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Detection of Tomato Leaf Disease Using Deep Learning and Computer Vision

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ABSTRACT

Tomato is a common food product consumed across the world. It has been used in preparing several meals around the world. There have been issues around its price changes due to the impact of diseases in its production. Farmers have had to spend so much to address the issue, hence, posing a significant threat to agricultural productivity. This has also led to losses for farmers. An efficient and more accurate detection system is hereby essential. In this research, a hybrid approach for detecting tomato leaf disease using a deep learning model and computer vision is proposed. This leverages the power of a convolutional neural network model, Efficientnet_b0, a subset of the EfficientNet model, for learning and extracting features from tomato plant images. This deep learning model was trained on a diverse dataset of annotated images representing various tomato diseases and healthy plants. The trained model demonstrates its ability to accurately classify and identify different disease manifestations in real-time using the plant village dataset from Kaggle. Computer Vision techniques are incorporated to enhance the system's overall performance. The approach returned an accuracy of 0.97 with a real-time deployment potential, enabling farmers to diagnose diseases in their fields early.

Keywords. Tomato, Agriculture, Deep learning, Computer vision, Disease detection

1. Introduction

Tomato production plays a vital role in global food security, but its yield is constantly threatened by various diseases. Early and accurate diagnosis is crucial for minimizing crop losses and implementing effective control measures. Traditional methods for disease detection often rely on visual inspection by experts, which can be time-consuming, subjective, and susceptible to human error. In the world of agricultural, the need for automatic detection of plant diseases is of major importance. Additionally, the early and timely detection of plant diseases improves agricultural production and quality. Farmers in most agricultural countries lose significant amounts of money each year to crop diseases (Nguyen, et al., 2020). Tomatoes are essential due to their high market demand and nutritional value. These antioxidants are very important for our overall health. The production of this famous commodity can be hampered by insects and pests that attack tomato plants and cause various diseases. To treat diseases on tomato plants by hand, farmers need to know about the disease. Farmers face many problems every year when they try to grow healthy crops (Sakkarvarthi , *et al.,* 2021). Although farmers use a variety of pesticides and insecticides to protect tomato plants from disease, they often fail to have knowledge about the disease and how to avoid it which could be dangerous. The excessive use of pesticides and insecticides is dangerous to human health and survival of the crops. Crop damage can be caused by misdiagnosing diseases and using too many or too few pesticides. Diagnosing tomato plant diseases is critical for optimal production. In contrast, manually diagnosing tomato diseases by closely observing the plants is a time-consuming and difficult process. Farmers often find it difficult to consult experts in remote locations and take preventive measures against rare diseases. Lacking prior knowledge, the visual examination of tomato plants may lead to incorrect disease prognosis. This also leads to the use of ineffective preventive measures. The use of deep learning can find diseased tomato plants, figure out what kind of disease they are affected by, and use that information to help the rest of the crop grow more efficiently and with fewer losses bring a lot of change to the survival of plants. Tomato, as one of the commonly grown vegetables, is widely cultivated as a subordinate produce. Indeed, tomatoes are considered the fourth most sought-after commercial vegetable next to potatoes, lettuce, and onions (Liu & Wang,

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2020). PSA (Philippine Statistics Authority) conducted a survey during the period of April to June of 2018. The production of the tomato in the Philippine increased by 1.8%, from last year's record of 72.19 thousand metric tons to 73.50 thousand metric tons (Luna, *et al.,* 2020). In spite of that, the biggest challenge is in what way to deliver the required quantity and quality of tomatoes through the whole year-round (Sakkarvarthi , *et al.,* 2021). The availability and inadequate supply of quality fresh tomatoes result in market price hikes during off-season. Tomato production throughout the regular planting season is affected by diseases leading to production losses (Bauer, et al., 2019) using a case study of lettuce production addresses the integration of advanced technologies in agriculture whereby the review underscores the role of aerial field phenotyping, which uses sensors to collect crop imagery for monitoring and managing crops effectively. The use of NDVI imagery is particularly noted for its correlation with biomass and leaf area index, making it a useful tool for yield-related phenotyping while it also introduces novel analysis functions to map lettuce size distribution, providing growers with valuable data to conduct precision agricultural practices, thereby improving actual yield and crop marketability before harvest (Luna, *et al.,* 2020) using The Philippines which are highlighted as an agricultural country with a significant portion of its land dedicated to agriculture. Their review identifies the physical challenges of farming, such as the labour-intensive nature of the work and exposure to chemicals. It also points out the seasonal challenges in tomato production, with oversupply in the dry season and shortages during the rainy season, leading to fluctuating market prices. It highlights the significance of machine vision in plant classification and identification, growth monitoring, and assessment. Augmented reality (AR) is also mentioned as a tool for increasing productivity, with reference to studies providing hardware designs for AR. Also covers research on object detection and classification using image processing and machine learning techniques, particularly for the detection of flowers, fruits, yield, and diseases in plants. (Mohammed *et al.*, 2017) focused on using deep learning techniques to classify and visualize tomato diseases. The authors use a large dataset of 14,828 images of tomato leaves infected with nine diseases. They employ Convolutional Neural Networks (CNN) as a learning algorithm to train their classifier. CNNs have the advantage of being able to learn and extract features directly from the images, eliminating the need for manual feature design. The results show that the proposed deep model achieves an accuracy of 99.18%, outperforming shallow models. The authors also utilize visualization methods to understand disease symptoms and localize the affected regions in the leaves. Overall, this study provides a robust approach for automated tomato disease classification and visualization. (Liu & Wang, 2020) research studies have used various deep learning models like GoogleNet, AlexNet, and VGG16 to classify plant diseases with high accuracy. Transfer learning has been used to overcome the lack of large datasets, and data augmentation techniques have been employed to enhance training datasets. Classification of tomato diseases using deep learning models, with findings indicating that deep learning models outperform traditional methods.

Object detection methods like Faster-RCNN have been used to detect tomato diseases, but these methods often suffer from limitations such as slow real-time performance. it identifies the need for early detection of diseases, the challenge of detecting diseases under complex backgrounds, and the difficulty of achieving real-time computing on mobile terminals. Disease Detection in Tomato Leaves via CNN with Lightweight Architectures by (Gonzalez-Huitron, et al., 2020) shows Tomato production is a significant agricultural activity worldwide, with Mexico being a major producer. he studies explores the use of deep learning, specifically Convolutional Neural Networks (CNN), for classifying diseases in tomato leaves. The authors train and evaluate four recent CNN models on a subset of the Plant Village dataset, which includes 18,160 RGB images of tomato leaves divided into ten classes. The CNN architectures chosen are lightweight and utilize depth wise separable convolutions, making them suitable for low-power devices. To enhance the dataset and prevent overfitting, the authors apply data augmentation techniques such as horizontal flipping and rotations. They employ transfer learning, initializing the CNN models with

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weights from the ImageNet dataset and retraining all layers to improve generalization. The trained models are implemented on a Raspberry Pi 4 microcomputer, demonstrating their potential for real-world applications. A graphical user interface (GUI) is developed to facilitate the use of the models on the Raspberry Pi 4, allowing for image capture, disease classification, and image saving. The paper presents a comprehensive approach to classifying tomato leaf diseases using CNNs, suitable for low-cost and low-power devices. The study's findings contribute to the development of accessible and efficient early detection systems for tomato crops, with potential implications for precision agriculture.

2. Materials and Method

According to data collected on Tomato production as of 2022 December tomato production has reached or exceeded the milli-tonne threshold in a large number of countries with a feature increase in the coming years. The increase in human population may far surpass the yield, even if the yield of the tomato is on the rise the yield is often threatened by various diseases and sometimes due to farmers not being able to adopt efficient methods. Early and accurate diagnosis is essential for minimizing crop losses and implementing effective control measures. This research introduces a novel AI-powered system that utilizes a hybrid approach of deep learning and computer vision to detect tomato diseases with high accuracy and efficiency. The tomato disease prediction AI is built with the purpose/sole reason of detecting diseases in tomatoes using its' external features (its leaf), it is able to monitor and watch over farmland with little/no human intervention making things easy for farms. The proposed system leverages the strengths of Convolutional Neural Networks (CNNs) using the "**Efficientnet_b0**" model and OpenCV libraries to analyse tomato leaf images and identify potential diseases.

2.1. Data Collection and pre-processing

A dataset of tomato leaf images (shown in Table 1) with different diseases and healthy conditions is collected from various sources, such as online databases, field surveys, and farmers. The dataset is divided into three subsets: training, validation, and testing. The dataset is also labelled with the disease type and severity for each image. This dataset is an open-access repository of images published online at the website www.PlantVillage.org and contains more than 50,000 images of leaves. From this dataset, we extract only images of tomato leaves. The total number of images in our dataset is 25,851 images and is then split into Ten disease classes as shown in Figure 1.

Table 1: Classification of Tomato Disease

Classes(diseases)	# images
Powdery mildew	1004
Healthy	3051
Tomato yellow leaf curl virus	2153
Tomato mosaic virus	2039
Target spot	1827
Spider mites	1747
Septoria spot	2882
Leaf Mold	2754
Late blight	3113
Early blight	2455
Bacterial spot	2826
Total	25,851

The dataset is then pre-processed to enhance the quality and reduce the noise of the images. Some common techniques are resizing, cropping, filtering, histogram equalization, and colour space conversion. The dataset is also augmented with various transformations, such as rotation, flipping, scaling, and cropping, to increase the diversity and size of the dataset.

2.2. Model Architecture and Training

A CNN model "Efficientnet_b0" is chosen for the tomato disease detection and classification using the tomato leaf images. The CNN model, which is a subset of the "EfficientNet" model, consists of multiple layers of convolution, pooling, activation, dropout, and

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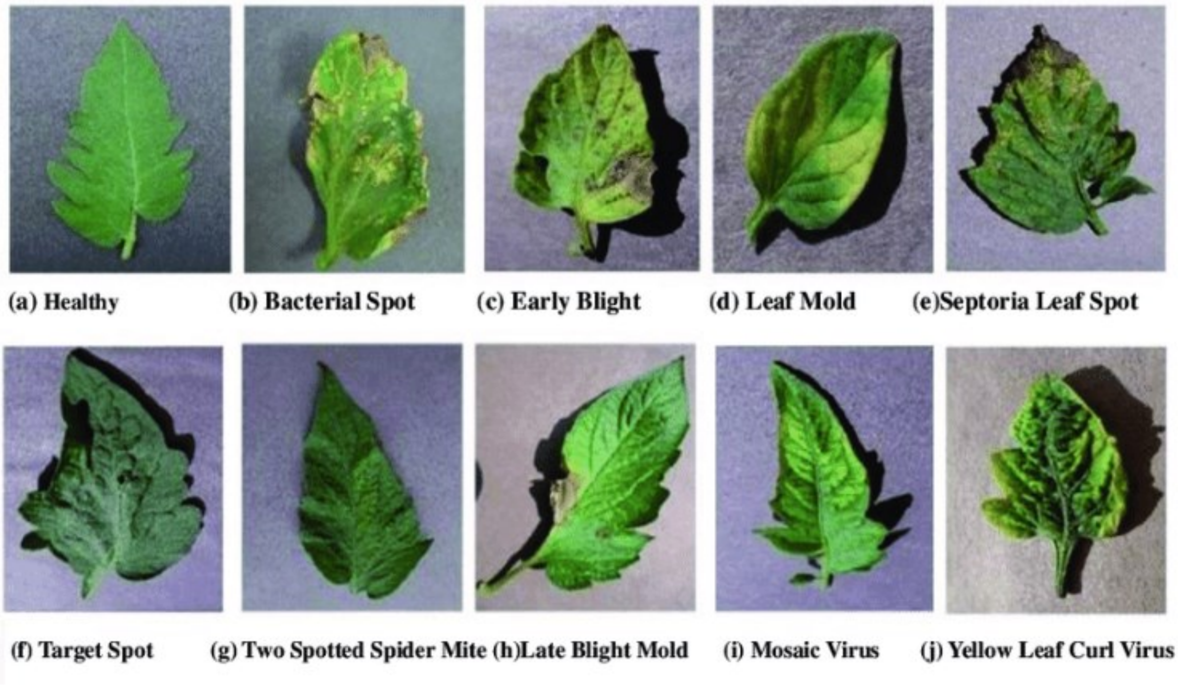

Figure 1: Classification of Tomato Disease

and fully connected layers. The CNN model is initialized with random weights or pre-trained weights from the foundational model. The "Efficientnet_b0" model is trained using the training subset of the dataset. The model parameters are updated using an optimization algorithm. The model performance is monitored using the validation subset of the dataset. The model hyperparameters, such as the learning rate, batch size, number of epochs, and regularization, are tuned using a grid search or a random search method. The model design and formulation process is shown in Figure 2.

2.3. Model Evaluation and Analysis

The "Efficientnet_b0" model is evaluated using the testing subset of the dataset. The model's performance is measured using various metrics, such as accuracy, precision, recall, F1-score, and confusion matrix. The model's performance is compared with other existing methods. the model is also analyzed to

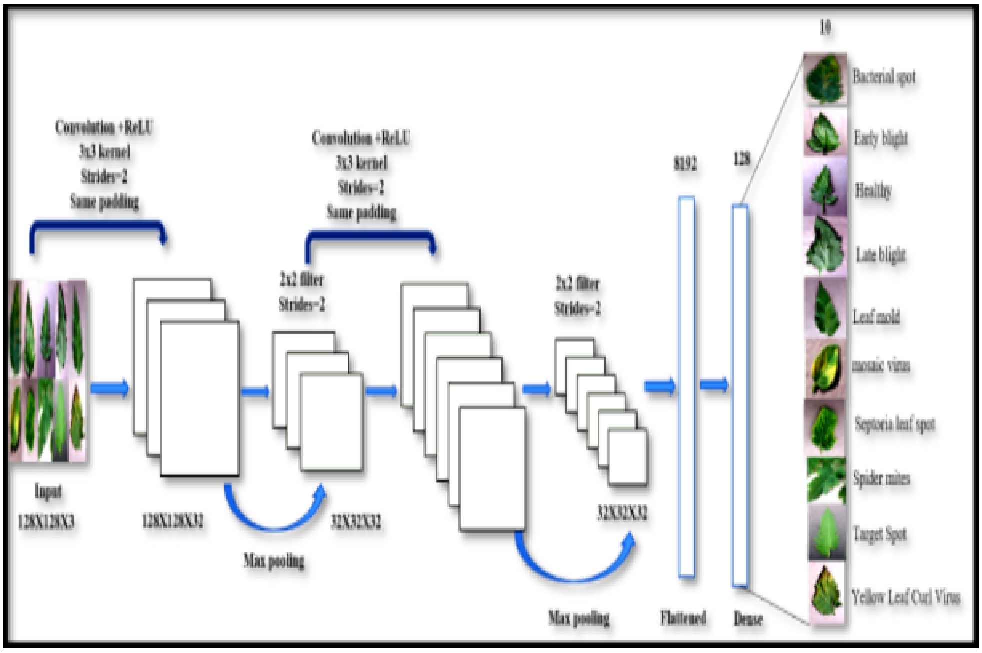

Figure 2: Model Design and Training

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to understand the factors that affect its accuracy and robustness, such as data augmentation, hyperparameters, and transfer learning. The model features, activations, and weights are visualized and interpreted using various methods, such as saliency maps, heat maps, or Grad-CAM. The model errors, limitations, and challenges are also identified

2.4. Deployment and Application

Based on the identified disease using a user-friendly interface, the system provides farmers with tailored recommendations for treatment, prevention, and crop management strategies. This empowers them with timely decision-making, potentially minimizing yield losses and maximizing crop health.

3. RESULTS

The main objective of this research is to develop a tomato disease detection system aimed at improving tomato security and accessibility to the general public and farmers. By integrating cutting-edge technologies such as web-based interfaces and machine learning models, the system offers accurate disease detection and supports real-time monitoring upon user request. The implementation phase covered designing a user-friendly interface, setting up the necessary hardware requirements, and ensuring data security and system reliability through rigorous testing and maintenance. The project showcases the transformative power of technology in bolstering food security. By carrying out this, the following activities were conducted: the development of a detection system, testing the program by capturing data to ensure efficient execution, and the preparation of the documentation. To develop the system, the data was collected from free sources like Kaggle which has already been sorted. The data were carefully examined and processed. Moreover the suggestion and recommendations on how to tackle the problem where put in place for users lacking required knowledge has shown in figure 5.

These recommendations were obtained through consultations and personal interviews conducted with the experts in the areas where they reside. The system achieved an accuracy of 97%, with high precision and recall metrics as shown in Figures 3 and 4. The integration of CNNs and computer vision techniques demonstrated superior performance in detecting and classifying tomato diseases compared to traditional methods. This result underscores the potential of hybrid AI systems in real-world agricultural applications. Figure 5 shows an output of the detection process.

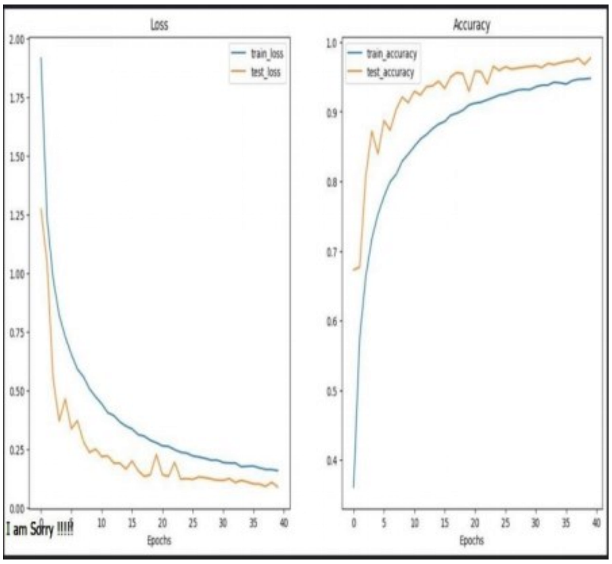

Figure 3: Model Loss vs Model Accuracy

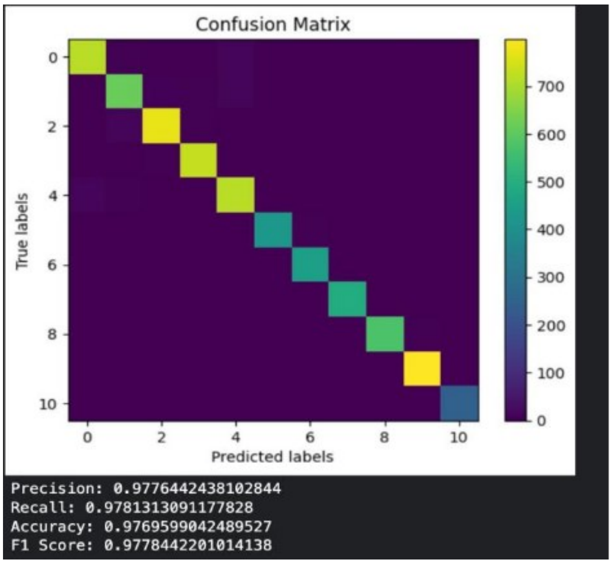

Figure 4: Confusion Matrix, Accuracy, Precision, Recall and F1- score

Figure 5: Prediction Result and Management Strategy

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4. Conclusion

This study underscores the efficacy of a hybrid AI system for tomato disease detection, which merges the computational power of EfficientNet-B0 with the visual analytical strengths of OpenCV. By leveraging convolutional neural networks for robust feature extraction and computer vision techniques for preprocessing, the system offers a comprehensive solution to one of agriculture's pressing challenges. The system not only achieved a high accuracy rate but also demonstrated scalability in adapting to different disease scenarios through data augmentation. It's real-time processing capability makes it a practical tool for proactive disease management Integration of visualization methods enhances its interpretability, which is crucial for widespread adoption by non-technical users. , we have created a system that addresses the longstanding issues associated with traditional methods of a detection system using the "Efficientnet_b0" and "OpenCV" while achieving an accuracy of 97.6%, precision of 97.7% and Recall of 97.8%.

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