

Crop type discrimination through low cost proximal RGB imaging and multivariate analysis

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Abstract

The current study is an attempt to use low cost red green blue (RGB) image based vegetation indices (VIs), obtained from simple RGB camera, in separating six different field crops. To achieve this, sixteen common VIs were calculated and used as inputs in different multivariate analysis for separating wheat (*Triticum* spp), mustard (*Brassica* spp), cabbage (*Brassica oleracea*), pigeon pea (*Cajanus cajan*), brinjal (*Solanum* spp) and chickpea (*Cicer arietinum*). Based on the variation in the green red ratio index (GRRi), Colour intensity index (INT), Color index of vegetation (CIVE) and Woebbecke index (WI) were identified performing significantly ($p < 0.05$) in discriminating six different crops e.g., cabbage, wheat, mustard, brinjal, pigeon pea, chick pea through classification and regression tree (CART) analysis. The results obtained from CART analysis were subsequently compared with discriminant analysis, which showed an accuracy of 96.3% of classifying different crops. The study meaningfully identified sensitive VIs that can be used to classify different field crop. The information achieved in this study can help in commercial and scientific decision making, planning in agribusinesses, and can be an important tool for conducting crop survey at regional scale.

Highlights

- Potentiality of RGB image based vegetation indices for crop discrimination is tried
- Variability of reflectance in RGB wavelengths for different crops aided in their discrimination through calculated vegetation indices and rule
- Identified sensitive vegetation indices is having potentiality to use in crop survey, crop type identification.

1. INTRODUCTION

A comprehensive understanding of spatial distribution of crop species is needed for sustainable crop management. It has been very challenging task to discriminate different crop species and to get an exact estimation of area covered by each of them spatially. The job becomes very cumbersome when the area is covered by heterogeneous crops. India is having rich crop genetic wealth, harboring about 4618 cultivars for 162 crops which include different promising cultivars, landraces, traditional varieties and hybrids in different phytogeographical regions (NBPGR, 2007). Majority of the farmers, in India, belongs to small and marginal category (86.2%; Census report, 2015-16), holding small crop area. Hence, field to field diversity of crop cultivation is much prominent. On the other hand, agricultural intensification through multiple cropping is one of the ways for increasing crop productivity (Heller et al., 2012). Therefore, detecting and estimating fine-scale changes in crop types is important from global and regional perspective.

Conventionally, fieldwork has been conducted for discriminating different crops which is thorough, time-consuming, laborious, and hardly covers larger area. Moreover, the whole process largely depends on taxonomical information and sometime cannot be done for inaccessible areas (Das et al., 2018). The remote sensing technique, due to its high spatial and temporal coverage with less cost and time involvement, is more meaningful than field-based methods in crop discrimination (Cao et al., 2010; Das et al., 2018). However, due to the high spatio-temporal heterogeneity of crop cultivation, which arises because of small landholding size, discrimination of crop type using remote sensing is sometimes challenging (Heller et al., 2012). Additionally, atmospheric hindrance due to cloud cover, absorption by different constituents pose problems in accurate crop discrimination. Efforts have been made to overcome these challenges by using pattern recognition (Lai et al., 1986), mathematical orthogonal transformation (Utku, 2000), digital image analysis techniques (Liu et al., 2004; Bandyopadhyay, 2005), visible and near-infrared spectral characteristics (Li and He, 2008), multispectral and (Heller et al., 2012), hyperspectral remote sensing (Schmidt and Skidmore, 2003), and thermal imaging (Banerjee et al., 2020; Banerjee et al 2018). Among all, the hyperspectral remote sensing is very useful in crop type or species discrimination. Many of these techniques are expensive and unsuitable in the rural communities, on the other hand, digital cameras that measure reflectance in blue, green, and red bands might provide the information needed to fill this need. RGB images (red/green/blue imaging cameras) provide a low-cost alternative to hyperspectral data for calculating vegetation indices (Gracia-Romero et al., 2017). Previous studies using RGB image based vegetation indices showed effectiveness in providing an extensive range of information about crop types based on the colour features (Casadesús and Villegas, 2014; Zhou et al., 2015; Yousfi et al., 2016; Gracia-Romero et al., 2017). Hamuda et al., 2017 reported colour features are most distinguishable and unique among the crops and could be useful in crop type separation. Vegetation indices, calculated as a ratio of two or more bands, are considered important for extracting meaningful information of the object sensed from a distance (Huent et al., 2013). Several RGB image based vegetation indices were analyzed under natural illumination conditions, where excess green (ExG) was found the best in sunny environment (Woebbecke et al., 1995). Mao et al (2003) combined ExG with another index called ExR (Meyer et al., 1998) and create a new index i.e., excess green minus excess red index (ExGR). Similar index, normalized difference index (NDI) was developed to differentiate plant part from no-plant part (Perez et al., 2000). Hague et al. (2006) proposed vegetative index (VEG) for estimating density map of both weed and crop. A linear combination of four different indices was developed to derive combination index (COM) (Guijarro et al., 2011). Previously, several studies showed usefulness of RGB image based VIs i.e., green red ratio index (GRRi), green blue ratio index (GBRI), red blue ratio index (RBRI), color intensity index (INT) etc. (Table 1), in separating crop and weeds or crop from soil/ other background (Hunt et al., 2013, Hamuda et al., 2016, Di Gennaro et al., 2017, Maimaitijiang et al., 2019). Hamuda et al. (2016) did a comprehensive survey on image-based plant segmentation techniques for identifying crop plant from weed. López-Granados et al. 2016 used RGB and multispectral cameras and found VIs like ExG and NDVI as effective for classifying Johnson grass (*Sorghum halepense*) from maize crop. Similarly, Hamuda et al. (2017) discriminated cauliflower crop from weeds using HSV (Hue, Saturation and Value) colour space technique. Jime'nez-Brenes et al. (2019) used thirty different RGB and NIR based VIs for discriminating bermudagrass (*Cynodon dactylon*) from soil background in a vineyard. However, the use of low cost RGB image based VIs in classifying different crops under field condition is remain untapped. Identification of sensitive vegetation indices using low cost tools/ methods for smallholder agriculture for separating crop types is the essence of this study. Keeping this all in background, the current study made an attempt to evaluate different RGB image vegetation based indices and to identify important indices for separating field crops using different multivariate techniques.

2. MATERIALS AND METHODS

2.1 Experimentation

RGB images of different filed crops e.g., spring wheat, mustard, cabbage, chickpea, pigeon pea and brinjal were taken from different farmers' fields of East Champaran, Bihar (26.6098° N, 84.8568° E) during *rabi* season 2021–2022. The area is having humid sub-tropical climatic type with temperature ranges between 22 and 46°C in summer, but the winter is having higher diurnal temperature variations with the minimum temperature of 5°C and frequent foggy atmosphere. Mean average annual rainfall is 1100mm where most of them are received during monsoon season.

2.2 Crop selection

Six different crops (both vegetables and cereals) namely, wheat, mustard, cabbage, chickpea, pigeon pea and brinjal, (Fig. 1& 2) which are generally grown by the local farmers, were selected for the study from different locations. All the crops were sown on recommended time i.e., Brinjal on 14th November, Pigeon pea on 25th October, mustard on 30th October, Chickpea on 16th November, Cabbage on 20th November and Wheat on 15th November, as prescribed for Indo-Gangetic plain. All the crops were managed properly with recommended package of practice during their growth period.

2.3 Image acquisition

RGB (R-Red; Band3, G-Green; Band 2 and B-Blue; Band 1) images were taken using Sony CyberShot (DSCW830, SONY Corporation, Tokyo, Japan) camera. The camera has CCD sensor (size 7.76 mm) with focal length of 35 mm, angle of view of 82° and gives an image of 20.1 megapixels (in .JPG format). Images were collected vertically (from nadir view) on January 12, January 20, and January 30, 2022 from 11.30–13.30 h under clear sky condition maintaining a constant height between canopy and the camera lenses during each time of image capturing. Images were taken from different plots in three replications for each crop type and dates.

2.4 RGB indices calculation

Reflectance obtained in R, G, and B bands for each crop and on each date were studied properly. Based on the reflectance values, vegetation indices of all the crops were calculated for each date. RGB images contain both soil and crop fraction, thus, soil fraction was masked prior to vegetation indices calculation. Therefore, preprocessing of all the RGB images were done as given in the work flow (Fig. 1). The spectral signature of all the crops, obtained from QGIS v3.22, in R, G and B band is shown in Fig. 2. A set of sixteen different indices were calculated using the RGB images for each date of observation for each crop using “raster” package (Hijmans, 2019) in R studio. Descriptive statistics of calculated VIs were obtained for each crop for different days of image acquisition. Latter, to identify significance of differences between pairs of group means, Tukey's Honest Significant Difference (HSD) was done in SPSS v16.

2.5 Classification and regression tree (CART) and Discriminant analysis (DA)

CART is a non-parametric statistical method (Breiman et al., 1984), which has the ability to select important variables from large number of explanatory variables (here it is RGB based indices) for separating categorical variables (here it is crop types) (Questier et al., 2005; Yang et al., 2003; Das et al., 2018). In this study, an attempt was made to identify sensitive RGB indices which will be useful for crop type discrimination using multivariate analysis.

Table 1
list of RGB image based VIs calculated in this study

Spectral indices	Definition	References
Green red ratio index	$GRRI = G/R$	Maimaitijiang et al., 2019
Green blue ratio index	$GBRI = G/B$	Maimaitijiang et al., 2019
Red blue ratio index	$RBRI = R/B$	Maimaitijiang et al., 2019
Colour intensity index	$INT = (R + G + B)/3$	Ahmad and Reid, 1996
Green red vegetation index	$GRVI = (G - R)/(G + R)$	Tucker, 1979
Normalized difference index	$NDI = (nR - nG)/(nR + nG + 0.01)$	Woebbecke et al., 1995
Woebbecke index	$WI = (G - B)/(R - G)$	Woebbecke et al., 1995
Kawashima index	$IKAW = (R - B)/(R + B)$	Kawashima and Nakatani, 1998
Green leaf index	$GLI = (2 \times G - R - B)/(2 \times G + R + B)$	Louhaichi et al., 2001
Visible atmospherically resistance index	$VARI = (G - R)/(G + R - B)$	Gitelson et al., 2002
Excess red vegetation index	$ExR = (1.4 \times nR - nG)$	Mao et al., 2003
Excess green vegetation index	$ExG = (2 \times nG - nR - nB)$	Mao et al., 2003
Excess green minus Excess red index	$ExG - ExR$	Mao et al., 2003
Vegetative index	$VEG = G/(R^{0.667} \times B^{(1 - 0.667)})$	Hague et al., 2006
Color index of vegetation	$CIVE = 0.441 \times R - 0.811 \times G + 0.385 \times B + 18.78745$	Kataoka et al., 2003
Combined index 1	$COM1 = ExG + CIVE + ExGR + VEG$	Guijarro et al., 2011

CART analysis was performed using ‘rpratt’ package in R studio. All the image-based vegetation indices were normalized and subsequently used for crop type discrimination by CART analysis. To validate the result, subsequently, discriminant analysis (DA) was performed using the sensitive RGB indices identified

from the CART. Discriminate analysis has the ability to discriminate variable bands on the function that gives maximum separation among the groups (Abdolshahi et al., 2015). Out of total dataset, one third data set were used for accuracy assessment during validation. In this study, DA was performed in SPSS v16.

3. RESULT

3.1 ANOVA analysis

Variations in the spectral response in R (band 3), G (band 2) and B (band 1) wavelengths were observed among the crops (Fig. 2). Irrespective of different days of observations, reflectance in B band (1) showed less variance as compared to G and R for all the crops used in this study. Image based vegetation indices were calculated for all the crops at different days of observations. One-way ANOVA showed existence of significant difference ($p < 0.05$) among the vegetation indices for the different crops (supplementary table 1). This further supported in discriminating different crop types using these VIs. Latter, Tukey's post hoc test was performed for pairwise combinations (supplementary table 2) for six different crops. The result showed significant difference ($p < 0.05$ and $p < 0.001$) between the crops (supplementary table 2). Descriptive statistics (mean and standard deviation) of RGB image-based VIs for each crop at each stage are shown in Table 2. In general, wheat showed the highest values in GBRI, RBRI, VEG, GRVI, ExG, NDI, ExGR, and GLI for all the dates. Mustard showed the highest values in ExR, CIVE, COM1 and the lowest in GRRI, GBRI, VEG, GRVI, ExG, NDI, ExGR, GLI and VARI for the first observation date (Table 2). During second date of observation, pigeon pea showed the lowest values for GRRI, GBRI, VEG, GRVI, ExG, NDI, ExGR, GLI, VARI and INT and the highest values in CIVE, ExR and COM1. Chickpea showed the highest values for INT both during first and third date of observations, while cabbage showed the lowest values for IKAW for all three dates of observations. Among the different VIs calculated in this study, ExGR and VARI gave the highest, and NDVI, CIVE, and COM1 gave the lowest variations irrespective of crop types (Table 2). Spatial map shows the variation in different image based vegetation indices in Fig. 3 for brinjal. Similarly, spatial maps of different vegetation indices are shown in supplementary Fig. 1.

Table 2
Descriptive statistics of all the RGB based indices (mean - μ and standard deviation- Sd) of all the crops for three different stages.

First Date- January 12, 2022																
Crops	DS	GRRI	GBRI	RBRI	INT	WI	GRVI	IKAW	ExG	NDI	ExR	ExGR	GLI	VARI	CIVE	VE
Brinjal	μ	1.092	1.126	1.050	94.264	-0.885	0.021	-0.002	0.030	0.021	0.113	-0.082	0.013	0.026	17.901	1.0
	Sd	0.039	0.045	0.018	9.269	0.180	0.017	0.005	0.021	0.017	0.011	0.032	0.016	0.042	2.016	0.0
Cabbage	μ	1.181	1.078	0.926	107.60	0.170	0.067	-0.074	0.033	0.067	0.075	-0.042	0.016	0.172	16.822	1.1
	Sd	0.013	0.024	0.009	1.832	0.119	0.005	0.013	0.009	0.005	0.005	0.009	0.008	0.018	0.362	0.0
Chickpea	μ	1.077	1.221	1.132	124.32	-1.556	0.029	0.035	0.062	0.029	0.110	-0.047	0.039	0.054	12.032	1.1
	Sd	0.025	0.027	0.007	2.751	0.148	0.009	0.005	0.011	0.009	0.009	0.020	0.007	0.015	1.210	0.0
Mustard	μ	1.004	1.063	1.069	103.39	-1.183	-0.022	-0.003	-0.029	-0.022	0.141	-0.171	-0.036	-0.068	23.181	0.9
	Sd	0.050	0.051	0.013	4.409	0.129	0.016	0.001	0.021	0.016	0.011	0.032	0.014	0.028	1.348	0.0
Pigeon pea	μ	1.041	1.132	1.138	82.740	-0.019	0.001	-0.005	-0.008	0.001	0.132	-0.140	-0.014	0.012	19.440	1.0
	Sd	0.040	0.134	0.136	13.851	0.340	0.003	0.016	0.012	0.003	0.004	0.008	0.014	0.023	0.025	0.0
Wheat	μ	1.291	1.623	1.238	95.580	-1.197	0.090	0.030	0.147	0.090	0.053	0.093	0.090	0.163	6.308	1.3
	Sd	0.041	0.076	0.019	2.299	0.060	0.004	0.009	0.009	0.004	0.007	0.015	0.004	0.009	0.617	0.0
Second Date- January 20, 2022																
Brinjal	μ	1.123	1.206	1.077	93.898	-0.952	0.036	0.001	0.050	0.036	0.101	-0.050	0.027	0.064	15.776	1.1
	Sd	0.058	0.106	0.009	9.090	0.083	0.021	0.001	0.033	0.021	0.021	0.054	0.022	0.041	2.056	0.0
Cabbage	μ	1.168	1.064	0.931	103.09	0.125	0.060	-0.071	0.025	0.060	0.080	-0.055	0.009	0.157	17.351	1.0
	Sd	0.014	0.041	0.040	4.369	0.155	0.007	0.017	0.007	0.007	0.004	0.005	0.005	0.027	0.123	0.0
Chickpea	μ	1.077	1.210	1.116	116.99	-1.208	0.029	0.025	0.055	0.029	0.109	-0.054	0.033	0.050	13.025	1.0
	Sd	0.044	0.049	0.014	6.529	0.256	0.017	0.003	0.025	0.017	0.014	0.039	0.017	0.035	2.630	0.0
Mustard	μ	1.040	1.066	1.036	117.05	-1.052	0.002	-0.005	0.001	0.002	0.127	-0.126	-0.010	-0.011	20.968	1.0
	Sd	0.033	0.045	0.019	2.971	0.108	0.011	0.010	0.021	0.011	0.008	0.028	0.014	0.022	1.887	0.0
Pigeon pea	μ	0.991	1.014	1.029	82.394	-0.371	-0.019	-0.022	-0.043	-0.019	0.141	-0.184	-0.042	-0.052	22.286	0.9
	Sd	0.017	0.014	0.021	15.332	0.783	0.008	0.016	0.010	0.008	0.002	0.009	0.008	0.011	1.238	0.0
Wheat	μ	1.286	1.610	1.214	94.197	-1.196	0.092	0.026	0.147	0.092	0.051	0.096	0.091	0.173	6.771	1.3
	Sd	0.020	0.061	0.057	3.816	0.103	0.005	0.016	0.004	0.005	0.005	0.002	0.003	0.011	0.836	0.0
Third stage- January 30, 2022																
Brinjal	μ	1.465	1.141	1.061	90.140	-0.884	0.025	0.000	0.036	0.025	0.110	-0.075	0.017	0.036	17.177	1.0
	Sd	0.519	0.011	0.010	3.392	0.038	0.003	0.001	0.004	0.003	0.002	0.005	0.003	0.010	0.581	0.0
Cabbage	μ	1.178	1.070	0.922	106.45	0.192	0.065	-0.079	0.026	0.065	0.075	-0.049	0.010	0.170	17.104	1.1
	Sd	0.003	0.015	0.008	0.900	0.033	0.001	0.004	0.005	0.001	0.001	0.006	0.004	0.001	0.233	0.0
Chickpea	μ	1.091	1.234	1.129	123.90	-1.384	0.034	0.030	0.066	0.034	0.105	-0.039	0.041	0.063	11.558	1.1
	Sd	0.011	0.013	0.005	0.668	0.130	0.004	0.003	0.004	0.004	0.004	0.007	0.002	0.006	0.461	0.0
Mustard	μ	1.035	1.084	1.063	106.68	-1.120	-0.009	-0.003	-0.011	-0.009	0.132	-0.143	-0.022	-0.039	21.962	1.0
	Sd	0.022	0.016	0.009	2.458	0.045	0.010	0.002	0.013	0.010	0.007	0.019	0.010	0.021	0.862	0.0
Pigeon pea	μ	1.030	1.130	1.138	81.400	-0.167	-0.007	-0.009	-0.020	-0.007	0.134	-0.154	-0.025	-0.004	20.263	1.0
	Sd	0.009	0.007	0.008	1.546	0.183	0.006	0.006	0.010	0.006	0.002	0.012	0.009	0.014	0.845	0.0
Wheat	μ	1.299	1.624	1.215	93.554	-1.189	0.093	0.025	0.149	0.093	0.049	0.100	0.091	0.175	6.821	1.3
	Sd	0.009	0.013	0.002	0.455	0.008	0.001	0.001	0.001	0.001	0.001	0.003	0.000	0.002	0.091	0.0

3.2 CART analysis

As the RGB image based VIs gave significant variations among different crops, we further used them in CART analysis and obtained most significant VIs that could be potentially used for crop type discrimination. The CART tree (Fig. 4), through its algorithm, examined VIs of different crops and picked out important indices that best classified crop types.

For classifying different crops, CART used 13 different nodes (Fig. 4). Node frequency showed the distribution of each crop in the tree and their relative probabilities. Like, in node 1 all the six crops were present (%100) with purity percentage of 22.2 (Fig. 4). Purity percentage indicates the dominating category of the dependent variables in that particular node. Table 3 shows the corresponding dominating percentage of individual crop at each node. In the node 3, GRRI was taken as separating variable, which classified wheat (pink colour) from other crops with the value (of GRRI) between 0.7–1.00 (Fig. 4) and the purity of this node was 100%. In this node, probability percentage of occurrence of other crops were zero (indicating only wheat can be classified).

Table 3
Node frequency

Node	Brinjal	Cabbage	Chickpea	Mustard	Pigeon pea	Wheat	Brinjal	Cabbage	Chickpea	Mustard	Pigeon pea	Wheat
1	6	5	6	6	5	8	16.67	13.89	16.67	16.67	13.89	22.22
2	6	5	6	6	5	0	21.43	17.86	21.43	21.43	17.86	0.00
3	0	0	0	0	0	8	0.00	0.00	0.00	0.00	0.00	100.00
4	6	5	0	6	5	0	27.27	22.73	0.00	27.27	22.73	0.00
5	0	0	6	0	0	0	0.00	0.00	100.00	0.00	0.00	0.00
6	6	0	0	6	0	0	50.00	0.00	0.00	50.00	0.00	0.00
7	0	5	0	0	5	0	0.00	50.00	0.0	0.00	50.00	0.00
8	5	0	0	0	0	0	100.00	0.00	0.00	0.00	0.00	0.00
9	1	0	0	6	0	0	14.29	0.00	0.00	85.71	0.00	0.00
10	1	0	0	1	0	0	50.00	0.00	0.00	50.00	0.00	0.00
11	0	0	0	5	0	0	0.00	0.00	0.00	100.00	0.00	0.00
12	0	0	0	0	5	0	0.00	0.00	0.00	0.00	100.00	0.00
13	0	5	0	0	0	0	0.00	100.00	0.00	0.00	0.00	0.00

Subsequently, in node five, INT (ranges between 0.905–1.00) along with GRRI (ranges between 0.70–1.00) were combined (Fig. 4) for separating chickpea from other crops and the purity of this node was 100%. Like this way, CIVE (value between 0.519– 0.691) and WI (value between 0.136–0.483) were counted in with GRRI (value between 0.00–0.7) and INT (value between 0.024–0.905) to classify Brinjal in node 8 (Fig. 4). The node with 100% purity denotes a particular crop was being classified with the decision rule as mentioned above. Similarly, in node 11, 12 and 13, mustard, pigeon pea and cabbage were classified as shown in Fig. 4. Gradually, CART model picked out four potentially important VIs (GRRI, INT, WI and CIVE) for classifying six different crop. Selection of GRRI, INT, WI and CIVE as important VIs from CART analysis can also be justified by looking their variation in different crops (Fig. 3 and supplementary Fig. 1)

Table 4
Accuracy assessment of crop type discrimination (a) calibration and (b) validation

from \ to	Brinjal	Cabbage	Chickpea	Mustard	Pigeon pea	Wheat	Total	% correct
Calibration stage								
Brinjal	6	0	0	0	0	0	6	100.00%
Cabbage	0	5	0	0	0	0	5	100.00%
Chickpea	0	0	6	0	0	0	6	100.00%
Mustard	1	0	0	5	0	0	6	83.33%
Pigeon pea	0	0	0	0	5	0	5	100.00%
Wheat	0	0	0	0	0	8	8	100.00%
Total	7	5	6	5	5	8	36	97.22%
Validation stage								
from \ to	Brinjal	Cabbage	Chickpea	Mustard	Pigeon pea	Wheat	Total	% correct
Brinjal	3	0	0	0	0	0	3	100.00%
Cabbage	0	4	0	0	0	0	4	100.00%
Chickpea	1	0	2	0	0	0	3	66.66%
Mustard	0	0	0	3	0	0	3	100.00%
Pigeon pea	2	0	0	0	2	0	4	80.00%
Wheat	0	0	0	0	0	1	1	100.00%
Total	8	4	0	3	2	1	18	91.11%

Confusion matrix of CART showed an accuracy of 97.22% during calibration stage in classifying different crops in this study (Table 4). Further, the study validated the usefulness of CART model for crop type classification using 18 new observations, which were not used during model development, and validation result showed an accuracy of 91.11% (Table 4).

3.3 Discriminant analysis

The discriminative potentiality of the identified VIs through CART method, was verified using discriminant analysis (DA). In discriminant analysis, VIs e.g., GRRI, INT, WI, and CIVE were used as independent inputs. Four functions discriminated all the crops and explained the variance of 62.9%, 24.1%, 8.8%, and 4.2% in the data set (Table 5). As compare to other functions, function one has the highest eigenvalue, percentage of variance explained and the highest canonical correlation in discriminating different crop types (Table 5).

Function 1 =	$-9.27 + 0.45 * GRRI - 0.48 * INT - 6.00 * WI + 12.84 * CIVE$
Function 2 =	$-5.13 - 12.25 * GRRI - 5.79 * INT + 2.16 * WI + 5.98 * CIVE$
Function 3 =	$-13.52 + 13.01 * GRRI + 5.30 * INT - 4.26 * WI + 12.17 * CIVE$
Function 4 =	$-0.60 - 3.55 * GRRI + 14.42 * INT + 5.87 * WI - 5.36 * CIVE$

Table 5

Summary of the discriminant analysis

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	20.40	62.90	62.90	0.97
2	7.82	24.10	87.00	0.94
3	2.84	8.80	95.80	0.86
4	1.35	4.20	100.00	0.75
Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 4	0.001	357.37	20	0.000
2 through 4	0.013	210.33	12	0.000
3 through 4	0.110	105.81	6	0.000
4	0.424	41.16	2	0.000
Structural matrix				
Input	Functions			
	1	2	3	4
CIVE	0.756	-0.340	0.147	-0.54
GRRI	-0.429	0.702	0.360	0.441
WI	0.354	0.421	-0.187	0.814
INT	-0.106	-0.418	0.585	0.687

Wilks' lambda gives a measure of how well each function separates cases into groups. In general, Wilk's lambda varies from 0 to 1, where the value closer to 0 indicates the group means are significantly different. In our study, Wilk's lambda value of 0.001, 0.013, 0.11 and 0.424 were obtained (Table 5) for function 1 through 4, 2 through 4, 3 through 4 and though 4 respectively which was highly significant ($p < 0.0001$) in discriminating the crops (Fig. 5). The associated chi-square statistic tests the hypothesis that the means of the functions are equal across crops. The small significance value indicates that the discriminant function performed better than chance in separating the crops. In the present study, the chi-square value of 357.37 was obtained for function 1 through 4 (Table 5), which was found effective in separating different crop. Eigenvalue provides information on each of the discriminating function. Larger the eigenvalue, the more the variance of the dependent variable is explained by that function. Here the eigenvalues of 20.4 and 7.82 (Table 5) were obtained for function 1 and 2, respectively, which are quite higher in explaining the function. Centroids are discriminant score for each group when the variable means are entered into the function (Fig. 5). Locations of the group centroids are also quite distinct and much apart from one another for different crop types (Fig. 5). The position of centroids showed that the classification of different crops is considerably accurate. Similarly, structural matrix showed those VIs that performed significantly with a score > 0.3 (Hair et al. 1992) in each canonical functions for discriminating different crops (Table 5). CIVE, GRRI, INT and WI performed effectively with highest score in function one, two, three and four respectively in discriminating different crop types (Table 5). Function one (Fig. 5, horizontal axis, and most effective parameter for this function is CIVE) discriminated chick pea and mustard from other crops and function two (vertical axis, most effective parameter for this function is GRRI) discriminated wheat and chick pea from other crops as shown in Fig. 5.

DA discriminated all crops with an overall accuracy of 96.3% (Table 6) using the selected inputs (four VIs) obtained from the CART analysis. This, in another way, proves the potentiality of selected VIs through CART in crop discrimination.

Table 6
Accuracy assessment of crop discrimination

Accuracy assessment of crop discrimination								
Classification Results								
			Crop	Predicted Group Membership				
				Brinjal	Cabbage	Chick pea	Mustard	Pigeon pea
Original	Count	Brinjal	8	0	0	1	0	0
		Cabbage	0	9	0	0	0	0
		Chick pea	0	0	9	0	0	0
		Mustard	0	0	0	9	0	0
		Pigeon pea	0	0	0	1	8	0
		Wheat	0	0	0	0	0	9
	%	Brinjal	88.9	.0	.0	11.1	.0	.0
		Cabbage	.0	100.0	.0	.0	.0	.0
		Chick pea	.0	.0	100.0	.0	.0	.0
		Mustard	.0	.0	.0	100.0	.0	.0
		Pigeon pea	.0	.0	.0	11.1	88.9	.0
		Wheat	.0	.0	.0	.0	.0	100.0
96.3% of original grouped cases correctly classified								

4. DISCUSSION

The field of geo-intelligence is witnessing development technologically at a startling rate (Cucho-Padin et al. 2020). Two main elements are responsible for this increase: first, data and technological advancements, such as the ease with which satellite imagery is now accessible (Dutta et al. 2023), and second, significant advancements in the domains of big data and machine learning (Mohammadi et al. 2018). On the other hand, a lot of private players are stepping up to the plate as there is an increasing need to resolve challenging and major difficulties (Attard et al. 2015). One of these issues is agriculture in developing countries to boost farm income. A few of the problems that afflict agriculture, particularly in emerging nations, are small, dispersed farms, inadequate resource planning on the side of farmers, a lack of precision farming, low farm output, and disaggregated farmer and farm-level information (Hill 2018, Cucho-Padin et al. 2020). In order to identify crops, segment farms, estimate crop health, and anticipate yields, data scientists are engaging in unstructured data mining using publicly available satellite imagery (Cravero et al. 2022). Crop identification is the initial step in this series of solutions. This article describes how multivariate analysis is used in conjunction with RGB photography to achieve crop identification.

The present study was undertaken to discriminate field crops using low cost RGB image-based VIs and multivariate techniques. RGB imaging mobile cameras are low costing and can cover large areas in one shot and thus provide multi information in short time. Multivariate techniques aid in observing and quantifying the relationship between dependent and independent variables. It provides the advantage of obtaining a more realistic or specific relationship among the observations than looking at a single variable. Additionally, multivariate techniques offer more powerful tests of significance compared to univariate techniques. Even though multivariate techniques are complex, and require huge data and mathematical analysis, they have been used in different crop-related studies. In this study, CART analysis was performed to discriminate different crop types and the result was compared with discriminant analysis. Unlike conventional data analysis approaches, CART is a tree-building technique that is based on clear decision rules at different nodes. In spite of its complexity of analysis, the popularity of CART analysis for tree induction is increasing in different studies. Due to the nonlinear relationship and interaction effect between features and outcomes, CART is more useful than the linear and logistic regression models (Lewis, 2000). In this study, CART examined all the possible variable combinations of vegetation indices on the basis of splitting rules and divided the parent node into child nodes, and classified different crops. Additionally, the most important VIs were identified in the tree structure using CART analysis. Subsequently, for validating the result obtained from CART, discriminant analysis was performed using the VIs as obtained from the CART analysis. Discriminant analysis is another multivariate technique used in this study provides a potential advantage of classifying ungrouped cases. In discriminant analysis, the functions were generated from samples of known group membership and later those functions were applied to new cases of unknown group membership for classification purposes. In comparison to different methodological approaches as mentioned previously (Lai et al., 1986; Utiku, 2000; Liu et al., 2004; Bandyopadhyay, 2005; Li and He, 2008; Heller et al., 2012; Schmidt and Skidmore, 2003; Das et al., 2018; Banerjee et al 2020), the hyperspectral technique was much useful in crop type and species discrimination due to its finer spectral resolution (Schmidt and Skidmore, 2003; Vaiphasa et al., 2007; Das et al., 2018). Although hyperspectral remote sensing has several advantages, it is costly and having inherent complexity, generate large volume of redundant data, limited spatial resolution, presence of noisy data, limited temporal resolution etc. (Das et al., 2018). Thus, in this study, we used easily available RGB image data which is less costly, and derived different VIs that could be potential for crop discrimination. Among sixteen different VIs, the current study identified the four most effective VIs i.e., GRRI, CIVE, INT, and WI that performed considerably in crop discrimination. The variations in the mean value of these VIs among different crops were due to difference in the reflectance or absorption value in R, G, and B bands. Vegetation indices GRRI, CIVE, INT, and WI are highly sensitive to the presence of vegetation. It uses the contrast between reflectance in R and G bands obtained from vegetation. Red and green bands are strongly associated with chlorophyll absorption and reflectance properties of healthy vegetation. GRRI is the ratio of reflectance in G/ R. In this study, GRRI classified wheat in node 3 (with value 0.7-1), cabbage in node 13

(with value 0.37–0.7) and pigeon pea in node 12 (with value 0–0.37). Canopy of wheat and cabbage are much greener as compare to pigeon pea, thus, more reflectance in G band was received (Fig. 2) as compare to R from wheat and cabbage. Thus pigeon pea and wheat were classified at higher range of GRRI (i.e., 0.37–0.7 and 0.7–1 respectively) as compare to pigeon pea i.e. <0.37. Similarly, classification of other crops at each nodes can be identified based on the reflectance and absorption properties of canopy surface. In the present study, different crops showed variation in absorption and reflectance based on their leaf reflectivity (variations in greenness in majority), which may be one of the reasons for their discrimination (Fig. 2). Leaf colour is thus an essential factor which control reflectance or absorption in R, G, and B bands and makes difference in the vegetation indices and held in crop discrimination in this study. By calculating these indices, the differences in vegetation reflectance can be emphasized (Fig. 3), making them effective for discriminating different crops (Fig. 4). During validation, the canonical discriminant function plot (Fig. 5) could confirm the accuracy of the result obtained from CART.

Previously, Lopez-Granados et al. (2016) discriminated *Sorghum halepense* from maize using object-based image analysis, where they found VIs like ExG and NDVI were performing significantly in the discrimination. Similarly, Hamuda et al. (2017) separated crop and weed from soil using HSV colour space using different VIs e.g., ExG, ExGR, CIVE, VEG, COM, and plant morphological characters. Jiménez-Brenes (2019) used both RGB and combination of RGB-NIR band and calculated several VIs for separating *Cynodon dactylon* in a vineyard orchard. Their study identified ExGR and GNDVI were performing best for separating weeds from the vineyard. Whereas in this study, we found, GRRI, CIVE, INT, and WI effective for discriminating different crops with a classification accuracy of 96.3% which is similar reported in Jiménez-Brenes (2019). The difficulties of crop type discrimination have, however, been addressed using pattern recognition techniques (Lai et al., 1986), mathematical orthogonal transformations (Utku, 2000), thermal image and multivariate analysis techniques (Banerjee et al 2020), visible and near-infrared spectral characteristics (Li and He, 2008), multispectral and (Heller et al., 2012), hyperspectral remote sensing (Das et al., 2018). However, for calculating vegetation indices, RGB images offers a less expensive option than hyperspectral data (Gracia-Romero et al., 2017). Previous research demonstrated that RGB image-based vegetation indices are effective for providing a wide range of information about crop types and their genotypic performance under various environmental circumstances (Gracia-Romero et al., 2017, Lopez-Granados et al. 2016, Jiménez-Brenes 2019, Hamuda et al. 2017). Our results confirmed that classification of different crops could be done with using RGB image based indices with the multivariate approaches.

The majority of farmers in India fall into the small and marginal group with access to limited cropland. Consequently there is a distinct and noticeable variation in cropping diversity from one field to another. Crop discrimination is also essential in precision agriculture, crop monitoring, land use planning resource management and assessing risk related to agriculture. We used a consumer-grade RGB camera, which is a great advantage for the practical application of crop type monitoring in a cost-effective way. Additionally, the present study considered the variation in vegetation spectral characteristics (color properties) by taking observation at different days after sowing. Thus, phenological changes in terms of reflectance/ absorption values at different stages are also taken care of. Methodological framework obtained in this study can also be tested for other crops. In summary, crop type discrimination using remote sensing tools provides critical information for optimizing agriculture, supporting food security, managing resources sustainably, and making informed decisions in various sectors related to agriculture and land use.

Conclusion

The use of spectro-temporal profiles of the VIs of different field crops assisted in obtaining important information, enabling better identification of crops from regional scale mapping using the RGB image data. This study provides a framework for identifying/ classifying different crop types distributed spatially with error analysis. The current study focused on crop discrimination utilizing straightforward RGB images where VIs e.g., CIVE, GRRI, INT, and WI were identified as the most useful in crop type classification under field conditions. The different vegetation indices in this study showed differences in understanding to vegetation identification, thereby prompting the quality of classification. The identified VIs generated spectral information that offered a better discrimination for mapping the crops under study. This valuable information may be used in commercial and political decision planning in agribusinesses, and can be viewed as a vital tool for survey conducted by official institutions. Selection of significant RGB based VIs using low-cost camera could be potentially useful in studying agricultural crops.

Declarations

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Conflict of interest: The authors declare no conflict of interest

Author Contributions:

Koushik Banerjee: Conceptualization, Data curation, Formal analysis, Writing – original draft

Suman Dutta: Methodology, Resources

Bappa Das: Software, Supervision

Debasis Roy.....Data collection, Paper drafting

Bhabani Prasad Mandal: Visualization

Arghya Chattopadhyay: Validation, Visualization

Suman Sen: Visualization, Writing – review & editing

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Figures

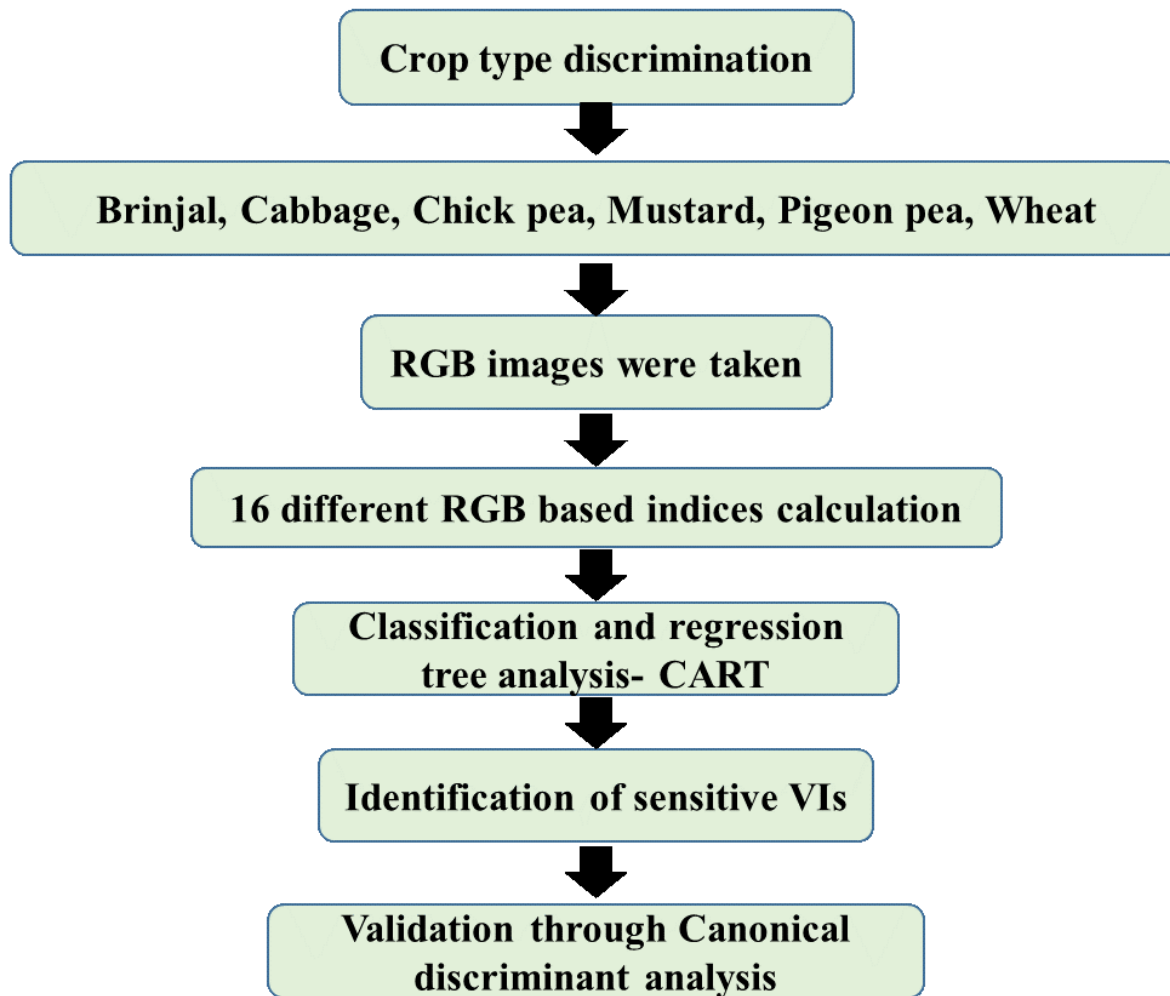


Figure 1

Overall theme of the study.

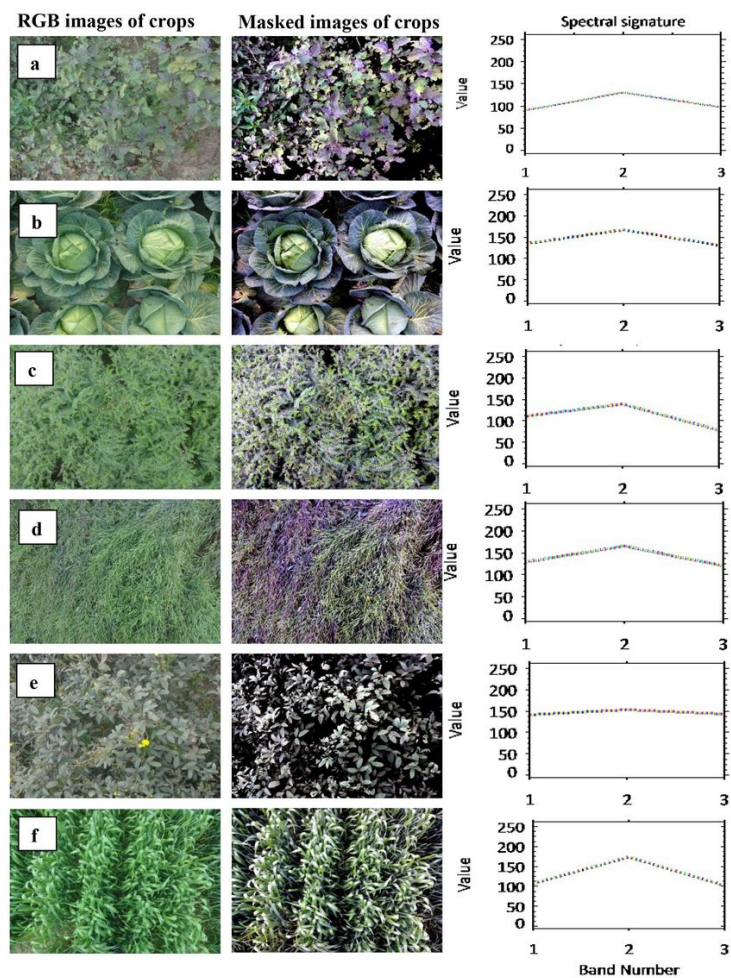


Figure 2
 RGB images, masked images and spectral signature in Red (Band 3), Green (Band 2) and Blue (Band 1) wavelength of Brinjal (a), Cabbage (b), Chickpea (c), Mustard (d), Pigeon pea (e) and Wheat (f).

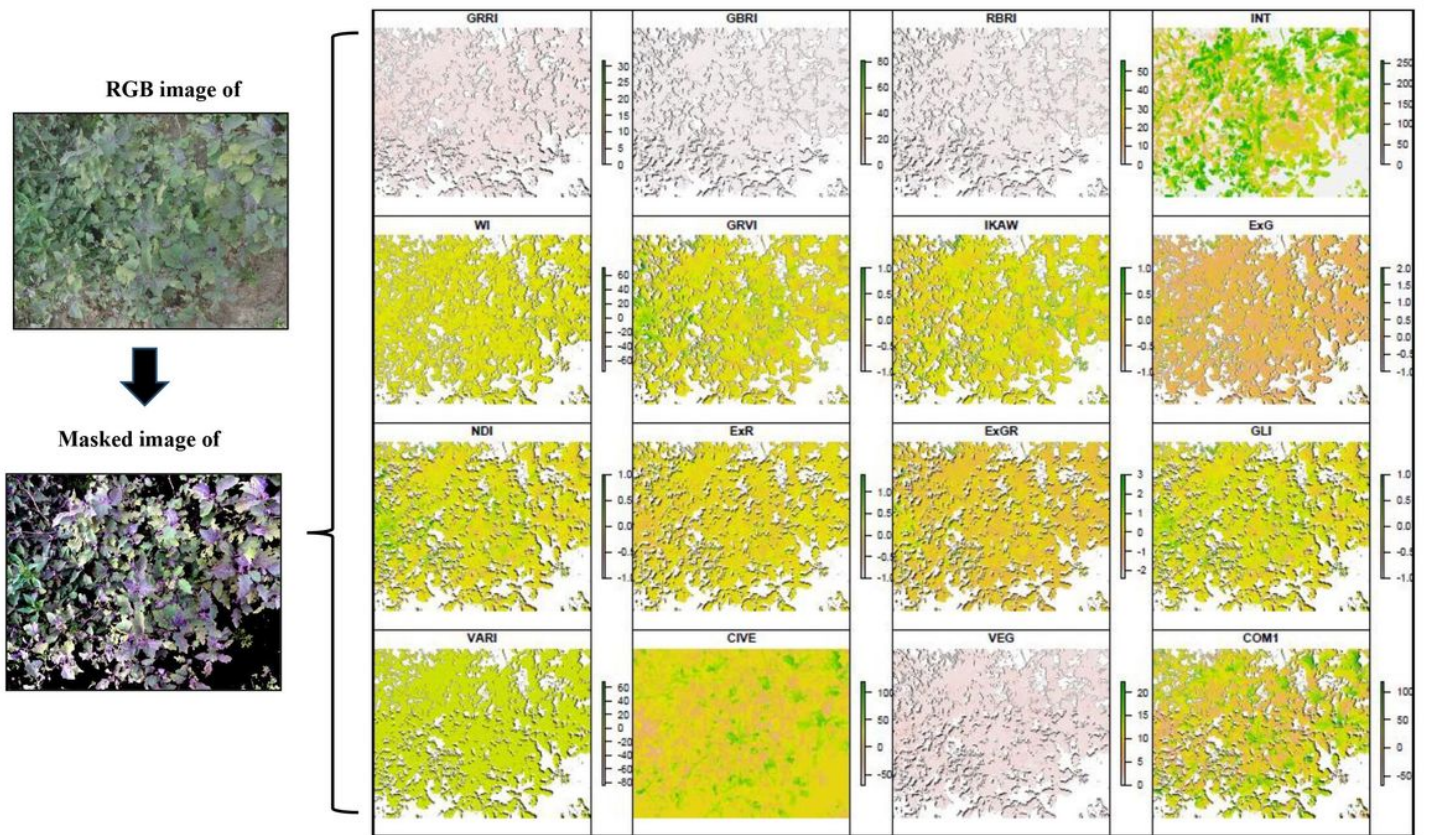


Figure 3

Original RGB image, masked image and VIs map for Brinjal crop.

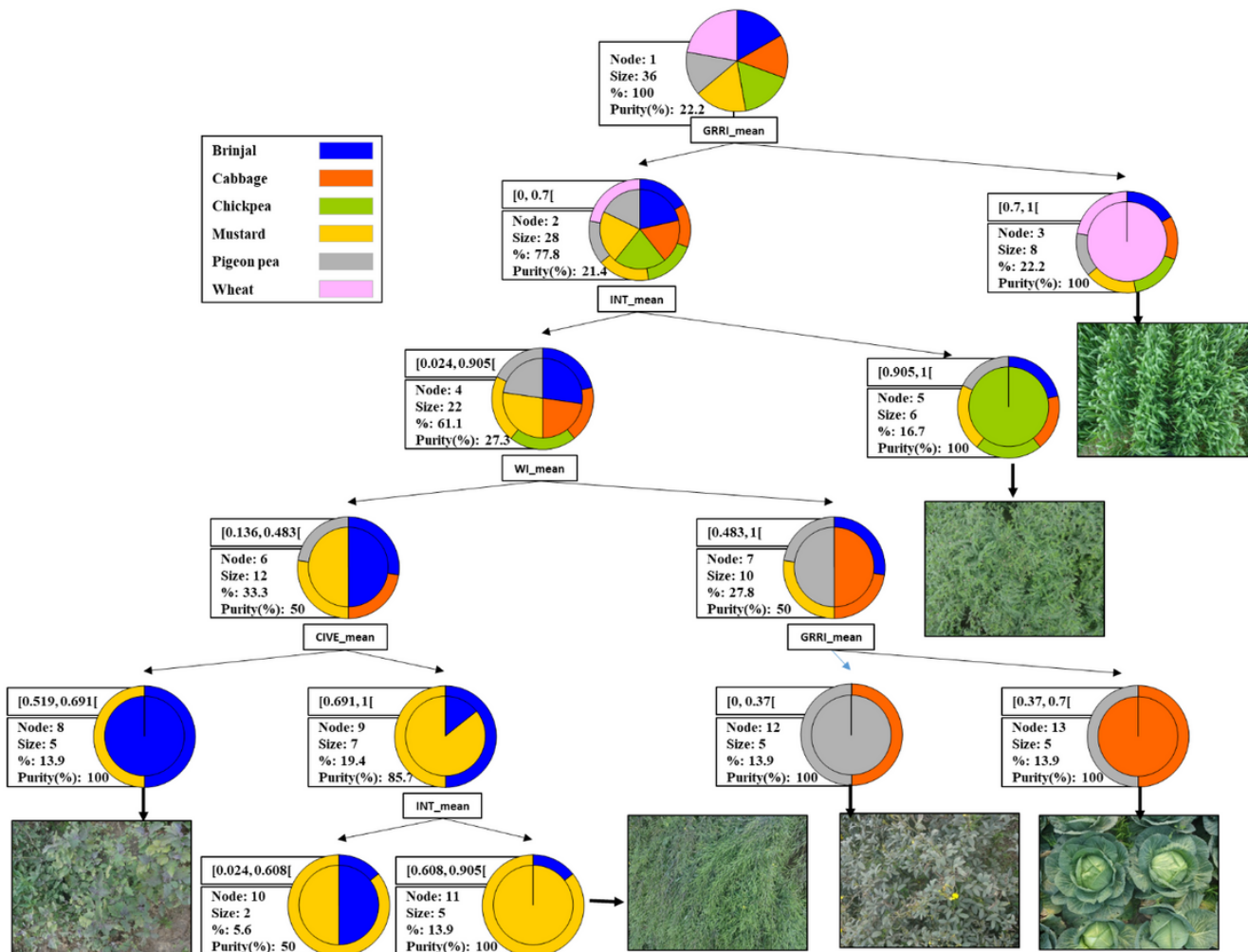


Figure 4
CART classification tree; showing rule based separation of crops

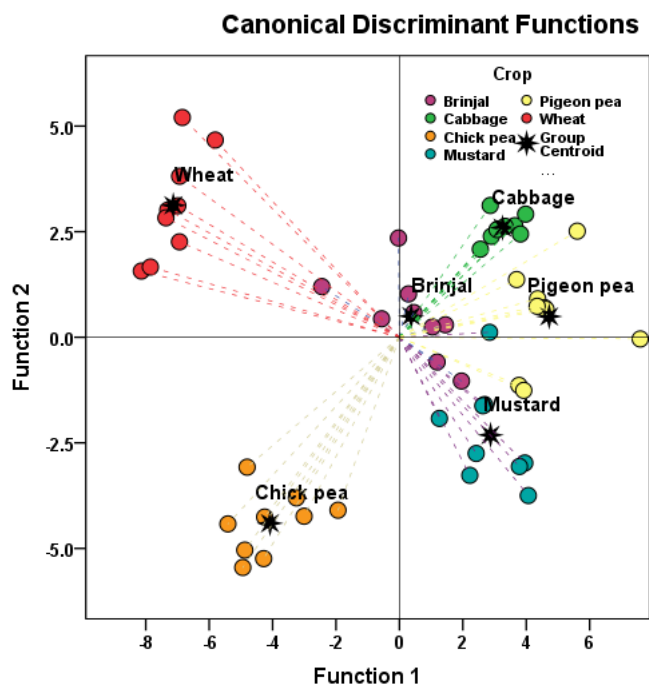


Figure 5

Combined group plot of canonical discriminant function.

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