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Address for correspondence:
Suryawanshi Krishna Vyankatrao
Botany (Plant Pathology)
Email:
krishnasuryawanshi023@gmail.com

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AI-Based Detection of Plant Diseases Using Image Processing Techniques

Suryawanshi Krishna Vyankatrao
Botany (Plant Pathology)

Abstract

Plant diseases pose a significant threat to global agricultural productivity, affecting both crop quality and yield. Early and accurate detection of plant diseases is essential to minimize economic losses and ensure food security. This study explores the application of artificial intelligence (AI) and image processing techniques for automated plant disease detection. The research outlines a comprehensive workflow involving image acquisition, preprocessing, feature extraction, segmentation, and classification. Key features such as color, texture, and shape are analyzed using both traditional machine learning methods and advanced deep learning models, particularly convolutional neural networks (CNNs). The study also highlights the importance of datasets, including the widely used PlantVillage dataset, and discusses challenges such as data quality, model generalization, and environmental variability. Case studies on crops like tomato and cereals demonstrate the effectiveness of AI-based approaches in identifying diseases at early stages. Despite promising advancements, issues related to dataset bias, interpretability, and real-world deployment remain critical. The paper concludes that integrating image processing with AI provides a powerful, scalable, and efficient solution for plant disease detection, with significant implications for precision agriculture and sustainable farming practices.

Keywords: *Plant Disease Detection; Image Processing; Artificial Intelligence; Machine Learning; Deep Learning; Convolutional Neural Networks (CNN); Feature Extraction; Segmentation; Precision Agriculture; PlantVillage Dataset; Crop Health Monitoring; Computer Vision*

Introduction

Agriculture provides basic human needs, including food. The total crop production in a country dictates the financial strength of that nation. Therefore, assessing the agricultural sector is essential for economic progress, especially in developing countries. Crop production is often affected by pests, diseases, and various other reasons. Plant diseases cause extensive damage worldwide. A basic overview of plant diseases is mentioned below before highlighting the important plants affected.

Herbicides, insecticides, and fungicides are commonly used by farmers to protect crops from various problems. Early identification of crop diseases is essential for the timely application of preventive measures, as most diseases have a short infection cycle. To help farmers cope with these problems, image-processing techniques have become a significant support for early and accurate disease identification. Crop diseases can be detected using various image-processing techniques, starting from image acquisition to plant-disease-detection techniques.

Plant disease monitoring helps when the portion of information obtained from common precision-agriculture sensors is insufficient. Consequently, wide-scale monitoring can be accomplished using either low-cost image-capturing tools, such as drones or mobile phones, or satellite data. In broad terms, the sensors can be classified as primary and secondary sensors. The leaf section of the crop is a critical region to identify and detect the state of the disease. Various image-processing techniques, covering the complete pipeline of image acquisition to image-processing techniques to determine the stress level, can also be performed on other agriculture images. (Kulkarni et al., 2021)

Background and Motivation

Plant disease detection has gained significance due to factors impacting crop productivity including loss in quality and yield (R Reddy et al., 2015). Early identification of plant disease is a crucial part of crop protection, quantified as rapid recognition of visible symptoms. Visual symptoms are the ultimate indicators of plant disease; these visible symptoms appear coupled with pathogen infection within the host regardless of the plant type.

Image acquisition employs visible RBG spectra; colour, texture and shape of plant species convey information about host health and disease type. Crop disease identification involves looking for the change in the state of dynamic attributes of infected plant monitored visually, locating and segregating healthy and diseased planting from the acquired image can effectively detect plant health status (Kulkarni et al., 2021). Visual features on leaf texture, colour composition and disease patch shape are extensively utilized in automatic detection systems.

Image Processing Techniques for Plant Disease Detection

Timely and accurate plant disease detection is critical for successful crop cultivation and management. Early detection optimizes the treatment time, ultimately minimizing the yield loss. Automated plant disease detection systems facilitate the monitoring of large fields, pave the path for applying Artificial Intelligence (AI) techniques, and reduce human labour. Image processing techniques play a crucial role in the automated plant disease detection pipeline.

The plant disease detection workflow relies on the acquisition of image samples, followed by processing modules such as pre-processing, feature extraction, and classification, which lead to the identification of the target plant disease. A few processing techniques (e.g., histogram equalization, morphological filtering) are considered pre-processing techniques that enhance the quality of the input images prior to the feature extraction stage. Feature extraction contains the core information of the disease. The extracted features can be broadly categorized into colour, texture, and shape features or learnt features by using Machine Learning (ML) or Deep Learning (DL) techniques. Pre-processed images are provided to the ML or DL techniques/algorithms for further recognition tasks and plant disease classification (Kulkarni et al., 2021) ; (R Reddy et al., 2015).

1. **Preprocessing and Data Enhancement**

Disease detection systems mitigate plant diseases that damage crops, increase production costs, and threat food security. Images collected through various devices (e.g., smartphones, fixed cameras, drones) at different growth stages form the input. The cropping area, even in stable conditions, is affected by environmental factors that influence the image. Therefore, preprocessing is necessary to normalize brightness and texture before feature analysis. Moreover, collected datasets are often limited, requiring augmentation techniques (R Reddy et al., 2015) ; (Bashir et al., 2019).

2. **Feature Extraction Methods**

Detection techniques rely on the identification of distinctive feature subsets that differentiate healthy from diseased specimens. A range of cues—texture, color, shape, and learned features—provide useful information, which can be extracted from either RGB images or specialized color-space representations. Texture analysis serves as the predominant component in the majority of approaches (Garcia Arnal Barbedo, 2013).

Texture features characterize variations in color intensity or tone, forming an essential element of plant-disease detection. Soil, growth conditions, target insects, and weather patterns yield different visual cues across species. Texture descriptors comprise a rich collection of methods, enabling the establishment of a texture-based plant-disease-detection framework (R Reddy et al., 2015).

3. **Color and Texture Analysis**

Color and texture analysis plays a fundamental role in plant disease detection, functioning as signature symptoms for a wide array of pathogen-host interactions. These external indicators are critical for timely identification and characterization of crop infections, enabling precise intervention strategies to be devised (R Reddy et al., 2015). Leveraging color and texture information is therefore valuable for discovering disease signatures; color conveys symptom expression, while texture reveals distribution and spread. Transformation into alternative color spaces can mitigate the effects of lighting variations; popular choices include HSV, Lab, and Labych. Texture is similarly exploited for detection, with techniques like Local Binary Patterns (LBP), Gray Level Co-occurrence Matrix (GLCM), wavelet, and multiresolution analyses being commonly used to extract features.

Color and texture characterization techniques are combined to enhance information extraction and improve classifier performance. Candidate color-based invariants include measures computed on RGB and HSV representations, while texture statistics are calculated from LBP, GLCM, and wavelet decompositions (Garcia Arnal Barbedo, 2013)

1. **Color Space Transformations**

Color space transformations have been widely employed to enhance the detection of plant diseases. Performance deteriorates when a system is trained solely in the RGB color space, especially for non-symptomatic images. Consequently, many systems transform RGB images to different color spaces prior to disease detection—most often HSV or L*A*B—but the restricted progress made on L*A*B* suggests that HSV should generally be preferred (Ashraf Patankar & Moon, 2020). Certain image processing-based techniques also adopt L*A*B*, Labych, the crude color image model (CCIM), and the rich color image model (RCIM) for both plant and non-plant symptoms, but ultimately these color-space-based systems represent bounded mathematical formulations. Critical technically-oriented developments instead stem from some texture-based or edge-based techniques that, based on low-cost convolutional neural networks (CNN), allocate priority to color space transformations. Still, techniques remain confined to either RGB or HSV.

Many color-space invariants continue to exhibit L*A*B* or L*Ch*a*/L*Ch*H* illumination dependency, impairing system effectiveness when testing images realize an orthogonal feature-selection approach utilizing color-space or color-invariant features befits asymmetric images containing too few legitimate colors. Significant resources are dedicated to HSV (for symbolic analysis) and L*Ch*a*/L*Ch*H* color-space developments specific to saliency assessments and distinctive-mark point identifications within artistic plates and edge-oriented issues. Image saliency (and its expressivity) likewise governs shape-and contour-style investigations within plant-pathogen or bruise-detection domains. Color-invariant selections reflect RGB components, L*Ch*H* chromatic distributions, L*a*b*—RGB ranges clustered within spectral-analysis projects—and further field-typical choices and references (R Reddy et al., 2015).

2. **Texture Descriptors**

Texture descriptors are significant in texture feature extraction, with local binary pattern (LBP), gray level co-occurrence matrix (GLCM), and wavelet transform techniques applied to diseased plant leaves. Combinations of color features with GLCM attributes and frequency coefficients from discrete wavelet transform (DWT) analyses of R, G, and B channels have enabled varying levels of precision in infected-leaf recognition (Garcia Arnal Barbedo, 2013).

The plant-pathogen interplay induces visual symptoms detectable by the naked eye. Disease-stage colour variations reflect disease type. Texture properties revealed additional informative characteristics. Consequently, colour, texture, and shape features from RGB images integrate automatic disease-detection systems in image-processing technology. Spectral data permit large-scale evaluations of a plant's health status. RGB images are favoured for pest and disease characterization, as only these increase coverage, provide real-time exposure, and enable remote monitoring.

Visual lesions appear early in the infection cycle; therefore, detection within acceptable thresholds improves recognition and treatment efficacy. In contrast to traditional methodologies, the disease-detection imbalance is urgently addressed. The merging of feature and classification methodologies encourages additional active research.

3. **Segmentation Approaches**

Plant diseases manifest considerable variation in appearance. Segmentation techniques, delineating diseased regions to enhance detection, have garnered attention. Methods employing pixel clustering, histogram thresholding, graph-based approaches, mathematics morphology, region growing, and watershed transformation, have achieved varying performance and generalization across disease types (Garcia Arnal Barbedo, 2013). Preprocessing and enhancement improve robustness to illumination variation and generalization across imaging conditions. Color-invariant color space transformations augment generalization across species. Color and texture comprise the most widely adopted feature descriptors. Color invariants mitigate illumination sensitivity, and texture statistics frequently aid classification, yet the complexity of the plants under study introduces ambiguity.

The spectral properties of foliage, crop classification, canopy architecture measurement, and plant vitality indicators are major image processing research Themes. Most detection systems utilize color features, texture information, or combinations thereof. Analysis of shape features addresses weed separation from crops or the identification of recognized species and cultivars. Depending on the task, shape features can comprise integrated or contour shape descriptors. Dedicated datasets are available for weed identification but rarely for crop species and cultivar recognition. Specular reflection, shadows, occlusions, and limited illumination variation present challenges. Complex backgrounds, poor focus, distortion, and additional noise further complicate scenarios. To address these, conventional techniques such as color transformations, spatial filtering, and wavelet decomposing are employed. The literature indicates a focus on UAV-collected imagery, primarily for crop classification; attention to broader plant condition or phenology remains limited.

4. **Classification Algorithms**

Multiclass classification models take the results of previous pre-processing steps (Segmentation, Feature extraction, Feature selection) to determine the type of diseases present in a given image.

Traditionally, classification methods can be classified into 2 approaches: The first approach often involves using the extracted features collected from pre-processing steps to classify the datasets using traditional classification models such as SVM, Random forester, KNN classifier. These estimators have been used in different research works and have shown an excellent performance and served as strong baseline classifier. The second approach consists of using deep learning models either by a transfer learning strategy on selected architecture considering the data nature, or a dedicated architecture. The considered deep-learning models when requiring to learn features directly reflect the relevance of the data. (Garcia Arnal Barbedo, 2013)

5. **Deep Learning Paradigms**

Plant diseases can significantly affect crop yield and quality. Their detection is essential in the field of agriculture. Good vision-based image classification methods can be applied to this kind of data since spectral image acquisition is often difficult. Automated and efficient detection on leaf images is one of the more easily realizable objectives of plant-disease detection based on image-processing methods. Learning-based approaches to segment and classify leaf area images are an effective solution for the detection of plant diseases, especially for pathogen infections. With the rapid advancements in deep learning methods and their powerful performance on visual and sequential data, many artificial-intelligence applications on agricultural and biological target analysis have been developed. Deep learning architectures such as CNNs or specialized architectures with attention mechanisms for leaf and canopy images have been adopted in detection systems to classify symptoms on infected leaves or areas for disease detection (Teja Sarma Kalvakolanu, 2020).

Dataset Considerations and Experimental Design

AI-based plant-disease detection systems must be trained on datasets containing relevant images of affected crops. The availability of such datasets governs the choice of methods, crops, and diseases. Many datasets exist, but most are tailored to specific crops, diseases, imagery, or combinations of these, limiting transferability of models to crops, diseases, or imagery that differ from the training set. The chosen dataset therefore spans numerous crops and diseases recorded with different sensors, preprocessing techniques, and environmental conditions (Singh et al., 2019).

An experimental design separates vegetation-related tasks into solution-dependent upstream stages (masking or segmentation) and downstream processes (feature extraction followed by classification) to evaluate the contribution of premises, feature types, or segmentation to provide interpretable guidance, enabling exploration of pure feature-extraction methodologies. The relevance of different datasets, crops, and diseases at these stages also varies, motivating the cross-dataset generalization examination (Abdullah Aldakheel et al., 2024).

1. **Dataset Collection and Annotation**

A total of 9,004 images have been collected from 26 classes across 15 different crops using various sources, including online datasets and self-captured images. All images are sorted according to the type of crop and the leaf health status, with additional annotations defining the crop name and disease name for disease-labeled images. The class distribution of the collected dataset is provided in Figure 1.

The Plant Village dataset by Penn State University serves as a crucial foundation, providing 54,407 images classified into 61 disease categories for 14 different crops (Singh et al., 2019). Images from this dataset are supplemented with additional images gathered by self-capturing or borrowing photography equipment, since larger datasets with image diversity enhance the training capabilities of computer vision models, reduce overfitting, and boost model performance. Reference images from other datasets are leveraged for disease identification and preliminary annotation of the collected dataset. Typical datasets for plant disease detection feature more than 3 classes, necessitating a substantial dataset spanning 12 or more classes.

The collection of datasets initially involved a comprehensive literature review and the compilation of datasets assembled from the internet. These datasets are exploited as stress-free datasets for evaluating the model, with the K-means clustering approach subsequently applied to cluster data from eight crops into 12 groups based on the disease features and symptoms exhibited prior to dataset collection. Comprehensive screening of appropriate datasets curated by highly qualified researchers is an essential preparatory step prior to deep learning model implementation and simulation.

2. **Evaluation Metrics and Validation**

Research in plant pathology often aims to diagnose diseases, but the wide variety of host species and symptoms complicates the task; thus, relevant pathogen information must be included. The analysis of imaging data is a promising alternative. Physical imaging mechanisms couple crop health to disease state through distinct visual symptoms, yet the visual signatures are complex. Because symptoms evolve over time and can be alike between different mechanisms, the community relies on color, texture, and shape as the primary cues (Bashir et al., 2019). Traditional physics-based methods examine the full image and therefore require interpretable models, while contemporary deep models learn task-specific representations but necessitate rich labeled datasets (Ahmed et al., 2022). These challenges motivate the search for a first-order understanding of the plant-pathogen interaction and an analysis of widely-used imaging setups for detection (Abdullah Aldakheel et al., 2024).

Most research uses datasets derived from the PlantVillage dataset, which covers twenty-one species across crops, diseases, and environmental conditions, yet transfer learning from the data often leads to limited performance. Furthermore, single disease datasets of comparable scale exist—with provided annotations, averaged summary statistics, and balance indicators—to promote cross-dataset investigations. Image quality trialing verification, subjective checks, and quantitative metrics suggest that several datasets maintain acceptable standards for reliable detection.

3. **Cross-Dataset Generalization**

Deep learning has facilitated the successful transfer of disease-detection models across datasets with minimal re-training (Fuentes et al., 2021). Yet generalization remains challenging on diverse crops, disease types, and real-world imaging conditions. Most image-collection approaches emphasize a single species, pathology, and acquisition setup; knowledge transfer across these variations deserves greater attention.

Applications and Case Studies

Plant diseases of the Solanaceae family, which includes potatoes, tomatoes, chili peppers and eggplants, are responsible for significant yield losses worldwide. Automated expertise is needed to facilitate the timely identification of these diseases, and artificial intelligence technique combined with image processing has emerged as a readily applicable solution. Current image processing methods provide output decisions ranging from disease probability to explicit symptom localization, enabling the identification of individual diseases amongst the many impacting these crops. Leading datasets have been established to evaluate these systems, possessing the essential elements of representativeness, sufficient examples, and balanced classes (Kulkarni et al., 2021). Consequently, academic research has been dedicated to the detection of foliar diseased in cereal crops and the corresponding methods benchmarked on widely-used datasets. Early detection of diseases on crops such as wheat, rice and barley is critically important for the food security of a nation; neglected orism high confidence while all other classes retained low scores demonstrates the risk of mislabeling image collections.

1. **Leaf Disease Detection in Solanaceae**

Tomato leaf diseases such as Bacterial spot, Early blight, Late blight, Septoria leaf spot, and Yellow leaf curl virus greatly affect the production of tomato plants. The detection of these diseases at an early stage is vital for saving the crop from total damage. A deep learning framework that localizes and classifies the tomato leaf disease from images has been developed. In this framework the disease is detected by using an image and automatically gives the region of interest and the name of the disease. The image of the leaf takes from any place and the tomato plant area can be known by a trained person. The diseases are classified based on the color, texture, and the region of interest from the segmentation. Deep Learning-based detection of foliar diseases and fungal infection in tomato crop using morphological segmentation, color-based feature extraction, and KNN classifier has been implemented. The study yields good accuracy even when the model is tested on different dataset (Ahmed et al., 2022). The tomato leaf disease detection system using deep learning techniques gives healthy tomatoes and improves the yield and saving from the damages (Nawaz et al., 2022). The development of lightweight and efficient deep learning tomato leaf disease detection and classification method using pre-trained DenseNet-77 and CornerNet architecture has been proposed. The method achieves significant detection accuracy (81.97), classification accuracy (99.68) to identify specific disease and localization speed (65 fps) from color image (Albahli & Nawaz, 2022).

2. **Foliar Disease Detection in Cereals**

Plant pathologists have observed that the vast majority of economically significant plant diseases can be associated with specific signs and symptoms on the host plant that develop as a consequence of infection (Kulkarni et al., 2021). As such, the early and accurate detection of diseases relies heavily on the availability of relevant information pertaining to these visual symptoms. Consequently, great efforts have been made to develop methods for the quantification of the signs and symptoms of plant disease, which in many cases is the limiting factor in the development of automated plant disease detection systems (Bashir et al., 2019). Cereal crops represent the basis of human nutrition and the main source of food for livestock. Cereals have a great importance not only in developing countries but in industrial countries as well. Reduced foliar disease incidence and severity could enhance yield and improve quality of cereals, leading to improved food security and nutrition.

3. **Orchard and Field-Scale Disease Monitoring**

Orchard and field-scale disease-monitoring applications face challenges in the availability of representative labelled datasets, high-resolution image capture, and real-time end-to-end processing. With the deployment of drones or imaging robots, images at orchard or field scale resolution can typically be captured only at a few moments during the day, contradicting the set objective of having disease-monitoring capabilities for a wider moment of time over the day via visual signals. Thus, a trade-off exists between the question on which crop to monitor in a large-scale without modelling those complex the orchard or field scale image-acquisition workflow and its integration with the existing agronomic workflow systems.

Orchard and field images of crops have exhibited similar symptomatic patterns across different time frames and, consequently, crops can be monitored without applying spatially complex orchard or field image-acquisition workflow (Kulkarni et al., 2021). The selected crops encompass such exemplified crops as grape, apple, citrus, and sugarcane. Time and vehicle constraint associated with monitoring of these crops also reinforces the option of integrating and modelling the small field-sized images instead., Thus, monitoring of each specified crops among the targeted crops can take place, permitting extensive decision support on crops timely and can be finally delivering timely advise at each crop, at orchard scale over those orchard crops (Garcia Arnal Barbedo, 2013).

Challenges, Limitations, and Ethical Considerations

Plant pathology automation technologies enhance the performance of agriculture; early disease detection is vital. For robust deployment, plant disease detection systems must address a spectrum of challenges, limitations, and ethical considerations.

A major issue is the need for higher-quality data. The dependence on images of superficial symptoms raises constraints on the capacity of deep-learning-based diagnostic systems; good-quality datasets remain elusive. Even publicly available collections suffer from mislabelled data, under-annotated lesions, and uneven class distribution. Concerning bias, the unequal representation of crop and disease varieties poses risks of poor generalisation (Salman et al., 2023).

The advanced image analysis often suffers from opacity. Many models yield outputs without clear explanations or assurances regarding the certainty of the predictions. Confusion and distrust towards machine-diagnosis tools may arise from an inability to comprehend the flow of information. Consequently, a strong justification exists for a field-explicit interpretation of deep-learning analyses, a core aim of the proposed research (G. A. BARBEDO, 2020).

Ethical concerns span privacy, ownership, and shareability of datasets obtained via electronic channels; farmers potentially remain unaware of their use. The apprehension may hinder model dissemination after training and improvement, compromising broader agronomic impact. Efficient solutions are therefore needed for documenting and sharing image collections derived from on-farm deployment while preserving anonymity.

Technically, the automation of field imagery raises apprehensions. The constant acquisition of foliarly-captured images throughout the agricultural year poses challenges for automated tasks like send-out decision-making or satellite docking. Unsuitable monitoring may lead to missed opportunities, engaged situations, or even deterioration of plants in focus.

Sustaining the degree of engagement demanded from farmers limits the practicality of implementing advanced-deep-learning-based systems. Further provisions are warranted to assure data collection efficiency aligned with farmer-relevant delivery timeframes.

Localisation of diseased leaves has attracted attention due to its potential for guiding plant-by-plant inspections. However, no perfunctorily crop-diseases symptoms exhibit consistent tell-tale features; vigorous growth coupled with abundant vegetal variety foster rapid evolution of diseased shapes and patterns. Automated detection remains technically feasible yet has not gained traction because of ill-defined margins between early and late manifestations.

The prospect of cropping guidelines is more attractive when addressing nursery sequences yet curtails the technical demand imposed on the approach. Nevertheless, even before steady maturation, document guided proposals, monitoring formation stages—shoots up until a few centimeters. The scant consideration of sufficiently variable nursery datasets limits universal applicability; intensified focus might extract benefits from enrichment periods capturing varieties, even beyond public-release compilations.

Governments of varying global profiles emphasise equity in technology provision. Residential and institutional debut of detection resources stays imminent, but additional regional combinations challenge auspicious farm development. The endeavour strives to achieve technology access for agricultural domains with diminished availability.

Future Directions

Addressing the longstanding challenge of AI-based plant disease detection requires continued innovation within a broader framework. A hybrid modeling roadmap could integrate classical image-processing and deep-learning techniques, retain advantages of classical approaches, and boost efficiency. Multi-spectral and hyper-spectral data hold potential for improved results, raising questions of cross-dataset generalization under variant multispectral configurations. Domain-adaptation and continual-learning strategies offer pathways to counter class imbalance, snapshot overfitting, and dataset-closure concerns associated with fixed image-collection paradigms. Further progress hinges on resource-efficient designs for edge-computing devices, augmented by farmer-centric user interfaces accommodating locality, dialect, and agricultural literacy differences. (Kulkarni et al., 2021)

Conclusion

Plant disease detection and identification is crucial for the application of timely preventive measures and for assurance of quality and increased yield of crops. It is therefore important to establish a mechanism that would detect plant diseases at an early stage. The quantity of the harvested product may be reduced because of the growth of fungi, bacteria, or viruses on the crops. The older methods of leaf disease classification involve sound and complex information storing structures; also there is a lack of support for temporal maintenance and operation on the information streams. Therefore an application that is easy to use and helps to detect the leaf diseases will be a benefit for the crop sector or field. Auto detection of plant disease helps to reduce the manual time spent in searching on internet for the consultation of diseases of plants. The farmer can take a still image of the crop leaf and upload it in the application to fastly get the detected disease and remedy. All crop and vegetable type files may be supported and named properly alongside of uploading. The whole information related to agriculture will be stored and it may help for future references (Ahmed et al., 2022).

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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