IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404

TomatoShield: ML-Powered Tomato Plant Disease Prediction App

Prajual Premanand Kotian[1], Dr. Sangeeta Vhatkar[2]

Graduate, Student, Department of Information Technology, Thakur College of Engineering & Technology, Mumbai, Maharashtra, India[1]

Associate Professor, Department of Information Technology, Thakur College of Engineering & Technology, Mumbai, Maharashtra, India[2]

Abstract: Agriculture is a key industry for world food security, but crop diseases are a major threat to agriculture productivity. Early and precise detection of diseases is critical to avoid loss of yield and achieve a sustainable agricultural system. Most of the farmers, particularly in India, have a hard time with disease diagnosis because they lack proper infrastructure, which results in improper management of the crops and lower yields. Machine intelligence and advanced learning provide cutting-edge techniques for detecting diseases early through computer vision approaches. In our research, we created TomatoShield, an app based on a mobile platform that has the capability of disease identification. We tested CNN models like Xception for classifying tomato plant disease using a 22,200 images dataset of leaves from Kaggle. The Xception model had achieved the accuracy of 93.64%. The app, developed with Python's Kivy library, allows farmers to take or upload images of leaves for immediate diagnosis. It also includes storing results in an SQLite database for easier recovery and analysis, delivering actionable information to farmers to increase agricultural productivity and crop health.

Keywords: Plant Disease Prediction, Xception, CNN, Disease Treatment, Image Classification, Machine Learning, Deep Learning.

I. INTRODUCTION

India's agricultural sector, dominated by the forces of globalization, is confronted with a range of complex issues, of which the widespread prevalence of diseases in high-value crops, especially tomatoes, is a cause of serious concern owing to their significance in domestic markets and foreign markets [1]. Tomato crops are most vulnerable to a wide range of diseases, such as blight, wilt, and leaf spot, all of which significantly compromise yield and quality of the produce. This issue is further exacerbated by the issue of early detection, as symptoms are not often observed in early stages, which leads to late interventions and huge economic losses for farmers [2]. In order to tackle these issues, more and more researchers and developers are implementing cutting-edge technologies anchored in artificial intelligence, in addition to increased focus on machine learning and deep learning, to improve the accuracy and overall efficiency of diagnosing plant diseases [1].

This research presents "TomatoShield," an Android application that utilizes new and advanced deep learning frameworks, mainly Convolutional Neural Networks (CNNs), to detect tomato crop diseases in an accurate and real-time manner. The architecture is methodical in approach: it begins with the acquisition of labeled datasets derived from open-source platforms such as Kaggle, moves through various phases of image pre-processing, and concludes with disease classification utilizing the Xception model, which has been found to achieve optimal results in plant disease classification tasks. By facilitating rapid infection identification, TomatoShield allows farmers to gain timely, actionable insights that enhance decision-making abilities, which ultimately lead to better disease management and enhanced tomato yield [3].

In addition to its operational intricacies, the paper also outlines a structured framework for discussion and analysis. Section 2 provides an in-depth analysis of pertinent studies and publications, setting the stage for subsequent exploration. Sections 3 and 4 delve into the detailed exposition of the algorithms and the proposed system, elucidating their underlying principles and functionalities. The implementation process is meticulously detailed in Section 5, offering insights into the practical realization of the system. Finally, Section 6 encapsulates the findings, conclusions, and outlines avenues for future research and development, providing a comprehensive overview of the project's scope and impact.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 14, Issue 4, April 2025
DOI: 10.17148/IJARCCE.2025.14404

II. RELATED WORK

Multiple research initiatives have studied the classification of diseases on tomato leaves using various deep and machine learning approaches, utilizing different datasets for the stated task. Most of these studies focused primarily on accuracy as an evaluation measure, while some incorporated additional measures such as F1-score, precision and recall. The accuracy results reported in these investigations ranged from 68.22% to 99.87%.

TABLE I. OVERVIEW OF PRIOR STUDIES: MODELS & THEIR ACCURACIES [1 – 10]

Ref.	Models Used	Dataset	Sample Size	Crops	Diseases Detected	Accuracy (%)
[1]	VGG-19	Plant Village Dataset	20600	Strawberry, Potato	Healthy, Early Blight, Late Blight	95.6%
[2]	CNN, VGG-16, VGG-19, ResNet50	Plant Village Dataset	10000	Tomato, Potato, Bell-Pepper	Healthy, Early Blight, Late Blight, Bacterial Spot	CNN – 98.60% VGG-16 – 92.39% VGG-19 – 96.15% ResNet50 – 98.98%
[3]	CNN, MobileNet	Kaggle	87000	Grape, Raspberry, Tomato, Orange	Healthy, Early Blight, Black Measles, Citrus Greening	CNN – 89% MobileNet – 96%
[4]	VGG-16, KNN, Random Forest	Plant Village Dataset	16102	Tomato	Not Mentioned	VGG-16 – 79.14% KNN – 74.56% Random Forest – 68.22%
[5]	EfficientNetV2-B0	Kaggle	11000	Tomato	Target Spot, Late Blight, Leaf Mold, Two-Spotted Spider Mite, Leaf Spot, Septoria, Mosaic Virus, Yellow Leaf Curl Virus, Powdery Mildew, Early Blight, Healthy, Bacterial Spot.	99.87%
[6]	ResNet18, ResNet50, InceptionV3	Live Captured Images	1493	Pomegranate	Bacterial Blight, Anthracnose, Fruit Spot, Wilt, Fruit Borer	ResNet18 – 87.5% ResNet50 – 97.92% InceptionV3 – 78.75%
[7]	CNN	Kaggle	10000	Tomato	Bacterial Spot, Early Blight, Late Blight, Septoria Leaf Spot, Mosaic Virus, Two-Spotted Spider Mite, Leaf Mold, Target Spot, Yellow Leaf Curl Virus	90.17%
[8]	Random Forest, SVM	CSV Files of Dataset	-	Rice, Jowar, Wheat, Soyabean, Sunflower, Cotton, Sugarcane, Tobacco, Onion, Dry Chili etc.	Not Mentioned	Random Forest – 86.35% SVM – 99.47%
[9]	Xception	Plant Village Dataset	13885	Tomato	Healthy, Bacterial Blight, Leaf Spot	98%

DOI: 10.17148/IJARCCE.2025.14404

[10]	ResNet50 CBAM + SVM	Plant Village Dataset	13885	Tomato	Bacterial Spot, Early Blight, Late Blight, Septoria Leaf Spot, Mosaic Virus, Two-Spotted Spider Mite, Leaf Mold, Target Spot, Yellow Leaf Curl Virus	97.2%

Past research has indicated that Xception perform well under large datasets, which makes them suitable for plant disease classification. Since they perform well, these models were assessed in this research, with the top-performing one incorporated into the mobile app for real-time disease identification.

Chemmengath et al. [11] proposed PlantAIM, a vision transformer-based hybrid approach, combining convolutional neural networks (CNNs) and transformers to leverage both local and global feature representations. PlantAIM proposes a double-path feature extraction approach with an additional Global-local Feature Fusion Attention (GLFA) block that synergistically learns crop-specific as well as disease-specific patterns simultaneously. In comparison with controlled datasets (Plant Village) and real-world datasets (IPM, Bing, and PlantDoc), PlantAIM outperformed previous state-of-the-art approaches with an accuracy rate of 99.67% on Plant Village, and 8.55%, 6.35%, and 0.52% improvement over IPM, Bing, and PlantDoc, respectively. Generalization over such a wide range of domains testifies to its potential as a powerful tool in efficient agricultural diagnosis.

Upadhyay et al. [12] present a systematic review of more than 278 deep learning-based studies in the field of plant disease detection, providing critical analysis of the incorporation of artificial intelligence in precision agriculture. The review discusses in detail multiple deep learning architectures—e.g., CNNs, vision transformers, and GANs—applied with imaging modalities like RGB, hyperspectral, and multispectral images. The authors mention that CNN-based models remain the most widely used due to their enhanced performance in visual feature extraction, while vision transformers exhibit increasing potential in handling long-range dependencies. Significantly, the survey points out that multiple models, especially CNN-based classifiers, have reached classification accuracy over 95%, while some benchmarked methods achieved over 99% on datasets like Plant Village. Notwithstanding such performance, the review points out challenges like the reliance on large labeled datasets, inability to generalize to real-world cases, and the need for interpretable models. The study concludes by proposing future research areas on lightweight models, explainability, and domain adaptation methods to close the gap between research and real-world agricultural deployment.

Alhwaiti et al. [13] propose a complete framework for plant disease detection based on YOLO deep learning frameworks (YOLOv3 and YOLOv4) to address the emerging need for a method of fast and accurate diagnosis of fruit leaf disease. Their research specifically aims to detect bacterial lesions on peach leaves and scorch disease on strawberry leaves using the publicly available Plant Village dataset. Results indicate that the YOLOv3 model provides a 97% accuracy rate with a mean average precision (mAP) of 92% and a total detection time of 105 seconds. The upgraded YOLOv4 model improved performance to 98% accuracy with an mAP of 98% plus a total detection time of only 29 seconds. The authors also include full class specific test assessments and confusion matrix analysis to confirm the capability of YOLOv4 for real-time applications. The results offer insight into the transformative potential of YOLO-based models for plant disease detection through highly efficient and accurate means of detection that can be especially important for developing countries impacted by plant disease effects to agricultural yield.

Yakkala et al. [14] suggest a deep learning strategy for improving crop health by early disease detection of plant diseases using a ResNet-9 convolutional neural network architecture for leaf condition classification of plants. The system is designed to detect subtle morphological changes like color changes, intensity changes, and shape deformation to distinguish between healthy and infected plants. The model was trained and tested on a well-curated dataset of plant diseases, where it reported high accuracy in classification as 98.5%, indicating its applicability in early diagnosis. The work also reports improvements in precision, recall, and F1-score over baseline models, indicating the robustness and generalization capability of the ResNet-9-based method.

These findings illustrate that the method can be used as an effective tool for real-time prediction of disease and active management of crops, enabling improved decision-making and optimization of yield in precision agriculture.

Aswini et al. [15] propose a practical transfer learning algorithm to aid disease detection and prediction in citrus plants. They effectively addressed significant issues including data imbalance and high computational cost. Their proposed framework uses Spatially Adaptive Histogram Equalization (SCLAHE) to enhance important features in citrus leaf

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 4, April 2025
DOI: 10.17148/IJARCCE.2025.14404

images, as well as a Reinforcement Learning Generative Adversarial Network (RL-GAN) for on-the-fly data augmentation. With mobile phone for the feature extractor, the overall detection accuracy for the Citrus Leaves and CCL-20 datasets was 99.42% with few parameters and FLOPS in their model, making the framework suitable for deployment on resource-limited devices. The authors' results show that their proposed method can predict disease rapidly, accurately, and efficiently, making it appropriate for precision agriculture applications.

III. PROBLEM STATEMENT

- The rising incidence of plant diseases, especially in tomato produce, is a major threat to agricultural productivity.
- Early detection is needed to avoid loss of yield, but conventional disease detection techniques are slow and ineffective, causing interventions to be made late and resulting in financial losses.
- Tomato crops are extremely prone to blight and wilt diseases, which drastically affect both quantity and quality.
- Limited availability of reliable diagnostic equipment prevents farmers, particularly those in rural areas, from making sound judgments on disease management.
- Inadequate infrastructure & resources also hamper correct disease identification, leading to late or ineffective treatments.
- Lack of a portable disease detection system results in inefficient crop management and subsequent reduction in overall productivity and sustainability.

IV. PROPOSED METHODOLOGY

TomatoShield is a cutting-edge solution designed to analyze, authenticate, and identify plant diseases using image classification powered by Convolutional Neural Network (CNN) technology — specifically the Xception model. This innovative approach proves highly beneficial for rural farmers who often struggle to recognize plant diseases, leading to significant crop losses. By leveraging advanced technologies, the TomatoShield App empowers farmers with crucial insights, enabling timely detection of plant diseases and enhancing overall crop productivity.

The system depicted in Figure 1 represents a mobile application developed using Python's Kivy framework, integrated with trained and tested models for plant disease recognition. The process initiates with the capture or upload of multiple leaf images, which are then pre-processed using OpenCV techniques such as resizing, noise reduction, and normalization to ensure optimal image quality. The Plant Disease Predictor utilizes the Xception deep learning model, trained on an extensive image dataset, to deliver precise classification of plant health conditions. Once predictions are made, the results are stored in an SQLite database, allowing efficient storage, retrieval, and visualization of diagnostic data. One of the notable features of the app is its ability to display the output in the form of a pie chart, illustrating the distribution of predicted disease classes from the multiple input images — offering a clear, visual summary of disease presence. The final output is presented through a user-friendly mobile interface, delivering actionable insights to users, thereby facilitating informed decision-making for timely treatment. By combining deep learning, robust data handling, and intuitive design, TomatoShield stands out as a powerful tool to boost agricultural efficiency and profitability.

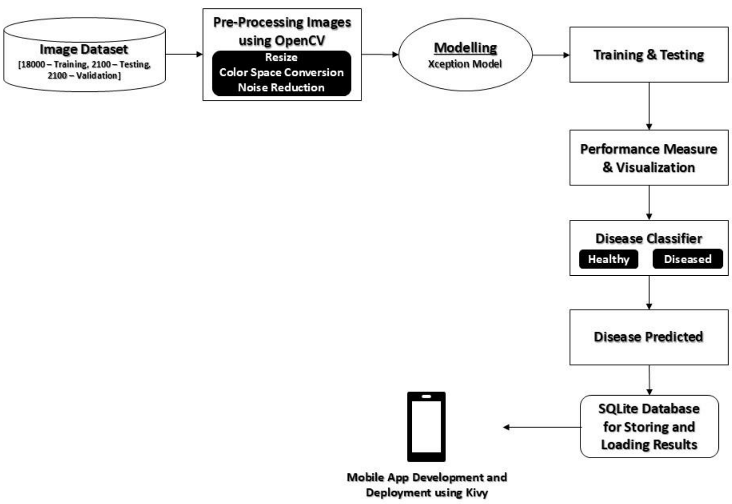


Figure 1. Design of the Proposed Model (Block Diagram)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⸎ Peer-reviewed & Refereed journal ⸎ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404

Here is the central component of the TomatoShield App:

Plant Disease Predictor:
The Plant Disease Predictor is an essential instrument for identifying and diagnosing crop diseases by analyzing live-captured plant leaf images, utilizing sophisticated methods like Image Classification and Xception algorithm. Furthermore, it conducts a comparative examination of tomato plants, assessing the quantity of identified diseases, thereby furnishing valuable insights into plant health and the prevalence of diseases.

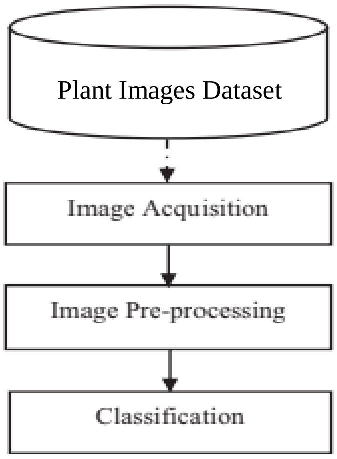


Figure 1. Image Classification Process

Plant Disease Predictor is an important application aimed at disease detection and diagnosis of crops using real-time leaf images of plants. It uses state-of-the-art Image Classification algorithms based on deep learning architectures like Xception to identify diseases in plants. It also compares the tomato plants by analyzing the count of diseases detected and offering important insights regarding plant health and disease occurrence.

A detailed block diagram (Figure 2) explains the major blocks of the system, describing the process of Dataset Collection, Image Acquisition, Pre-processing, and Classification with the chosen deep learning models. The organized workflow properly displays the complex process of disease detection and classification. The model with the highest accuracy will be combined with the Fertilizer Recommendation Module for easy mobile application deployment.

a] Dataset
The data comprises 22,200 images obtained from the Kaggle dataset with healthy and diseased leaves of tomato plants belonging to nine classes of diseases. 18,000 images were utilized for training and 2,100 images for validation and testing purposes to guarantee a stable model performance.

b] Image Acquisition
For model training, the dataset was retrieved from Kaggle's plant disease repository. The images were downloaded, classified, and saved in a structured database. The dataset contains 22,200 images of tomato leaves, representing both healthy plants and some diseased states.

c] Image Pre-processing
Image pre-processing improves the quality and uniformity of input images prior to model training. The images were resized to fit the input dimensions required (299 × 299 pixels) and color-adjusted to maintain uniformity. Other improvements like noise reduction and normalization were done to enhance classification accuracy. Pre-processing operations like image resizing, color space conversion, histogram equalization, and noise reduction were carried out using OpenCV (Open-Source Computer Vision Library) to provide high-quality input to the deep learning model.

d] Classification
Classification stage includes the extraction of features from intermediate and final layers, after which Xception model is employed to identify the disease. This model categorizes plant diseases on the basis of leaf features and differentiate between healthy and unhealthy tomato plants. Training is done under these set parameters:
Batch Size: 32
Epochs: 25
Maximum Learning Rate: 0.01
Gradient Clipping: 0.1

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⪢ Peer-reviewed & Refereed journal ⪢ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404

Weight Decay: 1e-4
Optimizer: torch.optim.Adam

The model that performs best in terms of highest accuracy with optimal training time will be incorporated into the mobile application for a real-time and effective plant disease detection system.

V. RESULTS AND DISCUSSION

TABLE II. CLASSIFICATION REPORT OF XCEPTION MODEL

Model	Train Loss	Train Accuracy	Val Loss	Val Accuracy	Precision	Recall	F1-Score
Xception	0.1184	96.39%	0.2113	93.64%	95%	95%	95%

Table II summarizes the Xception model's classification report which includes average training and validation accuracy, along with its loss as well as Precision, Recall and F1-Score.

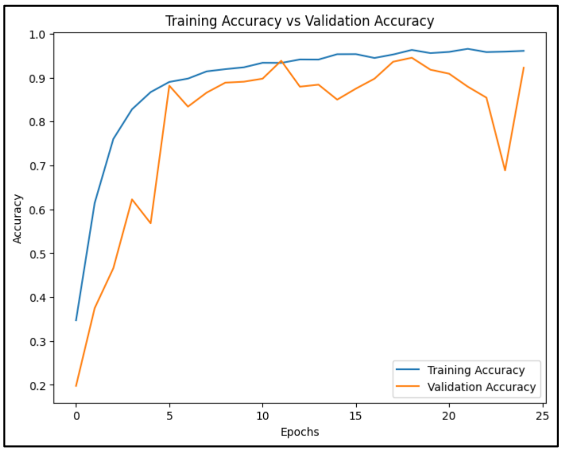


Figure 3. Training Accuracy Vs Validation Accuracy

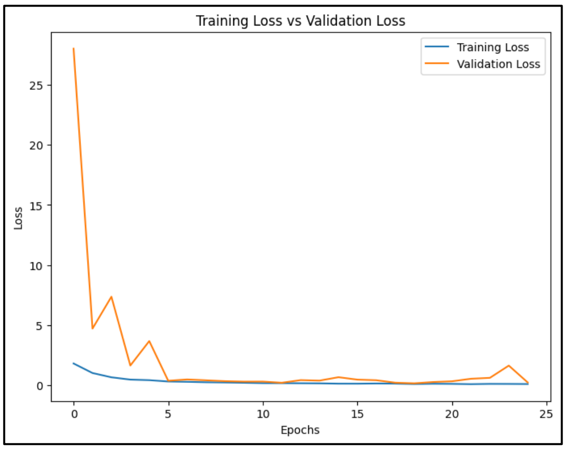


Figure 4. Training Loss Vs Validation Loss

Figure 3 illustrates the Xception model's learning curve across 25 epochs. The training accuracy steadily increases, reaching 96.39%, while the validation accuracy follows a similar trend, stabilizing around 93.64%. However, the validation accuracy exhibits fluctuations, with occasional drops, indicating some instability. Nevertheless, the minimal difference between learning and testing accuracy indicates that the model effectively adapts to new, unseen data. The fluctuations in validation accuracy could be attributed to minor overfitting, which might be mitigated using techniques like dropout or early stopping. Overall, the model demonstrates strong learning capability with minimal signs of overfitting, making it effective for tomato plant disease classification.

Figure 4 displays the optimization process of the model. The training loss drops steadily, reaching 0.1184, and the validation loss shows the same decreasing pattern, leveling at 0.2113. At the beginning, the validation loss oscillates enormously but soon coincides with the training loss, which indicates good learning. The slight difference between training and validation loss implies that the model does not have critical overfitting. But the slight oscillation in validation loss may reflect a little instability, which could be overcome using regularization methods like dropout. On average, the model exhibits good convergence, and reliable classification of the tomato plant diseases with less classification error is assured.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404

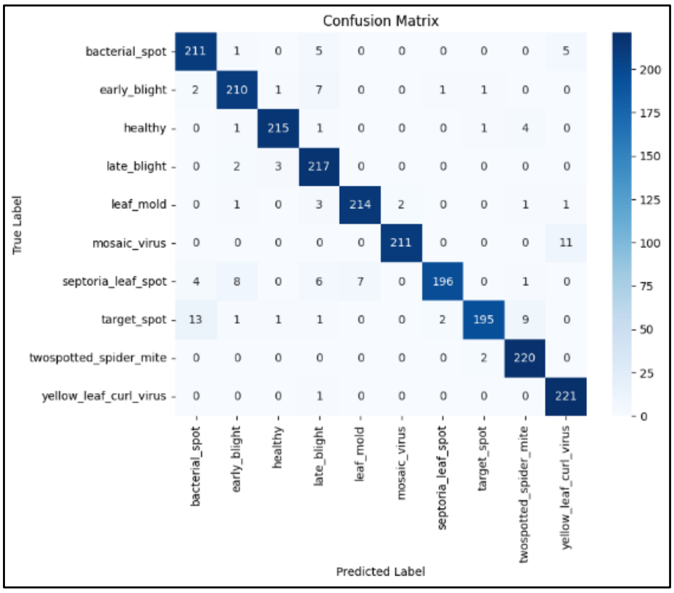


Figure 5. Confusion Matrix of Xception Model

Figure 5 displays the Xception model's accuracy in classifying plant disease. The confusion matrix indicates that the model classifies most instances perfectly, evidenced by high diagonal values, which are indicative of good classification performance. A majority of tomato plant diseases, including late blight (217), yellow leaf curl virus (221), and twospotted spider mite (220), are nearly perfectly classified with minor misclassifications. Some misclassifications are present, particularly for target spot, where 13 were incorrectly predicted as bacterial spot, and septoria leaf spot, which is plagued by some confusion with early blight and late blight. Additionally, the mosaic virus exhibits minor misclassification, with 11 being incorrectly classified. Generally, the model demonstrates high accuracy with minimal misclassification, which reflects its efficiency and reliability in classifying tomato plant diseases.

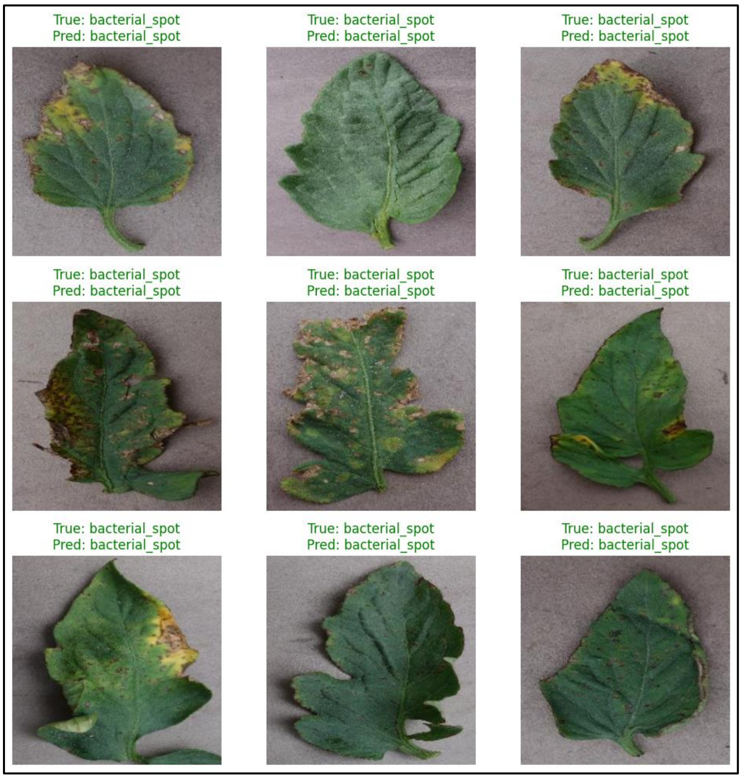


Figure 6. Testing of Image in the model

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404

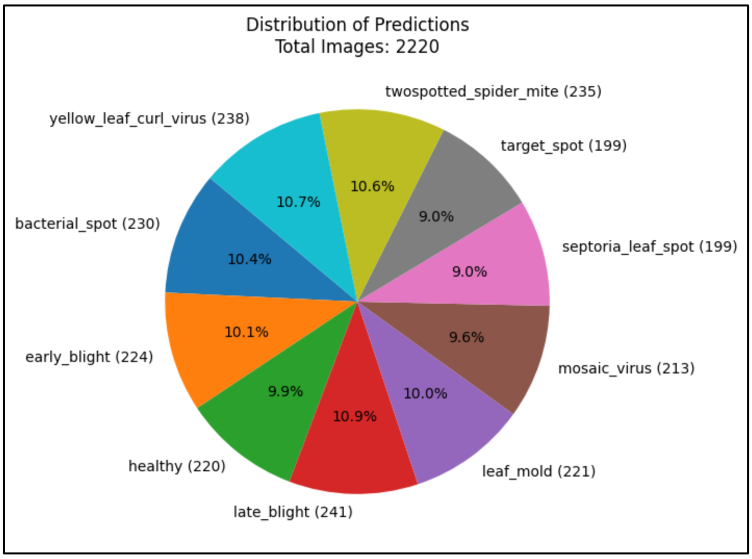


Figure 7. Distribution of Prediction Classes

Figure 6 and Figure 7 shows the Xception model's prediction of a test set of 2,220 images into ten plant healthy and diseased classes. The spread of predictions among various categories of diseases that affect tomato plants is relatively even, with each category exhibiting a comparable percentage of occurrences. The most predicted class is late blight, with 241 instances (10.9%), followed by yellow leaf curl virus with 238 instances (10.7%) and twospotted spider mite with 235 instances (10.6%), while target spot and septoria leaf spot have the least with 199 instances (9.0%). Such an even spread reflects that the model is not biased towards any class, thereby providing a balanced representation of all types of diseases. Such an even system of classification greatly increases the validity of the model in accurately identifying a vast array of diseases that affect tomato plants.

The TomatoShield App effectively incorporates deep learning for disease identification. The Xception model had 93.64% validation accuracy, successfully classifying diseases such as Early Blight, Late Blight, and Mosaic Virus. There were slight misclassifications between visually similar diseases like Early Blight and Late Blight, which could be resolved with more diverse training data. The training and validation loss of the model settled over several epochs, providing excellent generalization to novel data. Cross-validation also ensured its robustness, as accuracy was uniformly high across all dataset folds.

The Kivy mobile application ensures smooth user interaction, where farmers can upload or take pictures for disease identification as shown in Figures 8, 9 and 10.

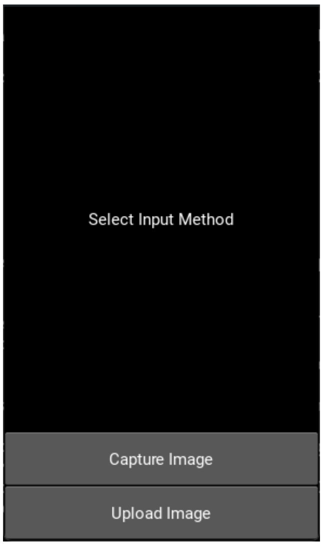


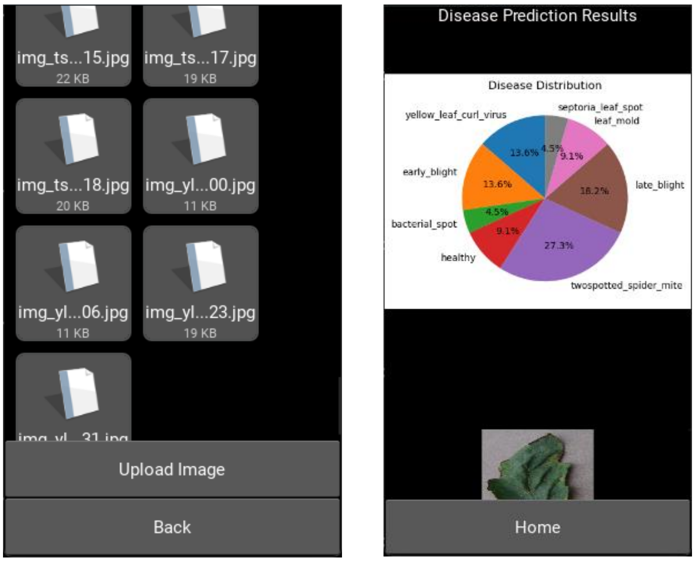
Figure 8. TomatoShield Home Screen

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

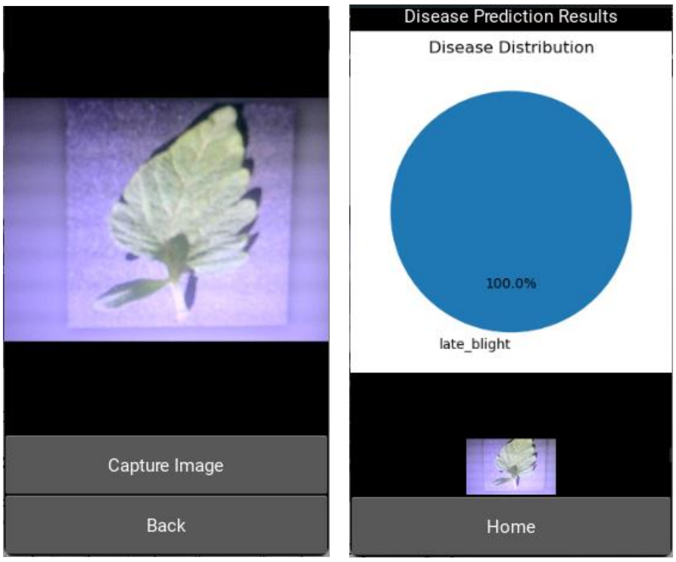
Impact Factor 8.102 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14404



[a] [b]

Figure 9 [a][b]. Tomato Leaf Disease Prediction using Upload Image option



[a] [b]

Figure 10 [a][b]. Tomato Leaf Disease Prediction using Capture Image option

VI. CONCLUSION AND FUTURE SCOPE

The TomatoShield App seeks to harness Convolutional Neural Networks (CNN) to reliably detect and classify tomato plant disease type using current pictures taken from a mobile phone camera, and utilizing prior datasets. The app separates its predictions into various disease types, such as Healthy, Early Blight, or Late Blight, providing farmers opportunities to consider timely identification and treatment for their crops. In addition to historical production data, the system offers farmers insight into agricultural trends and pricing to strengthen the allowable decision-making horizon.

Future enhancements will include improving the training model, increasing datasets to cover more disease variations, and customizing the system to particular climatic and environmental conditions. Location-specific data collection will enable more accurate disease modeling, providing customized recommendations. More iterations of training are likely to make the model more accurate, thus increasing reliability. Furthermore, the expansion of the app's capabilities to cover additional plant species and diseases will make it more user-friendly, thereby making it an all-encompassing tool for plant disease detection and management.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 4, April 2025
DOI: 10.17148/IJARCCE.2025.14404

Through the integration of these technologies, TomatoShield hopes to offer farmers instant and accurate diagnosis of diseases and crop advice, eventually enhancing agricultural productivity and efficiency.

REFERENCES

[1]. N. Shelar, S. Shinde, S. Sawant, S. Dhumal, and K. Fakir, "Plant Disease Detection Using CNN," *ITM Web of Conferences*, vol. 44, p. 03049, **2022**, doi: https://doi.org/10.1051/itmconf/20224403049.

[2]. Md. Manowarul Islam et al., "DeepCrop: Deep learning-based crop disease prediction with web application," Journal of Agriculture and Food Research, vol. 14, pp. 100764–100764, Dec. **2023**, doi: https://doi.org/10.1016/j.jafr.2023.100764.

[3]. Munaf Mudheher Khalid and O. Karan, "Deep Learning for Plant Disease Detection," *International Journal of Mathematics Statistics and Computer Science*, vol. 2, pp. 75–84, Nov. **2023**, doi: https://doi.org/10.59543/ijmscs.v2i.8343.

[4]. Lekha J, Saraswathi S, Suryaprabha D, and N. Thomas, "Tomato Leaf Disease Detection using Machine Learning Model," *Proceedings of the 1st International Conference on Artificial Intelligence, Communication, IoT, Data Engineering and Security (IACIDS)*, Jan. **2024**, doi: https://doi.org/10.4108/eai.23-11-2023.2343189.

[5]. M. F. El-Habibi and S. S. Abu-Naser, "Tomato Leaf Diseases Classification using Deep Learning," *International Journal of Academic Information Systems Research (IJAISR)*, vol. 8, no. 4, pp. 73–80, Apr. **2024**, Available: http://ijeais.org/wp-content/uploads/2024/4/IJAISR240410.pdf

[6]. V. Nirgude and S. Rathi, "A ROBUST DEEP LEARNING APPROACH TO ENHANCE THE ACCURACY OF POMEGRANATE FRUIT DISEASE DETECTION UNDER REAL FIELD CONDITION," *Journal of Experimental Biology and Agricultural Sciences*, vol. 9, no. 6, pp. 863–870, Dec. **2021**, doi: https://doi.org/10.18006/2021.9(6).863.870.

[7]. A. Save, A. Gupta, S. Pruthi, D. Nikam, and Prof. Dr. S. Paygude, "Plant Disease Detection and Fertilizer Suggestion," *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, no. 2, pp. 351–356, Feb. **2022**, doi: https://doi.org/10.22214/ijraset.2022.40275.

[8]. D. A. Bondre and S. Mahagaonkar, "PREDICTION OF CROP YIELD AND FERTILIZER RECOMMENDATION USING MACHINE LEARNING ALGORITHMS," *International Journal of Engineering Applied Sciences and Technology*, vol. 04, no. 05, pp. 371–376, Oct. **2019**, doi: https://doi.org/10.33564/ijeast.2019.v04i05.055.

[9]. Jayesh Krishnarao Kokate, S. Kumar, and A. G. Kulkarni, "Deep Learning Based Leaf Disease Classification," *Journal of Applied Research and Technology*, vol. 21, no. 5, pp. 764–771, Oct. **2023**, doi: https://doi.org/10.22201/icat.24486736e.2023.21.5.2026.

[10]. M. Altalak, M. A. Uddin, A. Alajmi, and A. Rizg, "A Hybrid Approach for the Detection and Classification of Tomato Leaf Diseases," *Applied Sciences*, vol. 12, no. 16, p. 8182, Aug. **2022**, doi: https://doi.org/10.3390/app12168182.

[11]. A. Yu, S. H. Lee, F. S. Tay, Hervé Goëau, P. Bonnet, and A. Joly, "PlantAIM: A New Baseline Model Integrating Global Attention and Local Features for Enhanced Plant Disease Identification," *Smart Agricultural Technology*, pp. 100813–100813, Feb. 2025, doi: https://doi.org/10.1016/j.atech.2025.100813.

[12]. A. Upadhyay et al., "Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture," *Artificial Intelligence Review*, vol. 58, no. 3, Jan. 2025, doi: https://doi.org/10.1007/s10462-024-11100-x.

[13]. Y. Alhwaiti, M. Khan, M. Asim, M. H. Siddiqi, M. Ishaq, and M. Alruwaili, "Leveraging YOLO deep learning models to enhance plant disease identification," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, doi: https://doi.org/10.1038/s41598-025-92143-0.

[14]. Venkata Santhosh Yakkala *et al.*, "Deep learning-based crop health enhancement through early disease prediction," *Cogent Food & Agriculture*, vol. 11, no. 1, Dec. 2024, doi: https://doi.org/10.1080/23311932.2024.2423244.

[15]. A. E, "Lightweight Transfer Learning-Based Pipeline for the Detection and Prediction of Citrus Plant Diseases," *SSRN*, 2025, doi: https://doi.org/10.2139/ssrn.5078738.