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Wavelength selection and classification of hyperspectral non-imagery data to discriminate healthy and unhealthy vegetable leaves

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Being the largest vegetarian population across the globe, vegetables are an integral part of Indian meals. The proposed research finds significant wavelengths to discriminate healthy and unhealthy vegetable plants. Spectral-reflectance (SR) and first-derivative (FD) in the visible, red edge and near infrared region (350–1000 nm) of three vegetables brinjal, cluster beans and long beans were used. The significant wavelengths were selected using ReliefF and Support-Vector-Machine (SVM). Random forest algorithm was used for classification. The binary classification was used for each vegetable separately, and multiclass classification was applied for all the samples. The most significant spectral wavelengths, for the prediction of diseased brinjal, correspond primarily to the red edge in SR. Long beans samples were classified accurately in the red-edge. In the case of cluster beans, SR is more effective than FD in the red-edge. The results substantiate the utility of HS data for discrimination of healthy and unhealthy vegetable plants and even vegetable types.

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HYPERSPECTRAL (HS) data are the spectral reflectance of target objects spread over a large number of narrow and continuous wavelengths over different portions of the electromagnetic spectrum (EMS). Crops exhibit different biophysical and biochemical characteristics like chlorophyll *a* and *b*, total chlorophyll, nitrogen content, carotenoid pigment, anthocyanin, plant stress, plant moisture and cell structure. HS remote sensing has the potential to detect subtle variations in these characteristics, which provide significant information about plant health, plant stress, crop yield and availability of nutrients. Analytical Spectral Devices, Inc. (ASD) spectroradiometer records reflectance spectra ranging from 350 to –2500 nm, covering the visible (Vis), near infrared (NIR) and shortwave infrared (SWIR) regions of the EMS help in the study and analysis of crops. A large number of bands ultimately result in multicollinearity and high correlation along many adjacent wavelengths[1–3]. The selection of significant spectral region and optimal wavelengths can alleviate the dimensionality, and reduce classification complexity and improve classification accuracy[4–6].

For the classification of peatland vegetation, random forest, support vector machine (SVM), regularized logistic regression and partial least square-discriminant analysis (PLS-DA) have been employed, where non-imagery HS data were used[7]. PLSR and linear discriminant analysis (LDA) methods are employed to find the most significant wavebands for discrimination of similar weeds and different species of crops. Diago *et al.*[8] captured HS images of three types of grapevines leaves for species discrimination. Images were captured using a camera and leaf reflectance was measured over 1040 wavelengths. Almost 92% classification accuracy was obtained by PLS classifier. Zapolska *et al.*[9] applied LDA, PLS regression and principal component regression (PCR) to find optimal wavelengths for discrimination between healthy and diseased *Olea europaea* L.

Researchers have used analysis of variance (ANOVA) for selecting optimal spectral bands from both spectral reflectance (SR) and first derivative (FD) for differentiating