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DEPLANT-Deep Learning for Plant Disease Prediction

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Plant Disease Detection, Deep Learning, Convolutional Neural Networks

Abstract- Plant diseases significantly reduced agricultural productivity and directly affected farmers' income, while manual inspection methods for disease detection remained laborious, subjective, and difficult to scale. This paper presented DEPLANT, a deep learning based system developed to detect plant diseases from images of leaves. Three deep learning architectures, namely Convolutional Neural Network CNN, VGG16, and Residual Network ResNet, were implemented and compared for the classification of sixteen categories of healthy and diseased plant leaves using the PlantVillage dataset. The dataset consisted of 22079 RGB images, split into 80 percent for training and 20 percent for validation. Experimental results showed that the ResNet model achieved the highest validation accuracy of 87.34 percent, followed by VGG16 with 85.47 percent, while the baseline CNN model reached 92.11 percent training accuracy but only 63.62 percent validation accuracy, indicating overfitting. These results demonstrated that transfer learning based architectures generalized considerably better than a shallow CNN trained from scratch on a limited dataset. The DEPLANT system was designed for real time deployment through a Streamlit based web application, allowing farmers and agricultural experts to upload leaf images and obtain instant predictions. The proposed framework supports smart farming and precision agriculture by enabling faster, more accurate, and more accessible plant disease diagnosis compared with traditional manual inspection methods.

Keywords: Ocean observing systems, Biogeochemical-Argo, Retrieval-Augmented Generation (RAG).

I. INTRODUCTION

Agriculture plays a critical role in ensuring food security and supporting economic stability worldwide. Plant diseases remain a major threat to crop yield and quality, causing significant economic losses across the globe [1], [9]. Early detection of plant disease is essential for preventing large scale crop damage and for maintaining sustainable agricultural productivity.

Traditional disease identification relies on expert visual inspection, which is time consuming, subjective, and often unavailable in rural regions where access to agricultural specialists is limited [5]. This limitation has motivated the development of automated systems for plant disease identification.

Recent advances in artificial intelligence and deep learning have enabled automated image based classification systems to achieve strong performance in identifying plant diseases from leaf images [2], [3]. Deep learning models such as Convolutional Neural Networks CNN, VGG16, and ResNet automatically extract complex visual features from images and have consequently demonstrated high accuracy in plant disease detection and classification tasks [10], [11]. Several recent studies have also explored the deployment of such models through web and mobile applications, making disease diagnosis more accessible to farmers and agricultural experts [4], [12].

This paper presented DEPLANT, a deep learning based system for plant disease detection. The proposed system utilized multiple deep learning architectures, including CNN, VGG16, and ResNet, to analyze plant leaf images and automatically identify disease categories. The DEPLANT system was made accessible to end users through a web interface built with Streamlit, allowing users to upload images of plant leaves and receive predictions in real time.

The major contributions of this work were the comparison and implementation of CNN, VGG16, and ResNet models for plant disease classification, the use of deep learning to automatically learn discriminative features from leaf images, the design of a framework capable of identifying plant disease categories with the potential to be extended toward disease severity prediction, the evaluation of model performance using accuracy metrics and confusion matrix analysis, and the development of a real time disease prediction web application using Streamlit.

II. LITERATURE SURVEY

Existing studies on plant disease detection were reviewed to examine the methods adopted and the limitations reported in prior work. The following subsections summarize key contributions and identify limitations across the reviewed literature.

A. Plant Disease Detection Using Deep Learning (2020)

This study employed CNN based image classification together with transfer learning and data augmentation and performed multi class classification on labeled plant leaf datasets. Although the model achieved good accuracy, it required large labeled datasets and high computational resources for real time deployment, and its performance was sensitive to variations in lighting conditions and environmental noise.

B. Plant Disease Detection Using Machine Learning (2019)

Traditional machine learning algorithms were applied using manually extracted features from leaf images. Cross validation together with dimensionality reduction techniques such as Principal Component Analysis was used to evaluate classification accuracy. The results were reasonable; however, diseases with multiple or subtle visual patterns led to reduced accuracy and limited scalability compared with deep learning based techniques.

C. Precise Plant Disease Detection Using Deep Learning Algorithms (2021)

This research utilized YOLO based object detection models, including YOLOv5 and YOLOv9, integrated with spatial pyramid pooling in IoT enabled cyber physical systems. Multi scale feature extraction and bounding box regression were used for disease localization, although the model required large and diverse datasets and faced difficulty detecting small scale infections while maintaining real time performance.

D. Plant Leaf Disease Prediction and Classification Using Deep Learning (2023)

Deep CNN architectures combined with data augmentation techniques and the Adam optimizer were applied for plant disease classification. While the approach improved accuracy considerably, challenges such as dataset imbalance, model complexity, and overfitting were observed when training on limited datasets.

E. Advanced Deep Learning Models Based Plant Disease Detection (2023)

This study explored advanced architectures, including CNN, Deep Belief Networks, and ensemble models combined with transfer learning, and used optimization algorithms such as RMSProp. Precision, recall, and F1 score were used as evaluation metrics. Despite improved accuracy, the computational complexity and reproducibility challenges of ensemble models limited their scalability for real world agricultural applications.

F. Plant Disease Detection and Classification by Deep Learning (2019)

Modified CNN architectures, such as GoogLeNet and VGG networks, were applied with extensive data augmentation and transfer learning from ImageNet. Although classification performance improved, these models required large labeled datasets and considerable computational resources, making real time deployment difficult in resource constrained environments.

G. Revolutionizing Agriculture with Artificial Intelligence (2024)

This study proposed AI and IoT based plant disease detection systems integrated with cloud computing platforms, combining environmental monitoring sensors with disease classification models to support agricultural decision making. Environmental noise, computational cost, and hardware limitations in rural environments, however, affected the reliability of the system.

H. Deep Learning Based Mobile Application for Plant Disease Detection (2025)

A custom CNN model trained on the PlantVillage dataset was deployed within a mobile application for predicting plant diseases, incorporating image preprocessing and severity prediction mechanisms to enhance usability. Limitations such as device hardware constraints, dataset imbalance, and reduced performance under real world agricultural conditions were reported.

I. Performance Optimized Deep Learning Based Plant Disease Detection (2023)

This study examined how transfer learning and fine tuning could improve deep learning models for detecting diseases in horticultural crops. The resulting models achieved improved accuracy and faster inference; however, large model size and uneven representation across plant types limited their applicability to real world horticultural disease detection.

J. Past, Present, and Future of Deep Plant Leaf Disease Recognition (2025)

This survey examined a range of deep learning techniques used for plant disease detection, including CNN architectures and object detection frameworks, and reviewed common data preprocessing techniques. The study highlighted challenges such as limited dataset diversity, the absence of standard benchmarks, and deployment constraints in resource limited environments.

K. InsightNet: A Deep Learning Framework for Enhanced Plant Disease Classification (2025)

InsightNet proposed a deep learning framework optimized for mobile deployment, using attention mechanisms to improve feature extraction. Although classification performance improved, the model required diverse datasets and substantial computational resources, which limited its scalability across multiple crop types.

L. Identified Research Gaps

The reviewed literature revealed a consistent reliance on large labeled datasets for training deep learning models and high computational requirements that limited real time deployment. Many existing frameworks offered limited capability for real time web or mobile integration and suffered from dataset imbalance and overfitting when trained on small datasets. Disease severity stage estimation was largely absent from existing frameworks, and scalability for deployment in rural agricultural environments remained poor. Generalization across multiple crops and environmental conditions was limited, and hardware constraints continued to restrict mobile based agricultural systems.

M. Motivation for the Proposed DEPLANT Framework

To address these limitations, the proposed DEPLANT framework integrated multiple deep learning architectures, including CNN, VGG16, and ResNet, for accurate plant disease classification. The framework focused on improving model performance while maintaining scalability for real time deployment. The system was further designed for integration with web based platforms using Streamlit, enabling accessible plant disease diagnosis for farmers and agricultural experts, and thereby supporting smart farming practices and precision agriculture through efficient AI driven plant disease detection.

III. MODELS USED

This section describes the deep learning models implemented in the proposed DEPLANT framework for plant disease detection and classification.

A. Convolutional Neural Network (CNN)

The Convolutional Neural Network was used to identify color, shape, texture, and pattern based features in images of plant leaves in order to classify plant diseases accurately. The CNN automatically learned hierarchical feature representations through convolutional and pooling layers [1], [5]. This model was selected because of its high accuracy and robustness in image recognition tasks, since it eliminated the need for manual feature extraction and enabled precise multi class disease identification [3], [10].

B. VGG16

VGG16 is a deep convolutional network that performs strongly on image classification tasks and was originally developed for the ImageNet Large Scale Visual Recognition Challenge. The architecture consists of sixteen weighted layers and uses small convolution filters within a deep structure to extract detailed visual features from images. In this research, VGG16 was implemented using transfer learning to leverage pretrained weights obtained from large scale datasets, which allowed efficient feature extraction and improved classification accuracy for plant disease detection tasks [6], [7].

C. Residual Network (ResNet)

ResNet was implemented for deep feature learning using residual connections that helped overcome the vanishing gradient problem in deep networks. The skip connections allowed better gradient flow during backpropagation, enabling the training of very deep neural networks [2], [4]. ResNet was selected to enhance classification accuracy and improve generalization on complex multi class plant disease datasets, and it could also be extended in future work for disease severity stage prediction across early, moderate, and severe categories [9], [12].

IV. DATASET DESCRIPTION

The PlantVillage dataset obtained from Kaggle was used to train and evaluate the proposed DEPLANT model. This dataset is widely used in plant disease detection research and contains labeled images of healthy and diseased plant leaves that were used to train the model to classify plant diseases [1], [5], [11]. The dataset comprised 22079 RGB images spanning sixteen plant disease categories, including both healthy and diseased leaves, and it was split into 80 percent of images for training the system and 20 percent for validating classification of healthy and diseased leaves.

Fig. 1. Sample images from the PlantVillage dataset

V. DATA PREPROCESSING

Data preprocessing is an important step when detecting plant diseases using computational models, since input images must be made consistent so that the model can process them reliably [1], [3]. Proper preprocessing improves model accuracy and training efficiency by reducing noise and ensuring consistent input dimensions.

A. Image Resizing

Images were resized to 224 by 224 pixels, since most Convolutional Neural Network architectures require this input size for image classification tasks [2], [10].

B. Normalization

Pixel values were rescaled to a range between 0 and 1, which helped stabilize the training process and improved convergence during deep learning model optimization [5], [11].

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 256)	22,151,424
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 16)	4,112

Total params: 22,248,784 (84.87 MB)
Trainable params: 22,248,784 (84.87 MB)
Non-trainable params: 0 (0.00 B)

Fig. 2. Data preprocessing workflow

VI. CNN ARCHITECTURE

The CNN architecture was composed of layers designed to extract important features from images of plant leaves for accurate disease classification [1], [3]. The architecture included convolution layers, max pooling layers, a dropout layer, a dense layer, and a softmax output layer covering sixteen classes. The convolution layers were responsible for extracting important spatial features such as edges, textures, and patterns from the input images, while the max pooling layers reduced the spatial dimensions of the feature maps while preserving the most significant features, which helped reduce computational complexity and prevent overfitting [5], [10]. The dropout layer improved model generalization by randomly deactivating a subset of neurons during training. The dense layer performed high level reasoning based on the extracted features, and the final softmax output layer was used for multi class classification to predict the probability of each disease class [2], [11], as shown in the softmax equation below.

$$P(y = i|x) = \frac{e^{zi}}{\sum_{j=1}^{K} e^{zj}} \quad (1)$$

```
import tensorflow as tf

IMAGE_SIZE = (224, 224)
BATCH_SIZE = 32

train_data = tf.keras.utils.image_dataset_from_directory(
    DATASET_PATH,
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE
)

val_data = tf.keras.utils.image_dataset_from_directory(
    DATASET_PATH,
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE
)

num_classes = len(train_data.class_names)
print("Total Classes:", num_classes)
```

```
Found 22079 files belonging to 16 classes.
Using 17664 files for training.
Found 22079 files belonging to 16 classes.
Using 4415 files for validation.
Total Classes: 16
```

Fig. 3. Proposed CNN architecture

VII. MODEL TRAINING

In this study, three deep learning models, namely Convolutional Neural Network CNN, VGG16, and Residual Network ResNet, were used for plant disease detection. These models are widely used in image classification tasks because of their ability to automatically extract complex and hierarchical features from plant leaf images [1], [11].

A. CNN Model Training

The CNN model was used as the baseline classifier for plant diseases. It was highly effective for image based tasks because it could automatically identify features such as edges, textures, and colors within the input image [3], [5]. During training, input images were passed through multiple convolution layers to extract important features, which were subsequently reduced using pooling layers and classified using fully connected dense layers [10]. The CNN model was trained using the Adam optimizer with sparse categorical cross entropy as the loss function, for ten epochs with a batch size of 32, using a Google Colab GPU. During each epoch, the CNN model processed the entire training dataset and updated the network weights through backpropagation. The Adam optimizer was used because it adapts learning rates automatically and improves convergence speed [2], [7].

B. VGG16 Model Training

VGG16 consists of sixteen weighted layers and uses small convolution filters to extract detailed visual features from images. In this research, VGG16 was implemented using transfer learning with pretrained weights obtained from the ImageNet dataset. The pretrained convolutional layers captured general image features, while the final fully connected layers were fine tuned using the plant disease dataset to perform multi class classification. The model was trained using the Adam optimizer with sparse categorical cross entropy loss, for ten epochs with a batch size of 32. Transfer learning with VGG16 improved feature extraction capability and helped achieve better classification performance even with limited training data [6], [7].

C. ResNet Model Training

ResNet is a deep neural network designed to address the vanishing gradient problem present in very deep architectures, using skip connections that allow gradients to flow more effectively during backpropagation [2], [4]. In this work, a pretrained ResNet model was used through transfer learning to improve feature extraction and classification accuracy. The pretrained layers captured complex visual patterns from the plant leaf images, while the final classification layers were fine tuned for the plant disease dataset. The model was trained using the Adam optimizer with sparse categorical cross entropy loss, for ten epochs with a batch size of 32. ResNet improved performance by enabling deeper network architectures while maintaining stable gradient flow, which helped capture more complex disease patterns and improved classification accuracy on the multi class plant disease dataset [9].

D. Training Strategy

The dataset was divided into two subsets, with 80 percent of the data used for training and 20 percent used for validation. The training subset was used to learn model parameters, while the validation subset was used to evaluate model performance after each epoch [8]. This approach enabled continuous monitoring of the learning process and helped identify overfitting, since training accuracy and validation accuracy were recorded during each epoch to analyze model convergence and generalization performance.

E. Hyperparameter Settings

Several hyperparameters influenced the performance of the deep learning models used in this work. The image size was set to 224 by 224 pixels, the batch size was set to 32, the Adam optimizer was used with its default learning rate, training was performed for ten epochs, and the number of output classes was set to sixteen. These parameters were selected to balance computational efficiency and model performance during training [3], [12].

F. Model Performance Monitoring

During training, performance metrics including training accuracy, validation accuracy, and loss values were monitored to evaluate how well the models learned disease patterns from the plant leaf images [1]. The CNN, VGG16, and ResNet models demonstrated strong capability in classifying plants by capturing complex visual features and achieving high classification accuracy for plant disease detection [3], [10].

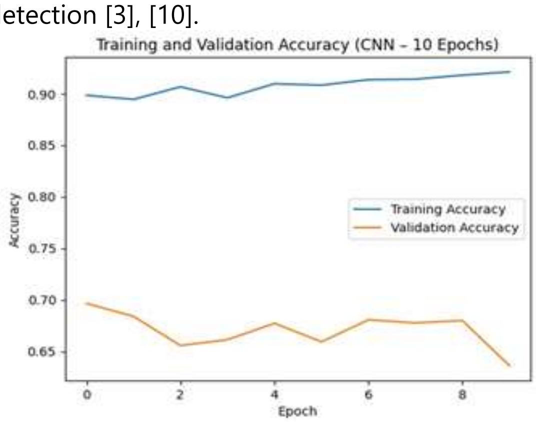

Fig. 4. Training and validation accuracy of the CNN model over ten epochs

VIII. RESULTS AND EVALUATION

The experimental results demonstrated the effectiveness of deep learning models for plant disease detection. In this study, three models, namely CNN, VGG16, and ResNet50, were evaluated. Deep learning approaches showed strong performance in image classification tasks because of their ability to capture complex spatial patterns from plant leaf images [1], [3]. The CNN model achieved a training accuracy of 92.11 percent and a validation accuracy of 63.62 percent. The VGG16 model achieved a training accuracy of 94.12 percent and a validation accuracy of 85.47 percent. The ResNet model achieved a training accuracy of 90.95 percent and a validation accuracy of 87.34 percent. These results are summarized in Table I.

TABLE I
Model Performance Comparison

Model	Training Accuracy	Validation Accuracy
CNN	92.11%	63.62%
VGG16	94.12%	85.47%
ResNet50	90.95%	87.34%

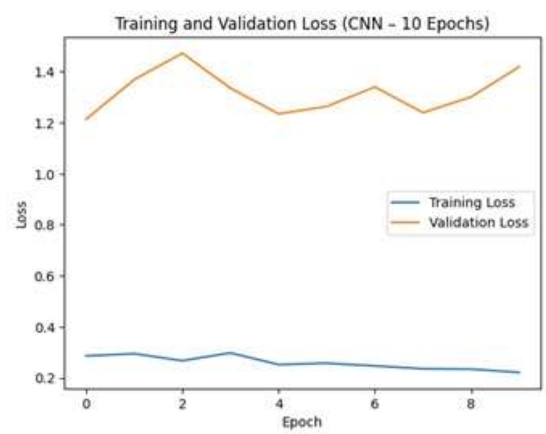

Fig. 5. Training and validation loss of the CNN model over ten epochs

The experimental results indicated that deep learning models performed effectively for plant disease recognition tasks. However, the CNN model showed a significant gap between training accuracy of 92.11 percent and validation accuracy of 63.62 percent, indicating potential overfitting, which occurs when a model learns the training data too specifically and fails to generalize well to unseen data. The overfitting observed in the CNN model could be attributed to factors such as limited dataset diversity, insufficient data augmentation, and the relatively shallow architecture compared with deeper networks. In contrast, transfer learning based models such as VGG16 and ResNet utilized pretrained weights, which enabled better feature extraction and improved generalization.

The VGG16 model improved classification performance by leveraging pretrained weights that helped capture more detailed and generalized visual patterns from the plant leaf images. Among the evaluated models, the ResNet architecture achieved the best validation accuracy because of its deeper architecture and residual learning mechanism, which facilitated efficient gradient flow and enhanced generalization performance. Deep learning models automatically learned hierarchical feature representations from the plant leaf images, leading to improved classification performance, and these findings aligned with previous research in which deep learning techniques consistently demonstrated strong performance in agricultural image classification problems [10], [11].

```
Confusion Matrix:
[[ 520    2  460    0    2    0    1    1    3    0    7    0    0    0
     0    1]
 [    3 1280  189    0    2    0    0    1    1    0    0    1    0    1
     0    0]
 [ 521  287  617    0    2    0    1    1    4    0    7    0    0    0
     0    1]
 [    3    1    5  955   18    0    0    2    6    0    6    0    0    0
     0    4]
 [    2    5    4   10  916    2    9    8    9    4   13    8    4    6
     0    0]
 [    0   19    1    1    5  125    0    0    0    0    0    1    0    0
     0    0]
 [    2    2    3    1    7    0 2036   13    8    2   44    1    0    8
     0    0]
 [    3    2    8    3    8    0   15  885   15    9   35    4    8    3
     1    1]
 [    1    4   11   13   25    0    8   29 1702   20   66   11    7    3
     2    7]
 [    1    2    7    1    3    0    2   37    7  839   40    3    1    2
     4    3]
 [   10    2   11   10    9    0   34   28   20   13 1596    8    6    8
     3    5]
 [    0    2    0    0    1    1    3    2    0    0    7 1627   19    5
     6    3]
 [    0    2    2    0   18    0   17   26    5    2   22   89 1199    0
     2   20]
 [    3    0    3    1    4    0    3    6    3    0   26   12    0 3141
     4    2]
 [    0    0    0    0    0    0    0    4    1    3    8   12    1   10
   334    0]
 [    0    1    0    0    8    0   21   10    8    3   13   59   42    5
     4 1417]]

Precision Recall F1-score
```

Fig. 6. Confusion matrix of the CNN model

IX. EVALUATION METRICS

Several evaluation metrics were used to measure the performance of the plant disease detection model. These metrics are widely adopted in machine learning and deep learning based agricultural image analysis systems [8], [12].

A. Accuracy

Accuracy measures the overall correctness of the classification model and is defined as

$$\frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

B. Precision

Precision indicates how many of the predicted positive samples were actually correct and is defined as

$$\frac{TP}{TP+FP} \quad (3)$$

C. Recall

Recall measures the model's ability to correctly identify positive samples and is defined as

$$\frac{TP}{TP+FN} \quad (4)$$

D. F1 Score

The F1 score provides a balanced measure between precision and recall and is useful when evaluating multi class classification models [3], and is defined as

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

X. SYSTEM ARCHITECTURE

The overall system architecture of the proposed DEPLANT framework consisted of several modules designed to perform automated plant disease detection from leaf images [4], [9]. The system comprised an image input module, an image preprocessing module, a disease classification module using CNN, VGG16, or ResNet, and a result output and visualization module.

The input image was first processed through preprocessing steps such as resizing and normalization. The processed image was then passed to the deep learning classifier, which extracted relevant features and predicted the disease category, after which the predicted result was displayed to the user through the web interface.

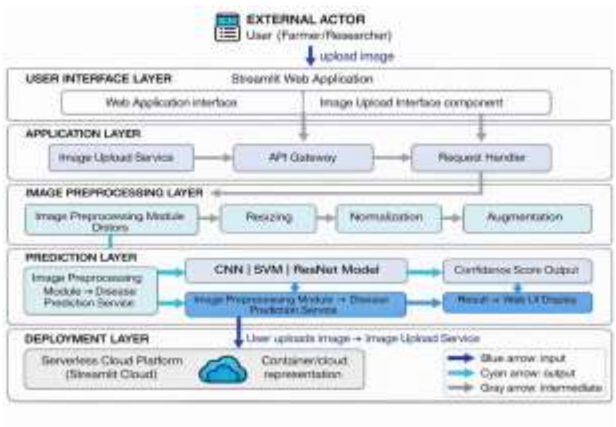

Fig. 7. Overall system architecture

XI. FUTURE WORK

Future enhancements to the DEPLANT system will focus on several improvements aimed at increasing its practical usability and scalability. Planned work includes Streamlit based real time web deployment for disease prediction, integration of the framework into a mobile application for field usage by farmers, incorporation of IoT sensors for environmental monitoring, and analysis of environmental parameters such as humidity, temperature, and soil conditions. Additional data augmentation and regularization techniques will also be implemented to reduce overfitting and improve model generalization. Future research will focus on making the models more robust and on incorporating real time monitoring systems to support precision agriculture and smart farming applications [2], [4], [9].

XII. CONCLUSION

DEPLANT is a deep learning based framework designed for automated plant disease detection using CNN, VGG16, and ResNet models. The experimental results demonstrated that deep learning approaches provided strong performance in plant leaf disease classification by effectively learning complex visual patterns from leaf images. Among the evaluated models, ResNet achieved the highest validation accuracy because of its deeper architecture and residual learning capability, making it highly suitable for complex image classification tasks. The proposed system is scalable and can be integrated with web based platforms for real time plant disease diagnosis, providing an efficient and user friendly solution to assist farmers in the early detection of plant diseases and enabling timely intervention and improved crop management. Overall, the DEPLANT framework contributes toward sustainable agriculture by supporting smart farming practices, improving plant health monitoring, and promoting AI driven agricultural solutions.

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