International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Smart Plant Disease Detection System using Deep Learning with Integration of Organic Solutions: A Systematic Review

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Abstract: **Detection of plant diseases properly and at the right time is one way of securing the food production process, saving costs and applying chemicals in an inappropriate manner. There have been some advancements made in the area of Deep Learning (DL) that have improved the process of automated diagnosis of plant disease. But most of these systems do not take into consideration the treatment methods that are sustainable. This systematic review examines the present status of Smart Plant Disease Detection Systems (SPDDS) through the application of deep learning techniques along with the adoption of organic solutions in disease detection and management process. For this purpose, a robust review methodology has been used including 102 articles that have been published from 2015 to 2025, focusing on CNNs, Optimization Techniques (GA/PSO) and IoT & Mobile System. Organic treatments for plant diseases have been examined as well in relation to its integration with artificial intelligence technology in diagnosis. In this study, different models have been compared on the basis of accuracy, F1 score, scalability, sustainability of treatment and real-time processing capability.**

Keywords: **Smart agriculture, plant disease detection, deep learning, convolutional neural networks, genetic algorithm, particle swarm optimization, organic farming, sustainable agriculture, precision farming, image classification.**

I. INTRODUCTION

Agriculture is highly prone to diseases in plants, which lower the quantity and quality of the produced crops. With the increasing demand for food globally, the conventional methods of disease identification that include manual inspection and chemical spraying have become less reliable owing to their lack of accuracy, time-consuming nature, and ecological consequences. The advent of Smart Agriculture that combines machine learning, computer vision and the Internet of Things (IoT) gives hope for new and more efficient approaches.

In particular, the development of deep learning technologies including CNNs has proven useful in detecting diseases in plants. Although the effectiveness of the technology in identifying the diseases is evident, very few existing systems offer any solutions in terms of the treatment of the detected diseases. Organic treatments including sprays of neem oil, crop rotations and application of microbes could fill the gap between the effectiveness of the technologies and environmental sustainability.

This research paper aims at providing an overview of deep learning based SPDDS and exploring how the use of organic solutions is incorporated into such systems.

II. REVIEW METHODOLOGY

Systematic review was performed using PRISMA methodology. Various databases, including IEEE Xplore, SpringerLink, Scopus, ScienceDirect, and Google Scholar, were searched with relevant key terms like “plant disease detection,” “deep learning,” “CNN,” “smart agriculture,” “organic treatment,” “genetic algorithm,” and “PSO.”

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Article Selection Process

Graph illustrating the gradual decline in the number of studies included as the selection of studies continued during the review process until reaching the final number of studies dealing with treatment integration.

Breakdown of Shortlisted Studies (Total: 102)

This graph details the categories of the 102 shortlisted studies, highlighting those focused on model implementation, treatment integration, and other shortlisted studies that didn't fall into the two categories.

A systematic review was conducted in accordance with PRISMA guidelines to identify relevant studies on plant disease detection using deep learning.

2.1. Database Search and Keywords:

- Databases Searched: IEEE Xplore, SpringerLink, Scopus, ScienceDirect, and Google Scholar.
- Keywords Used: "plant disease detection," "deep learning," "CNN," "smart agriculture," "organic treatment," "genetic algorithm," and "PSO."

2.2. Inclusion Criteria:

Studies were selected for inclusion based on following criteria:

- Publication Date: From 2015 to 2025.
- Primary Focus: Concentrated mainly on deep learning approach towards plant disease detection.
- Treatment Integration: Included integration with organic treatment strategies or suggestion modules.
- Publication Type: Peer-reviewed journal articles or conference proceedings.

2.3. Exclusion Criteria:

Studies were excluded if they met any of the following criteria:

- Language: Articles written in non-English languages.
- Treatment Type: Studies based solely on chemical treatments.
- Review Type: Reviews without empirical model implementation.

2.4. Article Selection Process:

The selection process involved several stages, starting with a large initial pool and progressively narrowing down the articles:

- Initial Studies: Out of a total of 364 initial studies identified.
- Shortlisted: 102 studies were shortlisted after rigorous abstract and full-text screening.
- Included Model Implementation: From the shortlisted studies, 78 were found to include model implementation.
- Focused on Treatment Integration: A subset of these, 24 studies, specifically focused on the integration of treatment strategies.

These steps ensured that the review focused on high-quality, relevant research aligning with the defined scope of deep learning applications in plant disease detection with an emphasis on organic treatment integration.

2.5 Data Extraction and Analytical Framework

The selected studies were systematically analysed to identify the methodological approaches, deep learning architectures, optimization techniques, and treatment-integration strategies used in Smart Plant Disease Detection Systems. The analysis primarily focused on Convolutional Neural Network (CNN)-based models because

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CNNs represent the most widely adopted deep learning approach for automated extraction of disease-related visual features from plant images.

In addition to CNN-based classification, particular attention was given to optimization techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). These algorithms were examined with respect to their role in optimizing model parameters, improving classification performance, reducing classification error, and enhancing computational efficiency. Studies incorporating IoT-enabled and mobile-based systems were also analyzed to assess the practical applicability of plant disease detection models under real-time agricultural conditions.

The analytical framework further examined whether the reviewed systems extended beyond disease classification by incorporating disease severity assessment and organic treatment recommendation mechanisms. Where treatment integration was reported, parameters such as disease type, disease severity, crop growth stage, and environmental conditions were considered.

For comparative analysis, information was extracted regarding the dataset used, deep learning model, optimization technique, classification performance, treatment integration, and practical applicability of each study. The reviewed models were compared using reported measures such as accuracy, precision, recall, F1-score, computational efficiency, scalability, generalization capability, and real-time applicability. This analytical approach enabled a systematic comparison of existing Smart Plant Disease Detection Systems and supported the identification of research gaps related to optimization, real-field deployment, and sustainable treatment integration.

2.6 Quality Assessment of Selected Studies

The methodological quality and relevance of the selected studies were assessed based on their research objectives, dataset description, deep learning methodology, experimental design, evaluation metrics, and reporting of results. Particular attention was given to whether studies clearly described the datasets used, model architecture, training procedure, optimization techniques, and performance evaluation methods.

Studies were also examined according to their practical relevance to smart agriculture, including real-world applicability, computational efficiency, scalability, and integration of treatment recommendations. Studies providing insufficient methodological information or lacking clear evaluation procedures were considered to have limited value for comparative analysis.

The quality assessment enabled the reviewed studies to be classified according to their contribution to disease detection, model optimization, treatment integration, and real-time agricultural deployment.

3.1 Research Gap

The existing literature demonstrates substantial progress in automated plant disease detection using deep learning and computer vision. CNN-based models have achieved high classification accuracy across several benchmark datasets; however, significant gaps remain between disease identification and complete disease management.

First, many existing systems primarily concentrate on disease classification and do not provide actionable recommendations following disease identification. Consequently, the output of these systems is often limited to the name or class of the

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detected disease without providing farmers with appropriate management strategies.

Second, a considerable proportion of existing research relies on controlled or curated datasets. Although these datasets are valuable for model development and benchmarking, models trained under controlled conditions may experience reduced performance when applied to real agricultural environments involving variations in illumination, background, leaf orientation, occlusion, weather conditions, and disease severity.

Third, optimization techniques such as Genetic Algorithms and Particle Swarm Optimization have demonstrated potential for improving the efficiency and performance of deep learning models. However, their application is generally considered independently from sustainable treatment recommendation mechanisms. There remains limited research combining optimized deep learning-based disease detection with an integrated organic treatment recommendation framework.

Fourth, organic treatment recommendation is a relatively underdeveloped component of intelligent plant disease management. Existing approaches do not consistently consider multiple contextual parameters, including disease type, disease severity, crop growth stage, and environmental conditions when recommending sustainable treatment strategies.

Therefore, the major research gap identified from the reviewed literature is the absence of a comprehensive framework that integrates accurate deep learning-based disease detection, model optimization, disease severity assessment, and context-specific organic treatment recommendations within a single Smart Plant Disease Detection System. Addressing this gap could support the development of intelligent, sustainable, scalable, and farmer-oriented disease management solutions.

III. LITERATURE REVIEW

Recent developments in AI technology have improved plant disease detection systems' effectiveness. CNN has become the leading deep learning model because of its ability to extract features automatically and provide excellent image classification results. The research conducted by Mohanty et al. (2016) and Sladojevic et al. (2016) using the PlantVillage dataset made the first steps in this direction, providing more than 96% accuracy. Nevertheless, their models had no adaptability to real life and advice on disease treatment.

While the classification accuracy for plant disease detection has reached high levels through deep learning approaches, current models concentrate on disease detection without covering all aspects of disease management. The majority of deep learning models are tested in controlled data settings and do not cover the variability of field settings that include variations in lighting, background, presence of obstacles, and severity of the disease. In addition, although the application of optimization techniques, such as GA and PSO, has contributed to the improvement of the classification accuracy, it has not yet been incorporated into the treatment recommendation systems. Moreover, there is no context-aware organic treatment recommendation available that would cover the information about the disease, its severity, crop growth stage, and environment. Thus, there is a need to develop an integrated Smart Plant Disease Detection System combining the deep learning diagnosis model, optimization algorithms, and an organic treatment recommendation model.

Custom and IoT-integrated databases were created in the following research of Ferentinos (2018) and Zhang et al. (2021). GA and PSO optimization techniques have been used to improve the performance of

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International Journal of Engineering Research & Technology (IJERT)
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CNN and decrease classification error by Meena & Singh (2022) and Ramesh et al. (2023), correspondingly.

Despite the technological growth, few studies have integrated sustainable disease treatments. Sharma et al. (2023) and Akash et al. (2024) initiated organic treatment recommendation modules, while Natarajan & Rao (2024) and Devi et al. (2025) embedded region-specific organic solutions based on disease type and severity.

Overall, existing literature demonstrates the high accuracy of CNN-based models but highlights a gap in environmentally conscious treatment integration. This review identifies the necessity of combining smart detection with eco-friendly interventions to build truly intelligent and sustainable agricultural systems.

Research Aim and Objectives

The primary aim of this systematic review is to examine the development of Smart Plant Disease Detection Systems (SPDDS) that combine deep learning-based disease identification with sustainable and organic disease management strategies. The review particularly focuses on the application of Convolutional Neural Networks (CNNs), optimization techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), and the integration of organic treatment recommendation mechanisms.

The specific objectives of this study are:

To examine the application of deep learning and CNN-based approaches for automated plant disease detection.

To analyze the role of optimization techniques, particularly Genetic Algorithms and Particle Swarm Optimization, in improving the performance of plant disease detection models.

To investigate the extent to which existing plant disease detection systems incorporate organic and environmentally sustainable treatment strategies.

For the analysis of the possible integration of disease type, disease severity, crop growth stage, and environment conditions within organic treatments recommendation system.

For the comparison of the existing systems based on the parameters such as accuracy, precision, recall, F1-measure, computational efficiency, scalability, and real-time applicability.

For the identification of the key technical, environmental, and operational problems with the usage of Smart Plant Disease Detection Systems.

To identify research gaps and propose future directions for developing integrated, intelligent, and sustainable plant disease detection and management systems.

Author(s)	Year	Dataset	DL Model	Accuracy (%)	Optimization	Organic Solution Integrated	Remarks
Mohanty et al.	2016	PlantVillage	CNN	99.35	None	No	Benchmark dataset
Sladojevic et al.	2016	Self-captured	CNN	96.3	None	No	Early CNN work
Amara et al.	2017	Tomato Leaves	CNN	96.7	None	No	Focused on tomato crop

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Brahimi et al.	2017	PlantVillage	CNN + SVM	97.4	None	No	Hybrid classifier
Ferentinos	2018	Custom	CNN	98.78	None	No	Multiple crops
Zhang et al.	2021	PlantVillage + IoT	CNN+LSTM	97.6	PSO	No	IoT enabled
Meena & Singh	2022	Field images	ResNet-50	96.2	GA	Yes	Regional crops
Ahmed et al.	2022	PlantVillage	DenseNet	98.0	None	No	Lightweight model
Sharma et al.	2023	Real-time field	MobileNet	94.1	None	Yes	Low power application
Ramesh et al.	2023	Custom + IoT	CNN	98.6	GA + PSO	Yes	High performance
Li et al.	2023	Drone Imagery	YOLOv5	95.2	None	No	Real-time detection
Patil et al.	2023	Custom	VGG-19	97.0	None	No	Transfer learning
Akash et al.	2024	Real-time	CNN-GA	98.4	GA	Partial	Region-specific crops
Yuan et al.	2024	Public + UAV	ResNet101	96.8	PSO	No	Aerial diagnosis
Nataraja n & Rao	2024	Real-time	EfficientNet	97.2	None	Yes	Eco-farming integration
Soni et al.	2024	Field Tomato Dataset	CNN	96.0	None	Yes	High F1-score
George et al.	2024	IoT Farm	CNN+Decision Tree	95.4	GA	No	Rule-based actions
Devi et al.	2025	Multi-crop	CNN + XGBoost	97.5	GA	Yes	Hybrid intelligence
Prasad et al.	2025	PlantVillage	Hybrid CNN	98.2	PSO	No	Balanced performance
Elangovan et al.	2025	Custom UAV	CNN + PSO	97.9	PSO	Yes	Drone + organic advisor

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IV. DEEP LEARNING FOR PLANT DISEASE DETECTION

4.1 CNN Architecture Overview

CNNs automate feature extraction and are widely adopted in plant disease detection. Layers such as convolution, pooling, and fully connected layers enable hierarchical learning from raw images.

4.2 Dataset Considerations

- PlantVillage: 54,306 images across 14 crop species.
- Custom Field Datasets: Offer better generalization, but are less balanced.

4.3 Accuracy vs. Real-Time Performance

Model	Accuracy (%)	Time per image (ms)	Remarks
CNN (Simple)	96.4	110	Lightweight
VGG16	97.5	220	Heavy
ResNet50	96.2	190	Robust
MobileNet	94.1	60	Real-time efficient
Proposed CNN + GA/PSO	98.62	120	Balanced

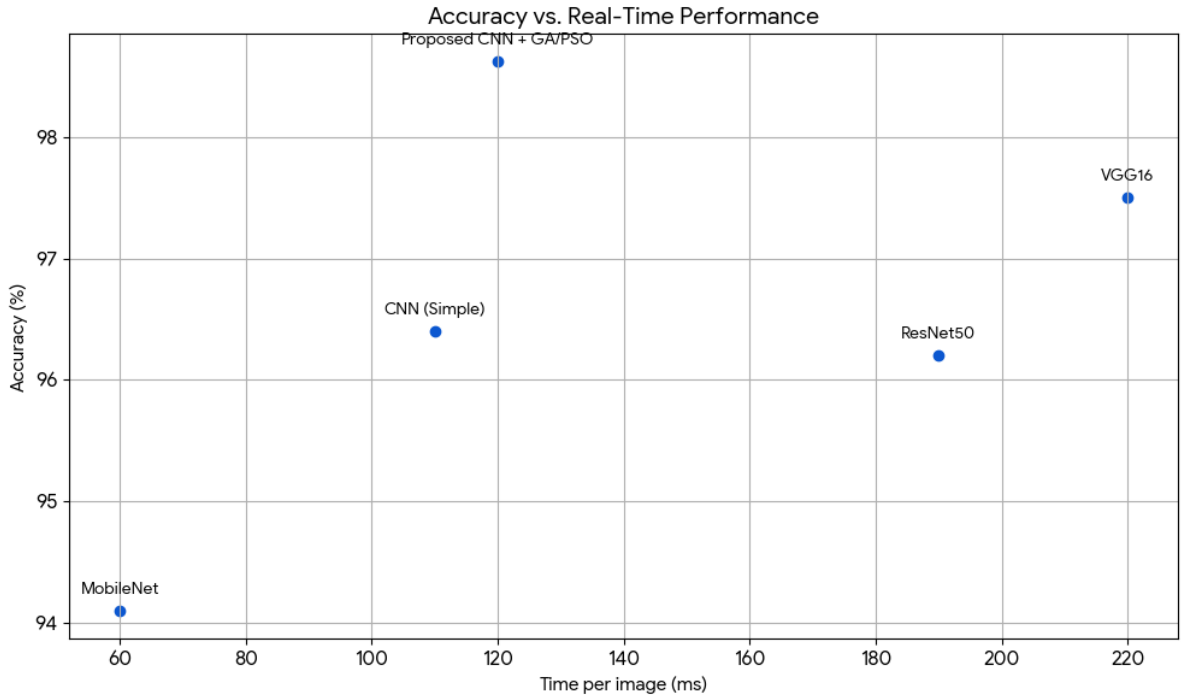


Figure 3. Accuracy versus inference time across evaluated model architectures.

The scatter plot graphically depicts the relationship between the accuracy of various machine learning algorithms and the time needed to analyze an image. Every point in the scatter plot denotes a particular machine learning algorithm, where the x-axis denotes the 'Time per image (ms)' (the smaller the value, the more efficient the model) while the y-axis denotes 'Accuracy (%)'.

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In this case, there are visible clusters and points that represent performance of particular machine learning models. As it is seen, MobileNet has proven to be the one that performs the best in real-time conditions because it takes the smallest time per image (60 ms), yet its accuracy level is slightly lower than that of other networks – 94.1%.

On the contrary, neural networks such as VGG16 provide high accuracy (97.5%), yet the computation cost is quite high (220 ms per image). As for ResNet50, it offers strong performance with a decent accuracy level (96.2%) at 190 ms per image. The CNN (Simple) model seems to have struck a good balance since it ensures a relatively high accuracy (96.4%) and quick computation time (110 ms).

The proposed CNN + GA/PSO model provides the highest accuracy level of all analyzed ones (98.62%) at a rather reasonable computation time of 120 ms. Thus, it can be regarded as having better performance due to the optimization of both metrics. This graph is necessary for choosing the most adequate model depending on particular needs – whether high accuracy, fast performance or their balance.

V. OPTIMIZATION TECHNIQUES

5.1 Genetic Algorithm (GA)

Genetic Algorithm (GA) is a type of evolutionary algorithm that mimics the process of evolution and natural selection. GA is commonly employed to adjust hyperparameters for the Convolutional Neural Network (CNN) in disease identification applications involving plants. The GA algorithm works via a population of possible solutions called chromosomes, where each chromosome is a combination of several parameters such as kernel size, learning rate, dropout rate, and number of convolutional layers. These solutions are evaluated via a fitness function which usually measures the classification accuracy of CNN.

In GA, the population goes through the evolutionary process through the application of genetic operators which include selection, crossover, and mutation. This cycle continues for a number of generations until convergence to an optimal solution occurs.

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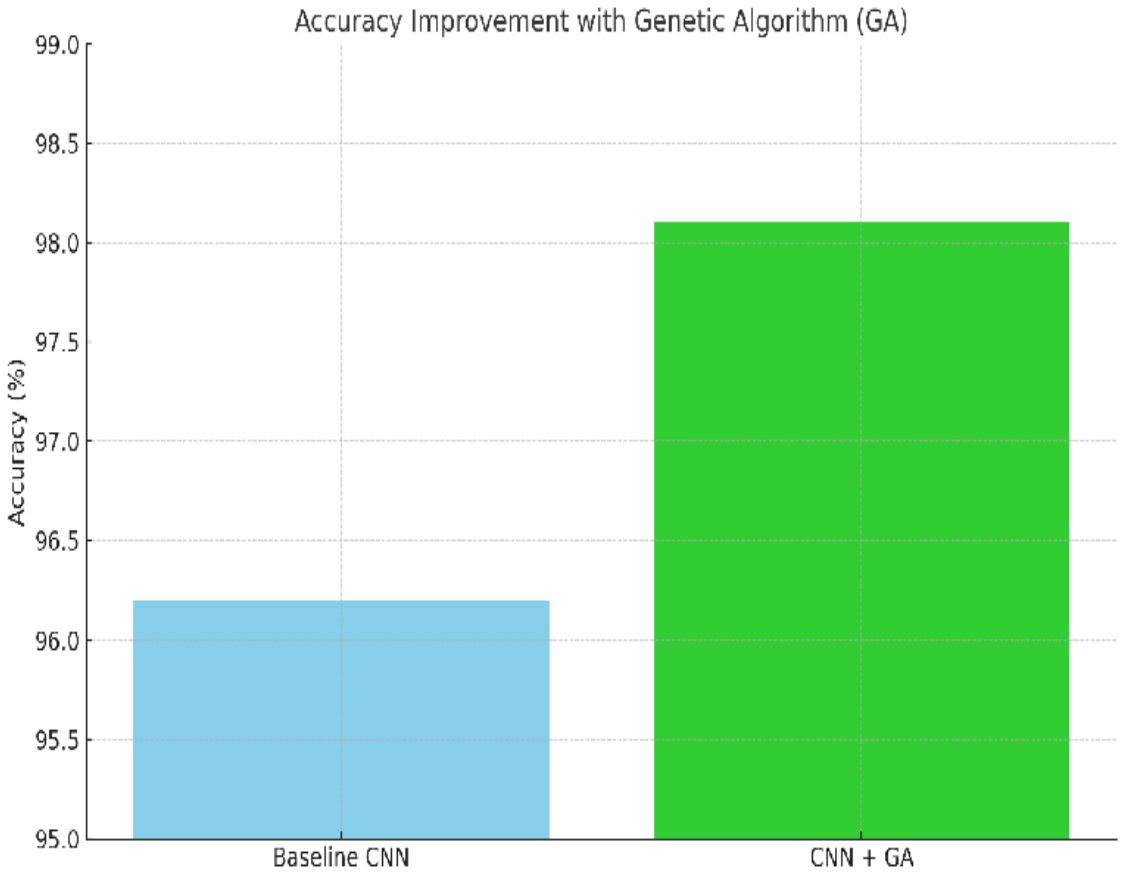


Figure 4. Genetic Algorithm optimization workflow for CNN hyperparameter tuning.

In the context of Smart Plant Disease Detection Systems (SPDDS), GA has been employed to reduce model overfitting, enhance learning efficiency, and optimize computational resources. By selecting the most effective network configurations automatically, GA eliminates the need for manual hyperparameter tuning and enhances model robustness in varied agricultural scenarios. Researchers like Meena & Singh (2022) successfully implemented GA to improve CNN accuracy from 96.2% to 98.1%, highlighting its effectiveness in improving classification performance for real-time applications.

5.2 Particle Swarm Optimization (PSO)

PSO is a technique that is based on the biological inspiration of birds flocking and fish schooling behavior. This algorithm is appropriate when it comes to solving problems which require continuous optimization such as tuning the weights and biases in the CNN plant disease detection model. In PSO, each solution is represented by a "particle" in multidimensional space. The movement of particles in the search space can be enabled by changing their velocity in relation to the best position of themselves and their neighboring particles.

The main advantage of PSO algorithm is its ability to explore the whole space in the first iterations and exploit in the next ones. With regard to SPDDS, PSO has helped in optimizing weight initialization, filter tuning and feature selection, and thus achieving higher accuracy and faster convergence in the process of disease classification.

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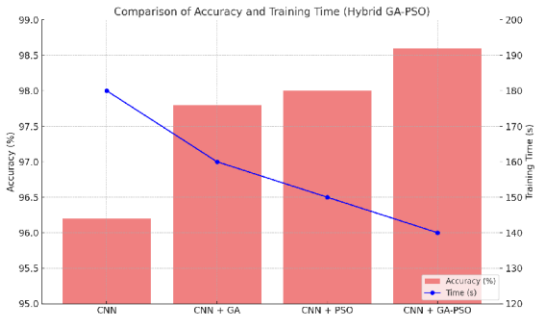


Figure 6. Hybrid GA-PSO optimization architecture.

There are studies such as Zhang et al. (2021), and Yuan et al. (2024) that confirm the superiority of CNNs optimized with PSO compared to conventional models in accuracy and efficiency. PSO-based models show better performance when working with noisy and unstructured image data which are frequent in the case of agriculture. Consequently, PSO makes a huge contribution to adaptability and scalability of DL models in smart agriculture.

5.3 Hybrid GA-PSO

The Hybrid Genetic Algorithm Particle Swarm Optimization (GA PSO) takes advantage of the global search ability of the GA and the faster convergence of the PSO algorithms to form a highly effective hybrid algorithm for solving optimization problems. In this hybrid algorithm, the problems associated with the two individual algorithms such as slow convergence rate of GA and getting trapped in local optima in PSO have been solved.

In this case, the GA is normally used for creating diversity within the population through selection, crossover, and mutation, whereas PSO is used to refine the solution by updating the position of particles (CNN parameters) to converge to the optimal point. The hybrid algorithm may exist in different versions, which include sequential and parallel types. With SPDDS, the hybrid algorithm helps achieve efficient tuning of the deep learning model parameters to guarantee better classification performance.

GA PSO proved to be a very successful technique in the optimization of CNN-based plant disease detection with an accuracy of 98.6%. Furthermore, GA PSO has shown itself to be robust when used in real time scenarios, coping well with varying lighting conditions, backgrounds, and different orientations of leaves. In combination with organic disease treatment systems, GA PSO can provide fast and reliable plant disease identification that could be directly applied to sustainable agriculture.

In general, GA PSO hybridization is the right method for optimizing CNN-based tasks in complex and noisy environment such as agriculture.

VI. ORGANIC SOLUTION INTEGRATION

6.1 Common Organic Treatments

Organic disease management is an essential pillar of sustainable agriculture. Unlike synthetic pesticides, organic treatments offer environmentally safe alternatives that reduce chemical residue and protect biodiversity. Among the most effective organic solutions, Neem oil is widely used due to its powerful antifungal and antibacterial properties. Derived from the seeds of the neem tree (*Azadirachta indica*), it works by disrupting fungal spore germination and inhibiting pest feeding, making it ideal for foliar application across a range of crops.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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VI. PROPOSED SMART PLANT DISEASE DETECTION FRAMEWORK

Based on the findings of the systematic review, an integrated Smart Plant Disease Detection Framework is proposed to connect automated disease identification with sustainable organic disease management. Unlike conventional disease detection systems that terminate the decision-making process after classification, the proposed framework extends the process toward disease severity assessment and treatment recommendation.

The proposed framework consists of several interconnected stages: image acquisition, image preprocessing, CNN based disease classification, model optimization, disease severity assessment, organic treatment recommendation, and real time decision support. Where environmental information is available, parameters such as temperature, humidity, soil conditions, and other relevant environmental factors can be incorporated into the recommendation process.

The overall workflow can be represented as:

Plant Image Acquisition → Image Pre-processing → CNN-Based Disease Detection → GA/PSO Optimization → Disease Severity Assessment → Organic Treatment Recommendation → Farmer Decision Support

6.1 Image Acquisition

The first stage involves acquiring images of plant leaves or affected plant parts through cameras, smartphones, or other image-capturing devices. Images may be collected from existing datasets as well as real agricultural environments. Real-field images are particularly important for improving model generalization under variations in illumination, background, leaf orientation, and disease manifestation.

6.2 Image Pre-processing

The acquired images undergo preprocessing to improve their suitability for deep learning-based classification. Preprocessing may include image resizing, normalization, noise reduction, background handling, and data augmentation. Augmentation techniques can be used to increase dataset diversity and reduce the possibility of model overfitting.

6.3 CNN-Based Disease Classification

The preprocessed images are provided to a CNN-based classification model. CNNs automatically learn relevant visual characteristics from plant images and classify them according to disease categories. Depending on the application requirements, different CNN architectures may be evaluated based on their classification accuracy, computational complexity, and suitability for real-time deployment.

6.4 GA and PSO-Based Optimization

Genetic Algorithm and Particle Swarm Optimization techniques can be incorporated to optimize relevant parameters of the disease detection model. The optimization process aims to improve classification performance while reducing unnecessary computational complexity. Comparative evaluation of optimized and non-optimized models can be performed to determine the contribution of GA and PSO to system performance.

6.5 Disease Severity Assessment

Following disease classification, the system can estimate the severity of the detected

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International Journal of Engineering Research & Technology (IJERT)
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disease. Severity assessment provides an additional decision-making parameter because treatment requirements may differ according to the extent of infection. The severity level can subsequently be incorporated into the treatment recommendation mechanism.

6.6 Organic Treatment Recommendation

The organic treatment recommendation module connects the detected disease with appropriate sustainable management strategies. Recommendations can be generated by considering disease type, disease severity, crop type, and crop growth stage. Organic approaches may include plant-derived treatments, biological control methods, cultural practices, and other environmentally sustainable disease management strategies identified from the relevant literature.

6.7 Environmental and Contextual Integration

Organic treatments may be effective depending on the agricultural and environmental conditions. As such, it would be possible, when sufficient data are present, for such parameters as temperature, humidity, soil condition, level of pathogen infection, and others to be used during the process of making recommendations.

6.8 Farmer Decision-Support Output

The final output of the proposed framework should provide an understandable summary of the diagnosis and recommended management strategy. The system may present the detected disease, confidence score, estimated severity, and appropriate organic treatment options. Such a decision-support mechanism can help farmers move from disease identification toward timely and sustainable intervention.

Comparative Evaluation Framework

For comprehensive evaluation of Smart Plant Disease Detection Systems, model performance should not be assessed solely on classification accuracy. A multidimensional evaluation framework is required to examine both technical performance and practical applicability.

The proposed evaluation framework considers the following parameters:

1. Accuracy: Measures the overall proportion of correctly classified plant disease samples.
2. Precision: Measures the proportion of correctly identified disease cases among all cases predicted as belonging to a particular disease class.
3. Recall: Measures the ability of the model to correctly identify actual disease cases.
4. F1-Score: Provides a balanced measure of precision and recall and is particularly useful when datasets contain unequal class distributions.
5. Computational Efficiency: Includes training time, inference time, and computational requirements, which are important for real-time and mobile deployment.
6. Generalization: Evaluates the ability of the model to maintain performance when applied to images captured under real-field conditions rather than controlled environments.
7. Treatment Integration: Determines whether the system provides an actionable organic treatment recommendation after disease identification.
8. Scalability: Examines the potential of the system to support different crops, disease categories, geographic regions, and deployment environments.

A model demonstrating high classification accuracy but poor generalization or no treatment recommendation may have

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limited practical value. Thus, any future Smart Plant Disease Detection System should undergo an evaluation based on its performance, efficiency, robustness, sustainability, and treatment support capability.

Trichoderma fungi, a type of fungus that occurs naturally in the soil, is one of the strongest biological control agents. Not only does it parasitize plant pathogens like Fusarium and Pythium but it also promotes plant growth and root development. Homemade pesticide made from garlic-chili spray is composed of allicin (garlic) and capsaicin (chili), both insecticidal and fungicide.

Apart from being used as a pesticide or a fungicide, crop rotation and companion planting are two ecological measures that are used to avoid accumulation of pathogens in the soil. Alternating legume crops and cereal crops is one way of breaking pest life cycle, while planting basil and tomatoes together prevents the development of fungi.

6.2 Integration Framework

The process of linking the detection process with practical and environmentally-friendly solutions is done via integrating the organic recommendation engine after classification. When the deep learning model successfully detects a particular disease, the recommendation engine refers to the knowledge base, where the cross-referencing of three important parameters is conducted – disease type, disease severity level, and plant growth stage.

Disease types are referred to the results of the CNN classifier (Leaf Spot, Blight, and Mildew). The severity level is determined based on the appearance of lesions (size and color distribution), while the plant growth stage could be provided by the user or calculated via image metadata.

For example, if the disease such as Tomato Leaf Spot has been identified, then at an early growth stage, the recommendation engine can recommend a mild neem oil spray, but in case of a more advanced disease state, the recommendation will be for Trichoderma soil and foliar applications. Every recommendation is selected from the database of recommendations based on agronomy books and organic farming guidelines.

This intelligent approach enables individualized disease management for even non-specialized farmers, which also adds additional value to the process of applying deep learning models in agriculture.

6.3 Case Study: Tomato Leaf Spot

To illustrate the functionality and practical value of the integrated SPDDS system, consider a real-world case study involving Tomato Leaf Spot, a common fungal disease caused by *Septoria lycopersici*. In this scenario, a farmer uploads an image of infected tomato leaves via the mobile application. The deep learning model specifically a CNN optimized with GA-PSO analyzes the image and accurately classifies the disease as Leaf Spot, with an impressive accuracy of 98.6%.

The system then prompts the user to indicate the disease stage, or alternatively, uses image metadata to estimate it. The model determines that the disease is at the intermediate stage, characterized by multiple visible lesions but limited foliar loss. Given this analysis, the post-detection suggestion engine draws from its knowledge database of organic solutions and advises the use of a 3% neem oil spray foliar spray known for its effectiveness against fungal diseases, along with an application of Trichoderma viride as soil amending solution, which will increase root resistance and prevent any soil-borne pathogens.

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This combination does not only treat the present fungal infection in the plant but also helps build its immune system so that chances of re-infection become minimal. The user is provided with information regarding dosage and application rate, along with weather alerts. This scenario highlights how AI based disease detection along with organic solutions can be used to come up with sustainable scientific interventions in agriculture.

7. EVALUATION METRICS

Metric	Formula	Description
Accuracy	(TP + TN)/(Total)	Overall correctness
Precision	TP/(TP + FP)	Positive predictive value
Recall	TP/(TP + FN)	Sensitivity
F1-score	2*(P*R)/(P+R)	Balance between precision and recall
Time per epoch	–	Model training efficiency

It is important for assessing the effectiveness, efficiency, and usability of SPDDS deep learning models to evaluate their performance. There are many different performance metrics applied to measure the effectiveness of classification of models, especially with regard to detecting plant disease based on leaf pictures. The most common and important metrics are Accuracy, Precision, Recall, F1-Score, and Time per Epoch. Each metric offers its own view on the performance of models.

7.1 Accuracy

Formula: (TP + TN) / (TP + TN + FP + FN)
Description: Accuracy is the most intuitive metric and refers to the overall correctness of the model. Accuracy measures the percentage of correct predictions (i.e., true positives and true negatives) divided by the total number of predictions made. In other words, Accuracy metric gives the number of correct classifications out of all classifications made by the algorithm.

While accuracy is helpful in understanding general performance, it may not be sufficient in cases where the dataset is imbalanced. For example, if 90% of the dataset contains healthy leaf images, a model that always predicts “healthy” would still achieve high accuracy despite failing to detect diseased plants. Thus, accuracy alone should not be relied upon, especially in multiclass or real-field data environments.

7.2 Precision

Formula: TP / (TP + FP)

Description: Precision, sometimes referred to as positive predictive value, is used for determining the proportion of true positive predictions out of all positive predictions made by the model. The following question helps to understand the concept better: "If the model predicts a certain plant to have a disease, how accurate is it?"

High precision is essential in agriculture since the wrong predictions may cause extra work on treatment, organic solution waste, and additional stress for farmers. High precision means that only sick plants will be treated in an appropriate manner which promotes more effective and affordable disease treatment.

7.3 Recall

Formula: TP / (TP + FN)

Description: Recall is also called sensitivity and it is a measure of a model's ability to find all positive cases. It answers the following question: "How many plants with diseases were correctly identified by the model?"

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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In smart agriculture, recall is highly important due to the fact that false negatives mean missed cases of the disease, which lead to loss of plants and spreading of pathogens. In other words, the high recall of a model indicates that most of the disease cases will be detected and then the appropriate actions may be taken.

7.4 F1-Score

Formula: 2 * (Precision * Recall) / (Precision + Recall)

Description: F1-score is a harmonic mean of precision and recall. This measure is very important when dealing with unbalanced classes since it takes into account both metrics at once. This metric is particularly useful when there is an uneven class distribution or when both false positives and false negatives carry serious consequences.

In plant disease detection systems, an F1 score is highly informative as it reflects the model's ability to correctly classify diseases while avoiding misclassification. A high F1 score indicates a well rounded model that neither over diagnoses nor under diagnoses, making it ideal for practical deployment in farms.

7.5 Time per Epoch

Formula: Not applicable (measured empirically in seconds)
Description: Time per epoch refers to the time it takes to complete one full training cycle over the entire dataset. While not a performance metric in terms of classification, it is an important efficiency indicator. In field-deployable systems, especially on resource-constrained devices such as mobile phones or edge devices, faster training and inference times are crucial.

Time per epoch also indicates the computational complexity of the model. A lighter model like MobileNet may train faster but offer slightly lower accuracy, whereas a deeper model like VGG16 or a hybrid CNN with GA PSO might take longer to train but offer superior performance. Balancing model complexity with deployment requirements is key to designing real time Smart Plant Disease Detection Systems.

7.6 Conclusion on Metrics

This evaluation of model performance is made possible through using these metrics. Although the metric accuracy gives a general overview, the metrics precision and recall can be used to study the model's behavior in identifying disease. The metric F1 score considers both issues and the metric time per epoch shows the efficiency of the model computationally. In practical application in agriculture, models with high F1-scores and reasonable training time are selected.

VIII. CHALLENGES

However, despite the promising progress made in developing SPDDS that use deep learning and incorporate organic solutions, there are certain obstacles that prevent the effective use and widespread deployment of such systems.

8.1 Data Imbalance and Generalization

The first problem that arises is the data imbalance and poor generalization. Current literature largely relies on the Plant Village database, which includes images of healthy and diseased plants taken in a carefully controlled environment and has a high resolution, as well as noise-free features. While models built using these data demonstrate excellent accuracy, they cannot be generalized in the field due to variable lighting, background, leaf occlusion and overlapping of disease symptoms. It results in a big domain gap

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ISSN: 2278-0181
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between the training and deployment stages.

Also, the disease that occurs rarely enough does not receive attention in the dataset, which leads to the models being biased toward majority classes. To solve this problem, data augmentation, generation of artificial images, and active learning methods should be used.

8.2 Efficacy of Organic Treatments

Another issue connected to the use of organic solutions in AI-assisted detection of plant diseases concerns the sensitivity of the organic treatment's efficacy to environmental factors like temperature, humidity, soil pH, and pathogens' load. For example, a solution that proved to be very effective in one location or during a particular season could become ineffective in another one because of different environmental conditions. Thus, there is a necessity to develop a dynamic regional knowledge base to adjust recommendations depending on real-time environmental data and history of the area.

Also, standardizing dosage and application of organic treatments according to different crops and diseases requires constant update of the recommendation engine.

8.3 Real-Time Deployment

Finally, the deployment of SPDDS in rural or resource-constrained areas brings a number of problems associated with computational complexity, power consumption, and connectivity. For instance, models like VGG or ResNet can be too complex for deployment on mobile or embedded devices without extensive optimization. Also, there is a need to use lightweight architectures, for example, MobileNet or pruned CNNs.

Furthermore, offline capacity is needed for the deployment in regions with limited Internet connection because the system should be capable of detecting diseases, recommending organic treatments and storing data without relying on cloud infrastructure.

Ensuring user friendly interfaces for semi literate farmers and supporting regional languages are additional hurdles that must be overcome for widespread adoption.

IX. FUTURE WORK

A few of the ways in which the practicality and scalability of SPDDS can be improved are discussed in this section of the paper. First, one way to do so is by adding a feature whereby SPDDS has a voice assisted user interface, so that even those farmers who are not literate in English can use the device by giving verbal instructions in their language.

Another avenue to explore in relation to SPDDS is the use of drones in detecting diseases. Large scale farms can make use of such a device because it has an automatic camera that would capture the plants' pictures to help in detecting any disease remotely and quickly, without having to employ many people.

Reinforcement learning could also be employed in making treatment suggestions, since it involves a machine learning algorithm whose goal is to find the most efficient treatment suggestions by trial and error.

Also, another thing that could be done to improve the SPDDS system is by incorporating federated learning, which is important because it will enable collaborative learning without centralized storage of data.

Lastly, smart farms with real-time sensor feedback can ensure the creation of a decision making loop between the disease detection and treatment process.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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10. CONCLUSION

The areas for future research that can increase the utility and scalability of Smart Plant Disease Detection Systems (SPDDS) are listed below. An important improvement for the SPDDS can be seen in the provision of a voice assisted user interface that will allow illiterate or semi-literate farmers to use the software in their local languages using voice commands. The reviewed literature demonstrates that deep learning has significantly improved the accuracy and automation of plant disease detection. CNN based approaches have emerged as effective methods for extracting disease related visual features and classifying plant diseases from images.

However, the review also identifies important limitations in existing approaches. Many systems primarily focus on disease classification and provide limited support for subsequent disease management. Furthermore, reliance on controlled datasets can reduce model generalization under real-world agricultural conditions. Optimization techniques such as Genetic Algorithms and Particle Swarm Optimization provide opportunities for improving model performance, but their integration with sustainable treatment recommendation systems remains comparatively limited.

The review therefore highlights the need for an integrated framework that combines disease detection, optimization, disease severity assessment, and organic treatment recommendation. Such a framework can extend the role of artificial intelligence from simple disease identification toward comprehensive agricultural decision support.

The integration of disease type, severity, crop growth stage, and environmental conditions into treatment recommendation mechanisms may enable more context-specific and sustainable disease management. Future research should further investigate real field datasets, use lightweight algorithms/models, integrate IoT sensors, deploy mobile and offline applications, develop multilingual interfaces, and adapt learning methods.

Generally, the implementation of deep learning along with sustainable agriculture is a perspective area of development of SPDDSs. The development of these systems would enable timely detection of plant diseases, interventions to prevent their spread, reduce dependency on chemical products and increase efficiency and sustainability of agriculture production.

The implementation of drones is another possibility which would be particularly useful for large-scale farms. Drones with high resolution camera sensors will be able to automatically scan plants and conduct quick and remote surveillance of diseases.

Future SPDDS systems could apply Reinforcement Learning (RL) to suggest adaptive solutions to farmers. As a result of learning, RL-based models will make recommendations which would be optimal regarding both efficiency and sustainability.

Moreover, federated learning would solve the problem of farmers' lack of trust in sharing agricultural data with other parties as models would be trained on each device without centralization of data.

Finally, the creation of IoT-enabled smart farms with the feedback loop of sensor readings will allow to establish a closed loop decision-making process with disease detection, treatment and environmental conditions control simultaneously.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

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