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GreenGuard - PLANT LEAF DISEASE DETECTION SYSTEM

Shaurya Gahlot[1], Kasim[2], Md Abuzar[3], Prince Tyagi [4], Mr. Virat Raj Saxena[5]

[1]Department of CSE (AI&ML), RKGIT, Ghaziabad,
[2]Department of CSE (AI&ML), RKGIT, Ghaziabad,
[3]Department of CSE (AI&ML), RKGIT, Ghaziabad,
[1]shoryagahlot13@gmail.com ,[2]kasimchoudhary6478@gmail.com ,[3]abkhan7867khan@gmail.com,
[4]princetyagi101974567@gmail.com
[4]Assistant Professor, Department of CSE (AI&ML), RKGIT, Ghaziabad
[4]viratfai@rkgit.edu.in

ABSTRACT :

In the realm of modern agriculture, early and accurate detection of plant diseases plays a critical role in ensuring crop health, yield stability, and food security. Traditional methods for diagnosing plant diseases primarily rely on manual inspection, which is both time-consuming and error-prone, especially in large-scale farming operations.

This research proposes an intelligent and automated solution utilising image processing techniques in combination with machine learning algorithms—specifically Convolutional Neural Networks (CNN) and Support Vector Machines (SVM)—to detect leaf-based plant diseases. Implemented using Python and OpenCV, the system analyzes high-resolution images to identify and classify diseases in real time with an accuracy of up to 78%.

The framework also incorporates a drone-based imaging model designed to autonomously scan agricultural fields, thereby enhancing scalability and reducing the need for human intervention. Upon detection, the system not only identifies the disease type and severity but also recommends relevant remedies and pesticide treatments.

The proposed solution holds promise for supporting farmers with precision agriculture tools, ultimately aiming to reduce crop loss and improve sustainability in the agricultural sector.

1. Introduction

Agriculture forms the backbone for many developing countries, including India. it serves as the primary livelihood for more than 50 percent of the population. With increasing population pressure, changing climate conditions, and evolving pest and disease patterns, it has become essential to adopt technological solutions to secure crop health and productivity. One of the significant challenges faced by farmers is the early detection and proper diagnosis of plant diseases, especially in widely cultivated crops such as tomatoes. A delay in identifying infections can lead to widespread damage, reduced yields, and severe economic losses.

Traditional methods of disease detection largely depend on visual inspections performed by farmers or agricultural experts. These methods, although intuitive, suffer from subjectivity, limited accessibility to expert knowledge, and inefficiency in large-scale operations. Moreover, improper identification may lead to the misuse of pesticides, further degrading soil and crop health.

This research introduces a novel approach to disease detection in plant leaves through the use of digital image processing and machine learning techniques. By leveraging OpenCV and Python, the system performs end-to-end analysis from image acquisition to classification and remedy suggestion. The model utilizes Convolutional Neural Networks for feature learning and an SVM classifier for robust categorization of plant diseases. In addition to the software model, a drone-based system has been developed to automate field-level image collection, enhancing the system's applicability in real-world agricultural environments.

This research paper explores the following process such as development, implementation, and evaluation of the proposed system, detailing its design methodology, experimental results, and potential for large-scale agricultural deployment. The goal is not only to automate disease detection but also to bridge the gap between traditional farming practices and advanced technological interventions, thereby contributing to the vision of smart and sustainable agriculture.

2. Literature Review

Over the past decades, various researchers have attempted to automate plant disease recognition using image processing and machine learning methods. Initial efforts focused on pest detection using morphological features such as color and texture. Later studies explored the use of Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Radial Basis Functions (RBF) for classification tasks.

While these techniques demonstrated potential, most models were either species-specific or heavily dependent on image capture conditions. Moreover, the small size and lack of diversity in datasets often led to overfitting. Recent approaches have leveraged deep learning, particularly Convolutional Neural Networks (CNN), which automatically extract relevant features from images and perform classification with higher accuracy.

Research also indicates that hybrid models combining CNN with texture-based feature extractors like GLCM and HOG yield better results. However, most existing studies lack real-time field integration or a user-friendly delivery mechanism for detection results and remedies..

Methodology

The methodology adopted in this research follows a structured image processing and machine learning pipeline, optimized for accuracy, scalability, and ease of deployment. The entire process is divided into the following key phases:

1. **Image Acquisition:** The first step involves collecting high-resolution images of healthy and diseased plant leaves. These images are captured using a digital camera or a drone-mounted camera system, ensuring uniform lighting and background contrast. The dataset comprises multiple classes of tomato leaf diseases, such as early blight, late blight, bacterial spot, and healthy leaves. To ensure consistency, images are taken from a fixed distance under similar environmental conditions.
2. **Image Preprocessing:** To prepare the images for analysis, a preprocessing stage is implemented. This involves converting images from the RGB color space to HSI (Hue, Saturation, Intensity), where the hue component proves more effective for identifying discoloration and infection under varied lighting conditions. Histogram equalization is used to enhance contrast and expose hidden features, while noise is removed using filtering techniques such as mean and median filters. These filters smooth the image while preserving important details. For consistency, all images are resized to a standard dimension before entering the segmentation phase.
3. **Segmentation:** Once preprocessed, the images undergo segmentation to isolate diseased areas from healthy regions. Green pixel masking is applied first to eliminate healthy leaf regions, allowing the algorithm to focus on infected zones. K-means clustering is then used to group similar pixel values and segment the image into clusters representing the background, healthy leaf areas, and potential disease spots. Morphological operations like erosion and dilation are used after clustering to refine the segmented regions, removing noise and connecting disjointed infected zones.
4. **Feature Extraction:** With the diseased areas segmented, various features are extracted to describe the visual characteristics of the affected regions. Texture features are being calculated using the Grey-Level Co-occurrence Matrix (GLCM), which provides statistical metrics such as contrast, correlation, energy, and homogeneity. Shape and edge descriptors are obtained via the Histogram of Oriented Gradients (HOG), which identifies structural outlines of disease symptoms. Additionally, Gabor filters are employed to analyze the frequency components of the textures. Average color values in the HSI and RGB spaces are also computed to capture the discoloration patterns associated with different diseases.
5. **Classification:** The extracted features are then fed into a Support Vector Machine (SVM) for classification. This supervised learning algorithm is selected for its high accuracy in distinguishing between multiple classes, and it employs a Radial basis function (RBF) kernel to effectively separate the non-linear data from the linear Data. The dataset is divided into training and testing sets, using a 70:30 split, and 10-fold cross-validation is applied to reduce overfitting and ensure model generalization. Upon classifying an image, the model returns the disease label, confidence score, and a relevant treatment suggestion. This recommendation is retrieved from a structured database containing pesticide names, dosages, and application guidelines for each type of disease.
6. **System Integration:** This end-to-end pipeline—from image acquisition through classification—is designed for real-world scalability. It can be integrated with field-deployable platforms such as autonomous drones and farmer-facing mobile applications. The entire system aims to deliver a practical, intelligent tool for real-time plant disease detection and agricultural decision support.

4. Proposed Work

- **Drone-Based Monitoring:** A drone-mounted camera system captures real-time images of crop fields, reducing the need for manual inspection and enabling rapid data collection over large areas.
- **Onboard Preprocessing:** The drone is equipped with lightweight preprocessing algorithms to discard irrelevant or low-quality images, saving bandwidth and processing time. Only relevant images are transmitted for full-scale analysis.
- **Automated Image Pipeline:** The collected images are processed through a cloud-based or edge-based system that applies the trained model for disease identification. This automated pipeline ensures faster turnaround and consistent results, even across large farms.
- **Integrated Classification and remedy Module:** Once a disease is detected, the system cross-references the result with a built-in knowledge base that contains curated pesticide information, recommended treatment strategies, dosages, and application schedules.
- **Farmer Notification Interface:** The system is connected to a real-time alert module that delivers SMS or app-based notifications to the farmer, including the disease name, confidence score, suggested remedy, and treatment urgency level.
- **Scalability and Adaptability :** The system's modular architecture allows it to be scaled to cover multiple types of crops and geographical conditions. Future modules can include support for more complex drone controls, disease severity mapping, and predictive analytics.

- **Offline Functionality:** In rural or remote areas with poor internet connectivity, the drone and associated mobile application are capable of offline operation. Pretrained models and remedy data are being stored locally, allowing system to function without cloud access.
- **Data Logging and Visualization:** All identified cases, treatment suggestions, and outcomes are stored in a centralized system for visualization and decision-making. This historical data helps in generating disease spread trends and monitoring crop health over time.

5. Results

- The proposed system was trained and evaluated using dataset of over 400 Tomato leaf images with various disease classes.
- The model achieved a classification accuracy of **78%**, with especially strong performance on early blight and bacterial spot.
- **Precision** and **recall** values exceeded 0.80 in key classes, showing balanced performance.
- The average time from image input to remedy suggestion was under **45 seconds**.
- In field testing, the drone-based prototype detected 14 disease occurrences with a reliability rate of **92%**.
- Compared to manual inspection, the system achieved a **12x improvement in speed** and significantly reduced human error.
- Farmers involved in pilot testing reported high satisfaction and appreciated the clarity of remedy recommendations.

6. Future Scope

There is significant scope for enhancement and scaling of this project including.

- **Dataset Expansion:** Include more plant species and disease types for broader applicability.
- **Deep Learning Integration:** Employ advanced models such as ResNet or EfficientNet for improved accuracy.
- **Mobile App Development:** Launch a farmer-friendly mobile application with multilingual support.
- **Context-Aware Treatment:** Integrate weather data to refine treatment suggestions.
- **Autonomous Navigation:** Upgrade drones with GPS-based path planning and obstacle avoidance for fully autonomous monitoring.

7. Conclusion

This research presents a comprehensive and practical solution for detecting plant leaf diseases and defects using a combination of machine learning techniques.

The system not only automates the identification process but also provides actionable remedies and integrates seamlessly with drone-based monitoring.

With real-time alerts and a farmer-facing interface, this approach aims to transform conventional agriculture into a smart and responsive system. Future upgrades will focus on scaling the solution, improving model robustness, and enhancing accessibility for widespread adoption.

8. REFERENCES

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