Saeideh Fayyazi[1,2] / Mohammad Hossein Abbaspour-Fard[3] / Abbas Rohani[3] / S. Amirhassan Monadjemi[4] / Hassan Sadrnia[3]

Identification and Classification of Three Iranian Rice Varieties in Mixed Bulks Using Image Processing and MLP Neural Network

[1] Department of Biosystems Engineering, College of Agriculture, Shiraz University, Shiraz, Iran, E-mail: s.fayyazi@shirazu.ac.ir
[2] Department of Agricultural Machinery Engineering, College of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran, E-mail: s.fayyazi@shirazu.ac.ir
[3] Department of Biosystems Engineering, College of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran, E-mail: abaspour@um.ac.ir, arohani@um.ac.ir, Hassan.sadrnia@um.ac.ir
[4] Department of Computer Engineering, College of Engineering, University of Isfahan, Isfahan, Iran, E-mail: monadjemi@eng.ui.ac.ir

Abstract:
Due to variation in economic value of different varieties of rice, reports indicating the possibility of mixing different varieties on the market. Applying machine vision techniques to classify rice varieties is a method which can increase the accuracy of classification process in real applications. In this study, several morphological and textural features of rice seeds' images were examined to evaluate their efficacy in identification of three Iranian rice varieties (Tarom, Fajr, Shiroodi) in their mixed samples. On the whole, 666 images of rice seeds (222 images of each variety) were acquired at a stable illumination condition and totally, 17 morphological and 41 textural features were extracted from seeds images. Principal component analysis (PCA) method was employed to select and rank the most significant features for the classification. Subsequently, the MLP neural network classifier was employed for classification of rice varieties in the mixed bulks of three and two varieties, using top selected features. The network was three-layered feed forward type and trained using two training algorithms (BB and BDLRF). The classification accuracy of 55.93, 84.62 and 82.86 % for Fajr, Tarom and Shiroodi, 86.96 and 93.02 % for Fajr and Shiroodi, 86.84 and 96.08 % for Tarom and Shiroodi and 91.49 and 95.24 % for Fajr and Tarom were obtained in test phase, respectively.

Keywords: rice, morphological features, textural features, image processing, MLP neural network
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1 Introduction

Rice is one of the major world food products and is the principal nutrition of Iranian people after wheat, so the study on its various aspects is of the utmost importance to ensure that the required quality of product is provided and can also attract customers. One of the factors that reduce the quality of rice and consequently reduce customer satisfaction is because of impure samples, i. e. some other low-valued varieties are mixed with the desirable variety mistakenly or intentionally. In this regard, samples of rice should be controlled before launch to ensure its purity. Thus, we need methods and techniques that can detect and identify different varieties in mixed bulks. Although, it is now possible to identify pure and impure bulks, but these methods are mostly manual and are done by manpower, so they are time consuming. Thus unmanned, semi-automatic procedures, which have less dependence on manpower, can be used in order to control the mixed samples under consideration. Overview of studies on image processing techniques shows that its combination with classification methods like artificial neural networks (ANN) can have potential ability for these applications.

Although the concept of ANN analysis was almost discovered 50 years ago, only in the last two decades its application software has been developed to handle practical problems. ANN basically provides a non-deterministic mapping between sets of random input–output vectors. Absence of any preliminary assumed relationship between input–output quantities, in-built dynamism and robustness toward data errors, are some advantages of this technique over statistical methods [1]. The ANN approach has been successfully employed in cereal classification and the following studies are efforts in that direction.

Saeideh Fayyazi is the corresponding author.

Liu, Ouyang, Wu and Ying [2] used machine vision technology as an automatic method for identifying different variety of rice seeds. Color features in RGB (red, green, blue) and color spaces were computed. A back-forward neural network was trained to identify rice seeds. The identifying accuracies of rice varieties ranged from 82.82 % to 99.99 %. Verma [3] used morphological features from rice kernels for grading and classification of rice. The developed machine vision system was able to sort rice into sound, cracked, chalky, broken and damaged kernels with an accuracy ranging from 90–95 %. Wu, Liu and Ouyang [4] investigated the real-time identification of seed rice variety by machine vision technology. The features of the images were extracted by image processing and the seed varieties were identified by back-propagation (BP) neural network. The identifying accuracies of five rice varieties ranged from 78.82 % to 99.99 %. Jana et al. [5] classified aromatic and non-aromatic rice using electronic nose and ANN. With unknown rice samples, aroma-based classification accuracy observed to be more than 80 %. Marini et al. [6] classified six durum wheat cultivars from Sicily (Italy) using ANNs. Two different ANN architectures (multi-layer feed-forward, MLF-NN, and counter propagation, CP-NN) were used. When considering predictive ability over an independent test set, counter propagation NN performed the best, being able to correctly predict about 82 % of the external validation samples. Pazoki and Pazoki [7] used ANN as a classification system for rain-fed wheat grain cultivars. First, data on six colors, 11 morphological features and four shape factors were extracted, then these candidate features were fed into a Multilayer Perceptron (MLP) neural network. The average accuracy of classification of rain-fed wheat grains cultivars was 86.48 % and after feature selection application with UTA (utility additive) algorithm, the accuracy increased to 87.22 %.

OuYang, Gao, Sun, Pan and Dong [8] used machine vision technology for identifying different varieties of rice. Color features in RGB and color spaces were computed. A back-forward neural network was trained to identify rice seeds. The accuracy of classification for five rice varieties under study ranged from 82.82 % to 99.99 %. MousaviRad, Akhlaghian Tab and Mollazade [9] developed an algorithm for classifying five varieties of rice (Fajr, Neda, Hashemi, Mahali and Gerde), using the color and texture features. The most significant features for classification were selected using four methods based on: Branch and bound, standard forward sequential, standard backward sequential, and plus-l-takeaway-r algorithm. A BP neural network-based classifier was developed to classify the rice varieties. The overall classification accuracy was achieved as 96.67 %. MousaviRad, Rezaee and Nasri [10] identified the above rice varieties with another method, using morphological features and an ensemble classifier (combination of K-nearest neighbor, Support vector machine, BP neural network classifiers). SFS (sequential forward selection) algorithm was employed for features selection. The overall classification F-measure was achieved as 99.86. Liu, Cheng, Ying and Rao [11] developed a digital image analysis algorithm to identify six varieties of rice seeds (ey7954, syz3, xs11, xy5968, xy9308 and z903). Seven color and fourteen morphological features were used for discriminant analysis. To optimize the number of features that contributed significantly to the classification, PROC STEPDISC was used and 17 features were selected. Neural network was used to identify rice seed varieties. The identification accuracies ranged from 74 % to 95 %. Silva and Sonnadara [12] presented a neural network (MLP) approach for classification of nine rice varieties (AT307, BG250, BG358, BG450, BW262, BW267, W361, BW363 and BW364). Morphological, color and textural features were extracted from color images of individual seed samples. Different neural network models were developed for individual feature sets and for the combined feature set. In order to reduce the dimension of the input feature set, principal component analysis (PCA) was applied. An overall classification accuracy of 92 % was obtained from combined feature model. Guzman and Peralta [13] investigated the use of a machine vision system and multilayer neural networks (MLP) for automatic identification of the sizes and shapes of five varietal groups of Rough rice seed in the Philippines (lowland irrigated, lowland rainfed, saline prone, cool elevated and upland). Several MLP were developed for sizes, shapes and varietal types of classification, using morphological features. The ANNs classifiers were able to identify the grain sample sizes and shapes at overall average accuracies of 98.76 % and 96.67 %, respectively.

These research works indicate that the combination of image processing technique with ANNs is a feasible approach for identification and classification of different grains such as rice. The aim of this study was to develop an image processing technique to identify three Iranian rice varieties using images captured from their mixed bulks. This can help the market authorities to detect the impure bulks of rice and prevent any rice market fraud. Several morphological and textural features were extracted and their capabilities in rice varieties identification were evaluated. In order to achieve the highest classification accuracy, the optimum set of different morphological and textural features was selected by PCA method, and subsequently fed into neural network classifier. Finally, the classification accuracy of the rice varieties was evaluated in test phase. Having specified the classification accuracy in test phase, it is possible to achieve the same accuracy in every mixed bulk.

Based on the literature review, in spite of developing several methods for identification and classification of various rice varieties such as Iranian varieties, this paper aims to improve the accuracy of identification and classification of rice varieties by combination of morphological and textural features in conjunction with the PCA method for feature selection and also incorporation of the MLP neural network using two different algorithms. More specifically the approach is used for identification and classification of three Iranian rice varieties.

2 Materials and methods

2.1 Grain samples

Three Iranian rice seed varieties (Tatom, Fajr and Shiroodi) were considered. Grain samples were acquired from Sari region in the north of Iran. The images of each variety were taken from same distance and under the same illumination and moisture conditions.

2.2 Image acquisition

A total of 222 images were taken from each variety. A CCD camera (Sony DSC-H1) was employed for image acquisition and 4X zoom adjustment was applied to fill the camera field of view with samples and the images were taken from mixed samples (with separated kernels). Figure 1shows the single kernel of each variety.

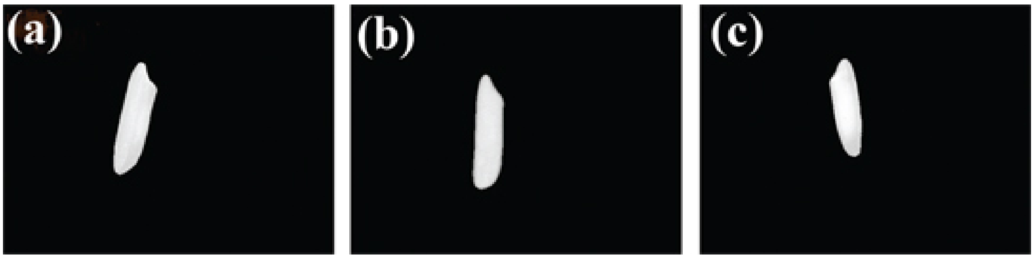

Figure 1: Gray-scale images of three Iranian rice seeds with identical zoom and distance adjustments (a) Fajr, (b) Shiroodi, (c) Tarom.

A cubic box with black internal surfaces was used for imaging and its door was closed for imaging to avoid any light reflection and shade interventions. Two fluorescent lights on the ceiling of the box (inside the box) were installed for illumination. A hole in the middle of the roof was provided for camera installation with fixed lens distance. A schematic of the imaging box is shown in Figure 2.

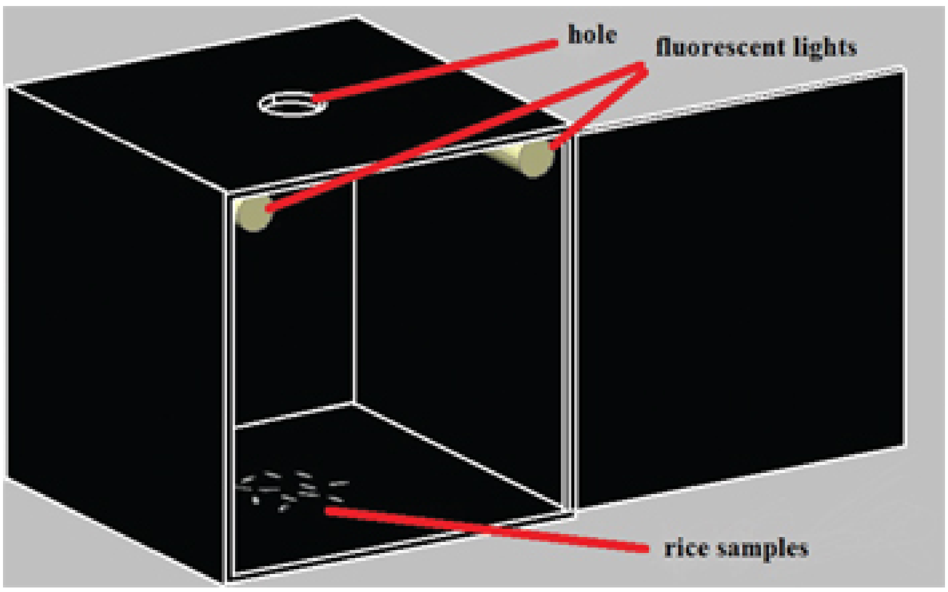

Figure 2: A schematic of the imaging box.

2.3 Image preprocessing and segmentation

The purpose of preprocessing is to improve the image by reducing unwanted defects and making prominent the features that are important for future processing. Noise removing is one of these stages. Images that are taken by CCD cameras may have different types of noises. In this study, after taking the pictures, the background was not completely uniform and had some bright spots. Because of the white color of the rice kernels, it could be a problem for thresholding and segmentation. Therefore, before binarization of images, a mean filter was applied on the images, resulting in a smoother image. Then the picture was segmented and the zero value assigned to the background pixels and 1 assigned to the foreground pixels. As a result, the background and kernels were shown with black and white colors, respectively. The binarization process, i. e. the original image transformed to a binary image was only applied for extracting morphological features. For extracting textural features, the binary images were multiplied by the original images, so the zero value was assigned to background and the foreground pixels remained without any change. Then the segmented images were labeled so that every kernel became identifiable from other kernels.

2.4 Feature extraction

In this study, both morphological and textural features of rice kernels were considered. For each monochrome image of the seeds, according to literatures, 41 textural and 17 morphological features were extracted. For extracting these features, some algorithms were developed in Matlab software (version 7.7).

2.4.1 Textural features

Textural features include: 25 gray-level textural features (mean, standard deviation, smoothness, third moment, uniformity, entropy, 7 moment invariants and 12 histogram groups (HG)), 6 features of local binary pattern (LBP) matrix (mean, standard deviation, smoothness, third moment, uniformity, entropy), 10 gray-level co-occurrence matrix (GLCM) features (mean, variance, entropy, uniformity, homogeneity, inertia, cluster shade, cluster prominence, maximum probability and correlation). The corresponding equations for the textural features are shown in Table 1and Table 2. The definition of parameters in the equations can be obtained from Gonzalez and Woods [14], and Majumdar and Jayas [15].

Table 1: Features extracted from gray and LBP matrices [14].

Feature	Equation
Mean	$\mu = \sum_i p(i)$
Standard deviation	$\sigma = \sqrt{\sum_i (i-\mu)^2 p(i)}$
Smoothness	$1 - 1/(1+\sigma^2)$
Third moment	$\sum_i (i-\mu)^3 P(i)$
Uniformity	$\sum_i P(i)^2$
Entropy	$-\sum_i P(i) \log\{p(i)\}$

Table 2: Features extracted from GLCM matrix [15].

Feature	Equation
Mean	$\mu = \sum_{i,j} iP(i,j)$
Variance	$\sigma^2 = \sum_{i,j} (i-\mu)^2 P(i,j)$
Entropy	$-\sum_{i,j} P(i,j) \log\{p(i,j)\}$
Uniformity	$\sum_{i,j} \{P(i,j)\}^2$
Homogeneity	$\sum_{i,j} P(i,j)/\left\{1+(i-j)^2\right\}$
Inertia	$\sum_{i,j} (i-j)^2 P(i,j)$

Cluster shade	$\sum_{i,j}(i+j-2\mu)^3P(i,j)$
Cluster prominence	$\sum_{i,j}(i+j-2\mu)^4P(i,j)$
Maximum probability	$\max\{p(i,j)\}$
Correlation	$\sum_{i,j}(i-\mu)(j-\mu)/\sigma^2P(i,j)$

In order to extract histogram group features (HG1– HG25) from gray matrix, 256 gray values were grouped into 25 histogram bands and the number of pixels in each band was counted [16]. Due to the zero values of bands 2–14, only the remaining 12 bands including HG1, HG15-HG25 were used.

2.4.2 Morphological features

Morphological features include area (number of pixels in the segmented region), eccentricity (ratio of the distance between two center of ellipse to its major axis length), extent (ratio of the number of pixels of segmented region to the number or pixels of smallest environmental rectangle), solidity (ratio of the number of pixels of the segmented region to the number of pixels of environmental convex polygon), diameter (the maximum distance between two pixels in the region), major axis length (the length of the smallest environmental rectangle), minor axis length (the width of the smallest environmental rectangle), roundness (ratio of the area of segmented region to the area of smallest environmental circle), Feret diameter (the diameter of a circle that its area is equal to the area of segmented region), perimeter (the number of the boundary pixels of segmented region), aspect ratio (ratio of major axis length to the minor axis length) and six moments that acquired from the boundary of each kernel. For calculating these moments, first the boundary ($g(r)$) is normalized and then it is treated as a histogram. In other words, $g(r_i)$ is evaluated as the probability of happening r_i. Here r is a random variable and K is the number of boundary points and moments are calculated from the following equation [14]:

$$\mu_n=\sum_{i=0}^{K-1}(r_i-m)^n g(r_i) \tag{1}$$

where

$$m=\sum_{i=0}^{K-1}r_i g(r_i) \tag{2}$$

2.5 Feature selection

The PCA method was employed to determine the features with the highest level of contribution to the classification. This method was performed using MATLAB software. All extracted features were evaluated and ranked.

PCA is a method of orthogonalizing data. Its main idea is finding the directions in which a set of data points is stretched most (eigenvectors of data correlation matrix), and then finding the projections of data points on these directions (principal components). Finally representing the data points only with a few principal components that are correspondent with the larger eigenvalues [17].

2.6 Data preprocessing

After applying the PCA method on 58 extracted morphological and textural features of every seed, the features with the highest level of contribution to the classification were acquired according to PCA basics. Then these features were selected as variable inputs and three rice varieties (Tarom, Fajr and Shiroodi) were selected as variable outputs for neural network. Prior to any ANN training process with the trend free data, the input data must be normalized over the range of [0,1]. This is necessary for the neurons' transfer functions, because a sigmoid function is calculated and consequently these can only be performed over a limited range of values. If the data used with an ANN are not scaled to an appropriate range, the network will not converge on training or it will not produce meaningful results. The most commonly employed method of normalization involves mapping the data linearly over a specified range, whereby each value of a variable x is transformed as follows [1]

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (r_{\max} - r_{\min}) + r_{\min} \tag{3}$$

where x is the original data, x_n the normalized input or output values, $x_{\max}$ and $x_{\min}$, are the maximum and minimum values of the concerned variable, respectively. $r_{\max}$ and $r_{\min}$ correspond to the desired values of the transformed variable range. A range of 0.1–0.9 is appropriate for the transformation of the variable onto the sensitive range of the sigmoid transfer function.

Subsequently, the normalized input data were shuffled and split into two subsets: a training set and a test set. The splitting of samples plays an important role in the evaluation of an ANN performance. The training set is used to estimate model parameters and the test set is used to check the generalized ability of the model. The training set should be a representative of the whole population of input samples. In this study, the training set and the test set include 80 % and 20 % of total data, respectively. There is no acceptable generalized rule to determine the size of training data for a suitable training; however, the training sample should cover all spectrums of the data available [18]. The training set can be modified if the performance of the model does not meet the expectations [19]. However, by adding new data to the training samples, the network then can be retrained.

2.7 The multilayer perceptron neural network

For identification of rice varieties in mixed samples, multilayer perceptron (MLP) neural network was used. Among various ANN models, MLP has maximum practical importance. MLP is a feed-forward layered network with one input layer, one output layer and some hidden layers. Figure 3shows a MLP with one hidden layer. Every node computes a weighted sum of its inputs and passes the sum through a soft nonlinearity. The soft nonlinearity or activity function of neurons should be non-decreasing and differentiable. The most popular function is unipolar sigmoid [17]:

$$f(\theta) = \frac{1}{1 + e^{-\theta}} \tag{4}$$

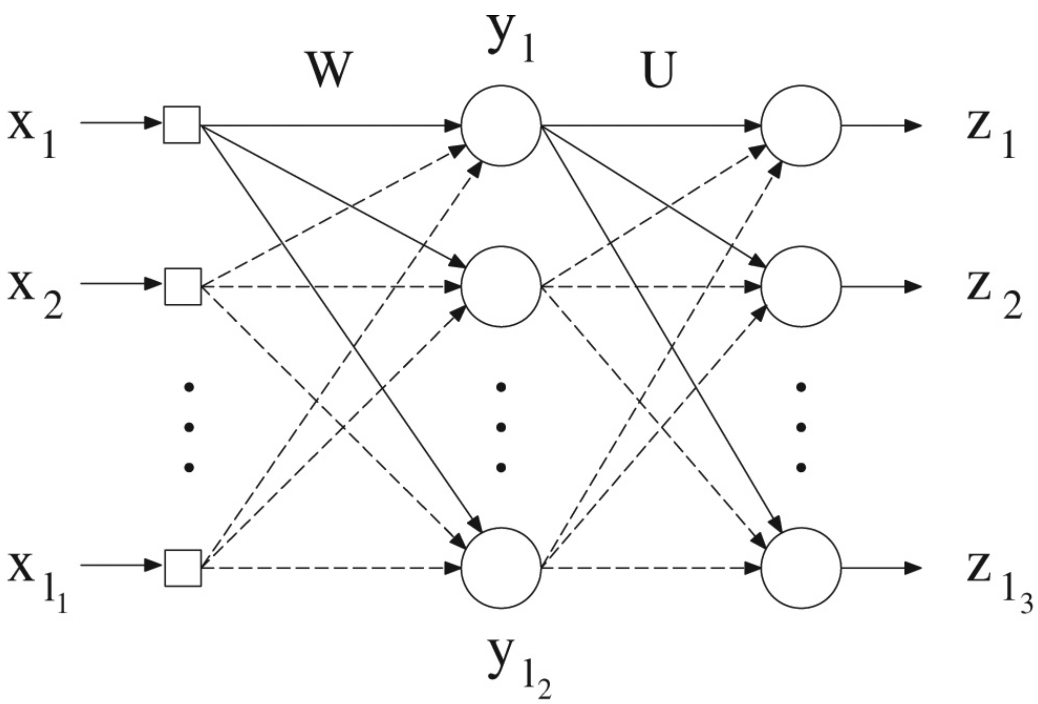

Figure 3: Configuration of the MLP with one hidden layer [17].

The network is in charge of vector mapping, i. e. by inserting the input vector, x^q the network will answer through the vector z^q in its output (for $q = 1, \ldots, Q$). The aim is to adapt the parameters of the network in order to bring the actual output z^q close to corresponding desired output d^q (for $q = 1, \ldots, Q$). The most popular method of

MLP training is the BP algorithm, and in literatures there exist many variants of this algorithm. This algorithm is based on minimization of a suitable error cost function. In this study, two variants of MLP training algorithm, i. e. Basic Back-propagation (BB) and Back-Propagation with Declining Learning-Rate Factor (BDLRF) were employed [17].

An ANN model was developed in Matlab software in order to identify three rice varieties. The network was three-layered feed forward type, trained using both BB and BDLRF training algorithms.

2.7.1 BB algorithm

In this algorithm the total sum-squared error (TSSE) is considered as the cost function and can be calculated as

$$TSSE = \sum_q E_q \tag{5}$$

$$E_q = \sum_k (d_k^q - z_k^q)^2 \qquad for \quad (q = 1, \dots, Q) \tag{6}$$

where d_k^q and z_k^q are the k^{th} components of desired and actual output vectors of the q^{th} input, respectively. Network learning happens in two phases: forward pass and backward pass. In forward pass an input vector is inserted to the network and the network outputs are computed by proceeding forward through the network, layer by layer:

$$\begin{cases} net_j = \sum_i x_i w_{ij} \\ y_j = \frac{1}{1+e^{-net_j}} \end{cases} , \quad j = 1, \dots, l_2 \tag{7}$$

$$\begin{cases} net_k = \sum_j y_j u_{jk} \\ z_k = \frac{1}{1+e^{-net_k}} \end{cases} , \quad k = 1, \dots, l_3 \tag{8}$$

where w_{ij} is the connection weight between nodes i and j, and u_{jk} is the connection weight between nodes j and k; w_{ij} and u_{jk} are set to small random values [−0.25, 0.25]; l_2 and l_3 are the number of neurons in the hidden and output layers. In backward pass the error gradients versus weight values, i. e. $\frac{\partial E}{\partial w_{ij}}$ (for $i = 1, \dots, l_1$, $j = 1, \dots, l_2$) and $\frac{\partial E}{\partial u_{jk}}$ (for $j = 1, \dots, l_2$, $k = 1, \dots, l_3$) are computed layer by layer starting from the output layer and proceeding backwards. The connection weights between nodes of different layers are updated using the following equations:

$$u_{jk}(n+1) = u_{jk}(n) - \eta \times \frac{\partial E}{\partial u_{jk}} + \alpha(u_{jk}(n) - u_{jk}(n-1)) \tag{9}$$

$$w_{ij}(n+1) = w_{ij}(n) - \eta \times \frac{\partial E}{\partial w_{ij}} + \alpha(w_{ij}(n) - w_{ij}(n-1)) \tag{10}$$

where η is the learning rate adjusted between 0 and 1, α is the momentum factor at interval [20]. Momentum factor is used to speed up the convergence. The decision to stop training is based on some test results of the network, which is carried out every N epoch after TSSE becomes smaller than a threshold value. The details could be seen in Vakil-Baghmisheh and Pavešic [21]. The number of input and output nodes is determined by functional requirements of the ANN.

2.7.2 BDLRF algorithm

We have also used a modified version of BB algorithm which is Back-Propagation with Declining Learning-Rate Factor (BDLRF) algorithm [22]. This training algorithm is started with a relatively constant large step size of learning rate η and momentum term α. Before destabilizing the network or when the convergence is slowed down, choose a point (n_1), after that for every T epoch ($3 \le T \le 5$) the values of α and η are decreased monotonically by means of arithmetic progression, until they reach to x% (equals to 5) of their initial values. η (and similarly α) was decreased using the following equations:

$$m = \frac{Q - n_1}{T} \tag{11}$$

$$\eta_n = \eta_0 + n\eta_0 \frac{x-1}{m} \tag{12}$$

where m, n_1, η_n and η_0 are the total number of arithmetic progression terms, the start point of BDLRF, the learning rate in nth term of arithmetic progression, and the initial learning rate, respectively.

2.8 Performance evaluation criteria

To evaluate the performance of a model some criteria have been defined. These criteria include total sum of squared error (TSSE) and the percentage of recognition error (R.E.(%)).

R.E.(%)=(the total number of samples that are classified incorrectly in the last epoch of training phase/the total number of input samples to this phase)×100 **(13)**

3 Results and discussion

3.1 Feature selection

Analysis of each feature's contributions to the principal components shows valuable information about the importance of each in the dataset. Within these components, HG24, HG21, cluster prominence, cluster shade, HG23 and HG22 are the important features

3.2 MLP topology (number of neurons in the hidden layer)

Based on universal approximation theorem, a neural network with a single hidden layer and sufficiently a large number of neurons can well approximate any arbitrary continuous function [23]. Therefore, the ANN designed in this study was equipped with a single hidden layer. Determination of the number of neurons in the hidden layer is rather an art than science, because it may vary, depending on the specific problem under study. In this study, the optimal number of neurons in the hidden layer was selected using a trial-and-error approach and keeping the learning rate, momentum term and epoch size constant (η = 0.4, α = 0.8 and epoch = 10,000). Table 3shows the effect of number of neurons in the hidden layer on the performance of BB-MLP model. It is observed that the performance of BB-MLP is improved as the number of hidden neurons increased. However, too many neurons in the hidden layer may cause over-fitting problems, which results in good network learning and data memorization, but lack of ability to generalize. On the other hand, if the number of neurons in the hidden layer is not enough, the network may not be able to learn. Considering Table 3, a BB-MLP model with eight neurons in the hidden layer seems to be appropriate for identifying three rice varieties, because the recognition error percent and TSSE is the least in this number of neurons.

Table 3: Performance variation of a three-layer BB-MLP with different number of neurons in the hidden layer.

Criterion	**Number of neurons in the hidden layer**								
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TSSE*	218.62	187.76	177.12	160.52	157.53	144.44	130.58	131.04	136.19
R.E. (%)	39.96	26.27	25.33	22.33	21.01	19.32	17.82	19.51	18.20

* TSSE is estimated during training phase.

3.3 Learning rate and momentum term

In order to speed up convergence, an extra term called momentum (α) is used to the weights update [17, 24]. The learning rate and momentum factors are only used in the learning process, so the criteria used to optimize them are based on the learning error and the iteration number. When the optimal topology of the neural network was found, the learning rate (η) and momentum term (α) was also optimized throughout a trial–error method. For the selected topology, several learning processes were performed with different coefficients, ranged from 0.1 to 0.99 and 0 to 0.99 for learning rate and momentum term, respectively.

Figure 4shows the total sum of squared error (TSSE) values versus the learning rate and momentum term. The learning rate and momentum factors have interactive impacts on network training. This makes parameter tuning a difficult task where momentum term is added. It is observed that the error value is increased and the convergence speed of the learning process is decreased as the learning rate is growing. Also, with a very high learning rate and momentum term (close to 1), the neural network will not converge to its true optimum and the learning process will be instable. It is also evident that, the convergence speed of the learning process was improved through an appropriate choice of parameters η and α. The optimum factors for these two parameters must reach the minimum error in the lower iteration number. So according to Figure 4, 0.2 and 0.6 were used as optimal parameters for learning rate and momentum term, respectively.

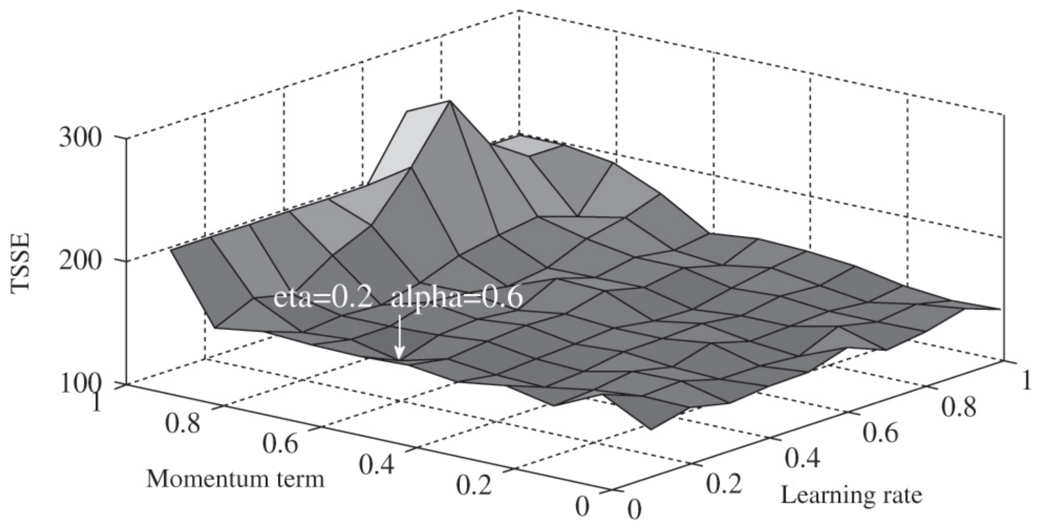

Figure 4: TSSE profile as a function of learning rate and momentum term.

According to Vakil-Baghmisheh and Pavešic [22], in order to improve the behavior of MLP during training, and due to simplicity of adjusting process of network parameters, we also used BDLRF algorithm. The results obtained by BDLRF have shown that the best performance of MLP was obtained via a constant momentum term equals to 0.8. Therefore, when the convergence was slowed down, a point was chosen for n_1 and η was only decreased using eq. (12). The initial and final values of η were 0.8 and 0.04, respectively. In this study, 600 epochs was selected as start point of the BDLRF (n_1) according to Figure 5. After this point, for every 5 epochs, parameter η (and similarly α) was calculated using eq. (12). The epochs were the same in both BB and BDLRF algorithms.

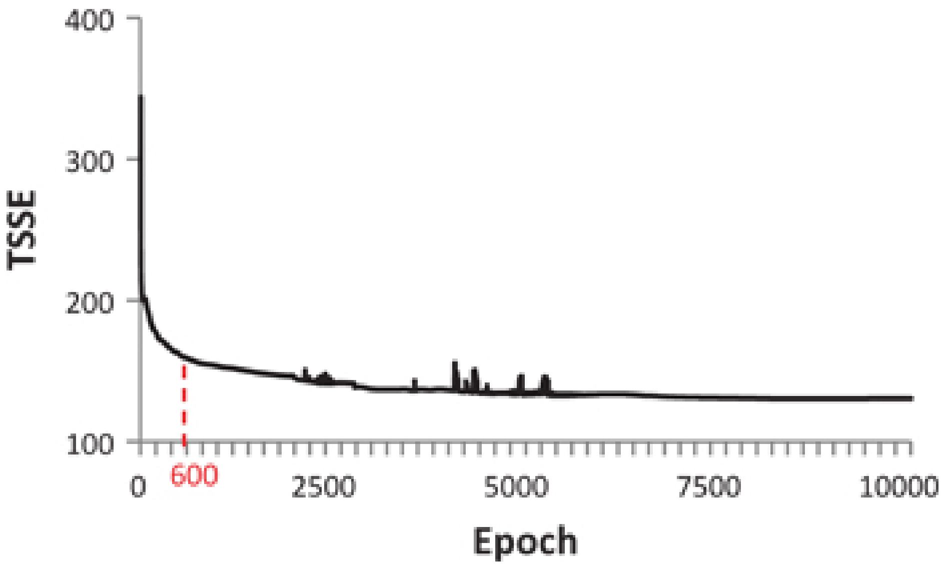

Figure 5: Number of epochs as start point of the BDLRF algorithm (n_1).

3.4 Classification accuracy for three rice varieties

3.4.1 Training phase

Training phase of the network started using the training data set. Training was continued until a steady state was reached. The BB and BDLRF algorithms were utilized for model training. Classification accuracies values in the training phase with different training algorithms are shown in Table 4. As it can be seen, by using BB algorithm, the classification accuracy of Fajr variety is better than using both (BB and BDLRF) algorithms, but the classification accuracy of the other two varieties (Tarom and Shiroodi) is better by using both algorithms. In general, the classification accuracies of Tarom and Shiroodi varieties are better than that of Fajr for BB and combined BB and BDLRF algorithms. This can probably be due to high similarity of this variety to other two varieties. Therefore, the network could not learn the training data set of this variety well and hence some errors occurred. Since the classification accuracy of other two varieties (Tarom and Shiroodi) is good, it can be found that the neural network has been learned the training set, hence the training phase has been completed.

Table 4: Classification accuracies of three rice varieties.

	Training algorithm	Variety	Accuracy
Training phase	BB	Fajr	69.14
		Shiroodi	82.32
		Tarom	93.79
	BB and BDLRF	Fajr	63.80
		Shiroodi	83.96
		Tarom	93.99
Test phase	BB	Fajr	40.43
		Shiroodi	85.37
		Tarom	82.22
	BB and BDLRF	Fajr	55.93
		Shiroodi	82.86
		Tarom	84.62
Total phase	BB	Fajr	63.06
		Shiroodi	82.88
		Tarom	91.44
	BB and BDLRF	Fajr	61.71
		Shiroodi	83.78
		Tarom	92.34

3.4.2 Test phase

In test phase, we used the selected topology with the previously adjusted weights. The objective of this step was to test the network generalization property and to evaluate the competence of the trained network. Therefore, the network was evaluated by data, outside the training data set. Table 4shows the classification accuracies values in test phase with different training algorithms. Although the results of training phase were generally better than the test phase, the latter reveals the capability of neural network to classify rice varieties with new data and also this fact can be justified since test data are completely new for the MLP. Also by using BB algorithm, the classification accuracy of Shiroodi variety is better than using combined BB and BDLRF algorithms, but the classification accuracy of the other two varieties (Tarom and Fajr) is better by using both algorithms.

3.4.3 Total phase

In this step, the total results of rice seed classification were obtained that is the whole results of classification in the test phase and the last epoch of training phase. Table 4shows the classification accuracy values of this section associated with different training algorithms. As it can be seen, by using BB algorithm, the classification accuracy of Fajr variety is better than using combined BB and BDLRF algorithms, but the classification accuracy of the other two varieties (Tarom and Shiroodi) is better by using both algorithms. Also the classification accuracy of Tarom and Shiroodi varieties is better than Fajr variety and the best accuracy is observed for Tarom variety.

3.5 Classification accuracy using two rice varieties

In this section, three arrangements (twofold) of two rice varieties (Tarom-Fajr, Tarom-Shiroodi, Fajr-shiroodi) were used and the classification accuracies of these varieties in mixed samples of any two varieties were obtained in training, testing and total phases, that is shown in Table 5, Table 6and Table 7. The results of these tables were acquired using the combination of BB and BDLRF algorithms. As it can be seen from Table 5, the classification accuracy of Shiroodi variety is more than Fajr variety in their twofold sample. Table 6shows that for twofold sample of Tarom and Fajr, the classification accuracy of Tarom variety is more than Fajr variety. Table 7indicates that the classification accuracy of Shiroodi variety is more than Tarom variety in their mixture. Generally, according to Table 5, Table 6and Table 7, the least classification accuracy is related to Fajr variety.

Table 5: Classification accuracies of two rice varieties (Fajr and shiroodi) using both (BB and BDLRF) algorithms.

	Variety	**Accuracy**
Training phase	Fajr	91.48
	Shiroodi	94.97
Test phase	Fajr	86.96
	Shiroodi	93.02
Total phase	Fajr	90.54
	Shiroodi	94.59

Table 6: Classification accuracies of two rice varieties (Fajr and Tarom) using both (BB and BDLRF) algorithms.

	Varietiy	**Accuracy**
Training phase	Fajr	92.57
	Tarom	98.33
Test phase	Fajr	91.49
	Tarom	95.24
Total phase	Fajr	92.34
	Tarom	97.75

Table 7: Classification accuracies of two rice varieties (Tarom and shiroodi) using both (BB and BDLRF) algorithms.

	Variety	Accuracy
Training phase	Tarom	94.02
	Shiroodi	95.32
Test phase	Tarom	86.84
	Shiroodi	96.08
Total phase	Tarom	92.79
	Shiroodi	95.50

4 Conclusions

This article focused on the application of combined image processing and ANN to identify and classify three Iranian rice varieties in mixed bulks to prevent rice market fraud. To show the applicability and superiority of the proposed approach, some textural and morphological features of three rice varieties were used as input data. To improve the output, the data were first preprocessed and a MLP network was employed. After training and testing the network with the data set, it has been demonstrated that MLP network with 8 neurons had the best output. Moreover, the network trained by both BB and BDLRF learning algorithms. The results showed that this procedure can identify and classify rice seeds in any twofold samples with reasonable accuracy. Also in mixed bulks of three rice varieties (triplet samples), the classification accuracy of two varieties (Tarom and Shiroodi) was fairly good, but for Fajr variety it was relatively low that can probably be due to high similarity of this variety to other two varieties. Acquiring good classification accuracies for two varieties (Tarom and Shiroodi) shows that the ANN network has the capability of detection impure rice bulks of different rice varieties. However, more efforts in this field still required to increase the accuracy of process for bulks of more than two varieties. Such works can focus on RGB images rather than gray-scale image as input data for classification.

Also, because the ANN does not assume any fixed form of dependency in between the output and input values, unlike the regression methods, it seems to be more successful in the application under consideration. Additional research on ANNs is required to improve the results of this procedure and to make use of these networks more appealing.

TSSE is estimated during training phase.

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