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Research Article

Corn Seed Varieties Classification Based on Mixed Morphological and Color Features Using Artificial Neural Networks

[1]Alireza Pazoki, [2]Fardad Farokhi and [2]Zohreh Pazoki
[1]Department of Agronomy and Plant breading, Shahr-e-Rey Branch, Islamic Azad University, P.O.Box: 18155.144, Tehran, Iran
[2]Department of Electrical and Electronic Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran

Abstract: The ability of Multi-Layer Perceptron (MLP) and Neuro-Fuzzy neural networks to classify corn seed varieties based on mixed morphological and color Features has been evaluated that would be helpful for automation of corn handling. This research was done in Islamic Azad University, Shahr-e-Rey Branch, during 2011 on 5 main corn varieties were grown in different environments of Iran. A total of 12 color features, 11 morphological features and 4 shape factors were extracted from color images of each corn kernel. Two types of neural networks contained Multilayer Perceptron (MLP) and Neuro-Fuzzy were used to classify the corn seed varieties. Average classification's accuracy of corn seed varieties were obtained 94% and 96% by MLP and Neuro-Fuzzy classifiers respectively. After feature selection by UTA algorithm, more effective features were selected to decrease the classification processing time, without any meaningful decreasing of accuracies.

Keywords: Artificial Neural Networks (ANNs), corn, Feature selection, Multi layer perceptron (MLP), neuro-fuzzy, seed

INTRODUCTION

Corn is one of the major foods in the world. In some crops as corn, because of differences between variety's morphology and quality, the seeds identification is very important. Color and morphological features are the main visual factors in seed inspection and grading so classification of different seed varieties are determined according to these features generally. Several grading systems using different morphological features for the classification of different cereal grain varieties have been reported in literature (Barker *et al*., 1992a, b, c, d; Majumdar and Jayas, 2000; Zapotoczny *et al*., 2008).

Features for various corn damages were identified by red, green and blue pixel value inputs to a neural network (Steenhoek *et al*., 2001). Recently, researchers combined various external features (Morphological, Color and Textural) to improve the classification accuracy of grain kernels. The classification of grain kernels cannot be easy using a unique mathematical function because of the variation in morphology, color and texture, so neural networks have the potential of solving problems in which some inputs and corresponding output values are known, but the relationship between the inputs and outputs is difficult to translate into a mathematical function. Neural network classifiers have been successfully implemented for solving the problems of agriculture such as grain quality inspection and especially grain identification. Many studies have been reported on application of Artificial Neural Networks (ANNs) in agriculture (Jiang *et al*., 2004; Uno *et al*., 2005; Movagharnejad and Nikzad, 2007; Savin *et al*., 2007; Zhang *et al*., 2007; Ehert *et al*., 2008).

Pazoki and Pazoki (2011) classified 5 rain fed wheat grain cultivars using artificial neural network. The experiment results indicated that the average accuracy was 86.48 % and after feature selection application by UTA algorithm increased to 87.22%.

Chen *et al*. (2010) proposed a vision-based approach combined with pattern recognition techniques and neural networks to identify corn varieties. Experiment showed the average classification accuracy for five varieties was up to 90%. Yun (2004) presented a detection algorithm based on Back Propagation (BP) network for classification of corn. The average recognition accuracy of the standard corn, broken corn and different kernel's genotype could reach 95%.

Neuro-fuzzy networks are combination of artificial neural networks and fuzzy logic. Neuro-fuzzy techniques are applied in many fields as model

Corresponding Author: Alireza Pazoki, Associate Professor, Department of Agronomy and Plant breading, Shahr-e-Rey Branch, Islamic Azad University, P O Box: 18155.144, Tehran, Iran

identification and forecasting of linear and non-linear systems. Rutkowaska and Starczewski (2004) presented an approach to classification of Iris based on neuro-fuzzy systems and hybrid learning algorithms in the field of image processing and analysis.

In this study, MLP and Neuro-fuzzy neural networks efficiency is presented for corn seed varieties classification and the accuracy differences before and after feature selection is compared. The specific goal is to extract the external features of corn kernels and then generate the optimal features set for corn variety identification using feature selection algorithm.

MATERIALS AND METHODS

Due to identification of 5 corn (Zea mays L.) seeds varieties which are grown in different environments of Iran, this research was done in Islamic Azad University, Shahr-e-Rey Branch during 2011. The experimented corn varieties were included: KSC260, KSC403, KSC400, KSC600 and KSC704 (Fig. 1).

In the presented method, at first, different types of the features were extracted and fed to Multilayer Perceptron (MLP) and neuro-fuzzy networks for classification. These features consisted of color features, morphological features and shape factors.

The MLP and neuro-fuzzy networks were trained on the randomly selected instances and tested on the rest of the data for classification of corn seeds varieties. Finally, the UTA feature selection algorithm was performed in order to determine the more effective features (Utans *et al*., 1995). The program is written in MATLAB version 7.8. The proposed method was implemented using a Pentium V personal computer with 4GB RAM and 2.67 GHz CPU. The system architecture is shown in the Fig. 2.

Image acquisition: Digital image analysis offers an objective and quantitative method for estimation of morphological parameters. This process uses digital images to measure the size of individual seeds and mathematically extract features and shape related information from the images.

A Panasonic camera (Model SDR-H90) with zoom lens 1.5-105 mm focal length used to take the images of corn seed samples. Images format was 24 bit color JPEG with resolution of 360×640 pixels. The camera was mounted over the illumination chamber on a stand which provided easy vertical movement.

The distance between the camera and each seed sample was fixed (27 cm) to regret the effect of the distance on saved images. In order to reduce the influence of surrounding light, a black illumination chamber is located between the samples and the lens and equal number of the images (90 images) was taken for each variety. The acquired corn seed varieties are shown in Fig. 1.

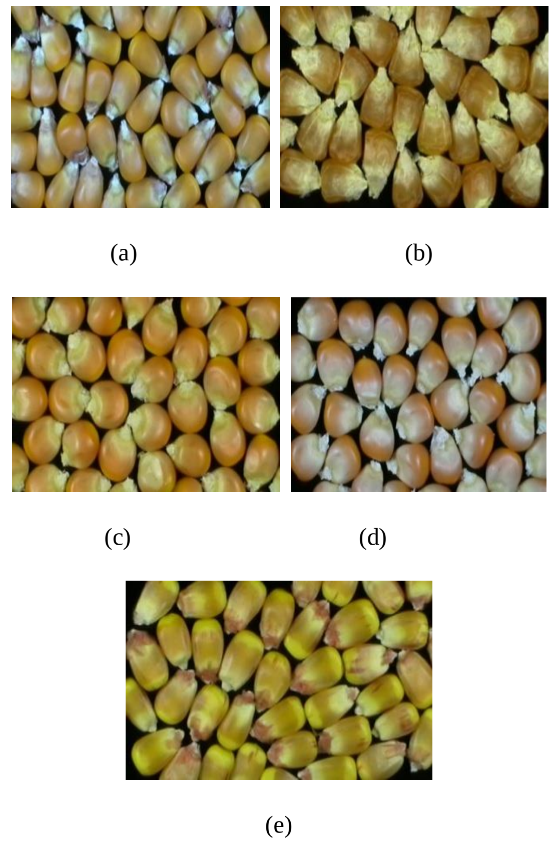

Fig. 1: Five corn seed varieties: (a) KSC260, (b) KSC403, (c) KSC400, (d) KSC600 and (e) KSC704

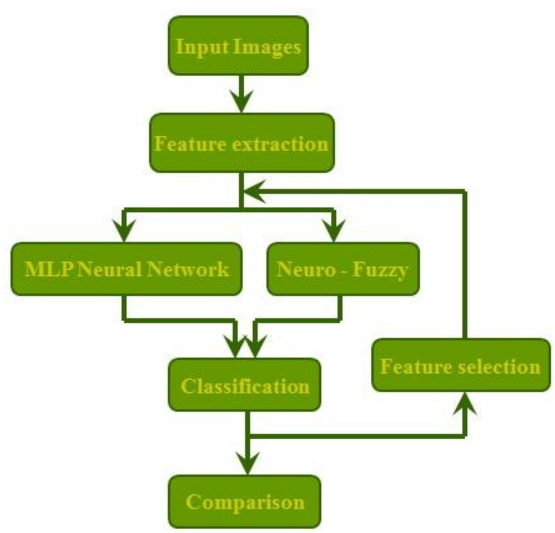

Fig. 2: System architecture

Feature extraction: In this research, color, morphological features and shape factors used for extracting of individual corn seeds as follows.

- **Color feature extraction:** Color is an important feature that human perceive when viewing an image. Human vision system is more sensitive to color information than gray levels so color is the first candidate used as the feature. There are several color spaces. In order to study the effect of color features on the identification performance of corn varieties, three transformations of RGB (red, green and blue) color space were evaluated, i.e., HSV, YCbCr and $I_1I_2I_3$.

RGB: RGB color space is the most common used one for image representation on computers. An RGB image, sometimes referred as a true color image, is stored as an m-by-n-by-3 data array that defines red, green and blue color components for each individual pixel.

HSV: MATLAB and the Image Processing Toolbox m-files do not support the HSI color space (Hue Saturation Intensity). Therefore, we used the HSV color space that is very similar to HSI.

From the Red (R), Green (G) and Blue (B) color bands of an image, Hue (H), Saturation (S) and Value (V) were calculated using the following equations (Image Processing Toolbox, 2007):

$$\mathrm{Max} = \mathrm{Max}\ (R, G, B) \tag{1}$$

$$\mathrm{Min} = \mathrm{Min}\ (R, G, B) \tag{2}$$

$$V = \mathrm{Max} \tag{3}$$

$$S = \frac{\mathrm{Max} - \mathrm{Min}}{\mathrm{Max}} \tag{4}$$

$$H = \begin{cases} \frac{1}{6}\frac{G-B}{\mathrm{Max}-\mathrm{Min}} & V = R \\ \frac{1}{6}\frac{B-R}{\mathrm{Max}-\mathrm{Min}} + \frac{1}{3} & V = G \\ \frac{1}{6}\frac{R-G}{\mathrm{Max}-\mathrm{Min}} + \frac{2}{3} & V = B \end{cases} \tag{5}$$

$$\text{if } H < 0 \rightarrow H = H + 1.$$

YCbCr: The Y element represents the luminance component and the Cb; Cr elements represent two chrominance components. Equation (6) represents the YCbCr transformation of RGB color space (Umbaugh, 2005).

$$\begin{cases} Y = 0.299\,R + 0.587\,G + 0.114\,B \\ Cb = -0.1687\,R - 0.3313\,G + 0.500\,B + 128 \\ Cr = 0.500\,R - 0.4187\,G - 0.0813\,B + 128 \end{cases} \tag{6}$$

$I_1I_2I_3$: The transformation of RGB color space into $I_1I_2I_3$ color space can be achieved by the Eq. (7) (Ohta, 1985).

$$\begin{cases} I_1 = (R + G + B)/3 \\ I_2 = (R - B)/2 \\ I_3 = (-R + 2G - B)/4 \end{cases} \tag{7}$$

Furthermore, mean (m) of these color components were calculated. In total, 12 color features were extracted for identification.

- **Morphological feature extraction:** The following morphological features were extracted from labeled images of individual corn seeds varieties. Geometry related features including area, perimeter and major and minor axis lengths were measured from the binary images (Paliwal *et al.*, 2001; Zhao-Yan *et al.*, 2005).

Area (A): The area of a region is defined as the number of pixels contained within its boundary.

Perimeter (P): The perimeter is the contour length of the boundary.

Major axis length (L): The length of the major axis is the longest line that can be drawn through the object.

Minor axis length (l): The length of the minor axis is the longest line that can be drawn through the object perpendicular to the major axis.

Aspect ratio: $$K = \frac{\text{Major axis length}}{\text{Minor axis length}} \tag{8}$$

Equivalent diameter (Eq): It was the diameter of a circle with the same area as the corn seed region.

$$\mathrm{Equadial} = \sqrt{\frac{4 \times \mathrm{Area}}{\pi}} \tag{9}$$

Convex area (C): It was the number of pixels in the smallest convex polygon that can contain the corn seeds region.

Solidity (S): The proportion of the pixels in the seeds region that are also in the convex hull.

Extent (Ex): The proportion of the pixels in the bounding box which are also in the seeds region.

Roundness (R): This is given by

$$R = \frac{4 \times \pi \times \mathrm{Area}}{\mathrm{Perimeter}^2} \tag{10}$$

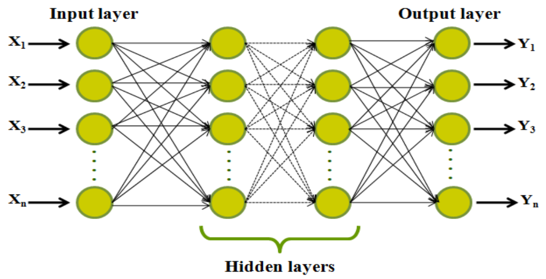

Fig. 3: Multilayer perceptron neural network

Compactness (CO): The compactness provides a measure of the object's roundness:

$$CO=\frac{\sqrt{\frac{4\times Area}{\pi}}}{L} \quad (11)$$

- **Shape features:** From the values of axis length and Area, shape factors were derived (Symons and Fulcher, 1988a) as follow:

$$\text{Shape factor1(SF1)}: \frac{\text{Major axis length}}{\text{Area}} \quad (12)$$

$$\text{Shape factor2(SF2)}: \frac{\text{Area}}{\text{Major axis length}^3} \quad (13)$$

$$\text{Shape factor3(SF3)}: \frac{\text{Area}}{(\text{Major axis length}/2)(\text{Major axis length}/2)\,\pi} \quad (14)$$

$$\text{Shape factor4(SF4)}: \frac{\text{Area}}{(\text{Major axis length}/2)(\text{Minor axis length}/2)\,\pi} \quad (15)$$

The feature vector was made from above features and fed two artificial networks for classification.

Artificial neural networks: Artificial Neural Networks (ANN) is a mathematical tool, which tries to represent low-level intelligence in natural organisms and it is a flexible structure, capable of making a non-linear mapping between input and output spaces (Rumelhart *et al.*, 1986). In this study, Multi Layer Perceptron network (MLP) and Neuro-fuzzy network were used to classify corn varieties.

Multi Layer Perceptron (MLP) network: An artificial neural network is composed of many artificial neurons that are linked together according to specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs.

The MLP network consists of an input layer, one or more hidden layers and an output layer. Each layer consists of multiple neurons. An artificial neuron is the smallest unit that constitutes the artificial neural network (Kantardzic, 2003).

The network needs to be trained using a training algorithm such as back propagation. The goal of every training algorithm is to reduce the global error by adjusting the weights and biases.

We applied a MLP neural network with 2 hidden layers. The input layer had 27 neurons because the data sets contained 27 parameters and 5 neurons (KSC260, KSC403, KSC400, KSC600 and KSC704) in the output layer. The applied training structure for corn seeds varieties classification was 27-30-10-5.

Typical Multilayer perceptron neural network architecture is shown in Fig. 3.

Neuro-fuzzy classification network: Many different systems have been applied in classification problems. In the area of computational intelligence, neural networks, fuzzy systems and neuro-fuzzy systems are widely employed as classifiers. In the field of artificial intelligence, neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic.

In this study, we propose an approach to design fuzzy system where the membership functions are chosen in such a way that certain criterion is optimized. The structure of the fuzzy system is specified first and some parameters in the structure are free to change, then these free parameters are determined according to the input-output pairs (Wang, 1997).

First, we specified the structure of the fuzzy system. The fuzzy system was chosen with product inference engine, singleton fuzzifier, center average defuzzifier and Gaussian membership function.

We applied a neuro-fuzzy classifier with the structure as MLP neural network that contained 60 neurons (rules). The fuzzy system was derived as follow (Wang, 1997):

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^{l}\left[\prod_{i=1}^{n} \exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n} \exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]} \quad (16)$$

where, M is the number of rules considered and y^{-l}, x^{-l}_i and σ^l_i (q) are free parameters and would determine in learning phase. Designing a fuzzy system means determining these three parameters. To determine these parameters in some optimal fashion, it is helpful to represent the fuzzy system f (x) of Eq. (16) as a feed forward network.

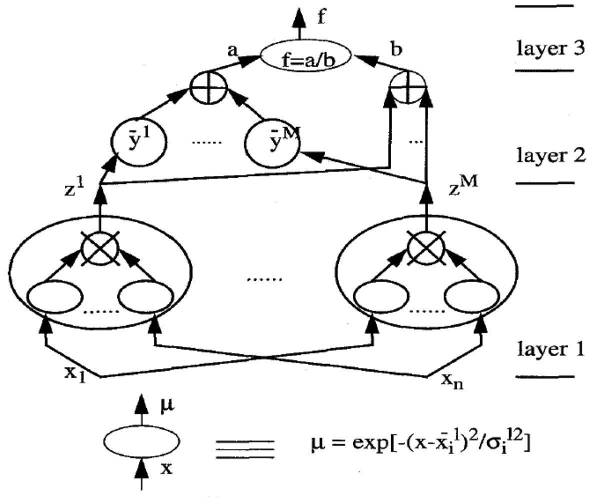

Fig. 4: Network representation of the fuzzy system (Wang, 1997)

Specifically, the mapping from the input $x \in U \subset R^n$ to the output $f(x) \in V \subset R$ can be implemented according to the following operations (Wang, 1997):

- The input x is passed through a product Gaussian operator:

$$z^l = \prod_{i=1}^{n} \exp\left(-\left(\frac{x_i - \bar{x}_i^l}{\sigma_i^l}\right)^2\right) \tag{17}$$

- The z^l are passed through a summation operator and a weighted summation operator to obtain b and a:

$$b = \sum_{l=1}^{M} z^l \tag{18}$$

$$a = \sum_{l=1}^{M} \bar{y}^l z^l \tag{19}$$

- Finally, the output of the fuzzy system is computed:

$$F = \frac{a}{b} \tag{20}$$

Neuro-fuzzy system for identification of corn varieties is shown in Fig. 4.

Feature selection: Feature selection is the problem of choosing a subset of features ideally necessary to perform the classification task from a larger set of candidate features.

There are several ways to determine the best subset of features. UTA is a simple method which is based on trained artificial neural network. In the basis of this method, average of one feature in all instances is calculated. Then the selected feature in all input vectors has been replaced by the calculated mean value. Then the trained network was tested with the new features Utans *et al.* (1995). The comparison error was defined in our strategy as follow:

$$E = (FP\ (new) + FN\ (new)) - (FP\ (old) + FN\ (old)) \tag{21}$$

where,
FP (old) = False positive
FN (old) = False negative using the whole original features

FP (new) and FN (new) is those values when one of the feature replaced by the mean value.
Three different states could happen:

- One input is considered relevant if E is positive and the higher the E is, indicates the features importance among other features.
- One input is ineffective if E is zero.
- One input is not only ineffective but also noisy and should be removed from the input vector if E is negative.

RESULTS AND DISCUSSION

Identification of corn seed varieties on image of each corn kernel that contained samples of 5 varieties tested. There were 90 images for each variety. Images

Table 1: Average accuracy before UTA algorithm

	Varieties accuracy (%)					
Neural networks	KSC260	KSC403	KSC400	KSC600	KSC704	Average accuracy (%)
MLP	98	97	91	87	97	94
Neuro-fuzzy	99	99	92	91	99	96

Table 2: Comparison error of morphological features in UTA algorithm (MLP)

	Feature's Error (E)														
Varieties	A	P	L	l	R	C	S	EX	Eq	K	CO	SF1	SF2	SF3	SF4
KSC260	0	0	0	-2	-2	-1	0	0	0	-1	0	-1	-1	0	0
KSC403	-1	3	-1	10	-1	0	0	0	0	6	-1	0	15	-1	-1
KSC400	0	3	1	10	2	0	0	4	0	9	0	1	16	2	1
KSC600	-1	-2	-3	3	-5	0	-1	1	-2	5	-4	-2	9	-2	-4
KSC704	0	4	1	7	0	1	1	-1	2	5	1	2	9	1	2
Total (T)	-2	8	-2	28	-6	0	0	4	0	24	-4	0	48	0	-2

Table 3: Comparison error of color features in UTA algorithm (MLP)

	Feature's error (E)											
Varieties	Rm	Gm	Bm	Hm	Sm	Vm	Ym	Cbm	Crm	I_1m	I_2m	I_3m
KSC260	0	0	-1	0	3	-1	0	-1	0	-1	1	-3
KSC403	-1	4	0	1	4	0	1	-1	-1	2	20	3
KSC400	0	3	0	3	2	1	2	0	0	1	10	20
KSC600	-1	-3	0	1	-1	-5	-4	-2	2	-1	7	10
KSC704	0	4	-1	1	4	1	3	0	1	1	12	4
Total (T)	-2	8	-2	6	12	-4	2	-4	-2	2	50	34

Table 4: Comparison error of morphological features in UTA algorithm (Neuro- fuzzy)

	Feature's error (E)														
Varieties	A	P	L	l	R	C	S	EX	Eq	K	CO	SF1	SF2	SF3	SF4
KSC260	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0
KSC403	0	1	0	0	0	7	0	1	0	0	0	0	0	0	3
KSC400	1	1	1	1	3	1	1	1	-1	2	1	1	4	-2	1
KSC600	1	1	1	1	3	1	1	1	-1	2	1	1	2	-1	1
KSC704	0	1	0	0	0	6	0	1	0	0	0	0	2	1	9
Total (T)	2	4	2	2	6	14	2	4	-2	4	2	2	8	-2	8

format was 24 bit color JPEG and 360×640 pixels considered for images size.

There were 60 training data and 30 test data for each corn seed varieties (300 training data and 150 test data for 5 experimented corn seed varieties). Twelve color features (Rm, Gm, Bm, Hm, Sm, Vm, Ym, Cbm, Crm, I_1m, I_2m and I_3m), 11 morphological features (Area, Perimeter, Major axis length, Minor axis length, Aspect ratio, Equivalent diameter, Convex area, Solidity, Extent, Roundness and Compactness) extracted from seed varieties images and features such as area, perimeter, major and minor axis length computed on the binary images and four shape factors (SF1, SF2, SF3 and SF4) were derived from these main geometric features. The program written and tested using MATLAB 7.8 software.

Many features were highly correlated with each others and if one of the features was selected, the rest of the features will not contribute significantly in classification.

The MLP and neuro-fuzzy neural networks, accuracies were evaluated (Table 1). The average accuracy in MLP and neuro-fuzzy neural networks were 94% and 96% respectively. As it was shown the performance of neuro-fuzzy neural network was better in overall classification. In this case, maximum accuracies belonged to KSC260 in MLP (98%) and neuro-fuzzy (99%).

Due to determine the more effective features and discard the irrelevant features, UTA algorithm applied and total feature's error (T) evaluated. In the MLP structure, 8 effective features I_2m (50), SF2 (48), I_3m (34), Minor (28), Aspect ratio (24), Sm (12), Perimeter (8) and Hm (6) selected (Table 2 and 3) because of their higher feature's error (Utans *et al*., 1995).

After doing UTA algorithm in neuro-fuzzy structure the feature error calculated and 9 effective features Sm (68), Hm (20), I_3m (20), Convex Area (14), I_3m (14), I_1m (10), SF2 (8), SF4 (8) and Roundness (6) selected (Table 4 and 5). So nineteen less effective features for MLP and 18 features in neuro-fuzzy removed from the input vector.

As seen in Table 6, the average accuracies after doing UTA algorithm in MLP neural network and

Table 5: Comparison error of color features in UTA algorithm (Neuro- fuzzy)

Varieties	Feature's error (E) Rm	Gm	Bm	Hm	Sm	Vm	Ym	Cbm	Crm	I_1m	I_2m	I_3m
KSC260	0	0	1	0	20	0	0	0	0	5	0	1
KSC403	0	0	0	6	16	0	0	0	0	0	-1	0
KSC400	1	1	3	5	5	1	0	1	1	1	3	6
KSC600	1	1	1	6	2	1	0	1	1	0	3	6
KSC704	0	0	1	3	25	0	0	0	0	4	-1	1
Total (T)	2	2	6	20	68	2	0	2	2	10	4	14

Table 6: Average accuracy after UTA algorithm

Neural networks	Varieties accuracy (%) KSC260	KSC403	KSC400	KSC600	KSC704	Average accuracy (%)
MLP	100	97	93	93	96	96
Neuro-Fuzzy	99	97	91	90	97	95

Table 7: Difference of accuracies before and after UTA

Neural networks	Varieties accuracy (%) KSC260	KSC403	KSC400	KSC600	KSC704
MLP	+2	0	+2	+6	-1
Neuro-Fuzzy	0	-2	-1	-1	-2

neuro-fuzzy were 96% and 95% respectively. Comparison of variety's accuracies showed that the highest accuracy in MLP observed in KSC260 variety (100%) and the lowest one belonged to KSC400 variety (93%) and in neuro-fuzzy, KSC260 variety (99%) had the highest accuracy and KSC600 variety (90%) had the lowest accuracy.

The differences between accuracies before and after performing UTA algorithm for MLP and neuro-fuzzy networks was shown in Table 7.

In MLP structure, feature selection reduced accuracy only in KSC704 variety (-1%) and accuracy of the other varieties increased. So feature selection had positive effect for corn varieties classification using MLP neural network.

In the neuro-fuzzy case, feature selection was ineffective in KSC260 variety (0%) and reduced accuracies for the rest varieties. Therefore, the results showed that feature selection for neuro-fuzzy classifier was not increased the average accuracies of corn varieties. As the mater of fact, the average accuracy before and after evaluating the UTA algorithm was near to each other and we think that the overall features selection is acceptable enough to get the best corn seed classification with lowest time and cost by using the minimum number of features.

CONCLUSION

Neural networks can present internally the knowledge necessary to solve a given problem. After learning the neural network's knowledge about solving problems, it spread in agricultural science, so the MLP and neuro-fuzzy neural networks presented for classifying 5 corn seed varieties. All 450 samples seed varieties investigated and 27 features extracted from seeds by MATLAB version 7.8.

After feature selection using UTA algorithm, the optimum sets of features for two neural networks created individually. It found that, after feature selection doing in MLP method 8 features (I_2m, SF2, I_3m, Minor and Aspect ratio, Sm, Perimeter and Hm) and in neuro-fuzzy structure, 9 effective features (Sm, Hm, I_3m, Convex Area, I_3m, I_1m, SF2, SF4 and Roundness) extracted among 27 original inputs. The highest accuracy for seeds identification in MLP (100%) and neuro-fuzzy (99%) belonged to KSC260 variety, So we conducted that feature selection in MLP increased and in neuro-fuzzy decreased average accuracies, however neuro-fuzzy before feature selection gained to highest accuracy average (96%) among all experimented cases.

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