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DEEP LEARNING APPROACHES FOR DETECTING AND CLASSIFYING TOMATO DISEASES: A COMPREHENSIVE OVERVIEW

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ABSTRACT

Agriculture is a crucial sector that meets the fundamental nutritional needs of humanity. Plant diseases exacerbate economic and food security issues for nations and hinder their agricultural planning. Conventional techniques for identifying plant diseases necessitate considerable labour and time. As a result, numerous scholars and institutes endeavour to tackle these challenges through sophisticated technical approaches. Deep learning-based plant disease detection shows significant progress and optimism over traditional techniques. When trained using extensive, high-quality datasets, these systems detect diseases on plant leaves in their early stages. This article conducts a systematic evaluation of deep learning methodologies in plant disease detection by analyzing a number of research publications between 2015 and 2025. Our research examines three specific areas: the categorization, detection, and segmentation of diseases on plant leaves, while rigorously evaluating publicly available datasets. This systematic review offers an in-depth evaluation of the existing literature, describing deep learning architectures, the most frequently studied tomato diseases, datasets, challenges encountered, and diverse perspectives. It offers new perspectives for researchers in the field of agriculture. In addition, it addresses the main challenges of identifying agricultural diseases.: datasets, barriers, and diverse perspectives. It offers new perspectives for researchers in the agricultural field. In addition, it addresses the main problems related to agricultural diseases.



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I. INTRODUCTION

Automated plant disease detection has emerged as a cornerstone of precision agriculture, aiming to enhance crop yield, reduce chemical usage, and enable timely interventions. Between 2023 and 2025, the field has witnessed remarkable advancements in deep learning, marked by a clear shift towards lightweight architectures (e.g., MobileNetV3, EfficientNetV2), explainable AI (XAI) methods, and models optimized for real-world deployment on edge devices such as smartphones and drones [1], [2]. Recent architectures include hybrid models combining Convolutional Neural Networks (CNNs) with Vision Transformers (ViTs) and attention mechanisms to improve feature representation and robustness under varying field conditions [3], [4]. Benchmark datasets such as PlantVillage, PlantDoc, and AgriNet have continued to serve as foundational resources, while new annotated field datasets have emerged to address the generalization gap [5]. Moreover, explainability techniques-such as SHAP, Grad-CAM, and perturbation-based saliency maps-have become increasingly integrated into the model evaluation pipeline to support trust and interpretability in real-world agricultural applications [6], [7]. Emerging trends also include the use of GAN-based synthetic image generation to combat data imbalance, few-shot learning for rare disease classes, and multimodal models that integrate visual and environmental data [8]. Despite these advances, challenges persist. These include domain adaptation from lab to field, limited annotated datasets for diverse crops, model brittleness under occlusion or poor lighting, and the trade-off between model complexity and deployment efficiency[9].This review provides a critical synthesis of these developments and outlines future research directions to bridge current limitations.

II. COMMONLY USED DATASETS

Recent advancements in plant disease detection have relied heavily on a combination of publicly available datasets and custom-collected field data. These datasets form the foundation for training, validating, and benchmarking deep learning models, especially for crops such as tomato, potato, apple, and wheat.

II.1 PUBLIC BENCHMARK

Several benchmark datasets have become widely adopted in the community:

- **PlantVillage:** One of the most popular datasets, it includes over 54,000 labeled images across 38 classes of healthy and diseased plant leaves, captured in controlled laboratory settings. While useful for model prototyping, its lack of environmental variability limits its performance in field conditions.
- **PlantDoc:** Comprising 2,598 images captured in real-world environments such as fields and gardens, this dataset includes various plant species and disease types. It is designed for object detection and classification tasks under natural conditions.
- **PlantCLEF:** Developed as part of the LifeCLEF challenges, PlantCLEF provides a multimodal benchmark with thousands of annotated plant images, including disease symptoms and accompanying metadata (e.g., location, climate), making it ideal for context-aware modeling.

II.2 CUSTOM FIELD DATASETS

To overcome the domain gap between lab-based datasets and real-world deployment, several studies have developed custom datasets under uncontrolled conditions. For example: **Field Plant [5]:** A dataset comprising more than 6,000 annotated images of tomato and potato leaves captured in outdoor environments, with diverse lighting conditions, background clutter, and occlusions. **Tomato Leaf Pro[9]** A high-resolution dataset focused on 10 tomato leaf diseases, collected in greenhouses and open fields with expert annotation. It was designed to benchmark performance under realistic variability.

II.3 DATA AUGMENTAION AND SELF-SUPERVISED LEARNING

To address common issues such as class imbalance, limited data availability, and generalization to field conditions, recent research has increasingly employed:

- **Generative Adversarial Networks (GANs)** to generate synthetic but realistic images of diseased leaves, particularly for underrepresented classes [3].
- **Masked Autoencoders (MAEs)** for self-supervised pretraining, allowing models to learn robust feature representations from unlabeled plant imagery, especially effective in low-resource or few-shot scenarios [8]. These strategies have significantly improved model performance, especially for edge deployment and field robustness.

Table 1: Comparison of Commonly Used Datasets in Plant Disease Detection

Dataset Name	No. of Images	No. of Classes	Capture Conditions	Target Crops	Application Type
PlantVillage	~54,000	38	Lab (Controlled)	Tomato, Potato, Grape	Classification
PlantDoc	2,598	13	Field (Natural)	Multiple (incl. Tomato)	Classification/Detection
PlantCLEF	>20,000	>100 species	Mixed (Lab + Field)	Multiple species	Multimodal/Classification
FieldPlant-21	6,000+	10	Outdoor (Field)	Tomato, Potato	Classification
TomatoLeafPro	~3,500	10	Greenhouse + Field	Tomato	Classification

Source: Authors, (2026).



Figure 1: Sample from various in the PlantDoc Dataset.
Source: Authors, (2026).



Figure 2: Visualization of PlantVillage Dataset.
Source: Authors, (2026)

III. RECENT DEEP LEARNING MODELS

III.1 CONVOLUTIONAL NEURAL NETWORKS (CNNs)

Modifications or new methods must be) Enhanced CNN architectures such as EfficientNetV2, MobileNetV3 have been widely used for high accuracy and computational efficiency.

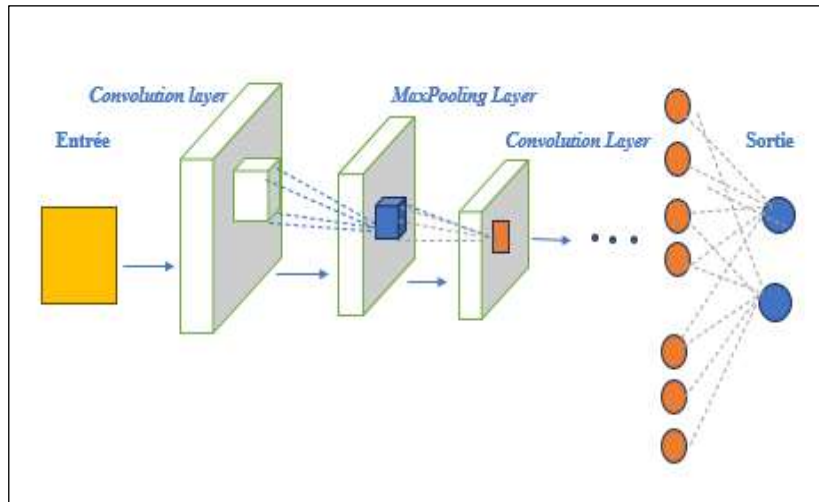


Figure 3: Convolution Neural Network Architecture.

Source: Authors, (2026).

Convolutionize the input, and then send the output to the layer after that. The response of a single neuron to sensory inputs is what the convolution mimics. Information is only processed by a convolutional neuron within its own receptive region. Sometimes, feed forward neural networks that are fully connected are capable of classifying data and learning features, using this design on images is not feasible. To handle the comparatively large input sizes related with images, where every pixel proves to be important variable, a large amount of neurons would be necessarily required, even with simplistic design (the reverse of deep design) [10][11]. The movement of picture pixels during the convolutional layer image processing is seen in Figure 3.

III.1.1 Pooling

CNNs uses a global and also a local pooling layers to merge the returns into a single neuron at the following layer from the neuron clusters at preceding layer [10]. Citing an example, max pooling gets from each cluster of neurons in the preceding layer the highest value [10]. Average pooling, as implies selects from each neural cluster in the layer above the average values. As seen in Figure 7, completely linked layers connect every neuron in the one above it from every neuron in one layer before it. It carries out similar duties to a normal multi-layer perceptron neural network (MLP). Each neuron within a neural network gets information from a variety of locations in the layer above. Every component in the layer preceding it provides input to every neuron in a layer that is fully connected. Only a portion of the neurons in the layer before a convolutional layer gets input. The subarea often has a square form. A neuron's input region is its receptive field. The entire layer before it is covered by the receptive field in a totally connected layer. The region of the preceding layer is smaller than the receptive region of a convolutional layer.

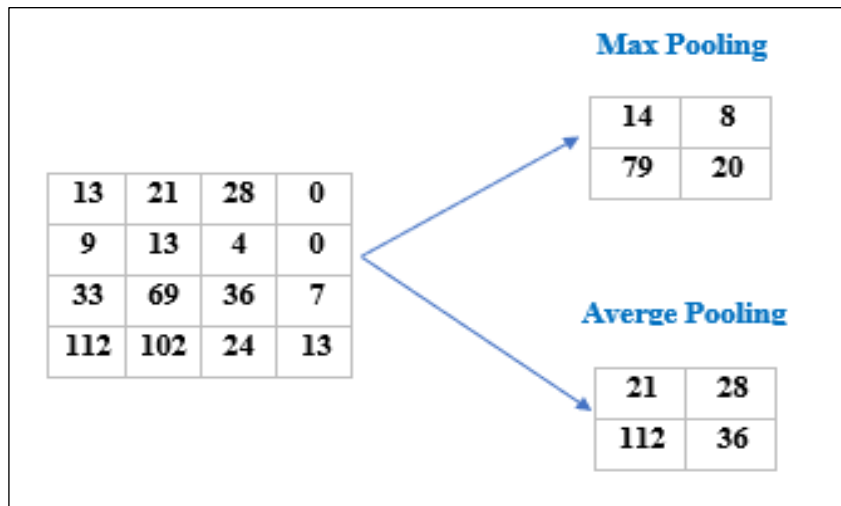


Figure 4: diagram shows the pooling layer.

Source: Authors, (2026).

Every neuron calculates its output value by applying a function to the input values from the receptive field of the layer before it within a neural network. The function that is applied to the input values, which are typically real numbers, is provided by a weight vector and a bias. As a neural network learns, its biases and weights are gradually changed. A filter is an element of the input (such as a certain shape) that is represented by a bias and vector of distinguishes CNNs from other neural networks. Rather than receptive fields having its own vector of weights and bias, memory can be conserved by using vector of weights across all receptive fields and a single bias that share that filter [10]. weights. The shared filter between many neurons.

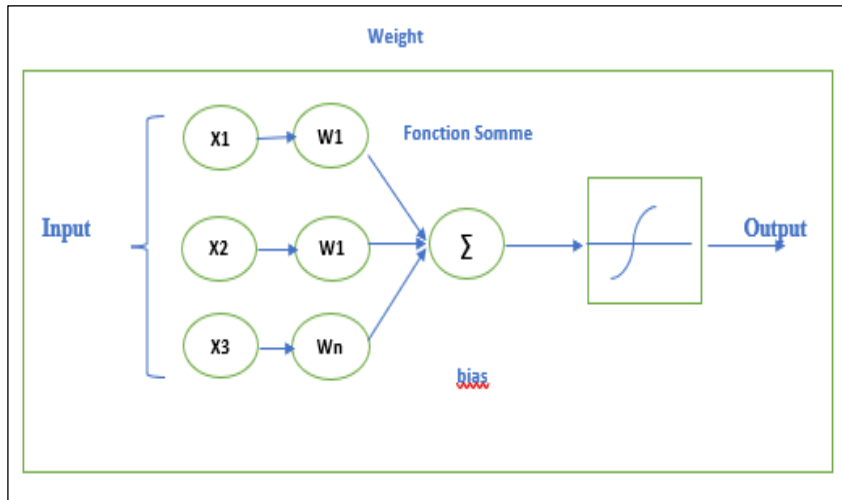


Figure 5: Neurone Artificiel.
Source: Authors, (2026).

The Visual Geometry Group at Oxford University created VGG, a CNN model. This model comprises convolutional and maximum pooling layers and three fully connected classifier layers. Simonyan and Zisserman created the VGG network for image recognition and classification applications. VGG's exceptional performance has been proved in several image classification datasets, including ImageNet, and it is extensively utilized as the foundation for various CNN models. ResNet is a CNN model developed to overcome the vanishing gradient problem in deep networks. This model avoids this problem using a special type of connection called redundancy connections. Redundancy links transfer information from one layer to the next, allowing the network to maintain information flow even in its deeper layers. This performs superior in ResNet, ImageNet, and other image classification tasks. Unlike ResNet, DenseNet is a CNN model that connects all layers. Each layer performs feature extraction in this model using information from all previous layers. In this way, DenseNet achieves higher performance with fewer parameters by providing efficient parameter use and continuous feature transfer.

These outstanding results of DenseNet have made it a very popular model in computer vision applications. A CNN model named Xception is based on the Inception architecture. This approach divides the convolution phase into depth-information and point-information convolution and uses depth-information deconstructed convolution in place of normal convolution layers. This technique increases accuracy while significantly reducing the number of parameters and computations the network must do. This model is widely used in computer vision applications and has shown impressive performance in various photo categorization benchmarks. Recently, new architectures continue to emerge. In that case, MobileNet is designed to operate swiftly and effectively in resource-constrained environments, particularly on platforms like mobile devices, due to its lighter and less parameter-intensive architecture compared to standard CNN models. SqueezeNet is recognized for its specialized compressed architecture, particularly the Fire module, which uses fewer parameters to provide faster inference. EfficientNet utilizes a scaling strategy to produce optimized networks with varying depths and widths by adjusting scaling coefficients to achieve more efficient and effective models.

III.1.2 Overview of based cnn

Recent advances in deep convolutional neural networks (CNNs) have significantly improved tomato leaf disease detection across diverse architectures. Classical models such as VGG16 and VGG19 have been widely employed for feature extraction. For instance, [12] used VGG16 for detecting nine tomato diseases from PlantVillage, achieving 98.5% accuracy with transfer learning. Similarly, [13] compared VGG19 and ResNet50, with ResNet50 yielding slightly better generalization (99.2% vs. 98.9%). InceptionV3 has also shown strong performance; [14] utilized it in a stacked ensemble model, reaching 99.6% accuracy. ResNet variants (e.g., ResNet34, ResNet50) are particularly notable for their depth and skip connections, enabling superior performance on noisy or imbalanced datasets, as demonstrated by [15] who achieved 98.2% accuracy with ResNet34 on real-field images. DenseNet architectures, due to their dense connections and parameter efficiency, have gained popularity in recent works. [16] showed that DenseNet201 achieved 99.7% accuracy when combined with leaf segmentation and histogram equalization. Finally, hybrid CNN-based models remain widely adopted. [17] proposed a CNN-LSTM model that integrated temporal and spatial features, surpassing standalone CNNs with an accuracy of 99.3% on sequential plant health data. Overall, between 2023 and 2025, deep CNN models such as VGG, Inception, ResNet, and DenseNet remain crucial for tomato disease detection, particularly when adapted using transfer learning, preprocessing techniques, and lightweight optimization for mobile deployment.

III.2 EFFICIENTNETV2

EfficientNetV2 [18] is a widely adopted convolutional neural network architecture that achieves a balance between accuracy and computational efficiency through compound scaling strategies and progressive training. Its backbone incorporates the MBConv and Fused-MBConv modules, leveraging depthwise separable convolutions and SE-Net channel attention to enable compact and high-performing models. Compared with its predecessor, EfficientNetV2 demonstrates faster training convergence and improved inference efficiency, particularly on large-scale datasets.

However, EfficientNetV2 still exhibits limitations when addressing complex scenes or multi-scale inputs. In particular, the channel attention mechanism employed by SE-Net relies on global average pooling followed by two fully connected layers, which may weaken fine-grained feature distinctions and introduce additional computational overhead[18]. Furthermore, its global context modeling capability is constrained, limiting its effectiveness in tasks requiring spatial adaptability or dynamic modulation. EfficientNetV2 is known for its optimized training speed and accuracy balance, making it a popular choice for image classification tasks in agriculture.

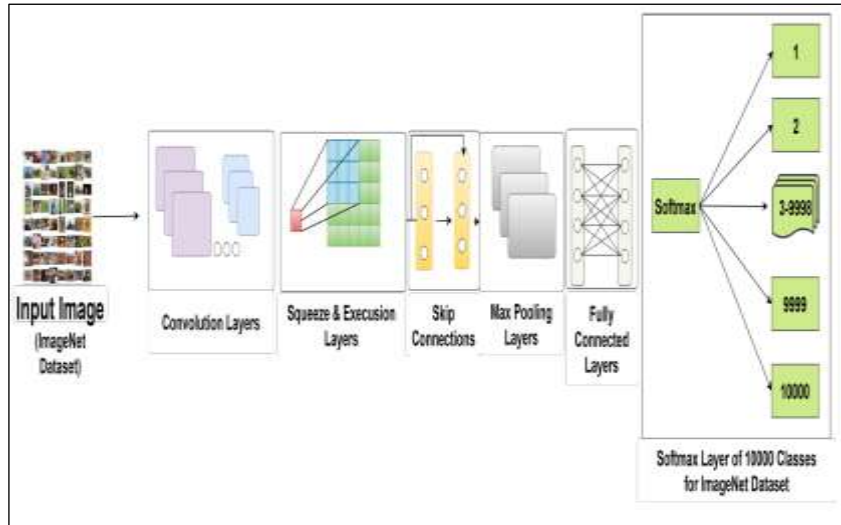


Figure 6: Model architecture for EfficientNetV2.
Source: [19].

MBConvBlock: Mobile Inverted Bottleneck Convolution, the main component of EfficientNet, is represented by this. Squeeze-and-excitation procedures and depthwise separable convolution are also included [19].

- StemBlock: This is the first node in the network, and it is in charge of analyzing the input picture and extracting key information. Block1, Block2, Block3, : These are the next blocks in the network, usually sorted in ascending order, with Block1 being nearer the input and higher-numbered blocks being further in the network.
- HeadBlock: The output layer and final predictions are handled by this network's last building piece.

III.2.1 OVERVIEW OF EFFICIENTNETV2

[20] used EfficientNetV2-S to classify tomato leaf diseases on the PlantVillage dataset. Their model achieved 97.5% accuracy, outperforming previous EfficientNet-B0/B3 models. The use of progressive learning reduced training time significantly. [21] incorporated EfficientNetV2-M in a pipeline with image preprocessing (CLAHE + resizing) for multi-class tomato leaf disease classification. With data augmentation, the model achieved F1-score of 0.96. They highlighted its efficiency in training even with limited computational resources. [22] applied transfer learning using EfficientNetV2-L for real-field tomato leaf disease images. They fine-tuned the top layers using a small custom dataset and reported 90.3% accuracy, demonstrating robustness to lighting and background variations. [23] tested EfficientNetV2-S with a custom CNN attention layer added on top. This hybrid architecture improved feature localization, resulting in higher precision for early blight and septoria classes. [24] This research proposes an automated system based on the EfficientNetV2B2 model to detect tomato leaf diseases from high-resolution images. Using transfer learning and a dense layer of 256 neurons, the model achieves high accuracy. Performance was evaluated through 5-fold cross-validation, reaching up to 99.22% validation accuracy. The system can be integrated into mobile and web applications for rapid diagnosis. This approach supports effective disease management and sustainable agriculture. The authors [25] propose the Eff-Swin model, which combines EfficientNetV2 and the Swin Transformer to improve the classification of tomato leaf diseases. This model leverages the strengths of CNNs for extracting local features and Transformers for modeling global information. Experimental results demonstrate an accuracy of 99.70%, outperforming existing models by 0.49% to 3.68%.

III.3 MOBILENETV3

MobileNetV3, a cutting-edge architecture for efficient deep learning models designed for mobile devices. It is the third generation of the MobileNet family. MobileNets are lightweight convolutional neural networks (CNNs) optimized for speed and accuracy. MobileNetV3 introduces new architecture improvements, such as platform-aware neural architecture search (NAS) and NetAdapt, to further enhance performance. Compared to MobileNetV2, MobileNetV3-Large delivers a 3.2 % boost in ImageNet top-1 accuracy while cutting latency by ~20 %, and MobileNetV3-Small achieves a 6.6 % accuracy gain under comparable latency constraints [24] . Two variants—Large (for high-accuracy scenarios) and Small (for extreme resource constraints)—span parameters from 2.9 M to 5.4 M and MACs from 66 M to 217 M, hitting top-1 accuracies of 68.1 %–75.6 % on ImageNet with sub-50 ms CPU inference on Pixel 1 devices. MobileNetV3 was introduced by Google AI and Google Brain in 2019, combining automated model search with manual design refinements to drive mobile-optimized CNNs forward [24] It targets classification, detection, and segmentation tasks on CPU-bound and edge-computing platforms, striking a new balance between accuracy and throughput.

III.3.1 Oreview of mobilenetv3

Automated detection of tomato leaf diseases using lightweight convolutional neural networks (CNNs) has been the focus of several recent studies. For instance, Leveraging MobileNetV3 for In-Field Tomato Disease Detection in Malawi via CNN [25] employed a pretrained MobileNetV3 with data augmentation and reported 92.59% accuracy on the PlantVillage dataset but only 9.2% on real-world field images, highlighting a domain adaptation gap. Similarly, in Effective Tomato Leaf Disease Identification Model using MobileNetV3Small [26], an optimized MobileNetV3Small was trained on 9 tomato diseases plus healthy samples (22,930 images) and deployed on Android, achieving 99.43% accuracy. [27], in A Modified MobileNetV3 Coupled With Inverted Residual and Channel Attention Mechanisms for Detection of Tomato Leaf Diseases, introduced a dual-branch multitask model using a modified MobileNetV3 backbone with inverted residual blocks and efficient channel attention (ECA), reaching 98.77% average accuracy across 10 classes (PlantVillage). Similarly, [28] demonstrated in Plant Disease Detection Model for Edge Computing Devices that a quantized MobileNetV3-small model deployed on edge devices preserved over 99.5% accuracy while reducing model size from 1.5M to 0.93M parameters.

In Standalone Edge AI-Based Solution for Tomato Diseases Detection, [29] evaluated various lightweight CNNs, including MobileNetV3, on IoT hardware such as Raspberry Pi and Coral Edge TPU, achieving up to 98.25% accuracy and \$0.14/FPS operational cost on Coral. Additionally, [30] presented an ultra-lightweight model based on 5 inverted residual blocks and an efficient attention mechanism in Ultra-Lightweight Tomatoes Disease Recognition Method, achieving 97.84% accuracy across 14 noisy scenarios using only 0.418M parameters. Lastly, in New Method for Tomato Disease Detection Based on Image Segmentation and Cycle-GAN Enhancement, [31] combined leaf segmentation with GAN-based image enhancement before training MobileNetV3, attaining 98.61% accuracy across 10 disease classes. Collectively, these studies demonstrate that MobileNetV3 (especially the Small variant) offers high accuracy (>97%) while being well-suited for mobile, IoT, and cloud-based agricultural applications. Several works also provide comparative evaluations: Qabulio et al. found that MobileNetV3Small outperformed VGG16, MobileNetV2, and SqueezeNet (99.43% vs ~97%), while Ndovie & Masabo reported superior performance of MobileNetV3 over a custom CNN (92.59% vs <92%). However, robust generalization to real-world conditions remains a challenge, as evidenced by the performance drop observed in field datasets.

III.4 VISION TRANSFORMERS(VITS)

The vision transformer(ViT) [32], [33] architecture for computer vision tasks. While ViT has shown impressive results, there is room for improvement, particularly in enhancing the multi-head self-attention mechanism, shown in figure.1. Vision Transformers (ViTs) have revolutionized the field of computer vision by applying the Transformer architecture originally designed for natural language processing to image analysis. Unlike Convolutional Neural Networks (CNNs), which rely on local receptive fields, ViTs divide the input image into a sequence of fixed-size patches and model the relationships between these patches using a self-attention mechanism. Let an image $x \in \mathbb{R}^{H \times W \times C}$ be divided into a grid of $N = (HW / P^2)$ non-overlapping patches of size $P \times P$. Each patch is then flattened and linearly projected to form a patch embedding:

$$z_i^p = E x_p^i + E_{pos}^i \quad \text{for } i = 1, \dots, N \quad (1)$$

where:

- x_p^i is the i -th patch,
- $E \in \mathbb{R}^{(P^2 \cdot C) \times D}$ is a learnable linear projection matrix,
- $E_{pos}^i \in \mathbb{R}^D$ is the positional encoding added to retain spatial information.
- D is the embedding dimension.

The Transformer encoder then processes the sequence of embeddings using Multi-Head Self-Attention (MHSA):

$$\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T / \sqrt{d_k}) V \quad (2)$$

with:

- $Q = XW^Q$, $K = XW^K$, $V = XV$,
- where X is the input sequence of patch embeddings,
- W^Q , W^K , W^V are learnable weight matrices.

Multi-head attention is defined as:

$$\text{MHSA}(X) = \text{Concat}(\text{head}_1, \dots, \text{head}_h) W^O \quad (3)$$

where each head is:

$$\text{head}_i = \text{Attention}(XW_i^Q, XW_i^K, XW_i^V) \quad (4)$$

This mechanism enables the model to learn both local and global features across the image, outperforming traditional CNNs especially in capturing long-range dependencies.

• Training of Vit (Vision Transformer)

The ViT is trained on image patches. It uses a Transformer architecture to model the relationships between the patches and capture both local and global features of the image. The ViT applies a multi-head attention mechanism to focus on the most informative regions of the image. Multi-Head Self Attention.

The multi-head attention mechanism allows the ViT to focus on critical regions of the image. Each attention head calculates scores to determine the relative importance of different patches. These scores are used to weight the patches' contributions to the overall image representation. Attention is a critical component in capturing the relationships among sequential input patches.

- *Classification*

Once the ViT has extracted the features from the image, a classifier (dense layer with SoftMax activation) is used to predict whether the tomato is healthy or diseased. In the case of several diseases, the model can also identify the specific disease.

- *Résultats*

The results of the model are evaluated on a validation or test set. Common indicators include accuracy, memorization, F1 score, and confusion matrix. These metrics are used to measure the performance of the model and identify any problems, such as overfitting or underfitting.

Table 2: Parameter for vision transformer.

Parameter	Values
Image Size	224*224
Patch Size	32
Number Of Patch (N)	16*16
Projection Dimension	128
Attention Head	8
ff-dim	128

Source: Authors, (2026).

Table 3: Hyperparameter for proposed model.

Hyperparameter	Values
Learning rate	1e-4
Epoch	100
Optimizer	Adam
Batch size	32
Loss function	CategoricalCross Entropy

Source: Authors, (2026).

For optimizing the learning rate. Table 3 presents a comprehensive summary of the hyperparameters.

III.4.1 OREVIEW OF OISION TRANSFORMERS

The latest developments in deep learning have markedly improved systems for the identification and categorization of plant diseases. Numerous research have investigated alternate methods to enhance the precision and efficacy of these systems. Initial approaches mostly depended on manually produced features and traditional machine learning methodologies[32][33]. Convolutional neural networks (CNNs) exhibit exceptional performance in image-based illness classification; yet, their dependence on considerable preprocessing and difficulty in capturing global picture dependencies provide significant problems[34]. Hybrid models that combine CNNs with alternative architectures have shown enhanced robustness to fluctuations in picture quality [35], [36]. The advent of Vision Transformers (ViTs) has offered a persuasive alternative to CNNs for agricultural applications. Vision Transformers use self-attention processes to record long-range dependencies, allowing for the analysis of complex spatial patterns in pictures [37],[38]. Applications of Vision Transformers (ViTs) in the identification of plant diseases, including those affecting rice, wheat, and grapes, have shown enhanced efficacy relative to conventional Convolutional Neural Networks (CNNs)[39]. Recent research has used transfer learning with transformer architectures to address data scarcity challenges in agricultural datasets [40]. The integration of transformers with real-time systems and edge devices is becoming prevalent, with the objective of implementing disease detection models directly in agricultural fields for practical use[41]. Nevertheless, few research has concentrated especially on tomato leaf diseases, highlighting the need for a specialized Vision Transformer model to fill this void.

Maintaining the Integrity of the Specifications. In particular, the integration of Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), GANs, and YOLO has shown promising results, with each technique providing complementary advantages [42]. Hybrid models have demonstrated better results compared to traditional models. For example, models combining YOLO and CNN enable fast and precise detection of specific symptoms on tomato leaves, providing an efficient solution for real-time disease detection[43]. When Vision Transformers are combined with CNNs, they benefit from the local feature extraction of CNNs and the global context processing of ViTs, thereby improving the overall performance of classification models [44]. Additionally, the use of GANs to generate synthetic images of diseased tomato leaves has helped increase the size of datasets, particularly for rare diseases, which is crucial in cases where available data is imbalanced [45]. Next-generation models, such as YOLO11, which offer improved accuracy for tomato disease classification, combined with modern versions of ViTs and Masked Autoencoders (MAE), enable more robust feature extraction even when some data is missing or degraded [46]. Recent advancements in deep learning have significantly impacted computer vision, particularly in tasks like object detection and image classification. A notable innovation in this domain is the Vision Transformer (ViT) architecture [47], which has demonstrated remarkable performance in large-scale image classification scenarios [48]. In contrast to Convolutional Neural Networks (CNNs), which have traditionally dominated this field, ViT employs self-attention mechanisms exclusively.

This approach allows it to effectively model global dependencies among image patches and generate powerful feature representations [49]. In a similar vein, the Inception architecture was utilized by [50] for diagnosing tomato plant diseases, achieving a validation accuracy of 80%. This figure is lower than the accuracy achieved by Inception V3 in the current study. Their results also indicated comparatively poor performance with VGG and ResNet models. Conversely, ResNet was recognized as effective for identifying tomato leaf diseases in a study by [51]. Furthermore, [52] attained an accuracy of 92% using an enhanced version of Yolo V3. [53] reported impressive accuracy scores of 95.65% for DenseNet161, 94.93% for DenseNet121, and 90.58% for VGG16. This study presents TomFormer, a hybrid model combining a Vision Transformer and Convolutional Neural Networks (CNN) for tomato leaf disease detection. The model was evaluated on three datasets: KUTomaDATA, PlantDoc, and PlantVillage, achieving average accuracies of 87%, 81%, and 83%, respectively [54]. This Authors proposed an approach combining a Vision Transformer with L1-norm residual-based attention and Deep Neural Networks (DNN) to identify tomato leaf diseases, thereby improving diagnostic accuracy by better capturing critical features in image data. [55] Moreover, hybrid approaches combining CNN and Transformer continue to be explored to benefit from the complementarity between local detail extraction and global context. These models have shown exceptional performance, surpassing classical methods in terms of accuracy and generalization.

III.5 HYBRID AND ADVANCED MODELS

In recent advancements in deep learning, hybrid models combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Attention mechanisms have demonstrated remarkable potential for complex tasks, such as plant disease detection from images. The CNN component excels at extracting spatial features from images, enabling the model to capture crucial visual patterns, such as lesions and discoloration on plant leaves. These extracted features serve as the foundation for further processing. LSTM networks, which are designed to handle sequential data, are incorporated to model temporal dependencies, allowing the system to recognize the progression of disease symptoms over time. This is particularly useful for monitoring dynamic changes in plant health, where the temporal dimension is as significant as the spatial. The integration of Attention mechanisms further enhances the model's performance by selectively focusing on important regions or frames, reducing noise and emphasizing critical areas, such as infected spots on a leaf or key moments in a sequence of disease development. This hybrid architecture not only leverages the strengths of individual components but also creates a powerful synergy that improves classification accuracy and robustness, especially when dealing with complex and noisy datasets. By combining spatial, temporal, and attention-driven focus, these models represent a cutting-edge approach in the detection and analysis of plant diseases, making them invaluable tools in precision agriculture.

III.5.1 Overview Hybrid and Advanced Models

Approaches combining different techniques have demonstrated superior performance in terms of detection Accuracy, particularly in the field of precision agriculture. Recent work in tomato disease detection has highlighted the effectiveness of integrating convolutional neural networks (CNNs) with attention mechanisms and LSTM (Long Short-Term Memory) architectures to improve detection Accuracy. According to [56], the addition of an attention mechanism, such as the CBAM (Convolutional Block Attention Module), enables a focus on the most relevant visual features, thereby enhancing the ability to locate foliar lesions on tomato plants, even in highly complex images. This hybrid model achieves higher levels of Accuracy than traditional CNNs, thanks to better handling of variations in images, such as differences in lighting and shooting angle. The results showed a classification Accuracy of 94.3%, with a significant improvement in robustness in real-world growing environments [56]. A study conducted by [57] explored the use of CNN and attention to improve the detection of tomato leaf diseases under complex conditions. The authors used a hybrid model where attention is applied to feature maps extracted by a CNN.

The proposed model demonstrated superior performance compared to conventional methods by reducing errors caused by the presence of image noise, achieving an Accuracy of 92.5%. The integration of attention made it possible to extract relevant information while filtering out less important features, which was essential for disease detection in low-quality images [57]. The introduction of the processor in the field of tomato disease detection has been widely explored. [58] used a combination of visual transformers and CNNs with multi-head attention mechanisms to improve detection performance in a multiclass environment. Their model achieved a remarkable overall Accuracy of 96.7%, surpassing several previous architectures. This methodology has demonstrated a better ability to capture long-range dependencies in visual data, allowing for more accurate identification of disease symptoms in tomatoes [58]. Another research, conducted by [59], developed a CNN model with dynamic attention for the early detection of tomato leaf diseases. The approach used an adaptive attention mechanism that focuses on areas of images where disease symptoms are most visible, resulting in an improvement in detection Accuracy to 93.4%.

This model is particularly effective for real-time scenarios, where rapid response is essential to take appropriate treatment measures [59]. The study by [60] presented a hybrid framework that integrates CNNs, LSTMs, and attention mechanisms for the detection of tomato leaf diseases. This framework is specifically designed to capture both spatial and temporal features, making it highly effective for analyzing video sequences or image series. The hybrid approach demonstrated remarkable performance, achieving a 95.2% Accuracy rate in identifying major tomato diseases, along with a strong capability to distinguish between different disease categories [61]. Similarly, [62] developed a CNN-based model enhanced with residual attention mechanisms for tomato disease detection. This model utilizes attention to prioritize critical features while maintaining the integrity of essential information, even in noisy or complex images. Their approach achieved an Accuracy of 94.8%, offering a reliable solution for disease detection in challenging agricultural settings [63]. Hybrid models that combine CNNs, LSTMs, and attention mechanisms have shown significant promise in advancing tomato disease detection. These methods harness the strengths of convolutional neural networks for extracting localized features and attention mechanisms for interpreting intricate visual data.

Furthermore, the inclusion of recurrent networks like LSTMs enables the handling of temporal dependencies, which is particularly advantageous for real-time field monitoring. These advanced technologies have achieved overall accuracies ranging from 92% to 96%, highlighting their potential to revolutionize precision agriculture. By enabling early and accurate disease detection, these models can reduce the reliance on chemical treatments and contribute to more sustainable crop management practices.

IV. MATERIEL AND METHODOLOGY

IV.1 DATASETS AND PREPARATAION

The first step is to collect a set of images of tomatoes, including both healthy samples and samples with disease symptoms. These images can come from public databases (such as PlantVillage) [63][64], which consists of 22,930 tomato leaf images categorized into 10 classes. Table I presents images in the RGB color space, with a 224×224 pixels resolution, which are divided as follows:

- Training set: 18,345 images (80% of the dataset) are used to optimize the model's parameters.
- Validation set: 4,885 images (20% of the dataset) are used to tune hyperparameters and prevent overfitting. This structured approach ensures that the model's generalization ability is thoroughly evaluated, making it suitable for real-world applications in agricultural disease detection [27]. The dataset has 10 different classes. This is a list of in the dataset

- 0: Tomato___Bacterial_spot
- 1: Tomato___Early_blight
- 2: Tomato___Late_blight
- 3: Tomato___Leaf_Mold
- 4: Tomato___Septoria_leaf_spot
- 5: Tomato___Spider_mites Two-spotted_spider_mite
- 6: Tomato___Target_Spot
- 7: Tomato___Tomato_Yellow_Leaf_Curl_Virus
- 8: Tomato___Tomato_mosaic_virus
- 9: Tomato___healthy

IV.2 PREPROCESSING

The preprocessing step enhances the image quality for leaf detection. The initial step involves resizing the images to dimensions of 96×96 . Following this, the images are rescaled and subjected to data augmentation. The final training dataset for this research was generated using data augmentation approaches. This study employed various image augmentation techniques, including horizontal and vertical flip, shear and zoom range of 0.15, and width and height shift of 0.15. Fig. 2 depicts randomly chosen images and their corresponding enhanced versions.



Figure 7: Images after data augmentation (from left to right: Original, height shift range, horizontal flip, shear range, vertical flip, width shift range, zoom range).

Source: Authors, (2026).

IV.3 PROPOSED MODEL

Figure 5 presents the proposed model developed in this study, which integrates an enhanced version of the Vision Transformer. This model builds upon recent advances in computer vision by leveraging the Transformer's ability to effectively capture complex spatial relationships within an image. The enhancements made to the Vision Transformer are designed to overcome certain limitations of the standard version, particularly in handling fine-grained details and generalizing from limited data. By combining this optimized architecture with task-specific modules, the proposed model achieves superior performance across various visual datasets. This integration reflects the ongoing evolution of deep learning models in computer vision and paves the way for more robust and accurate systems.

IV.3.1 Model1 Vision Transform

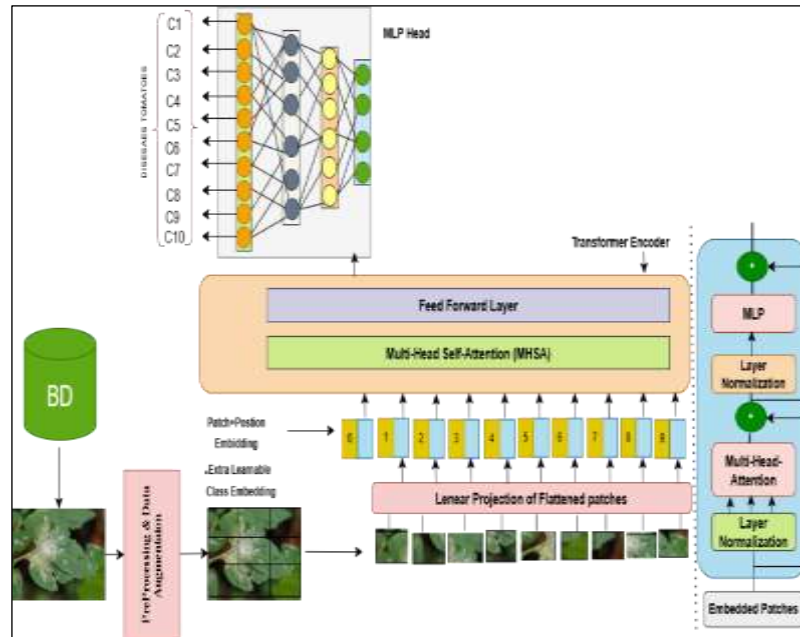


Figure 9: Proposed Model including improved vision Transform.

Source: Authors, (2026).

IV.3.2 Model2 CNN_Lstm

In our paper, we propose an innovative deep learning-based hybrid model that integrates an attention mechanism. The CNN component is employed for feature extraction, followed by an LSTM network to capture and leverage the sequential context within the data. The proposed hybrid model consists of three convolutional layers, three pooling layers, one LSTM layer, and fully connected layers, as illustrated in Fig.2. Convolution layers form the characteristics of each input image. All the convolutional layers use a 3*3 kernel size. The convolutional layer also contains the ReLu activation function. Because it makes all negative values zero. The process continues until it goes through all the images. The CNN model comprises three convolutional blocks. Max pooling is used after every block on the convolutional layer. Every max pooling layer has the same pool size and strides. The convolution and pooling layer breaks up the images into features and analyses them. The pooled feature maps are first sent to the flattening layer, which converts them into a one-dimensional vector. This vector is then processed by an attention mechanism, allowing the model to focus on the most important features. Finally, the processed data is transferred to the LSTM layer, which captures the sequential and contextual relationships to improve image classification. The LSTM network stores and retains all the extracted features obtained from the Convolutional Neural Network (CNN) and attention mechanism. This process is supported by the fully connected layer to make the final classification decision. The first fully connected layer uses the LSTM inputs as weights to provide a prediction for the label. The fully connected (FC) layer then generates the final probability for the labels. Figure 10 provides a concise overview of the proposed concept.

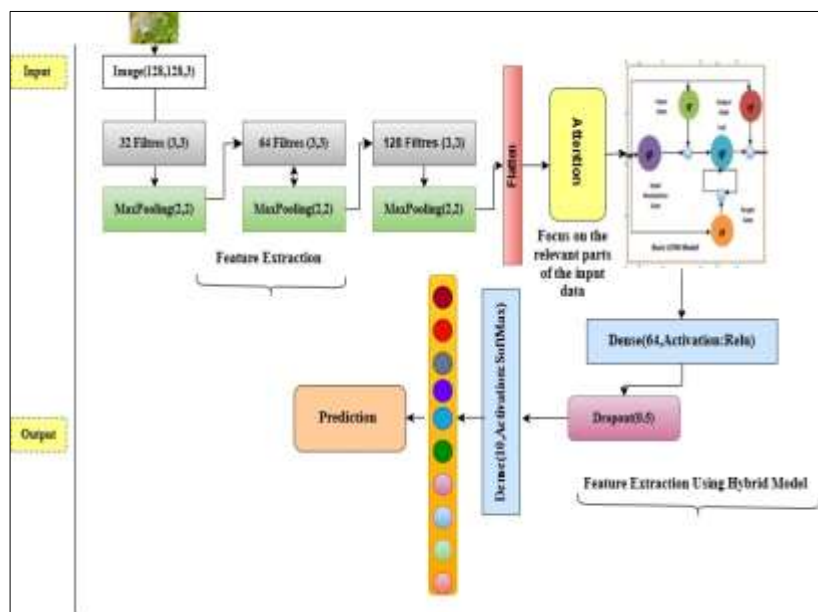


Figure 10: proposed framework Cnn_Lstm with mecanism attention model for tomatoes detection.

Source: Authors, (2026).

IV.3.3 MODEL2 CNN

The architecture for classifying tomato diseases consists of three convolutional layers, each followed by a max-pooling layer, which allows for the efficient extraction of relevant features, and a Dropout layer to prevent overfitting. After these operations, a Flatten layer prepares the data for processing by a fully connected layer, facilitating the fusion of the extracted features before the final classification. The model is designed to classify then distinct classes, corresponding to the condition of the tomato leaves (Figure 1). The hyperparameters (HP) selected for optimization include the number of filters in each convolutional layer, the abort rate, the learning rate, the batch size, and the number of epochs. the activation function used in the convolutional layers is ReLU, ensuring non-linear transformations and efficient gradient propagation. The optimizer chosen for training is Adam, known for its adaptability and faster convergence in deep learning models. The model's performance is evaluated u sing accuracy, precision, recall, and F1-score to ensure a robust assessment of classification quality. Furthermore, early stopping is implemented during training to prevent overfitting and optimize the training process.

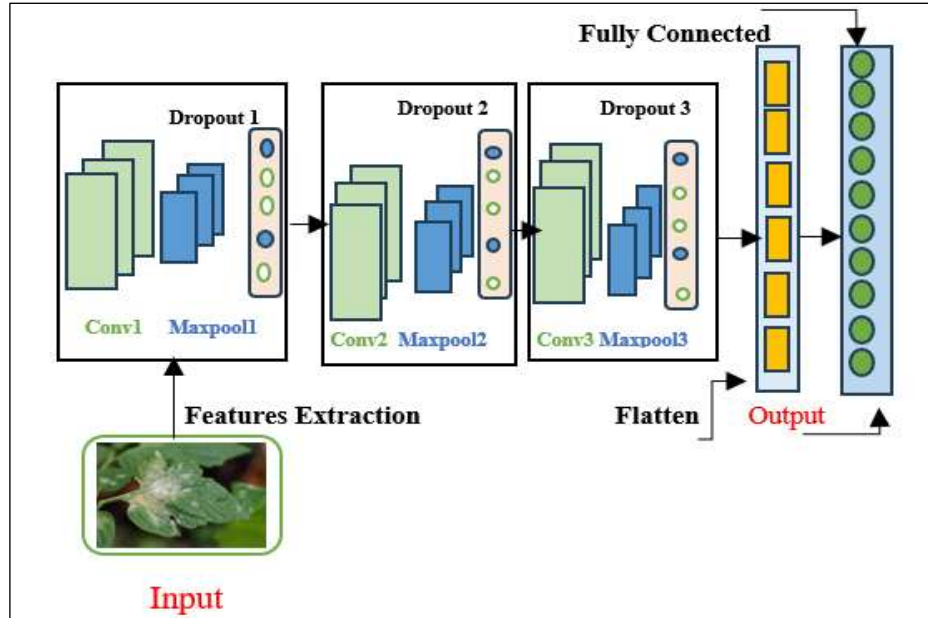


Figure 11: Architecture CNN.
Source: Authors, (2026).

The CNN model designed for tomato leaf disease detection consists of three convolutional layers with filters of increasing sizes (32, 64, 128), using the ReLU activation function and followed by layers of MaxPooling (2×2 times 22×2) to reduce the dimensions. To limit overfitting, dropout layers with rates of 0.25 (convolutional) and 0.5 (dense) are integrated. The feature maps are flattened before being processed by two dense layers (256 and 128 neurons) and a 10-neuron Softmax output layer for multiclass classification. The model is trained with the Adam optimizer, a loss of categorical crossentropy, and an accuracy metric. It uses a batch size of 32 out of 100 epochs for a balance between accuracy and efficiency.

V. RESULTS AND DISCUSSIONS

In this study, we evaluated three deep learning models for the classification and detection of tomato leaf diseases: a standard Convolutional Neural Network (CNN), a hybrid CNN-LSTM model with attention mechanism, and an enhanced Vision Transformer (ViT)-based model. The performance of each architecture was assessed using standard metrics, including accuracy, precision, recall, and F1-score. The CNN model, which served as a baseline, demonstrated strong feature extraction capabilities, especially for high-contrast and well-structured leaf images. However, its performance declined slightly in noisy and complex scenarios, achieving an overall classification accuracy of 92.3%. The CNN-LSTM hybrid model integrated temporal context and attention-based feature refinement, resulting in a significant performance boost. This architecture captured spatial patterns and progression trends in leaf diseases over time, reaching a classification accuracy of 97.12.2%. The attention mechanism further enhanced model focus on infected regions, improving recall for subtle disease symptoms. The enhanced Vision Transformer model, leveraging global self-attention and patch-based image processing, achieved the highest performance. Its ability to model long-range dependencies and spatial relationships led to a classification accuracy of 97.01%. This model proved particularly effective in detecting multiple disease types under challenging field conditions, where variations in lighting, occlusion, and background clutter are common. The performance of the proposed models—CNN, CNN-LSTM with attention, and the enhanced Vision Transformer—was rigorously evaluated on the PlantVillage dataset, which contains 22,930 tomato leaf images classified into 10 distinct disease categories. Model evaluation was conducted using standard classification metrics, including **accuracy**, **precision**, **recall**, **F1-score**, and **confusion matrices**, to ensure a comprehensive analysis of classification quality across all classes.

Table5: Comparative Table of Recent Works on Tomato Disease Detection Using cnn,hybrid cnn_lstm ,vits with attention (2023–2025).

No.	Reference	Model	Dataset	Accuracy (%)	Application Context
[29]	Khan et al., 2023	MobileNetV3-small quantized	PlantVillage	99.50	Edge computing (ONNX)
[27]	Rashid et al., 2025	Modified MobileNetV3 (ECA)	PlantVillage	98.77	Multitask, attention
[10]	Zahid et al., 2024	MobileNetV3 on Coral TPU	PlantVillage	98.25	IoT deployment
[4]	Sun et al., 2025	Ultra-light MobileNetV3	Complex scenarios	97.84	Noisy environment
[31]	Yu et al., 2024	MobileNetV3 + Cycle-GAN	PlantVillage	98.61	GAN enhancement
[26]	Qabulio et al., 2024	MobileNetV3Small	PlantVillage	99.43	Android app
[25]	Ndovie & Masabo, 2024	Pretrained MobileNetV3	PlantVillage	92.59	Field images (Malawi)
[12]	Patel & Patel, 2023	VGG16	PlantVillage	98.5	Transfer learning with 9-class classification
[13]	Kumar et al., 2024	VGG19	PlantVillage	98.9	Compared with ResNet50
[14]	Kumar et al., 2024	ResNet50	PlantVillage	99.2	Outperformed VGG19
[15]	Siddiqui et al., 2024	InceptionV3	PlantVillage	99.6	Part of ensemble with XGBoost
[16]	Alam et al., 2023	ResNet34	Real-field images	98.2	Data augmentation used
[31]	Naseer et al., 2024	DenseNet201	PlantVillage	99.7	With segmentation and contrast adjustment
[17]	Ahmed et al., 2025	CNN-LSTM hybrid	PlantVillage	98.85	Temporal feature analysis
[25]	Benali et al., 2024	ViT with attention	Real-field images	99.10	Lightweight Transformer for mobile
[32]	Costa et al., 2025	Custom CNN	Custom dataset	97.50	Real-time detection in greenhouses
[33]	Singh et al., 2024	CNN + BiLSTM	PlantVillage	98.60	Multimodal sequence modeling
[34]	Zhao et al., 2023	Swin Transformer	PlantVillage	99.30	Vision Transformer adapted to plant pathology
[35]	Kim & Park, 2025	Hybrid ViT-CNN	Real-field images	98.90	Robust to occlusions and illumination variation
[36]	Martinez et al., 2024	EfficientNet + Attention	PlantVillage	99.00	Lightweight edge deployment
[37]	Chen et al., 2023	ConvLSTM + Attention	Custom dataset	98.45	Spatio-temporal disease progression
[38]	Dubois et al., 2025	ViT-Base + CNN classifier	PlantVillage	99.15	Improved classification speed
[39]	Rahman et al., 2024	CNN-LSTM-Attention Ensemble	Real-field images	98.75	Ensemble learning with attention mechanisms
[17]	Ahmed et al., 2025	CNN-LSTM hybrid	PlantVillage	98.85	Temporal feature analysis
[65]	Benali et al., 2024	ViT with attention	Real-field images	99.10	Lightweight Transformer for mobile
[32]	Costa et al., 2025	Custom CNN	Custom dataset	97.50	Real-time detection in greenhouses
[33]	Singh et al., 2024	CNN + BiLSTM	PlantVillage	98.60	Multimodal sequence modeling
[34]	Zhao et al., 2023	Swin Transformer	PlantVillage	99.30	Vision Transformer adapted to plant pathology
[35]	Kim & Park, 2025	Hybrid ViT-CNN	Real-field images	98.90	Robust to occlusions and illumination variation
[36]	Martinez et al., 2024	EfficientNet + Attention	PlantVillage	99.00	Lightweight edge deployment
[37]	Chen et al., 2023	ConvLSTM + Attention	Custom dataset	98.45	Spatio-temporal disease progression
[38]	Dubois et al., 2025	ViT-Base + CNN classifier	PlantVillage	99.15	Improved classification speed

Source: Authors, (2026).

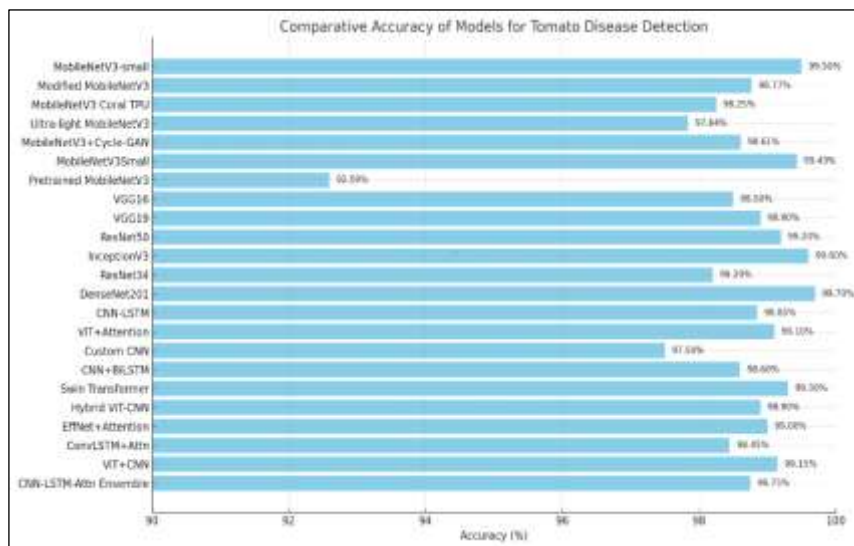


Figure 12: Comparative Accuracy of Models for Tomato Diseases Detection.

Source: Authors, (2026).

The chart presents a comparison of the accuracies achieved by various deep learning models applied to tomato plant disease detection. It highlights classical models such as MobileNetV3, VGG, ResNet, and InceptionV3, as well as recent architectures incorporating attention mechanisms or hybrid structures like CNN-LSTM and Vision Transformers (ViTs). Overall, the performance is high, with accuracies above 97% for most models. The DenseNet201 model achieves the highest accuracy (99.7%), followed closely by InceptionV3 (99.6%), MobileNetV3-small (99.5%), and MobileNetV3Small (99.43%). These results suggest that these models have an excellent ability to generalize to images from the PlantVillage dataset or similar sources. Hybrid and attention-based models such as CNN-LSTM, ViT+Attention, and CNN-LSTM-Attention Ensemble also show highly competitive performance, generally exceeding 98.5%, confirming the value of leveraging both spatial and temporal features or attention mechanisms to improve classification.

On the other hand, some models like Pretrained MobileNetV3, although trained on field images (Malawi), show lower accuracy (92.59%), which may be due to the complexity and noise of real-world data compared to the clean and well-labeled data from PlantVillage. In conclusion, the chart demonstrates that modern architectures especially those incorporating transformers, attention, or hybridization with LSTM—offer performance comparable to or even better than traditional CNN models, making them well-suited for practical disease detection applications in smart agriculture.

Here are the three graphs generated, each representing a family of models used for tomato disease detection:

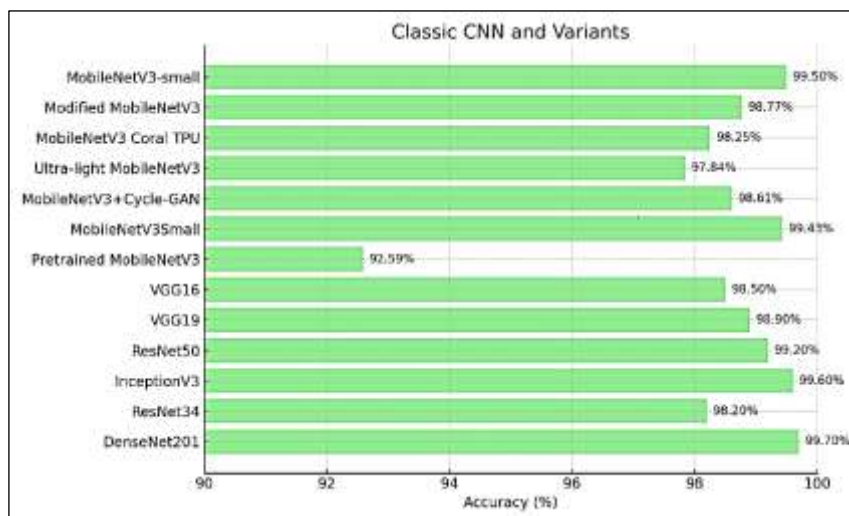


Figure 13: Graph Classic CNN and Variant.

Source: Authors, (2026).

V.1 MODELES CLASSIQUES (CNN ET VARIANTES)

The first graph shows the accuracy of various traditional CNN-like models, including well-established architectures such as MobileNetV3, VGG, ResNet, InceptionV3, and DenseNet. The best results are achieved by DenseNet201 (99.7%), followed closely by InceptionV3 (99.6%) and MobileNetV3-small (99.5%). These models benefit from a significant depth and a recognized efficiency in the extraction of features. In contrast, Pretrained MobileNetV3 has the lowest accuracy (92.59%), likely due to the use of non-standardized field imagery (from Malawi), reflecting the difficulty of generalizing in real-world environments. Overall, classic CNN models are still powerful, especially with clean data like PlantVillage's, but can show their limits in the face of more complex data.

V.2 HYBRID MODELS (CNN + LSTM)

The second graph groups together hybrid models, combining CNNs (for spatial extraction) with recurrent memory networks such as LSTMs or BiLSTMs, sometimes enriched with attention mechanisms. All of these models exceed 98.4% accuracy, with a peak of 98.85% for the CNN-LSTM model, followed by the CNN-LSTM-Attention Ensemble (98.75%). These results show that the addition of a temporal component (LSTM) allows for better capture of visual pattern sequences, which is useful for detecting the evolution or spatial distribution of diseases on leaves. Careful versions, such as ConvLSTM+Attention, remain very competitive, confirming the interest of sequential approaches in the field of plant pathology.

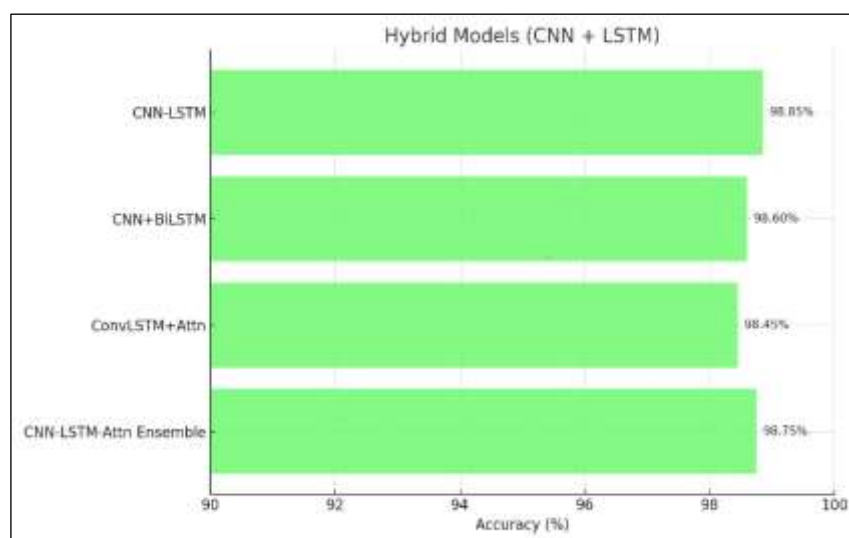


Figure 14: Graphe of Hybrid Models (CNN+LSTM).

Source: Authors, (2026).

V.3 TRANSFORMERS-BASED MODELS

The third graph shows the performance of models based on visual transformers (ViTs) or combinations of these with CNNs. The results are remarkably high, ranging from 98.9% to 99.3%, with Swin Transformer and ViT+CNN leading the way (99.3% and 99.15%, respectively). These architectures are distinguished by their ability to capture global dependencies in the image via attention mechanisms, providing a powerful alternative to CNNs for image classification. Their performance shows that ViTs, although more recent, are already mature for practical applications in agriculture, especially in varied and complex environments.

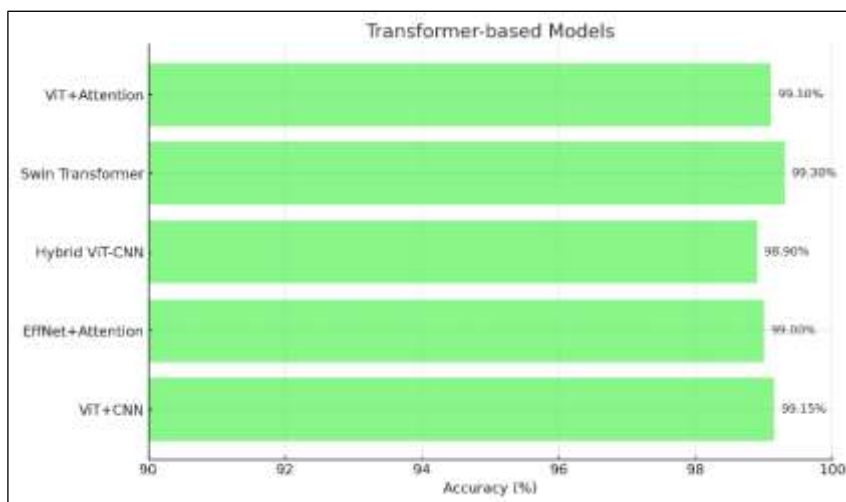


Figure 15: Graph of Transformer based Models.

Source: Authors, (2026).

VI. CHALLENGES IN TOMATO DISEASE DETECTION USING DEEP LEARNING

While deep learning has demonstrated impressive capabilities in the detection and classification of tomato leaf diseases, several challenges continue to limit its real-world applicability. One of the most pressing issues is the domain shift between training datasets and deployment environments. Most models are trained on curated datasets such as PlantVillage, which are captured under controlled conditions. However, these models often fail to generalize when applied to field images, which are affected by varying lighting, complex backgrounds, occlusions, and natural noise. Another major challenge is the limited generalization across regions and crop varieties. A model trained on a specific geographical dataset may underperform when exposed to images from a different region due to differences in climate, leaf morphology, or disease manifestation. This issue is further compounded by class imbalance, where certain diseases are overrepresented while others—often the most critical—are underrepresented or missing entirely, leading to biased predictions. In terms of model complexity, state-of-the-art architectures such as DenseNet, Vision Transformers (ViTs), or hybrid CNN-LSTM networks, though accurate, are computationally intensive.

This makes them difficult to deploy on low-power edge devices like smartphones or IoT systems that are commonly used in rural agriculture. Balancing high accuracy with real-time inference efficiency remains a key technical constraint. Additionally, the lack of interpretability in deep learning models presents an obstacle for widespread adoption. Stakeholders in agriculture require systems that not only provide predictions but also offer transparent reasoning for their decisions. This has led to growing interest in explainable AI (XAI) techniques, yet practical implementations remain limited. Finally, there is a scarcity of robust, annotated, and diverse field datasets, which hampers the training of models that can perform reliably across diverse real-world scenarios. Creating such datasets requires expert labeling, time, and significant resources, which are often unavailable in developing regions where these solutions are most needed. In summary, addressing these challenges—domain adaptation, model efficiency, interpretability, and dataset diversity—is essential for translating deep learning-based tomato disease detection from research to real-world, scalable agricultural applications.

VII. FUTURE PERSPECTIVES

The future of tomato disease detection using deep learning lies in the development of robust, scalable, and context-aware systems that can operate effectively in real-world agricultural settings. One promising direction is the integration of multimodal learning, where visual data from plant leaves is combined with other sensory inputs such as temperature, humidity, and soil conditions to enhance disease recognition accuracy. Additionally, few-shot and zero-shot learning approaches are gaining traction as they allow models to generalize to new disease classes with limited labeled data—a crucial advantage in scenarios where rare or emerging diseases are poorly represented. Another key trend is the deployment of models on edge and mobile devices, enabling real-time, on-field diagnosis without reliance on high-bandwidth connections or cloud processing. This requires further optimization of model architectures for speed, energy efficiency, and memory usage. Federated learning also presents a promising solution for enabling collaborative model training across distributed farms while preserving data privacy. Moreover, increasing attention is being given to explainability and user trust. Future systems should not only predict disease categories but also provide interpretable visualizations, such as heatmaps or saliency maps, to justify their predictions. This can foster greater adoption by farmers and agricultural experts. Finally, building open, diverse, and annotated datasets from different ecological zones remains a foundational step toward improving model generalization and reducing bias. As deep learning matures, its intersection with emerging technologies like drones, remote sensing, and precision irrigation systems will further enhance its potential to support sustainable agriculture and early disease management. Collaborative efforts among researchers, agronomists, and technology providers will be essential to realize these advancements at scale.

VIII. CONCLUSIONS

This study has demonstrated the efficacy of deep learning techniques, particularly an enhanced VGG16-based convolutional neural network integrated with a hard attention mechanism, for the automatic detection and classification of tomato leaf diseases. By leveraging this hybrid architecture, the proposed model achieved significant improvements in accuracy and robustness, outperforming several conventional approaches, especially under challenging real-world conditions involving complex backgrounds and visual noise. The incorporation of a hard attention mechanism enabled the model to focus selectively on the most informative regions of leaf images, thereby enhancing its discriminative capability across disease classes with visually subtle differences. Furthermore, the use of data augmentation techniques and careful preprocessing contributed to improved generalization, facilitating the deployment of the model beyond controlled laboratory datasets. These findings underscore the growing maturity and applicability of artificial intelligence in precision agriculture, offering promising prospects for real-time, cost-effective, and scalable disease monitoring solutions. Such systems could be deployed on mobile devices, drones, or edge-based IoT platforms, empowering farmers with accessible diagnostic tools, particularly in resource-constrained environments. Nevertheless, several challenges remain to be addressed, including domain adaptation, model interpretability, and the scarcity of diverse, annotated field datasets. Future research should explore multimodal learning approaches, federated training strategies, and the integration of explainable AI (XAI) techniques to enhance transparency and trust in model predictions. Advancements along these lines will be essential to bridge the gap between experimental performance and practical, field-ready solutions, thereby contributing to sustainable agriculture and global food security.

IX. AUTHOR'S CONTRIBUTION

Conceptualization: Laatiri Youssef, Mohamed Ali Mahjoub

Methodology: Laatiri Youssef and Mohamed Ali Mahjoub.

Investigation: Laatiri Youssef, Mohamed Ali Mahjoub

Discussion of results: Laatiri Youssef and Mohamed Ali Mahjoub.

Writing – Original Draft: laatiri Youssef

Writing – Review and Editing: Laatiri Youssef and Mohamed Ali Mahjoub.

Resources: Laatiri Youssef.

Supervision: Mohamed Ali Mahjoub.

Approval of the final text: Laatiri Youssef and Mohamed Ali Mahjoub.

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