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Evaluation of Image Processing Technique on Quality Properties of Chickpea Seeds (*Cicer arietinum L.*) Using Machine Learning Algorithms

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ABSTRACT

Chickpea is an important edible legume consumed worldwide because of rich nutrient composition. The physical parameters of chickpea are crucial attributes for design of processing and classification systems. In this study, effects of seven different irrigation treatments (I_1-rainfed, I_2-pre-flowering single irrigation, I_3-beginning of flowering single irrigation, I_4-50% pod set single irrigation, I_5-irrigation at 50% flowering and 50% pod fill, I_6-irrigation before flowering and at 50% pod set, I7-full irrigation) on size, shape, mass, and color properties of chickpea seeds were investigated, and machine learning algorithms were used to estimate mass and color attributes of chickpea seeds. In terms of physical attributes, the best results were obtained in I_1 and I_5 irrigation treatments. According to the findings, among the irrigation treatments, I_5 had the greatest mass, volume, geometric mean diameter, projected area with the values of 0.50 g, 394.86 cm^3, 9.10 mm and 65.03 mm^2, respectively. In addition, I_1 had the highest shape index and elongation as 1.33 and 1.34, respectively. The results showed that multilayer perceptron (MLP) had the greatest correlation coefficients for mass (0.9997), chroma (0.9998) hue angle (0.9998) and color index (0.9992). The MLP yielded better outcomes than random forest for both mass and color estimation. Additionally, single or couple irrigation treatment at different physiological stages instead of full irrigation treatment might be sufficient to improve the physical attributes of chickpea.

Keywords: Chickpea, Mass, Color, Irrigation treatments, Machine learning

1. Introduction

Chickpea (*Cicer arietinum* L.) is an important grain legume for human nutrition and animal feeding (Gaur et al. 2015; Kirnak et al. 2017). It has a great place in daily diets of low-income countries and is largely grown in the Mediterranean countries, Asia, Africa, and Europe (Sastry et al. 2019). Healthy and balanced nutrition is among the most significant problems of developing countries (Hawkes 2006). Daily protein intake per capita is around 70.9 g worldwide and a balanced and healthy nutrition can be mentioned when 60% of such intake come from plant-originated and 40% come from animal-originated foodstuffs (Onder et al. 2014). Chickpea seeds contain 29% protein, 59% carbohydrate, 5% oil, 4% ash and 3% fiber (Iqbal et al. 2006). Seeds are used in imitation milk, infant formulas, bakery products and ready-to-eat products (Ashokkumar et al. 2015). Chickpea has also various health benefits and prevents various diseases such as obesity, colon cancer, diabetes, and cardiovascular diseases (Yildirim and Oner 2015; de Camargo et al. 2019). Among the edible legumes, chickpea had the third place (14,776,827 tons) worldwide. However, in Turkey, chickpea has the first place (470,000 tons) among the edible legume grains (FAOSTAT 2019).

The main chickpea types include Indian-originated desi type with small seeds, colored seed coat and angular shape; Mediterranean and Middle East-originated kabuli type with large seeds, beige color, owl's head shape; intermediate type with medium-to-small seeds, cream color (Sastry et al. 2019). Just because of larger seeds, kabuli type is generally preferred by consumers (Masoumi & Tabil 2003).

Agbola et al. (2002), indicated the seed quality characteristics of Indian chickpea varieties as color, size and “dhal (half a kernel)” recovery rate.

Chickpea is generally grown under rainfed conditions. However, supplementary irrigations especially in dry seasons may improve yield levels (Varol et al. 2020). Irrigation also improves the availability of nutrients within the rootzone (Ronnenberg & Wesche, 2011). There are significant relationships between soil moisture and available plant nutrients (Kaplan et al. 2019). Limited water resources and current water deficits exert serious stress on cultivated crops. Chickpea has a relatively shorter growing season, thus consume less water than many other broadleaf crops (Benjamin & Nielsen 2006). In any case, drought is the most important abiotic stressor also in chickpea farming (Mehta et al. 2015).

Shape, size and color parameters of chickpea seeds are used in design of transportation, classification, drying, storage and separation systems. Such parameters also play a great role in breeding studies, consumer demands and culinary preferences (Mirzaee et al. 2009; Cetin et al. 2020). The seeds with greater weight and thickness generally have greater mechanical resistance (Sastry et al. 2019). Computer vision techniques has great potential for the agricultural industry. This technology has been applied in numerous applications because of the low cost, quick inspection rate, the ability to provide reliable and consistent information (Beyaz et al. 2010; Beyaz & Ozturk 2016; Martinez et al. 2018). In addition, image processing system, which is a practical technique for automatic evaluations, was used to determine the physical properties of the seeds (Kara et al. 2013). This method has broadly contributed to relevant agricultural morphological analyzes in different products (Kupe et al. 2021).

General appearance, especially colors, greatly influence overall impression of consumers. Thus, color is considered as an important criterion in selection of foodstuffs (Costa et al. 2011). International Commission on Illumination (CIE) color space is largely used to measure color parameters (L^*, a^*, b^*) of foodstuffs. Quality classifications are successfully performed in food and agricultural industry based on color, shape, and size parameters (Omid et al. 2010).

Machine learning (ML) approaches are effective tools used in the design of accurate and reliable predictors. Such applications include various algorithms such as artificial neural network (ANN), DT, genetic algorithm, fuzzy logic, and regressions. Furthermore, there are verified models for training several ML algorithms and for adapting difficult input-output mapping strategies as well as selecting and removing useful features. These algorithms are mostly utilized for the correct selection of descriptive features in the quality assessment of agricultural products (Omid et al. 2010; Mollazade et al. 2012). ANN are consisted of interconnected processing elements like biological neurons and weighted connections corresponding to brain snaps (Karray & Silva 2004). Multilayer perceptron (MLP) is a feed-forward neural network (FFNN). Data flow through input layers toward to output layers in a single direction in FFNN (Omid et al. 2010). ANN and random forest (RF) most popular ML algorithms used in estimation of food properties (Marini et al. 2004; Mollazade et al. 2012). RF algorithm generates more than one DT with the use of bootstrap samples from the original training data to train each tree and is a good separator (Breiman 2001).

Several researchers previously investigated physical parameters (shape, size, and color) of chickpea seeds (Masoumi & Tabil 2003; Nikoobin et al. 2009; Kibar et al. 2014; Queiroz et al. 2015; Eissa et al. 2010; Jogihalli et al. 2017; Sastry et al. 2019; Soares et al. 2013; Rad et al. 2017; Gurbuz et al. 2018; Kus et al. 2017; Demir 2018; Cetin et al. 2021). Also, the image processing method applied in the present study was used in studies such as walnut (Ercisli et al. 2012; Demir et al. 2018), bean (Kara et al. 2013), orange (Sayinci et al. 2012), cherry laurel (Sayıncı et al. 2015a), hazelnut (Sayıncı et al. 2015b; Cetin et al. 2020), almond (Demir et al. 2019), grape (Küpe et al. 2021), corn (Beyaz & Gerdan 2021), soybean (Çetin 2022) and rice (Cinar & Koklu 2022). These parameters were used to estimate some other critical aspects of chickpea seeds. However, there are any studies in literature about color and mass estimation of chickpea seeds grown under different irrigation regimes. Image processing which is common technique for the identification of some physical attributes of the agricultural products. Therefore, objectives of the present study were set as to:

- Determine the effects of different irrigations performed in different physiological stages on physical quality traits which is determined computer vision techniques of chickpea seed,

- Estimate seed mass from the physical attributes with the use of different machine learning algorithms (MLP and RF),

- Estimate color parameters [color index (CI), chroma (C^*) and hue angle (h°)] from CIE color values (L^*, a^* and b^*) with the use of machine learning algorithms.

2. Material and Methods

2.1. Field experiments and samples

Present research was implemented at the Agricultural Research and Implementation Center of Erciyes University in Kayseri, Turkey in growing season of 2017 (Figure 1). Chickpea cultivar of Aksu, commonly used by local farmers, was used in present experiments. Aksu cultivar has owl's head seeds with about 8.1 mm diameter. Each pod general has 1-2 seeds. It is a mid-early cultivar with about 109 days of vegetation period. It is highly tolerant to drought and cold temperatures. Plant growth is semi-erect, branching is intense and leaf type is normal. The cultivar is resistant to wilt disease and anthracnose. Experimental soils were clay-loam in texture with an EC_e of 0.220, 0.173 and 0.258, pH of 8.13, 8.17 and 8.14, bulk density of 1.27, 1.24 and 1.22 g cm^{-3} and organic matter of 1.25, 1.05 and 0.69 % for soil depth of 0-30, 30-60 and 60-90 cm, respectively, field capacity (FC) of 30.3%, permanent wilting point of 10.5% and infiltration rate of 23.3 mm h^{-1}. The average temperature and relative humidity at growing season were 21.5 °C and 51.9%, respectively. Total precipitation through the growing season (April - August) was 137.0 mm (Table 1).

Figure 1- Some photos of the experimental area

Table 1- Weather conditions during the study period

Climatic Data	*April*	*May*	*Jun*	*July*	*August*
T_{mean} (°C)	24.2	14.9	19.6	23.7	25.3
T_{max} (°C)	20.2	21.9	27.9	33.0	34.3
T_{min} (°C)	4.4	7.8	11.3	14.4	16.2
Wind Speed (m sn^{-1})	1.6	1.6	1.4	2.0	1.6
Precipitation (mm)	25.9	57.2	50.6	0	3.3
RH_{max} (%)	81.9	87.3	87.8	68.5	73.1
RH_{min} (%)	25.7	30.8	25.5	16.5	22.2

Experimental design was randomized blocks with 3 replicates. Sowing was performed manually on 13th of April 2016. Experimental plots (5x1.75 m) had 6 rows spaced 35 cm apart and plant spacing was 5 cm. Fertilization was practiced at sowing as to have 15 kg ha^{-1} diammonium phosphate (18-46-0). Harvests were performed manually from the inner 4 rows and two side rows were committed as to consider side effects. The photographs of the experiment are given in Figure 2.

Figure 2- The map of the experimental location

Drip irrigation system with 16 mm dripper lines and 2l h^{-1} inline emitters with 25 cm spacing was used in irrigations. Seven different irrigation treatments were practiced (I_1-rainfed, I_2-pre-flowering single irrigation, I_3-beginning of flowering single irrigation, I_4-50% pod set single irrigation, I_5-irrigation at 50% flowering and 50% pod fill, I_6-irrigation before flowering and at 50% pod set, I_7-full irrigation) from sowing to full grain fill period as to bring the deficit moisture to FC when 40% (±5) of available moisture at 60 cm soil profile was depleted.

A time domain reflectometer (TDR) (Minitrase TDR, Soilmoisture Equipment Corp. USA) device was used to monitor soil moisture continuously. Soil moisture measurements were performed at 10 cm by the plant rows with a 60 cm uncoated TDR probe. Measurements were carried out manually, once a week. TDR calibrations were performed under field conditions in accordance with Akpinar (2016) and calibration equation of P_{vp}=1.922, K-0.2186 was used. Following equation was used to calculate irrigation water quantity of each irrigation:

$$d = \frac{(P_{vfc} - P_{VP})}{10} \times D \times P$$

where; d is irrigation water quantity to be applied, mm; P_{vfc} is moisture at FC, %; P_{vp} is moisture before irrigation, %; D is soil depth to be irrigated, cm; P is cover ratio.

2.2. Image acquisition and processing for dimensional attributes

In order to determine the dimensional attributes of the images of chickpea, an acquisition method described in the present study. In this method, there is a digital camera (Nikon D300, Japan) and illumination system. The chickpea images were captured without a shadow on the background in a dark room. The chickpeas were placed on a white fiberglass at horizontal and vertical orientations. The digital camera was vertically positioned at a constant height of approximately 45 cm (Kara et al. 2013; Sayıncı et al. 2015a; Cetin et al. 2020). For the image processing analysis, 100 chickpea seeds were sampled from each irrigation treatment (Cetin et al. 2020). The length (L, mm), width (W, mm), thickness (T, mm), projected area (PA, mm^2), aspect ratio (AR) and roundness (R) at both orientation of each chickpea were identification by image processing. The equations used for calculation of the volume (mm^3), geometric mean diameter (D_g, mm), surface area (S, mm^2), shape index (SI), sphericity (φ, %) and elongation (E) were presented in Table 2. Seed mass was measured with a precision electronic scale (±0.001 g).

Table 2- Equations used for size, shape and color attributes

Variables	*Equations**	*Literature*
Shape Index (SI)	$SI = (2 \cdot L)/(W+T)$	Ozkan & Koyuncu (2005)
Volume (V, mm^3)	$V = (\pi/6) \cdot D_g^3$	Volume of ellipse
Surface area (S, mm^2)	$S = \pi D_g^2$	Sayıncı et al. (2015)
Sphericity (φ)	$\varphi = (D_g / L) \cdot 100$	Mohsenin (1986)
Geometric mean diameter (D_g, mm)	$D_g = (L \cdot W \cdot T)^{(1/3)}$	Mohsenin (1986)
Elongation (E)	$E = L / W$	Fıratlıgil-Durmuş et al. (2010)
Chroma (C*)	$C^* = \sqrt{(a^*)^2 + (b^*)^2}$	McGuire (1992)
Hue angle (h°)	$h^\circ = \tan^{-1}(b^* / a^*)$, $(if\ \ a^* > 0\ \ and\ b^* \geq 0)$	McGuire (1992)
Color index (CI)	$CI = \frac{1000 \cdot a^*}{L^* b^*}$	Jimenez-Cuesta et al. (1982)

*L: Length (mm), W: Width (mm), T: Thickness (mm), D_g: Geometric mean diameter (mm), A_p: Projected area (mm^2), A_c: The biggest circular area (mm^2)

2.3. Chromatic parameters

Chromatic parameters (L^*, a^* and b^*) were measured with the use of a chromameter (Konica Minolta CR-400, Japan). Measurements were made in CIE color space. L^* (lightness; 0 dark, 100 light), a^* (+ values are redness, - values are greenness) and b^* (+ values are yellowness, - values are blueness) values were measured. CI, h° and C^* were calculated from provided in Table 2 (Jimenez-Cuesta et al. 1982; McGuire 1992).

2.4. Statistical analysis

Experimental data were subjected to one-factor analysis and significant means were compared with the use of Tukey's multiple comparison test at 95% significance level. Differences between the treatments were assessed with linear discriminant analysis (LDA). Group centroids of treatments obtained from LDA were used to generate a scatter plot. The principal components were evaluated for multivariate tests (MANOVA). Similarities or dissimilarities of irrigation treatments were tested with the use of Hotelling's pair-wise comparisons with squared Mahalanobis distances and Bonferroni correction. Statistical analyses were performed by using SPSS v20.0 (IBM SPSS® 2010) and PAST v3.20 software (Hammer et al. 2001).

2.5. Validation methodology

In the study, to validate the generated estimation models, the k-fold cross-validation technique was applied. The k value is usually preferred as 5 or 10 in the ML estimation (Ataş et al. 2012) which is 10 was chosen in the present study. Cross-validation evaluates the generalization ability of each model by comparing its performance in a dataset not used during training to fit the parameters of different ML algorithms. This technique is applied effectively in estimation (Stegmayer et al. 2013). In this technique, dataset was divided into

10 subsets by 10-fold cross-validation technique and every subset had an equal proportion of each class. Training and testing were performed with 10 iterations. In each iteration, 1 subset was used for testing and the rest of the subsets which is 9 subsets were used for training and with each of the k subsamples used exactly once as the testing respectively (Figure 3).

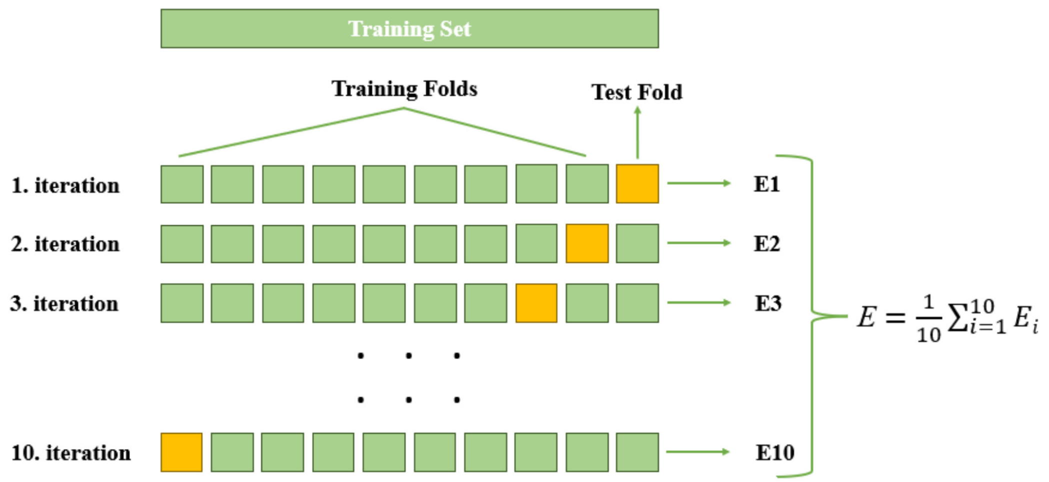

Figure 3. 10-fold cross validation methodology

2.6. Machine learning algorithms

In the current study, an estimation technique of ML algorithms was utilized by the Weka® v3.8 software (Hall et al. 2009). Two ML estimators were performed as ANNs and random forest. The estimation of seed mass belong to different irrigation treatments by ML was based on the main physical attributes. Size (V, L, W, T, D_g, SA and PA) and shape (R, φ, E, SI and AR) were used as criteria for estimation. In addition, the estimation of C*, h° and CI were based on the L*, a* and b* color properties. In this study, 100 samples were measured for each feature. A total of 9100 values were used for mass estimation, and a total of 2100 values were used for C*, h° and CI estimation for each irrigation treatments.

2.6.1 ANNs

In the present study, a MLP was used as feedforward ANN. The neural network parameters of the MLP structure were chosen as momentum 0.2, learning rate 0.3, and the number of periods 500. In addition, 12-6-1 MLP structure consisting of neurons in 12 input, 6 hidden and 1 output layers for mass estimation and 3-6-1 MLP structure consisting of neurons in 3 inputs, 6 hidden and 1 output layers for mass estimation for color estimation were considered. Applied MLP model structure is presented in Figure 4.

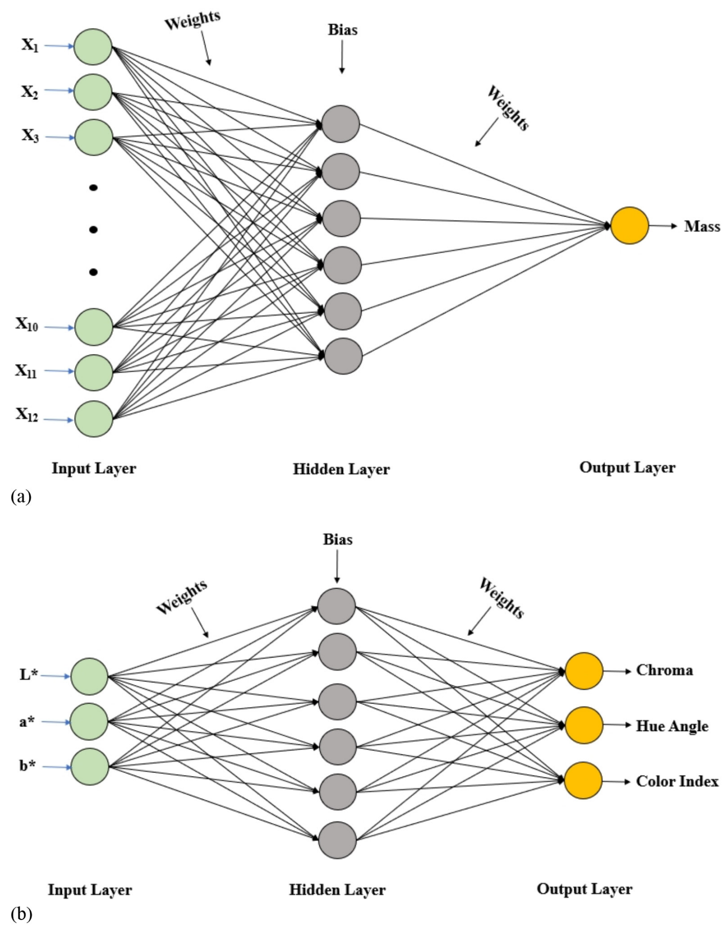

Figure 4- Model structures of the MLP for estimation of the mass (a) and color (b) attributes

In this study, RF algorithms was also utilized for estimation. RF contrary to decision tree (DT), a decision is performed with the majority of ensemble of trees built by RF in data sets assigned class (Berhane et al. 2018). Afterwards, bootstrap and ensemble scheme could overcome overfitting problem inherited from DT, there is no pruning step in RF. In addition, RF has a high estimative correlation coefficient and is robust against noise (Breiman 2001; Rodriguez-Galiano et al. 2012).

2.7. Model Performance Evaluation

Performance of MLP and RF models were assessed based on the following statistical indices: correlation coefficient (r), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE):

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\frac{(M_i - \dot{M})\,(E_i - \dot{E})}{S_M\ S_E}$$

$$MAE = \sum_{i=1}^{n}\frac{|\ E_i - M_i\ |}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(E_i - M_i\right)^2}{n}}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E_i - M_i}{E_i}\right| \times 100$$

Where is the n; data instances number, M_i; measured target value, E_i; predicted target value, M; measured target values mean, Ė; predicted target values mean, SM; measured target values sum, and SE; predicted target values sum. The correlation coefficient (r) was analyzed for assessing the goodness of the prediction according to Colton (1974). The correlation coefficient of between 0-0.25 indicate "little - no relationship", 0.25-0.50 indicate "fair relationship", 0.50-0.75 indicate "moderate - good relationship" and 0.75-1.0 indicate "very good - excellent relationship".

3. Results and Discussion

3.1. Shape, size, mass and chromatic parameters

This study was carried out to determine the effects of irrigations at different physiological stages on chickpea physical quality parameters. Gravitational, dimensional and area attributes are given in Table 3. Effects of irrigation treatments on shape, size, mass and color attributes were found to be significant at a 1% level. The greatest mass values were obtained from I_5 (0.50 g) while the lowest values were obtained from I_4 (0.42 g) treatments. The greatest length, width and thickness values were determined from I_5 as 11.01, 8.27 and 8.27 mm, respectively. Also, I_5 had greatest geometric mean diameter (9.10), PA (65.03 mm^2) and surface area (260.11 cm^2). PAs of chickpea seeds varied between 61.80 (rain-fed -I_1) and 57.49 mm^2 (50% pod set single irrigation-I_4). Similar findings were also reported by Masoumi & Tabil (2003) for PA between 60.87 mm^2 and 72.84 mm^2. Authors indicated that average length values were changed between 9.76 mm and 10.47 mm. George et al. (2007) stated that drying rate increased with increasing surface areas of the seed. Kibar et al. (2014) indicated that water deficits reduced average surface area and volume values from 236.99 mm^2 to 223.18 mm^2 and form 213.97 mm^3 and 200.62 mm^3 and significantly influenced thousand-seed weights of dry bean. Present findings comply with the results of Nikoobin et al. (2009) reporting decreasing geometric mean diameter and mass values with increasing from to 4.32 mm to 8.59 mm and 0.28 g to 0.42 g under different seed moisture contents.

Table 3- Mass, Dimension and Area attributes

Variables	*Mass (M, g)*	*Volume (V, cm^3)*	*Length (L, mm)*	*Width (W, mm)*	*Thickness (T, mm)*	*Geometric mean diam. (D_g, mm)*	*Projected area (PA, mm^2)*	*Surface area (SA, cm^2)*
I_1	0.47±0.04^{b}	365.99±34.97^{b}	10.70±0.47^{b}	8.18±0.38^{ab}	7.97±0.33^{b}	8.87±0.29^{b}	61.80±3.96^{b}	247.18±15.82^{b}
I_2	0.45±0.03^{bc}	350.80±29.27^{bc}	10.39±0.39^{cd}	8.12±0.39^{abc}	7.93±0.32^{bc}	8.74±0.24^{bc}	60.09±3.33^{bc}	240.36±13.33^{bc}
I_3	0.44±0.05^{c}	346.15±39.26^{c}	10.5±03.45^{bc}	7.95±0.38^{c}	7.88±0.41^{bc}	8.70±0.33^{c}	59.52±4.50^{c}	238.07±18.01^{c}
I_4	0.42±0.04^{d}	328.59±37.36^{d}	10.00±0.47^{f}	8.05±0.46^{bc}	7.78±0.39^{c}	8.55±0.32^{d}	57.49±4.36^{d}	229.95±17.44^{d}
I_5	0.50±0.03^{a}	394.86±30.80^{a}	11.01±0.43^{a}	8.27±0.32^{a}	8.27±0.31^{a}	9.10±0.24^{a}	65.03±3.38^{a}	260.11±13.50^{a}
I_6	0.44±0.05^{cd}	345.15±42.06^{c}	10.22±0.50^{de}	8.11±0.42^{abc}	7.93±0.40^{bc}	8.69±0.36^{c}	59.39±4.85^{c}	237.56±19.40^{c}
I_7	0.44±0.06^{cd}	338.83±48.07^{cd}	10.05±0.60^{ef}	8.07±0.45^{bc}	7.94±0.48^{bc}	8.63±0.42^{cd}	58.63±5.62^{cd}	234.50±22.47^{cd}
Mean	0.45±0.05	352.91±42.75	10.41±0.58	8.11±0.41	7.96±0.40	8.75±0.36	60.28±4.90	241.11±19.61
Min-max	0.24-0.63	178.25-488.26	7.85-12.12	6.20-9.95	6.37-9.57	6.98-9.77	38.29-74.97	153.17-299.86
F values	34.499**	32.884**	58.496**	6.460**	15.771*	31.788**	32.3880**	32.388**

Means indicated with different letters in the same column are significantly different ($p<0.05$). Min: Minimum, Max: Maximum
*Significant at $p<0.05$
**Significant at $p<0.01$

The shape in all treatments was described as oval because their average SI values were greater than 1.25. The greatest SI was obtained from I_1, I_3 and I_5 treatments while the greatest r was obtained from I_4 and I_7 treatments. Contrary to present findings, Kibar et al. (2014) reported increasing volumes with increasing irrigation water quantities. Comply with the present study, Sastry et al. (2019) reported average sphericity of desi, kabuli and intermediate type chickpea respectively seeds as 79.5, 85.7 and 84.5%. Surface area is closely correlation with the evaporation from the seed surfaces. r values close to unity indicate an almost circular shape. Contrary to present findings, Eissa et al. (2010) reported decreasing r values with decreasing moisture contents. AR, R, and sphericity values decreased, but SI and E values increased with increasing water deficit (Table 4).

Table 4- Shape attributes

Variables	*Sphericity (%)*	*Shape Index*	*Roundness*	*Aspect ratio*	*Elongation*
I_1	82.96±2.29^{c}	1.33±0.06^{a}	0.69±0.04^{c}	0.75±0.04^{d}	1.34±0.07^{a}
I_2	84.20±2.95^{b}	1.30±0.07^{b}	0.71±0.05^{b}	0.76±0.04^{bc}	1.31±0.07^{bc}
I_3	82.69±2.31^{c}	1.33±0.06^{a}	0.68±0.04^{c}	0.75±0.04^{cd}	1.34±0.07^{ab}
I_4	85.57±2.72^{a}	1.26±0.06^{c}	0.73±0.05^{a}	0.78±0.04^{ab}	1.29±0.07^{cd}
I_5	82.67±2.90^{c}	1.33±0.06^{a}	0.68±0.05^{c}	0.75±0.04^{cd}	1.33±0.07^{ab}
I_6	85.12±2.54^{ab}	1.27±0.06^{bc}	0.73±0.04^{ab}	0.78±0.03^{ab}	1.29±0.06^{cd}
I_7	85.99±3.09^{a}	1.26±0.07^{c}	0.74±0.05^{a}	0.79±0.05^{a}	1.27±0.08^{d}
Mean	84.17±3.02	1.30±0.07	0.71±0.05	0.77±0.04	1.31±0.07
Min-max	72.33-100.68	0.99-1.62	0.52-1.01	0.62-1.01	0.99-1.62
F values	27.111**	27.321**	26.894**	18.085**	17.718**

Means indicated with different letters in the same column are significantly different ($p<0.05$). Min: Minimum, Max: Maximum
**Significant at $p<0.01$

Color attributes are provided in Table 5. The greatest CI (8.46) and a^* (8.68) values were obtained from I_4 treatment (50% pod-set). However, the greatest C^* value was obtained from I_7 treatment (full irrigation) with values of 23.87. Queiroz et al. (2015) reported increasing L^* values under drying conditions. But in present study, water deficits reduced L^* values and the lowest value was obtained from the 50% pod-set (I_4) treatment as 55.26. Nevertheless, irrigation generally had a positive effect on color properties. Similarly, Jogihalli et al. (2017) in a study investigating the effects of roasting at different time and temperature conditions, reported b^* values (22.43-26.07) of close to the present values. The results showed that the change of physical attributes of chickpea seed grown in different supplementary irrigation treatments with the novelty of this study was revealed.

Table 5- Color attributes

Variables	*L^**	*a^**	*b^**	*Chroma*	*Hue angle*	*Color index*
I_1	60.25±7.50^{a}	7.43±1.05^{d}	21.32±2.94^{b}	22.60±2.92^{b}	70.64±2.80^{a}	6.01±1.57^{d}
I_2	58.92±4.92^{a}	7.66±.76^{cd}	20.21±2.11^{c}	21.64±2.06^{bc}	69.12±2.43^{b}	6.55±1.11^{cd}
I_3	60.14±5.83^{a}	8.09±0.99^{bc}	20.19±2.62^{c}	21.80±2.43^{bc}	67.92±3.65^{bc}	6.91±1.73^{bc}
I_4	55.26±5.47^{b}	8.68±1.20^{a}	19.01±2.19^{d}	20.95±2.05^{c}	65.31±3.90^{d}	8.46±1.80^{a}
I_5	56.00±11.00^{b}	7.57±1.14^{d}	19.98±3.00^{cd}	21.41±2.87^{c}	68.99±3.75^{b}	7.48±3.47^{b}
I_6	57.95±6.44^{ab}	8.11±0.98^{b}	19.41±2.05^{cd}	21.07±1.92^{c}	67.19±3.25^{c}	7.48±2.07^{b}
I_7	58.95±5.28^{a}	7.80±1.12^{bcd}	22.52±2.86^{a}	23.87±2.69^{a}	70.65±3.46^{a}	6.06±1.49^{d}
Mean	58.21±7.11	7.91±1.11	20.38±2.78	21.91±2.62	68.55±3.78	6.99±2.17
Min-max	21.86-75.81	1.60-12.18	13.44-34.96	14.40-35.52	54.51-86.30	1.18-24.31
F values	7.869**	16.594**	21.442**	17.496**	32.600**	19.192**

Means indicated with different letters in the same column are significantly different ($p<0.05$). Min: Minimum, Max: Maximum
**Significant at $p<0.01$

3.2. Discrimination of the irrigation treatments

The results of discriminant functions are presented in Table 6. The highest the eigen values, higher function gives dependent variable. Square of the correlation explains the effect size of functions. The first two functions explained 79.5% of total variation (respectively as 52.8 and 26.7%). Wilks' lambda explains best estimations. Wilks' lambda is significant for each estimator variables that is ideal, in this case, it was significant for 5 results. In the Wilks's lambda statistics, unexplained part of the differences between the groups was 34.6%.

Table 6- Discriminant analysis results

Eigenvalue statistics of discriminant functions	***Function 1***	***Function 2***	***Function 3***	***Function 4***	***Function 5***	***Function 6***
Eigenvalues	0.677	0.342	0.158	0.056	0.038	0.012
% of variance	52.8	26.7	12.3	4.3	3.0	0.9
% of cumulative variance	52.8	79.5	91.8	96.1	99.1	100.0
Canonical correlation	0.635	0.505	0.369	0.230	0.191	0.108
Significance test of canonical functions	1-5	2-5	3-5	4-5	5-6	6
Wilks' Lambda	0.346	0.580	0.779	0.902	0.952	0.988
Chi-square	730.934	374.777	171.902	71.107	33.739	8.013
df	78	60	44	30	18	8
p (sigma)	0.000**	0.000**	0.000**	0.000**	0.014**	0.432
Standardized canonical discriminant function coefficients	***Function 1***	***Function 2***	***Function 3***	***Function 4***	***Function 5***	***Function 6***
Mass	0.221	0.323	-0.137	-0.703	-0.899	0.695
Volume	1.287	1.730	6.769	4.057	3.568	-3.280
Length	3.529	-0.405	2.844	-3.589	-6.478	-5.662
Width	-2.527	-2.931	-6.976	-3.042	2.297	3.301
Thickness	-2.276	0.372	-4.692	1.941	0.875	6.167
Sphericity	2.784	1.716	4.484	1.691	-1.145	1.064
Shape index	-0.643	-2.282	-3.523	0.134	6.432	5.981
Elongation	-0.065	3.501	2.035	4.641	-2.650	2.479
L^*	0.548	-0.515	-0.213	0.034	0.718	-0.875
a^*	0.620	0.362	-1.039	-0.284	1.114	0.637
b^*	8.453	6.300	-6.132	-4.412	11.232	1.398
C^*	-8.431	-5.491	6.503	4.791	-11.362	-1.726
CI	0.953	-0.212	0.509	-0.118	0.891	-0.759

**Highly significant ($p<0.01$)

The discriminant function coefficients give relative importance of 13 estimators. According to the loadings, the function 1 and 2 had the highest loading for the b^* and C^*. For function 3, width and volume had greatest function coefficients. Figure 5 shows the centroids of 7 different irrigation treatments based on their canonical discriminant functions. Differences between components, color and size properties was considered as a significant distinguishing trait. The traits of sphericity and r for I_4, I_6 and I_7 treatments confirmed the location on the left of the canonical function 1 axis. In addition, b^* and C^* for I_1 and I_7 treatments were located on the bottom of canonical function 2 axis. Canonical function 3 had greatest load for width and volume with the negative and positive correlation, respectively. According to these attributes, I_1 and I_5 treatments and I_2 and I_3 treatments together constituted a separate group.

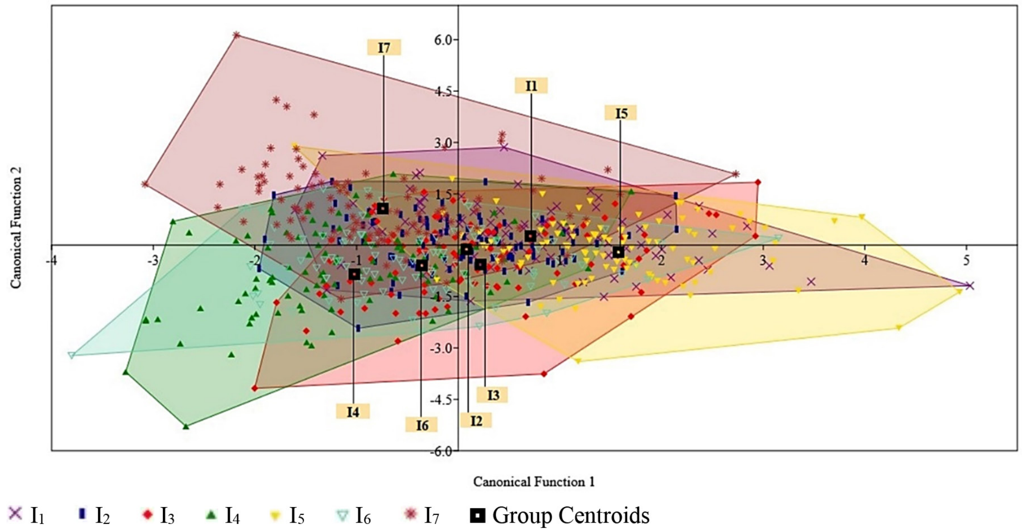

Figure 5- Scatter plots of the irrigation treatments in terms of group centroids of canonical function 1 and 2

3.3. MANOVA and pair-wise comparison

All treatments were found to be significant in terms of the shape, size and color as indicated by Wilks' Lambda, Pillai Trace and Hotelling Trace statistics ($p<0.01$). The results of the MANOVA test, Bonferroni corrected and Mahalanobis distances are provided in Table 7. Wilks' Lambda statistics expressed the percentage of variance in dependent variables and explained them with differences in independent variables. The smaller "Wilks' Lambda" statistic show that differences between groups to be analyzed increase and varies between 0 and 1 (Sayıncı et al. 2015a). Pillai Trace statistics, considered to be the most reliable among multivariate evaluations, takes into account the sum of the variance that explains the greatest discrimination of independent variables in dependent variables. Generally, the treatments with Mahalanobis distance of lower than 3 indicate significantly similar physical attributes ($p>0.05$). It concluded that the I_1 and I_2 treatments with the lowest Mahalanobis distances had the similar attributes. In the reference of Mahalanobis distances among the irrigation treatments, the closest distances were observed between I_1 and I_2 treatments, and between I_2 and I_3 treatments, while distance among the I_4 and I_5 treatments had highest value. Pair-wise comparisons revealed that there were not any similarities among the irrigation treatments.

Table 7- Differences among the irrigation treatments based on chickpea outlines

The results of MANOVA						
Effect	***Statistics***	***Value***	***Hypothesis df***	***Error df***	***F***	***p (sigma)***
	Pillai's trace	0.960	108	4086	7.204	0.000**
Variables	Wilks' Lambda	0.322	108	3881	7.867	0.000**
	Hotelling Trace	1.368	108	4046	8.542	0.000**
Hotelling's pairwise comparisons. Bonferroni corrected p values in upper triangle, Mahalanobis distances in lower triangle							

Variables	***I_1***	***I_2***	***I_3***	***I_4***	***I_5***	***I_6***	***I_7***
I_1		1.33E-03	3.10E-04	7.80E-21	2.45E-08	1.38E-09	1.60E-15
I_2	0.88		7.59E-02	5.26E-12	1.36E-16	1.05E-02	5.12E-12
I_3	1.38	0.93		3.85E-11	7.65E-15	6.13E-03	2.41E-18
I_4	4.78	2.85	2.67		2.52E-30	7.17E-03	5.63E-17
I_5	2.14	3.81	3.43	7.37		1.75E-19	5.39E-30
I_6	2.37	1.10	1.14	1.13	4.46		2.57E-13
I_7	3.57	2.85	4.20	3.89	7.27	3.11	

**Highly significant ($p<0.01$)

3.4. Estimation results of machine learning algorithms

Machine learning models were separately built based on data from 7 irrigation treatments. The results were evaluated based on the correlation coefficient of the estimation of mass and color properties. A 10-fold cross-validation was followed to test estimation correlation coefficient. The dataset of 700 measurements was divided randomly into 10 equally-sized subsets. Mass estimation results by MLP and RF were tabulated in Table 8. The best estimation criteria were higher correlation coefficient (r) and lower RMSE, MAE. Overall, each base learner performed all evaluation parameters very well with all achieving an r value of >0.98 for MLP. In the MLP algorithm, the greatest correlation coefficient for mass estimation was 0.997 and 0.996 in I_2 and I_7 treatments, respectively. The lowest RMSE and MAPE values obtained from I_2 treatment as 0.0010 and 0.0980, respectively. In addition, the lowest MAE was determined as 0.0008 for I_2 and I_6 treatments. In the RF algorithm, all r values obtained higher than 0.87. The highest r values was 0.9850 and 0.9755 for I_2 and I_7 treatments, respectively. The lowest RMSE, MAE and MAPE was found as 0.0079, 0.0053 and 0.6876 in I_2 treatment.

Table 8- Neural network parameters of the MLP structure and performance results of machine learning algorithms*

NN Type	*η*	*A*	*NoE*	*n_i*	*n_h*	*n_o*	*g (.)*	*Inputs*	*Outputs*	*Total records*
MLP	0.3	0.2	500	12	6	1	sigmoid	L, W, T, V, Dg, SA, PA, S, SI, R, AR, E	Mass	9100
MLP	0.3	0.2	500	3	6	1	sigmoid	L^*, a^*, b^*	Chroma Hue Angle Color Index	2100

	Mass				*Chroma*				*Hue angle*				*Color index*			
MLP	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***
I_1	0.9992	0.0009	0.0015	0.1173	0.9998	0.0019	0.0028	0.0003	0.9996	0.0007	0.0011	0.0001	0.9988	0.0092	0.0141	0.0012
I_2	0.9997	0.0008	0.0010	0.0980	0.9996	0.0020	0.0029	0.0002	0.9998	0.0006	0.0008	0.0001	0.9992	0.0053	0.0076	0.0006
I_3	0.9989	0.0010	0.0018	0.1273	0.9998	0.0019	0.0025	0.0003	0.9997	0.0010	0.0014	0.0003	0.9981	0.0082	0.0128	0.0009
I_4	0.9989	0.0012	0.0023	0.1463	0.9972	0.0035	0.0095	0.0004	0.9985	0.0015	0.0031	0.0002	0.9963	0.0103	0.0295	0.0011
I_5	0.9848	0.0017	0.0082	0.1976	0.9996	0.0021	0.0037	0.0002	0.9978	0.0015	0.0035	0.0001	0.9982	0.0224	0.0785	0.0025
I_6	0.9994	0.0008	0.0012	0.0990	0.9998	0.0014	0.0019	0.0002	0.9997	0.0009	0.0013	0.0002	0.9945	0.0078	0.0164	0.0010
I_7	0.9996	0.0010	0.0016	0.1141	0.9984	0.0025	0.0050	0.0003	0.9994	0.0010	0.0018	0.0001	0.9980	0.0111	0.0192	0.0012
RF	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***	***R***	***MAE***	***RMSE***	***MAPE (%)***
I_1	0.9531	0.0064	0.0115	0.8470	0.9826	0.0152	0.0269	0.0015	0.9430	0.0103	0.0153	0.0010	0.9484	0.0607	0.0868	0.0061
I_2	0.9850	0.0053	0.0079	0.6876	0.9775	0.0128	0.0201	0.0013	0.9619	0.0081	0.0124	0.0008	0.9612	0.0411	0.0589	0.0041
I_3	0.9563	0.0062	0.0114	0.8319	0.9789	0.0158	0.0232	0.0016	0.9618	0.0116	0.0164	0.0012	0.9449	0.0484	0.0717	0.0049
I_4	0.9381	0.0089	0.0160	1.1296	0.9697	0.0179	0.0314	0.0018	0.9234	0.0129	0.0243	0.0013	0.8672	0.0655	0.1391	0.0065
I_5	0.8745	0.0066	0.0212	0.8007	0.9889	0.0143	0.0229	0.0014	0.8971	0.0112	0.0224	0.0011	0.9613	0.0472	0.0591	0.0097
I_6	0.9591	0.0063	0.0100	0.8005	0.9742	0.0135	0.0204	0.0013	0.9523	0.0114	0.0168	0.0011	0.9253	0.0528	0.0820	0.0053
I_7	0.9755	0.0082	0.0121	1.0385	0.9399	0.0156	0.0320	0.0016	0.9676	0.0091	0.0145	0.0009	0.9477	0.0657	0.1635	0.0066

*η: Learning rate, α: Momentum, NoE: Number of epochs, n_i: Number of input layers, n_h: Number of hidden layers; n_o: Number of output layers, g (.): Activation function, MLP: Multilayer perceptron; RF: Random forest, RMSE: Root mean square error, MAE: Mean absolute error, MAPE: Mean absolute percentage error

Similar to the present study, Soares et al. (2013) reported that in the mass estimation of banana, the R^2 were found between 0.63 and 0.91 in ANN algorithm. Authors also indicated the lowest mean prediction-error (MPE, %) values were obtained as 0.41. Rad et al. (2017) presented the best R^2 and MPE (%) values for ANN estimation of eggplant mass were 0.93 and 2.01, respectively. Gurbuz et al. (2018) used Find Laws algorithm for the mass estimation of almonds. The authors reported the greatest R^2 of 0.9561. Demir et al. (2020) to estimate the mass of the walnut was applied ANN algorithm and RMSE of MNN structure ranged from 0.60 to 0.89, while RMSE of Radial Basis Neural Network structure was found to be very low (0.0002) in all walnut varieties. Saglam & Cetin (2021) were applied MLP, k-nearest neighbor (kNN), RF, Gaussian processes (GP) to estimate mass (nut and kernel) of six different pistachio cultivars. Shape and size attributes were used as the input parameters and GP had the greatest correlation coefficients 0.976 for nut and 0.948 for kernel and the lowest RMSE values 0.038 for nut and 0.029 for kernel. This result conforms to the present study.

In the mass estimation, MLP yielded the best results in all treatments. ANN topology is an important factor in designing MLPs because it has an important effect on estimation. The number of hidden layers, neurons and epochs is also important. Additionally, it is preferable that the number of neurons in the hidden layer was low since it leads to an increase in the network learning speed and a decrease in the network size. In this case, ANN estimation of the individual mass in advance could make it possible for growers to prefer economical support with full assurance of a timely refund (Soares et al. 2013).

The highest r value in C^* estimation was determined in I_3 (0.9996) and I_5 (0.9997) treatments for MLP. However, the lowest RMSE, MAE and MAPE were found as 0.0718 (I_3), 0.0487 (I_6) and 0.0002 (I_2, I_5 and I_6) for MLP. In the RF algorithm, while the highest r values were obtained in I_1 (0.9826) and I_5 (0.9889) treatments the lowest was obtained in I_7 (0.9399) treatment. The lowest prediction error values were found as 0.4349 (RMSE) in I_5, 0.2792 (MAE) in I_2 and 0.0013 (MAPE) in I_2 and I_6 treatments.

The greatest r value for h° estimation determined from I_7 treatment as 0.9993 and 0.9676 for MLP and RF, respectively. In the MLP algorithm, the lowest RMSE and MAE values obtained in I_7 treatment as 0.1404 and 0.0693, respectively. I_1 treatment had the lowest RMSE for RF algorithm as 1.0587. Additionally, MAE and MAPE values were found in I_2 treatment as 0.5544 and 0.0008, respectively.

In the CI estimation, I_2 treatment had the highest r (0.9989) and the lowest RMSE (0.0528), MAE (0.0387) and MAPE (0.0006) values for MLP. The lowest RMSE, MAE and MAPE values for CI estimation were observed in I_2 as 0.3761, 0.2673 and 0.0041, respectively. However, the greatest r value was seen in I_5 treatment as 0.9613.

Comply with the present study, Kus et al. (2017) estimated C^*, hº and CI from L^*, a^* and b^* in 6 different apple varieties and reported the lowest RMSE findings as 0.5463 and 0.0001 for ANN and adaptive neuro-fuzzy interface system (ANFIS) algorithms, respectively. Demir (2018) estimated CI, C^* and hº parameters of 10 different walnut cultivars with the use of ANFIS. The author indicated that RMSE values ranged between 0.01 and 0.02, and the highest R^2 values 0.999 for h°. Germšek et al. (2017) was estimated fruit skin color (especial a color parameter a^*), for three apple varieties with the use of six different algorithms. The authors reported that the highest estimation accuracy values as 96.65% in logistic model tree algorithm. van Roy et al. (2017) estimated the color of tomatoes using hyperspectral imaging. The authors reported that partial least square (PLS) method was found to achieve the best R^2 results as 0.86, 0.93, 0.42, 0.95 and 0.51 for L^*, a^*, b^*, h° and C^*, respectively. Huang et al. (2014) used PLS regression algorithm to estimate of soybean color during drying from hyperspectral imaging and the better color estimation results obtained from mean reflectance as 0.862 (R) and 1.04 (RMSE). Present findings revealed that all ML methods had sufficient success in mass and color estimation of irrigation treatments. In the present study, physical and color properties of chickpea seeds grown under different conditions were estimated. It is thought that these data will facilitate the classification and discrimination of the seeds.

3.5. Limitations of the proposed study and the future research directions

Limitations of this study were the laboriousness of the data acquisition process. In addition, processing the obtained data and handling the applications separately caused the processes to take longer in estimations. Also, the choice of structure for ANN was also a limitation of the study. In future studies, it is recommended to preprocess the data before estimation or to reduce the data. Besides, different ML algorithms such as support vector machine, GP and kNN could be tried for similar studies. In fact, the usage of deep learning methods with image recognition and classification instead present methods of could contribute to the rapid of the process.

4. Conclusion

In this study, discrimination and estimation was performed for mass and color estimation of chickpea seeds at 7 different irrigation treatments using LDA and ML. The MLP yielded better outcomes as compared to the RF in both mass and color estimation. MLP with a 12-6-1 topology for mass estimation and 3-6-1 topology for color estimation also yielded quite a well discrimination for chickpea seeds. Present findings showed single or couple irrigations at different physiological stages could be sufficient to have desired yields and quality traits. The best results were achieved in I_5 for size and mass, I_4 and I_7 for shape and I_7 for color attributes. Present findings should also be considered in irrigation treatments and food processing technologies for chickpea.

Data availability: Data are available on request due to privacy or other restrictions.

Authorship Contributions: Concept: İ.S.V., N.Ç., H.K., Design: N.Ç., Data Collection or Processing: İ.S.V., N.Ç., Analysis or Interpretation: N.Ç., H.K., Literature Search: İ.S.V., Writing: İ.S.V., N.Ç., H.K.,

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