato and grape production. EfficientDet has been shown to achieve a higher level of accuracy than other DL models using fewer computational resources. Because of its efficient construction, it has the potential to be used in the agricultural industry in real time. Overall, EfficientDet has the potential to benefit farmers around the world by enabling the efficient and accurate detection of plant diseases.

### *D. Training Models with Faster Region-based CNNs*

The Faster R-CNN architecture is often used for object recognition tasks [42]. This method uses an instrument known as a Region Proposal Network (RPN), which generates prospective object regions before classifying and refining them. Faster R-CNN has been applied to plant health monitoring by using aerial images to detect and classify different types of plant stress, such as nutrient deficiencies or pest infestations. Training the Faster R-CNN model on annotated images of healthy and stressed plants can accurately identify stress areas and provide valuable information to farmers for targeted interventions.

### *E. Training Models Using YOLO v5*

YOLO (You Only Look Once) is a widely used method for object recognition that has undergone several iterations, the latest being YOLO v5. The design of YOLO v5 exhibits improved efficiency compared to its predecessors, resulting in improved accuracy and speed for object recognition. The architectural components of YOLO v5 include a backbone network, a neck network, and a head network. The primary function of the backbone network is to extract distinctive characteristics from the input picture. The aforementioned variables are then sent to the neck network, which is responsible for the fusion of features and the aggregation of geographical data. Subsequently, the brain network makes predictions about the object's class labels and bounding boxes, depending on the specific characteristics of the picture.

The CSPDarknet design has been revised and adapted for use in the development of the YOLO v5 backbone network. To enhance the process of feature extraction, this architecture integrates convolutional layers with shortcut layers. The neck network has two modules, namely the Path Aggregation Network (PAN) and the Spatial Pyramid Pooling (SPP) module. These modules contribute to enhancing the precision of object recognition by integrating data from various scales. The primary neural network uses a hybrid architecture consisting of convolutional and linear layers to provide estimations on the classification labels and the bounding boxes of objects. Upon acquiring the YOLO v5 repository, the necessary plugins were installed to begin its customization. Subsequently, a model was trained on a Tesla 4, presumably using a freely accessible environment provided by Google Collab. The data were then partitioned into training, testing, and validation sets using the Roboflow platform. Following the preprocessing procedures and augmentation methods, the YOLOv5 PyTorch format was used to annotate the images. Ultimately, the training, testing, and validation processes were completed in Google Collab using Python. Table III shows the results of the training assessment metrics obtained from the analysis of the custom and public datasets. Each dataset had a total of 1000 photos. Training and testing were performed independently for each dataset.

TABLE III. YOLO V5 MODEL USING CUSTOMIZED AND PUBLIC DATASET

| Type of Dataset | Accuracy | Precision | Recall |
|---|---|---|---|
| Dataset from field | 61% | 60% | 62% |
| Public | 60% | 61% | 63% |

## IV. RESULTS AND DISCUSSION

YOLO v5 is a cutting-edge object detection model capable of achieving high mAP with only a small amount of necessary resources. At first, YOLO v5 was used in the field dataset created in this study. However, since there was only a limited number of pictures available, it was combined with a publicly available dataset to attain an acceptable level of average accuracy. The YOLO v5 YAML required two files to be loaded to begin training. The test and training data locations were provided in the first YAML file. Along with the names of the individual things that belonged to each class, it also included the total number of object classes that could be recognized.

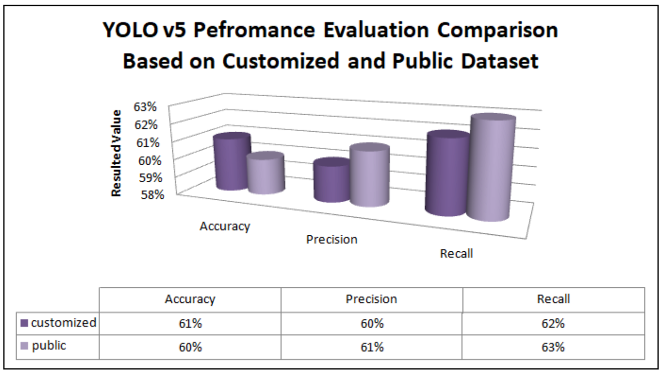


Fig. 3. Performance metrics of the enhanced YOLO v5 model.

The results showed that the model achieved an accuracy of 93%, a precision of 75%, and an mAP score of 95%. YOLO v5 was 2.5 times faster than R-CNN while achieving superior results and recognizing even smaller objects. This was one of the finest aspects of the functionality of YOLO v5. Figure 4 shows the mAP score for the three methods examined. The study included a growing number of epochs, which increased the overall mean area of the curve. The concepts of accuracy, recall, and Intersection over Union (IoU) were used throughout the process of graph construction.

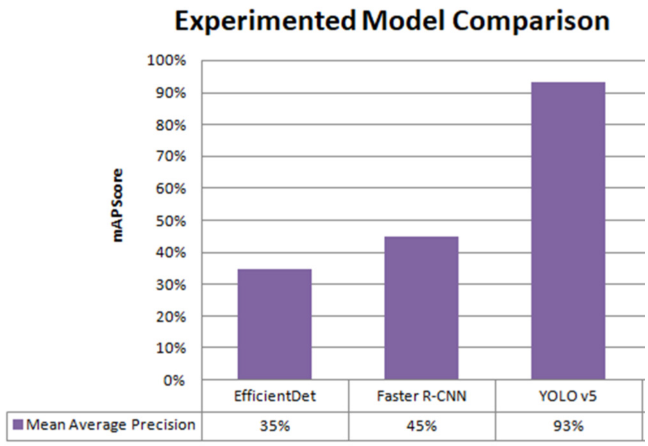


Fig. 4. Comparative analysis between all implemented models.

## V. CONCLUSIONS

This study used DL algorithms to distinguish between healthy and unhealthy tomato leaves. The initial phase was to collect images of tomato leaves, which were divided into two groups. The dataset contained both private and public images. Labeling was the most crucial step in the preparation since it had to be performed in a manner that satisfied the selective neural network used to recognize items and indicate an area of interest. This study used enrichment methods to increase the quantity and improve the quality of the collected samples. This study conducted a comparative analysis of three deep neural network models in a real-world setting to identify optimal hyperparameters and effective data validation techniques. For Faster R-CNN, the precision, recall, and accuracy achieved were 0.49, 0.47, and 0.35, respectively. The observed values exhibited a significant disparity compared to the other models. The results showed that the YOLO v5 model achieved a 93% mAP rate, which was significantly higher compared to the Faster R-CNN and EfficientDet models.

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