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AI-BASED PLANT DISEASE DETECTION AND PESTICIDE SPRAYING SYSTEM

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Abstract**:** This work introduces an AI-powered system for real-time crop disease detection and precision pesticide spraying. Leveraging deep learning models (CNN) and computer vision, the system accurately identifies diseases from leaf images captured by onboard cameras. The robotic platform then performs targeted pesticide application using a smart spraying mechanism, optimizing chemical usage and minimizing environmental impact. This work supports sustainable agriculture by integrating AI, robotics, and precision farming techniques to enhance crop productivity while minimizing expenses and environmental impact.

Keyword- Deep learning, multi-class classification, CNN, smart agriculture.

I INTRODUCTION

Agriculture is essential to ensuring global food supplies, but the widespread impact of crop diseases continues to reduce harvests each year, threatening economic stability and food supply chains. Traditional methods of disease detection rely on manual inspection, which is time-consuming, labor-intensive, and often inaccurate. Additionally, conventional pesticide spraying techniques are inefficient, leading to excessive chemical usage, environmental pollution, and increased production costs. To address these challenges, AI-driven real-time disease detection systems integrated with autonomous pesticide spraying robots have emerged as a transformative solution in precision agriculture.

Plant diseases are caused by fungi, bacteria, viruses, and pests, can devastate entire crops if not detected early. Farmers typically identify infections through visual symptoms such as leaf discoloration, lesions, or wilting. However, human observation is subjective and may fail to detect diseases at early stages. Moreover, blanket pesticide spraying—where chemicals are uniformly applied across fields—results in overuse of agrochemicals, harming beneficial organisms, contaminating soil and water, and increasing pesticide resistance in pests. Architectures like CNNs, along with models like YOLO (You Only Look Once) and ResNet have demonstrated high accuracy in classifying diseases from leaf images captured via RGB cameras. When combined with robotic systems, these AI models enable real-time disease identification and targeted pesticide application, minimizing chemical usage while maximizing efficiency.

A real-time pesticide spraying robot equipped with AI-based vision systems follows a structured workflow to enhance agricultural efficiency. The workflow starts by capturing images, where the robot uses high-resolution cameras or multi spectral sensors to capture real-time images of plants. These images are gathered either by drones or ground-based robotic vehicles that scan crops periodically to monitor disease progression. A pre-trained convolutional neural network (CNN) model, such as VGG16, Efficient Net, or MobileNet, processes the captured images to identify disease symptoms.

The AI system classifies the type of disease, such as powdery mildew, blight, or rust, and assesses the severity of the infection. Based on this assessment, the decision-making component of the AI determines the optimal pesticide dosage and identifies specific locations requiring treatment. GPS and computer vision technologies assist the robot in accurately targeting only the infected plants, thereby minimizing chemical usage. The autonomous spraying mechanism then comes into play, utilizing precision nozzles, variablerate sprayers, or electrostatic spraying systems for efficient pesticide application. These AI-driven pesticide spraying robots offer several key benefits: they significantly reduce pesticide usage—by 30 to 60%—thereby cutting costs and minimizing environmental harm; they identify the diseases at an early stage, often before visible symptoms manifest, preventing large-scale crop loss; they enhance labor and cost efficiency through automation; and they support data-driven farming by recording disease trends to inform future agricultural decisions.

II. LITERATUREREVIEW

The survey evaluates the recent advances of AI technologies with specific attention on deep learning and machine learning methods in plant disease detection using image analysis systems integrated with smart technology. The aim is to consolidate methodologies, challenges, and breakthroughs that enhance plant health monitoring technologies.

Sladojevic et al. [1] reported a custom Convolution Neural Network (CNN) model for the identification of plant diseases using leaf images. The model enables early diagnosis without the need for human intervention and was trained on a data containing 13 different plant disease categories, including healthy leaves, from various crops such as apples, grapes, corn, and tomatoes. The CNN architecture incorporated convolution layers, ReLU activation functions, max-pooling layers, and densely connected layers. To enhance generalization, the training process included data augmentation tasks like image rotation and zooming, along with image resizing and normalization. The model demonstrated an accuracy exceeding 96%, significantly outperforming traditional methods that rely on hand-crafted features. These results demonstrate the effectiveness of CNNs for real-time plant health monitoring, suitable for deployment on mobile or cloud platforms.

In [2], Ferentinos evaluated several CNN architectures for identifying the disease of plants using a comprehensive dataset comprising 87,848 images representing 25 diseases and healthy leaf samples across 58 plant species. The research evaluated the performance of Alex Net, Google Net, VGG, and a custom CNN model was trained from scratch. Among these, the custom CNN achieved the highest accuracy of 99.53%. While larger models like VGG demonstrated superior performance, they also required significantly longer training times. A slight drop in accuracy was observed when the models were tested on real-world field images, attributed to image noise and variability. The findings highlight that with sufficiently large and diverse datasets, deep CNNs can provide precise plant disease identification, supporting their application in agricultural monitoring systems.Deep Learning V/S Traditional Machine Learning. In this paper [3] by, Brahimi et al. conducted a comparative study between deep learning (DL) and traditional machine learning (ML) approaches for plant disease classification using a dataset, comprising over 50,000 labeled images spanning 14 crops and 26 diseases. Traditional ML models, including Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Random Forests, were trained using hand-crafted features such as color, texture, and shape. In contrast, DL models such as Alex Net, VGGNet, and Google Net were used for automatic feature extraction and classification. The results showed that convolution neural networks (CNNs) consistently achieved accuracies exceeding 99%, whereas traditional ML models achieved between 80% and 90%. Additionally, DL models demonstrated better generalization capabilities and greater robustness to noise. The study concluded that DL methods are superior for plant disease classification, provided that a sufficiently large dataset is available.

The investigation by Fuentes[4] and collaborators presented a meta-review analyzing more than 100 studies that assessed multiple machine learning (ML) and deep learning (DL) approaches for disease detection. The evaluation discovered that convolution neural networks (CNNs) demonstrated superior performance when compared to traditional ML approaches in both accuracy and scalability. However, traditional ML approaches still hold value, especially in scenarios with less data or computational resources. The study also highlighted the performance of hybrid models—such as those combining image segmentation with ML—in improving robustness and diagnostic reliability. Despite these advancements, key challenges remain, including dataset imbalance, the scarcity of labeled field data, and difficulties in achieving real-time deployment. The authors concluded that while AI and computer vision have significantly enhanced agricultural diagnostics, further work is needed to enable effective field-level implementation. A machine learning model—based on Support Vector Machines (SVM) or decision trees—is used to classify plant diseases. The system's microcontroller processes the data in real-time and controls the pesticide spraying mechanism accordingly. A mobile dashboard enables user interaction and system monitoring. The results demonstrated a reduction in pesticide usage by up to 40% while maintaining a disease classification accuracy exceeding 90%. The study concluded that the integration of AI and IoT enables sustainable and scalable solutions for modern agriculture.

Key Findings and Trends

✓ Deep Learning Superiority: CNNs dominate in accuracy, feature learning, and scalability for plant disease detection.

✓ Classical ML Value: ML remains viable in limited-data or low-power contexts.

✓ Dataset Dependency: DL models require diverse, annotated datasets for generalization. ✓Deployment Challenges

✓ Field image variability (lighting, noise).

✓ Need for lightweight, mobile-compatible models.

✓ IoT Integration: Enhances real-time monitoring and precision application of agrochemicals.

✓ Hybrid Techniques: Improve robustness by combining traditional CV methods with AI.

✓ Evaluation Metrics: Standardized benchmarking is needed for cross-study comparisons.

III. Methodology

This section outlines the data collection, pre-processing, model selection, and system integration strategies used to develop a deep learning-based system, that assess the plant health, with autonomous pesticide spraying capabilities. The aim is to detect diseases in Basale (Malabar spinach) and Red Amaranth (Red Spinach) using a custom dataset and deploying the trained model on an ESP32based robotic car having a camera.

Leaf images were manually collected from local farms and gardens in the Mangaluru region, focusing on two plants of interest: Basale (Malabar Spinach), Red Amaranth (Red Spinach), Green Amaranth (Red Spinach), and two garden crops. The images were captured under natural lighting conditions, utilizing mobile phone cameras and an ESP32-CAM module mounted on a robotic car. To create a well-organized dataset, the images were categorized into three classes based on observational evaluation and consultation with agricultural experts. The first category, Healthy, included leaves that exhibited no visible damage or discoloration. The second category, Moderately Damaged, consisted of leaves showing mild spots, edge damage, or early signs of fungal or bacterial infection. The final category, Severely Damaged, comprised leaves displaying extensive wilting, holes, discoloration, or necrosis. Each category was carefully balanced with an equal number of samples to avoid bias in the dataset. Once collected, the images were annotated and organized into separate folders to prepare for supervised training.

The preprocessing of the images was a crucial step in ensuring the model's efficiency and robustness in real-world conditions. The pictures were adjusted to 224×224 pixels to align with the input shape required by the ResNet model. To enhance training speed and ensure proper model convergence, the pixel values were normalized to the range [0, 1]. To further improve the dataset and reduce chances of overfitting, data augmentation methods were utilized, including rotation, horizontal and vertical flipping, zooming, and brightness adjustments. These augmentations helped increase the variability of the dataset. Additionally, noise filtering techniques such as Gaussian blurring and median filtering were employed to remove background noise caused by real-field conditions. The health states of the leaves—Healthy, Moderate, and Severe—were encoded using one-hot encoding for classification purposes.

Healthy Unhealthy

Figure 1: Basale

Healthy Unhealthy

Figure 2: Red Amaranth

Healthy Diseased

Figure 3: Garden plant

The model used for plant health classification was ResNet, which help prevent the vanishing gradient problem in deep networks. ResNet was selected for its ability to strike a balance between high performance and computational efficiency. During training, the model utilized cross-entropy loss, the Adam optimizer, and learning rate scheduling to optimize the network. A portion of the dataset (20%) was reserved for validation, during which metrics such as accuracy, F1-score, and the confusion matrix were tracked. After training, the final model was exported in a lightweight format, making it suitable for deployment on embedded systems or edge devices.

To enable real-time detection and autonomous pesticide spraying, a custom-built ESP32-based robotic car was designed, featuring several essential components. The ESP32-CAM module was used to capture live images of the leaves for classification. The ESP32 microcontroller acted as the control unit, handling tasks such as image capture, inference, and motion control. The motor driver and wheels allowed the robotic car to navigate across crop rows with ease, while the pesticide sprayer module was activated based on the output of the classification. Depending on the health state of the leaf, the system provided different actions: a green light indicated the leaves were healthy, meaning no spraying was necessary; a yellow light signalled moderate damage, prompting an optional spraying; and a red light meant the leaf was severely damaged, triggering the automatic spraying of pesticides. The model was deployed on a remote server or an edge device connected to the ESP32, allowing the classification results to be sent back for the appropriate action to be taken.

The system followed a clear workflow: the ESP32-CAM captured an image of the leaf, which was then pre-processed and passed to the ResNet model, either on-device or through an edge server. After the model predicted the health class of the leaf, the ESP32 microcontroller interpreted the results and controlled the lights and pesticide sprayer accordingly, ensuring timely and efficient treatment of the plants.

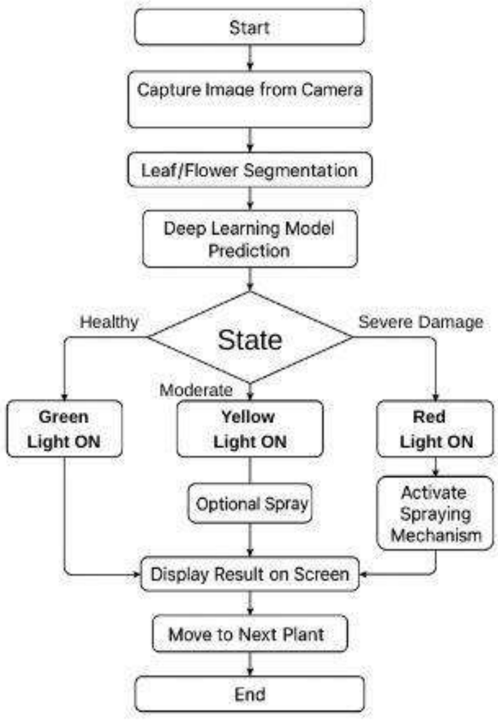

Figure 4: Process Flow Diagram of proposed system

IV. EXPECTED OUTPUT

Based on the literature surveyed and the methodology proposed, several key outcomes are anticipated from the implementation of the deep learning-powered system combined with a robotic spraying mechanism. Firstly, the system is expected to give high accuracy in classification, with the ResNet CNN model enabling greater than 90% accuracy in classifying plant leaf health into categories such as healthy, moderately damaged, and severely damaged, even under real-world field conditions. Secondly, the integration of the ESP32-CAM module with real-time inference capabilities should enable the robotic car to capture and analyze images on-the-go, allowing it to make immediate, autonomous decisions without requiring human intervention.

Thirdly, the system is anticipated to significantly reduce pesticide usage by up to 40%. By applying targeted spraying based on the severity classification, the system will help reduce unnecessary pesticide application, promoting sustainable agricultural practices and minimizing the environmental impact of pesticide use. Additionally, the system's scalability and portability are notable benefits. With the implementation of lightweight models and cost-effective hardware, like ESP32 microcontroller and camera module, the system can be easily scaled to larger fields or adapted to other types of crops, all with minimal added cost or complexity.

Moreover, the system is expected to improve farmer decision-making. Through a visual alert mechanism that uses colorcoded lights, farmers will have easy-to-interpret insights into the health status of their plants. This will enable them to make timely and informed decisions regarding treatment and care. Finally, the proposed system will lay the groundwork for autonomous smart farming. It will combine computer vision, artificial intelligence to create a comprehensive plant health monitoring and treatment framework, paving the way for future autonomous agricultural robots.

REFERENCES

[1] Sladojevic, S., Arsenovic, M., Anderla, A., "Plant Disease Detection Using Convolutional Neural Networks (CNN)," Computers and Electronics in Agriculture, vol. 137, pp. 104–112, 2016, doi: 10.1016/j.compag.2016.08.007.

[2] J. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018. doi: 10.1016/j.compag.2018.01.009.

[3] Brahimi, M., Boukhalfa, K., and Moussaoui, A., "A Comparative Study of Deep Learning and Machine Learning for Plant Disease Classification," IEEE Access, vol. 8, pp. 82015–82028, 2020, doi: 10.1109/ACCESS.2020.2992444.

[4] S. Fuentes, Y. Y. Y. Tongson, and M. Gonzalez Viejo, "Automatic Plant Disease Detection Using Machine Learning and Computer Vision Techniques: A Review," Agronomy, vol. 11, no. 5, p. 886, 2021. doi: 10.3390/agronomy11050886.

[5] Kumar, A., Sharma, P., and Singh, R., "IoT and AI-Based Smart Pesticide Spraying System for Disease Management in Crops," Sensors, vol. 22, no. 14, p. 5321, 2022, doi: 10.3390/s22145321.