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Tomato Leaf Disease Detection Using Deep Learning

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ABSTRACT

Tomato leaf diseases pose a significant threat to crop yield and quality, demanding timely and accurate diagnosis for effective management. In recent years, deep learning has emerged as a transformative tool in plant disease detection, offering automated, precise, and rapid diagnostic capabilities. This paper presents a comprehensive review of deep learning approaches applied to tomato leaf disease detection from 2020 to 2024. We focus on key architectures including Convolutional Neural Networks (CNNs), transformer-based models, and hybrid frameworks. Special attention is given to Dense Net, Efficient Net, Vision Transformers, and lightweight models, evaluated across metrics such as classification accuracy, computational efficiency, and real-world applicability. Furthermore, we discuss critical challenges in deploying these models in agricultural settings, including data scarcity, model interpretability, and scalability. Finally, we outline future research directions aimed at integrating deep learning technologies into precision agriculture systems for sustainable crop management.

Index Terms:— *Tomato leaf disease, deep learning, convolutional neural networks, plant pathology, precision agriculture, computer vision.*

I. INTRODUCTION

Tomato is among the most economically important vegetable crops in the world, with over 180 million tonnes produced annually all over the world[5]. However, diseases like early blight, late blight, bacterial spot, leaf mold, and a variety of viral infections significantly affect the tomato plant, causing yield losses as high as 80% under severe conditions [16]. Traditional methods for the identification of diseases depend on the visual inspection of plants by agricultural experts, which is time-consuming and subjective and often not applicable on a large scale for farming. The development in DL technologies has provided the avenue towards various automation-based detection systems for agricultural disease management. Applications of computer vision have indicated immense development in the recognition of plant diseases, especially in the field of using convolutional neural networks, which achieved very outstanding performance related to classifying the diseases affecting tomato leaves (Zhang et al., 2023[10]). This review aims to discuss all the architectural innovations, analysis of performance metrics, challenges of implementation, and prospects for future directions in the light of state-of-the -art DL approaches for detecting diseases of tomato leaves.

II. CLASSIFICATION OF TOMATO LEAF DISEASES

Planting tomatoes most diseases, include bacterial spots, fungus, algae, and other organisms, are caused by bacterial spots, fungus, algae, and other organisms. The healthy class of tomato plant leaf and the 9-

leaf disease class of tomato plant leaf diseases are the two classifications. 18160 images from the Plant Village Dataset were used to test validation. Tomato plant leaves are infected with a variety of diseases. In tomatoes, there are nine Classes of diseases and healthy classes as shown in Figure 1) Target-Spot 2) Mosaic-Virus, 3) Bacterial-Spot, 4) Late-Blight, 5) Leaf-Mold, 6) Yellow-Leaf-Curl Virus, 7) Spider-Mites: Two-spotted spider mite, 8) Early- light, and 9) Septoria Leaf-Spot and Healthy class diseases Tomato plant leaf disease, sometimes known as late blight, was extremely harmful.

Fungal Diseases: About 85 percent of plant diseases may be traced back to fungi or organisms with similar structures. To infect other plants and trees, fungi, and bacteria only need to land on a nearby surface, as they are so tiny and light. Besides being susceptible to insect pests, tomatoes are also susceptible to several fungal diseases that create replay disease spots on the plant's leaves, stems, and fruit. Diseases caused by fungi in tomatoes are often exacerbated by wet, humid conditions. At first look, the symptoms of the three most frequent fungal infections of tomatoes appear to be relatively similar but at closer investigations should reveal which fungus is to blame.

Bacterial Diseases: Bacteria of over 200 different varieties cause it. Insects, splashing water, other infected plants, or equipment can all transmit the illness. It is caused by Xanthomonas bacteria, namely Xanthomona's performance, and only affects green tomatoes, not red ones. As with peppers, diseases have spread to peppers. The disease tends to spread more during the rainy seasons. Spots on the leaves and fruits reduce crop output and can even kill plants or cause them to wither and die from sun damage. Symptoms include spots on the leaves that range from angular to irregular and wet to dry and buy or scabby spots on the fruit. The leaf dots may have a golden halo around them. Cores lose moisture and become brittle over time.

Viral Diseases: It is the rarest sort of plant disease and is caused by viruses. However, there are no chemical therapies for a virus after it has been infected, thus all suspicious plants should be destroyed to halt the infection. They must physically penetrate the plant, and insects are the most common carriers . By examining various diseases, we can see the various sorts of surgeries and aspects that must be considered. Several disease variations are discussed in further detail.

Bacterial Spot: Spots generated by the bacterium Xanthomonas are called bacterial infections. When combined with high temperatures, heat, and rain, it can cause crops to lose their leaves and get damaged.

Early Blight: Fungi or bacteria are responsible for early blight. On elder leaves, little black dots develop first. Infected leaves might become brown and fall off, or they can become dead, dry leaves that attach to the stem.

Late Blight: Fungal pathogen viruses are responsible for late blight. Symptoms of late blight in leaves include water-soaked lesions with an uneven outline and a lighter halo ring.

Leaf Mold: Known scientifically as a fungus, Leaf Mold thrives in damp conditions and high relative humidities (above 85%). Yellow dots on the upper leaf surface are a replay indicator of the diseases.

Septoria Leaf Spot: Septoria Leaf Spot is a fungal infection that affects the leaves. It usually appears on the lower leaves after the first fruit has formed. Per leaf, there are many circular regions with dark brown borders and multiple dots. The leaves turn yellow, then brown, and eventually, wither if there are multiple leaf lesions.

Two-spotted spider mite: The two-spotted spider mite causes white spots to form on tomato leaves. Diseased areas appear on plant leaves, and the leaves turn yellow or grey before falling off after many days of heavy pest feeding.

Target spot: The ideal growing conditions for tomatoes are temperatures between 68 and 82 degrees Fahrenheit and leaf wetness intervals of up to 16 hours. On leaves, it causes necrotic tumors to form in circular patterns.

Target Mosaic virus: The yellowing and shrinking of tomato plants caused by the tomato mosaic virus is a major cause of crop failure caused by this virus. Curled, distorted, or abnormally small leaves are symptoms.

Yellow leaf curl Virus: To put it simply, the Yellow Leaf Curl Virus causes massive economic losses in tropical and subtropical regions. The fungus gnats, a type of bug, is the vector for this disease. Leaf size is drastically reduced, and the leaves curl or cup upward, as a result of this disease.

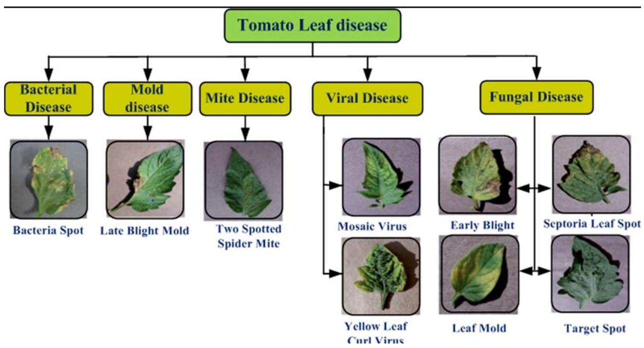

Figure 1 : Tomato Leaf Diseases Sample Images [5].

III. DEEP LEARNING ARCHITECTURES USED IN PLANT DISEASE DETECTION

i. Convolutional Neural Networks (CNNs)

The CNN architecture generally comprises convolutional layers, pooling layers, and fully connected layers that inherently extract features from input images because it has a hierarchical feature learning capability. Due to this salient capability of CNN, it has been the linchpin in image-based plant disease detection. Several recent works have shown that CNNs can learn discriminative patterns associated with various pathological conditions without explicit feature engineering.

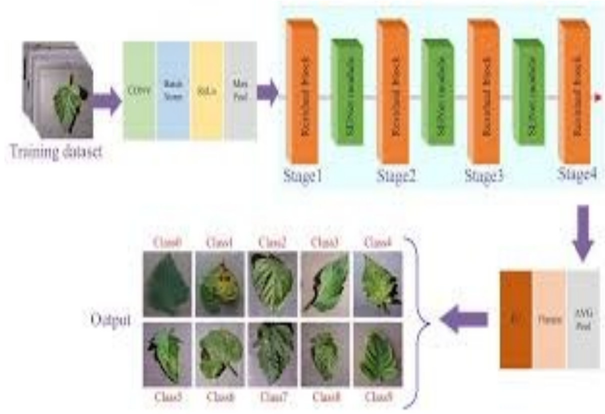

Figure 2 : Convolutional Neural Networks

ii. Transfer Learning in Tomato Plant Disease Recognition

Specifically, this has turned out to be a powerful strategy, especially when dealing with limited labeled datasets. With the use of pre-trained models on large-scale datasets such as ImageNet, remarkable performances were achieved by researchers even for relatively small agricultural datasets. This significantly reduces the training time and computational requirements while improving the generalization capability.

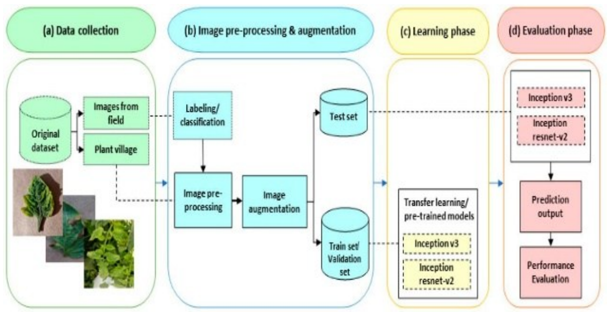

Figure 4 : Transfer Learning Model is used for Tomato Leaf Disease Detection

iii. Emerging Architectures: Vision Transformers

Recently, there has been a keen interest in the adoption of Vision Transformers for plant disease classification. Unlike CNNs, which process images through local receptive fields, ViTs leverage self-attention mechanisms to capture global contextual information and may give superior performance on the complex patterns associated with diseases. Wang and Liu, 2024[13]

IV. RECENT ADVANCES IN THE DETECTION OF TOMATO LEAF DISEASES: 2020-2024

i. Performance of CNN-based Models

Recent research has widely investigated different CNN architectures for classifying diseases of tomatoes. DenseNet variants have given very impressive results with an accuracy of 99.4% recorded for DenseNet-161 on the PlantVillage dataset by Kumar et al. (2023) [12]. The dense connectivity pattern allows feature reuse, overcomes the problem of vanishing gradients, and hence these networks are quite effective in complex classification problems. ResNet architectures have also shown promising results with ResNet-50 when 98.7% accuracy was realized in the identification of multiple diseases under controlled conditions affecting tomatoes (Patel and Singh, 2023)[11]. Residual connections allow very deep networks to be trained without degradation in performance, allowing for the capture of intricate disease patterns at several levels of abstraction. The models from EfficiencyNet indeed attracted much interest due to their balanced scaling approach, achieving competitive accuracy of 98.2-98.9% with drastically reduced computational requirements by Balakrishnan et al. (2023). This will particularly make them very suitable in resource-constrained environments and for mobile applications.

ii. Lightweight Models for Mobile Deployment

Lightweight models need to be developed for the practical implementation of disease detection systems in agricultural settings. MobileNetV3 and ShuffleNetV2 have recently been considered important archetypes for mobile deployment, recording an accuracy of 96.8% and 95.7%, accordingly, with minimum computational overhead by Zhang and Li (2024)[10]. Both models employ depthwise separable convolutions and channel shuffling operations to reduce parameters and FLOPs with minimum loss of accuracy.

iii. Transformer-based Approaches

The adaptation of transformer architectures has opened up new avenues for plant disease detection. Performance of ViTs in this regard is comparative, while hybrid CNN-Transformer models have achieved state-of-the-art results of 99.1% on comprehensive datasets of tomato diseases. A self-attention mechanism ensures that the model focuses on diagnostically relevant areas of input images, keeping the whole context in view.

iv. Data augmentation and synthetic data generation

It remains one of the most inhibiting aspects for applications of AI in agriculture: the limitation in data. Recently, many works have explored a number of techniques for data augmentation and different generative models. GANs have been used to generate realistic images of diseased leaves, improving model robustness and generalization (Chen et al., 2022)[3]. Among these, some StyleGAN-based approaches show their effectiveness in generating training samples with great diversity to capture multiple disease stages and variations in environmental conditions.

iv. Comparative Analysis of Model Performance fvdsd

Table 1 : Performance of Various Deep Learning Models Reported in Recent Studies (2020-2024)

Model Architecture	Dataset	Accuracy
DenseNet-161	PlantVillage	99.4%
EfficientNet-B4	AICChallenge	98.9%
ResNet-50	PlantVillage	98.7%
Vision Transformer	Tomato-DB	99.1%
MobileNet V3-Large	Field Tomato	96.8%
CNN-Transformer Hybrid	PlantVillage+	99.2%
ShuffleNetV2	Field Tomato	95.75

V. IMPLEMENTATION CHALLENGES AND LIMITATIONS

i. Real-World Variability and Domain Adaptation

One of the major issues in the deployment of deep learning models for tomato disease detection is domain shift, which arises between the laboratory datasets and the field conditions. Models developed from clean and standardized images mostly show poor performance in a real environment due to changes in illumination, complex backgrounds, occlusion, and multiple growth stages of plants (Singh et al., 2023). Newer methods have been involving domain adaptation techniques and training of the model on field-collected datasets.

ii. Early Disease Detection and Assessment

Most of the existing systems take the disease classification into consideration once the symptoms have already appeared. However, detection during the incubation period remains a great challenge. Recent works have analysed hyper spectral imaging and temporal analysis for presymptomatic detection; these systems involve special equipment and huge datasets (Zhou et al., 2024)[13].

iii. Multi-disease Coinfection and Similar Symptomatology

Matters are further complicated by the fact that a single plant may host several diseases simultaneously. Some diseases, such as early blight and Septoria leaf spot, have somewhat similar looks; therefore, their classification needs more advanced feature learning ability (Roberts and Chen, 2023).

iv. Computational Requirements and Edge Deployment

While high-accuracy models exist, their computational demands often preclude real-time deployment on edge devices. Optimizing the accuracy-efficiency trade-off is an active research area, and knowledge distillation, neural architecture search, and model pruning have recently emerged as promising solutions.

VI. FUTURE RESEARCH DIRECTIONS

i. Multimodal Learning Approaches

Therefore, this might be a promising direction of work on enhancing detection reliability when integrating a number of data sources. Merging visual data with environmental sensors, spectral information, and meteorological data will enhance model robustness and enable proactive management against disease.

ii. Explainable AI for Agricultural Applications

I. Developing interpretable models creates trust among farmers and agricultural experts. Recent work involving attention mechanisms, Grad-CAM visualizations, and explainable AI techniques provide insight into model decision -making processes, thus helping with practical adoption.

iii. Federated Learning for Privacy-Preserving Agriculture

Federated learning methods can be used to train models across different farms with no sensitive data being shared, thus making the entire process private by taking advantage of various agricultural conditions to increase generalization.

iv. Real-Time Monitoring Systems and Mobile Applications

UAVs integrated with IoT sensors and mobile applications represent the future in precision agriculture. Such systems create the potential for continuous monitoring and timely intervention, which could change crop management practices beyond recognition.

VIII. CONCLUSION

Deep learning-based approaches have been highly effective for disease detection in tomato leaves, with very recent models able to achieve accuracies above 99% in controlled conditions. The evolution from a standard CNN to more sophisticated architectures such as

DenseNet, EfficientNet, and Vision Transformers brought large improvements in detection performance. Lightweight models have made great strides toward practical deployment in resource-constrained environments. However, challenges regarding real-world variability, early disease detection, and computational efficiency do still exist. Future work needs to be directed more towards multimodal learning, explainable AI, and integrated systems that bridge the gap between laboratory performance and field application. As these technologies mature, they hold tremendous potential to transform agricultural practices, enable timely disease management, and contribute towards global food security. Deep learning-based systems for disease detection therefore require the convergence of efforts between computer scientists, plant pathologists, and agricultural stakeholders to develop solutions that are technologically advanced yet practically applicable and economically viable for farming communities across the world.

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