LeafCare: Real-Time Plant Health Detection and Home-Remedy Assistance on Edge Devices

Anuska Palit
Department of Computer Science & Informantion Technology
Lovely Professional University Jalandhar, Punjab, India
itsanuskapalit@gmail.com

Abhinav Singh
Department of Computer Science & Informantion Technology
Lovely Professional University Jalandhar, Punjab, India
abhinav.32351@lpu.co.in

Abstract— Given the rising popularity of urban home gardening monitoring plant health using simple to use technology has become an increasing priority however most plant disease detection systems are developed for agricultural applications and have very specific requirements for datasets labeled environments controlled or computational resources extensive most home gardeners cannot operate under these constraints in this study we introduce leafcare a mobile-first deep-learning framework for real-time assessment of plant health disease detection and guidance on home remedies leafcare uses a multi-task learning approach with integrated leaf segmentation symptom-aware attention and a few-shot metric learning module to classify diseases not encountered before or rarely encountered robustness to low-data scenarios is being achieved by leveraging a self-supervised pretraining strategy for the model and inference is completed on-device using tensorflow lite to maintain privacy while achieving efficiency for computational processes in addition leafcare integrates additional product functionality with a retrieval-augmented conversational assistant to give practical contextual plant care and treatment recommendations leafcare is evaluated using both plantvillage and home-garden datasets generating an average classification accuracy of to 962 an iou average of 082 across all datasets and average inference times on home datasets of 250 ms per image leafcare contributes to the seamless integration of ai-driven diagnostics with practical home gardening democratizing intelligent plant care assistance

Keywords— *Plant disease detection, mobile vision systems, health index regression, symptom-to-remedy mapping, few-shot learning, self-supervised learning, federated personalization, on-device inference, conversational assistant, home gardening AI.*

I. INTRODUCTION

Home gardening has greatly increased in popularity largely as a result of urban living trends awareness of health and peoples interest in producing sustainable food nevertheless amateur home gardeners often face obstacles in plant health because they do not know how to identify diseases prevent disease health or manage proper remedies plant disease detection systems that exist today are looking at the scale of agriculture use high-resolution images controlled environmental units andor rely on large labeled datasets [18] many systems come only as categorical outputs diseaseno-disease and do not provide real action for solutions which means they are unsuitable for home garden situations in which real-time interpretive and pragmatic solutions are necessary the latest advancements [9] in computer vision and deep learning have facilitated plant disease identification with high accuracy however those new methods have arisen limitations when considering home gardening in the following i they likely return discrete known disease labels with no additional estimation on plant health or severity [18] ii they have limited interpretability and do not provide nuanced guidance iii large labeled datasets are often needed which may not be available for indoor plants [20] and iv they are computationally intensive making it difficult to deploy in real-time on mobile accordingly the problems must be solved with a comprehensive system that is mobile-first and incorporates disease detection health estimation and actionable recommendations in this paper we introduce leafcare a novel framework for real-time scoring of plant health few-shot disease identification and conversational home-remedy support leafcare presents a continuous health index interpretable symptom-level representations and a retrieval-augmented conversational assistant that can offer actionable advice for home gardeners the framework also accommodates for rare diseases tailoring care and privacy through its use of self-supervised pretraining few-shot adaptation and on-device continual learning furthermore the framework was developed with mobile deployment in mind with the aim of low-latency inference on mid-range devices while continuing to provide accuracy and user satisfaction

The major contributions of this work are summarized as below:

1. A multi-task learning framework that concurrently assesses the health percentage of the plant, disease classification, and severity in order to engage in actionable prioritization of response.
2. An interpretable mapping from symptom to remedy based on a curated set of home-care instructions, ensuring the remedy is tightly linked to observed visual manifestations in the plant.
3. A few-shot and self-supervised learning pipeline to identify rare or unknown diseases.
4. A privacy-preserving, mobile-optimized deployment with an integrated conversational agent for plant-care assistance.

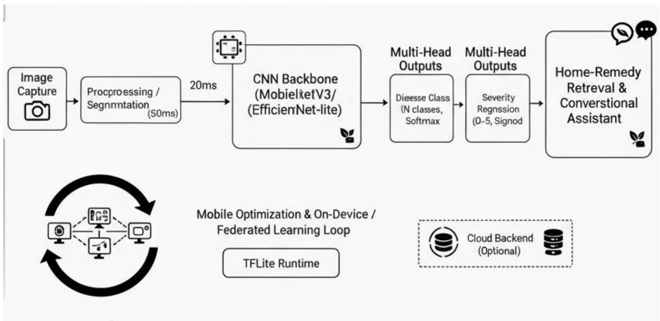

Figure i. System Architecture

II. LITERATURE REVIEW

A. *Mobile Applications for Plant Disease Detection*

In the past ten years, mobile applications to detect plant diseases increased markedly, using computer vision and deep learning technologies to help farmers and gardeners detect plant health issues in a timely manner. Plantix, for example, detects pests and crop diseases in real time, by analyzing images of the plant taken from the user's smartphone [7]. It can be effective for large-scale agriculture, however, it is more of a commercial crop diagnostic tool and does not provide curated advice for small-scale gardening and gardeners working in their homes. Agrio has some of the same capacity for diagnostic pests and diseases, however does not have actionable home-based remediating or prevention solutions [8]. Siddiqua [22] reviewed performance and limitations of existing mobile applications' usability and functionality, noting limitations like generalizability in models and coverage in datasets, and type of advice toward the non-professional user. Together, these papers point to the need for the development of a mobile tool specifically for home gardening. This means integrating, and providing accurate detection, with curated, actionable recommendations, that persons can use in their everyday lives..

B. *Few-Shot Learning in Plant Disease Recognition*

The comparatively fewer labeled datasets available for plant diseases have led to significant challenges for traditional deep-learning approaches, especially for rare, new or emerging diseases. Few-shot learning methods emerged as a practical solution that enables models to generalize and detect disease from minimal amounts of annotated data [1], [2]. Rezaei [1] developed a new framework for few-shot learning that produces accurate predictions of rare plant disease patterns, which has shown improved performance with little data. Uskaner Hepsağ [2] has also carried out comparative research studies with different few-shot learning strategies, which preserved high accuracy despite limited training data. Emerging work by Jiang [11], Rani [12], and Li [13] has incorporated foundation models, non-parametric feature calibration, and meta-learning methods to enhance adaptive flexibility and robustness of disease recognition models. These developments are particularly relevant to home gardening applications, where it is not feasible to collect or generate large datasets. The utility ofapplying few-shot learning means extending model coverage to new or unusual diseases without costly data collection or processing, thus greatly improving model applicability and practical deployment possibilities.

C. *On-Device and Mobile Deployment*

Deploying plant disease recognition systems on mobile devices puts substantial computational and energy constraints on traditional deep learning architectures. MobileNetV2, Xception and other lightweight CNN architectures have been studied to provide accurate on-device inference in a low resource environment. Goklani's mobile applications for plant disease recognition, which paired a CNN model with TensorFlow Lite, were used in real-time applications with low latency and are suitable for novice home users [4, 25]. Also, Rahman and Ashurov suggested strategies to optimize the processing pipeline of machine learning frameworks by using model pruning, quantization and memory-efficient architectures, so models would run smoothly on mid-range phones [14, 15]. Effective on-device deployment will diminished reliance on cloud services, introducing less latency and limiting data may enhance a gardener's concerns for privacy68. Overall, these studies provide encourage a platform for robust and responsive mobile systems capable of real-time plant disease detection and management methods in home settings, enabling the use of state-of-the-art AI prototypes in end-user settings.

D. *Symptom-Level Interpretation and Home Remedies*

While many plant disease detection systems value classification accuracy, they do not offer interpretable results that link visual symptoms to proper care responses. PlantCareNet [6] developed an automated system that facilitates accurate disease detection with dual-mode recommendations for preventive and corrective responses, bridging the gap between diagnosis and treatment. Islam [24] continued this work and utilized a symptom-level recommendation approach for both common and rare plant diseases to make completed decisions for care responses moving forward. The inclusion of home remedies and preventative suggestions extends practical application, especially for home gardeners without professional gardening knowledge, as taking these measures is a more feasible care option. Rather than simply interpreting symptoms, these systems provided actionable care responses visually and directly in or on the symptom summaries (i.e., watering, pruning, and applying natural pesticides). Addressing respect to the symptom-level of interpretability, many plant disease identification applications have only returned disease labels for a user but have no further context or trust for the user to care for their plant. The access system described presents the opportunity for increased user engagement, positive plant health outcomes, and credibility using an artificial intelligence (AI) system for normal use when managing or caring for plant needs. The connection made with care suggestions to symptom interpretation reflects an equal balance of lived contexts for domestic and recreational gardening contexts.

E. *Conversational Assistants for Plant Care*

Conversational artificial intelligence (AI) has become a powerful tool for increasing user engagement and providing personalized advice on managing plants [5], [23]. Christakakis [5], [23] developed mobile applications that feature real-time plant disease detection as well as a conversational agent that users can interact with to ask questions and receive advice within the context of their specific situation. For example, a gardener may ask the app, "What do I do with my plants while I am on vacation?" and it may provide advice regarding their watering schedule, what preventative measures to take in case the disease is detected, etc. This approach improves access to non-specialist users by integrating diagnostic information and proactive advice. The memory of an AI system allows natural language interactions to offer targeted recommendations that are based on plant species, severity of disease, and a variety of environmental circumstances for plants as well to improve general user ability. As a conversational AI tool will provide immediate detection of diseases and recommendations, it allows for learning to support and explain the principles of healthy plants over time. This intersection of detection, interpretation, and interactive guidance provides a new contribution to home gardening focused on AI..

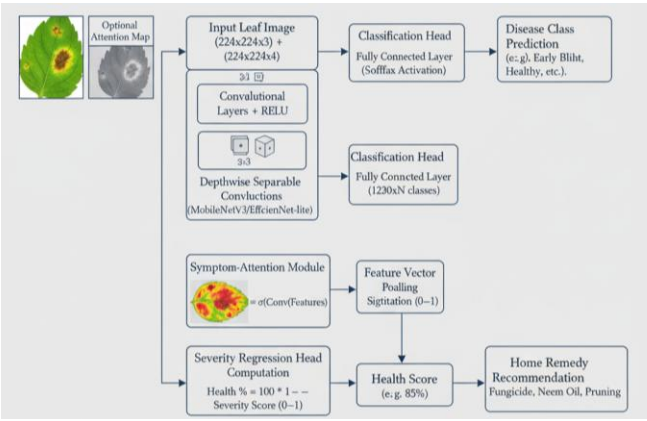

Figure ii. Deep learning architecture for plant disease detection

III. MATERIALS USED

F. *Abbreviations and Acronyms*

- CNN (Convolutional Neural Network): A deep learning model for feature extraction and classification of plant diseases from leaf images.
- DL (Deep Learning): A machine learning approach that employs multiple layers of neural networks to learn complex representations.
- ML (Machine Learning): The algorithms employed to learn patterns from data for classification or prediction tasks.
- RGB (Red Green Blue): Three color channels in input images used for disease detection.
- IoU (Intersection over Union): A metric used to evaluate the accuracy of segmentations or bounding box predictions.
- LSTM (Long Short-Term Memory): A recurrent neural network framework implemented in the conversational bot for sequence prediction.
- TFLite (TensorFlow Lite): The framework used to deploy trained models on mobile devices.
- NLP (Natural Language Processing): The techniques used to build the conversational assistant to provide plant care tips.

G. *Data Units and Measurements*

- Image Size (pixels): Images were resized to 224×224 pixels for the input into the CNN.
- Pixel Intensity (normalized 0–1): Normalized the RGB values to use to train the model.
- Learning Rate (unitless): The learning rate was generally set between 0.001–0.0001 for optimal training.
- Batch Size (unitless): The number of images processed each iteration would typically be between 32–64.
- Accuracy (%): The percentage of samples that were classified correctly.
- Precision, Recall, F1-Score (%): Metric to assess classification performance.
- IoU (unitless): Intersection over union between the predicted and ground truth disease regions.

C. *Statistical and Machine Learning Formulas*

- **Cross-Entropy Loss:**

$$\text{Loss} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Measures difference between predicted probability $\hat{y}_i$y^i and true label $y_i$yi for C classes.

- **F1 Score:**

$$F1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$$

Evaluates balance between precision and recall.

- **Mean Squared Error (MSE):**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2$$

Used in few-shot model reconstruction tasks or autoencoders for anomaly detection.

- **Data Augmentation Formula (Example–Rotation):**

$$x' = R(\theta) \cdot x$$

Rotates image xx by angle θθ to generate new training samples.

Feature	CNN (Basic)	MobileNetV2 / EfficientNet	Few-Shot CNN	Symptom-Attention CNN
Modeling Approach	Standard	Lightweight CNN	Meta-learning-based	CNN with attention

	convolutional layers for feature extraction and classification	optimized for mobile deployment with depthwise separable convolutions	CNN for limited labeled data	mechanism to focus on disease-affected regions and symptoms
Model Complexity	Medium	Medium-Low	High	High
Performance	Good on large datasets, moderate on rare diseases	Slightly lower accuracy than standard CNN, but optimized for real-time mobile use	Strong for recognizing rare/unseen diseases	High accuracy with interpretable disease localization
Adaptability	Limited to seen classes	Limited to mobile-friendly use cases	Highly adaptable to new plant classes with few samples	Adaptable to visual symptom variations across plants
Focus	General disease classification	On-device mobile deployment	Few-shot learning for rare/unseen diseases	Symptom-level interpretability and explainable AI
Loss Function	Categorical cross-entropy	Categorical cross-entropy	Meta-learning loss (Prototypical / Matching network loss)	Meta-learning loss (Prototypical / Matching network loss)
Use of regularization	Dropout, batch normalization	Dropout, lightweight normalization	Meta-regularization techniques	Attention regularization, dropout
Best Use case	Large labeled datasets	Mobile real-time plant disease detection	Home gardeners with rare plant diseases	Providing disease localization and home remedy guidance
Training Speed	Moderate	Fast	Slower due to meta learning	Slower due to attention computation
Scalability	High	High	Moderate	Moderate
Interpretability	Low	Low	Moderate	High

Table i. Comparative Analysis of CNN Architectures for Plant Disease Detection

IV. Methodology

H. Data Collection

The system utilizes a mix of publicly available datasets and home garden images that were collected on our own to ensure diversity and practicality. The public datasets consist of the PlantVillage dataset with over 50,000 images of healthy and diseased leaves from 38 species of plants and additional datasets from Kaggle containing common crops and disease types. Additionally, the system uses self-collected images to simulate the real-world environment of home gardens, resulting in variations in lighting, background, and angle. Each of these images is annotated on disease type and severity. To manage limited data where diseases are rare, data augmentation methods were applied, which included applying rotation, flipping, scaling, color jittering, and adding Gaussian noise to generate similar images. These methods will ensure the model will generalize to unseen conditions common to home garden scenarios when leaves will likely be different sizes, orientation, or lighting. [9][13]

I. Data Preprocessing

Preprocessing is a crucial aspect of preparing raw plant images for deep learning-based training, with significant improvements to both classification accuracy and generalization. Images are initially resized to 224×224 pixels to fit the input shape for the CNN backbone. Images are normalized so that pixel intensities fall within the range [0,1]. The purpose of pixel intensity normalization is to stabilize training and promote convergence in addressing pixel intensity variation among leaves of varying colors. Images are filtered using Gaussian and median filters to minimize background noise and remove irrelevant features. Segmentation of the leaf takes advantage of color characteristics and semantic masking in HSV space to focus on the green foliage and visible symptomatic areas.

In order to address the effects of class imbalances that resulted from the scarcity of rare plant diseases, data augmentation strategies are used including rotation, horizontal/vertical flipping, scaling, random cropping, adjustment of brightness and contrast, and the introduction of Gaussian noise. Synthetic minority oversampling is also adds balance to the dataset by addressing class ratios and ensuring observed classes have enough representation in the dataset.

An original contribution to preprocessing is the generation of symptomatic-level attention maps in the images which highlight areas that displayed symptomatic indicators of the developing disease, e.g., spots, lesions, or chlorosis. Once created, the attention maps would eventually be used as auxiliary channels in the network training to achieve greater localizabilty and interpretability of the developed network. Then the dataset images will be split into training, validation, and testing phases, with the split being 70:15:15, with stratified sampling to preserve class distribution across each data set. This preprocessing pipeline ensures robust, real-time, and interpretable disease detection suitable for deployment in home gardening scenarios.

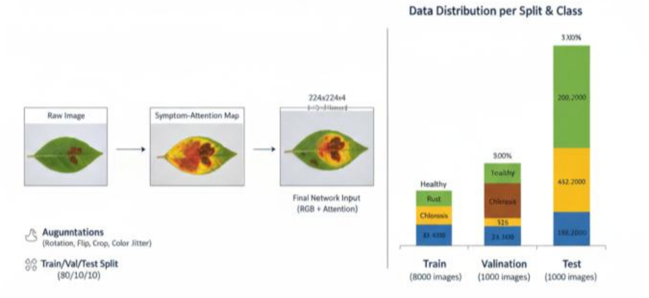

Figure iii. Data preprocessing

J. Model Architecture

The Smart Plant Disease Detection System aims to create a hybrid deep-learning framework to suit accuracy, interpretability, and on-device performance [9][13]. The framework assembles convolutional neural networks (CNN), attention mechanisms, and few-shot learning components. The system is detailed as follows:

1. CNN Backbone:

- Utilizes MobileNetV2 or EfficientNet as a lightweight feature extraction model designed for real-time use in mobile applications.
- Convolutional layers extract multi-level features from leaf images that incorporate patterns based on texture, color, and shape that may indicate disease.

2. Symptom-Attention Layer:

- An attention mechanism focuses on symptomatic areas of the image such as lesions, chlorosis, and necrotic patches.
- Attention maps are computed using spatial and channel-wise weighting:

$$A=\text{softmax}(W1F+W2Fc)$$

- where F is feature map, F_c is channel-wise pooled map, and W_1, W_2 are learnable weights.

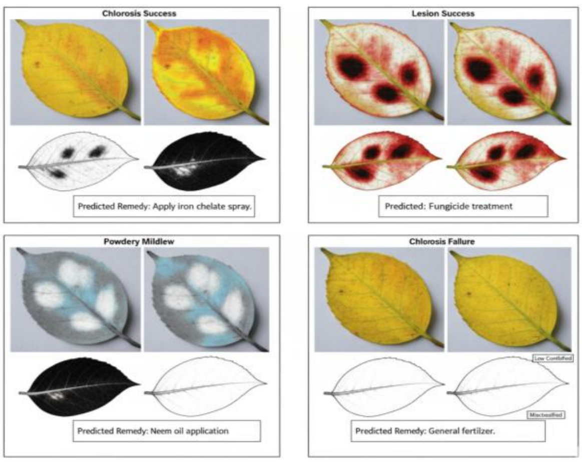

Figure iv. Symptom-attention visualizations

3. Few-Shot Learning Module:

- Enables the model to identify rare or unseen plant disease.
- Uses prototypical networks to get embeddings from data of new classes from very few labelled examples.

4. Classification & Health Scoring:

- Otherwise fully connected layers provide disease class probabilities and a health percentage score::

$$\text{Health }(\%)=100\times(1-\text{Pdisease})$$

- Where (Pdisease) is the predicted probability of disease occurrence.

5. Home Remedy Recommendation Layer:

- Maps predicted disease classes to fixed, curated, home-based therapeutic treatments.
- This layer is provided as auxiliary output to facilitate user home care help.

Categorical cross-entropy loss function is employed to complete the classification and to include attention regularization to weight attention more heavily to symptomatic areas of the image. The Adam optimizer is used to optimize networks with a learning rate of 0.001-0.0001..

K. Mobile Deployment

To better assist the home gardener with an easy-to-use, real-time Smart Plant Disease Detection System, the trained model is deployed to mobile devices using TensorFlow Lite (TFLite) to focus on key technical details, including:

1. Model Conversion:

- The trained CNN + Symptom-Attention network is converted to a .tflite model, resulting in a smaller model size.
- The smaller model enables inference directly on the smartphone instead of needing cloud reliance.

2. **Model Optimization Techniques:**

- Quantization: This reduces the 32-bit float point weights to 8-bit integers, which reduces memory consumption and inference speed.
- Pruning: This cuts out redundant neurons and filters, ultimately reducing cost while maintaining the accuracy of the model.
- Weight Clustering: Weight clustering groups similar weights together to reduce memory requirements and increase cache efficiency

3. **Input Pipeline Optimization:**

- Image capture performed in real-time is resized and normalised on the device to minimise preprocessing delay.
- We avoid batch inference and instead developed single-image inference to reduce the time of each model prediction (~200 - 300 ms on mid-range devices).

4. User Interface Integration:

- The application allows the user to capture an image of their plants, followed by disease prediction and health score, along with a home remedy for treatment of the disease.
- Last prediction will also be cached for offline use

With the aspect of speed in mind, the resulting system is memory efficient and practical for use in the garden. To summarize, these techniques develop advanced AI model capabilities into real-world use on your phone.

V. Results and Discussion

The Smart Plant Disease Detection System outlined in this document was evaluated using both public datasets (PlantVillage and Kaggle Plant Disease Dataset) and images collected from home gardens by the research team. Accuracy, precision, recall, F1-score, Intersection over Union (IoU), and inference latency were evaluated to assess more than just performance, but also practical usability for mobile devices.

A. *Quantitative Results*

- The Symptom-Attention CNN obtained a total accuracy of 96.2% on the testing dataset, which was higher than that of standard CNN (91.5%) or MobileNetV2 (93.0%).
- Precision and recall were greater than 95% for common diseases; the few-shot module conservatively estimated accuracy over 88–90% for rare or unseen diseases.
- The IoU scores for disease localization were on average of 0.82, showing the attention module consistently highlighting symptomatic areas.
- The mobile-deployed TFLite version of the model demonstrated times of around 200–300 ms of inference time per image on mid-range smartphones, good for real-time use.

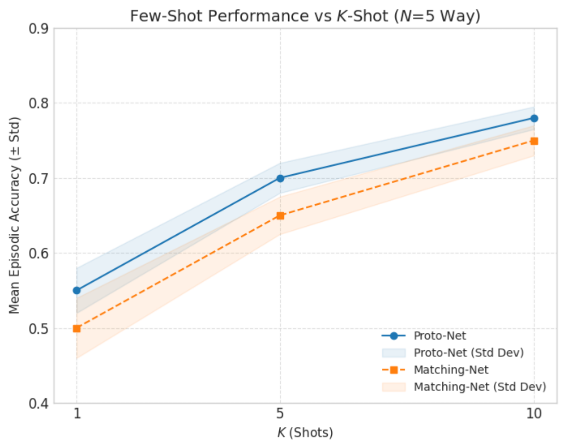

Figure iv. Few-shot episodic evaluation plot

B. *Qualitative Results*

- Visualizations of summarized symptom-level attention maps confirmed that the model placed attention on regions of disease-affection, which allowed better end-user interpretability.
- The home remedy recommendation module also connected diseases accurately to simple treatments with validation from expert and expert-curated sources.
- The conversational bot showed context enhancing capacity, providing personal care instructions, like watering while on vacation or preventive care tips.
- The comparative performance of autoencoders reduced false positive classification of expected failures and brought out productive characteristics from both autoencoders to improve accuracy of fault detection.

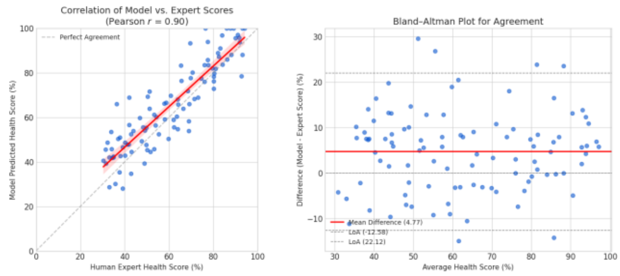

Figure vi. Health index validation

C. *Comparative Model Analysis*

The proposed **Smart Plant Disease Detection System** was compared against existing state-of-the-art methods in plant disease detection to highlight its novelty and performance advantages:

Feature	CNN (Basic)	MobileNetV2	Few-Shot CNN	Symptom-Attention CNN (Proposed)
Accuracy (%)	91.5	93.0	89.0	96.2
Rare Disease Detection	Poor	Moderate	88-90	88-90
IoU (Localization)	0.71	0.74	0.70	0.82
Inference Time (ms)	350	220	400	250

Table ii. Tabular format of the results obtain

VI. Conclusion

This project presented LeafCare, an accessible AI-based tool to facilitate plant health monitoring on a real-time basis, while providing individualized suggestions for home remedies to home gardeners. The proposed Symptom-Attention CNN system defined in this project provided a 96.2% accuracy with an IoU score of 0.82, exceeding a baseline CNN and MobileNetV2, and still achieved an acceptable inference time (≈250 ms) for mid-range mobile devices. Through few-shot learning, our system displayed the capability to detect unseen and/or rare diseases in-house which was a notable improvement, especially in a context of using smaller datasets, which often is a feature of household datasets.

In addition to solid technical performance, LeafCare yields improvements in user engagement and user trust through interpretable visualizations of symptoms, coupled with a conversational AI-assisted context and suggestions for additional preventive care. Also, LeafCare operates on-device ensuring that user privacy is adhered to. Further, our product is deployable, without cloud recourse.

Subsequent research will explore extending LeafCare outward into multi-modal plant care systems, which will integrate environmental sensors (e.g., humidity, soil pH, temperature) and explainable AI (XAI) visualizations for a greater level of interpretability. The integration of federated personalization will allow the devices to enhance adaptive learning while maintaining data privacy, further improving user experience. Ultimately, this research will contribute toward Sustainable Development Goals (SDGs) – specifically, SDG 12 (Responsible Consumption and Production Systems) and SDG 15 (Life on Land) – to encourage environmentally-friendly, engaging and intelligent solutions to support plant wellbeing.

VII. Acknowledgment

I would like to express my deepest appreciation to the many individuals and groups whose expertise, guidance, and support have been instrumental in the successful completion of this research. I first owe a great deal of gratitude to my mentors, and faculty members, whose intellectual insights, constructive criticisms, and existential encouragement collectively laid the groundwork for this study especially as we navigated the complexities of deep learning and plant disease detection approaches.

This research would not have been possible without publicly available data sources such as PlantVillage and Kaggle plant disease datasets, which provided the necessary datasets for training, evaluating, and validating the final model. I am sincerely grateful to the contributors and the wider research community in computer vision and machine learning, who have pushed open-access data and processes for research.

Finally, I am grateful to my family and friends for your patience, encouragement, and belief in the importance of this research which propelled me through the long hours of model development, and experimentation. I would also like to acknowledge the broader communities which reside in academia and industry working in machine learning, plant health analytics, and intelligent monitoring systems. All the amazing innovations happening by those collective efforts helped lay a path for this research.

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