The Journal of Animal & Plant Sciences, 24(1): 2014, Page: 336-343
ISSN: 1018-7081

CLASSIFICATION OF RICE GRAIN VARIETIES USING TWO ARTIFICIAL NEURAL NETWORKS (MLP AND NEURO-FUZZY)

A. R. Pazoki [1*] , F. Farokhi[2] , Z. Pazoki [3]

[1,*] Department of Agronomy and Plant breading, Shahr-e-Rey Branch, Islamic Azad University, Tehran, Iran
[2] Department of Electrical & Electronic Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran
[3]Young Researchers and Elite Club, Central Tehran Branch, Islamic Azad University, Tehran, Iran
Corresponding author email: pazoki@iausr.ac.ir

ABSTRACT

Artificial neural networks (ANNs) have many applications in various scientific areas such as identification, prediction and image processing. This research was done at the Islamic Azad University, Shahr-e-Rey Branch, during 2011 for classification of 5 main rice grain varieties grown in different environments in Iran. Classification was made in terms of 24 color features, 11 morphological features and 4 shape factors that were extracted from color images of each grain of rice. The rice grains were then classified according to variety by multi layer perceptron (MLP) and neuro-fuzzy neural networks. The topological structure of the MLP model contained 39 neurons in the input layer, 5 neurons (Khazar, Gharib, Ghasrdashti, Gerdeh and Mohammadi) in the output layer and two hidden layers; neuro-fuzzy classifier applied the same structure in input and output layers with 60 rules. Average accuracy amounts for classification of rice grain varieties computed 99.46% and 99.73% by MLP and neuro-fuzzy classifiers alternatively. The accuracy of MLP and neuro-fuzzy networks changed after feature selections were 98.40% and 99.73 % alternatively.

Key words: Artificial neural networks (ANNs), Grain, Multi layer perceptron (MLP), Neuro-Fuzzy, Rice

INTRODUCTION

Rice (*Oryza sativa* L.) is a staple food for populations worldwide, especially in East and South Asia, Latin America, India and Iran. Rice is a grass cereal belonging to the Poaceae family. This study was done to classify rice and to investigate the quality of products according to their external structure and morphological features (Shouche *et al.*, 2001; Jayas *et al.*, 2000; Harper *et al.*, 1970).

In many researches, external features such as morphology, color and texture have been combined to modify the accuracy of grain classification (Neuman *et al.*, 1987; Majumdar and Jayas, 2000; Zapotoczny *et al.*, 2008). Huang *et al.* (2004) proposed that Bayes decision theory be applied for classification of rice variety with 88.3% accuracy.

Determining grain variety using a simple mathematical function is difficult because grain has various morphologies, colors and textures. However artificial neural network (ANNs) classifiers have been applied in some circumstances such as for grain quality control and identification of variety. ANNs can be trained with data for inputs and outputs. The inputs of neural network classifiers can be extracted from digital images. Many agricultural researches have applied ANNs (Jiang *et al.*, 2004; Uno *et al.*, 2005; Movagharnejad and Nikzad, 2007; Savin *et al.*, 2007; Zhang *et al.*, 2007; Ehert *et al.*, 2008).

Chen *et al.* (2010) identified five corn varieties with accuracy of more than 90% using pattern recognition techniques and neural networks. Pazoki and Pazoki (2011) presented an approach to classify 5 rain fed wheat grain cultivars using an 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%.

Neuro-fuzzy systems (networks) are one of the most visible sections of a hybrid system that can apply a combination of artificial neural networks and fuzzy systems. Neuro-fuzzy techniques have practical applications in many fields such as model identification and forecasting for linear and non-linear systems. Rutkowska & Starczewski (2004) presented an approach to classify Irises based on neuro-fuzzy systems and hybrid learning algorithms.

In this paper efficiency is evaluated for MLP and neuro-fuzzy neural networks in classification of rice grain varieties. Results demonstrated that accuracies changed after feature selection in the applied classifiers. The specific goal was to evaluate the external features of rice grains and determine the best feature sets for classification of five rice varieties according to a feature selection algorithm.

METHODS AND MATERIALS

This study involved the identification of 5 rice (Oryza sativa L.) grain varieties grown in Guilan and

Mazandaran provinces using neural networks (MLP and neuro-fuzzy) before and after a feature selection and comparison. This research was done at Islamic Azad University, Shahr-e-Rey Branch during 2011-2012. The following rice varieties tested in the study were: Khazar, Gharib, Ghasrdashti, Gerdeh and Mohammadi (Fig. 1A). Classification was made in terms of the thirty-nine features that were extracted and fed to the multilayer perceptron (MLP) and neuro-fuzzy networks. The topological structure of this MLP model consisted of 39 neurons (24 color features, 11 morphological features and 4 shape factors) in the input layer; 5 neurons (Khazar, Gharib, Ghasrdashti, Gerdeh and Mohammadi) in the output layer and two hidden layers with 30 neurons in the first and 10 neurons in the second. The neuro-fuzzy network had the same size in input and output layers with 60 rules.

After training the MLP and neuro-fuzzy networks using MATLAB version 7.8, models were applied for the classification in terms of rice grain variety. Finally, the UTA feature selection algorithm was applied and the more effective selected features were used for new training and a comparison of the networks (Utans *et al.*, 1995).

Image Acquisition: A Panasonic camera (Model SDR-H90) with a zoom lens 1.5-105 mm in focal length was applied to take images of single grains to extract the morphological features for the digital image analysis for evaluations of size and shape. In order to reduce the effect of peripheral light, the samples and lens were placed together into a black illumination chamber and the camera was mounted over the chamber on a stand that provided easy vertical movement. The distance from the camera lens and the grain surface was 27 centimeters and ninety images, selected randomly were taken for each variety. The format of the images was 24-bit color JPEG with a resolution of 360×640 pixels. The proposed method was implemented by a Pentium V personal computer with 4GB RAM and 2.67 GHz CPU. Images for rice grain varieties are shown in Fig 1(A).

Image Segmentation: Image segmentation was proposed for processing images to classify an image into several regions according to the features of an image. Image segmentation is useful in many applications and several image segmentation algorithms have been proposed to segment images before recognition or compression. One of the most efficient methods for segmentation is the histogram-based method. An image histogram can compute from all image pixels. The peaks and valleys of the histogram serve to separate an object from its background in an image. After acquiring a color image, single rice grains were separated from the black background by a certain threshold, thus determining a suitable threshold as the main part of image segmentation, and threshold amount was extracted from the red plane histogram (Zhao-Yan *et al.*, 2005). Red plane histograms of rice grain varieties are shown in Fig.1 (B). There were two peaks in the color histogram. The right and left peaks refer to pixels related to grain and black background, respectively. The average lowest point between two peaks was around the value of 110. Therefore, the threshold value for this research was set at 110. Any pixel with a red value of more than 110 was considered as a rice grain; otherwise, it was background. Segmented images are shown in Fig.1 (C).

Feature Extraction: In this research, color, morphological features and shape factors were used to identify individual rice grains. These features were assessed with MATLAB software version 7.8.

Color Feature Extraction: Color is a main factor of feature extraction, because the human vision is sensitive to color. There are several color spaces. In this research, HSV, YCbCr and $I_1I_2I_3$ as color features calculated from RGB (red, green and blue) color space.

RGB: RGB is one of the most usual color spaces for images. A RGB image expresses red, green, and blue color components for each exclusive pixel.

HSV: MATLAB and Image Processing Toolbox software are tools that do not support HSI color space (hue saturation intensity). Therefore, HSV was used, which is very similar to HSI.

Hue (H), saturation (S) and value (V) color spaces of images were evaluated by the equations below (Image Processing Toolbox, 2007):

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

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

$$V = \mathrm{Max} \quad (3)$$

$$S = \frac{\mathrm{Max} - \mathrm{Min}}{\mathrm{Max}} \quad (4)$$

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

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

YCbCr: The Y element represents the luminance component, and the Cb, Cr elements represent two chrominance components. The Cb and Cr components are the difference between the blue and red components with subsequent reference values.

Equation (6) is the formula of YCbCr transformation (Umbaugh, 2005).

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

$I_1I_2I_3$: The color space of $I_1I_2I_3$ was calculated from RGB color space, using the following equations (Ohta, 1985):

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

Mean (m) and standard deviation (d) amounts of color components were evaluated for each image by MATLAB software 7.8. So 24 color features were extracted for rice grain classification.

Morphological Feature Extraction: The morphological features below were extracted from images of sole rice grain varieties. The features relating to geometry (area, perimeter, and major and minor axis lengths) were calculated from binary images. Each pixel in a binary image had only one of two discrete values (0 or 1). Binary images were calculated for each individual rice grain variety by MATLAB 7.8 program and any false objects were omitted.

Paliwal *et al.* (2001) and Zhao-Yan *et al.* (2005) extracted the most effective morphological features for cereal grain classification used as below:

Area (A): A region area was determined as the number of pixels within its boundary.

Perimeter (P): The perimeter was determined as the length of its boundary.

Major axis length (L): The longest line that can be drawn through an object.

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

Aspect ratio: $$\mathrm{K} = \frac{L}{l} \quad (8)$$

Equivalent diameter (Ed): The diameter of a circle with the same area as the rice grain area (Zhao-Yan *et al.*, 2005).

$$Ed = \sqrt{\frac{4 \times A}{\circledR}} \quad (9)$$

Convex area (C): Pixel number in the smallest convex polygon that could contain the area of a rice grain (Zhao-Yan *et al.*, 2005).

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

Extent (Ex): The proportion of pixels in the bounding box that were also in the grain region.

Roundness (R): Was calculated with the formula below:

$$\mathrm{R} = \frac{4 \times \circledR \times A}{P^2} \quad (10)$$

Compactness (CO): Provided the measurement of an object's roundness:

$$\mathrm{CO} = \frac{\sqrt{\frac{4 \times A}{\circledR}}}{L} \quad (11)$$

Shape Features: Shape factors were extracted from major axis length (L), minor axis length (l) and area with the following formulas (Symons and Fulcher, 1988):

$$Shape \ \ factor1(SF1) = \frac{L}{A} \quad (12)$$

$$Shape \ \ factor2(SF2) = \frac{A}{L^3} \quad (13)$$

$$Shape \ \ \mathrm{factor}3(SF3) = \frac{\mathrm{A}}{(L/2)(L/2)\pi} \quad (14)$$

$$Shape \ \ \mathrm{factor}4(SF4) = \frac{\mathrm{A}}{(L/2)(l/2)\pi} \quad (15)$$

The feature vector comprised of all of the assessed features. The vector was entered into two neural networks that were identified as the multi layer perceptron (MLP) network and the neuro-fuzzy network for grain identification.

Artificial Neural Networks: Artificial neural network (ANN) is a computational model, which resolves non-linear and complex problems. It consists of many artificial neurons that connect together according to a special network structure. Neurons are the smallest unit and constitute the main components of each layer within a neural network. The main aim of a neural network is the conversion of inputs to significant outputs (Rumelhart *et al.*, 1986). In this study, MLP and neuro-fuzzy networks were based on a back propagation-learning rule that was applied to classify 5 rice varieties.

Multi Layer Perceptron (MLP) Network: A Multi Layer Perceptron (MLP) network is a popular network with different applications. The structure of an MLP network includes an input layer, one or more hidden layers and one output layer (Kantardzic, 2003). After making the structure of a network, it is trained by a training algorithm such as back propagation. The training algorithm decreases error using weights and bias adjustments.

A MLP neural network with 2 hidden layers was applied. The input layer had 39 neurons because data sets contained 39 parameters and 5 neurons (Khazar, Gharib, Ghasrdashti, Gerdeh and Mohammadi) in the output layer. The applied training structure for classification of rice grain varieties was 39-30-10-5. Two-thirds of the samples (60 kernels for each rice variety) were randomly selected as the training set, while the rest of the samples were used as a test set for classification (300 training data and 150 test data for 5 experimented rice grain varieties in total).

Neuro-Fuzzy Classification Network: Many different systems have been applied to classification problems. In the area of computational intelligence, neural networks, fuzzy systems and neuro-fuzzy systems are widely used for classification problems. A Neuro-fuzzy system is a combination of an artificial neural network and fuzzy logic.

An approach to fuzzy system design is proposed where by the membership functions are chosen in such a way that only specific criterion is optimized. At first, the fuzzy system structure is determined leaving some parameters free to change, then those free factors are selected according to input-output pairs (Wang, 1997). The product inference engine, singleton fuzzifier, center average defuzzifier, and Gaussian membership function were selected for the fuzzy system. A neuro-fuzzy classifier was applied with the structure as MLP neural network that contained 60 rules using trial and error.

The fuzzy system was derived as follows (Wang, 1997):

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

Rules number (M) and free parameters (y^{-l}, x^{-l}_i and σ^l_i (q)) were determined in the learning phase. Designing a fuzzy system means determining these three free parameters. In determining these parameters, it is useful to represent the fuzzy system f (x) of equation (16) as a feed forward network.

Mapping from the input x ϵ U R^n to the output f(x) ϵ V R can be done by the equation below (Wang, 1997):

1. The input x is passed through a product Gaussian operator:

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

2. The z^l is passed through a summation operator and a weighted summation operator to obtain b and a:

$$b=\sum_{l=1}^{M} z^l \quad (18)$$

$$a=\sum_{l=1}^{M} \bar{y}^l z^l \quad (19)$$

3. Finally, the output of the fuzzy system (F) is computed:

$$F=\frac{a}{b} \quad (20)$$

Feature Selection: Features selection involves choosing optimal features. There are several commonly used methods to determine the best features for a subset. The UTA algorithm is a simple method based on trained artificial neural networks (Utans *et al.*, 1995). On the basis of this method, each feature's mean was calculated and replaced in all instances of the input vector. The comparison error was defined after training the network as presented below:

$$E= (FP\ (new) + FN\ (new)) - (FP\ (old) + FN\ (old)) \quad (21)$$

Where FP (old) is a false positive and FN (old) is a false negative, using the whole feature set and FP (new) and FN (new) are the resulting values when one feature was replaced by the mean value.

There are three outcomes in this method:

1. An input was considered to be more relevant if E was positive and had a higher value than values for other features.
2. An input was ineffective if E was zero.
3. An input was not only ineffective but also noisy and was removed from the input vector if E was negative.

RESULTS AND DISCUSSION

This study involved the identification of rice grain varieties using an algorithm based on images of 5 rice grain varieties. Identification was made according to twenty-four color features (Rm, Gm, Bm, Hm, Sm, Vm, Ym, Cbm, Crm, I_1m, I_2m, I_3m, Rd, Gd, Bd, Hd, Sd, Vd, Yd, Cbd, Crd, I_1d, I_2d and I_3d), 11 morphological features (Area (A), Perimeter (P), Major axis length (L), Minor axis length (l), Aspect ratio (K), Equivalent diameter (Ed), Convex area (C), Solidity (S), Extent (Ex), Roundness (R) and Compactness (CO)) that were extracted from images of grain varieties using features such as area, perimeter, major and minor axis length computed on a binary image using MATLAB 7.8 software. Four shape factors (SF1, SF2, SF3 and SF4) were calculated from the main geometric features. By trying the MLP and neuro-fuzzy neural networks, accuracies were evaluated (Table 1). The average accuracy in MLP and neuro-fuzzy networks were 99.46 % and 99.73% respectively. So the performance of two classifiers was near to each other. In this case, maximum accuracies belonged to Khazar, Gharib and Gerdeh in MLP (100%) and Khazar, Gharib and Ghasrdashti in neuro-fuzzy network (100%).

Determination of the best and lowest features for getting the highest accuracy was made by applying a UTA algorithm and total feature error (T) was evaluated because many features were highly correlated with each other so if one of them was select, the others would not have participated significantly enough to identify the model.

In the MLP structure, 2 effective morphological features SF2 (28), SF3 (2) and 2 effective color features

Crd (4), and Hd (0) were selected (Tables 2-3) because they had more positive and higher feature errors (Utans *et al.*, 1995). After applying the UTA algorithm in the neuro-fuzzy structure, calculations were made for feature error and the following 9 more effective features were determined: SF2 (50), Aspect ratio (4), SF3 (4), Minor axis length (2) and Roundness (2) as morphological features and Cbd (6), Bm (4), Hm (4) and I_3d (2) as color features selected for rice grain varieties (Tables 4-5).

As seen in Table 1, the average accuracy after applying the UTA algorithm in MLP and neuro-fuzzy networks were 98.40% and 99.73% respectively. Comparison of genotype accuracies showed that the highest accuracies in MLP were observed in Gharib and Gerdeh (99.33%) and the lowest in Ghasrdashti and Mohammadi varieties (97.33%). In the neuro-fuzzy network, the maximum accuracies were evaluated for Khazar, Gharib and Ghasrdashti varieties (100%) and there was lower accuracy for Gerdeh and Mohammadi varieties (99.33%).

The differences between accuracies before and after application of UTA algorithm for the two networks are shown in Table 1. Interestingly, amounts for average accuracy before and after application of the UTA algorithm were the same (99.73%), consequently the best rice grain classification with the lowest time, cost and feature is thus determined.

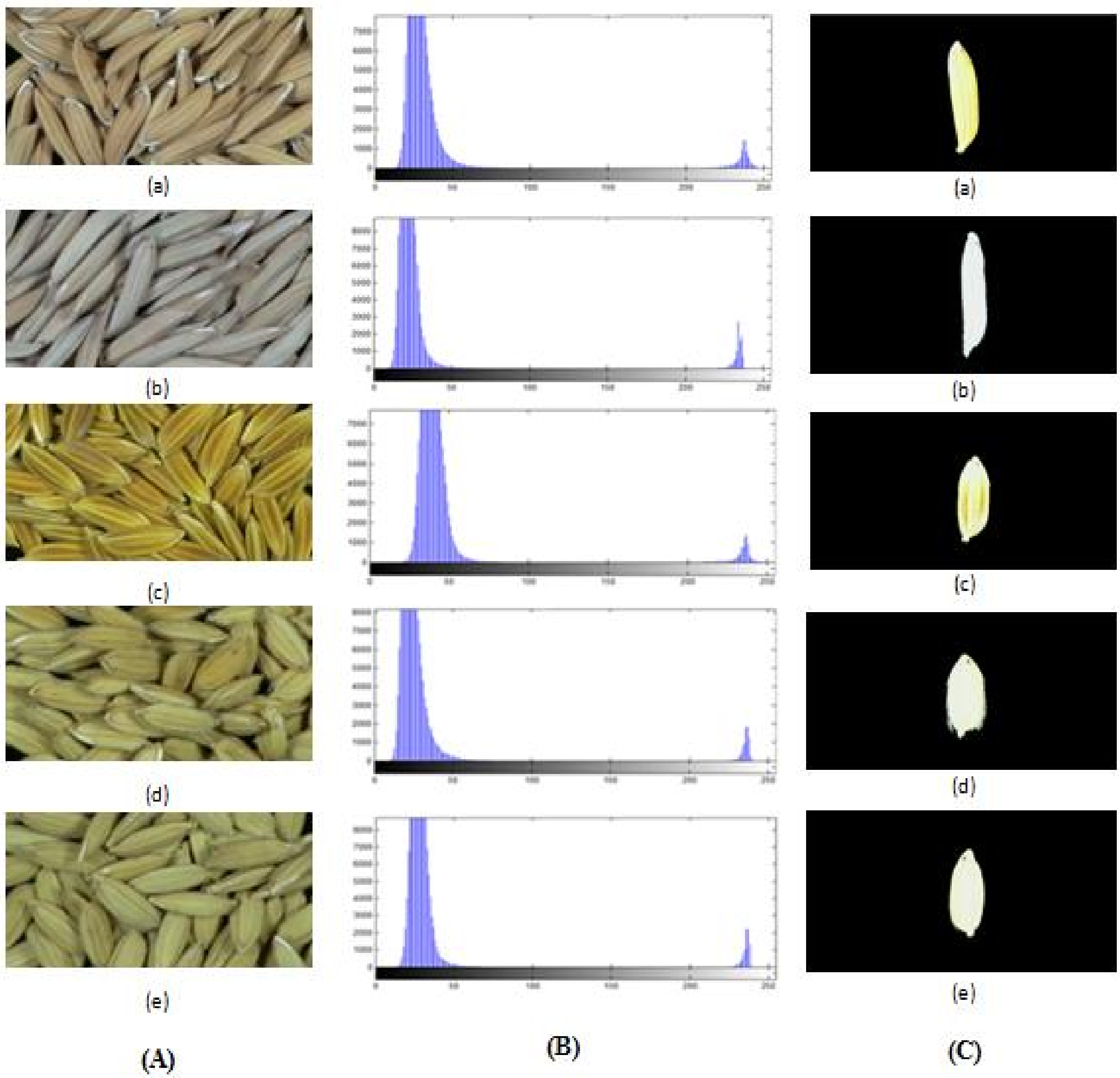

Fig. 1: Rice varieties: (a) Khazar, (b) Gharib, (c) Ghasrdashti, (d) Gerdeh and (e) Mohammadi (A), Red plane histograms (B) and segmented images (C).

Table 1. Accuracies before and after UTA algorithm

Neural networks	Varieties accuracy (%)					Average accuracy (%)
	Khazar	Gharib	Ghasrdashti	Gerdeh	Mohammadi	
MLP (Before UTA)	100	100	98.66	100	98.66	99.46
Neuro-Fuzzy (Before UTA)	100	100	100	99.33	99.33	99.73
MLP (After UTA)	98.66	99.33	97.33	99.33	97.33	98.40
Neuro-Fuzzy (After UTA)	100	100	100	99.33	99.33	99.73
MLP (Difference of accuracies)	-1.34	-0.67	-1.33	-0.67	-1.33	_
Neuro-Fuzzy (Difference of accuracies)	0.00	0.00	0.00	0.00	0.00	_

Table 2. Morphological feature's error in UTA algorithm for rice grain varieties (MLP)

Varieties	Feature's error (E)														
	A	P	L	l	R	C	S	EX	Eq	K	CO	SF1	SF2	SF3	SF4
Khazar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gharib	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghasrdashti	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gerdeh	0	0	0	0	0	0	0	0	0	0	0	0	14	1	0
Mohammadi	0	0	0	0	0	0	0	0	0	0	0	0	14	1	0
Total (T)	0	0	0	0	0	0	0	0	0	0	0	0	28	2	0

Table 3. Color feature's error in UTA algorithm for rice grain varieties (MLP)

Varieties	Feature's error (E)																							
	Rm	Gm	Bm	Hm	Sm	Vm	Ym	Cbm	Crm	I_1m	I_2m	I_3m	Rd	Gd	Bd	Hd	Sd	Vd	Yd	Cbd	Crd	I_1d	I_2d	I_3d
Khazar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Gharib	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghasrdashti	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Gerdeh	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Mohammadi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Total (T)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0

Table 4. Morphological feature's error in UTA algorithm for rice grain varieties (Neuro- fuzzy)

Varieties	Feature's error (E)														
	A	P	L	l	R	C	S	EX	Eq	K	CO	SF1	SF2	SF3	SF4
Khazar	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Gharib	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghasrdashti	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0
Gerdeh	-1	0	0	1	0	0	0	0	0	0	0	0	25	2	0
Mohammadi	-1	0	0	1	1	0	0	0	0	1	0	0	25	2	0
Total (T)	-2	0	0	2	2	0	0	0	0	4	0	0	50	4	0

Table 5. Color feature's error in UTA algorithm for rice grain varieties (Neuro- fuzzy)

Varieties	Feature's error (E)																							
	Rm	Gm	Bm	Hm	Sm	Vm	Ym	Cbm	Crm	I_1m	I_2m	I_3m	Rd	Gd	Bd	Hd	Sd	Vd	Yd	Cbd	Crd	I_1d	I_2d	I_3d
Khazar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Gharib	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghasrdashti	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	1
Gerdeh	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mohammadi	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1
Total (T)	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	2

Conclusion: In this study, MLP and neuro-fuzzy neural networks were used in conjunction with one another and presented as an effective method to classify 5 rice grain varieties. All 450 rice grain samples and 39 extracted features were analyzed by MATLAB software version 7.8. After feature selection using an UTA algorithm, the most effective features were created separately for two neural networks.

Results showed that the average accuracy of varieties classification was more than 98%, and after feature selection accuracy decreased for the MLP neural network (-1.06%) and did not change for the neuro-fuzzy network.

Acknowledgements: The authors acknowledge the great help and assistance provided Dr. Davood Habibi Assistant professor of Islamic Azad University, Karaj Branch and Cereal Research Department (SPII) for their constant support and useful suggestions.

REFERENCES

Chen, X., Y.Xun, W.Li, and J .Zhang (2010). Combining discriminant analysis and neural networks for corn variety identification. Computers and Electronics in Agriculture. 71S: S48-S53.

Ehert, D.L., B.D. Hill, D.A. Raworth, and B. Estergaard (2008). Artificial neural network modeling to predict cuticle cracking in greenhouse peppers and tomatoes. Computers and Electronics in Agriculture. 61: 108–116.

Harper, J.L., P.H. Lovell, and K.G. Moore (1970). The shapes and sizes of seeds. Annu. Rev. Ecol. Syst. 1: 327–356.

Huang, X.Y., J. Li, and S. Jiang (2004). Study on identification of rice varieties using computer vision. J. Jiangsu University (Natural Science Edition). 25(2): 102-104 (in Chinese).

Image Processing Toolbox for O-Matrix (2007). Reference manual, Version 1.0, Anona Labs Ltd, www.anonalabs.com , 5 Sep 2010.

Jayas, D.S., J. Paliwal, N.S. Visen (2000). Multi-layer neural networks for image analysis of agricultural products. J. Agricultural Engineering Research. 77: 119–128.

Jiang, S.D., X .Yang, N .Clinton, and N. Wang (2004). An artificial neural network model for estimating crop yields using remotely sensed information. International J. Remote Sensing. 25(9): 1723–1732.

Kantardzic, M . 2003. Data Mining Concepts, Models, Methods, and Algorithms. *IEEE, Piscataway*, NJ, USA.

Majumdar, S. and D.S. Jayas (2000). Classification of cereal grains using machine vision. IV. Combined morphology, color and texture models. Trans. ASAE . 43(6): 1689-1694.

Neuman, M.R., H.D. Sapirstein, E. Shwedyk, and W. Bushuk (1987). Discrimination of wheat class and variety by digital image analysis of whole grain samples. J. Cereal Science. 6: 125–132.

Ohta, Y (1985). Knowledge-Based Interpretation of Outdoor Natural Color Scenes. Pitman Publishing Inc., Marshfield, MA.

Paliwal, J., N.S. Visen, and D.S. Jayas (2001). Evaluation of Neural Network Architectures for Cereal Grain Classication using Morphological Features. J. agric. Eng Res.79 (4): 361-370.

Pazoki, A.R. and Z. Pazoki (2011). Classification system for rain fed wheat grain cultivars using artificial neural network. African J. Biotechnology. 10(41): 8031-8038.

Rumelhart, D.E., J.L. McClelland, and R.J. Williams (1986). Parallel Recognition in Modern Computers, in Processing: Explorations in the Microstructure of Cognition, 1. MIT Press, Foundations, Cambridge, MA.

Rutkowska, D. and A. Starczewski (2004). A Multi-NF approach with a hybrid learning algorithm for classification. Machine Intelligence: World Scientific Publishing Co. Pte. Ltd.

Savin, I.Y., D. Stathakis, and T. Negre, V.A. Isaev (2007). Prediction of crop yields with the use of neural networks. Russian Agricultural Sciences. 33(9): 361–363.

Shouche, S.P., R. Rastogi, S.G. Bhagwat, and J.K. Sainis(2001). Shape analysis of grains of Indian wheat varieties .Computers and Electronics in Agriculture. 33: 55–76.

Symons, S.J. and R.G. Fulcher (1988). Determination of wheat kernel morphological variation by digital image analysis, I Variation in eastern Canadian milling quality wheats. J. Cereal Sci. 8: 211–218.

Umbaugh, S.E (2005). Computer Imaging: Digital Image Analysis and Processing. Taylor & Francis, New York.

Uno, Y., S.O. Prasher, R. Laeroix, P.K. Goel, Y. Karimi, A .Viau, and R.M. Patel (2005). Artificial neural networks to predict corn yield from compact airborne spectrographic imager data. Computers and Electronics in Agriculture. 47:149–161.

Utans, J., E. Moody, and S. Rehfuss (1995). Input variable selection for neural networks: Application to predicting the U.S. Business cycle, in: proceeding of IEEE/IAFE computational Intelligence for Financial Engineering. pp.118-122.

Wang, L.X (1997). Design of fuzzy systems using gradient descent training. A course in fuzzy systems & control. Prentice Hall international , 168- 179. Inc Press.

Zapotoczny, P., M. Zielinska, and M. Nita (2008). Application of image analysis for the varietal classification of barley: Morphological features. J. Cereal Science. 48: 104–110.

Zhang, W., X.C. Bai and G. Liu (2007). Neural network modeling of ecosystems: a case study on cabbage growth system. Ecological Modelling. 201: 317–325.

Zhao-Yan, L., C. Fang, Y. Yi-bin and R. Xiu-qin (2005). Identification of rice seed varieties using neural network. J. Zhejiang University Science. 6B(11):1095-1100.