

Research Paper

TOMATO LEAF MOBILE AN ANDROID BASED REAL TIME DISEASE DETECTION SYSTEM

¹Praveen Kumar Saddala, ²Adithya Vemula¹Associate Professor, Department of Electronics and Communication Engineering, JNTUH University College of Engineering Jagtial, Jagtial, Telangana. 505501²PG Scholar, Department of Electronics and Communication Engineering, JNTUH University College of Engineering Jagtial, Jagtial, Telangana. 505501²adithyav7777@gmail.com

Abstract— Tomato leaf diseases are very critical to the agricultural production, quality of the crop and global food security. Thus, prompt and precise disease identification is crucial for sustainable farming methods. Manual inspection is labour-intensive, subjective and often ineffective and is the major drawback for large-scale agriculture, where intelligent automated diagnosis is needed. The proposed approach is based on the publicly available PlantVillage tomato leaf disease 1 dataset, which consists of labeled images of healthy and diseased tomato leaves collected under controlled conditions, spanning various categories of diseases. The image scaling, normalisation, data augmentation, one-hot encoding and train-validation-test partitioning are part of the processing pipeline to enhance the representation of the features, model generalisation and reduce the over-fitting effect. Implementations of different DL architectures such as Custom CNN, ResNet50, DenseNet121, MobileNetV2, Xception, NASNetLarge, and Hybrid Ensemble of Xception and NASNetLarge are done for benchmarking. The modified MobileNetV3, incorporating Inverted Residual Blocks and Efficient Channel Attention mechanisms, on the other hand, improves the efficiency of lightweight feature extraction. The accuracy, precision, recall, F1 score, confusion matrix, ROC analysis and learning curves of training-validation are used to assess the performance. The experimental results revealed that the best performance in terms of accuracy, precision, recall and F1-score was obtained by the Hybrid Ensemble with 99.9%, 99.9%, 99.9% and 99.9% respectively. The interpretability and usefulness of the visualisation was enhanced by the GradCAM visualisation, while the diagnosis interface and treatment suggestions along with the GTTS voice assistance were rendered more useful and practical through Flask. Finally, the proposed framework provides the intelligent agriculture applications with high accuracy, efficiency and interpretability of tomato leaf diseases detection.

Keywords— *Tomato Leaf Disease Detection, Deep Learning, MobileNetV3, Efficient Channel Attention (ECA), Hybrid Ensemble Learning, Explainable Artificial Intelligence (XAI).*

I. INTRODUCTION

Tomato is one of the most extensively produced vegetable crops and is an important source of nourishment and revenue for millions of people throughout the world. Thus, it is essential to promote the healthy tomato production for sustainable agriculture, food security and economic stability. Tomato plants can, however, suffer from several diseases which are easily spread on the leaves and if not treated early can result in poor yield and poor fruit quality. As digital imaging technology and intelligent agricultural platforms continue to become more available, automated crop monitoring systems are becoming more popular that can facilitate early disease detection and decision-making. The

technologies have been part of the precision farming and have given the opportunity to evaluate the field at any time, reduce manual evaluation, and increase the operational efficiency and uniformity [1] [2] [3].

Several efforts have been made for the automated identification of plant diseases, but numerous limitations prevent its use at a wider scale. The traditional approach to diagnosis is mainly carried out by the visual recognition of competent agricultural experts and uses a lot of labour, is subjective and can be hard to access in many rural agricultural settings. In addition, the like appearance of the illnesses, shifts in lighting, backgrounds, and the angle of the leaves, and disease intensity can reduce diagnostic accuracy. In addition, the use of existing intelligent solutions is often constrained in terms of categorisation accuracy, and interpretability, and is not accompanied by decision assistance and usability for farmers with limited technical skills. This limitation indicates the critical need for effective and user-friendly systems of disease diagnosis that could offer a reliable prognosis that would give substantial guidance for effective agricultural management [4] [5] [6].

The primary goal is to develop an intelligent framework for the diagnosis of tomato leaf diseases, capable of accurately and reliably diagnosing multiple disease categories from digital leaf images, along with an environment for an agricultural application of the system which is practical and user friendly. Beyond predicting diseases, the framework will be aimed to provide descriptive information on diseases, potential causes, suggested treatment and helpful advice to assist the user in making informed crop management decisions. Also, the framework allows for a visual interpretation of the results and provide visualisation of areas of the image that have the greatest impact on the diagnostic conclusion, which enhances the confidence in prediction results. Integrated functions are intended to enhance transparency, accessibility and usefulness without increasing the burden on end users in terms of operation complexity [7] [8].

The proposed framework combines the accurate disease detection with practical decision support in one system, which is suitable for real world application and promotes the concept of intelligent agriculture. Early and reliable diagnosis of disease allows for timely intervention, reduction in use of unneeded pesticides, minimisation of crop loss and sustainable methods in agriculture. Intelligent diagnostic systems can be more widely adopted and trusted by farmers and agricultural extension and service providers if they are

accompanied by explanatory visualisation and user-friendly interaction. This work has the potential to enhance monitoring of crop health, agricultural productivity and to facilitate the greater adoption of digital technologies to precision farming and sustainable food production in various farming environments [9] [10].

II. RELATED WORK

In recent years, the use of AI, Computer vision and automation in smart agriculture has proven to be of growing relevance in crop monitoring and disease management. Chittoor et al. presented a ML and GAI based design framework for an autonomous urban landscape fumigation service robot and showcased the feasibility of intelligent robotic systems in agricultural and environmental applications, specifically the support system in the design and deployment phase [11]. Kong et al. introduced a node re-recognition technique using a homography transformation for the detection of the site where the pruning was carried out for a winter grapevine in the field, proving the effectiveness of vision-based localization strategies in various field conditions. The method improved recognition robustness but primarily was used for crop management, not for disease detection, and thus mostly limited to use for plant health assessment [12].

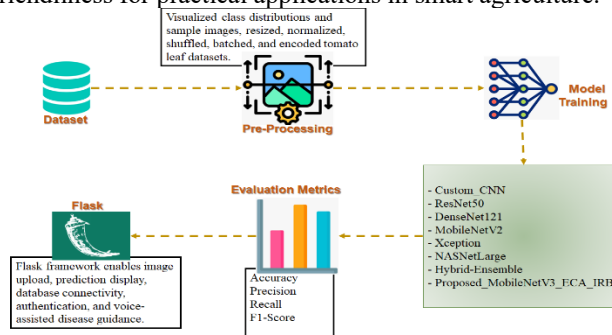
The performance of visual identification using DL techniques has been significantly improved and suitable for agricultural applications. To showcase the continuous improvements in terms of detection speed, localisation accuracy, and computational efficiency, Hasan et al. examined the progression of the YOLO family of object detection models. Lightweight deployment and generalisation in a wide variety of agricultural contexts were also problems captured by the poll [13]. Ujai et al. proposed a DL based IoT enabled plant disease detection framework for plant condition automated monitoring. Although the IoT integration enabled the remote access, the framework was not very interpretable or decision-supportive other than disease prediction [14]. Islam et al. created a DL based rose disease detection system utilising YOLO which detects diseases accurately from plant photos. However, the application is restricted to the identification performance without any diagnostic support and interpretability for the end users [15].

With improved neural network architecture, several approaches have been proposed for classification-based disease recognition with higher accuracy. There are several approaches that have been proposed to improve the accuracy of disease recognition in terms of using classification such as a better neural network architecture. To improve the accuracy of plant leaf disease classification, Pandian et al. introduced a deep residual convolutional neural network that boosts the extraction of the features and reduces the classification error. But, all these developments [16] did not make the model yet cost-effective for implementation on resource-limited platforms. To tackle this limitation, Garg et al. [97] designed the optimised CNN models for resource-constrained settings and proved that efficient CNN models can perform on par with the resource-heavy CNN counterparts with reduced computation requirements. However, the realisation of lightweight deployment with stable performance on various illness categories is still a tough goal [17]. Rajmohan et al. showed that the traditional image analysis methods are effective in groundnut leaf disease detection. These systems, however, were based on handcrafted features, and were therefore not very adaptable to more complex disease patterns and variable environmental conditions [18].

Recently, studies have been suggested to explore the improved learning paradigms of recognition by limited data availability. In order to provide a good generalisation capability when only a few images are labeled, Zhou et al. proposed a vision-language model for few-shot crop disease picture classification. The method described will reduce the burden of annotation, but its implementation could require significant computing resources and a specific training procedure [19]. The effectiveness of enhanced deep residual convolutional networks for detecting plant leaf diseases has been demonstrated by Pandian et al. [20] which highlights the importance of strong feature learning in accurate plant disease classification and suggests the direction for improving the efficiency and applicability of the model. These works collectively indicate some promising steps towards automated plant disease diagnosis, but still pose the challenges of achieving high classification accuracy while maintaining computational efficiency, explainable prediction, and ease of user interaction and practical decision support simultaneously. These are overcome by the current design, which combines the ability to accurately categorize the illnesses, interpretability of the visualisation, valuable diagnosis and treatment recommendations, and a fully interactive application environment for in-farm use.

III. MATERIALS AND METHODS

The proposed approach will help in the accurate and intelligent diagnosis of the tomato leaf diseases using the publicly available PlantVillage dataset and a DL pipeline for image classification. The whole process, from the standardized data preparation to data partitioning, model training, validation and performance assessment, is conducted within a single learning framework. This is achieved by comparing the performance with Custom CNN, ResNet50, DenseNet121, MobileNetV2, Xception, NASNetLarge, Hybrid Ensemble of Xception and NASNetLarge, and the improved MobileNetV3 which includes Inverted Residual Blocks and Efficient Channel Attention mechanisms to boost discriminative feature extraction without sacrificing speed. We have added explainable AI to the model, with GradCAM visualizing the regions affected by the disease to make the model more transparent, and better understand the prediction results. The entire framework is built as a flask based web application with user authentication secured by SQLite which supports secure image upload, automatic disease recognition, disease description, therapy suggestions and GTTS (voice assisted) instructions. The integrated technique provides accurate disease detection, with interpretability and user-friendliness for practical applications in smart agriculture.



“Fig. 1. System Architecture”

The proposed system design offers a comprehensive solution for automated detection of tomato leaf diseases.

Visualisation, resizing, normalisation, shuffling, batching and label encoding are implemented to first collect and preprocess the PlantVillage dataset to ensure the model receives standardised inputs. The accuracy, precision, recall and F1-score are used to train and compare the performance of several DL architectures. The best model is presented in an online application for disease prediction in a flask providing an intelligent farmers decision supporting and voice-assisted guiding features, where the user is able to log in to the application and upload an image, and store and access the image in the database.

A) Dataset Collection

It is implemented using the publicly available PlantVillage dataset, obtained from the PlantVillage repository. There are labelled RGB images of the tomato leaves for various disease categories. This dataset is comprised of good quality images of leaves in folders, with each image representing an input feature and the disease class as a class label. It has a wide spectrum of disease symptoms gathered under standardized imaging conditions, allowing for uniform visualisation for the development of models and comparison assessments. The PlantVillage dataset is well annotated, balanced and has been extensively used for plant disease classification making it a good standard for developing a reliable and accurate automated tomato leaf disease detection system.

B) Pre-Processing

Extensive and meticulous preparation step, including careful exploration, visualization, normalization, validation, splitting and evaluation of the tomato leaf image dataset prepares it for efficient DL classification, and produces robust, precise and effective disease prediction.

1. *Data Exploration*: Before building the model, the data set was explored to get an overview of the structure of the data, distribution of images and arrangement of the disease categories. The analysis included checking photos availability for various classes, as well as analysing the samples to find out the representativeness for visual diversity and consistency of the labels. This exploration was a full understanding of the features of the datasets that enabled sound decisions to be made in the subsequent stages of the processing. It was also used to identify any class imbalance issues and to check the suitability of the dataset for accurate classification of tomato leaf diseases.

2. *Data Visualization*: The distribution of disease classes was analysed by using typical pictures of tomato leaves of each class. Class frequencies and visual differences between healthy and sick leaves were represented graphically. This enabled us to grasp the composition of the dataset and ailments features prior to training the algorithm. Visual inspection also proved helpful in quality checking the dataset for quality, inconsistencies and sufficient variance for optimal classification performance.

3. *Image Data Pre-processing*: The input data was standardised and the learning ability of DL models was improved by doing image preprocessing. The photos of tomato leaves had been reduced to the same dimensions, processed into the same colour space, normalised, shuffled and structured into numerical formats that can be used to train the model. The class labels were encoded into a machine-readable format to allow classification of more than one class. These pre-processing methods contribute to higher reliability in terms of disease recognition, better consistency of data, elimination of unnecessary variations and faster convergence of the model.

4. *Dataset Partitioning*: The prepared data set was divided into multiple parts for training and validating the model which would give an unbiased performance evaluation. By segmenting the image, the salient features of the disease could be learnt from one part of the image and the evaluation could be done on unseen images which are part of the test set. This was done to prevent over-fitting and to get a reasonable approximation of the model's generalisation. The data set was accurately split to be able to utilise these models in reality and construct robust and accurate algorithms to classify tomato leaf diseases.

5. *Model Training Preparation*: Preprocessed picture data was put in an optimal layout for training multiple DL architectures. To enable a fair comparison, the evaluation was performed using a standardised representation of the images in the format and the class labels encoded in the same format that were presented to all the classification models. This preparation ensured efficient use of computational resources and ensured data integrity during learning. A well-designed training set helped to learn the features, provided stability in the classification and allowed to fairly compare the performance of various DL architectures.

6. *Performance Evaluation Preparation*: The dataset was processed and then subjected to the normal performance evaluation procedures of the classification models. This assessment allowed for a detailed analysis of the accuracy, reliability and consistency of categorisation across different disease categories and quantitative assessment measures were obtained by comparing the predictions made by each model to the ground-truth labels. The performance measures derived from these were used to provide objective evidence to determine the most effective model and to confirm the overall effectiveness of the illness diagnosis framework.

7. *User Authentication Preparation*: Securely prepared user authentication information for the controlled access to the illness diagnosis platform. The registration information was checked and stored in a structured database for enabling personalised prediction services to be accessed by authenticated users. Authentication management enhanced the security of the program and also helped stop unauthorized people from accessing into the system resources and forecasting functions. This preparation created a solid basis for a safe interaction with the user while keeping the data integrity and preserving sensitive user data in web application.

8. *Input Image Validation*: The photos of tomato leaves were cross-checked with the tomato leaf categorisation system to guarantee the compatibility of the images used for prediction of the disease. The given photographs were pre-processed to check the propriety of the content and their applicability and then handed on to the trained classification models. The advantage of this validation approach is that a high level of findings was preserved, because false and/or inconsistent inputs did not disturb the accuracy of the prediction and the stability of the system. The framework only permitted including acceptable photographs in the diagnostic process which resulted in better dependability of predictions and a more holistic user experience.

9. *Result Generation and Post-processing*: The prediction outputs were categorised and translated to relevant diagnostic information to the end users. The framework provides integrated results of disease diagnosis with visualisation of infected areas, descriptions of the diseases, suggestions for treatment, and voice actuated information. This post-processing step made the outcome of this categorisation more

usable and understandable as agricultural information, and thus made the numerical predictions more useful. The technology therefore provided good decision assistance for precision farming applications and management of tomato diseases.

C) Algorithms

Custom CNN: The custom CNN is trained to learn the features of the input images, which includes the texture, edges and the structure. The layered architecture provides visual representation learning with reliable classification accuracy and architectural flexibility of meeting the various computational and application requirements.

ResNet50: ResNet50 utilises residual learning to enable the effective training of deep neural networks, and to maintain key feature information over several layers. The architecture is able to capture complex visual information successfully, thus reducing the optimisation problem and improving the accuracy of the classification, stability and resilience of the learning.

DenseNet121: To make the feature propagation more powerful, DenseNet121 uses dense connection: every layer can access the information from all the previous layers. This technique achieves better feature reusability, gradient flow, redundancy reduction and classification accuracy with maintaining the computational efficiency and good visual representation learning.

MobileNetV2: MobileNetV2 is a light-weight DL architecture to do picture categorisation with low computing complexity. The optimised convolutional structure preserves important visual properties with minimal resource usage, allowing for fast inference and a real-time deployment with only a modest reduction in predictive performance.

Xception: Xception uses depthwise separable convolutions in an efficient way to extract discriminative spatial and channel-wise data. Such architecture enhances the feature learning as well as decreases the computing burden, thereby elevating the classification accuracy, stabilising the optimisation and making it possible to reliably recognise complex visual patterns in multiple classes.

NASNetLarge: NASNetLarge is an auto-optimized neural network to efficiently learn hierarchical visual representation. The search-based structural design enhances the feature extraction ability, improves the classification performance and promotes the robust recognition by properly modelling the complicated spatial relationships in the input images.

Hybrid Ensemble: Prediction using multiple DL architectures are used to gain from their complementing capabilities in the Hybrid Ensemble. By combining the various feature representations and decision patterns, it can enhance the classification accuracy, reduce the uncertainty of prediction, enhance the generalisation ability, and give more reliable recognition results.

Proposed MobileNetV3 with ECA and IRB: The MOBILENETV3 integrates Inverted Residual Blocks and Efficient Channel Attention to further enhance lightweight feature extraction and attention to useful feature channels. Such design can improve computing efficiency, boost discriminative representation learning, and achieve accurate, robust and efficient picture classification for real-time applications.

IV. EXPERIMENTAL RESULTS

Accuracy: The percentage of correct classification of healthy and patient cases by a test. The percentage of correct positive and correct negative results when all instances analyzed should be determined to assess accuracy of a test. Mathematically:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision is the number of correctly categorised occurrences or samples divided by the number of instances or samples classified as positives. Thus, the formula to get the precision is:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2)$$

Recall: Recall is an evaluation metric in ML which assesses the model's ability to find all the actual instances of a given class. It is the proportion of correctly classified positive examples to the number of positive examples and it is a good indicator of the completeness of the model's ability to capture positive examples.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

F1-Score: F1 Score is a ML evaluation metric which calculate the accuracy of a model. This is a combination of the precision score and recall score of a model. Accuracy statistic: The proportion of correct predictions a model made for the entire data set.

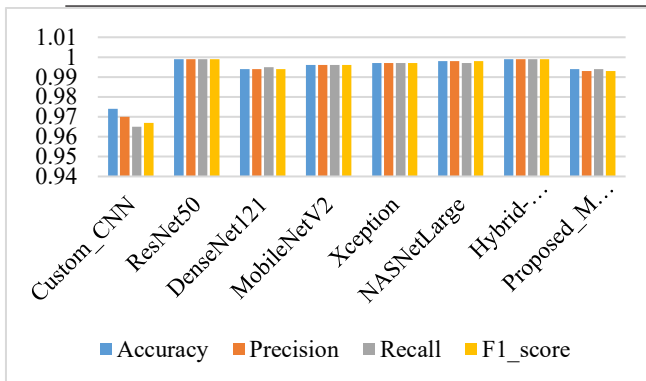
$$\text{F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} * 100 \quad (5)$$

“Table. 1. Performance Evaluation”

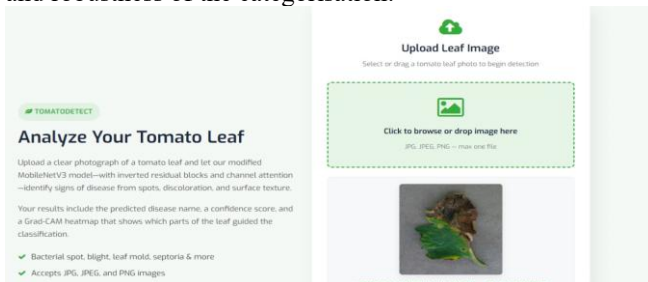
Model	Accur acy	Precis ion	Rec all	F1_sc ore
Custom_CNN	0.974	0.970	0.965	0.967
ResNet50	0.999	0.999	0.999	0.999
DenseNet121	0.994	0.994	0.995	0.994
MobileNetV2	0.996	0.996	0.996	0.996
Xception	0.997	0.997	0.997	0.997
NASNetLarge	0.998	0.998	0.997	0.998
Hybrid-Ensemble	0.999	0.999	0.999	0.999
Proposed_MobileNetV3_ECA_IRB	0.994	0.993	0.994	0.993

A comparative performance evaluation of eight DL models has been performed using accuracy, precision, recall and f1-score, as presented in Table 1. The best performance was obtained by the ResNet50 and Hybrid-Ensemble models and were demonstrated to be accurate and reliable classifiers.

“Fig. 3. Comparison Graph”

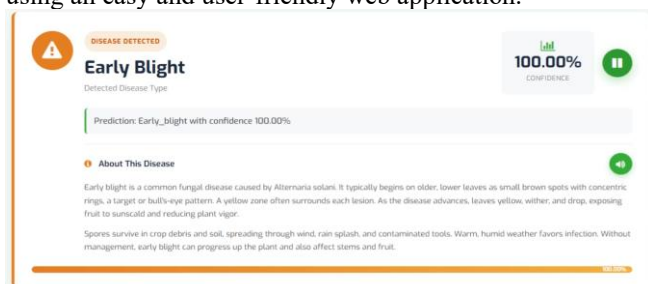


The results of the DL models are compared in terms of accuracy, precision, recall and F1-score as depicted in Figure 3. The results show that ResNet50 and Hybrid-Ensemble achieved the best scores consistently indicating the efficacy and robustness of the categorisation.



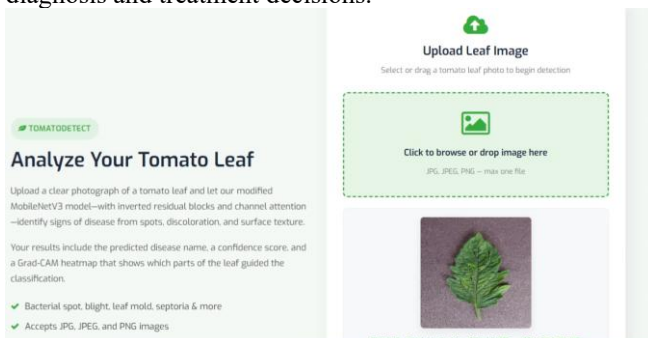
“Fig.2 Upload the Image”

Figure 2. Uploading tomato leaf images: user interface. The user can either browse or drag and drop the leaf image for analysis. Thus providing automatic illness prediction using an easy and user-friendly web application.



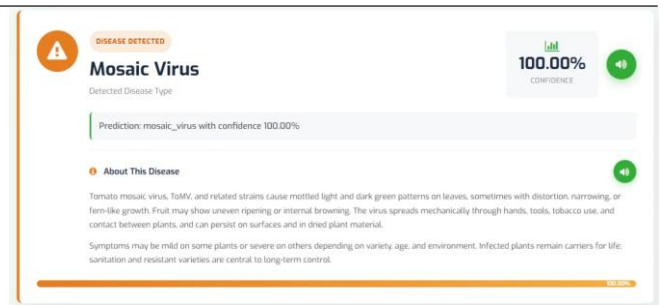
“Fig.3 Predicted Result”

Fig. 3 depicts the result of illness prediction for Early Blight, the system has a confidence value of 100.00% regarding the detection of Early Blight. The interface also provides disease details, which helps users to make a correct diagnosis and treatment decisions.



“Fig.4 Upload the Image”

The tomato leaf picture upload page is displayed with selected tomato leaf image for analysis is shown in figure 4. The intelligent prediction framework verifies and processes the image sent to perform an automatic disease classification.



“Fig.5 Predicted Result”

Fig. 5 shows the output of disease prediction for Mosaic Virus. The algorithm is 100.00% confident in its prediction of the disease. The interface also presents disease information which can be used to make an accurate diagnosis and an effective disease management decision.

V. CONCLUSION

To summarise, the main aim was to design an intelligent and reliable framework for disease detection in tomato leaves that might help in early and precise detection of plant illnesses, and thereby promote precision agriculture and improve crop management. The framework is based on PlantVillage tomato leaf disease dataset and consists of various DL architectures such as Custom CNN, ResNet50, DenseNet121, MobileNetV2, Xception, NASNetLarge, Hybrid Ensemble model and modified MobileNetV3 with Inverted Residual Blocks and Efficient Channel Attention mechanisms for full comparative classification. The developed framework also includes the use of explainable AI using GradCAM for enhanced transparency in the predictions, and a Flask based web application backed by a sqlite database for user authentication, disease descriptions, treatment recommendations, and GTTS voice-assisted guidance for improved user interaction. The experimental evaluation showed the usefulness of the suggested framework. Overall, the accuracy of the classification of the Hybrid Ensemble model was 99.9%, which confirms the potential of the model for a very accurate diagnosis of tomato leaf disease. Explainable visualisation, lightweight architectural changes and smart deployment environment result in higher prediction confidence and usability. Overall, the proposed framework offers an accurate, efficient, interpretable and user-friendly approach to facilitate automated disease detection, knowledgeable agricultural decision making and real-world smart farming applications.

Expansion of the framework to other crop species and broader variety of plant diseases using other real field data acquired in various environmental conditions can be a future challenge. Mobile and edge computing systems can be integrated to enable real-time diagnosis of diseases in the fields of agriculture. Weather and soil data could be used in conjunction with other multimodal data to enhance diagnosis. The precision agriculture is more accessible, scalable and practically adopted by the use of cloud-based monitoring, multilingual user support and enhanced decision-support capabilities.

REFERENCES

- [1] Zhang, K., Chai, Q., Qian, X., Gao, R., Liu, X., Yang, L., ... & Sun, J. (2025). Potential of machine learning in leaf-based multi-source data driven tomato growth monitoring. *Smart Agricultural Technology*, 10, 100854.
- [2] Mohamed, A. G. E., Abdin, F. A., Hamdallah, M. R., Mohammed, M. A., Khawaja, S. G., Yousaf, J., ... & Hassan, T. (2025, August). A Systematic Review of AI-Driven Wearable Plant Disease Recognition

- Systems. In 2025 12th International Conference on Future Internet of Things and Cloud (FiCloud) (pp. 424-430). IEEE.
- [3] Kasera, R. K., Nath, S., Das, B., Kumar, A., & Acharjee, T. (2025). IoT Enabled Smart Agriculture System for Detection and Classification of Tomato and Brinjal Plant Leaves Disease. *Scalable Computing: Practice and Experience*, 26(1), 96-113.
 - [4] Wang, J., Chen, Y., Huang, J., Jiang, X., & Wan, K. (2025). Leveraging machine learning for advancing insect pest control: A bibliometric analysis. *Journal of Applied Entomology*, 149(3), 293-308.
 - [5] Lyu, Y., Lu, F., Wang, X., Wang, Y., Wang, Z., Zhu, Y., ... & Dong, M. (2025). A CNN-Transformer Hybrid Framework for Multi-Label Predator-Prey Detection in Agricultural Fields. *Sensors*, 25(15), 4719.
 - [6] BOUDOUDA, S., & BOUKALLEL, M. (2025). Intelligent Soil Classification for Precision Agriculture in Algeria: Integrating Machine Learning and Image Processing for Optimized Crop Yield and Recommendation. *Algerian Journal of Signals and Systems*, 10(2), 65-74.
 - [7] Oberti, R., Caffi, T., & Calcante, A. (2025). Developments in precision crop protection systems. In *Precision agriculture for sustainability* (pp. 463-502). Burlington: Dodds Science Publishing.
 - [8] Niam, S., Rahman, T., Patwary, M. A., & Hossain, M. (2025). A machine learning framework integrating seed traits and plasma parameters for predicting germination uplift in crops. *arXiv preprint arXiv:2510.23657*.
 - [9] Atsmon, G., Kizel, F., Eizenberg, H., & Lati, R. (2025). Spectral remote sensing approaches for monitoring broomrape parasitism dynamics. In *Precision agriculture'25* (pp. 254-262). Wageningen Academic.
 - [10] Zhu, M., & Rastelli, R. (2025). Bayesian Additive Regression Trees (BART) in Food Authenticity: A Classification Approach to Food Fraud Detection. *arXiv preprint arXiv:2510.15105*.
 - [11] Chittoor, P. K., Dandumahanti, B. P., Veerajagadheswar, P., Samarakoon, S. B. P., Muthugala, M. V. J., & Elara, M. R. (2025). Developing an urban landscape fumigation service robot: A Machine-Learned, Gen-AI-Based design trade study. *Applied Sciences*, 15(4), 2061.
 - [12] Kong, S., Liu, X., Huang, Q., Jia, B., Huang, J., Chen, Y., ... & Fu, L. Homography transformation-based node re-recognition for winter pruning position identification of horizontal trellis cultivated grapevine. Available at SSRN 5654873.
 - [13] Hasan, M., Rabby, M. K. M., Jahan, I., Soeb, M. J. A., & Jubayer, M. F. (2025). The Evolution and Advancement of YOLO Algorithms in Object Detection: From Real-Time Breakthroughs to Modern Architectures.
 - [14] Ujai, B. C., VV, B. M., Siddharth, V., Sai, A. V. R., Ssathyan, S. R., & Angulakshmi, M. (2023). Plant Disease Detection From Images Using Deep Learning Techniques based on the Internet Of Things. *International Journal of Computer Science Research (IJCSR)*, 2(4), 111-117.
 - [15] Islam, P., Ziden, Z. D., Abdullah, S., Asif Hasan, M., Ahaduzzaman Asif, M., Khan, M., & Mitra, T. (2024, December). Rose Disease Detection Using YOLO. A Deep Learning-Based Approach. In *International Conference on Information and Communication Technology for Competitive Strategies* (pp. 147-159). Singapore: Springer Nature Singapore.
 - [16] Pandian, A., Kanchanadevi, K., & Rajalakshmi, N. R. (2022). An improved deep residual convolutional neural network for plant leaf disease detection. *Computational Intelligence and Neuroscience*, 2022, 5102290.
 - [17] Garg, P., Srivastava, G., & Kumari, L. (2024, December). Plant Disease Detection Using Optimised Cnn Models for Resource Constrained Environment. In *2024 4th International Conference on Innovative Sustainable Computational Technologies (CISCT)* (pp. 1-7). IEEE.
 - [18] Rajmohan, M., Reddy, D. S. S., Krishna, C. M., & Krishna, N. M. S. (2022, October). Groundnut leaf disease identification using image processing. In *AIP Conference Proceedings* (Vol. 2519, No. 1, p. 030110). AIP Publishing LLC.
 - [19] Zhou, Y., Yan, H., Ding, K., Cai, T., & Zhang, Y. (2024). Few-shot image classification of crop diseases based on vision-language models. *Sensors*, 24(18), 6109.
 - [20] Pandian, A., Kanchanadevi, K., Rajalakshmi, N. R., & Arulkumaran, G. (2022). Research Article An Improved Deep Residual Convolutional Neural Network for Plant Leaf Disease Detection.
 - [21] Li, X., Hou, B., Zhang, R., & Liu, Y. (2023). A review of RGB image-based internet of things in smart agriculture. *IEEE Sensors Journal*, 23(20), 24107-24122.
 - [22] Wattad, M., & Filin, S. (2024). Trait-focused low-cost and stereo-based 3D plant modeling for phenotyping via deep neural detection. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48, 455-461.
 - [23] Raj, P., Kumar, A., & Singh, P. (2024, December). Detecting Paddy Leaf Diseases Using MobileNetV2 and Machine Learning Techniques. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 120-128). IEEE.
 - [24] Mehta, S., & Bhalla, A. (2024, December). Improving Orange Quality and Yield: A Smart Agriculture Framework for Ripeness Detection. In *2024 IEEE International Conference on Intelligent Signal Processing and Effective Communication Technologies (INSPECT)* (pp. 1-5). IEEE.
 - [25] Dikshit, S., Bhuyan, S., Mohapatra, P., & Subham, P. (2024, December). Weed Identification using Deep Learning and Meta-heuristic Algorithms. In *2024 International Conference on Communication, Control, and Intelligent Systems (CCIS)* (pp. 1-6). IEEE.