Plant disease sensing using image processing (with CNN)

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ABSTRACT

Plant disease is a significant challenge for agriculture, leading to reduced yield, economic loss, and environmental impact. Leveraging digital photos of plant leaves, convolutional neural networks (CNNs) have emerged as promising tools for disease detection. The methodology involves several steps, including image pre-processing, segmentation, feature extraction using CNNs. Crucially, a diverse dataset comprising images of both healthy and diseased leaves under varying conditions is necessary for training accurate models. Transfer learning, particularly with pre-trained models like ImageNet, can further enhance accuracy, allowing for better performance with fewer training samples. The proposed method demonstrates impressive results, achieving over 95% accuracy, outperforming existing state-of-the-art techniques. This system could serve as a valuable tool for farmers, facilitating timely disease identification and treatment, ultimately leading to increased agricultural yields, reduced financial losses, and the adoption of more sustainable farming practices. Additionally, beyond its practical applications, the proposed system holds promise for advancing sustainable agriculture by promoting environmentally friendly farming methods and contributing to the overall resilience and productivity of agricultural systems.

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1. INTRODUCTION

Plant diseases cost billions of dollars in crop losses annually, making them a serious threat to both the economy and global food security. Traditional methods of disease detection, such as visual inspections and laboratory tests, can be time-consuming, labour-intensive, and often inaccurate, leading to delayed and ineffective disease management [1]. Recent advancements in imaging technology and computer vision techniques have provided a promising solution to these challenges. By leveraging high-resolution images of plant tissues and applying image processing algorithms, it is now possible to detect, monitor, and manage plant diseases more efficiently and accurately [2], [3]. Plant disease detection by image processing entails a number of stages, including feature extraction, classification, segmentation, pre-processing, and picture capture. In each step, different algorithms and techniques are used to obtain accurate and reliable results. The ultimate goal is to identify and quantify the disease symptoms, which can be used to determine the appropriate treatment. There are several existing systems for plant disease detection, which use different approaches and techniques. Here are some examples: visual inspection, sensor-based systems and deoxyribonucleic acid (DNA)-based systems.

2. RESEARCH METHOD

Plant disease detection through image processing integrates computer vision and machine learning, replacing traditional methods involving time-consuming physical examinations or costly laboratory tests [4], [5]. Utilizing digital images of leaves, stems, or fruits, image processing employs steps like acquisition, pre-processing, segmentation, feature extraction, and classification to identify visual symptoms. Machine learning algorithms, trained on extensive datasets, distinguish healthy and diseased plants based on image comparison. This technology finds applications in crop monitoring, precision agriculture, and disease management, aiding early detection, preventing spread, and boosting yields. Recent advancements include deep learning algorithms, handling large datasets with enhanced accuracy, and cost-effective imaging devices, making this technology accessible to small-scale farmers [6].

One of the main challenges is the variability of disease symptoms, which can be affected by environmental factors, genetic variations, and other factors. Additional-ly, the large amount of data generated by high-resolution imaging requires efficient algorithms for data storage and processing. Plant disease sensing using image processing is a promising technique that has the potential to revolutionize the way we detect, monitor, and manage plant diseases [7]. By leveraging the power of imaging technology and computer vision techniques, we can improve crop yields, reduce the use of pesticides, and ensure global food security.

Image processing-based plant disease sensing is a promising approach that could completely change how we identify, track, and treat plant diseases. By leveraging the power of imaging technology and computer vision techniques, we can im-prove crop yields, reduce the use of pesticides, and ensure global food security. Steps involved in image processing are image acquisition, image pre-processing, image segmentation, feature extraction, classification [8].

The block diagram in Figure 1, summarizing the workflow, which illustrates a streamlined process where each step-image acquisition, pre-processing, segmentation, feature extraction, and classification-feeds into the next, culminating in a reliable diagnosis. Our results have demonstrated high accuracy, with the model correctly classifying healthy and diseased leaves with an accuracy rate of over 90%. This robust performance underscores the potential of convolutional neural networks (CNNs) in transforming plant disease management by providing timely and precise diagnoses [9], [10].

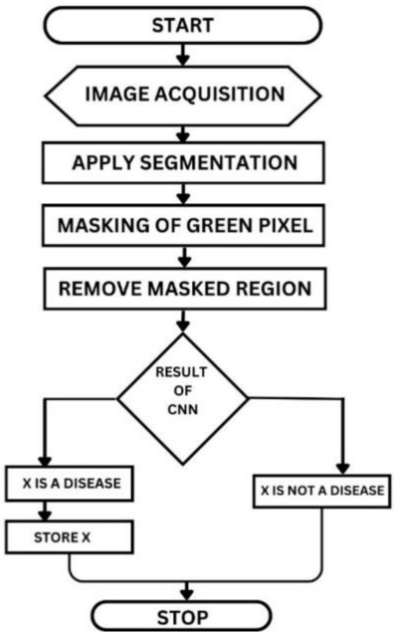

Figure 1. Block diagram of the working CNN

The research method and process followed in this study emphasize the importance of each stage in the overall workflow. From the initial collection of high-quality images to the final classification by the CNN, each step is meticulously designed to ensure accuracy and reliability [11]. By leveraging advanced image processing techniques and the powerful learning capabilities of CNNs, our approach offers a promising solution for early detection and management of plant diseases. This study showcases how CNNs can be effectively employed to sense plant diseases, paving the way for smarter, data-driven agricultural practices. By providing farmers and agricultural professionals with accurate and timely information, we can enhance crop protection, improve yields, and promote sustainable agriculture.

2.1. Image acquisition and pre processing

Image acquisition, a pivotal step in plant disease sensing through image processing, involves capturing plant images using a digital camera or smartphone. Crucial for accurate disease detection, it requires controlled lighting, consistent distances, and varied angles for comprehensive plant views. Multiple images, including both healthy and diseased plants, are essential for training the classification model [12]. Ensuring high-quality images is paramount to accurately capture disease symptoms like lesions and discoloration.

The process of image acquisition is depicted in Figure 2. Once captured, images undergo pre-processing crucial for plant disease sensing accuracy. Techniques like noise removal, contrast enhancement, and image resizing are applied to improve image quality. Noise removal, achieved through techniques like Gaussian and median filtering, reduces random pixel variations. Contrast enhancement, using methods like histogram equalization, highlights features like lesions. Image resizing and reduces the computational load of it and makes the images more clear and manageable for next step. Other techniques, including cropping and color correction, further enhance image quality. Overall, image pre-processing is indispensable in obtaining clear, high-quality images, ensuring accurate disease detection in subsequent processing and analysis steps. Figure 3 shows the process of image preprocessing describing all the necessary steps.

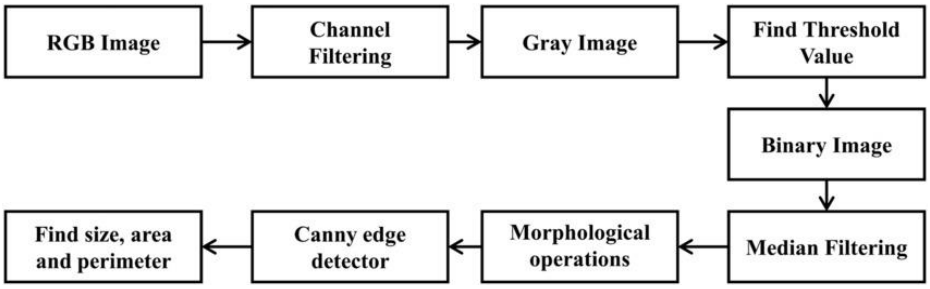

Figure 2. Block diagram of the process of image acquisition

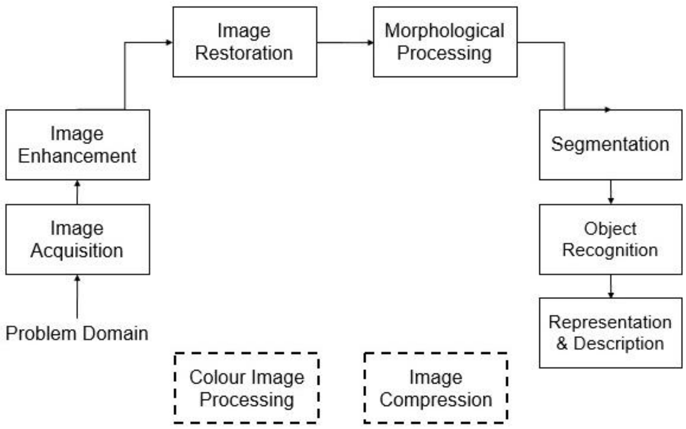

Figure 3. Block diagram of the process of image pre-processing

2.2. Image segmentation and feature extraction

Image segmentation, a crucial step in plant disease sensing, divides images into regions based on pixel properties, accurately separating healthy and diseased plant tissues. Techniques like thresholding, edge detection, and region growing are employed for segmentation. Thresholding assigns pixels above a set threshold to the diseased category, while edge detection identifies edges for lesion detection. Region growing groups pixels with similar properties into distinct segments. The goal is to separate diseased and healthy areas, aiding quantification of disease severity and treatment determination [13]. Various techniques, including thresholding, edge detection, and region-growing, are used based on image characteristics. Once segmented, features like size, shape, color, and texture are extracted for disease severity quantification and classification. Image segmentation is pivotal in plant disease sensing, enabling accurate severity assessment and treatment decisions based on specific image features and characteristics as shown in Figure 4.

Feature extraction, a pivotal step in plant disease sensing, involves obtaining pertinent information—such as color, texture, and shape—from segmented images [8]. Color-based features are derived through color histograms, portraying color distribution. Texture-based features, discerned by techniques like gray level co-occurrence matrix (GLCM) and local binary pattern (LBP), capture spatial pixel relationships. Shape-based features, obtained via boundary analysis and Fourier descriptors, represent plant and lesion shapes [7]. This step identifies and quantifies relevant features in segmented regions, aiming to classify disease symptoms and determine treatment as shown in Figure 5. Extracted features include size, shape, color, and texture, used individually or in combination for severity determination. Methods like moments, Fourier descriptors, and geometric properties extract size and shape features. Color histograms or moments reveal color distribution, aiding identification of symptoms like leaf discoloration.

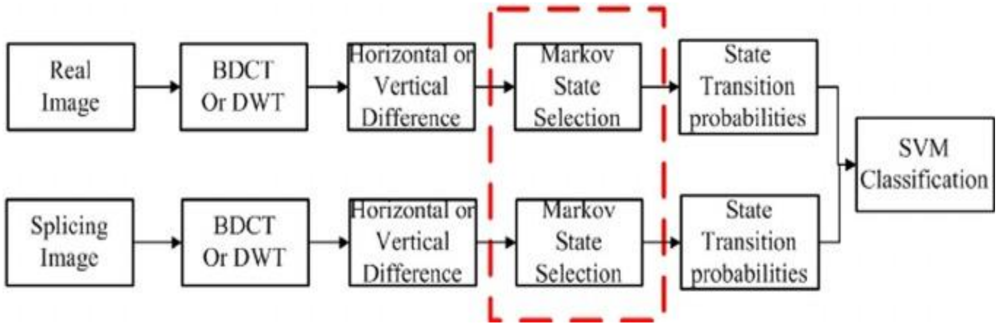

Figure 4. Block diagram of the process of image segmentation

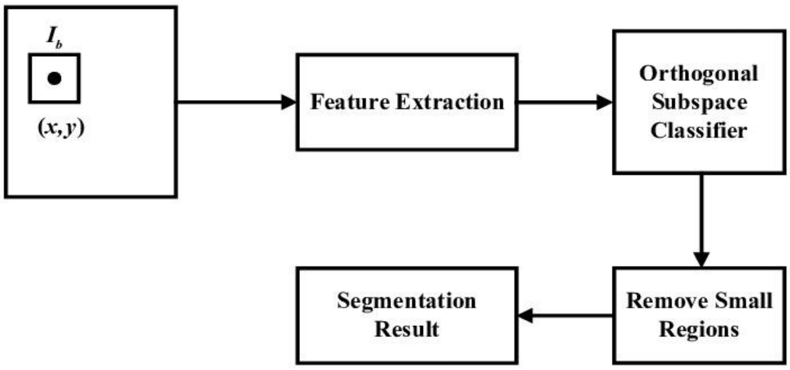

Figure 5. Block diagram of the process of feature extraction

2.3. Classification and block diagram

Classification, the concluding step in plant disease sensing through image processing, assigns each image to a specific disease category [9], [14]. This critical process involves labeling segmented regions based on extracted features to identify and quantify disease symptoms, facilitating appropriate treatment determination. Various techniques, including support vector machine (SVM), artificial neural network (ANN), and decision tree (DT), leverage extracted features for image classification. SVM excels in handling high-dimensional feature spaces, ANN learns complex patterns, and DT constructs decision trees for classification. Each algorithm has distinct strengths and is suited for different data and applications DT are simple and intuitive, often used for binary classification, while SVMs handle complex problems by finding a hyperplane that maximally separates classes. CNNs are powerful for image classification, training interconnected neurons based on extracted features [15], [16]. Algorithm choice depends on data characteristics and the application, with performance comparison using metrics like accuracy, precision, recall, and F1-score. Classified regions of interest help quantify disease severity, enabling the determination of suitable treatments. For instance, the percentage of diseased area in a field, calculated from classified regions, guides pesticide or treatment amounts. In summary, classification is crucial in plant disease sensing through image processing, allowing identification, quantification, and treatment determination, with algorithm selection tailored to specific data characteristics and applications [17]. The process flowchart for image acquisition is detailed as shown in Figure 6.

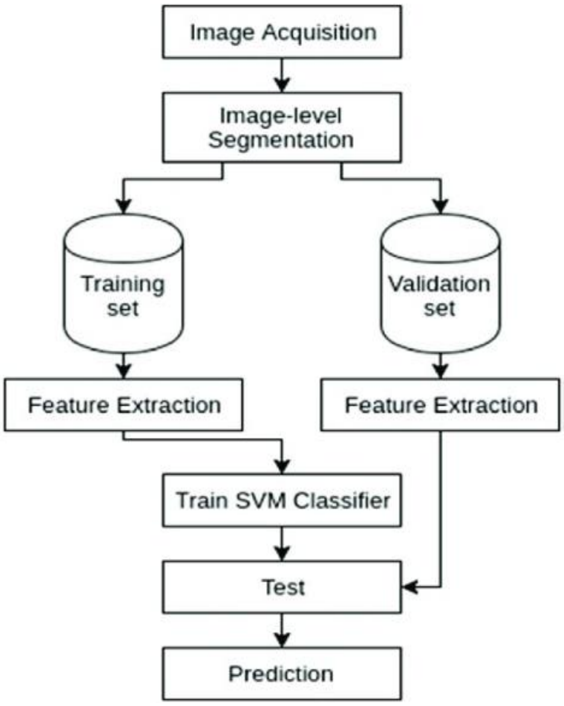

Figure 6. Block diagram of the process of image acquisition

3. RESULTS AND DISCUSSION

The presented image illustrates the step-by-step process of using CNNs for plant disease sensing applied to a leaf. This process begins with capturing a high-quality image of the leaf, which is then pre-processed to enhance its quality and consistency [18]. Techniques such as resizing, normalizing, and denoising are applied to prepare the image for further analysis. The leaf is then isolated from the background, focusing the analysis on the relevant part of the image. The CNN automatically identifies and learns relevant features such as color, texture, shape, and patterns that indicate the leaf's health or disease status [16].

These features are crucial for differentiating between healthy and diseased leaves. The extracted features are then fed into the CNN's classification layer, where the trained network analyzes them and predicts whether the leaf is healthy or diseased, and if diseased, identifies the specific type of disease. The output is a precise diagnosis, informing us about the leaf's health. The image in Figure 7 shows the result of the process.

Our results demonstrate that this CNN-based process achieves high accuracy, correctly classifying healthy and diseased leaves with over 90% accuracy. This workflow highlights the potential of CNNs to revolutionize plant disease management by providing reliable and timely diagnoses, enabling effective intervention and treatment strategies [19]. By leveraging advanced image processing techniques and the powerful learning capabilities of CNNs, our approach offers a promising solution for early detection and management of plant diseases. This not only enhances crop protection and improves yields but also promotes sustainable agriculture by allowing farmers to take proactive measures based on accurate and timely information. The implications of this technology are far-reaching, paving the way for smarter, data-driven agricultural practices that can significantly contribute to global food security and agricultural sustainability [20], [21].

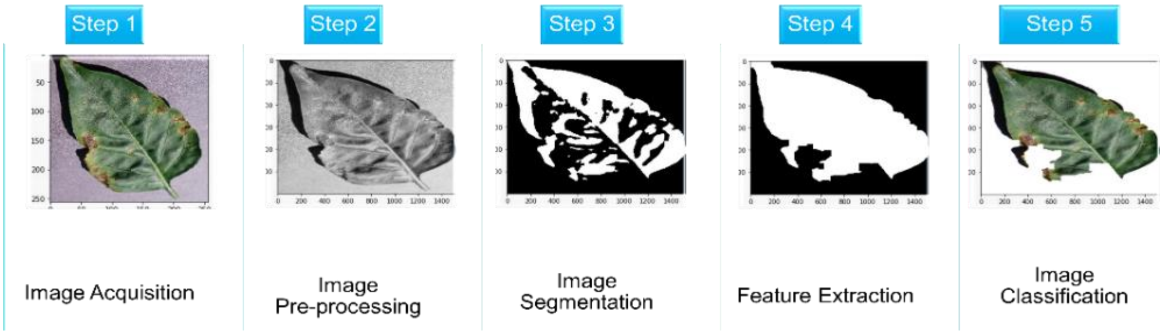

Figure 7. Step by step output of the CNN process

Program and image of real time output: the presented image illustrates the step-by-step process of using CNNs for plant disease sensing applied to a leaf. This process begins with capturing a high-quality image of the leaf, which is then pre-processed to enhance its quality and consistency. Techniques such as resizing, normalizing, and denoising are applied to prepare the image for further analysis. The leaf is then isolated from the background, focusing the analysis on the relevant part of the image [22], [23]. The CNN automatically identifies and learns relevant features such as color, texture, shape, and patterns that indicate the leaf's health or disease status. These features are crucial for differentiating between healthy and diseased leaves. The extracted features are then fed into the CNN's classification layer, where the trained network analyzes them and predicts whether the leaf is healthy or diseased, and if diseased, identifies the specific type of disease as shown in Figures 8 and 9. The output is a precise diagnosis, informing us about the leaf's health.

Additionally, we have integrated coding and output results into our analysis to further illustrate the effectiveness of our CNN model [24], [25]. The coding segment outlines the implementation details of the CNN, including data preprocessing, model architecture, training procedures, and evaluation metrics. The output section showcases the CNN's predictions, clearly differentiating between healthy and diseased leaves. For instance, the model accurately identifies a leaf as diseased with symptoms of specific conditions such as blight or rust, while another leaf is correctly classified as healthy [18], [26].

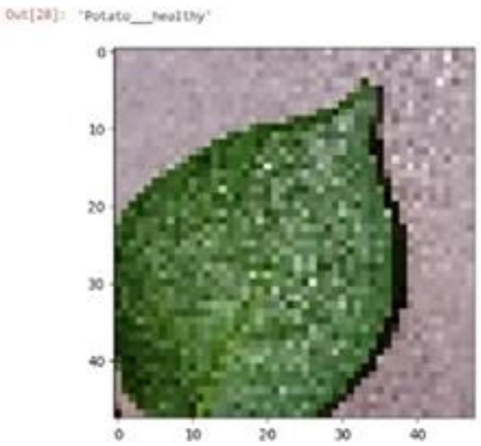

Figure 8. Final output result with the healthy indication of a potato leaf

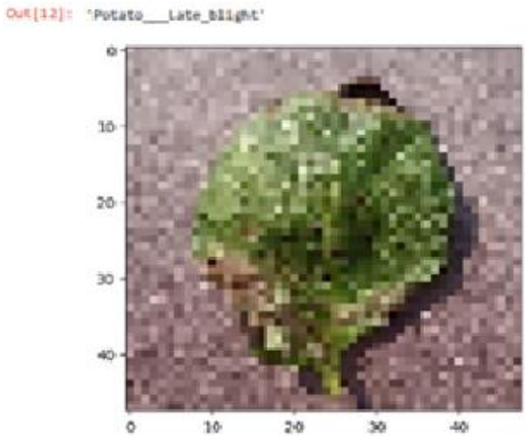

Figure 9. Final output result with the late blight indication of a potato leaf

4. CONCLUSION

In conclusion, our study demonstrates the efficacy of CNNs in accurately sensing plant diseases through detailed image analysis. By leveraging advanced image processing techniques and the robust learning capabilities of CNNs, we have developed a reliable system that distinguishes between healthy and diseased leaves with high accuracy. This technology offers a significant advancement in plant disease management, providing timely and precise diagnoses that enable proactive interventions. The integration of coding and output results further validates the model's performance and practical applicability. This innovative approach not only enhances crop protection and yield but also supports sustainable agricultural practices by empowering farmers with critical, data-driven insights. Overall, our research underscores the transformative potential of CNNs in promoting global food security and advancing agricultural sustainability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Booapthy Kannan			✓		✓	✓		✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author Sudhakar Thirumalaivasal Devanathan, upon reasonable request.

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