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AN INTELLIGENT-BASED MECHATRONICS SYSTEM FOR GRADING THE IRANIAN'S EXPORT PISTACHIO NUTS INTO HULLED AND NON-HULLED GROUPS

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ABSTRACT

This paper presents an intelligent based system for grading hulled and non-hulled pistachio nuts. The first step in the pistachio nuts preparation process is to hull and to peel the picked crops. In pistachio preparation terminals, the manual separation of hulled pistachios from those without hull, increases price and contamination and decreases the quality. The proposed research introduces an automatic system based on image processing technique to enhance the accuracy in detecting the hulled and non-hulled pistachio nuts. Three ordinary classifiers including: Multilayer Feed forward Neural Network (MFNN), Radial Basis Function Neural Network (RBFNN) and Support Vector Machine (SVM) are then applied to select the best classifier for pistachio nuts process. To evaluate the performance of the system 200 pistachio nuts from four native Iranian pistachio nuts varieties are used. Each variety consists of 100 hulled and 100 non-hulled nuts. Experimental results show an accuracy of 95% and average time period of about 0.02 second for the best selection of the system.

KEYWORDS: Mechatronics System, Image Processing, Machine Vision, Pistachio, Artificial Neural Networks, Classification

The pistachio tree belongs to the family anacardiaceae, of which the cashew, mango, sumac and poison oak are also members. There are more than sixty species of pistachio in different regions of Iran. One of the important steps of pistachio nuts grading is to separate the non-hulled pistachio nuts from the hulled ones. Pistachios processing factories begin to hull pistachio nuts after harvesting process. In practice, non-hulled pistachio nuts might be separated manually from the hulled ones at the end of the processing line and with traditional methods.

Insects, fungus and aflatoxin increasing are also observed due to the unpeeled crops. Consequently, the price and the quantity of the harvested crops would be reduced [1, 2]. At the end of the line processing, samples would be classified into five groups in order to their type of hull as shown in fig. 1.

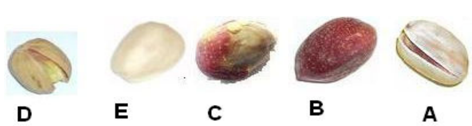

Figure 1: Types of pistachios at the end of processing line: (A) the image of cracked hulled pistachio(open), (B) non-hulled pistachio, (C) half-hulled pistachio, (D) non-cracked hulled pistachio(close), (E) cracked, hulled pistachio as wastes.

In this research, a mechatronics system is proposed to select samples one by one and to separates hulled and non-hulled samples automatically by processing the images. In half-hulled type, at least %15 of the pistachio nuts is hulled. Some methods and solutions are proposed to recognize cracked and semi-cracked pistachios [3]. In order to decrease Aflatoxin (A toxin specifically to plant) and increase the quality of the exported pistachio, some works are conducted as follows:

Pearson et al. proposed a sorting system which has been developed for the separation of small in-shell pistachio nuts from kernels without shells on the basis of vibration generated when moving samples strike a steel plate. Impacts between the steel plate and the hard shells are measured using an accelerometer attached to the bottom of the plate, produce higher frequency signals than impacts between the plate and the kernels.

On the other hand, signal amplitudes were highly variable which made them useless for the separation of samples. They developed another system by using both amplitude and frequency information to classify the signals. The algorithm activated an air nozzle to divert in-shell nuts away from the kernel stream. A prototype sorter was tested at throughput rates of 0.33, 10, 20, and 40 nuts per second using a mix of 10% in-shell and 90% kernels at the lowest throughput rate; classification accuracies were 96% for in-shell nuts and 99% for kernels. For throughput rates between 10 and 40 nuts/s, correct classification ranged from 84 to 90% for in-shell nuts. For kernels, accuracy was 95% at 10 and 20 nuts/s and 89% at 40 nuts/s [4]. Another research is led in California to grade pistachios with shell by image processing; this research illustrates the feasibility of using color imaging

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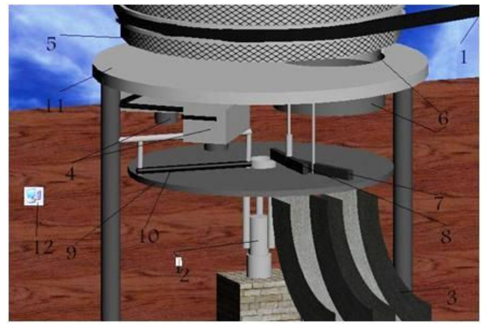
as a basis to recognize both regular and small in-shell pistachio nuts from kernels in the pistachio nut process stream. Two approaches were applied to classify images of in-shell nuts; the first approach utilized a discriminate analysis(DA) routine to evaluate features extracted from the images based on histograms of red, green and blue (RGB) pixel intensities, and resulted in a 99.9% overall accuracy for grading regular in-shell pistachio nuts from kernels. The second approach used a k-nearest neighbors (knn) routine to evaluate features based on color histograms plus intensity slop information. The knn routine was similar to the accuracy of the DA approach for recognizing regular in-shells from kernels with 99.9% correct [5]. Hojat Joseph et al. designed a sound based grading system to separate Pistachios from defective ones. This machine has the ability to separate darkly-stained Pistachios using perfect light intensity gradient of one column of matrix. However, as the defective Pistachios may not be necessarily stained; the implemented research shortcomings the required accuracy to sort the samples, but it separates the darkly-stained pistachios very accurately [6].

Benefits of automatic hulled and non-hulled pistachio inspection compared with human inspection

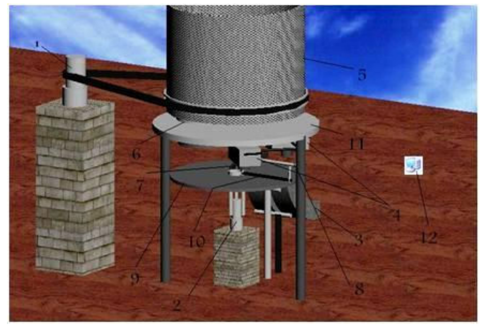
Nowadays, most of classification processes, such as pistachio inspection, are being applied manually in the lines with human visual inspectors. However, this procedure has some shortcomings such as non-uniform behavior; in other words, applying a repetitive work results in making some mistakes [7]. Furthermore, for novel high-speed manufacturing lines, an automatic system is the only feasibility; because the speed is too high rather than the visual inspectors.

Architecture of the proposed inspection system

Fig. 2 and Fig. 3 show different views of the proposed inspection system. It includes two camera beams for imaging, light source beams, alternative current motor, and gear box and operator station for administrating the total system. Pistachio defects data is sent to the operator station via camera beams. The operator station contains a desktop computer and combines the data coming from both cameras to form various user views and reports. To achieve a strong and sufficient illumination, we used fluorescent tubes which are typically used. The proposed PC-based classifier sorts the defects and saves the defect data in SQL database to simplify a fast reporting for the next step. Commends for sorting are then sent to the mechatronics system. More details are given in tables 1 and 2.

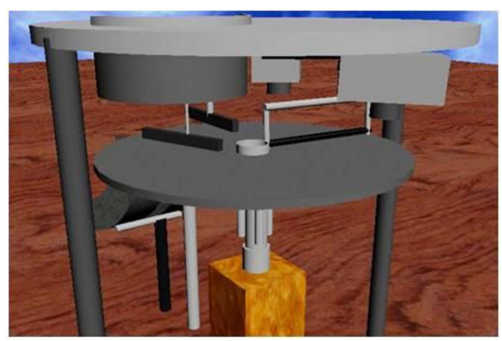


(A)

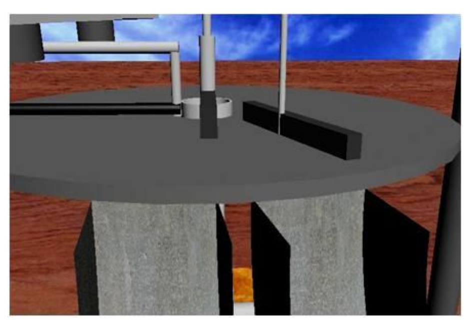


(B)

Figure 2: Proposed mechatronics system to select one Pistachio for imaging two sides of it: (a) and (b) are different view of the system



(A)



(B)

Figure 3: Another view of the proposed electromechanical system

Table 1: More details from Fig. 2 and Fig. 3

Row	Number	Function and efficiency of each part based on the number determined in fig. 2
1	1	Ac electric motor (engine) with gearbox for the rotary motion of inlet source (tank) of the pistachio to prevent sample accumulation of the samples and the output of them to the plate No.11 that the number of its revolutions are determined based on eq.4.
2	2	Ac motor with gear box for the motion of the plate No.9 to the located samples in front of the imaging system. Number of the revolutions of motor can be determined by eq. 4.
4	4	Two cameras are used for imaging the samples.
5	4	Two optical transmitter and receiver sensor are used to determine the entry of the samples for the imaging stage.
6	4	Imaging cameras are provided from Sony company with 12 Mega pixel lens.
14	12	Computer is used to process delivered images from the cameras and sending required commands to the blocking factor of the route (No.8)

Table 2: More details from Fig. 2 and Fig. 3

Row	Number	Function and efficiency of each part based on the number determined in fig. 2
3	3	Output routes specifically for hulled and non-hulled samples.
7	5	Inlet source (take) of the samples.
8	6	The output of the sample from a circle with 2.5 cm diameter, connected to plate No.11 to select a sample and transfer the selected sample to the plate No.9 based on fig. 2.
9	7	Blocking factor of the final route to exit all samples including non-hulled type based on fig. 3.
10	8	Blocking factor of the route for the selection of hulled type to transfer into the first outlet (No.3) based on fig. 3 that has a better clarity than fig. 2.
11	9	Rotary circular plate for locating samples in front of imaging system to remove a frame from the image based on fig. 3.
12	10	Rotary roller with 5cm diameter with belt and gear connected to engine (motor) No.2 that makes the other side of the sample to be shown clearly in imaging by rotation of the sample based on fig. 3.
13	11	Plate No.11 with case and ridging over it, used for imaging samples one by one. Mentioned plate is motionless based on fig. 3 with a better clarity than fig. 2.

To reduce the processing time, all the images cropped into a size of 149×163 and a computer with 1.-8 GHz processor used to process the image. Samples used in this research, gathered from pistachio processing terminals from IRAN gardens.

Description of the mechatronics system

The proposed system contains a gyrating source (tank). Ripe and healthy samples have been placed inside the tank and enter to the outlet plate by gyrating motion of the samples. An alternative current (AC) motor is employed to pull up the pistachios from the pressure in the inlet tank. Ac motor is utilized to prevent the compression of the pistachios into the entry tank and for tank movements after leaving the plate No.11. Samples are located in the plate (No.8, fig.2); then sensors identify their inlet to the imaging part and send the image of the pistachio to the computer. If the pistachio type has not been identified in this step, next camera takes another image from the other side of the object. This image is then taken as a result of the rotation of the sample by rotary roller No.10 and the next image of the pistachio is leaded into the computer; if the computer recognizes that the type of sample is hulled, it will send a command to close the blade of the route (No.8, fig.2) that closes the route for the sample exhaust. The number of samples which can lead into the exhaust (No.3, fig. 2) can be achieved by eq. (1).

$$x = fix(t/(t_p + t_b)) \tag{1}$$

Where t_b is time range between two cameras, t_p is the processing time of one sample, t is time in second(s), function «fix» converts the achieved number into the integer values and x is the number of samples in specified time. If the type of sample is not identified in the first step and the second step is required, then the processing time will be repeated:

$$t_{pnew} = 2 \times t_p \tag{2}$$

By assuming the processing time equal to 0.1, the number of samples which can sent by the system to the outlet at time t , can be achieved by eq. (3).

$$n = \frac{t_s}{0.1} \tag{3}$$

where t_s is the time of the entry of samples to the imaging step and 0.1 is the elapsed processing time of a sample.

Grading hulled and non-hulled pistachios

A machine vision system is utilized for grading hulled and non-hulled pistachios as below:

1. Image acquisition
2. Remove the pistachio image from background by thresholding (the gray level of the image) and morphological operations (background removal)
3. Detect hulled and non-hulled pistachios
4. Send the command to the mechatronics system for separating the pistachios as hulled and non-hulled

Image Acquisition

The sample set in the experiment includes 200 random selected pistachios (minimum, maximum and width of taken pistachios are 1cm, 2cm and 0.7cm respectively) from the Iranian rafsanjan pistachio farms. Before storing, the samples are bagged after cleaning away the soil and have been wiped by a dry dish cloth. 149×163 RGB images are taken from the samples and a 1.8 GH processor is used for processing the image. Fig. 1 shows the typical samples of potato RGB images.

Image Filtering

Both digital cameras and conventional film cameras will take some kind of noise from different sources. In practical image processing purposes and computer vision, we often need to smooth the image to reduce the noise reduction on the image [8]. This operation is a generic pre-processing step to develop the results of the next processing like image thresholding. A Gaussian Low Pass Filter (GLPF) has an extensive application in image processing and machine vision because, under certain conditions, it retains edges while removing noise [9]. Generally, a Gaussian filter reclaims the input signal by convolution with a Gaussian function which is known as the Weierstrass transform [10].

The transfer function of the GLPF is presented below:

$$H(u,v) = e^{-D^2(u,v)/2\sigma^2} \tag{4}$$

$$D = \sqrt{u^2 + v^2}$$

Where σ demonstrates the standard deviation [11].

When the composition has been implemented in two dimensions, it will generate a surface whose contours are concentric circles with a Gaussian distribution from the center point. Quantities from this distribution are utilized to make a convolution matrix which is applied to the main image.

Each new quantity of the pixel is placed to a weighted average of that pixel's neighborhood. The main pixel's quantity receives the heaviest weight which comprises the highest Gaussian quantity and neighboring pixels receive smaller weights as their distance to the main pixel grows [12-14]. In this work a 3×3 Gaussian filter is used to reduce any possible noise particles from cameras.

Image Thresholding and Morphological Operations

After applying the GLPF filtering (Fig. 4), the binary image extracted by using Kapur’s method [15]; kapur’s method minimizes the entropy between bisects of the histogram created by a threshold which is explicated as a measure of class compactness and accordingly, of class resolution. The probability distribution of the gray levels over a black part of the image is:

$$\frac{p_0}{P_B}, \frac{p1}{P_B} \cdots \frac{p_s}{P_B}, \tag{5}$$

And for the white sect:

$$\frac{p_{s+1}}{1-P_B}, \frac{p_{s+2}}{1-P_B} \cdots \frac{p_{n+1}}{1-P_B}, \tag{6}$$

In which, s is the threshold; p_i (i=0, 1…n-1) is the statistical probability of pixels with gray level i in the whole image; P_B is the probability of pixels with gray level less than or equal to threshold s.

$$P_B = \sum_{i=0}^{s} p_i, \tag{7}$$

The entropy of the black sect (object) is:

$$H_B^{(S)} = -\sum_{i=0}^{s} \frac{p_i}{P_B} \log_2(\frac{p_i}{P_B}) \tag{8}$$

and for the white sect it is

$$H_W^{(S)} = -\sum_{i=s+1}^{n-1} \frac{p_i}{1-P_B} \log_2(\frac{p_i}{1-P_B}), \tag{9}$$

The total entropy of the image can be specified as:

$$H_T^{(S)} = H_B^{(S)} + H_W^{(S)}, \tag{10}$$

The threshold s is chosen as the one which maximizes $H_T^{(S)}$.

The desired pixels extracted by Kapurs method considered as pistachio. By starting the AC motor in the mechatronics system makes the voltage to drop and turning the motor off makes it to rise. These changes make some disturbances to be created. Such disturbances along with noise, spikes, and momentary interruptions of power, may affect the camera and hence for discarding or reducing these noises from the captured cameras, mathematical morphology is applied after capturing [16, 17].

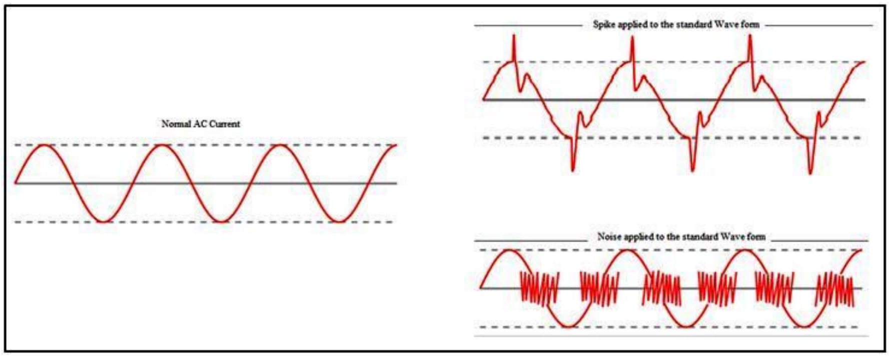


Figure 4: Two main disturbances which are often applied to the captured image.

Closing, region filling and area opening are three morphological operations which are utilized to reduce the noise [16]. Region filling comprises three morphological operations as: dilation, complementation, and intersections [18]:

$$X_k = (X_{k-1} \oplus B) \cap A^c, k = 1,2,3\ldots \tag{11}$$

where A is a set of boundary and B is structuring Element. The algorithms terminates at iteration step k if $X_k = X_{k-1}$. The opening of A by B is achieved by the erosion of A by B, followed by dilation of the obtained image by B. as below:

$$A \circ B = (A \Theta B) \oplus B \tag{12}$$

The main purpose of area opening is to remove small area blemishes that can be relinquished by the pistachio processing industries. Generally, area closing makes counters smooth, fuses narrow breaks, long thin gulfs, omits small holes, and fills gaps in the contour. The closing of set A by structuring element B, signified by A·B and is described and mixing thin distances as:

$$A \bullet B = (A \oplus B) \Theta B \tag{13}$$

Closing might result in merge of disconnected components which made new holes. Fig.9 shows the result of closing operation on the the threshold image.

Finally, a simple subtraction between original and the binary processed images result the segmented image.

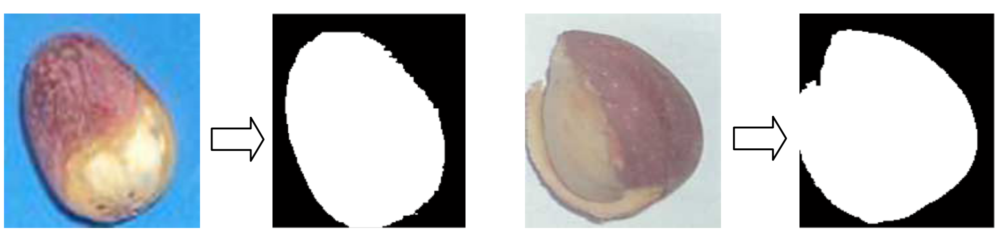


Figure 5: experimental result of pistachio segmentation: white and black pixels show the object (pistachios) and back ground respectively

Detecting the hulled and non-hulled pistachios

For detecting the hulled pistachios from non-hulled ones in a straight away and real-time mode, supervised classifiers are used; the main purpose of classification in image processing is to arrange all pixels in a digital image into several classes [19]. Pistachio hull (skin) color is a case that can be categorized by the classification method. The purpose of pistachio hull color pixel classification is to determine whether a pistachio is a hulled or non-hulled type. There are several classification approaches which have been extended from K-nearest neighborhood classifier to Support Vector Machine (SVM) classifiers.

This paper confirms to the analysis and usage of a strong type of neural networks, Support Vector Machines (SVMs). The functional form of SVMs is same as to neural networks and radial basis functions, both popular data mining approaches. However, the results of these algorithms are not as good as SVM and the quality of extension and training facility of SVM is far beyond the content of these more popular methods. SVM can model complex and real-time for the purposes as text and image classification, face recognition analysis. SVM implements well on data sets that have many properties, even if there are less cases on which to train the model. There is no range on the number of properties; the only limitation is those imposed by hardware. Popular neural networks do not implement well under these circumstances [20, 21]. Support vector machines used in this paper are also compared by the other approaches.

Support Vector Machines

Generally, a Support Vector Machine (SVM) is a classification algorithm for maximizing a particular mathematical function with regard to a given collection of data. SVMs reduce the classification error rate with two limitations contemporary which both search to a hyper plane with a major margin (i.e. the distance from the nearest template for detaching hyper plane) and minimize the number of false ratio using slack variables. SVMs utilize the results of statistical learning and optimization approach for maximizing the generalization potency for samples. These features proposed us that SVM could develop performance on the pistachio hulled and non-hulled classification. The main objective is to find a decision surface which gives the best result in classification of data sets into two groups:

$$y = \operatorname{sgn}\left(\sum_{i=1}^{N} y_i \alpha_i K(x, x_i) + b \right) \tag{14}$$

where x is the d-dimensional vector of a test sample, $y \in \{-1,1\}$ is a class label, x_i is the vector for the ith training sample, $K(x, x_i)$ is a kernel function, N is the number of training samples, $\alpha = \{\alpha_1 \ldots \alpha_N\}$ and b are the parameters of the model. α_i Can be leaded from [21].

The good result in any classification task is captured by defining a suitable kernel (i.e., similarity) between objects. The task of kernel is to transform data from the input to the feature space. There are several applications for kernel functions from linearity to non-linearity which can be expressed in terms of dot products. In this paper, 3 types of these kernels are tested which are listed below:

Linear-kernel $\quad k(x, y) = x^T y + c \quad$ (15)

Polynominal-kernel $\quad k(x, y) = (\alpha x^T y + c)^d \quad$ (16)

Quadratic-kernel $\quad k(x, y) = 1 - \dfrac{\|x - y\|^2}{\|x - y\|^2 + c} \quad$ (17)

where c is constant, and d is polynomial degree. Sequential minimal optimization (SMO) is also utilized to get better result of the work; training a support vector machine needs the resolving of a complicated quadratic programming (QP) optimization problem. SMO splits the QP problem into a chain of smallest possible QP problems. These divided QP problems are solved analytically, which eschews using a time-consuming numerical QP optimization as an inner loop. SMO needs linear value for training set size which authorizes it to handle complicated training sets. Because matrix computation is eschewed, SMO scales some whiter between linear and quadratic in the training set size for different test problems, while the standard fragment SVM algorithm scales somewhere between linear and cubic in the training set size. SMO can performs1000 times faster than the chunking algorithm for the real world sparse data sets. In QP problem, a suitable Lagrange is need; multipliers α_i to achieve the following function gains its maximum value. QP problem to the train SVM is presented below:

$$Max W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j k(x_i, x_j) \alpha_i \alpha_j, \quad \forall i, 0 \le \alpha_i \le C \tag{18}$$

Subject to

$$\sum_{i=1}^{n} y_i \alpha_i = 0 \tag{19}$$

The SMO algorithm will terminate when all of the Karush-Kuhn-Tucker (KKT) optimality conditions of the QP problem are fulfilled. These KKT conditions are particularly simple:

$$\alpha_i = 0 \Rightarrow y_i f(x_i) \ge 1 \tag{20}$$

$$0 \le \alpha_i \le C \Rightarrow y_i f(x_i) = 1 \tag{21}$$

$$\alpha_i = C \Rightarrow y_i f(x_i) \leq 1 \tag{22}$$

Experimental Results

Two classification areas (as nun-hulled and hulled pistachios individually) have been utilized in this paper; we discuss pixel-based pistachio detection classifiers, which classify each pixel, independently from its neighbors.

Databases are 149×163 in size and the others convert into this size for easier comparisons. The construction of the classifier is a vector of 3×n pixel coefficient vectors from each image either nun-hulled or hulled image which n is the number of neurons in hidden layer.

Thus, the output of the neural network needs to be reclaimed so that it is either 0 or 255. Morphological processing including the filling holes and opening followed by closing is then performed to the result images [22]. In this article, artificial neural network consists of support vector machines has been implemented with features of image RGB color pixel values taken as input values, and nun-hulled or hulled pistachios as the output. 3 different kernels and sequential minimal optimization are used to investigate a real-time and accurate classification for pistachio sorting system. The optimal parameter (C) and end-accuracy for SVMs selected as 100 and 10^{-4} respectively. The evolutional situation was quite the same for each of the kernels. We are also utilized MLP and 4 nearest neighborhood classifiers to achieve the best type of classification. Tables.1 and 2 present the performance for compared classifiers in accuracy and speed.

Table 3: Classification Comparison of time speed in the algorithm in half-hulled type

Method	Operation Time (seconds)
Knn	0.15
MLP	0.19
SVM-Linear kernel	0.06
SVM-Poly Nominal kerne	0.11
SVM-Quadratic Kernel	0.08
SVM-SMO based	**0.02**

Table 4: Classification Comparison of Performance in the algorithm in half-hulled type

	Accuracy					
Sample	Knn	MLP	SVM-Linear kernel	SVM-Poly Nominal kernel	SVM-Quadratic Kernel	**SVM-SMO based**
Open	77.5%	78.5%	81%	81.5%	81.5%	82%
Closed	80%	81%	83%	84%	84.5%	85%
Half-hulled	81%	81%	83%	84%	84.5%	85%
Whole-hulled	80%	81%	83%	84%	84.5%	85%

The above tables show that the support vector machine with sequential Minimal Optimization outperforms the others in both accuracy and time.

Studying the efficiency of the design

After the pistachios separated by the system, each one kilo of hull pistachio in processing line is computed about 900 to 950 (due to their types and sizes). The efficiency of the design is given in table 5.

Table 5: Required time for piling one kilo of sample based on the type of sample in the proposed electromechanical design

Type of sample	variance (sec)	Time (sec) for one kilo of the sample
Open	3	74
Closed	2	21
Half- hulled	3	46
Whole- hulled	2	75

CONCLUSIONS

Decreasing the time between harvesting and piling is a significant case to increase the quality of the pistachios. A mechatronics system is designed and implemented to sort of hulled and non-hulled pistachios. 6 different classifiers are used to classification step to find the best classifier in both time and accuracy. Performance evaluation in the system shows that the system is very efficient for the pistachio grading purposes. The capability of the system in experimental tests is approximately 1 kilo per second and the accuracy is about 85%. Finally the mechatronics system should be designed in a way that grades each one of the samples, if they are of hulled or non-hulled type.

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