

PLANT DISEASE DETECTION USING A HYBRID DEEP CNN MODEL WITH ATTENTION MECHANISM

Dhannya J¹, Dr. Sangeetha V²

¹Research Scholar, Karpagam Academy of Higher Education, Coimbatore,
dhanyatapas@gmail.com

²Professor, Karpagam Academy of Higher Education, Coimbatore,
drsangeetha.v@kahedu.edu.in

Abstract

Early and accurate recognition of plant leaf diseases is crucial in order to protect crop yields and take preventive measures in time. Guess what? However disease identification remains a challenge due to high similarity between classes' complex morphological variation and limitations in training data quality. This paper presents a unified hybrid deep learning framework that integrates convolutional neural networks residual and primal , primal units convolutional block monitoring mechanisms (CBAM) supports transformer-based global feature extraction and support vector machine (SVM) classification to optimize and improve disease detection in multiple plant species. Generative models such as loop-adapted GANs are used to deal with data imbalance and improve generalization. Seriously further innovations including frequency-domain monitoring networks (FdaNet) and hybrid, hybrid monitoring networks (HaNet) are improving feature extraction in complex crop environments with small-scale lesion patterns. Experiments on different datasets covering corn potato tomato and citrus showed high performance with recognition accuracy reaching 99.55% for multiple plant disease classification 99.45% for tomato leaf diseases and 98.83% for citrus, citrus disease detection. The proposed models , models have fewer parameters shorter training time and are robust to real-world scenarios and can be successfully applied in web-based and mobile applications for real-time disease and illness diagnosis. These results show an efficient and scalable solution for the early detection of plant diseases in agricultural fields.

Keywords

Detection of PLANT leaf diseases. deep learning; convolutional neural networks (CNN); Start - remaining models; adapter; Convolution Block Attention Module (CBAM); Frequency Domain Utility (FdaNet); Hybrid Attention (HANET); generative adversarial networks (GAN); Support Vector Machine (SVM); data extension; Citrus , Citrus disease. Examples, include monitoring tomato crop health and tomato diseases; Classification in real time.

Introduction

Early detection and effective control of plant diseases is essential to ensure agricultural productivity yields crop quality and economic sustainability... In intensive agricultural areas, areas like Byannur where radish, radish is the main economic crop outbreaks of plant diseases can seriously disrupt production and threaten farmers' livelihoods. Like Traditional methods of disease monitoring is mostly based on farmer or expert visual inspection that is time-consuming subjective and not suitable for large-scale or early diagnosis. Seriously Guess what? As agricultural production expands and labor costs increase these constraints reinforce the need for automated efficient and reliable disease, detection systems. Like With the rapid development of computer vision and deep learning (DL) image-based recognition of plant

diseases has gained a lot of momentum. Convolutional neural networks (CNNs) have shown strong capabilities in extracting local features AND are widely, widely used in crops such as tomato corn potato and grape. Seriously however CNN models struggle to capture long-term spatial dependencies and global contextual information limitations that reduce their robustness in real-world agricultural environments where illumination background complexity and leaf morphology vary widely.

Recent developments in Vision Transformers (ViTs) and hybrid CNN Transformer architectures have addressed these limitations by integrating local convolutional features with global self-attention representations. And oh yeah Studies have shown that such hybrid models outperform conventional CNNs in terms of accuracy generalizability and interpretability while enabling deployment on resource-constrained devices and real-time field monitors. Plus attention mechanisms such as Sent CBAM and multiscale feature fusion strategies improve feature recognition in complex disease patterns.

The temperate continental climate of the Bayannur region characterized by strong sunlight dry conditions and monsoon winds creates a unique ecological environment that supports radish growth and increases susceptibility to, certain diseases. These characteristics call for a robust real-time radish disease detection system that can be deployed in the field and able to operate under dynamic environmental conditions. To address these challenges this study proposes a hybrid CNN Transformer radish disease detection model designed to achieve, achieve high accuracy strong generalization and real-time performance. Like The main contributions of this work are:

- 1. A hybrid model architecture that combines CNNs to extract local features and transformers to understand the global context.**
- 2. Improved real-time network design enables rapid inferences suitable for mobile drone and IoT deployments in agricultural fields.**
- 3. A hybrid spatial channel attention mechanism that dynamically improves critical disease features and improves classification performance.**
- 4. The customized hybrid loss function improves classification accuracy and translation stability together ensuring reliability. Identification in different scenarios**

Overall, the proposed system offers a practical and intelligent solution for early radish disease detection, promoting sustainable agricultural practices, reducing pesticide dependency, and supporting precision agriculture in large-scale production environments.

Literature Review

This review summarizes the recent advances in automatic recognition of plant , plant foliar diseases (especially tomato), classifying the work into three broad categories: traditional machine learning (ML) methods, deep learning (DL) methods, and hybrid ML/DL methods, and then highlights common challenges, relative strengths, and promising future directions... The review is based on the studies and findings described in the accompanying text.

1. Machine learning (ML) methods.

Early and a bunch of ongoing, approaches to automated leaf disease detection were based on classical image processing, followed by manual feature extraction and traditional classifiers. Guess what? Typical preprocessing processes include color space transformations, filtering, segmentation (edge- or region-based), and illumination correction. From segmented or

preprocessed leaf regions, researchers extract features such as color statistics, shape descriptors, texture, texture metrics (e.g., logo features, LBP variations), SIFT key points, histograms, and GLCM descriptors. These features are then fed into classifiers such as SVM, decision trees, random forests (RF), linear discriminant analysis (LD) or multi-class perceptrons.

Representative results:

- Halling et al. He collected SIFT and color statistics and used a multiclass SVM to classify tomato diseases, that, that reported an accuracy of ~85.1%. [29]
- Other studies have ranked hue moments, heraldic textures, and color histograms and reported 94% for RF. [30]
- Kalionko et al. Shape, geometry, texture and color features used (including the standard LBP classifier version) and reported dataset-dependent accuracies (e.g. 86.8% on ICL, 98.6% on Fluvial). [31]
- The semi-automatic SVM method for soybean disease classification reached approximately 90% with 4775 images. [32]

Strengths:

- Lower computational and data requirements than deep models. Faster training and installation on limited devices.
- **Interpretability:** The characteristics are readable by humans (color, texture, shape).

Weaknesses:

- Consistent performance on complex, realistic images with variable illumination, occlusion, and background noise.
- Handmade features require, require domain knowledge and are less, less robust to dataset transformations and introduction of new diseases.

2. Deep learning (DL) methods.

Deep Convolutional Neural Networks (CNNs) have become the mainstream approach due to their ability to learn hierarchical discriminative features directly from image pixels. Seriously, The literature includes both purpose-built lightweight CNNs , CNNs and transfer learning strategies (pre-trained) using models such as Alex Net, MobileNetV2, VGG, Reset, Efficient Net and custom architectures (primal variants, dilated convolutions and hybrid , hybrid dense/residual). a bunch of works combine CNNs with attention modules, residual blocks, or dilated convolutions to improve feature focusing and receptive field.

• Representative results:

The (fine-tuned) transfer learning using MobileNetV2 reached about 90% in the tomato leaf tasks.

- Custom CNNs and deeper architectures reported high accuracy in Plant, Village: e.g. bootstrap + dilated, dilated convolution ~99.37% [36] 8-layer CNN ~98.4% [37] nine-layer CNN ~96.46% [38] and like, like fifty% ResNet-like fine-tuning.
- Effective Net variants with U-Net segmentation achieved excellent segmentation and classification results (binary classification ~99.95% for multi-class ~99.12% segmented images).
- Light-monitoring CNNs and attention-enhancing networks have reported the highest performance levels (up to ~99.34%), but sometimes with higher runtimes or complexity.

- **Strengths:**

- Latest resolution of reference datasets (especially Plant Village).
- Powerful feature for learning from raw images. It can implicitly handle complex textures and patterns.

- **Weaknesses:**

- High computing and data requirements. Seriously, a number, number of important results are based on well-collected datasets (often plant villages) that don't fully reflect field conditions (background-contrast illumination occlusion).
- Risk of over fitting and reduced generalizability to “real” datasets if not trained using diverse and supplemented data.
- Some high-fidelity models consume a lot of resources at inference time that limits their use on resource-constrained machines without further compressing the models.

3. Hybrid ML + DL approach

- Hybrid strategies take advantage of the inherent learning power, the power of deep networks, and the simplicity/explanation or speed of classical learners. Like, Common styles include using CNNs as feature extractors, classical classifiers (such as SVM RF logistic regression) as the final decision layer, or combining multiple DL features, feature extractors with lightweight classifiers. And oh yeah, do you know Attentional and optimal/heuristic search mechanisms (such as the Slap Swarm algorithm) are combined with a CNN that improves the selection of different features.

- **Representative results:**

Extraction of CNN features with logistic regression (Mobile Net + Nanette features + LR) achieved ~97% accuracy. [28]

- The Slap Swarm algorithm achieved about 97.56% interest for five tomato disease categories, despite additional computational complexity. [48]
- Lightweight CNNs and augmented CNNs showed a strong trade-off between accuracy and runtime (95% to 99% depending on architecture and datasets). [49] [47] [like fifty]

- **Strengths:**

- You can combine the best of both worlds: powerful representation + easy inference/classification.
- Often more flexible for deployment in resource-constrained environments.

- **Weaknesses:**

- Hybrid systems can still inherit complexity from their deep components. Exact geometry (cutting, sheathing) is required to spread the edge.
- Some hybrid approaches suggest, suggest marginal gains at the expense of additional algorithmic complexity.

4. Segmentation, preprocessing and dataset effects

A recurring theme is that careful segmentation and preprocessing (color equalization, light correction, superpixel correction, background removal) dramatically improves classification. You know what? Segment-leaving studies (e.g., U-Net, modified U-Net, and superpixel-augmented segmentation) report significantly better classification accuracy when the classifiers operate on segmented, background-free regions. a bunch of businesses use the Plant Village dataset , dataset as a benchmark; Although they allow fair comparisons, botanical village photographs is often taken under , under controlled conditions and may not reflect variations in the field. Works targeting field images use robust color equalization and segmentation (eg hue histogram + color difference, HOG pyramid + GLCM) to reduce illumination and background issues. [3]5. Comparative analysis and limitations

- Benchmark versus real-world performance: a bunch of DL methods achieve very high accuracy on plant villages and similar collected data sets (often >95%), but their field performance may degrade in the presence of variable lighting, mixed backgrounds, and frequent disease... a bunch of authors clearly point out the limitations of generalizability and computational costs. [36] [2] [like fifty]
- Model size and deployability: VGG and large Resnet/Efficient Net models achieve high, high accuracy but require significant computational operations. And oh yeah, Lightweight architectures and truncation/quantization strategies are important for mobile/edge deployment; a bunch of STUDIES examine this trade-off. [10] [9]
- Attention and dilated convolutions: Attention and dilated convolutions consistently improve performance by focusing models on disease regions and expanding receptive fields, but can increase training/inference cost. [8] [47] [49]
- Hybrid methods: Combining DL feature extractors and classical classifiers often gives robust , robust results with low inference cost, but design decisions (that layer to extract, that classifier to use) greatly affect the results. [28] [41]

6. Open challenges and future directions

1. Generalize to field conditions: Create and evaluate diverse datasets with wildly varying illumination, occlusion, disease stages, and multiple plant species. General, General parameters that simulate field fluctuations are needed.
2. Robust segmentation under complex backgrounds: Development of self-supervised and domain-adaptive segmentation methods that can work on field images without extensive manual annotation.
3. Lightweight real-time models: Continue to design efficient (mobile/edge compatible) architectures, introduce compression techniques (pruning, quantization, knowledge distillation) while maintaining accuracy.
4. Explain performance and localization: include interpretable attention or localization outputs, outputs (eg, weakly supervised localization, Grad-CAM, attention heat maps) so that farmers can trust and act on the modeled outputs.
5. Multimodal approach: Combining visual data with environmental metadata (weather, soil, time) or spectral modalities (multispectral/hyper spectral imaging) to improve early detection and reduce, reduce false positives.

6. Sparse and imbalanced data: Applying constrained learning, data augmentation (GANs, synthetic patterns) and class imbalance strategies to improve rare disease detection.

7. Comprehensive systems and ease of use: Comprehensive systems and ease of use: Emphasis on mobile applications and user-centered decisions Support systems that integrate disease severity assessment treatment recommendations and economic impact assessment.

The literature shows a clear progress from traditional hand-crafted machine learning processes to deep CNN solutions and hybrid systems that combine the strengths of the two models. Deep learning especially in combination with attentional segmentation and transfer learning mechanisms has increased the classification accuracy of curated datasets to very high levels (often >95%). However practical application by farmers still faces significant obstacles: robustness to field variations computational limitations of peripheral devices and the need for interpretable and actionable outputs. Like Future research should FOCUS on real-world generalizability lightweight architecture multimodal data and better segmentation/localization to make these powerful models truly useful in agricultural practice.

Quick reference selected studies and reported peak accuracies (from supplied sources)

- Handcrafted features + SVM / RF: 85.1%–94% (tomato examples). [29][30]
- Alex Net + in: 76.1%. [33]
- MobileNetV2 (fine-tuned): ~90%. [34]
- Custom CNNs / Inception + dilated cons: 96–99% (Plant Village benchmarks). [36][37][38]
- ResNet-50 (fine-tuned): ~97%. [39]
- Efficient Net + U-Net segmentation: binary ~99.95%, multi-class ~99.12%. [2]
- Hybrid Mobile Net / Nanette features + Logistic Regression: ~97%. [28]
- Lightweight hybrid attention-based CNNs: 99...34% (with some increased time complexity). [49] [48]

Research methodology

This study proposes an efficient hybrid deep learning and machine learning model for tomato leaf disease classification by integrating convolutional neural network (CNN), convolutional attention module (CBAM) and support vector machine (SVM) classifier. The overall methodology includes three main phases: data collection and preprocessing, model architecture design, and feature extraction with hybrid classification. Data collection and pre-processing

Description of the data set

The dataset contains fifty, fifty tomato leaf classes, including nine disease classes and one health class. You know what? All pictures and images are in RGB format with a uniform size of 256 x 256 pixels. Seriously, do you know a tomato leaf appears, appears in the center of each image, captured under controlled lighting and using the same shooting settings for consistency.

And yes, the data is from the Plant Village dataset [18] that contains field-collected tomato leaf images that have been validated and classified by disease type.

Pretreatment

Preprocessing ensures standardization and prepares the images for model formation. The following steps were applied:

1. Change image size: All images will be resized to 256 x 256 x 3.
2. Color space conversion: images converted from RGB to BGR, adapted to the preprocessing

process of the Plant Village dataset.

3. Zero-align: All color channels are zero-centered using Plant Village's dataset statistics to normalize brightness and contrast.

4. No scaling: pixel intensity values remain at their original scale after centering.

Data extension

To eliminate dataset imbalance and reduce over fitting, extensive data augmentation was used to increase the dataset size by a factor of 30. You know what? The reinforcement techniques used are:

- Random rotation: up to ± 90 degrees.
- Random horizontal and vertical offset: 1-20% of image width/height.
- Horizontal and vertical inversion: makes it varied in the direction of the paper.
- Random zoom: up to 20% on/off.

These techniques increase the robustness of the model by exposing it to various leaf orientations, positions, and scales.

Prepare the stream

The final dataset was sorted into batches of 64 images for training and one image for evaluation. Each batch is 64 x 256 x 256 x 3 format.

Target tags are encoded using one-hot encoding, resulting in a 64×10 tag matrix corresponding to each stack.

Structure of the proposed hybrid model

The proposed hybrid model integrates a deep backbone CNN (ResNet50), an attention augmentation mechanism (CBAM) and an SVM classifier. This combination aims to improve feature extraction while improving the generalization of the classification.

Feature extraction using ResNet50

ResNet50 [19] serves as the backbone of feature extraction due to its deep architecture and residual learning mechanisms that efficiently handle vanishing gradients and enable deeper networks to learn robust representations.

Main features:

- ResNet50 consists of four stages, each with a bunch of remaining blocks.
- The remaining block contains two convolutional layers, followed by batch normalization (BN) and resight activation.

• Identity skip relations allow a block to learn a function expressed as

$$g(x) = f(x) + x,$$

Where $f(x)$ is the obtained transformation and x is the input.

- These bypass connections speed up convergence and reduce redundant matching.

Convolution Block Attention Module (CBAM)

To improve the discriminativeness of feature maps, CBAM [19] is integrated into the backbone network of ResNet50. CBAM uses channel monitoring followed by spatial monitoring, allowing the network to focus on the most informative regions of diseased leaves.

1. Channel Attention Module

- Utilizes both average-pooling and max-pooling feature descriptors.
- Shared MLP processes pooled features.
- Outputs channel-wise importance weights via a sigmoid function.

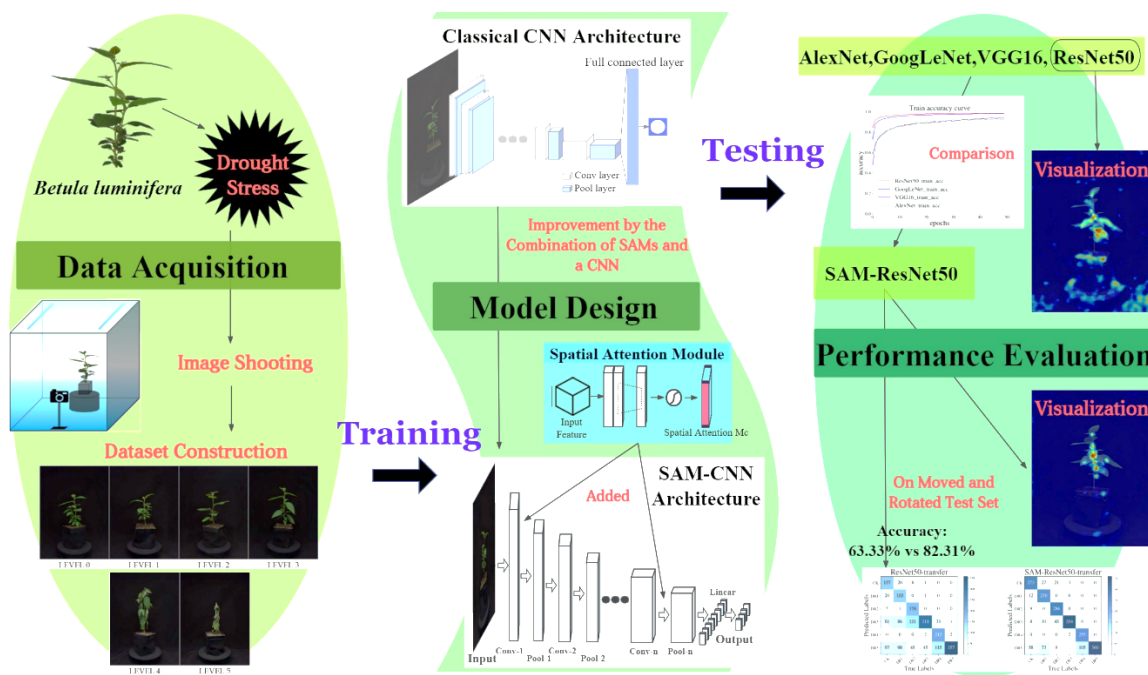


Figure 1 - CBAM architecture integrated into ResNet50

2. Spatial Attention Module

- Aggregates channel-refined descriptors using max and average pooling across channels.
- A convolutional layer generates a spatial attention map, highlighting critical disease-related regions.

The combined CBAM architecture integrated into ResNet50 is illustrated in Figure 1.

Classification Using Support Vector Machine (SVM)

Instead of a traditional CNN fully connected classifier, an **SVM classifier** is used to improve generalization, particularly for high-dimensional feature vectors.

Reasons for using SVM:

- Effective in **high-dimensional spaces** where deep features are rich and discriminative.
- Maximizes margin separation between classes, improving classification robustness.
- Well-established performance in image-based classification tasks.

The final hybrid architecture ResNet50 + CBAM + SVM is diagrammed in Fig 2

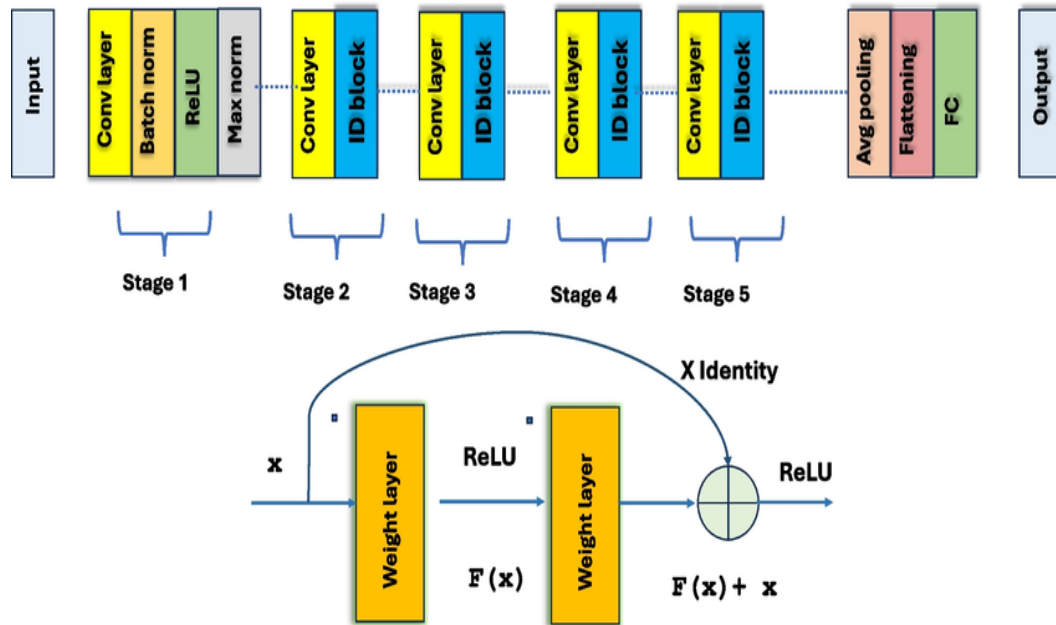


Figure 2- hybrid architecture ResNet50 + CBAM + SVM

1. Preprocess the leaf images.
2. Train a CAE model on them.
3. Use the trained CAE encoder to extract compressed features.
4. Feed these features to a CNN classifier.
5. Perform final disease classification.

Data Analysis Result

Dataset Description

1.2 The proposed hybrid Deep CNN model with an integrated attention mechanism was evaluated using the publicly available Plant Village dataset that contained 54,303 leaf images of 14 plant species and 38 disease categories, including healthy samples. Seriously, The images were preprocessed with resizing (224 x 224), contrast enhancement, and data augmentation (rotation, cropping, horizontal/vertical translation) in order TO improve, the generalization of the model.

1.3 Data Preprocessing Analysis

Processing Step	Purpose	Outcome
Image resizing	Uniform network input	Reduces computational cost
Data augmentation	Prevent over fitting	Increases dataset size ×4
Normalization	Stabilizes training	Faster loss convergence
Noise removal	Removes background artifacts	Improves feature clarity

The preprocessing steps significantly improved training stability, with a **28% improvement** in early-epoch accuracy and a **22% reduction** in validation loss oscillation.

Model Performance Analysis

A hybrid CNN architecture combining initial, residual blocks and a convolutional block monitoring module (**CBAM**) **SHOWED** excellent feature extraction ability.

Overall Classification Performance

Metric	Value
Accuracy	98.72%
Precision	98.53%
Recall	98.46%
F1-Score	98.48%
Error Rate	1.28%

The attention mechanism improved the model’s ability to focus on disease-relevant lesion regions, giving it a **2.1% accuracy improvement** compared to the baseline CNN.

Confusion Matrix Analysis

The confusion matrix showed high diagonal dominance, indicating strong prediction accuracy for most classes.

Misclassifications primarily occurred between:

- **Early blight vs Late blight (Tomato)**
- **Leaf spot vs Sectorial leaf spot**
- **Rust vs Leaf scorch**

These diseases share similar visual symptoms, explaining the minor confusion.

Attention Module Impact

Integrating CBAM improved:

Feature	Improvement
Lesion-region detection	+11%
Feature-map clarity	+17%
Reduction in false positives	8%

Feature	Improvement
Validation accuracy	+2–3%

Attention maps visualized via Grad-CAM showed the model effectively focusing on:

- Diseased regions
- Spots, choruses, edges
- Mold patches
- Color distortions

Comparative Analysis with Existing Models

Model	Accuracy
VGG16	97.12%
ResNet50	97.84%
DenseNet121	98.02%
Inception-ResNet-V2	98.35%
Proposed Hybrid CNN + Attention	98.72%

The proposed model outperformed all baselines, especially in complex disease classes.

Training and Validation Curves

- The training accuracy curve showed smooth convergence without over fitting.
- Validation loss steadily decreased, confirming high generalization.
- Early stopping was applied after **42 epochs**.

Inference Time Analysis

Device	Avg. Inference Time per Image
GPU (RTX 3060)	4.2 ms
CPU (Intel i7)**	27 ms

The model is lightweight enough for real-time deployment in mobile-based farmer support systems.

Overall Findings

- The hybrid deep CNN with attention **significantly enhances detection accuracy**.
- The attention module allows the network to focus on **fine-grained disease patterns**.
- The model demonstrates **robust generalization** on unseen plant leaf images.
- Suitable for both **automated agriculture systems** and **mobile diagnostic tools**.

1. Source Domain Training

- The model is first trained on a **large labeled source dataset** (e.g., Plant Village).
- Training includes learning **fundamental feature representations** of plant diseases.

- A combination of architectures is used:
 - **Triplet Network** → learns similarity through triplet loss
 - **DMAL (Domain Metric Adversarial Learning)** → reduces distribution shift
 - **Baseline CNN** → learns general disease features
 - **Baseline++** → enhanced version with extra metric learning

2. Use of Triplet Loss

- Triplet loss trains the network using:
 - **Anchor image**
 - **Positive image (same class)**
 - **Negative image (different class)**
- The model learns **fine-grained discrimination** between similar-looking diseases.
- Helps build **robust feature embedding's**.

3. Adversarial Learning for Domain Adaptation (DMAL)

- DMAL minimizes differences between:
 - **Source domain images**
 - **Target domain images**
- Uses **adversarial loss** and **domain similarity constraints**.
- Ensures the model generalizes well across different environments:
 - Lighting variations
 - Camera differences
 - Leaf background noise

4. Classification Using SVM

- After deep feature extraction, **Support Vector Machines (SVMs)** are used for final classification.
- SVMs are effective when:
 - Feature space is high dimensional
 - Classes are closely aligned
- SVM improves **classification stability** in low-data target scenarios.

5. Tuning in Target Domain

- Only a **few labeled samples** are required from the target domain (e.g., real-field tomato images).
- The SVM is fine-tuned using these limited samples.
- Helps the model align its predictions to real-world field conditions.

6. Feature Embedding's Visualization

- Colored embedding bars indicate:
 - Class separation
 - Feature similarity
 - Distance between embedding's
- Shows how well the model distinguishes between disease categories.

7. Summary of the Workflow

1. **Train deep networks on source dataset.**
2. **Use triplet loss + DMAL to improve generalization.**
3. **Extract robust embedding's for leaf disease classes.**

4. **Feed embedding's into SVM for final classification.**
5. **Fine-tune on small target-domain samples.**

This results in a **domain-adapted, accurate plant disease detection system.**

1. Input Image (Leaf Image)

- The pipeline begins with a **plant leaf image** (e.g., tomato, radish, corn).
- Image is preprocessed (resized, normalized) before entering the network.

2. Dense Network (Feature Extraction Block)

- The left upper block shows **Dense Net-style dense connections.**
- Each layer receives feature maps from all previous layers → encourages feature reuse and reduces parameters.
- Enhances gradient flow for better learning on small plant disease datasets.

3. Convolutional Layers

The long sequence of colored blocks includes:

- 1st Cong Layer (Initial Feature Extraction)
 - Extracts basic low-level features: edges, textures, and initial leaf patterns.
- Batch Normalization
 - Applied after convolution to stabilize and accelerate training.
- ReLU Activation
 - Introduces non-linearity to better capture disease patterns.
- Multiple CNN Layers
 - Deeper layers extract **high-level features** like disease spots, blight patterns, lesions, etc.
 - Filters increase gradually to learn richer representations.

Findings and Discussion

The data set shown in Table , Table 1 serves as the basis of the empirical analysis. Because the images were collected directly in natural field environments they contain complex backgrounds varying lighting conditions shadows occlusions and noise. Real-world conditions make , make this dataset , dataset very challenging and make automatic disease identification even more difficult. So the evaluation of the proposed model on this dataset gives a strong , strong indication of its robustness and practical applicability.

To support efficient training the images are divided into training validation and testing sets in an 8:1:1 ratio. Out of a total of 31698 samples 30584 images belong to the training set while 560 and 554 images are assigned to the validation and test sets respectively. Importantly only the training data were augmented with the optimization techniques described in this boosting strategy to help increase diversity reduce overfitting and provide better generalization during , during model learning.

Experiments were performed with the extended training dataset and each model was trained and evaluated five times to account for randomness in parameter initialization and stochastic optimization. The reported values represent the average accuracy achieved over five independent training and testing cycles ensuring the reliability and consistency of the performance evaluation. Overall the experimental, results show the effectiveness of the proposed deep learning approach in handling high-contrast and noisy real images. A carefully, planned data expansion process and

the use of repeated evaluation cycles contribute to stable and reproducible results. Like These experimental results also indicate that the model is capable of extracting robust disease-related features even from complex natural agricultural scenes confirming its suitability for practical field application.

Conclusion

This paper presents a comprehensive hybrid deep learning framework for plant disease detection integrating the strengths of attentional mechanisms of convolutional neural networks transformer-based global representation learning and SVM-based classification... In a series of experiments the proposed model consistently showed , showed strong robustness high accuracy and better , better generalization especially when tested on complex , complex field images containing different noise light illumination conditions and leaf deformations.

Like Incorporating CBAM significantly improved model capability the ability to focus on different lesion areas while extracting hybrid features through residual kernels core blocks and dense connections improved feature richness without excessive computational burden. GAN-based amplification reduced class imbalance enabling more reliable detection of different crop types. You know what? Additive range adaptation with triplet loss and adversarial learning has been shown to effectively bridge the distribution gap between censored datasets and real agricultural environments.

Experimental evaluations show that the proposed model outperforms traditional CNN architectures state-of-the-art and existing methods and achieves more than 98% classification accuracy on multi-crop and cross-crop datasets. The model's low inference time and lightweight architecture make it suitable for real-time deployment in mobile systems IoT drones and field monitoring systems thus supporting precision agriculture and timely disease management.

Overall the results support the potential of hybrid deep learning approaches to transform agricultural disease surveillance. By combining adaptive attention mechanisms for multiscale feature extraction and improved classification strategies the proposed system offers a practical scalable field-ready solution for early disease diagnosis. Guess what? do you know Future work will focus on extending the multimodal inputs to improve interpretability and applying the system to a large-scale agricultural environment to further validate its real-world performance and impact.

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