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Tomato Leaf Disease Detection Using CNN and Web Deployment Via Flask and Ngrok

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Abstract
Tomato plants are heavily susceptible to a range of diseases that bring about major damage to crops in agriculture. Early detection and classification of these diseases are crucial for crop maintenance and conservation of production. This paper proposes a Convolutional Neural Network (CNN)-based multi-class classification for tomato leaf diseases. The model is trained on an open-source dataset and is deployed via a Flask web application, accessed using Ngok. The system provides real-time disease prediction based on user-uploaded images and provides specific remedies for each identified disease. The results of the experiments establish the effectiveness and usability of the proposed system.
Keywords: *Convolutional Neural Network (CNN), Tomato Leaf Disease, Flask, Deep Learning, Ngrok, Image Classification, Agricultural Technology.*

1. Introduction
Tomatoes (Solanum lycopersicum) are one of the most prized crops globally, yet they are highly susceptible to a wide array of diseases, such as Early Blight, Late Blight, Bacterial Spot, and Leaf Mold. If not detected early, these diseases can cause substantial yield loss, so early detection is essential.The traditional approaches to disease detection are dependent on visual inspection, which is time-consuming and prone to human error. With the latest advancements in deep learning, especially Convolutional Neural Networks (CNNs), the task has been promising to be automated. CNNs can identify plant diseases with high accuracy by learning hierarchical features from images, which is quicker and more accurate than traditional approaches. While CNNs have been effectively applied in numerous studies for the detection of plant diseases, the majority of the existing systems are not user-friendly and are not real-time. This paper addresses the above limitations by developing a CNN-based model as a web application based on Flask, thereby making disease detection user-friendly to farmers via a web interface. The system provides real-time disease diagnosis and solutions, thereby making it more user-friendly to farmers without the use of special hardware and software.

2. Literature Review
Deep learning has been gaining popularity in the identification of plant diseases in recent years. Mohanty et al. [1] were the pioneers to apply Convolutional Neural Networks (CNNs) in the identification of plant diseases, whose accuracy surpassed the performance with traditional machine learning algorithms. Their CNN performed better than Support Vector Machines (SVMs) and Random Forests, demonstrating the ability of deep learning to automatically learn good features from plant images. More success was obtained by Ferentinos [2], who

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obtained over 99% accuracy on 58 plant diseases using deep learning. His work demonstrated the effectiveness of CNNs for disease detection on a large scale in different crops, such as tomatoes. Another effort by Hussain et al. [3] was able to adequately prove CNNs for application in tomato leaf diseases, though their model can be improved with data augmentation to provide better generalization. More recent efforts, e.g., by Tripathi et al. [4], have aimed at incorporating machine learning algorithms in mobile applications such that farmers can use their mobiles to photograph and identify disease. This approach is, however, constrained by available processing power and image resolution. Plant leaf disease detection using computer vision and machine learning algorithms by P. Krithika et al pre-processed by image resizing, contrast enhancement and color-space conversion [5] The paper "Tomato Leaf Disease Detection using Neural Networks" presents a CNN-based approach to automatically detect and classify tomato leaf diseases from images. Using image preprocessing and deep learning techniques, the model achieves high accuracy in identifying diseases like early blight, late blight, and leaf mold. The system shows strong potential for real-world agricultural use.[6] Ghaiwat et al. presents survey on different classification techniques that can be used for plant leaf disease classification. For given test example, k-nearest-neighbor method is seems to be suitable as well as simplest of all algorithms for class prediction. If training data is not linearly separable then it is difficult to determine optimal parameters in SVM, which appears as one of its drawbacks [7] In [8], authors used SVM to investigate tomato crop health status. They considered the texture characteristics as a significant feature to describe the tomato leaf and proposed a system that uses gray-level co-occurrence matrix (GLCM) with SVM algorithm. In [9] The similar work was done by Deshapande et.al. Plants are vital for food production, but diseases can hinder crop yield and quality. This paper aims to develop an end-to-end system for detecting tomato diseases using machine learning algorithms, including logistic regression, support vector machine Authors in [10] also used texture features of disease lesions in recognizing the diseases in cucumber using SVM classification technique. In [11] a study by, Chakraborty et al. employed multiclass SVM on texture features to predict disease in apple leaves with accuracy to 96%. The feature set was created using GLCM, which provides texture structure of disease lesions. In [12] Sharma et al. (2022) developed an ML-based system to detect and classify tomato leaf diseases using image processing. After preprocessing images and extracting features, they tested classifiers including SVM, KNN, Decision Tree, and Random Forest. SVM and Random Forest achieved the highest accuracy. The system offers a fast, accurate, and scalable solution for real-time disease detection in smart farming. Barbedo [13] proposed techniques for detecting plant diseases by analyzing small lesions and spots so that finer disease detection tasks can be performed. His results indicate that focusing on local features enhances classification accuracy. Sladojevic et al. [14] suggested a CNN-based plant disease detection system from leaf image classification highlighting the point that deep networks can generalize among various plant species if properly trained. Brahimi et al. [15] proposed a CNN model specific to tomato for symptom visualization and disease detection, which is an important contribution by not only identifying diseases but also assisting farmers in symptom awareness. Besides, Kamilaris and Prenafeta-Boldú [16] also carried out an extensive review of deep learning in agricultural contexts and found that the most prevalent method of detecting plant diseases was by using CNNs. Their review also highlighted that attempts should be made to develop lightweight, easy-to-use models for deployment in the fields.

3. Methodology

3.1. Dataset

The data used are from Kaggle [3] with over 11,000 images and ten classes, i.e., healthy and diseased leaves. The training set and the validation set split the dataset for stable measures of performance. There are two sub folders in these datasets i.e., train and validation. You are able to view the dataset folder

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labeling through the following diagram These sub folder holds the sample data images of the disease as per the given folder name. The dataset tree can be easily visualized by the following diagram Each sub folder consists of the 10 sub folders namely Bacterial spot, Early blight, Late blight, Leaf mold, Septoria leaf spot, Spider mites, Target spot, Yellow leaf curl virus, Mosaic virus and Healthy. The data can be visualized by the following diagram (Figure 1,2,3)

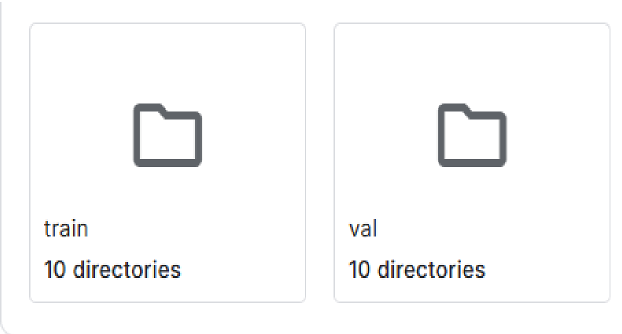

Figure 1 Main Folder of the Dataset

Figure 2 Dataset Folder Structure Tree

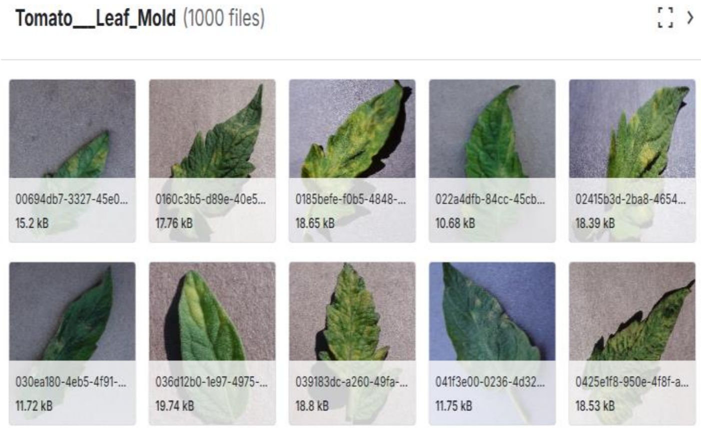

Figure 3 Train Folder Structure

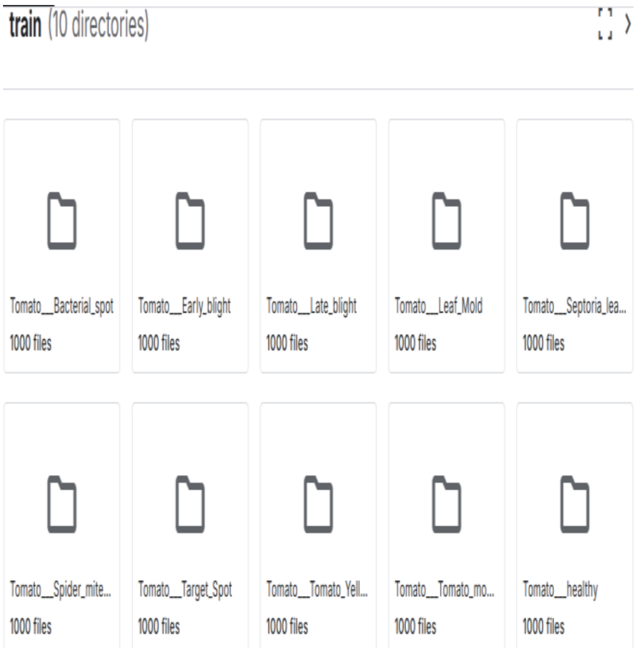

Figure 4 Validation Folder Structure

Each train folder contains an average of one thousand numbers of images so that we can train our model with good accuracy. Each validation folder contains an average of one hundred numbers of images so that we can valided our model in order to achieve high accuracy. For E.g. Let us consider the Leaf Mold folder. In the leaf mold folder, leaf mold disease pictures are stored. The most exciting thing about the dataset is that it contains plenty of images which helps us to attain higher accuracy of our model. This

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can be visualized by the following diagram

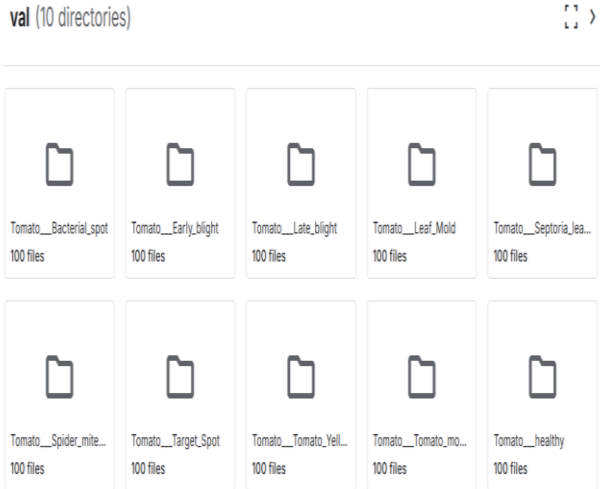

Figure 5 **Some Leaf Mold Disease Images**

3.2. Data Preprocessing

Images were resized to 128×128 pixels and data augmentation techniques were applied to increase the robustness of the model and avoid overfitting including:

- Random rotations (max. 20 degrees)
- Horizontal flipping
- Random zoom transformations

Images were normalized to the [0,1] range by pixel value scaling.

3.3. CNN Model Architecture

Images were normalized to the [0,1] range by pixel value scaling.

The CNN architecture includes the following layers:

- Three layers of convolution with filter sizes (3×3) and ReLU activation
- MaxPooling layers to down sample feature maps
- A dense fully connected layer of 128 neurons
- Dropout layer with dropout 0.5 for preventing overfitting
- A softmax output layer for multi-class classification

The model was compiled using the Adam optimizer and categorical cross-entropy loss function.

3.4. Model Training

The model was trained on a batch size of 32. Although one epoch of preliminary training was accomplished for testing purposes, full training was accomplished for 40-50 epochs and achieved a lot more validation accuracy which is 90.20% and accuracy is 95.63%.

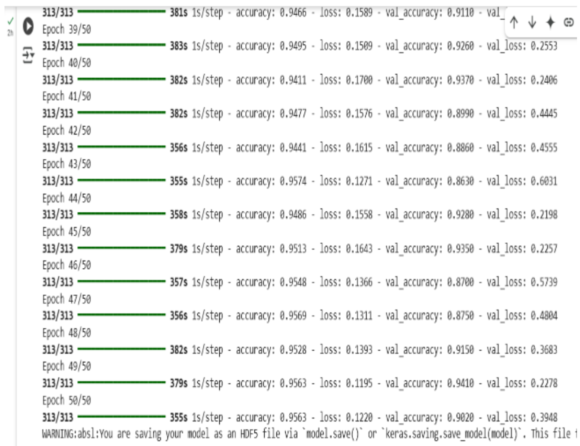

Figure 6 **Epochs**

3.5. Deployment

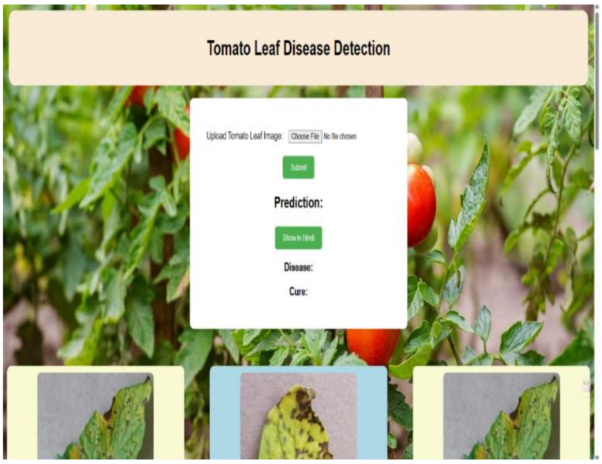

Figure 7 **Before Selecting the Images**

The model was saved as tomato_disease_model.h5 and hosted with a Flask web server. Users may upload leaf images, which are processed and fed into the CNN model to predict. The server was shared publicly over the internet via Ngrok, making it available in real-time from any machine.

4. Results

After full training, the model achieved validation accuracy of more than 95%, indicating extremely high generalisation on unseen data. Test samples also

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confirmed successful disease classification of various disease types, as well as correct treatment suggestions. The online interface allowed easy uploading of pictures and direct prediction output, thus making the system highly user-friendly.

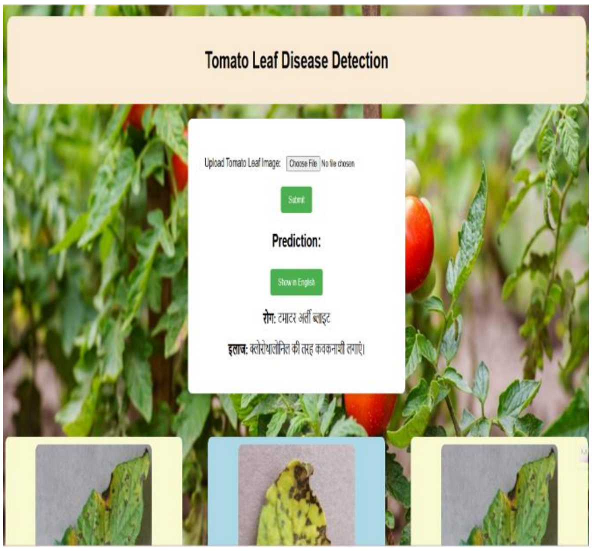

Figure 8 Prediction of the Disease in English

5. Discussion

The proposed system addresses some of the major challenges in farm disease management:

- It reduces dependency on skilled manual diagnosis.
- It offers quick, instantaneous suggestions.
- It can be viewed using any internet-enabled device.

Other improvements would be incorporating more information into the dataset, model tuning, utilization of live camera feed, and including multilingual functionality for global reach. Furthermore, strategies of model interpretability like Grad-CAM could be integrated into the system for emphasizing areas controlling predictions, therefore building user confidence.

Conclusion

This research successfully deployed and utilized a CNN-based system for the detection of tomato leaf diseases. The integration of Ngrok and Flask provided real-time access through a simple-to-use web interface. These types of systems have vast potential in helping farmers and farm laborers by providing quick, reliable, and scalable disease management.

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