

# DEVELOPMENT OF DISCRIMINANT MODELS FOR AUTOMATIC IDENTIFICATION AND CLASSIFICATION OF SORGHUM VARIETIES USING ITS OPTICAL PROPERTIES

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## ABSTRACT

*Industrial automation is not possible without artificial intelligence and machine learning. The goal of this study was to develop, verify, validate and train discriminant models for identification and classification of sorghum varieties using its optical properties. Three varieties of sorghum considered are NGB 01907 (Red Sorghum), NGB 01589 (White Sorghum) and NGB 01227 (Yellow Sorghum). Optical properties studied are colour (L a b), absorbance, reflectance and transmittance. Colour was measured using Chroma Meter, absorbance and transmittance were determined using spectrophotometer. Reflectance was calculated using Beer-Lambert equation. The experimental results shows that only about 15% of the light rays that reached the grains were absorbed, transmitted and directly reflected and almost 95% of the light rays shatteringly reflected. Two discriminant models were developed, the first one was found to be stronger than the second one. The colour properties (L a b) were found to have a greater impact on the models ability to discriminate than the other properties. Territorial map was developed that shows boundaries and regions which demarcate varieties or groups membership. The models predictive capacities were trained using the experimental data and the discriminant models verified and classified sorghum correctly for all varieties. The leave one cross validation method was used and the discriminant models also identify and classify 100% of all varieties group membership. The models ability was proven to predict both within and outside the experimental range of this study.*

## KEYWORDS

*Colour properties; Absorbance; Reflectance; Transmittance; modeling; sorghum.*

## 1. INTRODUCTION

Sorghum (*Sorghum bicolor* (L.) Moench) is a staple food in almost all developing nations. It's commercially used in the food, breweries, medicine, animal feeds and energy industries. It is from the grass family Gramineae and originated from the Northern part of Africa along the Nile River as early as 1000 BC (Kimbe, 2000; Jean, 2008; Tenywa et al. 2018). Records from FAOSTAT 2019 show that sorghum is the world's fifth largest most important cereal grain, after wheat, maize, rice and barley. Adebayo and Ibraheem (2015) reported that 10,400,000 metric tonnes was produced by USA which is the world largest producer as at 2014. Nigeria in that same year produces 6,300,000 metric tonnes being the largest in Africa and the third highest in the

world; the USA export 5,800,000 metric tonnes while the export for all developing nations in that year was less than 3,000,000 metric tonnes. This low export rate could be attributable to poor quality control of the sorghum grains in some developed and developing countries of the world which makes the crop fall below acceptable standard at the international market hence, the need to produce an accurate means grain quality determination and sorting becomes necessary. To produce any device or equipment for accurate sorghum grain quality identification and generally for efficient post harvest handling of biomaterials, there is a need to look at their engineering properties (Aremu et al., 2014; Ajav and Ogunlade, 2014; Jaiyeoba et al., 2020).

Engineering properties of agricultural produce is the observable and measurable phenomena or status when agricultural produce interact with the physical world. These properties include: physical, thermal, optical, electrical, mechanical, flow, rheological, magnetic, electromagnetic, acoustic and radioactive properties (Barbosa-Cánovas et al, 2006; and Figura et al. 2007; Audu et al., 2021). They are the first among other considerations for designing any device, equipment, machine or system that deals with planting, harvesting, processing, handling and storage of agricultural produce. Modern quality identification process involves sensing technology which uses the electrical, optical or electromagnetic properties of the sensed material through automation (Malambo et al., 2019).

Automation is the procedural or process technology which involves minimal or no human inspection (Groover, 2014, Olaniyi et al., 2019). It is also known as the control system. The need to involve automation process in large industrial work had been toughly discussed (Rifkin, 1995). For the developing and developed nations to increase their export, automation is needed for quality identification. Optical sensors had been suggested by Morris et al. (2012) to be one of best technology for identification. In order to achieve quality identification using optical sensors, the optical properties of the material to be sensed need to be modeled and trained to the sensor hence the need for this study for sorghum. Some automation requires modeling of certain operations which is the representation of concepts and happenings within our natural world by professionals (Scientist and Engineers) in order to study and predict future instances in the environment, models could be mathematical, graphical, conceptual or operationalize (Van Der Valk et al 2007: Ambitious science teaching, 2015: Tolk, 2015). The main vital aspects of food production are quality evaluation and sorting of materials. Engineers and researchers have studied several methods of evaluating food quality and distinguishing between food and foreign materials (Chen, 1978; Riederer and Miller, 2006). One of the more practical and successful techniques is the electro-optical technique, based on the optical properties of the product. The optical properties of biomaterials like light transmittance and reflectance have been explored in recent years for electronic sorting, grading, surface colour determinations and determination of the interior characteristics (Mohsenin, 1980, Gamal et al. 2019) however, there is dearth of information on the development, verification, validation and training of discriminant models for identifying the quality of sorghum varieties using its optical properties hence, the need for this study.

## **2. MATERIALS AND METHODS**

### **2.1. Sample Preparation**

Three varieties of Sorghum: NGB 01907 (Red Sorghum), NGB 01589 (White Sorghum) and NGB 01227 (Yellow Sorghum) were obtained at the National Center for Genetic Resources and Biotechnology, Ibadan, Nigeria. The samples were screened and sorted physically, defective ones were discarded and good ones were selected conditioned according to ASAE 2002 standard (S352.2) to 10, 13, 16, 19 and 22% moisture content db.

## 2.2. Optical Properties Determination

Colour properties were determined using Konica Minolta hunter Lab Chroma Meter (CR – 410). The L-a-b colour system was used to classify the samples. The L (L = Brightness; ranges from 0 which is black to 100 which is white), a (+ a (0 - 50) is red, - a (0 - 50) is green) and b (+ b (0 - 50) is yellow, - b (0 - 50) is blue), readings were read from the digital instrument. The absorbance and transmittance properties were obtained using Unico 1100RS spectrophotometer. The reflectance properties were calculated using Equations 1 and 2. Each experiment was replicated five times.

$$A = \log(1/R) \quad (\text{Beer-Lambert Law}) \quad (1)$$

$$R = 10^{-A} \quad (2)$$

Where: A is the Absorbance (%) and R is the Reflectance (%). The absorbance, reflectance and transmittance properties were measured at the visible light (UV) ranges of 320,420,520,620 and 720nm.

## 2.3. Analysis of the Discriminant Models

*Assumptions for carrying out multiple discriminant analysis are:*

1. Predictor variables are independent
2. Predictor variables are multivariate normal distribution, and within-group variance-covariance matrices are equal across groups.
3. Group membership (Dependant variables) is mutually exclusive and is categorical.
4. Linearity of discriminant function, Multivariate normality of independent variables, Independent variables not highly correlated and absent of outliers.

*The mathematical formulae and equations used for discriminant analysis are as follows:*

### 1. Discrimination Model

$$M_s = c_0 + c_1X_1 + c_2X_2 + c_3X_3 + \dots + b_nX_n \quad (3)$$

Where:  $M_s$  is discriminant model score,  $c$ 's are discriminant coefficients or weights and  $X$ 's are Predictors or independent variables

### 2. Eigen value

$$\lambda = \frac{SS_b}{SS_w} \quad (4)$$

Where:  $\lambda$  is the Eigen value,  $SS_b$  is sum of squares between groups and  $SS_w$  is sum of squares within groups

### 3. Canonical correlation

$$R_{CC} \text{ or } (\eta) = \sqrt{\frac{\lambda}{1+\lambda}} \quad (5)$$

Where:  $R_{CC}$  or  $(\eta)$  is the canonical correlation and  $\lambda$  is the Eigen value

4. Wilks' lambda

$$\Lambda = \frac{SS_w}{SS_T} \quad (6)$$

Where:  $\Lambda$  is Wilks' lambda,  $SS_w$  is sum of squares within groups and  $SS_T$  is total sum of squares

5. Chi-square

$$\chi^2 = -[(N - 1) - 0.5(M + k + 1)] \ln \Lambda \quad (7)$$

Where:  $\chi^2$  is Chi-square,  $n$  is the number of observations,  $m$  is number of discriminant function extracted,  $k$  is number of predictor variables and  $\Lambda$  is Wilks' lambda.

6. F-ratio (Fisher's)

$$F = 1 \left\{ \frac{-(\Lambda_{k-1})/(\Lambda_k)}{(\Lambda_{k-1})/(\Lambda_k)} \right\} \left\{ \frac{(N-G-1)}{(G-1)} \right\} \quad (8)$$

Where:  $\Lambda$  is Wilks' lambda,  $k$  is number of predictors,  $N$  is total sample size,  $G$  is number of discriminant variable groups.

7. Posterior probability of group membership (Bayes' Theorem)

$$P(G_i|M) = \frac{[P(M|G_i)P(G_i)]}{[\sum P(M|G_i)P(G_i)]} \quad (9)$$

Where:  $M$  is the discriminant score,  $P(G_i|M)$  is posterior probability that a case is in group  $i$ , given that it has a specific discriminant score  $D$ ,  $P(M|G_i)$  is conditional probability that a case has a discriminant score of  $M$ , given that it is in group  $i$ ,  $P(G_i)$  is prior probability that a case is in group  $i$ , which would be equal to  $(n_i / N)$ .

## 2.4. Statistical Analysis

The models were developed using Multiple Discriminant Analysis using direct approach or Simultaneous method (using all variables at once). SPSS version 20 (SPSS Inc., Chicago, IL, USA) was used for modeling and analysis of data. During the analysis, NGB 01589 (White Sorghum) was given the code 0, NGB 01227 (Yellow Sorghum) was given the code 1 and NGB 01907 (Red Sorghum) was given the code 2.

## 3. RESULTS AND DISCUSSION

Experimental results for multiple discriminant analysis and optical properties are shown in Table 1. The colour properties presented in the form (L, a and b) for varieties NGB 01589, NGB 01227, NGB 01907 range between (61 – 100; -3 – 4; 15 – 25%), (39 – 71; 7 – 17; 14 – 29%) and (24 – 46; 12 – 25; 11 – 22%) respectively. This implies that variety NGB 01589 has very bright colour and some yellowness, NGB 01227 has bright with reddish yellow colour and variety NGB 01907 has dark yellowish red colour. The absorbance, reflectance and transmittance values range from 0 – 4, 0 – 1, 0 – 9% respectively for NGB 01589 and also ranged from 0 – 3, 0 – 1, 0 – 7% for NGB 01227 (Yellow Sorghum) respectively while the absorbance, reflectance and transmittance values for NGB 01907 (Red Sorghum) variety ranged from (0 – 5%), (0 – 1%) and (0 – 6%) respectively. The results shows that only about 15% of the light that reach the bulk grains were

either absorbed; reflected or transmitted by the grains; the remaining portion of the incoming light however is used in Beer-Lambert equation for calculating reflectance to only account for direct reflectance and not for the scattered reflectance. So, we could assume that 95% of the incoming rays of light were scattered reflected. This behavior could be due to the irregular and smooth surfaces of sorghum grains. Similar behavior of light on other agricultural grains and seeds surfaces had been reported by: Dowell et al. (2001), Kawamura et al. (2003), El-Raie et al. (2009), Ambrose et al. (2016) and Omale et al. (2018).

Group descriptive statistic of the experimental data is presented in Table 2. Twenty five (25) observations were made for all optical properties measured for each variety. The mean values for NGB 01589 (White Sorghum) are L (77.902%), a (-0.862%), b (20.126%), absorbance (1.763%), reflectance (0.290%) and transmittance (2.260%). The means values of NGB 01227 (Yellow Sorghum) are L (52.121%), a (11.725%), b (21.003%), absorbance (1.444%), reflectance (0.193%) and transmittance (1.427%). The mean values of NGB 01907 (Red Sorghum) are L (32.376%), a (16.581%), b (14.210%), absorbance (1.941%), reflectance (0.365%) and transmittance (0.857%). The result shows that there was a large difference between the mean scores of the colour properties (L a b) across the three varieties than the absorbance, reflectance and transmittance properties, this makes the colour properties better predictors than other optical properties. The standard deviations given in table 2 for all optical properties for each variety show very small variation between experimental data. The group statistic gives a rough look at the behaviors of these optical properties. To be more accurate an ANOVA and Correlation matrix test was carried out.

Univariate ANOVA and Correlation matrix for optical properties of sorghum varieties are presented in Table 3. The ANOVA results show that colour (L a b) and transmittance properties are significant while the absorbance and reflectance properties are not significant at  $p < 0.05$ .

Table 1. Experimental data obtained for optical properties of three sorghum varieties.

SN	Variety	Code	Colour			Absorbance %	Reflectance %	Transmittance %
			L %	a %	b %			
1	NGB 01589 (White sorghum)	0	98.34	-2.81	24.17	0	1	0.16
2	NGB 01589 (White sorghum)	0	94.42	-2.27	23.55	3.45	0	0.77
3	NGB 01589 (White sorghum)	0	85.1	-2.64	19.99	2.53	0	0.74
4	NGB 01589 (White sorghum)	0	94.69	-3.06	21.9	3.78	0	0.61
5	NGB 01589 (White sorghum)	0	80.34	-2.61	18.91	3.37	0	0.62
6	NGB 01589 (White sorghum)	0	64.75	-1.61	15.94	0	1	0.28
7	NGB 01589 (White sorghum)	0	61.63	-1.55	15.24	1.3	0.05	5.98
8	NGB 01589 (White sorghum)	0	62.56	-1.44	15.46	1.86	0.01	1.78
9	NGB 01589 (White sorghum)	0	62.19	-1.48	15.32	0	1	0.5
10	NGB 01589 (White sorghum)	0	62.91	-1.64	15.34	0	1	0.5
11	NGB 01589 (White sorghum)	0	67.2	-1.64	16.23	0	1	2.12
12	NGB 01589 (White sorghum)	0	67.11	-1.75	15.95	1.11	0.08	2.15
13	NGB 01589 (White sorghum)	0	67.67	-1.93	15.95	1.39	0.04	2.51
14	NGB 01589 (White sorghum)	0	74.82	-2.05	17.33	1.6	0.03	2.74
15	NGB 01589 (White sorghum)	0	73.85	-1.99	17.25	1.86	0.01	2.73
16	NGB 01589 (White sorghum)	0	76.36	2.95	24.78	0	1	3.43
17	NGB 01589 (White sorghum)	0	72.29	3.49	24.34	2.1	0.01	1.43
18	NGB 01589 (White sorghum)	0	70.9	3.66	24.12	3.22	0	1.46
19	NGB 01589 (White sorghum)	0	71.74	3.65	24.28	3.25	0	1.8
20	NGB 01589 (White sorghum)	0	70.04	3.75	23.97	3.13	0	1.48
21	NGB 01589 (White sorghum)	0	99.96	-1.79	24.14	0	1	9.17
22	NGB 01589 (White sorghum)	0	95.44	-1.75	22.99	1.71	0.02	4.76
23	NGB 01589 (White sorghum)	0	100	-1.55	24.7	2.64	0	3.1
24	NGB 01589 (White sorghum)	0	85.79	-1.85	20.55	2.82	0	2.92
25	NGB 01589 (White sorghum)	0	86.46	-1.63	20.76	2.93	0	2.76
26	NGB 01227 (yellow sorghum)	1	57.86	12.26	23.27	0	1	0
27	NGB 01227 (yellow sorghum)	1	64.99	13.96	26.36	3	0	0.91
28	NGB 01227 (yellow sorghum)	1	71.34	15.72	29.12	2.5	0	0.05

SN	Variety	Code	Colour			Absorbance	Reflectance	Transmittance
			L %	a %	b %			
29	NGB 01227 (yellow sorghum)	1	68.97	16.8	28.52	2.56	0	0.05
30	NGB 01227 (yellow sorghum)	1	71.4	17.04	29.12	2.53	0	0.08
31	NGB 01227 (yellow sorghum)	1	39.28	7.62	14.37	0	1	0.2
32	NGB 01227 (yellow sorghum)	1	42.15	8.82	15.64	1.35	0.04	4.34
33	NGB 01227 (yellow sorghum)	1	41.65	9.33	15.61	1.86	0.01	1.2
34	NGB 01227 (yellow sorghum)	1	39.75	8.32	14.64	0	1	0.34
35	NGB 01227 (yellow sorghum)	1	41.11	8.91	15.28	0	1	0.3
36	NGB 01227 (yellow sorghum)	1	41.15	8.05	15.85	1.77	0.02	1.25
37	NGB 01227 (yellow sorghum)	1	41.45	8.2	15.97	2.25	0.01	0.56
38	NGB 01227 (yellow sorghum)	1	42.17	8.45	16.24	1.8	0.02	0.09
39	NGB 01227 (yellow sorghum)	1	42.56	8.71	16.48	1.78	0.02	0.09
40	NGB 01227 (yellow sorghum)	1	41.52	8.46	16.02	1.8	0.02	0.13
41	NGB 01227 (yellow sorghum)	1	50.06	12.02	20.22	1.51	0.03	6.97
42	NGB 01227 (yellow sorghum)	1	53.58	12.8	21.95	1.95	0.01	3.83
43	NGB 01227 (yellow sorghum)	1	54.29	13.1	22.28	1.57	0.03	4.79
44	NGB 01227 (yellow sorghum)	1	54.57	13.26	22.46	1.53	0.03	4.56
45	NGB 01227 (yellow sorghum)	1	56.65	13.91	23.43	1.51	0.03	4.77
46	NGB 01227 (yellow sorghum)	1	50.17	11.96	21.11	1.01	0.1	0.57
47	NGB 01227 (yellow sorghum)	1	56.5	13.47	24.15	1.15	0.07	0.44
48	NGB 01227 (yellow sorghum)	1	57.75	13.75	24.73	0.9	0.12	0.05
49	NGB 01227 (yellow sorghum)	1	60.11	14.04	25.75	0.87	0.13	0.05
50	NGB 01227 (yellow sorghum)	1	61.99	14.16	26.5	0.91	0.12	0.06
51	NGB 01907 (Red sorghum)	2	39.45	24.1	17.46	0	1	0
52	NGB 01907 (Red sorghum)	2	25.19	17.02	11.69	2.66	0	0.23
53	NGB 01907 (Red sorghum)	2	24.64	15.96	11.41	3.28	0	0.24
54	NGB 01907 (Red sorghum)	2	27.91	17.13	12.87	3.16	0	0.06
55	NGB 01907 (Red sorghum)	2	30.41	18.14	13.99	3.54	0	0.06
56	NGB 01907 (Red sorghum)	2	34.58	15.55	14.89	0	1	0.32
57	NGB 01907 (Red sorghum)	2	30.13	12.57	12.08	1.24	0.06	5.68
58	NGB 01907 (Red sorghum)	2	29.98	12.79	12.01	1.86	0.01	1.32
59	NGB 01907 (Red sorghum)	2	30.33	12.77	12.13	0	1	0.4
60	NGB 01907 (Red sorghum)	2	30.45	13.12	12.24	0	1	0.4
61	NGB 01907 (Red sorghum)	2	29.21	13.58	12.41	0	1	0.2
62	NGB 01907 (Red sorghum)	2	27.52	12.36	11.45	1.36	0.04	4.9
63	NGB 01907 (Red sorghum)	2	27.66	12.37	11.44	0	1	1.62
64	NGB 01907 (Red sorghum)	2	28.29	12.6	11.76	0	1	1.02
65	NGB 01907 (Red sorghum)	2	28.35	12.81	11.83	0	1	1.12
66	NGB 01907 (Red sorghum)	2	29.65	15.02	12.62	3.13	0	0.73
67	NGB 01907 (Red sorghum)	2	29.52	15.04	12.55	3.42	0	0.68
68	NGB 01907 (Red sorghum)	2	29.99	15.27	12.76	3.55	0	0.12
69	NGB 01907 (Red sorghum)	2	30.13	15.33	12.84	3.74	0	0.08
70	NGB 01907 (Red sorghum)	2	30.09	15.34	12.81	3.45	0	0.07
71	NGB 01907 (Red sorghum)	2	43.03	22.87	20.22	0	1	0.69
72	NGB 01907 (Red sorghum)	2	44.94	24.17	21.36	2.61	0	0.63
73	NGB 01907 (Red sorghum)	2	45.21	24.67	21.54	4.47	0	0.59
74	NGB 01907 (Red sorghum)	2	46.17	25.02	22.03	3.53	0	0.07
75	NGB 01907 (Red sorghum)	2	36.56	18.93	16.85	3.52	0	0.19

Table 2. Group descriptive statistics obtained for optical properties of sorghum varieties.

Group Statistics					
Variety (Group)		Mean	Std. Deviation	Valid N (list wise)	
				Unweighted	Weighted
NGB 01589 (White sorghum)	L	77.902	13.200	25.000	25.000
	a	-0.862	2.270	25.000	25.000
	b	20.126	3.771	25.000	25.000
	Absorbance	1.763	1.326	25.000	25.000
	Reflectance	0.290	0.452	25.000	25.000
	Transmittance	2.260	2.020	25.000	25.000
NGB 01227 (yellow sorghum)	L	52.121	10.532	25.000	25.000
	a	11.725	2.965	25.000	25.000
	b	21.003	5.020	25.000	25.000
	Absorbance	1.444	0.843	25.000	25.000
	Reflectance	0.193	0.362	25.000	25.000
	Transmittance	1.427	2.068	25.000	25.000

NGB 01907 (Red sorghum)	L	32.376	6.367	25.000	25.000
	a	16.581	4.289	25.000	25.000
	b	14.210	3.507	25.000	25.000
	Absorbance	1.941	1.642	25.000	25.000
	Reflectance	0.365	0.486	25.000	25.000
	Transmittance	0.857	1.406	25.000	25.000
Total	L	54.133	21.396	75.000	75.000
	a	9.148	8.077	75.000	75.000
	b	18.446	5.099	75.000	75.000
	Absorbance	1.716	1.311	75.000	75.000
	Reflectance	0.283	0.436	75.000	75.000
	Transmittance	1.515	1.921	75.000	75.000

This also confirms the expected observation made from the group statistic. The non significance of the absorbance and direct reflection was due to the small size of the sorghum grains, this causes the incidence light striking the grains to scatter, a similar behavior was reported by Figura *et al.* (2007). The Wilks' Lambda values also test the importance of the predictor variables; the smaller the Wilks' Lambda values the more important it is to the developed discriminant models hence, the orders of importance of the predictor (independent) variables with their Wilks' Lambda values to the developed models are: a (0.161), L (0.231), b (0.645), transmittance (0.909), reflectance (0.974) and absorbance (0.975) properties. The Correlation matrix within groups confirms the assumption that independent variables should not be closely related which makes it possible to use the discriminant analysis.

Table 3. Univariate ANOVAs and Correlation matrix for optical properties of sorghum varieties

Tests of Equality of Group Means							
	Wilks' Lambda	F	Df 1	Df 2	Sig.		
L	0.231	120.013	2	72	1.183x10 <sup>23</sup>	Significant	
a	0.161	187.978	2	72	2.627 x10 <sup>29</sup>	Significant	
b	0.645	19.802	2	72	1.404 x10 <sup>-7</sup>	Significant	
Absorbance	0.975	0.920	2	72	0.403	Not Significant	
Reflectance	0.974	0.978	2	72	0.381	Not Significant	
Transmittance	0.909	3.612	2	72	0.032	Significant	
Pooled Within-Groups Matrices							
		L	a	b	Absorbance	Reflectance	Transmittance
Correlation	L	1.000	0.438	0.832	0.238	-0.135	0.056
	a	0.438	1.000	0.801	0.300	-0.204	-0.112
	b	0.832	0.801	1.000	0.293	-0.187	-0.035
	Absorbance	0.238	0.300	0.293	1.000	-0.871	-0.123
	Reflectance	-0.135	-0.204	-0.187	-0.871	1.000	-0.102
	Transmittance	0.056	-0.112	-0.035	-0.123	-0.102	1.000

Table 4 shows test results of Box's test of equality of covariance matrices among varieties of sorghum. The table tests the assumption of multivariate normality; it was revealed that there is a significant difference between the variance of the three groups at  $p < 0.05$ . The Box's M test was significant which violates the assumption of equal covariance and multivariate normality. Nevertheless, Bian (2012) reported that discriminant analysis can still be used if the sample is large and the log determinant (the natural logarithm of determination of the covariance) differences between groups are small. The significance obtained shows that, there is no enough evidence to show that the three group's covariance are equal thus, the robustness of the discriminant analysis will take care of it (Bian, 2012). The test sample size is large (75) and the

Box's M test log determinant between groups are small (see table 4) thus, we proceed with the discriminant analysis. The 'rank' in Table 4 shows the number of independent variables (6) in the analysis. The strength of developed models (functions) was tested using their Eigen, Canonical Correlation and Wilks' Lambda values as presented in Table 5. The Eigen value gives the amount of variance that can be explained by the developed models (functions). For a strong model the Eigen value should be greater than one, the bigger the Eigen value, the stronger the model (function). The first model (function) developed has Eigen value of 21.723 while the second model has a Eigen value of 1.607. This implies that the first developed model is stronger because it explained more of the variance of the dependant variables than the second.

Table 4. Box's test of equality of covariance matrices among varieties of sorghum

Log Determinants		
Variety (Group)	Rank	Log Determinant
NGB 01589 (White sorghum)	6	2.820
NGB 01227 (yellow sorghum)	6	-1.474
NGB 01907 (Red sorghum)	6	0.025
Pooled within-groups	6	5.359
<i>*The ranks and natural logarithms of determinants printed are those of the group covariance matrices.</i>		
Box's Test Results		
Box's M		352.948
F	Approx.	7.391
	Df 1	42
	Df 2	15390.198
	Sig.	3.90x10 <sup>-42</sup>
Significant		
<i>*Tests null hypothesis of equal population covariance matrices.</i>		

Table 5. Eigen, Wilks' Lambda and Canonical Correlation values for testing the strength of the models (functions) developed

Eigen and Canonical Correlation values					
Function (Model)	Eigen value	% of Variance	Cumulative %	Canonical Correlation (R)	Canonical Correlation square (R <sup>2</sup> )
1	21.723 <sup>a</sup>	93.1	93.1	0.978	0.956
2	1.607 <sup>a</sup>	6.9	100.0	0.785	0.616
<i>a. First 2 canonical discriminant functions were used in the analysis.</i>					
Wilks' Lambda					
Test of Functions (Models)	Wilks' Lambda	Chi-square	df	Sig.	
1 through 2	0.017	283.678	12	1.246 x 10 <sup>-53</sup>	
2	0.384	66.604	5	5.206 x 10 <sup>-13</sup>	

Canonical Correlation measures the association of the predictors (independent) variable between the groups (varieties) and with the models (functions) developed. The range of the canonical correlation value lies between 0 – 1; the canonical correlation of 1 is a perfect association. The higher the canonical correlation value the stronger the model. The first model (function) gave canonical correlation value of 0.978 while the second model gave 0.785. The square of the canonical correlation value (R<sup>2</sup>) gives the overall model fitness which is the proportion of the variance explained by the model developed. The first model R<sup>2</sup> is 0.956 which implies that the first model (function) can explain 95.6% variations that occur in the group variables (varieties). The second model R<sup>2</sup> is 0.616 which means the second model (function) can explain 61.6% variations that occur in the group variables (varieties). The Wilks' Lambda test shows the significant of the models (functions) developed but not its accuracy and the amount of variance in



the discriminant scores of the models that are not explained by the differences among the varieties (groups). Small values near zero shows that the group's means discriminant scores differ from each other. The first model has a Wilks' Lambda value of 0.017 implying that 4.4% (i. e. 1- R<sup>2</sup>) of the total variance in the discriminant scores can't be explained by differences among varieties (groups) using the first model (function). The second model has a Wilks' Lambda value of 0.384 meaning that 38.4% (i. e. 1- R<sup>2</sup>) of the total variance in the discriminant scores can't be explained by differences among varieties (groups) using the second model (function). A Chi-square test for both models shows that there is a high significant difference at  $p < 0.001$  between the group's centroids (group means). The accuracy of models can now be examined by looking at the impact of the predictor (independent) on the discriminant models developed after standardizing (putting each variable on the same platform knowing that each variable have different units).

The impact of each variable on the discriminant function after standardization is shown in Table 6. The standardized canonical discrimination function coefficients indicate the importance of predicting optical properties across the varieties. Values with large absolute numbers indicate better ability to discriminate the varieties (dependent variables). For the first model the order of impact of the predictor variables discriminating ability and its coefficient values are b (-2.086), a (1.954), L (0.492), reflectance (0.138), transmittance (0.072) and absorbance (0.047). For the second model the order of impact of the predictor variables discriminating ability and its coefficient values are b (-2.406), L (1.641), absorbance (1.213), reflectance (1.103), a (0.674) and transmittance (0.184). These standardized canonical discrimination function coefficients were used in calculating the discriminant scores. The structured coefficients matrix is the correlation of the independent variables with the calculated discriminant scores of the models developed. This gives a more accurate order of importance, than the standardized canonical discrimination function coefficients. A more accurate order of importance for independent (predictor) variables of the models with their coefficient values can now be developed. For first model, the order of importance is: a (0.477), L (-0.391), transmittance (-0.068), b (-0.126), absorbance (0.012) and reflectance (0.015). For second model the order of importance is: a (-0.416), b (-0.359), absorbance (0.119), reflectance (0.118), L (0.085) and transmittance (0.022). After ascertaining the impact and accuracy of the predictors (independent variables) on each model developed. The Unstandardized Canonical Discriminant Function Coefficients is needed to finally develop the equations of the models as shown in Table 7. The Unstandardized Coefficients can now be used, to form the equations of the two developed models in this study. The equations for the two developed models are:

$$M_1 = 1.056 + 0.047(L) + 0.595(a) - 0.502(b) + 0.036(A) + 0.316(R) + 0.039(T) \quad (10)$$

$$M_2 = -2.165 + 0.158(L) + 0.205(a) - 0.58(b) + 0.924(A) + 2.527(R) + 0.099(T) \quad (11)$$

Where: M1 is the discriminant score used to predict group membership (varieties) for the first model; M2 is the discriminant score used to predict group membership (varieties) for the second model; L is colour properties for brightness (%); a is reddishness (%) if +ve and greenish (%) if -ve; b is yellowish (%) if +ve and blueness (%) if -ve, A is absorbance (%), R is reflectance (%) and T is transmittance (%).

Table 6. Impact and importance of predicting variables in the discrimination models (functions)

Standardized Canonical Discriminant Function Coefficients		
	Models (Functions)	
	1	2
L	0.492	1.641

a	1.954	0.674
b	-	-2.406
Absorbance	0.047	1.213
Reflectance	0.138	1.103
Transmittance	0.072	0.184

Structure Matrix		
	Function	
	1	2
a	0.477*	-0.416
L	-0.391*	0.085
Transmittance	-0.068*	0.022
b	-0.126	-0.359*
Absorbance	0.012	0.119*
Reflectance	0.015	0.118*

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables ordered by absolute size of correlation within function.

\*. Largest absolute correlation between each variable and any discriminant function

Table 7. Coefficients of the discrimination models (functions) and the average discriminant scores between the groups to be predicted

Canonical Discriminant Function Coefficients		
	Function	
	1	2
L	0.047	0.158
a	0.595	0.205
b	-0.502	-0.580
Absorbance	0.036	0.924
Reflectance	0.316	2.527
Transmittance	0.039	0.099
(Constant)	1.056	-2.165
*.Unstandardized coefficients		
Functions at Group Centroids		
Variety	Function	
	1	2
NGB 01589 (White sorghum)	-5.649	0.852
NGB 01227 (yellow sorghum)	0.113	-1.756
NGB 01907 (Red sorghum)	5.535	0.905

\*.Unstandardized canonical discriminant functions evaluated at group means

The group centroid is the mean discriminant scores of predictor variables of a group (variety). For the first model, the centroids are (-5.649), (0.113) and (5.535) for NGB 01589 (White sorghum), NGB 01227 (yellow sorghum) and NGB 01907 (Red sorghum) respectively. This shows that difference between group classes is about 5 units apart from each other. This makes a good classification boundary for classifying into group (variety) membership. For the second model, the centroids are (0.852), (-1.756) and (0.905) for NGB 01589 (White sorghum), NGB 01227 (yellow sorghum) and NGB 01907 (Red sorghum) respectively. This shows that difference between groups are not evenly spaced apart though, they still have a well defined boundary for classification into group membership. After getting the discriminant scores, other data for predicting the group membership need to be established.

Table 8 shows the prior probabilities of predicting groups and weights of predictor (independent) variables to group (variety) to be predicted. Prior probabilities of the dependent variables (varieties) are used for calculating the Posterior probability of group membership (see equation 6). For data that have equal group size like this study data (25 each). Prior probabilities will be the same (0.333 or 33.333%) for each of the three dependent variables or groups (varieties). The classification function coefficients are the unstandardized linear discriminant coefficients which can also be used to form model equations for calculating and classifying groups (varieties). This classical method of classification though little used is not as accurate as using the unstandardized canonical discriminant coefficients. The unstandardized linear discriminant coefficients were not use in this study. To have more insight about the behaviors of the groups (varieties) a plot of the two models (functions) need to be plotted.

Table 8. Prior Probabilities of Predicting Groups and Weights of Predictor Variables to Group to Be Predicted.

Prior Probabilities for Groups			
Variety	Prior	Cases Used in Analysis	
		Unweighted	Weighted
NGB 01589 (White sorghum)	0.333	25	25
NGB 01227 (yellow sorghum)	0.333	25	25
NGB 01907 (Red sorghum)	0.333	25	25
Total	1.000	75	75
Classification Function Coefficients			
	Variety		
	NGB 01589 (White sorghum)	NGB 01227 (yellow sorghum)	NGB 01907 (Red sorghum)
L	.324	.185	.860
A	-2.793	.101	3.876
B	2.070	.687	-3.579
Absorbance	6.261	4.058	6.713
Reflectance	18.867	14.101	22.542
Transmittance	1.155	1.119	1.594
(Constant)	-45.322	-18.822	-33.036

*Fisher's linear discriminant functions*

Three - groups discriminating plot is displayed in figure 1. For the first model (function 1) NGB 01907 (Red sorghum) had the highest value while NGB 01589 (White sorghum) had the lowest value. This means that the first model had high discriminating ability for NGB 01907 (Red sorghum) than for NGB 01589 (White sorghum). In the second model (function 2) NGB 01589 (White sorghum) had the highest value while NGB 01227 (yellow sorghum) had the lowest value. This means that the second model had higher discriminating ability for NGB 01589 (White sorghum) than for NGB 01227 (yellow sorghum). The reason can be taken from the importance of predictor (independent) variables reported in the standardized canonical discrimination coefficients and the structured matrix ranking. Also the varieties (groups) centroids in the first model (function 1) are well separated along the horizontal axis for all varieties. This means that the first model classifies all varieties better and the experimental data fits the model well. The varieties (group) centroids in the second model (function 2) had NGB 01589 (White sorghum) and NGB 01907 (Red sorghum) on the same level while NGB 01227 (yellow sorghum) was spaced apart along the vertical axis. This mean that second model was poor in classifying NGB 01589 (White sorghum) and NGB 01907 (Red sorghum), but was good with NGB 01227 (yellow sorghum). Further behavior of the models developed can be examined by looking at their group territorial map.

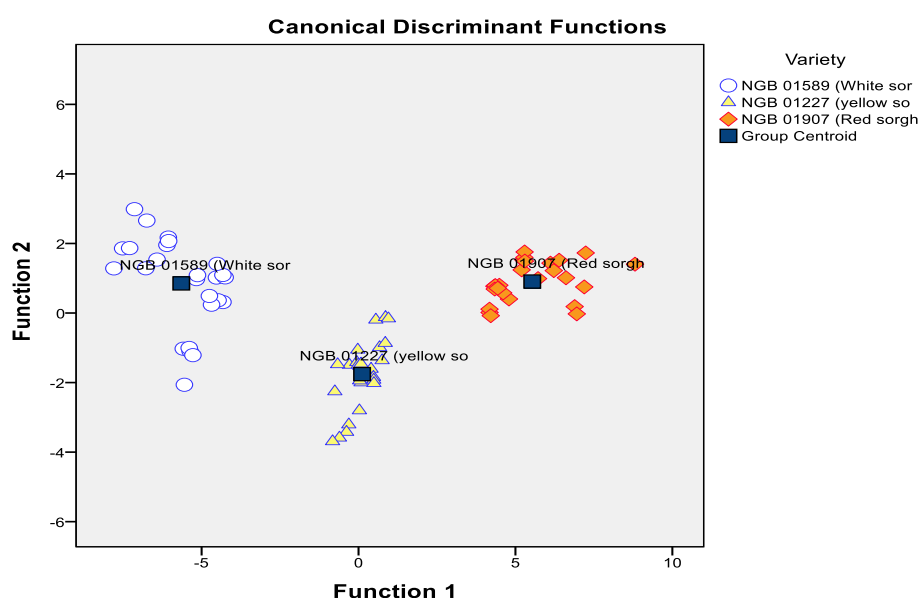


Figure 1. 3 - Group Discriminating plot.

The three groups' Territorial map is shown in figure 2. In the territorial map figures of 1s are used to demarcate discriminant scores (M1 or M2) region where both developed models (functions) can classify as group code 0 (NGB 01589 (White sorghum)). Figures of 2s demarcate discriminant scores (M1 or M2) region where both developed models (functions) can classify as group code 1 (NGB 01227 (yellow sorghum)). Figures of 3s are used to demarcate discriminant scores (M1 or M2) region where both developed models (functions) can classify as group code 2 (NGB 01907 (Red sorghum)). The territorial map can be used to manually categorized and classify sorghum varieties if the discriminant scores from both the first and second models are available.

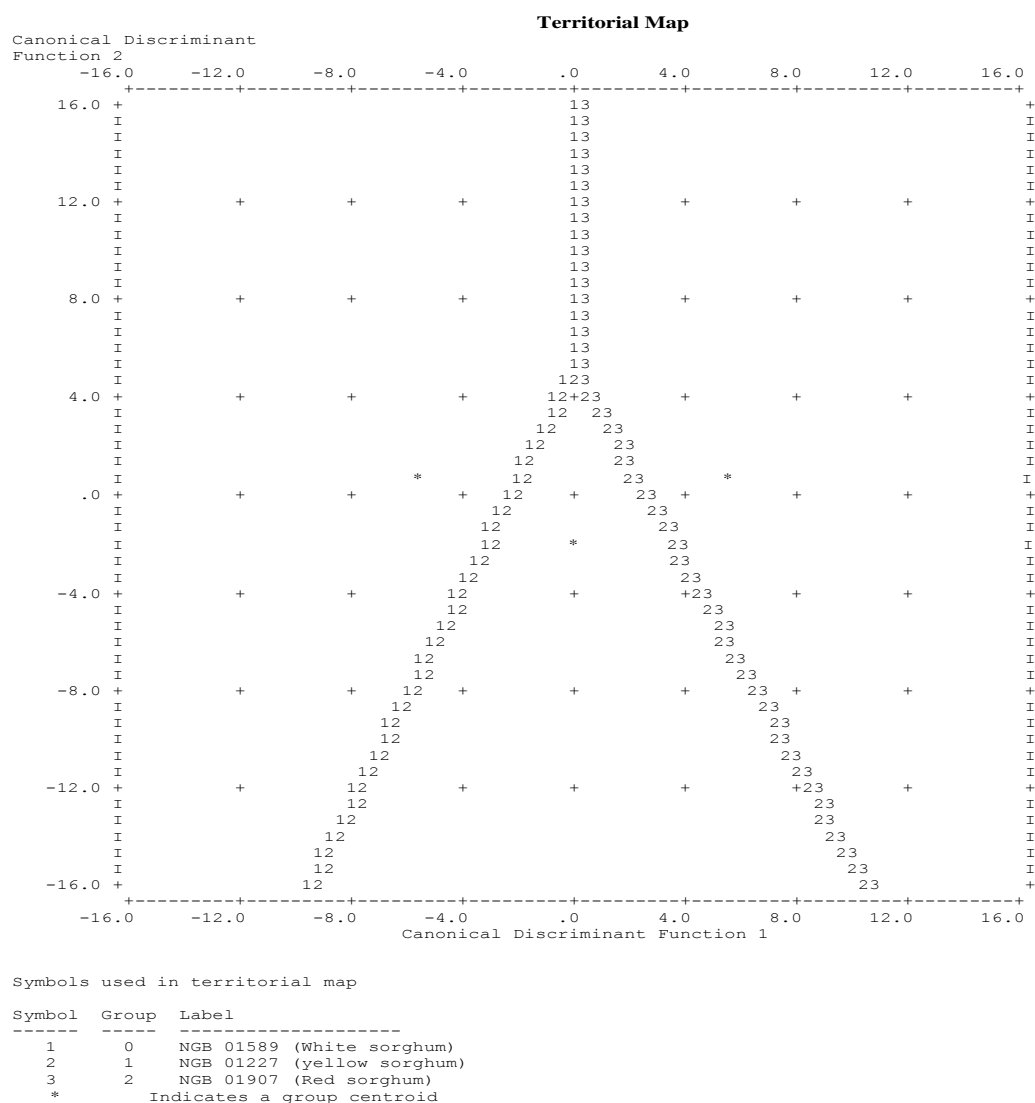


Figure 2. 3-Groups Territorial map.

After ascertaining the accuracy of the models the next thing to do is to verify the predictive capacity of the developed models.

The Classification or Confusion Matrix Table shown in table 9 was used to test, verify and validate the predictive capacity of the developed models. The 'count' shows the classification base on observation. The table shows that for NGB 01589 (White sorghum) variety, out of 25 sample classified. All samples were correctly classified as NGB 01589 (White sorghum). None of the samples were wrongly classified as either of the other two varieties. The same observations was noticed for NGB 01227 (yellow sorghum) and NGB 01907 (Red sorghum) classification. The '%' shows the percentage of that particular variety correctly classified. From the classification table 100% of NGB 01589 (White sorghum) was correctly classified using the two developed models. The same classification percentage results was obtained for NGB 01227 (yellow sorghum) and NGB 01907 (Red sorghum). The overall correctly classification for all varieties was 100%. This shows that the models developed are very good when used to predict the experimental data. How will we know if the developed models will do better if used to predict data outside the experimental range? To answer this question, a leave one out cross validation test was done. In this test, the variety to be classified data was left out and then classification was

done. The results of the cross validation, shows that out of 25 observations classified for each variety. All 25 observations were correctly classified with none wrongly classified. The cross validation classification percentage was 100% for all varieties cross validated. According to Agresti (1996), a good discriminant model should have its hit ratio about 25% more than what will be can classified by chance. Hit ratio is the percentage of group cases correctly classified. So by chance, there will be about 33.333% (1/3) chance of classifying any of the three varieties. The hit ratios of these classifications are all 100%, so the models capacities to predict both within and outside the experimental data ranges are very good. Table 10 shows all data used for classification and training of the models developed.

The optical properties have been used to evaluate certain characteristics near the surface of products. Possible applications include maturity evaluation of fruit; color-sorting, as in sorting green and red tomatoes on a harvester or separating lemons into different color groups; detection of surface defects and Contamination, such as defects on dried prunes, mechanical injury, rots, molds, scars, mite injury, and scabs on oranges, and bruise on apples; separation of foreign materials, such as stones and dirt clods from potatoes, onions, garlic, or tomatoes; detection of chicken broiler bruises, etc. Transmittance and absorption characteristics have been used to evaluate the internal quality of food products. Examples of applications include detection of blood spots in eggs, water core in apples, hollow heart in potatoes, smut content of wheat, pit fragments in peach halves, and seed in cherries; evaluation of fruit maturity, internal color of tomatoes, maturity of tomatoes, and many others. Fluorescence and delayed-light emission can be used to evaluate the maturity of fruits.

Classification Results <sup>a,c</sup>						
		Predicted Group Membership			Total	
		NGB 01589 (White sorghum)	NGB 01227 (yellow sorghum)	NGB 01907 (Red sorghum)		
Original	Count	NGB 01589 (White sorghum)	25	0	0	25
		NGB 01227 (yellow sorghum)	0	25	0	25
		NGB 01907 (Red sorghum)	0	0	25	25
	%	NGB 01589 (White sorghum)	100.0	0.0	0.0	100.0
		NGB 01227 (yellow sorghum)	0.0	100.0	0.0	100.0
		NGB 01907 (Red sorghum)	0.0	0.0	100.0	100.0
Cross-validated <sup>b</sup>	Count	NGB 01589 (White sorghum)	25	0	0	25
		NGB 01227 (yellow sorghum)	0	25	0	25
		NGB 01907 (Red sorghum)	0	0	25	25
	%	NGB 01589 (White sorghum)	100.0	0.0	0.0	100.0
		NGB 01227 (yellow sorghum)	0.0	100.0	0.0	100.0
		NGB 01907 (Red sorghum)	0.0	0.0	100.0	100.0

*a. 100.0% of original grouped cases correctly classified.*

*b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.*

*c. 100.0% of cross-validated grouped cases correctly classified.*

## 4. CONCLUSION

The following conclusions were drawn on this study

- When a ray of light strike the surfaces of bulk sorghum grains, only about 15% of the light rays are absorbed, transmitted or directly reflected.
- Up to 95% of the light rays that strike the grains surfaces were scatter reflected
- Two Discriminant models (functions) were developed

- The first Discriminant model was found to be stronger than the second model.
- The colour properties (L a b) had more impact on the discriminant models ability to discriminate than the other optical properties.
- Territorial map was developed to show boundaries and regions which demarcate Varieties (groups) membership.
- The models predictive capacities were verified to be 100% and validated to be 100%.
- The models ability was proven to predict both within and outside the experimental range of this study.
- This study is essential in practical applications for quality evaluations, grading, separation, image processing and sorting of biomaterials.

Table 10. Display of the Test and Training of the developed discrimination models (functions)

SN	Variety (Code)	L	a	b	A	R	T	PredVar	MS F1	MS F2	PM V0	PM V1	PM V2
1	White (0)	98.34	-2.81	24.17	0.00	1.00	0.16	White (0)	-7.80	1.28	1	0	0
2	White (0)	94.42	-2.27	23.55	3.45	0.00	0.77	White (0)	-7.52	1.86	1	0	0
3	White (0)	85.10	-2.64	19.99	2.53	0.00	0.74	White (0)	-6.42	1.54	1	0	0
4	White (0)	94.69	-3.06	21.90	3.78	0.00	0.61	White (0)	-7.14	2.99	1	0	0
5	White (0)	80.34	-2.61	18.91	3.37	0.00	0.62	White (0)	-6.06	2.17	1	0	0
6	White (0)	64.75	-1.61	15.94	0.00	1.00	0.28	White (0)	-4.53	1.02	1	0	0
7	White (0)	61.63	-1.55	15.24	1.30	0.05	5.98	White (0)	-4.32	0.31	1	0	0
8	White (0)	62.56	-1.44	15.46	1.86	0.01	1.78	White (0)	-4.48	0.37	1	0	0
9	White (0)	62.19	-1.48	15.32	0.00	1.00	0.50	White (0)	-4.25	1.02	1	0	0
10	White (0)	62.91	-1.64	15.34	0.00	1.00	0.50	White (0)	-4.32	1.09	1	0	0
11	White (0)	67.20	-1.64	16.23	0.00	1.00	2.12	White (0)	-4.50	1.41	1	0	0
12	White (0)	67.11	-1.75	15.95	1.11	0.08	2.15	White (0)	-4.68	0.24	1	0	0
13	White (0)	67.67	-1.93	15.95	1.39	0.04	2.51	White (0)	-4.75	0.49	1	0	0
14	White (0)	74.82	-2.05	17.33	1.60	0.03	2.74	White (0)	-5.17	0.97	1	0	0
15	White (0)	73.85	-1.99	17.25	1.86	0.01	2.73	White (0)	-5.13	1.09	1	0	0
16	White (0)	76.36	2.95	24.78	0.00	1.00	3.43	White (0)	-5.58	-1.03	1	0	0
17	White (0)	72.29	3.49	24.34	2.10	0.01	1.43	White (0)	-5.55	-2.06	1	0	0
18	White (0)	70.90	3.66	24.12	3.22	0.00	1.46	White (0)	-5.36	-1.10	1	0	0
19	White (0)	71.74	3.65	24.28	3.25	0.00	1.80	White (0)	-5.40	-1.00	1	0	0
20	White (0)	70.04	3.75	23.97	3.13	0.00	1.48	White (0)	-5.28	-1.21	1	0	0
21	White (0)	99.96	-1.79	24.14	0.00	1.00	9.17	White (0)	-6.75	2.66	1	0	0
22	White (0)	95.44	-1.75	22.99	1.71	0.02	4.76	White (0)	-6.78	1.29	1	0	0
23	White (0)	100	-1.55	24.70	2.64	0.00	3.10	White (0)	-7.29	1.87	1	0	0
24	White (0)	85.79	-1.85	20.55	2.82	0.00	2.92	White (0)	-6.11	1.96	1	0	0
25	White (0)	86.46	-1.63	20.76	2.93	0.00	2.76	White (0)	-6.05	2.07	1	0	0
26	Yellow (1)	57.86	12.26	23.27	0.00	1.00	0.00	Yellow (1)	-0.29	-1.49	0	1	0
27	Yellow (1)	64.99	13.96	26.36	3.00	0.00	0.91	Yellow (1)	-0.67	-1.48	0	1	0
28	Yellow (1)	71.34	15.72	29.12	2.50	0.00	0.05	Yellow (1)	-0.76	-2.26	0	1	0
29	Yellow (1)	68.97	16.80	28.52	2.56	0.00	0.05	Yellow (1)	0.08	-2.00	0	1	0
30	Yellow (1)	71.40	17.04	29.12	2.53	0.00	0.08	Yellow (1)	0.04	-1.94	0	1	0
31	Yellow (1)	39.28	7.62	14.37	0.00	1.00	0.20	Yellow (1)	0.55	-0.19	0	1	0
32	Yellow (1)	42.15	8.82	15.64	1.35	0.04	4.34	Yellow (1)	0.67	-0.99	0	1	0
33	Yellow (1)	41.65	9.33	15.61	1.86	0.01	1.20	Yellow (1)	0.85	-0.86	0	1	0
34	Yellow (1)	39.75	8.32	14.64	0.00	1.00	0.34	Yellow (1)	0.86	-0.12	0	1	0
35	Yellow (1)	41.11	8.91	15.28	0.00	1.00	0.30	Yellow (1)	0.95	-0.16	0	1	0
36	Yellow (1)	41.15	8.05	15.85	1.77	0.02	1.25	Yellow (1)	-0.05	-1.41	0	1	0
37	Yellow (1)	41.45	8.20	15.97	2.25	0.01	0.56	Yellow (1)	-0.02	-1.06	0	1	0
38	Yellow (1)	42.17	8.45	16.24	1.80	0.02	0.09	Yellow (1)	-0.01	-1.48	0	1	0
39	Yellow (1)	42.56	8.71	16.48	1.78	0.02	0.09	Yellow (1)	0.04	-1.53	0	1	0
40	Yellow (1)	41.52	8.46	16.02	1.80	0.02	0.13	Yellow (1)	0.08	-1.46	0	1	0
41	Yellow (1)	50.06	12.02	20.22	1.51	0.03	6.97	Yellow (1)	0.75	-1.36	0	1	0
42	Yellow (1)	53.58	12.80	21.95	1.95	0.01	3.83	Yellow (1)	0.40	-1.61	0	1	0
43	Yellow (1)	54.29	13.10	22.28	1.57	0.03	4.79	Yellow (1)	0.48	-1.84	0	1	0
44	Yellow (1)	54.57	13.26	22.46	1.53	0.03	4.56	Yellow (1)	0.48	-1.92	0	1	0
45	Yellow (1)	56.65	13.91	23.43	1.51	0.03	4.77	Yellow (1)	0.49	-2.02	0	1	0
46	Yellow (1)	50.17	11.96	21.11	1.01	0.10	0.57	Yellow (1)	0.03	-2.80	0	1	0
47	Yellow (1)	56.50	13.47	24.15	1.15	0.07	0.44	Yellow (1)	-0.31	-3.21	0	1	0
48	Yellow (1)	57.75	13.75	24.73	0.90	0.12	0.05	Yellow (1)	-0.38	-3.42	0	1	0
49	Yellow (1)	60.11	14.04	25.75	0.87	0.13	0.05	Yellow (1)	-0.61	-3.59	0	1	0
50	Yellow (1)	61.99	14.16	26.50	0.91	0.12	0.06	Yellow (1)	-0.83	-3.69	0	1	0
51	Red (2)	39.45	24.10	17.46	0.00	1.00	0.00	Red (2)	8.81	1.40	0	0	1
52	Red (2)	25.19	17.02	11.69	2.66	0.00	0.23	Red (2)	6.61	1.01	0	0	1

SN	Variety (Code)	L	a	b	A	R	T	PredVar	MS F1	MS F2	PM V0	PM V1	PM V2
53	Red (2)	24.64	15.96	11.41	3.28	0.00	0.24	Red (2)	6.12	1.43	0	0	1
54	Red (2)	27.91	17.13	12.87	3.16	0.00	0.06	Red (2)	6.22	1.22	0	0	1
55	Red (2)	30.41	18.14	13.99	3.54	0.00	0.06	Red (2)	6.39	1.52	0	0	1
56	Red (2)	34.58	15.55	14.89	0.00	1.00	0.32	Red (2)	4.79	0.40	0	0	1
57	Red (2)	30.13	12.57	12.08	1.24	0.06	5.68	Red (2)	4.18	0.01	0	0	1
58	Red (2)	29.98	12.79	12.01	1.86	0.01	1.32	Red (2)	4.17	0.11	0	0	1
59	Red (2)	30.33	12.77	12.13	0.00	1.00	0.40	Red (2)	4.33	0.77	0	0	1
60	Red (2)	30.45	13.12	12.24	0.00	1.00	0.40	Red (2)	4.49	0.80	0	0	1
61	Red (2)	29.21	13.58	12.41	0.00	1.00	0.20	Red (2)	4.61	0.58	0	0	1
62	Red (2)	27.52	12.36	11.45	1.36	0.04	4.90	Red (2)	4.21	-0.08	0	0	1
63	Red (2)	27.66	12.37	11.44	0.00	1.00	1.62	Red (2)	4.36	0.79	0	0	1
64	Red (2)	28.29	12.60	11.76	0.00	1.00	1.02	Red (2)	4.34	0.69	0	0	1
65	Red (2)	28.35	12.81	11.83	0.00	1.00	1.12	Red (2)	4.44	0.71	0	0	1
66	Red (2)	29.65	15.02	12.62	3.13	0.00	0.73	Red (2)	5.20	1.24	0	0	1
67	Red (2)	29.52	15.04	12.55	3.42	0.00	0.68	Red (2)	5.25	1.53	0	0	1
68	Red (2)	29.99	15.27	12.76	3.55	0.00	0.12	Red (2)	5.28	1.60	0	0	1
69	Red (2)	30.13	15.33	12.84	3.74	0.00	0.08	Red (2)	5.29	1.76	0	0	1
70	Red (2)	30.09	15.34	12.81	3.45	0.00	0.07	Red (2)	5.30	1.49	0	0	1
71	Red (2)	43.03	22.87	20.22	0.00	1.00	0.69	Red (2)	6.89	0.18	0	0	1
72	Red (2)	44.94	24.17	21.36	2.61	0.00	0.63	Red (2)	6.95	-0.03	0	0	1
73	Red (2)	45.21	24.67	21.54	4.47	0.00	0.59	Red (2)	7.24	1.73	0	0	1
74	Red (2)	46.17	25.02	22.03	3.53	0.00	0.07	Red (2)	7.19	0.75	0	0	1
75	Red (2)	36.56	18.93	16.85	3.52	0.00	0.19	Red (2)	5.72	0.99	0	0	1

L is colour properties for brightness %, a is reddishness if +ve value and greenish if -ve value, b is yellowness if +ve value and blueness if -ve value, A is absorbance in%, R is reflectance in %, T is transmittance in %, PredVar is the predicted variety using the models (functions) developed, MS F1 is discriminant score for function 1 (model equation 1), MS F2 is discriminant score for function 2 (model equation 2), PM V0 is the probability of membership to variety code 0, PM V1 is the probability of membership to variety code 1, PM V2 is the probability of membership to variety code 2.

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