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Identification of Indian jujube varieties cultivated in Saudi Arabia using an artificial neural network

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ABSTRACT

This study aimed to develop a method for identifying different cultivars of Indian jujube fruits (*Ziziphus mauritiana* Lamk.) based on a single Indian jujube fruit color and morphological attributes using an artificial neural network (ANN) classifier. Eleven Indian jujube fruit cultivars were collected during winter of season 2020 from a local orchard located at Riyadh region, Saudi Arabia to measure their lengths, major diameters, and minor diameters. Different morphological descriptors were calculated, including the arithmetic mean diameter, the sphericity percent, and the surface area. Moreover, the color values of L*, a*, and b* of the skin of fruits were recorded. The ANN classifier was used to identify the appropriate class of Indian jujube fruit by using a combination of morphological and color descriptors. The proposed method achieved an overall identification rate of 98.39% and 97.56% in training and testing phases, respectively. In addition to color and morphological features, ANN classifier is a useful tool for identifying Indian jujube fruit cultivars and circumventing the difficulties met during fruit grading.

1. Introduction

The global pomology sector has experienced numerous problems, leading to decline in the production of fruit crops because of inability of the producers to meet new production and quality (USAID, 2005). To have good quality of fruits, the fruit industry utilized quality monitoring systems which are able to quickly, precisely, and non-destructively classify fruit maturity stage and distinguishing between species and cultivars permitting thus to decrease wastes and rise market value (Ibba et al., 2021). However, the identification of fruits is usually done manually, increasing the time and economic resources required with several different accessions of fruit and items per class (Jana and Parekh, 2017).

The Rhamnaceae are a huge family of flowering angiosperm plants, mostly trees, shrubs, and some vines, usually called the buckthorn family (Midha et al., 2017), however, the family comprises about 55 genera and 950 species and have a worldwide distribution, but are more common in the tropical and subtropical regions. Furthermore, the genus Ziziphus is most predominant and includes 135 to 170 species (Jackson et al., 2011; Christenhusz and Byng, 2016), such as jujube (*Ziziphus jujuba*), Christ's thorn jujube, (*Ziziphus spina-christi*), and Indian jujube (*Ziziphus mauritiana*), which thrive well in temperate as well as warm regions to some extent (Ezz et al., 2011; Yao, 2016). The Rhamnaceae family has been shown to be represented in Saudi Arabia by four genera which are: Ziziphus, Rhamnus, Berchemia and Sageretia as reported by Almalki and Alzahrani (2018).

Ziziphus mauritiana Lamk. is ordinarily recognized as Indian jujube or ber, and its fruits are consumed locally in some parts of Saudi Arabia. Its cultivation is widespread due to its adaptability, ease of cultivation, xerophytic properties, early age of maturation, tolerance of harsh environments, including resistance to drought and salinity stress, minimal input requirements, high nutritional value, and economic value (Ezz et al., 2011; Anjum et al., 2018;

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Anjum et al., 2020). In the research field of nutritional and food sciences, the fresh Indian jujube fruits gained considerable attention because of its medicinal and nutritional properties (Pareek, 2013; Reza, 2014; Wang et al., 2016; Xia et al., 2017; Hossain, 2019). The morphological and chemical characteristics of Indian jujube fruit changed significantly between the different cultivars grown in Saudi Arabia, Komethry, Pakstany, Um-Sulaem, Toffahy, and Pu-yun (Obeed et al., 2008). Although all such qualities may change to some extent with changes in how they are grown, climatic conditions, and according to other biotic and abiotic factors. Yet, they offer a dependable basis for cultivar identification in Indian jujube fruit.

Recently, computer-based automated systems have been used to resolve this problem to a certain extent. These systems utilize image processing and identifiers to automatically identify fruits based on their visual descriptors, like color, texture, and shape (Jana and Parekh, 2017). The possible solution is to use color and geometrical descriptors with artificial neural network classifier methods to identify and differentiate between various cultivars to increase the market price and meet quality standards.

Morphological attributes, which are based on direct measurement, are useful for identifying detectable differences and separating fruits, as they are objective and reproducible (Rashidi and Arabsalmani, 2016). In fruit classification, fruit shape is determined using indicators computed from the geometric attributes of the fruit, such as for the cantaloupe (Rashidi and Arabsalmani, 2016) and kiwi fruit (Bahri et al., 2017). In addition, the measurement of geometric attributes can be done using a caliper, and no complicated device is required. Additionally, fruit color plays a significant part in identification, classification and grading systems. However, to describe the stage of maturity of fruits, most of the existing color systems comparing predefined reference colors with the fruits surface color (Naik and Patel, 2017). There are several existing color models to describe the maturity of fruits; however, detailed information regarding the color models is described by Cubero et al. (2011). Cardenas-Perez et al. (2017) evaluated the maturity stages of apples using the color values of L*, a*, and b*, with 100% accuracy.

Artificial neural networks (ANNs) are used in situations in which independent and dependent parameters are connected by a nonlinear relationship, but ANN models provide different answers to quantify grading quality in the same network. Thus, there are numerous revisions that implement ANNs to classify fruits (Espinoza et al., 2016; Mazen and Nashat, 2019) and to predict Indian jujube mass (Abdel-Sattar et al., 2021). The research progress in the field of fruit identification is limitless, as the use of image processing technique is increasing day by day in all fields and including the agriculture to classify fruits (Pratap et al., 2014) due to the manual grading results in high costs and low quality (Huynh et al., 2021) as well as accurate classification of fruit accessions in processing plants and during post-harvesting requests is a challenge that has been widely studied (Sabzi et al., 2018). Additionally, considering the importance of pomology sector, a significant concern is given to the fruits that we consume. Different techniques have been used over the past years for fruit identification using computer vision and image processing technologies. One of the most remarkable applications is the use of ANN to classify, identify, and distinguish between different accessions of fruits from a dataset of images display that they outperform other algorithms (Rocha et al., 2010).

Rocha et al. (2010) analyzed several appearance, color, texture, and shape-based image descriptors to classify fruits and vegetables in a multi-class scenario. They examined the best combination of features as well as various machine learning techniques such as support vector machine, linear discriminant analysis, classification trees, and K-nearest neighbors to find the best classification procedures and features for produce categorization. Pratap et al. (2014) proposed an algorithm for fruits classification based on the shape, color and texture. The shape was described by calculating fruit area, perimeter, major axis length and minor axis length. Mean and standard deviation is calculated for the color space like HSI, HSV. Gray Level Co-occurrence Matrix is used to calculate texture features. ANN classifier was used for classification of fruits. Results obtained are better over the previous techniques and gives the accuracy up to 96%. Bongulwar (2020) built an automatic system for feature extraction to identify and classify fruits using convolutional neural network. The dataset consists of five different categories of fruit images. The accuracy obtained was 92.23%. Also, the results confirmed that convolutional neural network outperforms machine learning algorithms.

In the literature, little attention has been devoted to the identification of specific Indian jujube varieties using fruit descriptors. However, on the basis of morphological features, the classifications of Indian jujube cultivars cause confusion because of the different morphological standards used (Razi et al., 2013). Therefore, this study aimed to propose a method of identifying different cultivars of Indian jujube fruits (*Ziziphus mauritiana* Lamk) based on a single Indian jujube fruit color (L*, a*, and b* of the skin of fruits) and values of the arithmetic mean diameter, the sphericity percent, and the surface area using an ANN classifier.

2. Materials and methods

2.1. Collection of Indian jujube fruit samples

The investigation was conducted on mature trees of 11 Indian jujube cultivars, namely, Zaytoni (V1), Kashmiri (V2), Komethry (V3), Um-Sulaem with spines (V4), Toffahy (V5), and Um-Sulaem without spines (V6) , Abdel-Sattar (V7), Pu-yun (V8), Pu-Pineau (V9), seedy ber (V10), and buddling ber (V11) (Fig. 1), which were grown at the Research and Agricultural Experimental Station of King Saud University, ate Dirab region, Riyadh, Saudi Arabia (24°24′43.0″N, 46°39′30.7″E).

The Indian jujube trees were grown for 12 years, and fruit samples were collected during the end of the winter of season 2020 when the fruit color turned to light green (ovary green). The trees were budded on Indian jujube rootstock, except for seedy ber, which was grown in sandy loam soil and received the same cultivation treatment, as usually applied in each orchard. Three uniform trees were selected from each cultivar and used in this investigation. At harvest time for each of the cultivars, samples of 30 mature fruits were taken at random from each tree and cleaned manually to remove all foreign materials. However, the moisture content of the samples was determined according to the standard method (AOAC, 2005) as it is desirable to display its valued during estimating the quality of fruits because of it is affected by cultivation conditions and cultivars (Maraghni et al., 2011).

We propose a model that recognizes Indian jujube fruits using their color and shape descriptors. Specifically, we collected Indian jujube fruits samples from 11 varieties. We acquired morphological and color descriptors manually for all the samples we collected, and then we split the data into two samples. Data belonging to the first sample were called the training set and were used to learn the ANN model. Whereas, the second sample of data were used for testing purposes. To recognize Indian jujube samples, we conducted a learning process, which started by introducing morphological and color features to the training dataset and using the ANN classifier to identify the test sample and variety it belonged to. The ANN classifier structure was designed using the software NeuroShell classifier (release 3) (Ward System Group, Inc., 2007). In general, the required data were first collected using manual

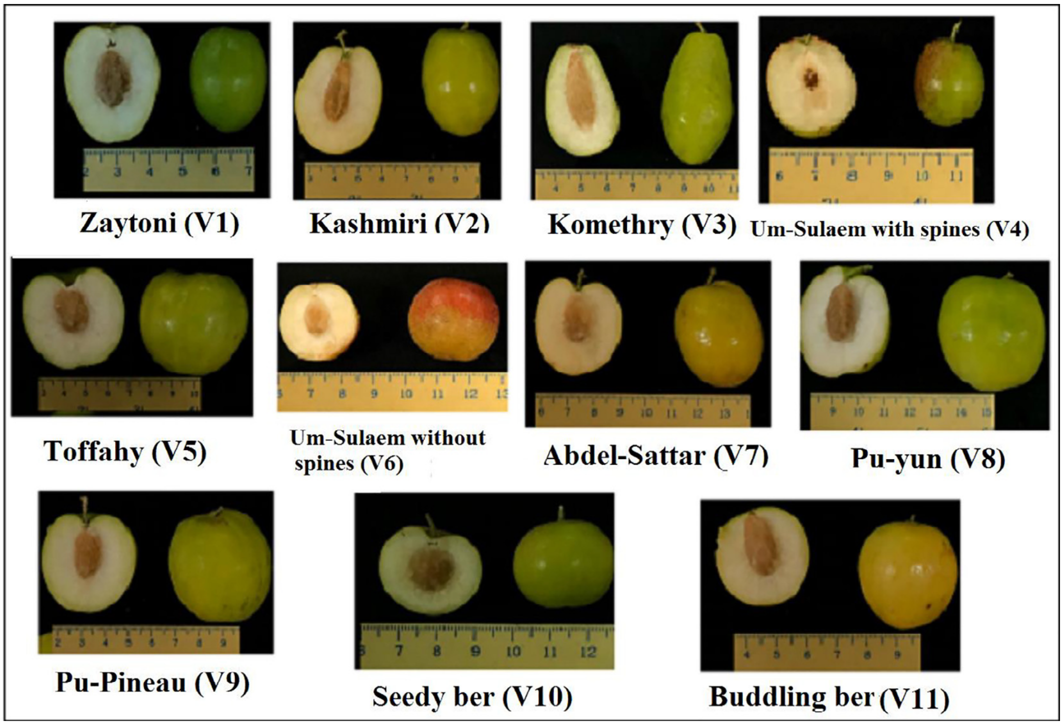

Fig. 1. The investigated Indian jujube varieties.

measurements for single Indian jujube fruits to acquire feature vectors ordered by each class. Then, the ANN classifier was trained and tested using the training and testing datasets, respectively. Finally, the effects of the morphological and color descriptors on the performance of the ANN classifier were analyzed.

2.2. Determining of morphological descriptors

Three perpendicular axes, major diameter (D1), length (L) and minor diameter (D2), were measured for single fruits using digital calipers with an accuracy of 0.01 mm. These measurements were conducted at the Fruit Laboratory, located at the College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia for each sample.

The morphological features include: the arithmetic mean of the fruit diameter (Da, mm) was calculated using the formula presented by Sunmonu et al. (2015):

$$Da = \frac{(L + D1 + D2)}{3} \quad (1)$$

The sphericity percent (ϕ, %) of the fruit was calculated using the formula presented by Vivek et al. (2018):

$$\varnothing = \frac{Dg}{L} \times 100 \quad (2)$$

The surface area (Sa, mm^2) was calculated using the formula presented by Altuntas et al. (2018):

$$\mathrm{Sa} = \pi \times \mathrm{Dg}^2 \quad (3)$$

The geometric mean of the fruit diameter (Dg, mm) was calculated using the formula presented by Vivek et al. (2018):

$$Dg = (L \times D1 \times D2)^{\frac{1}{3}} \quad (4)$$

2.3. Determining of color descriptors.

The color characteristics of the Indian jujube fruits were measured by a Minolta colorimeter (Konica Minolta, Model CR-400/410 Chroma Meters, Osaka, Japan) in terms of their L*, a*, and b* values. The L* coordinate specifies the darkness or lightness and ranges from black (0) to white (100). The coordinates a* and b* display color paths: +a* is the red direction, –a* is the green direction, +b* is the yellow direction, and –b* is the blue direction (Itle and Kabelka, 2009). Each Indian jujube sample was oriented on different axes, and L*, a*, and b* were captured, and the mean values were used to represent the color values. The dataset acquired from the 330 investigated fruits was used to build the ANN classifier and then validate it. This dataset was separated randomly into validation and training datasets using the ANN classifier strategy.

2.4. An artificial neural network model for Indian jujube identification

The identification of agricultural products using ANNs is done by learning from data created experimentally (Li et al., 2009). A common category of ANN is the backpropagation neural network, which is used to group features into different classes by identifying common appearances among the samples of the known feature class. The structure of ANNs consists of three or more layers, including the input layer, hidden layer (s), and the output layer. In each layer, the number of neurons depends on the number of inputs, the complexity of the identification task, and the number of output classes (Teimouri et al., 2016). A schematic representation of the ANN model that was used to distinguish Indian jujube varieties is shown in Fig. 2.

The data for the combination of morphological and color descriptors of Indian jujube fruit varieties were converted into a comma-separated values format file using Excel. NeuroShell software (release 3) was used to process the formatted file to conduct identifications. The best-hidden neurons were selected for use on the training dataset based on the highest overall accuracy. Three

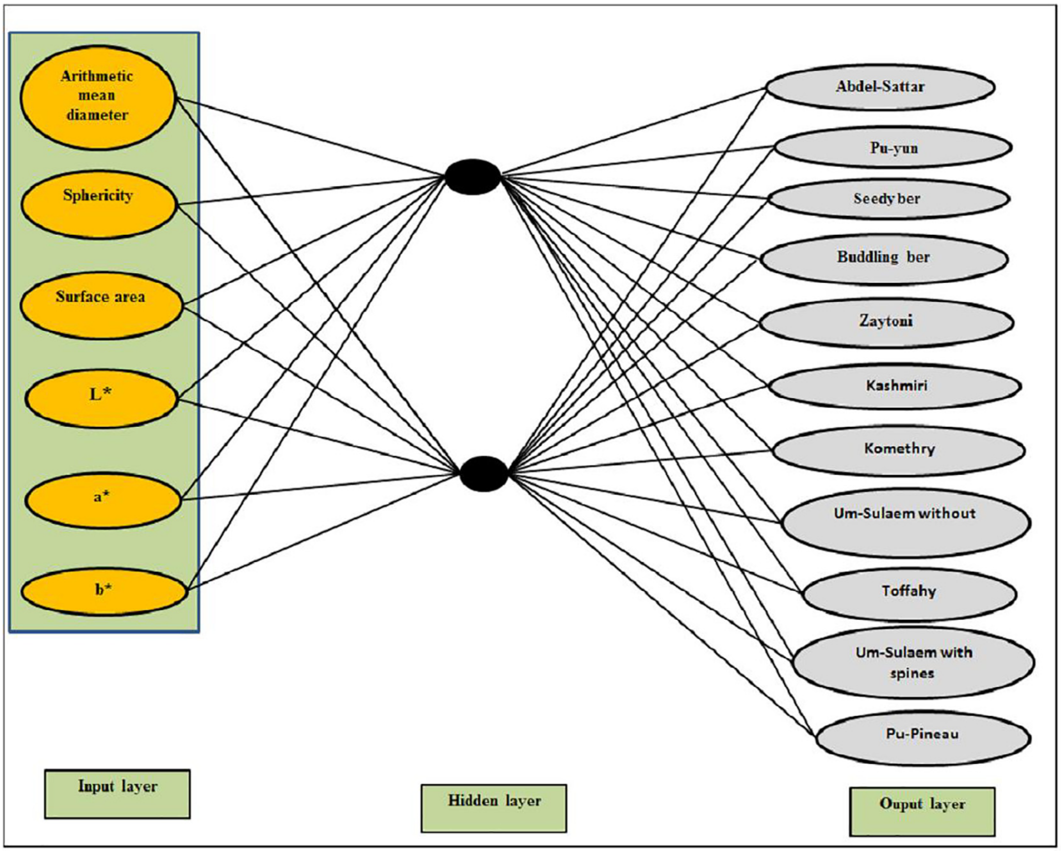

Fig. 2. A schematic representation of the artificial neural network model that was used to distinguish Indian jujube varieties.

morphological features and three color descriptors of L*, a*, and b* were used as inputs for the development of the ANN classifier, and 11 cultivars were identified in the output layer. The software was oriented to randomly select for training 248 patterns (75%) and for testing 82 patterns (25%).

2.5. Evaluation of ANN classifier performance

After gaining the class predictions, the ANN classifier performance was evaluated using a confusion matrix. This procedure, which covers information about the predicted and actual ratings gained by a classification system, is one of the most common methods used within the ANN techniques (Castro et al., 2019). A confusion matrix has two magnitudes: predicted and actual classes. Each row denotes the instances of an actual class, whereas each column denotes the cases of a predicted class. Some performance measures, namely sensitivity and specificity were extracted from the generated confusion matrix by NeuroShell software.

3. Results

3.1. Description of the related features of Indian jujube fruits

Fig. 3 shows the distribution of the mean color parameter L*, a*, and b* for each Indian jujube cultivar. The parameter L* presented slight variability across the cultivars with a minimum value of 64.41 and a maximum value of 96.69 (Fig. 3). The parameter a* showed no clear trend with a minimum value of –32.99 and maximum value of 4.11 (Fig. 3). Finally, the parameter b* fluctuated between 6.36 and 84.41 (Fig. 3).

Fig. 4 depicts the mean of three perpendicular axes L, D1, and D2 values of Indian jujube fruits of 11 different cultivars. However, these measurements were conducted at mean moisture content of the fruits of 74.1–84.3% (wet base). The parameter L showed high variability across the cultivars with a minimum value of 22.09 mm and maximum value of 44.75 mm (Fig. 4). The parameter D1 also showed high variation with a minimum value of 19.33 mm and maximum value of 42.73 mm (Fig. 4). Finally, the parameter D2 varied between 21.86 mm and 44.00 mm (Fig. 4). Furthermore, Table 1 shows maximum, minimum, mean and coefficient of variation of arithmetic mean diameter, sphericity, and surface area for 11 cultivars. It is clear that sphericity range was 71.74% to 98.66% with mean of 90.69%. Moreover, high variation was recorded for surface area as the coefficient of variation was 40.92%.

3.2. Performance of the developed artificial neural network classifier

The physical variables of agricultural products are vital to have an accurate assessment of physical descriptors and other properties which can be reflected the engineering variables for that product (Taner et al. 2018). These variables such as the length, thickness, width, sphericity, geometric mean diameter, volume, surface area, volume and aspect ratio are used in the processing, storage, handling, drying, grading, and designing equipment. Arithmetic mean diameter, sphericity, surface area, and color features were determined for Indian jujube fruits and they were determined to be used to identify Indian jujube cultivars. In the study, an ANN classifier was developed for precise identification. The building of the ANN classifier was set up to involve of a combination of arithmetic mean diameter, sphericity, surface area, and three color features of total 6 attributes. However, when tackling

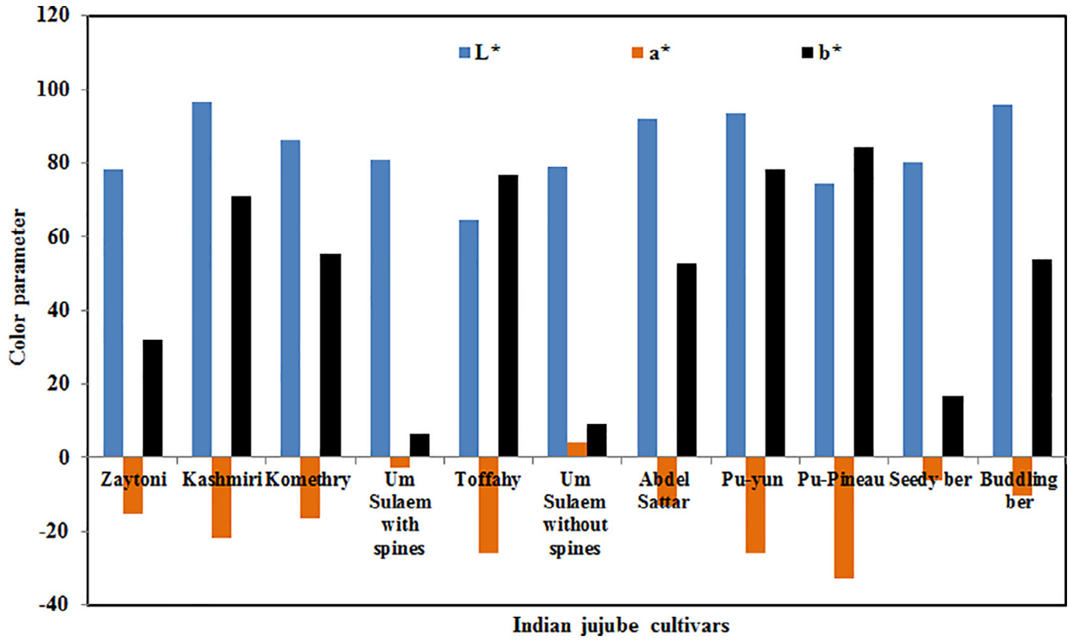

Fig. 3. Mean color parameter, L*, a*, and b*, values of Indian jujube fruits of 11 different cultivars.

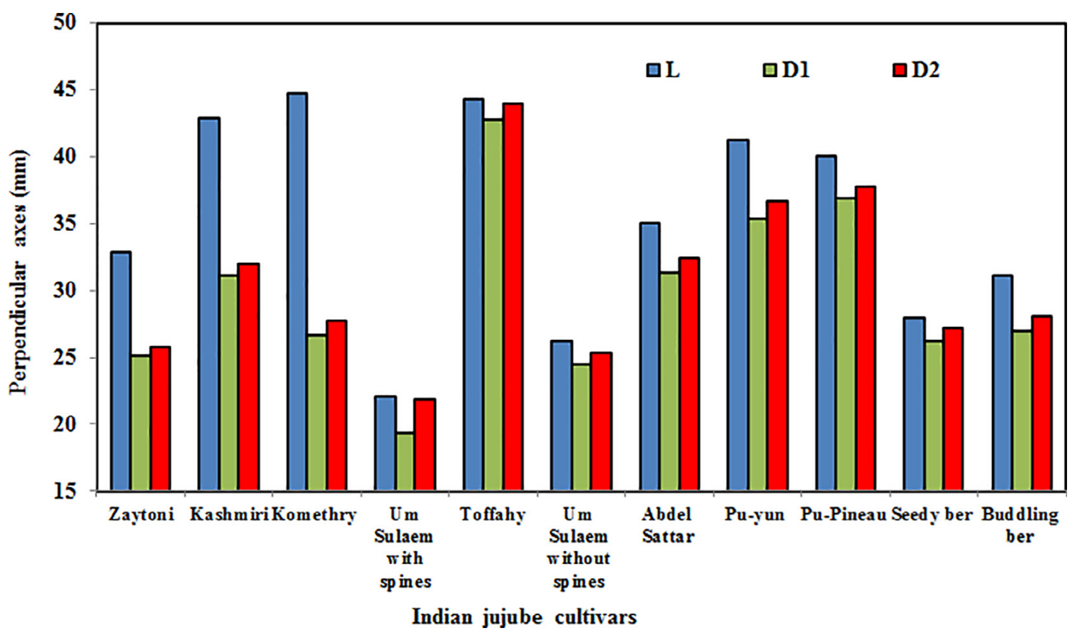

Fig. 4. Means values of three perpendicular axes (L, D1, and D2) of Indian jujube fruits of 11 different cultivars.

Table 1
Maximum, minimum, mean and coefficient of variation of arithmetic mean diameter, sphericity, and surface area for 11 Indian jujube fruits cultivars.

Statistical criteria	Arithmetic mean diameter (mm)	Surface area (mm^2)	Sphericity (%)
Minimum	21.09	1391.29	71.74
Maximum	43.69	5990.09	98.66
Mean	31.92	3290.39	90.69
Standard deviation	6.61	1346.47	8.23
Coefficient of variation (%)	20.70	40.92	9.07

complex classification problems, just one feature descriptor is not enough to capture the classes' separability (Rocha et al., 2010).

In the present study, the optimal number of hidden neurons in ANN classifier was two. The number of correct classification patterns was 244 which gave overall classification accuracy of 98.39% (244/248), as shown in Table 2 and this may be due to high combination among classification features. The number of incorrect classification patterns was 4 which gave overall miss classification accuracy (4/248 = 1.61%) as shown in Table 2 in the training phase. Based on the obtained results, the Indian jujube cultivars could be identified based on their combination of investigated descriptors. The ANN classifier could be a very useful tool in inspection of Indian jujube fruits quality based on morphological

Table 2
Confusion matrix for 11 Indian jujube fruits cultivars during the training phase.

		Actual cultivars											Total
		V1	V10	V11	V2	V3	V4	V5	V6	V7	V8	V9	
Predicted cultivars	V1	25											25
	V10		26							1			27
	V11			24						1			25
	V2				19	1							20
	V3					17							17
	V4						23						23
	V5							22					22
	V6								27				27
	V7									16			16
	V8										23		23
	V9							1				22	23
Total		25	26	24	19	18	23	23	27	18	23	22	248
Sensitivity (%)		100	100	100	100	94.44	100	95.65	100	88.89	100	100	
Specificity (%)		100	99.55	99.55	99.56	100	100	100	100	100	100	99.56	

V1 = Zaytoni, V2 = Kashmiri, V3 = Komethry, V4 = Um-Sulaem with spines, V5 = Toffahy, V6 = Um-Sulaem without spines, V7 = Abdel-Sattar, V8 = Pu-yun, V9 = Pu-Pineau, V10 = seedy ber, V11 = buddling ber.

Table 3
Confusion matrix for 11 Indian jujube fruits cultivars during the testing phase.

		Actual cultivars											
		V1	V10	V11	V2	V3	V4	V5	V6	V7	V8	V9	Total
Predicted cultivars	V1	5				1							6
	V10		4										4
	V11			6									6
	V2				11	1							12
	V3					10							10
	V4						7						7
	V5							7					7
	V6								3				3
	V7									12			12
	V8										7		7
	V9											8	8
Total		5	4	6	11	12	7	7	3	12	7	8	82
Sensitivity (%)		100	100	100	100	83.33	100	100	100	100	100	100	
Specificity (%)		98.7	100	100	98.59	100	100	100	100	100	100	100	

V1 = Zaytoni, V2 = Kashmiri, V3 = Komethry, V4 = Um-Sulaem with spines, V5 = Toffahy, V6 = Um-Sulaem without spines, V7 = Abdel-Sattar, V8 = Pu-yun, V9 = Pu-Pineau, V10 = seedy ber, V11 = buddling ber.

descriptors and three color features. Explaining of Indian jujube fruit cultivars by a single model gained with ANN displays that the ANN suggests an important ease of use. It will permit to manufacture more easily, economically and simply the equipment to be established thanks to this classifier. It would be probable to create automation machines, using the ANN model established, for sorting Indian jujube fruits. The preliminary work presented in this paper could be further enhanced by real time Indian jujube fruits identification by using digital image processing technique to capture the required classification attributes.

The sensitivity for all Indian jujube cultivars are illustrated in Table 2 for the training data set. Sensitivity is usually expressed as a percentage, ranging from 0% (very bad classification) to 100% (perfect classification). The sensitivity values for the Indian jujube cultivars were 100% expect for cv. V3 (Komethry), it was 94.44%, for cv. V5 (Toffahy), it was 95.65%, and for cv. V7 (Abdel-Sattar), it was 88.89%.

The specificity for all Indian jujube cultivars are illustrated in Table 2 for the training data set. Specificity is usually expressed as a percentage, ranging from 0% (very bad classification) to 100% (perfect classification). The specificity values for the Indian jujube cultivars were 100%, expect for cv. V10 (seedy ber), it was 99.55%, for cv. V11 (buddling ber), it was 99.55%, for cv. V2 (Kashmiri), it was 99.56%, and for cv. V9 (Pu-Pineau), it was 99.56% (Table 2). Table 2 also shows the classification accuracies for the 11 Indian jujube fruit cultivars in the training (calibration) phase. Among 27 samples of cv. V10 (seedy ber), 26 samples were identified correctly and also among 25 samples of cv. V11 (buddling ber), 24 samples were identified correctly, in the training phase. Moreover, among 20 samples of cv. V2 (Kashmiri), 19 samples were identified correctly and also among 23 samples of cv. V9 (Pu-Pineau), 22 samples were identified correctly, in the training phase. An overall classification accuracy of 98.39% shows that the manually measured morphological and color features are valid for identifying the different Indian jujube fruit cultivars.

During the testing stage, the cultivar Zaytoni (V1) was incorrectly assigned to one wrong classes as Komethry cv. V3, and also the cultivar Kashmiri (V2) was incorrectly assigned to one wrong classes as Komethry cv. V3 as shown in the confusion matrix (Table 3). This misidentification of varieties indicates that other varietal characteristics may influence the pattern of the investigated features. An average identification accuracy of 97.56% (80/82) (Table 3) showed that the manually measured descriptors were useful for classifying the different Indian jujube fruits cultivars. The sensitivity values for all cultivars were 100%, except for cv. V3 (Komethry), it was 83.33% (Table 3). The specificity values for all cultivars were 100%, except for cultivar V1 (Zaytoni), which had a specificity value of 98.70% and for cultivar V2 (Kashmiri), which had a specificity value of 98.59%. An overall classification accuracy of 98.78% (81/82) during testing phase also indicates that the manually measured morphological and color features are effective for identifying the different Indian jujube fruit cultivars.

4. Discussion

Cultivar identification is an indispensable tool for assuring fruit quality (Chen et al., 2010). Indian jujube fruits are different shapes and range in size, from the size of a cherry to the size of a plum, and the fruit of some cultivars are larger than a chicken's egg. Because of the relationship between genetic diversity and Indian jujube cultivars (Obeed et al., 2008), morphological parameters can be used to distinguish between them. Furthermore, it is impossible to successfully identify fruit without information on morphological descriptors and color features. However, until now, no ANN models have been developed for the identification of Indian jujube fruits.

We developed a simple, easy, and reliable ANN model to distinguish between 11 Indian jujube cultivars using a combination of morphological features and L*, a*, and b* color values. As the approach used was simple, the developed method can easily be used for future Indian jujube identification and grading studies and research aiming to develop more accurate and efficient automated methods. In previous studies, Cardenas-Perez et al. (2017) and Itle and Kabelka (2009) explained changes in the parameters L*, a*, and b*, and they stated that they are associated with increases in carotenoid intensities and a loss of chlorophyll in the pericarp. In addition, Wang et al. (2013) utilized the L*, a*, and b* color space to recognize mature Lingwu long jujubes, and the accuracy reached 92.6% through testing 50 natural images. The color parameters of *Ziziphus jujube Mill.* fruits of the GAL cultivar were 81.8, −5.6, and 19.6 for L*, a*, and b*, for the MSI cultivar, they were 79.4, −7.2, and 21.8, and they were 78.9, −6.2, and 22.1 for the PSI cultivar for fresh fruits, respectively (Wojdyło et al., 2019). Also, Zhang and Wu (2012); Mohana and Prabhakar (2014); Muhammad (2015); Bahri et al. (2017) and Çetin et al. (2020) indicated that shape, color, and texture features are significant in fruit identification. Moreover, the identification success rate reached 98.3% when a combination of the length/maximum diameter of the equatorial section and the projected area/length ratios were employed to identify kiwifruit (Fu et al., 2016).

Artificial neural networks are applied to achieve many agricultural research objectives, including the prediction of crop yields, identification of fruits and crops, and prediction of leaf area. Therefore, for complex input–output dependences, ANN modeling is becoming a popular tool. Different researchers have shown that using ANN for identification purposes in fruit, seeds, and crops often gives better results than traditional discrimination analysis (Golpour et al., 2014; Azizi, et al., 2016; Khazaei et al., 2016). The ability of ANN techniques depends on modeling complexity and nonlinearity, which is overlooked by tradition discrimination analysis and is possible due to the architecture of an ANN, which allows highly correlated inputs to be used. Moreover, ANN classifies, trained with different input features, are a promising alternative for real-time estimation of fruit ripeness (Ibba et al.,2021) and fruit identification (Anchan and Shabari, 2016; Figueredo-Ávila and Ballesteros-Ricaurte, 2016; Kurtulmuş et al. 2016; Hambali et al.,2017) directly, which could be a potential application technique for improving of fruits quality. Although we developed a suitable method for the nondestructive identification of Indian jujube cultivars, our system could be improved to recognize Indian jujube fruits using images, which can be captured automatically and without the need for any physical measurements. Moreover, the proposed classifier can be simply fixed into the processing chain of a fruit grading station after capturing the characteristics of fruits using computer vision and digital image processing techniques.

5. Conclusions

Quality identification of Indian jujube cultivars has a significant role to play in preventing commercial adulteration of this valuable product. In this research, a new approach based on artificial neural network technique for identifying eleven Indian jujube cultivars, which were grown in Saudi Arabia, has been presented, indicating its practical possibility through general series of experiments. The developed artificial neural network classifier was trained to identify Indian jujube cultivars using fruit morphological features like arithmetic mean diameter, the sphericity percent, and the surface area and color descriptors of L*, a*, and b*. The results indicate that the overall correct identification rate was 97.56% during the testing phase. The proposed method can be extended to real-time Indian jujube cultivar identification by capturing the characteristics of fruits using digital images, which had not previously been prominent in the literature.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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