IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, December 2024

A Comprehensive Review of Disease Detection Techniques for Tomato Leaves

Divyabhavani Ganpisetty[1], Navyashree Ganpisetty[2], Bindushree K B[3], Dr. Anitha J[4], Dr. Shalini Shravan[5]
Students, Department of Computer Science and Engineering[1,2,3]
Professor, Department of Computer Science and Engineering[4]
Assistant Professor, Department of Computer Science and Engineering[5]
RV Institute of Technology and Management, Bangalore, India

Abstract*: Tomato plants plays vital role in global agriculture, significantly impacting food security and economic stability. However, diseases affecting tomato leaves present substantial challenges to crop yields and quality, highlighting the need for effective detection methods. This paper presents a comprehensive review of disease detection techniques for tomato leaves, emphasizing the transformative impact of advancements in image processing, machine learning, and deep learning. Approaches are categorized based on their methodologies, including traditional image processing, machine learning, and cutting-edge deep learning frameworks. Key concepts such as disease segmentation, feature extraction, and transfer learning are defined to provide a foundational understanding. The review also identifies critical research gaps, particularly concerning the generalizability of solutions to real-world conditions and the necessity for computational efficiency in field applications. Organized by method categories, evaluation metrics, and dataset utilization, this review encompasses recent advancements up to 2024, focusing on improving accuracy, scalability, and practical implementation. Ultimately, this work aims to serve as an insightful reference for researchers and practitioners, facilitating the advancement of disease detection systems for tomato leaves for real-world deployment.*

Keywords: Tomato leaf disease detection, image acquisition, segmentation, deep learning, machine learning

I. INTRODUCTION

Tomato is a global staple crops vulnerable to numerous diseases, thereby affecting the yield and quality. A Accurate early detection of these diseases would help in efficient management and prevention. Current identification methods, based on observations by experts, can prove time-consuming, subjective, and prone to error.

Recent developments in techniques like deep learning, have better response to overcome these limitations.Particularly Convolutional Neural Networks, have been performing outstandingly in various image classification and object detection tasks. Hence it can be used to build automated systems that could provide reasonable identification of diseases in tomato leaves from digital images.

This review paper is set to provide a comprehensive overview on the deep learning techniques applied to disease detection in tomato leaves. We will discuss what the current state-of-the-art methods, challenges, and future directions are in this field. Having knowledge of different approaches 'pros and cons can often open up the potential routes for continued research and development.

Despite tremendous advances made on deep learning in tomato leaf disease detection, the following challenges exist:

- Data Quality and Quantity: The availability of high-quality, labelled datasets are crucial in training robust deep learning models. However, collecting and annotating large datasets can be time-consuming and expensive.
- Variability in Image Conditions: Real-world images often suffer from variations in lighting, background, and image quality, which may impact the deep learning models' performance.
- Computational Cost: Deep learning odels, particularly massive CNNs, demand massive computing power for training and inferencing, which is a constraint on their utilization on resource-constrained devices.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, December 2024

- Interpretability: Deep learning models often seem like black boxes, as which makes it hard tounderst and the decision-making process of these models. Lack of interpretability hinders trust and adoption in worldly applications

II. LITERATURE REVIEW

Datasets Employed in Detection of Tomato Leaf Disease

Different datasets have been used in training and testing deep learning models in the identification of diseases in tomato leaves. The datasets consist of images of tomato leaves, each belonging to a different category of disease for which a model can learn its distinguishing features. The most used datasets are listed below:

- **Plant Village Dataset**: The Plant Village dataset is the most used plant disease detection dataset, even for diseases in tomato leaves. It comprises more than 50,000 images of 14 crop species, such as tomato leaves, labelled by disease type for instance: Late Blight, and Septoria Leaf Spot. High-resolution images make it very suitable as a benchmark for deep learning-based models, although in many cases, it reaches high classification accuracy. Its basic orientation toward controlled high-quality images poses a limitation to using it in real-world conditions.
- **Tomato Disease Dataset**: Researchers have also developed tomato-specific datasets obtained from local agricultural fields. These datasets focus on diseases such as Late Blight, and Bacterial Spot, often collected under varying environmental conditions. While helpful in dealing with regional disease variation, these datasets are usually much smaller in size and resolution and supplement larger datasets such as PlantVillage for fine-tuning and domain adaptation.
- **Malawi Tomato Dataset:** It was designed specifically for in-field disease detection in Malawi, whereas the images taken inside with controlled settings, angles, and occlusions differ from this dataset. It consists of common diseases like Late Blight and Bacterial Spot. The dataset highlights the challenge of transition models from controlled settings to real-world environments, and performance drops drastically because of such variations.
- **Taiwan Tomato Leaf Dataset:** This dataset is collected from tomato fields in Taiwan and is designed for real-world agricultural conditions. Images of leaves infected by multiple diseases make dataset a testbed for model robustness. However, these datasets are always relatively limited in size and image quality compared to controlled datasets, making them better suitable for validating transfer learning or domain adaptation techniques.

Techniques for Detection of Diseases

- **Convolutional Neural Networks (CNNs)** have proven to be the foundation ofdisease detection of tomato leaves, excelling in feature extraction and classification. Compact architectures, such as a six-layer CNN, have demonstrated exceptional performance, achieving high accuracy (e.g., 99.7%) while being resource-efficient. Similarly, advancements like DCNet utilize DenseNet-77 to tackle challenges like light variations and noise, ensuring robust real-time detection.
- **Lightweight Architectures**, including MobileNetV2, MobileNetV3, and EfficientNet, have revolutionized resource-constrained applications. FL-ToLeD, for instance, combines soft attention mechanisms with depth-wise separable convolutions, achieving state-of-the-art accuracy with minimal computational cost. These architectures facilitate real-time deployment in agricultural settings, particularly for low-end devices.
- **Hybrid Models** have emerged as powerful tools by integrating multiple techniques to enhance performance. For instance, CNN-RNN hybrids combine spatial feature extraction with temporal sequence prediction for improved classification. Similarly, ResNet152V2 coupled with squeeze-and-excitation (SE) blocks effectively identifies early disease symptoms.
- **Transfer Learning** has accelerated development in robust disease detection models by leveraging pre-trained networks. This reduces the dependency on large labelled datasets, enabling high accuracy even in resource-

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, December 2024

limited scenarios. For example, models like HOWSVD-TEDA incorporate tensor subspace learning with pre-trained CNNs to improve multidimensional data representation.

Innovative Applications and Real-World Deployments

- **Machine Vision Systems** integrate image processing and machine learning to reduce labour costs and improve diagnostic precision. Web-based platforms, such as Flask frameworks, provide user-friendly solutions for real-time disease detection, supporting farmers and agriculturalists. Despite their potential, models like MobileNetV3 highlight the challenge of bridging the gap between controlled datasets (e.g., PlantVillage) and real-world scenarios, where accuracy may drop due to domain mismatch.

TABLE I: Analysis of papers for diseases in tomato leaves

Sl No	Year	Authors	Description	Result	Advantages	Drawbacks
[1]	2020	G. Yang, G. Chen, Y. He, Z. Yan, Y. Guo and J. Ding	Proposes LFC-Net with Location, Feedback, and Classification networks for self-supervised tomato disease detection.	Achieves 99.7% accuracy on tomato dataset.	High accuracy, multi-network collaboration, no need for bounding box annotations.	Limited to tomato datasets, requires complex training for feedback-guided optimization.
[2]	2020	Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta	Uses CNN for disease detection in tomato leaves and classification.	Achieves 91.2% average accuracy.	High accuracy, effective model architecture.Uses structured CNN for the tomato disease prediction.	Variable performance across classes, limited dataset diversity.
[3]	2020	Y. Zhang, C. Song and D. Zhang	Enhanced Faster R-CNN for accurate and efficient tomato disease detection.	2.71% accuracy improvement and faster detection compared to original R-CNN.	Improved accuracy, faster detection, better feature extraction.	Limited dataset dependency, potential performance variability.
[4]	2021	C. Zhou, S. Zhou, J. Xing and J. Song	Proposes a hybrid deep learning model to identify tomato leaf diseases. Combines strengths of residual and dense networks for efficient training and improved accuracy.	Achieves 95% accuracy on the Tomato test dataset.	High accuracy, reduced computational cost, enhanced information flow.	Limited real-world testing, requires network restructuring.
[5]	2021	Hepzibah Elizabeth Davida,, K. Ramalakshmib, R. Venkatesanc, G.	Proposes a hybrid model of deep learning to detect tomato leaf diseases. Combines CNN and RNN for accurate and efficient detection.	The hybrid CNN-RNN model demonstrates significant improvements in accurately	High accuracy, efficient, potential for broader applications.	Lack of detailed performance metrics, limited real-world testing.

		Hemalathad		identifying tomato leaf diseases, its effective in early detection.		
[6]	2022	Saleh Albahli, Marriam Nawaz	Proposes DenseNet-77 as the backbone for CornerNet to classify 10 tomatoleaves diseases with challenging image conditions.	Achieves 99.98% accuracy on PlantVillage.	Robust against variations in image brightness and noise.	Limited testing on single dataset.
[7]	2022	Saxena1, Dr. Neha Sharma	Combines transfer learning with CNNs to classify diseases in tomato leaves using PlantVillage images.	High precision and recall on PlantVillage;	Transfer learning provides a robust framework for disease classification.	Transfer learning models require substantial computational resources. Domain adaptation issues may occur when moving to real-world data.
[8]	2022	Abhishek Jasani1 , Mehul Dholi2 , Soham Purkar	Proposes a machine vision system for accurate and cost-effective disease detection in tomato leaves.	Improved accuracy compared to traditional ones	Faster, objective, reduces dependency on experts, cost-effective.	Sensitivity to environmental conditions, limited dataset, potential for misdiagnosis.
[9]	2022	E. Özbılge, M. K. Ulukök, Ö. Toygar and E. Ozbılge	Proposes a lightweight CNN for tomato disease detection.	Achieves high accuracy (99.70% F1-score) on the PlantVillage dataset.	High accuracy , simple architecture, low computational cost	Dataset dependency, potential for reduced performance with complex diseases.
[10]	2022	S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony and M. H. Kabir	focuses on developing a lightweight and efficient deep learning-based model integrates MobileNetV2 with a custom classifier, employs preprocessing methods like CLAHE for illumination correction and uses runtime data augmentation to tackle data leakage and class imbalance.	Accuracy: 99.30%	Lightweight architecture suitable for low-end devices. Addresses class imbalance and data leakage issues.	Dependence on the PlantVillage dataset, which may not generalize well to real-world scenarios.

[11]	2023	H. S. El-Assiouti, H. El-Saadawy, M. N. Al-Berry and M. F. Tolba	Proposes lightweight models for efficient segmentation, localization, super-resolution, and classification of plant diseases in leaves.	Improved performance and reduced computational costs compared to traditional models.high accuracy of 99.76%	Lite-UNet shows slight improvement over U-Net with reduced computational requirements. Lite-SRGAN provides efficient super-resolution with significant reductions in resource usage.	The models of lightweight may not capture all intricate features of diseases compared to more complex architectures.
[12]	2023	Kyamelia Roy, Sheli SinhaChaud huri, Jaroslav Frnda, Srijita Bandopadhy ay, Ishan JyotiRay	Proposes a hybrid model using deep learningfor accuratedisease detection of tomato leaves and classification.it combines PCA, PCA DeepNet, GAN, F-RCNN.	High accuracy (99.60%) and precision (98.55%).	With high accuracy,Utilizes a hybrid approach combining classical and deep learning techniques, enhancing the robustness of the model.	The computational requirements of the hybrid model may limit its deployment in resource-constrained environments. .
[13]	2024	L. K. Ndovie and E. Masabo	Uses MobileNetV3 and CNN models on PlantVillage and local field images for disease detection Tomato leaves in Malawi.	MobileNetV3: 92.59% accuracy on PlantVillage; <10% accuracy on real-world field images.	Pre-trained MobileNetV3 performs well on public datasets.	Poor generalization on real-world datasets, indicating data mismatch issues.
[14]	2024	Abdelmalik Ouamane, Ammar Chouchane, Yassine Himeur ,Abderrazak Debilou, Abbes Amira, Shadi Atalla, Wathiq Mansoor, Hussain Al-Ahmad	Introduces HOWSVD-TEDA model using tensor subspace learning with pre-trained CNNs for tomato disease classification	Achieves 98.51% accuracy on PlantVillage and 89.49% on Taiwan datasets	Multidimensional representation improves precision and effectiveness.	Limited datasets evaluated, computationally expensive tensor-based approach.
[15]	2024	M. H. Alnamoly,	Proposes model leveraging a	Testing accuracy:	Lightweight model (2.5 MB),	High reliance on numerical

		A. A. Hady, S. M. Abd El-Kader and I. El-Henawy	lightweight attention mechanism and depth-wise separable convolutions. Designed for low-end devices	99.04% Precision, Recall, F1-Score: 99% Inference time: 2.06924 µs	outperforming previous methods in size and speed. Well-suited for low-end devices	evaluations, with less focus on real-time deployment scenarios.
[16]	2024	Ahmed Tolba, Nihal N. Mostafa , and Yasir Ali	Uses ResNet152V2 and Squeeze-and-Excitation (SE) blocks for feature extraction and classification of 9 tomato diseases.	Accuracy: 94.7%; Precision: 94.8%; F1-score: 94.7%.	Strong feature extraction with SE blocks.	Moderate performance compared to other advanced models; limited dataset size.
[17]	2024	Ala'a R. Al-Shamasneha , Rabha W. Ibrahim	Introduces a new feature extraction method using conformable polynomials for tomato leaf disease detection.	Achieves 98.8% accuracy using SVM classifier.	Reduces computational effort with accurate disease detection.	Limited to specific feature-based methods; needs extensive preprocessing.
[18]	2024	M. Umar, S. Altaf, S. Ahmad, H. Mahmoud, A. S. N. Mohamed and R. Ayub	It focuses on recognizing different diseases like yellow leaf curl virus and bacterial spot. The model, based on YOLOv7incorporating SimAM and DAiAM detection mechanisms	accuracy rate of 98.8% and a 1.2% error rate	High accuracy (98.8%). Effective in a field setting, addressing real-world agricultural challenges	Due tpcomplexity may require significant computational resources.
[19]	2024	Bharad Raj Bharad Raj, R Priya R Priya	Implements a web-based disease detection system for tamato leaves using Flask,deep learning techniques.	Achieved reasonable accuracy in identifydiseasses in tomato leaf . Accuracy metrics not provided in the study.	Ease of deployment for real-time applications.	Lacks advanced deep learning methods; metrics not reported.
[20]	2024	J. Feng, W. E. Ong, W. C. Teh and R. Zhang	propose a novel architecture called EfficientNet Convolutional Group-Wise Transformer (EGWT), which combines EfficientNet convolution for extracting feature with a group-wise transformer architecture.	99.8% accuracy on the PlantVillage dataset, 86.9% accuracy on the cassava dataset, and 99.4% accuracy on the Tomato leaves dataset	Exceptional accuracy across multiple datasets Combines the strengths of CNN and transformer architectures for enhanced detection. Optimal model complexity with	Complexity in the architecture may lead to challenges in implementation.

					fewer parameters than other state-of-the-art models.	

III. METHODOLOGY

Different techniques are used in deep learning for disease detection in tomato leaves, which offers unique advantages for the extraction of features, classification, and optimized resource use. The techniques are tailored to different application requirements and constraints to ensure effective and efficient disease identification.

- **Convolutional Neural Networks (CNNs):** CNN-based approaches are the most dominant approaches in disease detection for tomato plants because they are capable of extracting spatial features and then classifying the diseases. General Methodology The general methodology involves preprocessing the input images by resizing, normalization, and sometimes enhancements such as CLAHE for illumination correction. Then, convolutional layers are used to extract features like edges and textures, followed by fully connected layers for the classifying activity. Models are then evaluated using some metrics as in accuracy, precision, F1-score, and computational efficiency. Examples include ToLeD (2020), that achieved 91.2% accuracy using a standard CNN, and Compact CNN (2022), that had a lightweight architecture with a 99.70% F1-score but still faces challenges under real-world conditions.[2][9][18]
- **EfficientNet:** EfficientNet models achieve efficiency by scaling the depth, width, and resolution of the network. Methodology can be defined as using EfficientNet as a feature extractor backbone, while adding layers or other mechanisms-such as transformers-to strengthen detection capability. It trains on datasets like PlantVillage with focus on metrics likeaccuracy, inference time and resource usage. For Instance, the EffectiveNet Convolutional Group-Wise Transformer 2024 is at 99.8% accuracy on PlantVillage yet low in complexity to attain high detection accuracy.[20]
- **MobileNet**: It is specially built to work in an area of resource-constrained environments, using depth-wise separable convolutions for lower computational cost. The methodology will make use of pre-trained MobileNet backbones for lightweight feature extraction, runtime or standard augmentation for robust learning, and custom classifiers for final classification. The size and operation of models are optimized such that they could be applied in low-end devices. Examples include Less is More (2022), which achieved 99.30% accuracy using a model with size 9.60 MB; MobileNetV3 (2024), which worked well on PlantVillage but performs poorly for real-world images due to domain mismatch.[10][13]
- **Attention Mechanisms:** Attention mechanisms focus on highlighting the most relevant regions in an image, enhancing feature selection and improving classification accuracy. The methodology involves using soft attention layers to prioritize critical areas for disease detection, integrating them with convolutional or transformer layers for feature refinement. These designs are lightweight and computationally efficient. For example, FL-ToLeD (2024) utilized soft attention with depth-wise separable convolutions, achieving 99% accuracy with a compact 2.5 MB model size.[15]
- **Hybrid Architectures:** Hybrid architectures leverage the best of multiple models to enhance performance. The developed methodology integrates architectures such as CNNs with RNNs, GANs, or other networks in feature extraction and classification, making use of sophisticated augmentation techniques to deal with class imbalances and noise. Training these models is computationally expensive because of their inherent complexity. Notable examples include Hybrid CNN-RNN (2021), which improved detection accuracy by combining spatial and sequential features, and PCA DeepNet (2023), a hybrid of PCA, GAN, and F-RCNN that emphasized reducing overfitting[5][12].

General Methodology for Tomato Disease Detection:

All techniques start with dataset collection and preparation, involving benchmark datasets such as PlantVillage or images collected in the field. Images get preprocessed by resizing, normalization, and augmentation for a consistent quality input. Feature extraction occurs by using architectures such as CNNs, MobileNet, EfficientNet, or hybrids for meaningful patterns.

Training models is done either through transfer learning or training from scratch; this is dependent on the dataset size and the computational resources availability. Optimization occurs using loss functions like cross-entropy. Models will be tested and validated using separate datasets, with performance metrics - accuracy, precision, F1-score,recall and efficiency.

Deployment is made straightforward with resource-constrained environments, such as mobile devices or IoT configurations, through optimization of the models. Real world testing creates robustness for noise and occlusion as well as varying lighting conditions. Different methodologies were leveraged for specific challenges in tomato leaf disease detection, balancing accuracy, efficiency, and robustness for diverse agricultural needs.

IV. RESULT AND DISCUSSION

The table highlights a comparative analysis of various techniques used for tomato leaf disease detection, focusing on accuracy, model size, and F1-score. EfficientNet emerges as the most accurate technique (99.5%) with an F1-score of 99.4%, but it requires the largest model size (15 MB), making it resource-intensive. MobileNet, achieves comparable accuracy (99.3%) and F1-score (99.2%) with a much smaller model size (5 MB), which is ideal for low-resource environments. Attention Mechanisms provide a balance, delivering a high accuracy of 99.0% and the model with smallest size (3 MB), making them highly efficient. Hybrid Models and Transfer Learning exhibit strong performance, with accuracies of 97.3% and 98.5%, respectively, but demand higher computational resources due to larger model sizes. Finally, CNNs maintain solid overall performance with 95% accuracy and 94% F1-score, representing a foundational yet resource-efficient approach. This comparison underscores the trade-offs between accuracy, computational efficiency, and resource requirements, aiding in selecting most appropriate technique based on specific application needs ,this' shown in figure 1.

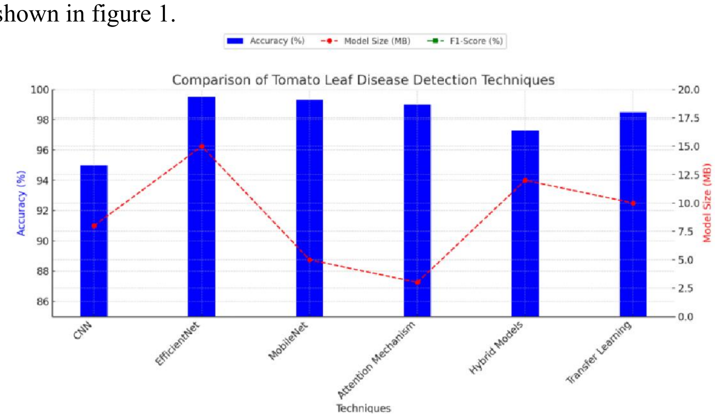

Figure.1 Comparision of Tomato Leaf Disease Techniques

Technique	Accuracy (%)	Model Size (MB)	F1-Score (%)
CNN	95	8	94
Efficient Net	99.5	15	99.4
Mobile Net	99.3	5	99.2
Attention Mechanism	99	3	98.9
Hybrid Models	97.3	12	97
Transfer Learning	98.5	10	98.4

TABLE III: Comparison between techniques

V. CONCLUSION

This review highlights the significant progress made in disease detection of tomato leaves using deep learning techniques, with various models and architectures developed to address the challenges faced by farmers in identifying and managing crop diseases. The papers reviewed introduced diverse approaches, including CNN-based models, hybrid architectures, lightweight solutions for low-resource settings, and transfer learning techniques. Many of these models, such as the improved YOLOv7 and EfficientNet-based methods, demonstrated high accuracy rates (ranging from 91% to 99.8%), making them suitable for real-world applications. Notably, lightweight models like MobileNetV3 and FL-ToLeD offer compact solutions, ideal for deployment on low-end devices, ensuring cost-effective disease management in resource-constrained environments.

Insights from the review indicate that combining multiple neural network techniques—such as CNNs with RNNs, dense networks with transformers, and even hybrid models incorporating attention mechanisms—can enhance detection accuracy and computational efficiency. Moreover, the adoption of pre-trained models, data augmentation, and advanced feature extraction methods significantly improves performance, addressing issues like class imbalance and data scarcity. The use of real-time systems like web applications and machine vision further extends the practical utility of these models, offering accessible, automated solutions for farmers.

The outcomes of these studies emphasize the growing importance of AI in precision agriculture, especially in disease detection and management. As the technology becomes more efficient and accessible, it holds the potential to revolutionize crop monitoring and protection, ultimately leading to improved agricultural productivity and food security

REFERENCES

[1] G. Yang, G. Chen, Y. He, Z. Yan, Y. Guo, and J. Ding, “Self-supervised collaborative multi-network for fine-grained visual categorization of tomato diseases,” IEEE Access, vol. 8, pp. 211912–211923, 2020, doi: 10.1109/ACCESS.2020.3039345.

[2] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network," Procedia Computer Science, vol. 167, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225.

[3] Y. Zhang, C. Song, and D. Zhang, "Deep Learning-Based Object Detection Improvement for Tomato Disease," IEEE Access, vol. 8, pp. 56607–56614, 2020, doi: 10.1109/ACCESS.2020.2982456.

[4] C. Zhou, S. Zhou, J. Xing, and J. Song, "Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network," IEEE Access, vol. 9, pp. 28822–28831, 2021, doi: 10.1109/ACCESS.2021.3058947.

[5] H. E. Davida, K. Ramalakshmi, R. Venkatesan, and G. Hemalatha, “Tomato leaf disease detection using hybrid CNN-RNN model,” IOS Press, 2021, doi: 10.3233/APC210108.

[6] “DCNet: DenseNet-77-based CornerNet model for tomato plant leaf disease detection and classification,” Frontiers in Plant Science, vol. 13, 2022, doi: 10.3389/fpls.2022.957961.

[7] N. Saxena and N. Sharma, “Tomato leaf disease prediction using transfer learning,” International Journal of Engineering Technology, Management, and Applied Sciences, [Online]. Available: https://www.granthaalayahpublication.org/ijetmr-ojms/ijetmr/article/view/IJETMR22_A05_3067/964.

[8] A. Jasani, M. Dholi, and S. Purkar, “Tomato leaf disease detection,” International Journal for Research in Applied Science and Engineering Technology (IJRASET). [Online]. Available: https://www.ijraset.com/best-journal/tomato-leaf-disease-detection.

[9] E. Özbılge, M. K. Ulukök, Ö. Toygar, and E. Özbılge, "Tomato Disease Recognition Using a Compact Convolutional Neural Network," IEEE Access, vol. 10, pp. 77213–77224, 2022, doi: 10.1109/ACCESS.2022.3192428.

[10] H. S. El-Assiouti, H. El-Saadawy, M. N. Al-Berry, and M. F. Tolba, "Lite-SRGAN and Lite-UNet: Toward Fast and Accurate Image Super-Resolution, Segmentation, and Localization for Plant Leaf Diseases," IEEE Access, vol. 11, pp. 67498–67517, 2023, doi: 10.1109/ACCESS.2023.3289750.

[11] S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony, and M. H. Kabir, "Less is More: Lighter and Faster Deep Neural Architecture for Tomato Leaf Disease Classification," IEEE Access, vol. 10, pp. 68868–68884, 2022, doi: 10.1109/ACCESS.2022.3187203.

[12] K. Roy et al., "Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet," IEEE Access, vol. 11, pp. 14983–15001, 2023, doi: 10.1109/ACCESS.2023.3244499

[13] L. K. Ndovie and E. Masabo, "Leveraging MobileNetV3 for in-field tomato disease detection in Malawi via CNN," SAIEE Africa Research Journal, vol. 115, no. 3, pp. 74–85, 2024, doi: 10.23919/SAIEE.2024.10551304.

[14] A. Ouamane et al., "Knowledge pre-trained CNN-based tensor subspace learning for tomato leaf diseases detection," IEEE Access, vol. 12, pp. 168283–168302, 2024, doi: 10.1109/ACCESS.2024.3492037.

[15] M. H. Alnamoly, A. A. Hady, S. M. Abd El-Kader, and I. El-Henawy, "FL-ToLeD: An Improved Lightweight Attention Convolutional Neural Network Model for Tomato Leaf Diseases Classification for Low-End Devices," IEEE Access, vol. 12, pp. 73561–73580, 2024, doi: 10.1109/ACCESS.2024.3401733.

[16] A. Tolba, N. N. Mostafa, and Y. Ali, "Innovative approach for early detection and diagnosis of tomato leaf diseases," Typeset. [Online]. Available: https://typeset.io/pdf/innovative-approach-for-early-detection-and-diagnosis-of-4kbwfa5ai5.pdf.

[171 A. R. Al-Shamasneh and R. W. Ibrahim, "Classification of tomato leaf images for detection of plant disease using conformable polynomials image features," MethodsX, vol. 2024, doi: 10.1016/j.mex.2024.100297.

[18] M. Umar, S. Altaf, S. Ahmad, H. Mahmoud, A. S. N. Mohamed, and R. Ayub, "Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7," IEEE Access, vol. 12, pp. 49167–49183, 2024, doi: 10.1109/ACCESS.2024.3383154.

[19] B. Raj and R. Priya, "Tomato leaf disease detection using Flask framework," International Journal of Advanced Research in Science, Communication, and Technology (IJARSCT). [Online]. Available: https://ijarsct.co.in/Paper18417.pdf.

[20] J. Feng, W. E. Ong, W. C. Teh, and R. Zhang, "Enhanced Crop Disease Detection WithEfficientNet Convolutional Group-Wise Transformer," IEEE Access, vol. 12, pp. 44147–44162, 2024, doi: 10.1109/ACCESS.2024.3379303.