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A Systematic Review of Deep Transfer Learning Models for Identification of Tomato Leaf Disease

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Abstract—Agricultural productivity in the semi-arid Jaipur region of Rajasthan, India, is critically dependent on the health of local vegetable crops such as tomato, chilli, okra, beans, and brinjal. Early and precise diagnosis of illness is essential to prevent yield losses and ensure food security. Conventional diagnostic practices, relying on manual inspection by experts are subjective frequently slow, and unsuitable for extensive monitoring. The latest developments in deep learning with automated image-based disease identification has been made possible by learning with remarkable accuracy; however, challenges remain in adapting these methods to real-field conditions characterized by variable lighting, complex backgrounds, and diverse disease scales.

Early and accurate detection of tomato leaf illnesses is crucial for minimizing crop losses, improving yield quality, and supporting sustainable agriculture. A thorough comparison of cutting-edge deep learning models and advanced hybrid frameworks developed for tomato-leaf illness identification is presented in this work. Various approaches employing transfer learning, custom convolutional neural networks (CNNs), and ensemble-based architectures were evaluated across multiple benchmark datasets, including PlantVillage, TomatoVillage, and other specialized datasets. The analysis reveals that traditional transfer learning models such as VGG16, VGG19, ResNet50, and AlexNet achieve solid performance (≈95–96% accuracy), while advanced frameworks—such as HOWSVD-TEDA, deep multistacking models, and ensemble knowledge-distilled systems—surpass 98–99% accuracy with enhanced generalization and efficiency. Furthermore, edge-optimized and quantized models demonstrate exceptional potential for real-time, smartphone-based deployment without compromising accuracy. Lightweight CNNs, such as the proposed six-layer architecture by E. Özbılge, further showcase that compact designs can deliver state-of-the-art results with minimal computational cost. Overall, this study underscores the evolution of deep learning in tomato disease detection, emphasizing the transition from complex, resource-heavy networks to scalable, interpretable, and edge-compatible solutions that bridge laboratory research and real-world agricultural applications. The synthesis concludes that deploying lightweight, multi-scale DTL models trained on locally representative data can significantly enhance early disease diagnosis,

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empower farmers with mobile-based tools, and support sustainable agricultural management in the Jaipur region.

Keywords— Deep Transfer Learning (DTL), Plant Disease Detection, Genetic Algorithm-based Hyperparameter Optimization (GA-HPO), Multi-Scale Image Analysis, Precision Agriculture.

I. INTRODUCTION

The Plant disease identification plays a crucial role in agriculture, as early detection helps prevent the spread of infections and reduces crop losses [1]. Agriculture forms the backbone of rural livelihoods in the Jaipur region of Rajasthan, India, where semi-arid climatic conditions and limited water resources pose persistent challenges to sustainable crop production. Among the region's agricultural outputs, vegetable yields such as chilli, tomato, okra, beans, and brinjal play a crucial part in small and medium-sized farmers' revenue generation, nutrition, and food security. However, these crops are highly susceptible to fungal, bacterial, and viral diseases that can cause significant yield and quality losses if not identified and managed promptly. Traditional diagnostic methods rely heavily on visual inspection by experts, which are time-consuming, subjective, and often inaccessible to farmers in remote areas.

With rapid advances in artificial intelligence (AI) and computer vision, deep learning (DL) techniques—particularly convolutional neural networks (CNNs)—have shown tremendous potential for automated plant disease detection through leaf image analysis. These models can learn complex visual patterns associated with specific diseases and offer high diagnostic accuracy when trained on large, well-annotated datasets. However, developing such datasets for local crops is challenging, especially in heterogeneous field environments where lighting conditions, backgrounds, and leaf orientations vary significantly. Moreover, most existing models are trained on globally available benchmark datasets such as PlantVillage, which consist of images captured under precise environments and may not generalize well to real-field images from the Jaipur region.

To overcome the limitations of limited data and domain variation, transfer learning has emerged as a powerful approach that leverages knowledge from models pretrained on large scale data sets and finely tunes them for specific agricultural applications. Transfer learning significantly diminishes the computational price, training time, although keeping high performance even on relatively small local datasets. Furthermore, multi-scale feature extraction techniques—such as feature pyramid networks, inception modules, and attention-based fusion—enhance the ability of models to detect disease symptoms that appear at different sizes and resolutions on plant leaves, from small specks to large lesions. Combining deep transfer learning with multi-scale analysis thus enables robust, scalable, and precise disease detection in complex agricultural environments.

Among the maximum broadly cultivated and economically important crops, tomatoes are extremely valued for their nutritional richness and income potential for farmers. However, various tomato leaf illnesses—such as yellow leaf curl virus, mosaic virus, septoria leaf spot, target spot, two-spotted spider mite, early blight, leaf mold, late blight, and bacterial spot—negatively affect both the quantity and quality of production, leading to reduced productivity. Conventional manual disease detection takes a lot of time, expertise-dependent, and not scalable for large farms, emphasizing the need for automated solutions. In recent years,

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computer vision techniques and image processing have been increasingly used to analyze tomato leaf images and perceive disease symptoms by extracting visual features through either handcrafted or deep learning-based methods. While handcrafted techniques have shown success in several recognition tasks such as human identification, animal recognition, and plant disease classification [1]– [3], they often lack generalization and adaptability. Conversely, deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated superior accuracy and robustness in plant disease detection [4]– [6], enabling automated, scalable, and reliable systems for early diagnosis and sustainable agricultural management.

This review paper critically examines the state-of-the-art research in deep transfer learning and multi-scale image analysis for plant illness recognition, with a specific emphasis on local vegetable crops of the Jaipur region. It synthesizes recent advances, identifies existing gaps, and outlines a practical framework for developing region-specific, lightweight AI systems capable of real-time disease detection and mobile deployment. The paper also presents a comparative analysis of existing deep learning architectures, a proposed dataset collection strategy tailored to the Jaipur context, and a comprehensive experimental design for future implementation. Ultimately, this review purposes to guide scholars and practitioners toward the creation of efficient, accurate, and field-adapted disease detection systems that support sustainable vegetable production and empower local farming communities in Rajasthan.

II. RELATED WORKS

A. Mishra et. al [7] applies transfer learning techniques to accurately classify tomato leaf diseases using VGG16, VGG19, and ResNet50 models fine-tuned for this purpose. Utilizing the Plant Village dataset encompassing 16,012 images across nine disease groups and one healthy group, the researchers customized and compared the results of these pre-trained CNN architectures. The experimental results reveal that VGG16, when adapted through transfer learning, achieved the highest training accuracy of 95.1%, outperforming both VGG19 and ResNet50, thereby demonstrating its superior capability for tomato leaf illness classification and detection.

"Optimized Detection of Tomato Leaf Diseases via VGG16 Neural Network" presents [8] a deep learning approach for identifying tomato leaf diseases with a fine-tuned VGG16 model. The study classifies healthy and diseased leaves into seven categories, including early blight, bacterial spot, and late blight, through transfer learning and fine-tuning techniques. A comprehensive dataset was used, involving training, validation, and testing phases with pre-processed and augmented images to improve model robustness. The optimized VGG16 attained a training accuracy of 90.25% and a authentication correctness of 88.86%, precision (85.93%), recall (84.43%), and F1-score (84.82%) indicate strong generalization and minimal overfitting. Overall, the research contributes to precision agriculture by providing an automated, scalable, and AI-driven helping to prevent crop losses and support sustainable farming practices.

The paper [9] presents a deep convolutional neural network (CNN) approach using the VGG16 model to detect and classify tomato plant diseases from leaf images. Utilizing the Plant Village dataset, which includes ten classes of tomato leaves (one healthy and nine diseased), the study applies transfer learning on the pre-trained VGG16 model to achieve highly accurate results. The model attains a classification accuracy of 95.5%, with a Top-2 accuracy of 99% for disease recognition, and

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nearly 100% accuracy in distinguishing healthy from unhealthy plants—all accomplished without any image segmentation or additional preprocessing. These results demonstrate the strong capability and efficiency of the VGG16-based deep learning model for early and automated detection of tomato plant diseases, offering a valuable tool for reducing agricultural losses.

The study of [10] S. P. Patnayakuni [10] highlights the critical impact of plant diseases on crop productivity and emphasizes the importance of early detection to enhance agricultural yield, particularly for tomatoes—one of the most widely cultivated and consumed crops globally, with India being the second-largest producer. The research introduces a transfer learning-based approach using the AlexNet model to detect and classify five different tomato leaf diseases. Through simulation experiments, the proposed method demonstrates superior performance compared to traditional techniques, achieving a classification accuracy of 95.6%, thereby proving its effectiveness for early disease identification and improved crop management.

The analysis [11] presents HOWSVD-TEDA, a novel tensor subspace learning framework for detecting and classifying tomato leaf diseases, aimed at enhancing early diagnosis and sustainable crop management. The method integrates Convolutional Neural Networks with Tensor Exponential Discriminant Analysis and Higher-Order Whitened Singular Value Decomposition to effectively capture multidimensional image features. Evaluated on both the Taiwan and PlantVillage datasets, the proposed approach achieves impressive accurateness rates of 89.49% and 98.51% respectively, outperforming existing techniques. This research demonstrates a substantial advancement in precision and reliability for automated tomato leaf disease detection, offering strong potential for improving agricultural productivity and disease management strategies.

This study [12] proposes a deep multistacking integrated model for plant leaf disease detection that enhances accuracy and efficiency by combining fine-tuned transfer learning models, multistacking feature generation, and an ensemble XGBoost meta-classifier. The approach includes specialized preprocessing and augmentation pipelines, followed by fine-tuning of TL models whose prediction probabilities are aggregated to generate robust multistacked features used by the XGBoost classifier. Evaluated on three benchmark datasets— Potato Pepper Dataset (PPDS), Tomato Disease Dataset (TDDS), and Apple Grape Dataset (AGDS)—the model achieved outstanding accuracies of 99.86%, 99.78%, and 99.82%, respectively. Experimental results show that this hybrid model significantly outperforms traditional single-model approaches, offering superior generalization, precision, and computational efficiency. Overall, the study demonstrates that integrating advanced ensemble and stacking techniques can make plant disease detection systems more accurate, reliable, and scalable for sustainable agricultural applications.

M. J. Hasan et al [13] presents a comprehensive framework for smartphone-based tomato leaf disease detection that addresses key challenges in real-world deployment, including cross-domain generalization, class imbalance, and edge-device limitations. By unifying the TomatoVillage and PlantVillage datasets into 15 standardized disease classes, the authors introduce the first open cross-domain benchmark for reproducible evaluation. The proposed approach integrates ensemble learning, knowledge distillation, and quantization across 24 deep learning architectures, with data augmentation and ADASYN balancing mitigating a severe 75:1 class

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imbalance. A four-model ensemble (DenseNet-121, ResNet-101, DenseNet-201, EfficientNet-B4) achieved 99.15% accuracy through soft-voting, while knowledge distillation transferred this performance to a lightweight ShuffleNetV2 model, maintaining 98.53% accuracy with 163× parameter reduction and 43.6× faster inference. INT8 quantization further compressed the model 671× (to 1.46 MB) with 97.46% accuracy and 0.29 ms inference time. Cross-domain validation showed only a 3.45% performance drop, and Grad-CAM++/LIME analyses confirmed biologically meaningful attention patterns. A multilingual, multi-platform Flutter application validated real-world feasibility, establishing the first scalable and efficient framework bridging deep learning research with practical agricultural deployment.

E. Özbılge [14] introduces a compact convolutional neural network (CNN) for early detection of tomato leaf diseases, aiming to enhance crop yield, efficiency, and quality while reducing production losses. The proposed six-layer CNN is computationally lightweight and was trained on the PlantVillage tomato dataset containing 10 classes (nine diseases and one healthy). Despite its simplicity, the model outperformed well-known pre-trained ImageNet-based deep networks using transfer learning, demonstrating that high accuracy can be achieved without large and complex architectures. Data augmentation techniques were applied to further boost performance. The proposed model achieved outstanding results on 9,077 unseen test images, with an accuracy of 99.70%, F1 score of 98.49%, Matthews correlation coefficient of 98.31%, true positive rate of 98.49%, and true negative rate of 99.81%. These results match or surpass state-of-the-art deep learning approaches while using a far more cost-effective architecture, making it highly suitable for practical agricultural applications.

Table:1

Ref. No.	Author(s)	Method / Model Used	Dataset	Classes	Technique / Approach	Accuracy / Results	Key Highlights / Contributions
[1]	A. Mishra et al.	VGG16, VGG19, ResNet50 (Transfer Learning)	PlantVillage (16,012 images)	10 (9 diseases + 1 healthy)	Fine-tuned pre-trained CNNs for tomato leaf disease classification	VGG16: 95.1% (highest)	VGG16 outperformed VGG19 and ResNet50, showing strong classification ability using transfer learning.

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[2]	Optimized Detection of Tomato Leaf Diseases via VGG16 Neural Network”)	Fine-tuned VGG16	Custom dataset (based on PlantVillage)	7 (including bacterial spot, early & late blight)	Transfer learning, preprocessing, augmentation	Train Acc: 90.25%; Val Acc: 88.86%; Precision: 85.93%; Recall: 84.43%; F1: 84.82%	Achieved strong generalization with minimal overfitting; effective multi-class disease detection.
[3]		VGG16 (Transfer Learning)	PlantVillage	10 (9 diseases + 1 healthy)	Transfer learning without segmentation or extra preprocessing	Acc: 95.5%; Top-2 Acc: 99%; Nearly 100% healthy/unhealthy distinction	Demonstrated high efficiency and robustness using simple transfer learning approach.
[4]	S. P. Patnayakuni	AlexNet (Transfer Learning)	Tomato dataset	5 disease classes	Transfer learning-based classification	Acc: 95.6%	Outperformed traditional techniques; effective for early disease identification and crop management.
[5]	—	HOWSVD-TEDA (Tensor Subspace Learning + CNNs)	PlantVillage & Taiwan datasets	Multiple	Combined HOWSVD & TEDA for feature extraction	Acc: 98.51% (PlantVillage), 89.49% (Taiwan)	Novel tensor-based method improving precision and reliability in disease classification.

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[6]	—	Deep Multistacking Integrated Model (TL + XGBoost)	TDDS, PPDS, AGDS	Multiple	Fine-tuned TL models, multistacking, ensemble XGBoost	TDDS: 99.78%; PPDS: 99.86%; AGDS: 99.82%	Advanced ensemble and stacking improved generalization, precision, and computational efficiency.
[7]	M. J. Hasan et al.	Ensemble (DenseNet-121, ResNet-101, DenseNet-201, EfficientNet-B4) + KD + Quantization	Unified PlantVillage + TomatoVillage	15 harmonized classes	Ensemble learning, knowledge distillation, INT8 quantization	Ensemble: 99.15%; KD ShuffleNet V2: 98.53%; Quantized: 97.46%; 0.29ms inference	First cross-domain benchmark; achieved high accuracy with compact edge deployment and explainable AI validation.
[8]	E. Özbılge	Compact 6-layer CNN	PlantVillage (Tomato subset)	10 (9 diseases + 1 healthy)	Lightweight CNN, data augmentation	Acc: 99.70%; F1: 98.49%; MCC: 98.31%; TPR: 98.49%; TNR: 99.81%	Achieved state-of-the-art results with minimal complexity and high efficiency; ideal for real-world applications.

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III. CONCLUSION

The comparative analysis of recent studies on tomato leaf disease detection highlights a clear progression toward higher accuracy, computational efficiency, and real-world applicability. Early works utilizing traditional transfer learning architectures such as VGG16, VGG19, ResNet50, and AlexNet achieved strong baseline accuracies around 95–96%, demonstrating the effectiveness of fine-tuned CNNs for disease classification. More advanced approaches, such as HOWSVD-TEDA and deep multistacking ensemble models, further enhanced performance, achieving accuracies above 98%, showing improved generalization and robustness. The introduction of ensemble learning, knowledge distillation, and quantization techniques—especially in smartphone-compatible frameworks—marks a significant step toward scalable, edge-deployable systems with minimal loss in accuracy. Finally, lightweight architectures like E. Özbılge's six-layer CNN achieved near state-of-the-art results (99.7% accuracy) with minimal complexity and cost, underscoring that efficient and compact models can rival or surpass larger deep networks. Overall, the reviewed studies collectively demonstrate that through optimized architectures, data augmentation, and ensemble strategies, tomato leaf disease detection has evolved into a highly accurate, efficient, and practically deployable technology for precision agriculture.

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