Comparison of different classification algorithms for certain weed seeds' species and wheat grains identification based on morphological parameters

E. M. Kamel[1], M. Wafy[2], H. M. Ibrahim[3] and I. A. Badr[4]

[1]Weed Research Central Laboratory, Agriculture Research Center, Giza, Egypt

[2]Faculty of Computer and Information, Helwan University, Cairo, Egypt

[3]Weed Research Central Laboratory, Agriculture Research Center, Giza, Egypt

[4]Mathematics Department, Faculty of Science, Helwan University, Cairo, Egypt

Abstract

The manual seeds identification takes a long time for practical applications. Therefore, automatic reliable plant seeds identification is of great technical and economic importance in agricultural industry. In this study, a system for automatic seed identification was developed based on optimal set of morphological features. The system uses digital images, which are processed to derive morphological features of the ten weed species seeds and wheat grains. The optimal morphological features are used for the discrimination of weed species seeds and wheat grains by using a classification step. Since the classification is a pivotal step for the seeds identification, four different classification algorithms namely K-Nearest Neighbours, Naïve Bayes, Quadratic Discriminant Analysis and Feed-Forward Backpropagation Neural Network classifiers are evaluated to select the effective one. Among the four tested classifiers, Quadratic Discriminant Analysis classifier reported the highest identification accuracy of 97.1% and the minimum running time of 0.49 second.

Keywords: *weed seeds; wheat grains; morphological features; identification; classification.*

1. Introduction

Plant weeds are identified as the presence of a plant species in wrong place and time. Interference of weed species with plant crops could cause up to 90% loss of yield production. Among the various applied methods for weed control, prevention of weed seeds from coexistence with desirable crops' grains or seeds is a reliable approach. In agriculture industry, the identification and elimination of weed seeds are among the most determined factors. For invasive weeds, the identification of seeds through state agriculture quarantines is the first step for subsequent actions for exportation or importation of such exotic species. Among different seeds identification methods based on certain morphological, textural and color features, visual mechanical approaches were successfully applied for both plant and weed species seed recognition and identification.

Brinkkemper et al [1] computed 23 features that describe the size and shape of seeds. Subsequently, they performed statistical analyses of the resulting dataset using quadratic discriminant analysis, correspondence analysis, and t-distributed stochastic neighbor embedding (t-SNE). The combination of analyses provided clues that successfully distinguished seven seeds varieties. Shantaiya and Ansaria [2] showed that morphological and color features can be used successfully with neural network to classify six rice varieties, the average classification accuracy was 84.8%. Chen et al [3] identify five China corn varieties with 90% accuracy. Furthermore, Discriminant Analysis and K-Nearest Neighbors built on morphological, color and texture features offer a different level of accuracy e.g. 99% for barely and wheat kernels classification, as repotted by Guevara-Hernandez and Gomez-Gil [4]. P. Zapotoczny [5] proposed a methodology that can perform a classification of 11 wheat varieties with an accuracy of 90–100% using geometric features and Meta Multi Class Classifier. While combination of two morphological features with five and six colour features resulted in a 100% accuracy of identification of rangeland seed species Anvarkhah et al [6]. Pandey et al [7] proposed the use of content base image retrieval technique (CBIR) for seed identification and the use of Euclidean distance and artificial neural network (ANN) for seed classification. 95% and 84.4 accuracies were obtained for ANN and Euclidean distance approaches respectively. The multi-layer Perceptron (MLP) and Neuro-Fuzzy neural networks were tested for classifying five corn seed varieties' giving accuracies of 94% and 96% respectively, Pazoki et al [8].

For weed seeds mixed with wheat grains, Wafy et al [9] applied Scale-Invariant Feature Transform (SIFT) algorithm with an accuracy of 90.5%, 89.2% and 95.3% for the three studied weed species. Using digital image analysis for rice cultivars, a new approach based on color features extraction of bulk grain images and neural networks gave a classification accuracy of 98.8, 100 and 100% for bulk paddy, brown and white rice respectively, Golpour et al [10]. Finally, Wafy and Kamel [11] developed an algorithm based on optimal morphological features of seeds to identify four weed species and wheat grains in mixed samples. The more effective five features used as input for three different classification techniques, K-Nearest Neighbors classifier, Naïve Bayes classifier, and Linear Discriminant Analysis classifier and the identification mean accuracies were 95.4%; 97.8% and 98.7% using the three classifiers respectively. Egypt is considered as one of the world wide wheat importers thus, cross contamination with weed seeds is prevalent. Accordingly, the present work aims to determine best characteristics morphological features based on digital image analysis to develop an algorithm capable of identifying several weed species seeds

mixed with wheat grains in a system of automatic seed identification.
This paper is organized as follows. Section 2 briefly describes the image acquisition, segmentation, morphological feature description, feature selection, and identification processes. Section 3 introduces the results and discusses the efficiency of the classifiers based only on the morphological seed characteristics. Finally, Section 4 summarizes the work and draws some conclusions.

2. Materials and method

2.1 Seed and grain source:

Ten weed species seeds and one wheat species grains were obtained from several research stations that affiliated to the Agriculture Research Center, Ministry of Agriculture and Land Reclamation, Egypt, namely *Phalaris minor* Retz., *Coronopus didymus* (L) Sm., 'Sakha 94' Wheat, *Ammi majus, Cichorium endivia, Malva parviflora, Avena sterilis, Bromus tectorum, Melilotus indica, Lolium multiflorum,* and *Rumex dentatus* which gave a code number from 1 to 11, respectively in Matlab software.

2.2. Image Acquisition

The images were captured in RGB colour representation with resolution of 300 dpi with low cost image acquisition system that consists of (HP ScanJet 3770) scanner and Pentium IV computer unit. Untouched seeds were randomly placed on the scanner plate and a black photo paper was placed over them to provide a black background. As training for our system, eleven selected captured photos, with fifty seeds of one species each were used. The set of tested images consisted of 762 images contains 14708 seeds of different types (1050 seeds of '1', 756 seeds of '2', 3473 grains of '3', 1074 seeds of '4', 847 seeds of '5', 1214 seeds of '6', 1265 seeds of '7', 1190 seeds of '8', 1691 seeds of '9', 1108 seeds of '10' and 1040 seeds of '11').

As shown in (Fig 1), three 3 types of images were captured expressing single seed, multiple seeds and mixture of weed species seeds and wheat grains.

2.3 Segmentation

Segmentation is the removal of non-essential information, such as the background, from images. According to the Equation 1:

(a) First kind of images **(b) Second kind of images** **(c) Third kind of images**

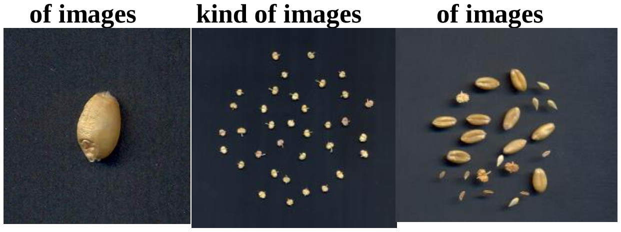

Figure 1. The database images.

$$I = S \cup Bg \quad [1]$$

Where:

- I is captured image
- S is seed (wheat grains and weed seeds).
- Bg is background.
- U is the union between two sets.

Non essential information was removed using segmentation. Images of weed seeds contain higher intensities in the Green (G) and Red (R) bands, where employed to differentiate between seeds and the background. For all pixels in the original image, the absolute values of red minus Blue (B) and those of green minus blue were calculated. These values provided measurements for the pixels' distance to the greyscale line. If both of these distance values are greater than x, the pixel is classified as S (Equation 2); if neither of the values or only one value is greater than x, the pixel is classified as Bg, where x is the threshold value. For the images of seeds that were considered in this study, x = 10, which has been proven to generate high-quality results (Fig. 1).

$$S \in \{|R\text{-}B|>x \,\&\, |G\text{-}B|>x\} \quad [2]$$

(a) **Original image** **(b) Binary image**

Figure 2. The original image and the corresponding binary image resulted from segmentation step.

2.4. Morphological features

An algorithm was developed using the Matlab programming language. It extracts features of weed seeds from images using the following morphological operations.

1- Area: The actual number of pixels in the seed.
2- Convex Area: The number of pixels inside a **convex hull** (the smallest convex polygon that can contain the seed).
3- Convex Ratio: was calculated as the ratio between difference between convex area and seed area, to the convex area.

$$\textbf{Convex ratio} = \frac{\text{Convex area - Seed area}}{\text{Convex area}} \quad [3]$$

4- Extent: The ratio between seed area to the area of a bounding box (the smallest rectangle containing the seed) and computed as:

$$\textbf{Extent} = \frac{\text{Seed area}}{\text{Bounding box area}} \quad [4]$$

5- Filled Area: The area of the seed after filling the holes inside it.

6- Perimeter: The perimeter is computed by calculating the distance between each adjoining pair of pixels around the border of the seed.

7- Solidity: Solidity describes the extent to which the shape is convex or concave and computed as the ratio of the seed area to its convex area.

$$\textbf{Solidity} = \frac{\text{Seed area}}{\text{Convex area}} \quad [5]$$

8- Eccentricity: The eccentricity of the ellipse that has the same second area moment as the seed. Eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length.

9- Equivalent Diameter: The diameter of the circle whose area is the same as the seed area and computed as:

$$\text{Equivalent Diameter} = \frac{\sqrt{4\times \text{ Seed area}}}{\Pi} \quad [6]$$

10- Major Axis Length: The length (in pixels) of the major axis of the ellipse that has the same normalized second central moment as the seed.

11- Minor Axis Length: The length (in pixels) of the minor axis of the ellipse that has the same normalized second central moment as the seed.

12- Circularity: The circularity ratio represents how similar a seed's shape is to a circle and is given by:

$$\textbf{Circularity} = \pi \times \frac{\text{Seed area}}{(\text{Perimeter})^2} \quad [7]$$

13- Elongation: The ratio of the length of the minor axis to the length of the major axis.

$$\textbf{Elongation} = \frac{\text{Minor axis length}}{\text{Major axis length}} \quad [8]$$

14- Ellipse-Ratio: The ratio of the seed area and the area of the ellipse with major and minor axes that are equal to the major axis length to the minor axis length, respectively, and computed as:

$$\textbf{Ellipse - ratio} = \frac{\text{Seed area}}{\pi \times (\text{Major axis length}) \times (\text{Minor axis length})} \quad [9]$$

15- Circle-Ratio: The ratio of the seed area to the area of the minimum circle inside the seed and computed as:

$$\textbf{Circle - ratio} = \frac{\text{Seed area}}{\pi \times (\text{Minor axis length})^2} \quad [10]$$

16- Compactness

$$\textbf{Compactness} = \frac{(\text{Perimeter})^2}{\text{Seed area}} \quad [11]$$

17- Aspect Ratio: The ratio of the major axis length to the minor axis length.

$$\textbf{Aspect Ratio} = \frac{\text{Major axis length}}{\text{Minor axis length}} \quad [12]$$

$$\textbf{18- Round} = \frac{(\text{Perimeter})^2}{4 \times \pi \times \text{ Seed area}} \quad [13]$$

$$\textbf{19- Roundness or thinness ratio} = \frac{4 \times \pi \times \text{Seed area}}{(\text{Perimeter})^2} \quad [14]$$

$$\textbf{20- Shape factor1} = \frac{(\text{Major axis length})^2}{\text{Seed area}} \quad [15]$$

$$\textbf{21- Shape factor2} = \frac{\text{Seed area}}{(\text{Major axis length})^3} \quad [16]$$

$$\textbf{22- Shape factor3} = \frac{\text{Seed area}}{\left(\frac{\text{Major axis length}}{2}\right)^2} \times \pi \quad [17]$$

$$\textbf{23- Shape factor4} = \frac{\text{Seed area}}{\left(\frac{\text{Major axis length}}{2}\right)^2 \left(\frac{\text{Minor axis length}}{2}\right)^2} \times \pi \quad [18]$$

The number of features extracted from the weed seeds and wheat grains were found too high for fast computation and didn't contribute significantly in seed classification in addition several redundant feature were found to cause decline of classifier performance, therefore, Weighted Absolute Difference of Means (WADM) used to optimize the number of morphological features that contribute significantly in seed identification.

2.5. Feature Selection

The Weighted Absolute Difference of Means (WADM) was used to select the optimal feature from all extracted features, through estimation of the possibility of separating data into two classes according to their means (m) and standard deviations (σ).

The WADM is defined by the absolute difference of two different means (mi, mj) divided by the square root of the summation of the corresponding two variances (σi2, σj2) as shown in following equation:

$$\textbf{WADM} = \frac{(|mi- mj|)}{\sqrt{\sigma_i^2 + \sigma_j^2}} \qquad \mathbf{i, j = 1, 2, \ldots, 11, i \neq j} \quad [19]$$

where i, j are the seed number and 11 is the total number of seeds used in this work.

In this study mean mi and standard deviation σi2 for each feature were calculated from 50 training samples for every seed. Seeds were taken in pairs of two different seed types as Seed#1&Seed#2, Seed#1&Seed#3, . . ., Seed#10&Seed#11 and the WADM was computed for each combination of seeds. Features were tabulated column-wise and the feature which gave the maximum WADM value is chosen for classification. The feature that had a larger value for WADM is the best one for distinguishing between the pair of seeds.

Results obtained by the statistical analysis based on the WADM formula indicated that only 13 features could be used in the identification instead of 23.
For more reduction of the features trial and error method have been used to select a smaller set of features to improve the results. After these trials the number of feature reduced from 13 to 6 features which were Perimeter, Solidity, Equivalent Diameter, Elongation, shape factor 1, shape factor 4.

2.6. Identification

Four different classification techniques were used to identify the seeds, which were K-Nearest Neighbors "KNN", Naïve Bayes "NB", Quadratic Discriminant Analysis "QDA" and Artificial Neural Network "ANN". Due to space limitations, for detailed information, please refer to references [12], [13], [14] and [15].
Using KNN classifier with K values of 1,2,3,4, highest classification accuracy was found for K value of 3.
Two- layer network feed-forward backpropagation with one middle layer with 40 neurons Artificial Neural Network (ANN) was built by using the Matlab R2009a neural network toolbox. The ANN was trained until the sum square error of 0.01 being reached as the final learning convergence criterion. The input feature vector matrix had a size 6 by 50 elements, so the network had 6 input layer nodes. The hidden layer consisted of 12 nodes. The output layer had eleven nodes, which corresponded to the eleven seed type classes. The results reported classification percentages in this study were averages of 10 trials of neural network.

3. Results

An optimal set of six morphological features was employed to identify ten weed seeds and one wheat species grains in three types of database images. These features were supplied to four different classifiers ("KNN", "NB", "QDA" and "ANN") for proper identification of examined seeds and grains.

3.1. Identification accuracy percentages of single seed or grain using the four applied methods:

The results (Table 1) indicate that morphological features can be used to successfully identify weed seeds and wheat grains in images contained single seed. The averages of accuracy for the identification of all weed seeds and wheat grains were found to be 95.6%, 95.8%, 95.5 and 94.3% for KNN, NB, QDA and ANN, respectively.

Table 1: Identification accuracies for images of single weed species seed or grain using the four applied methods.

weed species code	Total	Identification accuracy for different classifiers			
		KNN	**NB**	**QDA**	**ANN**
1	50	98	100	96	93.8
2	50	100	100	100	98
3	50	100	100	100	99.8
4	50	96	96	96	93.4
5	50	88	88	88	89.8
6	50	90	90	90	85.2
7	50	100	100	100	100
8	50	94	94	94	88.6
9	50	98	98	98	98.2
10	50	98	98	98	99.4
11	50	90	90	90	91.4
TOTAL	550	95.6	95.8	95.5	94.3

Accordingly, NB classifier was considered as the highest identification accuracy provider compared to other used methods.

3.2. Identification accuracy percentages of multiple seeds or grains of the same species using the four methods:

Table 2 shows that, the averages of accuracy for the identification of all weed seeds and wheat grains were found to be 89.2%, 97%, 97.1 and 97.3% for KNN, NB, QDA and ANN, respectively.
These results indicate that morphological features can also be used successfully to identify weed seeds and wheat grains in images contained groups of seeds of the same species but contrary to NB classifier for single seed identification for groups of seeds, the ANN classifier provided the highest identification accuracy of 97.3%.

Table 2: Identification accuracies for images of multiple seeds or grains of the same species using the four applied methods.

weed species code	Total	Identification accuracy for different classifiers			
		KNN	**NB**	**QDA**	**ANN**
1	519	97.3	97.9	96.3	95.8
2	306	95.1	99	98.7	97.1
3	1345	99.6	99.8	100	100
4	617	88.7	97.2	94.2	96.7
5	412	73.3	85.2	92.2	91.4
6	839	76.5	96.1	96.7	96.1
7	805	99.5	99.9	99.6	98.7
8	780	92.8	96	95.5	96.1
9	1335	88.9	97.5	97.2	98.5
10	603	95.4	98.8	99.2	99.6
11	699	66	93.1	94.6	94.9
TOTAL	8260	89.2	97	97.1	97.3

3.3. Identification accuracy of mixed weed species seeds and wheat grains

Based on obtained data for mixed weed seeds and wheat grains the QDA method gave the highest accuracy. Among the four applied methods where 93%, 96.9%, 97.1% and 95.8% were obtained for KNN, NB, QDA and ANN, respectively. (Table 3)

Table 3: Identification accuracies for images of mixed samples of different weed species seeds and wheat grains.

weed species code	Total	Identification accuracy for different classifiers			
		KNN	NB	QDA	ANN
1	481	98.3	98.8	98.8	94.7
2	400	95.3	98	98.3	95.7
3	2078	99	99.4	100	98.6
4	407	72.5	91.4	90.2	88.6
5	385	79.5	83.6	89.9	88.4
6	325	83.1	94.2	92.9	93
7	410	100	100	100	99.8
8	360	93.9	97.2	95	96.7
9	306	88.2	95.1	94.8	96.2
10	455	93.8	98	98.7	97
11	291	89	98.3	95.2	91.6
TOTAL	5898	93	96.9	97.1	95.8

As main goal of proposed investigation is to establish a powerful tool for identification of wheat grains contaminants weed seeds, the potentiality of four classifiers were investigated using the three cases (types of image). As shown in Table 4, the QDA classifier proves its highest sensibility (97.1%) compared to the three others for all wheat grains with weed seeds with least required time of 0.49 second.

Table 4: Identification accuracies for the three images' types in the database.

weed species code	Total	Identification accuracy for different classifiers			
		KNN	NB	QDA	ANN
1	1050	97.8	98.4	97.4	95.2
2	756	95.5	98.5	98.5	96.4
3	3473	99.3	99.5	100	99.2
4	1074	82.9	95	92.7	93.4
5	847	77	84.7	90.9	89.9
6	1214	78.8	95.3	95.4	94.8
7	1265	99.7	99.9	99.8	99.1
8	1190	93.2	96.3	95.3	95.9
9	1691	89.1	97.1	96.7	98.1
10	1108	94.9	98.5	98.9	98.5
11	1040	73.6	94.4	94.5	93.8
TOTAL	14708	91.0	96.9	97.1	96.6
Time for all steps in proposed method (in second)		4.8	4.8	0.49	4.99

The current results should be considered as a further step compared to Wafy and Kamel [11] where only five seed species were identified within wheat grains, Brinkkemper *et al* [1] used Discriminant Analysis, Correspondence Analysis and t-Distributed Stochastic Neighbor Embedding (t-SNE) methods to identify seven seed species using 23 morphological features therefore, the current method (QDA) that based on only 6 morphological features and gave accuracy of 97.1% in less than one second, could be improved for identification of other grains and seeds that accompanying wheat. (Table 5)

Table 5: Comparison between the methods used morphological features in the review and proposed methods.

Research	Seed & grain species	No. of seed species	Number of features	Methods	Average accuracy %
[1]	Myosotis	7	23	- Discriminant Analysis, - Correspondence Analysis - t-Distributed Stochastic Neighbor Embedding (t-SNE)	N.A.
[5]	Wheat	11	20	Meta MultiClass Classifier	90-100 (96.2)
[11]	weed species seeds & wheat grains	5	5	- K-nearest neighbor - Naïve Bayes - Quadratic Discriminant Analysis	95.4 97.8 98.7
Proposed methods	weed species seeds & wheat grains	11	6	- K-nearest neighbor - Naïve Bayes - Quadratic Discriminant Analysis - Neural network	91 96.9 97.1 96.6

As summarized in Table 6 several investigators have worked on several crop grains and seeds identification using number of morphological and color features. Number of studied grains and/or seeds was varied from 3 to 10 species or varieties with a range of accuracy percentage laid between 84.4 to 100%. Only Wafy *et al* [9] on 3 weed species seeds mixed with wheat grains with accuracy of 91.7% using SIFT algorithm. Present method based on QDA enable us to identify 10 weed species seeds that accompanying wheat grains with accuracy 97.1% which represents a more adapted tool for weed seeds identification.

4. Conclusion

The current results indicate that morphological features of weed species' seeds and one wheat grains species can be used for morphological identification using three images' types that contain either single or group seeds of weed species or mixture of weed and wheat grains. Among twenty three morphological features evaluated, only effective six features namely Perimeter, Solidity, Equivalent Diameter, Elongation, shape factor 1 and shape factor 4, were found to be the best set of features that gave higher identification accuracies. Among four studied classifiers (Quadratic Discriminant Analysis classifier, Naïve Bayes classifier, Artificial Neural Network and K-Nearest Neighbor classifier) the Quadratic Discriminant

Analysis showed the highest average of accuracies 97.1% (97.4%, *Phalaris minor* Retz., 98.5% *Coronopus didymus* (L) Sm., 100% 'Sakha 94' Wheat**,** 92.7% *Ammi majus*, 90.9 % *Cichorium endivia*, 95.4 % *Malva parviflora*, 99.8 % *Avena sterilis*, 95.3 % *Bromus tectorum*, 96.7 % *Melilotus indica*, 98.9 % *Lolium multiflorum*, 94.5 % *Rumex dentatus*) with the least running time which estimate to be 0.49 second.

Table 6: Comparison between the methods used color features and different combinations of color, morphological and texture features in the review and proposed methods.

Research	Seed & grain species	No. of seed species	No. & type of features	Methods	Average accuracy %
[2]	Rice varieties	6	15 morphological & color	Neural network	84.8
[3]	Corn varieties	5	28 morphological & color	Discriminant analysis combined with Neural network	90
[4]	Wheat and barley	2	3 morphological, color & texture	Discriminant analysis & K-nearest neighbors	99
[6]	Rangeland species	10	6 morphological & color	Neural network	100
[7]	Wheat, Rice & Gram	3	25 morphological & color	Neural network Euclidean Distance	95 84.4
[8]	Corn	5	27 morphological & color	Multilayer Perceptron neural network & Neuro-Fuzzy neural network	94 96
[9]	weed species seeds & wheat grains	4	-	(SIFT) algorithm	91.7%
[10]	Rice	5	13 (paddy) 10 (brown) 20 (white) color	Neural network	96.6 97.7 100
Proposed methods	weed species seeds & wheat grains	11	6 morphological	- K-nearest neighbor - Naïve Bayes - Quadratic Discriminant Analysis - Neural network	91 96.9 97.1 96.6

5. References

[1] O. Brinkkemper, L. V. Maaten and P. Boon, "Identification of Myosotis seeds by means of digital image analysis", Vegetation History and Archaeobotany, Vol. 20, 2011, pp. 435-445.

[2] S. Shantaiya, and U. Ansaria, "Identification Of Food Grains And Its Quality Using Pattern Classification", International Conference [ICCT], IJCCT, Vol. 2, Issue 2, 3, 4, 3rd-5th December, 2010.

[3] X. Chen, Y. Xun, W. Li and J. Zhang, "Combining discriminant analysis and neural networks for corn variety identification", Computer and Electronic in Agric., Vol. 71, 2010, pp. 48-53.

[4] F. Guevara-Hernandez and J. Gomez-Gil, "A machine vision system for classification of wheat and barley grain kernels", Spanish Journal of Agricultural Research, Vol. 9(3), 2011, pp. 672-680.

[5] P. Zapotoczny, "Discrimination of wheat grain varieties using image analysis: morphological features", Eur Food Res Technol, Vol. 233, 2011, pp. 769–779.

[6] S. Anvarkhah, M. Khajeh-Hosseini, A. D. E. Panah, "Seed identification of ten rangeland species based on machine learning using combination of RBF and Feed Forward neural networks", International Journal of Agriculture and Crop Sciences, 2012, Available: www.ijagcs.com.

[7] N. Pandey, S. Krishna and S. Sharma, "Automatic Seed Classification by Shape and Color Features using Machine Vision Technology", International Journal of Computer Applications Technology and Research, Vol. 2, Issue 2, 2013, pp. 208 – 213.

[8] A. Pazoki, F. Farokhi and Z. Pazoki, "Corn Seed Varieties Classification Based on Mixed Morphological and Color Features Using Artificial Neural Networks", Research Journal of Applied Sciences, Engineering and Technology, Vol. 6(19), 2013, pp. 3506-3513.

[9] M. Wafy, H. M. Ibrahim and E. M. Kamel: "Identification of weed seeds species in mixed sample with wheat grains using SIFT algorithm", in 9th International Computer Engineering Conference (ICENCO), Faculty of Engineering, Cairo University, Cairo, Egypt, 2013.

[10] I. Golpour, J. A. Parian and R. A. Chayjan: "Identification and classification of bulk paddy, brown, and white rice cultivars with colour features extraction using image analysis and neural network", Czech Journal of Food Science, Vol. 32, 2014, pp. 280–287.

[11] M. Wafy, E. M. Kamel, "Distinguish between some weed species seeds and wheat grains using image analysis", Imaging science journal, submitted for publication.

[12] Christopher M. Bishop, Pattern Recognition and Machine Learning, USA, Springer Science+Business Media, LLC, ch. 2, 4, 2006.

[13] Principles of Data Mining (Adaptive Computation and Machine Learning), David Hand, Heikki Mannila and Padhraic Smyth, (2001, August, 1), Available: http://www.amazon.com.

[14] "Quadratic Discriminant Analysis", Published on STAT 557 - Data Mining (https://onlinecourses.science.psu.edu/stat557), The Pennsylvania State University, 2014.

[15] T. Mitchell, Machine Learning, McGraw-Hill, March 1, 1997.

Enas Mohamed Kamel Mohamed received her B.Sc. degree in pure mathematics and computer sciences from Ain Shams University in 1997 and received her M.Sc. degree in Computer Sciences from Helwan University in 2009. Enas is working Assistant researcher at Weed Research Central Laboratory, Agriculture Research Center, Giza, Egypt.

Maged Hussein Wafy holds M.Sc. from Helwan University, and a Ph.D. degree in Uncertain Reasoning from Manchester University. He is Assistant Professor of the Department of Information Technology, Faculty of Computer and Information Systems, Helwan University. Currently, he works on the development of detection and identification of local features in images, visual cryptography,

identification gait, machine learning, and Bayesian statistics and their applications in computer vision.

Hashem Mohamed Mohamed Ibrahim received his B.Sc. Agriculture 1969, Vegetable Department, University of Alexandria, M.Sc. 1975, Horticulture Dept., Ain Shams University, Ph.D. 1981, Horticulture Dept. Ain Shams University. He is a professor of Weed Research Central Laboratory, Agriculture Research Center, Giza, Egypt.

Iman Badr received her PhD in Computer Engineering from Stuttgart University, Germany, and her M.Sc. and B.Sc. in Computer Science from the American University in Cairo, Egypt 1996 and from the Faculty of Computers and Information, Helwan University, Egypt, 2000, respectively. The topic of her PhD is "Agent-based dynamic scheduling for Flexible Manufacturing Systems". The topic of her M.Sc. thesis is agent-based information filtering for internet- based applications. Since 2011- present, lecturer at Helwan University, Egypt. 2006-2010: researcher and scientific employee at Stuttgart University, Germany. She is a member of the IEEE Industrial Electronics Society and the VDI/ VDE German Technical Committee on Multi-Agent Systems “FA 5.15”. Her research interests include agent-based computing, factory automation, operation research and bio-inspired optimization.

.