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Automated Detection and Classification of Tomato Crop Diseases Using Convolutional Neural Networks

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Abstract
Tomato plants, a globally significant horticultural crop, are frequently threatened by a range of diseases that compromise yield and quality. Traditional disease detection methods based on manual inspection by experts are often labour-intensive, time-consuming, and susceptible to human error. This study presents a machine learning-based approach that leverages Convolutional Neural Networks (CNNs) to automate the identification and classification of common tomato diseases using leaf images. A comprehensive dataset, including both healthy and diseased leaf images, was collected, pre-processed, and augmented to enhance model performance under various environmental conditions. A custom-designed CNN model was then trained and evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The model demonstrated high classification accuracy and robustness across multiple disease categories including early blight, late blight, and bacterial spot. Furthermore, the system was deployed as a user-friendly web and mobile application interface, allowing real-time diagnosis in the field. This enables farmers especially in resource-constrained settings to identify and respond to infections early, thereby reducing yield losses and limiting excessive pesticide use. The project underscores the potential of AI-driven solutions in modernizing agricultural practices and promoting sustainable crop management. Recommendations are made for future work to improve model adaptability, extend its disease coverage, and integrate environmental sensor data for multimodal analysis.

Keywords: *Tomato Disease Detection, Convolutional Neural Networks (CNNs), Deep Learning, Image Classification, Precision Agriculture.*

1.0 Introduction

One of the most produced and commercially important crops worldwide, tomatoes greatly help agriculture. However, they are also quite susceptible to several diseases that may seriously affect production and quality. Older approaches of disease identification in tomato crops are basically slow-moving, prone to human error and subjectivity visual detection by agricultural experts. But given illness detection techniques based on photos (Jiang et al., 2021), the development of artificial intelligence (AI) and machine learning (ML) technology has presented fresh opportunities to address this problem in recent years.
CNNs that automatically learn to extract

features from a picture and identify them as healthy or unhealthy plants with good accuracy can be used. Other agricultural uses for CNNs have been successfully exploited, including the diagnosis of tomato disease (Brahimi et al., 2018), hence transforming disease control into contemporary agriculture.

In current age of unsustainable farming methods and food demand, CNNs application of tomato crop disease detect is vital. Early and accurate illness identification not only allows time procurement action to prevent losses before they spread but also aids in the lowering of pesticide use, largely detrimental to nature. Moreover, especially in places without agricultural professionals, these automated disease detection systems can be very beneficial to farmers (Saleem et al., 2022).

The results of this work could lead to increased agricultural productivity at reduced environmental costs, along with higher income earning potential for farmers.

Tomato crops are essential components of agricultural production as they are a source of staple food and income to farmers in different parts of the world. However, these crops are also subject to a lot of disease incidences such as late blight, early blight, bacterial spot among others which greatly affect both the yields and quality of the crop. Conventional methods of disease detection are based on the knowledge and experience of agricultural experts who check for symptoms at the field or farm level. Although this methodology works, it is quite tedious, takes too much time and is often prone to bias due to the subjectivity of human beings (Jiang et al., 2021).

This study aims to develop and evaluate a Convolutional Neural Network (CNN) model for the automated detection and classification of tomato crop diseases using leaf images, thereby supporting early diagnosis and improved crop management. To achieve this, the research involves collecting and preprocessing a diverse dataset of tomato leaf images, designing a CNN-based classification model, training and validating the model, assessing its performance using key evaluation metrics, and identifying areas for further enhancement. The system promises to transform traditional agricultural practices by offering a fast, accurate, and cost-effective method for early disease detection, which can lead to increased yields, reduced pesticide usage, and minimized reliance on expert inspections. Ultimately, the solution empowers farmers especially in underserved areas with accessible technology for timely and precise crop disease management.

2.0 Literature Review

Tomatoes are among the most regularly grown and commercially valued crops found throughout the world. More and more important in the human diet (Chen et al., 2022) they provide essential nutrients and so support the agricultural economy. Still, tomato plants are rather vulnerable to certain illnesses, which can substantially lower output and quality. Early and accurate detection of these diseases determines both maintenance of high output and reduction of losses.

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Traditionally, hand inspection conducted by farmers and agricultural professionals has been the means of identifying illnesses in tomato plants. This approach advises closely examining the plants for symptoms of disease include drooping, color changes, and spots (Brahimi et al., 2021). Hand examination takes a lot of time and effort and is fairly challenging even if it could be rather effective. Moreover, exact diagnosis of diseases requires some degree of expertise and experience that might not always be present in every agricultural community.

Recently, increasing focus has been paid on using technology advancements to raise the accuracy and efficiency of disease recognition in the field of agriculture. Particularly those involving machine learning and deep learning algorithms, methods dependent on images have showed great promise in this area (Saleem et al., 2022). Among these options, convolutional neural networks (CNNs) have been found, by their efficiency, to be a helpful tool for jobs involving picture classification, including the diagnosis of plant diseases among others.

Even with their good outcomes in pertinent settings, CNN-based disease detection systems have several difficulties. Large and varied datasets, the computational capacity needed for deep learning model training, and the heterogeneity in illness symptoms brought about by different climatic conditions and tomato varieties are thus needed (Singh et al., 2025). If we are to correctly use these systems in real-world agricultural settings, these difficulties must be solved.

Many different diseases can harm tomato plants; hence the amount and quality of yield might be considerably reduced. Usually the leaves, stems, and fruits, fungi, bacteria, viruses, and environmental components can all start distinct diseases; each one generates symptoms that affect various regions of the plant. Affecting tomato plants, late blight caused by the oomycete Phytophthora infestans is a quite destructive disease. On fruits, stems, and foliage, it appears as damp patches that later turn brown and lifeless. Under ideal conditions with high moisture levels and low temperatures, late blight can quickly spread and badly damage crops (Patel et al., 2023). Control measures consist of resistant cultivars, fungicides, and appropriate cultural methods.

Driven on by the fungus Alternaria solani, another common and major threat to tomato plants is early blight. Usually showing up as circular spots on the leaves, it has a golden border. horizons in view. Early blight can cause the plant to lose its leaves under severe circumstances, therefore reducing strength and yield (Park et al., 2014). Among management practices include fungicide use, crop rotation, and elimination of polluted plant waste. Little, water-soaked lesions on leaves, stems, and fruits hint to bacterial spot the result of numerous kinds of Xanthomonas bacteria. These lesions may combine to produce more significant leaf loss. Bacterial spot is a major issue in warm and rainy settings that calls for keeping suitable sanitation practices, using resistant plant types, and applying bactericides like copper (Catara & Bella, 2020).

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2.1 Theoretical Framework in Tomato Crop Disease Detection Using Convolutional Neural Networks (CNNs)

Combining aspects from image processing, machine learning, and plant pathology, the fundamental ideas of identifying problems in tomato crops using CNNs draw from

Original: Next month the corporation wants to introduce a new product.

Techniques for improving image quality include color normalization, noise reduction, and change of contrast. These developments ensure that for next research inputs are more consistent and unambiguous.

Usually involving the tomato leaf, segmentation is isolating the area of concern from the surrounding background. This stage is crucial in guiding the investigation towards the significant part of the image, therefore lowering interference and improving the accuracy of feature recognition.

Image analysis techniques have always needed manual feature extraction of color, texture, and shape.

Even so, this procedure is automated within the structure of convolutional neural networks (CNN). CNN methods are quite interesting; they learn how to internalize and recognize such features from a set of images only during the training stage. The process of automation enhances the speed as well as the precision of disease diagnosis by changing due to variations in the characteristics of the leaves and disease indicators.

Such processes of image enhancement and data prepared for tomato plant disease detection processes of CNN models allow specialists and scientists to provide proper input in the models which leads to successful outcome of looking for tomato plant diseases.

Different functions in the processes of features' extraction and classification are performed by the arrangement of Convolutional Neural Networks (CNN) in specialized layers.

The very first layers referred to as convolution layers produce feature maps that bring out the edges, texture and patterns of the input images using convolution filters on the input images. Convolutional layers learn hierarchical representations of the picture data by methodically scanning input using these filters.

Rectified Linear Unit (ReLU) is one of non-linear activation functions used following convolutional processes. ReLU introduces non-linearity in the network, therefore helping CNNs to efficiently understand complex patterns and connections in data.

By using fresh marketing techniques, the corporation hopes to raise earnings. Confirmation and Learning Creating a tagged dataset with photographs of tomato leaves underlines the need of including images of various diseases together with images of healthy leaves. Usually, the dataset comprises training, validation, and testing sets.

Training the model entails CNN being trained using the training dataset. The network uses backpropagation to change filter weights, hence lowering classification error during training.

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3.0 Methodology

3.1 Data Collection

The first step is to collect a large and detailed database of the images of tomato plants in both healthy and disease states. This set encompasses both healthy and sick states of the plant while varying environmental conditions in order to enhance the diversity level. The images are obtained from the previous datasets, and in addition we do some image search on google. This wide range collection is targeted to include various disease symptoms and environmental conditions in order to enhance the generalization capability of the model.

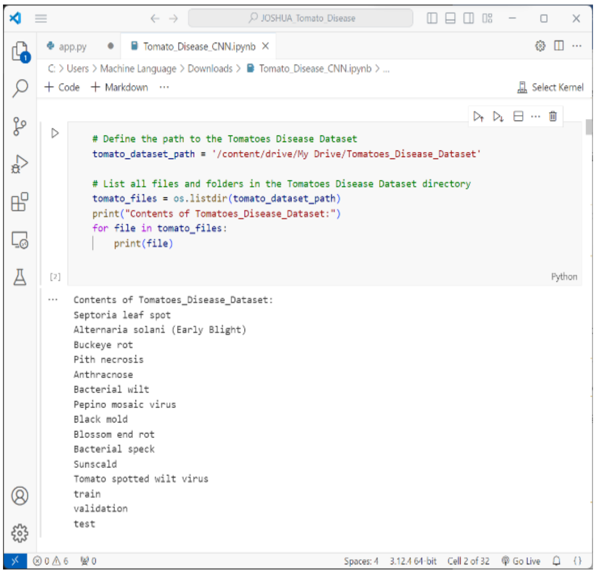

Figure 3.1 Data Collection

3.1.1 Sources of Data

To create a strong and balanced dataset, several free access image banks for the public were consulted. Such sources have provided clear enough images which concern different diseases of tomatoes as well as healthy tomatoes. Furthermore, pictures have been also taken from Google enforcing different conditions of tomato plants. Consequently, adopting this strategy made it possible to achieve diversity in the sample which helps to increase the validity of the model.

3.2 Data Preprocessing

Processing the images acquired is a fundamental stage because it helps to prepare the images prior to feeding them into the neural network. This consists of several images, which all aim to enhance the images. For instance, adjustments in contrast and reduction of interference and color were used to improve the images. Furthermore, the images were segmented such that the focus was on the tomatoes leaves alone without the other background. This ensured that only the useful areas in the image were analyzed. All images were adjusted to a size of 256 by 256 pixels to achieve uniformity of the input data. Some of the data augmentation strategies applied were images being turned, inverted, and cropped.

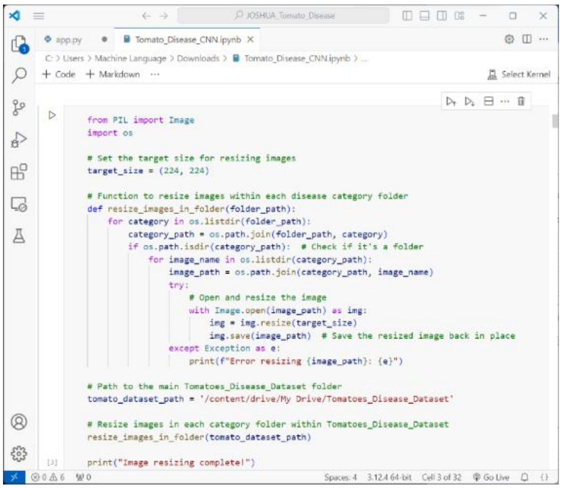

Figure 3.2: Data Preprocessing

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3.3 Feature Extraction

Instead of solely relying on the feature extraction of these deep learning AI models, convolutional neural networks, for instance which take in raw images and produce the desired features in an effortless manner; some traditional approaches to features extraction were also analyzed in view of highlighting and measuring some relevant features in the images. In a bid to analyze the color features to separate healthy leaf parts and even sick ones, color histograms were used. Some other techniques applied in texture feature analysis of the leaves, for instance, the Gray-Level Co-occurrence Matrix (GLCM) were used to analyze the textural aspects of the leaves. With the aim also of exploring their potential application for the detection and assessment of symptoms of diseases, shape features were also generated. These features which were extracted manually were adopted in addition to and to enhance the disease detection deep learning methods.

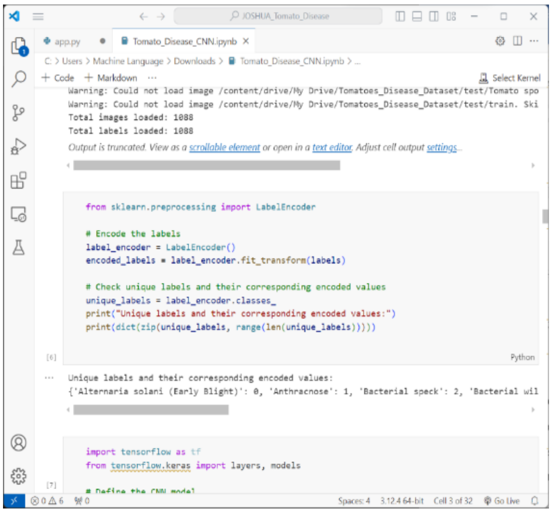

Figure 3.3: Feature Extraction

3.3.1 Neural Network Model Design

The neural network model design was intentionally focused on a way that the net would effectively work in detecting diseases. The input layer represents the processed image data. Several neuron layers hidden from the input and output contain weighted connections with activation functions and are applied to the image input data. These layers are the ones that learn how to perform feature extraction on the images. The output layer presents the class label of the image that has been classified into a particular category of diseases. This kind of structural design takes advantage of the levelled hierarchy structures of CNNs which start from low edge features to high-level shape and object features.

3.4 Model Training

Training a neural network includes certain fundamental steps that primarily aim at enhancing the accuracy of the model. In this regard, the dataset was split into three parts, namely training, validation, and test, for facilitating training and evaluation of the model. The training set was employed to change the network's weights as per backpropagation and its optimization algorithms like stochastic gradient descent. The validation set was used to assess the model's capacity aimed at hyperparameters tuning and to avert overfitting the model. Evaluation of the model was done at the final step using the test set to gauge the comprehensiveness of the performance assessment. Assessment of the model classification efficacy for tomato diseases involved accuracy measures, precision, recall, and a confusion matrix.

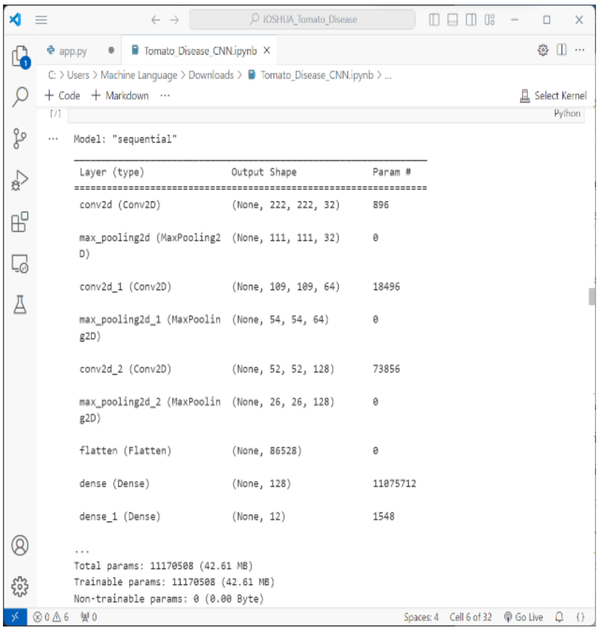

Figure 3.4: Model Architecture

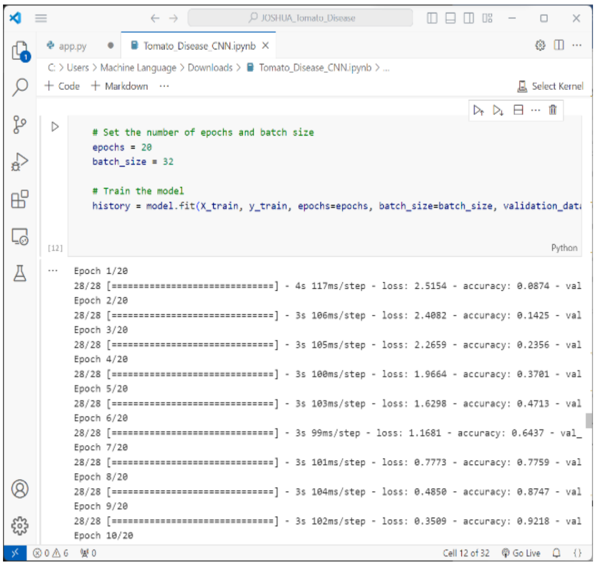

Figure 3.5: Model Training

Figure 3.6: Training and accuracy curve

3.5 Model Deployment

The final step was to use the trained model by embedding it in a system for its intended purpose. Thus, such a model was in-built in computer software or mobile application for use to farmers in the field. This provided the ability to conduct disease detection on the fly by creating a mechanism of constantly capturing and analyzing images. The application utilized predictive modeling results to provide timely feedback, intelligence, and recommendation to the farmers. In addition to this, there was also a feature that enabled the farmers to give feedback on the predictions made and upload more information for model improvement.

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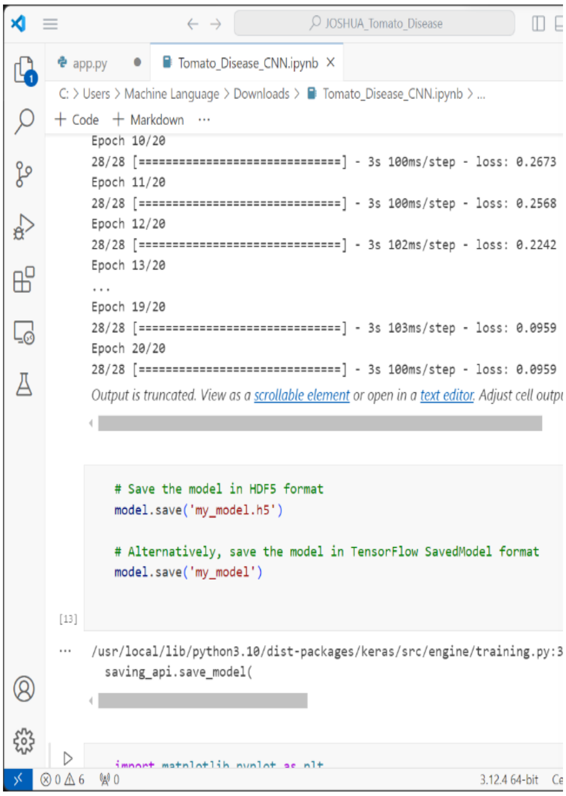

Figure 3.7: Model Saving and Deployment

3.5.1 Continuous Improvement

Model management and enhancement are part of the whole lifecycle of the system. The model was periodically improved by adding new information and retraining the model to consider new disease signs and new surrounding conditions. Their feedback was also gathered to enhance the accuracy of the model and ease of use. As a result of this, the system for diagnosing the disease is always modernized and functions optimally for agricultural practices and assists the farmers effectively in the management of their crops.

3.6 Overview of the New System

Classification of the images. The trained CNN is then further developed on finer levels of taxonomic classification and trained on healthy and unhealthy soil images for classification and segmentation of regions of interest in the healthy and unhealthy plants' images respectively.

3.6.1 Designing File Architecture

A Deconstructive Approach That Examines the Model A Deployed System Application File Structure Having to do with the Storage of Files and Managing their Content is concerned with networking. It is concerned with the process of networking, specifically the modelling, design and implementation of the computer networks in the system. The aim of this design is to provide security for the model and its associated information while allowing for updates and maintenance of the model. Packaged model files are kept in a specific folder located either on the premise server or in a cloud storage service.

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3.6.2 Flowchart

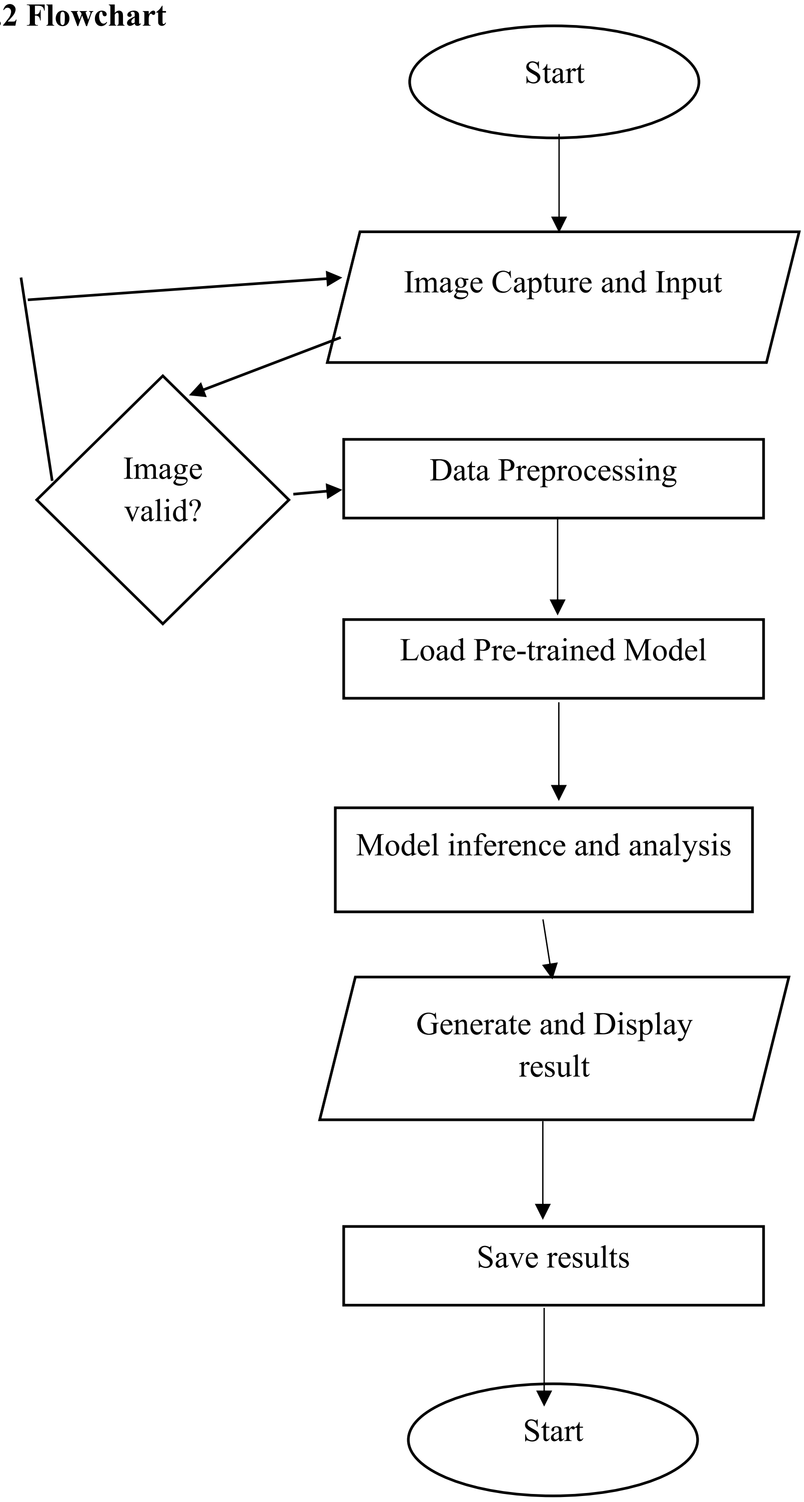

Figure 3.8: A Flowchart for the system

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3.7 UML Diagram

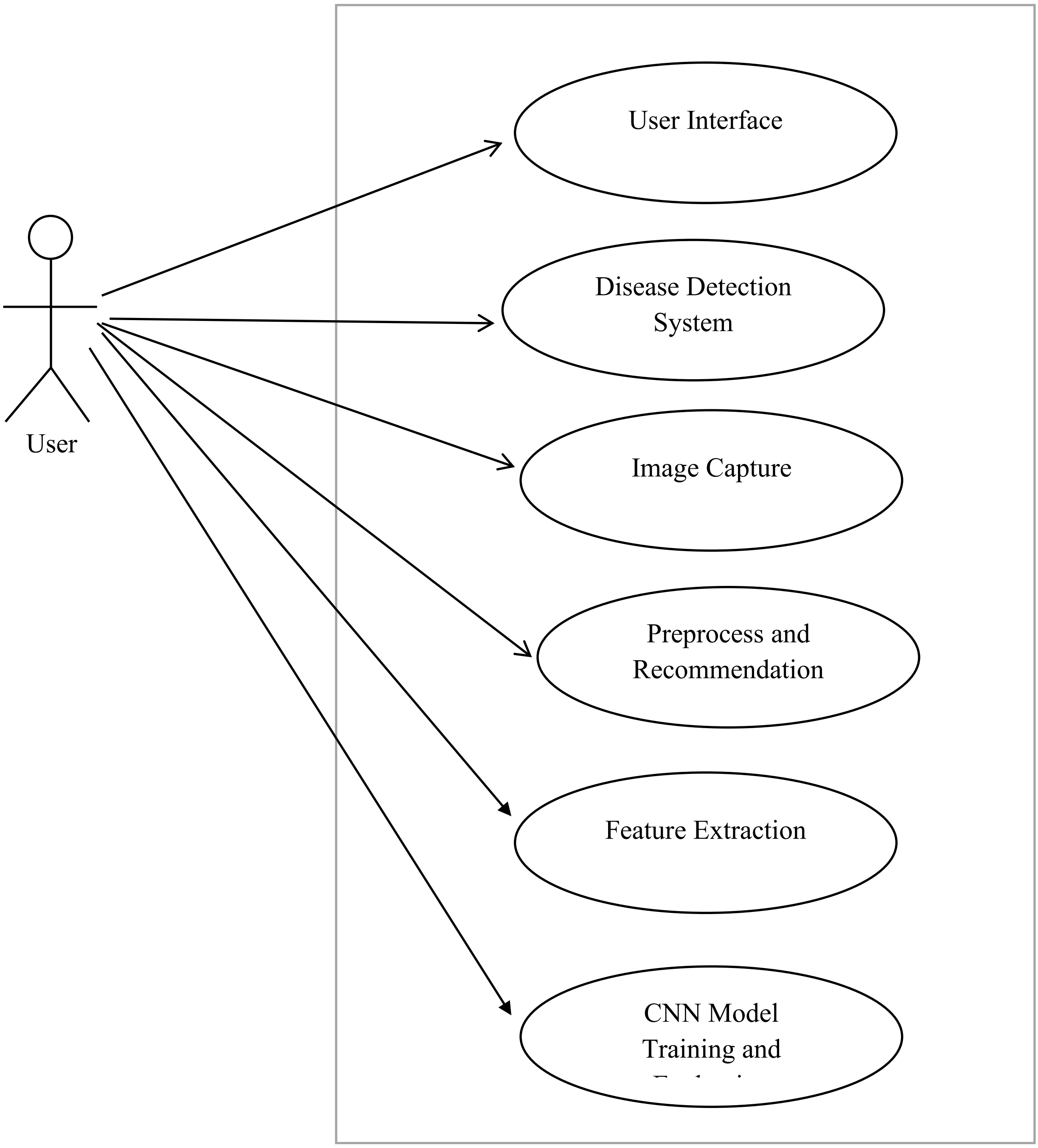

Figure 3.9: A UML diagram describing the system

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4.0 Presentation of Findings and Their Interpretation

This section discusses the tomato crop disease detection system, its results, its effectiveness, software and hardware needed for its execution, and its implementation.

4.1 Deployment Phase

The model was implemented in a Flask application which has the capacity to accept Python codes that identify Tomato diseases whenever the user provides a photograph of a tomato crop that has shown an abnormality and uploaded it on the site.

4.1.2 Display of Graphical Interface

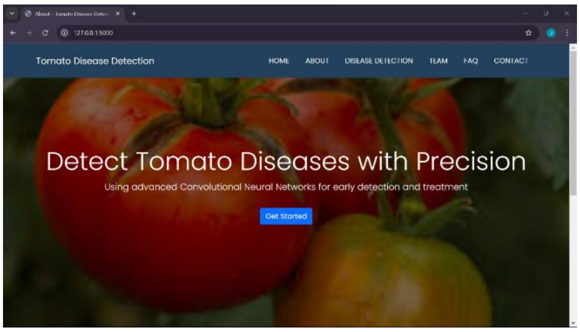

Figure 4.1: Homepage

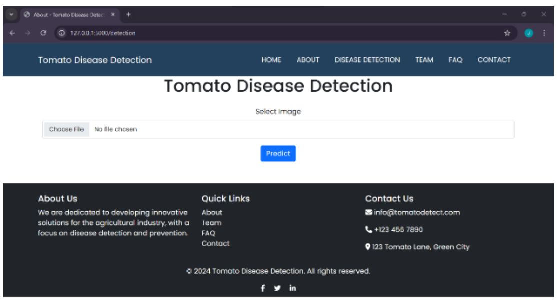

Figure 4.2: File Upload

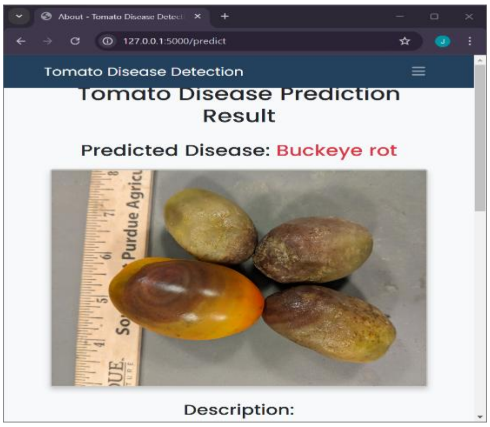

Figure 4.3: Result

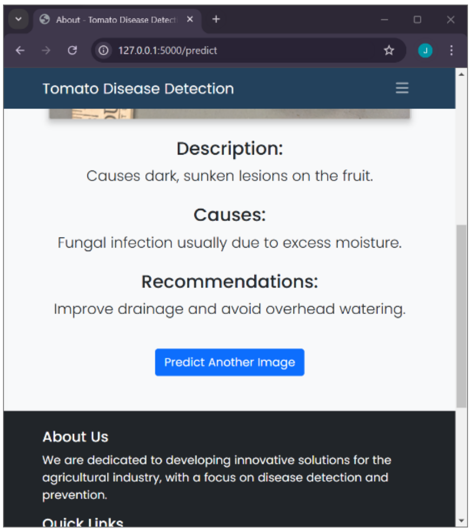

Figure 4.3.1: Result (Cont.)

5.0 Conclusion

The use of Convolutional Neural Networks (CNNs) for tomato crop disease detection has proven to be highly effective, offering an accurate, automated solution for diagnosing diseases that typically require time-consuming manual inspections. CNNs eliminate the need for feature engineering by automatically extracting features from images. This system, enhanced by advanced tools like drones and smartphones, can be deployed over large farmlands and reduces the costs associated

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with labor and clinical tests. The project highlights the importance of technology in improving disease detection, boosting production efficiency, and supporting sustainable agricultural development.

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