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APPLYING ARTIFICIAL NEURAL NETWORKS (ANN) TECHNIQUES TO AUTOMATED VISUAL APPLE SORTING

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Abstract

Nondestructive quality evaluation of fruits is important and very vital for the food and agricultural industry. Traditionally sorting of fruits is based on human visual inspection using size as a particular quality attribute. The Artificial Neural Networks (ANNs) are the imprecise, approximation and inexact set of computing methods that can study, examine and evaluate complex problems. These techniques deliver low cost solution as compared to hard computing and also provides a low cost solution with a tolerance of imprecision, vagueness, partial truth, uncertainty and approximation. A usual procedure is based on human visual inspection considering general fruit attributes like quality, size and color; furthermore, size information is vital in packing houses. Apple is an important fruit products in Albania. Its production calls for quality sorting for domestic and regional markets. In this paper we propose a combination of image processing and ANN techniques for developing an algorithm to sort apple fruits into size groups (Small, Medium and Large).

For this purpose, a backpropagation network model with a number of training functions were used for ANN modeling. A logsig transfer function was applied in input layer, which has 4 input parameters (Area, Perimeter, Max diameter and Min diameter), whereas a linear transfer function was used in the output layer. The hidden layer has different number of neurons and ANN models were trained by Training Batch. For evaluating and finding the most accurate ANN model the Evaluating Batch was used.

Results showed that algorithms based on 4 mentioned parameters and the ANN model, produced lower errors. Sorting records of each algorithm were compared to the relevant sorting data brought about by experts. Results show that sorting error can be 1.1%, thus apple fruits can be sorted at high speed, high accuracy and low costs by using the ANNs techniques.

The results reveal that apple fruits can be sorted at high speed, high accuracy and low costs by using the ANNs techniques.

***Key words**: Artificial Neural Network, Backpropagation, Training, MLP, Image processing, Machine vision, Apple sorting.*

1. Introduction

Fruit industry contributes in a major part in national growth. During the last decades has been a decrease in production of good quality fruits, due to improper cultivation, lack of maintenance, very high losses in handling and processing, manual inspection, lack of knowledge of preservation and quick quality evaluation techniques. These and other factors, such as rising labour costs, shortage of skilled workers, and the need to improve production processes have all put pressure on producers and processors and raised the need for a rapid, economic, consistent and nod-destructive inspection method [10]. In this framework, automation can reduce the costs by promoting production efficiency.

In Albania economically and industrially apple is one of the most important fruit. It is consumed in different forms such as: fresh fruit, purée, or juice. During the last decade the national production of apple was increased (according INSTAT). The production of apple require the quality sorting of this product for domestic and regional markets. Fruit packaging installations have been founded in several regions to process and pack it in advanced modern ways, but unfortunately grading and packaging is not yet done in the suitable and proper way.

Automation can reduce the costs by promoting production efficiency. Automatic fruit grading and sorting requires the implementation of computer vision systems. Its application in agriculture has increased considerably, since it provides substantial information about the nature and attributes of the produce, reduces costs and manual labour's, guarantees the maintenance of quality standards and provides useful information in real time. Automatic fruit classification offers an additional benefit of reducing subjectiveness arising from human experts.

Adoption of robotic technology is inevitable in modern agricultural and food systems, and can increase the efficiency of post-harvest tasks such as sizing and sorting fruits.

The task of fruit classification requires perceptual power or cognitive capability of human beings which leaves the von Neumann machine far behind. To overcome the limitations of traditional computing paradigm, several novel modes of computing have emerged which are collectively known as soft computing. The chief components of soft computing are artificial neural networks, fuzzy logic, evolutionary algorithms, swarm intelligence and support vector machines.

Numerous investigations have been carried out in this field. Brosnan and Sun [5] used different computer vision systems for blemish and disease detection of horticultural products. Garcia-Ramos *et al.*, [7] reviewed non-destructive sensors used for fruit firmness determination. Butz *et al.*, [6] compared different technologies for internal qualification of fruits and vegetables. Dara, [4] used ANN and machine vision to sort orange in different categories.

In recent years, the application of Artificial Neural Networks (ANN) has been increased. The Artificial Neural Network models are based on the neural structure of the brain. The brain learns from example and so do ANN. Previous research has shown that Artificial Neural Networks are suitable for pattern recognition and pattern classification tasks due to their nonlinear non-parametric adaptive-learning properties. Successfully trained ANN model can performs tasks such as predicting an output value, classifying an object, approximating a function, recognizing a pattern in multifactorial data, and completing a known pattern [17].

Artificial Neural Networks are computational modelling tools that have found extensive acceptance in many disciplines for modelling complex real-world problems. Agriculture is a most important sector for economy of the country. According to our survey at local level and through the literature, we found that the farmer manufacturer of apple product is having no computerized apple sorting method, but all of them are using manual fruit sorting system. Therefore we encourage application of ANN for the apple sorting. The farmers and manufacturers of apple fruit-based product (like: juice, jam, etc.) very much require the automatic apple sorter. Therefore, we are proposing utilization of a low-cost ANN-based classifier. The complete system is divided into two modules; in the first module, we are collecting input from the different sources by the software developed in Visual Basic through different input device like: web camera, weight machine, etc. We have developed interface program in visual basic for web camera, weight machine, etc., to extract the value of color, size, weight, defect, etc. In second module, the input data are used by ANN simulator to detect the apple quality. The ANN simulator program is developed in Matlab Compiler and Matlab Neural Network Toolbox. It can segregate apple according to: defect, size, color, etc.

Although many systems have been developed that are based on image analysis to estimate the external features of the fruits such as: size (Tao *et al.*, [18]; Varghes *et al.*, [19]), shape (Guyer [9]; Dickson *et al.*, [5], color (Ruiz *et al.*, [15], symmetry, weight, or damage (Growe and Delwiche [8]; Molto *et al.*, [14], currently the fruit classification is performed in a big plant and requires huge amount of investment or by people placed along the sorter, who classify the fruit manually or assisted by semiautomatic systems. Some current automatic sorters estimate the color using photoelectric cells or use color filters mounted on monochromatic cameras.

The described ANN-based apple classification system is rather faster and cost-effective. Manual system requires appointment of more skilled people who will judge the fruit quality, and even that doesn't ensures that the quality is judged properly or accurately. The Neural Network-based system shows more accurate result than manual system. Also, since manual quality assessment system requires more skilled manpower it is quite normal that it is more expensive than the Neural Network-based system. As a matter of fact, the Neural Network-based system requires one time cost, which in long run results in very cheaper system than the manual quality assessment system. The Neural Network-based system is very beneficial for the apple farmer, exporter, and trader. They can get the right price of their product, which will allow the consumers also to benefit by getting appropriate fruit of their choice for optimal price.

The ANN are used for: prediction (Wilkinson and Yuksel, [22], modelling complex unstructured human judgment, and for grading fruits according to their external quality. Among these qualities, size is one of the most important parameters identified by consumers. The size information is vital for packing houses also. Size can be estimated by image processing techniques (Blasco [1] or neural network techniques (Dara [4]).

2. Materials and Methods

The basic model for automatic fruit classification mainly contain four steps: as a first step, a database of the fruit is created at image acquisition step. After that various image processing techniques are applied to improve image quality. Then features are extracted and reduced (if required) to feed as input to the model. As a fourth step, classification is performed using a classifier.

2.1 System Overview

The prototype apple fruit sorter is consisted of an image acquisition and processing unit, and a sorting unit (Figure 1). The image acquisition and processing unit is including an image acquisition platform with a black background; a webcam (Creative Labs) installed on the top of the platform and connected to a computer (HP Compaq dc7600 Business Desktop, Intel Pentium D processor 820* Dual Core, 2.8-GHz) serve desired image to be acquired (600 × 800 pixel, RGB). The illumination system inside the platform contain six white LEDs located on the top inner side of the platform. The LEDs were used effects of rapid variations in brightness to be avoided. In order to prevent shadows and to reinforce the light, the inner walls of the platform were painted white. Inside the platform, a robotic arm was adopted to stop incoming fruits while the acquisition system captured images (Figure 2). This arm is controlled by a step motor connected to a microcontroller and finally to the serial port of the computer.

The system arrangement is done as shown below (Figure 1) and its basic aim is to obtain the fruit's features. The system consists of several steps like feature extraction, sorting and grading. Captured image is given as an input to the MATLAB software which extracts (detects) color and size of a fruit, and this data are transferred to ARM based system.

Sorting hardware consists of another robotic arm and step motor connected to the microcontroller. A gentle but adjustable slope was considered to promote fruit removal from the sorting table to the fruit bins (Figure 1).

A number of programs were developed in MATLAB for image processing purposes. These programs measured the pixel values of each incoming fruit picture. Also, a number of ANNs were developed and combined with the image processing algorithms for sorting purposes.

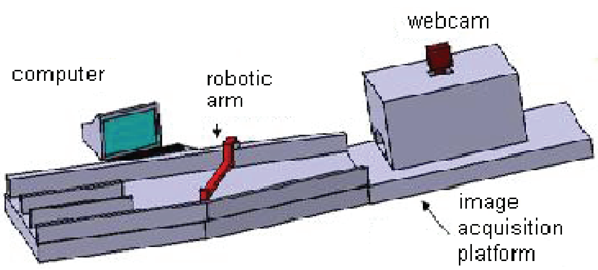

Figure 1. Schematic view of the sorting test device

2.2 Methodology

Through web camera sensor, we have captured the required parameter information of each fruit using non-destructive method. A program is developed in Visual Basic to extract information about: size, color (red, green, blue), and density of the fruit form images. The captured sensor information is pre-processed to extract the required parameter information. The pre-processing involves computer vision subsystem to extract information related to shape, size, color, etc., apart from other calibration routines, etc.

In second phase, an ANN-based system is developed for apple classification based on the parameter information available from the pre-processor subsystem. This also involves selection of appropriate type/architecture, activation functions of various stages, and learning strategy, etc. The training methodology and post-training learning strategies also are developed. The purpose of this subsystem is to categorize each fruit into one of the given number of quality categories. The flow diagram of machine vision subsystem and Artificial Neural Network classifier subsystem are shown in Figure 2.

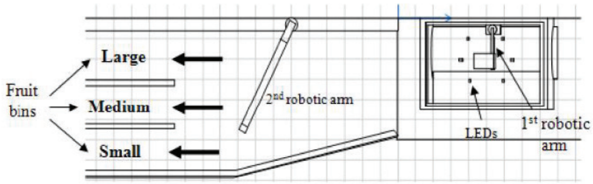

Figure 2. The view of sorting device

2.3 Neural Network training algorithm

The first simple Neural Network was developed by McCulloch and Pitts [12]. Presently, many types of ANN have been used. In this paper, a popular learning method that we have used is capable of handling apple classification is the back-propagation algorithm. It has been one of the most studied and used algorithms for Neural Networks learning ever since. The Back propagation (BP) Neural Network training algorithm is widely used to solve many classification problems by using the concept of multilayer perceptron (MLP) training, validation, and testing. The term "backpropagation" refers to the manner in which the error computed at the output layer of the ANN is propagated into the hidden layer. The gradient of the error of a network is calculated using the network's adjustable weights (German *et al.*, [7]). The learning process of BP Neural Network algorithm is made up of 2 parts. First is signal transmission toward; second, the error information is transmitted in the reverse direction and update the weight value. In this algorithm, the weights of the network are iteratively trained with the errors propagated backward from the output layer. However, the major disadvantages of BP are that its convergence rate is relatively slow

(Zweiri *et al.*, [21]) and being trapped at the local minima. But there are many solutions proposed by many Neural Network researchers to overcome the slow converge rate problem (Zakaria *et al.*, [20]) (Figure 1).

The back-propagation learning algorithm is developed for multilayer perceptions in the form of gradient descent. The back-propagation training algorithm is an interactive gradient descent algorithm designed to minimize the mean square error (MSE) between the actual output of a multilayer feedforward perceptron (MLP) and the desired output and updates the weights by moving them along the gradient-descendent direction. Gradient descent is a first-order optimization algorithm. There are many powerful optimization algorithms that have been devised, most of which have been based on simple gradient descent algorithm such as scaled conjugate gradient descent.

In this study, a number of Artificial Neural Network (ANN) algorithms were developed and used for classification. The Multilayer Feed-forward Neural Network (MFNN) was used for apple classification. This model can be constructed with more than 1 layer and is able to learn nonlinear and complex relationships (Lertworasirikul [11]). For apple fruit classification, a back propagation network model with various training functions including variable learning rate back propagation MLP-GDM, Resilient back Propagation (MLP-RP) and Scaled Conjugate Gradient (MLP-SCG) were used for ANN modelling. In the first layer of the network was applied a logarithmic sigmoid transfer function (logsig), and a linear transfer function (Purelin) was used in the final layer. For ANN modelling, in general, one hidden layer has been found to be adequate, and only in some cases, a slight advantage may be gained by using two hidden layers. In order to sort apple into three size groups, one hidden layer was employed for modelling; however, the number of neurons in the hidden layer differed from 1 to 6.

For ANN training, the fruit batch of the off-line stage, pre-classified based on the GMD, was used. The batch, consisting of 300 apple fruits, was fed into the sorter unit. Then, the algorithm started to capture images, segment the object and calculate pixel values for the four mentioned parameters (Area, Perimeter, Max diameter and Min diameter) based on the Red color band for each apple through image processing techniques. The data for image processing was then considerate as input information for the series of ANN classifiers. The inputs and outputs were normalized, gaining a value between 0 and 1 before being fed into the network. Finally, the ANNs were trained based on the pre-classified batch and the training ANNs were qualified to be employed for classifying the apple in real time conditions.

2.4 Training in MATLAB

We have used MATLAB Neural Network Toolbox for this study. In the Neural Network model by using MATLAB, there were several training algorithms that have a variety of different computation and storage requirements. However, no one algorithm is best suited to all application. In our work, we have tried to implement our system by using a Scaled Conjugate Gradient Algorithms (Moller *et al.*, [13]), which are numerical optimization techniques for Neural Network.

The apple classification pattern recognition tool is designed by arranging a set of input vectors of apple parameter, as rows in a matrix. Another set of target vectors is the apple's category. The target vector has 3 elements, where for each target vector, any one element is 1 and the other are 0. Network uses from 1 to 6 neurons in the hidden layer and 3 neurons in the output layer. The development of the ANN model involved 2 basic steps, training/learning and testing/validation. A Scaled Conjugate Gradient algorithm is then used for training the network. All the input and output data are randomly divided into three sets (Table 1): 80% (240 incidents) are used for training network, and 10% (30 incidents) are used to validate that the network is generalizing and to stop the training before over fitting occurs. The last 10% (30 incidents) are used as a completely independent test of network generalization. Following data show the training, validation, and testing ratio of the input data.

Table 1. Input/output data sets

Vectors	Ratio (%)
Training	80
Validation	10
Testing	10

2.5 Technology development

We have developed computer software that consists two module; in the first module, we have developed Visual Basic program for machine vision, to identify pixel values of each fruit and to determine its size. The second module is Neural Network-based program that is developed in MATLAB Neural Network Toolbox to classify the apple based on parameters collected by machine vision system.

A computer vision system consists of image capture device (web camera) and image analysis software program. The system receives images with a web camera. The image analysis was performed by a specific software application developed by ourselves using the programming language Visual Basic, which run under Windows 7 Operating System. Through the captured image, we have extracted the color of the apple in RGB value.

Four fruit parameters (Area, Perimeter, Max-diameter and Min-diameter) based on three color intensity bands (Red, Green and Blue) were considered as sorting criterions.

Each algorithm determined one parameter based on one color intensity band. Hence, a total of 12 algorithms were developed (for instance, algorithm #1 determined the area of the fruit based on the Red color intensity band, and algorithm #2 determined the perimeter of the fruit based on the Red color band and so on). To evaluate each algorithm, the pixel information of each fruit given by the particular algorithm was compared to the relevant size information measured manually to test the strength of their relationships. Therefore, each fruit was placed into the image acquisition platform and the webcam was triggered to capture an image and send it to each of the 12 processing algorithms developed earlier in the MATLAB software. Each algorithm would then segment the object and calculate pixel values relevant to one of the mentioned parameters. Segmentation was used to transform RGB images to binary ones. Segmentation determined which regions of an image corresponded to the background and which represented the object itself.

In the second step, we have extracted size of the fruits. As per our program, we have converted the background of image into black-white pixel. We have segmented the image, and after segmentation, we have easily calculated the size of the image into pixel.

Our software program clearly extracted the damage area as we have given in the following screen shots of damage detection. The black pixel denotes the damage area. For instance, in the regions composed of pixels of any of the damage area, the length and the area were calculated in pixel. The length of the major damage is defined as the length of the major region, classified as damage, found in any of independent views.

After collecting all above data, we have transferred them to the MS-Excel sheet. Then the Artificial Neural Network classifier subsystem gives the output. The Artificial Neural Network-based program is developed in MATLAB Neural Network Toolbox to classify the apple based on the parameters collected by machine vision system, which are already saved in Excel Sheet.

Area: After making the binary image, the number of "on" pixels represented the area of the fruit in pixels.

Perimeter: The perimeter of the fruit is represented by the number of pixels on the border of the fruit picture in the binary image.

To determine max and min diameters, the coordinates of each pixel of the binary image are first calculated and considered as a data point. Then, a matrix of the two variables of each pixel (x, y) is formed where x is the length and *y* is the width of each pixel coordinate. Assuming *N* as the length of vector of each pixel, the following equations are used to calculate the max and min diameter values:

$$u_{xx} = \frac{1}{N}\sum x^2 + \frac{1}{12} \tag{2}$$

$$u_{yy} = \frac{1}{N}\sum y^2 + \frac{1}{12} \tag{3}$$

$$u_{xy} = \frac{1}{N}\sum xy \quad + \frac{1}{12} \tag{4}$$

$$Common = \sqrt{(u_{xx} - u_{yy})^2 + 4u_{xy}} \tag{5}$$

$$MaxDiameter = 2\sqrt{2}\sqrt{u_{xx} + u_{yy} + common} \tag{6}$$

$$MinDiameter = 2\sqrt{2}\sqrt{u_{xx} + u_{yy} - common} \tag{7}$$

Furthermore, correlations between pixel values, as identified by each program with the corresponding actual size of the fruit (*GMD*), were established. Each test was carried out in five replications.

To allocate a single fruit into one of the three size groups (Small, Medium and Large) two thresholds ((TH1&TH2) or (TH3&TH4)) had to be identified and expressed in terms of pixels. To identify threshold values, a subroutine program was developed. Although the two thresholds were defined based on consumer standards as default thresholds, the new program was flexible. In other words, size thresholds are modifiable according to the users' desires. The subroutine program was able to calculate threshold values for each algorithm based on the following. The models were arbitrarily defined and found to give rational threshold values:

$$TH1 = \frac{MaxS+MinM}{2} \qquad TH2 = \frac{MaxM+MinL}{2} \tag{8}$$

$$TH3 = \frac{MeanS+MeanM}{2} \qquad TH4 = \frac{MeanM+MeanL}{2} \tag{9}$$

Where Max, Min and Mean are abbreviations for Maximum, Minimum and Mean pixel values respectively, while S, M and L are abbreviations for Small, Medium and Large groups, respectively.

The above equations can be used to calculate threshold values based on either Area, Perimeter, Max or Min diameter.

The 4 selected algorithms from the off-line stage, that is, the four algorithms segmenting one of four parameters (Area, Perimeter, Max diameter or Min diameter) based on Red color band, were combined with the two relevant thresholds models to form 8 comprehensive algorithms to be used in real time tests. These algorithms are capable of measuring fruit parameter and comparing it with the threshold values to conclude fruit size group.

2.6 Performance Tests

Evaluation tests were carried out in three subsequent stages as follows:

Preliminary stage

In this stage, a batch of apple fruits was selected. For each fruit, three perpendicular axial dimensions were measured and calculated the geometric mean diameter (*GMD*) of each fruit as a criterion of its actual size:

$$GMD = \sqrt[3]{abc} \tag{1}$$

Where:
- a - the longest intercept,
- b is the longest intercept normal to a and
- c is the longest intercept normal to *a* and *b* [14].

Off-line stage

In this stage, the batch of apple fruits was fed into the sorter unit. Then, the algorithm started to capture images, segment the object and calculate pixel values for the four parameters. The data for image processing was then regarded as input information for the series of ANN classifiers. The inputs and outputs were normalized, gaining a value between [0, 1] before being fed into the network.

Real-time stage

In this stage, the ANNs were trained based on real-time evaluation in which the complete test device was used, to investigate which combinations of algorithms and thresholds provide a more accurate performance.

3. Results and Discussion

Three subsequent stages of evaluation tests were carried out to find the sorting accuracy and time required to sort a single fruit as well as the throughput capacity of the sorting unit.

3.1 Preliminary test results

To evaluate the developed algorithms, equal batches of small, medium and large apples were chosen from the fruit market based on local consumer preferences expressed in terms of GMD. Table 1 shows information on the apple sizes measured/calculated for each batch.

Table 1. GMD of fruit batch used in preliminary evaluation

Type	Average GMD (mm)	Max. GMD (mm)	Min. GMD (mm)
Small	68.79	70.02	66.57
Medium	72.21	74.15	70.30
Large	75.49	77.18	73.89
Overall	72.02	77.18	66.57

3.2 Off-line tests results

At this stage, fruits were fed into the unit in a single array indiscriminately. The correlation coefficients between pixel values identified by each of the above 12 algorithms with the corresponding actual size of the fruit (GMD) were computed in 5 replications (Table 2). The table reveals that segmentations based on Red and Green color bands were more satisfactory as compared to the Blue color band as far as high correlation coefficients were concerned. This indicates larger differences between contrasts of an apple fruit and its background image in R and G color bands. For the real time evaluation, considering equal correlation values between algorithms based on R and G color bands (Table 2), only the four algorithms based on the R color band were employed and evaluated in the real time stage.

Table 2. Correlation coefficients between machine vision size measurements vs. GMD

Segmentation methods	Parameters	Rep1	Rep2	Rep3	Rep4	Rep5	Average	Overall
Based on Red	Area	0.98	0.97	0.98	0.97	0.98	0.98	0.97
	Perimeter	0.98	0.97	0.97	0.97	0.97	0.97	
	Max Diameter	0.97	0.95	0.97	0.96	0.95	0.96	
	Min Diameter	0.98	0.97	0.97	0.97	0.98	0.97	
Based on Red	Area	0.98	0.97	0.98	0.97	0.97	0.98	0.97
	Perimeter	0.98	0.97	0.98	0.98	0.98	0.98	
	Max Diameter	0.97	0.95	0.97	0.95	0.95	0.96	
	Min Diameter	0.98	0.97	0.97	0.98	0.98	0.98	
Based on Red	Area	0.96	0.95	0.95	0.96	0.96	0.96	0.82
	Perimeter	0.96	0.95	0.96	0.96	0.96	0.96	
	Max Diameter	0.97	0.96	0.66	0.85	0.84	0.86	
	Min Diameter	0.96	0.91	0.92	0.94	0.94	0.93	

3.3 Real-Time tests results

As mentioned, real-time evaluation was conducted in which the complete test device was used. In this stage, the two models of size thresholds were incorporated in the four image processing algorithms selected for the real time study. Thus, a total of 8 comprehensive algorithms were developed and evaluated. To investigate which combinations of algorithms and thresholds provided a more accurate performance, the outputs of the system's classifications were compared to the classification data based on GMD and the errors were calculated in 4 replications. The same evaluating process was then carried out for ANNs and the errors of each NN classifier were computed.

Table 3 demonstrates that the Multi-Layer Perceptron with RP and SCG transferring functions had least errors (1.1%). Since increasing the number of neurons in each layer increases processing time, the number of neurons has to be optimized. The optimum neuron number for MLP-SCG is 4 for the input layer, 3 for the hidden layer and 3 neurons for the output layer. Similarly, the optimum number of neurons for MLPRP is 4 neurons for the input layer, 3 for the hidden and 3 for the output.

Table 3. Percentage of errors associated with neural network classification as compared to classification based on GMD

Percentage of errors (%)						
Type of training function	**Neural Network Structure**					
	4-1-3	**4-2-3**	**4-3-3**	**4-4-3**	**4-5-3**	**4-6-3**
MLP-GDM	43.33	41.11	37.22			
MLP-SCG	27.22	7.78	1.1*	1.1*	1.1*	1.1*
MLP-RP	28.33	7.78	1.1*	5.55	1.1*	1.1*

Classification errors of eight image processing algorithms as well as errors for the most accurate ANN model (MLP-SCG or MLP-RP with 3 neurons in the hidden layer) are shown in Table 4. This table reveals that algorithms #5 (Area & TH3, 4), algorithm #6 (Perimeter & TH3, 4) and ANN have the least errors (1.1%) and algorithm #3 (Max diameter & TH1, 2) has the maximum error rate (7.78%) when sorting the fruits.

Statistical analysis (Table 5) revealed that there were significant differences among algorithms. However, there were no significant differences among replications which mean that different rest positions did not have significant effects on the sorter's performance.

Comparing the sorting mean errors by Least significant difference test (LSD) (Table 6) indicates that although algorithms #5 (based on Area & TH3, 4), #6 (based on Perimeter & TH3, 4) and ANN exhibit lower errors (1.1%), there are no significant differences between algorithms #1 (Area & TH1, 2 - with 1.66% error), #2 (Perimeter & TH1, 2 - with 1.66% error) and #4 (Min diameter & TH1, 2 - with 3.33% error). As a result, adoption of each of the above 6 algorithms does not make a difference.

Table 5. Results of the real-time tests' statistical analysis

Source	DF	SS	MS	F	P
Replication	3	13.579	4.5264	0.86 ^{ns}	0.474
Algorithms	8	211.559	26.4448	5.04**	0.001
Error	24	125.940	5.2475		
Total	35	351.078			

ns Not significant
** Highly significant differences ($p < 0.01$).

Table 4. Percentage of errors associated with classification based on the machine vision and ANN as compared to the classification based on GMD

Sorting based on	% error				
	Rep1	Rep2	Rep3	Rep4	Average
Area & TH1,2	4.44	0.0	0.00	2.2	1.66
perimeter & TH1,2	0.00	2.2	0.00	4.44	1.66
Max diameter & TH1,2	8.89	8.89	6.67	6.67	7.78
Min diameter & TH1,2	4.44	0.00	2.2	6.67	3.33
Area & TH3,4	2.2	2.2	0.0	0.00	1.1
perimeter & TH3,4	2.2	2.2	0.0	0.00	1.1
Max diameter & TH3,4	8.89	6.67	2.2	4.44	5.55
Min diameter & TH3,4	6.67	4.44	11.11	2.2	6.11
ANN	0.00	2.2	2.2	0.0	1.1

Algorithms #5 and #6 (1.1%) have highly significant differences (0.01p) with algorithms #3 (7.78%) and #8 (6.11%) and have significant difference (0.05p) with algorithm #7 (5.55%). Therefore, algorithms #3 (Max diameter & TH1, 2), #7 (Max diameter & TH3, 4), and #8 (Min diameter & TH3, 4), are not recommended for sorting as compared to algorithms #5 and #6.

To summarize, both threshold models were reliable for sorting and adopting algorithms #1, #2, #4, #5 and #6. In addition, ANN is recommended for sorting purposes because it shows the least possible sorting error.

3.4 Throughput rate

The total time required for real time sorting, including time required for software and hardware operations, was measured during evaluation. The first position of the second arm was considered as the initial point for measuring operation times. Table 7 shows that when image processing algorithms were used, the test rig sorted apples into three size groups, in periods of 530, 755 and 935 ms/fruit, respectively. However, when image processing algorithms and ANN were used, sorting speeds were 569, 794 and 974 ms/fruit, for Large, Medium and Small fruits, respectively. The degrees of the second arm's movement are the main cause of time differences.

Minimum and maximum speeds were about 1fruits/s and 2fruits/s, depending on the uniformity of the fruits. Measuring the throughput rate of the single sorter revealed that it could sort 1 t of apple fruits into three size groups in 1 hour, the average speed for sorting the fruits being found to be 1.87 fruits/second. Although the average throughput rate for the single sorter was limited to 1 t/h^{-1}, it could easily be increased to the desired capacity by accommodating a number of sorters in a parallel bank arrangement.

4. Conclusions

- The sorter test rig was able to classify the fruits into three categories with considerably low errors. The comprehensive algorithms along with the ANN model were used at evaluation stages.

- Results showed that although algorithm #5 and algorithm #6 and the ANN model exhibit smaller errors, there are not significantly different from algorithms #1, #2 and #4. The real time performance revealed that a single test rig unit could sort fruits at minimum and maximum rates of about 1fruit/s and 2 fruits, respectively.

- The overall results revealed that image processing and ANN techniques used in the present test rig along with state of the art electrical circuit were capable of sorting apple fruits at high speed, high accuracy and low costs as compared to common sorters which use cup belt technology.

5. References

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Table 6. Mean error comparisons for various sorting algorithms

Type	#1	#2	#3	#4	#5	#6	#7	#8
#2	1.000							
#3	.001**	.001**						
#4	.309	.309	.010*					
#5	.730	.730	000**	.177				
#6	.730	.730	000**	.177	1.000			
#7	.023*	.023*	.177	.178	.010*	.010*		
#8	.010*	.010*	.307	.095	.004**	.004**	.733	
ANN	.730	.730	0.000**	0.177	1.000	1.000	0.010*	0.004**

Significant differences according to LSD test ($p < 0.05$).
Highly significant differences according to LSD test ($p < 0.01$).

Table 7. Details of time requirements for sorting a single fruit

Task	Large-apple Sorting time (ms)	Medium-apple sorting time (ms)	Small-apple sorting time (ms)
Image processing	309	30	30
ANN	69	69	69
Arms movement	500	725	905
Total time for image processing algorithm	530	755	935
Total time for ANN	569	794	974

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