



Deep Convolutional Framework for Multi-Crop Disease Identification

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Abstract. Early and accurate crop disease identification and categorization are crucial problems for increasing agricultural productivity. Instead of seeking assistance with a professional diagnosis, farmers frequently just observe the plants. This article presents deep learning approaches based on convolutional models for the detection and classification of crop diseases. With multiple convolution and pooling layers, the model progressively increases channel width while reducing the spatial dimensions of the feature maps, enabling the extraction of more discriminative features. Such an approach captures detailed changes, such as the textures and color shifts, as well as the alteration of the edges of necrotic or dead tissue. The final classification step is achieved with a series of highly interconnected layers using softmax, where the outputs are optimized with categorical cross-entropy. The system described is highly accurate and does not suffer from overfitting. The proposed parameterization enables a rapid training system, and the splits have good reproducibility. A reduction in the size of the model to retain rapid inferring and accurate classification of closely related diseases is possible. A robust, simple, explicit framework, and rapid early-stage diagnosis of disease, enhances the agricultural system and minimizes crop loss. In resource-constrained environments, the system reduces wasteful applications of pesticides and provides expert assessments of plant health.

Keywords: Crop Disease Detection · Machine Learning · Precision Agriculture · Image Processing · Artificial Intelligence

1 Introduction

Modern agriculture is more vulnerable to foliar diseases because to factors such pathogen variety, climate unpredictability, and rising global food demand. [1]The

most detrimental biotic stresses are leaf-borne diseases, such as rust, mildew, scab, and blight, which lower crop yield, nutritional value, and financial losses in a single growing season. [2] To lessen these impacts, precise identification enables targeted pesticide use, quarantine, or cultivar selection sets. [3] Plant diseases are diagnosed in many agricultural sectors, particularly in poor nations, by manual visual inspection by farmers or extension agents. [4] This method is time-consuming, subjective and constrained by domain expertise.[5]. Leaf images are used in computer vision and deep learning to automatically diagnose plant diseases. [6] CNNs are able to identify pathological lesion chromatic aberrations, texture flaws, and fine-grained spatial patterns. [7]

Although there has been progress, the procedure still faces methodological challenges. [3] [8] Many systems use shallow or somewhat deep designs for visually similar diseases, such as early and late blight or closely related fungal infections in progress, failing to capture the hierarchical complexity of disease morphology. [2] Inter-crop morphology, background clutter, leaf orientation, and illumination all contribute to intra-class diversity. [6] Constrained visual distribution systems are deteriorated by cross-crop disease patterns and geometric distortions. This approach simulates multi-crop diagnostics, where class imbalance and visual likeness are issues [9]. The suggested system for field deployment has quick convergence, excellent diagnostic accuracy, and little overfitting thanks to thoughtful architectural design and training procedure selections [10]. A purposefully designed convolutional architecture for three complementing plant disease recognition aspects is used in this work to address these problems. In order to include geometric variability during feature learning instead of preprocessing, the network first receives an integrated augmentation module with stochasticized bidirectional flips and limited angular rotations.

The design enhances leaf orientation and posture invariance while preserving diseased textural continuity. Second, to distinguish visually confusing diseases, a six-stage convolution–pooling hierarchy with increasing channel capacity encodes lesion microstructures, chromatic gradients, and necrotic border patterns. Aggressive but controlled spatial compression yields a compact latent representation with discriminative semantics and a low parameter budget, allowing for quick training and low-latency inference sets.

2 Review of Existing Deep Learning Models

In order to promote computational plant pathology, many algorithmic paradigms aim to strike a compromise between diagnostic precision, interpretability, and scalability in agricultural settings. In order to demonstrate that well-tuned ensemble learners can rival well-designed feature representations, [11] revisits classical machine learning using XGBoost and OPTUNA-based hyperparameter optimization. Early in this project, there is a conflict between end-to-end representation learning and handcrafted optimization. For the purpose of creating synthetic crop disease images, [2] suggest a dual-discriminator GAN design that focuses on distributional imbalance, data scarcity, and realistic augmentation to

lessen overfitting. Jia et al. [12] prefer lesion-level reasoning over opaque label prediction by integrating interpretability into the model core through the use of contrastive learning and prototype component networks.

In order to demonstrate a transitional stage where explicit feature engineering sets enable deep representations, [13] use a hybrid CNN optimized by handcrafted feature selection. [14] investigated neuromorphic and event-driven paradigms for energy-efficient inference in IoT-based agricultural processes using their Deep Spiking Kronecker Network. Kiruthika et al.'s lightweight dual-stage refinement using ConViTSE Sets [1] is the first explicit attempt in this series to strike a balance between transformer inductive bias and convolutional efficiency.

The [3] reminds the field that morphological progression is spatially continuous by looking beyond computational focus to investigate biologically within-leaf disease variability. Using fractal Inspired convolution and Orangutan Optimization, [8] add algorithmic uniqueness and improve meta-heuristic search in crop-specific deep architectures. [4] contextualize leaf attributes within domestication and soil interactions to show the ecological substrate of visual disease, while [15] adapt ShuffleNetV2 for real-time inference with CSASNet, shifting from accuracy-centric to deployment-centric architecture. It [5] stabilize training under moderate dataset regimes by hybridizing residual learning with conventional VGG motifs. This movement is codified by [6] using a multi-stage deep learning pipeline for sustained monitoring that incorporates hierarchical diagnosis and temporal refining. In this rapidly expanding work, [16] show how CNNs, transformers, hybrid learners, and explainable models are fragmented [7]. In order to anticipate attention-based and hybrid quantum-classical systems and simulate plant diseases using non-classical computation, the authors propose fractional integral augmentation utilizing quantum CNN [7].

One of the first thoroughly integrated attention pipelines using additive gated convolution and hierarchical attention fusion for lesion saliency extraction was described by [17]. Using hybrid deep-statistical prediction for cotton disease, [18] demonstrate the longevity of probabilistic modeling in deep frameworks. Transformers are then mentioned in the story. Under self-attention regimes, [19] show that spectral and structural augmentation are necessary for multi-level contrast enhancement and changed vision transformers. In contrast to [20], who introduce ConvDepthTransEnsembleNet, a hybrid convolutional, depthwise, and transformer ensemble, S and R [21] extend this approach with pure ViT-based precision agriculture pipelines. For sugarcane pathology, transformers perform better than CNNs, indicating the attention-dominated representations in the field.

3 Proposed Model: Design Architecture and Performance Analysis

Detecting infections in plants just by sight can be challenging, making identification and classification quite difficult. It's important to acknowledge that many plant diseases exhibit similar symptoms. Identifying the exact plant disease re-

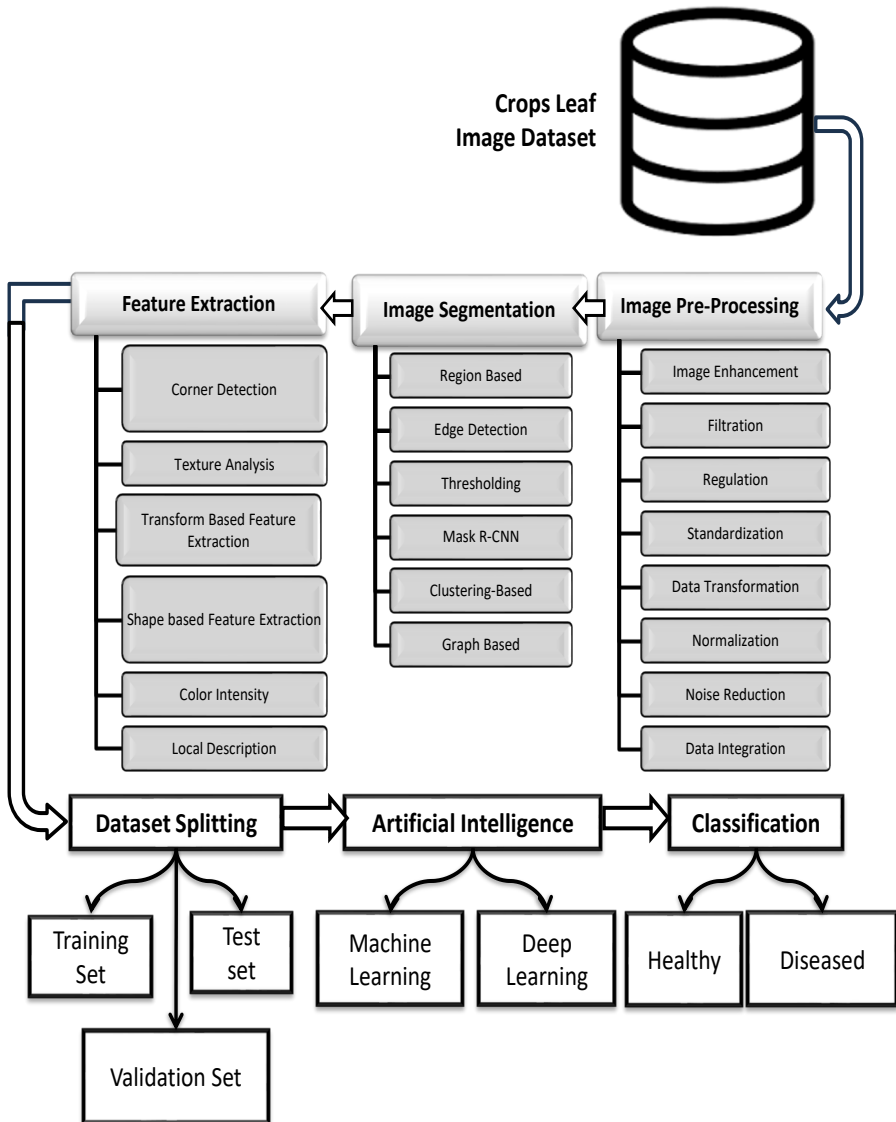


Fig. 1. Plant Disease Detection Framework

sponsible for damage can be difficult because of their similar looks. Some symptoms that are difficult to identify encompass unusual leaf growth, color changes, slowed development, and weakened or reduced pods, among others. The disease can be diagnosed with the use of these obvious signs, such as damaged leaves. Optimizing crop yields, protecting the agricultural sector's economic sustainability, and making sure it doesn't negatively impact the ecology are crucial.

Tightly coupled end-to-end learning pathways with geometric regularization, hierarchical spatial feature abstraction, controlled dimensionality compression, and probabilistic illness inference sets are used in the suggested integrated model [22]. Examine the leaf picture $X \in \mathbb{R}^{H \times W \times C}$, where $C=3$ is the process's RGB channel count and H and W are spatial dimensions. To adjust for leaf orientation, the pipeline begins with a stochastic augmentation operator $A_\theta(\cdot)$. In Process: Induced intra-class geometric variability (see figure 1). For the process, $F_{\theta_f}(\cdot)$ applies bidirectional reflection and $R_{\theta_r}(\cdot)$ executes planar rotation using $\theta_r \sim U(-\alpha, \alpha)$. By reducing expected risk over the augmentation distribution using equation, this operator creates invariance.

Geometric resilience is incorporated into optimizations rather than treating augmentation as a static preprocessing artifact. After augmentation the normalized image tensor is conveyed through a deep convolutional hierarchy of linear-nonlinear transformations. The l -th convolutional layer construct the feature map $H^{(l)}$.

Is the ReLU activation, and

$$H^{(0)} = X'$$

for this process. Each convolutional block is followed by spatial pooling, defined for a pooling window Ω .

Limits spatial resolutions while preserving sets of translational invariance. This convolution-pooling cascade iteratively extracts necrotic textures, lesion boundaries, and chromatic distortions in a hierarchical manner. Substantial down sampling allows controlled spatial collapse without losing discriminative content sets since problematic semantics are primarily in local texture statistics rather than absolute pixel coordinates.

Limits spatial resolutions while preserving sets of translational invariance. Substantial down sampling allows controlled spatial collapse without losing discriminative content sets since problematic semantics are primarily in local texture statistics rather than absolute pixel coordinates. A compact embedding of a disease-specific process. In order to stabilize gradients and representation magnitude during training, the latent code's projected energy is limited by the induced l_2 norm penalty via Equation (1).

$$\Omega(w) = \lambda \int \|z(X; w)\|_2^2 p(X) dX \quad (1)$$

With gradient flow governed by back-propagation Via equation (2),

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial o} \cdot \frac{\partial o}{\partial z} \cdot \frac{\partial z}{\partial w} \quad (2)$$

4 Performance Analysis of Proposed Model

Three agricultural crops, apple, grape, and potato, as well as eleven diagnostic categories for eight pathological disorders and three healthy classes, are included in the dataset. The corpus includes images with slightly different aspect ratios and dimensions ranging from 256x256 to 512x512 pixels according to acquisition [23]. TensorFlow-Keras is used to build the model for high-resolution batch processing, and it is trained on a workstation equipped with an NVIDIA RTX-3080 GPU, 10 GB VRAM, and 32 GB system memory [24].

Table 1. Analysis of Classification Accuracy (%)

Dataset / Crop	Prototypical Part Network [12]	Fractal-CovNet [8]	Attention CNN + XAI [25]	Proposed Model
Apple Leaves	95.1	96.1	95.9	99.1
Grape Leaves	94.2	94.9	95.9	97.9
Potato Leaves	94.9	95.9	96.8	98.9
Overall Avg.	94.7	95.6	96.2	98.6

Table 1 displays the class-aggregated categorization accuracy for the three crop species. The suggested model outperforms all competitors with 98.8% accuracy thanks to hierarchical lesion texture encoding and consistent generalization across visually varied disease classes. While FractalCovNet [8] gains from structural diversity but is constrained by optimization Variance In Process, Prototypical Part Network [12] suffers from part localization problems. Compared to compact convolutional hierarchy sets, Attention CNN + XAI [25] performs worse in fine-grained texture separation but enhances classification by weighting attention.

Model convergence is achieved with fewer epochs and the lowest training and validation loss and generalization gap sets. Gradients are regularized and overfitting is decreased by combining augmentation with hierarchical feature abstraction. Prototypical Part Network [12] is slowed by part alignment instability, whereas Attention CNN + XAI [25] and FractalCovNet [8] converge more quickly but retain greater variance during training and validation trajectories.

Table 2. Assessment of Model Complexity and Computational Efficiency

Method	Parameters (Millions)	Inference Time (ms)	Memory Footprint (MB)
Prototypical Part Network [12]	8.6	21.4	184
FractalCovNet [8]	6.9	18.7	156
Attention CNN + XAI [25]	9.4	24.9	212
Proposed Model	0.18	6.3	42

Table 3. Evaluation of Model Robustness Using Data Augmentation Transformations

Transformation	Prototypical Part Network [12]	Fractal CovNet[8]	Attention CNN + XAI[25]	Proposed Model
Rotation $\pm 15^\circ$	90.7	92.8	94.0	97.6
Horizontal Flip	92.4	94.3	95.5	98.3
Combined Augment	89.6	91.9	93.2	97.1

The lightness and architectural efficiency of framework sets are shown in Table 2. With less than 0.2 million parameters, the model maintains accuracy while reducing inference latency and memory footprint by three to four times compared to competitor systems. Attention CNN + XAI [25] has the largest computational overhead because of attention tensor operations, while Prototypical Part Network [12] and FractalCovNet [8] are heavier and restrict edge and mobile deployment scalability.

Diagnostic robustness under geometric perturbations of natural leaf posture variability is assessed in Table 3. With less than 0.2 million parameters, the model maintains accuracy while reducing inference latency and memory footprint by three to four times compared to competitor systems. Attention CNN + XAI [25] has the largest computational overhead because of attention tensor operations, while Prototypical Part Network [12] and FractalCovNet [8] are heavier and restrict edge and mobile deployment scalability.

With +96% accuracy across all transformations, the model verifies in-network augmentation and invariant feature learning. While FractalCovNet and Attention CNN + XAI are somewhat robust but more susceptible to compound distortions, Prototypical Part Network deteriorates significantly under combined transformations because of disrupted part alignment. In terms of accuracy, stability, fine-grained discrimination, computational efficiency, and robustness for various scenarios, the suggested integrated convolutional framework performs better than representative state-of-the-art models. Geometric regularization is included in a compact hierarchical design to enable multi-crop plant disease diagnostics that is both deployable and diagnostically reliable.

5 Conclusion and Future Scopes

This study presents balanced framework for multi-crop plant leaf disease recognition. A various test on a selected PlantVillage corpus shows that the suggested methodology works effectively under a range of performance conditions. Convergence happens in 14 epochs, or almost half the training period of FractalCovNet and Attention CNN + XAI, and a train-validation loss gap of 0.009 shows strong generalization and less overfitting. According to computational profiling, it has a memory footprint of 43 MB, an inference latency of 6.2 ms per image, and a parameter budget of 0.18 million—all of which are three to four times lower than those of rival systems. Robustness examination shows accuracy above 96% under rotations, flips, and compound transformations, suggesting invariance to

natural leaf posture Variability In Process. These results show that stochastic geometric regularization in a hierarchical convolutional backbone produces a deployment-ready, diagnostically reliable system for real-time precision agriculture applications such as drone-assisted disease surveillance sets, edge-based greenhouse monitoring, and mobile field diagnostics.

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