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Original Paper

Data Collection Techniques for Leaf Disease Detection: A Systematic Review

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ABSTRACT

For ensuring crop health and agricultural productivity accurate and timely detection of leaf diseases is important. Due to advancement in sensor technologies and imaging modalities, various data collection techniques have emerged to support automated disease detection. This systematic review aims to distinguish and explain various kinds of data gathered for leaf disease detection (e.g., visual, multispectral, hyperspectral, thermal). Different methods of data acquisition are analyzed such as field-based sensing, remote sensing and laboratory analysis. The advantages and disadvantages of each data collection technique should be identified. The insights and recommendations are provided to researchers and practitioners in the selection of appropriate data collection strategies. explore and categorize the various types of data used in leaf disease detection, including visual, multispectral, hyperspectral, and thermal imaging data. It further analyzes different methods of data acquisition, such as field-based sensing, remote sensing via aerial or satellite platforms, and controlled laboratory analysis. Each technique is evaluated in terms of its precision, scalability, cost-effectiveness, and applicability across different crop types. The review highlights the strengths and limitations inherent to each data collection approach and provides practical insights to guide researchers and practitioners in selecting suitable strategies tailored to specific diagnostic goals and resource constraints. Through this synthesis, the paper contributes to the development of more effective and context-aware plant disease monitoring systems.

KEYWORDS

Leaf Disease Detection, plant disease imaging, data acquisition techniques, plant disease.

1. INTRODUCTION

Agriculture depends on plant health not only to be secure in the ability to provide food but also to ensure the economic viability of its enterprises. Through plant health monitoring, crop diseases can be detected early and managed for the early disease prevention of wide crop loss [1]. One instance of such increasing need is leaf disease detection, in particular, as leaves are the most typical places where diseases show their signs [2]. Routine visual inspection methods are largely subjective, time consuming, and may not detect diseases during early stage unless the pathologies are very obvious [3]. However, with more advanced technique, including machine learning and deep learning, there has a potential for automatic and fast disease detection [4]. However, for these techniques to be successful the data used to train and validate models need to be high quality and to have certain characteristics. Motivated by the critical role of data collection in advancing plant disease detection, this paper provides a systematic review of current data collection methods.

The scope of this review encompasses studies focusing on data collection techniques used for the detection of diseases in plant leaves. It includes research utilizing various imaging modalities and acquisition methods, with a focus on data suitable for machine learning-based disease detection system.

2. LITERATURE REVIEW

The methodologies used to collect data have evolved greatly with the rise of leaf disease detection with data collection going from traditional visual inspection to high throughput digital imaging and spectral analysis. Commonly, the detection of plant diseases has traditionally been done by means of visual inspection using trained experts which can be subjective, time consuming, and inconsistent. However, manual diagnosis of plant diseases is slow and highly reliant on the skill of a pathologist [5], [6]. In the modern times, a lot of techniques have been utilized that use data from various sources such as hyperspectral data, thermal imaging, fluorescence imaging, etc. [7], all of which provide a different perspective into plant health. With the help of machine learning algorithms and image-based techniques some promising solution came out that helps rapidly and accurately identifying the crop diseases [8]. An increasingly greater demand on the part of growers necessitates the use of automated disease detection systems to achieve timely and accurate diagnosis to effectively manage diseases and mitigate crop losses. To overcome the inherent limitations of the previously used methods, application of various image processing techniques is a much-researched area [9]. Currently, there are a number of resources available regarding machine learning and deep learning methods, which could possibly increase the accuracy of disease detection and diagnosis [10]. Computational intelligence through machine learning gives machine the capability to learn automatically and predict outputs without human intervention [11]. Selection of such data collection techniques is crucial for developing robust and reliable disease detection models [4], [12]. Models are better if, machine learning models are trained on data having higher quality and characteristics. Support Vector Machines, Random Forests, etc. machine learning algorithms have demonstrated much better accuracy and robustness in the leaf detection by analyzing extracted features of leaf [13]. In view of this, this review intends to give a complete review over the data assembly scene for leaf sickness identification, distinguishing between the focal points and banes of various strategies and proposing an opportunity of future hypothetical and advancement. Plant disease recognition has been done by means of laboratory-based techniques, including enzyme–linked immunosorbent assay, polymerasechain reaction and DNA microarray, which are however complex and dependent on specific reagents [14].

2.1. Data Collection Techniques for Leaf Disease Detection

Various data collection techniques are used (Table 1) to detect leaf disease, which range from techniques that are advantageous, to other that are limited [15]. These methods can be generalized into visual imaging, spectral imaging and other advanced methods of imaging that can capture different aspects of plant health. Although not always the best solution, visual imaging, especially through RGB cameras, can be applied to detect leaf disease [16]. The visible light spectrum is captured by RGB images with detailed information regarding color and texture of leaves [17]. They use these images to detect visual symptoms of diseases, for instance; spots, lesions and discoloration [18]. Digital photographing of plant leaves with standard cameras or smartphone cameras forms image acquisition. RGB imaging is quite successful with diseases which give distinct symptoms visible to human eye to detect, however it might not be so sensitive to minor changes in that same health which leads to those diseases but before any visible symptoms appear. Spectral imaging, such as hyperspectral or multispectral imaging, goes far beyond what the human eye can see, providing a greater degree of plant health assessment. A hyperspectral image acquires data over hundreds of narrow spectral bands on a continuous spectrum for every pixel in the image. The rich spectral information can be used to identify even the slightest change in leaf physiology and biochemistry; hence the disease can be detected before the outset of visual symptom [19]. Multispectral imaging collects data on a few discrete spectral bands, and as such, considers a compromise between spectral resolution and the amount of data to collect. However, these imaging modalities normally need the use of specific equipment and expertise and additionally supply vital information for early detection and accurate diagnosis of diseases. Measuring the temperature of plant leaves via thermal radiation emitted (thermography) is another non-destructive method [20]. The selection of the data collection technique is dependent on multiple parameters, two of which are the type of disease and the plant species and the final determinant is the desired accuracy level and number of resources available. Developing reliable and robust disease detection models thus requires the appropriate selection of methods for data collection [5].

Table 1. Comparative study of data collection techniques

Technique	Description	Tools / Technologies Used	Application Area	Advantages	Limitations
RGB Imaging	acquire images in red, green, and blue light to detect visual changes in plant health.	RGB cameras	Early disease detection, plant morphology	Simple, cost-effective, widely available	Limited to visible symptoms
Fluorescence Imaging	Observe how plants respond to light for early stress detection.	Fluorescence sensors/cameras	Transpiration monitoring, stress detection	Detects changes before visible symptoms, sensitive to physiological stress	Limited in spectral range; may not distinguish overlapping stressors
Hyperspectral Imaging	Captures detailed spectral info in hundreds of narrow bands for biochemical/biophysical analysis.	Hyperspectral sensors/cameras	Disease detection, chlorophyll analysis	High sensitivity, detects early/subtle changes, pixel-level spectral data.	Complex, expensive, large data volume, overlapping biotic/abiotic factors
High-Throughput Phenotyping	Uses multiple imaging methods for quantitative trait studies (e.g., growth, yield, stress response).	RGB, IR, hyperspectral, etc. (via phenotyping platforms)	Trait estimation, stress adaptation studies	Multi-dimensional data, enables large-scale trait analysis	Infrastructure-intensive
Spectroscopy (Remote Sensing)	Detects changes in optical properties of plants over large areas for disease detection.	Remote sensing, spectroscopy (possibly via drones/satellites)	Large-scale disease monitoring	Covers wide area quickly, non-invasive	May struggle with similar spectral signatures from multiple

					stress sources
Machine Learning with RGB	Uses RGB images and machine learning algorithms to classify infected vs. healthy plants.	RGB cameras + ML models (e.g., SVM, CNN)	Disease classification, image-based diagnosis	Automated, scalable, adaptable to various crops and conditions	Performance depends on data quality and model generalization
Image-based Prospecting	Automated or assisted identification of disease using various image techniques.	Combination of imaging + expert systems or AI	Decision support, field scouting	Enhances expert judgment, reduces manual workload	Requires integration of multiple sensors and expert knowledge

High throughput phenotyping platforms use the different imaging techniques to obtain data for quantitative studies of complex traits, including growth, yield and adaptation to biotic or abiotic stress [21]. The traits e.g. plant canopy, biomass, can be estimated by combining the imagery falling into red, blue, green light and color infrared [22]. Indirect methods of early disease identification and health prediction are imaging technologies like RGB, fluorescence, and hyperspectral imaging based on monitoring changes in morphology and transpiration rate [23]. In general, fluorescence imaging can be used to understand how plants respond to light as hyper spectral imaging can be employed for a broader parameter regarding plants chlorophyll fluorescence [24]. Even though relatively new in plant pathology, hyperspectral imaging provides novel opportunities to evaluate diseases objectively [25]. The images it acquires are in hundreds of narrow, contiguous bands and it provides detailed spectral information for each pixel, and this detailed information allows subtle changes in the plant's biochemical and biophysical properties to be detected which may signal presence of disease before visible symptoms appear [26]. The employment of remote sensing technologies, such as spectroscopy, is able to rapidly and over large scales, identify plant diseases through the detection of changes in the plant optical signatures leading to rapid identification of diseases large areas [27]. Some diseases have different spectral characteristics which can be easily reconstructed in some cases, but detecting them difficult when there are multiple biotic and abiotic having same spectral characteristics [28]. RGB images with machine learning techniques were also used for detecting infected plants [29]. These challenges can be addressed by automatic prospecting using image-based techniques or by aiding the expert with such techniques.

2.2. Advanced Methods

In recent times, sensing technologies have improved greatly, encouraging the development of data collection methods for leaf disease detection that are more raised level. Some of these techniques include thermal imaging, fluorescence imaging, and 3D imaging that provide access to one-of-a-kind information of plant health. However, some of these methods requires an expertise or specialized equipment, yet they yield useful data for the early and correct detection of a disease. Plant disease detection is dependent on a crucial step in data collection involving the use of manual inspection that is tedious, subjective and prone to human error [9]. Use of global navigation satellite system and geographic information system and imaging sensors to introduce the technical aids of remote sensing of diseases establishes ties at the link between sensor data on the plant status to the spatial data on the whereabouts of the plant [30]. However, unlike most common visual rating and detection methods, the pathogen induced changes in plant physiology can be measured noninvasively and objectively with the optical sensors [31].

3. Inclusion and Exclusion Criteria

In this review of leaf disease detection wide range of search comprehensive literature search was carried out using scientific databases which includes SpringerLink, Scopus, Web of Science, IEEE Xplore, and Science Direct. We used keywords that were (e.g. “leaf disease detection”, “plant disease imaging”, “data acquisition techniques”, “multispectral imaging”, “hyperspectral imaging”, “remote sensing”, “thermal imaging”, “field phenotyping”) also combinations of keywords were used for search ("leaf disease" OR "plant disease") AND ("data collection" OR "data acquisition") AND ("remote sensing" OR "multispectral" OR "hyperspectral"). The articles published between 2010 to 2025. Relevance and quality of research were ensured by the selected studies on inclusion and exclusion criteria. Inclusion criteria include Peer-reviewed journal or conference publications. Studies focused on data collection for leaf or plant disease detection. Utilization of imaging or sensor-based data acquisition methods, articles written in English (Figure 1). Exclusion criteria include studies unrelated to agriculture or plant pathology, papers lacking sufficient methodological details on data collection, duplicate publications or non-peer-reviewed sources (e.g., theses, editorials).

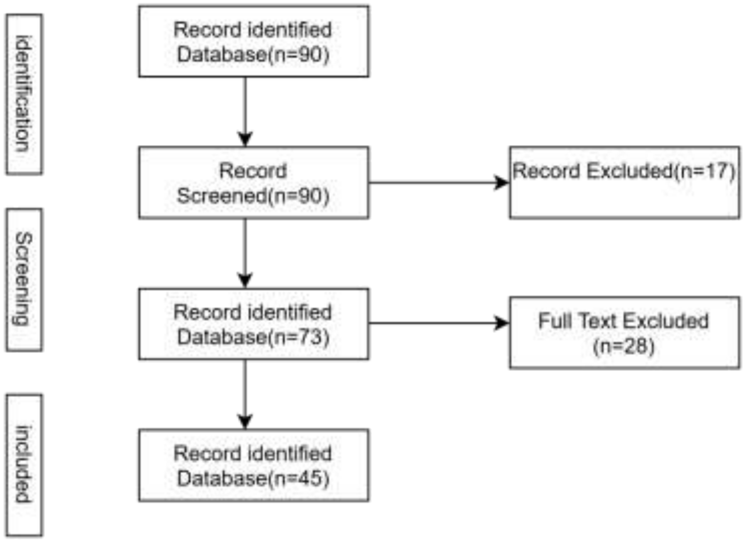

Fig. 1. Prisma flow diagram showing flow of different phases of systematic review.

4. METHODOLOGY

The methodology encompasses data acquisition and preprocessing, feature extraction and selection, and classification, as outlined in Table 2.

4.1. Data Acquisition and Preprocessing

Image acquisition in [32] refers to the capturing of images of plant leaves with different imaging techniques. Standard digital cameras or smartphone cameras may be used to acquire RGB images while hyperspectral or multispectral cameras are needed to acquire spectral images. Preprocessing is applied to the images in order to improve quality and decrease noise. Image resizing, color correction, or noise reduction may be included in these steps.

4.2. Feature Extraction and Selection

Feature extraction involves extracting relevant features from the preprocessed images that can be used to differentiate between healthy and diseased leaves. The extracted features are then selected based on their ability to discriminate between different disease classes.

4.3. Disease Classification

As classification model, the features are fed and are trained to classify the leaves into different disease categories. With this, convolutional neural networks have worked great in deep part of tasks image classification [33]. Even though the process of machine learning based disease detection encompasses several steps, it includes preparation of data, feature extraction, and training of model [34]. After the training, the model could be used to predict the diseases in new leaf images whether the disease is present in the leaves [34], [35]. Deep learning and other machine learning algorithms have promise in healthcare, for instance as in chatbots, imaging solutions, identification of particular types of cancer and rare diseases [11]. Disease detection can be implemented through different methods and algorithms [36]. For instance, epidemics outbreak prediction and monitoring using such information include data from various sources like social media, web-based platforms and satellites [11]. Various layers of the convolutional neural network can be used to automatically detect and classify plant diseases with high classification accuracy and high processing speed [37]. Stress detection is done using deep CNN algorithms with triplets' loss function, and CNN, ANN and RNN are prevailing techniques in a deep learning framework [38].

Table 2. Data processing workflow

Stage	Step	Description	Tools/Methods	Purpose
Preprocessing	Image Acquisition	Capturing images with different imaging devices	RGB, hyperspectral, multispectral, thermal cameras	To collect raw image data
	Image Preprocessing	Enhancing image quality, removing noise	Resizing, color correction, noise reduction	Improve data quality for analysis
Feature Engineering	Feature Extraction	Identify key attributes in image	Texture, color, shape, spectral bands	Distinguish between healthy & diseased leaves
	Feature Selection	Choose most relevant features for classification	Statistical & ML-based methods	Reduce dimensionality, improve performance
Classification	Disease Classification	Classify leaves based on extracted features	CNN, ANN, RNN, SVM	Predict disease class from input image

5. DISCUSSIONS

The use of computer vision and machine learning techniques to develop automated plant disease detection systems is a great leap ahead for such a purpose [39], [40]. Optical images are a critical modality for plant disease recognition, given their many uses from the point of extracting useful information [41]. RGB images are particularly attractive as they have ease of acquisition and encapsulate a wealth of visual data that can be utilized for deciding dissertated aberrances within plant leaves [5]. Such features allow extraction of key features that include color, texture and morphological features that act as discriminative markers between healthy and afflicted foliage [42]. In addition, the combination of RGB imagery with advanced machine learning can be used to produce automated disease detection systems that are fast and accurate to detect infected plants [43]. However, RGB images are easy to acquire and flexible to use; however, due to the necessity of RGB images to rely on good lighting conditions, high enough image resolution, and distinct disease symptoms, there is still room for improvement.

Choice of data collection technique depends on various factors, including the type of disease, the plant species, the desired level of accuracy, and the available resources. The use of appropriate methodologies is crucial for effective disease detection and management. The spectral reflectance patterns of leaves can reveal, from a finite distance, small physiological perturbations induced by disease in order to be used as an indicator of plant health [44]. By combining remote sensing data with data analytics techniques such as machine learning algorithms, predictive models can be developed to predict the occurrence of disease outbreaks as well as help optimize disease management strategies [45].

6. Conclusions

The interaction between electromagnetic radiation and plant tissues is a nondestructive method that enables to assess the plant health using spectroscopy. The spectral reflectance patterns of leaves can reveal, from a finite distance, small physiological perturbations induced by disease in order to be used as an indicator of plant health. Additionally, face to current development of remote sensing technologies (satellite-based imaging and unmanned aerial vehicles), plant disease detection has evolved and has become possible to monitor crop health over extensive geographical areas. They allow for the acquisition of multispectral and hyperspectral data that supplies a landscape view of plant health and enables time of intervention strategies to prevent disease outbreak. By integrating remote sensing data with complex data analytics techniques such as machine learning algorithms, predictive models can be developed to predict the occurrence of disease outbreaks as well as help optimize disease management strategies.

Authors Contributions:

Ms. Ashwini Tayde-Nandure and Dr. Adiba Shaikh Conceptualize the Topic. Ms. Ashwini Tayde-Nandure Performs the literature review and wrote the Manuscript. Dr. Adiba Shaikh guides and Approved the Manuscript writing.

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