Research Article

Received: 4 May 2016 Revised: 5 October 2016 Accepted article published: 8 October 2016 Published online in Wiley Online Library: 10 November 2016

(wileyonlinelibrary.com) DOI 10.1002/jsfa.8080

Computer vision-based method for classification of wheat grains using artificial neural network

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Abstract

BACKGROUND: A simplified computer vision-based application using artificial neural network (ANN) depending on multilayer perceptron (MLP) for accurately classifying wheat grains into bread or durum is presented. The images of 100 bread and 100 durum wheat grains are taken via a high-resolution camera and subjected to pre-processing. The main visual features of four dimensions, three colors and five textures are acquired using image-processing techniques (IPTs). A total of 21 visual features are reproduced from the 12 main features to diversify the input population for training and testing the ANN model. The data sets of visual features are considered as input parameters of the ANN model. The ANN with four different input data subsets is modelled to classify the wheat grains into bread or durum. The ANN model is trained with 180 grains and its accuracy tested with 20 grains from a total of 200 wheat grains.

RESULTS: Seven input parameters that are most effective on the classifying results are determined using the correlation-based CfsSubsetEval algorithm to simplify the ANN model. The results of the ANN model are compared in terms of accuracy rate. The best result is achieved with a mean absolute error (MAE) of 9.8×10^{-6} by the simplified ANN model.

CONCLUSION: This shows that the proposed classifier based on computer vision can be successfully exploited to automatically classify a variety of grains.
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Keywords: classification; wheat grains; image processing; artificial neural network (ANN); multilayer perceptron

INTRODUCTION

Cultivation of wheat has been increasing in line with population growth. The quality of the flour used for end-products such as bread, macaroni and cake depends highly on the quality of the wheat. The most important factor affecting the quality of the wheat is the amount of protein in it. Durum wheat (used for macaroni) has more protein than bread wheat, so mixing of bread wheat grains with durum wheat leads to a reduction in the latter's protein content. Classification of grains is very important for increasing quality and decreasing cost. Therefore automatically classifying wheat grains into bread or durum according to their visual features has become more significant in recent years.

Computer-aided systems are being developed for evaluating the quality of agricultural products. Systems based on computer vision[1] employ the visual attributes of grains or products obtained from image-processing techniques (IPTs).[2] Artificial intelligence (AI) can be integrated with computer vision so as to provide automatic quality assessment. Thus a rapid and unmanned system with high accuracy can be developed for the classification of grains.[3–5] The most used AI techniques applied to modelling classifiers are artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), decision tree (DT), k-nearest neighbors (KNN), naive Bayes (NB) and discriminant analysis (DA).[6–9]

Several classifiers for various agricultural products have been studied in the literature. Berman *et al.*[10] classified wheat grains using near infrared hyperspectral image analysis. The efficiencies of cotton seeds were appraised using classifiers depending on DT and multilayer perceptron (MLP) by Jamuna *et al.*[11] In the classification of wheat and barley seeds, DA and KNN were used to design a classifier.[12] Progressive analysis and a meta-multiclass method were employed to classify wheat grains by Zapotoczny.[13] A study using classifiers and UV–visible spectrophotometry was conducted to classify spices through KNN.[14] Prakash *et al.*[15] studied the classification of objects for machine vision implementations with classifier algorithms of KNN and NB. ANN and ANFIS were utilized to classify rice grains into five species with respect to their morphological features.[16] An MLP-based ANN was modelled by Muñiz-Valencia *et al.*[17] for the classification of coffee grains according to their mineral content. An ANN together with NB was designed by De Oliveira *et al.*[18] for the classification of green coffee grains into four group. It is seen that those proposed classifiers varied among the used techniques, the features of products taken into account and the classification accuracy. Some of them might be difficult to implement, while several took into account fewer

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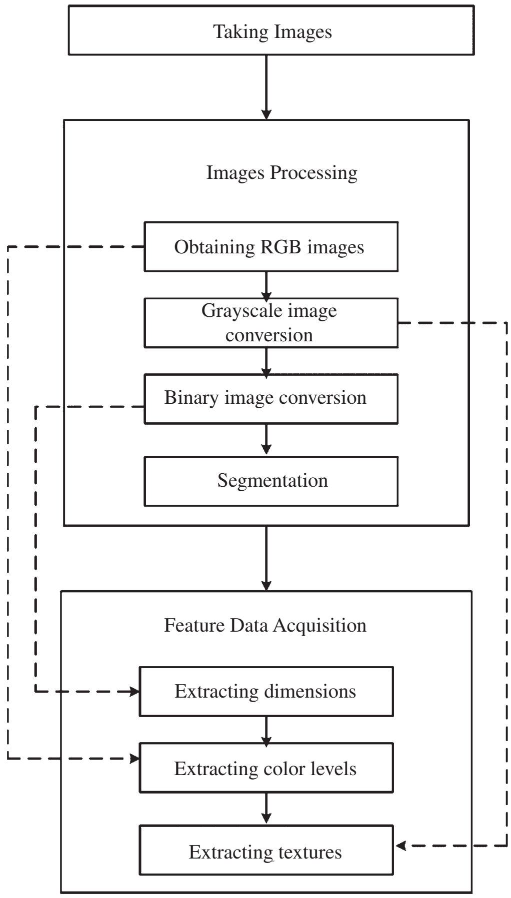

Figure 1. Flowchart for taking images and feature data acquisition.

parameters in classification. Therefore their mean errors concerning the accuracy of classification maintained limited.

In this study, a simplified classifier with high accuracy supported by computer vision is designed to classify wheat grains into bread or durum according to their visual features. The classifier is built on a feedforward back propagation (FFBP) ANN model based on MLP. To input the ANN model, 12 main visual features of 200 wheat grains are acquired for each grain through IPTs and then 21 visual features are reproduced from the 12 main features. The feature data of 180 grains and 20 grains uniformly selected from a total of 200 grains are respectively employed to train and test the accuracy of the classifier. Moreover, four data subsets related to features such as dimension, color and texture are constituted to investigate the impact of these categorized subsets on the classifying results. The FFBP-ANN model is then simplified by determining the most effective input parameters within the 21 visual features. Note that the results of the classifier are highly dependent on seven input parameters, which means that they can merely be utilized in the simplified model. A comparison of results is then performed according to accuracy rate. The best mean absolute error (MAE) appreciating the classification accuracy is achieved as 9.8×10^{-6} using the simplified classifier over the literature classifiers.

TAKING IMAGES AND DATA ACQUISITION

In this section, images are taken and exposed to IPTs to acquire data related to visual features of the wheat grains in order to model the FFBP-ANN. This process is illustrated as a flowchart in Fig. 1.

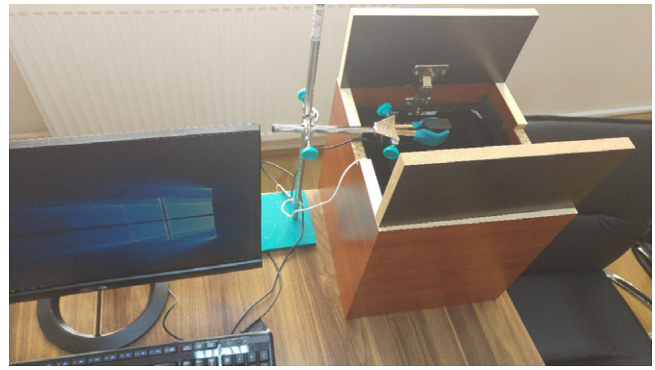

Figure 2. Setup for taking images.

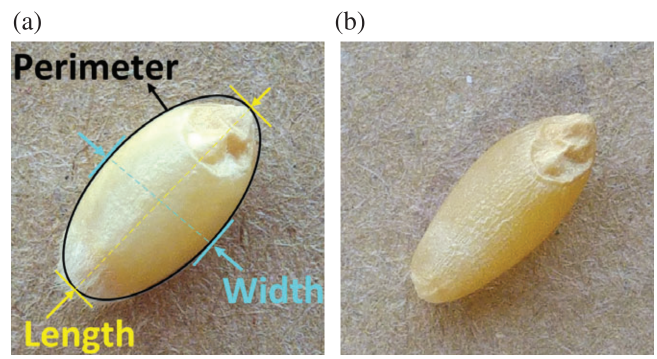

Figure 3. Grain images of (a) bread wheat and (b) durum wheat.

Taking images

In order to obtain the images, a setup including a computer, a camera and a box arranged with a camera holder and strip LED lighting is used as shown in Fig. 2. The computer used in this study has an Intel Core i7 CPU with 3.1 GHz and 8 GB DDR3 RAM. The camera is a Logitech C920 CCD with specifications of full HD (1080p), 15 MP, H.264 encoding and Carl Zeiss optics. The photographs are taken by the camera fixed at 35 cm height from the wheat at the bottom of the box, which is closed and self-illuminated with the strip LED. The inside of the box is covered with black background.

Figure 3 presents images of a bread wheat grain and a durum wheat grain taken by the camera. Note that the main discrimination between the two grains is that the durum wheat grain is bigger than the bread wheat grain. Besides, the bread wheat grain is close to yellow in color, while the durum wheat grain is darker yellow. Their texture features differ as well. Therefore three features related to dimension, color and texture are considered in this study to model a classifier based on computer vision.

In order to acquire feature data of the wheat grains (cultivated in Konya, Turkey) for classification, photographs of 100 bread wheat grains (Fig. 4(a)) and 100 durum wheat grains (Fig. 4(b)) are taken with the high-resolution camera.

Image-processing techniques

IPTs are conducted through MATLAB® software to acquire the feature data. Firstly, the RGB level of each pixel in the images is acquired. These images are then converted to grayscale format as shown in Fig. 5. Secondly, the grayscale images are converted to binary images (Fig. 6) including only black or white pixels using Otsu's method.[19] This method, based on image clustering,

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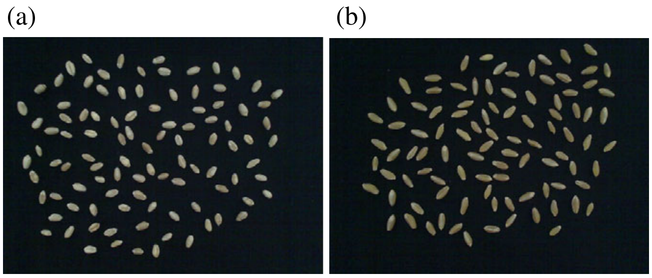

Figure 4. RGB images of 100 grains of (a) bread wheat and (b) durum wheat.

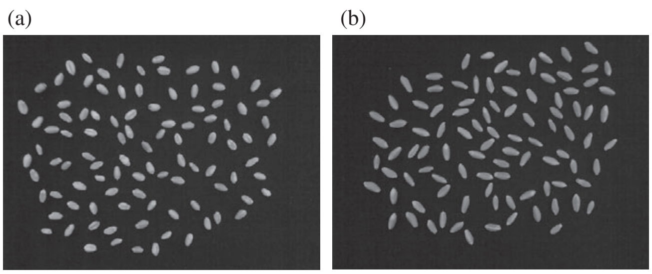

Figure 5. Grayscale images of 100 grains of (a) bread wheat and (b) durum wheat (originally given in Fig. 4).

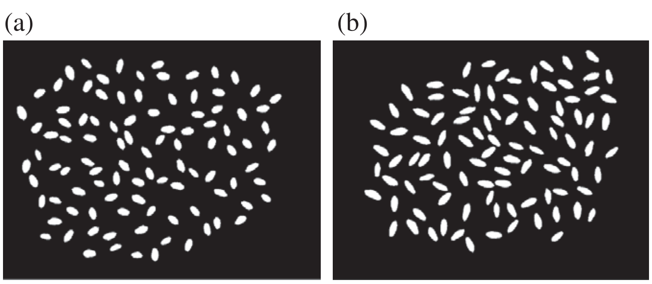

Figure 6. Binary images (black or white) of 100 grains of (a) bread wheat and (b) durum wheat (originally given in Fig. 4).

converts the grayscale image to a binary image in accordance with a threshold value. This value is a keystone optimally determined between 0 and 1 by Otsu's method. The gray level of each pixel is normalized from 0–255 to 0–1 values. The method then splits the normalized image into two classes having lower or higher gray level than the threshold value. Each pixel is set white (1) if the gray level is higher than the threshold value, otherwise it is set black (0). In this study, threshold values of 0.30588 and 0.25882 are determined for bread and durum grains respectively. The noise of each image is then eliminated using a morphological process.[20] Eventually, each grain's position is fixed and it is tagged according to its position through a segmentation process.

Feature data acquisition

Each grain's visual features related to dimension, color and texture are acquired to form the data set given in Table 1. Each grain's dimensions in terms of length (L), width (W), perimeter (P) and area (A) are extracted from binary images. To provide robustness of the classifier, some features related to dimensions are reproduced from these parameters, namely fullness (F) calculated by Eqn (1), L/W and P/A.

$$F = 4\pi A/P^2 \tag{1}$$

Table 1. Main features and data set reproduced from main features

Input of ANN	Number of features	Dimension	Color	Texture
Main feature	12	**L**, **W**, **P**, **A**	**R**, **G**, **B**	**C**, **COR**, **E**, **H**, **ENT**
Data set	21	**L**, **W**, **P**, **A**, F, L/W, P/A	**R**, **G**, **B**, all in Eqn (2)	**C**, **COR**, **E**, **H**, **ENT**

The R, G and B levels of each pixel within each grain are then extracted from the images in Fig. 4 and the means of R, G and B for each grain are calculated. Likewise, several features regarding color are reproduced as follows.

$$R/TRGB \tag{2a}$$

$$G/TRGB \tag{2b}$$

$$B/TRGB \tag{2c}$$

$$R - G \tag{2d}$$

$$G - B \tag{2e}$$

$$R - B \tag{2f}$$

where TRGB is the total of R + G + B levels. Texture features such as contrast (C), correlation (COR), energy (E), homogeny (H) and entropy (ENT) are extracted using the gray-level co-occurrence matrix (GLCM)[21] from the images in Fig. 5.

DESIGN OF ANN MODEL

The ANN consists of neurons organized into different layers. These neurons, employing nonlinear-type functions, are mutually connected by synaptic weights. During training, these weights weaken or strengthen to bring the output closer to the target of the ANN. In order to classify the wheat grains into bread or durum according to their visual features, an FFBP-ANN model based on MLP is designed as shown in Fig. 7 along with the set parameters given in Table 2. The program is coded by the agency of MATLAB® for designing the ANN model. The model is constructed with three layers: input layer, hidden layer with five neurons and output layer with one neuron. The number of input layer neurons equals the number of input parameters. A 'tangent sigmoid' function is used for both the input and hidden layers, while a 'purelin' function is utilized for the output layer. The Levenberg–Marquardt (LM) algorithm[22] is exploited in training the ANN model as a learning algorithm. The LM algorithm is a combination of the Gauss–Newton algorithm and steepest descent (back propagation) method. As the accuracy is ensured by Gauss–Newton, convergence is provided by steepest descent. The LM algorithm generally thus obtains successful results for highly nonlinear problems. Moreover, it is capable of faster learning and better convergence than other learning algorithms.[23]

Table 3 presents the data set and data subsets containing visual features of 100 bread and 100 durum wheat grains. The subsets in this table are reorganized from the data in Table 1 to regenerate

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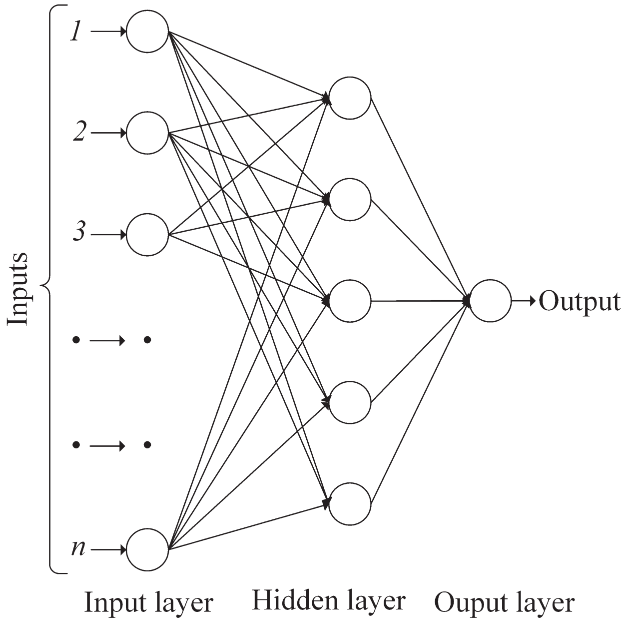

Figure 7. ANN model for classification of wheat grains into bread or durum.

Parameter	Set type/value
Number of epochs	250
Minimum gradient descent	10^{-10}
Momentum parameter (μ)	0.0001
μ increment value	4
μ decrement value	0.1
Maximum μ value	10^{10}

Table 2. Parameters used to set ANN model

Table 3. Data set and subsets containing visual features of 100 bread and 100 durum wheat grains

Input	Number of features	Dimension	Color	Texture
Data set	21	L, W, P, A, F, L/W, P/A	R, G, B, all in Eqn (2)	C, COR, E, H, ENT
Data subset 1	7	L, W, P, A, F, L/W, P/A	–	–
Data subset 2	9	–	R, G, B, all in Eqn (2)	–
Data subset 3	5	–	–	C, COR, E, H, ENT
Data subset 4	16	L, W, P, A, F, L/W, P/A	R, G, B, all in Eqn (2)	–

new sets to particularly investigate the correlation between them and thus inspect the effects of the features on the classifying results. The data sets are considered as input parameters for training and testing the ANN model; 180 out of 200 wheat grains are used for training and the remaining 20 for testing the model.

Training and testing the ANN model

The ANN model is trained and tested according to the flowchart shown in Fig. 8, consisting of six main steps. Training and testing

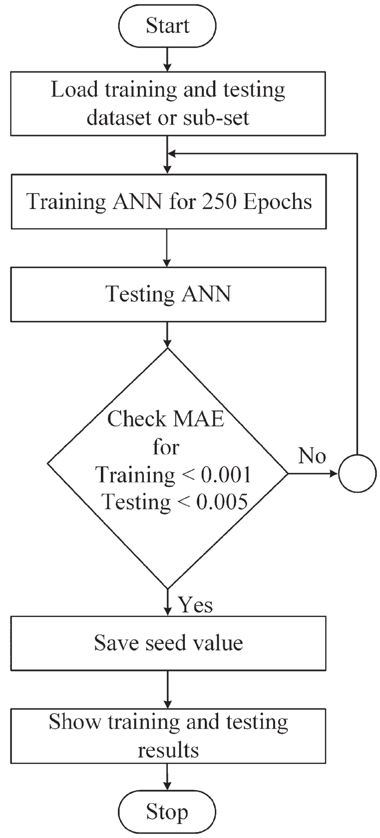

Figure 8. Flowchart for training and testing ANN model.

data sets in Table 3 are first loaded separately when starting the algorithm. Training of the ANN starts with a random seed value and it is trained through the loaded data for 250 epochs, which is the number of return cycles in this step. The seed value is a factor that fixes the weights of the network for getting the same result in every run. The trained ANN then computes testing results with loaded data. After training and testing of the ANN model, if the MAEs evaluated according to Eqn (3) for training and testing are less than the objective values of 0.001 and 0.005 respectively, the seed value is saved for subsequent runs of the ANN to obtain the same results. Otherwise, the training and testing steps are repeated with a new random seed value. The training and testing results are obtained at the last step.

$$\mathrm{MAE} = \sum \left|\mathrm{target} - \mathrm{output}_{\mathrm{ANN}}\right| / \mathrm{number\ of\ grains} \quad (3)$$

RESULTS

The input data related to visual features of the wheat grains given in Table 3 are classified by the trained ANN model. The results in terms of MAE and accuracy are presented in Table 4, which also includes the seed values determined in the training steps. It is seen that the ANN model with data subset 1 concerning only seven dimension features classifies the wheat grains with most accuracy among the data sets. On the other hand, the worst accuracy is obtained with data subset 3 related to texture features. It is worth noting that although the seven-feature input of data subset 1 is much lower than the 21-feature input of the data set regarding all features, data subset 1 is more effective on the results

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Table 4. MAE and accuracy of ANN for testing data

Input	Number of features	Seed value	MAE	Accuracy (%)
Data set	21	99321114	0.000727	99.9273
Data subset 1	7	311036311	0.000518	99.9482
Data subset 2	9	1270837852	0.015313	98.4687
Data subset 3	5	1379005758	0.025013	97.4987
Data subset 4	16	3033176	0.001733	99.8227
Selected data	7	295504528	0.000098	99.9902

Table 5. Selected data of bread and durum wheat grains

Input	Number of features	Dimension	Color	Texture
Selected data	7	L, L/W	G, B, G/TRGB	H, ENT

of wheat grain classification. This situation stimulates us to investigate a new input data set taking account of the features with most impact on the results. In order to simplify the ANN model, selected data of seven features given in Table 5 are determined using CfsSubsetEval,[24] which is a correlation-based feature subset selection algorithm. There are also other attribute evaluation algorithms in the literature such as chi-square, gain-ratio, information-gain, relief, symmetrical uncertainty and principal component analysis. They commonly appreciate the attributes of a subset by evaluating the individual effectiveness of each feature on the classifying results. Features that are highly related with the results and lowly correlated between each other are selected. These algorithms are essayed in this study to simplify the ANN model as well. They rank all attributes in accordance with relevance to the classifying results. CfsSubsetEval gives only the most correlated features and achieves more satisfactory results over the classification. Therefore CfsSubsetEval is preferred in this study for feature selection. The ANN results with selected data of seven features are also given in Table 4. It is evident that the most accurate results are achieved with the selected data.

The selected data including seven visual features of 20 grains (ten bread wheat grains and ten durum wheat grains) and their testing results are presented in Table 6 to further review the data and results. The number '2' is assigned to specify bread grains and the number '1' to specify durum grains as target of the ANN model. From Table 6, the average values of the L, L/W, G, B, G/TRGB, H and ENT parameters are 67.11343, 1.86156, 0.54578, 0.47382, 0.34966, 0.79737 and 6.90395 respectively for ten bread wheat grains, while those for ten durum wheat grains are 81.8729, 2.60101, 0.45482, 0.36039, 0.35368, 0.82267 and 6.66636 respectively. The discriminations between bread and durum wheat grains support our argument that visual features can be employed to classify the grains. The ANN model proposed in this study accurately classifies 19 grains with zero (0) absolute error and one grain with an absolute error of 195×10^{-6}. Therefore it classifies all 20 grains with a negligible MAE of 9.8×10^{-6}. This demonstrates that the proposed computer vision-based classifier using ANN can be successfully utilized to classify wheat grain varieties in an automatic manner.

CONCLUSION

A computer vision-based technique using ANN is proposed for the accurate classification of wheat grains into bread and durum. A FFBP-ANN model based on MLP with three layers is designed for this purpose. Twelve main visual features of dimension, color and texture for 100 bread and 100 durum wheat grains are acquired

Table 6. Testing results of classifying wheat grains with ANN model for selected data

Grain #	Visual features of selected data: L (p × l)	L/W	G	B	G/TRGB	H	ENT	Target	Result: $Output_{ANN}$	Absolute error	Classification
1	69.5679	1.8624	0.5534	0.4912	0.3486	0.8032	6.7973	2	2	0	Bread
2	63.6663	1.8090	0.5647	0.4925	0.3490	0.7791	6.7760	2	2	0	Bread
3	69.3322	2.0454	0.5328	0.4538	0.3472	0.7684	6.5521	2	2	0	Bread
4	73.5171	2.2993	0.4989	0.4152	0.3512	0.8302	6.7857	2	1.9961	195×10^{-6}	Bread
5	66.2957	1.7472	0.5751	0.4908	0.3504	0.8305	6.8620	2	2	0	Bread
6	66.6693	1.6249	0.5471	0.4899	0.3473	0.7577	6.9861	2	2	0	Bread
7	65.1759	1.8755	0.5497	0.4776	0.3476	0.8071	7.0326	2	2	0	Bread
8	63.0120	1.8252	0.5528	0.4835	0.3522	0.8138	7.1052	2	2	0	Bread
9	68.0608	1.6953	0.5404	0.4740	0.3491	0.8109	7.0796	2	2	0	Bread
10	65.8371	1.8314	0.5429	0.4697	0.3540	0.7728	7.0629	2	2	0	Bread
11	80.5652	2.2486	0.4611	0.3755	0.3545	0.8493	7.0623	1	1	0	Durum
12	85.4882	2.5266	0.4267	0.3144	0.3593	0.8319	6.4350	1	1	0	Durum
13	87.0308	3.0332	0.4361	0.3291	0.3577	0.8103	6.4205	1	1	0	Durum
14	90.6658	3.1075	0.4590	0.3878	0.3472	0.8420	6.8855	1	1	0	Durum
15	73.6011	2.5941	0.4613	0.3642	0.3493	0.8355	6.6034	1	1	0	Durum
16	76.5508	2.6234	0.4774	0.3869	0.3514	0.7606	6.8248	1	1	0	Durum
17	87.2399	2.4641	0.4851	0.4077	0.3495	0.7833	6.6096	1	1	0	Durum
18	81.1672	2.3156	0.4141	0.3054	0.3607	0.8439	6.4827	1	1	0	Durum
19	82.8189	2.5029	0.4661	0.3687	0.3579	0.8344	6.7364	1	1	0	Durum
20	73.6011	2.5941	0.4613	0.3642	0.3493	0.8355	6.6034	1	1	0	Durum
MAE										9.8×10^{-6}	

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using IPTs. The ANN model is trained with 180 grains and its accuracy tested with 20 grains from a total of 200 wheat grains. Twenty-one visual features are reproduced from the 12 main features in order to diversify the population data for training and testing the ANN model using the LM learning algorithm. Moreover, visual features that are more effective on the results are investigated to simplify the model input. As a result, an ANN model with seven inputs is achieved with the help of the feature selection algorithm CfsSubsetEval. The effects of the features on the results are compared according to their accuracy rate. The ANN model with selected features classifies the wheat grains with an MAE of 9.8×10^{-6}. The proposed method can be easily integrated into industry to automatically classify agricultural grains.

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