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Research paper

Rice Classification with Fractal-based Features based on Sparse Structured Principal Component Analysis and Gaussian Mixture Model

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Abstract

Development of an automatic system in order to classify the type of rice grains is an interesting research area in the scientific fields associated with the modern agriculture. In the recent years, different techniques have been employed to identify the various types of agricultural products. Also different color-based and texture-based features have been used to yield the desired results in the classification procedure. In this paper, we propose a classification algorithm in order to detect the different rice types by extracting features from the bulk samples. The feature space in this algorithm includes the fractal-based features of the extracted coefficients from the wavelet packet transform analysis. This feature vector is combined with the other texture-based features used to learn a model related to each rice type using the Gaussian mixture model classifier. Also a sparse structured principal component analysis algorithm is applied to reduce the dimension of the feature vector and lead to the precise classification rate with a less computational time. The results of the proposed classifier are compared with those obtained from the other presented classification procedures in this context. The simulation results along with a meaningful statistical test, show that the proposed algorithm based on the combinational features is able to detect precisely the type of rice grains with a more than 99% accuracy. Also the proposed algorithm can detect the rice quality for different percentages of combination with other rice grains with a 99.75% average accuracy.

1. Introduction

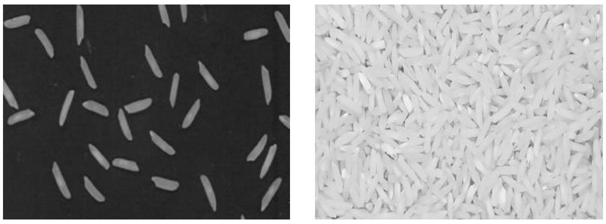
In the recent years, rice classification, as an important research area in image processing, has attracted many researchers' attentions since it has many potential applications in the modern agriculture. Rice is one of the most important food products for the people in the world, especially in Iran [1]. The traditional methods based on vision and olfaction are very common to detect the rice type but they are typically time-consuming with a low precision, and are not reliable for an inexperienced buyer. Moreover, the diagnostic procedure in this evaluation can be affected by the mental conditions such as the fatigue of a person. Thus using the image processing techniques in this field of study is necessary to result in a more precise classification at a shorter time. The quality of various agricultural products can be identified using these processing techniques and extraction of proper feature vectors. The feature extraction step includes a color-based, morphological-based, and texture-based coefficient calculated from the training image of each rice type [2, 3]. Although this study field is important, little research works have been carried out in this area.

In [3], the classification results of some agricultural products have been considered using a combination of color, texture, and morphological-based features. In [4], a color-based and texture-based feature vector has been applied to train a neural network and detect wheat, barley, oats, and rye grains. The bulk and individual samples of some agricultural products are classified using the color and texture-based features in [5] that lead to the proper results.

In individual sampling, just separated rice grains should be placed on the surface and thoroughly spread. However for bulk samples of rice products, more rice grains are placed on the surface. An example of these two types of rice samplings is shown in Figure 1.

In [6], a method for classification of different rice types using the color and morphological features is presented. Various color features and morphological properties of rice grains are employed in the classification procedure.

In individual sampling in [7], the length, area, perimeter, maximum length, maximum width, and compression of three rice types are considered, and the classification step is carried out by the neural network. In [8], the appearance of rice grains such as color characteristics has been processed to detect the rice type.



(a) (b)

Figure 1. Two types of rice samplings: a) Individual sample, b) Bulk sample.

Also the quality of rice type has been considered using the observed broken grains by calculating the length and width of grains of bulk sampling data in [9]. In [10], the color-based characteristics and gray level co-occurrence matrix (GLCM) have been extracted from the rice samples to train a neural network-based classifier.

In [11], the morphological features of some Iranian rice types, linear discriminant analysis (LDA), and neural network have been applied to classify the rice types. The classification of three Iranian rice products has been performed by the combinational coefficients including GLCM and the local binary pattern (LBP) features in [12]. A combination of the Fisher and principal component analysis (PCA) coefficients has been used to select the appropriate features in the classification procedure using a learning vector quantization (LVQ) neural network. The rice classification procedure using individual samples has been proposed in most research papers [7, 11, 12].

Other rice classification approaches work based on the bulk samples [13, 16-18]. In [15], the texture-based features based on GLCM and back-propagation neural network have been used to classify five Iranian rice products. In my previous work, [16], a rice categorization algorithm has been introduced using sparse representation and dictionary learning techniques to achieve over-complete models, and represent the structural content of four Iranian rice types. A combinational feature vector based on GLCM, a histogram of oriented gradients (HOG), LBP, and moments is applied to learn the incoherence models. Also, the bulk samples are used in the training and test steps.

In the commercial trading of rice products, a profiteer can mix each rice type with other poor varieties. In this case, the quality detection or purity of rice grains is considered. The quality detection of rice product has only been investigated in [17] based on the bulk samples of rice grains. In this paper, the Hashemi rice is regarded as the main rice type and is mixed in different percentages with the Basmati rice [17]. In fact, the Basmati rice has a less quality and a lower price than the Hashemi rice. The extracted feature in [17] is using the histogram-based features, GLSM, and LBP coefficients. Also, the genetic algorithm is applied to select the main coefficients in the extracted feature vector.

In this paper, a new method for classification and quality detection of the rice products is presented. The feature coefficients are fractal-based features of wavelet packet transform (WPT) analysis in combination with other texture-based and statistical-based features such as LBP, GLCM, and moments. This combinational feature vector is applied to learn the models with different rice types based on the Gaussian mixture model. The sparse structured principal component analysis (SSPCA) is applied to reduce the dimension of the calculated feature vector. The presented algorithm using this texture-based feature vector is not sensitive to the rotation and light of the environment that are prominent challenging problems in this research field. Different rice types considered in this work are Tarom, Shiroodi, Fajr, and Hashemi that are the main agricultural products in the north of Iran.

In Section 2 of this paper, the different feature extraction methods and also the employed dimension reduction algorithm are considered. In Section 3, the presented rice classification procedure is introduced. In Section 4, the results of the proposed algorithm are reported and compared with other presented methods in this regard. The paper is concluded in the last section.

2. Feature Extraction and Dimension Reduction Algorithm

In the feature extraction step that is the first step after pre-processing of data in the rice classification problem, two types of features including the texture-based and statistical-based features are applied. These feature extraction methods are considered in the following. Also the dimension reduction algorithm based on SSPCA is explained.

2.1. Fractal Analysis of Texture

In this work, the segmentation-based fractal texture analysis (SFTA) is applied as the main feature vector for classification of the texture used in different processing fields such as medical imaging [19]. SFTA is employed in general domains such as the texture feature extraction procedures. The input grayscale image using SFTA is decomposed to a set of binary regions and detects the textural patterns. Then the fractal dimensions of these regions are calculated in order to represent the segmented textural patterns. This decomposition procedure is carried out using a two-threshold binary decomposition (TTBD) algorithm [19]. The efficiency of this feature vector was considered, and the proper results were yielded in the classification field [19].

In the first step of feature extraction in this work, the WPT analysis is carried out over the input image, and the wavelet coefficients in the decomposition level 2 are computed. The dimension of input image after 2 level decomposition using WPT is reduced to a quarter. In the decomposition level 2 of WPT, 16 sub-bands exist. Then the fractal analysis is performed over each transformed sub-band images. If the number of thresholds (n_t) in the TTBD algorithm is set to 4, that is a common value in this feature extraction algorithm, the dimension of the extracted fractal-based feature vector or SFTA will be 21 since the relation between the dimension of the resulted feature vector with n_t is ($6n_t-3$) [19]. Therefore, each sub-band converts to a 1×21 feature, and after concatenation of all feature vectors for 16 sub-bands, a 1×336 fractal-based feature vector is achieved.

2.2. Local Binary Pattern

The local binary pattern (LBP) algorithm is a rotation-invariant descriptor to extract the properties of the adjacent textures from grayscale images [20]. This robust feature extraction procedure is widely used in the different fields of signal processing such as image retrieval and object detection. This characteristic leads to a less adverse effect in the classification routine when there is a change in the position, light, or rotation of an object. Different procedures to calculate the local binary pattern coefficients depend on the choice of neighborhood type that can be diagonal or circular with different radius [20].

2.3. Gray Level Co-occurrence Matrix

The gray level co-occurrence matrix (GLCM) determines the texture properties of the image [21]. The textural structure of a grayscale image can be considered by a matrix with relative abundances $P(i,j)$, where the value of each row with the number of row i and the column number j indicates the number of occurrence neighborhoods with the same gray level value in the different directions such as 0°, 45°, 90°, 135°, and 180°. Usually, the calculated GLCM coefficients are not used directly for feature extraction, and the texture characteristics of the image are represented by some computed statistical parameters from these coefficients. These second-order properties contain the mean, variance, energy, range of variations in relative abundance, contrast, homogeneity, uncertainty, maximum relative frequency, correlation, and entropy. The selection of all or some of these statistical parameters will be effective in the quality of image texture analysis [21].

2.4. Moments

The other important rotation-invariant feature employed in the field of texture processing is the moments of the image [22, 23]. The values of this statistical feature set consist of seven coefficients of the first to seventh moments, and do not change with the rotation of image in each direction. Therefore, this feature set is very important in the classification or object detection algorithms that suffer from the rotation problem.

2.5. Dimension Reduction using SSPCA Algorithm

The dimension reduction is a main procedure in the classification procedure. One of the basic approaches for dimension reduction is the principal component analysis (PCA) that is a statistical technique to seek the variables with a maximum variance from the input data [24]. PCA

finds the linear combinations of the input components in such a way that the calculated output components are within a k-dimensional subspace and k is smaller than the initial dimension of input data. Using the sparse PCA technique, the principal components with sparse constraints (SPCA) are estimated. An approach to perform the SPCA technique is designed based on the regression criterion [25].
The SPCA technique leads to a flexible control over the sparsity structure of the calculated components that has various advantages such as computational efficiency, high explained variance, and ability in the identification of the main variables [25].
The SSPCA technique is a generalization of the sparse PCA algorithm. Using this technique, the data variance by sparse constraints as well as a priori structural constraints to model the data content is found [26]. A non-convex variant of the regularization form in [27] is introduced for the problem of structured sparse dictionary learning. SSPCA applies an efficient block-coordinate descent algorithm with closed-form updates for a better decomposition of the data. This algorithm is robust to occlusion problem since this technique has a local dictionary learning-based procedure.

3. Proposed Rice Classification Method

The rice classification problem in the proposed algorithm, similar to most classification methods, includes the data pre-processing, feature extraction, and categorization steps. These steps are discussed below.

3.1. Collecting Rice Samples

Before the pre-processing step, the image data related to each rice type is recorded using a designed box. The bulk samples are recorded using this box with dimensions of 30 cm × 40 cm × 60 cm, as shown in Figure 2. Also four LED strips are utilized with the length 25 cm in the inner and upper sides of the box to prevent from shadowing over samples and have a consistent light in the interior of the box.
A circle with the diameter of 5 cm was created at the center of the upper level of the box to mount the camera. The Sony Imaging Camera with a 300imx sensor and 19-Megapixel resolution was employed to record images of the bulk samples. A rectangular container with dimension 10 cm × 10 cm was embedded to put the samples there. The rice samples are placed in this container, and its surface was flattened to no shadow create over the samples.
In the pre-processing step, each recorded color was converted to a grayscale image. Then, the feature vectors were extracted from these images. Some samples of this recorded data are shown in Figure 3.

3.2. Proposed Feature Vector

After pre-processing, the feature vectors related to each rice type were extracted to learn the models using GMM. Firstly, the wavelet packet transform was applied to the input image. The level of decomposition according to the experimental results obtained in the simulation procedure was set to 2. The size of the input images was 350 × 600, and after this transform with 2 decomposition levels, this size was reduced to a quarter. Also this decomposition level leads to 16 subbands with dimension 88 × 150. Figure 4 indicates the WPT tree, and the first and last sub-bands for a bulk sample of the Hashemi rice. As it can be seen, by increasing the sub-band number at the decomposition level 2, the details of the input image are extracted. Then the fractal analysis is carried out over each image sub-band to result in the fractal feature vector 1×21 when the threshold number was adjusted to 4. Therefore, a fractal-based feature vector 1×336 was obtained extracted for all the 16 sub-bands. Along with this procedure, the statistical-based and texture-based features such as GLCM, LBP, and moments were calculated, and a composite feature vector consisting of all the mentioned coefficients resulted.
At first, three color channels were determined for the input image, and the gray levels of each channel were computed. The feature extraction of each channel was performed, and then the extracted features for each one of these three channels were used to make the final feature vector. This combinational feature vector was applied in order to learn the training models with GMM. A block diagram of the proposed method to detect rice type is shown in Figure 5.

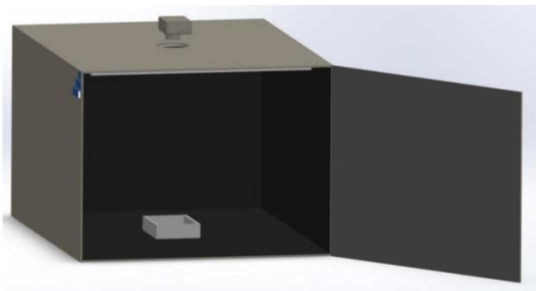


Figure 2. Box designed to capture image from rice grains.

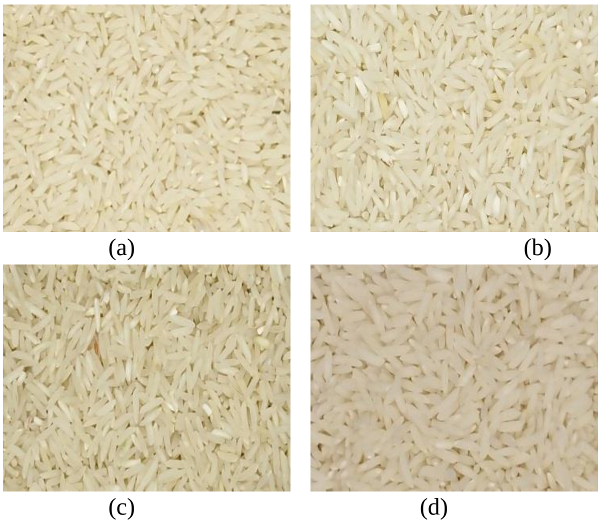


Figure 3. Some bulk samples of training data used in the rice classification problem. a) Tarom rice. b) Shiroodi rice. c) Fajr rice. d) Hashemi rice.

4. Simulation Results

In order to evaluate the proposed method, a dataset for each rice product was recorded, as described in Section 3. This collection contained 400 color image data for each rice variety with the image size 350 × 600. The feature extraction was carried out, and then the extracted combinational features for each rice type including the fractal analysis of WPT coefficients, GLCM, LBP, and moments were used to make the training models.

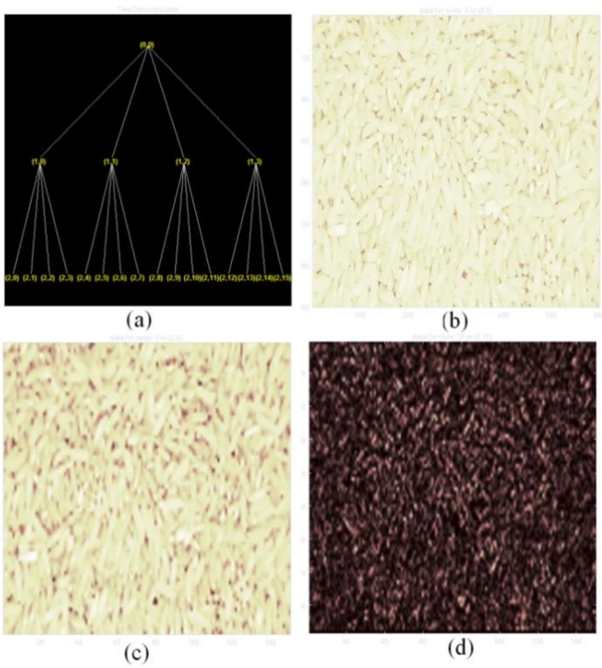


Figure 4. a) Wavelet packet transform tree with decomposition level 2. b) Bulk sample of Hashemi rice in the node (0, 0) of the analysis tree. c) Transformed image in the first sub-band of decomposition level 2 (node (2, 0)). d) Transformed image in the last sub-band of decomposition level 2 (node (2, 15)).

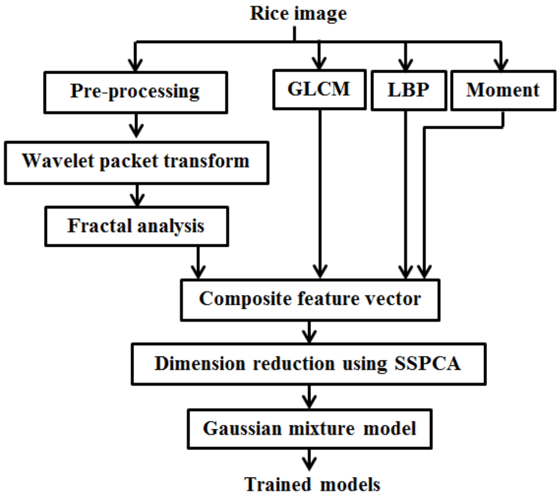


Figure 5. A block diagram of the proposed rice classification algorithm.

The results of the proposed method are comprised with other classifiers such as the neural network, support vector machine (SVM), and also the feature extraction procedure proposed in [16].

In the simulations, a feed-forward NN was employed using MATLAB toolboxes, in which the weight and bias parameters were updated according to the scaled conjugate gradient method. The performance of the neural network was calculated based on the cross-entropy between the targets and estimated classes. The transfer function selected for each hidden layer was a hyperbolic tangent sigmoid, and the number of neurons in each hidden layer was set to 20. The number of neurons in the input layer depends on the feature dimension that is different in each simulation.

Also, a linear kernel was regarded for the SVM classifier, and a sequential minimal optimization method was used to find the separating hyperplane. The maximum number of iterations to find the best separator was set to 15000. The MATLAB toolboxes were utilized for simulation of the NN and SVM classifiers, and adjusting the parameters of these classifiers was based on the experimental results. In the training step, 300 images of each rice type were used to learn the models with GMM, and 100 images are considered in the test step in order to evaluate the performance of the proposed algorithm. The performance evaluation of different methods was determined using the classification accuracy rate calculated by the percentage of test data categorized divided by the total number of test data. In the proposed classification method, the orthogonal Daubechies wavelets result in the best accuracy between the other wavelet families. Also, from this family, “db1” was selected in the simulations procedure. In the first simulation, in order to consider the role of each feature in the combinational feature vector, the classification results were calculated only by the fractal analysis of the WPT coefficients. As mentioned earlier, the size of the feature vector related to each input image was 1 × 336, and a 336 × 300 training matrix was yielded. In this simulation, 10% of the training matrix dimension was reduced before learning based on GMM. The results of this simulation are reported in Table 1.

Table 1. Accuracy percentages of rice classification based on fractal analysis of WPT coefficients for the feed-forward neural network, support vector machine, the proposed algorithm in [16], and the proposed learning-based classifier.

	SVM	Neural Network [15]	Sparse-based [16]	Proposed method
Tarom rice	90.5	92	94	**95.5**
Shiroodi rice	91	92.5	94.5	**96**
Fajr rice	92.5	93.5	**95**	**95**
Hashemi rice	91.5	93	94	**94.5**

As it can be seen, the proposed algorithm can obtain better results than the other mentioned algorithms but these results are not sufficient for a precise categorization. Thus in the following, it was tried to use other texture-based features along with the introduced fractal-based coefficients. In order to consider the effect of each part in the mentioned combinational feature, the classification accuracy resulting from adding each new feature to the feature vector introduced in the previous simulation was calculated. The first feature was GLCM and its nine characteristics including the mean, variance, energy, range of relative abundances, contrast, homogeneity, maximum relative frequency, correlation, and entropy were obtained. These GLCM coefficients were calculated in the four directions of 0°, 45°, 90°, and 135°. Therefore, a feature vector with 36 coefficients was obtained for each input image. Along with the fractal-based feature vector 1 × 336, a composite feature vector 1 × 372 was yielded. Then 10% of the feature dimension related to the training matrix (372 × 300) was reduced before using the GMM algorithm. The classification results with the calculated feature vector are expressed in Table 2. By combining these two features, the results obtained were slightly improved. It should be noted that this combination was performed with some statistical or texture-based features but the results obtained were not reported due to the undesirable classification. The simulation results concluded with this training data dimension was not sufficient to result in a precise classification rate. Therefore, this extracted feature vector should be used in combination with the other features. Among these features, the coefficients derived from the LBP with a dimension of 10 for each image data were applied.

Table 2. Accuracy percentages of rice classification based on the feature vector including the fractal analysis of WPT coefficients and GLCM parameters for the feed-forward neural network, support vector machine, the proposed algorithm in [16], and the proposed learning-based classifier.

	SVM	Neural network [15]	Sparse-based [16]	Proposed method
Tarom rice	92	94.5	96	**97**
Shiroodi rice	92.5	94.5	96.5	**97.5**
Fajr rice	93.5	94	95	**97**
Hashemi rice	93	95	96.5	**98**

The results of combining these features to solve the rice classification problem are presented in Table 3. The dimension of the training matrix using the fractal/GLCM/LBP for each rice class was 382 × 300, and after ten percentage reduction, it was 344 × 300. Also the classification results obtained with a combinational matrix including the fractal analysis of WPT coefficients, GLCM parameters, LBP, and seven moments coefficients are reported in Table 4.

The final dimension of the training matrix in this simulation after applying the SSPCA algorithm was 389 × 300. The results obtained show that using the statistical characteristics such as the extracted fractal parameters of WPT coefficients along with the other features such as GLCM, LBP, and moments, leads to the desired results in the rice classification problem. Certainly, the superiority of the proposed method is due to training the comprehensive models for each data class. Also, considering different statistical and texture-based features lead to a precise classifier.

Another issue discussed in this paper is the consideration of the rice quality. This means that the next step in the classification of the rice types is to determine the percentage of the impurity of rice. Tarom rice has a higher quality and price than the rice varieties considered in this paper. Therefore, mainly in the rice trade market, only this product may be combined with other rice types that have a lower quality and price. Therefore, in the first step of the proposed procedure, different sets of Tarom rice were combined with 5%, 10%, 15%, and 20% of a mixture from other rice varieties.

Obviously, the combination of more than 20% with the main rice is not common due to the fundamental changes in the appearance of rice that is easily visible by the eye.

Table 3. Accuracy percentages of rice classification based on the feature vector including the fractal analysis of WPT coefficients, GLCM parameters, and LBP for the feed-forward neural network, support vector machine, the proposed algorithm in [16], and the proposed learning-based classifier.

	SVM	Neural network [15]	Sparse-based [16]	Proposed Method
Tarom rice	93	95.5	97	**99**
Shiroodi rice	93.5	96	97.5	**98**
Fajr rice	94.5	95	96.5	**98.5**
Hashemi rice	94	95.5	97.5	**99**

Table 4. Accuracy percentages of rice classification based on the feature vector including the fractal analysis of WPT coefficients, GLCM parameters, LBP, and moments for the feed-forward neural network, support vector machine, the proposed algorithm in [16], and the proposed learning-based classifier.

	SVM	Neural network [15]	Sparse-based [16]	Proposed Method
Tarom rice	94	97.5	98	**99**
Shiroodi rice	95.5	97.5	**100**	**100**
Fajr rice	95.5	96	98.5	**100**
Hashemi rice	96.5	97	99	**100**

After classification of the rice type, the purity or impurity of rice type was investigated. This experiment was performed using the extracted combinational feature including the fractal analysis of WPT coefficients, GLCM parameters, LBP, and seven moments coefficients that resulted in the best results in the rice classification procedure in the previous simulations. The results of the proposed algorithm to detect the rice quality are reported in Table 5, which emphasizes the precise performance of the proposed GMM-based classifier.

Table 5. Accuracy of Tarom rice classification and detection of purity or impurity based on the combinational features for neural network, support vector machine, the proposed algorithm in [16], and the proposed GMM-based classifier.

	SVM	Neural network [15]	Sparse-based [16]	Proposed method
Pure Tarom rice	93	94.5	98.5	**99**
Impure Tarom rice 5%	93.5	95	98	**100**
Impure Tarom rice 10%	95.5	96	99	**99**
Impure Tarom rice 15%	94	93.5	99.5	**100**
Impure Tarom rice 20%	95	95.5	**100**	**100**

In order to have a more consideration about the efficiency of the proposed algorithm, the average computational time of the proposed algorithm in second for different methods including SVM-based, neural network-based, learning-based [16], the proposed algorithm without dimension reduction step, and the proposed algorithm is shown in Table 6. The proposed method contains the introduced combinational feature vector that obtained the best results, and is reported in Table 4. Also the average accuracy rate for the classification of all four rice types is reported in Table 6. The calculated results indicate that the dimension reduction step using the SSPCA algorithm has the main role in the detection of rice type, and leads to a classification at a slightly less time The accuracy rate in this table is the average value of the reported results in Table 4. It can be concluded that different steps of the proposed classification procedures including the feature extraction process, dimension reduction method, and GMM-based classification algorithm are efficient enough to precisely extract the texture structure of rice grains and detect the class of the input data. The model learning based on the texture-based features and removing unnecessary features can increase the ability to distinguish between the similar input bulk samples. In order to make a proper decision on the efficiency of the different methods in the mentioned different conditions, a statistical significance test was used. In this work, the Friedman test with the Holms post hoc test was used to compare the results of more than two algorithms [28, 30]. This test was applied to the results of all four classifiers (neural network, support machine, the proposed algorithm in [16], and GMM-based technique), in four states of rice classification problem, as well as four extracted features specified in Tables 1-4. Therefore, in this test, the number of different methods and conditions are $J = 4$ and $I = 4 \times 4$, respectively. It should be noted that better results would be obtained from this test if the number of conditions compared to the number of examined methods was higher. The non-parametric Friedman test is one of the best methods to compare several methods in different situations without the need for the initial assumptions. The routine of this test is that the average performance rank of the j-th method from the J methods is initially calculated in I different conditions as follows:

$$R_j = \frac{1}{I}\sum_{i=1}^{I} r_{ij} \quad (1)$$

where r_{ij} is the performance rank of j -th method in the i -th test state.

Table 6. Average accuracy rate and computational time (in second) in the classification of different rice types based on the combinational feature vector for different methods.

	Classification accuracy	Computational time
SVM	25	95.375
Neural network [15]	19	97
Sparse-based [16]	17	98.875
Proposed method without SSPCA	17	99
Proposed method	**15**	**99.750**

It should be noted that the method with the best performance in this statistical test will earn the lowest rank value. This significance test starts with a null-hypothesis, in which all algorithms have the same performance, and then it is proved that this assumption is wrong and then the rank of different methods is calculated according to their efficiency [28]. This test begins with the introduction of the critical value, as follows:

$$\chi_F^2 = 12I / J(J+1) \times [\sum_{j=1}^{J} R_j^2 - (J(J+1)^2)/4] \qquad (2)$$

Moreover, the modified statistical value of the Friedman test, which is based on the F distribution, is defined by $(J-1)$ and $(I-1)\times(J-1)$ degrees of freedom [29]:

$$F_F = (I-1)\chi_F^2 / \left(I(J-1) - \chi_F^2\right) \qquad (3)$$

If the F_F value in this statistical test is greater than the critical value χ_F^2, the null-hypothesis is rejected. It means that the mentioned algorithms do not have the same performance. The next step is to determine which algorithm will perform better. This decision is made using the post-hoc test. In this case, at first, the Z_j parameter for each evaluation method in this test is calculated as follows [30]:

$$Z_j = \left(R_0 - R_j\right) / \sqrt{J(J+1)/6I} \qquad (4)$$

where R_0 is the method that achieves the lowest performance level and the highest average rate obtained by Eq. 1. The Z value to achieve the ρ parameter is calculated at a statistical significance level of $\alpha = 0.05$. The value of ρ in the probability density of the standard normal distribution, corresponding to the underlying surface of this distribution, will be outside of the range (-Z , Z) [30]:

$$\rho = 1 - \int_{-Z}^{Z} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \qquad (5)$$

The simulation results of this statistical test based on the Holm assessment measure for the classification methods mentioned in this work are reported in Table 7 [28]. These results were calculated to determine the average rank for different classifiers based on the various features. The value of the parameter χ_F^2 for the results of this table according to Eq. 2 was 35.42. Also, the value of the F_F parameter according to Eq. 3 will be 27.31. The critical F value with the degrees of freedom (4-1) and (4-1) × (16-1) is 2.8154 [29].

It can be seen from the reported results that all F_F values obtained in this statistical test are more than the critical values of F , and therefore, the initial null hypothesis based on the similarity of the performance for all mentioned algorithms is rejected. Therefore, the post-hoc test can be used to determine the performance rank of different methods.

As expressed, the rank R_0 belongs to the method that has the lowest level of performance and the highest average rank among the mentioned methods. This rank in the statistical test is related to the support vector machine. In order to calculate the Z parameter to calculate the ρ -value at a statistical significance level $\alpha = 0.05$, Eq. 4 is used. Also the value of i in $\left(\alpha/(J-i)\right)$ to calculate the Holm measure corresponds to the row number in Table 7, and starts from 1, which includes a method with a better performance and the lowest average rank, up to $J-1$ that means the method with the lowest performance and higher average rank value.

Table 7. The results of a statistical test to compare the performance of neural network, support vector machine, the proposed algorithm in [16], and the proposed GMM-based classifier to categorize the rice types using different features.

	R_j	Z	ρ -value	Holm $\left(\alpha/(J-i)\right)$
Proposed method	1.02	5.0120	0	0.0167
Sparse-based [16]	1.76	2.6541	0.008	0.0250
Neural network [15]	2.34	1.8726	0.0193	0.0500
SVM	3.58	0	-	-

Also, the results for the last row of Table 7 are not achieved since the comparisons are based on the method with a lower performance according to Eq. 4.

In this table, the ρ -value is lower than the corresponding Holm critical value for all methods. Therefore, it can be concluded that the methods are listed in Table 7 from the best performance to the worst performance in the rice classification problem. The results of the statistical test for the proposed method have a rank value that is close to 1. This means that this method has a better performance than the other algorithms.

Also, in this table, the classification algorithm based on support vector machine is introduced as a method with an average rating of R_0, and the value of z parameter for this algorithm is set to zero so the parameter value of ρ for this method cannot be calculated.

5. Conclusion

The rice classification and detection of its quality are very applicable in the field of rice trade. This paper proposed a new algorithm to solve this problem using a combinational feature vector including different statistical and texture-based features such as the fractal analysis of WPT coefficients in different sub-bands, GLCM, LBP, and moment coefficients. Also the SSPCA dimension reduction algorithm was utilized to a precise classification algorithm, and a lower computation time was yielded. This composite feature vector was applied to train a GMM-based classifier. The simulation results along with the statistical test indicated that the proposed rice classification method properly performed the categorization and quality detection of different rice varieties.

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دسته‌بندی برنج به کمک ویژگی‌های مبتنی بر فراکتال براساس تحلیل مولفه‌های اساسی ساختار تُنُک و مدل مخلوط گاوسی

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چکیده:

توسعه یک سیستم اتوماتیک به منظور طبقه‌بندی دانه‌های برنج یک زمینه تحقیقاتی جالب در حوزه‌های علمی مرتبط با کشاورزی مدرن است. در سال‌های اخیر، روش‌های مختلفی برای شناسایی انواع مختلف محصولات کشاورزی استفاده شده است. همچنین از ویژگی‌های مختلف مبتنی‌بر رنگ و بافت استفاده گردیده تا نتایج مطلوبی را ارائه دهد. در این مقاله، یک الگوریتم دسته‌بندی پیشنهاد می‌شود تا انواع مختلف برنج را با استخراج ویژگی از نمونه‌ها تشخیص دهد. فضای ویژگی در این الگوریتم شامل ویژگی‌های مبتنی بر فراکتال ضرایب استخراج شده از تحلیل تبدیل بسته موجک است. این بردار ویژگی با سایر ویژگی‌های مبتنی‌بر بافت برای یادگیری یک مدل مربوط به هر دسته برنج با استفاده از طبقه‌بندی مدل مخلوط گاوسی ترکیب شده است. همچنین الگوریتم تحلیل مولفه‌های اساسی ساختار تُنُک برای کاهش ابعاد بردار ویژگی و کاهش زمان محاسباتی مورد استفاده قرار می‌گیرد. نتایج دسته‌بند پیشنهادی با نتایج بدست آمده از سایر روش‌های طبقه‌بندی ارائه شده در این زمینه مقایسه می شود. نتایج شبیه‌سازی همراه با آزمون آماری معنی‌دار نشان می‌دهد که الگوریتم پیشنهادی مبتنی‌بر ویژگی‌های ترکیبی پیشنهادی قادر است انواع رایج ارقام برنج را با دقت بیش از ۹۹٪ شخیص دهد. همچنین الگوریتم پیشنهادی می‌تواند کیفیت برنج را برای درصدهای مختلف ترکیب با سایر ارقام برنج با دقت متوسط ۹۹/۷۵٪ تشخیص دهد.

کلمات کلیدی: دسته‌بندی برنج، تبدیل بسته موجک، ویژگی مبتنی بر فراکتال، تجزیه و تحلیل مولفه‌های اساسی ساختار تُنُک، مدل مخلوط گوسی.