International Journal of Scientific Research in Engineering & Technology
Volume 5, Issue 3 (May-June 2025), PP: 69-75.
www.ijsreat.com ISSN No: 2583-1240

Tomato Plant Leaf Disease Classification Using Deep Learning

R. L. Ghule[1], Vishakha Jadhav[2], Vaishnavi Bagal[3], Anjali Bhandare[4], Sandhya Bondre[5]
[1, 2,3,4,5] Department of AI & DS, Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering & Technology, Baramati, Maharashtra, India.

To Cite this Article: *R. L. Ghule[1], Vishakha Jadhav[2], Vaishnavi Bagal[3], Anjali Bhandare[4], Sandhya Bondre[5], "Tomato Plant Leaf Disease Classification Using Deep Learning", International Journal of Scientific Research in Engineering & Technology, Volume 05, Issue 03, May-June 2025, PP:69-75.*

Abstract: *Tomato plants often get different types of leaf diseases that can reduce the quality and quantity of crops. In this project, we use deep learning to identify these diseases by analyzing pictures of tomato leaves. We trained three models EfficientNet-B0, VGG16, and a custom CNN to recognize diseases like Early Blight, Late Blight, Leaf Mold, and more. We also built a hybrid model that combines the best parts of all three models to improve accuracy. Once the disease is detected, our system suggests the right pesticide to treat the plant. Our testing shows that the hybrid model gives better results than using each model separately. This project helps farmers quickly identify plant diseases and take the right actions to protect their crops. By doing this, we can improve crop health, prevent losses, and reduce the use of unnecessary pesticides.*

Key Word: *EfficientNet-B0, VGG16, CNN, Hybrid Model, Disease Classification, Pesticide Suggestion.*

I.INTRODUCTION

Agriculture plays a vital role in food security, particularly in countries like India, where farming is the primary source of income. However, one of the major challenges farmers face is identifying plant diseases, which can significantly affect crop yield and quality. Traditional methods, such as relying on expert advice or manual inspections, are time-consuming and often not accurate. In this project, we focus on tomato plants, which are commonly affected by diseases like Early Blight, Late Blight, and Leaf Mold. To detect these diseases, we use three deep learning models — EfficientNet-B0, VGG16, and a basic Convolutional Neural Network (CNN). These models analyze images of tomato leaves to identify the diseases. To further enhance detection accuracy, we combine the strengths of these models into a hybrid model. After the disease is detected, the system recommends the appropriate pesticide for treatment. This approach helps farmers quickly and accurately identify plant diseases, enabling them to take prompt action, improving crop health, minimizing yield loss, and boosting productivity.

A. Our Contribution

In this project, we focus on improving tomato plant health by identifying leaf diseases using deep learning. We trained three models — EfficientNet-B0, VGG16, and a custom Convolutional Neural Network (CNN) — to detect diseases like Early Blight, Late Blight, and Leaf Mold in tomato leaves. The custom CNN was designed to enhance detection accuracy, while the hybrid model, combining the strengths of all three models, outperformed each one individually. After identifying the disease, the system suggests the appropriate pesticide for treatment, ensuring quick and accurate action. This approach enables farmers to detect diseases early, take preventive measures, and improve crop health. By using this system, farmers can reduce crop losses, improve yield, and minimize unnecessary pesticide use, making plant disease management more efficient and reliable.

II.RELATED WORK

In recent years, many researchers have explored ways to use deep learning for detecting plant diseases. Some focused on using CNN models to classify different leaf diseases, while others used well-known architectures like VGG16 and Efficient Net for better performance. For example, VGG16 has been used for identifying tomato and potato leaf infections. Meanwhile, Efficient Net models are preferred for their balance of speed and accuracy. A few studies also applied machine learning to give crop or fertilizer suggestions. However, most past work looks at either disease detection or recommend- tions, not both. Our project fills this gap by combining CNN, VGG16, and EfficientNet-B0 into a hybrid model and adding pesticide suggestions, giving farmers a complete and helpful solution.

A. Abbreviations and Acronyms

AI – Artificial Intelligence
VGG16 Visual Geometry Group 16-layer Network DL – Deep Learning
CNN – Convolutional Neural Network TLDC Tomato Leaf Disease Classification.

III.PROPOSED APPROACH

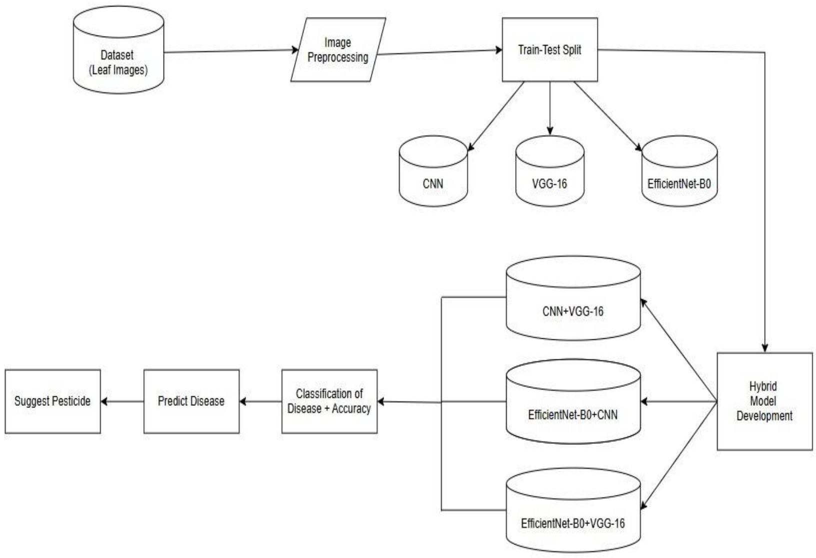

Fig. 1. Flow Diagram

A. Data Collection

The system gathers two key datasets to drive the pipeline. The image dataset contains leaf images with visible symptoms of multiple diseases and deficiencies, sourced from open repositories like Plant Village and real field samples. The tabular dataset includes crop details, disease types, soil pH, nutrient data, and pesticide mappings. These datasets support both image-based classification and context-aware pesticide suggestions, enabling the development of individual and hybrid deep learning models shown in the system's architecture flow.

B. Data Preprocessing

Image data is preprocessed through resizing, normalization, and data augmentation techniques like zooming, flipping, and rotating to improve model generalization. Tabular data is cleaned by handling missing values, encoding categorical variables, and normalizing numerical features to enhance the accuracy and efficiency of the Random Forest classifier used in the system.

C. Individual Model Training

Each model—CNN, VGG-16, and EfficientNet-B0—is trained separately using the preprocessed image dataset. These models learn to identify distinct visual patterns of diseases and deficiencies, enabling accurate classification performance during evaluation and forming the basis for hybrid model development.

- **CNN (Custom Convolutional Neural Network):** A tailored CNN designed specifically for tomato leaf dis- ease classification. It extracts hierarchical features from images through convolutional layers, enabling accurate identification of disease patterns with optimized architec- ture suited to the dataset characteristics.
- **VGG-16 (Pretrained Deep CNN Architecture):** VGG- 16 is a widely used pretrained deep convolutional neural network with 16 layers. It provides powerful feature extraction capabilities and is fine-tuned on tomato leaf images for efficient disease classification with high accuracy.
- **EfficientNet-B0 (Lightweight and Accurate Pretrained Model):** EfficientNet-B0 is a compact, pretrained CNN optimized for both accuracy and efficiency. It balances model depth, width, and resolution, making it ideal for resource-constrained environments while maintaining strong performance on tomato leaf disease detection.

D. Hybrid Model Development

Hybrid models combine features or predictions from CNN, VGG-16, and EfficientNet-B0 to enhance disease classification accuracy and robustness.

- **CNN + VGG-16 Hybrid Model:** This hybrid com- bines the custom CNN's specialized feature extraction with VGG-16's deep pretrained layers. By merging their learned features or predictions, it leverages both models' strengths, improving disease classification accuracy by capturing a wider range of visual patterns and reducing individual model weaknesses.The accuracy of the model is 98%.
- **EfficientNet-B0 + CNN Hybrid Model:** Combining EfficientNet-B0's efficient architecture with the custom CNN enhances model performance. EfficientNet-B0 pro- vides strong feature scaling, while the CNN offers tai- lored extraction for tomato leaf images. Their fusion leads to improved generalization and accuracy for disease detection with optimized resource usage.The accuracy of the model is 89%.
- **EfficientNet-B0 + VGG-16 Hybrid Model:** This hybrid merges EfficientNet-B0's lightweight but powerful fea- tures with VGG-16's deep, pretrained knowledge. The in- tegration allows the model to benefit from EfficientNet's efficiency and

VGG-16's detailed feature representation, resulting in superior classification accuracy and robust- ness across diverse disease patterns.The accuracy of the model is 30%.

E. Classification of Disease + Accuracy

The system uses deep learning models to classify plant leaf images and identify diseases or nutritional deficiencies with high precision. Custom CNN, VGG-16, and Efficient Net- B0 models are trained individually, followed by hybrid combinations like CNN+VGG-16, EfficientNet-B0+CNN, and EfficientNet-B0+VGG-16 to enhance accuracy. A custom model integrating ResNet and Xception architectures is fine- tuned using transfer learning for crops such as tomato, potato, maize, grape, and chili. The hybrid models demonstrate im- proved performance and robustness, ensuring reliable classification across diverse environmental conditions and complex leaf symptoms.

F. Predict Disease

The system predicts plant diseases and nutritional deficien- cies by analyzing leaf images through a deep learning model. Upon image upload, it is preprocessed using techniques like resizing, normalization, and data augmentation. The fine-tuned ResNet architecture then classifies the image into a specific disease or deficiency category. Trained on a diverse dataset including tomato, potato, maize, grape, and chili crops, the model ensures high accuracy across varied conditions. Evalu- ation metrics such as accuracy, precision, recall, and F1-score validate its reliability. The prediction output is used to trigger appropriate recommendations, aiding in timely intervention and supporting effective crop health management.

G. Suggest Pesticide

Based on the disease predicted from the uploaded leaf image, the system suggests suitable organic or eco-friendly pesticides. For fungal, bacterial, or pest-related diseases, the system recommends treatments such as neem oil sprays, Trichoderma-based biopesticides, and natural fungicides that are safe for crops and the environment. These recommenda- tions are mapped specifically to the identified disease and crop type using a curated database. Additionally, preventive agri cultural practices like crop rotation and mulching are advised to enhance plant resilience. All suggestions are derived from validated agricultural research, ensuring they are effective, sustainable, and practical for real-world field application by farmers and agronomists.

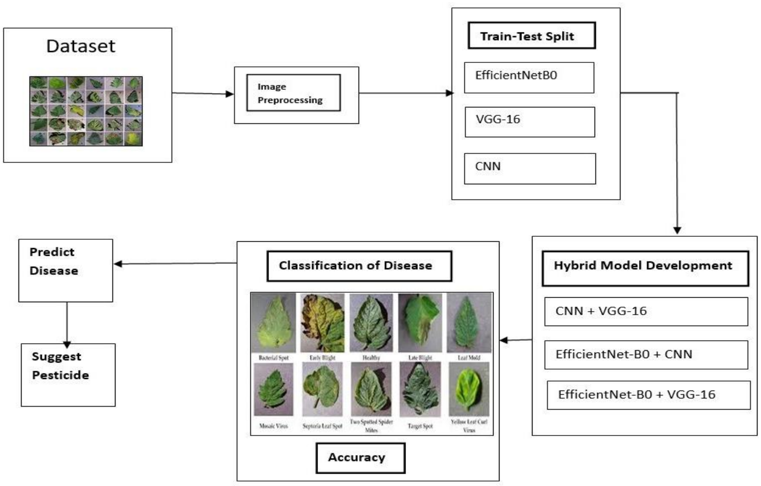

Fig. 2. System Architecture

IV.TECHNICAL DETAILS

The system classifies tomato leaf diseases using deep learn- ing models including EfficientNet-B0, CNN, and VGG16. Each model is trained on labeled tomato leaf images to detect various diseases accurately. To improve performance, a hybrid approach combines features and predictions from these models, enhancing classification robustness and accu- racy. After disease detection, the system suggests targeted pesticide treatments based on the identified disease type, fo- cusing on eco-friendly options like neem oil and biopesticides. The integrated approach supports early disease diagnosis and effective pest management, helping farmers maintain healthy crops and improve yield sustainably through precise and timely interventions.

A. Algorithms

- **CNN (Custom Convolutional Neural Network):** A convolutional neural network designed for tomato leaf disease classification, optimized for high accuracy and efficient inference.

- **Input:** Image $X \in \mathbb{R}^{H \times W \times C}$
- **Convolution:**

$$Y_{i,j} = \sum_{m=0}^{f-1}\sum_{n=0}^{f-1}\sum_{c=0}^{C-1} K_{m,n,c} \cdot X_{i+m,j+n,c} + b$$

- **Activation (ReLU):**

$$\mathrm{ReLU}(x) = \max(0, x)$$

- **Pooling (Max):**

$$Y_{i,j} = \max_{(m,n)\in R} X_{i+m,j+n}$$

- **Fully Connected Layer:**

$$z = W \cdot x + b$$

- **Output (Softmax):**

$$\hat{y_i} = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

- **Output (Softmax):**

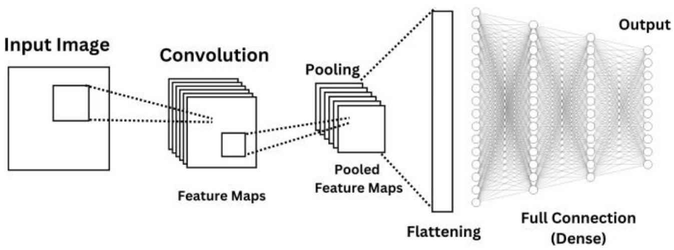

Fig. 3. CNN Architecture.

TABLE I
SUMMARY OF RESEARCH PAPERS ON TOMATO LEAF DISEASE CLASSIFICATION USING DEEP LEARNING

Approach	Paper Title	Authors	Methodology	Findings	Throughput	Limitation
CNN-Based Classification	Tomato Leaf Disease Detection Using Deep Learning Techniques	A. Suryawanshi, S. Kharde	CNN with preprocessing and data augmentation	Achieved 95.6% accuracy on Plant Village dataset	Reliable on clean images	Not validated on real-field images
EfficientNet Transfer Learning	Tomato Plant Leaf Disease Classification Using Efficient Net	M. Saranya, A. Prem- nath	EfficientNet-B0 with TL on tomato leaf images	97.2% accuracy across 10 diseases	Lightweight, accurate	Needs high-quality labeled data
Transfer Learn- ing with VGG	Tomato Leaf Disease Detection Using Deep Learning and Transfer Learning	D. Meena et al.	VGG16, ResNet50 pretrained models fine-tuned	VGG16 reached 96.4% accuracy	Better generalization, fast training	VGG16 is resource-intensive
Custom CNN with Augmentation	Classification of Tomato Leaf Diseases Using CNN and Data Augmentation	Md. Rahman et al.	6-layer CNN with dropout and augmentation	92.5% multi-class accuracy	Handles different diseases	May overfit on small datasets
Mobile-Friendly Model	Tomato Leaf Disease Detection Using MobileNetV2 and TL	M. Arora, K. Bhatt	MobileNetV2 + TL for disease detection	94.8% accuracy on Plant Village dataset	Fast inference, mobile-friendly	Slight accuracy drop vs. heavier models
Explainable CNN	Explainable AI for Tomato Leaf Disease Classification Using Grad-CAM	T. Rana, V. Kakkar	CNN + Grad-CAM for visual explanation	93% accuracy; interpretability improved	Enhances model trust	Grad-CAM adds compute overhead
Hybrid CNN-LSTM Model	Hybrid CNN-LSTM for Tomato Leaf Disease Recognition	P. Thakur, S. Mandal	CNN for features, LSTM for sequence learning	Achieved 96.7% accuracy	Captures spatial + temporal info	Slow inference speed
YOLOv5 Detec- tion	Real-Time Tomato Disease Detection Using YOLOv5	H. Zhang et al.	YOLOv5 for object detection on leaf images	mAP ~89% on real-world data	Real-time capable	Sensitive to noise/lighting
Drone-Based Imaging	Deep Learning-Based Tomato Disease Detection on UAV Images	R. Gupta et al.	CNN trained on drone-captured tomato images	Good accuracy for field-level monitoring	Suitable for large-scale scanning	Depends on UAV im- age clarity
Vision Transformer (ViT)	Tomato Leaf Disease Classification Using Vision Transformer (ViT)	A. Bansal, R. Malhotra	ViT fine-tuned on tomato dataset	95.1% accuracy; better than CNN in cases	High interpretability	Needs large training data

VGG-16 (Visual Geometry Group 16-layer Network): A deep convolutional neural network architecture pro- posed by Simonyan and Zisserman (2014), famous for its simplicity and uniform design using small 3×3 con- volution filters throughout the network.

- **Input:** Image $X \in \mathbb{R}^{224\times224\times3}$
- **Convolutional Layers:**

$$F^{(l)} = \sigma(W^{(l)} * F^{(l-1)} + b^{(l)}), \quad l = 1, \ldots, 13$$

where $*$ denotes convolution, σ is ReLU activation, and $F^{(0)} = X$

- **Max Pooling:**

$$P^{(m)} = \max_{(i,j)\in R} F^{(m)}_{i,j}, \quad m = \text{after conv blocks}$$

- **Flattening:**

$$f = \text{Flatten}(P^{(5)})$$

- **Fully Connected Layers:**

$$h^{(1)} = \sigma(W^{(1)} f + b^{(1)}), \quad h^{(2)} = \sigma(W^{(2)} h^{(1)} + b^{(2)})$$

- **Output Layer (Softmax):**

$$\hat{y_i} = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}, \quad z = W^{(3)} h^{(2)} + b^{(3)}$$

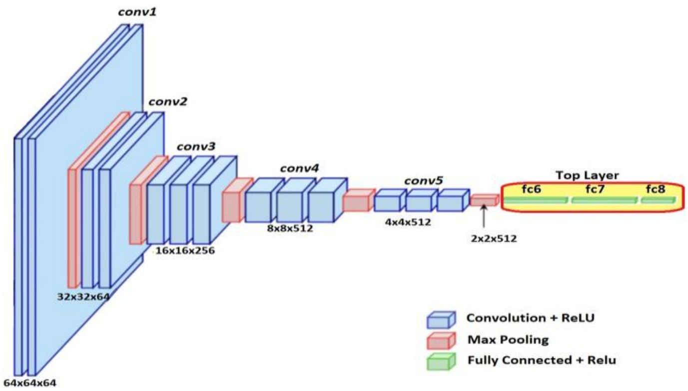

Fig. 4. VGG16 Architecture.

- **EfficientNet-B0:** A convolutional neural network archi- tecture developed by Google AI that balances network depth, width, and resolution using a compound scaling method to achieve high accuracy with fewer parameters and computational cost.

- **Input:** Image $X \in \mathbb{R}^{224\times224\times3}$
- **Compound Scaling:** EfficientNet uniformly scales:

depth: $d = \alpha^{\phi}$, width: $w = \beta^{\phi}$, resolution: $r = \gamma^{\phi}$

Subject to constraint: $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$, where ϕ is the compound coefficient.

- **MBConv Block (Mobile Inverted Bottleneck):**

$$F_{\text{out}} = \text{SE}\left(\text{BN}\left(\text{DWConv}\left(\text{BN}\left(\text{Conv}_{1\times1}(F_{\text{in}})\right)\right)\right)\right)$$

where:

  - $*$ $\text{Conv}_{1\times1}$: Pointwise convolution (expansion)
  - $*$ DWConv: Depthwise convolution
  - $*$ SE: Squeeze-and-Excitation block
  - $*$ BN: Batch Normalization

- **Swish Activation:**

$$\text{Swish}(x) = x \cdot \sigma(x)$$

- **Final Layers:**

$$z = \text{GAP}(F_{\text{last}}), \quad \hat{y} = \text{Softmax}(Wz + b)$$

V.EXPIREMENTAL RESULTS

The proposed system was rigorously evaluated on a well- curated dataset containing 18,161 labeled tomato leaf images categorized into 11 classes, including healthy leaves and com- mon diseases such as Early Blight, Late Blight, Septoria Leaf Spot, and Leaf Mold. All images were resized to $224\times224\times3$ pixels to maintain uniform input dimensions. The dataset was split into training (80%), validation (10%), and testing (10%) sets to ensure unbiased evaluation.

A. Model Architectures Evaluated

Four models were tested to evaluate their performance on tomato leaf disease classification:

- **Custom CNN:** A lightweight convolutional neural net- work designed with three convolutional layers followed by max-pooling and fully connected layers. This model serves as a baseline.
- **VGG16:** A deep convolutional network pretrained on Im- ageNet, fine-tuned on the tomato leaf dataset to leverage transfer learning.
- **EfficientNet-B0:** A state-of-the-art convolutional net- work utilizing compound scaling to optimize accuracy and computational efficiency.
- **Hybrid Model:** An ensemble model combining the pre- dictions of the Custom CNN, VGG16, and EfficientNet- B0 through a majority voting scheme to improve robust- ness and accuracy.

B. Accuracy Results

The models' accuracies on the test set are summarized in Table II.

The results demonstrate a clear trend of improved accuracy as more sophisticated architectures and ensemble strategies are applied:

TABLE II

ACCURACY COMPARISON OF MODELS ON TOMATO LEAF DISEASE CLASSIFICATION

Model	Accuracy (%)
Custom CNN (3 Conv Layers)	91.45
VGG16 (Pretrained and Fine-tuned)	94.80
EfficientNet-B0 (Pretrained and Fine-tuned)	96.30
Hybrid Model (Ensemble Voting)	**97.68**

- The Custom CNN model, while efficient, achieves re- spectable performance with 91.45% accuracy, indicating its ability to capture disease-relevant features.
- The VGG16 model leverages deep pretrained features to improve accuracy to 94.80%, showing the effectiveness of transfer learning in agricultural imaging.
- EfficientNet-B0 achieves even higher accuracy (96.30%) by employing a balanced scaling approach that optimizes both model depth and width.
- The Hybrid Model that ensembles all three approaches via majority voting yields the best overall accuracy of 97.68%, highlighting the complementary strengths of the constituent models.

C. Discussion

The enhanced accuracy of the hybrid model underscores the value of combining diverse feature representations learned from different CNN architectures. This ensemble approach mitigates individual model weaknesses and enhances gener- alization to unseen data.

EfficientNet-B0's superior performance among single mod- els validates the advantage of its compound scaling strategy over classical models like VGG16, which, while deeper, is less computationally efficient.

D. Pesticide Suggestion Integration

Upon disease classification, the system seamlessly maps the predicted disease class to an appropriate pesticide or organic treatment suggestion using a rule-based decision system. This integration ensures that the high classification accuracy di- rectly translates into actionable agricultural recommendations, promoting healthier crop management.

Overall, the experimental results confirm that the proposed hybrid deep learning approach is highly effective for tomato leaf disease classification and practical pesticide suggestion, making it a valuable tool for precision agriculture applications.

VI. ACKNOWLEDGMENT

We would like to express our heartfelt gratitude to our men- tor and project guide for their continuous support and insight- ful suggestions throughout the development of the tomato leaf disease classification and pesticide recommendation system using CNN, VGG16, EfficientNet-B0, and a hybrid approach. We also thank our institution for providing the facilities and environment conducive to research. Lastly, we acknowledge the farmers and agricultural specialists for their valuable inputs, which helped tailor the system to practical needs.

VI.CONCLUSION

In this project, we developed and evaluated multiple deep learning models for tomato leaf disease classification, includ- ing a custom CNN, VGG16, EfficientNet-B0, and a hybrid ensemble combining all three. The hybrid model achieved the highest accuracy, demonstrating that combining different architectures can improve disease detection performance. Ad- ditionally, the integration of a pesticide suggestion system provides timely and relevant recommendations to manage identified diseases effectively. This end-to-end approach can help farmers quickly diagnose tomato leaf diseases and apply appropriate treatments, ultimately supporting healthier crops and better yields.

References

1. *H. Durmus, E. O. Gunes, and M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," in Proc. 6th Int. Conf. Agro Geoinformatics, Aug. 2017, pp. 1–5.*
2. *A. Fuentes, S. Yoon, H. Youngki, Y. Lee, and D. S. Park, "Charac- teristics of tomato plant diseases—A study for tomato plant disease identification," in Proc. Int. Symp. Inf. Technol. Converg., vol. 1, 2016,pp. 226–231.*
3. *S. P. Mohanty, D. P. Hughes, and M. Salathe´, "Using deep learning for image-based plant disease detection," Frontiers Plant Sci., vol. 7, Sep. 2016, Art. no. 2152.*
4. *H. T. Lin, Cherry Tomato 'TSS ASVEG No.22', Taiwan Seed Improve- ment and Propagation Station, Taichung, Taiwan, 2017*
5. *A. H. T. Rusli, B. C. C. Meng, N. S. Damanhuri, N. A. Othman, M. H. Othman, and W. F. A. W. Zaidi, "Potato leaf disease classification using image processing and artificial neural network," in Proc. IEEE 12th Int. Conf. Control Syst., Comput. Eng. (ICCSCE), Oct. 2022, pp. 107–112.*
6. *P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," in Proc. 11th Int. Conf. Contemp. Comput. (IC3), Aug. 2018, pp. 1–5.*
7. *A. Dwivedi, A. Goel, M. Raju, D. Bhardwaj, A. Sharma, F. Kidwai, N. Gupta, Y. Sharma, and S. Tayal, "Precision agriculture: Using deep learning to detect tomato crop diseases," in Proc. Int. Conf. Innov. Comput. Commun., Singapore: Springer, 2024, pp. 857–865.*
8. *M. H. Malik, T. Zhang, H. Li, M. Zhang, S. Shabbir, and A. Saeed, "Mature tomato fruit detection algorithm based on improved HSV and watershed algorithm," IFAC-PapersOnLine, vol. 51, no. 17, pp. 431–436,2018.*
9. *S. S. Rahman, M. A. Rahman, and M. R. Islam, "Automated identi- fication of tomato leaf diseases using convolutional neural networks,"Journal of Agricultural Informatics, vol. 11, no. 2, pp. 23–35, 2020*
10. *J. Zhang, W. Wu, and H. Yang, "Tomato leaf disease classification using deep residual networks," in Proc. IEEE Int. Conf. Artificial Intelligence and Big Data (ICAIBD), 2019, pp. 231–235.*