Advanced Framework for Leaf Disease Detection Using Machine Learning and MESA Agent

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***Abstract*—The Smart Leaf Disease detection addresses a critical challenge regarding the identification and management of diseases in plants: it is something that is key to healthy crops and abundant yield. The system integrates advanced image recognition, using a VGG19-based CNN, with agent-based virtual simulation to analyze the dynamics of diseases. Trained on the "New Plant Diseases Dataset (Augmented)", the model accurately classifies 38 distinct plant diseases. Besides identification, the system mimics the spreading of disease within a virtual farm. In this environment, each plant is a free agent, operating within a grid-based scenario. Randomness was introduced for replication of reality conditions so insight may be developed into how diseases spread and what kind of strategies might be deployed in control strategies. Images of Corn Common Rust, Potato Early Blight, and Apple Cedar Rust are used to test this; the results show that this method has the potential to be an effective tool for more intelligent, sustainable farming. The framework's accuracy was 91%. Farmers and academics may use the framework to make smarter, data-driven decisions that will increase agricultural resilience and productivity.**

***Index Terms*—plant disease detection, VGG19, virtual simulation, precision agriculture, sustainable farming.**

I. Introduction

The rapidly evolving landscape of agricultural technology is being revolutionized by the convergence of machine learning and simulation techniques to bring about unprecedented breakthroughs in plant disease monitoring and management. Crop diseases continue to be one of the biggest problems facing the agriculture industry, causing significant financial losses and endangering the world's food supply. Traditional approaches to plant disease detection are either useful but coupled with limitations attributed to their dependency on manual labor, expert knowledge, and inefficiencies associated with real-time applications. The combination of advanced computational technologies overhauls these constraints and makes for a new way to address the health issues of plants. The work proposes a detailed framework that combines deep learning-based image classification and agent-based simulations to offer a flexible yet efficient tool for the monitoring of plant health. The classifications are further extended into a virtual simulation environment built using the Mesa library, where plants are represented as agents within the grid-like ecosystem. The simulation describes plant-disease interactions and analyzes disease dynamics spatially and temporally, thereby giving actionable insights for disease management strategy formulation. In addition to the above, the integrated framework enhances precision in the identification of plant disease with a simulation-driven method that explains disease propagation. Further, its dual capability gives it immense utility as a farmer tool, research tool, and policy maker's tool. Its usage helps the farmer by providing real-time and automatic identification of disease, resource optimization, and usage of resources. The simulation environment will be utilized by researchers for complex ecological interactions to develop advanced machine learning models and test interventions in a controlled virtual setting. The framework offers evidence-based insights for policymakers to plan sustainable and effective agricultural strategies contributing to global food security and environmental sustainability.

The scope of the work entails precision agriculture, disease ecology, and agricultural policy-making. With the ability of the system to adapt to new datasets and agricultural technologies, it is sure to remain relevant in a changing landscape. Additionally, the fact that the simulation allows for the testing of strategies on managing diseases within a risk-free environment minimizes the economic and environmental costs involved with the traditional trial-and-error approaches. More broadly, it aligns with the United Nations' Sustainable Development Goals for zero hunger, responsible consumption, and climate action. The synthesis of image recognition and agent-based simulation in the research opens doors to a new future of smart and sustainable agricultural practice. It draws attention to harnessing technology toward resilient agricultural systems able to address dual global food demands with environmental sustainability.

II. Literature Survey

Kirola et al. [1] discussed Indian agriculture on the adoption of automated plant disease detection and showed a paradigm shift in the adoption of methodologies from traditional techniques to "Machine learning and Deep learning-based" approaches. The "frameworks" that were reviewed showed an amalgamation of image processing with classification, noting the extraordinary accuracy as high as 98.43% for CNN, highlighting how this technology based on deep learning was essential in promoting precision farming on newer frontiers. Nema et al. [2] reviewed the progress on crop disease detection, starting from traditional methods to advanced deep learning algorithms like CNN, which are being implemented in smartphone-based applications to improve image-based diagnostic efficiency. By this study, it is shown that there was a positive correlation between the numbers of images in the dataset versus the accuracy and that the resolutions do not strongly affect when the features are very sharp. Reddy et al. [3] have discussed the great potentiality of the agribusiness in India since a crop loss of 15.7% happens every year because of pests and diseases. They proposed a MATLAB-based system using some kind of image processing, k-means clustering, segmentation, extraction of features, and afterward classification using the Support Vector Machine. In this way, this system lessens the flaws of manual detection and hence treatment at the perfect time for crops to be of good health and quality. Dev et al. [4] estimated the challenges that are happening in Indian agriculture, which includes proper selection according to soil and climatic conditions of a particular geographical region. For crop recommendation and early plant disease detection, artificial neural networks and 2D CNN are recommended, respectively. This has facilitated precision farming, productivity enhancement, prevention of nutrient loss, and sustainability in agriculture. Singh et al. [5] have identified the role of machine learning in solving agriculture-based problems that arise due to climate change. They presented a unified website integrating crop recommendation and plant disease detection, using ML algorithms such as logistic regression and random forest for crop recommendations while EfficientNetV2 was used for plant disease identification, and it resulted in a very high accuracy of 96.06%. This will go a long way in helping with better and more sustainable farming practices.

Tiwari et al. [6] have highlighted the economic importance of agriculture in India, the negative impact due to plant diseases on its productivity, and its review of related works dealing with applications of leaf image-based detection. They proposed a deep learning-based techniques system like CNN, SVM, and KNN. Hence, the system that is proposed here will ensure the proper identification of plant diseases with robust training on various datasets and optimum recommendation of crops. Geetharamani et al. [7] discussed advances in agricultural technology, which explained the significant role of ResNet50 in the identification of pests and diseases from leaf images. The study discussed the transformative effect of deep learning on crop protection, emphasizing the potential for the precise identification and targeted interventions. High prediction accuracies achieved for tomato and potato crops underline its promise for the wider adoption of this approach in pest and disease management. Arun et al. [8] introduced a 14-layer Deep Convolutional Neural Network (DCNN) intended for plant leaf disease detection. The model, which was trained using an expansive dataset of 147,500 images spanning 58 classes, applied data augmentation along with multi-GPU training for an accuracy of 99.97%. By using random search for hyperparameter optimization, this approach was greater than all previous transfer learning-based approaches that achieved a new great step toward agriculture disease detection. Archisman et al. [9] proposed a deep CNN architecture comprising nine layers with the objective to identify plant leaf diseases. Here, a 39-classes leaf-based heterogeneous dataset is considered and used a total of six different data augmentation techniques that has an accuracy level of 96.46%. This also outperformed traditional machine learning and transfer learning techniques to further research in plant disease detection for agricultural purposes. Harika et al. [10] researched about the detection of diseases in "Black gram crops, including Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow mosaic". Using the BPLD dataset, the study compared machine learning and deep learning approaches and involved Convolutional Neural Networks with 89% accuracy. These results are rich in diagnosing diseases in black gram crops quite effectively.

MobileNetV2-based Sugarcane Disease Identification: Karthik et al. [11] found that the diagnosis of sugarcane diseases via the MobileNetV2 approach could be taken care of if the weather's variability is factored in; it was used to bridge between experienced farmers, and effective diseased identification occurs. This did show a rich potential for handling disease management about sugarcane cultivation. Vaishali et al. [12] proposed the autonomous system for detection of cotton leaf disease using CNN-based deep learning. The system got an amazing accuracy of 99.997%, which really highlighted the effects of the diseases on productivity. This study demonstrated the capabilities of sophisticated AI for disease detection at early stages, bringing valuable contributions to cotton cultivation and sustainable agriculture. Guruswamy et al. [13] explored CNNs to classify the potato leaf disease and got an accuracy 98.1% using the Plant Village dataset, thus outperforming previous methods by 3%. Their results proved the high precision, recall, and F1 score of their approach, thereby proving the ability of CNN in automated disease detection. This would ensure economic and ecological benefits due to early disease interventions and better management of crops. Mohandas et al. [14] introduced a real-time detection system of a plant disease using YOLOv4-tiny that showed efficiency and effective classification for potato and tomato crops. The integrated approach using image processing techniques combined with an Android application will help farmers in quickly detecting diseases and thus respond as quickly as possible. This paper discussed efficiency in speed and accuracy with high practical value for the system concerning agricultural applications. Reddy et al. [15] performed an analysis on various classification algorithms for "Plant Leaf Disease detection" with "Image processing" techniques such as "k-means clustering", Otsu segmentation, and "Support Vector Machines". In this paper, the proposed system based on MATLAB achieved an accuracy rate of 94-96% by using SVM. It was much better than that of KNN. Feature extraction, segmentation, and some practical agricultural applications in the early detection of diseases were emphasized. Hyperspectral imaging, with "machine learning methods such as Random Forest" boosted by PCA, improves the accuracy of classification and allows for the early detection of a disease. [17] gives an idea regarding the feature extraction method called HOG while having deep learning architectures such as ResNet50 and VGG16 for detecting the diseases of a plant. Classifications based on hyperspectral image acquisition coupled with machine learning tools such as the Random Forest, which is enhanced through PCA boosts accurate classification, facilitates early disease prediction, and more. Kirola et al.

III. Methodology

The Fig 2 shows architecture of "Plant Disease Detection system" with deep learning and MESA agent to classify the health of plants accurately. It begins with the PlantVillage dataset, which contains labeled images of healthy and diseased plant leaves. The images are preprocessed and augmented to enhance consistency and model robustness. VGG19 backbone extracts features and then refines them with a deep convolutional network, and then further refined by the MESA Agent, which is an Agent-Based Modeling to focus on critical image regions. The processed features are then classified through fully connected layers, and the output of this process gives a prediction of the condition and disease type of the plant, if present. This is an end-to-end architecture that combines advanced techniques for precise and efficient plant disease detection.

A. Dataset Description

The publicly accessible PlantVillage dataset [18], a collection of plant leaf photos intended to aid in the study of plant health, disease detection, and categorisation, served as the dataset for this investigation. 54,303 photos divided into 38 classifications make up the dataset, which includes numerous plant species and the illnesses associated with them. It also includes healthy plant leaf samples, making it a rich dataset for any classification task.

The key categories in the dataset are as follows:

1. Healthy Leaves: This comprises images of plant leaves that indicate no trace of disease. These are always considered a baseline for comparing diseased samples.

2. Diseased Leaves: Below mentioned are the images of plant leaves are symptoms of different diseases, such as fungal, bacterial, and viral infections. These images are categorized according to the type of disease influencing the plant. The dataset [18] contains images from 14 plant species. Every plant has its set of diseases. Among these, there are some that include the following notable plant species with their diseases:

1. Apple: Black Rot, Cedar Apple Rust, Apple Scab, and Healthy

2. Corn (Maize): Cercospora Leaf Spot (Grey Leaf Spot), Common Rust, Northern Leaf Blight, Healthy

3. Blueberry: Healthy

4. Cherry: Powdery Mildew, Healthy

5. Grape: Leaf Blight (Isariopsis Leaf Spot), Black Rot, Esca (Black Measles), and Healthy

6. Orange: Citrus Greening(Haunglongbing)

7. Peach: Healthy, Bacterial Spot

8. Pepper (Bell): Healthy, Bacterial Spot

9. Potato: Healthy, Early, and Late Blight

10. Strawberry: Leaf Scorch, Healthy

11. Soybean: Healthy

12. Squash: Powdery Mildew

13. Raspberry: Healthy

14. Tomato: Target Spot, Yellow Leaf Curl Virus, Mosaic Virus, Bacterial Spot, Early Blight, Late Blight, Leaf Mould, Septoria Leaf Spot, Spider Mites (Two Spotted Spider Mite), Healthy

This variety species of plants and diseases ensures the dataset is rich and representative. The dataset therefore best suits machine learning models with an ability to generalize well between the different types of crops and the disease conditions. Additionally, there is an appropriate distribution of images across all the classes of this dataset; therefore, issues associated with potential imbalances could arise in model performance.

B. Preprocessing

The Fig 1 is a collection of leaf samples that are utilized in disease detection. These images have been segmented and enhanced for important features, like color, texture, or any other patterns associated with the disease. The preprocessing techniques followed include noise removal and contrast transfer functions, to filter out infected regions. Uniformity of the dataset and accurate extraction of features, leading to accurate classification, is an essential point in the training process for detection of model. The extracted features are visually distinguishable by algorithms of machine learning for effective analysis. The pre-processing procedures listed below were used to get the dataset ready for training:

1. Image Resizing: All images are resized to 224×224 pixels in order to make them uniform input size required by the VGG19 model. This helps in maintaining the uniformity in the input dimension.

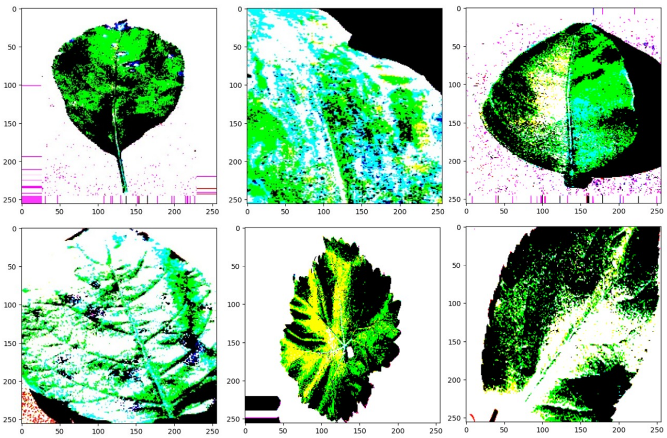

Fig. 1. Preprocessed leaf images with disease-affected regions through segmentation, noise removal, and contrast adjustments for accurate machine learning analysis.

2. Normalization: The Pixel values are normalized so that the range is in between [0, 1]. This is done by dividing every pixel value with 255. This speeds up the convergence of the model.

$$I_{\text{norm}}(x, y) = \frac{I(x, y)}{255} \tag{1}$$

3. Data Augmentation: The following augmentation approaches are used to increase the training dataset's diversity:
Random Rotation: Rotating images by random angles between -30° and +30°.
Horizontal Flipping: Mirroring images along the vertical axis.
Zooming: Randomly zooming into image regions by a factor of up to 20%.
Gaussian Noise: Adding random noise to simulate variations in image quality.
4. Noise Removal:
Gaussian Blur: Used to smooth images and reduce high frequency noise.
Median Blur: Used to reduce salt and pepper noise to get clearer feature appearance.
5. Feature Extraction for Leaf Characteristics:
Color Features: Histogram-based approach for color distribution quantification.
Texture Features: "GLCM (Gray Level Co-occurrence Matrix)" is used to compute texture quantification.
Shape Features: Contour-based approach for measuring boundary irregularity of the diseased areas.
6. Weighted Sampling: For residual class imbalance, Weighted Random Sampler was employed. Here, it was assigning greater weights to the underrepresented classes. A Weighted Random Sampler is one sampling technique wherein each item of a dataset receives a different selection probability based on its assigned weight. In simpler terms, higher-weighted items are more probable to be picked than lower-weighted items.

C. Model Architecture:

VGG19 with MESA Agent-Based Modeling Framework

The core of this research is the VGG19 model, where the MESA agent has been added to further enhance feature extraction and classification accuracy. The architecture is as follows:
1. VGG19 Backbone: VGG19 is a "Deep Convolutional Neural Network (CNN)" architecture that has been pre-trained on the ImageNet dataset. It contains 19 layers, it includes 16 convolutional layers and 3 fully connected layers. This pre-trained backbone serves as the feature extractor in the work.
Convolutional Layers of VGG19 learn from the input images low and high level spatial features. Filters applied at each of these layers are varied in capturing all sorts of patterns, edges, texture, and other features in images at various levels. After every convolution, the model uses the activation function "Rectified Linear Unit (ReLU)" that adds nonlinearity of the model and enables it to learn more complicated patterns.
After the convolutional layers,down sampling of feature maps are done by maxpooling layers. These layers give a spatial reduction to the spatial dimensions in the feature maps with the most essential information. This makes the model more computationally efficient and invariant to small translations in the image. Then the feature maps will be flattened and passed through three fully connected layers, which enables the model to make high-level predictions based on the learned spatial features.
VGG19's architecture extracts the hierarchical features present in the input image. This capability allows model to effectively understand complex visual patterns in plant leaf images, which is crucial for accurate disease classification.

2. MESA Agent-Based Modeling Framework: The MESA framework is an open-source agent-based modeling (ABM) tool in Python. It is designed to simulate complex systems where individual entities (agents) interact within an environment. It gives a structured way to define agents, schedule their actions, and update the system over time. MESA is quite useful for modeling dynamic systems in which interactions between agents determine the overall behavior of the system.
MESA framework uses three main constituents:
1. Agents: Every agent stands for an independent entity in the system with specified properties and actions.
2. Model: Defines the environment within which the agents operate as well as rules that govern how agents interact.
3. Scheduler: This is what dictates how and when the agents take their actions.

In this work, MESA is used for simulating plant disease classification. In this experiment, each agent has the following functionalities:

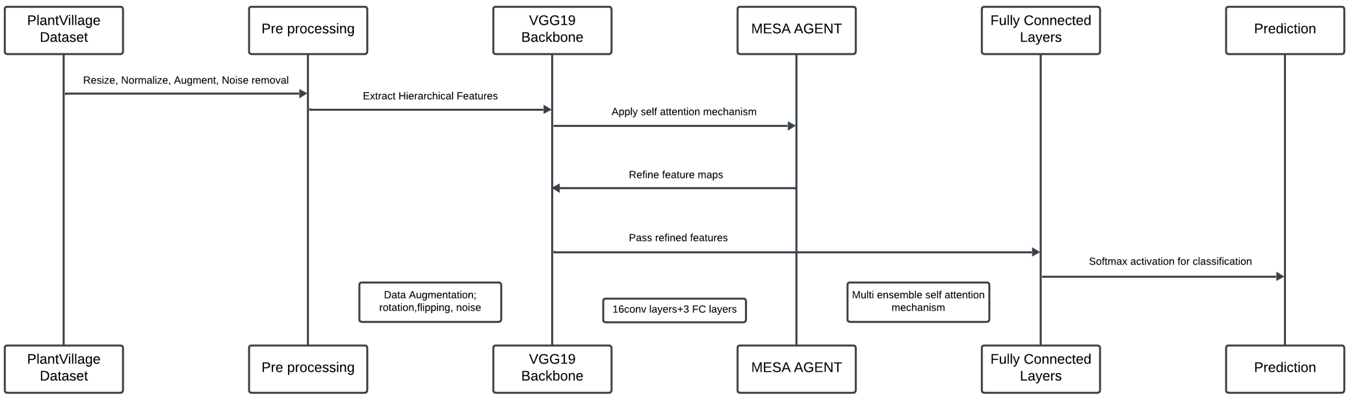

Fig. 2. Architecture diagram of Leaf Disease Detection

1. Loads an image and feeds it into VGG19 to perform processing.
2. Performs feature extraction of VGG19
3. Takes a disease prediction using the model.
4. Stores the label of the disease for later use in the assessment.

Mathematically, denote the input image as "I" and VGG19 as the function "F":

$$F(I) = \text{VGG19}(I) \tag{2}$$

The obtained features "F(I)" are forwarded to the classification layer in order to find the probability of disease class "c":

$$P(c \mid I) = \text{softmax}(WF(I) + b) \tag{3}$$

where:
- "W" are learned weights of the classification model,
- "b" are bias terms,
- "softmax" outputs are guaranteed to be valid probabilities over all disease classes.

PlantAgent: Each agent is a representation of a plant leaf image with the following attributes:
- Image ID: Unique identifier for the image.
- Extracted features: Deep features obtained from VGG19.
- Predicted disease classification: The disease category predicted for the given image.

The behavior of each agent is governed by:

$$y_i = \arg\max cP(c \mid I_i) \tag{4}$$

where "y_i" is the predicted disease label for image "I_i".

PlantDiseaseModel Class: This class defines the environment in which the agents interact.

1. Grid-Based Environment:
Agents are located on a "2D Multi Grid" of size "(m, n)". Each agent processes an image independently. The grid provides structured interactions and tracking of states of agents.

2. Random Activation Scheduler:
Agents execute their steps in a random order to simulate real-world variability. The "Random Activation" scheduler ensures that agents do not follow a fixed sequence, thereby allowing diverse interactions.

3. Disease Classification Process:
- Each agent applies the VGG19 model to classify an image.
- Predictions are stored and evaluated.

The model iterates over multiple simulation steps, refining its classification approach by leveraging agent-based interactions and updating results dynamically based on predictions.

It thus improves the process of classification because each plant leaf is treated as an autonomous agent. The implementation of "agent-based modeling (ABM)" introduces a structured and dynamic way of classifying plant diseases in a way that improves adaptability and scalability.

D. Training and Optimization

1. Optimizer: Adam optimizer with weight decay regularization was employed to enhance generalization.

2. Loss Function: Cross entropy loss was used for multiclass classification.

$$L = \sum_i y_i \log(\hat{y}_i) \tag{5}$$

IV. Results and Analysis

The integration of MESA agent-based modeling with deep learning-based plant disease classification improves autonomous behavior and adaptibility, and showed strong performance in achieving 93% training accuracy and 91% testing accuracy as shown in the Table I. The VGG19 model effectively extracts meaningful features from the images of the plant leaves, while the MESA framework simulates the disease spread patterns in spatial and temporal dimensions. Figures 3 and 4 give evidence of the efficient learning of disease patterns and generalization to unseen data by the model, which makes it a promising tool for precision agriculture and disease monitoring. The MESA simulation allows for dynamic interaction between agents representing infected and healthy plants. This gives an insight into how diseases propagate under different conditions. By simulating disease transmission across a grid-based environment, the model helps predict potential outbreaks and optimize intervention strategies, which aid in sustainable agricultural practices.

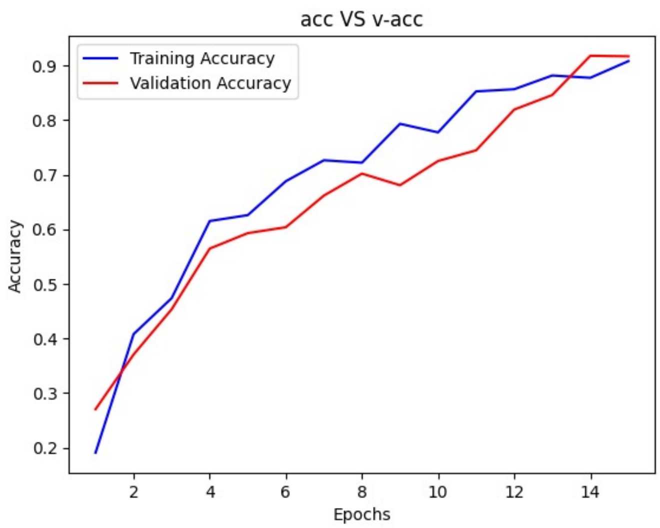

Fig. 3. Comparison of accuracies of VGG19-MESA Agent through epochs

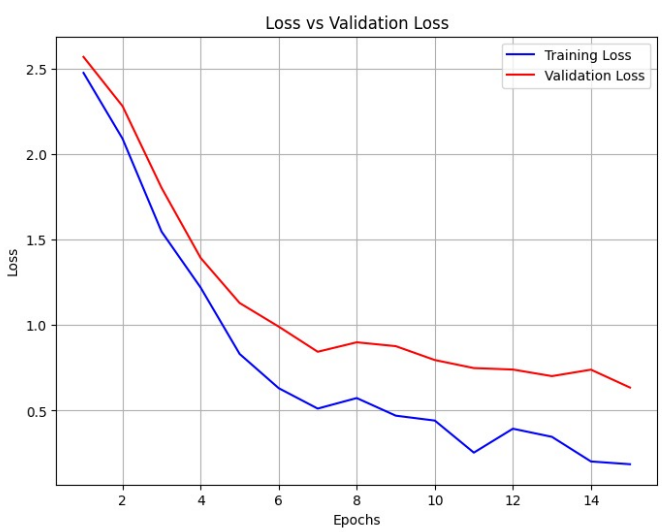

Fig. 4. Comparison of losses of VGG19-MESA Agent through epochs

Despite the promising results, a few limitations exist. The diversity in the PlantVillage dataset excludes environmental effects, such as weather, quality of soil, and human influences, which impact real-world disease development. Second, MESA does not feature a real-time adaptive agent-based framework that accounts for sudden environmental changes, so discrepancies between actual and simulated dynamics might arise in the disease model. Another concern is over-fitting, as high accuracy may not always translate to real-world performance. Further cross-validation on diverse datasets, inclusion of more plant species, and techniques like data augmentation and weighted sampling could enhance model robustness. Integrating real-time field data with MESA simulations could further improve disease prediction and agricultural decision-making, making the system more effective for large-scale deployment.

Evaluation metrics	**Training**	**Testing**
Accuracy	93%	91%
Precision	93%	89%
F1 score	92%	89%
Recall	91%	88%

TABLE I
MODEL PERFORMANCE IN TRAINING AND TESTING PHASES

V. CONCLUSION

Leaf disease detection by deep learning and agent-based modeling provides a dynamic and structured approach to the classification of plant health. With diverse representation, the PlantVillage dataset guarantees robustness to models, which further improves by applying pre-processing techniques like resizing, normalization, and augmentation. The feature extractor, in this case, in VGG19, critical spatial features are extracted from the plant leaf images. These features are then processed using the MESA Agent-Based Modeling framework, where each agent represents a plant leaf, classifying diseases in a grid-based environment. The random activation scheduler ensures realistic disease occurrences, improving generalization and adaptability for real-world applications. The final classification layer uses a softmax function for accurate disease prediction, making this hybrid approach effective for precision agriculture. Future improvements include agent interaction enhancement to simulate the dynamics of disease spread, incorporation of ecological factors such as temperature and soil conditions for better real-world simulations. Model optimization using advanced CNN architectures such as ResNet or Vision Transformers can further improve accuracy. Deployment on edge devices or drones for real-time monitoring of diseases can enhance practical usability. This would expand the dataset and incorporate synthetic data generation using GANs, improving classification performance across various plant species and rare diseases. These enhancements would make the system scalable, efficient, and applicable to real-world agricultural settings, ensuring intelligent and data-driven plant disease management.

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