Optimized Custom CNN for Real-Time Tomato Leaf Disease Detection

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Abstract. Early diagnosis and treatment of tomato leaf diseases enhance plant productivity, efficiency, and quality. Misdiagnosis can lead to inadequate treatment, damaging both the plants and the agroecosystem. Therefore, accurate disease detection is essential. A rapid, precise approach to disease identification will benefit farmers significantly. Traditional manual inspection methods, while effective, are labor-intensive and prone to human error. To address these challenges, this research proposes an automated disease detection system using a custom Convolutional Neural Network (CNN). A comprehensive dataset of tomato leaves was collected, and a comparative performance analysis was conducted between YOLOv5, MobileNetV2, ResNet18, and our custom CNN model. The custom CNN model achieved an impressive accuracy of 95.2%, significantly outperforming the other models. Finally, the best-performing model was deployed in a web-based end-to-end (E2E) system, allowing tomato cultivators to classify tomato leaf diseases efficiently in real time.

Keywords: Convolutional Neural Networks (CNN), Deep learning, Tomato leaf, YOLOv5, MobilenetV2, ResNet18

1 Introduction

Agriculture plays a key role in feeding the global population, and technological advancements, particularly Artificial Intelligence (AI), have significantly improved farming practices. AI helps farmers increase crop yields, optimize resource use, and streamline operations. AI-driven solutions are widely used for optimizing irrigation [1], predicting crop yields [2], and automating pest control [3]. These technologies leverage machine learning (ML) algorithms to analyze large volumes of agricultural data, enabling informed, real-time decision-making. A key application of AI is computer vision for plant health monitoring, where deep learning (DL) techniques allow for accurate disease detection. Studies show how ML can optimize crop output and minimize environmental impact [4], enhancing farm productivity. Another study [5] examines AI integration in vertical farming, highlighting its role in improving decision-making in controlled environments.

Tomatoes are one of the most widely cultivated and economically significant crops globally. In addition to being nutrient-rich, tomatoes offer pharmacological

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(a) Healthy leaf images

(b) Diseased leaf images

Fig. 1: sample of leaf images(random) collected from the field

benefits, providing protection against conditions such as hypertension, hepatitis, and gingival bleeding [6]–[7]. However, various leaf-borne diseases adversely affect tomato yield and quality. As illustrated in Fig. 1, healthy tomato leaves typically exhibit vigor, uniform coloration (unless variegated), open growth, and an upright posture. In contrast, diseased leaves often display visible symptoms and deformities. The inability to accurately detect leaf diseases can significantly reduce both yield and quality, which in turn can negatively impact a country's economy [9]. According to the Food and Agriculture Organization (FAO) of the United Nations, global agricultural output must increase by 70% by 2050 to meet rising food demands [10]. However, the use of disease-control chemicals like fungicides and bactericides can pose risks to the environment, and misdiagnosis of diseases often leads to ineffective treatments that further damage crops. Expert-led field assessments are time-consuming and costly. As a result, there is an urgent need for a fast and reliable method for disease classification in agriculture. Recent advancements in technology—particularly image processing offer promising solutions for early identification of tomato leaf diseases [8] which helps reduce crop loss, lower processing expenses, and minimize environmental harm caused by chemical contamination of soil and water [11]. Our key contributions:

1. We proposed a new dataset consisting of 482 healthy leaves and 546 diseased leaves for disease detection.
2. We propose an optimized custom CNN model for classifying tomato leaf diseases into healthy and diseased categories.
3. Our proposed custom CNN model achieved satisfactory classification accuracy and outperformed pre-trained models such as MobileNetV2, ResNet18, and YOLOv5, as well as other existing models.
4. The model has been deployed in a web-based application, providing farmers with an accessible and user-friendly tool for early disease detection.

2 Literature Review

Several studies have been conducted to detect and classify tomato leaf diseases, leveraging various machine learning and deep learning (DL) techniques to improve classification accuracy. Hatuwal et al. [13] explored multiple machine learning models, including Support Vector Machine (SVM), K-nearest Neighbour (KNN), Random Forest Classifier (RFC), and CNN for plant disease detection.

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Among these, the CNN model achieved the highest accuracy of 97.89%, surpassing RFC, SVM, and KNN. Madhulatha et al. [15] used a deep CNN model based on the AlexNet architecture, achieving 96.50% accuracy for the Plant Village dataset, which contains 54,323 images across 38 disease categories. Zhang et al. [16] introduced an improved Faster RCNN to classify four disease categories and healthy tomato leaves using a depth residual network for image feature extraction and a k-means algorithm for bounding box clustering.

On recent study, Zhao et al. [19] utilized a deep CNN with residual blocks and attention extraction modules, achieving 96.81% accuracy with the SE-ResNet-50 model on a dataset of 22,925 augmented images across ten classes. Kannan et al. [20] used a pre-trained ResNet model to classify tomato leaf diseases, achieving 97.00% accuracy with ResNet-50 on a dataset of 12,206 images, demonstrating the effectiveness of deep CNN models in plant disease classification. Another study by Rajasree et al. [14] used YOLOv5 for real-time detection of tomato leaf diseases, achieving a notable accuracy of 93%. They compared YOLOv5 with MobileNetV2-YOLOv3 techniques, showing that the latter provided superior accuracy and stability for tomato leaf spot detection. Agarwal et al. [12] proposed a CNN model that outperformed pre-trained models such as VGG16 (77.2%), MobileNet (63.75%), and Inception (63.4%), achieving 91.2% accuracy. Their study emphasized the advantages of using a custom CNN model, which required less storage space (1.5 MB) compared to pre-trained models (100 MB). Elhassouny [21] developed a CNN-based model deployed on a mobile application for recognizing tomato leaf diseases, achieving 90.30% accuracy. While deep CNN models show great potential, there remains a gap in classifying diseases under varying lighting conditions. This study proposes a custom CNN model deployed in a web application, providing a practical tool for farmers to detect tomato leaf diseases and take timely action.

3 Methodology

Fig 2 illustrates the system architecture in two phases: building and deployment. In the building phase, tomato leaf images are augmented (rescaling, rotation, shifting, zooming, flipping) and used to train a custom CNN for binary classification with the Adam optimizer and binary cross-entropy loss. In the deployment phase, models are evaluated using accuracy, loss, and confusion matrix metrics, and the best-performing model is deployed via an Web-based system for predicting tomato leaf diseases.

3.1 Dataset Description

We collected tomato leaf images from fields in Mohammadpur, Brahmanbaria, Bangladesh, using two smartphones: the Redmi Note 10 Pro and Samsung Galaxy A10 [17]. The images, which included healthy leaves, diseased leaves, and those affected by environmental stresses, were taken with the consent of the

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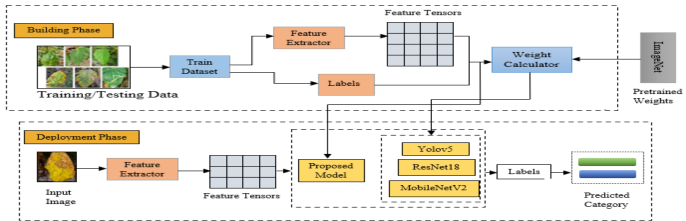

Fig. 2: A systematic representation of our proposed approach

garden owners in early February 2024. The weather varied between sunny (26-29°C) and foggy (17-18°C) days. A total of 482 healthy leaves and 546 diseased leaves were captured and organized into 'Healthy' and 'Diseased' separately. Data preprocessing is essential for improving model performance and reducing training time. First, we annotated the images with bounding boxes for each leaf to be detected, using the YOLO annotation format (class labels and bounding box coordinates). The images were manually labeled using the MakeSense [3] software and exported the annotations in a text file.

3.2 Proposed Custom CNN:

The proposed custom CNN model processes resized tomato leaf images of 224×224 dimensions with three color channels. The architecture consists of 4 convolutional layers, each with a 2×2 kernel and "same" padding, followed by max pooling layers of the same size for down-sampling. This reduces spatial dimensions and improves computational efficiency. The model includes 3 dropout layers with a 20% rate to prevent overfitting, and a fully connected (FC) layer connected to a dense output layer using SoftMax for multiclass classification. Weights are initialized using the Xavier Glorot uniform method($r = \sqrt{\frac{6}{X_i + X_o}}$) where X_i and X_o are the input and output connections. The ReLU activation function ($y = \max(0, x)$) is used in hidden layers for non-linearity and faster learning . The Adam optimizer, with a learning rate of 0.001, is used to minimize prediction error and adjust weights efficiently. Categorical Cross-Entropy is used as the loss function, combining SoftMax and Cross-Entropy to calculate the model's prediction accuracy. The training involves 100 epochs with a batch size of 32. Callbacks monitor validation loss to ensure the best-performing model is saved. Training parameters are summarized in Table 1.

4 Experiment

4.1 Benchmark Models

- **CNNs:** CNNs consist of convolution layers (for feature extraction), pooling layers (e.g., max pooling for dimension reduction), and fully connected layers

[3] https://www.makesense.ai/

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Table 1: Training Parameters for the Proposed Custom CNN Model

Parameter	Description
Optimization algorithm	Adam optimizer
Learning rate (α)	0.001
Weight initialization	Xavier Glorot uniform
Batch size	32
Number of epochs	100
Dropout rate	0.2 (20%)
Loss function	Categorical Cross-Entropy
Activation function (hidden layers)	ReLU
Activation function (output layer)	SoftMax
Kernel size (convolution layers)	2×2 with "same" padding
Kernel size (max pooling layers)	2×2

for classification. Techniques like ReLU activation, dropout, and batch normalization help improve performance and prevent overfitting, making CNNs ideal for tasks like image classification [8].

- **YOLOv5:** It is a powerful object detection model which incorporates dynamic anchor boxes, spatial pyramid pooling, and a CSPDarknet backbone for feature extraction. The model uses SiLU and Sigmoid activations, optimizing training with Binary Cross Entropy and CIoU loss [14].
- **MobileNetV2:** It is a lightweight CNN designed for mobile and embedded vision applications using depthwise separable convolutions, inverted residuals, linear bottlenecks, and squeeze-and-excitation blocks to reduce complexity while maintaining performance.
- **ResNet18:** It is a deep residual network that mitigates the vanishing gradient problem using residual learning. Its 18 layers with residual blocks, Batch Normalization, and ReLU activations improve feature extraction and training efficiency [18].

4.2 Evaluation Metrics

Model effectiveness is evaluated using accuracy(A), precision (P), recall(R), and F1-score(F1). Accuracy, defined as the percentage of correct predictions ($\frac{TP+TN}{TP+TN+FP+FN}$, where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively). Precision ($\frac{TP}{TP+FP}$), measures the proportion of true positives among predicted positives. Recall ($\frac{TP}{TP+FN}$), measures the proportion of true positives among actual positives. The F1-score ($2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$), is the harmonic mean of precision and recall, providing a balanced measure of a model's performance..

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5 Experimental Results

Table 2 presents the experimental results, including validation loss (L). Our proposed model achieved the highest performance across all metrics, with an accuracy of 95.2%, a recall of 0.92, and a balanced F1 score of 0.92, indicating strong performance in identifying diseased leaves. YOLOv5 achieved 84% accuracy, with a recall of 0.82 and F1 score of 0.83. MobileNetV2 performed similarly, with 89% accuracy, a recall of 0.88 and precision of 0.87. ResNet18 showed the lowest performance, with 82% accuracy and an F1 score of 0.84. These results highlight the challenges faced by pre-trained models in this specific task.

Table 2: Comparison among different models

Model	**R**	**P**	**F1**	**A**	**L**
Custom CNN	0.92	0.93	0.92	95.2%	0.22
YOLOv5	0.82	0.84	0.83	84%	0.48
MobileNetV2	0.88	0.87	0.88	89%	0.30
ResNet18	0.81	0.88	0.84	82%	0.51

Table 3: Result comparisons with related studies

Reference	**Best Model (Accuracy)**
Agarwal et al. [12]	Custom CNN (91.2%)
Zhang et al. [16]	ResNet with SGD (96.51%)
Basavaiah et al. [11]	RT (94.00%)
Zho et al. [19]	ResNet-50 (97.00%)
Elhassouny [21]	MobileNet (90.3%)
Our proposed approach	Optimized CNN (95.00%)

Table 3 presents recent works on tomato leaf disease classification, listing the applied architectures and best-performing models with their accuracy. Various CNN models, including transfer-learning-based CNNs and custom CNNs, have been used for this task, along with ML models, Fuzzy SVM, and R–CNN. Unlike many studies that used small datasets, our study utilizes a larger dataset with images captured in diverse environments. Additionally, our study processed a compact and efficient model that achieves higher accuracy compared to other research in this area. Furthermore, we deployed the best-performing model in a web-based application for real-time classification of tomato leaf diseases. Fig. 3 illustrates the process of the locally deployed tomato leaf disease system, where users can upload a tomato leaf image for classification by the proposed model. The system's frontend is built using HTML and CSS, while the backend utilizes the Python Flask framework. The result is displayed on the screen after classification.

6 Conclusion

This study used deep learning to classify healthy and diseased tomato leaves, comparing YOLOv5, MobileNetV2, ResNet18, and our proposed Custom CNN

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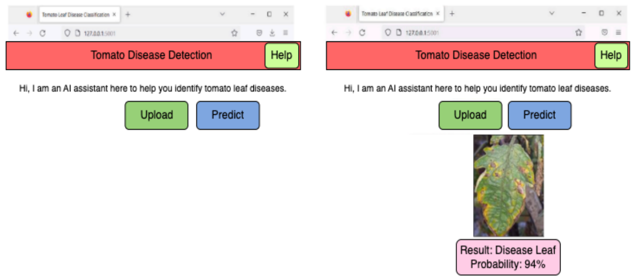

Fig. 3: Web application for tomato leaf disease classification using our proposed Custom CNN model.

model. The Custom CNN achieved the highest accuracy of 95.00%, outperforming the other models. While YOLOv5 and MobileNetV2 performed well, ResNet18 showed weaker results, particularly in recall and precision. The study also deployed the best model in a webapp for real-time tomato leaf disease prediction. Future work can expand on these findings for real-time classification tasks and apply the approach to other plants, combining techniques like segmentation and feature extraction for improved results.

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