Agri Articles
(e-Magazine for Agricultural Articles)
Volume: 04, Issue: 01 (JAN-FEB, 2024)
Available online at http://www.agriarticles.com


# Hyperspectral Imaging: A Tool for Plant Disease Detection

(*Vaishnavi P. Kharbadkar and Aniket Sunil Gaikwad)
Post Graduate Institute, Mahatma Phule Krishi Vidyapeeth, Rahuri, Ahmednagar, Maharashtra, India – 413722
*Corresponding Author's email: vkharbadkar@gmail.com

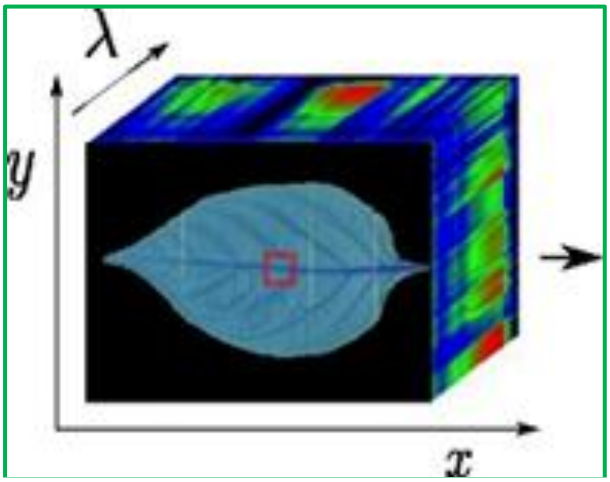
## Abstract
Detecting and identifying plant diseases is crucial for sustainable crop production. Accurately assessing disease impact on yield quality and quantity is vital in various agricultural areas. Hyperspectral imaging of afflicted plants provides valuable insights into pathogenesis processes. Integrating this method with data analysis enables timely and precise identification and quantification of plant diseases. This approach, applicable across different scales, enhances our understanding of plant-pathogen interactions. It contributes to proactive disease management, particularly in precision crop production, horticulture, plant breeding, fungicide screening, and both basic and applied plant research.

**Keywords:** Plant diseases, hyperspectral imaging, crop production, disease detection, pathogenesis and disease management

## Introduction
Accurate plant disease assessment is crucial for precision crop production. In field and greenhouse cultivation, timely evaluations predict disease spread. Traditional methods (visual detection, microscopic analysis, molecular assays, serology, microbiology) identify diseases. Yet, non-invasive optical sensors, like hyperspectral imaging, now prevail in plant disease detection. These sensors, used in diverse applications from lab to field, surpass traditional methods in precision agriculture and resistance breeding. Hyperspectral imaging, especially, plays a vital role in identifying diseases, offering advantages in various scales, from single-plant assessments to canopy-level observations.

Hyperspectral imaging is a non-invasive alternative to invasive molecular analyses, allowing researchers and breeders to conduct time series measurements on sample plants. This reduces the need for numerous samples, enhancing long-term experiment efficiency. The non-invasive approach eliminates subjectivity in manual rating systems, providing an objective, automatable methodology, reducing labor-intensive tasks. This not only improves economic efficiency but also benefits the ecology by minimizing costs in agricultural production. Diseases induce diverse alterations in plant physiology, affecting factors like tissue color, leaf shape, transpiration rate, crop canopy morphology, and density. The intricate interplay of these factors results in variations in the optical properties of plants. Hyperspectral imaging proves to be a powerful tool for detecting plant diseases across different scales and pathosystems.

Hyperspectral imaging has achieved significant success in plant disease characterization, detection, modeling, and classification (Mahlein *et al.*, 2012). This technique involves capturing reflected light from plants across narrow bands in the electromagnetic spectrum, creating a hypercube (**Figure 1a**). **Figure 1b** illustrates the typical spectral reflectance of a healthy plant. The plant's interaction with different electromagnetic spectrum segments depends on leaf biochemical compounds and anatomical structure. In the visible range (VIS 400-700 nm), healthy plants absorb light primarily due to photosynthesis pigments. The near-infrared range (NIR 700-1000 nm) reflects sensitivity to light scattering based on leaf cell structure. Short-wave infrared (SWIR 1000-2500 nm) leaf reflectance is mainly influenced by factors like leaf water content and chemical composition.



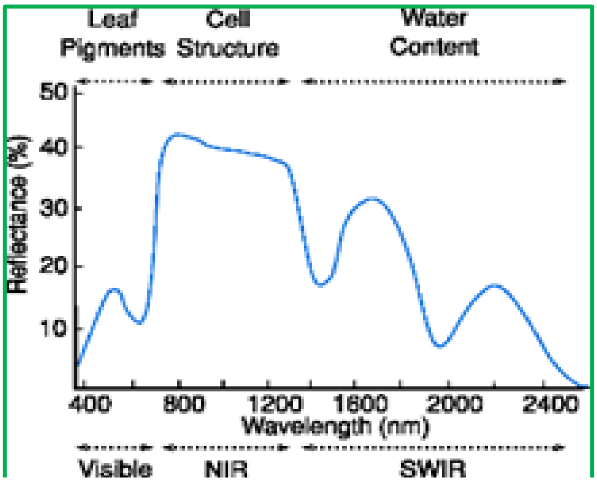




**Fig.1: (a) An example of a hypercube (b) Spectral reflectance of a healthy plant**

Plants undergo biophysical and biochemical changes in response to various stresses, including chlorophyll degradation and alterations in leaf cell structures. Hyperspectral imaging is effective in detecting subtle shifts in plant spectral reflectance. Machine learning utilizes these values for automated plant disease classification. The process involves extracting features from spectral reflectance, training a classifier model with images of diseased and healthy plants, and using the model to predict diseased leaves in new data (Rumpf *et al.*, 2010; Xie *et al.*, 2016).

Feature extraction often employs spectral Vegetation Indices (VIs) related to specific physiological parameters. However, these VIs may not be optimized for distinguishing between healthy and diseased plants. Hyperspectral imaging captures high-fidelity color reflectance data across a broad light spectrum beyond human vision, promising detection of subtle alterations in plant growth and development. This review comprehensively explores hyperspectral imaging applications in both laboratory and field settings for classifying and identifying initial phases of plant foliar diseases and stress. Beginning with foundational theory and a survey of hyperspectral imaging technology, the review delves into various domains where this approach can be applied in plant and crop sciences.

## Colour Digital Imaging

Understanding hyperspectral technology starts with examining a standard non-hyperspectral color digital image, where light wavelengths correspond to colors (e.g., blue at 475 nm, green at 520 nm, and red at 650 nm). Such images blend three broad wavelength bands (red, green, and blue) to create a color image perceptible to human eyes. In hyperspectral systems, the captured light extends from ultraviolet (UV) at around 250 nm to short-wave infrared (SWIR) at approximately 2500 nm. Cameras typically focus on specific sub-ranges, like visible and near-infrared (VIS–NIR, 400–1300 nm) or SWIR (1300–2500 nm) or UV (250–400 nm). True multispectral images involve more bands, including the infrared region beyond 700 nm, whereas hyperspectral images consist of numerous contiguous narrow wavelength bands, creating a dense and information-rich dataset with ample spatial resolution.

For plant analysis, optimal wavelength ranges include the visible and near-infrared ranges for assessing variations in leaf pigmentation (400–700 nm) and mesophyll cell structure (700–1300 nm). However, broader wavelength ranges (1300–2500 nm) are necessary for discerning alterations in plant water content, as observed in instances of intense dehydration impacting mesophyll structure, leading to changes in near-infrared reflectance. In contrast, marginal drought stress typically lacks a significant impact detectable through hyperspectral imaging (Penuelas et al., 1998; Satterwhite et al., 1990).

## Hyperspectral Imaging Technology

Various hyperspectral imaging spectrometers employ diverse hardware methodologies, such as push broom, filter wheel, and liquid crystal tunable filters (Fong *et al.*, 2008). For instance, in the push broom approach, incident light passes through a convex grating or prism, dispersing light into narrow wavelengths. This spectral separation is recorded on a photosensitive chip, similar to a conventional digital camera. The push broom setup comprises a camera, a spectrometer, and a lens, allowing the simultaneous capture of a single spatial line across the entire color spectrum range (**Figure 2**). The camera or object moves, and the next line is incrementally captured as the broom is advanced, making the camera function as a line scanner. The entire image is reconstructed after completing the scan. An alternative is the snapshot approach, capturing the entire image in a single instance. While push broom technology has historically dominated, recent advances in snapshot technology are expanding its adoption and potential applications in phenotyping and analysis.

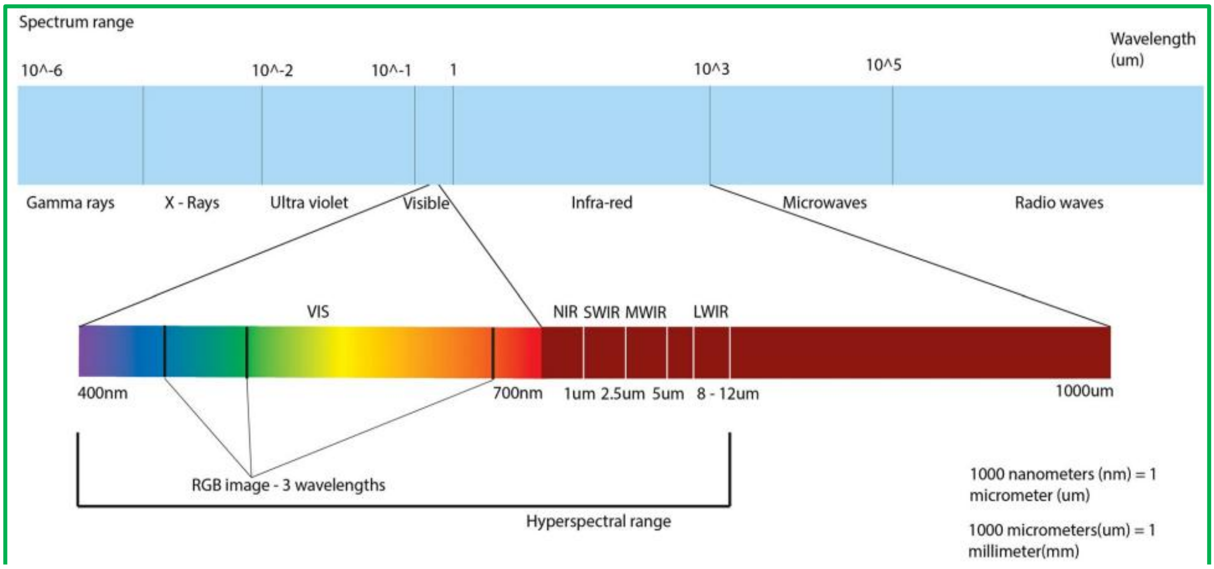



**Fig 2: Electromagnetic spectrum with the lower bar displaying visible and infra-red light**

## Practical Applications: Detection and Classification of Healthy and Diseased Plants

Classification methods, which categorize data into healthy and diseased classes, can be dichotomized based on their spectral approach. They are broadly divided into two types: those focusing on specific key wavelengths and those utilizing the entire spectrum response. Furthermore, discussions on disease classification include considerations for identifying multiple diseases and detecting specific diseases.

## Existing Vegetation and Disease Indices

Before the widespread availability of hyperspectral imaging devices, researchers used multispectral imaging or hyperspectral point-source devices (e.g., spectroradiometers) for colour data acquisition. Hyperspectral devices require a user-defined capture process, and the resulting voluminous numerical datasets demand thorough analysis. Various indices, driven by biological rationale or equipment constraints, aid in data interpretation and are commonly known as 'vegetation indices' when analysing plant material. These indices cover a range of plant properties, including general features or specific growth-related parameters. The normalized difference vegetation index (NDVI), calculated from near-IR and visible light ratios, is a widely adopted metric for gauging overall crop health (Lasaponara *et al.*, 2007). NDVI has diverse applications, such as identifying stress induced by the Sunn pest in wheat crops (Genc *et al.*, 2008). Another method involves detecting changes in reflectance at the 'red edge,' a narrow segment (690–740 nm) marking the transition from visible to near-infrared (**Figure 3**).

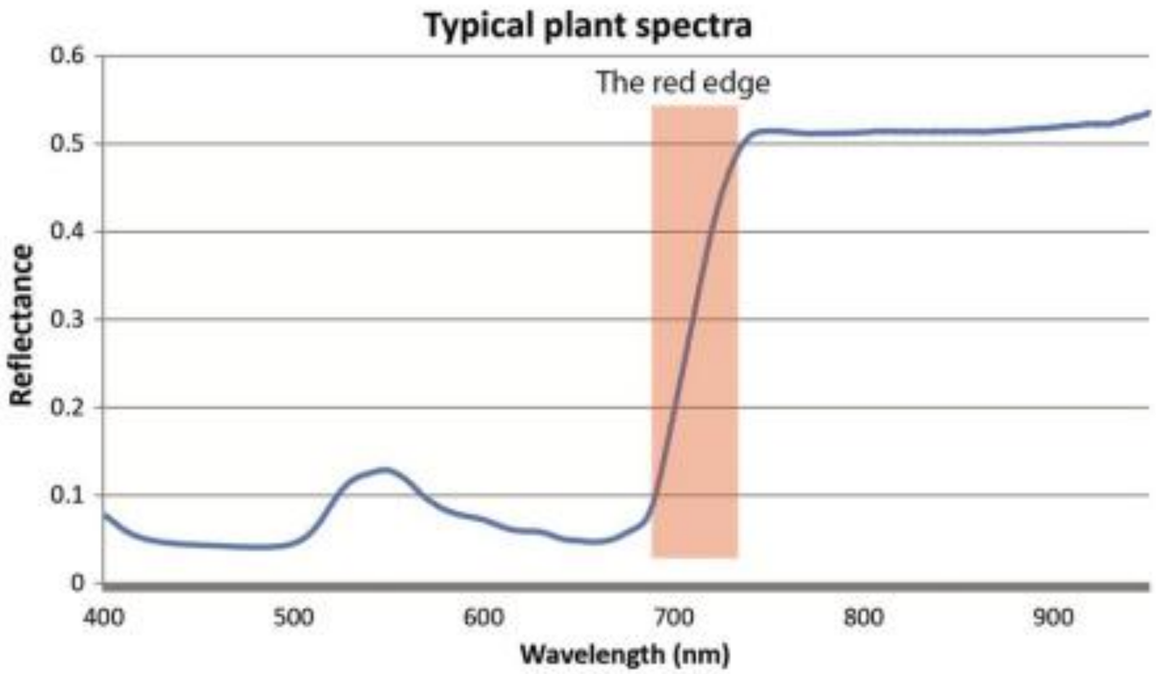



**Fig. 3: A typical healthy vegetation spectra (400–1000 nm) with the red edge section highlighted in red (690–740 nm)**

## Disease identification

To identify specific pathogens, researchers explore spectral information divergence classification, a method that evaluates the difference between observed spectra and reference spectra. Reference spectra are derived from a spectrum library or average spectra of interest within the data. A smaller divergence value signifies greater similarity between the spectra, and values surpassing a predefined threshold classify spectra as not aligning with the reference spectra (Du *et al.*, 2004). This approach enhances the precision of disease discrimination in hyperspectral imaging research.

## Quantifying severity of disease

Spectral Angle Mapper (SAM) methodologies involve pixel classification by comparing pixel spectra to reference spectra. This is achieved by calculating the angle between the spectra, treating them as n-dimensional vectors in spatial analysis. In Mahlein et al. (2012) study on sugar beet diseases, specifically, Cerospora leaf spot, powdery mildew, and leaf rust, they employed SAM with a spectral range of 400–1000 nm, a 2.8 nm spectral resolution, and a 0.19 mm spatial resolution. The analysis spanned over 20 days to monitor different disease stages, classifying leaves as healthy or diseased. The classification accuracy varied for each disease: Cerospora leaf spot (89.01–98.90%), powdery mildew (90.18–97.23%), and sugar beet rust (61.70%, with no classification before day 20 using SAM).

## Detection of early-stage stress symptoms

Detection systems aim to identify plant diseases or abiotic anomalies with minimal observable perturbations. Timely detection is crucial, and the integration of hyperspectral technology with rigorous analytical approaches holds promise for preemptively identifying stress symptoms beyond human observation. Drought poses a significant challenge for crops, with visible signs often delayed, impacting yield and quality. Recent investigations show the ability to identify the initiation of drought conditions before Vegetation Indices and observable symptoms. Simplex Volume Maximization (SiVM), a data clustering technique, is gaining prominence for early drought stress identification (Thurau et al., 2015). SiVM selects spectral signatures representing healthy and stressed plants, clustering data based on these classes, allowing for plant state categorization when signatures resemble pre-learned samples.

**Table 1: Summary of techniques successfully used to detect drought and diseases in plants**

| Technique | Plant (stress) | Accuracy | References |
|---|---|---|---|
| Quadratic discriminant analysis (QDA) | Wheat (yellow rust)<br>Avacado (laurel wilt) | 92%<br>94% | Bravo *et al.*, 2003<br>Sankaran *et al.*, 2012 |
| Decision tree (DT) | Avacado (laurel wilt)<br>Sugarbeet (cerospora leaf spot)<br>Sugarbeet (powdery mildew)<br>Sugarbeet (leaf rust) | 95%<br>95%<br>86%<br>92% | Sankaran *et al.*, 2012<br>Rumpf *et al.*, 2010 |
| Multilayer perceptron (MLP) | Wheat (yellow rust) | 98.9/99.4% H/D | Moshou *et al.*, 2004 |
| Partial least square regression (PLSR) Raw<br>Savitsky-Golay 1st derivative<br>Savitsky-Golay 2nd derviative | Celery (sclerotinia rot) | 88.92%<br>88.18%<br>86.38% | Huang *et al.*, 2006 |
| Partial least square regression (PLSR) | Wheat (yellow rust) | 92% | Yuan *et al.*, 2014 |
| Fishers' linear determinant analysis | Wheat (aphid)<br>Wheat (powdery mildew)<br>Wheat (powdery mildew) | 60%<br>90% | Zhang *et al.*, 2012 |
| Fishers' linear determinant analysis (FLDA) | Wheat (yellow rust)<br>Wheat (powdery mildew) | 93% | Yuan *et al.*, 2012 |
| Erosion and dilation | Cucumber (downey mildew | 90% | Tian *et al.*, 2012 |
| Spectral angle mapper (SAM) | Sugarbeet (cerospora leaf spot)<br>Sugarbeet (powdery mildew)<br>Sugarbeet (leaf rust)<br>Wheat (head blight) | 89.01–98.90%<br>90.18–97.23%<br>61.7%<br>87% | Mahlein *et al.*, 2012<br>Bauriege *et al.*, 2011 |
| Artifcial neural network (ANN) | Sugarbeet (cerospora leaf spot)<br>Sugarbeet (powdery mildew)<br>Sugarbeet (leaf rust) | 96%<br>91%<br>95% | Rumpf *et al.*, 2010 |
| Support vector machine (SVM) | Sugarbeet (cerospora leaf spot)<br>Sugarbeet (powdery mildew)<br>Sugarbeet (leaf rust)<br>Barley (drought) | 97%<br>93%<br>93%<br>10 days before visible signs | Rumpf *et al.*, 2010<br>Behmann *et al.*, 2014 |
| Spectral information divergence (SID) | Grapefruit (cankerous, normal, greasy spot. Insect damage, melanose, scab, wind scar) | 95.2% | Qin *et al.*, 2009 |
| Simplex volume maximisation | Barley (drought) | 4 days before Vegetation Indices | Römer *et al.*, 2012 |
| SiVM with DAR | Barley (drought) | 1.5wk Before visible signs | Kersting *et al.*, 2015 |
| LSSVM | Wheat (drought) | 86.6%(H)/76.3%(S) | Moshou *et al.*, 2014 |

## Conclusion

Scientific literature on hyperspectral image analysis for plant stress detection has surged recently. Identifying plant diseases is crucial for effective crop management in agriculture and horticulture. Early stress and disease detection offer significant benefits, enabling preemptive interventions to prevent crop loss and maintain crop quality. Hyperspectral imaging, a non-invasive process, captures high-resolution plant data, gaining popularity due to affordable camera production costs. Various techniques analyze hyperspectral data for detecting biotic and abiotic stress in plants, focusing on classifying healthy and diseased plants, assessing disease severity, and early symptom identification. The growing number of vegetation and disease indices reflects their proliferation, providing insights into species-specific health or disease status. While indices like NDVI and PRI excel in determining general plant health, applying them across different species and datasets poses challenges. Considering a broader range of wavelengths holds the potential for more robust and generalized results.

## References


1. Bauriegel, E. Giebel, A. Geyer, M. Schmidt, U. and Herppich, W.B. 2011. Early detection of *Fusarium* infection in wheat using hyper-spectral imaging. Comput Electron Agric, 75:(304)–12.
2. Behmann, J. Steinrücken, J. and Plümer, L. 2014. Detection of early plant stress responses in hyperspectral images. ISPRS J Photogramm Remote Sens.93:98–111.
3. Bravo, C. Moshou, D. West, J. McCartney, A. and Ramon, H. 2003. Early disease detection in wheat fields using spectral refectance. Biosyst Eng.84:137–45.
4. Du, Y., Chang, C.I., Ren, H., Chang, C.C., Jensen JO, D'Amico FM 2004. New hyperspectral discrimination measure for spectral characterization. Opt Eng. 43:1777–86.
5. Fong, A.Y., Wachman, E. 2008. Hyperspectral imaging for the life sciences. Biophotonics Int. 15:38.
6. Genc, H., Genc, L., Turhan, H., Smith, S.E. and Nation, J.L. 2008.Vegetation indices as indicators of damage by the sunn pest (Hemiptera: Scutelleridae) to feld grown wheat. Afr J Biotechnology.
7. Huang, J.F. and Apan, A. 2006. Detection of Sclerotinia rot disease on celery using hyperspectral data and partial least squares regression. J Spat Sci.51:129–42.
8. Kersting, K., Xu, Z., Wahabzada, M., Bauckhage, C., Thurau, C., Roemer, C.2012. Pre-symptomatic prediction of plant drought stress using dirichlet-aggregation regression on hyperspectral images. Lasaponara, R. and Masini, N.2007. Detection of archaeological crop marks by using satellite QuickBird multispectral imagery. J Archaeol Sci.34:214–21.
9. Mahlein, A.K., Oerke, E.C., Steiner, U., and Dehne H.W. 2012. Recent advances in sensing plant diseases for precision crop protection. European Journal of Plant Pathology, 133(1):197–209.
10. Mahlein, A.K., Steiner, U., Hillnhütter, C., Dehne, H.W., Oerke, E.C.2012. Hyperspectral imaging for small-scale analysis of symptoms caused by diferent sugar beet diseases. Plant Methods.8:3
11. Moshou, D., Bravo, C., West, J., Wahlen, S., McCartney, A., and Ramon H. 2004. Automatic detection of "yellow rust" in wheat using refectance measurements and neural networks. Comput Electron Agric. 44:173–88
12. Moshou, D., Pantazi, X.E., Kateris, D. and Gravalos, I. 2014. Water stress detection based on optical multisensor fusion with a least squares support vector machine classifer. Biosyst Eng.117:15–22.
13. Peñuelas, J. and Filella, I. 1998. Visible and near-infrared refectance techniques for diagnosing plant physiological status. Trends Plant Sci. 3:151–6.

14. Qin, J., Burks, T.F., Ritenour, M.A. and Bonn WG. 2009. Detection of citrus canker using hyperspectral refectance imaging with spectral information divergence. J Food Eng. 93:183–91.
15. Römer, C., Wahabzada, M., Ballvora, A., Rossini, M., Panigada, C. and Behmann J. 2012. Early drought stress detection in cereals: simplex volume maximisation for hyperspectral image analysis. Funct Plant Biol.39:878–90.
16. Rumpf T., Mahlein A. K., Steiner U., Oerke E. C., Dehne H. W. and Plu¨mer L. 2010. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance Computers and Electronics in Agriculture. 74:91–99.
17. Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W. and Plümer, L.2010. Early detection and classifcation of plant diseases with support vector machines based on hyperspectral refectance. Comput Electron Agric. 74:91–9.
18. Sankaran, S., Ehsani, R., Inch, S.A. and Ploetz, R.C. 2012. Evaluation of visible-near infrared reflectance spectra of avocado leaves as a non-destructive sensing tool for detection of laurel wilt. Plant Dis. 96:1683–9.
19. Satterwhite, M.B. and Henley, J.P. 1990. Hyperspectral signatures (400 to 2500 nm) of vegetation, minerals, soils, rocks, and cultural features: laboratory and feld measurement.
20. Thurau, C., Kersting, K. and Bauckhage, C. 2010. simplex volume maximization for descriptive web-scale matrix factorization. In: Proceedings of 19th ACM international conference on information and knowledge management. New York, NY: ACM; 1785–8.
21. Tian, Y. and Zhang, L. 2012. Study on the methods of detecting cucumber downy mildew using hyperspectral imaging technology. Phys Procedia. 33:743–50
22. Xie, C. and He, Y. 2016. Spectrum and image texture features analysis for early blight disease detection on eggplant leaves. Sensors 16-676.
23. Yuan, L., Huang, Y., Loraamm, R.W., Nie, C., Wang, J. and Zhang, J.2014. Spectral analysis of winter wheat leaves for detection and diferentiation of diseases and insects. Field Crops Res.156:199–207.
24. Yuan, L., Zhang, J., Zhao, J., Du, S., Huang, W. and Wang J. 2012. Discrimination of yellow rust and powdery mildew in wheat at leaf level using spectral signatures. First international conference on agro-geoinformatics. 1–5.
25. Yuhas, R.H., Goetz, A.F. and Boardman JW. 1992. Discrimination among semi-arid landscape endmembers using the spectral angle mapper (SAM) algorithm. In: Summaries of the third annual JPL airborne geoscience workshop Pasadena, CA: JPL 147–9. http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19940012238. pdf
26. Zhang, J.C., Pu, R., Wang, J., Huang, W., Yuan, L. and Luo J. 2012. Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements. Comput Electron Agric. 85:13–23.