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ARTIFICIAL NEURAL NETWORKS AND DEEP LEARNING (AI253IA)

Plant Disease Detection: A Vision-Based Solution

Presented by

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Introduction

Problem Definition:

- Impact on Agriculture: Plant diseases severely affect global food security and economic stability.
- Challenges in Detection: Manual detection is time-consuming, prone to human error, and often requires expert knowledge.
- Consequences: Delay in identifying diseases leads to reduced crop yield, increased use of pesticides, and economic losses for farmers.

Statistical Reasoning

- Over $220 billion lost annually due to plant diseases worldwide (FAO).
- Diseases in staple crops like rice, wheat, and maize account for up to 30% of yield loss in developing countries.
- More than 70% of farmers in rural areas lack access to reliable disease detection tools, relying on traditional methods.

Introduction

Solution Proposed:

- A computer vision-based system for real-time plant disease detection.
- Utilizes image recognition techniques and machine learning algorithms to identify diseases from leaf images.
- Provides actionable insights through a mobile or web application interface.

Potential Impact:

- Prevents crop losses ,reduces dependence on chemical treatment, minimizes excessive pesticide use
- Offers a low-cost, efficient solution for farmers in rural and underdeveloped areas.

Stakeholders:

- Farmers who are the primary beneficiaries, Agri-Tech Companies can implement it on a large scale and optimize yield and NGOs & Development Organizations who can deploy the system in underdeveloped regions to ensure food security.

Objective

1. **Enhance Early Disease Detection**

   Enable the system to identify diseases at early stages to facilitate timely intervention and minimize crop yield losses.

2. **Integrate Severity Grading and Treatment Recommendations**

   Grade the severity of the detected disease and provide actionable treatment solutions, including eco-friendly options, to guide farmers effectively.

3. **Automated Detection**

   Automate the process of diagnosing plant diseases to reduce dependency on manual inspection.

4. **Achieve High Prediction Accuracy**

   Develop a robust machine learning model to accurately detect and classify plant diseases across diverse crops and environmental conditions.

Agenda

1. Introduction
2. Literature Survey
3. Summary of Literature Survey
4. Objectives
5. Requirement analysis – hardware and software specification
6. System architecture
7. Methodology
8. Module specification –
    a. Module 1 : Data collection and pre processing
        i. Input ii. Process iii output
    b. Module 2 : Implementation of ANN / DL algorithm
        i. Input ii. Process iii output
    c. Module 3 : Testing and Validation
        i. Input ii. Process iii output

Requirement Analysis

Hardware Requirements:

- Processor: Minimum **Intel i5** or equivalent for training models; **Intel i7** or above for faster processing.
- GPU: **NVIDIA GTX 1050 Ti** or higher for efficient deep learning model training and inference.
- RAM: **8 GB** (minimum); **16 GB** (recommended) for handling large datasets.
- Camera: Camera capable of capturing a minimum resolution of 224x224 pixel plant images in field conditions (for real-world testing).

Software Requirements:

- Programming Language: Python (Version 3.8 or above).
- Libraries & Frameworks:
- TensorFlow (Version 2.x) or PyTorch (Version 1.10 or above) for model development.
- OpenCV (Version 4.x) for image preprocessing.
- Scikit-learn (Version 1.x) for data analysis and evaluation metrics.
- Integrated Development Environment (IDE): Jupyter Notebook, PyCharm, or VS Code.
- Operating System: Windows 10/11, Linux (Ubuntu 20.04+), or macOS.

Dataset Description:

- Name: PlantVillage Dataset
- Source: Open-source dataset from Kaggle.
- Size: 16,000 images labeled for disease detection.
- Classes: 16 categories, including healthy and diseased leaves of crops like tomato, potato, and corn.
- Image Details:
  - High-quality images captured in controlled environments.
  - Includes variations in lighting and background.
- Distribution: Balanced dataset with healthy samples for each crop.
- Applications: Benchmarking machine learning models for plant disease detection.
- Preprocessing:
  - Resized to 224x224 pixels.
  - Pixel values normalized for consistency.

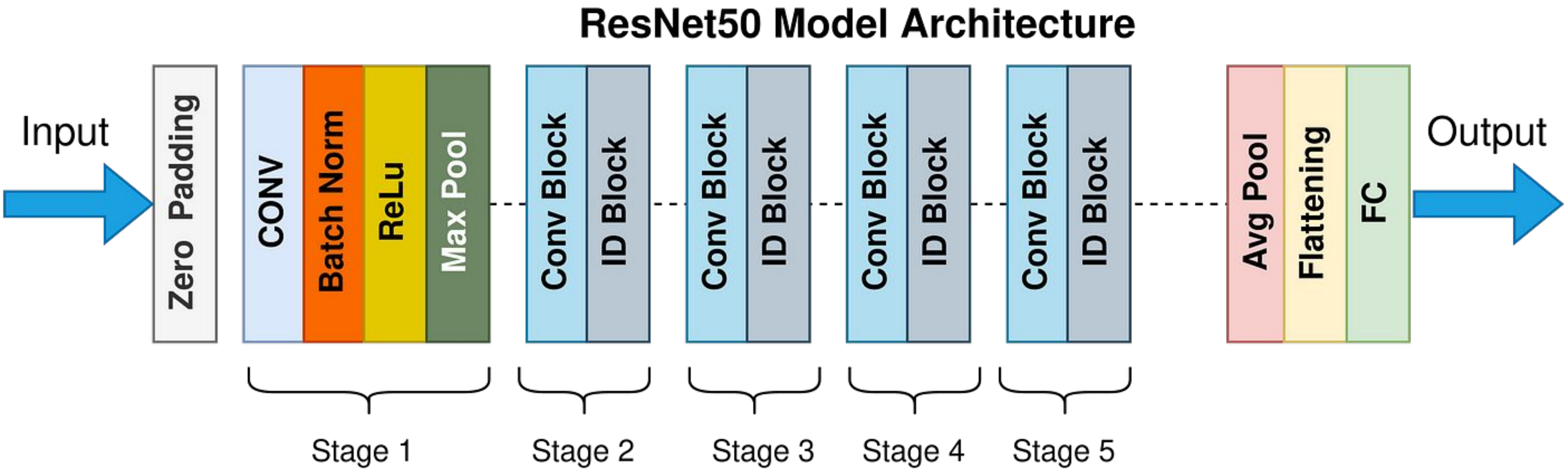
System Architecture

ResNet50 is a 50-layer deep convolutional neural network that uses residual connections (skip connections) to overcome the vanishing gradient problem and enable efficient training of deep networks.

Key Components:

- **Convolutional Layers**: Extract features from input images using filters.
- **Residual Blocks**: Shortcut connections that skip one or more layers, allowing the network to learn residual mappings. These blocks help in maintaining performance as the network depth increases.
- **Batch Normalization**: Helps stabilize and speed up training by normalizing the input to each layer.
- **ReLU Activation**: Introduced after convolutional layers to add non-linearity to the model.
- **Global Average Pooling**: Reduces the dimensions of feature maps before the final classification.
- **Fully Connected Layers**: These layers perform the final classification based on the learned features.

CNN -ResNet


ResNet50 Model Architecture
Input
Zero Padding
CONV
Batch Norm
ReLu
Max Pool
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Avg Pool
Flattening
FC
Output
Stage 1
Stage 2
Stage 3
Stage 4
Stage 5

System Architecture

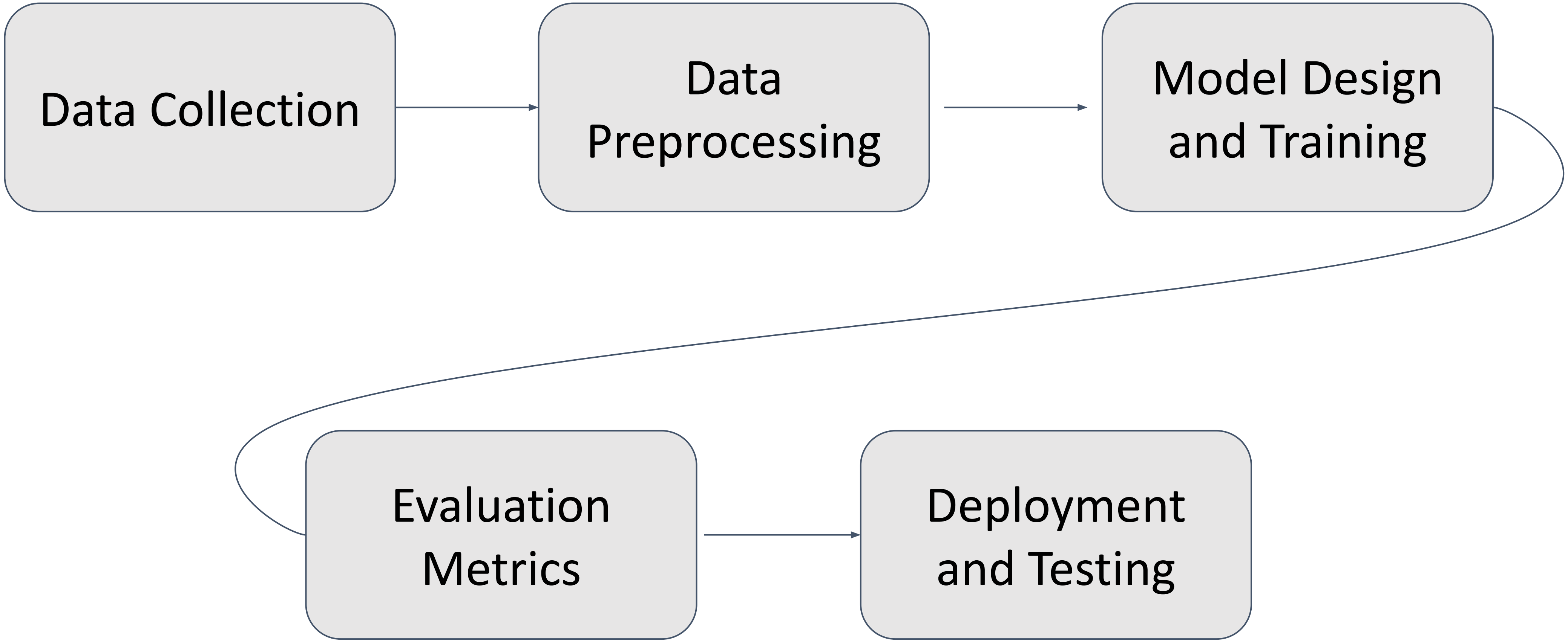
1. Input Layer:

- ➢ Image input: Typically an image with 224x224x3 dimensions (RGB).
- ➢ Preprocessing: Includes resizing, normalization (mean subtraction), and scaling to prepare the image.

2. Hidden Layers:

- ➢ Convolutional Layers: Extract features using filters (kernels) applied across the image.
- ➢ Residual Blocks: A key feature of ResNet. Each block has skip connections (bypass connections) that add the input directly to the output of the block. This helps to preserve information and reduces the problem of vanishing gradients during backpropagation.

Methodology



System Architecture

- Batch Normalization: Normalizes the outputs of each layer to stabilize and speed up the training process.
- ReLU Activation: Introduces non-linearity to the network, allowing it to learn complex patterns.
- Pooling Layers: Typically max pooling reduces the spatial size of the image, focusing on the most important features.

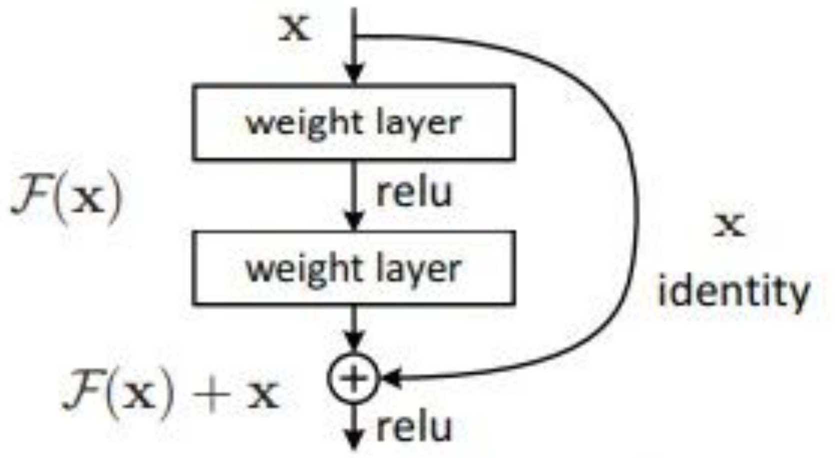
3. Output Layer:

- Fully Connected Layer: After the feature extraction, the output of the convolutional layers is flattened and passed through one or more fully connected layers.
- Softmax Activation: For classification tasks, the final layer uses softmax to convert the outputs into probabilities, representing class predictions.

Residual Learning : A Building Block

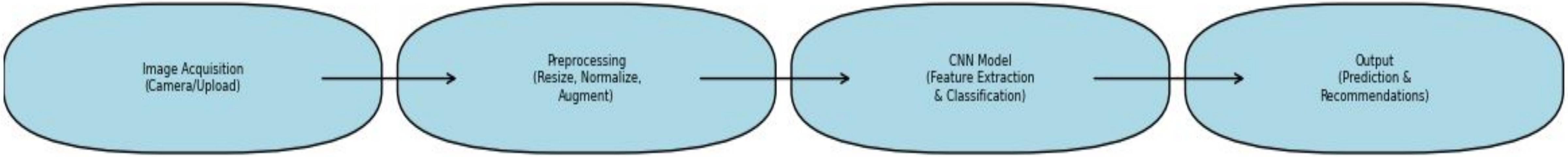
Degradation Problem: In deep networks, increasing layers can lead to saturated and degraded accuracy, not caused by overfitting.

- **Residual Learning**: Instead of learning the direct mapping, the network learns the residual (difference between input and output).
- **Skip Connections:** These connections bypass convolutional blocks, adding the input to the output of later layers, allowing for efficient learning.
- **Identity Mapping:** Adding layers doesn't hurt performance because it only adds useful weights or skips over unnecessary ones.



Methodology

Workflow Diagram:



Methodology

1. Data Collection

- Images of plant leaves were obtained from publicly available datasets and field data collections.
- The dataset was curated to include diverse lighting conditions, angles, and disease severity levels.
- All images were labeled with corresponding disease types, including severity where applicable.

2. Data Preprocessing

- Images were resized to standardized dimensions (e.g., 224x224 pixels) to ensure model compatibility.
- Pixel intensity values were normalized to the range [0,1] to enhance model convergence.
- Data augmentation techniques, such as rotation, flipping, cropping, and brightness adjustments, were applied to increase dataset variability.
- Background noise is minimized using image segmentation techniques like contour detection in OpenCV.

Methodology

3.Model Design and Training

- A Convolutional Neural Network (CNN) architecture employed for feature extraction and disease classification.
- Transfer learning with pre-trained models (ResNet) is explored to accelerate training and improve accuracy.
- The model layers included convolutional layers with ReLU activation, pooling layers for dimensionality reduction, and fully connected layers for classification.
- Dropout layers were incorporated to prevent overfitting,
- The dataset is split into training, validation, and test sets in a 70-20-10 ratio.

4. Evaluation Metrics

- Model performance is assessed using accuracy, precision, recall, F1-score, and a confusion matrix.

5. Deployment and Testing

- The trained model is deployed via a web-based interface, enabling users to upload leaf images for real-time predictions.
- The system hosted on cloud platforms for scalability and tested in real-world conditions with farmers to gather feedback for further improvements.

Module 1 : Data Collection and Preprocessing

Input:

- Images of plant leaves (healthy and diseased).
- Sources include PlantVillage dataset, field-collected images, or IoT devices like cameras in agricultural settings.
- Metadata (e.g., plant type, disease type, image conditions).

Process:

- Image resizing (224x224 pixels).
- Normalization and scaling.
- **Preprocessing:**
  Resize images to 224x224 pixels for ResNet compatibility.
  Normalize pixel values to a range of 0 to 1 for consistent model performance.
  Augment data (e.g., flipping, rotation, scaling) to increase diversity.

Output:

Preprocessed dataset ready for training and testing.

Module 2 : Implementation of ANN / DL algorithm

Input:

- Preprocessed dataset (training and validation sets).
- Network configuration (e.g., ResNet-50 architecture).
- Hyperparameters: learning rate, batch size, number of epochs.

Process:

- Build the ResNet architecture with residual blocks.
- Train the model using the dataset with a defined loss function (e.g., cross-entropy) and optimizer (e.g., Adam).
- **Validation:** Evaluate model performance after each epoch on validation data.
- Save the trained model for evaluation.

Output:

- Trained ResNet model file (.h5 or .pth).
- Training logs, including loss curves, accuracy, and hyperparameter details.

Module 3 : Testing and Validation

Input:

- Trained ResNet model.
- Test dataset (images not seen during training).
- Performance metrics to compute (accuracy, precision, recall, F1 score, confusion matrix).

Process:

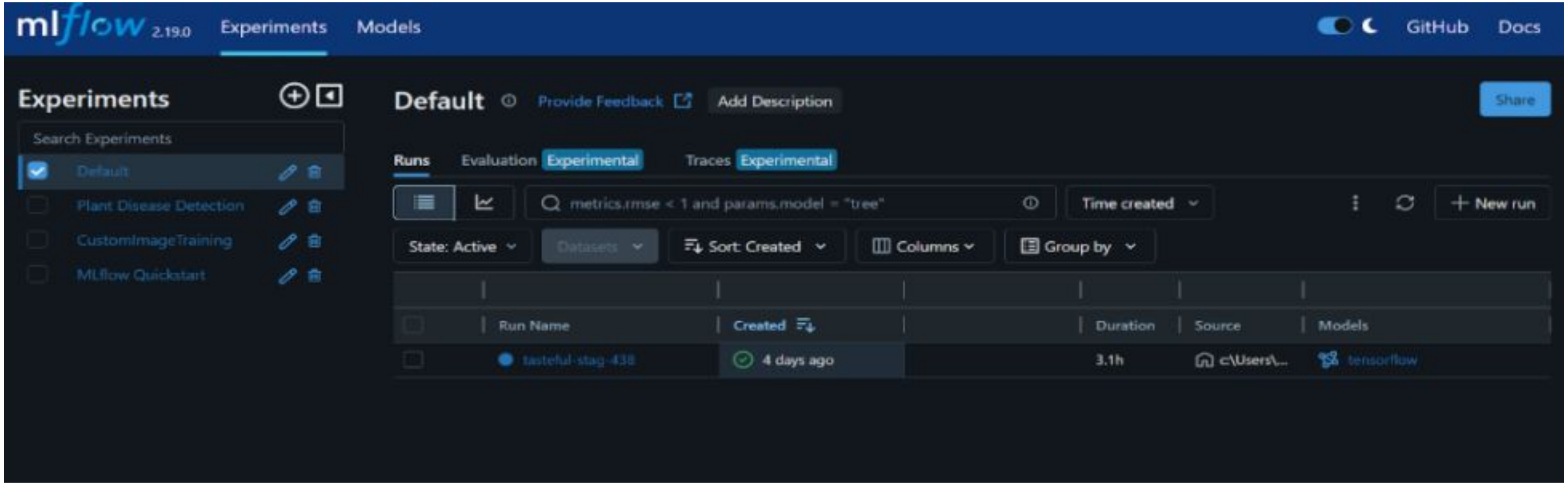
- **Testing:** Feed test images through the trained ResNet model. Compare predictions with ground truth labels.
- **Validation:** Evaluate model generalizability on unseen data. Perform fine-grained analysis of misclassifications.
- **Visualization:** Generate confusion matrix, ROC curves, and misclassified image samples.

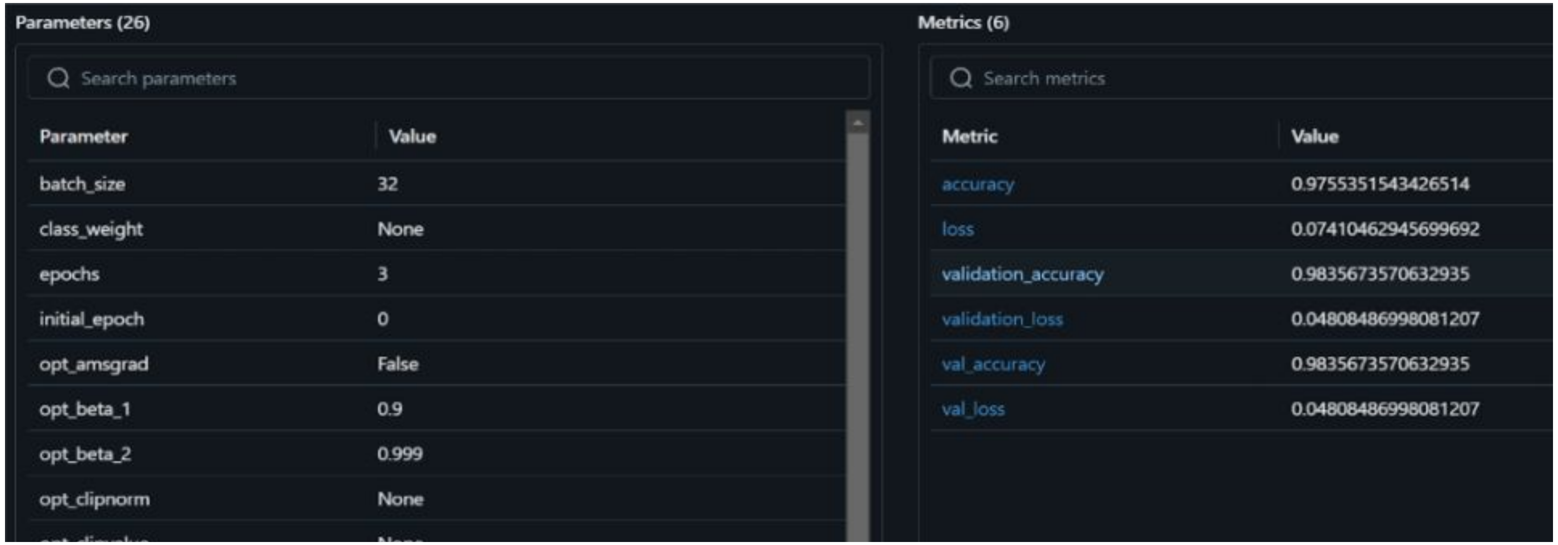
Output:

- Performance metrics
- Detailed report on model performance, including strengths and limitations.
- Refined model ready for deployment.

Result and discussion

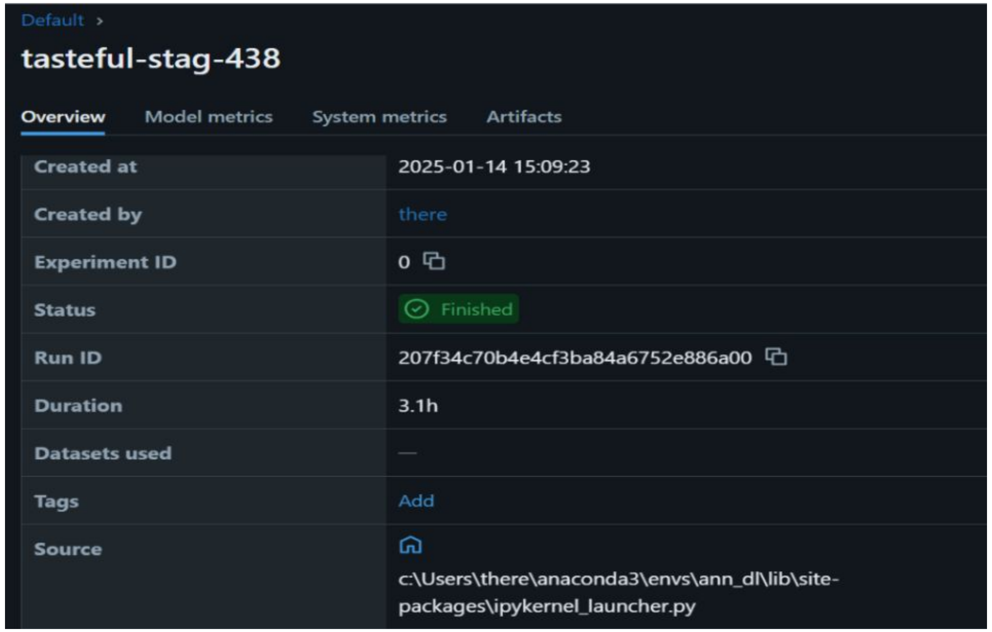
MLflow





Result and discussion

MLFlow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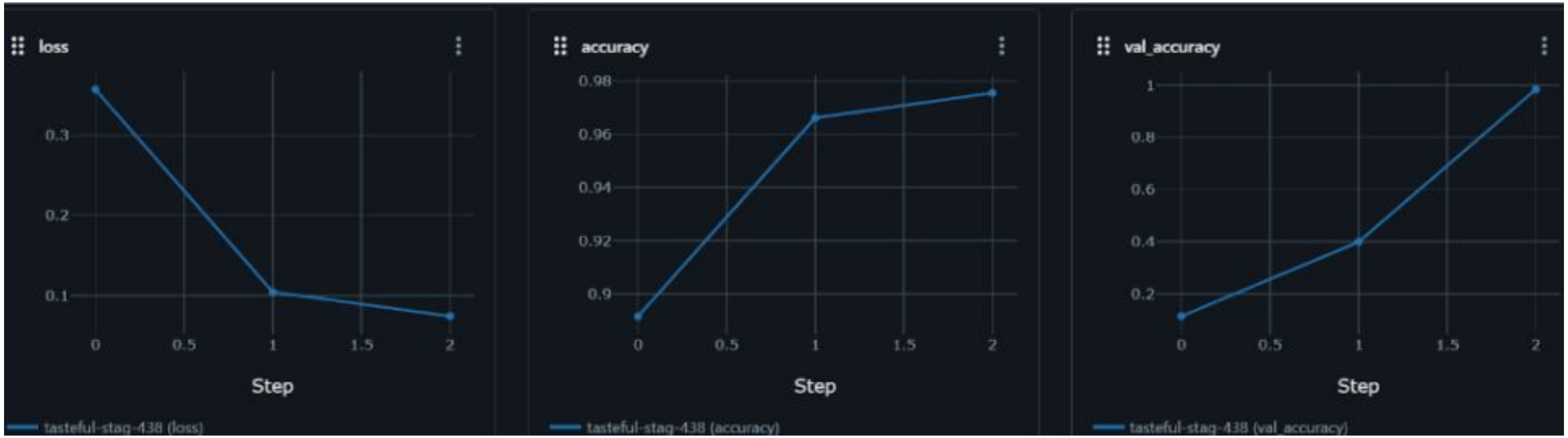
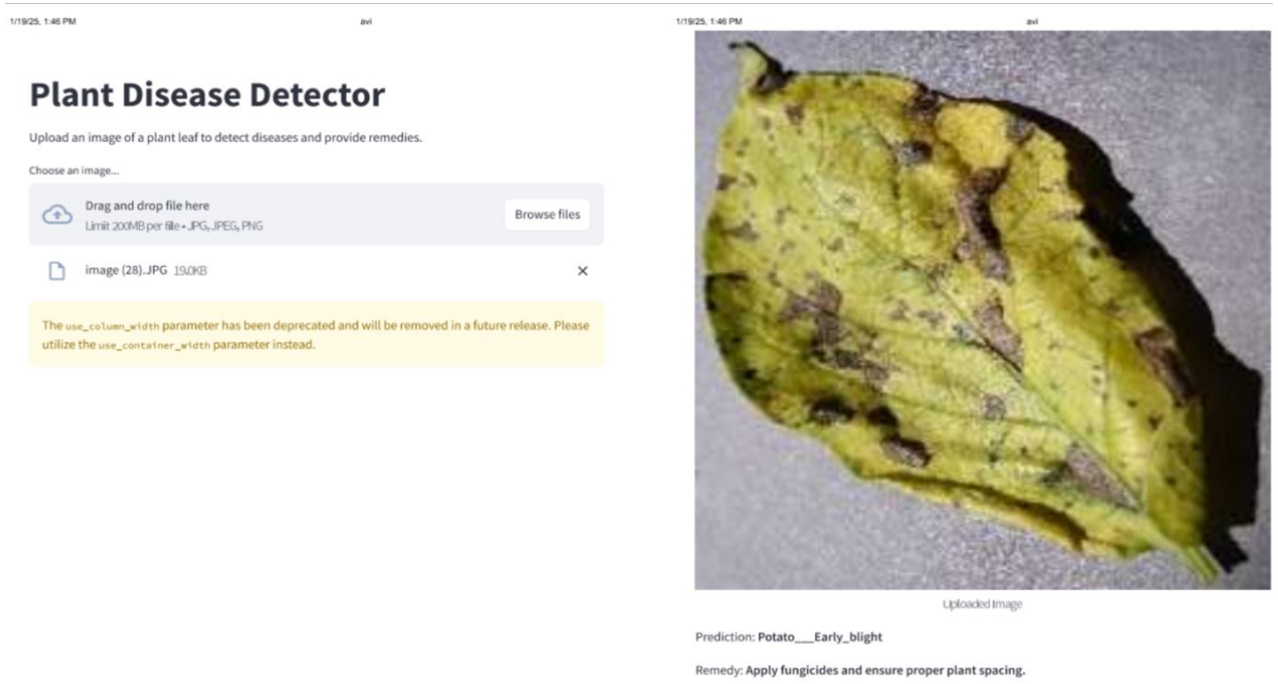
Overview | Model metrics | System metrics | Artifacts

Created at	2025-01-14 15:09:23
Created by	there
Experiment ID	0
Status	Finished
Run ID	207f34c70b4e4cf3ba84a6752e886a00
Duration	3.1h
Datasets used	—
Tags	Add
Source	c:\Users\there\anaconda3\envs\ann_dl\lib\site-packages\ipykernel_launcher.py



Results

Graphical user interface



Input Image

Preprocessed Image

Disease :Tomato Early Blight
Remedy: apply fungicides like chlorothalonil or mancozeb and practice crop rotation with resistant varieties.

Output

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Literature Survey

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
1	Computer Vision-Based Automated Detection and Severity Grading of Rice Spot Disease for Precision Management *(M. Kumar and I. Sethi)*	IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-4, doi: 10.1109/IATMSI60426.2024.10503168	The research introduces a hybrid model combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to automatically identify rice spot disease and grade its severity. The model, trained on an extensive rice spot dataset, achieved an accuracy rate of 95.59%. This system enables precise disease management, offering a practical solution for farmers to improve crop yield by addressing disease early.
2.	Vision Based Plant Leaf Disease Detection and Recognition Model Using Machine Learning Techniques *(R. Sathya, S. Senthilvadivu, S. Ananthi, V. C. Bharathi and G. Revathy)*	7th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2023, pp. 458-464, doi: 10.1109/ICECA58529.2023.10395620	The paper uses supervised machine learning to recognize diseases in brinjal leaves, including Cercospora solani, Tobacco Mosaic Virus, and others. By applying feature extraction methods like LIV, PCA, and GLCM, the model achieved an accuracy of 98.48% with SVM RBF. The system offers a robust solution for detecting and diagnosing brinjal leaf diseases with high precision.

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
3	A Bibliometric and Word Cloud Analysis on the Role of IoT in Agricultural Plant Disease Detection *(Rutuja Rajendra Patil, Sumit Kumar, Ruchi Rani, Poorva Agrawal, Sanjeev Kumar Pippal)*	Applied System Innovation, vol. 6, no. 1, pp. 27, 2023. DOI: 10.3390/asi6010027	IoT-based systems with environmental sensors (tracking humidity, temperature, and soil moisture) enable early disease detection, improving yield prediction and reducing pesticide overuse. Combining IoT with AI enhances precision in agricultural disease forecasting
4.	FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning *(Emmanuel Moupojou, Appolinaire Tagne, Florent Retraint, Anicet Tadonkemwa, Dongmo Wilfried, Hyppolite Tapamo, Marcellin Nkenlifack)*	IEEE Access (2023), this study introduces FieldPlant, a dataset for realistic plant disease detection in field conditions. DOI: 10.1109/ACCESS.2023.3263042	Most deep learning models trained on lab datasets (like PlantVillage) fail in field conditions due to complex backgrounds. The FieldPlant dataset, designed with annotated field images, addresses this gap and improves disease classification under real-world scenarios Models like MobileNetV2 and YOLO demonstrate high accuracy in plant disease detection

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
5	Apple Leave Disease Detection Using Collaborative ML/DL and Artificial Intelligence Methods: Scientometric Analysis *(Anupam Bonkra, Pramod Kumar Bhatt, Joanna Rosak-Szyrocka)*	International Journal of Environmental Research and Public Health (2023), this paper reviews AI-driven methods for detecting apple leaf diseases. DOI: 10.3390/ijerph20043222	Collaborative ML/DL approaches like CNNs and hybrid techniques effectively classify diseases like scab, rust, and black rot in apple leaves. Pre-processing steps like segmentation and feature extraction play a vital role in boosting model accuracy
6.	Pepper bell leaf disease detection and classification using optimized convolutional neural network *(Hassan Mustafa, Muhammad Umer, Umair Hafeez, Ahmad Hameed, Ahmed Sohaib, Saleem Ullah & Hamza Ahmad Madni)*	Multimed Tools Appl 82, 12065–12080 (2023). https://doi.org/10.1007/s11042-022-13737-8	This study highlights the importance of early plant disease detection for agricultural productivity. It proposes a five-layered CNN model trained on 20,000 augmented images for automatic identification of diseases in plant leaves. The optimized model achieves 99.99% accuracy in distinguishing healthy and bacterial-infected pepper bell leaves, demonstrating its potential as a real-time disease detection tool in agriculture.

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
7	A Systematic Review on the Detection and Classification of Plant Diseases Using Machine Learning *(Deepkiran Munjal, Laxman Singh, Mrinal Pandey, Sachin Lakra)*	IJSI vol.11, no.1 2023: pp.1-25. https://doi.org/10.4018/IJSI.315657	This study reviews ML, DL, and computer vision techniques for early plant disease detection, highlighting their superiority over traditional methods. It evaluates state-of-the-art approaches, discussing their strengths, limitations, and potential for improving disease management in agriculture.
8.	PLDD—A Deep Learning-Based Plant Leaf Disease Detection *(R. K. Lakshmi and N. Savarimuthu)*	IEEE Consumer Electronics Magazine, vol. 11, no. 3, pp. 44-49, 1 May 2022, doi: 10.1109/MCE.2021.3083976	The research presents a transfer learning-based optimized EfficientDet deep learning framework for plant disease detection. The model, evaluated using mean average precision (mAP), achieved an mAP of 74.10%. The system offers a practical solution for automated disease detection on handheld devices, providing quicker results with fewer computational resources compared to other models.

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
9	Vision-Based Wilted Plant Detection *(J. Madake, S. Shinde, S. Singh, S. Talwekar, S. Bhatlawande and S. Shilaskar)*	IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2022, pp. 1-6, doi: 10.1109/IATMSI56455.2022.10119325.	This study focuses on detecting wilted plants using image processing and feature extraction techniques, such as ORB and SIFT. The model uses classifiers like Random Forest, AdaBoost, Decision Tree, and Logistic Regression, with the Random Forest classifier yielding an accuracy of 85.41%. The system provides valuable insights into plant health, helping in the detection of indoor plant watering needs.
10.	Detection and classification of chilli leaf disease using a squeeze-and-excitation-based CNN model *(B.Nageswararao Naik, R.Malmathanraj, P. Palanisamy)*	Ecological Informatics 69(6):101663 DOI:10.1016/j.ecoinf.2022.101663	This study focuses on detecting and classifying five chilli leaf diseases using images and comparing the performance of machine learning and deep learning models. Twelve pretrained networks were tested, with DarkNet53 achieving the highest accuracy (99.12%) with augmentation. A novel squeeze-and-excitation CNN (SECNN) model further improved accuracy, achieving 99.28% on 43 plant leaf classes, including chilli and other datasets.

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11	Plant Disease Detection Using Deep Convolutional Neural Network *(J. Arun Pandian, V. Dhilip Kumar, Oana Geman, Mihaela Hnatiuc, Muhammad Arif, and K. Kanchana Devi)*	Applied Sciences, vol. 12, no. 14, pp. 6982, 2022. DOI: 10.3390/app12146982	The paper introduces a 14-layer deep convolutional neural network (DCNN) achieving 99.97% accuracy for detecting plant diseases across 58 plant leaf classes. Data augmentation methods like BIM, GANs, and NST enhanced the dataset's diversity and model robustness. Hyperparameter optimization through random search significantly improved the model's performance. High-performance GPUs and TensorFlow were used for efficient training and testing, ensuring scalability
12.	Plant Disease Detection using AI based VGG-16 Model *(A. A. Alatawi, S. M. Alomani, N. I. Alhawiti, and M. Ayaz)*	International Journal of Advanced Computer Science and Applications (IJACSA), vol. 13, no. 4, pp. 477–482, 2022. DOI: 10.14569/IJACSA.2022.0130484.	The study leverages the VGG-16 model, achieving a 95.2% accuracy on a dataset of 15,915 plant leaf images (both healthy and diseased) from the PlantVillage dataset. It utilizes CNN for efficient disease classification across 19 plant disease classes, enabling timely interventions. With a testing loss of 0.4418, the study demonstrates the model's capability for scalable application in agricultural disease management

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
13	Investigation on Object Detection Models for Plant Disease Detection Framework *(K. L. R and N. Savarimuthu)*	IEEE 6th International Conference on Computing, Communication and Automation (ICCCA), Arad, Romania, 2021, pp. 214-218, doi: 10.1109/ICCCA52192.2021.9666441.	The paper investigates the use of computer vision-based object detection methods (YOLOv4, EfficientDet, Scaled-YOLOv4) for early plant disease detection. By utilizing the PlantVillage dataset, the study highlights that Scaled-YOLOv4 is highly effective for detecting small infected areas in real-time, providing a quick and efficient solution for early diagnosis, which is crucial in reducing crop losses.
14	Disease Detection in Apple Leaves Using Deep Convolutional Neural Network (*Prakhar Bansal , Rahul Kumar and Somesh Kumar*)	Bansal, P.; Kumar, R.; Kumar, S. Disease Detection in Apple Leaves Using Deep Convolutional Neural Network. Agriculture 2021, 11, 617. https://doi.org/10.3390/agriculture11070617	It proposes a model for classifying diseases in apple leaves using an ensemble of pre-trained deep learning models. The proposed model outperforms previous models and achieves an accuracy of 96.25% . Deep learning techniques, such as convolutional neural networks (CNNs), are particularly effective in image classification tasks, making them well-suited for identifying diseases

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15	Paddy Leaf Disease Detection Using an Optimized Deep Neural Network *(Sankaranarayanan Nalini)*	Published in Computers, Materials & Continua (CMC), Volume 68, Issue 1, February 2021, with DOI 10.32604/cmc.2021.012431,	Key methodology includes preprocessing images, using k-means clustering for disease region segmentation, extracting color, shape, and texture features, and applying a novel deep learning approach with optimized weights and biases.The proposed method significantly outperforms traditional support vector machine (SVM) algorithms achieving 96.96% accuracy
16	Identification of disease using deep learning and evaluation of bacteriosis in peach leaf *(*Saumya Yadav , Neha Sengar , Akriti Singh , Anushikha Singh , Malay Kishore Dutta*)*	Ecological Informatics Volume 61, March 2021, 101247,doi.org/10.1016/j.ecoinf.2021.101247	This work develops a convolutional neural network (CNN) model for detecting bacteriosis in peach crops using leaf images. The model, trained on augmented datasets, achieved 98.75% accuracy in 0.185 seconds per image. It performs well on both field and laboratory images, making it a potential early warning tool for real-world farming conditions, with possibilities for integration with unmanned aerial vehicles for practical use.

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
17	Identification of Pathological Disease in Plants using Deep Neural Networks *(R. Biswas, A. Basu, A. Nandy, A. Deb, R. Chowdhury and D. Chanda)*	Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN), Rajpura, India, 2020, pp. 45-48, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181339.	The paper introduces a mobile or web application powered by deep learning and computer vision for the automated identification of plant diseases. Users can upload an image or video feed, and the system provides a disease diagnosis with a bounding box and accuracy score. The system targets five plant diseases, enabling users to receive insights on treatment and prevention.
18.	SVM-Based Detection of Tomato Leaves Diseases *(Usama Mokhtar, Nashwa El Bendary, Aboul Ella Hassenian, E. Emary, Mahmoud A. Mahmoud, Hesham Hefny & Mohamed F. Tolba)*	In: Filev, D., et al. Intelligent Systems 2019. Advances in Intelligent Systems and Computing, vol 323. Springer, Cham. https://doi.org/10.1007/978-3-319-11310-4_55	This study detects tomato leaf health using image processing with GLCM for feature extraction and SVM for classification. Using 800 images and N-fold cross-validation, it achieved 99.83% accuracy with a linear kernel.

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
19	A Computer Vision System for Guava Disease Detection and Recommend Curative Solution Using Deep Learning Approach *(A. S. M. Farhan Al Haque, R. Hafiz, M. A. Hakim and G. M. Rasiqul Islam)*	22nd International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 2019, pp. 1-6, doi: 10.1109/ICCIT48885.2019.9038598.	The study focuses on developing an automated system using CNN to detect diseases in guava, specifically anthracnose, fruit rot, and fruit canker. By using images of diseased and healthy guava, the model achieved a high accuracy of 95.61%. This system provides an early detection tool to help mitigate economic losses in guava production and suggest curative actions for farmers.
20.	Plant Disease Detection and Classification by Deep Learning *(Muhammad Hammad Saleem, Johan Potgieter and Khalid Mahmood Arif)*	Plants (Basel). 2019 Oct 31;8(11):468. doi: 10.3390/plants8110468. PMID: 31683734; PMCID: PMC6918394.	This review discusses how deep learning (DL) advancements have improved plant disease detection and classification, surpassing traditional machine learning. It explores DL models, visualization techniques, and performance metrics while identifying gaps for enhancing early, symptom-free disease detection.

Summary of Lit. Survey

Common Themes Across Studies:

- **Deep Learning (DL) Dominance:** Techniques like CNNs, VGG-16, and transfer learning models (EfficientDet, YOLO, etc.) are widely used for plant disease detection due to high accuracy and scalability (Summaries 1, 13, 14, 17).
- **Machine Learning (ML) & Hybrid Approaches:** Some papers combine traditional ML with DL for improved performance, emphasizing feature extraction and SVM-based classification (Summaries 2, 6, 9).
- **Image Processing Techniques:** Preprocessing, feature extraction (GLCM, ORB, SIFT), and augmentation play crucial roles in boosting model performance (Summaries 7, 18).

General Observations:

- **High Accuracy Models:** Many studies report models achieving 95–99% accuracy, demonstrating potential for real-world deployment (Summaries 2, 8, 17).
- **Dataset Importance:** Augmentation and diverse datasets (e.g., PlantVillage, FieldPlant) enhance model robustness for real-world conditions (Summaries 11, 13, 14).

Summary of Lit. Survey

Identified Gaps:

- **Field Data Challenges:** Models often underperform in field scenarios due to complex backgrounds and environmental noise (Summary 11).
- **Scalability Concerns:** High computational resources required for some DL models limit their real-world deployment (Summaries 4, 15).

Scope for Improvement:

- **Real-World Applicability:** Incorporate IoT and UAVs to bridge lab-to-field performance gaps (Summaries 10, 20).
- **Early Detection Focus:** Develop models capable of detecting diseases before visible symptoms appear (Summary 15).
- **Efficiency Optimization:** Lightweight and resource-efficient models are needed for handheld or low-power devices (Summary 4).

Comparison

Algorithm	Key Features	Performance
SVM	Good for small datasets; requires manual feature extraction.	Moderate accuracy; limited scalability.
CNN	Automatic feature extraction; handles high- dimensional image data.	Good accuracy but less effective than ResNet.
ResNet (CNN)	Solves vanishing gradient, supports very deep networks.	High accuracy and best performance for image classification.

CNN-ResNet :

Outperforms other models in accuracy and robustness; scalable for diverse and field-based datasets.

THANK YOU !!