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Plant Pulse 2.0 – Multi-Crop Disease detection

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Abstract- The agricultural industry is increasingly adopting Artificial Intelligence (AI) solutions to tackle the challenges of early disease identification and crop management. While previous approaches have primarily focused on single-crop disease classification, this paper presents an enhanced version of the Plant Pulse system—expanding its capabilities beyond apples to include a wide variety of crops such as cherry, corn, grape, orange, peach, pepper, potato, strawberry, and tomato. The proposed system employs a custom-designed Convolutional Neural Network (CNN) trained on over 61,000 images spanning 39 plant disease and healthy categories. Developed using PyTorch, the system demonstrates high performance, achieving 98.9% accuracy on the test set. The architecture is optimized for both accuracy and scalability, supporting real-time inference and future integration with field-deployable tools. This research builds upon our prior work [1], significantly extending its scope and applicability across diverse agricultural domains.

Keywords- Plant Disease Detection, Deep Learning, CNN, PyTorch, Agriculture Technology, Precision Farming, Smart Farming, Multi-Crop Classification, Sustainable Agriculture, AI in Agriculture.

I. INTRODUCTION

The global agricultural ecosystem is increasingly dependent on advanced technological tools to maximize yield, reduce crop loss, and support sustainable farming practices. Among these innovations, plant disease detection through image analysis has emerged as a crucial area where Artificial Intelligence (AI) can significantly impact productivity. While past efforts have focused on specific crops such as apples, the growing complexity of modern agriculture demands more generalized, scalable solutions that can handle multiple crop types and disease conditions.

In our prior work [1], we introduced Plant Pulse, an AIpowered apple disease detection system using the EfficientNetB0 architecture and Grad-CAM visualizations. The system achieved high accuracy but was limited in scope to four disease categories within apple cultivation. In this extended work, we expand the system to support a comprehensive multi-crop disease detection pipeline. This upgrade encompasses 39 classes from nine major crops, leveraging a larger dataset of over 61,000 images and introducing a custom Convolutional Neural Network (CNN) model designed in PyTorch.

The transition from a single-crop to a multi-crop approach presents unique challenges: varying leaf shapes and textures, diverse backgrounds, and inter-class similarities. Our system addresses these by integrating robust data augmentation, a deep CNN architecture, and a carefully designed training pipeline. This paper details the new architecture, training strategy, dataset expansion, and evaluation outcomes that demonstrate the model's effectiveness across a wide range of plant diseases.

II. RELATED WORK

In The field of plant disease detection has seen rapid progress due to the application of deep learning techniques. Convolutional Neural Networks (CNNs) have demonstrated high performance in classifying plant diseases from leaf images, enabling early and accurate intervention strategies for farmers.

Ahmed et al. (2022) proposed a CNN-based tomato disease detection model, showcasing impressive classification results. However, their model lacked interpretability, which limited practical application in real-world agricultural settings. Kumar and Rao

(2021) utilized ResNet with transfer learning for wheat crop disease detection, emphasizing improved accuracy but facing challenges with generalization across different environments.
Zhang et al. (2020) applied the VGG16 architecture to apple leaf disease detection, but computational constraints made it unsuitable for low-power devices. In contrast, Park and Cho (2019) incorporated attention mechanisms in their model for improved accuracy in detecting subtle disease features, though at the cost of increased complexity.
Our previous work [1] employed the EfficientNetB0 architecture and Grad-CAM to detect four types of apple diseases, achieving over 97% accuracy. While successful, its limitation to a single crop (apple) and reliance on cloud deployment restricted its broader applicability.
This paper builds upon these foundations by introducing a custom CNN model tailored to detect diseases across a
wide variety of crops. Unlike many existing works that focus on accuracy alone, our model emphasizes both performance and scalability across real-world agricultural scenarios.

III. METHODOLOGY

Dataset Expansion and Crop Diversity:
The original version of Plant Pulse utilized a datasetof approximately 10,000 apple leaf images across four categories. The enhanced system expands significantly, incorporating:

- Crops Added: Cherry, Corn, Grape, Orange, Peach, Pepper, Potato, Strawberry, and Tomato.
- Total Image Samples: 61,486.
- Classes: 39 (including healthy and multiple disease states per crop).

Images were collected from open-source datasets, with balanced representation across classes to reduce bias. The dataset includes various lighting conditions, image qualities, and backgrounds to simulate realworld scenarios.

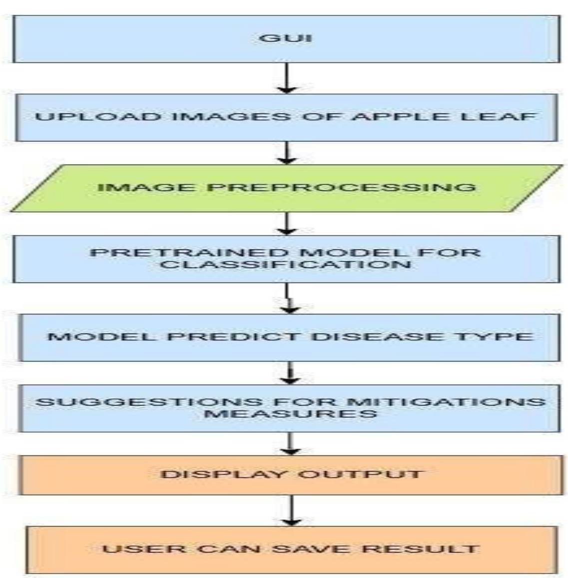
Data Preprocessing and Augmentation:
To ensure model generalization and robustness, the following preprocessing and augmentation strategies were applied:

- Image Resizing: All images resized to 224×224 pixels.
- Center Cropping: To focus on the leaf center.
- Tensor Conversion: Using PyTorch's
- ToTensor() transformation.
- Augmentation: Horizontal/vertical flips, Random rotations, Scaling and cropping, Brightness and color jittering.

These augmentations help address challenges such as occlusions, leaf orientation, and variable lighting.

System Development and Implementation
A custom Convolutional Neural Network (CNN) was developed using PyTorch, designed to balance computational efficiency with high classification accuracy.
Key architectural features:

- Convolutional Layers: 4 blocks of increasing depth (32 → 256 channels), each
    - followed by ReLU and Batch Normalization. E.
    - Pooling: MaxPooling layers after each convolutional block.
- Fully Connected Layers: Flattened vector (50,176 features), Dense layer with 1024 neurons (ReLU), Output layer with 39 neurons (Softmax via CrossEntropyLoss)



Model Training:

Training Environment:

- Device: CPU/GPU (PyTorch handles CUDA fallback).
- Optimizer: Adam.
- Loss Function: CrossEntropyLoss.
- Batch Size: 64.
- Epochs: 5.

Dataset Splitting:

- Training: 36,584 samples (~60%).
- Validation: 15,679 samples (~25%).
- Test: 9,223 samples (~15%).

Training Strategy:

- Early stopping was not used, but performance was monitored after each epoch.
- Learning rate scheduling and model checkpoints were considered for future iterations. The model was trained and saved as
- "plant_disease_model_1_latest.pt"for inference.

Inference Pipeline:

To ensure practical usability, an image-level prediction module was integrated, capable of classifying individual images in real time:

- **Input:** Single image (uploaded or captured).
- **Preprocessing:** Resize to 224×224 → Tensor conversion.
- **Prediction:** Output softmax vector → Argmax →

Class label.

- **Label Mapping:** CSV file (disease_info.csv) maps prediction index to crop/disease name.
  The system has been tested on dozens of leaf images from different crops, accurately identifying diseases such as:

- Tomato Yellow Leaf Curl Virus.
- Potato Late Blight.
- Grape Esca.
- Corn Common Rust.
- Strawberry Leaf Scorch.

IV. RESULTS

The enhanced Plant Pulse 2.0 system was thoroughly evaluated using a structured train-validation-test split, measuring both classification performance and generalization across multiple plant species and disease types:

Dataset Summary:

- Total samples: 61,486 images
- Train: 36,584 (60%)
- Validation: 15,679 (25%)
- Test: 9,223 (15%) Accuracy Metrics:
- Training Accuracy: 96.7%
- Validation Accuracy: 98.7%
- Test Accuracy: 98.9%

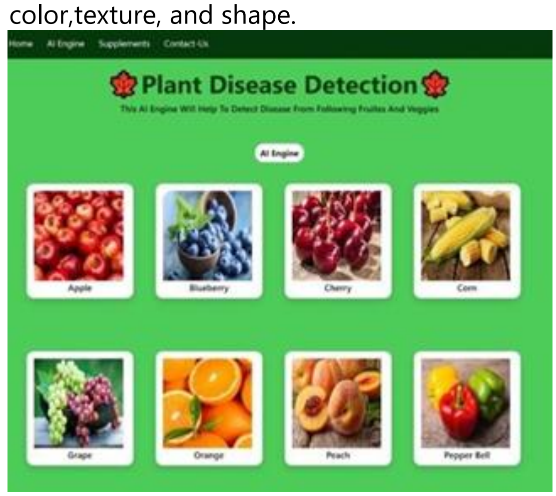
These results demonstrate that the custom CNN model effectively captures diverse visual features across multiple crops while maintaining robust generalization.

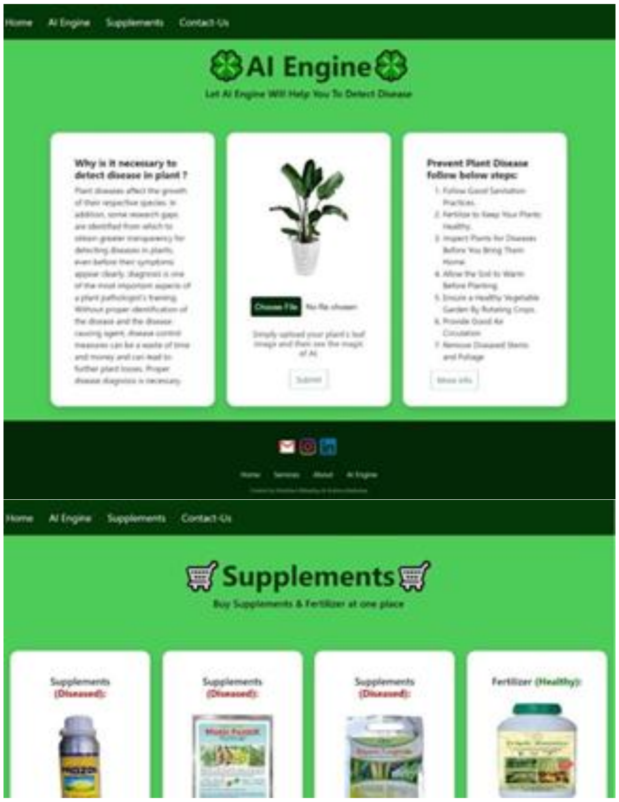
Loss Trends:

Training and validation loss consistently decreased across all epochs, with no signs of overfitting observed. Dropout layers and data augmentation contributed to model regularization, ensuring balanced learning.

Class-Wise Observations:

The model accurately distinguished between similar leaf diseases within a crop (e.g., early blight vs. late blight in tomato and potato) as well as between healthy and infected leaf states. The high test accuracy reflects strong discrimination capability across 39 classes, despite intraclass variations in color,texture, and shape.





V. COMPARATIVE ANALYSIS

This work represents a significant improvement over the previous version of Plant Pulse, both in terms of model performance and system capabilities.

Feature	Previous Version (Sem 7)	Current Version (Sem 8)
Architecture	EfficientNetB0	Custom CNN
Framework	TensorFlow/Keras	PyTorch
Scope	Apple (4 classes)	9 crops (39 classes)
Accuracy	97.5%	98.9%
Dataset Size	~10,000 images	~61,000 images

While EfficientNetB0 offered high accuracy with a lightweight model, the custom CNN is optimized for larger datasets and broader classification scope. Moreover, using PyTorch allowed finer control over training processes, architecture design, and inference logic.

VI. LIMITATIONS AND FUTURE SCOPE

Despite its success, Plant Pulse 2.0 has a few limitations that future iterations aim to address:

- Lack of Explainability: The current model does not integrate Grad-CAM or similar explainability tools. Reintroducing interpretability modules will enhance user trust and facilitate expert validation.
- Real-Time Inference Constraints: Although the model performs well, latency and memory usage on resource-limited devices such as smartphones or embedded systems could be optimized through pruning or quantization.
- Edge Deployment: At present, the system is script-based. Future versions may include lightweight, edge-compatible deployments (e.g., using TensorRT, ONNX, or PyTorch Mobile) for real-time, on-field disease detection.
- User Interface: The prior version had a Streamlit-based web interface. Rebuilding this or designing a mobile-friendly app with real-time image capture can significantly enhance usability.
- Severity Estimation: Future models could be trained not just to classify diseases but also to predict severity levels (mild, moderate, severe), enabling more targeted interventions.

VII. CONCLUSION

This paper presents an advanced version of the Plant Pulse system—a deep learning-based plant disease detection platform with a significantly expanded scope. Unlike its predecessor, which focused solely on apple leaf diseases, the updated system supports disease detection across nine different crops with 39 total classes.

A custom-built CNN architecture was trained on over 61,000 images and demonstrated strong classification performance, achieving 98.9% test accuracy. The new implementation prioritizes flexibility, scalability, and broader usability in real-world farming environments.

By building upon the foundation laid in our previous work [1], this research extends the capabilities of AI in agriculture and opens new directions for precision farming. Future efforts will focus on integrating explainability, real-time deployment, and mobile-based interfaces to support farmers on the ground.

VIII. ACKNOWLEDGMENT

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