Imran Ul Haq
Siddra Ijaz *Editors*

Trends in Plant Disease Assessment

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Editors
Imran Ul Haq
Department of Plant Pathology
University of Agriculture Faisalabad
Faisalabad, Pakistan

Siddra Ijaz
Centre of Agri Biochemistry and Biotech
University of Agriculture Faisalabad
Faisalabad, Pakistan

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Preface

Disease assessment is an essential aspect of the plant disease epidemics study. Phytopathometry is the foundation for all subsequent analyses, interpretations, characterization, and comparisons of plant disease epidemics. Disease quantification represents the magnitudes of the effectiveness of management strategies adopted in controlling plant diseases and also provides numerical estimates of crop losses due to these diseases. The accuracy in plant disease assessment is the pillar of integrated disease management. An assessment in a precise way to represent a quantitative link between theory and practice of disease management. If someone wants to develop a predictive model in a meaningful way, disease intensity must be quantified with a high degree of accuracy. Therefore, we are attempting to provide the readers with comprehensive information in a well-compiled way. Any manuscript reflects the authors' specialty, interest, and training. As the title of this manuscript depicts, it deals with plant disease assessment approaches. In this manuscript, a broad topic of study, "Plant diseases assessment," has tried to break down into different striking chapters. It will give a comprehensive picture of approaches to visual estimation for assessing plant diseases.

This book will help plant scientists directly or indirectly deal with plant disease diagnosis and management. It will be helpful for researchers and students in gaining knowledge and skills in disease quantification, developing predictive models for plant disease epidemics, assessing crop losses, and the magnitude of plant disease control methods. This book deals with the classical concept of plant disease assessment and methods based on visual observations to knowledge regarding the modern and emerging technologies in phytopathometry, predictive models, disease warning systems, and decision support systems. It will delineate remote sensing approaches for assessing diseases in plants. Here, we squeeze it with a statement that this manuscript gives a beautiful shift from classical to modern approaches to explaining plant disease assessment.

Faisalabad, Pakistan

Imran Ul Haq
Siddra Ijaz

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About the Editors

Imran Ul Haq with a bright career in agriculture, plant pathology, and fungal molecular biology, had Post Doc from the University of California Davis, USA. He is currently serving as an Associate Professor in the Department of Plant Pathology, University of Agriculture Faisalabad, Pakistan. He has supervised more than 40 graduate students and established the Fungal Molecular Biology Laboratory Culture Collection (FMB-CC-UAF), an affiliated member of the World Federation for Culture Collections (WFCC). He has published more than 50 research articles, 6 books, 4 laboratory manuals, and several book chapters. He has made colossal contributions to fungal taxonomy by reporting novel fungal pathogen species in plants. His research interests are fungal molecular taxonomy and nanotechnology integration with other control strategies for sustainable plant disease management.

Siddra Ijaz with a vibrant career in agriculture and biotechnology, had a Post Doc from the Plant Reproductive Biology Laboratory, University of California Davis, USA. She is currently serving as an Associate Professor in the Center of Agricultural Biochemistry and Biotechnology (CABB), University of Agriculture, Faisalabad, Pakistan. She is also serving as Deputy Managing Editor of an international impact factored Journal. She has supervised more than 50 M.Phil and Ph.D. students. She has published more than 50 research articles, 7 books, and several book chapters. Her research focus includes plant genome engineering using transgenic technologies, genome editing through CRISPR/Cas systems, nanobiotechnology, and exploration of genetic pathways in plant–fungus interactions.

Phytopathometry: A Transdisciplinary Concept

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Imran Ul Haq and Siddra Ijaz

Abstract

Globalization, modern cultivation techniques, climate change, and human activities have promoted the distribution of plant pathogens, resulting in frequent host–pathogen interactions and disease incidences. These causative factors are impossible to control as even the most rigorous quarantine system could not completely avoid the movement of plant pathogens and germplasm across countries and continents. Susceptibility of cultivated varieties against plant pathogens, especially fungi, has significantly increased because varieties are developed focusing on higher yield. Additionally, plant pathogens undergo frequent mutations and genetic changes to adapt to climate changes, overcome pesticide resistance, and infect plant germplasm previously resistant. Plant disease identification, quantification, and estimation of subsequent yield losses are crucial in modern-day agriculture to ensure food safety and security for the increasing global population. Phytopathometry utilizes systematized and specialized approaches for plant disease assessment and presents qualitative and quantitative data. Phytopathometry underpins all activities in plant pathology and extends into other related disciplines such as agronomy, plant breeding, and horticulture. Digital and biotechnology underpinned by contemporary artificial intelligence efficiently process sensory data for plant disease measurement. Modern phytopathometry tools aided with detailed knowledge of pathogen–host system biology are poised to become an integral part of precision agriculture.

I. Ul Haq (✉)
Department of Plant Pathology, University of Agriculture Faisalabad, Faisalabad, Pakistan

S. Ijaz
Centre of Agricultural Biochemistry and Biotechnology (CABB), University of Agriculture Faisalabad, Faisalabad, Pakistan

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Use of machine learning, deep learning, digital technology, biotechnology, engineering, and nanotechnology in phytopathometry is exposing plant pathologists to new terminology, concepts, and ideas which were not even thinkable a few decades ago. Moreover, innovations in robotics have provided flexibility and precision in deploying these sensors for accurate disease assessment, even in large field areas. In this chapter, we have discussed various phytopathometry tools and approaches and their transdisciplinary uses.

Keywords

Disease index · Visual assessment · Remote sensing · Digital imagery · Artificial intelligence · Advanced technology

1.1 Introduction

Phytopathometry is the branch of plant pathology that utilizes systematized and specialized approaches to assess and measure plant diseases. This neologism was first coined by Large (1953) in his research article on late blight of potato and choke of cocksfoot diseases. He researched acquiring valuable data/information from disease surveys based on the new science of phytopathometry (Large 1953). Phytopathometry was derived from the Greek words "phyton" plant, "pathos" disease, and "metron" measure. Phytopathometry is a ""branch of phytopathology that deals with detection, identification, and measurement of plant diseases indicated by disease symptoms or pathogen signs on particular disease sample/s."

Gregory (1982) recapitulated E.C. Large's disease measurement requirements focusing on resulting yield losses: morphological characteristics and development of healthy crop plants; disease path and trajectory on field plants; evaluation of disease intensity by devising/utilizing standard area diagram or field key; assessment of disease progression in field trials over the course of several years and comparing yield with control plots; assessment of disease severity concerning particular host growth stage and its effect on yield by using disease progress curves. This tactical and expanded perspective of phytopathometry, stated by E.C. Large and reiterated by P.H. Gregory, encompasses yield losses on disease (Gregory 1982; Nutter et al. 1991; Large 1966). However, phytopathometry should not be considered synonymous with an estimation of plant disease losses because it is a broader term aiming to ameliorate the recording and reporting of plant diseases by presenting qualitative and quantitative results. This encompassing approach makes phytopathometry a transdisciplinary concept as it helps in forecasting yield losses (agronomy), breeding aiming for resistance against plant diseases (plant breeding and genetics), evaluation of disease control methods and their application time, system biology and co-evolution of host–pathogen interaction (biotechnology), and myriad other reasons. Hence, phytopathometry underpins all plant pathology activities and extends into other related disciplines. Artificial intelligence (AI) and digital technology have recently been used to design automated sensors in phytopathometry (Madden et al. 2007b; Bock et al. 2010, 2016).

It is worth mentioning that phytopathometry measures plant diseases but is not limited or subservient to disease epidemiology or crop yield losses as its services intersect with statistics and measurement science and also interface closely with visual disease assessment and imaging and sensing technology. Historically, visual disease estimation was standard as compared to instrument-based disease measurement. Recent advances in imaging and sensing technology have significantly improved and opened new horizons for remote phytopathometry, especially in achieving the goals of plant disease quantification. This sensor-based and remote sensing approach in phytopathometry is transdisciplinary as it involves plant pathology, engineering, agronomy, and information technology (Bock et al. 2021).

1.2 Role of Phytopathometry in Precision Agriculture

Globalization, recent cultivation techniques, climate changes, and human activities promoted the distribution of plant pathogens and resulted in frequent plant–pathogen interactions and disease incidences. These causative factors are almost impossible to control, and the most rigorous system of quarantine and preventive measures could not completely avoid the movement of pathogens and plant germplasm across continents. Susceptibility of plants against pathogens, especially fungi, has increased in modern cultivation practices because crop varieties are developed focusing on higher yield. These varieties, as compared to wild relatives, are less adaptive to local conditions and less resistant to pathogens. Additionally, pathogens have undergone genetic changes to adapt to climatic changes and overcome plant and pesticide resistance. New pathogenic strains have emerged, posing new challenges to sustainable agriculture. Cultivation of genetically uniform crop plants, unbalanced fertilizers and pesticides, reduced crop rotation, and low tillage cultivation may further aggravate the crop yield losses. With new challenges to crop production, demand for innovative strategies to identify and control plant pathogens has also increased. Plant pathogens compromise the quality, quantity, and input costs, seriously threatening world food safety and security. For practical crop production, balanced approaches to integrated plant protection are being proposed by researchers. These approaches recommend crop rotation, resistant verities, effective chemical and biological plant protection strategies, accurate estimation of disease severity, and monitoring of the spread of plant pathogens (Parnell et al. 2017; Oerke and Dehne 2004; Gewin 2003; Fisher et al. 2012; Brasier 2008; Ul Haq and Ijaz 2020; Ul Haq et al. 2020).

1.3 Phytopathometry Tools in the Modern Era

Today, visual disease assessment based on scientific reasoning and understanding provides a firm base to reliably and accurately assess plant diseases, i.e., standard area diagrams (Del Ponte et al. 2017) and ordinal disease scale (Chiang et al. 2014). However, digital technology underpinned by contemporary artificial intelligence incredibly processes sensor data for measuring disease severity. Image analysis, thermal imaging, and chlorophyll fluorescence are innovative and practical assets of disease measurement. Innovations in robotics have provided flexibility and precision in the application of these assets. Hence, digital technologies are poised to become an integral part of precision agriculture. AI has been applied to plant pathometry, though recently, and is crucial for the field success of ingeniously designed sensors. The use of AI and digital technology in phytopathometry exposes plant pathologists to new concepts, terms, and ideas that were not even thinkable a few decades ago (Bock et al. 2022).

1.4 Phytopathometry Approaches

Disease quantification by symptomatology falls under the umbrella term "remote sensing." Remote sensing could be defined as gathering and monitoring the physical information about an area/object by measuring the radiation (reflected/emitted) without direct contact. Various methods are used to detect, identify, and quantify the symptoms such as thermograph, laser induced fluorescence, nuclear magnetic resonance imaging, radar, microwave, and cameras. Visual estimation and image analysis technologies fall under remote sensing (Abazov et al. 2006).

Disease severity is determined by analyzing the digital image of a given sample. It could be inferred by the disease-affected area, and the texture and color of the infected area by using the segmentation step are quantification algorithms which isolate the affected area from healthy plant parts and process. Disease severity analysis based on symptoms, even if performed by plant pathologists who follow the complete diagnostic guidelines, results in variability or error due to some degree of subjectivity. This statement means that methods employed to validate the automatic approaches to disease quantification are also subject to some degree of variability. It should be considered when evaluating the performance of remote sensing methods (Arnal Barbedo 2013; Merga 2018).

1.4.1 Visual Disease Assessment

In visual assessment, the eye and the relevant parts of the brain, in combination, work rapidly to acquire an image, process and interpret it, and act as an image analysis system. This quick process helps the observer to assess the disease type and severity of a particular plant sample. The observer's response regarding detection and disease estimation depends upon the visual rater's cognitive ability, eye health, and how light/color is perceived (Bock et al. 2010). Various disease assessment scales are used in visual phytopathometry:

1.4.1.1 Nominal Scales

These scales differentiate disease stages through simple descriptive terms such as "mild," "moderate," or "severe." These scales are subjective and lack quantitative information. These scales are used only when the observer performs the task at a particular location and in a specific season (Bock et al. 2021; Nutter et al. 1991).

1.4.1.2 Ordinal Scales

Ordinal scales are widely used while rating disease severity for viral diseases as symptoms are difficult to measure quantitatively (Madden et al. 2007a; Bock et al. 2010). These disease severity scales are also descriptive, simple, and have use for a particular observer, location, and season. These scales divide disease severity stages into different classes which represent the increasing disease symptoms severity. These scales are further explained by different diagrams and mostly in descriptions explaining symptoms intensity. Sometimes, mostly in case of fungal diseases, these grade fungal disease severity divides the symptoms into numerals, e.g., ranging from 0 to 9. These are also used in disease resistance breeding programs while assessing genotypes.

1.4.1.3 Interval Scales

Disease interval scales, also known as category scales, comprise different categories that contain numerals representing disease severity in percentage. These scales include a standard area diagram of different levels, e.g., 1–5 for rust diseases, illustrating symptoms severity of 1%, 5%, 10%, 20%, and 50%. Hence, the sample leaf is assigned a specific category by the observer.

1.4.1.4 Ratio Scales

The ratio scale is a percent scale and has been used in phytopathometry over the years for studying various diseases. In this scale, the observer has a continuous range of percentages from 0% to 100% and grades the sample leaf according to the percentage area covered by the disease symptoms. Observers, according to their ability, vary in accuracy and reliability while assessing disease severity.

1.4.1.5 Advantages and Disadvantages of Visual Disease Assessment

Visual disease assessment is quick. Rater's ability to identify and differentiate between different diseases could be enhanced with some training. Rater can choose from various available disease rating scales and can assess disease severity without any equipment. Visual assessment accuracy depends only on the observer's ability, health, and concentration. This subjectivity results in significant variability in disease assessment. However, visual inspection is used by farmers and plant pathologists to assess the disease for the foreseeable and more appropriate disease control strategy. Other remote sensing and phytopathometry approaches are making significant contributions.

1.4.2 Digital Imaging in Phytopathometry

Visual monitoring is a widely used method in plant disease detection and, if combined in a prognosis system with regional weather and other epidemiological parameters, can help forecast disease spread in specific regions. It, especially the moisture and temperature data, could help in timely and effective plant protection strategies to avoid the upcoming disease threat in fields or greenhouses (Bock et al. 2010). However, visual disease assessment by an expert in the area is time-consuming and requires an observer, which is a bottleneck in disease management, especially when monitoring large fields. Hence, various other innovative methods are being developed to estimate and accordingly adapt disease control strategies effectively.

Disease severity plays a crucial role in understanding the disease development and consequent losses in various pathosystems but is challenging to achieve in visual and sensory-basedphytopathometry approaches. Since the first visual assessment attempt of disease quantification by Cobb in 1892, it has significantly improved and is better understood (Cobb 1892). Though instruments, cameras, and aerial photography, were used in the first half of the twentieth century (Bawden 1933) but usage of proximal tools for remote sensing was performed and reported in the late twentieth century, i.e., thermal spectrometers (Pinter et al. 1979), image analysis (Lindow and Webb 1983), and multispectral radiometer (Nutter et al. 1985). The nascent remote sensing field owing to sophisticated sensors is significantly effective in identifying, detecting, and measuring the disease (Mahlein et al. 2018; Bock et al. 2022).

1.4.2.1 Principles of Photography

Photography has been used in phytopathometry for many decades. Aerial photography started in the 1920s still and continue to use to detect and quantify plant disease severity. Microscopic digital image analysis is widely used in plant pathology to study pathogen's morphology. Digital cameras are inexpensive and commonly used in laboratories and fields. These are the primary device while sampling and are easy to use, and the rater could study the disease symptoms later. Digital cameras include a light-sensitive screen (which captures the light from the image), a lens (increase magnification), and a display screen. Monochromatic cameras measure the intensity of the incoming light with photo sensors on their screen. Photo sensors convert captured light into electric charge and release proportional to the received light intensity. Photo sensors are memory cells whose contents, analog signals, are then converted into binary signals (0, 1) with the help of a frame grabber, and the binary data is transmitted to the computer. Computer based on these binary digital readings of 0 and 1 draws the image on the screen. So, each photo sensor on a digital camera's screen is represented on the computer screen by a pixel whose location and brightness are determined through image processing. On their photosensitive screen, color cameras have specific photo sensors for red, green, and blue. These photo sensors could be re-arranged in different ways. Each photo sensor is sensitive to particular wavelength/color, and the final image is prepared by advanced image analysis, which compares each pixel with its surrounding pixels using an interpolation algorithm. This algorithm portrays the original color of the sample by using the RGB color model.

1.4.2.2 Factors Responsible for Image Quality

Various factors that affect digital image quality, such as focus, light on the object, and light uniformity, are affected by image analysis.

1.4.2.3 Pros and Cons of Digital Photography

Image analysis systems with agreement verification are quick, accurate, reliable, powerful, and relatively inexpensive. According to needs and issues, specific software is adapted in phytopathometry. However, there is tremendous variability in plant color, shape, texture, and disease symptoms which influence the performance and results of image analysis. Software should deal with various diseases on various plants and varying physiological conditions or damage on sample leaves. Hence, program training and ground trothing are done to make it more efficient and ensure quality disease severity measurement results.

1.4.3 Android Applications to Quantify Plant Disease Severity

Android portable applications are new tools for semiautomatic disease assessment. These are used for individual leaves and other samples. These applications, such as "Leaf Doctor," use an algorithm to accurately, precisely, and robustly identify leaf shapes, lesion types, and disease severity. The accuracy of Leaf Doctor has been evaluated in various research articles, and it was found to have a low degree of error; however, in some cases, such as mallow rust and lilac powdery mildew, due to high color contrast between diseased and healthy leaf sections. Compromising contrast results in reduced accuracy and robustness of the Leaf Doctor Algorithm, such as in powdery mildew of Lilac (Barbedo 2014). Coefficient variation shows a significantly negative relationship (both linear and nonlinear) with mean observed disease severity, which is also observed in individual raters estimating disease severity manually. These applications are accurate, precise, and robust for most diseases with faster processing time. This application also helps rapidly construct standard area diagrams from actual host–pathogen systems, estimated by an expert. These SADs improve the accuracy and precision of estimates with excellent reproducibility (Braido et al. 2014; Pethybridge and Nelson 2015).

1.4.3.1 Image Processing Software

Image processing software allows the editing of the obtained image in various ways, i.e., contrast correction, image rotation, sharpness, inversion, and various other manipulations. It is achieved by using multiple image-enhancing software such as Adobe Photoshop. Image editing, modification, geometric correction, and edge enhancement are also performed using image analysis programs (Bock et al. 2010; Merga 2018). Specific image analysis protocols must be followed regardless of the software being explored. The color image is composed of red, green, and blue, and each image pixel has a specific value for each respective color based on the RGB model. This model generates the correct color in a three-dimensional color space.

1.4.4 Statistical Methods in Phytopathometry

Statistical models are used to analyze the false positives and negatives in image analysis by comparing them with visual observations of an expert. Statistical methods evaluate the quality of image analysis results compared with the estimated actual value for assessing disease severity. Moreover, the repeatability and reproducibility of various image analysis methods and statistical methods are explored (Zhao et al. 2009; Bock and Nutter 2011).

1.4.4.1 Regression Analysis

Regression analysis is widely used in image analysis to evaluate the quality of disease severity measurements. It judges the accuracy, precision, and reliability of results; however, it should be applied carefully as specific circumstances could generate incorrect conclusions. Standard errors, slope, and intercept are regression parameters assessing the estimated measurements' quality. Reliability and precision are measured using the coefficient of determination; its higher value indicates high precision. Various color and monochrome images of different disease samples assessed through image analysis were evaluated for accuracy and precision using a regression model.

1.4.4.2 Concordance Correlation Coefficient

Lin's concordance correlation coefficient quantifies agreement in disease severity by evaluating the degree to which the observations fall on the concordance line. It combines the systematic and constant bias measure of accuracy with precision to consider the relational fit to the concordance line. It was used in image analysis of citrus canker symptoms severity to investigate the precision and accuracy of results (Bock and Nutter 2011).

1.4.4.3 Analysis of Variance and General Linear Modeling

ANOVA and GLM investigate the source of error in disease severity estimates. Another method, Kruskal–Wallis test, compared the image analysis and visual assessments of powdery mildew on cherry leaves and found that image analysis produced significantly negative results compared to visual rating.

1.4.4.4 Correlation Coefficient

The correlation coefficient indicates the degree of precision in disease severity assessment obtained using various methods. It quantifies the strength between variables and measures it by working as a component of the concordance correlation coefficient, i.e., strawberry Phomopsis disease severity rating methods and citrus canker severity on grapefruit. Hence, it evaluates and compares various image analysis methods and raters. Bland–Altman plots, absolute error, relative error, and chi-square hypothetical variance tests are also used to assess the precision of image analysis by comparing with visual assessments.

1.5 Hyperspectral Imaging

Optical sensors operate within different regions of the electromagnetic spectrum to measure the changes in plant physiology either due to abiotic stress or due to the disease. Biotic or abiotic diseases cause changes in tissue color, canopy morphology, leaf shape, plant density, transpiration rate, and interaction of radiation with plant surface; these variations could be measured using highly sensitive and powerful sensors (Fiorani et al. 2012; Mahlein 2016). These sensors are noninvasive and provide information beyond the visible light spectrum, except RGB imaging, which expands human perception and phytopathometry capabilities. Hyperspectral sensing showed promising results in identifying various plant parameters and diseases. It enables the detection of biotic diseases and abiotic stresses, resulting in new opportunities for field phenotyping and disease management.

1.5.1 Spectral Resolution Range of Hyperspectral Sensors

Hyperspectral sensors have increased spectral resolution compared to conventional (RGB) digital cameras. These can assess the RGB, visible spectrum (400–700 nm), near-infrared spectrum (700–1000 nm), and shortwave infrared (1000–2500 nm). Hence, the modern hyperspectral sensor covers high complexity spectral range from 350 to 2500 nm. These sensors are categorized into various classes based on their respective spectral resolution, scale, and imaging principles. Spectral resolution depends on measured wave bands; spectral scale could be ultraviolet, visible, near-infrared, or shortwave infrared, whereas imaging principle could be based on imaging or non-imaging system.

In the case of the non-imaging sensor system, spectral information over a specific area and within the sensor's field of view is averaged with spatial resolution information. Hyperspectral data is observed as three dimensions in huge matrices with spatial *x*-axes, *y*-axes, and on *z*-axes, spectral information depicting intensity/wave band is represented. Due to spatial dimension, HSI systems provide extra details such as color, gradient, and shape and are preferred over non-imaging methods (Behmann et al. 2015). Though multispectral sensors are comparable to HS sensors but are less complex and informative and provide object's spectral information in broad wave bands such as RGD and NIR. These are less expensive and are used in unmanned airborne vehicles due to their lightweight. The reflectance average of non-imaging hyperspectral sensors provides spatial resolution with a specific allocation of the hyperspectral pixel. Research on HSI helped to design and develop new materials, efficient detectors, and software, and is widely used in various fields, e.g., food production, agriculture, and medicines (Cheng et al. 2017). Hyperspectral imaging provides site-specific, selective, and reliable information that significantly improves sustainable agricultural management and is recommended and used in precision agriculture and plant phenotyping (assessing genotypes) (Simko et al. 2017).

1.5.2 Setup of Hyperspectral Sensors

Setups consist of a hyperspectral sensor, a light source (efficient in both sunlight and artificial light), and a control unit to measure and save the captured data (images). This setup could easily be mounted on any platform, such as tractors, unmanned airborne vehicles, robots, satellites, and handheld. The collected data from HSI is saved in a hyperspectral data cube, which displays spatial information data in a two-dimensional image. Wavelength range and targeted object determine the required imaging detector. The most commonly used sensors for visible and near-infrared spectra are complementary metal-oxide semiconductors and Si-based charge coupled devices, which are implemented on various sensing types, e.g., full-frame and push-broom cameras. Light interaction with the plant is the crucial knowledge required for hyperspectral analysis and interpretation of signals. The optical properties of the leaf depend upon light transmission through the leaf, light absorbed by the leaf, and light reflected (either from internal structure or from the waxy cuticle and cell wall). The maximum absorption and reflectance capacity of various compounds of the electromagnetic spectrum have been studied to explain the optical properties of plants (Mahlein et al. 2018; Merzlyak et al. 2008).

Several biochemical and histological changes could be characterized and interpreted during plant pathogenesis through HSI. Light reflectance from plant due to the involvement of various biophysical and biochemical interactions is a complex phenomenon. Visible light spectrum is mainly absorbed by leaf pigments such as chlorophyll, anthocyanins, and carotenoids (Gay et al. 2008). Near-infrared and shortwave infrared stimulate molecular motion and induce high reflectance and absorption by characteristic spectral pattern compounds. Leaf and cell structure influence the NIR reflectance due to matter interaction (Slaton et al. 2001), whereas SWIR can detect the plant/cell's water content (Seelig et al. 2008). Hence, remote sensing through hyperspectral imaging can determine the reflected and transmitted light and characterize the absorption activities of leaf compounds. Various android applications are being developed to determine the leaf compounds by observing reflected and transmitted light through HSI. However, due to its handling and setup complexity, transmittance sensing is used by only a few experts in phytopathometry.

1.5.3 Pathogenesis and Reflectance Signatures

Diseases are a gradual and dynamic process that consists of a series of events, one autonomously leading to the next, once pathogenesis is triggered. Pathogenesis triggers changes/abnormalities in various processes of the host plant's physiology and biochemistry. The resulting symptoms of pathogenesis influence the optical properties of the infected host. We must dive further than identification based on characteristic symptomatology or visible signs of plant–pathogen interaction. Different plant–host interaction stages should be understood in more depth. Every plant pathologist knows that plant pathogens could be biotrophs (obtain nutrients from living tissues), necrotrophs (get nutrients from dying or dead tissues), or hemibiotrophs (could be both depending upon the developmental stage and environmental conditions). Each interaction consists of complex biochemical, biophysical, and histological processes regulating disease symptoms. Hence, reflectance changes during plant–pathogen interaction could be explained by abnormalities in the cell's chemical composition, ultimately generating changes in leaf appearance (e.g., chlorosis) and structure (e.g., lesions) during different stages of pathogenesis and at specific spatial and temporal dynamics host influence the reflective light's wavelength (Villa et al. 2013; Virlet et al. 2016).

Close-range HSI improves the spatial resolution of pathogenesis while considering specific space and time and results in more accurate hyperspectral analysis. The human eye and even the conventional HSI systems are challenged by deciding on early host–pathogen interactions when the size is observed in the submillimeter. This submillimeter size could be observed by improving the camera's spatial resolution through hyperspectral microscope setups, which could observe small and subtle reactions of the host plant. This ability opens up new opportunities for plant disease management, especially in breeding systems and compound testing. Hyperspectral image must be linked with the biological process involved in host–pathogen interaction. Consequently, an objective and accelerated plant phenotyping process could be achieved with reduced human and plant material involvement.

1.5.4 Potential of Hyperspectral Imaging in Phytopathometry

HIS, being a non-targeted remote sensing approach, collect a considerable amount of extra information about changes in processes and chemical composition of the host plant cell. This information is scattered across the measured spectrum, changing relevance over time (Behmann et al. 2015). Thus, analyzing the data to acquire a small proportion of specific information from the gathered hyperspectral signals is challenging. Recently, several approaches have been applied to improve HIS results for effective phytopathometry:

1.5.4.1 Preprocessing and Data Handling

Data is preprocessed to be normalized, having no illumination. In the case of sunlight as an illumination source, complex algorithms increase robustness against variation. This spectral normalization of data becomes critical if HIS involves extensive field observation data where continuous observations are impossible to make, and the interpolation strategy could fail. It is achieved by complex and robust approaches involving standard normal variant and explicit modeling by choosing suitable radiation transfer models. In an experiment, using the REGLOGSEP model based on singular value decomposition significantly improved the data quality, but plant geometry was challenging (Jay et al. 2016). However, another model incorporating a radiative transfer model, PROCOSINE, was introduced for close-range scenarios, which can estimate local illumination and plant-physiological parameters (e.g., the content of plant pigments) and is less affected by plant geometry (Féret et al. 2017).

1.5.4.2 Vegetation Indices: An Important Tool in HSI

Hyperspectral experiment's massive data have various variable factors, but mostly only one is required for disease severity analysis. Vegetation indices highlight specific factors while reducing the impact of others (e.g., while assessing anthocyanins concentrations variable and unwanted chlorophyll content factor is suppressed by using anthocyanin reflective index). These express the spectral changes in a manageable manner. Though developed through remote sensing satellites, this technique is now being applied in proximal and close-range disease detection scenarios. In different disease studies, vegetation indices were successfully applied to deduce plant diseases, chlorophyll content, and yield estimation (Gitelson et al. 2014; Jay et al. 2017). However, vegetation indices do not cope with most bands, blank them out, and could not take full advantage of hyperspectral data.

1.5.5 Machine Learning

Machine learning approaches cope with hundreds of reflective bands and can detect, quantify, and characterize plant disease severity in laboratory and field conditions. Machine learning learns about model characteristics from the obtained data rather than using a specific model. These highly complex methods reveal the important unknown aspects of the hyperspectral data. Supervised approaches such as regression analysis rely on annotated training data, whereas unsupervised techniques don't. Unsupervised methods can recognize patterns because they can identify statistical coherences and uncover unknown relations in the data set. In a hyperspectral image analysis-based study to detect early Alternaria pathogenesis in oilseed crops, different machine learning algorithms were evaluated for their respective efficacy, and it was found that multilayer perception produced results with the highest accuracy (Baranowski et al. 2015). Zhu et al. evaluated the HSI machine learning algorithms for presymptomatic tobacco mosaic virus detection. Eight bands out of 434 variable bands were combined with texture features for evaluating machine learning algorithms. Three machine learning algorithms, namely neural network, random forest, and support vector machine, were assessed, and it was found that the neural network approach was able to detect tobacco mosaic virus, just after 2 days of inoculation, with high accuracy of 90% (Zhu et al. 2017). Powdery mildew of grapevine was detected by incorporating spatial and spectral characteristics with hyperspectral image analysis data. Various relevant wavelength bands in visible, near-infrared, and shortwave infrared spectrums were obtained using two cameras. When spatial context was integrated with HSI, it generated more informative hyperspectral images and increased the accuracy of results compared with HIS data processing without incorporating spatial context (Knauer et al. 2017).

Unsupervised methods exploit all the available hyperspectral data but generate results with the target specification. Established data clustering methods are applied to hyperspectral data in preprocessing for segmentation and labeling. More advanced machine learning approaches could reparametrize the data informatively. Mixed techniques such as self-taught, semi-supervised, and transfer learning can deal with limited available information but are rarely used in phytopathometry.

1.5.6 Deep Learning

Deep learning represents the data more abstractly and informatively while optimized for a specific task. It has great potential for analyzing a large amount of hyperspectral data involving hundreds of bands and where particular optimal disease features are unknown (LeCun et al. 2015). Deep learning is a practical approach in HSI, where images have high dimensions with limited training data. HSI provides large amounts of data, complex features, and unknown and unfocused relations, which are beneficial for deep learning. In deep learning, specific programs are used to analyze the data on specialized servers. Resulted classification is sent to the smartphone and service providers by using the latest algorithms, detect and quantify the disease. This approach also improve the underlying model being used. For successful machine learning use in disease detection and quantification specific feature and model selection, optimization of data sets is required.

1.5.7 HSI for Disease Resistance Breeding

Continuous research in plant breeding for disease resistance is required because plant pathogens evolve to overcome resistant varieties and start pathogenesis. Due to their fast reproduction rate, it is a challenging process as plant pathogens mutate rapidly with varying impacts on growing varieties. Several sophisticated methods enable rapid screening of various genotypes for resistance against a particular pathogen. Plant phenotyping by a rater is done as, after several hybridizations and generations, a specific genotype could vary in its resistance against a pathogen in changing environmental conditions (Mahlein et al. 2018). Hence, when implemented in breeding programs, HSI improves the pace of breeding progress. Resistance could be qualitative or quantitative with or without observable changes. In a breeding experiment, a novel hyperspectral microscope evaluated resistance against powdery mildew for the barley. Gene-based vertical resistance mildew locus was responsible for hypersensitive response in the host plant, which was possible to retrospectively analyze hyperspectral features of the hypersensitive response in a particular space and time. It was possible because, after 5 days of inoculation, the response was visible as small brownish spots. Additionally, barley resistance response was detected using hyperspectral imaging 2–3 days before symptoms appeared (Fiorani and Schurr 2013; Kuska et al. 2017). Type and amount of spectral properties along with temporal response are poorly understood for plant–pathogen resistance reaction. To screen unknown genotypes or new varieties, independent spectral patterns of particular resistance mechanisms are desirable.

1.5.8 HSI in Protected Horticulture

The increasing global population demand sustainable agricultural practices to fulfill its food demands. Protected horticulture by using greenhouses has proved effective in the judicious use of inputs and higher yields; however, diseases are a significant concern for growers in greenhouses as these can significantly limit profitability. Due to controlled and favorable conditions inside the greenhouse, fungal and bacterial pathogens can proliferate exponentially. Gummy stem blight in cucumber was automatically and accurately (95%) detected using point spectroscopy and spatial color imaging (Swinkels 2016). Hyperspectral line scan imaging was evaluated to assess the spinach growth in greenhouses. For this, induced water and nitrogen stress identified variables strictly related to plant geometry and leaf area index. Hyperspectrogram manages many hyperspectral images by data extraction and compression while retaining spatial information (Corti et al. 2017). It provides evidence that noninvasive sensors could significantly improve disease detection and quantification in controlled environments by regulating environmental factors to comparatively higher levels. Shortly, horticultural production is expected to have been supported by innovative digital technologies.

1.6 Challenges in Automated Field Sensing

Generally, diseases can easily be detected and quantified through remote sensing if they are widely spread throughout the field and if only the top canopy crop layer is affected by it. Most remote sensing studies have been carried out under controlled conditions using artificial illumination, regulation of incoming light's direction, and sensor placement at a certain angle toward the leaf to absorb desired reflected light. These conditions are not available in the field, so the application of remote sensing technologies for large-scale field assessment is limited.

Among all the factors, light illumination is the most disturbing variable in the field. Leaves in the top most canopy layer appear brighter, in natural illumination source, compared to leaves in lower crop canopy layers. A threshold is required to distinguish between healthy and diseased tissue, which could be achieved by considering the overall image brightness while assessing a specific disease in a particular location. This threshold setting requires intensive research in crop phenotyping. Image brightness shows a higher heterogeneity in the natural canopy when sunny conditions are present, whereas heterogeneities in cloudy weather are less severe because scattered radiation, compared to direct radiation, reaches abundance in the crop canopy. To avoid these radiation variations under field conditions, modern plant phenotyping setups allow plant disease assessment/monitoring at the appropriate time, such as dawn and dusk, when direct radiation on the crop canopy is limited. Sophisticated machine and deep learning approaches are incorporated into hyperspectral imaging and expert opinion to define, detect, and refine the traits extracted from a hyperspectral image.

1.7 Other Indirect Methods of Plant Disease Detection in Phytopathometry

Thermography differentiates the plant samples based on surface temperature. Thermographic cameras capture the emitted infrared radiations from the plant surface, and then color differences are analyzed. It has been reported that pathogenesis increases the plant surface temperature due to rapid cell activity; hence, thermographic techniques could prove effective in directly detecting plant diseases under field conditions. Thermographs have also been reported to monitor the pathogen heterogeneity in soil-borne diseases. However, thermographic detection is susceptible and is affected by slight environmental conditions (Stoll et al. 2008; Oerke et al. 2011).

Profiling of the volatile organic compounds, released upon plant–pathogen interaction and are highly indicative of stress type, has also proved effective in phytopathometry. Crown rot fungus of strawberry (*Phytophthora cactorum*) causes plants to release characteristic *p*-ethylguaiacol and *p*-ethylphenol volatile compounds. Hence, profiling of volatile compounds could be used to detect the type and nature of disease infection (Fang et al. 2014).

1.8 Conclusion

Phytopathometry is crucial for plant disease management in the era of precision and sustainable agriculture. Phytopathometry is not limited to plant pathology. Various traditional and modern plant disease measurement approaches have been discussed. Current practices of phytopathometry are complex, require expertise to operate, and are also time-consuming due to massive data analysis. Additionally, most of the approaches are not suitable for actual field conditions.

However, advancements and AI and modern nano-fabricated biosensors have huge potential in phytopathometry.

References

Abazov, V., B. Abbott, M. Abolins, et al. 2006. The upgraded DØ detector. *Nuclear Instruments Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors Associated Equipment* 565: 463–537.

Arnal Barbedo, J.G. 2013. Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus* 2: 1–12.

Baranowski, P., M. Jedryczka, W. Mazurek, et al. 2015. Hyperspectral and thermal imaging of oilseed rape (Brassica napus) response to fungal species of the genus Alternaria. *PLoS One* 10: e0122913.

Barbedo, J.G.A. 2014. An automatic method to detect and measure leaf disease symptoms using digital image processing. *Plant Disease* 98: 1709–1716.

Bawden, F. 1933. Infra-red photography and plant virus diseases. *Nature* 132: 168–168.

Behmann, J., A.-K. Mahlein, T. Rumpf, et al. 2015. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. *Precision Agriculture* 16: 239–260.

Bock, C.H., and F.W. Nutter-Jr. 2011. Detection and measurement of plant disease symptoms using visible-wavelength photography and image analysis. *CAB Reviews: Perspective in Agriculture, Veterinary Science, Nutrition and Natural Resources* 6: 27.

Bock, C., G. Poole, P. Parker, et al. 2010. Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Sciences* 29: 59–107.

Bock, C., K. Chiang, and E. Del Ponte. 2016. Accuracy of plant specimen disease severity estimates: concepts, history, methods, ramifications and challenges for the future. *CAB Reviews* 11: 1–21.

Bock, C.H., S.J. Pethybridge, J.G. Barbedo, et al. 2021. A phytopathometry glossary for the twenty-first century: towards consistency and precision in intra-and inter-disciplinary dialogues. *Tropical Plant Pathology* 47: 1–11.

Bock, C.H., J.G. Barbedo, A.-K. Mahlein, et al. 2022. A special issue on phytopathometry—visual assessment, remote sensing, and artificial intelligence in the twenty-first century. *Tropical Plant Pathology* 47: 1–4.

Braido, R., A.M. Goncalves-Zuliani, V. Janeiro, et al. 2014. Development and validation of standard area diagrams as assessment aids for estimating the severity of citrus canker on unripe oranges. *Plant Disease* 98: 1543–1550.

Brasier, C. 2008. The biosecurity threat to the UK and global environment from international trade in plants. *Plant Pathology* 57: 792–808.

Cheng, J.-H., B. Nicolai, and D.-W. Sun. 2017. Hyperspectral imaging with multivariate analysis for technological parameters prediction and classification of muscle foods: a review. *Meat Science* 123: 182–191.

Chiang, K.-S., S.-C. Liu, C.H. Bock, et al. 2014. What interval characteristics make a good categorical disease assessment scale? *Phytopathology* 104: 575–585.

Cobb, N.A. 1892. Contributions to an economic knowledge of the Australian rusts (Uredineae). *Agricultural Gazette of New South Wales* 3: 44–48.

Corti, M., P.M. Gallina, D. Cavalli, et al. 2017. Hyperspectral imaging of spinach canopy under combined water and nitrogen stress to estimate biomass, water, and nitrogen content. *Biosystems Engineering* 158: 38–50.

Del Ponte, E.M., S.J. Pethybridge, C.H. Bock, et al. 2017. Standard area diagrams for aiding severity estimation: scientometrics, pathosystems, and methodological trends in the last 25 years. *Phytopathology* 107: 1161–1174.

Fang, Y., Y. Umasankar, and R.P. Ramasamy. 2014. Electrochemical detection of p-ethylguaiacol, a fungi infected fruit volatile using metal oxide nanoparticles. *Analyst* 139: 3804–3810.

Féret, J.-B., A. Gitelson, S. Noble, et al. 2017. PROSPECT-D: towards modeling leaf optical properties through a complete lifecycle. *Remote Sensing of Environment* 193: 204–215.

Fiorani, F., and U. Schurr. 2013. Future scenarios for plant phenotyping. *Annual Review of Plant Biology* 64: 267–291.

Fiorani, F., U. Rascher, S. Jahnke, et al. 2012. Imaging plants dynamics in heterogenic environments. *Current Opinion in Biotechnology* 23: 227–235.

Fisher, M.C., D. Henk, C.J. Briggs, et al. 2012. Emerging fungal threats to animal, plant and ecosystem health. *Nature* 484: 186–194.

Gay, A., H. Thomas, M. Roca, et al. 2008. Nondestructive analysis of senescence in mesophyll cells by spectral resolution of protein synthesis-dependent pigment metabolism. *New Phytologist* 179: 663–674.

Gewin, V. 2003. Bioterrorism: agriculture shock. *Nature* 421: 106–109.

Gitelson, A.A., Y. Peng, and K.F. Huemmrich. 2014. Relationship between fraction of radiation absorbed by photosynthesizing maize and soybean canopies and NDVI from remotely sensed data taken at close range and from MODIS 250 m resolution data. *Remote Sensing of Environment* 147: 108–120.

Gregory, P. 1982. Plant pathology, EC large, and phytopathometry. *Plant Pathology* 31: 7–8.

Jay, S., R. Bendoula, X. Hadoux, et al. 2016. A physically-based model for retrieving foliar biochemistry and leaf orientation using close-range imaging spectroscopy. *Remote Sensing of Environment* 177: 220–236.

Jay, S., N. Gorretta, J. Morel, et al. 2017. Estimating leaf chlorophyll content in sugar beet canopies using millimeter-to centimeter-scale reflectance imagery. *Remote Sensing of Environment* 198: 173–186.

Knauer, U., A. Matros, T. Petrovic, et al. 2017. Improved classification accuracy of powdery mildew infection levels of wine grapes by spatial-spectral analysis of hyperspectral images. *Plant Methods* 13: 1–15.

Kuska, M.T., A. Brugger, S. Thomas, et al. 2017. Spectral patterns reveal early resistance reactions of barley against Blumeria graminis f. sp. hordei. *Phytopathology* 107: 1388–1398.

Large, E. 1953. Some recent developments in fungus disease survey work in England and Wales. *Annals of Applied Biology* 40: 594–599.

Large, E.C. 1966. Measuring plant disease. *Annual Review of Phytopathology* 4: 9–26.

LeCun, Y., Y. Bengio, and G. Hinton. 2015. Deep learning. *Nature* 521: 436–444.

Lindow, S., and R. Webb. 1983. Quantification of foliar plant disease symptoms by microcomputer-digitized video image analysis. *Phytopathology* 73: 520–524.

Madden, L.V., G. Hughes, and F. van den Bosch. 2007a. Estimating plant disease by sampling. In *The study of plant disease epidemics*, 279–318. St. Paul, MN: APS Press.

———. 2007b. *The study of plant disease epidemics*. St Paul, MN: American Phytopathological Society.

Mahlein, A.-K. 2016. Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease* 100: 241–251.

Mahlein, A.-K., M.T. Kuska, J. Behmann, et al. 2018. Hyperspectral sensors and imaging technologies in phytopathology: state of the art. *Annual Review of Phytopathology* 56: 535–558.

Merga, W. 2018. Measuring and analysis of plant diseases. *International Journal of Research Studies in Agricultural Sciences* 4: 1–8.

Merzlyak, M.N., O.B. Chivkunova, A.E. Solovchenko, et al. 2008. Light absorption by anthocyanins in juvenile, stressed, and senescing leaves. *Journal of Experimental Botany* 59: 3903–3911.

Nutter, F., Jr., P. Teng, and F. Shokes. 1991. Disease assessment terms and concepts. *Plant Disease* 75: 1187–1188.

Nutter, F., R. Littrell, and V. Pederson. 1985. Use of a low-cost, multispectral radiometer to estimate yield loss in peanuts caused by late leaf-spot (*Cercosporidium personatum*). In *Phytopathology*, 502. St Paul, MN: American Phytopathological Society.

Oerke, E.-C., and H.-W. Dehne. 2004. Safeguarding production—losses in major crops and the role of crop protection. *Crop Protection* 23: 275–285.

Oerke, E.-C., P. Fröhling, and U. Steiner. 2011. Thermographic assessment of scab disease on apple leaves. *Precision Agriculture* 12: 699–715.

Parnell, S., F. van den Bosch, T. Gottwald, et al. 2017. Surveillance to inform control of emerging plant diseases: an epidemiological perspective. *Annual Review of Phytopathology* 55: 591–610.

Pethybridge, S.J., and S.C. Nelson. 2015. Leaf Doctor: a new portable application for quantifying plant disease severity. *Plant Disease* 99: 1310–1316.

Pinter, P., Jr., M. Stanghellini, R. Reginato, et al. 1979. Remote detection of biological stresses in plants with infrared thermometry. *Science* 205: 585–587.

Seelig, H.D., A. Hoehn, L. Stodieck, et al. 2008. The assessment of leaf water content using leaf reflectance ratios in the visible, near-, and short-wave-infrared. *International Journal of Remote Sensing* 29: 3701–3713.

Simko, I., J.A. Jimenez-Berni, and X.R. Sirault. 2017. Phenomic approaches and tools for phytopathologists. *Phytopathology* 107: 6–17.

Slaton, M.R., E. Raymond Hunt Jr., and W.K. Smith. 2001. Estimating near-infrared leaf reflectance from leaf structural characteristics. *American Journal of Botany* 88: 278–284.

Stoll, M., H.R. Schultz, G. Baecker, et al. 2008. Early pathogen detection under different water status and the assessment of spray application in vineyards through the use of thermal imagery. *Precision Agriculture* 9: 407–417.

Swinkels, G.J. 2016. Automated detection of Mycosphaerella melonis infected cucumber fruits. *IFAC-PapersOnLine* 49: 105–109.

Ul Haq, I., and S. Ijaz. 2020. History and recent trends in plant disease control: an overview. In *Plant disease management strategies for sustainable agriculture through traditional and modern approaches*, 1–13. Cham: Springer Nature.

Ul Haq, I., S. Ijaz, Q. Shakeel, G. Li, L. Yang, and I. Rashid. 2020. Fungi: cynosure of ornamental palms diseases. In *Etiology and integrated management of economically important fungal diseases of ornamental palms*, 85–113. Cham: Springer Nature.

Villa, A., J. Chanussot, J.A. Benediktsson, et al. 2013. Unsupervised methods for the classification of hyperspectral images with low spatial resolution. *Pattern Recognition* 46: 1556–1568.

Virlet, N., K. Sabermanesh, P. Sadeghi-Tehran, et al. 2016. Field Scanalyzer: an automated robotic field phenotyping platform for detailed crop monitoring. *Functional Plant Biology* 44: 143–153.

Zhao, X., T. Burks, J. Qin, et al. 2009. Digital microscopic imaging for citrus peel disease classification using color texture features. *Applied Engineering in Agriculture* 25: 769–776.

Zhu, H., B. Chu, C. Zhang, et al. 2017. Hyperspectral imaging for presymptomatic detection of tobacco disease with successive projections algorithm and machine-learning classifiers. *Scientific Reports* 7: 1–12.

Visual Estimation: A Classical Approach for Plant Disease Estimation

2

Amer Habib, Ahsan Abdullah, and Anita Puyam

Abstract

Quantifying plant disease in terms of disease severity, prevalence, incidence, or intensity is very important to make decisions for applying treatments or management practices. Quantifying any plant disease is based on the estimation methods dependent on visual estimation or image analysis of infected portions. Foreseeing the yield losses, tracking and predicting epidemics, evaluating crop germplasm for the source of resistance against a specific disease, and comprehending basic biological processes, such as coevolution, all depend on accurate estimations of disease severity. Inaccurate or vague disease evaluations may cause wrong conclusions from the data, which may cause inappropriate actions to be performed in disease management verdicts. Visual estimation is a highly traditional technique in phyto-pathometry. In the visual estimation of disease, human eye and brain play significant roles in analyzing the degree of disease. It is well established that the number of lesions in proportion to the infected region affects the accuracy and precision of visual estimations; the more lesions there are concerning the infected area, the more overestimation there is. Variability in raters' disease assessment ability, preferences of disease ratings for severity, amount of lesions and their size, color blindness, and time spent on estimation

A. Habib (✉)
Department of Plant Pathology, Faculty of Agriculture, University of Agriculture, Faisalabad, Pakistan
e-mail: amer.habib@uaf.edu.pk

A. Abdullah
Department of Plant Pathology, College of Plant Protection, China Agricultural University, Beijing, China

A. Puyam
Rani Lakshmi Bai Central Agricultural University, Jhansi, India

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