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Leaf identification of sesame varieties using artificial neural networks (MLP and Neuro-Fuzzy)

Alireza Pazoki [1*], Zohreh Pazoki [2], Farzad Paknejad [3]

[1]*Department of Agronomy and Plant breading, Shahr-e-Rey Branch, Islamic Azad University, Tehran, Iran*

[2]*Young Researchers and Elite Club, Central Tehran Branch, Islamic Azad University, Tehran, Iran*

[3]*Department of Agronomy, Karaj Branch, Islamic Azad University, Alborz, Iran*

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Abstract

This study focused on the identification of sesame leaf varieties using two artificial neural networks. Artificial neural network (ANN) is one of the efficient ways for solving complex problems such as identification tasks. This research was done in Islamic Azad University, Shahr-e-Rey Branch, during 2011 on 7 main sesame leaf varieties (Darab14, Dashtestan, Karaj1, Naz, Oltan, Varamin and Yekta) were grown in Varamin region of Iran. Different types of features (morphological, color, shape and chlorophyll) were extracted from color images using various methods. A multi layer perceptron (MLP) and Neuro-Fuzzy neural network were applied to classify leaf varieties. The MLP topological structure consisted of 42 input neurons, 7 output neurons and two hidden layers. The applied Neuro-fuzzy classifier had input and output layers as MLP and 60 rules instead of hidden layers. The identification accuracies computed 88.43% and 87.34% by MLP and Neuro-Fuzzy classifiers consequently, so the MLP classifier had better performance for classifying sesame leaf varieties.

* **Corresponding Author:** Alireza Pazoki ✉ pazoki@iausr.ac.ir

Introduction

Sesame (*Sesamum indicum* L.) is one of the ancient cultivated plants and oilseed in the world. 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.

Feature extraction is also a long discussed topic on how to extract or measure leaf features (Li *et al*., 2005, Nam *et al*., 2005, QI and Yang 2003, Hong *et al*., 2005). Many approaches employ k-nearest neighbor (k-NN) classifier (Du *et al*., 2007, Gu *et al*., 2005) while some papers adopted Artificial Neural Network (ANN). The classification of leaf genotypes cannot be easy using a special mathematical function because of the variation in morphology, Color and texture etc, so among all approaches, ANN has the fastest speed and best accuracy for classification work (Fu and Chi, 2006). Neural network classifiers have been successfully implemented for solving problems of agriculture such as grain and leaf quality inspection and especially their identification. Many studies have been reported on application of artificial neural networks (ANNs) in agriculture (Chen *et al*., 2010).

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 using UTA algorithm increased to 87.22%.

Heymans *et al* (1991) proposed an application of ANN to classify opuntia species. Wu *et al* (2007) applied a leaf recognition algorithm for plant classification using probabilistic neural network. Fu and Chi (2003) investigated combined thresholding and neural network approach for vein pattern extraction from leaf images.

The neuro-fuzzy systems are one of the most hybrid systems which apply a combination of artificial neural networks and fuzzy systems. Neuro-fuzzy techniques are finding a practical application in many fields such as in model 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. They indicated that the multi-NF system can solve classification problems which have many classes, but their efficiency increase when two classes are distinguished.

The specific goal was to extract the external features of sesame leaf varieties and evaluate MLP and Neuro-fuzzy neural network efficiencies for leaf identification.

Materials and methods

This study involved the identification of 7 sesame (*Sesamum indicum* L.) leaves were grown in Varamin region using MLP and Neuro-fuzzy neural networks. This research was done in Islamic Azad University, Shahr-e-Rey Branch during 2011. The experimented sesame leaves were included: Darab14, Dashtestan, Karaj1, Naz, Oltan, Varamin and Yekta (Figure 1).

Forty two features were extracted, these features fed to Multilayer Perceptron (MLP) and neuro-fuzzy networks for identification. The topological structure of this MLP model was consisted 42 neurons (24 color features, 11 morphological features, 4 shape and 3 chlorophyll factors) in the input layer, 7 neurons (sesame leaf varieties) in the output layer and two hidden layers with 30 neurons in first and 20 neurons in second hidden layers. The neuro-fuzzy network had the same size in input and output layers with 60 rules.

After training MLP and neuro-fuzzy networks using MATLAB version 7.8, the results applied for identification of sesame leaves.

Image acquisition

Digital image analysis offers an objective method for the estimation of morphological parameters.

This process used digital images to extract features and shape related information from the images.

A Panasonic camera (Model SDR-H90) with a zoom lens 1.5-105 mm in focal length was used to take ninety sampled leave's images from pods formation part of sesame main stem varieties. The format of the images was 24 bit color JPEG with a resolution of 360×640 pixels. The camera was mounted over an illumination chamber on a stand that provided easy vertical movement.

The distance between the camera and each leaf sample was 27 cm. In order to reduce the influence of surrounding light, a black illumination chamber was placed between the samples and the lens and ninety images were captured for each variety. The proposed method was implemented by a Pentium V personal computer with 4GB RAM and 2.67 GHz CPU. Sesame leaf varieties images are shown in Figure 1.

Image segmentation

Image segmentation proposed for processing image to classify an image into several regions according to the feature of image. It is useful in many applications and several image segmentation algorithms have proposed to segment an image before recognition or compression. One of the most efficient segmentation methods is histogram-based method. Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image.

After acquiring a color image, sesame leaves were isolated from their black background using a given threshold. Thresholding is an important part of image segmentation. The threshold value is generated according to the results of the histogram analysis and was constant for the same environment conditions. In this study, it was found that the red value was very different between the background and the objects. A fixed threshold value determined from the histogram of the red plane could separate the sesame leaves from its background (Zhao-Yan *et al.*, 2005). The average histogram to RGB of sesame leaf images is shown as Figure 2. There are two peaks in color's histogram. The left and right peaks refer to pixels related to the leaf and white background respectively. The lowest point between two peaks is around the value 110 on the average.

All the pixels with value more than 110 pixels were assigned the value 0, and all pixels with value less than 110 pixels were not processed in any operation. The level 0 area was the background, and the unchanged area was the sesame leaves region. Segmented images are shown in Figure 3.

Feature extraction

In this research, color, morphological features, shape factors and chlorophyll factor were used for identifying individual sesame leaves. These features were assessed with MATLAB version 7.8.

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 for feature extraction. There are several color spaces. In order to study the effect of color features on the identification performance of sesame leaf 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 one used for images on computer. An RGB image, sometimes referred as a truecolor 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 software do not support the HSI color space (Hue

Saturation Intensity). Therefore, we used the HSV color space, which is very similar to HSI.

From the red (R), green (G), and blue (B) color bands of the image, hue (H), saturation (S), and value (V) were calculated using the following equations (Image Processing Toolbox 2007):

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

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

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

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

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

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

YCbCr: The Y element represents the luminance component, and the Cb, Cr elements represent two chrominance components. Component Cb is the difference between the blue component and a reference value. Component Cr is the difference between the red component and a reference value.

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

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

Furthermore, mean (m) and standard deviation (d) of these color components were calculated for each image by MATLAB 7.8. In total, 24 color features were extracted for identification.

Morphological feature extraction

The following morphological features were extracted from labeled images of individual sesame leaf varieties. Geometry related features include area, perimeter, and major and minor axis lengths, which were measured from the binary images (Paliwal *et al.*, 2001, Zhao-Yan *et al.*, 2005).

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

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

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

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

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

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

$$\text{Equadial} = \sqrt{\frac{4 \times \text{Area}}{\pi}} \quad (9)$$

Convex area (C): It was the number of pixels in the smallest convex polygon that could contain the sesame leaves region.

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

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

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

$$R=\frac{4\times\pi\times \text{Area}}{\text{Perimeter}^2} \qquad (10)$$

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

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

Shape factors

From the axis length and area, shape factors were derived (Symons and Fulcher, 1988a) with the following formulas:

$$\text{Shape factor 1(SF1)}:\frac{\text{Major axis length}}{\text{Area}} \qquad (12)$$

$$\text{Shape factor 2(SF2)}:\frac{\text{Area}}{\text{Major axis length}^3} \qquad (13)$$

$$\text{Shape factor 3(SF3)}:\frac{\text{Area}}{(\text{Major axis length}/2)(\text{Major axis length}/2)} \qquad (14)$$

$$\text{Shape factor 4(SF4)}:\frac{\text{Area}}{(\text{Major axis length}/2)(\text{Minor axis length}/2)} \qquad (15)$$

The feature vector was comprised of all of the assessed features. The vector was entered into two artificial neural networks which were called the Multi Layer Perceptron (MLP) network and neuro-fuzzy for sesame leaves identification.

Chlorophyll factors

Chlorophyll is a green pigment that absorbs sun's radiation and uses its energy to synthesis carbohydrates from CO_2 and water. Chlorophyll a (Chl a) is one kind of chlorophylls. It absorbs most energy from wavelengths of violet-blue and orange-red light. Chlorophyll b (Chl b) is another form of chlorophyll and absorbs blue light. Arnon's method used for evaluating Chlorophyll a, b and a+b, so 500 mg of fresh leaf selected randomly from each sesame leaf variety and ground by pestle and mortar with 10 ml of 80% acetone. The homogenate was centrifuged at 2500 rpm for 15 minutes. The residue was re-extracted with 80% acetone and obtained supernatant applied for chlorophylls measurement. The samples absorbance was measured at 645 and 663 nm wavelengths and replaced in arnon (1949) equation as bellow:

$$\begin{cases} Chla = 0.0127A_{663} - 0.00269A_{645} \\ Chlb = 0.0229A_{645} - 0.00468A_{663} \\ Chla+b = 0.0202A_{645} + 0.00802A_{663} \end{cases} \qquad (16)$$

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 paper, Multi Layer Perceptron network (MLP) and Neuro-fuzzy network based on back propagation learning rule were used to classify leaf 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 Multi Layer Perceptron (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 within an 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 42 neurons because the data sets contained 42 parameters and 7 neurons (Darab14, Dashtestan, Karaj1, Naz, Oltan, Varamin and Yekta) in the output layer. The applied training structure for leaf varieties identification was 42-30-20-7. Typical Multilayer perceptron neural network architecture is shown in Figure 4.

Neuro-fuzzy classification network

Many different systems have been applied in identification 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 rules. The fuzzy system was derived as follow (Wang, 1997):

$$f(x)=\frac{\sum_{l=1}^{M}\bar{y}^{l}\left[\prod_{i=1}^{n}\exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n}\exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]} \qquad (17)$$

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 equation (17) as a feed forward network.

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):

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

$$z^l = \prod_{i=1}^{n}\exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right) \qquad (18)$$

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

$$b = \sum_{l=1}^{M} z^l \qquad (19)$$

$$a = \sum_{l=1}^{M} \bar{y}^l z^l \qquad (20)$$

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

$$F = \frac{a}{b} \qquad (21)$$

Neuro-fuzzy system for leaf identification of sesame leaf varieties is shown in Figure 5.

Results

This study involved the leaf identification of sesame varieties using an algorithm based on images of 7 varieties. There were 90 images for each variety. The format of the images was 24 bit color JPEG and the size of each image was 360×640 pixels.

Table 1. Varieties accuracy for MLP and Neuro-Fuzzy neural networks.

Neural networks	Varieties accuracy (%)							Average accuracy (%)
	Darab14	Dashtestan	Karaj1	Naz	Oltan	Varamin	Yekta	
MLP	85.71	90.47	91.42	89.04	85.71	90.95	85.71	88.43
Neuro-Fuzzy	83.80	89.04	90.00	91.42	85.71	89.04	82.38	87.34

There were 60 training data set and 30 test data set for each sesame leaf varieties (420 training data and 210 test data for 7 experimented leaf varieties).

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, Perimeter, Major axis length, Minor axis length, Aspect ratio, Equivalent diameter, Convex area, Solidity, Extent, Roundness and Compactness) extracted from image of varieties that features such as area, perimeter, major and minor axis length computed on the binary image using MATLAB 7.8 software. Four shape factors (SF1, SF2, SF3 and SF4) were derived from these main geometric features. Three chlorophyll factors (Chl a, Chl b and Chl a+b) were extracted from calibration equations from the index value.

By trying the MLP and neuro-fuzzy neural networks, accuracies were evaluated (Table 1). The average accuracy in MLP and neuro-fuzzy neural networks were 88.43 % and 87.34% respectively.

Discussion

In this paper we described the development of two neural networks that gives users the ability to classify sesame leaf varieties based on color and morphological features and shape factors took by a Panasonic camera (Model SDR-H90) and chlorophyll content factor measured with Arnon method.

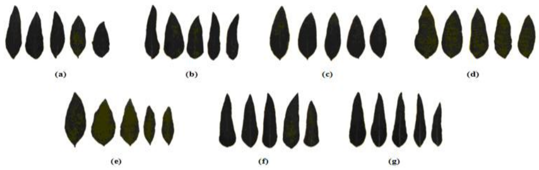

Fig. 1. Sesame leaf varieties: Darab14, Dashtestan, Karaj1, Naz, Oltan, Varamin and Yekta.

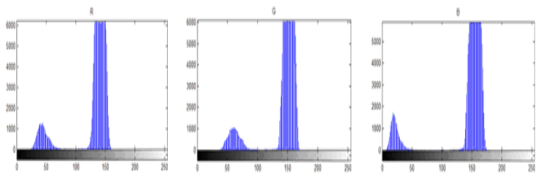

Fig. 2. RGB (Red, Blue, Green) histogram.

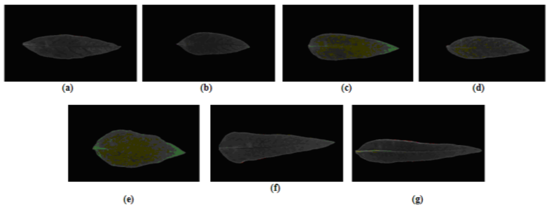

Fig. 3. Sesame leaf varieties after segmentation: Darab14, Dashtestan, Karaj1, Naz, Oltan, Varamin and Yekta.

The results indicated that the average performance of neuro-fuzzy classifier was near to MLP. In this case, maximum accuracy belonged to Karaj1 in MLP and Naz in neuro-fuzzy (91.42%) and the lowest one gained for Darab14, Oltan and Yekta (85.71%) using MLP and Yekta (82.38%) by neuro-fuzzy classifiers (Table 1), consequently in any cases the accuracy for sesame leaf varieties was not lower than 82.33%, so it conducts that the mentioned results can be successfully employed for leaf identification with lowest time and costs. Similar results were obtained by Gang Wu *et al* (2007) where was used a neural network with image and data processing methods to implement general purpose automated leaf recognition for plants classification. The applied technique classified 32 kinds of plants (instead of sesame) with accuracy more than 90%.

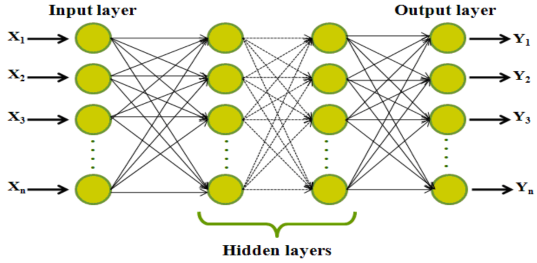

Fig. 4. Multilayer perceptron neural network.

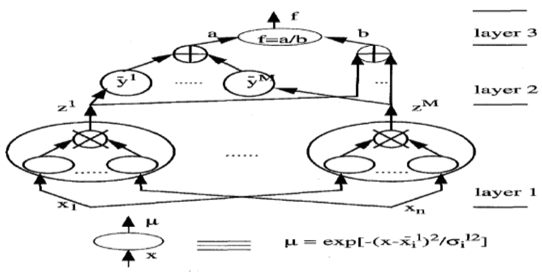

Fig. 5. Network representation of the fuzzy system (Wang, 1997).

Conclusion

The development and use of digital image analysis based on morphological, color features and chlorophyll factors for sesame leaf identification depends on capability of accurate identification for different varieties. In this study, MLP and neuro-fuzzy neural networks presented for identifying seven sesame leaf varieties. All 630 leaves investigated, and 42 features extracted from each leaf by MATLAB version 7.8. The average identification accuracy for sesame leaf varieties was up to 86%. The MLP and neuro-fuzzy method's efficiency for leaf varieties were near to each other.

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