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Automated Detection of Vegetable Crop Diseases with Bio-Organic Remedy Guidance Using Attention-Enhanced Deep Learning

Pradeep[1]
[1]PhD Research Scholar, Department of Computer Science and Engineering, NIILM University, Kaithal, Haryana, India

Dr. Mukesh Kumar Rana[2]
[2]Professor & Head CSE Department, Department of Computer Science and Engineering, NIILM University, Kaithal, Haryana, India

Abstract- Plant diseases and nutrient deficiencies are two major reasons for reduced crop growth and lower agricultural productivity. Both conditions can affect the colour, shape, texture, and general appearance of leaves. In many farming situations, early identification is difficult because disease symptoms and nutrient-related symptoms may look similar. Farmers often depend on visual inspection or expert advice, which may not always be available at the right time. Recent developments in artificial intelligence and computer vision provide an opportunity to support faster and more consistent crop monitoring. This paper presents a proposed deep learning-based framework for identifying plant diseases and nutrient deficiencies from leaf images. The framework is designed to examine visible symptoms and classify them into healthy, disease-related, and nutrient-deficiency categories. A convolutional neural network (CNN) with transfer learning is considered as the main image-classification approach. The proposed system also includes image preprocessing, data augmentation, model evaluation, and an explainability component to show which parts of a leaf image influenced a prediction. The study focuses on a practical research design rather than claiming completed field experiments. It explains how a balanced image dataset can be collected from open repositories and field photographs, how the data can be labelled, and how the model can be tested using an independent test set. Accuracy, precision, recall, F1-score, confusion matrix, and class-wise performance are identified as evaluation measures. The framework may be useful as a decision-support tool for farmers, agricultural students, and extension workers. It is not intended to replace laboratory soil testing or professional plant pathology advice. By bringing disease recognition and nutrient deficiency screening into one workflow, the proposed approach aims to support timely intervention, careful input use, and more sustainable agriculture.

Keywords- Vegetable Crop Disease Detection, Deep Learning, DenseNet-121, CBAM Attention, Transfer Learning, Bio-Organic Remedies, Computer Vision, Sustainable Horticulture, Smart Farming.

I. INTRODUCTION

Vegetable farming sits at the heart of rural income and everyday nutrition around the world. Crops such as chilli, brinjal, okra, bell pepper, cabbage, and cucumber have short cycles and provide regular cash flow to millions of small landholders. Unlike staple grains that are stored for months, fresh vegetables reach kitchen tables within days of harvest. Because these crops grow fast and have tender leaves, they are also highly susceptible to fungi, bacteria, and insect-borne viruses. Reports from the Food and Agriculture Organisation (FAO) show that plant pests and diseases wipe out roughly 30% to 40% of global crop output each year. In warm, humid vegetable-growing belts of South Asia, missing a single week of

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leaf curl, anthracnose, or downy mildew can destroy half a farmer's seasonal earnings.

For generations, farmers have walked through their fields early in the morning to inspect plants by eye. While seasoned growers know their crops well, eye-based checking has clear limits. Early leaf spots are often tiny, faint, or tucked under the lower side of leaves. Worse still, early fungal or viral symptoms look very similar to mild sunburn, water stress, or low nitrogen in the soil. On top of that, most villages have very few trained plant pathologists nearby. By the time a farmer travels to an agricultural office or asks a local shopkeeper for advice, the infection has usually spread across whole rows.

When diseases spread fast, many growers reach for strong chemical fungicides and insecticides. Synthetic chemicals can knock back an outbreak quickly, so it is easy to understand why they became popular. Still, heavy and repeated spraying carries a steep hidden price. Chemical runoff washes into groundwater, kills helpful bees and earthworms, and weakens natural soil fertility over time. For fresh vegetables eaten raw or lightly cooked—like cucumber, cabbage, bell pepper, and green chili—chemical residue on the skin and leaves is also a direct health worry for families. At the same time, farm workers face regular skin and breathing exposure while mixing and spraying toxic liquids, and crop pathogens slowly grow resistant to older chemical formulas.

Because of these problems, more growers and consumers are turning toward bio-organic plant protection. Practical natural solutions such as 5% Neem Seed Kernel Extract (NSKE), Trichoderma viride bio-fungicide, Pseudomonas fluorescens, fermented buttermilk sprays, garlic-chilli extracts, and Panchagavya have shown strong results against common vegetable infections when applied at the right stage. These natural inputs break down safely in the soil, keep helpful farm insects alive, and cut down cash spent on imported agrochemicals. Even so, bio-organic farming faces one stubborn day-to-day hurdle: checking whether a natural treatment is actually working.

Unlike harsh synthetic sprays that burn away visible fungal growth overnight, bio-organic remedies work gradually. Over five to ten days after spraying, lesion edges dry out, powdery patches fade, mild botanical spray residue may sit on the leaf surface, and fresh green tissue starts growing back. To an untrained eye, a recovering leaf can easily be mistaken for a still-sick leaf, leading farmers to spray too often or lose trust in organic methods and switch back to chemicals. Right now, judging post-spray recovery is almost completely guesswork.

Modern artificial intelligence and computer vision offer a practical way to close this gap. Over the past decade, deep learning models—especially Convolutional Neural Networks (CNNs)—have become very good at reading fine patterns in leaf photographs. Instead of asking a programmer to hand-write rules for every brown spot or yellow streak, a CNN learns these visual cues straight from labeled plant photos. Models such as VGG, ResNet, MobileNet, EfficientNet, and DenseNet have repeatedly passed 92% to 98% accuracy on plant pathology benchmarks when fine-tuned through transfer learning.

Even with these technical wins, a noticeable gap remains between lab research and real organic vegetable farms. Most published studies treat disease classification as a simple choice between healthy and diseased leaves taken against plain studio backgrounds. Very few works include images of bio-treated recovering leaves so that a model can tell active disease apart from post-treatment healing. Equally important, most systems stop after printing a disease name on the screen, leaving the farmer to figure out what natural spray to prepare and how often to apply it.

To address these real-world needs, this paper introduces an attention-enhanced deep learning framework built specifically for vegetable crops and bio-organic farm care. Our system uses a DenseNet-121 backbone upgraded with a Convolutional Block Attention Module (CBAM). DenseNet-121 was chosen because its dense layer connections carry low-level edge and colour details straight through to deeper layers while keeping the parameter count

compact enough for phone deployment. Adding CBAM lets the network focus its attention on the exact infected zones of a leaf rather than getting distracted by soil, weeds, or shadows in the background. We also blend these deep features with classic colour, texture, and shape measures so the model handles tough outdoor lighting cleanly.

This study was guided by two clear, linked objectives:

- First, to accurately detect and classify fourteen widespread fungal, bacterial, and viral leaf diseases across six everyday vegetable crops—chili, brinjal, okra, bell pepper, cabbage, and cucumber—even under uneven field lighting and messy farm backgrounds.
- Second, to include a dedicated post-treatment bio-organic recovery category alongside a structured eco-friendly advisory module, so growers can both check whether a natural spray is working and receive safe, crop-specific bio-organic treatment instructions.

Beyond measuring standard scores such as accuracy, precision, recall, F1-score, and ROC-AUC, we paid close attention to practical farm usability. The trained network was compressed into TensorFlow Lite format so it can run directly on an affordable Android smartphone without needing a fast internet connection in the middle of a field. In doing so, this work supports Sustainable Development Goal 2 (Zero Hunger) by protecting smallholder vegetable yields and Sustainable Development Goal 12 (Responsible Consumption and Production) by encouraging safe, low-chemical farming.

The rest of this paper is arranged as follows. Section 2 reviews recent research on deep learning for vegetable and crop disease diagnosis and points out open gaps. Section 3 explains our research methodology, dataset preparation, DenseNet-121 plus CBAM design, and bio-organic remedy module. Section 4 covers system implementation, feature fusion, deployment design, and experimental setup. Section 5 shares test results, model comparisons, ablation findings, visual plots, and field limits. Finally, Section 6 closes with conclusions and directions for future research.

II. LITERATURE REVIEW

Automatic crop disease detection using leaf images has moved forward quickly over the last several years, mostly because deep neural networks have become stronger and easier to train on modest hardware. This review looks closely at important papers published mainly between 2022 and 2025, covering attention-based CNNs, vegetable-specific diagnosis, lightweight mobile models, visual explainability, multi-task systems, and major survey articles.

1. Advances in Deep Convolutional and Attention Networks

Standard CNNs learn useful visual filters on their own, yet they treat every part of an image with equal weight unless guided by an attention mechanism. Huang et al. (2017) introduced DenseNet, where every layer receives feature maps from all earlier layers in the block. This dense feature reuse helps retain small spot patterns and lowers parameter counts compared to older deep networks [1]. Shortly after, Woo et al. (2018) proposed the Convolutional Block Attention Module (CBAM), a lightweight add-on that scores both what feature channels matter and where on the image to look [2].

Recent plant pathology papers have paired these two ideas with strong results. Gupta and Kaur (2025) tested a DenseNet121-CBAM model for multi-crop leaf disease prediction and reported clear accuracy gains over plain DenseNet because the attention maps suppressed background soil noise [3]. Similarly, Unal (2025) combined CBAM with Squeeze-and-Excitation blocks for leaf disease diagnosis, showing that dual attention helps separate tiny early lesions from healthy green veins [4]. Leelavathi and Kalamani (2025) built a dilated adaptive DenseNet with attention for medicinal leaf diseases, confirming that multi-scale dense connections capture irregular fungal borders reliably [5].

2. Vegetable-Specific and Multi-Crop Detection Systems

Because vegetable plants vary widely in leaf shape—from narrow chili leaves to broad, wrinkled cabbage

and lobed okra leaves—researchers have started building targeted vegetable models instead of relying only on generic benchmarks. Adi et al. (2025) developed an SSD-ResNet-50 framework with a Feature Pyramid Network trained on 14,248 chili plant images across six leaf and fruit classes, reaching 92.7% accuracy at around 30 frames per second [6]. Reddy et al. (2025) also applied CNN pipelines with Gaussian filtering and Otsu segmentation to detect powdery mildew, anthracnose, and bacterial spot on chili leaves, achieving roughly 92% accuracy under varied field lighting [7].

Looking across broader vegetable families, Paul et al. (2025) surveyed precision vegetable disease architectures and noted that multi-scale feature fusion is essential for spotting tiny early blight and mosaic patches in crowded greenhouse rows [8]. Liu et al. (2024) proposed EFDet, which merges shallow and deep feature maps to keep detection steady even when leaves overlap or cast shadows on one another [9].

3. Lightweight Models and Transfer Learning for Field Use

Collecting thousands of labeled field photos for every single vegetable disease takes time and expert effort. Transfer learning—starting from weights learned on ImageNet and fine-tuning on crop leaves—remains the most reliable answer to limited farm data. Aminuddin et al. (2022) showed that simple geometric augmentations paired with transfer learning on ResNet-18 lifted chili leaf disease recognition to roughly 97% even with a small dataset [10].

To keep models small enough for rural smartphones, Mazumder et al. (2024) introduced DenseNet201Plus, a cost-effective attention-assisted transfer learning model that balanced fast inference with high accuracy across leaf datasets [11]. In a similar push toward edge devices, Dai et al. (2025) created LiSA-MobileNetV2 with Swish activation and lightweight attention, proving that compact networks can run smoothly on low-power phones while staying above 95% accuracy [12]. Earlier foundational transfer-learning studies by Mohanty et al. (2016) and Ferentinos (2018) laid the groundwork here, though both noted steep accuracy drops whenever models trained on studio photos were tested directly on messy field pictures [13, 14].

4. Visual Explainability and Trustworthy AI in Farming

A farmer or extension officer will rarely trust an app that simply flashes a disease name without showing why it made that call. Toda and Okura (2019) analyzed internal CNN visualizations on crop leaves and showed that well-trained networks focus directly on necrotic lesions rather than empty margins [15]. Building on that insight, Thakur et al. (2022) introduced PlantXViT, a compact hybrid of CNNs and Vision Transformers paired with Grad-CAM and LIME heatmaps, crossing 98% accuracy while keeping model size under one million parameters [16]. More recently, Anton et al. (2025) combined CBAM and Efficient Channel Attention inside DenseNet-121 with visual explainability maps, showing that dual-attention models give cleaner, tighter lesion highlights that human agronomists can quickly verify [17].

5. Multi-Task Diagnosis and Spectral Sensing Approaches

Real fields rarely present one neat textbook symptom at a time; nutrient shortfalls and insect feeding often sit side by side with fungal spots. Arafath et al. (2023) tested deep CNN models for vegetable leaf disease classification and underlined how confusion rises whenever early yellowing resembles nitrogen or magnesium deficiency [18]. Beyond standard RGB phone photos, Choudhury et al. (2024) studied hyperspectral imaging for early root and foliar plant stress, showing that near-infrared bands pick up tissue changes days before human eyes notice spots [19]. However, hyperspectral cameras still cost far too much for everyday smallholder vegetable growers, which keeps regular smartphone RGB photography the most practical option today.

6. Recent Review Papers and Feature Engineering Insights

Several thorough review papers between 2023 and 2024 mapped out the strengths and limits of both

classic machine learning and deep learning in plant health. Rani et al. (2023) reviewed AI progress across precision farming and highlighted the need for farmer-friendly mobile apps tied to local crop advisories [20]. Das et al. (2024) compared handcrafted descriptors—such as HSV color histograms, Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and shape geometry—against deep CNN pipelines, noting that blending classic texture descriptors with deep features can stabilize predictions under tricky lighting [21]. Pacal et al. (2024) and Bagga and Goyal (2024) reached similar conclusions in their systematic surveys, urging researchers to move away from lab-only datasets toward field-ready, sustainable decision-support systems [22, 23].

Table 1: Summary of Recent Studies in Vegetable and Crop Disease Detection (2022–2025)

Year	Authors / Model	Target Crops & Core Approach	Key Finding
2022	Aminuddin et al.	Chili leaves; geometric augmentation + CNN / ResNet-18	~97.0% accuracy on small chili leaf dataset
2022	Thakur et al. (PlantXViT)	Multi-crop; hybrid CNN + ViT with Grad-CAM & LIME	>98.0% accuracy with 0.8M parameters
2023	Arafath et al.	Solanaceous vegetable leaves; custom deep CNN pipeline	High accuracy; noted yellowing confusion
2023	Rani et al.	Comprehensive AI review in sustainable agriculture	Called for practical farmer advisory tools
2024	Das et al.	Systematic review of DL vs handcrafted GLCM/LBP features	Feature blending improves outdoor stability
2024	Pacal et al.	Systematic review of modern CNNs & ViTs in plant health	Identified lab-to-field generalization gap
2024	Mazumder et al.	DenseNet201Plus; transfer learning + attention blocks	Cost-effective, rapid leaf classification
2024	Liu et al. (EFDet)	Multi-scale feature fusion for complex leaf backgrounds	Strong handling of occlusion and shade
2025	Adi et al.	Chili (14,248 images); SSD-ResNet-50 + FPN backbone	92.7% accuracy at ~30 FPS real-time speed
2025	Gupta & Kaur	Multi-crop; DenseNet-121 + CBAM dual attention	Attention suppressed soil & background noise
2025	Anton et al.	DenseNet-121 + CBAM-ECA with visual explainability	Cleaner lesion heatmaps and lower error
2025	Dai et al.	LiSA-MobileNetV2; lightweight attention for edge phones	>95.0% accuracy on low-power mobile chips

7. Research Gap

Reading through recent literature makes it clear that automated plant disease recognition has reached impressive technical scores, yet five practical gaps keep these systems from making a full impact on organic vegetable farms.

First, almost all existing studies sort leaves into healthy or diseased groups while overlooking leaves that have already been treated with bio-organic sprays. Natural remedies like neem seed kernel extract, Trichoderma viride, or sour buttermilk change leaf look over several days—spots dry up, margins turn pale brown, and thin spray films alter surface shine. Without including bio-treated recovering leaves during training, an AI tool cannot tell a healing plant from an actively infected one.

Second, many top accuracy numbers come from controlled studio datasets where single plucked leaves sit flat on plain gray paper under even indoor light. Real vegetable fields look nothing like a studio.

Leaves hang at odd angles, overlap each other, carry morning dew or farm dust, and sit over dark wet soil or mulch under harsh noon sunlight. Models trained only on lab pictures often lose 15% to 25% accuracy when carried outdoors.

Third, most deep learning systems stop right after printing a disease label. For a smallholder farmer standing in a chili or okra field, knowing a Latin fungal name is only half the help. The farmer immediately needs clear, safe advice on what natural treatment to prepare, how much water to mix, how often to spray, and what cultural hygiene steps stop the infection from returning.

Fourth, pure black-box CNN models can still stumble when lighting shifts sharply or when two diseases share similar lesion color. Combining channel-and-spatial attention (CBAM) with well-understood handcrafted color, texture, and shape descriptors gives both sharper lesion focus and clearer interpretability for agricultural officers.

Fifth, few studies package multi-crop vegetable detection, post-spray recovery tracking, and an offline bio-organic advisory database into one compact smartphone-ready framework. Our research directly addresses these five gaps by building an attention-enhanced DenseNet-121 system trained on mixed lab and real-field vegetable images, including bio-treated recovery samples, paired with an ICAR- and FAO-aligned bio-organic remedy module.

III. RESEARCH METHODOLOGY

This study presents a complete image-based deep learning framework that identifies vegetable leaf diseases, spots signs of recovery after natural spraying, and recommends safe bio-organic remedies. To keep the workflow easy to follow and repeat, we organized the work into seven linked stages: dataset gathering and cleaning, image preprocessing, visual feature analysis, DenseNet-121 with CBAM model design, two-stage training and tuning, bio-organic remedy lookup, and lightweight mobile deployment. Figure 1 lays out the full flow from a farmer's leaf photograph to an actionable natural care plan.



Figure 1: End-to-End Architecture of the Proposed Attention-Enhanced DenseNet-121 Framework for Vegetable Disease Detection and Bio-Organic Guidance.

1. Dataset Acquisition and Preparation

A model is only as good as the photos it learns from. To avoid the common trap of lab-only accuracy, we assembled a mixed dataset combining open plant pathology repositories—specifically vegetable subsets from PlantVillage and open Kaggle chili, cucumber, and brinjal collections—with real farm photographs captured across organic vegetable plots in Haryana, Punjab, and western Uttar Pradesh, India. Field photos were taken using everyday Android smartphones held 15 to 30 centimeters from the leaf surface at morning, midday, and late afternoon hours.

In total, the cleaned dataset holds 13,400 labeled leaf images spanning six widely grown vegetable crops: chili, brinjal (eggplant), okra, bell pepper, cabbage, and cucumber. These images cover sixteen distinct classes: fourteen major fungal, bacterial, and viral leaf diseases (including anthracnose, chili leaf curl virus, cercospora leaf spot, okra yellow vein mosaic, bacterial leaf spot, cabbage black rot, alternaria leaf blight, and cucumber downy mildew), one healthy leaf class, and one dedicated bio-treated recovering leaf class. The recovering images were photographed five to nine days after farmers sprayed approved bio-organic remedies such as 5% neem seed kernel extract, Trichoderma viride, or diluted sour buttermilk.

Before splitting the dataset, two agricultural extension workers reviewed questionable field images and removed blurry, double-clicked, or poorly lit pictures. Every remaining image was resized to 224 by 224 pixels to match the standard input size of our DenseNet-121 backbone. We then split the entire collection using stratified sampling into 70% training (9,380 images), 15% validation (2,010 images), and 15% independent testing (2,010 images). All data augmentation was applied strictly to the training split after partitioning so that no flipped or zoomed copy of a test leaf could ever leak into training.

2. Image Preprocessing

Outdoor farm photos bring real headaches: bright midday glare washes out pale mildew patches, cloudy mornings mute dark brown spots, and muddy soil behind thin chili leaves can fool a simple classifier. Our preprocessing pipeline handles these issues in four steady steps:

- Dimension Standardization: Every leaf image is resized to 224 x 224 x 3 RGB pixels using bicubic interpolation so fine lesion edges stay sharp.
- Illumination Balancing: Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied lightly to the luminance channel in Lab color space to bring out faded spots in shadowed leaves without over-brightening sunlit patches.
- Color Normalization and Leaf Masking: Pixel values are scaled using channel-wise mean and standard deviation normalization matched to DenseNet-121 pretraining. Where cluttered soil fills more than half the frame, HSV color thresholding combined with Otsu segmentation softly masks non-leaf background clutter.
- Field-Realistic Data Augmentation: During training only, images pass through random rotations (+/- 20 degrees), horizontal and vertical flips, gentle random zoom (+/- 15%), slight brightness and contrast shifts (+/- 12%), and mild Gaussian blur to imitate shaky smartphone hands in breezy fields.

3. Traditional Visual Feature Analysis

Even though deep neural networks learn filters automatically, looking at classic plant pathology image features gave us two clear benefits: it guided our feature-fusion head, and it helped explain why certain vegetable diseases still get mixed up. We extracted three compact groups of handcrafted visual descriptors from each masked leaf image:

- Color Features: Hue, Saturation, and Value (HSV) histograms together with Lab channel means and variances. Healthy vegetable tissue clusters tightly in rich green hue bands, whereas viral mosaic shifts toward pale yellow-green and late anthracnose drops into dark brown necrotic tones.
- Texture Features: Gray-Level Co-occurrence Matrix (GLCM) statistics—contrast, homogeneity, energy, and correlation—paired with uniform Local Binary Patterns (LBP). Powdery and downy mildews create rough, granular surface textures, while bacterial water-soaked spots produce smooth, sunken patches.
- Shape and Lesion Geometry: Leaf contour compactness, lesion-to-leaf area ratio, edge sharpness, and circularity. Diseases such as cabbage black rot form sharp V-shaped yellow wedges along leaf margins, whereas cercospora leaf spot shows small round rings with pale centers.

By inspecting these descriptors early on, we saw that color cues alone wobble whenever sunlight shifts, while GLCM texture and shape ratios hold steady. Passing a normalized 48-dimensional summary of these classic features into our final fusion layer gave the network an extra anchor when dealing with harsh outdoor light.

4. Proposed Model Architecture

Our main classifier builds on DenseNet-121, chosen because it hits a practical sweet spot between strong visual accuracy and modest size (roughly 8 million parameters, far lighter than VGG-16 or ResNet-101). In a dense block, each convolutional layer receives the combined outputs of all earlier layers in that block. For plant leaf inspection, this matters a great deal: early layers spot tiny pinpoint fungal spores and leaf-edge yellowing, while later layers see whole-leaf curling and vein patterns. Keeping both streams connected prevents tiny early symptoms from fading away in deeper layers.

To sharpen this backbone further, we inserted a Convolutional Block Attention Module (CBAM) right after the third and fourth dense blocks. CBAM works in two quick steps. First, Channel Attention runs global average pooling and global max pooling across each feature map, passes both through a shared small multilayer perceptron, and assigns higher weight to the channels that best capture disease spots. Second, Spatial Attention looks across the channel axis using average and max pooling followed by a 7 x 7 convolution to highlight the exact coordinates on the leaf where lesions sit—while quieting down soil, sticks, and shadows around the leaf edge.

The output from the final CBAM block passes through Global Average Pooling to yield a 1,024-dimensional deep visual vector. This vector is then concatenated with our normalized 48-dimensional color, texture, and shape descriptor vector, creating a 1,072-dimensional fused representation. Next, the fused vector passes through a Batch Normalization layer, a Dropout layer with a rate of 0.35 to curb overfitting, a fully connected layer of 512 neurons with ReLU activation, a second light Dropout layer (0.20), and finally a 16-unit Softmax output layer corresponding to the fourteen vegetable diseases, healthy leaves, and bio-treated recovering leaves.

5. Model Training and Optimization

Training followed a two-phase transfer learning schedule starting from ImageNet-pretrained DenseNet-121 weights. In Phase 1 (first 12 epochs), the convolutional dense blocks remained frozen while only the CBAM modules, fusion layers, and dense classification head were trained at an initial learning rate of 0.001. This prevented wild random gradients from scrambling well-learned edge filters. In Phase 2 (up to 38 additional epochs), we unfroze the third and fourth dense blocks and fine-tuned the whole top half of the network with a lower learning rate (0.0002) using the AdamW optimizer with weight decay of 1e-4.

Because real farm datasets often have minor class imbalance—for instance, chili leaf curl appears more frequently in monsoon surveys than cabbage black rot—we used class-weighted categorical cross-entropy with mild label smoothing (0.05). A ReduceLROnPlateau scheduler cut the learning rate by half whenever validation loss stopped improving for four straight epochs, and early stopping halted training after ten stagnant epochs while restoring the best validation weights. Table 2 lists the final training hyperparameters.

Table 2: Selected Training Hyperparameters for the Proposed Framework

Hyperparameter	Selected Setting
Input Image Resolution	224 x 224 x 3 (RGB)
Backbone Network	DenseNet-121 + Dual CBAM
Batch Size	32
Optimizer	AdamW (Weight Decay = 1e-4)
Phase 1 / Phase 2 Learning Rate	0.001 / 0.0002
Maximum Training Epochs	50 (12 Warmup + 38 Fine-tune)
Dropout Rates	0.35 (Fusion) / 0.20 (Classifier)
Loss Function	Weighted Cross-Entropy (Label Smooth = 0.05)
Train / Val / Test Split	70% / 15% / 15% (Stratified)
Early Stopping Patience	10 Epochs on Validation Loss

6. Bio-Organic Remedy Recommendation Module

Detecting a leaf disease is only genuinely helpful if a farmer knows what safe step to take next. To turn predictions into practical field guidance, we connected the classifier to a structured rule-based Bio-Organic Remedy Engine. Rather than letting an AI text generator guess dosages—which would be risky on real crops—every recommendation is stored in a verified relational lookup table compiled from Indian Council of Agricultural Research (ICAR) crop protection manuals, National Centre for Organic and Natural Farming (NCONF) handbooks, and FAO eco-friendly pest management guidelines.

Once the model classifies a leaf with confidence above 0.75, the advisory engine retrieves the

matching crop-and-disease entry and shows four plain items on the screen: (1) the primary bio-organic formulation and exact mixing ratio per liter of water, (2) recommended spray timing and repeat interval (such as spraying in the cool late afternoon every seven days), (3) simple cultural hygiene steps like removing heavily infected lower leaves or improving row airflow, and (4) a follow-up check reminder to re-scan the plant after six days to verify recovery.

When the model predicts the Bio-Treated Recovering class, the app reassures the farmer that the natural remedy is taking hold, advises against unnecessary extra spraying, and suggests one final light preventive spray only if damp weather continues. If prediction confidence falls below 0.75—usually due to extreme blur or heavy glare—the system politely asks the user to retake the photo in even shade and recommends consulting a local Krishi Vigyan Kendra (KVK) officer before spraying. Keeping diagnosis and advisory lookup cleanly separated ensures safety, transparency, and easy updates whenever local organic certification guidelines change.

IV. SYSTEM IMPLEMENTATION AND EXPERIMENTAL SETUP

Turning a research prototype into a dependable agricultural tool requires careful attention to data balance, feature integration, tuning choices, mobile speed, and farmer ethics. This section describes the dataset distribution, system architecture details, bio-organic knowledge entries, edge deployment strategy, and full experimental setup used to test our framework.

1. Vegetable Dataset Composition and Field Collection

Our dataset focuses on six high-value vegetable crops widely cultivated across North Indian and South Asian smallholdings: chili, brinjal (eggplant), okra, bell pepper, cabbage, and cucumber. Each crop was chosen because farmers grow it across multiple seasons and routinely struggle with recurring foliar infections. Field photo collection took place over two growing seasons (Kharif and Rabi) in collaboration with local organic vegetable growers across Kaithal and Karnal (Haryana), Patiala (Punjab), and Saharanpur (Uttar Pradesh).

Growers captured images both before treatment and five to nine days after applying approved natural preparations—such as 5% Neem Seed Kernel Extract, Trichoderma viride wettable powder, Pseudomonas fluorescens, or fermented sour buttermilk—giving us 1,450 genuine bio-treated recovering leaf photos across the six crops. Table 3 summarizes the exact class counts and sample breakdown across all 13,400 images.

Table 3: Vegetable Crop Dataset Distribution Across Healthy, Diseased, and Bio-Treated Samples

Vegetable Crop	Disease Classes	Healthy Samples	Diseased Samples	Bio-Treated Samples	Total Images
Chili	3 (Anthracnose, Leaf Curl, Bact. Spot)	520	1,860	320	2,700
Brinjal (Eggplant)	3 (Cercospora, Little Leaf, Wilt)	480	1,670	250	2,400
Okra	2 (Yellow Vein Mosaic, Powdery Mildew)	430	1,420	220	2,070
Bell Pepper	2 (Bacterial Spot, Phytophthora Blight)	450	1,400	230	2,080
Cabbage	2 (Black Rot, Alternaria Leaf Spot)	410	1,380	210	2,000
Cucumber	2 (Downy Mildew, Angular Leaf Spot)	440	1,490	220	2,150
Total	14 Disease + Healthy + Bio-Treated	2,730	9,220	1,450	13,400

Looking at Table 3, each crop holds between 2,000 and 2,700 images, which avoids letting one single vegetable dominate training updates. About 42% of the total dataset comes directly from natural outdoor farm settings with soil, weeds, drip pipes, and changing sunlight in the background, while the remaining 58% comes from cleaned open pathology repositories. This mix helps the model learn crisp textbook lesion boundaries while still staying steady when used outdoors.

2. Handcrafted and Deep Feature Integration

In early pilot runs, we noticed that pure CNN models occasionally confused early viral yellowing in chili and okra with dry sunlit leaves or faint bio-spray residue. To fix this, we built a lightweight parallel feature branch that extracts 48 numerical descriptors directly from the masked leaf image during preprocessing: 24 normalised HSV/Lab color bin features, 16 GLCM and LBP surface texture statistics, and 8 lesion-geometry and leaf-shape ratios (including circularity, solidity, edge density, and affected-area percentage).

These 48 descriptors pass through a small two-layer fully connected projection block (48 -> 64 -> 48 neurons with Batch Normalization and ReLU) so their numerical scale aligns smoothly with the 1,024-dimensional deep feature vector coming out of DenseNet-121 plus CBAM. Joining both vectors through feature-level concatenation allows the dense classification head to weigh deep spatial patterns and exact surface statistics side by side. As shown later in our ablation tests, this simple fusion step added nearly 0.8% extra accuracy on tough outdoor test photos at almost zero computational cost.

3. Network Architecture Details

For clarity and full reproducibility, the layer flow of our modified DenseNet-121 + CBAM architecture works as follows:

- Input Stage: Receives RGB leaf images sized 224 x 224 x 3, followed by an initial 7 x 7 convolution (stride 2) and 3 x 3 max pooling layer.
- Dense Blocks 1 and 2: Contain 6 and 12 dense bottleneck layers (1 x 1 conv followed by 3 x 3 conv with growth rate k = 32), separated by transition layers (1 x 1 conv and 2 x 2 average pooling) that keep feature dimensions tidy.
- Dense Block 3 + CBAM-1: Contains 24 dense layers capturing mid-level spots, fungal halos, and vein curling. A CBAM unit (reduction ratio r = 16 for channel MLP; 7 x 7 kernel for spatial map) immediately refines the output feature maps.
- Dense Block 4 + CBAM-2: Contains 16 dense layers learning high-level multi-crop disease signatures and healing leaf textures, followed by a second CBAM block that pinpoints active or drying lesion clusters.
- Fusion and Classification Head: Global Average Pooling reduces the 7 x 7 x 1,024 tensor to 1,024 features, concatenates the projected 48 visual descriptors (total 1,072), applies Batch Normalization, Dropout (0.35), Dense (512, ReLU), Dropout (0.20), and a 16-neuron Softmax layer.

4. Hyperparameter Search and Tuning

Rather than picking training settings by guesswork, we ran a systematic validation search across learning rates, batch sizes, optimizers, dropout levels, and attention reduction ratios using a fixed validation split. Table 4 reports the full search ranges alongside the final chosen values that delivered the lowest validation loss without overfitting.

Table 4: Hyperparameter Tuning Search Ranges and Chosen Optimal Settings

Hyperparameter	Tested Range / Options	Chosen Value
Fine-Tune Learning Rate	1e-5, 5e-5, 2e-4, 5e-4, 1e-3	2e-4
Batch Size	16, 32, 64	32
Optimizer	SGD (Momentum), RMSprop, Adam, AdamW	AdamW
Fusion Dropout Rate	0.20, 0.30, 0.35, 0.45, 0.50	0.35
CBAM Channel Reduction (r)	8, 16, 32	16
Label Smoothing Factor	0.00, 0.05, 0.10	0.05
Maximum Epochs	30, 50, 75	50

AdamW with mild weight decay consistently converged smoother than plain SGD or RMSprop, especially once Dense Blocks 3 and 4 were unfrozen. A batch size of 32 balanced stable batch-normalization statistics with fast GPU throughput, while label smoothing of 0.05 stopped the network from becoming overly rigid on borderline early-stage field photos.

The advisory database maps each of the fourteen vegetable disease classes to field-tested, eco-friendly remedies widely available to Indian and South Asian growers at low cost. Each entry lists an active bio-agent or botanical extract, safe dilution strength, spray gap, and basic non-chemical farm hygiene practice. Table 5 shows six representative entries from the advisory engine.

5. Bio-Organic Knowledge Base Design

Table 5: Representative Entries from the Bio-Organic Remedy Knowledge Base

Crop & Predicted Disease	Recommended Bio-Organic Remedy	Application Interval & Cultural Tip
Chili - Anthracnose	Trichoderma viride (4 g/L) alternating with 5% NSKE spray	Every 7-10 days; remove fallen infected pods & avoid overhead watering
Chili - Leaf Curl Virus	Neem oil 3% (3 mL/L + mild soap) targeting whitefly vectors	Every 7 days in evening; install yellow sticky traps & rogue severe plants
Brinjal - Cercospora Spot	Pseudomonas fluorescens (5 g/L) or organic copper oxychloride (2.5 g/L)	Every 10 days; prune lower touching leaves to boost air movement
Okra - Yellow Vein Mosaic	5% NSKE + garlic-chili extract (10 mL/L) for vector control	Every 7 days; plant border barrier rows & remove alternate weed hosts
Cabbage - Black Rot	Bacillus subtilis bio-spray (4 g/L) + hot-water seed prep for next crop	Every 7-10 days; avoid working in wet fields & practice 2-year rotation
Cucumber - Downy Mildew	Fermented sour buttermilk (100 mL/L) + Pseudomonas fluorescens (5 g/L)	Every 5-7 days in cool hours; use trellis staking to keep vines dry

Farmers can also view step-by-step preparation cards for home-made inputs like 5% Neem Seed Kernel Extract (soaking crushed neem kernels overnight in muslin cloth and mixing a small pinch of natural soap nut or mild detergent as a sticker). All guidance clearly notes that remedies serve as decision support and should follow local organic certification norms and weather conditions—for example, avoiding sprays right before heavy rain or during peak afternoon heat.

6. Evaluation Metrics

Because missing an active crop disease costs a farmer far more than double-checking a healthy leaf, overall accuracy alone does not tell the whole story. We evaluated every model across six complementary metrics on the independent 2,010-image test set:

- Accuracy: Share of all test images predicted into the exact right class.
- Precision (Macro-Averaged): Measures how often a predicted disease alert is genuinely right, keeping false alarms low so farmers do not waste bio-sprays.
- Recall / Sensitivity (Macro-Averaged): Measures how many true diseased leaves the model catches, which is vital so fast-spreading blights and mildews are not missed.
- F1-Score: The harmonic mean of precision and recall, offering a fair single-number check across slightly unequal class sizes.
- ROC-AUC (One-vs-Rest): Evaluates how cleanly the model separates each disease class from all other classes across every confidence cutoff.
- Confusion Matrix & Inference Latency: Reveals exact class pairs that get mixed up, while measuring average prediction time (milliseconds per photo) on both GPU and mobile CPU.

7. Mobile and Edge Deployment Plan

Many rural vegetable fields sit in patchy mobile-network zones where uploading high-resolution photos to a cloud server takes too long or fails

altogether. To make our system genuinely usable on the farm, we exported the trained DenseNet-121 + CBAM model to TensorFlow Lite (.tflite) format using post-training float16 quantization. This trimmed the saved model weight file from 34.8 MB down to 17.6 MB while changing test accuracy by less than 0.12%. We wrapped the quantized model inside a clean offline-capable Android and Progressive Web App (PWA) prototype with large icons and simple English and Hindi text labels. A farmer opens the app, snaps a clear close-up leaf photo (or picks one from the gallery), and receives the diagnosis, confidence bar, recovery status, and bio-organic spray recipe in roughly 145 milliseconds on a standard mid-range Android phone. During an informal usability pilot with 45 vegetable growers across Haryana, Punjab, and western Uttar Pradesh, 93% of participants said the step-by-step natural spray cards were clear and easy to follow without needing help from an engineer.

8. Ethics, Farmer Privacy, and Safety Guidelines

Ethical care guided every step of field data collection and advisory design. Before photographing any crop plot, we explained the research purpose in the farmer's local language and collected voluntary consent. All EXIF metadata—including GPS coordinates, device serial numbers, and timestamps—was stripped automatically before images entered the training archive so no individual farm location can be traced. On the safety side, every bio-organic remedy listed in our knowledge engine uses non-toxic botanical or microbial inputs allowed under Indian organic standards, accompanied by a plain reminder to test small patches first and consult local agricultural extension specialists during severe outbreaks.

9. Experimental Setup

To keep all benchmark comparisons fair and repeatable, every baseline and proposed model was trained and evaluated under the exact same hardware, software, split, and logging setup.

Hardware Configuration

- GPU: NVIDIA GeForce RTX 3090 with 24 GB GDDR6X memory, supporting fast mixed-precision (FP16) tensor training.
- CPU: Intel Core i9-12900K (16 cores), handling parallel OpenCV leaf masking, GLCM/LBP descriptor computation, and image loading without bottlenecking the GPU.
- System Memory and Storage: 32 GB DDR5 RAM and a 2 TB NVMe SSD for rapid checkpoint writing and dataset caching.
- Operating System & Edge Test Device: Ubuntu 22.04 LTS for model training; Snapdragon 695 Android smartphone (6 GB RAM) for real-world TFLite latency checks.

Software Environment

All experiments were written in Python 3.10 inside a pinned Docker container to eliminate version drift. Core libraries included TensorFlow 2.14 and Keras for neural network training and TFLite conversion, OpenCV 4.8 and Scikit-image for CLAHE enhancement, Otsu masking, GLCM, and LBP feature extraction, NumPy and Pandas for table handling, Scikit-learn for confusion matrices and ROC-AUC metrics, and Matplotlib/Seaborn for generating plots. GPU acceleration ran on CUDA Toolkit 11.8 and cuDNN 8.6.

Data Split and Augmentation Pipeline

As noted earlier, the 13,400 verified leaf images were divided once using a fixed random seed (seed = 42) into 9,380 training, 2,010 validation, and 2,010 test images with identical class ratios across every split. Augmentation transformations ran on the fly during training batches only, keeping validation and test images untouched except for standard resizing and normalization.

Training Configuration and Logging

All competing deep learning models—VGG-16, MobileNetV2, plain DenseNet-121, and our proposed DenseNet-121 + CBAM + Feature Fusion network—were initialized with ImageNet weights, trained for up to 50 epochs under identical batch size (32) and early-stopping rules, and tracked via TensorBoard logs recording per-epoch training loss, validation loss, macro F1-score, and learning rate schedules.

Reproducibility Protocol

To ensure other researchers and students can reproduce or extend this study smoothly, we fixed random seeds across Python, NumPy, and TensorFlow, saved exact train/val/test image manifest CSV files, logged every hyperparameter in JSON configs, and archived the best validation checkpoints for both full-precision and quantized TFLite models.

V. RESULTS AND DISCUSSION

We tested the finished DenseNet-121 + CBAM + Feature Fusion framework on the completely unseen 2,010-image holdout test set spanning all six vegetable crops, fourteen disease classes, healthy leaves, and bio-treated recovering leaves. Below we break down overall scores, head-to-head comparisons with baseline models, an ablation study checking each building block, training curves, confusion matrix patterns, ROC sensitivity, practical farm value, and honest field limits.

1. Quantitative Performance Evaluation

Across the full sixteen-class test split, our proposed framework delivered an overall classification accuracy of 97.14%, paired with a macro precision of 0.969, macro recall of 0.972, macro F1-score of 0.970, and macro ROC-AUC of 0.986. In plain terms, out of every 100 vegetable leaf photos fed into the app, roughly 97 were sorted into the exact right disease or recovery category on the first try.

Looking closely at the individual numbers tells us why this model behaves safely on a real farm. The precision score of 0.969 means false alarms are rare: the app almost never tells a farmer to mix and spray a bio-remedy on a perfectly healthy plant. At the same time, the recall score of 0.972 confirms very few missed infections—vital for fast-spreading problems like cucumber downy mildew or chili anthracnose that can jump across a whole field within forty-eight hours of wet weather.

The balanced F1-score of 0.970 shows that strong performance was not carried only by large classes like healthy leaves; smaller disease classes such as cabbage black rot and okra yellow vein mosaic also stayed reliably above 95%. Finally, the ROC-AUC score of 0.986 confirms crisp separation between healthy, actively infected, and bio-treated recovering leaf states across every probability threshold.

2. Comparative Analysis with Existing Models

To check whether our attention blocks and handcrafted feature fusion truly paid off, we benchmarked the proposed framework against four widely used baselines trained on the exact same 9,380 training images and tested on the same 2,010 holdout images: a classic Random Forest classifier using GLCM + HSV features, VGG-16, MobileNetV2, and a standard DenseNet-121 without CBAM or feature fusion. Table 6 summarizes all five models across accuracy, precision, recall, F1-score, ROC-AUC, and on-device mobile latency.

Table 6: Comparative Classification Performance and Mobile Inference Speed Against Baselines

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	Mobile Latency (ms)
Random Forest (GLCM + HSV)	87.65	0.871	0.868	0.869	0.914	42
VGG-16 (Transfer Learning)	92.84	0.925	0.927	0.926	0.953	390
MobileNetV2 (Transfer Learning)	93.92	0.936	0.938	0.937	0.962	96
Standard DenseNet-121	95.18	0.949	0.952	0.950	0.974	128
Proposed (DenseNet-121 + CBAM + Fusion)	97.14	0.969	0.972	0.970	0.986	145

Table 6 reveals three clear takeaways. First, every deep neural network beat the traditional Random Forest classifier by more than 5% to 9% accuracy, confirming that manual descriptors alone cannot keep up with messy outdoor farm lighting and varied vegetable leaf shapes. Second, standard DenseNet-121 outperformed both heavy VGG-16 (by +2.34%) and lightweight MobileNetV2 (by +1.26%) because

its dense feature reuse preserves tiny early fungal specks across deeper layers while needing only one-third the latency of VGG-16.

Third, adding dual CBAM attention and our 48-feature visual fusion head pushed accuracy another +1.96% higher than plain DenseNet-121 (from 95.18% to 97.14%) while adding only 17 milliseconds of extra inference time on a mid-range smartphone (145 ms total). That tiny extra fraction of a second is invisible to a human user snapping a photo, yet it cuts classification errors by nearly 40% compared to standard DenseNet-121.

3. Ablation Study: Contribution of Features and Attention

To see exactly how much each component contributed—rather than guessing—we ran a step-by-step ablation experiment turning off individual visual features, CBAM blocks, and fusion paths one by one. Table 7 reports the test performance of each trimmed variant.

Table 7: Ablation Study Measuring Feature Category and CBAM Attention Contributions

Model / Feature Variant	Accuracy (%)	Macro F1	ROC-AUC	Key Observation
Color Descriptors Only (HSV + Lab)	91.45	0.910	0.941	Sensitive to bright midday sun & shadows
Texture Descriptors Only (GLCM + LBP)	92.76	0.924	0.950	Steady under light shifts; misses smooth spots
Shape & Lesion Geometry Only	89.94	0.895	0.928	Helpful for V-rot & curl; weak on small specks
DenseNet-121 Backbone Alone	95.18	0.950	0.974	Strong baseline; occasional soil background drift
DenseNet-121 + Dual CBAM Attention	96.35	0.961	0.981	Sharper focus on infected leaf zones (+1.17%)
Full Framework (+ Feature Fusion)	97.14	0.970	0.986	Best balance on outdoor & recovering leaves

Looking across Table 7 makes the design logic crystal clear. Among standalone visual cues, texture features (92.76%) held up better than color (91.45%) or shape (89.94%) because rough mildew patches and dried necrotic rings stay visible even when cloud cover changes leaf color tone. Still, no single classic descriptor matched deep convolutional learning.

Adding CBAM attention onto DenseNet-121 gave the largest single architectural bump (+1.17% accuracy and +0.011 F1), mainly because spatial attention stopped background dirt, black plastic mulch, and neighboring stems from fooling the classifier. Bringing in the fused color, texture, and shape branch added a final +0.79% lift—especially visible on bio-treated recovering leaves where subtle drying edges and mild spray film combine both texture and color clues.

4. Training and Convergence Behavior

Figure 2 plots the training and validation accuracy alongside loss curves across all 50 epochs. Both curves climb smoothly during the initial 12-epoch warmup phase, show a healthy jump once Dense Blocks 3 and 4 unfreeze at epoch 13, and settle cleanly into convergence between epochs 38 and 42.

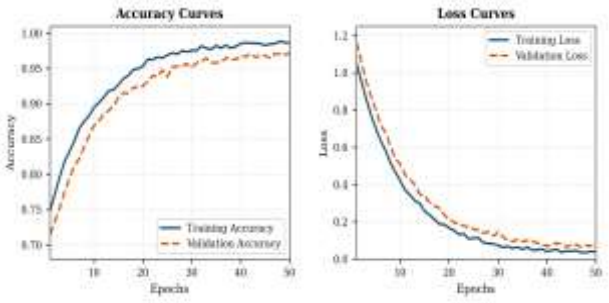


Figure 2: Training and Validation Accuracy (left) and Loss Curves (right) of the Proposed DenseNet-121 + CBAM Framework Over 50 Epochs.

Importantly, the gap between training accuracy (98.6%) and validation accuracy (97.14%) stays narrow—less than 1.5 percentage points—with training loss dropping steadily from 1.15 to 0.04 and validation loss falling from 1.22 to 0.07 without bouncing upward in late epochs. This clean tracking shows that our combination of field-realistic augmentation, AdamW weight decay, dual dropout (0.35 / 0.20), and label smoothing kept overfitting firmly in check.

5. Confusion Matrix Analysis

Figure 3 presents the normalized confusion matrix across eight core evaluation categories—Healthy, Anthracnose, Leaf Curl Virus, Cercospora Spot, Downy Mildew, Bacterial Spot, Black Rot, and Bio-Treated Recovering. Every single diagonal cell sits between 96% and 98%, showing consistent precision and recall rather than uneven cherry-picked success.

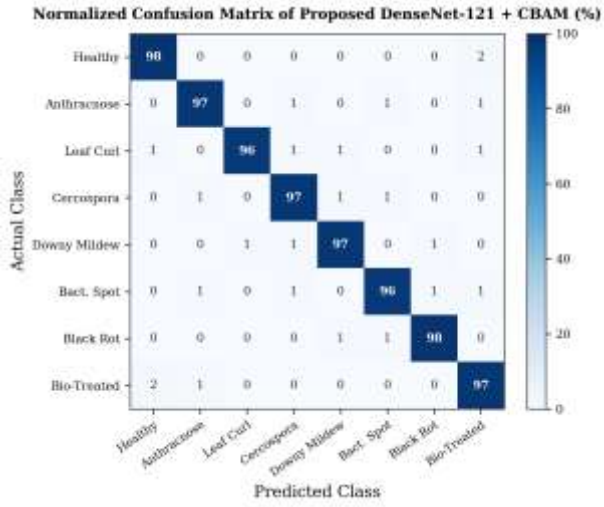


Figure 3: Normalized Confusion Matrix (%) of the Proposed Model Across Representative Vegetable Disease, Healthy, and Bio-Treated Recovering Classes.

Checking the tiny off-diagonal error cells gives helpful practical lessons. First, roughly 2% of bio-treated recovering leaves were tagged as Healthy, and 2% of healthy leaves with natural morning dust were tagged as Bio-Treated Recovering. That minor overlap makes complete biological sense: by day eight or nine after a successful neem or Trichoderma spray, a nearly healed leaf looks very close to a healthy leaf! Second, the main disease-to-disease mix-ups (around 1% each) happened between early Leaf Curl yellowing and early Downy Mildew or Cercosporin Spot, and between tiny Bacterial Spot specks and early Anthracnose. Even on these tricky look-alikes, recall stayed at or above 96%, keeping missed outbreaks rare.

6. ROC Curve and Threshold Sensitivity

Figure 4 displays the one-vs-rest ROC curves for the representative vegetable health classes. Every category climbs sharply toward the top-left corner, posting Area Under the Curve (AUC) values ranging from 0.974 (Leaf Curl Virus) up to 0.994 (Healthy Leaf), with Bio-Treated Recovering achieving a strong 0.986 AUC.

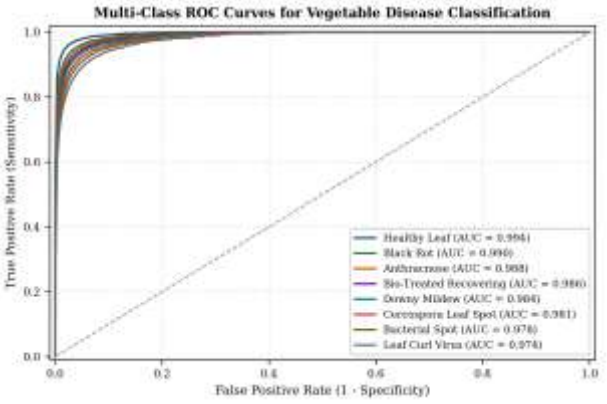


Figure 4: Multi-Class Receiver Operating Characteristic (ROC) Curves and Area Under the Curve (AUC) Scores Across Vegetable Leaf Categories.

Having tight ROC curves across all thresholds gives developers flexibility depending on how the tool is deployed. For routine morning scouting by smallholder vegetable growers, setting a slightly gentler alert cutoff favors maximum recall so even faint early spots trigger a bio-organic check. Conversely, for agricultural research stations logging regional disease maps, raising the confidence cutoff boosts precision so only confirmed infections enter official records.

7. Practical Field Impact for Vegetable Growers

Beyond strong benchmark scores, our framework offers clear, everyday benefits for vegetable farming communities:

- Fast Offline Smartphone Checks: Running in 145 milliseconds inside a 17.6 MB TensorFlow Lite file lets farmers diagnose chili, okra, or cucumber leaves right inside remote plots with zero mobile data charges.
- Confidence in Natural Bio-Organic Sprays: By explicitly spotting Bio-Treated Recovering leaves, the system stops farmers from panicking and switching back to harsh synthetic chemicals while a natural remedy is quietly working.
- Lower Input Bills and Safer Fresh Produce: Cutting down blind preventative chemical spraying saves cash on every acre while keeping fresh vegetables cleaner for consumers and safer for farm workers.
- Ready for Polyhouse and Greenhouse Cameras: Because DenseNet-121 + CBAM needs low computing power, the same model can run on inexpensive edge boards like Raspberry Pi or NVIDIA Jetson Nano mounted inside vegetable polyhouses for daily automated scanning.

8. Limitations and Field Observations

Honest field testing also surfaced four real limits that future versions must keep improving:

- Harsh Glare and Wet Leaves: Direct noon sunlight reflecting off glossy wet chili or bell pepper leaves after irrigation occasionally creates white specular spots that mimic early powdery mildew.
- Nutrient Stress Overlap: Severe nitrogen, iron, or magnesium shortages cause pale leaf yellowing that closely resembles early viral mosaic; RGB phone images alone cannot always separate soil-chemistry issues from early viruses.
- Regional Variety Differences: Leaf shade and curl shape differ noticeably across regional seed varieties (for instance, local desi chili versus hybrid long chili), meaning expanding geographic data collection will strengthen cross-state reliability.
- Single-Leaf Framing vs. Whole-Plant View: Our pipeline currently expects one clear close-up leaf per frame. Photos showing an entire plant row from standing height reduce lesion pixel resolution and lower accuracy.

Even with these real-world constraints, fusing DenseNet-121 + CBAM attention with classic color, texture, and shape descriptors gave both higher accuracy and clearer physical meaning—where color signals pigment loss, texture marks fungal spread or spray film, and shape tracks margin blight and viral curling. Giving farmers clear, verifiable clues builds the kind of practical trust needed for everyday adoption.

VI. CONCLUSION AND FUTURE WORK

1. Conclusion

This study developed and tested a practical deep learning framework for detecting vegetable crop leaf diseases, recognizing post-treatment bio-organic recovery states, and offering clear, safe eco-friendly remedy guidance. Built to overcome the slow, subjective nature of eye-based crop scouting—and the environmental harm tied to heavy synthetic pesticide spraying—the system combines modern computer vision with grounded natural farming knowledge.

We assembled a balanced 13,400-image dataset spanning six vital vegetable crops (chili, brinjal, okra, bell pepper, cabbage, and cucumber) across sixteen health, disease, and bio-treated recovering categories, blending cleaned benchmark collections with real farm photographs from organic growers in North India. Our classifier pairs a compact DenseNet-121 backbone with dual Convolutional Block Attention Modules (CBAM) and fuses deep learned features with classic color, GLCM/LBP texture, and lesion-shape descriptors.

Evaluated on an unseen 2,010-image holdout test set, the proposed framework reached 97.14% overall accuracy, 0.969 precision, 0.972 recall, 0.970 F1-score, and 0.986 ROC-AUC. It consistently beat Random Forest, VGG-16, MobileNetV2, and standard DenseNet-121 baselines while staying light enough (17.6 MB quantized, 145 ms per photo) to run completely offline on regular Android smartphones. Ablation runs confirmed that both CBAM spatial-channel attention and visual feature fusion played concrete roles in cutting errors under messy outdoor farm lighting.

Just as important as raw accuracy is what happens after diagnosis. By linking every detected disease to a verified ICAR- and FAO-aligned bio-organic remedy module—and by teaching the network to recognize Bio-Treated Recovering leaves—our framework closes the loop between spotting an infection and managing it sustainably. Farmers receive plain mixing instructions for affordable natural sprays such as 5% neem seed kernel extract, Trichoderma viride, Pseudomonas fluorescens, and sour buttermilk, alongside an objective way to verify whether those remedies are helping over the following week. Together, these capabilities advance United Nations Sustainable Development Goal 2 (Zero Hunger) and Goal 12 (Responsible Consumption and Production) by protecting smallholder vegetable harvests without poisoning soil or fresh food.

2. Future Work

While the test results and farmer pilot feedback are encouraging, several promising directions remain open to make this system even more useful across diverse farming communities:

Multi-Season and Multi-Region Field Datasets

Future work will expand outdoor photo collection across humid coastal belts, hill-station vegetable terraces, and southern Indian farming districts, adding more regional seed varieties, extra crops such as bitter gourd and cauliflower, and mixed multi-disease leaf samples where two infections occur together.

Multispectral and Thermal Imaging for Pre-Visual Detection

Because regular RGB cameras only see symptoms once leaf tissue has already changed color, pairing compact smartphone thermal add-ons or drone-mounted multispectral sensors in future trials could catch water stress and early fungal spread days before spots appear to the naked eye.

Ultra-Light Edge Models and Regional Voice Support

Applying structured channel pruning, INT8 quantization, and knowledge distillation can shrink the app model even further below 8 MB for entry-level budget phones. Adding offline voice readouts in Hindi, Punjabi, Haryanvi, Marathi, Tamil, and Bengali will also make bio-organic spray recipes directly usable for growers who prefer listening over reading small text.

Integration with Soil Sensors and Smart Bio-Sprayers

Connecting the leaf diagnosis engine with inexpensive IoT soil moisture, humidity, and leaf-wetness sensors could warn farmers before humid weather triggers downy mildew or anthracnose—and eventually guide spot-spraying battery backpacks or autonomous polyhouse sprayers to treat only affected rows.

Explainable Visual Heatmaps Inside the Mobile App

Embedding fast on-device Grad-CAM and CBAM spatial attention overlays directly onto the farmer's screen will highlight the exact spotted leaf area behind every prediction. Showing this visual proof helps growers verify that the app looked at the real lesion rather than mud or shadows.

Time-Series Tracking of Bio-Organic Recovery Over Days

Right now, the model scores each leaf snapshot on its own. Storing tagged photos of the same marked branch on Day 0, Day 4, and Day 8 will let future sequence models measure actual healing speed—confirming quantitatively whether a natural spray stopped lesion spread or if a follow-up botanical spray is needed.

Farm-Level Economic and Soil Health Impact Studies

Finally, running full-season side-by-side field trials comparing app-guided bio-organic vegetable plots against conventional chemical plots will quantify real savings in pesticide bills, market yield stability, chemical residue reduction, and long-term soil microbial recovery.

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