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An Application of ANN Trained by ABC Algorithm for Classification of Wheat Grains

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Abstract: Artificial Neural Networks (ANNs) have emerged as an important tool for classification problem. This paper presents an application of ANN model trained by artificial bee colony (ABC) optimization algorithm for classification the wheat grains into bread and durum. ABC algorithm is used to optimize the weights and biases of three-layer multilayer perceptron (MLP) based ANN. The classification is carried out through data of wheat grains (#200) acquired using image-processing techniques (IPTs). The data set includes five grain's geometric parameters: length, width, area, perimeter and fullness. The ANN-ABC model input with the geometric parameters are trained through 170 wheat grain data and their accuracies are tested via 30 data. The ANN-ABC model numerically calculate the outputs with mean absolute error (MAE) of 0.0034 and classify the grains with accuracy of 100% for the testing process. The results of ANN-ABC model are compared with other ANN models trained by 4 different learning algorithms. These results point out that the ANN trained by ABC optimization algorithm can be successfully applied to classification of wheat grains.

Keywords: *Classification, wheat grains, image processing technique, artificial neural network, artificial bee colony algorithm*.

1. Introduction

The quality of bakery products is largely dependent on the wheat used to obtain flour. The amount of protein contained in each wheat specie is different and therefore different wheat species are used for each flour product. For example, durum wheat contains more protein than bread wheat. The bread wheat grains mixing into durum grains lead to a reduction in its protein content. For this reason, classification of wheat grains is important to reduce costs and increase quality. Agricultural products are classified manually and automatically with different techniques. Manual classification has disadvantages in terms of time and cost. In the literature, image processing techniques (IPT) are widely used for the classification of agricultural products. In addition, image processing techniques and artificial intelligence techniques (AITs) are used in combination to increase classification accuracy [1-2]. Neural networks such as artificial neural network (ANN), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS) and decision tree (DT), K-nearest neighbors (KNN), Naive Bayes (NB) and discriminant analysis (DA) are the most utilized with IPT for classifying agricultural products [3-7]. Over a last decade ANN which is widely used artificial intelligence technique model adopts remarkable importance in classification of agricultural grains due to its fast and accurate modelling.

Studies which is classified the agricultural products by various methods are presented in the literature. The wheat grains were classified using a near infrared hyperspectral image analysis technique by (Berman et al; 2007). (Jamuna et al; 2010) determined the efficiencies of cotton seeds by classifying based on the DT and the multilayered perceptron (MLP). In (Guevara-Hernandez et al; 2011), the wheat and barley seeds were classified using DA and KNN. A progressive analysis and meta-multiple class method was used by (Zapotoczny; 2011) to classify wheat grains. The KNN method based ultraviolet visible spectrophotometry was used for classification of the spice (Anibal et al; 2012). The classification of objects was studied for machine vision implementations with classifier algorithms of the Naive Bayes and KNN by (Prakash et al; 2012). In (Pazoki et al; 2014), the rice grains into five species with respect to the morphological features were classified with ANN and ANFIS models. By (Muñiz-Valencia et al; 2014) were utilized a model which is MLP based ANN for classification of coffee grains according to their mineral content. The classification of green coffee grains into four groups was carried out using ANN by (Oliveira et al; 2016). The wheat grains as durum and bread were classified using computer vision based ANFIS and ANN methods by (Sabanci et al; 2017). In (Aslan et al; 2017), three different wheat species from the UCI library were classified with ANN and extreme learning machine (ELM) techniques.

The combination of ANN models and optimization algorithms based on the swarm intelligence has been used to solve complex learning problems. Swarm intelligence algorithms are used to carry out some complications in the construction of the ANNs. Swarm intelligence algorithms were used to adjust the parameters of neural networks in the literature [20-24]. Artificial bee colony (ABC) algorithm which is one of the swarm intelligence algorithms was proposed by (Karaboga; 2005) and it was inspired by collective behaviours of bees gathering honey. Training neural networks are one of the most interesting application of the ABC algorithm [26]. The ABC algorithm has good performance in the training of neural networks.

In this study, an ANN model combining with an ABC algorithm (ANN-ABC) is used for classification of the wheat grains into bread and durum according to their dimension features with high accuracy. The ABC algorithm has been used to determine the weight and bias values of the neural network model by minimizing the mean square error value of between target and out of the ANN model. Thus, the ABC algorithm in the network training phase provides for avoiding the local minima solutions by performing a high-performance search process in the solution space. 5

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dimension features of 200 wheat grains are acquired for each grain through IPTs for input ANN-ABC model. The feature data of 170 grains and 30 grains which are uniformly selected from the total number of 200 grains are respectively employed to train and test the accuracy of the model. In the wheat grains classification, ANN is used as modelling technique and ABC employed as learning algorithm. The weights of the network are obtained by using artificial bees to search best training parameters in an iterative manner. The purpose of this study is to improve the classification of wheat grains accuracy by using the convergence and optimization ability of ABC. The ANN-ABC model correctly classifies the wheat grains into durum and bread with 100% for the training process. Moreover, the results of ANN-ABC model are compared with other ANN models trained by different learning algorithm such as Levenberg Marquardt (LM), Bayesian regularization (BR), one step secant (OSS) and scaled conjugate gradient (SCG) [27].

2. Proposed ANN-ABC Model

The application of the ABC algorithm is relatively simple [26] and it has the advantage of not requiring a lot of parameters to be tuned [28]. All processes related to proposed ANN-ABC model are illustrated in (Figure.1). The processes in the (Figure.1) will be described in the subsections.

2.1. Image Processing Technique and Data Preparation

In this section, the data set is obtained by applying IPT to the wheat images in order to model the AITs as shown in (Figure.2). A setup including a computer, a camera and a box arranged by camera holder and a strip LED lighting is used in order to obtain the images as shown in (Figure.3). The camera is a Logitech C920 CCD with the specifications of full HD (1080p), 15 MP, H.264 encoding, 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. The inside of the box is covered with black background.

The images of the wheat grains for bread and durum taken by the camera are illustrated in (Figure.4). As can be seen, the main discrimination between the two grains is that the durum wheat grain is bigger than that of bread wheat. Therefore, dimension features of the wheat grains are considered in this study to model. As given in (Figure.5), the photographs of 100 bread wheat grains and 100 durum wheat grains are taken via the high resolution camera. The wheat used for classification is cultivated in Konya, Turkey.

The IPTs are conducted through MATLAB®2014b software to acquire the feature data. Firstly, the RGB level of each pixel in the images are determined. These images are then converted to grayscale format as shown in (Figure.6a & 6b). Secondly, the grayscale images seen from (Figure.6c & 6d) are converted to binary images (black/white) using Otsu's method [29]. Thus the noise of each image is eliminated using morphological process. Thirdly, each grain's position is fixed and they are tagged according to its position through a segmentation process.

Each grain's dimensions in terms of the length (L), width (W), area (A) and perimeter (P) are extracted from binary images. Feature of fullness (F) related to dimension is reproduced from these parameters by (Equation.1).

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

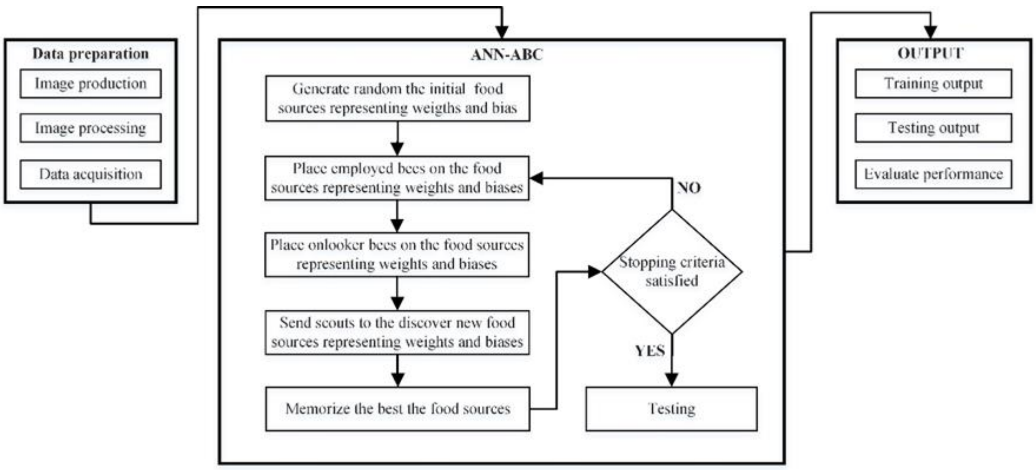


Figure 1. Proposed ANN-ABC model process

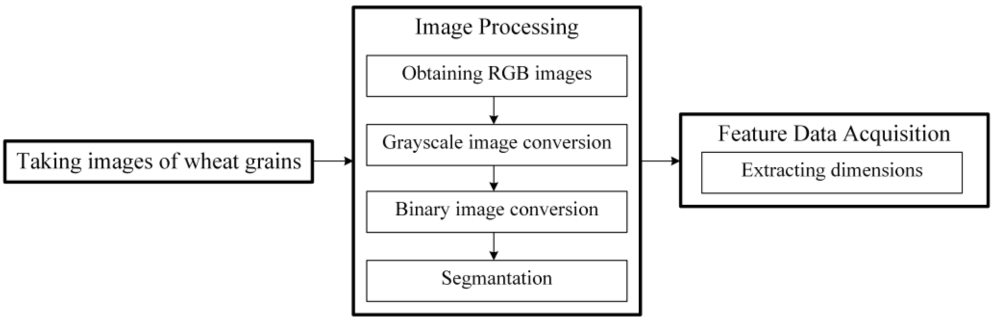
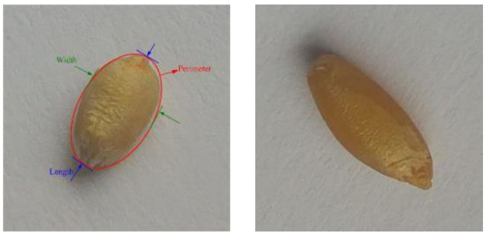


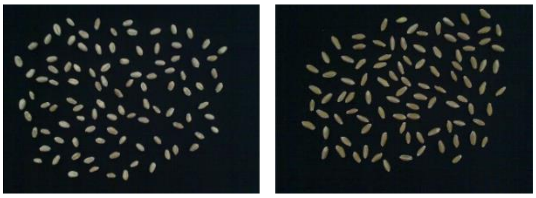
Figure 2. Flowchart of extracting dimension features

Figure 3. The setup for obtaining the images



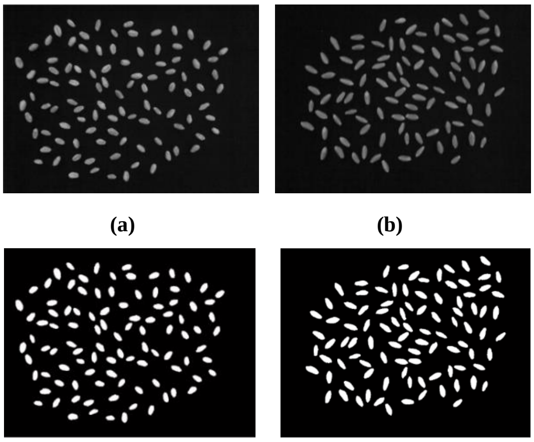
(a) (b)

Figure 4. The images of the grains for a) bread wheat, b) durum wheat



(a) (b)

Figure 5. The RGB images of 100 grains for a) bread wheat, b) durum wheat



(a) (b) (c) (d)

Figure 6. The images of 100 grains for a) grayscale of bread wheat, b) grayscale of durum wheat a) binary images of bread wheat, b) binary images of durum wheat (originally given in Figure 5)

2.2. Artificial Neural Network

ANN consists of neurons organized into different layers. These neurons containing non-linear types of functions are mutually connected by synaptic weights [30]. The neuron number of the input layer equals to the number of the input parameters. A function given in (Equation.2) processes in each neuron.

$$y_j = f\left(\sum_{j=1}^{n}(w_{ji}x_i + \theta_i)\right) \quad (2)$$

here, i and j are respectively indexes for neurons of input and hidden layers. Neurons in the input layer act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum and θ_i is the threshold (or bias) of the node. During training, these strengths weaken or strengthen to bring closer the output to the target of the network. f can be a simple threshold function such as sigmoid, hyperbolic tangent, tangent sigmoid, radial basis, purelin etc. The goal is to minimize the mean square error (MSE) function given by (Equation. 3)

$$E(w(t)) = \frac{1}{n}\sum_{k=1}^{n}(d_j - o_j)^2 \quad (3)$$

where $E(w(t))$ is the error at the t_{th} iteration; $w(t)$, the weight in the connections at the t_{th} iteration; d_j is the desired output node; o_j is the target value for the j_{th} output node.

2.3. Artificial Bee Colony Algorithm

The ABC algorithm as named of heuristic technique is a powerful optimization method by (Karaboğa et al; 2007). In ABC algorithm phases, the search process performed for solution of optimization problems mimics the foraging behavior of honey bees.

The detailed implementation of the ABC algorithm is shown in Algorithm 1. At the initial of the ABC algorithm, the bee population (P) having a randomly distributed is generated. The number of solutions (represented food source positions, SN) is equal to the half of the population. Each solution x_i ($i=1, 2, ..., SN$) has a D-dimensional vector named of optimization parameters. Therefore, these vectors having D-dimensional will be optimized solutions by ABC algorithm. The positions representing of possible solutions are improved by employed, onlooker and scout bee phases until reach maximum cycle (MCN, cycle=1, 2, …, MCN).

A modification position from the position of the employed bee is generated by using (Equation.4). If the nectar quality of previous position is lower than new position, the new position is memorized by a bee and then the old position is abandoning. Otherwise, the old position is kept by a bee in the memory.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (4)$$

where $k \in \{1, 2,\dots\dots SN\}$ and $j \in \{1, 2,\dots\dots D\}$ are randomly chosen indexes. k is determined randomly and should be differ from i. Φ_{ij} us a random generated number between [-1,1].

The search process is completed by all the employed bees and then the information about the food sources found by the employed bees is shared with the onlooker bees. These information covers of the nectar quality and position of the food sources.

A food source is selected by an onlooker bee evaluating the probability value of food sources. This probability p_i related to the nectar quality of the food source is calculated by (Equation.5).

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (5)$$

Algorithm 1: Public ABC algorithm [25]

Produce the initial positions of bees in the population x_i; $i = 1, \ldots, SN$
Evaluate the nectar quality of the initial position point.
cycle = 1
repeat
    Generate new positions representing of new solutions v_i by the employed bees using (Equation.4) and evaluate the nectar quality of new positions.
    Apply greedy selection process to solutions found by employed bees.
    Compute the probability values p_i of the solutions x_i by using (Eq. 5)
    Generate the new solutions v_i for the onlookers from the solutions x_i selected depending on p_i values and evaluate the nectar quality of new positions.
    Apply greedy selection process to solutions found by onlooker bees.
    Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produce solution x_i by (Equation.6)
    Memorize the best solution achieved so far
    cycle = *cycle*+1
until Until cycle = MCN;

fitness value of the solution *i* and SN is the number of food sources. A modification position from the position of the onlooker bee is generated by using (Equation.4). If the nectar quality of previous position is lower than new position, the new position is memorized by a bee and then the old position is abandoning. Otherwise, the old position is kept by a bee in the memory. If the nectar of a food source is consumed by an employed bee. This employed bee transforms a scout bee and the old food source is abandoned. A position of a new food source is found by scout bee using (Equation.6).

$$x_i^j = x_{\min}^j + rand(0,1)(x_{\max}^j - x_{\min}^j) \tag{6}$$

3. Results of Classification of Wheat Grains

In this study, the ABC optimization algorithm is used in the ANN model as learning algorithm. ABC updates the weight/bias values and minimizes a linear combination of squared errors. It also modifies the linear combination so that at the end of the training the resulting network has good generalization qualities.

3.1. Training Process of ANN-ABC Model

The dimension parameters (*L*, *W*, *A*, *P* and *F*) of the wheat grains were given as inputs and their respective classification results of IPT were given as output to the ANN-ABC model. The data set of 170 wheat grains representing the overall problem space is used to train the ANN-ABC model and the remainders 30 wheat grains that are not included in the training process are utilized to test the accuracy of the model. ANN-ABC model based on MLP having one input layer with five neurons, one hidden layer with five neurons and one output layer with one neuron was constructed, as shown in (Figure.6).

Table 1. The parameters used to set the ANN-ABC model

Parameter	Set type/value
Swarm number (NP)	100
Dimension (D, the sum of weight and bias numbers)	66
Limit (L)	NP*D/2
Upper bound (Ub)	20
Lower bound (Lb)	-20
Maximum cycle number (MCN)	10000

"Log-sigmoid" function is used for input and output layers while "tangent sigmoid" function is utilized for the hidden layer. The parameters of the ANN-ABC model used in this work are listed in Table 1. The training results are checked according to the following mean absolute error (MAE),

$$MAE = \frac{\sum |\text{Target} - \text{Output}|}{\text{Number of grains}} \tag{7}$$

3.2. Testing Process Results of ANN-ABC Model

The testing data including 5 dimension features of 30 grains (15 bread wheat grains and 15 durum wheat grains) and their testing results are tabulated in Table 2 to further inspect the data and results. While the number of "2" is assigned to specify bread grains, "1" is appointed to define the durum grains as targets of the ANN-ABC model. The ANN-ABC model proposed in this study accurately classifies 19 grains with 0 (zero) and 11 grains with very small absolute errors. Therefore, it classifies the total grains of 30 with a negligible MAE of 0.0034 and with 100% accuracy. It demonstrates that the proposed IPT based ANN-ABC model can be successfully utilized to classify the wheat grain varieties in an automatic manner.

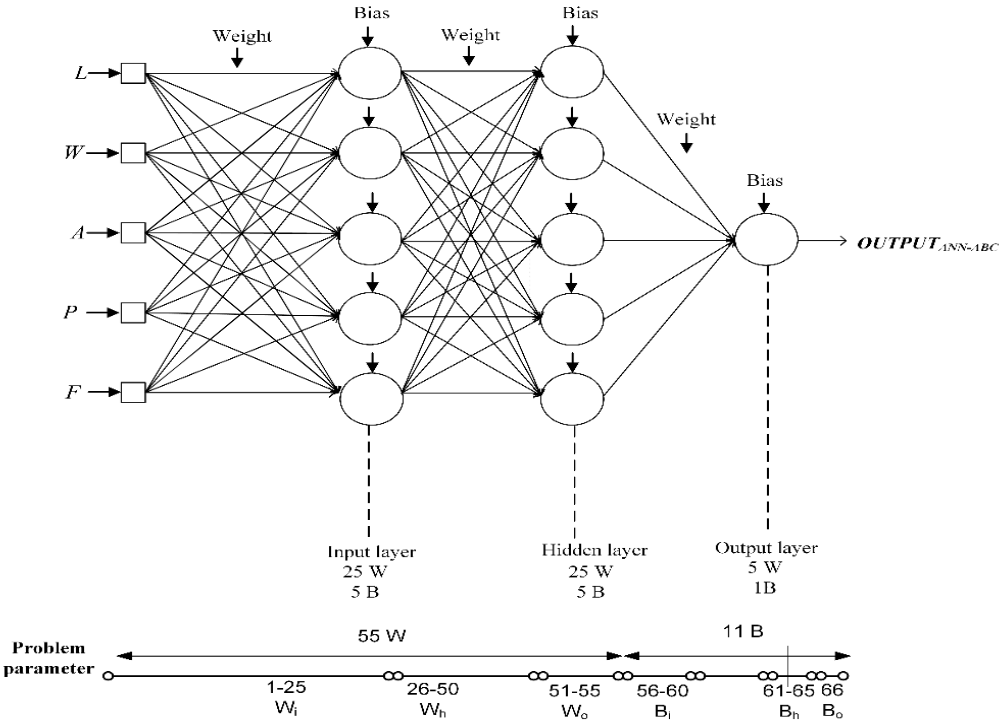


Figure 6. ANN-ABC model and problem parameters

Table 2. The testing results of classifying the wheat grains with the ANN-ABC model

Grain #	Dimension features					Target	Result		
	Lenght (*pxl*)	Width (*pxl*)	Area (*pxl*^{2})	Perimeter (*pxl*)	Fullnes		$\text{Output}_{\text{ANN-ABC}}$	Absolute error	Classification
1	80.5652	35.8292	2256	202.7523	0.6896	1.0000	0.9966	0.0034	Durum
2	85.4882	33.8357	2256	208.3675	0.6530	1.0000	1.0000	0.0000	Durum
3	87.0308	28.6928	1938	206.4092	0.5716	1.0000	0.9996	0.0004	Durum
4	90.6658	29.1766	2066	212.3675	0.5757	1.0000	0.9996	0.0004	Durum
5	73.6011	28.3721	1630	177.5391	0.6498	1.0000	1.0000	0.0000	Durum
6	76.5508	29.1798	1745	183.4386	0.6517	1.0000	1.0002	0.0002	Durum
7	87.2399	35.4049	2415	214.0660	0.6623	1.0000	1.0000	0.0000	Durum
8	81.1672	35.0524	2214	203.9655	0.6688	1.0000	1.0004	0.0004	Durum
9	82.8189	33.0887	2140	205.1371	0.6391	1.0000	1.0000	0.0000	Durum
10	73.6011	28.3721	1630	177.5391	0.6498	1.0000	1.0000	0.0000	Durum
11	85.9925	35.0192	2359	210.1076	0.6715	1.0000	1.0000	0.0000	Durum
12	76.2105	34.2426	2031	189.7229	0.7091	1.0000	1.0006	0.0006	Durum
13	85.5031	35.2557	2356	207.3797	0.6884	1.0000	1.0000	0.0000	Durum
14	69.7812	25.9654	1410	169.6812	0.6154	1.0000	1.0000	0.0000	Durum
15	87.1869	36.9060	2519	220.3087	0.6522	1.0000	1.0000	0.0000	Durum
16	69.5679	37.3539	2014	188.6518	0.7111	2.0000	2.0000	0.0000	Bread
17	63.6663	35.1940	1757	166.2670	0.7987	2.0000	2.0000	0.0000	Bread
18	69.3322	33.8972	1841	175.9239	0.7475	2.0000	2.0000	0.0000	Bread
19	73.5171	31.9743	1835	186.1665	0.6653	2.0000	1.9570	0.0430	Bread
20	66.2957	37.9450	1967	177.6812	0.7829	2.0000	2.0000	0.0000	Bread
21	66.6693	41.0286	2140	180.8528	0.8222	2.0000	2.0000	0.0000	Bread
22	65.1759	34.7517	1772	171.6812	0.7555	2.0000	2.0000	0.0000	Bread
23	63.0120	34.5241	1702	165.2965	0.7828	2.0000	2.0000	0.0000	Bread
24	68.0608	40.1471	2138	187.8234	0.7616	2.0000	2.0000	0.0000	Bread
25	65.8371	35.9484	1851	176.3087	0.7483	2.0000	2.0000	0.0000	Bread
26	66.5339	33.0084	1721	170.7107	0.7421	2.0000	1.9994	0.0006	Bread
27	58.9533	32.4715	1499	156.2670	0.7714	2.0000	1.9990	0.0010	Bread
28	74.3373	34.7865	2023	190.9949	0.6969	2.0000	1.9870	0.0130	Bread
29	70.0801	32.4960	1775	177.1960	0.7104	2.0000	1.9620	0.0380	Bread
30	64.6870	33.6098	1686	173.5807358	0.703177	2.0000	2.0000	0.0000	Bread
MAE								**0.0034**	
Accuracy									**100%**

3.3. Comparison Results

In this study, wheat grains are also classified with the ANN models trained by 4 different learning algorithms to show the success of the ANN-ABC model. LM, BR, OSS and SCG learning algorithms are used for this purpose. The ANN models based MLP which is used LM, BR, OSS and SCG learning algorithms are constructed as in the ANN-ABC model. The activation functions used for the ANN models trained by different learning algorithms are also selected as in the ANN-ABC model. " Log-sigmoid" function is used for the input layer and output layer, and " Tangent sigmoid" activation function is used for the hidden layer. In the ANN-ABC model, the number of network parameters is less than the other ANN models. This shows that the appropriate ANN-ABC structure is more easily modelled. This shows that the appropriate ANN-ABC structure is modelled more easily than ANN trained by four different learning algorithms. For further comparison, the numerical results of ANN models are also listed in Table 3. It is apparent from Table 3 that, ANN-ABC and ANN-LM models give the remarkable results in comparison with other models. MAE values of the ANN-ABC and ANN-LM models are close to each other and successful. However, among these learning algorithms, ANN-ABC model gives best result for classification of wheat grains into bread and durum. From the testing results presented in Table 4, while the MAE result of the ANN-BC is 0.0034, MAE results of ANN-LM, ANN-BR, ANN-OSS and ANN-SCG models are 0.0052, 0.0206, 0.0558 and 0.0661, respectively. Computational time for the five models is almost the same for testing process.

Table 3. The comparative test results for classification with ANN models

Grain #	Target	Artificial neural network results									
		Numerical Output					Absolute Error				
		ANN-ABC	ANN-LM	ANN-BR	ANN-OSS	ANN-SCG	ANN-ABC	ANN-LM	ANN-BR	ANN-OSS	ANN-SCG
1	1.0000	0.9966	1.0000	1.0000	1.0092	1.0195	0.0034	0.0000	0.0000	0.0092	0.0195
2	1.0000	1.0000	1.0000	1.0000	1.0092	0.9998	0.0000	0.0000	0.0000	0.0092	0.0002
3	1.0000	0.9996	1.0000	1.0000	1.0092	0.9995	0.0004	0.0000	0.0000	0.0092	0.0005
4	1.0000	0.9996	1.0000	1.1799	1.0092	0.9995	0.0004	0.0000	0.1799	0.0092	0.0005
5	1.0000	1.0000	1.0000	1.0000	1.0092	1.0060	0.0000	0.0000	0.0000	0.0092	0.0060
6	1.0000	1.0002	1.0000	1.0019	1.0092	1.0012	0.0002	0.0000	0.0019	0.0092	0.0012
7	1.0000	1.0000	0.9999	1.0000	1.0092	0.9998	0.0000	0.0001	0.0000	0.0092	0.0002
8	1.0000	1.0004	1.0000	1.0000	1.0092	1.0104	0.0004	0.0000	0.0000	0.0092	0.0104
9	1.0000	1.0000	1.0000	1.0000	1.0092	1.0007	0.0000	0.0000	0.0000	0.0092	0.0007
10	1.0000	1.0000	1.0000	1.0000	1.0092	1.0060	0.0000	0.0000	0.0000	0.0092	0.0060
11	1.0000	1.0000	0.9999	1.0000	1.0092	0.9998	0.0000	0.0001	0.0000	0.0092	0.0002
12	1.0000	1.0006	1.0000	1.0000	1.0092	1.0575	0.0006	0.0000	0.0000	0.0092	0.0575
13	1.0000	1.0000	1.0000	1.0000	1.0092	0.9999	0.0000	0.0000	0.0000	0.0092	0.0001
14	1.0000	1.0000	1.0000	1.0000	1.0092	1.0222	0.0000	0.0000	0.0000	0.0092	0.0222
15	1.0000	1.0000	1.0000	1.0000	1.0092	1.0009	0.0000	0.0000	0.0000	0.0092	0.0009
16	2.0000	2.0000	2.0000	2.0000	2.0051	2.0016	0.0000	0.0000	0.0000	0.0051	0.0016
17	2.0000	2.0000	2.0000	2.0000	2.0051	2.0015	0.0000	0.0000	0.0000	0.0051	0.0015
18	2.0000	2.0000	2.0000	2.0004	1.9976	1.9314	0.0000	0.0000	0.0004	0.0024	0.0686
19	2.0000	1.9570	1.8433	2.1742	0.9964	1.1497	0.0430	0.1567	0.1742	1.0036	0.8503
20	2.0000	2.0000	2.0000	2.0000	2.0051	1.9992	0.0000	0.0000	0.0000	0.0051	0.0008
21	2.0000	2.0000	2.0000	2.0000	2.0051	1.9981	0.0000	0.0000	0.0000	0.0051	0.0019
22	2.0000	2.0000	2.0000	2.0000	2.0051	2.0035	0.0000	0.0000	0.0000	0.0051	0.0035
23	2.0000	2.0000	2.0000	2.0000	2.0051	2.0008	0.0000	0.0000	0.0000	0.0051	0.0008
24	2.0000	2.0000	2.0000	2.0000	2.0051	1.9982	0.0000	0.0000	0.0000	0.0051	0.0018
25	2.0000	2.0000	2.0000	2.0000	2.0051	2.0004	0.0000	0.0000	0.0000	0.0051	0.0004
26	2.0000	1.9994	2.0000	2.0000	2.0051	2.0265	0.0006	0.0000	0.0000	0.0051	0.0265
27	2.0000	1.9990	2.0000	2.0000	2.0051	1.9987	0.0010	0.0000	0.0000	0.0051	0.0013
28	2.0000	1.9870	2.0001	1.7444	1.6556	1.4612	0.0130	0.0001	0.2556	0.3444	0.5388
29	2.0000	1.9620	2.0002	1.9960	1.8698	1.6429	0.0380	0.0002	0.0040	0.1302	0.3571
30	2.0000	2.0000	2.0000	1.9967	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
MAE							**0.0034**	**0.0052**	**0.0206**	**0.0558**	**0.0661**

4. Conclusion

In this article ANN model trained by ABC optimization algorithm is proposed for accurate classification of the wheat grains into bread and durum. The ANN-ABC model based on the MLP with three layers is designed for this purpose. 5 features of dimensions for 100 bread and 100 durum wheat grains are acquired by using IPTs. The ANN-ABC model is trained by 170 grains and its accuracy is tested through 30 grains of 200 wheat grains data. The ANN-ABC model classifies the wheat grains with the MAE of 0.0034 for the testing process. Moreover, proposed model is compared with 4 different learning algorithm such as LM, BR, OSS and SCG and it is seen to be more successful. The results achieved in this study show that ANN-ABC model based on IPT can be successfully used to classify the wheat grains according to their dimension features with high accuracy.

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