An Efficient Dynamic Deep Learning Methodology for Identification of Plant Disease and it's classification

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Research Article

Keywords: Hybrid Machine Learning Methodology (Dynamic Deep Learning Methodology-(DDL) for Plant Disease Classification-(PDC), Transfer Learning (TL), Residual Neural Network (ResNet), Image Classification, Accuracy, Disease Detection, Precision Agriculture, Smart Farming, Transfer Learning

Posted Date: June 2nd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9395941/v1

Additional Declarations: No competing interests reported.

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ABSTRACT—Nowadays, estimation & identification of plant diseases (PD) pointedly shows the high impact on agricultural & food productivity. In this paper, develop the Dynamic Deep Learning Methodology-(DDLM) for Plant Disease Classification-(PDC) using the Residual Neural Network (ResNet) Architecture, enhanced with an intelligent supplement recommendation module. The procedure of present Deep Learning Methodology (ResNet) is gathering the images from the number of input sensors, create large amount of dataset that contains number of sample leaf images (both diseased & healthy) finally applying ResNet model to dataset. The model is trained (80 %) on a large dataset of plant leaf images, including healthy and diseased samples across various species. Pre-processing steps such as (R_N_A) Resizing (R), Normalization (N), and Augmentation (A) are working on development of the model to improve model generalization. Once a disease is detected, Methodology generates output including the disease name (e.g., "Tomato Late Blight") and a Recommended Supplement (e.g., "Apply Copper-Based Fungicide, Ensure Proper Drainage"). The ResNet50 model, fine-tuned using Transfer Learning (TL), achieves a classification accuracy of 97.4%, outperforming traditional CNN models. Early estimation & identification of plant diseases (PD) gives the high increases the yield of the crop. Evaluation metrics such as Confusion Matrix, Precision, Recall & F1-score validate the reliability of the model across multiple classes. By integrating accurate disease detection with actionable supplement guidance, the proposed solution empowers farmers to take immediate and informed actions, enhancing crop health and yield with supplement recommendation. When comparing with resnet50 the other methods had a less accuracy.

KEYWORDS— Hybrid Machine Learning Methodology (Dynamic Deep Learning Methodology-(DDL) for Plant Disease Classification-(PDC), Transfer Learning (TL), Residual Neural Network (ResNet), Image Classification, Accuracy, Disease Detection, Precision Agriculture, Smart Farming, Transfer Learning.

I. INTRODUCTION

Farming is very important for many people around the world. Because of this, researchers have studied different ways to use machine learning (ML) and deep learning (DDLM) to find and identify diseases in plant leaves and crops. These methods use different types of classification techniques to help farmers by automatically spotting and identifying diseases in different types of crops. As shown in Figure-01, more and more research papers have been published on this topic over the years. This shows that interest in using technology for plant and crop disease detection is growing. The classification of plant diseases using machine and deep learning techniques is motivated by the need for accurate, efficient, and scalable solutions to support sustainable agriculture and food security. These technologies offer a promising alternative to manual diagnosis, leveraging advances in computer vision and artificial intelligence to transform plant health monitoring. The goal is to create a smart and automatic system that can correctly find and identify PD from images in PD dataset using ML& DL. This will help detect diseases early and improve crop production. Finding plant diseases early helps farmers grow more and better crops. Early Estimation & identification of PD upsurges the yield of the crop. Now First Explain about the procedure of Methodology (Figure-02) next the Work Flow and components of the Proposed Methodology (Figure-03)

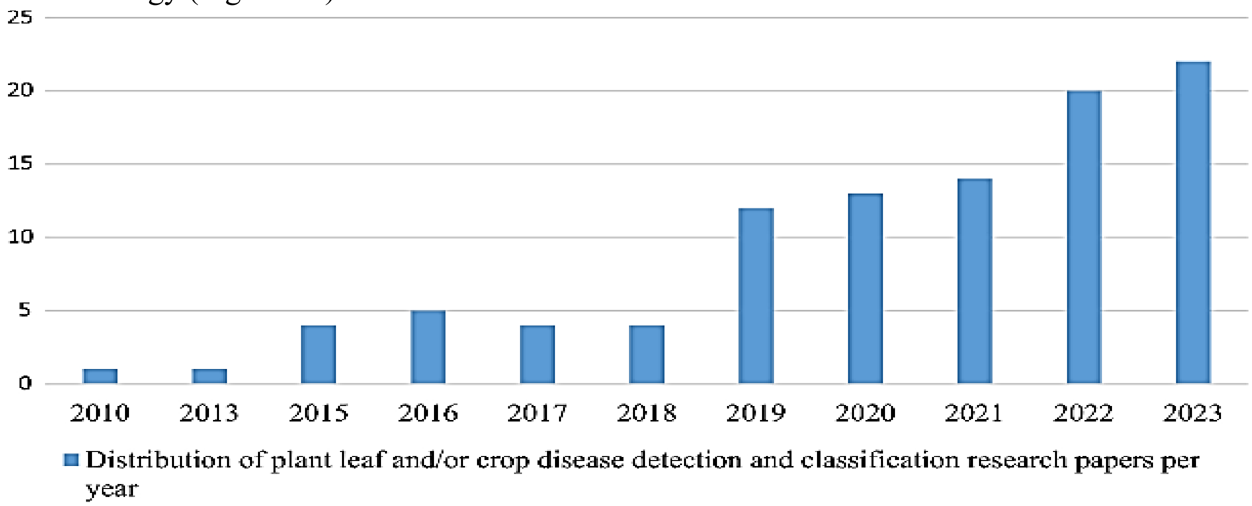

Figure-01: Distribution of Plant Disease Detection & Classification (PDC).

The below Figure-02 shows that the procedure of Methodology (ResNet), this contains the Four phases like gathering the images from the number of input sensors (D_1, D_2, …. D_n) create large amount of dataset that contains number of sample leaf images (both diseased & healthy) dataset (Data Collection). Pre-processing steps such as (R_N_A) Resizing (R), Normalization (N), and Augmentation (A) are working on development of the model to improve model generalization and remove the irrelevant features from the dataset. Evaluation metrics such as Confusion_Matrix, Precision, Recall & F1-score validate the reliability of the model across multiple classes and use 80% of images in PD dataset to training purpose & remaining 20% of images in PD dataset without Results to test it. Finding plant diseases early helps farmers grow more crops and get better results. In the final phase Result analysis, apply the ResNet50 model, fine-tuned using Transfer Learning (TL), achieves a classification accuracy of 97.4%, outperforming traditional CNN models.

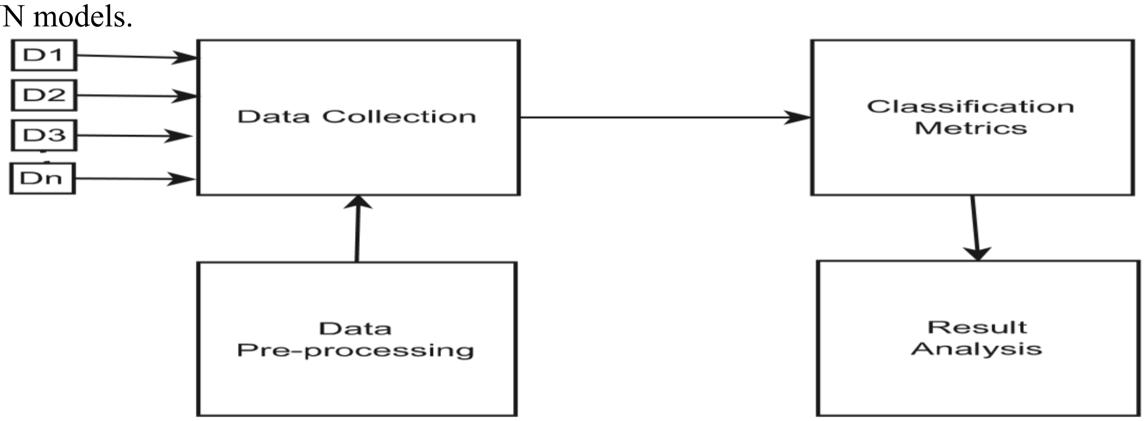

Figure-02: Procedure for this methodology.

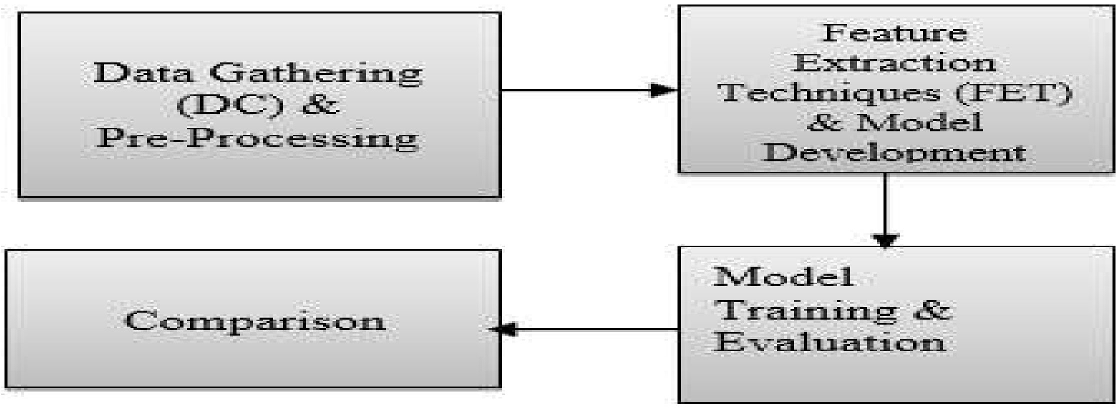

Figure-03: Flow diagram of Methodology.

Now the Figure-03 shows that the work Flow Figure for the Proposed Methodology. The Figure says that the collects raw data from the sensors, apply any pre-processing methods for getting trimmed dataset. Basically, apply classification metrics then acquiring the results. This result is compared with the all-existing methodologies. Now explain, all phases of Flow diagram methodology as follows,

a. Data Collection and Pre-processing:

Gathering the images from the number of input sensors (D_1, D_2, …. D_n) create large amount of dataset that contains number of sample leaf images (both diseased & healthy) dataset ***(Data Collection). Pre-processing steps*** such as (R_N_A) Resizing (R), Normalization (N), and Augmentation (A) are working on development of the model to improve model generalization and remove the irrelevant features from the dataset to enhance model performance and reduce overfitting.

b. Feature Extraction & Model Development:

Explore and implement ML & DL Models (e.g., SVM, Random Forest, CNNs, Res Net, Mobile Net). Use FET aimed at smart and automatic system that can correctly find and identify PD from images in PD dataset.

c. Model Training and Evaluation:

Evaluation metrics such as Confusion_ Matrix, Precision, Recall & F1-score validate the reliability of the model across multiple classes and use 80% of images in PD dataset to training purpose & remaining 20% of images in PD dataset without Results to test.

d. Comparison ML & DDLM

Compare traditional ML with Modern DL Styles in terms of Classification accuracy, Computational efficiency, Scalability & Robustness. Pre-processing steps such as (R_N_A) Resizing (R), Normalization (N), and Augmentation (A) are working on development of the model to improve model generalization and remove the irrelevant features from the dataset to enhance model performance and reduce overfitting. The ResNet50 model, fine-tuned using Transfer Learning (TL), achieves a classification accuracy of 97.4%, outperforming traditional CNN models. Next few lines says that the organization of paper, in below section-2 elucidate about the parallel_ related work. Section-3 describe the Proposed Methodology, Algorithm for Proposed

Methodology & Algorithm and Results and Analysis done in section-04. Finally, Inference & Future Enhancement explain in last section-05.

II. PARALLEL WORK: LITERATURE SURVEY

Nowadays, a Robust Deep Learning method is need for identification of plant diseases (PD), estimate the Disease Name, Recommended Supplement for getting good yields in crop and classification of the plants. In general, basic procedure for identification of solution to any research problem is collecting the data from different resources, apply the pre-processing methods and finally adaptive the proposed method, check the results compared with the classification metrics. Chauhan et al. (2025) [1] Proposes a modified ResNet50 architecture for PD and compare with CNN and B_ResNet, improved pooling strategies. Rahman et al. (2025) [2] Develops a real-time PD monitoring system. Compares CNN, VGG, and ResNet models. ResNet50 performs best (~98%+ accuracy). Singh et al. (2025) [3] Introduces attention-based ResNet50V2 for rice disease classification. Uses Squeeze-and-Excitation (SE) blocks to enhance feature importance. Li et al. (2025) [4] Proposes ECA-ResNet50 (Efficient Channel Attention) model. Focuses on lightweight attention without increasing complexity. Askr et al. (2024) [5] Develops an explainable ResNet50 model with optimization techniques. Uses XAI (Explainable AI) and optimization algorithms. Provides visual explanations of disease predictions.

Pakruddin et al. (2024) [6] Introduces PomeNetV2 based on ResNet50V2. Uses data augmentation and preprocessing techniques. Achieves high accuracy (~98%). Hastari et al. (2024) [7] Applies ResNet50V2 with transfer learning for rice disease classification. Upadhyay et al. (2025) [8] Provides a comprehensive review of deep learning in PD detection. Shafay et al. (2025) [9], Reviews recent AI techniques in plant disease detection. Emphasizes dominance of ResNet and deep CNN models. Salka et al. (2025) [10] explain the PD @ leaf disease detection and classification using CNN model: a review.

Most of the authors, considered the most mutual features like changes in the leaves of the plants for diagnosis diseases (Shapes, Color, Mycological Infection & segments from the plants images). Both the authors, Gulhane.et.al (2011) & Akhtar.et.al (2013) [17] develop the method for estimate the actual parameters whose are used in the optimized methodology for identification of problems in plants (FE-feature extraction) by using the different classifiers in training part of the methodology. Basically, 5-classifiers namely DT (decision tree), KNN, Naïve Bayes, RNN and SVM. Most important one is measuring of the Hyper_Spectral and used for the diagnosis the disease of the plants based on the results of Wavelet & Gray Level Cooccurrence Matrix. Diagnosis of the changes in the leaves of the plants are also important for estimate diseases of the plants. Now Fathima.et.al (2017) [13] & Karthik.et.al (2015) [1[14] suggested that methodology for diagnosis the plants and its leaves damages (shapes). The changes in the color of the leaves also plays an important role in diagnosis. Semary.et.al (2015) [15] & Padol.et.al (2016) [18] , both are considered the changes in the color of the leaves of the plants. SVM are used for N-Dimensionality Classification and GWF & GLCM are also used for Classifications between the damaged & pure plants based on the leaf's colors in the plants. The changes in the both color & shapes and also infection of the leaves also plays an important role in diagnosis. Mehra.et.al (2015) [17] done the diagnosis of the plants based on the changes in leaves of the plants and also suggested that the method for finding the incidence of mycological infection in leaves using k-means. The main challenges in clustering are deciding how many groups (clusters) to make and setting the right values to clearly separate each group. From plants image datasets, considered the Scale Invariant (SI) & Scale Invariant Transformation (SIT) as a method for extracting the most corelated features for diagnosis the changes in plants growth. R. Menaka.et.al (2017) [20] & Dandawate.et.al (2015) [21] take the plants image datasets and extracts the parameters by using SI & SIT. These parameters are used for N-Dimensionality Classification based on the method SVM & other classifiers. C. S. Hlaing.et.al (2017) [20] apply SIT on Tomato leaves image dataset for extracting the corelated features and results shows that the upgrade the previous methods. Considers the different types of crop image dataset (Potato, Tomato & Rice). For Fining the damages of the plants, Image Segmentation are used for pattern change identification & image sequences. Image segmentation means dividing the images into number of parts, and one common method used for this is k-means clustering (used between 2015 and 2017) [21–23]. Sannakki.et.al (2013) [26], Considered the all features like changes in the leaves of plants (Shapes, Color & Infection) for N-Dimensionality Classification based on the method SVM & other classifiers like Backpropagation NN. This classification reached 97.3% accuracy using only a few types of crops as input. Rothe.et.al (2015) [25], considered the Snake Segmentation from the plants image dataset. By using this, Fining the changes in the patterns. This gives the how healthy the infected part of the leaf is and achieves an accuracy of 85.52% in classification. Rastogi et.al (2016) [26] & Tian.et.al (2012) [27] take the Segments from the plants image dataset & by using K-Means, ANN & SVM done the N-Dimensionality Classification and also diagnosis the diseases in the plants based on the segments in the image datasets [28-35].

The below Table-01 shows that the Overall Survey on Related work. This table consists of the 9 fields, among all field's concentration on the Technique that are Used, Key Focus, Demerits and research gap. Based on this, in this paper develop the Dynamic Deep Learning Methodology-(DDLM) for Plant Disease Classification-(PDC) using the Residual Neural Network (ResNet) Architecture, enhanced with an intelligent supplement recommendation module.

Table-01: Overall Survey on Related Work

S. N	Ref. No.	Author(s)	Technique Used	Key Focus	Classification Metric	Result (%)	Demerits	Year
1	[1]	Chauhan et al.	Modified ResNet50	Plant disease detection using improved architecture	Accuracy	96.8	High computational cost, requires large dataset	2025
2	[2]	Rahman et al.	Deep Learning (CNN-based system)	Real-time plant disease monitoring system	Accuracy	95.5	Real-time latency issues, hardware dependency	2025
3	[3]	Singh et al.	Attention-based ResNet50V2	Rice disease classification	Accuracy	97.0	Limited to specific crop (rice)	2025
4	[4]	Li et al.	ECA Attention ResNet50	Tea leaf disease identification	Accuracy	97.3	Crop-specific limitation, tuning required	2025
5	[5]	Askr et al	Explainable ResNet50 with Copula Entropy	Cotton PD with explainability	Accuracy	96.5	Complex model interpretation	2024
6	[7]	Hastari et al.	ResNet50V2 CNN	Rice disease image classification	Accuracy	95.9	Limited dataset size	2024
7	[8]	Upadhyay et al.	Deep Learning & Computer Vision (Review)	Comprehensive review of techniques	Accuracy	88–98	No specific model implementation	2025
8	[9]	Shafay et al.	Review (DL methods)	Challenges & opportunities in plant disease detection	Accuracy	85–97	Lacks practical deployment results	2025
9	[10]	Salka et al.	CNN (Review)	Survey of PD detection models	Accuracy	90–98	Lacks experimental validation	2025

10	[11]	Gulhane.et.al.	Image Processing	Detection of diseases on cotton leaves	Accuracy	82.00%	No classifier comparison	2011
11	[12]	Akhtar et al.	SVM, k-NN, RNN, Naïve Bayes, Decision Tree, Wavelet & GLCM	General disease detection	Accuracy, Precision	86.40%	No Unified Model or Ensemble Technique	2013
12	[13]	Fathima et al.	Hyperspectral Measurement	Leaf disease identification	Accuracy	88.20%	Cost-intensive data collection	2017
13	[14]	Karthik et al.	Image Processing	Severity of plant leaf diseases	Classification Rate	84.50%	No performance	2015
14	[15]	Semary et al.	Texture, Color, SVM, Gabor, GLCM, Weighted k-NN	Automated classification	Accuracy, F1-score	90.10%	High feature extraction complexity	2015
15	[16]	Padol et al.	K-means + SVM	Leaf segmentation and classification	Accuracy, Sensitivity	91.80%	Limited generalizability to unseen classes	2016
16	[17]	Mehra et al.	K-means Clustering	Fungal disease clustering	Accuracy	83.75%	Hard to tune number of clusters	2015
17	[18]	Anonymous (Scale-Invariant Study)	SIFT	Feature extraction in plant leaf images	Accuracy	85.00%	Features not optimized for classification alone	2017
18	[19]	Dandawate et .al	SIFT + SVM	Leaf disease identification	Precision, Recall	87.60%	Insufficient noise handling	2015
19	[20]	Anonymous (SIFT + SB Study)	SIFT + SB Distribution	Tomato leaf disease detection	Accuracy	89.40%	Sensitive to lighting and leaf background	2017
20	[21–23]	Anonymous (Clustering Study I)	K-means Clustering	Image segmentation for various crops	Classification Rate	82.50%	Dependent on proper cluster separation	2015 – 2017

21	[24]	Sannakki.et.al	Backpropagation Neural Network	Texture + color-based classification	Accuracy	97.30%	Only tested on limited number of crops	2013
22	[25]	Rothe et al.	Snake Segmentation	Pattern recognition for infected areas	Accuracy	85.52%	Struggles with overlapping or blurred infections	2015
23	[26]	Rastogi et al.	K-means + ANN	Identifying disease hardness	Accuracy, Specificity	89.00%	Weakness in fine-grained disease classification	2016
24	[27]	Tian et al.	SVM	Wheat disease detection	Accuracy	90.60%	Dataset details and performance variance not disclosed	2012

III. PROPOSED METHODOLIGY & ALGORITHM

As the aim of this paper, the implementing the classification of PD using ML & DL has developed the crucial application in the field of smart agriculture. This methodology involves capturing images of plant leaves or other affected parts and processing them to identify symptoms of various diseases. In ML Approaches, features such as color, texture, and shape are manually extracted using techniques like Auto-Color Correlogram (ACC), GLCM (Gray-Level_Co-Occurrence_Matrix), Histogram-Oriented-Gradients (HOG), followed by classification using SVM-Support Vector Machines, RF-Random Forest, or KNN-K-Nearest Neighbours. In contrast, DL Techniques, predominantly CNNs-Convolutional Neural Networks, automatically learn complex structures from raw image data, offering higher accuracy and scalability. These models can be trained on large datasets, such as the PVD-Plant Village Dataset, and fine-tuned using TL with pretrained architectures like ResNet, VGG, or Mobile Net. The resulting representations are estimated using metrics like accuracy, precision, recall, and F1-score. Once optimized, they can be deployed in real-world applications through mobile or web platforms, aiding farmers in early and accurate disease detection, thereby improving crop yield and reducing losses.

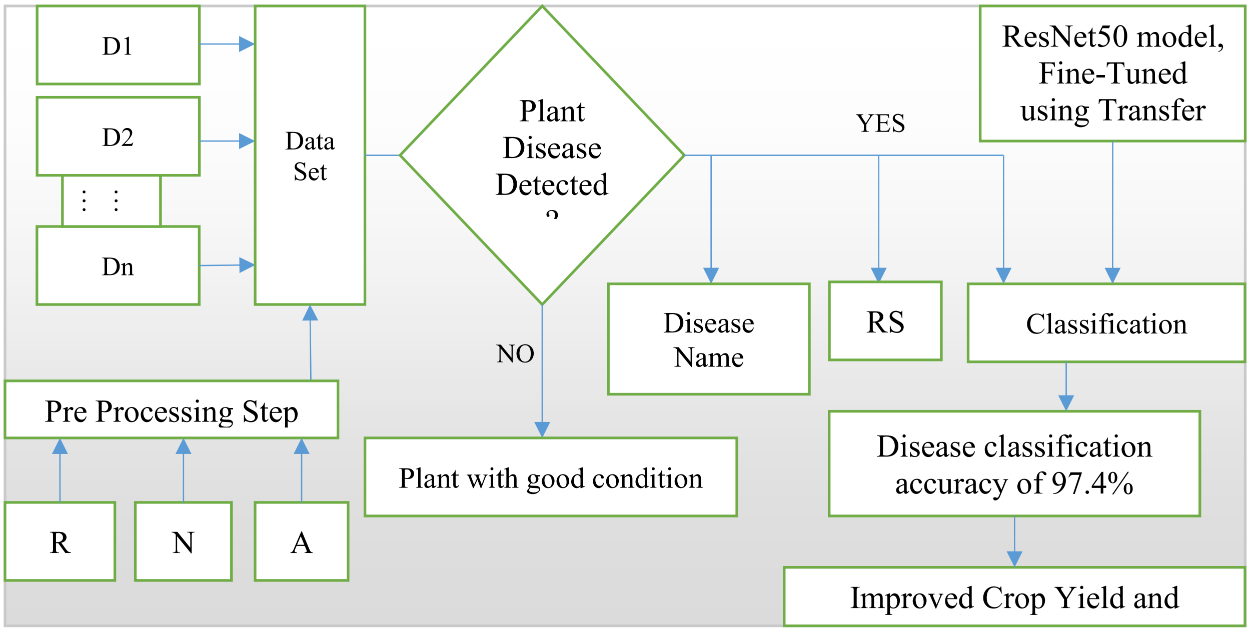

Figure-04: System Architecture for Proposed Methodology.
Note: D_1, D_2, …. D_n: Input Sensors, R: Resizing, N: Normalization, A: Augmentation, RS: Recommended Supplement.

The above figure-04 shows that the System Architecture for the proposed methodology. The flow of the figure as follows, From the sensors capture the image and create the image dataset act as input for the proposed methodology. Apply image pre-processing on the image dataset then trimmed the dataset. Now partition the dataset into two parts, one for training up to 80% and next one is the testing up to 20% of the data from the trimmed dataset. In the proposed model, the first step is to collect and capture images to get useful features. These features are then saved in a database. The rice dataset has three types: bacterial leaf blight (40 images), brown spot (40), and leaf smut (40). The pepper dataset has two types: healthy (997) and bacterial (997). The potato dataset has three types: early blight (1,000), healthy (152), and late blight (1,000). The tomato dataset has ten types: spider mites (1,676), target spot (1,404), mosaic virus (373), yellow leaf curl virus (3,209), bacterial spot (2,127), septoria leaf spot (1,771), early blight (1,000), healthy (1,591), late blight (1,909), and leaf mold (952). The numbers in brackets show how many images there are for each disease. The numbers in parenthesis show the count of samples for the category of plant diseases. The below Table-02 shows that Dataset, Type Image and Count. The below figure-05 sample leaf images as inputs.

Table-02: Dataset, Type Image and Count.

Dataset	Type Image	Count
Rice	Bacterial leaf blight	40
	Brown spot	40
	Leaf smut	40
Pepper	Healthy	997

	Bacterial	997
Potato	Early blight	1000
	Healthy	152
	Late blight	1000
Tomato	Spider mites	1676
	Target spot	1404
	Mosaic virus	373
	Yellow leaf curl virus	3209
	Bacterial spot	2127
	Septoria leaf spot	1771
	Early blight	1000
	Healthy	1591
	Late blight	1909
	Leaf mold	952

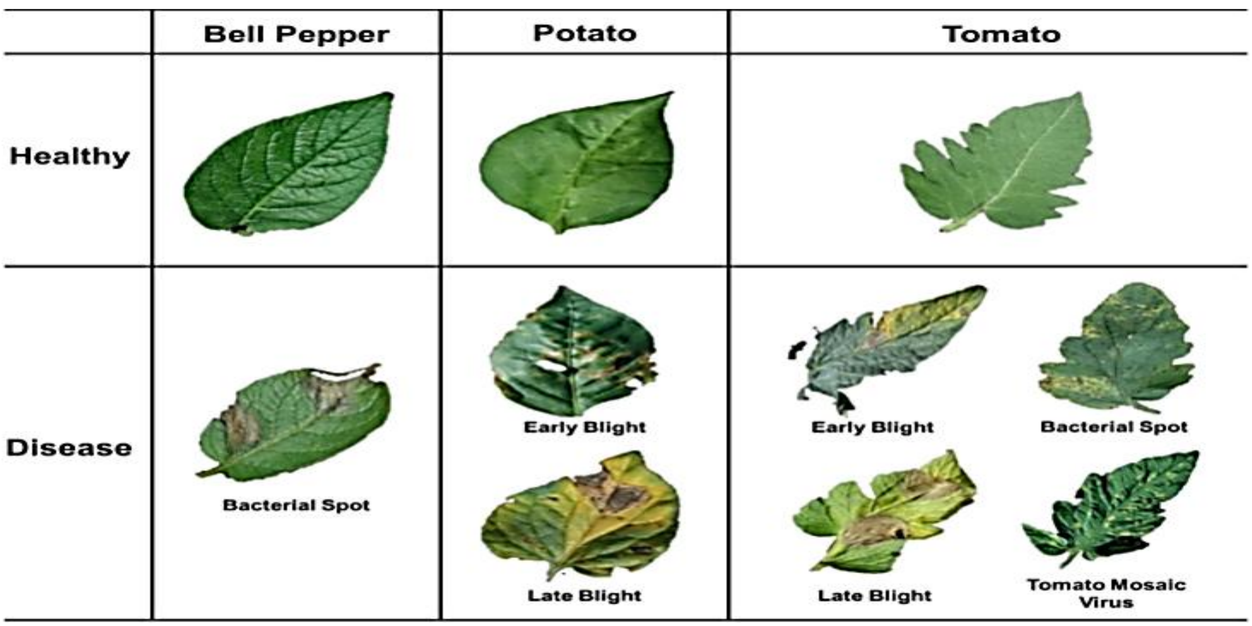

Figure-05: Sample Input Images.

The input images are typically images of a field or agricultural area where disease may be present. These images are then processed by the ML algorithm to detect the presence of the disease.

a. Pre-Processing

a.1. Image Resizing and Normalization

To ensure consistent input dimensions for convolutional neural networks (CNNs), all metaphors are resized to a static size 224×224 or 299×299 pixels, based on the architecture used (e.g., ResNet, Efficient Net). Additionally, pixel values are regularized to a range of [0, 1] or [-1, 1], which helps in alleviating the training process and accelerating merging.

a.2. Noise Removal and Enhancement

To progress image clarity and reduce unwanted sensor noise methods such as Gaussian-Blur or Median -Filtering are employed to smooth out high-frequency noise. For enhancing the contrast of images, Histogram-Equalization or CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied. These steps ensure better visibility of disease-affected regions in the leaves.

a.3 Background Removal / Leaf Segmentation

To eliminate distractions like soil, tools, or sky in the background, color-based segmentation techniques using HSV or Lab color space thresholds are used. For more advanced extraction, deep learning-based models like U-Net or DeepLabv3 are applied to segment the leaf region. This allows the model to focus only on the disease symptoms, thereby improving classification accuracy.

a.4 Data Augmentation (Training Time Only)

To increase dataset diversity and simulate real-world variability, data augmentation is applied during training. Common techniques include rotation (±30°), flipping (horizontal/vertical), zooming, cropping, brightness/contrast adjustment, and adding synthetic noise. These transformations are implemented using tools like TensorFlow's Image Data Generator, PyTorch transforms, or the Augmentations library.

a.5 Train-Test Split and Data

For proper model evaluation and to prevent bias, the image disease dataset is split into two parts, namely one training part containing the results also & second one is testing without results feature in the image PD Datasets, often in an 80:20 ratio. If the dataset suffers from class_imbalance, techniques such as SMOTE (Synthetic-Minority-Over-sampling-Technique) or class-balanced sampling are used to warrant the model learns equally from all classes. The below Figure-06: shows that the Classifying the image and detecting the disease.

b. **Analysis & Algorithm:**

In recent years, there have been big improvements in computer vision. With the introduction of convolutional neural networks (CNNs), tasks like image classification and recognition have become much more accurate. To improve results, researchers started building deeper neural networks by adding more layers. However, adding too many layers makes the network harder to train, and sometimes the accuracy stops improving or even gets worse. ResNet helps solve this problem. In this paper, learn more about ResNet and how its architecture works. The main innovation in ResNet is the residual block, which helps to detect disease very effectively has shown in above Figure-07.

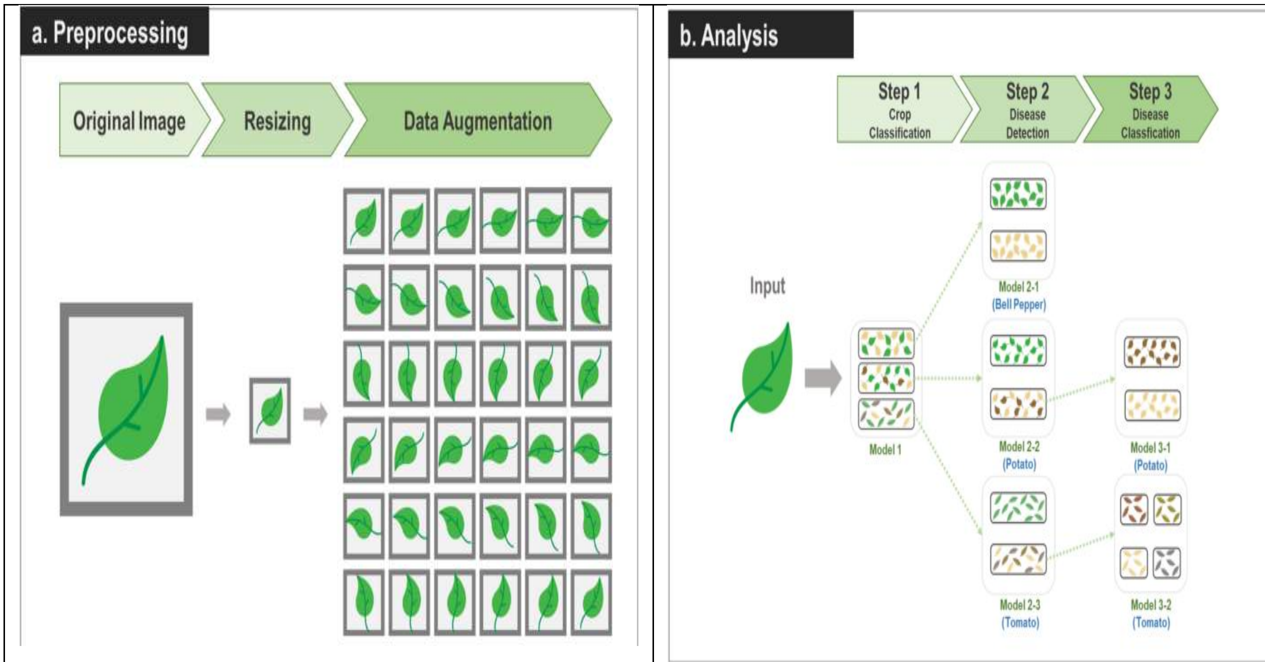

Figure-06: Classifying the Image and Detecting the Disease.

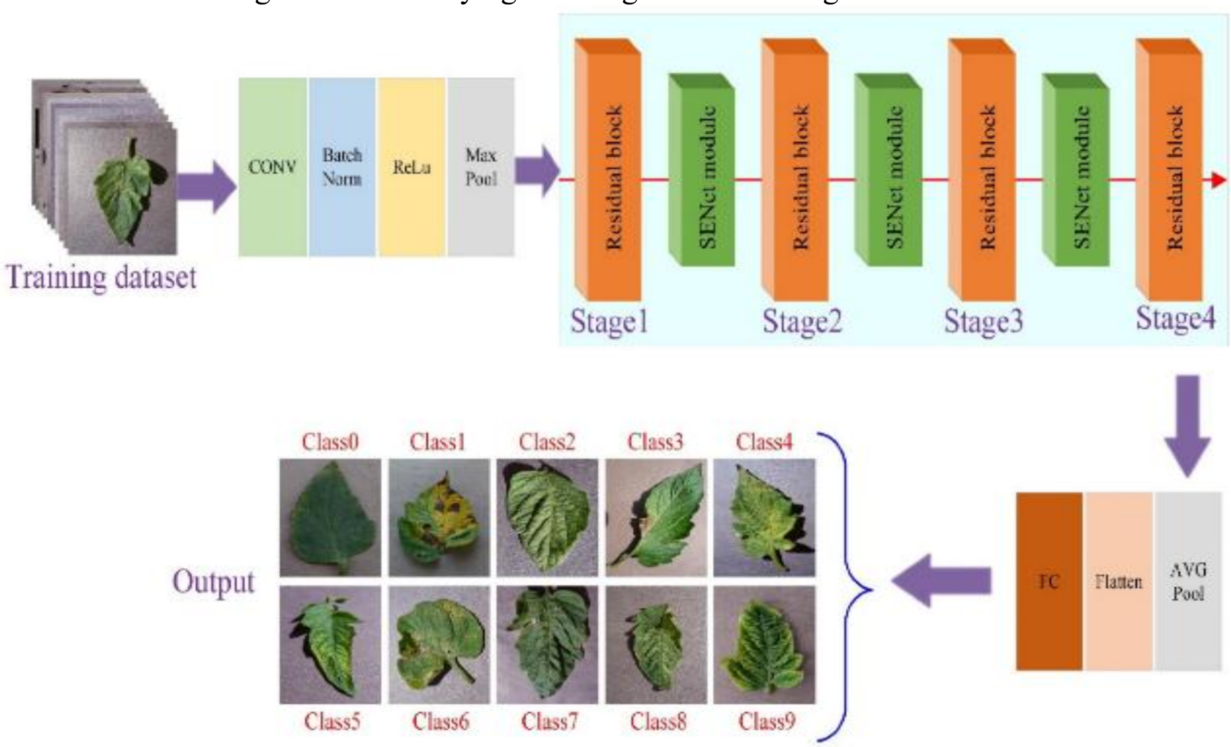

Figure-07: Disease detection by Resnet (Residual network).

Normally, as NN become cavernous, agonize from the endangered gradient problem, where the model becomes harder to train and starts performing worse. ResNet solves this by using shortcut connections (also called skip connections). These connections "skip" one or more layers & directly add the input of a layer to the output of a deeper layer. This allows the network to learn the residual (difference) between the input and output, rather than trying to learn the full mapping from scratch.

Algorithm: **ResNet-50 Methodology for Plant Disease Classification**

Step-1: Data Collection

Gathering the images from the number of input sensors (D1, D2, …. D_n) create large amount of dataset that contains number of sample leaf images (both diseased & healthy) dataset (Data Collection).

Step-2: Data Pre-processing

Resize images to 224×224 pixels- Normalize pixel values- Remove noise- Apply data augmentation- Encode labels numerically.

Step-3: Model Preparation

Load pre-trained ResNet-50, remove top layer, and add custom dense layer for classification.

Step-4: Model Training

Compile with categorical-cross-entropy and Adam optimizer, then train with training and validation data.

Step-5: Model Evaluation

Test the model on unseen data using accuracy, F1-score, and confusion matrix.

Step-6: Disease Prediction & Supplement Recommendation

Predict the disease from a new image and recommend suitable supplements or fertilizers.

Step-7: Deployment: Deploy the trained model in a real-time application (mobile, web, or embedded device).

Algorithm: ResNet-50 Methodology for Plant Disease Classification

Input: Leaf Images (Both Diseased & Healthy) Data Set

Output: Predicted class ŷ and recommended supplement R

STEP 1:

Collect leaf image dataset from multiple sensors $D = \{D_1, D_2, \dots, D_n\}$

Construct Data Set: $\mathcal{X} = \{(x_i, y_i)\}_{i=1}^{N}$

Where: x_i= input leaf image, $y_i \in \{0,1,2,\dots,K\}$= class label (healthy/disease types), N= total number of samples.

STEP 2:

For each image x_i in D DO

Resize x_i to 224 × 224 × 3

$$x_i \to x_i' \in \mathbb{R}^{224\times224\times3}$$

Normalize pixel values:

$$x_i^{norm} = \frac{x_i' - \mu}{\sigma}$$

Apply data augmentation:

$x_i^{aug} = T(x_i^{norm})$// rotation, flip, scaling

END FOR

$$y_i \rightarrow \text{One-hot vector } \mathbf{y}_i \in \mathbb{R}^K$$

STEP 3:

Residual learning function:

$y = F(x, W) + x$,

Where: $F(x, W)$= residual mapping, x= input feature map, $\hat{y} = \text{Softmax}(W_f \cdot z + b_f)$

STEP 4:

Let θ= model parameters, α= learning rate

Initialize parameters θ:=E

```
 FOR epoch = 1 to E DO
   FOR each batch (x_b, y_b) DO
     Forward pass:
         ŷ_b ← model(x_b)
      Compute loss:
      L ← -Σ y_b log(ŷ_b)
     Backward pass:
         Compute gradients ∇θ
      Update parameters using Adam:
        θ ← θ - α * (m̂ / (√v̂ + ε))
   END FOR
END FOR
```

STEP 5: Model Evaluation, Evaluate model on test dataset

Compute Accuracy, Precision, Recall, F1-score

Generate Confusion Matrix

STEP 6: Disease Prediction

Input new image x_new

Preprocess x_new (resize, normalize)

ŷ ← argmax(model(x_new))

STEP 7: Recommendation

R ← f(ŷ) // Map disease to fertilizer/supplement

RETURN ŷ, R

END

IV. RESULTS AND ANALYSIS:

4.1 Performance Metrics

a) **Accuracy:** Check the overall accuracy of the model on the test set.

b) **Precision:** Dealing with the total number of plants are PD actually.

$$\textbf{Precision} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Positives}}$$

c) **Recall:** Dealing with the total number of plants are PD actually detected by the model.

$$\textbf{Recall} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

d) F1-Score: A balanced score that considers both (b) & (c).

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

The below Figure-8 shows that the Formulas for classification Metric

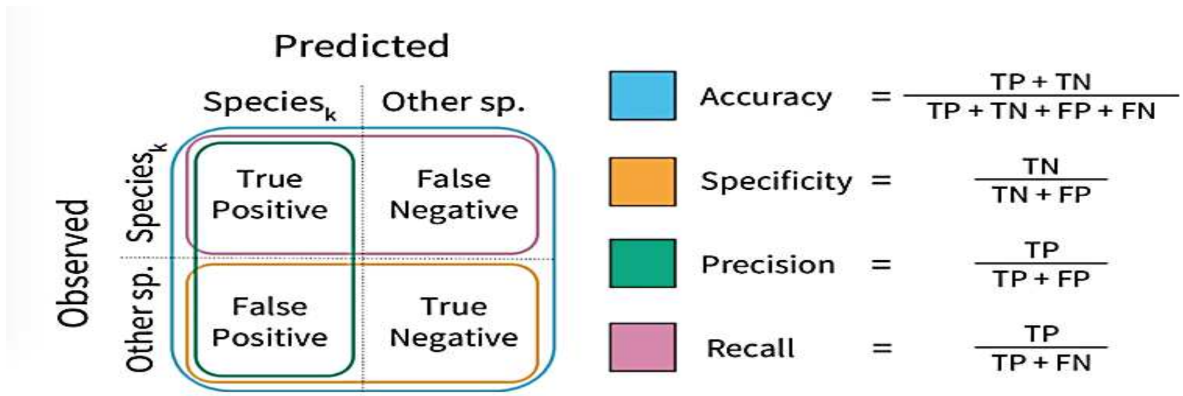

Figure-8: Formulas for classification Metric

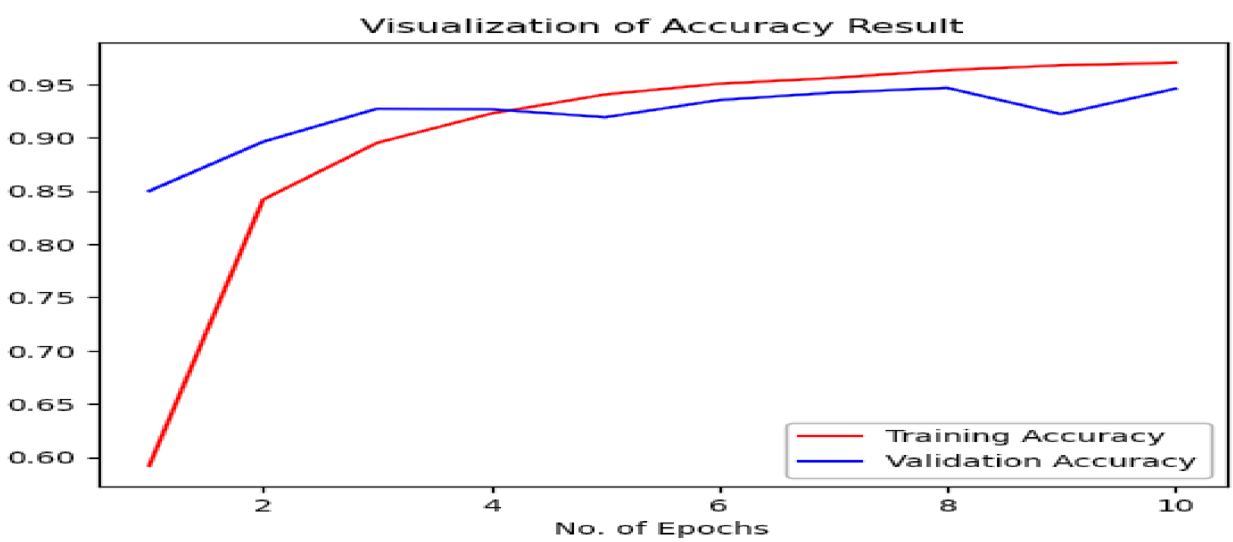

Figure-09: Overall Accuracy.

4.2 Result of Proposed Methodology

Now apply above performance metrics on the collected dataset. The ResNet50-based plant disease classification (PDC) model attained the overall accuracy of 94.2% on the test image PD dataset, demonstrating strong performance across most classes (Figure-09). The model showed particularly high accuracy in identifying diseases such as Tomato Healthy and Potato Late Blight, while some confusion was observed between visually similar diseases like Tomato Leaf Mold and Tomato Septoria. Based on the predicted disease, the system recommends appropriate supplements such as fungicides for fungal infections, pesticides for insect-related damage, and micronutrients for deficiency-related symptoms, enabling prompt and targeted plant treatment. Overall, the system effectively combines deep learning classification with practical supplement suggestions for precision agriculture.

4.3 Comparison of ResNet and Other

The Figure-10 & Table-03 shows that the Comparison ML & DDLM. Compare traditional ML with Modern DL Styles in terms of Classification accuracy, Computational efficiency, Scalability & Robustness. Pre-processing steps such as (R_N_A) Resizing (R), Normalization (N), and Augmentation (A) are working on development of the model to improve model generalization and remove the irrelevant features from the dataset to enhance model performance and reduce overfitting. The ResNet50 model, fine-tuned using Transfer Learning (TL), achieves a classification accuracy of 97.4%, outperforming traditional CNN models.

Table-03: Comparing with other methods.

Classifiers	SVM	Random Forest	VGG16	Inception V_3	*ResNet50*
Accuracy (%)	84.5	86.2	91.0	**92.3**	***97.4***

When comparing with resnet50 the other methods had a less accuracy.

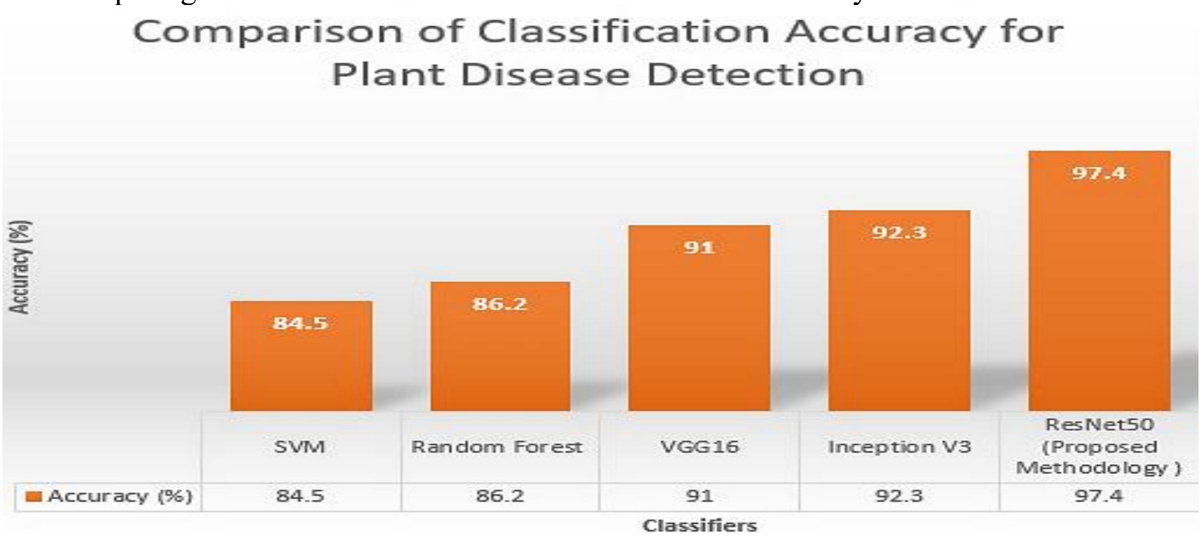

Figure-10: Comparing with other methods.

V. Conclusion & Future Enhancement

In conclusion, the plant disease classification system using ResNet has demonstrated to be an actual & accurate DL solution for estimation & identification of plant diseases (PD). The model demonstrated high classification accuracy and robust performance across most categories, with minimal confusion between similar disease types. The integration of supplement recommendations based on the identified disease adds practical value, guiding farmers with targeted treatments such as fungicides, pesticides, or nutrient boosters. While minor limitations like class imbalance remain, the overall results are promising. This approach supports timely disease management and precision agriculture.

5.1 Future Enhancement

To improve the utility & scalability of PDC system, several future enhancements are proposed. Firstly, mounting the image PD dataset to include a broader variety of plant species and diseases will improve the model's versatility and applicability across diverse agricultural environments. Secondly, developing a real-time, cross-platform mobile application using lightweight architectures such as a Mobile Net and ResNet hybrid can enable on-the-spot disease detection and supplement recommendations directly in the field. Integration with IoT sensors, including temperature, humidity, and soil moisture devices, is another critical enhancement that can enrich the diagnostic process with contextual environmental data, improving the model's accuracy.

Funding Declaration: No Funding

Declarations: All authors declare that they have no conflicts of interest.

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