



The effect of drought stress of sorghum grains on the textural features evaluated using machine learning

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Abstract

This study aimed to determine the discriminatory power of textural features to differentiate the sorghum grains subjected to normal, mild deficit, and severe deficit irrigation. The studies were carried out with the use of image processing, discrimination analysis, analysis of variance and cluster analysis using the selected texture parameters calculate for images from individual color channels *L*, *a*, *b*, *R*, *G*, *B*, *U*, *V*, *S*, *X*, *Y* and *Z*. The results indicated that different levels of irrigation can discriminate the sorghum grain with an accuracy of up to about 100%. Most of the genotypes for each level of irrigation were different in the terms of values of textural features and formed separate homogeneous groups. Drought is one of the limiting factors contributing to a decrease in sorghum grain productivity and nutritional quality, especially when it is cultivated in a marginal area. Therefore, low-quality grains produced under water stress should be recognized before they enter into the food and feed chain. The application of image analysis based on textures of sorghum grain images proved to be useful for the discrimination of sorghum grains subjected to drought stress. The applied procedure provided the fast, objective results that may be applied in practice for screening distinguishing the sorghum grains with different irrigation levels.

Keywords Irrigation level · Image analysis · Texture parameters · Discrimination analysis · Clustering

Introduction

Sorghum [*Sorghum bicolor* (L.) Moench] is the fifth most important cereal crop throughout the world after wheat, rice, maize, and barley cultivated as fodder crop or staple food in tropical and semi-tropical areas of Asia and Africa [1]. Sorghum grains are gluten-free with a great deal of potential in foods and beverages markets including cookies [2], noodles [3, 4], tortilla chips [5], bread [6, 7] and chicken nuggets [8].

A major constraint on crop production under a climate change scenario is water shortage during the crop season. As sorghum is a C₄ drought-tolerant crop, it is predominantly cultivated in those areas [9, 10], although it has been proven that it responds positively to irrigation [1]. The reduction of grain quality and quantity under drought stress even in sorghum occurs at both pre- and post-anthesis growth stages [11, 12]. Water stress during seed filling influences various metabolic processes in the leaves which are involved in the biosynthesis of functional constituents such as seed reserves and minerals [13]. Drought is extremely detrimental for seed production by reducing seed size and number and seed quality [13]. The negative impact of water stress on chemical parameters including protein, nitrogen-free extracts, sugar, crude fiber, and total ash has been reported [14, 15]. Underwater stress conditions, plants accumulate more neutral detergent fiber (NDF) and lignin [16]. So, screening of sorghum seeds produced under well-watered conditions is essential before processing.

Post-harvest classification and sorting of health and vigor seeds can be an important marketing issue from the farmers' point of views or from the consumers' point of view. It has been reported that discriminating underdeveloped, poorly

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filled seeds from those fully developed, well-filled seeds could be a struggle [17]. This is due to the increased occurrence of mainly hollow seeds inside under drought which feature a relative volume. Therefore, it is vital to differentiate between poorly and well-filled seeds at post-harvest quality control [17].

The application of Image-based technology in the analysis of seed surface texture may lead to a more powerful measurement of quality factors. Numerous devices such as CCD cameras, flatbed scanners, hyperspectral cameras, ultraviolet cameras, CT, and NMR have been employed for imaging [18]. Computer vision requires no prior information about the sample seeds. Due to the low costs, high accuracy, high flexibility, and repeatability of machine vision, it has been successfully used in industry, medicine, and plant biology. It has been implemented in seed research for the investigation of diversity, cultivar identification, cultivar registration, and plant breeding [18, 19]. Image processing has been applied for post-harvest assessment of wheat and barley kernel infections with *Fusarium* [20] and for the classification of boiled potatoes [18]. To the best of our knowledge, discrimination of seeds produced under normal irrigation or drought has never been evaluated by image analysis. Thus, this study aimed to evaluate the efficacy of textural features for the differentiation of seeds produced under normal or drought conditions using discriminative models.

Materials and methods

Field experiment

Ten sorghum genotypes were cultivated at the experimental field of Fars Agricultural and Natural Resources Research and Education Center on 6 June 2018 (52°43' E and 29°46' N; altitude 1604 m). While genotypes MGS2 and KGS23 were promising lines improved by SPII, the other eight genotypes were landraces kindly provided by the National Plant Gene-Bank of Iran, SPII.

The experiment was conducted as a split-plot. The deficit irrigation was considered as the main factor and genotype as the sub-factor. Subplots were 12 m² including four rows of 5 m long with a row distance of 0.6 m. The fertilizers were distributed based on soil test results. Irrigation treatments were applied to main plots at normal water irrigation [irrigation when the evaporation rates from pan class A reached 60 mm (Ir_{60})], mild water-deficit irrigation [irrigation when evaporation rates from pan class A exceeded 120 mm (Ir_{120})], and severe water-deficit irrigation [irrigation when evaporation rates from pan class A exceeded 180 mm (Ir_{180})]. Water stress treatment was started 26 days after sowing and continued during the season. FAO-CROPWAT 8.0 was used to calculate the reference crop evapotranspiration

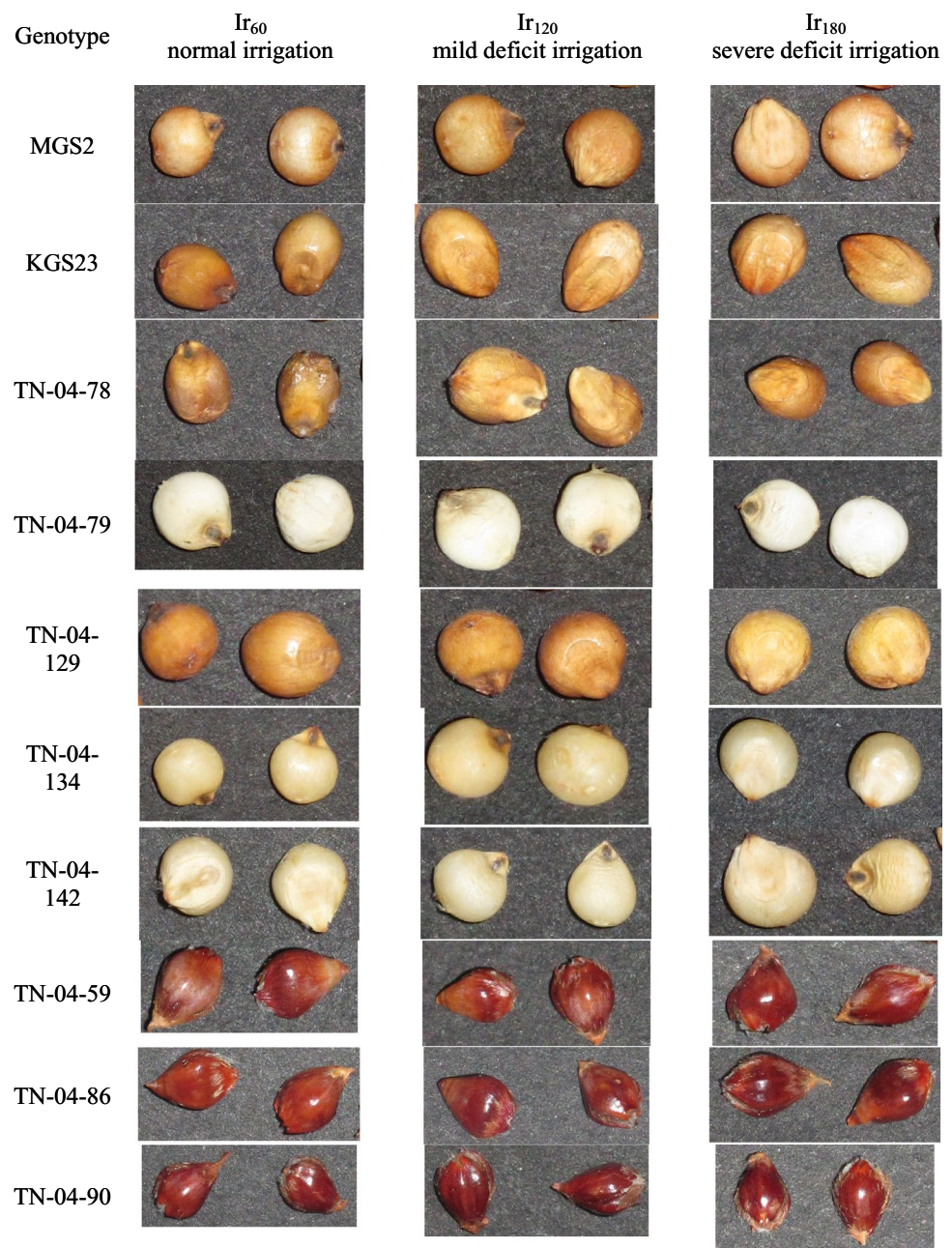
(ET_0) and schedule different levels of irrigation according to Doorenbos and Pruitt [21]. Grains were harvested at physiological maturity.

Image processing and textural features

Grain images were acquired using a camera (Canon PowerShot G11, 10 Megapixel) placed on a tripod stand in a completely dark room. The images of sorghum grain are presented in Fig. 1. The light source was a 10-W fluorescent lamp with a 400 mm diameter placed above the samples on the stand. Zoom adjustment was 5× to fill the camera window with the grains arranged on a black background. The images of 100 grains positioned on the dorsal or the ventral side were acquired for each sorghum genotype and saved in TIFF format. Sorghum grain images were processed using the MaZda software (Łódź University of Technology, Institute of Electronics, Poland) [22]. Each sorghum seed clearly separated from the black background was considered as one region of interest (ROI). Afterward, the sorghum seed images were converted to individual color channels *L*, *a*, *b*, *R*, *G*, *B*, *U*, *V*, *S*, *X*, *Y*, and *Z*. For each ROI in each color channel, about 200 textures were calculated [22].

Statistical analysis

The analyses of obtained results were performed using the WEKA 3.9 application (Machine Learning Group, University of Waikato) [23], Statistica 13 software, and GenStat 12. The WEKA was used for discrimination analysis to distinguish the sorghum grains with different deficit irrigation. Firstly, the attribute selection was performed using the Best First with the correlation-based feature selection (CFS) algorithm. Due to this step, the textural features with the highest discriminative power were chosen for the analysis. The attribute selection was carried out for the set including the textures from all color channels (*R*, *G*, *B*, *L*, *a*, *b*, *X*, *Y*, *Z*, *U*, *V*, *S*) and then the textures were selected for individual color spaces. The highest results (discrimination accuracies) were obtained for Lab color space. Therefore, only these results are presented in this paper. In the following step of the analysis, the discriminative models were developed based on selected texture parameters. The discrimination analysis was carried out using the dataset manually split into training and test set with a ratio of 70/30. For the discrimination of grains with different deficit irrigation, three classifiers, which provided the highest results, were used: Bayes Net from Bayes group, SMO (Sequential Minimal Optimization) from Functions group, and Random Forest from Decision Trees [24]. The discrimination analyses were carried out for a set of selected textures from all color channels and then for textures selected from the Lab color space. The results

Fig. 1 The images of sorghum grain

are presented in the form of confusion matrices and average accuracy for sorghum grain with three irrigation levels.

One-way analysis of variance (one-way ANOVA) was performed using Statistica 13 to the determination of differences in the texture attributes between sorghum grains belonging to different genotypes. The analysis was performed separately for each irrigation level at a significance level of $P \leq 0.05$. The normality of distribution was tested using Shapiro–Wilk, Lilliefors, and Kolmogorov–Smirnov tests. The homogeneity of variance was checked with the use of the Brown–Forsythe test and Levene’s test. The Newman–Keuls and the Kruskal–Wallis tests were applied.

Factorial ANOVA and clustering were performed using GenStat 12.0 software. To determine the statistical significance of all data, a factorial ANOVA was performed to determine the effect of water stress, genotype, classifier, and their interactions. Means were compared using Duncan’s multiple range tests at a 0.05 level of probability. Average linkage was applied as a criterion in hierarchical cluster analysis. The Euclidean distance was used to form the same clustering.

Table 1 The confusion matrices and accuracies of discrimination based on a set of textures selected from all color channels (*R, G, B, L, a, b, X, Y, Z, U, V, S*)

Classifier	Predicted class (number of cases)			Actual class	Average accuracy (%)	Predicted class (number of cases)			Actual class	Average accuracy (%)
	MGS2					TN-04-134				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes.	100	0	0	Ir60		100	0	0	Ir60	
Bayes Net	0	100	0	Ir120	100	0	91	9	Ir120	95.00
	0	0	100	Ir180		0	6	94	Ir180	
functions.	100	0	0	Ir60		99	1	0	Ir60	
SMO	0	100	0	Ir120	100	0	95	5	Ir120	96.33
	0	0	100	Ir180		0	5	95	Ir180	
trees.	100	0	0	Ir60		100	0	0	Ir60	
Random Forest	1	99	0	Ir120	99.67	0	92	8	Ir120	94.67
	0	0	100	Ir180		0	8	92	Ir180	
	KGS23					TN-04-142				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes.	100	0	0	Ir60		100	0	0	Ir60	
Bayes Net	0	94	6	Ir120	97.67	0	95	5	Ir120	97.33
	0	1	99	Ir180		2	1	97	Ir180	
functions.	100	0	0	Ir60		99	1	0	Ir60	
SMO	0	95	5	Ir120	97.33	1	96	3	Ir120	97.33
	0	3	97	Ir180		2	1	97	Ir180	
trees.	100	0	0	Ir60		98	1	1	Ir60	
Random Forest	0	93	7	Ir120	97.00	0	97	3	Ir120	97.67
	0	2	98	Ir180		0	2	98	Ir180	
	TN-04-78					TN-04-59				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes.	95	1	4	Ir60		90	10	0	Ir60	
Bayes Net	3	75	22	Ir120	81.00	17	77	6	Ir120	84.00
	2	25	73	Ir180		4	11	85	Ir180	
functions.	97	1	2	Ir60		90	9	1	Ir60	
SMO	1	74	25	Ir120	82.33	15	80	5	Ir120	86.67
	3	21	76	Ir180		5	5	90	Ir180	
trees.	94	0	6	Ir60		91	9	0	Ir60	
Random Forest	2	75	23	Ir120	80.33	18	74	8	Ir120	83.67
	7	21	72	Ir180		5	9	86	Ir180	
	TN-04-79					TN-04-86				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes.	98	2	0	Ir60		57	23	20	Ir60	
Bayes Net	4	92	4	Ir120	93.33	29	48	23	Ir120	58.00
	1	9	90	Ir180		17	14	69	Ir180	
functions.	99	1	0	Ir60		52	31	17	Ir60	
SMO	3	95	2	Ir120	95.67	22	54	24	Ir120	57.00
	1	6	93	Ir180		20	15	65	Ir180	
trees.	97	3	0	Ir60		56	24	20	Ir60	
Random Forest	5	94	1	Ir120	94.67	26	50	24	Ir120	58.33
	0	7	93	Ir180		18	13	69	Ir180	
	TN-04-129					TN-04-90				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		

Table 1 (continued)

Classifier	Predicted class (number of cases)			Actual class	Average accuracy (%)	Predicted class (number of cases)			Actual class	Average accuracy (%)
bayes.	90	9	1	Ir60		77	19	4	Ir60	
Bayes Net	6	88	6	Ir120	87.33	25	69	6	Ir120	79.00
	3	13	84	Ir180		4	5	91	Ir180	
functions.	90	8	2	Ir60		78	17	5	Ir60	
SMO	8	87	5	Ir120	86.33	32	66	2	Ir120	79.33
	5	13	82	Ir180		3	3	94	Ir180	
trees.	90	8	2	Ir60		80	15	5	Ir60	
Random Forest	8	85	7	Ir120	86.00	21	73	6	Ir120	81.67
	4	13	83	Ir180		3	5	92	Ir180	

SMO sequential minimal optimization, Ir_{60} normal water, Ir_{120} mild deficit irrigation, Ir_{180} severe deficit irrigation

Table 2 Results of factorial ANOVA with the effect of genotype, irrigation, classifier and their interaction on classification accuracy

Source	df	Mean square	F	P
Genotype	9	1447.6	497.896	0.000
Irrigation	2	403.144	138.661	0.000
Classifier	2	2.7	0.944	0.399
Genotype × irrigation	18	107.848	37.094	0.000
Genotype × classifier	18	2.744	0.944	0.537
Classifier × irrigation	4	1.778	0.611	0.657
Error	36	2.907		

Results and discussion

The results of the discriminant analysis revealed sorghum grain differentiation in terms of the textures of the outer surface of the images depending on the irrigation level. The classification accuracy (%) of sorghum grains produced under normal irrigation and drought based on the selected textures from all color channels (R , G , B , L , a , b , X , Y , Z , U , V , S) using three analyzed classifiers are presented in Table 1. The classification accuracy of the investigated classifiers reached 100% in the case of genotype MGS2 for the Bayes Net and SMO classifiers. It means that the irrigation level had the greatest effect on the texture parameters of the grain of this sorghum genotype that resulted in a complete distinction between grains produced under different levels of irrigation. Very high discrimination accuracy, greater than 90%, was also revealed for genotypes KGS23 (97.00–97.67%), TN-04-79 (93.33–95.67%), TN-04-134 (94.67–96.33%), and TN-04-142 (97.33–97.67%). Much lower accuracies were observed for the grain of one genotype (TN-04-86) in the range of 57.00–58.33% depending on the classifier. This

proved that it is not possible to discriminate accurately the grains of genotype TN-04-86 subjected to different maternal irrigation levels based on texture features. The reason could be due to the rigid shiny seed coat that is less affected by environmental condition such as water stress. Additionally, the results indicated that the models developed for discrimination of the grains produced under normal irrigation could distinguish sorghum grains more accurately (up to 100% for MGS2, KGS23, TN-04-134, TN-04-142) than production under mild or severe water stress.

Analysis of variance (ANOVA) on accuracy values revealed the significant differences in discrimination accuracy among genotypes, irrigation, and interaction of genotype × irrigation ($P < 0.001$), while the accuracy was not statistically significant for classifier performance and its interaction with genotype or irrigation level ($P \geq 0.399$) (Table 2).

Table 2 showing the ANOVA results confirms the statistical differences in accuracy of discrimination that have also been depicted in Table 1. In order to figure out which genotypes, irrigation levels, and classifiers are significantly different from each other, Duncan's multiple range tests were applied (Fig. 2). The highest discrimination accuracy based on textural features from color channels belonged to genotype MGS2 (99.9%) followed by genotypes TN-04-142 (97.4%) and KGS23 (97.3%). It can be concluded that textural features could not distinguish genotype TN-04-86 with the low accuracy of classification under each level of irrigation. Moreover, a comparison of means revealed the highest accuracy for normal irrigation (90.6%) and the lowest for mild stress (83.4%) (Fig. 2). Textural properties have been considered to be influenced by cultivar and maturity at harvest in the food industry [25–28].

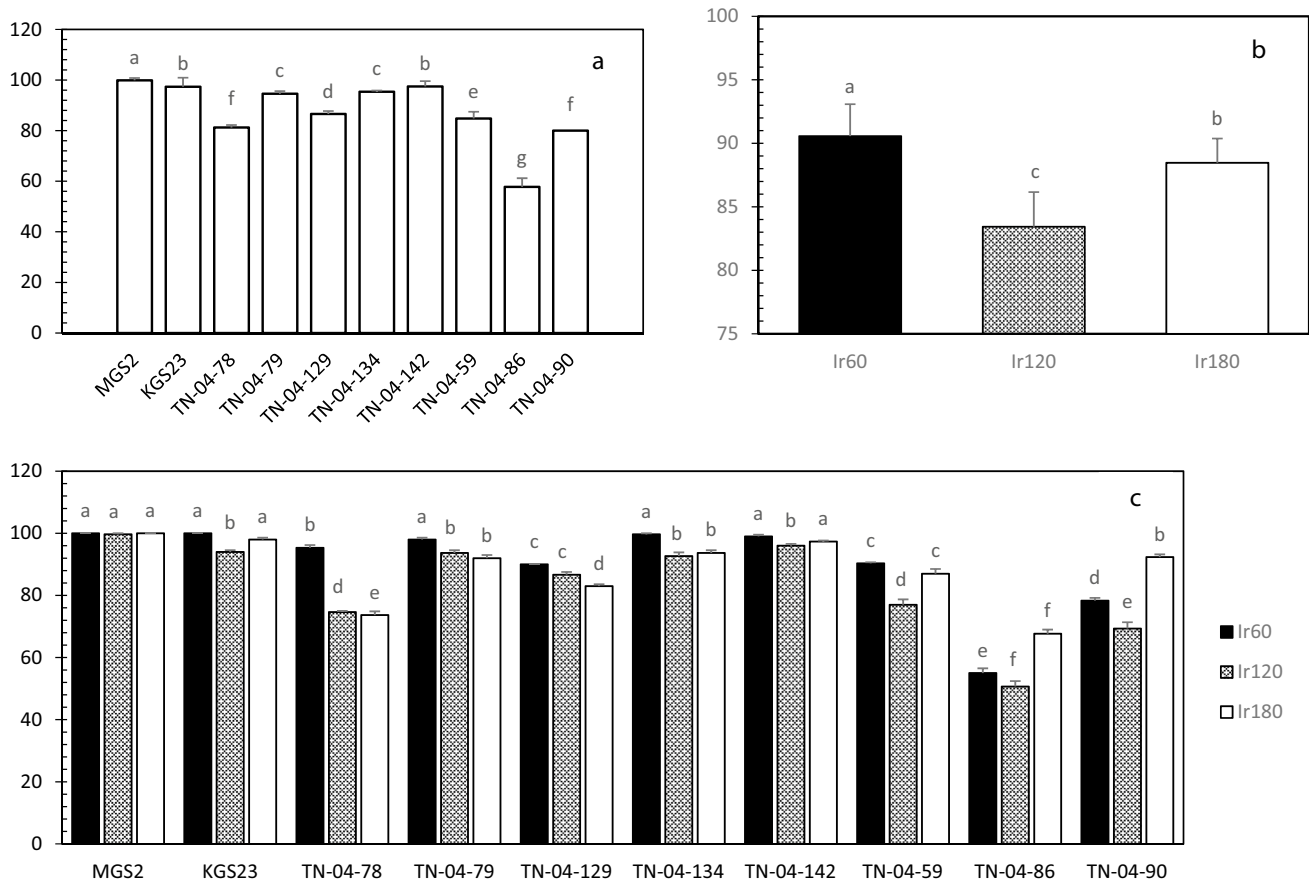


Fig. 2 Accuracy percent for classification of the grains among **a** ten genotypes, **b** irrigation levels, and **c** interaction of genotype \times irrigation, based on textural features of sorghum grain. For each irrigation

level, means followed by the same letter are not significantly different ($P \leq 0.05$). Means were compared using Duncan's multiple range test at a 0.05 level of probability

The highest accuracy under normal irrigation was attained by genotypes MGS2, KGS23, TN-04-134, TN-04-142, and TN-04-79 ranging from 100 to 98%. The highest value of accuracy under mild stress was associated with genotype MGS2, while in the case of severe water stress the highest value was related to genotypes MGS2, KGS23, and TN-04-142 (Fig. 2).

For discrimination of different sorghum genotypes, the large sets of textural features from the color channels were selected using WEKA application: 139 textures in the case of normal irrigation, 120 textures for grains subjected to maternal mild deficit irrigation, and 109 textures for grains produced under severe deficit irrigation. Four textural features including RH_{mean} , BH_{mean} , bH_{mean} , and UH_{mean} were chosen to exemplify the discriminatory power of textural features to differentiate sorghum grain of the genotypes

produced under different levels of irrigation (Table 3). The mean values of these features for each level of irrigation with the results of comparison of means are presented in Table 3. According to these mean values, most of the genotypes formed separate homogeneous groups. However, some genotypes formed a common group. For instance, 10 genotypes were categorized into eight groups for the RH_{mean} parameter under normal irrigation as genotypes TN-04-59 and TN-04-86 were placed in the same group and the same for genotypes TN-04-79 and TN-04-142. The scatter plots for selected variables (VH_{mean} vs. SH_{mean}) between the genotypes are shown in Fig. 3. Separation of the analyzed genotypes is more evident under normal irrigation and severe water stress in comparison to the case of genotypes grown under mild water stress. It is a confirmation of the classification accuracy presented in Table 1.

Table 3 Differences in the texture attributes from selected color channels among sorghum genotypes

Genotype	Texture parameter			
	RH _{mean}	BH _{mean}	bH _{mean}	UH _{mean}
Normal irrigation				
MGS2	209.91 ^f	109.85 ^f	154.62 ^f	92.22 ^c
KGS23	184.37 ^c	56.60 ^b	162.26 ^h	83.62 ^a
TN-04-78	190.60 ^d	79.81 ^e	156.36 ^g	90.74 ^b
TN-04-79	225.34 ^g	174.40 ^h	142.29 ^b	107.21 ^f
TN-04-129	202.94 ^e	69.76 ^d	162.51 ^h	82.94 ^a
TN-04-134	233.88 ^h	163.83 ^g	148.68 ^e	98.77 ^d
TN-04-142	227.63 ^g	174.40 ^h	143.91 ^c	105.13 ^e
TN-04-59	145.48 ^b	63.21 ^c	143.84 ^c	109.29 ^g
TN-04-86	144.91 ^b	56.70 ^b	144.87 ^d	108.96 ^g
TN-04-90	126.34 ^a	51.77 ^a	141.08 ^a	113.68 ^h
Mild deficit irrigation				
MGS2	202.45 ^d	91.51 ^d	158.71 ^f	87.31 ^d
KGS23	228.08 ^g	99.49 ^e	163.34 ^h	80.16 ^b
TN-04-78	217.65 ^f	99.06 ^e	159.98 ^g	85.01 ^c
TN-04-79	233.84 ^h	196.16 ^h	139.44 ^a	110.88 ^h
TN-04-129	210.14 ^e	69.76 ^c	165.36 ⁱ	78.80 ^a
TN-04-134	216.37 ^f	138.34 ^f	151.49 ^e	95.64 ^c
TN-04-142	215.52 ^f	150.94 ^g	147.27 ^d	100.99 ^f
TN-04-59	160.65 ^c	65.38 ^b	146.79 ^d	105.96 ^g
TN-04-86	136.20 ^b	53.55 ^a	143.63 ^c	110.26 ^h
TN-04-90	127.05 ^a	51.51 ^a	141.45 ^b	113.35 ⁱ
Severe deficit irrigation				
MGS2	216.31 ^e	109.76 ^g	156.24 ^d	89.97 ^d
KGS23	214.89 ^e	78.54 ^d	165.32 ^g	78.21 ^a
TN-04-78	208.71 ^d	91.84 ^f	159.37 ^e	86.20 ^c
TN-04-79	236.62 ^g	213.70 ^j	134.53 ^a	117.25 ⁱ
TN-04-129	220.61 ^f	87.90 ^e	164.18 ^f	79.58 ^b
TN-04-134	210.50 ^d	142.36 ⁱ	148.33 ^b	99.79 ^f
TN-04-142	209.33 ^d	132.55 ^h	150.25 ^c	97.33 ^e
TN-04-59	178.80 ^c	69.62 ^c	150.91 ^c	100.50 ^f
TN-04-86	156.06 ^a	56.81 ^a	148.39 ^b	104.46 ^g
TN-04-90	166.72 ^b	65.20 ^b	147.73 ^b	105.75 ^h

^{a,b}The same letters in columns denote no statistical differences between samples

As a result of clustering the textural features of the grains by the Hierarchical Cluster analysis method and considering the Euclidean distance as a similarity index, the genotypes were placed in the different groups (Fig. 4). The figure indicated that the 10 sorghum genotypes could be divided into three groups for the grains produced under

normal irrigation and severe deficit irrigation, while the genotypes where grain production occurred under mild water stress could be categorized into four groups (slicing in similarity = 0.8). Moreover, it can be noticed that water stress can create textural changes on the surfaces of grains with different degrees that might change similarities and dissimilarities between the genotypes. For instance, under normal irrigation, genotype TN-04-79 were clustered into a group along with TN-04-134 and TN-04-142, while under mild and severe water stress it had the highest distance with other genotypes and clustered alone in a group (Fig. 4).

In the following steps, the discrimination analyses were performed for the color space Lab, for which the highest accuracies were obtained (Table 4). The discriminatory power of selected textural features from the color space Lab was slightly lower compared to those values from color channels. According to the selected features from the color space Lab, sorghum grains subjected to different maternal irrigation levels were discriminated more efficiently based on SMO classifier with an average accuracy of up to 99.67% in the case of genotype MGS2. Also, very high correctness results were obtained for KGS23 (up to 92.33%), TN-04-79 (up to 95.00%), TN-04-134 (up to 96.67%), and TN-04-142 (up to 97.67%). The lowest accuracies ranging from 54.00% to 56.67% were determined for the genotype TN-04-86 (Table 4).

The results indicated that image processing based on the textural parameters is useful for discrimination between grains produced under normal irrigation and those harvested under deficit irrigation. Texture parameters considered as quantitative values calculated from the images may provide significant reliable data on the structure and quality of tested objects. By using the textures, there is possible to notice the changes difficult to observe visually. The digital images may have different textures if the distribution of color is dissimilar, even those they have the same number of pixels and color histograms [29–31]. Therefore, the application of image analysis based on texture parameters of grain images is so important. The applied procedure provided the objective, independent of the human factor results and it may be successfully useful in practice to—screen for healthy sorghum grains which are harvested from the fields with optimum irrigation management.

Abiotic stresses significantly affect the reproductive growth of various crops resulting in a reduction in ultimate economic yields. Drought stress can decrease grain yield

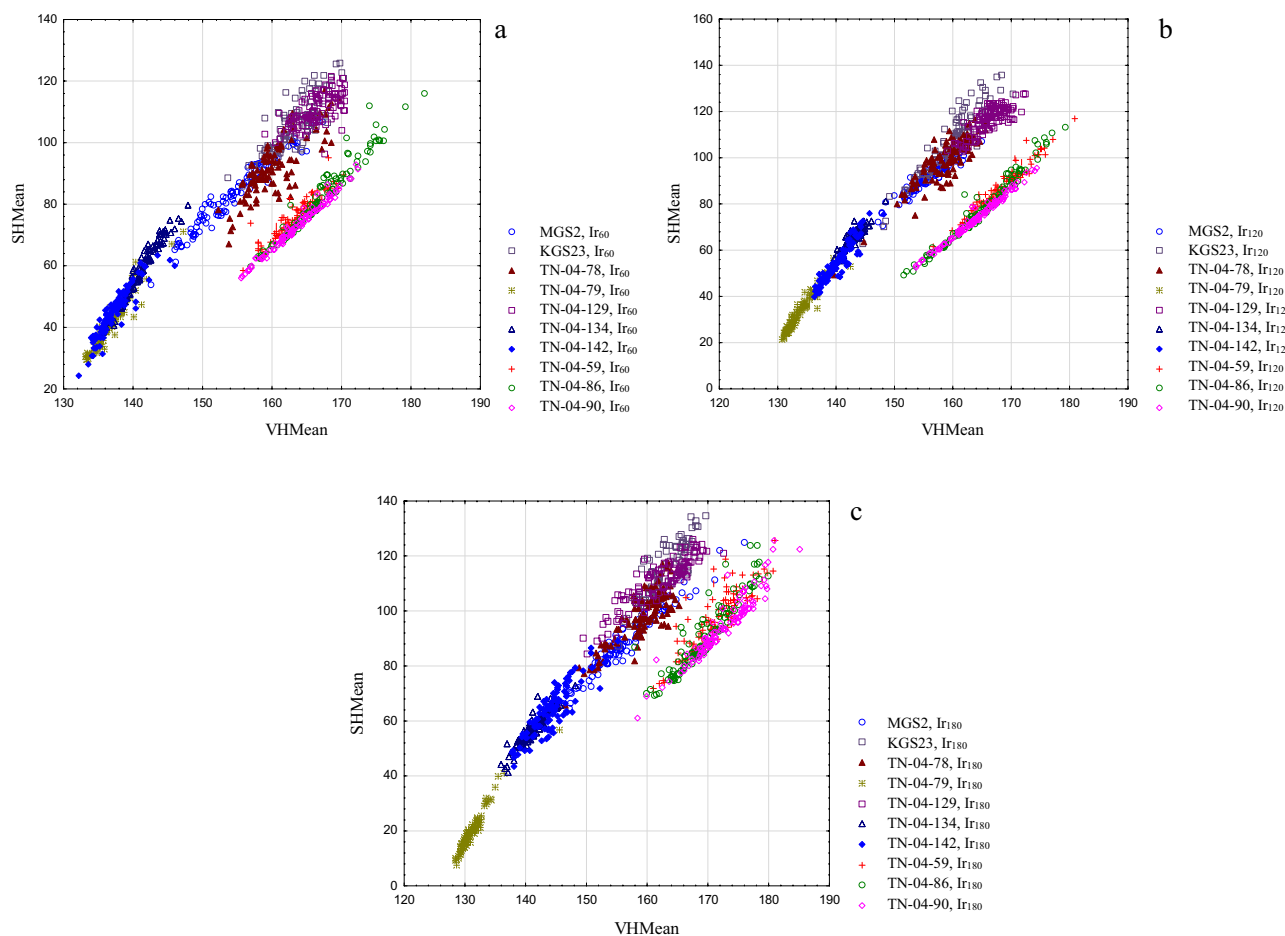


Fig. 3 The scatter plots for selected variables related to textural features of sorghum grain under normal irrigation (a), mild deficit irrigation (b) and severe deficit irrigation (c)

through processes such as fertilization, nutrient assimilation, and mobilization to reproductive organs as well as seed development [13]. Water stress during the seed filling stage may negatively influence seed weight and seed composition and hence, resulting in a reduction in quantitative and qualitative yield [32]. Water stress can prevent the various nutrient accumulation in seeds, primarily protein and starch [33, 34].

Although sorghum crops are tolerant to drought stress, the quantity and quality of the grain yield can adversely be affected when imposed to water stress [1]. The tractability of biotic and abiotic stress on phenotypic characteristics of crops in the field through computer vision, machine learning, and image processing techniques have been demonstrated in

several reports [35–37]. Crops display several mechanisms including morphological, physiological, and biochemical mechanisms to mitigate the effect of water stress resulting in different phenotypes that can be differentiated using the feature extraction method [38].

Sorghum may be used either for food for human consumption, feed, or exported [39]. Water stress could result in the deterioration of grain quality and its products. Therefore, a method to trace which grains are produced under well-watered conditions is vital in the food industry.

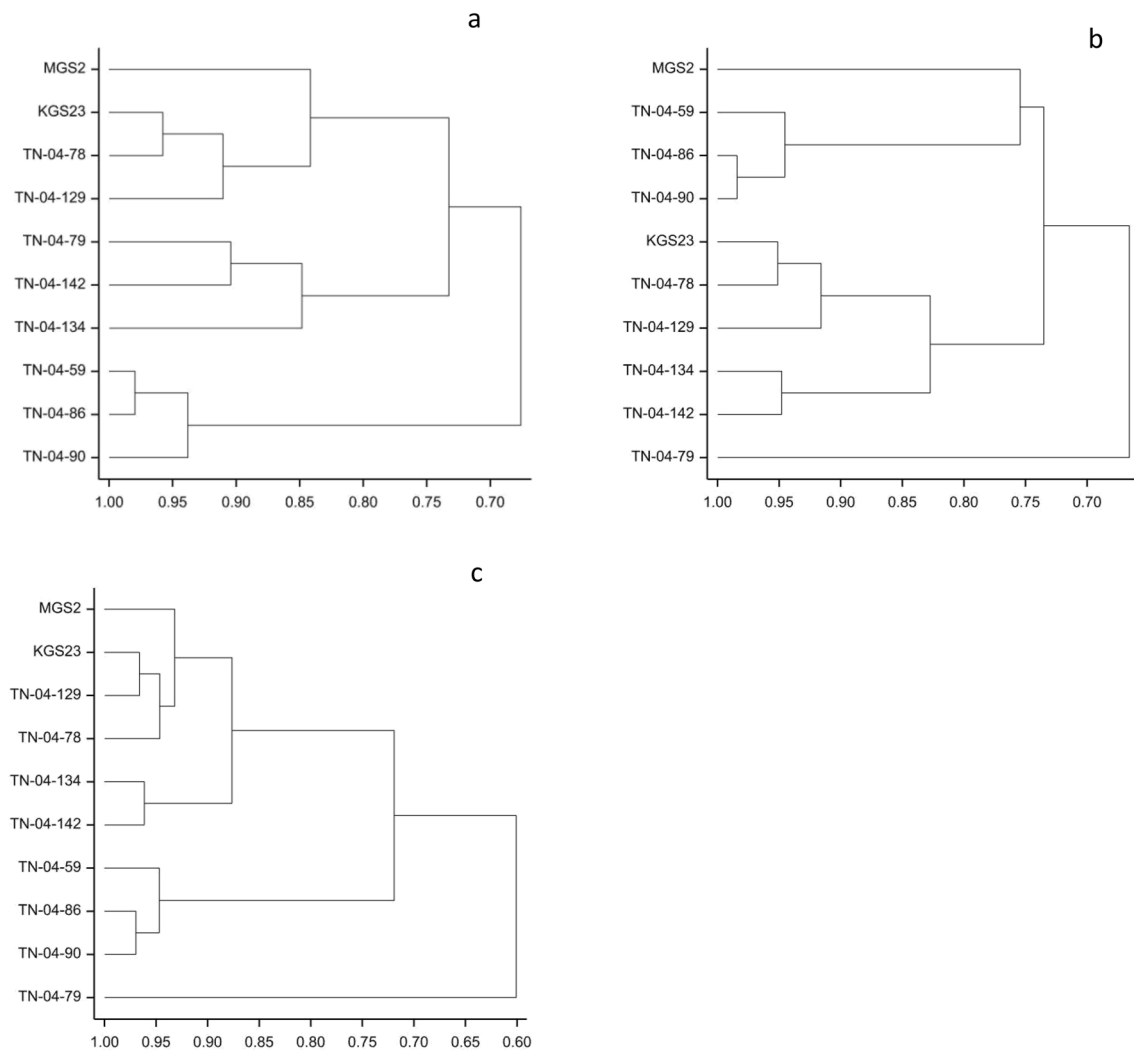


Fig. 4 Dendrograms of the cluster analysis among 10 sorghum genotypes based on all selected textural features under normal irrigation (**a**), mild deficit irrigation (**b**), and severe deficit irrigation (**c**)

Conclusions

The possibility of image processing application in distinguishing the seeds from the maternal plants grown in different levels of irrigation has not been studied previously. Water irrigation levels applied at three levels considerably affected the analyzed texture parameters of sorghum grains. This was achieved by discrimination methods, ANOVA, and clustering. The discriminatory power of textural features for the identification of sorghum grains under normal irrigation and water stress was genotype-dependent. The highest accuracy of discrimination based on color channels ranged from 99.9% related to

genotype MGS2 to 80.0% and 57.8% belonging to genotypes TN-04-90 and TN-04-86, respectively. Over an average of all genotypes, the highest accuracy was obtained for normal irrigation (90.6%) and the lowest for mild stress (83.4%). There were no significant differences in the performance of classifiers with a mean of 87.3%, 87.8%, and 87.4% for Bayes Net, SMO, and Random Forest, respectively.

Table 4 The confusion matrices and accuracies of discrimination based on a set of textures selected from Lab color space

Classifier	Predicted class (number of cases)			Actual class	Average accuracy (%)	Predicted class (number of cases)			Actual class	Average accuracy (%)
	MGS2					TN-04-134				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes. Bayes Net	96	3	1	Ir60	97.33	98	2	0	Ir60	93.67
	1	99	0	Ir120		0	88	12	Ir120	
	3	0	97	Ir180		0	5	95	Ir180	
functions. SMO	99	1	0	Ir60	99.67	100	0	0	Ir60	96.67
	0	100	0	Ir120		0	95	5	Ir120	
	0	0	100	Ir180		0	5	95	Ir180	
trees. Random Forest	98	1	1	Ir60	98.33	100	0	0	Ir60	94.33
	1	99	0	Ir120		1	88	11	Ir120	
	2	0	98	Ir180		0	5	95	Ir180	
	KGS23					TN-04-142				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes. Bayes Net	99	0	1	Ir60	91.67	98	1	1	Ir60	97.33
	0	83	17	Ir120		0	98	2	Ir120	
	0	7	93	Ir180		3	1	96	Ir180	
functions. SMO	99	0	1	Ir60	92.33	98	1	1	Ir60	96.00
	0	85	15	Ir120		0	98	2	Ir120	
	2	5	93	Ir180		4	4	92	Ir180	
trees. Random Forest	99	0	1	Ir60	92.33	99	0	1	Ir60	97.67
	0	87	13	Ir120		0	98	2	Ir120	
	0	9	91	Ir180		2	2	96	Ir180	
	TN-04-78					TN-04-59				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes. Bayes Net	93	2	5	Ir60	77.00	78	16	6	Ir60	77.00
	2	72	26	Ir120		22	74	4	Ir120	
	3	31	66	Ir180		6	15	79	Ir180	
functions. SMO	97	0	3	Ir60	79.00	90	10	0	Ir60	81.67
	1	74	25	Ir120		20	73	7	Ir120	
	4	30	66	Ir180		5	13	82	Ir180	
trees. Random Forest	92	0	8	Ir60	73.67	84	12	4	Ir60	79.00
	3	71	26	Ir120		23	68	9	Ir120	
	6	36	58	Ir180		5	10	85	Ir180	
	TN-04-79					TN-04-86				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		
bayes. Bayes Net	96	4	0	Ir60	91.00	47	26	27	Ir60	54.67
	7	89	4	Ir120		29	48	23	Ir120	
	1	11	88	Ir180		17	14	69	Ir180	
functions. SMO	96	4	0	Ir60	93.67	48	31	21	Ir60	56.67
	3	94	3	Ir120		18	54	28	Ir120	
	1	8	91	Ir180		18	14	68	Ir180	
trees. Random Forest	98	2	0	Ir60	95.00	54	28	18	Ir60	54.00
	5	94	1	Ir120		28	49	23	Ir120	
	1	6	93	Ir180		22	19	59	Ir180	
	TN-04-129					TN-04-90				
	Ir60	Ir120	Ir180			Ir60	Ir120	Ir180		

Table 4 (continued)

Classifier	Predicted class (number of cases)			Actual class	Average accuracy (%)	Predicted class (number of cases)			Actual class	Average accuracy (%)
bayes.	87	9	4	Ir60		73	23	4	Ir60	
Bayes Net	8	85	7	Ir120	82.67	32	59	9	Ir120	73.33
	3	21	76	Ir180		3	9	88	Ir180	
functions.	91	6	3	Ir60		71	25	4	Ir60	
SMO	7	83	10	Ir120	86.00	24	74	2	Ir120	78.33
	5	11	84	Ir180		5	5	90	Ir180	
trees.	89	7	4	Ir60		77	18	5	Ir60	
Random Forest	10	82	8	Ir120	83.00	22	70	8	Ir120	79.67
	4	18	78	Ir180		2	6	92	Ir180	

SMO sequential minimal optimization, Ir_{60} normal water, Ir_{120} mild deficit irrigation, Ir_{180} severe deficit irrigation

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Declarations

Conflict of interest The authors declare no conflict of interest.

Human and animal rights This article does not contain any studies with human or animal subjects.

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References

- Naoura G, Sawadogo N, Atchouze EA et al (2019) Assessment of agro-morphological variability of dry-season sorghum cultivars in Chad as novel sources of drought tolerance. *Sci Rep* 9:19581
- Morad MM, Doherty CA, Rooney LW (1984) Effect of sorghum variety on baking properties of U.S. conventional bread, Egyptian pita "balady" bread and cookies. *J Food Sci* 49:1070–1074
- Suhendro EL, Kunetz CF, McDonough CM, Rooney LW, Waniska RD (2000) Cooking characteristics and quality of noodles from food sorghum. *Cereal Chem* 77:96–100
- Liu L, Herald TJ, Wang D, Wilson JD, Bean SR, Aramouni FM (2012) Characterization of sorghum grain and evaluation of sorghum flour in a Chinese egg noodle system. *J Cereal Sci* 55:31–36
- Rooney LW, Waniska RD (2000) Sorghum food and industrial utilization. In: Smith CW, Frederiksen RA (eds) *Sorghum: origin, history, technology, and production*. John Wiley & Sons Inc., Canada, pp 689–729
- Schober TJ, Messerschmidt M, Bean SR, Park SH, Arendt EK (2005) Gluten free bread from sorghum: quality differences among hybrids. *Cereal Chem* 82:394–404
- Schober TJ, Bean SR, Boyle DL (2007) Gluten free sorghum bread improved by sourdough fermentation: biochemical, rheological, and microstructural background. *J Agric Food Chem* 55:5137–5146
- Devatkal SK, Kadam DM, Naik PK, Sahoo J (2011) Quality characteristics of gluten free chicken nuggets extended with sorghum flour. *J Food Qual* 34:88–92
- Ejeta G, Knoll JE (2007) Marker-assisted selection in sorghum. In: Varshney RK, Tuberosa R (eds) *Genomic-assisted crop improvement genomics applications in crops*, vol 2. Springer, pp 187–205
- Ramazanzadeh S, Asgharipour MR (2011) Physiological growth responses of sorghum genotypes to impairment of crop photosynthesis using potassium iodide. *Aust J Basic Appl Sci* 5(11):1884–1890
- Blum A (2011) *Plant breeding for water limited environments*. Springer
- Tuinstra MR, Grote EM, Goldsbrough PB, Ejeta G (1997) Genetic analysis of post-flowering drought tolerance and components of grain development in *Sorghum bicolor* (L.) Moench. *Mol Breed* 3:439–448
- Sehgal A, Sita K, Siddique KHM, Kumar R, Bhogireddy S, Varshney RK, Hanumantha Rao B, Nair RM, Prasad PVV, Nayyar H (2018) Drought or/and heat-stress effects on seed filling in food crops: impacts on functional biochemistry, seed yields, and nutritional quality. *Front Plant Sci* 9:1705
- Bibi A, Sadaqat H, Tahir M, Usman BF, Ali M (2012) Genetic analysis of forage quality traits in sorghum-sudangrass hybrids under water stress. *J Anim Plant Sci* 22:1092–1100
- Kuchenmeister K, Küchenmeister F, Kayser M, Wrage-Mönnig N, Isselstein J (2013) Influence of drought stress on nutritive value of perennial forage legumes. *Int J Plant Prod* 7:693–710
- Carmi A, Aharoni Y, Edelstein M, Umiel N, Hagiladi A (2006) Effects of irrigation and plant density on yield, composition and

- in vitro digestibility of a new forage sorghum variety, Tal, at two maturity stages. *Anim Feed Sci Technol* 131:121–133
17. Schmidt J, Claussen J, Wörlein N et al (2020) Drought and heat stress tolerance screening in wheat using computed tomography. *Plant Methods* 16:15
 18. Ropelewska E (2021) Effect of boiling on classification performance of potatoes determined by computer vision. *Eur Food Res Technol* 247:807–817
 19. Tapu R, Mocanu B, Zaharia T (2017) A computer vision-based perception system for visually impaired. *Multimed Tools Appl* 76:11771–11807
 20. Ropelewska E (2019) Post-harvest assessment of wheat and barley kernel infections with fungi of the genus *Fusarium* using thermal analysis. *J Stored Prod Res* 83:61–65
 21. Doorenbos J, Pruitt WO (1977) Crop water requirements. FAO irrigation and drainage paper 24. FAO of the United Nations, Rome, p 144.
 22. Szczypiński PM, Strzelecki M, Materka A, Klepaczko A (2009) MaZda—a software package for image texture analysis. *Comput Methods Programs Biol* 94(1):66–76
 23. Bouckaert RR, Frank E, Hall M, Kirkby R, Reutemann P, Seewald A, Scuse D (2016) WEKA manual for version 3-9-1. The University of Waikato, Hamilton
 24. Witten IH, Frank E (2005) Data mining. Practical machine learning tools and techniques, vol 525, 2nd edn. Elsevier, San Francisco
 25. Kidmose U, Grevsen K (1992) Quality of vining pea varieties for deep freezing. *Tidsskr Planteavl* 96:353–360
 26. Kjølstad L, Isaksson T, Rosenfeld HJ (1990) Prediction of sensory quality by near infrared reflectance analysis of frozen and freeze dried green peas (*Pisum sativum*). *J Sci Food Agric* 51:247–260
 27. Ottosson L (1958) Growth and maturity of peas for canning and freezing. *Almqvist & Wiksell*, Uppsala
 28. Periago MJ, Ros G, Martínez C, Rincón F, Lopez G, Ortuño J, Rodrigo J (1996) Relationships between physical-chemical composition of raw peas and sensory attributes of canned peas. *J Food Qual* 19:91–106
 29. Fernández L, Castellero C, Aguilera JM (2005) An application of image analysis to dehydration of apple discs. *J Food Eng* 67:185–193
 30. Strzelecki M, Szczypiński P, Materka A, Klepaczko A (2013) A software tool for automatic classification and segmentation of 2D/3D medical images. *Nucl Instrum Methods Phys Res* 702:137–140
 31. Armi L, Fekri-Ershad S (2019) Texture image classification based on improved local quinary patterns. *Multimed Tools Appl* 78:18995–19018
 32. Prasad PVV, Djanaguiraman M (2014) Response of floret fertility and individual grain weight of wheat to high temperature stress: sensitive stages and thresholds for temperature and duration. *Funct Plant Biol* 41:1261–1269
 33. Behboudian MH, Ma Q, Turner NC, Palta JA (2001) Reactions of chickpea to water stress: yield and seed composition. *J Sci Food Agric* 81:1288–1291
 34. Farooq M, Gogoi N, Barthakur S, Baroowa B, Bharadwaj N, Alghamdi SS et al (2017) Drought stress in grain legumes during reproduction and grain filling. *J Agron Crop Sci* 203:81–102
 35. Singh A, Ganapathysubramanian B, Singh AK, Sarkar S (2016) Machine learning for high-throughput stress phenotyping in plants. *Trends Plant Sci* 21:110–124
 36. Naik HS, Zhang J, Lofquist A, Assefa T, Sarkar S, Ackerman D, Singh A, Singh AK, Ganapathysubramanian B (2017) A real-time phenotyping framework using machine learning for plant stress severity rating in soybean. *Plant Methods* 13:23
 37. Chandel NS, Chakraborty SK, Rajwade YA et al (2020) Identifying crop water stress using deep learning models. *Neural Comput Appl*. <https://doi.org/10.1007/s00521-020-05325-4>
 38. An J, Li W, Li M, Cui S, Yue H (2019) Identification and classification of maize drought stress using deep convolutional neural network. *Symmetry* 11:256
 39. Winger M, Houryieh H, Aramouni F, Herald T (2014) Sorghum flour characterization and evaluation in gluten-free flour tortilla. *J Food Qual* 37:95–106

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