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Innovative Methods for Diagnosis Evergreen Utilizing Ultraspectral Image Inspection: A Review

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ABSTRACT

Plant diseases result in large financial losses in the global agricultural production industry. Regarding crop production, early disease detection, measurement, and identification are essential for the focused use of control measures. Extensive scientific research is now underway to provide novel hyperspectral technology-based solutions for plant disease diagnosis. By looking at the reflectance spectrum of plant tissue, you can tell the difference between healthy and sick plants, figure out how bad the disease is, name different pathogen species, and find early signs of biotic stress, even when the symptoms are not readily apparent to the unaided eye during the incubation phase. The review covers of fundamentals determining the reflectance spectrum of plant tissue. There is a discussion and evaluation of the potential applications of several kinds of hyperspectral Sensor technology and platforms for plant disease examination. Hyperspectral analysis, a relatively new field, employs techniques from image analysis and optical spectroscopy to measure physiological and morphological characteristics simultaneously. The following are the key phases of hyperspectral data analysis: modeling and data analysis; data extraction and processing; and picture collection and pre-processing. The algorithms and techniques used in each step are listed, then examine the primary uses of hyperspectral sensors in plant disease diagnosis, which include illness detection, disease classification and identification, damage assessment, and genetic resistance evaluation. An extensive analysis of scholarly literature highlights the advantages of hyperspectral technology in investigating pathogen-plant interactions across various measurement scales. Despite significant advancements in plant disease monitoring using hyperspectral technology over the past few decades, several unresolved technical issues still hinder their practical application. Finally, we explore the issues and future directions for the application of new technology in agriculture.

Key Words: Evergreen Diseases, Image Analysis, Hyper spectral Technology, Plant Diseases, Spectral Analysis.

1. INTRODUCTION

Evergreen diseases cause crop losses, lower agricultural product quality, and may even pose a health risk to humans worldwide. Accordingly, agricultural producers require cutting-edge and efficient instruments in order to identify and diagnose plant diseases early [1]. Large agricultural operations are unable to employ traditional diagnostic approaches because they require a significant amount of time and human resources, such as visual examination and microbiological laboratory investigation. In the last several years, with the use of robots, computer vision, machine learning, and sensor technologies, new non-invasive techniques when it comes to identifying plant diseases are emerging quickly [2, 3, 4]. They operate well, provide real-time data, and let you examine a wide variety of physiological indicators [5].

Many contemporary sensors provide vast amounts of data that, by computer data processing and modeling, are converted into new knowledge, filling the gap between fundamental science and real-world application. [6]. By automating the diagnosis process, these methods can greatly improve its speed and accuracy while removing the subjectivity that comes with using human judgment [7].New digital technologies enable the use of various spectral areas for picture analysis. Image registration uses optical sensors such as fluorescence sensors, tomographs, thermal, RGB, and hyperspectral cameras [8].There has been substantial advancement in the methods for analyzing hyperspectral pictures to diagnose plant diseases [9]. Hyperspectral analysis integrates optical spectroscopy and image analysis techniques to simultaneously examine physiological and morphological aspects. This essay provide the reader with a comprehensive introduction to modern methods that utilize hyperspectral image analysis for the diagnosis of perennial illnesses. The article's first section covers the fundamental ideas and instruments of hyperspectral technology. This section describes the algorithms and techniques for analyzing hyperspectral pictures. The next section provides a succinct summary of research papers on this subject. The final section covers the issues and future directions of modern technology use.

2. BASIC PRINCIPLES AND TOOLS OF HYPERSPECTRAL TECHNOLOGIES

2.1. Electromagnetic Radiation (EMR) And Plant Interaction With Light

Plant tissue may interact with light in the following broad ways: transmission, absorption, scattering, and reflection. The metabolic makeup and physical characteristics of plant tissue determine the reflecting feature [10]. The wavelength also has an impact on how plants and light interact. Because photosensitive pigments (carotenoids, anthocyanins, and chlorophylls) absorb light, plant surfaces have poor reflectivity in the visible wavelength range (400–700 nm). Light scattering in the intercellular gap causes an increase in reflectance in the near-infrared (700–1100 nm) region. Healthy plants exhibit low reflectance in the shortwave infrared region (1100–2500 nm) because of light absorption by proteins, water, and other carbon components [11]. The leaf's unique reflectance peak at 550 nm is compatible with its green hue. Plants in good health may have different spectral signatures than those that are sick. Plant tissues undergo biochemical composition changes due to biotic and abiotic stresses. These changes manifest themselves in plant cover morphology, transpiration rate, leaf color and shape, and ultimately in plant spectral properties (4). Furthermore, distinct plant-pathogen interactions have unique temporal and spatial dynamics that impact various electromagnetic spectrum ranges. Thus, for instance, variations in photosynthetic activity brought on by pathogen exposure impact reflectance throughout the visible spectrum.

The near-infrared spectrum is significantly impacted by cellular changes. An increase in reflectance in the short-wave infrared spectrum is a result of tissue necrosis (6). The study of spectrum aspects related to the effects of biotic and abiotic stressors is what leads to the creation of new technologies that can find plant diseases.

2.2. Using hyper spectral Platforms And The Detectors

The fundamental idea behind RGB and multispectral cameras is similar to that of hyperspectral sensors [12]. Each of these devices records the amount of light that reaches the sensor by measuring it. Within its wavelength range, a hyperspectral sensor may measure several hundred bands of the electromagnetic spectrum. This is in contrast to RGB cameras, which only measure three spectral bands, and multispectral cameras, which record less than twenty bands. Each of these spectral bands only covers a small portion of the electromagnetic spectrum in terms of wavelengths, achieving a high degree of spectral resolution. Various applications often utilize two types of sensors: image sensors and non-imaging sensors. Rather than storing spatial information, non-imaging sensors measure the average reflectance spectrum across a given surface area. The focal length, viewing angle, subject distance, and standing posture influence the average area size. The majority of non-imaging sensors are handheld and don't need as complicated platforms as measuring instruments do. These objects weigh 1-2 kg and have a wide range of wavelengths from 300–2500 nm, as well as a high level of precision in distinguishing between different wavelengths with a resolution of 1-3 nm. The most well-liked spectrometers are ImSpector [13,14], frequently use these spectrometers in laboratory, greenhouse, and field settings. Additionally, unmanned aerial vehicles (UAVs) can utilize micro spectrometers like the STSVIS spectrometer from Ocean Optics Inc. In the USA Spectrophotometers can only detect a limited number of early plant disease signs because they frequently manifest in sizes less than 1 mm. This is due to the measuring area's averaged spectrum of healthy and ill tissue [16].

By creating a spectrum profile for every single pixel, hyperspectral image sensors combine spectral and spatial resolution. The resultant image is a hypercube, or a three-dimensional data matrix, with one extra spectral dimension in addition to two spatial dimensions of information. There are four methods to produce a data hypercube based on the kind of sensors being utilized: point scanning, linear scanning, spectrum scanning (spectral scanning), and snapshot [17]. Typically, hyperspectral imaging sensors span a small range, such as VNIR (300–1000 nm) or SWIR (1000–2500 nm), with a spectral resolution of 1-3 nm. Depending on the sensor's properties and the distance to the object, the spatial resolution can range from micrometers to centimeters. In the case of line or point scanning sensors (such as pushbrooms and whistlebrooms), moving the subject or camera is required in order to capture the spectrum of each unique point or line and produce a hyperspectral image. Scientific research is the main use for specific brand scanning cameras are primarily used for scientific research. In laboratory settings, specialized moving platforms mount the majority of hyperspectral scanning cameras, enabling both linear movement and camera stabilization [18].

Researchers use stationary rail systems in greenhouse conditions wheeled vehicles in field conditions or unmanned aerial vehicles (UAVs) [18,5]. One drawback of scanning sensors is that, based on the region being measured's size, they might take a while to get an image, making it more difficult to snap pictures of moving objects. Specim IQ portable cameras eliminate this flaw with an integrated scanner [19,20]. Sensors based on the spectrum scanning concept use LCTF filters, which only transmit light of

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a certain wavelength that varies quickly during recording [21]. For any wavelength within the spectral spectrum, these sensors provide two-dimensional spatial pictures.

To obtain a hypercube when working with them, neither the subject nor the camera need to move. When you primarily control the exposure time throughout the image capture process, picture registration occurs more quickly in contrast to line or spot scanning. This kind of measurement may result in contradicting spectra if the object is moving since various bands show at different times. Researchers have created new sensors that can provide hyperspectral images (snapshots) without the need to scan an item. They take advantage of the traditional RGB camera's mosaic concept. Compared to conventional ones, these sensors offer a noticeably faster rate of picture capture, but at the expense of a reduced spatial resolution. Some well-known brands of these cameras are Ultris, FireFleye, Senop, and Rikola. They are ideal for usage on UAVs due to their small size, quick acquisition time, and capacity to provide sequences of hyperspectral pictures of a moving object [22,5].

3. HYPERSPECTRAL IMAGE ANALYSIS ALGORITHMS AND TECHNIQUES

Hyperspectral photos pose a novel and highly complicated challenge for non-trivial solutions because they contain massive amounts of data with a high degree of collinearity. These days, neural networks, machine learning, and discriminant and cluster analysis techniques have all been effectively applied for these uses [23]. Specialized software, such as MATLAB, Python (Python Software Foundation), and ENVI (Research Systems Inc.), performs data processing. Typically, the steps involved in evaluating hyperspectral pictures are as follows: image capture and pre-processing, data extraction, processing, modeling, then data analysis.

3.1. Receipt and Image Pre-Processing

The most crucial and initial stage in the analysis of plant diseases is to collect high-quality hyperspectral pictures that satisfy the study's goals. Proper lighting design, scanning speed, frame rate, exposure duration, and spatial and spectral resolution are all necessary for accurate results, as is the selection of sensors and platforms [24].

Image pre-processing, which involves spectrum correction and calibration, is the next stage. Standardizing the spectral and spatial axes, increasing precision, guaranteeing data repeatability under different experimental settings, removing the influence of the recording surface's curvature, and removing instrumental mistakes are all goals of calibration [25]. Reflectance calibration is the conventional method, and two reference spectra "black" and "white" are utilized. By placing an opaque cover over the camera lens, the "black" spectrum may be produced. To acquire the maximum intensity of each pixel at each wavelength, the "white" spectrum is recorded using a common white surface (such as Teflon) with a reflectivity of around 99.9%. Next, the formula is applied to calibrate the original hyperspectral picture.

$$R = \frac{IS - ID}{IW - ID}$$

Where: IS represents original image, ID and IW denote the dark and white reference pictures, respectively, and R denotes the finalized image.

Methods to remove the surface curvature effect during calibration include the adaptive spherical transform [25], Lambert transform [26], and spectral image normalization [27]. Enhancing image quality is the goal of spectrum modification. For instance, we employ smoothing methods like moving average, To reduce noise in spectral data, apply a median filter, a Gaussian filter, Fourier, and wavelet transforms. The spectral baseline shift is adjusted by the first and second derivatives. Multiplicative correction of scattering or normalization using a standard transformation are two methods used to rectify scattering.

3.2. Data Extraction and Processing

After picture segmentation, select informative features for further analysis.

Before spectral analysis, image segmentation typically serves as a data pre-processing phase, separating target objects from the background and creating regions of interest (ROI). There are known segmentation techniques, such as these: the watershed algorithm, the clustering techniques (Kmeans), the threshold value (threshold-based) and the edge detection methods [28]. Finding meaningful features in hyperspectral pictures is one of the most important steps in the analysis process. By merging and refining spectral, spatial, and textural properties, Making new feature vectors and extracting them is its aim., which it then feeds into different machine learning algorithms or classifiers. Disease indicators (DI) and vegetation indices (VI) can offer informative features [29]. In this instance, the number of wavelengths needed for analysis is minimal. Researchers apply techniques to decrease dimensionality and remove autocorrelations when examining the whole spectrum. They include principal component analysis, stepwise discriminant analysis, linear discriminant analysis, discriminant analysis of partial least squares (also known as partial least squares discriminant analysis), noise reduction algorithms, and other techniques.

3.3. Evaluating Data And Modelling

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Choosing a model and applying it to the data is the last stage in image analysis. Regression models are one type of these (for anticipating and assessing the relationship between spectral response and goal variables) or classification models (for identifying and classifying disorders), depending on the objectives of the investigation. Classification models utilizing neural networks, machine learning, and algorithms are the most popular models [30Various techniques are employed, Regression techniques include maximum likelihood classifier, knearest neighbor, support vector machine, and spectral angle mapper; they also include multiple linear regression, binary logistic regression, partial least squares regression, and Dirichlet aggregation regression. [31].

4. APPLICATION DOMAINS FOR HYPERSPECTRAL TECHNOLOGY

Detecting the illness, differentiating and identifying the kind of disease, estimating the extent of damage, and estimating genetic resistance are the primary tasks involved in diagnosing plant diseases. The corresponding measurement scales at various levels of the living systems organization resolve these issues.In the lab, scientists use hyperspectral microscopes to measure at the cellular or plant tissue scale, seeing fungal spores and identifying metabolic alterations in tissue brought on by plant-pathogen interactions. Basic research often conducts these studies to identify pathogens and assess genetic resistance to some extent.Measurements at the level of specific organs, or the entire plant, in a laboratory, greenhouse, or outdoor environment, aid in the early identification and classification of diseases.Plant-scale measurements resolve the issues of diagnosing the illness and estimating the extent of plant damage.

4.1. Disease Detection

When diseases are discovered, plants must be identified as healthy or sick. The study's focus is on a single particular disease and all of its manifestations, dynamics, and circumstances. Look at how different sensors might be used to find fusarium (Fusarium graminearum and F. culmorum) in wheat ears early on. The experiments used chlorophyll fluorescence sensors, hyperspectral imaging, and infrared thermography in controlled laboratory settings. As early as the fifth day following plant inoculation, infrared thermography reveals the temperature differential inside infected spikelets. On day five, a shift in the fluorescence of the chlorophylla spikelets indicated a breach in photosynthetic activity. On the third day, it was possible to tell the difference between spikelets that had Fusarium and those that had not yet been injected by using a simple ratio based on pigments that was derived from hyperspectral images in the 400–2500 nm wavelength range. We employed the support vector machine (SVM) for categorization. For hyperspectral imaging, it was 78%; for thermography, it was 56%; and for chlorophyll fluorescence, it was 78%.

In the study, contrast two approaches. The study focuses on two approaches for hyperspectral imaging-based citrus canker disease (Xan thomonas citri) detection: in vitro imaging and UAV-based remote sensing. Two classification techniques are used radial basis function and knearest neighbors in the lab to identify citrus canker on leaves and immature fruits at various stages of the disease's development. The same sensor installed on a UAV to detect citrus canopy in the field. For identifying leaf canker in the lab, the RBF method's overall classification accuracy was greater (94, 96, and 100%) than the KNN method's (94, 95, and 96%). It was feasible to distinguish between healthy and canker-infected trees with 100% classification accuracy by using UAVs for remote sensing. Of the thirty-one vegetation indicators examined, in the field and in the lab, the most reliable methods for recognizing cankers are the modified chlorophyll absorption index (TCARI) and the water index (WI), respectively. Furthermore, the proposed method yielded a 92% classification accuracy in late-stage canker-infected fruit identification.

4.2. Identification of Diseases

Determining the type of pathogen affecting the plant is essential for making medical diagnoses. This study focus on various illness types and their distinguishing characteristics. A.K. Mahlein and associates suggested using certain "spectral disease indices" to distinguish between disease plants. Sugar beet plants with three leaf diseases (Powdery mildew, sugar beet rust, and Cercospora leaf spot) comprised the model system. the spectral profiles of both healthy and sick sugar beet leaves was captured at varying phases of growth and damage using a spectroradiometer, eliminating the need for imaging. Using the RELIEF approach, we identified the key wavelengths and two-band normalized changes that accurately represented the disease's effect on the reflectance spectrum of the leaf in the dataset. The spectral sickness index was computed by employing the best weighted combination of a single wavelength and the normalized difference in wavelengths. The enhanced disease indicators underwent testing. The difference between sugar beet leaves with a Cercospora leaf spot and healthy leaves with excellent sensitivity and accuracy. The classification accuracy for powdery mildew and rust was 85%, 92, 87, and 89, respectively.The study showed a new way to use hyperspectral photos to tell the difference between yellow rust (P. striiformis) and wheat leaf rust (Puccinia triticina). This work demonstrates the interpretation of spectral reflectance combinations during pathogenesis.

4.3. Assessment of the Extent of Damage

One of the key applications of hyperspectral research is the quantitative diagnosis of the extent of disease damage to plants. The degree and frequency of the lesion and its frequency are the primary factors used to determine the disease's severity.

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Furthermore, we sometimes regard water content, structural factors, and pigment content as indirect assessment criteria, contingent upon the infections and the symptoms they induce. Utilized hyperspectral imaging to determine the spatial arrangement of carotenoids and chlorophyll in cucumber leaves affected by an angular patch. The researchers used biochemical studies to assess the pigment content [32].

In this study constructed partial least squares regression (PLSR) models for five damage degrees and conducted a quantitative examination of the correlation between the degree of damage, spectrum, and pigment content. Next, select the ideal wavelengths for the models. In conclusion, and applied optimum models to hyperspectral pictures to achieve pixel-by-pixel mapping of the distributions of carotenoids and chlorophyll in cucumber leaves. A study used spectral analysis to determine the extent of powdery mildew damage on wheat leaves [33].

The lab used a spectroradiometer to measure the hyperspectral reflectance of powdery mildew-damaged and healthy leaves. A disease index scale with nine points is used to assess the extent of damage. A total of 32 spectral indices computed and analyzed using an independent t test and correlation analysis. We used two regression models, partial least squares regression (PLSR) and multivariate linear regression (MLR), to determine the severity of powdery mildew. We selected seven spectral indices through analysis of the cross-validation findings to successfully reduce the relative root-mean-square error. Using the seven chosen indices, the PLSR model fared better than the MLR model, obtaining a relative root mean square error of 0.23 and a coefficient of determination of 0.80.

4.4. Evaluating Gene Type Resistance

Analyzing the pathogen-host interaction is crucial to breeding efforts because it makes it possible to segment genotype resistance to a particular disease. In breeding practice, we phenotype plant genotypes through costly and time-consuming visual evaluation. Within this framework, hyperspectral analysis is a viable, non-invasive technique to expedite and mechanize traditional phenotyping approaches.

The study evaluated the resistance of five genotypes of sugar beets against Cercospora leaf spot. Scientists conducted the experiment under strict controls. We evaluated the extent of leaf damage using hyperspectral analysis in conjunction with traditional quantitative and qualitative approaches. We have demonstrated that the density and spatial distribution of pathogen spores on the surface determine the spectral properties of the diseased leaf sections. This enables genotypes that are unstable and resistant to the disease to be differentiated according to the extent of damage. A method called hyperspectral sporulation analysis-based lesion severity assessment might be a good way to find small genetic differences that make plants resistant to disease.

5. PROBLEMS AND PROSPECTS FOR THE USE OF HYPERSPECTRAL TECHNOLOGIES

Despite significant advancements in plant disease monitoring using hyperspectral technology over the past few decades, several obstacles still hinder the practical application of these techniques. The pursuit of answers will define future trends. Early field identification of plant diseases is one of these issues. Currently, agricultural production makes extensive use of low-altitude, aerial, and satellite multispectral systems to monitor the condition of plant cover based on vegetation indices [34]. However, trustworthy observation is typically only possible once symptoms have fully manifested, so it may be too late to start taking preventative action. Although there has been much advancement in the science of using hyperspectral sensors for early plant disease diagnosis, there are still obstacles to be overcome before these sensors can be used in field and greenhouse settings for precision farming systems. We position a camera or sensor at a specific angle to the leaf tissue to record the directions of incoming and reflected light. Most scientific investigations on this topic typically take place in well controlled environments, often with artificial lighting. Accurately detecting illnesses is quite difficult because the light in the field is very different from that in the lab. The foliage's brightness is noticeably greater in the sun than in the shadow. Another factor influencing the subject's spectral characteristics is its inclination angle with respect to incident and reflected sunlight. The brightness of a picture varies every minute. Consequently, the overall brightness of an image at a specific location and When determining a threshold to differentiate between healthy and sick tissue, the angle of incidence of light is a crucial factor that has been the subject of much investigation [35]. Accurately defining a particular sickness under real world circumstances presents another challenge when several factors are affecting the culture at the same time. Nowadays, the majority of monitoring investigations are conducted in experimental areas where the pathogen's type has already been identified. When such information is lacking, it is challenging to obtain precise and dependable findings. Several diseases and abiotic stimuli share similar symptoms and spectral signatures. Some contemporary techniques, such as deep learning algorithms, can facilitate the distinction between biotic and abiotic stresses in both field and greenhouse settings.

6. CONCLUSION

Worldwide, plant diseases result in large financial losses for the agricultural production industry, particularly in light of the recent impact of climate change. The utilization of hyperspectral sensors and platforms is a viable technological solution for

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the non-invasive, rapid, efficient, and trustworthy diagnosis and detection of plant diseases. Information outside of the visible spectrum is provided by new technologies, which improve human vision. Plant tissue reflection spectrum analysis makes it possible to identify various pathogen types, classify healthy and ill plants, assess the severity of the disease, and identify early indicators of biotic stress. There are many stages to this process, one of which is the incubation phase, during which the symptoms are not readily apparent.

Machine learning and neural networks show enormous promise in analyzing hyperspectral data because of their vast quantity of information. Hyperspectral approaches for plant disease diagnosis are still in the early stages of development. Several technological challenges restrict the use of this costly technology in the production process. Hyperspectral imaging holds enormous promise as a beneficial tool for comprehending plant diseases, provided that sensor technology and data analysis methodologies advance.

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