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## ARTIFICIAL NEURAL NETWORK-BASED METHOD TO IDENTIFY FIVE VARIETIES OF EGYPTIAN FABA BEAN ACCORDING TO SEED MORPHOLOGICAL FEATURES

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### KEYWORDS

Faba bean, quality, classification, artificial neural network, features.

### ABSTRACT

One of the new crop varieties that have been adopted for high yield is the Egyptian faba bean. However, poor-quality faba bean has reduced economic value. Quality evaluation is thus important and can be performed using computational intelligence. We developed a robust method based on morphological features and artificial neural network for quality grading and classification of Egyptian faba-bean seeds, covering five varieties: Giza3, Giza461, Misr1, Nobarya1, and Sakha1. Fifteen seed morphological features were then calculated, and artificial neural networks classified faba beans into different varieties. The results indicated an overall classification accuracy of 77.5% was achieved in training phase and it was 100% when testing dataset was used. The preliminary work presented in this paper could be further enhanced by real time faba beans identification by capturing seed morphological features through the help of digital images.

### INTRODUCTION

*Vicia faba* L. is a well-known crop, particularly in Eurasia and North Africa. In the countries where it is grown, it has received many names according to its size and use (e.g., vegetable, food legume, feed legume) (Torres et al., 2012). The average crop yields in farmers' fields have been low, ranging from 3.78 tons per hectare in old lands to 3.60 tons per hectare in new lands and 3.2 tons per hectare in Upper Egypt (ICARDA, 2019). It is quite an important legume for closing bridge the protein deficit (25–35%), because it has a higher protein content than other legumes and is similar to animal protein (Sozen & Karadavut, 2016).

The faba bean can be affected by environmental conditions (Belal et al., 2018). Thus, agronomists should adopt new cultivars for high yield. On the other hand, Egyptian agronomists have adapted faba bean cultivars to suit local environmental conditions. These cultivars usually grow within one season harvested. Moreover, they may be combined via commercial adulteration to gain the benefits of one or more cultivars.

The poor quality of a faba bean reduces its economic value because it increases the energy requirements for cooking (Alban et al., 2012). Therefore, it

is preferable to provide an efficient faster and effortless objective evaluation method to classify faba-bean varieties, in case they are adulterated combined. Besides, faba-bean seed size is an important factor during handling, mechanical planting, and cooking. Based on seed size, two subspecies of *Vicia faba* (*paucijuga* and *faba*) have been recognized (Bond et al., 1985). Subspecies *faba* was further subdivided into var. *minor* (small, rounded seeds; 1 cm long), var. *equine* (medium-sized seeds; 1.5 cm), and var. *major* (large, broad, flat seeds; 2.5 cm). The faba-bean cultivars showed significant differences in all morphological features (Najafabadi & Farahani, 2012). These features may be grouped into area, perimeter, major- and minor-axis lengths, eccentricity, convex area, extent, compactness, aspect ratio, Feret diameter, roundness, and elongation.

Quality evaluation is one of the key factors that have a major impact on the final prices of agricultural products. Agricultural classification systems enable farmers to predict or identify agriculture properties such as seed, leaf, growth, and diseases of plants (Singh et al., 2016). The grading of seeds is achieved for industrialization or commercialization purposes, via scientific research for the improvement of the species.

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Seed classification is a process in which seeds of different varieties are categorized into different classes based on their morphological features.

Many researchers have done much work and achieved some significant results in the area of seed classification. Most feature extraction and classification techniques have been based on seed size, shape, color, and texture features (Xinshao & Cheng, 2015; Chitra et al., 2016; Tańska et al., 2018). The use of morphology, color and texture patterns extracted from images using the digital imaging processing techniques are effective for grain classification (Ribeiro, 2016). Moreover, morphological characteristics are easiest to obtain from the image (Kubik-Komar et al., 2018). Seed morphological features have been used to identify 67 Italian bean accessions belonging to 58 Italian landraces (Bianco et al., 2015).

Artificial neural network (ANN) classifiers can be trained with sample data concerning inputs and corresponding outputs only. These classifiers have shown promise in solving certain problems in agriculture, especially seed identification. The applicability of ANN is associated with situations where input and output information are interconnected by a nonlinear relationship of dependent and independent variables. Thus, ANN can be used for the development of techniques for solving complex problems (Abreu et al., 2020). In this sense, seed classification through ANN classifiers is a critical methodology for grading process. ANNs classify different answers that quantify grading quality in the same network. Thus, there exist several studies that implement ANNs applied to classify seeds (Anchan & Shabari, 2016; Kurtuluş et al., 2016).

Therefore, the objective of this study was to train and validate an ANN classifier for identifying five Egyptian faba-bean varieties using morphological features. Whether this technique will assist in identifying varieties which can then be implemented in processing of seeds through sorting machine if considered. Designing the structure of the ANN classifier and training and testing it were all done using the software NeuroShell Classifier (release 3).

## MATERIAL AND METHODS

### Faba-bean samples

The faba-bean varieties used in this study were freshly harvested from a field located at the Zarzoora Experimental Station, El Beheira Governorate, Egypt. The investigated varieties were Giza3, Giza461, Misr1, Nobarya1, and Sakha1. The harvested seeds were cleaned manually to remove all foreign materials and broken seeds. The initial moisture content of the seeds was determined via the oven method (ASAE, 1998). The average moisture content of the seeds was found to be in the range of 5.2 to 6.3% (wet base).

### Feature extraction

The three axial dimensions of the seeds were measured using a digital caliper to an accuracy of 0.01 mm. These measurements were carried out at the Tractors and Farm Machinery Testing and Research Station, Alexandria Governorate, Egypt. The length (L) and width (W) of a faba-bean seed were measured as depicted in

Figure (1). On the other hand, the thickness (T) of the seed was defined as the measured distance between the two seed faces. Fifty seeds for each sample were utilized.

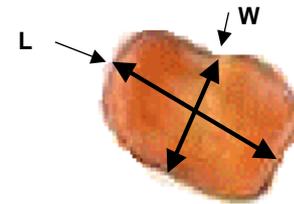


FIGURE 1. Length (L) and width (W) of faba-bean seed.

The geometric mean of the seed diameter ( $D_g$ , mm) was calculated using the following formula (Mohsenin, 1986):

$$D_g = (L \times W \times T)^{1/3} \quad (1)$$

The arithmetic mean of the seed diameter ( $D_a$ , mm) was calculated using the following formula (Sunmonu et al., 2015):

$$D_a = \frac{(L+W+T)}{3} \quad (2)$$

The flat surface area ( $A_f$ , mm<sup>2</sup>) was calculated using the following formula (El-Raie et al., 1996):

$$A_f = \frac{\pi}{4} \times L \times W \quad (3)$$

The thickness surface area ( $A_t$ , mm<sup>2</sup>) was calculated using the following formula (El-Raie et al., 1996):

$$A_t = \frac{\pi}{4} \times W \times T \quad (4)$$

The surrounded surface area ( $A_s$ , mm<sup>2</sup>) was calculated using the following formula (El-Raie et al., 1996):

$$A_s = \frac{\pi}{2} \times (L + D_g) \times D_g \quad (5)$$

The seed volume ( $V$ , mm<sup>3</sup>) was calculated using the following formula (Deshpande et al., 1993):

$$V = \frac{\pi}{6} \times D_g^3 \quad (6)$$

The sphericity percent ( $\phi$ , %) of the seed was calculated using the following formula (Mohsenin, 1986):

$$\phi = \frac{(L \times W \times T)^{1/3}}{L} \times 100 \quad (7)$$

Three aspect ratios ( $A_1$ ,  $A_2$ , and  $A_3$ , dimensionless) based on the axial dimensions were developed for use in this research (Jahanbakhshi et al., 2018), as follows:

$$A_1 = \frac{L}{W} \quad (8)$$

$$A_2 = \frac{L}{T} \quad (9)$$

$$A_3 = \frac{W}{T} \quad (10)$$

The shape index (SI, dimensionless) was calculated as follows (Abd Alla et al., 1995):

$$SI = \frac{L}{\sqrt{W \times T}} \quad (11)$$

The coefficient of contact surface (CC, %) was calculated as follows (Abd Alla et al., 1995):

$$CC = \frac{(Af - At)}{Af} \times 100 \quad (12)$$

The elongation of the seed (E, dimensionless) is a measurement of how long and narrow the seed was. It was calculated as follows (Tian et al., 2000):

$$E = \frac{(L - T)}{(L + T)} \quad (13)$$

The logarithm of the ratio of length to width (LHW, dimensionless) gives a symmetric measure of the aspect ratio of the object. It was calculated as follows (Tian et al., 2000):

$$LWH = \log_{10} \left( \frac{L}{W} \right) \quad (14)$$

The surface area (Sa, mm<sup>2</sup>) was calculated as follows (Deshpande et al., 1993):

$$Sa = \pi \times Dg^2 \quad (15)$$

### Artificial neural network classifier

ANN is a data processing system based on the structure of the biological neural system. Prediction via ANN is not like modeling and simulation, but by learning from data generated experimentally or using validated models. ANNs differ from conventional programs in their ability to learn about the system to be modeled without prior knowledge of the relationship of the process variables (Li et al., 2009). It is one of the data mining methods that are developed in various contexts such as function approximation, modeling, and classification of agricultural products (Marini et al., 2004). The structure of ANN consists of three or more layers, including the input layer, hidden layer(s), and output layer. In each layer, the number of neurons respectively depends on the number of inputs, complexity of classification task, and number of output classes (Teimouri et al., 2016). In the present study, the data for the morphological features of faba-bean varieties were converted into a comma-separated values (CSV) format file using Excel spreadsheet. NeuroShell Classifier (release 3), which was developed by Ward System Group, Inc. (2007), processed the formatted file for classification purposes. The best-hidden neurons were

selected based on the highest overall accuracy for the training dataset. All morphological features were used as inputs for the developed ANN classifier. The data were randomized, and 240 patterns were randomly selected for training the classifier, while the remaining 22 patterns were used for testing.

### Performance evaluation of the ANN

The NeuroShell software classifier allows the quick building of a powerful classification model. Its performance criteria for evaluating the classifier are: true-positive ratio, false-positive ratio, true-negative ratio, and false-negative ratio. The classifier outcome was compared with that of a known visual class, and the performance of the classifier was judged based on its accuracy of prediction.

## RESULTS AND DISCUSSION

### Description of the morphological features

The average values of the five parameters describing the axial dimensions of the Egyptian faba bean for the investigated cultivars are shown in Figure (2). It is clear from the figure that the Nobarya1 variety had the largest length and width. The length, width, and thickness values for the Nobarya1 variety were 18.87, 14.23, and 6.48 mm, respectively. In the study by Abd-Elrahman & Abd El-Khalek (2013), they found that Sakha1 and Nobarya1 were the tallest Egyptian faba bean cultivars when compared with Giza2, Giza40, and Giza843 cultivars. Additionally, the Misr1 and Giza3 varieties had the largest thicknesses compared with those of the other varieties. As shown in Figure (2), the length, width, and thickness values affected the arithmetic and geometric means of the seed diameter. Therefore, when classification analysis based on only the seed length as a criterion to identify varieties is conducted, low accuracy will occur because of overlapping and convergence in seed length, as shown in Figure (2).

Figure (3) illustrates the averages of the different area features of the Egyptian faba-bean varieties. These four areas included the flat surface area, thickness surface area, surrounded surface area, and surface area. For all varieties, the surrounded surface area clearly had the largest value compared with the other areas, as shown in Figure (3). The surrounded surface area values for Giza3, Giza461, Misr1, Nobarya1, and Sakha1 were 488.2, 466.45, 454.16, 583.33, and 474.01 mm<sup>2</sup>, respectively. In the study by El-Raie et al. (2004), they found that the average of surrounded surface area was 459.15 mm<sup>2</sup> for Misr1 cultivar.

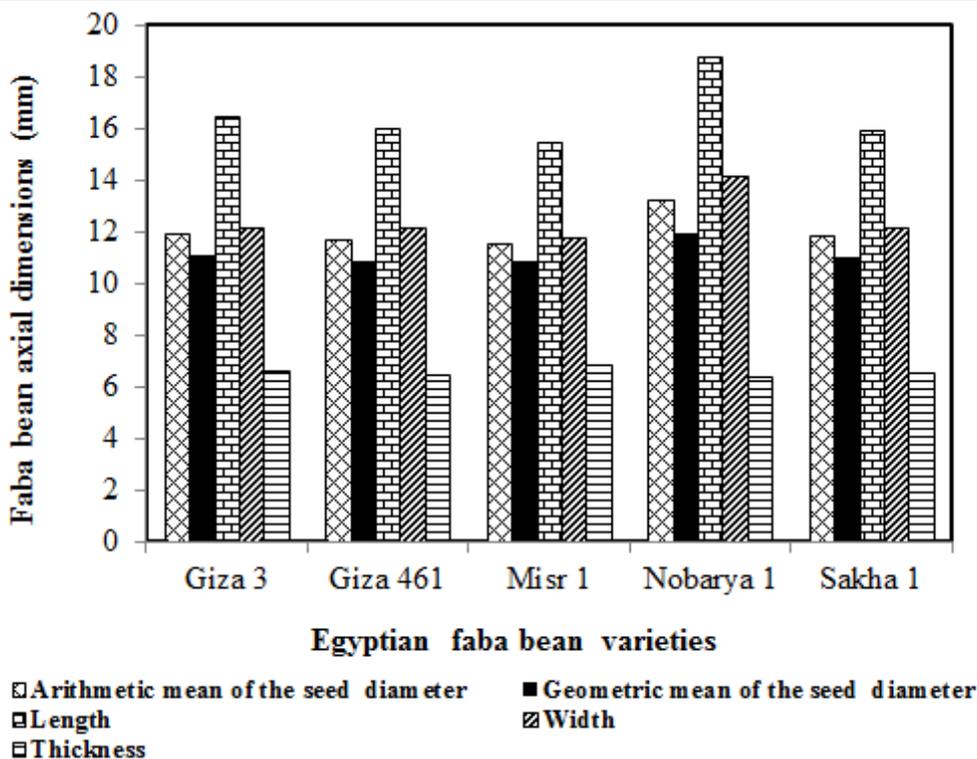


FIGURE 2. Averages of the axial dimensions of the Egyptian faba-bean varieties.

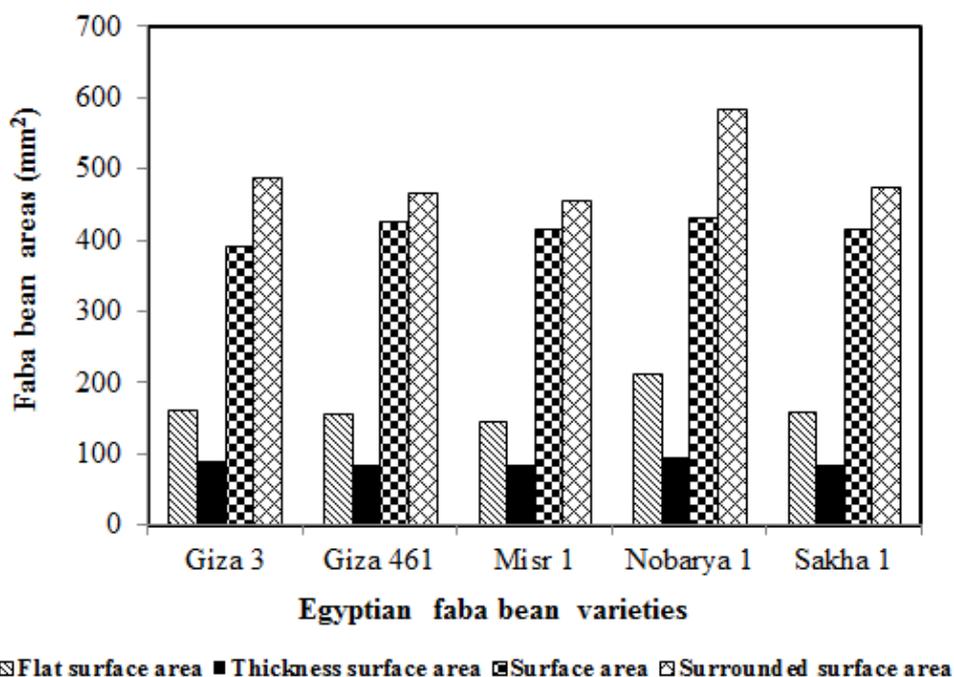


FIGURE 3. Averages of the areas of the Egyptian faba-bean varieties.

Figure (4) illustrates the averages of the dimension percentages of the Egyptian faba-bean varieties. These dimension percentages were the sphericity percent and coefficient of contact surface of the seeds. The values of sphericity percent of the seeds were clearly larger than the coefficient of contact surface of the seeds. The values of

sphericity percent of the seeds were 66.86, 67.97, 69.90, 63.95, and 68.01% for Giza3, Giza461, Misr1, Nobarya1, and Sakha1, respectively, as shown in Figure (4). In the study by El-Raie et al. (2004), they found that the average of sphericity was 68.76% for Misr1 cultivar.

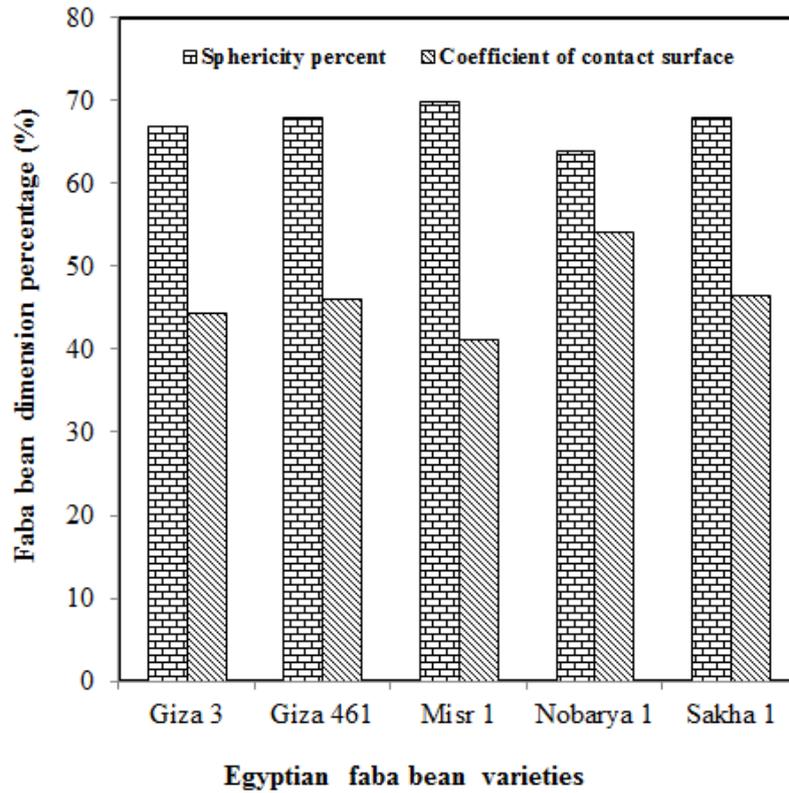


FIGURE 4. Averages of the dimension percentages of the Egyptian faba-bean varieties.

Figure (5) illustrates the averages of the seed volumes of the Egyptian faba-bean varieties, which were recorded to be 729.66, 693.73, 680.82, 912.18, and 710.18 mm<sup>3</sup> for Giza3, Giza461, Misr1, Nobarya1, and Sakha1, respectively. In the study by El-Raie et al. (2004), they found that the average of the seed volume was 605.34 mm<sup>3</sup> for Misr1 cultivar.

Figure (6) illustrates the averages of the dimension ratios of the Egyptian faba-bean varieties. These six ratios included the shape index, ratio of length to width, ratio of

length to thickness, ratio of width to thickness, elongation, and logarithm of the ratio of length to width of the seed. The elongation and logarithm of the ratio of length to width values were clearly less than one. Furthermore, the ratio of length to thickness values was above two. Meanwhile, the shape index and ratio of width to thickness values were nearly in the same range, as depicted in Figure (6). The values of ratio of length to width were 1.37, 1.31, 1.31, 1.33, and 1.31 for Giza3, Giza461, Misr1, Nobarya1, and Sakha1, respectively.

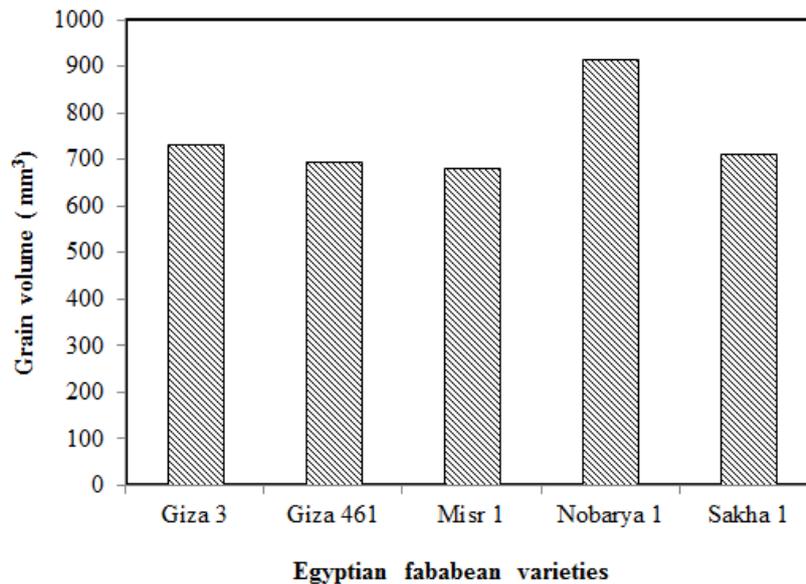


FIGURE 5. Averages of the seed volumes of the Egyptian faba-bean varieties.

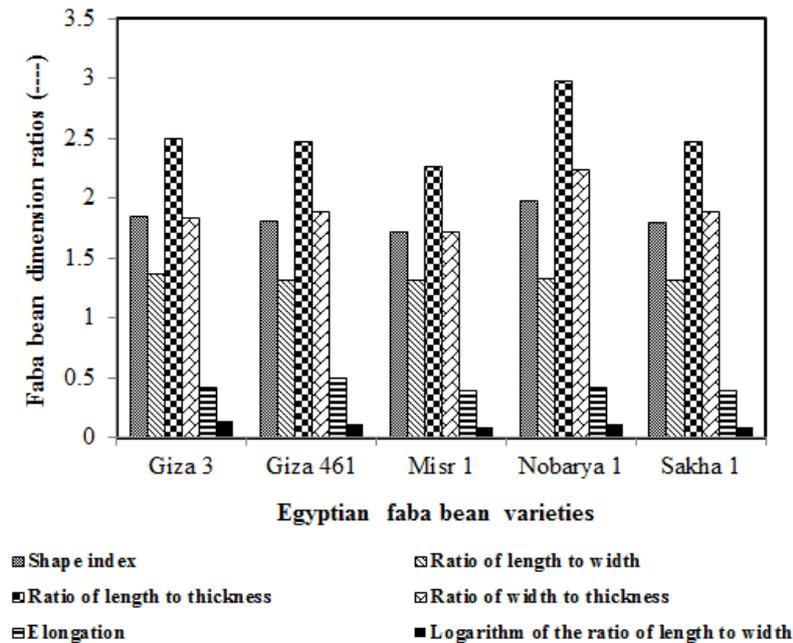


FIGURE 6. Averages of the dimension ratios of the Egyptian faba-bean varieties.

### Performance of the developed ANN classifier

The physical parameters of agricultural materials are important to have an accurate estimate of physical features and other characteristics which can be considered as engineering parameters for that product (Taner et al., 2018). These parameters such as the length, width, thickness, geometric mean diameter, sphericity, volume, volume, aspect ratio, and surface area are used in the grading, handling, sieving, storage, drying, processing and designing equipment. Fifteen seed morphological features were determined for Egyptian faba-bean varieties. It was determined that these properties found to be different could be used to classify faba-bean varieties. In the study, an ANN model was developed for classification. The structure of the model was set up to consist of 15 input and the number of hidden neurons trained was 98, and the optimal number of hidden neurons was 96. The output layer had five Egyptian faba-bean varieties.

In the present study, the number of correct classification patterns was 186 which gave overall classification accuracy of 77.5% (86/240), and the number of incorrect classification patterns was 54 which gave overall miss classification accuracy (54/240= 22.5%) as shown in Table (1) in the training phase and this may be due to high variations in the morphological features. Based on the obtained results, the Egyptian faba-bean varieties could be classified based on their morphological features. The ANN classifier could be a very useful tool in inspection of faba-bean seed quality based on seed morphology. Moreover, the ANN classifier could be used for the improvement of faba-bean species during scientific research. In this research, some varieties were incorrectly assigned to one or two wrong classes. This misidentification of varieties indicates that other varietal characteristics may influence the pattern of the investigated features. Explaining five faba-bean varieties by a single model obtained with ANN shows that the ANN offers a significant ease of use. It will enable to manufacture more easily, simply and economically the equipment to be developed thanks to this model. It would be possible to

construct automation systems, using the ANN model developed, for grading faba-bean varieties to use in grading stations. The preliminary work presented in this paper could be further enhanced by real time faba beans identification by capturing seed morphological or other features through the help of digital images.

The true-positive ratios (also called sensitivity) for all varieties are illustrated in Table (1) 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 varieties Giza3, Giza461, Misr1, Nobarya1, and Sakha1 were 0.8039, 0.5306, 0.8444, 0.9020, and 0.7955, respectively. The true-negative ratios (also called specificity) for all varieties are illustrated in Table (1) 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 varieties Giza3, Giza461, Misr1, Nobarya1, and Sakha1 were 0.9259, 0.9634, 0.9282, 0.9630, and 0.9388, respectively.

Table (1) also shows the classification accuracies for the five faba-been varieties in the training (calibration) phase. Among 55 samples of variety Giza3, 41 were classified correctly in the training phase. Similarly, 26 out of 33 Giza461 samples, 38 out of 52 Misr1 samples, 46 out of 52 Nobarya1 samples, and 35 out of 47 Sakha1 samples were classified correctly in the training phase. An average classification accuracy of 77.5% shows that the manually measured morphological features are applicable for classifying the different faba-bean varieties.

The developed ANN classifier model still needs to be tested with unseen data. Hence, the testing sample classification rate represents the model performance for unseen data. The best overall classification accuracy was 100% for the testing data set. The agreement matrix, true-positive, false positive, true-negative, and false-negative ratios, and sensitivity and specificity values for the testing

data are displayed in Table (2). As indicated in Table (2), the summary result of the ANN classifier using all features together showed that from a total of 22 test examples, 22

were correctly classified. These test instances included 3 for Giza1, 3 for Giza461, 6 for Misr1, 4 for Nobarya1, and 6 for Sakha1.

TABLE 1. Confusion matrix for Egyptian faba-bean varieties using training dataset.

		Actual cultivars					Total	Positive predictive value
		Giza1	Giza461	Misr1	Nobarya1	Sakha1		
Predicted cultivars	Giza1	41	5	4	2	3	55	74.55%
	Giza461	3	26	2	0	2	33	78.79%
	Misr1	3	7	38	1	3	52	73.08%
	Nobarya1	1	5	0	46	1	53	86.79%
	Sakha1	3	6	1	2	35	47	74.47%
Total		51	49	45	51	44	240	
True positive ratio		0.8039	0.5306	0.8444	0.9020	0.7955		
False positive ratio		0.0741	0.0366	0.0718	0.037	0.0612		
True negative ratio		0.9259	0.9634	0.9282	0.963	0.9388		
False negative ratio		0.1961	0.4694	0.1556	0.0980	0.2045		

TABLE 2. Confusion matrix for Egyptian faba-bean varieties using testing dataset.

		Actual cultivars					Total	Positive predictive value
		Giza1	Giza461	Misr1	Nobarya1	Sakha1		
Predicted cultivars	Giza1	3	0	0	0	0	3	100%
	Giza461	0	3	0	0	0	3	100%
	Misr1	0	0	6	0	0	6	100%
	Nobarya1	0	0	0	4	0	4	100%
	Sakha1	0	0	0	0	6	6	100%
Total		3	3	6	4	6	22	
True positive ratio		1.0	1.0	1.0	1.0	1.0		
False positive ratio		0	0	0	0	0		
True negative ratio		1.0	1.0	1.0	1.0	1.0		
False negative ratio		0	0	0	0	0		

## CONCLUSIONS

Quality classification of faba-bean varieties has an important role in preventing commercial adulteration of this valuable product. In this research, the Egyptian faba bean was classified into five varieties, and trained to identify those using ANN classifier and seed morphological features. The results indicate that the overall correct classification was 100% using testing dataset. The confusion matrix and statistical parameters show that the use of seed morphological features and ANN classifier to identify Egyptian faba-bean products is very efficient and successful. The proposed method can be extended to real time faba beans identification by capturing seed morphological or other features through the help of digital images.

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