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Smart Diagnosis: Early Detection and Management of Plant Diseases

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***Abstract:** Plant diseases threaten global food security and cause significant financial losses in agriculture. Early detection and precise diagnosis are critical for effective disease management. This study explores a novel approach to plant disease identification using the You Only Look Once (YOLOv12) algorithm combined with few-shot learning techniques. By leveraging a limited dataset, the model is trained to classify citrus plant leaf images into four categories: healthy, greening, black spot, and canker. The proposed system enhances disease detection efficiency, enabling farmers to take timely preventive measures. Our approach demonstrates the potential of few-shot learning in agricultural disease diagnosis, reducing the need for extensive labeled datasets while maintaining high accuracy.*
***Keywords:** YOLOv12, Plant disease detection, Few Short Learning, Semi supervised Learning, Chatbot*

I. INTRODUCTION

In India, several plant diseases currently pose significant challenges for farmers, with major pathogens affecting staple crops like rice, wheat, and various fruits and vegetables. The recurring issue of rice blast, caused by the fungus Magnaporthe oryzae, has severely impacted rice yields in the major rice-growing regions, especially during high humidity seasons. This disease, along with bacterial leaf blight, continues to hamper productivity and is challenging to control without early intervention.

Wheat crops also face persistent threats from yellow rust and stem rust, exacerbated by changing climate patterns that favour these pathogens' spread. Efforts to develop rust-resistant wheat varieties are ongoing, but these diseases still lead to substantial yield losses. Additionally, fruit crops, including citrus and bananas, are commonly affected by citrus greening and Panama disease, respectively. Panama disease, caused by the Fusarium fungus, particularly affects bananas in southern regions and is difficult to manage due to soil persistence.

Newer methods in pathogen detection, such as real-time diagnostics using molecular techniques like PCR and Loop-mediated Isothermal Amplification (LAMP), are being increasingly adopted to provide rapid and accurate in-field identification. These technologies, combined with digital monitoring and data from IoT-based devices, help manage crop diseases more effectively, offering a timely response for Indian farmers who rely heavily on disease forecasting to protect yields.

Despite these advancements, addressing plant disease in India remains complex due to variations in climate across regions, diverse crop types, and the limited access some farmers have to these technologies. Improving accessibility to diagnostic tools and advancing disease-resistant crop varieties are critical to sustaining agricultural productivity in India. Agriculture plays a vital role in every country's economy, and advancements in the field are essential to meet the growing population's demands. To sustain productivity, modernization is crucial. However, crops are highly susceptible to bacterial and fungal diseases, which can significantly reduce farmers' yields. Ensuring crop health is key to maximizing agricultural output.

Identifying plant diseases with the naked eye is challenging, requiring continuous farm monitoring—a tedious and costly process, especially for large-scale farms. Due to the complexity of plant diseases, agricultural professionals often face difficulties in diagnosis and treatment. An automated disease detection system would greatly benefit farmers by providing timely insights and enabling preventive measures.

Plant diseases can affect various parts of the plant, including leaves, fruits, and seeds. Among these, leaves play a critical role in plant health, as diseases impacting them can disrupt the entire plant life cycle. Common leaf diseases include bacterial and fungal infections, making early detection essential for effective disease management.

A. Ideal State

An ideal plant disease diagnosis system combining few-shot learning (FSL) and computer vision (CV) would revolutionize agricultural disease management by enabling accurate identification with minimal training data. This cutting-edge system would allow farmers to capture high-resolution images of potentially diseased plants using smartphones or drones, then instantly analyze these images to detect subtle symptoms like leaf discoloration, spotting, or structural abnormalities—even at early stages when intervention is most effective.

The power of FSL means the system could recognize new or rare diseases with just a handful of examples, adapting continuously as it encounters novel conditions in the field. By integrating environmental data like weather patterns, soil conditions, and crop specifics, the system would provide tailored management recommendations suited to each farmer's unique situation, suggesting targeted interventions rather than broad-spectrum pesticide applications.

This technology democratizes access to expert-level plant pathology knowledge, particularly benefiting regions with limited agricultural extension services, while simultaneously promoting more sustainable farming practices through precise, timely interventions that minimize chemical use and crop losses. As computing power increases and machine learning techniques advance, such systems become increasingly practical, offering a powerful tool in addressing global food security challenges while supporting environmentally responsible agriculture.

B. Possible Solutions And Innovation

1) Building Image Databases: Create high-quality image collections of diseased plants from various environments and growth stages. Use crowdsourcing via mobile apps to let farmers upload photos of diseased plants. Train FSL models on these diverse images to improve disease recognition across different contexts.
2) Using Transfer Learning and Meta-Learning: Transfer Learning: Adapt knowledge from one task (e.g., common crop diseases) to another (e.g., rare diseases), enabling quick model adjustments with minimal data. Meta-Learning: Teach models to "learn how to learn," allowing them to adapt rapidly to new diseases.
3) Self-Supervised and Semi-Supervised Learning: Self-Supervised Learning: Models learn patterns from unlabeled data, identifying common features of diseases. Semi-Supervised Learning: Combine labeled and unlabeled data for training, enhancing model robustness even in areas with limited labeled data.
4) Real-Time Feedback and Recommendations: Provide tailored treatment suggestions based on disease type, crop species, and environmental factors like weather or soil pH. Recommend sustainable practices such as organic treatments or crop rotation to minimize pesticide use.
5) Impact of FSL in Agriculture: Enables accurate disease diagnosis with minimal data. Offers early detection tools for smallholder farmers. Promotes sustainable agriculture by optimizing chemical use and improving crop yields.

II. METHODOLOGY

A. Transfer-Based Few-Shot Classification Framework

A typical few-shot classification framework based on transfer learning involves splitting a dataset into source and target domains. The source domain contains abundant labeled data used to train a model, which learns basic knowledge. This trained network, along with its parameters, is then transferred to the target domain as transferred knowledge. In the target domain, only a few labeled data points are available for updating the model through fine-tuning. This scenario, characterized by limited labeled samples, is known as few-shot classification.

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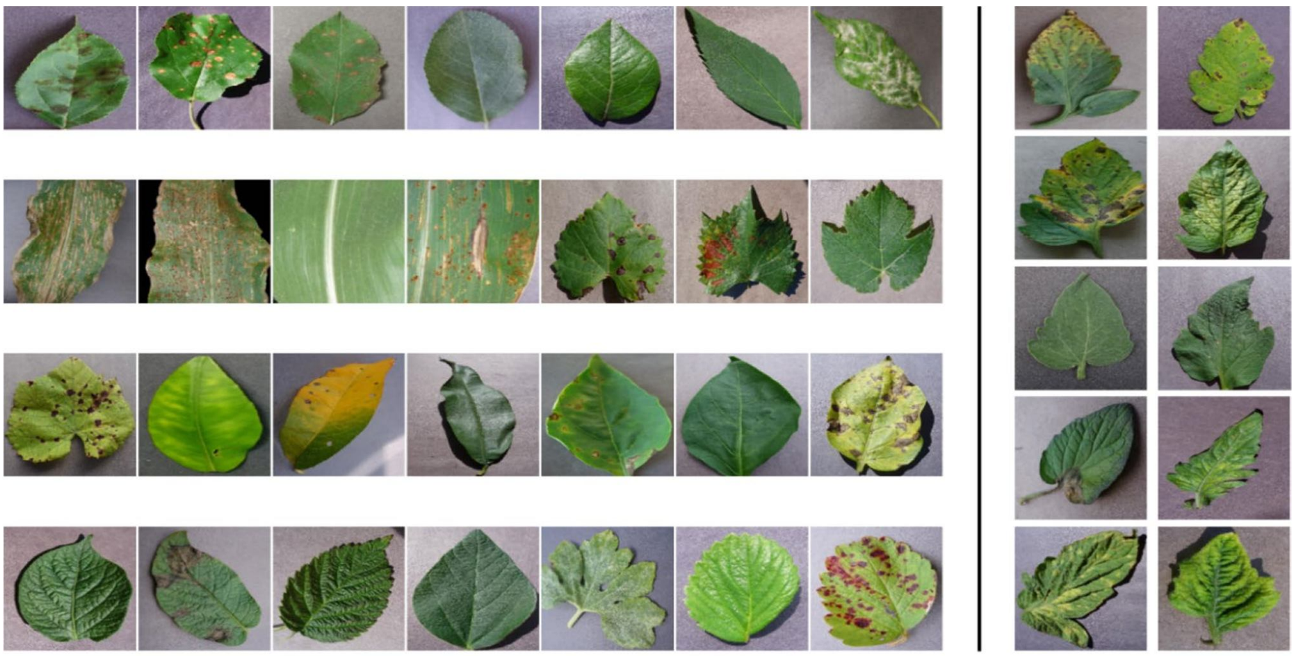
B. Model Structure

The model is based on a convolutional neural network (CNN). In both source and target domains, the model structure is identical, featuring seven convolutional layers and three pooling layers. The initial two convolution layers use 64 filters with the same padding. Max-pooling layers halve the space size while maintaining the number of channels. Subsequent convolution layers use 128 and 256 filters, respectively. The last dense layer is a softmax classifier, with the number of output neurons (N) matching the number of categories being classified. In the source domain, N is 28, as all 28 classes are used for training. In the target domain, N varies.

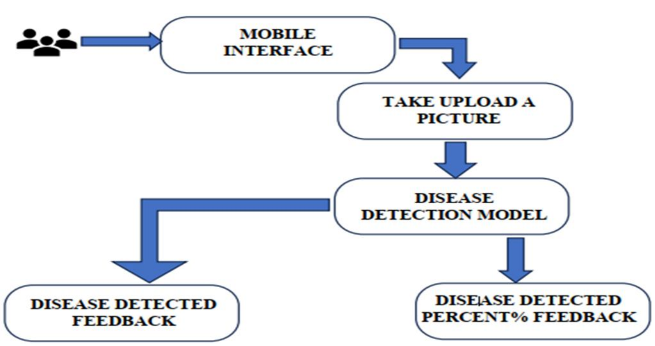
Few-shot classification is defined as N-way k-shot, where N is the number of categories and k is the number of samples per category available for fine-tuning the transferred model.



Source domain **Target domain**

C. Training, Fine-Tuning, and Testing

1) Training: In the source domain, training is conducted with a batch size of 16, using the Adam optimizer and categorical cross-entropy loss function. A validation set (20% of the data) is used to monitor training progress.
2) Fine-Tuning: In the target domain, the model transferred from the source domain is fine-tuned using a few labeled data. The number of neurons in the last dense layer is adjusted to N. To avoid overfitting, only the parameters in the last two dense layers are fine-tuned, while the others are fixed.
3) Testing: Testing occurs in the target domain using the fine-tuned model. The problem is defined as N-way k-shot, with N classes randomly selected from the ten classes in the target domain. Each N-way k-shot experiment is performed ten times, and the average accuracy is reported.



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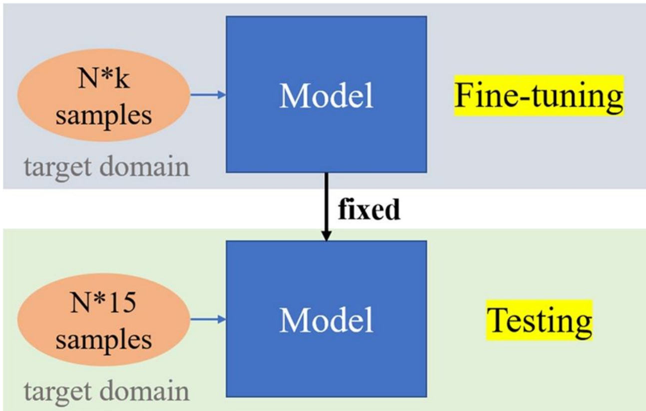
D. Semi-Supervised Few-Shot Classification

Semi-supervised few-shot classification operates in the target domain. The approach involves:

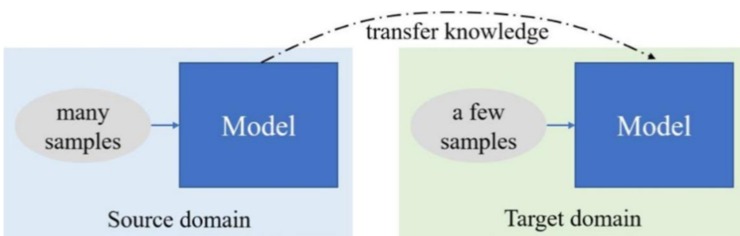
1) Using N*k samples to update the last two dense layers' parameters and fix the fine-tuned model.
2) Randomly selecting 15 samples per category (totaling N*15 samples) to test the model's few-shot performance.

To enhance performance, a semi-supervised method is used, consisting of two steps:



a) Step 1: Fine-tune the transferred model using the N*k labeled samples, then fix all parameters. Feed all unlabeled samples into the fixed model to make predictions and select some as pseudo-labeled samples.
b) Step 2: Use both the Nk labeled samples and the selected pseudo-labeled samples from Step 1 to fine-tune the model again, with only the last two dense layers being trainable. Fix the model and test it on the N15 samples.

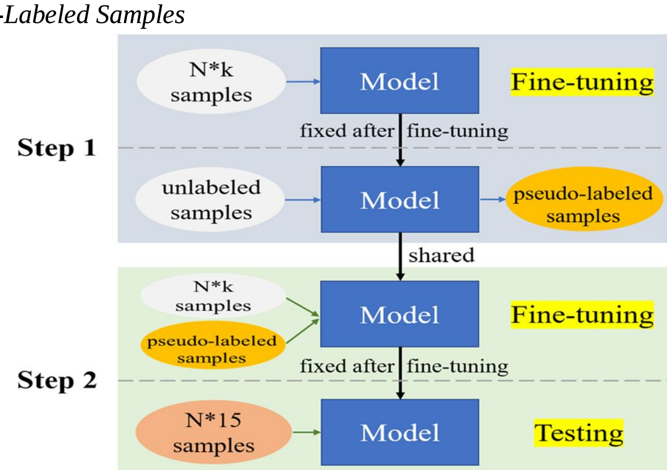
This process is termed single semi-supervised few-shot classification, as pseudo-labeled samples can be selected once or multiple times.



E. Iterative Semi-Supervised Few-Shot Classification

The iterative approach includes three steps. Step 1 mirrors that of the single semi-supervised method. After fine-tuning in Step 2, the remaining unlabeled samples (excluding those pseudo-labeled in Step 1) are fed into the fixed model to select pseudo-labeled samples again. In Step 3, both the Nk labeled samples and the pseudo-labeled samples from Steps 1 and 2 are used to fine-tune the last two dense layers. The model is then fixed and tested on the N15 samples.

F. Adaptive Selection of Pseudo-Labeled Samples



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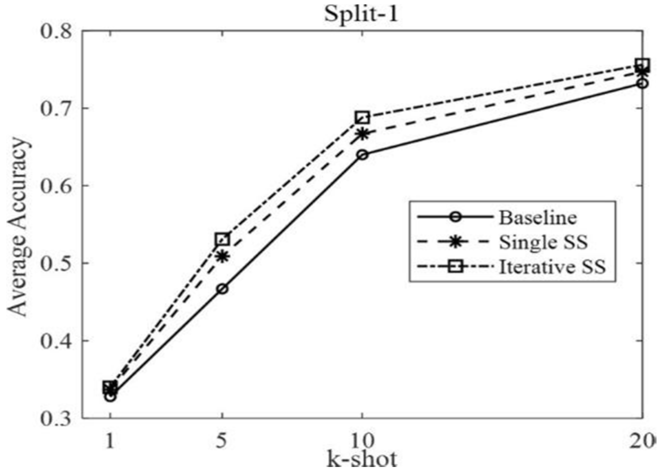
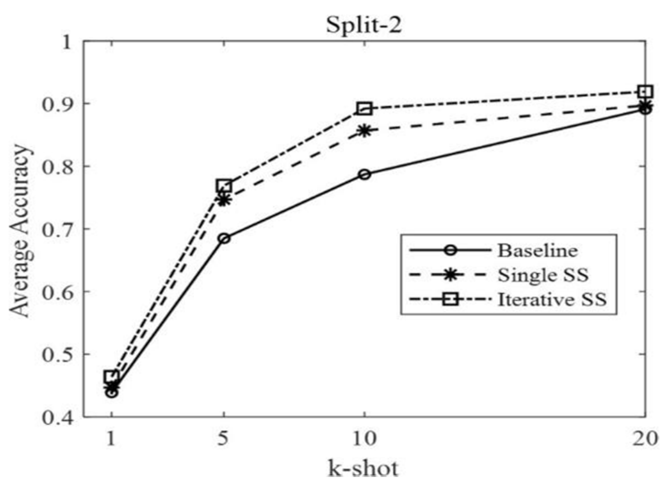
To adaptively select pseudo-labeled samples, a confidence interval-based method is used. An unlabeled sample is selected for pseudo-labeling only if the prediction confidence exceeds 99.5%. This ensures that pseudo-labels are highly consistent with real labels. The model adaptively determines the number of pseudo-labeled samples under varying experimental conditions.

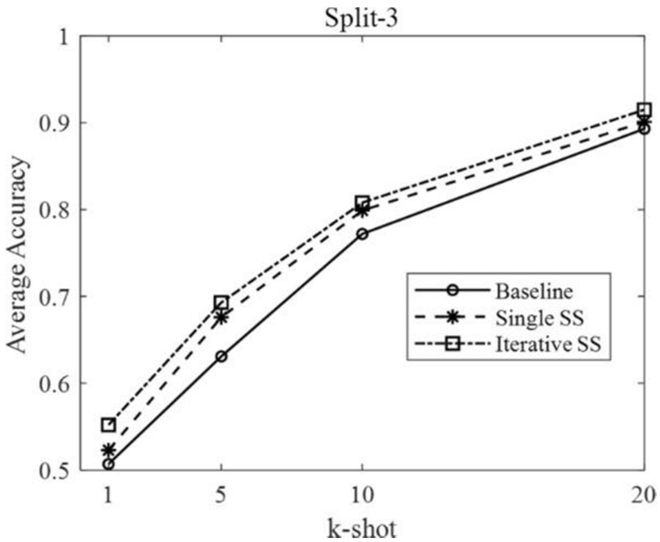
Split Mode	Source (28 classes in total)	Target (10 classes in total)
	Crop (number of categories)	Crop (number of categories)
Split-1	Apple(4), Blueberry(1), Cherry(2), Corn(4), Grape(4), Orange(1), Peach(2), Pepper(2), Potato(3), Raspberry(1), Soybean(1), Squash(1), Strawberry(2)	Tomato(10)
Split-2	Blueberry(1), Corn(4), Orange(1), Peach(2), Pepper(2), Potato(3), Raspberry(1), Soybean(1), Squash(1), Strawberry(2), Tomato(10)	Apple(4), Cherry(2), Grape(4)
Split-3	Apple(4), Blueberry(1), Cherry(2), Orange(1), Pepper(2), Potato(3), Raspberry(1), Soybean(1), Squash(1), Strawberry(2), Tomato(10)	Corn(4), Grape(4), Peach(2)

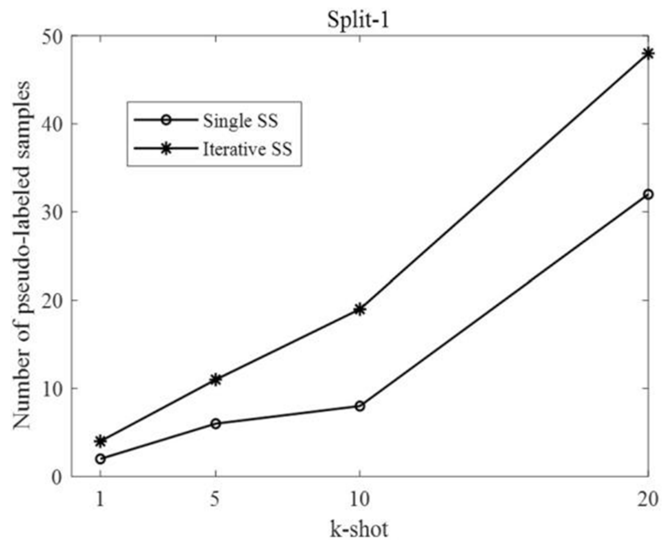
III. EXPERIMENTAL RESULT



This section carried out the comparison experiment with other related work and further experiments considering the factors of domain split, few-shot parameters, and semi-supervised iteration. The experimental hardware and software environments are the NVIDIA TITAN Xp with 12 GB memory and the Jupyter Notebook with libraries of Tensorflow (version 1.12.0), Numpy (version 1.19.2), Keras (version 2.2.4), and OpenCV







Having established our semi-supervised method's advantage in the initial comparison, we conducted further experiments to verify its consistent performance and ability to generalize. We recognized that different ways of splitting the data into source and target domains can affect how well knowledge transfers from the pre-trained network. Therefore, we tested our methods under varying conditions, specifically:

1) Three different domain split modes (as defined previously).
2) Varying few-shot parameters (N-way k-shot).

For these tests, we used a 5-way k-shot setup (N=5), meaning for each task, 5 classes were randomly selected from the target domain classes. We ran each experiment ten times with k set to 1, 5, 10, and 20 shots, averaging the classification accuracy.

A. We Compared Three Approaches

Baseline: A standard few-shot classification method using only transfer learning.
Single SS: Our proposed single-stage semi-supervised method.
Iterative SS: Our proposed iterative semi-supervised method.

Key Findings:
The results consistently demonstrated the benefit of our semi-supervised approach:

- Consistent Superiority: Across all three domain splits and for all tested k-shot values (1, 5, 10, 20), both the Single SS and Iterative SS methods achieved higher average accuracy than the Baseline method. (While baseline accuracy varied between splits, reflecting different levels of task difficulty, the SS methods always provided an improvement).
- Performance Trade-offs: The Iterative SS method consistently yielded the highest accuracy, demonstrating the benefit of its additional refinement stage. However, this comes at the cost of increased computational operations. The Single SS method provides a strong balance, offering significant accuracy gains over the baseline while being computationally less intensive than the iterative version.
- Quantified Improvements: When averaged across all domain splits and k-shot values:

The Single SS method improved accuracy by an average of 2.8% over the baseline. The Iterative SS method improved accuracy by an average of 4.6% over the baseline. [1] (Improvements varied by split, reaching up to 3.7% for Single SS and 6.05% for Iterative SS under specific splits).

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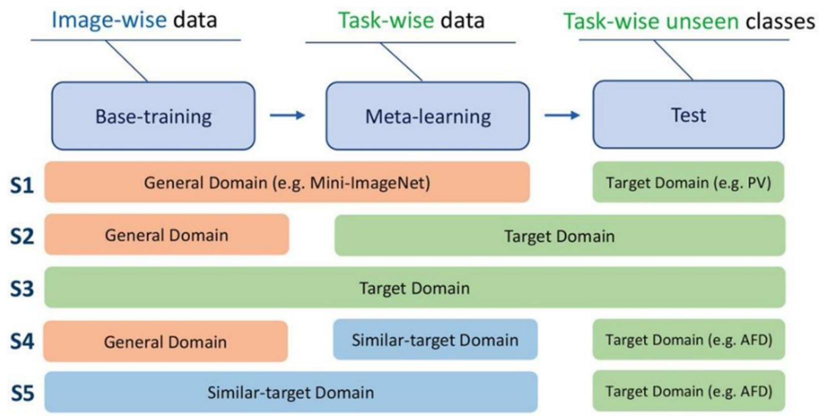
IV. BUSINESS PITCHING



A. Value Propogation
• Early disease detection
• Accurate diagnostics
• Accessibility and ease of use
• Sustainability focus
• Data_driven insights

B. Customer Segments
• Primary users
• Secondary users
• Government and ngo's

C. Channels
• Mobile application
• Website
• Dashboard
• Api access
• Parterting with agriculture extensions and ngo

D. Key Partnership
• Agricultural research institutions
• Agricultural ngos and governmental bodies
• Tech companies

E. Customer Relationship
• automated diagnostics and feedback
• support and training
• communitiy building
Customer Segments:
• Smallholder farmers, commercial farms, and agricultural experts who need quick, accurate plant disease diagnostics.
• NGOs and government agencies focused on sustainable agriculture.
Value Propositions:
• Quick, reliable plant disease detection with minimal data.
• Accessible diagnosis through mobile and web interfaces.

• Environmentally-friendly guidance for disease management to reduce chemical use.

Channels:

• Mobile app, website, and API for ease of use.
• Partnerships with agricultural organizations to promote adoption.

Customer Relationships:

• Automated feedback via app or website.
• Educational resources for first-time users.
• Community forums for shared knowledge.

Revenue Streams:

• Freemium model with a basic free tier and premium features.
• Subscription fees for advanced users.
• Partnerships with other agricultural platforms.

Key Activities:

• Model development, data collection, and app maintenance.
• Continuous research on FSL and computer vision improvements.

Key Resources:

• Cloud infrastructure, a database of plant images, and funding.
• Skilled staff in machine learning and agriculture.

Key Partnerships:

• Agricultural research bodies, NGOs, and tech providers for data, resources, and support.

Cost Structure:

• R&D, cloud infrastructure, staffing, marketing, and data acquisition

F. Mock Pitch

Introduction: Imagine a world where farmers can quickly identify and manage plant diseases with just a few photos and get instant, accurate guidance on treatment—all from their phone. Plant diseases are a significant threat, affecting yield, quality, and farmer income globally. Existing solutions often require extensive data or expert knowledge, making them inaccessible to small farmers. Our Plant Disease Diagnosis System, using few-shot learning (FSL) and computer vision, solves this problem by delivering reliable diagnostics with minimal data, empowering farmers to take control of their crop health.

Problem Statement: Millions of farmers struggle with plant diseases that reduce productivity and impact livelihoods. Identifying diseases early and accurately is crucial, but traditional methods are limited, relying heavily on experts or large amounts of labeled data. Smallholder farmers and new entrants in agriculture often lack the knowledge, time, or financial resources to access such expertise. There is a clear need for a more accessible, scalable solution that provides early disease detection and precise recommendations.

Solution: Our solution harnesses the power of few-shot learning and computer vision to deliver a user-friendly, scalable plant disease detection system. Unlike traditional machine learning models, which require thousands of images, FSL needs only a few labeled examples, making it highly efficient for identifying diseases with limited data. Here’s how it works:

• Few-Shot Learning: Our FSL model is pre-trained on a large dataset to recognize plant diseases, enabling accurate identification with minimal data. When a farmer uploads a photo of a diseased plant, the system compares it to the few samples in its database, providing a reliable diagnosis.
• Computer Vision: High-quality image processing is used to analyze plant leaves, stems, or fruits, detecting symptoms like color changes, spots, or lesions, which are essential for accurate diagnosis.
• Contextual Recommendations: Using environmental data (like weather and soil conditions), the system provides tailored advice for each disease, minimizing the need for unnecessary chemicals and promoting sustainable practices.

G. How It Works for Farmers

• Simple Interface: Farmers use our app or web platform to take a picture of their plant. They receive an instant diagnosis, disease probability score, and step-by-step management advice.
• Real-Time Feedback: Immediate results mean farmers can take timely action, reducing the risk of disease spread.
• Actionable Insights: The platform offers treatment options, preventative measures, and tips on improving yield sustainably.

Market Opportunity: Agriculture is a $5 trillion global industry, with plant disease management alone representing a multi-billion-dollar market. Our product is designed for smallholder farmers, who constitute 85% of the world's farmers and are underserved by existing high-cost diagnostic solutions. By providing an affordable, scalable tool, we aim to capture this market, especially in emerging economies where agriculture is a primary livelihood.

Revenue Model: Our primary revenue streams include:

1) Freemium Model: Basic diagnostics are free; premium subscribers receive advanced analytics, historical data tracking, and personalized advice.
2) API Licensing: Licensing our API to agricultural software platforms or agtech companies that want to incorporate disease detection in their services.
3) Data Insights: Selling aggregated, anonymized data insights to governments, NGOs, and agri-businesses, which can use this information to monitor crop health trends and improve food security.

H. Competitive Advantage

Our solution stands out with three main advantages:

1) Minimal Data Requirement: Unlike traditional ML models, our FSL-based system requires only a few images, making it faster and more adaptable to new plant diseases.
2) Accessibility: Designed to be affordable and accessible to small farmers worldwide through mobile devices.
3) Sustainability: By offering precise, eco-friendly treatment recommendations, we help farmers reduce chemical use, supporting longterm agricultural health.
4) Social Impact: Our platform supports sustainable agriculture by providing ecofriendly, targeted interventions. By helping farmers reduce crop losses, improve yield, and avoid unnecessary chemical usage, we contribute to food security, environmental protection, and economic resilience, especially in rural communities.

V. FUTURE SCOPE:

The future of plant disease diagnosis through few-shot learning (FSL) and computer vision is poised to revolutionize sustainable agriculture, providing farmers with precise, accessible, and real-time support. This innovative approach allows models to identify diseases accurately, even with limited data, making it ideal for diverse and dynamic agricultural environments. By integrating with IoT devices, future systems could capture environmental factors like humidity and soil moisture, enabling predictive disease diagnostics. Hybrid machine learning approaches, such as combining FSL with transfer learning, will further improve model accuracy and adaptability. Additionally, offline functionality will make these tools accessible to farmers in remote areas with limited connectivity. Through partnerships with governments and agricultural organizations, these advanced systems could also support large-scale disease monitoring and rapid response efforts. Overall, future developments in FSL-based plant disease diagnosis will enhance food security, support sustainable farming, and offer tailored, environmentally friendly solutions for farmers worldwide.

A. Expanding the Database of Plant Diseases and Crop Varieties

With increasing data on different plant species, disease types, and geographical variations, future systems can support even more crops and diseases. As FSL can work with limited data, expanding the model's training base incrementally with more disease samples and rare conditions will enhance its ability to generalize effectively across new plants and diseases without requiring a complete retraining process.

B. Increased Accuracy through Hybrid Models

By combining FSL with other machine learning techniques, such as transfer learning or reinforcement learning, the accuracy of disease detection models can improve. This hybrid approach could lead to the development of adaptive models that self-learn and update in response to new disease data, making them more resilient and accurate over time.

C. Enhanced User Engagement and Decision Support Systems

Future applications may incorporate decision support systems (DSS) that not only diagnose diseases but also provide users with a comprehensive set of actions and recommendations, including precise pesticide dosages, organic treatments, or preventive measures. The system could evolve into a holistic crop management tool, guiding farmers from disease identification through to yield optimization.

D. Ecosystem and Environmental Monitoring

In the future, the system could expand beyond plant disease diagnosis to monitor overall ecosystem health, identifying not only diseases but also pests, soil degradation, and environmental factors affecting crops. This holistic monitoring would enable better resource management, supporting sustainable and resilient farming practices.

VI. CONCLUSION

Automatic classification of plant leaf diseases based on a few labeled samples is significant to guarantee the yield and quality with low cost of data. In this work, we proposed the semi-supervised few-shot learning scheme, which can improve the average accuracy of few-shot classification by adaptively selecting the pseudo-labeled samples to help fine-tune the model. Through literature research, to our best knowledge, we carried out the first semi-supervised work in the field of few-shot plant diseases classification. The PlantVillage dataset was divided into three split modes, and extensive comparison experiments were executed to prove the correctness and generalization of proposed methods. Considering all the different domain splits and k-shot, the average improvement by the proposed single semi-supervised method is 2.8%, and that by the iterative semi-supervised method is 4.6%. The study utilized the PlantVillage dataset, a publicly available collection of over 54,000 images of both healthy and diseased plant leaves across 38 different classes, representing 14 species of crops. These images were captured under controlled environmental conditions with uniform backgrounds. While widely used as a benchmark in plant disease classification , the controlled nature of the PlantVillage dataset might limit the generalizability of models trained on it to the more complex and variable conditions found in real-world agricultural fields.

REFERENCES

[1] Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. Plant Methods. 2021;17(1):1–18.
[2] Wen BQ, Li Y, Kan Z, et al. Experimental study on microstructure and mechanical properties of stalk for Glycyrrhiza Glabra. J Biomech. 2021;118:110198.
[3] Sheng X, Li Y, Lian M, et al. Influence of coupling interference on arrayed eddy current displacement measurement. Mater Eval. 2016;74(12):1675–83.
[4] Nie J, Li Y, She S, et al. Magnetic shielding analysis for arrayed eddy current testing. J Magnet. 2019;24(2):328–32.
[5] Wang Y, Long A, Xiang L, et al. The verification of Jevons' paradox of agricultural Water conservation in Tianshan District of China based on Water footprint. Agric Water Manag. 2020;239:106163.
[6] Nie J, Wang N, Wang K, et al. Effect of drip irrigation with magnetised water and fertiliser on cotton nutrient absorption. Earth Environ Sci. 2021;697(1):012009.
[7] Li Y, Chao X. ANN-based continual classification in agriculture. Agriculture. 2020;10(5):178.
[8] Garhwal AS, Pullanagari RR, Li M, et al. Hyperspectral imaging for identification of Zebra Chip disease in potatoes. Biosys Eng. 2020;197:306–17.
[9] Gao Z, Khot LR, Naidu RA, et al. Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyperspectral imaging. Comput Elect Agric. 2020;179:105807.
[10] Hu G, Yin C, Wan M, et al. Recognition of diseased Pinus trees in UAV images using deep learning and AdaBoost classifier. Biosys Eng. 2020;194:138–51.
[11] Misra T, Arora A, Marwaha S, et al. SpikeSegNet-a deep learning approach utilizing encoder-decoder network with hourglass for spike segmentation and counting in wheat plant from visual imaging. Plant Methods. 2020;16(1):1–20.
[12] Liu J, Wang X. Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model. Plant Methods. 2020;16:1–16.
[13] Too E, Yujian L, Njuki S, et al. A comparative study of fine-tuning deep learning models for plant disease identification. Comput Electron Agric. 2019;161:272–9.
[14] Nagasubramanian K, Jones S, Singh AK, et al. Plant disease identification using explainable 3D deep learning on hyperspectral images. Plant Methods. 2019;15(1):98.
[15] Jiang F, Lu Y, Chen Y, et al. Image recognition of four rice leaf diseases based on deep learning and support vector machine. Comput Electr Agric. 2020;179:105824.