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Wheat Seeds Classification using Multi-Layer Perceptron Artificial Neural Network

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***Abstract* – Wheat seeds classification is an important agriculture process. In this paper a wheat classification system based on Artificial Neural Network (ANN) is presented. The proposed system aims to classify three different wheat seeds into their corresponding classes. The system consisted of two stages. In the first stage image processing is applied on the obtain images and important geometrical features are extracted. In the second stage the extracted features are fed in to a Multi-layer Perceptron (MLP) neural network trained using back propagation learning algorithm. Three experiments were conducted; the first experiment using all the data, the second experiment using noisy data, and the final experiment using part of the training data. The empirical results show that the proposed classification system was able to classify the wheat seeds with a testing accuracy of around 95%.**

***Keywords* – Wheat Classification, Neural Networks, Multi-Layer Perceptron, Back Propagation.**

I. Introduction

Pattern classification has inspired scientists over the last few decades. Its application can be widely seen in the fields of medical diagnosis [1-5], industrial fault detection [6-9] and many other fields [10]. Wheat classification is one of the important tasks for breeders and geneticists. However, the classification task is not an easy task. It requires an expert to classify wheat seeds, which is time and cost inefficient. Artificial intelligence is used to classify wheat seeds as shown in literature. In [11] a machine algorithms is proposed to classify wheat according to its quality. Two machine learning algorithms, that is, Support Vector Machine (OVR) and Neural Network (LM) were used. For classification, images of wheat grain are captured using digital camera and thresholding is performed. Following this step, features of wheat are extracted from these images and machine learning algorithms are implemented.

In [12] different types of wheat seeds are classified using neural networks. First images were captured, and a features which include average, variance, skewness and kurtosis images in RGB and l*a*b* color spaces were extracted. Eleven features of the 280 images were used in the training stage of ANN, 40 images for validation, and testing of the ANN was performed with 80 images.

In [13] classification of four Iranian wheat cultivars was carried out using morphological features and artificial neural networks. After preparing samples, 164 images of grains were acquired for each cultivar in a lighting chamber. Ten morphological features were extracted from images using image processing techniques. For classifying wheat varieties, various topologies of artificial neural networks (ANN) with different number of neurons in the hidden layers were developed. The nine important morphological features extracted from images were used as input for developed ANN.

In this paper a wheat classification system is proposed. The proposed classification system is an application of image processing techniques and ANNs for classifying wheat seeds. The proposed system consists of two main stages. In the first stage images of the wheat seeds undergo image processing phase in order to extract meaningful features from them. The extracted features are fed into a feed forward neural network trained using back propagation learning algorithm.

The paper is organized as follows; section two will introduce the image processing techniques used to extract features from the wheat seeds. The multi-layer neural network with back propagation is introduced in section three. Then in section four the experiments and results are presented. Finally section five gives the conclusion of the paper.

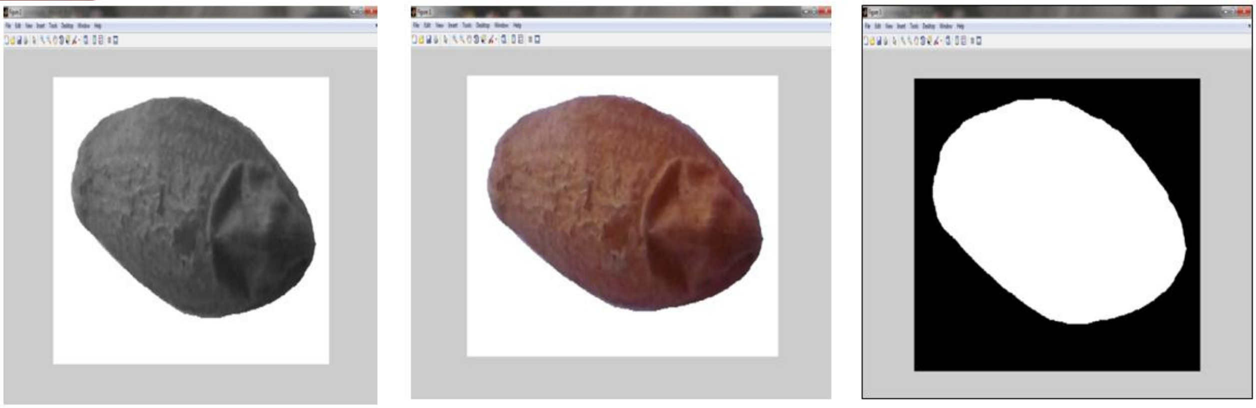
II. Image Processing

In order to extract meaningful features from the wheat images, these images must undergo an image processing stage. In this section image processing techniques used for feature extraction are introduced.

The obtained images are colored images. The first step is to change the colored images into gray scale images. The colored image has three properties: hue, saturation and luminance, to change the colored image to a gray image we should eliminate the hue an saturation values from the original image but keeping the luminance value which correspond to the gray image. The next step the gray scale image is converted into black and white image using thersholding as shown in figure 1.

The next step is to apply morphological operations on the binary image. Opening is the process of smoothing the contour of the object, it breaks narrow isthmuses and eliminates these protrusions [14]. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. It is less destructive than erosion in general.

Closing also tends to smooth sections of the contour, but it's opposed to opening, it generally fuses narrow breaks and long thin gulfs , eliminates small holes , and fills gaps in the contour [14].



(a) (b) (c)

Fig.1. Converts the color image to the gray scale intensity image:
(a) the original image, (b) the gray scale image and (c) black and white image.

The next step is to extract features from the wheat seeds images. These features will be used to train the ANN. The features extracted are as follows:

1. Area : the actual number of pixels in the region.
2. Minor Axis Length : the length (in pixels) of the minor axis of the ellipse that has the same second-moments as the region.
3. Eccentricity : the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1.
4. Major Axis Length : the length (in pixels) of the major axis of the ellipse that has the same second-moments as the region.
5. Equivalent Diameter : the diameter of a circle with the same area as the region. Computed as sqrt(4*Area/pi).
6. Perimeter : the distance around the boundary of the region. The perimeter is calculated by calculating the distance between each adjoining pair of pixels around the border of the region.
7. Entropy : a scalar value representing the entropy of gray scale image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

In the next section a brief description of the back propagation learning algorithm is presented.

III. Artificial Neural Network

A neural network can be defined as a model of reasoning based on the human brain. The brain consists of a densely interconnected set of nerve cells, or basic information-processing units, called neurons. The human brain incorporates nearly 10 billion neurons and 60 trillion connections, synapses, between them. By using multiple neurons simultaneously, the brain can perform its functions much faster than the fastest computers in existence today.

A multilayer perceptron is a feed forward neural network with one or more hidden layers [15-18]. Typically, the network consists of an input layer of source neurons, at least one middle or hidden layer of computational neurons, and an output layer of computational neurons. The input signals are propagated in a forward direction on a layer-by-layer basis. A multilayer perceptron with two hidden layers is shown in Figure 2.

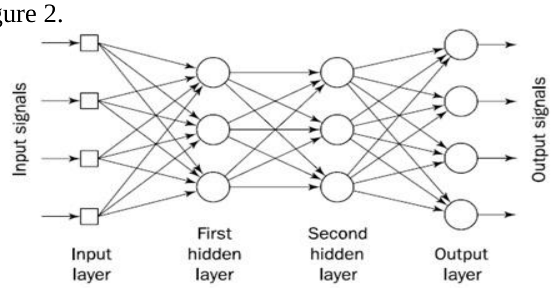


Fig.2. Multilayer Neuron with Two Hidden Layers

More than a hundred different learning algorithms are available, but the most popular method is back-propagation. This method was first proposed in, but was ignored because of its demanding computations. Only in the mid-1980s was the back-propagation learning algorithm rediscovered.

Learning in a multilayer network proceeds the same way as for a perceptron. A training set of input patterns is presented to the network. The network computes its output pattern, and if there is an error or in other words a difference between actual and desired output patterns the weights are adjusted to reduce this error.

In a perceptron, there is only one weight for each input and only one output. But in the multilayer network, there are many weights, each of which contributes to more than one output. Typically, a back-propagation network is a multilayer network that has three or four layers. The layers are fully connected, that is, every neuron in each layer is connected to every other neuron in the adjacent forward layer. The back propagation learning algorithm consists of the following steps:

Step 1: Initialization

Set all the weights and threshold levels of the network to random numbers uniformly distributed inside a small range:

$$\left(-\frac{2.4}{\mathrm{Fi}}, +\frac{2.4}{\mathrm{Fi}}\right) \qquad (1)$$

Where Fi is the total number of inputs of neuron i in the network. The weight initialization is done on a neuron-by-neuron basis.

Step 2: Activation

Activate the back-propagation neural network by applying inputs

X1 (p) ,X2 (p),….Xn(p) and desired outputs Yd, 1(p), Yd, 2(p)…..Yd, n(p).

1. Calculate the actual outputs of the neurons in the hidden layer:

$$Y_j(p)=\text{sigmoid}\left\lfloor\sum_{j=1}^{m} Xjk(p) * Wjk(p) - \emptyset k\right\rfloor \quad (2)$$

where n is the number of inputs of neuron j in the hidden layer, and sigmoid is the sigmoid activation function.

2. Calculate the actual outputs of the neurons in the output layer:

$$Y_k(p)=\text{sigmoid}\left\lfloor\sum_{j=1}^{m} Xjk(p) * Wjk(p) - \emptyset k\right\rfloor \quad (3)$$

where m is the number of inputs of neuron k in the output layer.

Step 3: Weight Training

Update the weights in the back-propagation network propagating Backward the errors associated with output neurons.

1. Calculate the error gradient for the neurons in the output layer:

$$\delta k(p) = yk(p) * \left(1 - Yk(p)\right) * ek(p) \quad (4)$$

where: : e_k(P) = Y d,k (P) – Yk (P) (5)

Calculate the weight corrections:

$$\Delta W_{jk}(p) = \alpha * Y_j(p) * \delta_K(P) \quad (6)$$

Update the weights at the output neurons:

$$W_{jK}(P+1) = W_{jk}(p) + \Delta W_{jk}(p) \quad (7)$$

2. Calculate the error gradient for the neurons in the hidden layer:

$$\delta_j(p) = Y_j(p) * \lfloor 1 - Y_j(p)\rfloor * \sum \delta_K(P) * W_{jk}(p) \quad (8)$$

Calculate the weight corrections:

$$\Delta W_{ij}(p) = \alpha * x_i(P) * \delta_j(p) \quad (9)$$

Update the weights at the hidden neurons:

$$W_{ij}(p+1) = W_{ij}(p) + \Delta W_{ij}(p) \quad (10)$$

Step 4: Iteration

Increase iteration p by one, go back to Step 2 and repeat the process until the selected error criterion is satisfied.

IV. Experiment and Results

In this paper three types of wheat seeds are classified. According to an expert opinion these three types are the most common wheat seeds in the market. A total of 150 seeds were collected, with each class having 50 seeds. Throughout the experiments, the total number of samples was divided into 3 sets as follows: 60% for training, 20% for validation and 20 %for testing. The experiments were repeated 10 times, in each time the total number samples are randomized.

Three different experiments were conducted; the first experiment used all 150 samples without applying any noise in which 90 samples were used for training, 30 samples for validation and the rest were used for testing. In the second experiment noise was applied to the total number of sample dataset in the shape of missing data. In this experiment 90 samples were used for training, 30 samples for validation and the rest were used for testing. In the third experiment the total number of samples was reduced to 90 samples. The 90 samples were divided as follows: 54 samples were used for training, 18 samples for validation and the remaining 18 samples for testing.

The MLP with back propagation using one hidden layer is a universal approxiamtor that can be used as a classification system. In this experiment the total number of hidden layers used is one hidden layer. Matlab ® 2014a is used as the experiment program. The number of epochs was set to 1000 epochs. The activation function used was the sigmoid activation function. The learning rate was set to 0.01. The experiment was repeated 10 times and the average of the testing accuracy and number of epochs were reported. All the experiments were conducted using Intel core i5 computer with 6 GRAM.

In the first experiment all the 150 samples where fed to a two layer NN. As table 1 shows the average testing accuracy was 95.2 %, and it took an average 664 epochs to reach the stopping condition which was 6 successive epochs with no improvement on the validation dataset.

Table 1: The experimental results of the three experiments

Experiment	Average testing accuracy	Average number of epochs
150 sample without noise	95.2%	664
150 samples with noise	89.5%	921
90 samples	87.4%	639

In the next experiment, 10 samples were randomly removed from each class of the dataset and replaced by zeros. This is to simulate noise applied to the dataset. As shown in table 1 the average testing accuracy decreased by around 5% compared to data without noise. From table 1, one can see that the average number of epochs reported for the data with noise was 921 which is much higher than the data without noise. This shows that the training process is much harder than the data without noise.

In the final experiment the total number of samples was reduces to 90 samples (30 samples per class). As table 1 shows the average testing accuracy was 87.4% with an average number of epochs of 639 epochs. This shows that when the training data was reduced the testing accuracy decreased. Although the number of epochs did not change much between experiment 1 and experiment 3.

V. Conclusion

In this paper a wheat seed classification system was introduced. The system consisted of two stages. The first stage is an image processing stage, were images of wheat seeds underwent image processing in order to extract features from them. In the second stage a MLP neural network with back propagation learning algorithm was used to classify the wheat seeds. The empirical results show that the proposed system was able to classify the wheat seeds into their corresponding classes with a testing accuracy of around 95%.

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