VISION TRANSFORMERS IN PRECISION AGRICULTURE: A COMPREHENSIVE SURVEY

A PREPRINT

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ABSTRACT

Detecting plant diseases is a crucial aspect of modern agriculture, as it plays a key role in maintaining crop health and increasing overall yield. Traditional approaches, though still valuable, often rely on manual inspection or conventional machine learning techniques, both of which face limitations in scalability and accuracy. Recently, Vision Transformers (ViTs) have emerged as a promising alternative, offering advantages such as improved handling of long-range dependencies and better scalability for visual tasks. This review explores the application of ViTs in precision agriculture, covering a range of tasks. We begin by introducing the foundational architecture of ViTs and discussing their transition from Natural Language Processing (NLP) to Computer Vision. The discussion includes the concept of inductive bias in traditional models like Convolutional Neural Networks (CNNs), and how ViTs mitigate these biases. We provide a comprehensive review of recent literature, focusing on key methodologies, datasets, and performance metrics. This study also includes a comparative analysis of CNNs and ViTs, along with a review of hybrid models and performance enhancements. Technical challenges such as data requirements, computational demands, and model interpretability are addressed, along with potential solutions. Finally, we outline future research directions and technological advancements that could further support the integration of ViTs in real-world agricultural settings. Our goal with this study is to offer practitioners and researchers a deeper understanding of how ViTs are poised to transform smart and precision agriculture.

1 Introduction

Plant diseases pose a significant challenge to global agriculture, affecting crop yields, food security, and the economic well-being of farmers. Early and accurate detection is essential to effectively manage these diseases and minimize their impact [11]. Traditionally, diagnosing plant diseases has relied on labor-intensive manual inspections by experts or conventional machine learning techniques—both of which come with limitations. Manual inspection is not only time-consuming but also subject to human error and inconsistency, making it impractical for large-scale agricultural operations [48, 23]. To address these limitations, researchers are increasingly turning to automated solutions that harness recent advances in Machine Learning (ML) and computer vision. CNN, a widely used traditional Deep Learning (DL) method, have shown some success in automating the disease detection process [77, 43]. However, these models

often struggle with scalability and with capturing complex spatial patterns in images—both of which are vital for accurate detection and classification of plant diseases across varied environmental conditions [50]. This has created a growing demand for more robust, scalable, and intelligent systems for plant disease detection. In response, several studies have explored the potential of DL to meet these challenges. Some existing surveys provide general overviews of DL approaches, highlighting their advantages over traditional methods and outlining the progress made in applying these techniques to plant disease detection tasks. For example, one study [73] reviews how DL and ML techniques have been employed for plant disease detection from image data. The study describes the transition from handcrafted features with the traditional DL methods to deep models like CNNs, DBNs, and segmentation models. It also discusses the implementation of object detection algorithms like YOLO and Faster R-CNN, and segmentation architectures like U-Net and Mask R-CNN, for pixel-level accuracy-based detection quality improvement. Another work [34] discusses the application of ML and DL techniques in the early detection and classification of plant diseases, highlighting their importance in improving agricultural yield and reducing crop loss. It presents an extensive list of ML techniques such as Naïve Bayes, k-Nearest Neighbors, Decision Trees, Support Vector Machines, Random Forests, and Multi-layer Perceptrons, and explores their applications in plant disease classification using environmental and image inputs. The study also discusses preprocessing techniques and image segmentation methods, demonstrating how ML has enabled the automation of disease diagnosis and soil testing from models trained with crop data. The contrast between classical ML and DL methods shows that DL outperforms ML in terms of accuracy and scalability. It emphasizes the importance of addressing current deficiencies and proposes DL as a promising direction for creating automatic, systematic, and scalable plant disease diagnostic systems that support both scientists and farmers in agricultural decision-making. Another overview of studies [2] explores the use of DL techniques for plant disease detection and management in agriculture. It addresses key challenges including dataset quality, imaging sensors, model generalizability, estimation of severity, and performance comparison with human capabilities. Commonly used datasets are categorized, along with their limitations in practical scenarios. The study outlines various DL techniques—particularly CNN-based models—used for image classification, object detection, and semantic segmentation. It identifies shortcomings in existing models' ability to generalize to field conditions due to overfitting and imbalanced data. Additionally, significant research areas are highlighted, such as universal severity estimation, multi-disease detection, and model generalization across diverse conditions. A separate study [44] explores the application of DL in plant disease recognition and classification, emphasizing its critical role in agricultural productivity and food security. It illustrates how DL improves upon traditional image processing techniques through automated feature extraction and enhanced objectivity and efficiency. The paper discusses foundational concepts, model performance criteria, and the evolution of DL in plant disease recognition. It also addresses the need for data augmentation to manage limited datasets and the use of visualization methods to improve model interpretability. The study concludes with future challenges, such as the need for more varied datasets, enhanced model robustness, and the integration of hyperspectral imaging for early detection.

The success of the Transformer architecture in NLP has revolutionized the field, establishing new benchmarks in tasks such as machine translation, text summarization, and language modeling [60]. By leveraging parallel processing and self-attention mechanisms, Transformers excel at capturing long-range dependencies and contextual relationships. This breakthrough has inspired researchers to explore the application of Transformers in other domains, including computer vision. It was soon recognized that the same properties that made Transformers effective in NLP—namely, their ability to model long-range dependencies and contextually relevant information—could also benefit image analysis tasks [19]. Unlike CNNs, which rely on inductive biases such as local connectivity and spatial hierarchies, Transformers offer a more flexible architecture with fewer assumptions about input structure. This flexibility enables them to learn rich, complex patterns directly from visual data, making them a promising alternative for various computer vision applications, including automated plant disease detection.

The use of ViTs in agriculture is a novel and rapidly emerging research area. To the best of our knowledge, there are a few works whose focus is on ViTs; however, most of them mention it only briefly and do not provide a comprehensive analysis of their applications in precision agriculture. For example, a review [54] categorizes DL techniques applied to plant disease detection, organizing the literature into three tasks: classification, detection, and segmentation of plant diseases from leaf images. The review evaluates a broad range of DL models, with a strong focus on CNNs such as ResNet, VGG, and EfficientNet, alongside growing interest in ViTs. Another study [85] examines the use of DL and computer vision in plant disease detection, systematically analyzing the transition from traditional image processing to modern DL-based approaches. It assesses the suitability and performance of image processing techniques like thresholding, edge detection, and region-based segmentation in real-world agriculture. The study categorizes various DL architectures—including CNNs, Generative Adversarial Network (GAN), ViTs, and Vision Language Models—and highlights their scalability and practical implementation. It covers advanced models like YOLO and Faster R-CNN for real-time object detection, and discusses the emerging relevance of ViTs for capturing global context in image analysis. However, while ViTs are introduced, the review lacks a deep evaluation of specific architectures or performance benchmarks in agricultural contexts.

In this work, we examine the use of ViT in the agriculture domain with the objective of identifying how this architecture has been used and adapted for agricultural applications such as crop classification, disease detection, yield prediction, and precision agriculture. With ViT's success in computer vision across numerous domains, its application to transforming agricultural image analysis holds much promise. By analyzing the existing literature, we aspire to extract current trends, evaluate model performance, and identify challenges specific to agricultural environments and datasets. This initial exploration will lay the groundwork for future studies and build a sound body of knowledge within this emerging interface of DL and agriculture.

In summary, the key contributions of this work are as follows:

- An overview of the Transformer and Vision Transformer architectures and their functionality is provided.
- We have comprehensively addressed the concept of inductive biases and their role in ML models, especially CNNs and ViTs.
- A comprehensive survey is presented on the application of ViTs in the context of precision agriculture, systematically analyzing 42 high-impact peer-reviewed studies.
- We critically analyze the current challenges and unresolved issues in the field, highlight emerging research trends, formulate key open challenges, and suggest promising directions for future investigation.

The structure of this paper is organized as follows: Section 2 provides an overview of the Transformer architecture, followed by a discussion on ViTs. Section 3 explores the concept of inductive biases in ML, with a particular focus on how these biases manifest in CNNs and ViTs. In Section 4, we review the applications of ViTs in precision agriculture, categorizing the models into two groups: pure and hybrid models. Section 5 highlights key findings and outlines the open challenges identified in the reviewed literature. Finally, Section 6 presents the conclusions of the paper.

2 Background

2.1 Transformer

The Transformer model, proposed by [86], brought a groundbreaking shift to NLP. Its core innovation is the self-attention mechanism, which enables the model to assess the significance of various words within a sentence during sequence encoding and generation. This mechanism addresses the limitations of earlier architectures, such as Recurrent Neural Networks (RNNs) and CNNs, which often struggled with long-range dependencies and parallelization challenges. By processing all tokens in a sequence simultaneously, self-attention enables the Transformer to model long-range dependencies more effectively, making the architecture highly efficient and scalable for various sequence tasks. In the following subsection, we examine its main components.

2.1.1 Encoder-Decoder structure

The Transformer consists of an encoder and a decoder, both of which are composed of multiple layers of Self-Attention and Feed-Forward Neural Networks. The encoder processes the input sequence, while the decoder generates the output sequence. This architecture is typically used in tasks like machine translation, although variations of the Transformer, such as GPT [10], use only the Decoder for language modeling. Figure 1 illustrates the Encoder-Decoder structure.

Each encoder layer consists of two main components:

- 1. Self-Attention Mechanism
- 2. Feed-Forward Neural Network

These components are followed by residual connections and layer normalization. Each decoder layer includes:

- 1. Masked Self-Attention Mechanism
- 2. Encoder-Decoder Attention Mechanism
- 3. Feed-Forward Neural Network

Similar to the encoder, these components are followed by residual connections and layer normalization.

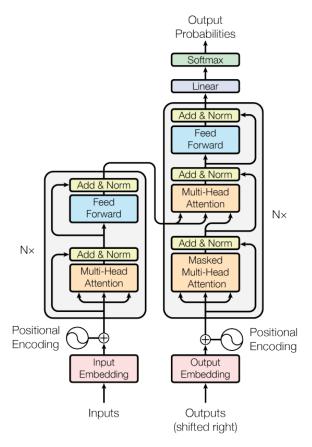


Figure 1: The Encoder-Decoder architecture of the Transformer model [86]. The encoder processes the input sequence to generate contextualized representations, which are then passed to the decoder to produce the output sequence. This structure enables efficient parallel processing and captures long-range dependencies through self-attention mechanisms, allowing for better modeling of relationships between distant elements in the sequence.

2.1.2 Self-Attention mechanism

The self-attention mechanism is the core innovation of the Transformer architecture, allowing the model to dynamically focus on different parts of the input sequence. As shown in Figure 2, this attention is computed using the following steps:

- 1. Input Matrices: The inputs consist of queries (Q), keys (K), and values (V), all derived from the input embeddings.
- 2. Attention Scores: Calculate the dot products of the query (Q) with all keys (K). This results in a matrix of raw attention scores, which determines how much attention each query should pay to the different keys.
- 3. Scaling: Scale the attention scores by the square root of the dimension of the keys, $\sqrt{d_k}$, to avoid large values that could result in very small gradients during training.
- 4. Softmax: Apply the softmax function to the scaled attention scores to normalize them, turning them into probabilities (attention weights) that sum to 1.
- 5. Weighted Sum: Compute the weighted sum of the values (V) using the attention weights. The result is a new set of embeddings (or representations), where each one is a mixture of the original values weighted by how much attention was paid to the corresponding key.

2.1.3 Multi-Head Attention

To allow the model to focus on different parts of the sequence simultaneously, the Transformer uses multi-head attention, which involves multiple parallel attention layers (heads). The process can be summarized as follows:

Scaled Dot-Product Attention

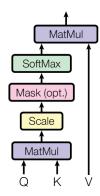


Figure 2: The Attention mechanism [86]. The attention computation uses queries (Q), keys (K), and values (V) to generate weighted representations, allowing the model to focus on relevant parts of the input sequence based on learned attention scores.

- 1. Linear Projections: Linearly project the queries, keys, and values h times using different learned projection matrices for each head, resulting in h distinct sets of queries, keys, and values.
- 2. Parallel Attention Heads: Apply the scaled dot-product attention mechanism independently to each set of queries, keys, and values in parallel. This allows the model to attend to different parts of the input sequence from different subspaces.
- 3. Concatenation: Concatenate the outputs of all h attention heads, forming a single vector of combined information.
- 4. Final Linear Projection: Apply a final linear transformation to the concatenated output, resulting in the final multi-head attention output that will be passed to subsequent layers.

Figure 3 shows the multi-head attention mechanism.

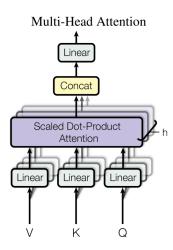


Figure 3: multi-head attention [86]. It runs multiple Self-Attention operations in parallel, each with different learned projections of Q, K, and V, allowing the model to capture diverse contextual relationships from different representation subspaces.

2.2 Vision Transformer

Inspired by the success of Transformers in NLP, [19] adapted the Transformer architecture for computer vision tasks, leading to the creation of ViT. Before this breakthrough, visual attention mechanisms were typically combined with convolutional networks or used to enhance specific components, while retaining the overall CNN structure. Early attention-based architectures had shown promise in computer vision [33], but their implementation on hardware accelerators often required complex and specialized engineering, as these systems were primarily optimized for convolutional operations. The key insight of ViT was to show that convolutional networks are not essential: a simple Transformer applied directly to sequences of image patches can achieve strong results in image classification. In ViT, images are divided into fixed-size patches, each treated as a token, similar to words in NLP. These patches are linearly embedded, combined with positional embeddings, and processed through multiple Self-Attention layers. This design enables ViTs to effectively capture long-range dependencies and contextual relationships within images, leading to performance that often surpasses traditional CNNs on various classification benchmarks. By leveraging the Self-Attention mechanism of Transformers, ViTs have revolutionized the field of computer vision. The following section delves into the architecture of ViTs, explaining their key components and operations in detail. Figure 4 shows the structure of ViT. The architecture of ViT consists of the following key components: Patch Embedding, Positional Embedding, Transformer Encoder, and Classification Head.

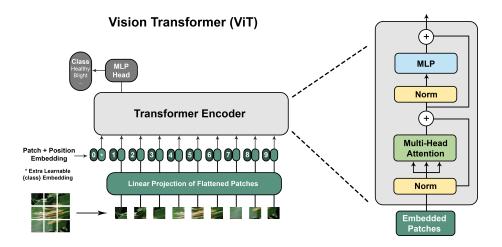


Figure 4: Vision Transformer architecture [19]. The image is split into fixed-size patches, which are linearly embedded, combined with positional embeddings, and fed into a Transformer encoder. The model captures global image context through Self-Attention across all patches.

2.2.1 Patch Embedding

In ViTs, the input image is divided into fixed-size patches. Each patch is then flattened and projected into a lower-dimensional space.

Given an image $X \in \mathbb{R}^{H \times W \times C}$ with height X, width W, and C channels, it is divided into patches of size $P \times P$. Thus, the number of patches N is $\frac{HW}{P^2}$.

Each patch is then linearly transformed into an embedding vector using a trainable projection matrix $E \in \mathbb{R}^{(P^2 \cdot C) \times D}$ where D is the dimensionality of the embedding space.

- The embedding dimension D in a ViT plays a crucial role in transforming the flattened image patches into a suitable format for processing by the Transformer architecture.
- An embedding is a vector representation of the input data. For image patches, it means converting the flattened pixel values into a high-dimensional vector that captures more meaningful information.
- Directly using the raw pixel values of image patches may not be efficient or effective for the Transformer model. Embedding helps transform these raw values into a more abstract, dense representation.
- The choice of the embedding dimension D in a ViT is a crucial design decision that balances the model's representational power and computational efficiency.

Let $z_0^P \in \mathbb{R}^D$ denote the initial embedding of the P^{th} image patch. It is obtained by flattening the patch and projecting it into a D-dimensional space using a learnable linear transformation:

$$z_0^P = \text{Flatten}(x^P)E, \quad \text{for } P = 1 \text{ to } N$$
 (1)

where $z_0^P \in \mathbb{R}^D$ is the embedding of the P^{th} patch at Transformer layer-0 (before any attention layers), x^P is the P^{th} image patch before projection and $E \in \mathbb{R}^{(P^2,C)\times D}$ is a learnable weight matrix that projects each flattened image patch into a D-dimensional embedding space.

2.2.2 Positional Embedding

To retain the spatial information, the positional embedding $P \in \mathbb{R}^{N \times D}$ is added to the patch embeddings:

$$z_0 = [x_1 E \; ; \; x_2 E \; ; \; \dots \; ; \; x_N E] + P$$
 (2)

where z_0 is the full embedded input sequence after adding positional information at Transformer layer-0 (before any attention layers), $x_i \in \mathbb{R}^{P^2.C}$ is the i^{th} flattened image patch, $E \in \mathbb{R}^{(P^2.C) \times D}$ is the patch embedding projection matrix and $P \in \mathbb{R}^{N \times D}$ is the positional embeddings. The positional embeddings added to the patch embeddings can be either learned or fixed.

2.2.3 Transformer Encoder

The Transformer encoder consists of multiple layers, each composed of a multi-head self-attention mechanism and a feed-forward neural network.

1-Multi-Head Self-Attention (MHSA):

The self-attention mechanism computes a weighted sum of the input sequences, focusing on different parts of the sequence for each output element. Given an input sequence $z \in \mathbb{R}^{N \times D}$

$$Attention(Q, K, V) = \operatorname{softmax}\left(\frac{QK^{T}}{\sqrt{D}}\right)V \tag{3}$$

where $Q = zW_Q$, $K = zW_K$, and $V = zW_V$ are query, key, and value matrices, respectively. W_Q , W_K and W_V are learned projection matrices.

For multi-head attention, multiple attention heads are used:

$$MHSA(z) = [head_1; head_2; ...; head_h]W_O$$
(4)

where head_i = Attention(Q_i, K_i, V_i) and $W_O \in \mathbb{R}^{hD \times D}$ is a learned projection matrix.

2- Feed-Forward Neural Network (FFN)

Each encoder layer also includes a feed-forward neural network, applied to each position separately and identically:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \tag{5}$$

where $W_1 \in \mathbb{R}^{D \times D_{ff}}$ and $W_2 \in \mathbb{R}^{D_{ff} \times D}$ are learned weight matrices, $b_1 \in \mathbb{R}^{D_{ff}}$ and $b_2 \in \mathbb{R}^D$ are learned bias vectors, and D_{ff} is the dimensionality of the feed-forward layer.

3- Layer Normalization and Residual Connections

Each sub-layer (MHSA and FFN) is followed by layer normalization and a residual connection:

$$z'_{l} = \text{LayerNorm} \left(\text{MHSA}(z_{l-1}) + z_{l-1} \right) \tag{6}$$

$$z_l = \text{LayerNorm} \left(\text{FFN}(z_l') + z_l' \right) \tag{7}$$

where z_{l-1} is the output from the previous encoder layer, $MHSA(z_{l-1})$ is the result of applying multi-head self-attention to that output, z'_l is the input to the feed-forward network (FFN) sub-layer. z_l denotes the output of l^{th} layer.

2.2.4 Classification Head

The output of the Transformer encoder is a sequence of embeddings, one for each input token. For classification tasks, a special learnable classification token z_0^0 is prepended to the input sequence before encoding. After passing through all L encoder layers, the corresponding output embedding z_L^0 is used as a compact representation of the entire image. This embedding is then passed through a multi-layer perceptron (MLP) to produce the final class scores:

$$logits = MLP(z_L^0)$$
(8)

where the output logits $\in \mathbb{R}^K$ (for K classes) is used for prediction.

3 Inductive biases in ML and DL Models

3.1 Definition of Inductive Biases

Inductive biases refer to a set of built-in assumptions that a ML model creates, which can facilitate the generalization process, especially when working with limited data. We can consider these biases as prior knowledge that the model uses to make predictions about data that it hasn't seen before. In general terms, inductive biases guide the learning algorithm to solutions that possess particular characteristics [7, 27].

In supervised learning, when the data is frequently incomplete or noisy, inductive biases are essential for the model's effectiveness. For example, in vision tasks, models such as CNNs assume that adjacent pixels are more likely to be correlated, which indicates an inductive bias based on the spatial structure of images. Similarly, in NLP, RNNs and Transformers utilize sequential and contextual relationships as biases to process and understand text. The type of inductive biases has a direct impact on a model's performance on particular tasks. In computer vision—for example, in CNNs—some of the built-in inductive biases are locality and translation equivariance [18, 63, 22]. Locality assumes that important features, such as edges and textures, are restricted to small spatial regions within an image, while translation equivariance guarantees that these features are identified regardless of their position in the image. These biases enable CNNs to perform exceptionally well in tasks like image classification and object detection, where spatial hierarchies play a key role [39, 64].

3.2 Inductive Biases In CNNs and ViTs

CNNs have demonstrated remarkable effectiveness in modeling spatial hierarchies and capturing local dependencies within data. Their architecture, comprising convolutional layers succeeded by pooling layers, makes them very suitable for image recognition, object detection, and segmentation—areas where spatial relationships must be learned [71, 29]. The efficiency of CNNs is largely attributed to the strong inductive biases natively built into their design, including locality, two-dimensional neighborhood structure, and translation equivariance [19]. These are uniformly applied across all layers in the network, enabling CNNs to learn invariant and spatially-conscious feature representations.

In particular, two dominant inductive biases—locality and weight sharing—serve as architectural constraints that significantly reduce the number of learnable parameters and enhance the model's generalization capabilities [20]. Locality is the design principle whereby each neuron in a convolutional layer only connects to a small, spatially localized subset of the input—the receptive field. This local computation enables CNNs to effectively extract low-level features such as edges, corners, and textures. As data passes through deeper layers, local features are hierarchically combined to detect more abstract and global representations [25]. Weight sharing, meanwhile, ensures the same filters (kernels) are employed at different spatial locations, which makes the model equivariant to translation. As a result, inductively learned patterns in one region of an image are recognizable wherever they are, thereby making the model stronger and more efficient, significantly reducing the number of trainable parameters, enabling it to generalize well, and improving computational efficiency [16]. Together, these inductive biases not only reduce the model's complexity but also add prior knowledge about the structure of visual data, which accelerates training and improves performance, especially in scenarios with limited labeled data. Although CNNs' intrinsic inductive biases can be very effective when

data is insufficient, they can be limiting when there is sufficient data. In this situation, we need to choose the most effective inductive biases—not necessarily all of them. [20]. The benefit of inductive biases tends to diminish with very large datasets, implying that transfer learning scenarios—where only a limited number of examples are available for the new distribution—provide a valuable context to assess the effectiveness and implementation of these biases [27]. It is due of these characteristics that a randomly initialized CNN can perform well in object localization tasks without any learning [12]. Despite all these advantages, the locality characteristic of CNNs causes them to degrade in their ability to capture long-range dependencies [20].

ViTs have demonstrated remarkable effectiveness in modeling spatial hierarchies and capturing local dependencies within data. Unlike CNNs, which are specifically designed to operate with local data by spatially bounded filters, ViTs depend on self-attention mechanisms where every token (or image patch) can attend to any other token in the image regardless of their spatial positions [19]. In the ViT architecture, while Multi-Layer Perceptron (MLP) layers function locally and maintain a degree of translational equivariance, the self-attention layers are inherently global, enabling ViTs to integrate information across the entire spatial domain at every layer. Rather than relying on the strong inductive biases embedded within CNNs—such as locality, translation equivariance, and weight sharing—ViTs replace these constraints with global processing through multi-head self-attention. This design allows ViTs to learn flexible and context-dependent representations by dynamically attending to different parts of the image. As a result, ViTs are capable of incorporating broader contextual cues at earlier stages in the network, which can lead to superior performance in tasks that benefit from understanding long-range relationships between image regions. On the other hand, CNNs must build up such spatial relationships incrementally through repeated layers of local convolutions, making the learning process more architecture-biased than data-driven.

However, this lack of built-in inductive biases also presents some challenges. The absence of explicit mechanisms for capturing local details can make ViTs less effective at modeling fine-grained patterns, especially in the early layers [61]. Additionally, ViTs exhibit high sensitivity to the choice of hyperparameters, such as the optimizer, learning rate schedule, and network depth, which makes their training more delicate and often requires large-scale datasets and computational resources [90]. Surprisingly, despite these architectural differences, recent results show that ViTs can implicitly learn some of the inductive biases that are commonly found in CNNs. For instance, early self-attention heads in ViTs prefer to attend to local regions, mimicking the effect of convolutional kernels [90]. This observation shows that with sufficient training data and good optimization, ViTs are capable of learning some of the beneficial priors that CNNs have by nature. While ViTs offer a more flexible and globally conscious architecture for visual representation learning, they lack the strong, human-crafted inductive biases that cause CNNs to excel so thoroughly in data-scarce regimes. This trade-off between flexibility and architectural bias highlights the importance of knowing when and how to use ViTs effectively—especially in terms of the scale and nature of the data in question.

3.3 Strategies to Mitigate the Lack of Inductive Biases in ViTs

ViTs lack the explicit inductive biases that are inherent in CNNs, such as locality and weight sharing, which can make it challenging for them to learn effectively, especially with limited data. One approach to mitigate this lack of inductive biases involves injecting convolutional inductive biases into ViTs. This can be done through convolutional patch embedding, which modifies how image data is turned into input tokens for the Transformer. Specifically, it replaces or enhances the original flat patch embedding with convolutional layers to capture local spatial patterns more effectively. Alternatively, a convolutional stem can be added at the beginning of the network to create hybrid models, helping the model learn local features more effectively.

Another strategy involves using knowledge distillation from a teacher model that possesses strong inductive biases. Distilling the knowledge in a neural network involves training a smaller neural network—known as the student or distilled model—to replicate the behavior of a larger, more complex model or a group of models, often referred to as the teacher or cumbersome model. The main goal is to transfer the broader understanding and generalization capability learned by the larger model into the smaller one [30]. In this approach, one or more pre-trained CNN models are often used as the teacher to transfer their inductive biases to the ViT student model [66]. This method has been shown to improve the performance of ViTs, particularly on smaller datasets.

Using hierarchical structures is another way to mitigate the lack of inductive biases by introducing a multi-stage architecture that processes visual information similarly to CNNs. Instead of attending globally from the start, these models apply self-attention within local windows and gradually merge or downsample tokens across layers, creating a spatial hierarchy [47]. This setup embeds locality and spatial coherence—key inductive biases of CNNs—allowing the model to first capture low-level features locally and then build up to more abstract, global representations [88]. Therefore, the most common approaches used to mitigate the lack of inductive biases in ViTs can be summarized as follows:

- Convolutional Patch Embedding: It means replacing simple patch embedding with convolutional layers to preserve local structures in the image, or using recursive token aggregation—which behaves similarly to convolutions in capturing local spatial relationships—is a method employed in models like Tokens-to-Token ViT (T2T-ViT) [94].
- **Hybrid Models:** As mentioned earlier, CNNs are effective at capturing local dependencies, while ViTs excel at modeling long-range global dependencies. One way to mitigate the lack of inductive biases in ViTs is to use a CNN or convolutional backbone to extract low-level features, then feed this output into a ViT. This approach combines the spatial inductive biases of CNNs with the global modeling capabilities of ViTs. Introducing a few convolutional inductive biases in the early stages of ViT processing can strike a balance between inductive bias and the learning capacity of Transformer blocks, while also influencing the optimization behavior of ViTs [90].
- **Knowledge Distillation:** Distilling knowledge that comes from CNN into ViTs during training is another possible solution. As an example, DEiT uses this technique [83]. It uses a CNN as the teacher and a ViT as the student to improve its performance by learning from the teacher during the training process
- **Hierarchical Structure:** Designing ViTs with hierarchical architectures to process multi-scale features is what Swin Transformer (SwinT) does, which results in improved efficiency and local feature awareness [47].

4 Applications of ViTs in Precision Agriculture

ViTs have been increasingly applied to plant disease detection, leveraging their powerful feature extraction and attention mechanisms. Various studies have explored different adaptations of ViTs to improve performance in this domain. These adaptations can be broadly categorized into two types: those that use ViTs and its variants in their pure form or with minor modifications, which we categorize as **Pure Models**, and those that implement significant changes to the architecture and combine it with convolutional characteristics, which we categorize as **Hybrid Models**.

4.1 Pure Models

In this section, we review studies that employ pure ViT models or their variants with minor modifications. These modifications include fine-tuning or other adjustments that maintain the overall ViT structure but aim to improve the model's performance. In Table 1, we provide a summary of such models. The main goals of these studies are to implement a task-specific model by fine-tuning on a specific dataset, to reduce the model's parameters to decrease resource consumption, or to create lightweight models for real-world deployment.

A simple use-case of ViT is shown in the study by [52], which proposed a ViT-based approach for the automatic classification of strawberry diseases using transfer learning and fine-tuning techniques. The authors enhanced the ViT model by adding new layers such as ReLU activation, batch normalization, dropout, and a softmax classifier. Comparative evaluations against conventional CNN models like VGG16, VGG19, ResNet50V2, and MobileNet showed that the proposed ViT model, especially when combined with data augmentation, significantly outperformed other methods. In their best setting, the model achieved an accuracy and F1-score of 92.7% on the test set. The research highlights the strengths of Transformer-based architectures in precision agriculture, especially in complex visual tasks such as disease recognition from strawberry leaves, fruits, and flowers. The study also evaluated the proposed method on the PlantVillage dataset to assess generalizability, where it attained 98.9% accuracy, outperforming both the original ViT and previous state-of-the-art methods like Mask R-CNN and MCLCNN. The authors concluded that the ViT model's ability to capture global image features makes it a powerful alternative to CNNs for agricultural disease detection tasks.

In another study, GreenViT [57], a novel ViT-based model, is proposed to improve plant disease detection by addressing the limitations of traditional CNNs. Unlike CNNs, which may lose spatial information due to pooling layers, GreenViT segments input images into smaller patches to effectively capture essential features. The model was evaluated using three datasets: PlantVillage (PV), Data Repository of Leaf Images (DRLI), and a new Plant Composite (PC) dataset created by merging the first two datasets. PlantVillage consists of 54,305 images spanning 38 classes (26 infected, 12 healthy). DRLI includes 4,502 images of 12 plant species. GreenViT achieved impressive accuracy rates of 100% on PV, 98% on DRLI, and 99% on PC, outperforming state-of-the-art models such as VGG16, MobileNetV1, and ViT-Base. The model's efficiency is highlighted by its reduced parameter count (21.65 million compared to 86 million in ViT-Base), making it computationally lightweight and suitable for edge devices.

As we discussed in Section 3, using hierarchical architecture is one of the possible solutions to mitigate the lack of inductive biases in ViTs. SwinT is a type of ViT designed to address some challenges associated with traditional ViTs, such as high computational cost for processing high-resolution images and the need for a hierarchical structure to effectively capture features at multiple scales [47]. There are some studies that used the SwinT model in precision

agriculture. One use of SwinT was introduced by [98], in which the authors examined the use of Transformer models in accurate fruit ripeness classification. They addressed the problem of performing fruit selection and pickup effectively in the absence of professional labor. They created their own fruit datasets, including apples and pears, to train, test, and compare various Transformer models, like ViT, SwinT, and MLP-based models. The MLP model performed well for smaller models but was prone to overfitting when having higher capacity. The moving window-based self-attention in SwinT, as can be seen in Figure 5, facilitated better feature extraction of visual objects. The experiments demonstrated that SwinT yielded the best results, achieving a precision of 87.43% for fruit object detection. The work also combined the Transformer module and YOLO module to effectively classify the ripeness stages of apples and pears.

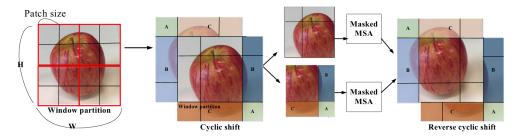


Figure 5: The Shifted window mechanism in Swin Transformer based on MSA [98]. The red box indicates a window where self-attention is applied, while black boxes represent individual image patches. The shaded region B illustrates the area that is masked out during shifted window self-attention to preserve the locality of each window.

[87] suggested an improved framework of the SwinT architecture to identify cucumber leaf diseases, to address complex backgrounds and the problem of limited sample sizes. The authors developed a SwinT-based and attention-guided GAN (STA-GAN) model, which is capable of producing diseased images without changing the background integrity. The leaf extraction module (Figure 6), which includes the proposed backbone network and Grad-CAM, was incorporated into the GAN to create STA-GAN (Figure 7). They employed a modified SwinT model, which uses an improved feature extraction technique of step-wise small patch embeddings and Coordinate Attention (CA), without adding any extra parameters. Their results showed that STA-GAN and the improved SwinT have the potential to minimize dependency on large sizes of manually annotated datasets, while at the same time improving disease detection.

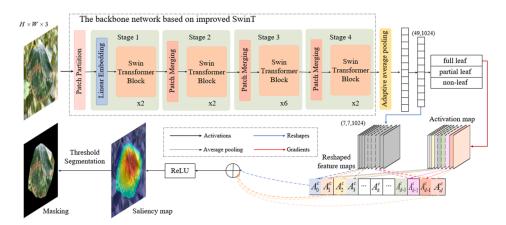


Figure 6: Overview of the proposed leaf extraction module [87]. It includes an improved SwinT-based backbone for leaf region determination, Grad-CAM for generating a saliency map, and threshold segmentation for extracting the leaf region from complex backgrounds.

There are some studies whose main contribution is the use of new self-built or custom datasets. For instance, [8] presents a customized ViT model that was created to identify and categorize Java Plum leaf diseases. The dataset used in this experiment was self-collected, featuring six classes: Bacterial Spot, Brown Blight, Powdery Mildew, Sooty Mold, Dry, and Healthy leaves. The study showcases the capabilities of ViT for the improvement of plant disease detection technologies with respect to the example of Java Plum crops. The model that was developed in this work surpasses the performance of traditional CNN-based models and was able to provide better accuracy in detection. [17] explores the use of ViTs for plant disease detection using multispectral images taken in natural environments. This paper aims at assessing the performance of ViTs models in the area of plant disease recognition applied to multispectral imagery

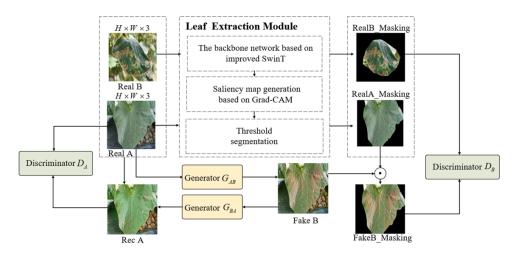


Figure 7: The framework of the proposed STA-GAN [87]. The generator transforms healthy images (A) into diseased images (B) using a series of convolutional, residual, and transposed convolutional layers. Leaf region masks guide both the generator and discriminator to focus on leaf areas, enhancing disease translation accuracy.

captured in natural conditions. The authors created a novel dataset named the "New Multispectral Dataset," which contains pictures of five agricultural plants: avocados, tomatoes, lime, passionfruit, and gooseberries. This database includes pictures taken under both visible and near-infrared (NIR) capture modes, thus offering more information for parsing the diseases than the RGB-only capture. Four ViT models—ViT-S16, ViT-B16, ViT-L16, and ViT-B32—were trained from scratch and fine-tuned with ImageNet-21k weights. The research examined the roles of model size, patch size, and transfer learning on the ability of the models to classify diseases. The findings indicate that ViT's model aimed at the B16 architecture and augmented with transfer learning provided the best results, with training and testing accuracies of 93.71% and 90.02%, respectively.

In addition to using a self-built dataset, [99] proposed a novel residual-distilled Transformer architecture for the identification of rice leaf diseases. The authors argue that existing works on rice leaf disease identification are unsatisfactory, either in terms of identification accuracy or model interpretability. To address these issues, they introduce a new method that combines a ViT and a distilled Transformer in a residual block for feature extraction, followed by a MLP for prediction. The researchers collected their own dataset on rice leaf disease from the years 2019 to 2020. This dataset, which they refer to as the rice leaf disease dataset, consists of pictures of four rice leaf diseases: bacterial blight, brown spots, blast, and tungro. The proposed method achieved an 89% F1-score and 92% top-1 accuracy on the rice leaf disease dataset, outperforming other state-of-the-art models.

In another work, LEViT was proposed, which is a model based on ViT for identifying and classifying leaf diseases in agriculture, with an emphasis on enhancing interpretability using Explainable AI techniques [59]. Integrating Grad-CAM offers a visual explanation of the model's predictions in the form of important regions in the images of the leaves. Their model achieved high performance, with a training accuracy of 95.22%, validation accuracy of 96.19%, and test accuracy of 92.33%. Notably, Grad-CAM visualizations enhance the trustworthiness and usability of the model by elucidating its decision-making processes. Their findings show that LEViT's advanced structure helps to improve leaf disease recognition and diagnosis, which is essential in precision farming. The integration of interpretability allows LEViT to solve real-world issues of early disease detection and management.

As we mentioned, one of the approaches that can be taken is to create efficient models by reducing parameters or employing transfer learning strategies. [91] proposes an innovative transfer learning strategy in the context of plant disease recognition, designed for scenarios with limited data. Pre-training was done using the PlantCLEF2022 dataset [35], which includes 2,885,052 images across 80,000 classes. The authors used a ViT model, initially self-trained using ImageNet and subsequently trained on the PlantCLEF2022 dataset. Several benchmark models, such as CNNs and other ViT-based systems, were used to validate the proposed method. The results indicated that the model outperformed the previous models in all dataset configurations, including few-shot learning scenarios. For instance, it achieved remarkable results even when trained with only 20 images per class and also performed well in plant growth stage prediction and weed recognition. Moreover, the dual transfer learning approach improved accuracy while also demonstrating faster convergence, showcasing the strength of the method across various dataset types. This study underscores the effectiveness of large-scale, plant-related datasets combined with advanced models like ViT for transfer learning. It

emphasizes the necessity of appropriate source datasets, self-supervised pre-training, and fine-tuning processes for plant disease recognition.

[89] used the SwinT network to improve the identification of weeds in agriculture. To address the challenges posed by limited training data at scale, the authors employed a two-stage transfer learning strategy. First, they pre-trained the SwinT model on the ImageNet dataset, and then fine-tuned it on the Plant Seedlings dataset and a private dataset named MWFI (Maize/Weed Field Image). This strategy leveraged pre-trained network parameters to specialize in feature extraction for weed recognition. The proposed method achieved a recognition accuracy of 99.18%, outperforming other CNN-based architectures such as EfficientNetV2

LeafViT, a ViT-based model tailored for detecting leaf diseases in plants, specifically targets fine-grained features critical for classification [38]. Experiments underscored the robustness of LeafViT across various configurations, validating its computational efficiency relative to models like VGG16. The authors highlighted its potential for deployment on edge devices and its adaptability for object detection and segmentation tasks. [6] introduced a novel application of ViT models for detecting diseases in tomato plants, leveraging smartphone-based technology. A smartphone application developed as part of this study integrates the ViT model for real-time, field-level disease detection. By deploying the model on a smartphone application via TensorFlow Lite, this work provides a practical tool for field use, empowering farmers with real-time insights to enhance crop health and yield.

In another study, IEM-ViT was proposed as an innovative approach to detect tea leaf diseases [96]. It incorporates an information entropy weighting (IEW) method to prioritize regions within images that hold significant information, enhancing the feature extraction process. This model uses a masked autoencoder (MAE) with an asymmetric encoder-decoder architecture, effectively masking 75% of the input image to filter out redundant and irrelevant background data. This method enables proper model development and facilitates accurate disease recognition even when low-quality images are used. The findings indicate that the IEM-ViT model surpasses previously developed algorithms. Therefore, IEM-ViT may be suitable for fast and large-scale tea disease recognition and could also be deployed for recognizing diseases in other crops, contributing to enhanced agricultural management and sustainability.

[79] introduced FormerLeaf, a Transformer-based cassava leaf disease classification model. The model consists of 12 Transformer encoder layers with optimized self-attention mechanisms, which help reduce resource usage while still ensuring high classification accuracy. To enhance FormerLeaf, two optimization techniques were proposed: the Least Important Attention Pruning (LeIAP) algorithm and Sparse Matrix-Matrix Multiplication (SPMM). LeIAP identifies and removes less critical attention heads, resulting in a 28% reduction in model size and a 15% increase in inference speed without significant accuracy loss. SPMM reduces computational complexity from $O(n^2)$ to $O(n^2/p)$, improving training efficiency by 10% and lowering resource consumption. These improvements make FormerLeaf suitable for real-world applications in precision agriculture, where computational efficiency is critical. The authors also mention challenges, including dataset imbalance and variable image quality due to diverse lighting conditions. To address these, they suggest using advanced augmentation techniques, such as GANs [26], to improve model performance.

Table 1: Summary of pure models. These models employ the pure form of ViT, aiming to enhance its performance or fine-tune it. (Reported metrics are directly extracted from the original publications. In certain studies, per-class metrics are provided; metrics that are not reported are indicated with a "-".)

Paper	Dataset(s)	Accuracy	Precision	Recall	F1	Main Contribution	
[52]	PlantVillage and Strawberry Disease Detection dataset	92.7%	-	-	0.927	Fine-tuning a ViT model with additional dense and normalization layers for precise strawberry disease classification	
[98]	Self-built	-	0.8743	-	-	Adopt SwinT for accurate ripeness classification of various fruit types	
[87]	Self-built	98.97%	-	0.9873	-	Improving patch partition of SwinT and using SwinT-based Attention-guided GAN	
[8]	Self-built	97.51%	Per-class	Per-class	Per-class	Introducing customised ViT model for effective classification of Java Plum leaf diseases	

Continued on next page

Paper	Dataset(s)	Accuracy	Precision	Recall	F1	Main Contribution
[99]	Self-built	92%	0.88	0.91	0.89	Residual-distilled Transformer architecture for rice leaf disease identification
[59]	New Plant Diseases Dataset	92.33%	-	-	-	ViT-based model incorporating Explainable AI (XAI) features
[91]	PlantCLEF2022	Varies	-	-	-	Novel transfer learning strategy for versatile plant disease recog- nition
[89]	Plant Seedling and a self-built dataset	99.18%	0.9933	0.9911	0.9922	Fine-grained recognition using SwinT and two-stage transfer learning
[38]	Plant Pathology 2020	97.15%	Per-class	Per-class	Per-class	ViT-based approach to identify and amplify subtle discriminative regions
[6]	PlantVillage	90.99%	Per-class	Per-class	Per-class	Smartphone-based plant disease detection
[57]	PlantVillage DRLI PlantComposite	100% 98% 99%	- - -	- - -	- - -	Reducing number of learning parameters
[96]	Tea leaves disease classification (Kaggle)	93.78%	0.9367	0.9380	0.9364	Asymmetric encoder-decoder ar- chitecture for masked autoen- coder with selective patch encod- ing and pixel reconstruction
[79]	Cassava Leaf Disease Dataset (Kaggle)	98.52%	-	-	0.9682	Proposing LeIAP algorithm for selecting key attention heads in Transformer

4.2 Hybrid Models

In this section, we review models that use ViT with specific adjustments, particularly those that combine ViT with certain CNN characteristics. A summary of the papers is shown in Table 2.

In a comparative study, the authors evaluate the performance of standalone and hybrid models and propose a lightweight DL approach utilizing ViT for automated plant disease classification [9]. They compare ViT-based models, CNNs, and hybrid architectures that combine both techniques. These models were evaluated on three different datasets: the Wheat Rust Classification Dataset (WRCD), the Rice Leaf Disease Dataset (RLDD), and the PlantVillage dataset. A ViT-based model achieved a 100% F1-score on WRCD with a 200×200 resolution, outperforming EfficientNetB0 in computational efficiency. For RLDD, hybrid models balanced accuracy and computational cost, with the ViT-based model achieving the highest average precision. On the larger PlantVillage dataset, the ViT-only model reached an F1-score of 98.77%, surpassing CNN-based architectures. Models that combine attention blocks and CNNs as hybrid models offered a balance between accuracy and speed. They were comparatively faster than pure ViT models and more accurate than CNN-only models. For instance, a hybrid model achieved high accuracy in the PlantVillage experiments, indicating the potential of integrating attention mechanisms into CNNs for real-world applications. It is worth mentioning that this study highlights the need for a practical, lightweight, real-time implementation for agricultural purposes. Multi-label classification with object localization for detailed disease identification is the focus of future research.

EfficientRMT-Net is a novel hybrid model that integrated ResNet-50 and ViT in order to classify potato plant leaf diseases effectively [70]. EfficientRMT-Net employs depth-wise convolution for computational efficiency and utilizes a stage-block architecture to enhance scalability and feature sensitivity. This paper emphasizes that the ability of EfficientRMT-Net to process high-dimensional data efficiently while maintaining high accuracy positions it as a valuable tool for smart farming. [95] proposed SEViT model combining Squeeze-and-Excitation ResNet101 and ViT to tackle large-scale and fine-grained plant disease classification challenges. The preprocessing network employs Squeeze-and-Excitation modules in ResNet101 to enhance channel-specific feature representation, while the ViT component leverages its global attention mechanism for feature extraction and classification. SEViT improves upon the

limitations of CNN-based methods, which often struggle to distinguish diseases in visually similar crops. Although comparisons with popular models such as MobileNetV3, EfficientNet, and VGG16 highlight the efficiency of SEViT in handling visually similar diseases across different crops, SEViT faces challenges including high computational requirements due to the depth of the preprocessing network and its reliance on pretrained weights to optimize the performance of ViT.

[53] introduced an enhanced ViT model based on the MaxViT [84] architecture for identifying diseases in maize leaves. By adapting the MaxViT structure with the addition of Squeeze-and-Excitation (SE) blocks and implementing Global Response Normalization (GRN) in the MLP layers, the proposed model achieves significant improvements in both accuracy and inference speed. The researchers created a comprehensive maize dataset by merging the PlantVillage, PlantDoc, and CD&S datasets, forming the largest publicly available maize disease dataset. This combined dataset, featuring four disease classes, was split into training, validation, and testing sets to rigorously evaluate the generalization capabilities of DL models. The model was benchmarked against 28 CNN and 36 ViT architectures. It achieved a record-breaking accuracy of 99.24% on the test set, outperforming existing methods in both accuracy and inference speed, making it particularly well-suited for real-world agricultural applications.

A Spatial Convolutional Self-Attention-based Transformer (SCSA-Transformer) [40] for strawberry disease identification is proposed to address challenges such as complex image backgrounds and dataset imbalances. The architecture incorporates hierarchical feature mapping through convolutional modules and multi-head self-attention to capture dependencies across diverse image regions. Experimental results demonstrate that the proposed method achieves an accuracy of 99.10% and underscore the SCSA-Transformer's capability for precise disease recognition, even in complex scenarios, with faster convergence and reduced computational requirements compared to alternative methods.

In another study, a novel Convolutional SwinT (CST) model was proposed to address challenges in plant disease detection [28]. By integrating convolutional layers into the SwinT architecture, the CST model enhances feature extraction from noisy and complex agricultural images. The study evaluated the model on multiple datasets: the Cucumber Plant Diseases Dataset, Banana Leaf Disease Images, Potato Disease Leaf Dataset, and a tomato subset of PlantVillage. Notably, CST maintained an accuracy of 0.795 even with 30% salt noise, demonstrating its robustness. In addition to its strong classification performance, CST showed notable resilience to noise, outperforming baseline models such as ResNet50 and LeViT-192 under salt noise conditions. While CST outperformed existing models in noisy data accuracy, its computational complexity—exceeding 48 million parameters—was noted as a limitation.

[72] proposed an automated system for identifying two prevalent mango leaf diseases—anthracnose and powdery mildew—commonly found in the Andhra Pradesh region of India. The authors employed Compact Convolutional Transformer (CCT) models, specifically CCT-7/8×2 and CCT-7/4×2, to classify diseased leaves using DL-based ViT architectures. These models were selected for their efficiency in handling small datasets with reduced computational requirements. The experimental evaluation was conducted using a self-built mango leaf image dataset collected from over 50 trees. The dataset comprised 574 images labeled across four classes: healthy, dead, anthracnose, and powdery mildew. The study confirmed that compact Transformers like CCT are highly effective for disease detection in resource-limited agricultural contexts. The authors plan to extend their work by incorporating additional disease categories and expanding the dataset to improve the generalizability of the proposed model.

A novel approach using ViTs was also introduced to address challenges in paddy leaf disease identification [68]. The model incorporates a multi-scale contextual feature extraction mechanism to capture both local and global representations of lesions on paddy leaves. This is complemented by a weakly supervised Paddy Lesion Localization (PLL) unit that prioritizes significant lesion areas to enhance classification accuracy. The model's performance was evaluated on the Paddy Doctor dataset [58]. The proposed model outperformed several state-of-the-art models, including DenseNet169, ResNet50, and SwinT, achieving an impressive accuracy of 98.74%, an F1-score of 98.18%, and an AUC of 99.49%. These results demonstrate significant improvements over baseline models, highlighting the efficacy of lesion-focused feature extraction and context-aware learning in accurately classifying complex diseases. The authors emphasize that integrating lesion localization with multi-scale ViT structures enables robust performance across diverse visual challenges. The model's enhanced ability to identify and prioritize discriminative lesion areas provides more reliable disease detection, supporting its potential for real-world applications in precision agriculture.

A Hybrid Pooled Multihead Attention (HPMA) model has been proposed for agricultural pest classification, enhancing both local and global feature extraction in images [69]. HPMA integrates hybrid pooling and ViT techniques to address the limitations of conventional attention mechanisms and CNN models. It utilizes a novel attention mechanism that combines max and min pooling to improve feature weighting and discriminative power. The model was tested on a newly collected dataset of 10 pest classes, achieving an impressive testing accuracy of 98%. Its effectiveness was further validated on two benchmark datasets: a medium dataset (MD) with 40 classes and a large dataset (LD) with 102 classes. For the MD, HPMA achieved a testing accuracy of 98.02%, while for the LD, it reached 95.98%. These results emphasize the model's adaptability to varying dataset sizes and complexities. Comparisons with state-of-the-

art CNN and Transformer models highlight HPMA's efficiency, offering competitive accuracy with relatively lower computational requirements. An innovative approach for accurate tomato disease identification is presented through the development of the NanoSegmenter model, which integrates Transformer structures with lightweight techniques such as the inverse bottleneck, quantization, and sparse attention mechanisms [46]. This method aims to balance high precision with computational efficiency, addressing challenges in traditional models such as detailed instance segmentation and efficient deployment on mobile devices. The use of lightweight processing enables smartphone integration, which is vital for practical field use by farmers, streamlining disease detection and supporting timely agricultural interventions.

[97] introduced the CRFormer model, designed to address challenges in segmenting grape leaf diseases from complex natural backgrounds. The model employs a unique cross-resolution mechanism to retain high-resolution (HR) and low-resolution (LR) feature maps in parallel, enhancing contextual understanding. It features a Large-Kernel Mining (LKM) attention mechanism for adaptive spatial and channel encoding, and a Multi-Path Feed-Forward Network (MPFFN) for multi-scale representation. The model uses a lightweight Hamburger decoder for effective multi-resolution data fusion. The results highlight CRFormer's capability to handle the complexities of real-world agricultural segmentation tasks.

EfficientNet Convolutional Group-Wise Transformer (EGWT) is a novel architecture for crop disease detection [21]. It combines the convolutional capabilities of EfficientNet with the hierarchical and lightweight group-wise Transformer mechanism. This architecture addresses challenges in computational efficiency and parameter constraints while maintaining high accuracy. EGWT extracts local features via EfficientNet convolution and processes them through grouped Transformer modules, reducing redundancy and emphasizing relevant spatial relationships. The EGWT architecture was validated using three benchmark datasets: PlantVillage, Cassava, and Tomato Leaves. Visualization of intermediate layers confirmed its ability to focus accurately on disease-affected regions. Despite challenges in recognizing complex Cassava leaf patterns and imbalanced datasets, EGWT demonstrated superior performance across metrics. Its lightweight design makes it an excellent choice for deployment in resource-constrained environments, potentially transforming automated crop disease diagnosis in agriculture.

[75] proposed an innovative approach to enhance plant disease diagnosis through synthetic data augmentation. The research introduces LeafyGAN, a GAN framework comprising a pix2pix GAN for segmentation and a CycleGAN for disease pattern generation. By generating synthetic images to address dataset imbalances, LeafyGAN ensures robust augmentation, producing high-quality representations of diseased leaves. A MobileViT classification model [49], selected for its lightweight architecture and computational efficiency, was trained on augmented datasets, achieving impressive accuracies of 99.92% on the PlantVillage dataset and 75.72% on the PlantDoc dataset. These results highlight the efficacy of LeafyGAN in supporting models tailored for low-resource environments. LeafyGAN demonstrated notable advancements over existing augmentation methods, such as the LFLSeg module and traditional GANs, by preserving the background during disease pattern translation and producing visually coherent images. The integration of MobileViT, with its blend of ViT and convolutional operations, underscores the balance between performance and efficiency. Compared to resource-heavy architectures, MobileViT effectively handled the augmented datasets, demonstrating scalability for real-world applications. This framework marks a significant step in addressing data scarcity and computational limitations, paving the way for practical deployment in agriculture for disease diagnosis and prevention.

One idea for creating a hybrid model is using ensemble models. [65] introduced the MDSCIRNet architecture, a novel DL model combining Depthwise Separable Convolution (DSC) and ViT-based multi-head attention mechanisms for detecting potato leaf diseases. In addition to the standalone model, hybrid approaches integrating classical machine learning methods (e.g., SVM, Random Forest, Logistic Regression, and AdaBoost) with the MDSCIRNet model were proposed. These combinations yielded competitive results, particularly in cases leveraging ensemble learning techniques.

In another study, the authors introduced an ensemble learning approach with hard and soft voting strategies that integrates three CNN models (MobileNetV3, DenseNet201, ResNext50) and two Transformer models (ViT and SwinT) to classify leaf diseases [42]. Experimental results show that ensemble learning improved classification accuracy, with ViT achieving superior performance as a standalone model. The authors also employed Grad-CAM visualization to highlight the regions of input images most influential for classification decisions, demonstrating that the models effectively localized disease areas. Their results show that ensemble learning combining CNN and Transformer models provides a powerful approach for effective classification of plant diseases, which is useful in practical agriculture.

A novel ensemble model, Residual Swin Transformer Networks (RST-Nets), was proposed to address the challenges of plant disease recognition, including noise, varying image intensities, and the subtle differences between healthy and diseased plants [36]. The model integrates residual convolutional blocks with SwinT, leveraging the latter's hierarchical architecture for scalable complexity and global context awareness. Residual connections enhance the feature extraction process by retaining crucial information from earlier layers. The model achieved outstanding results,

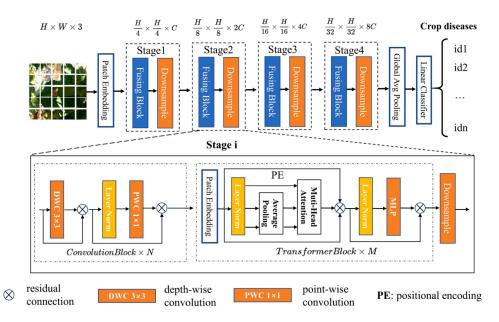


Figure 8: Overview of the ConvViT architecture [45]. The top row illustrates the overall hierarchical structure of ConvViT, while the bottom row presents a detailed view of Stage 2. Each stage is composed of N convolutional blocks followed by M Transformer blocks.

surpassing state-of-the-art models such as ResNet and GoogleNet, but its computational overhead limited its suitability for resource-constrained IoT and edge devices.

Another way to create a hybrid model is to build a multi-stage model that combines CNN and ViT by dividing the network into sequential stages. This hierarchical approach reduces computational costs while preserving essential information, enabling robust performance in complex environments. As shown in Figure 8, [45] proposed a novel model, ConvViT, which combines ViT and CNNs to identify kiwifruit diseases in complex natural environments. The authors developed a custom dataset of 25,168 images capturing six types of kiwifruit leaf diseases and validated the model's performance on this dataset, as well as on the publicly available PlantVillage and AIChallenger2018 datasets. To enhance feature extraction, the model employs overlapping patch embeddings and alternating convolutional and Transformer layers, ensuring both global and local feature representation. On the kiwifruit dataset, ConvViT achieved a top identification accuracy of 98.78%, surpassing benchmarks like ResNet, ViT, and ResMLP, while maintaining a lightweight design with reduced parameters and FLOPs. Key improvements include overlapping patch embedding to preserve local image continuity and reduce computational complexity, as well as a multi-stage design to balance feature extraction efficiency and computational cost. The Transformer's global attention complements CNN's local feature extraction, making ConvViT highly effective in complex environments with variable lighting, backgrounds, and noise. The model's innovative design and lightweight adaptability make it a valuable backbone for broader identification tasks in agriculture, potentially aiding real-world crop disease management efforts.

[100] presented a hybrid model combining CNN with Transformer encoders to improve the accuracy and generalization of crop disease diagnosis. They emphasize handling complex backgrounds and disease similarities, challenges that traditional CNNs struggle to address. Using the PlantVillage dataset, the model achieved a high recognition accuracy of 99.62%. For real-world applications, datasets with complex backgrounds were also used: Dataset1 (apple, cassava, and cotton diseases) and Dataset2 (apple scab, cassava brown streak, and cotton boll blight), where the proposed model attained balanced accuracies of 96.58% and 95.97%, respectively, demonstrating robust generalization capabilities. The key to the success of this model is the integration of a Transformer encoder to capture global features, which compensates for the limitation of CNN in extracting global context. Furthermore, a novel hybrid loss function, combining crossentropy with Centerloss, was introduced to optimize feature separability and reduce intra-class variance. [13] integrated lightweight CNNs and Transformer-based frameworks, specifically the Bidirectional Encoder Representations from Transformers for Images (BEiT [4]) model. This fusion leverages the feature extraction strengths of CNNs and the contextual learning capabilities of Transformers to detect rice leaf diseases effectively. The model processes images by dividing them into visual tokens and applying a two-stage mechanism: reconstruction of visual elements and masked image modeling. The reconstruction stage extracts meaningful patterns, while the masked image modeling stage

predicts hidden sections of the image, enhancing its understanding. To improve interpretability, the Local Interpretable Model-Agnostic Explanations (LIME) technique is employed, coupled with segmentation using Simple Linear Iterative Clustering (SLIC), which highlights the critical regions contributing to predictions. The explainable nature of the model, supported by attention mapping and segmentation, provides transparency in decision-making, fostering trust among end-users in agricultural diagnostics. This architecture is particularly suited for deployment on resource-constrained devices, enabling real-time application in smart agriculture.

There are also studies that use transfer learning in addition to hybrid models. In the research by [78], the authors propose a hybrid model, TLMViT, for plant disease classification that combines transfer learning models followed by a ViT. They incorporate data augmentation techniques, which address class imbalance and mitigate overfitting, along with a two-phase feature extraction process: initial extraction using pre-trained CNNs models (e.g., VGG16, VGG19, ResNet50, AlexNet, and Inception V3), and deep feature extraction using ViT. Final classification is conducted using an MLP classifier. The model achieved a validation accuracy of 98.81% on the PlantVillage dataset (VGG19-ViT combination) and 99.86% on the Wheat Rust dataset. These results represent a 1.11% and 1.099% improvement in accuracy compared to transfer learning models without ViT. These findings indicate the effectiveness of combining transfer learning and ViT for deep feature extraction. The authors also highlight that TLMViT effectively leverages pre-trained models to reduce dimensionality and computational complexity.

[32] proposed the FOTCA model, which combines the strengths of Transformers and CNNs for plant leaf disease detection. By integrating an Adaptive Fourier Neural Operator (AFNO) with traditional convolutional down-sampling, FOTCA effectively captures both global and local features. Key innovations in FOTCA include the use of learnable Fourier features for positional encoding, which enhance feature representation by mapping images to the frequency domain. This approach improves robustness to variations such as rotation and scaling, addressing limitations of ViT on small and medium-sized datasets. Transfer learning on a pre-trained ImageNet model also optimized training efficiency, enabling quick convergence.

There are some studies that use multi-track—especially dual-track (or dual-path)—models that integrate two parallel architectures, for example, a ViT and a CNN, to leverage the strengths of both. Figure 9 shows COFFORMER, a novel dual-path visual Transformer designed for efficient and interpretable diagnosis of coffee leaf diseases, which integrates lesion segmentation and disease classification into a unified framework [67]. The segmentation path employs a U-shaped architecture built on COFFORMER blocks, which use multiscale convolutional pooling for token mixing, while the classification path incorporates a Coffee Lesion Attention (CLA) module to focus on critical lesion regions. The framework evaluates both the type and severity of diseases, enabling real-time and explainable disease diagnosis. The dataset used for evaluation consists of 1,685 images of Arabica coffee leaves captured under controlled conditions and annotated for five disease types and severity levels. Experimental results demonstrate COFFORMER's superior performance compared to state-of-the-art models. For segmentation, it achieved a Dice Similarity Coefficient (DSC) of 98.14% and a mean Intersection over Union (mIoU) of 97.98%, outperforming baselines such as Swin-Unet and PSPNet. In classification tasks, COFFORMER achieved an accuracy of 99.1% and an F1-score of 99.32% for disease type detection, alongside 99.12% accuracy for severity estimation. These results demonstrate its robustness in identifying diverse lesions and disease severity across real-world coffee leaf images.

For classification of citrus diseases, a novel dual-track deep fusion network was proposed that integrates a CNN-based Group Shuffle Depthwise Feature Pyramid (GSDFP) and a SwinT [37]. In this architecture, the GSDFP branch extracts local features using convolutional layers and a Feature Pyramid Network (FPN) for multiscale feature fusion, while the SwinT branch captures global features through hierarchical feature maps and self-attention mechanisms. The outputs from these branches are fused and passed through a Shuffle Attention (SA) module to enhance contextual relationships between features. This dual-track design effectively combines local and global feature extraction, enabling precise classification. The proposed network achieved state-of-the-art results, outperforming existing models. It obtained a classification accuracy of 98.19%, surpassing benchmarks such as DenseNet-121 (92%) and AlexNet (94.3%).

For classification of apple leaf diseases, a dual-branch model, named DBCoST, integrates CNN and SwinT [74]. This model includes a Feature Fusion Module (FFM) that combines information from both branches to improve accuracy. To enhance feature integration, the paper also introduces a channel attention mechanism that adjusts the importance of different feature channels. The model aims to overcome challenges such as noise from the natural environment, including overlapping branches and fruits in the images. In comparative experiments with state-of-the-art methods, including EfficientNetV2S and MobileNetV3L, DBCoST demonstrated superior performance in recognizing apple leaf diseases, particularly in challenging natural environments.

[55] introduced a hybrid DL model, DCTN, designed to detect crop diseases in complex field environments. Recognizing the limitations of conventional CNN-based models in handling diverse real-world scenarios, the authors propose a dual-branch network that fuses CNNs for local feature extraction and Transformers for global context modeling. The architecture incorporates a four-layer pyramid structure and a novel attention mechanism, using multi-head self-attention

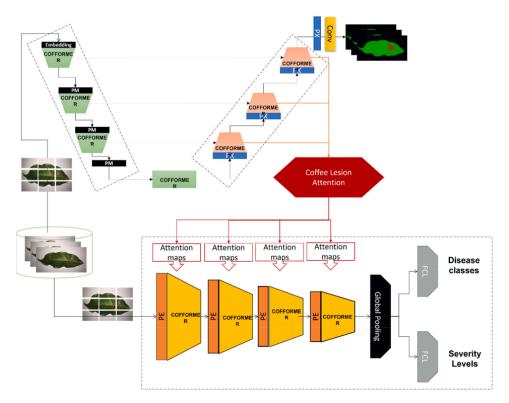


Figure 9: The architecture of COFFORMER. It consists of three main components: a segmentation subnetwork for detecting biotic stress lesions, a dual-head classification subnetwork for identifying disease type and severity, and a CLA block that enhances feature representation using guidance from the segmentation decoder [67].

enhanced by depthwise separable convolutions and downsampling to reduce computational overhead. This design ensures that critical disease-related areas on leaves are emphasized while mitigating the influence of noisy backgrounds. To validate their model, the authors curated a custom dataset of 45,547 images depicting twelve categories of healthy and diseased crops, captured under real-world field conditions and sourced from both competitive and open datasets. Additionally, DCTN was evaluated on the publicly available CD&S dataset, which includes maize leaf diseases photographed at Purdue University's agricultural research facility. DCTN achieved state-of-the-art accuracy rates of 93.01% on their own dataset and 99.69% on the CD&S dataset, outperforming popular CNN- and Transformer-based models such as ResNet50, EfficientNetB5, and DeiT-small. These results highlight DCTN's robustness and generalization capability in realistic agricultural settings, offering a promising direction for practical plant disease diagnostics.

The Triple-Branch SwinT Classification (TSTC) network has been proposed for the simultaneous and separate classification of plant diseases and their severity [93]. The proposed model uses a multitask feature extraction module with a triple-branch structure, integrating SwinT for feature extraction and compact bilinear pooling (CBP) for feature fusion. It also employs a deep supervision module to enhance feature discrimination across both hidden and output layers, improving the model's accuracy and generalization. Unlike single-task models, TSTC's multitask approach avoids species dependency and improves flexibility, addressing challenges like imbalanced datasets through robust feature fusion and supervision strategies. A critical contribution of this study lies in its end-to-end multitask framework, which leverages CBP to enhance feature fusion and deep supervision to improve training efficiency. The findings suggest that TSTC is highly effective in agricultural applications, providing accurate predictions that can inform targeted disease management strategies.

There are still other hybrid models that introduce additional novelties. A novel multi-label model, LDI-NET, which is shown in Figure 10, is proposed for the simultaneous identification of plant type, leaf disease, and severity [92]. The model stands out due to its single-branch architecture, which avoids complex network designs and excessive categorization. LDI-NET is built around three main modules: the feature tokenizer, token encoder, and multi-label decoder. The feature tokenizer integrates the strengths of both CNN and Transformers, combining CNN's ability to capture local details with the Transformer's proficiency in extracting long-range global features. This module tokenizes

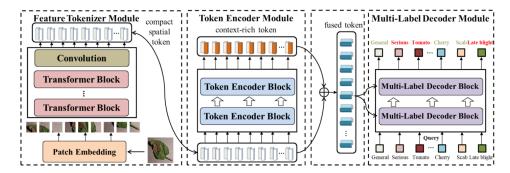


Figure 10: The architecture of LDI-NET [92]. It includes a feature tokenizer module that leverages both CNN and Transformer strengths, a token encoder module for modeling relationships among plant type, disease, and severity, and a multi-label decoder for selectively extracting features to enable accurate multi-label identification.

image data into compact spatial features, enhancing both local and global context awareness. The token encoder module plays a crucial role in enriching the extracted tokens by facilitating information exchange among them through multi-head self-attention and MLP structures. This design allows LDI-NET to understand complex relationships among plant type, disease, and severity features. The multi-label decoder module, which incorporates a residual structure, processes these context-rich tokens. It integrates shallow and deep-level features through adaptive feature embeddings and cross-attention mechanisms to efficiently output multi-label identification results. The results underscore the model's ability to handle multi-label identification tasks effectively, showcasing its potential for enhancing plant disease detection in practical agricultural applications.

The Spatial Convolutional Self-Attention-based Transformer (SCSA-Transformer) has been proposed to enhance strawberry disease identification under complex backgrounds [41]. The research addresses challenges like class imbalance, limited large-scale datasets, and background complexity in agricultural disease detection. The SCSA-Transformer leverages convolutional layers to encode spatial features alongside a Transformer module for global feature extraction, improving efficiency and precision compared to existing models. The proposed model reduced the number of parameters by nearly half compared to the SwinT, facilitating lighter deployment and faster training. These enhancements underscore the method's applicability to real-world agricultural scenarios, particularly for identifying diseases with diverse and complex visual backgrounds.

A real-time plant disease identification framework called CondConViT has been proposed, integrating a Vision Transformer (ViT) with a Conditional Convolutional Neural Network (CondConv), and further enhanced by a novel attention mechanism—Conditional Attention with Statistical Squeeze-and-Excitation (CASSE) [80]. To improve generalization and robustness, the authors introduce a data augmentation technique based on a modified CycleGAN, termed C3GAN, which synthesizes realistic in-field images from healthy plant samples. The model is designed to be lightweight, with only 0.95 million parameters, and is deployable on edge devices for drone-based surveillance. CondConViT is evaluated against seven state-of-the-art models and demonstrates superior interpretability and classification performance across diverse environmental conditions using both Grad-CAM and LIME techniques. They used six datasets: five public datasets—PlantVillage [51], Embrapa [5], Plantpathology [82], Maize and Rice [14], and a newly created in-field drone image dataset named IIITDMJ-Maize [81], which includes 416 labeled images of maize plants under various weather conditions. C3GAN was employed to augment the IIITDMJ-Maize dataset by generating 300 synthetic images for three maize diseases: common rust, northern leaf blight, and gray leaf spot. The CondConViT model achieved the highest or near-highest performance across all datasets in terms of accuracy, F1-score, and AUC. Furthermore, it showed strong generalization on unseen raw drone images and outperformed heavier models, making it suitable for real-time and resource-constrained agricultural applications.

Table 2: Summary of hybrid models. These models are designed to leverage the complementary strengths of ViT and CNN architectures. (Reported metrics are directly extracted from the original publications. In certain studies, per-class or scenario-specific metrics are provided; metrics that are not reported are indicated with a "-".)

Paper	Dataset(s)	Accuracy	Precision	Recall	F1	Main Contribution
[9]	Wheat Rust Classification Dataset (WRCD), the Rice Leaf Disease Dataset (RLDD), and PlantVillage	Scenario- specific	Scenario- specific	Scenario- specific	Scenario- specific	Proposing lightweight DL approach based on ViT, CNN, and hybrid models for real-time automated plant disease classification
[70]	PlantVillage	99.24%	Scenario- specific	Scenario- specific	Scenario- specific	Proposing hybrid model of ResNet-50 and ViT for classify- ing potato plant leaf diseases
[95]	Gathered from search engines	88.34%	0.8833	0.8761	0.8750	Combining Squeeze-and- Excitation ResNet101 and ViT for large-scale and fine-grained disease classification
[53]	Combination of PlantVillage, Plant-Doc, and CD&S	99.24%	0.9915	0.9937	0.9926	Adapting MaxViT structure with SE blocks and implementing Global Response Normalization in MLP layers for 4-class maize data
[40]	Self-built	99.10%	0.9777	0.9847	0.9775	Proposing SCSA-Transformer to solve strawberry disease recognition under complex backgrounds
[28]	Cucumber, Banana, Potato, Tomato datasets	Different in model variants	-	-	-	Proposing Convolutional Swin Transformer (CST) model for ro- bust and accurate plant disease de- tection under natural, controlled, and noisy conditions
[72]	Self-built	94.17%	0.9334	-	0.9459	Proposing Compact Convolu- tional Transformer (CCT)-based model for automated detection of anthracnose and powdery mildew diseases in mango leaves
[68]	Paddy Doctor	98.74%	0.9853	0.9786	0.9818	Introducing lesion-aware visual transformer with multi-scale con- textual feature extraction and weakly supervised lesion localiza- tion
[69]	Self-built	98%	0.97	0.98	0.97	Introducing Hybrid Pooled Multihead Attention (HPMA) model that improves pest classification by effectively capturing local and global features
[46]	Self-built	-	0.98	0.97	-	Proposing lightweight NanoSegmenter model based on Transformer architecture for high-precision and efficient tomato disease detection, incorporating inverted bottleneck, quantization, and sparse attention techniques

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Paper	Dataset(s)	Accuracy	Precision	Recall	F1	Main Contribution
[97]	Field-PV, PlantVillage, Syn-PV	-	Per-class	Per-class	-	Proposing Cross-Resolution Transformer (CRFormer) with large-kernel attention and multi-path feed-forward net- work for accurate grape leaf disease segmentation in complex backgrounds
[21]	PlantVillage Cassava leaves Tomato leaves	99.8% 84.29% 99.9%	0.9998 0.8107 0.9980	0.9997 0.8205 0.9993	0.9997 0.7929 0.9990	Combining EfficientNet with group-wise Transformer for leaf disease detection
[75]	PlantVillage PlantDoc	99.92% 75.72%	0.996 0.75	0.996 0.74	0.995 0.72	Proposing LeafyGAN, a GAN- based augmentation framework for synthetic leaf disease data gen- eration, enabling lightweight Mo- bileViT models to achieve high diagnosis accuracy even with lim- ited real data
[65]	Potato Leaf Dataset (Kaggle)	99.33%	Per-class	-	-	Using ensemble models for potato disease classification
[42]	PlantVillage & Kag- gle	Varies by voting ways	Using ensemble models for leaf disease classification			
[36]	PlantVillage	Per-class	Per-class	Per-class	Per-class	Using ensemble of SwinT and residual CNN models
[45]	PlantVillage AIChallenger2018 Self-built	99.84% 86.83% 98.78%	0.9850 0.8534 -	0.9898 0.8342 -	0.9865 0.8539 -	Proposing a hybrid model (ConvViT) for kiwifruit disease with improved patch embedding and reduced complexity
[100]	PlantVillage Custom1 Custom2	99.62% 96.58% 95.97%	-	-	-	Proposing a hybrid model of CNN and Transformer to enhance diagnosis in complex scenes
[13]	PlantVillage Dhan-Shomadhan	97.43% 96.22%	0.97 0.96	0.96 0.95	0.96 0.95	Introducing an interpretable hybrid model of lightweight CNN and Transformer for rice leaf disease
[78]	PlantVillage Wheat Rust Dataset	98.81% 99.86%	0.9872 0.9978	0.9876 0.9965	0.9873 0.9971	Proposing hybrid model combin- ing transfer learning and Vision Transformer for deep feature ex- traction and classification of plant diseases
[32]	PlantVillage	99.8%	-	-	0.9931	Proposing hybrid model combining adaptive Fourier Neural Operators and CNNs to enhance global and local feature extraction for plant leaf disease recognition
[67]	Coffee leaf stresses dataset	99.1%	-	-	0.9932	Proposing a Dual-path ViT for efficient and interpretable diagnosis

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Paper	Dataset(s)	Accuracy	Precision	Recall	F1	Main Contribution
[37]	Citrus datasets	98.19%	0.9839	0.9819	-	Proposing a dual-branch network combining GSDFP (Group Shuf- fle Depthwise Feature Pyramid) for local multi-scale feature ex- traction and SwinT for global con- text learning for citrus disease classification
[74]	PlantPathology	97.32%	0.9733	0.9740	0.9736	Introducing DBCoST, a dual- branch architecture that integrates CNN for extracting local fea- tures and SwinT for capturing global information, with a Fea- ture Fusion Module (FFM) to en- hance disease identification in ap- ple leaves
[55]	Custom CD&S	93.01% 99.69%	0.9299 0.9969	0.9301 0.9969	0.9299 0.9969	Proposing the DenseCNNs and Transformer Network (DCTN), featuring a novel multi-head self- attention mechanism for accurate detection of field crop diseases
[93]	AIChallenger2018	99.00%	-	-	Per-class	Proposing the TSTC network, a triple-branch Swin Transformer model for simultaneous disease and severity classification, utilizing multitask feature extraction, compact bilinear pooling, and deep supervision to enhance performance and achieve high accuracy on both tasks
[92]	AIChallenger2018	Varies by plant	-	-	-	Proposing LDI-NET, a multi- label network for simultaneous identification of plant type, leaf disease, and severity using a single-branch model, combining CNN and Transformer strengths for feature extraction and employ- ing a multi-label decoder for im- proved feature utilization
[41]	Self-built	99.10%	0.9777	0.9847	0.9775	Using Multi-Head Self-Attention (MSA) and a Spatial Convolutional Self-Attention-based Transformer (SCSA-Transformer) for accurate and efficient recognition of multiple strawberry disease classes
[80]	5 Public, 1 Self-built	Varies by dataset	Varies by dataset	Varies by dataset	Varies by dataset	Proposing a real-time plant disease identification system using drone-based surveillance, featuring a lightweight ViT and CNN fusion model with conditional attention and statistical squeeze-and-excitation

5 Findings and Open Challenges

5.1 Key Findings

Several important findings have emerged from the review of ViTs in precision agriculture. ViTs have shown substantial improvements over traditional CNNs in various agricultural tasks, notably in plant disease detection and crop monitoring. Their ability to capture long-range relationships within images enables more accurate identification of plant diseases and pests, even in complex environments. Combining ViTs with CNNs in hybrid models has further boosted classification accuracy and robustness, making them a promising approach for agricultural challenges. Furthermore, transfer learning—where ViTs pre-trained on large datasets are fine-tuned for agricultural applications—has proven effective in addressing data limitations, improving model performance without requiring vast amounts of labeled data. We can summarize the key findings as follows:

- ViTs demonstrate strong performance in plant disease detection: Many studies have shown that ViTs
 can achieve high accuracy in classifying plant diseases, often outperforming traditional CNN models. Their
 ability to learn long-range dependencies in images is particularly beneficial for plant disease detection, where
 symptoms can be distributed across the leaf.
- Self-attention mechanism is a key advantage: The self-attention mechanism allows ViTs to focus on the most important parts of an image without manual feature extraction. This is helpful in detecting small, subtle spots on leaves. ViTs can dynamically weigh different regions of the input image, ensuring that significant features receive adequate attention during classification. This helps capture both local and global contextual information. This approach is different from CNNs, which apply convolution operations uniformly across an image and can sometimes miss small but significant features. The ability of ViTs to focus on key features helps improve accuracy and reduce the need for extensive pre-processing of images.
- ViTs can be optimized for improved performance: Transfer learning can be effectively used to enhance the performance of ViTs for plant disease identification, even with limited data. This involves pre-training the model on a large dataset and then fine-tuning it on a smaller, disease-specific dataset. Attention head pruning can reduce model size and improve inference speed by removing less important attention heads without significant loss of accuracy. Sparse matrix multiplication in self-attention blocks can improve training efficiency and reduce GPU consumption without sacrificing performance. Knowledge distillation can be used to train a smaller, faster model that retains the performance of a larger model, which is especially useful in situations where computational resources are limited.
- Hybrid models are highly effective in improving performance: Combining ViTs and CNNs can leverage the strengths of both architectures. For example, CNNs, by extracting local features, can help ViTs see better, allowing the model to capture fine-grained details of the image while maintaining the ability to understand global relationships and context. This ultimately improves performance in tasks such as plant disease detection and image classification.

These findings highlight the potential of ViTs in precision agriculture and demonstrate their effectiveness in automated plant health monitoring systems, contributing to precision farming. These developments underscore the increasing importance of ViTs in revolutionizing precision agriculture, particularly for tasks that demand high accuracy and scalability in large-scale agricultural operations.

5.2 Open Challenges

Despite the significant progress made with ViTs in precision agriculture, several challenges still hinder their wider adoption. A key issue is the absence of inductive biases in ViTs. Unlike CNNs, which take advantage of spatial hierarchies and local patterns in images through convolutional filters, ViTs do not possess these built-in inductive biases. Consequently, ViTs require large, high-quality datasets to perform well, making them data-hungry. This reliance on vast amounts of data can be a major obstacle in agriculture, where acquiring labeled datasets is both costly and time-consuming. As a result, ViTs may struggle to reach optimal performance without substantial data augmentation or pre-training on large-scale datasets like ImageNet.

Another challenge is the high computational cost and resource demands of ViTs. The self-attention mechanism that enables ViTs to capture long-range dependencies within images is computationally expensive, particularly when dealing with the high-resolution images common in agricultural applications. This leads to high memory and processing power requirements, making it difficult to deploy ViTs on resource-limited devices such as drones or edge sensors used in agricultural fields. Additionally, training ViTs can take considerably longer than training CNN-based models, which may hinder their use in real-time agricultural applications where fast responses are essential. Lastly, generalizing

across varied agricultural environments presents another significant challenge. While ViTs have demonstrated strong performance on specific datasets, they may not be as effective in different climates, crop types, or farming practices. The agricultural landscape is highly diverse, and models trained on data from one region or crop type may fail to adapt to new environments with different lighting conditions, backgrounds, or plant variations. This lack of environmental robustness could limit the practical application of ViTs in precision agriculture on a global scale. Therefore, enhancing the ability of ViTs to generalize across diverse conditions—through methods like domain adaptation or synthetic data generation—is a critical area for future research. We can summarize the open challenges as:

- Need for more comprehensive and diverse datasets: Many studies use publicly available datasets such as PlantVillage, which may not fully represent the variability of real-world scenarios. Real-world conditions involve a multitude of factors, such as diverse plant species, various disease types and stages, and different environmental and lighting conditions—factors that are often not captured in standard datasets. Datasets also need to account for image variations, including different angles, distances, and image quality. The lack of diverse data can lead to models that are not robust and may not generalize well to new, unseen data. Although some studies have created their own datasets to address this issue, collecting and annotating large-scale, high-quality datasets remains expensive and time-consuming. Table 3 shows the number of times each dataset has been used.
- Improving the interpretability of models: While ViTs have shown promising results, their internal workings can be less interpretable than those of traditional CNNs. The self-attention mechanisms in ViTs enable the model to learn complex relationships between different parts of an image, but it is not always clear why the model makes a particular prediction or which features are most influential in its decision-making process. This lack of interpretability can make it difficult for farmers and agronomists to trust the model or understand how to use it effectively. Some studies address this by using techniques such as Grad-CAM to visualize the areas of an image that are most important for classification. Further research is needed to develop methods that provide deeper insight into the inner workings of ViTs and the rationale behind their predictions, such as feature visualization and saliency maps.
- Reducing computational costs: Transformer-based models can be computationally expensive, requiring significant computing resources. This cost stems from the self-attention mechanism, whose complexity scales with the input size, making it more difficult to train on larger images and datasets. As a result, deploying these models on resource-constrained devices—such as smartphones or edge devices—can be challenging, especially in areas with limited access to high-performance computing infrastructure. Some studies propose solutions such as pruning less important attention heads or using sparse matrix multiplication to reduce computational overhead and enhance practicality in real-world applications. Other approaches, including knowledge distillation and hybrid models that combine ViTs with CNNs, also aim to improve the efficiency of ViTs for deployment. Further research is needed to develop more efficient architectures and training techniques to make ViTs more accessible and suitable for practical use in plant disease detection.
- Addressing the severity of disease: Most existing studies focus only on detecting the presence or absence of a disease, without considering its severity. However, disease severity can significantly impact crop yield, and determining it is important for developing appropriate treatment plans. More research is needed to develop methods that not only detect the presence of a disease but also assess its severity. This may involve classifying the disease into different stages or using metrics to quantify its extent. Such approaches would require modifying models to output not just a class label but also a measure of disease severity. Additionally, datasets may need to be labeled with more detailed information, including both disease classes and severity levels. Future studies should explore severity assessment methods to support more practical and informed plant disease management strategies.

Table 3: Frequency of dataset usage across the analyzed studies. Datasets created by gathering images from the internet or by combining other datasets are categorized under the 'Custom' category. Datasets created by the authors themselves are categorized under the 'Self-built' category. Datasets that do not have a unique name or DOI link and are simply accessible from Kaggle are categorized under the 'From Kaggle' category.

Dataset	Description	Number of use
PlantVillage [51]	Contains over 50,000 images of plant leaves across 14 species and 26 diseases	18

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Dataset	Description			
Self-built	Dataset built by the authors	12		
From Kaggle	Other publicly available datasets	12		
Custom	Datasets gathered from search engines, created by combining other datasets, or not easily accessible	8		
PlantPathology2020 [82]	Contains over 3,000 high-quality real-life images of apple leaf diseases under varying conditions	3		
PlantDoc [76]	Contains over 2,000 images across 13 plant species and 17 disease classes	2		
CD&S [3]	Contains over 4,000 corn images comprising field images and augmented images	2		
PaddyDoctor [58]	Contains over 16,000 annotated paddy leaf images across 13 classes	1		
Plant Seedling [24]	Contains over 900 unique plants belonging to 12 species	1		
PlantCLEF2022 [35]	Contains over 2,000,000 images and 80,000 classes	1		
DRLI [15]	Contains over 4,000 images of healthy and diseased leaves	1		
PlantComposite [56]	Contains over 58,000 images of healthy and diseased leaves	1		
Citrus Fruits and Leaves dataset [62]	Contains over 600 images of citrus leaves and 150 images of citrus fruits, with five classes for each	1		
Dhan-Shomadhan [31]	Contains over 1,100 images of five rice leaf diseases	1		
Strawberry Disease dataset [1]	Contains 2,500 images of seven types of strawberry diseases	1		
Embrapa [5]	Contains over 56,000 images of 171 diseases and other disorders affecting 21 plant species	1		
Maize and Rice dataset [14]	Contains 500 rice images and 466 maize images	1		

These challenges highlight that, while ViTs hold great potential for plant disease detection, much work remains to ensure that they are robust, accurate, and practical for real-world applications. Addressing these challenges will be crucial for realizing the full potential of ViTs in precision agriculture.

6 Conclusion

The use of ViTs in agriculture marks a noteworthy deviation from traditional DL paradigms, with promising potential to model complex visual patterns without relying on the strong inductive biases of convolutional architectures. While CNNs have traditionally excelled at agricultural tasks due to their locality and translation equivariance, ViTs offer a more versatile and scalable approach—especially when paired with appropriate training methods and hybrid models that reintroduce inductive biases in a controlled manner.

In this survey, we have highlighted the evolution of ViT-based approaches in agriculture, ranging from vanilla Transformer models to hybrid models that leverage the strengths of both CNNs and Transformers. The literature presented demonstrates the potential of ViTs for a range of agricultural tasks such as disease identification, yield prediction, and precision agriculture, with most models outperforming or complementing traditional approaches. Despite these advances, several open issues remain, including data scarcity, computational demands, and the need for task-specific model customization. Addressing these challenges will be essential to fully realizing the potential of ViTs in real-world agricultural applications. As the research field continues to mature, future work must prioritize model efficiency, domain adaptation, and the creation of robust, annotated agricultural datasets. In conclusion, ViTs represent

a compelling paradigm shift for agricultural vision tasks. As innovation and synergy between agricultural sciences and machine learning continue, they are likely to drive smarter, more sustainable, and more precise agricultural solutions in the future.

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