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Classification of Some Fruits using Image Processing and Machine Learning

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ABSTRACT

In this study, an image processing algorithm and classification unit were developed to classify the fruits according to their size and color characteristics. For this purpose, a total of 300 fruits (50 fruit samples from each of the Starkrimson Delicious and Golden Delicious apple varieties, Washington Navel and Valencia Midknight orange varieties, Ekmek and Eşme quince varieties) were used in the experiments. The size and color values measured with a caliper and a spectrophotometer were entered in the developed image processing algorithm to determine the success rates of classifying the fruits. The integration of image processing algorithm with the classification unit classified 88%, 100%, 96%, 82%, 86%, respectively. On the other hand, the size and color values read in fruits with the image processing algorithm were evaluated using predictive techniques used in data mining. For this purpose, K Nearest Neighbor (KNN), Decision Tree (DT), Naive Bayes classification and Multilayer Perceptron Neural Network (MLP) algorithms were used. Algorithms were run with 10-fold cross validation method. In the training of artificial classifiers, the success was 93.6% for KNN, 90.3% for DT, 88.3% for Naive Bayes, 92.6% for MLP and 94.3% for RF.

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Introduction

The external features such as color, size, texture, different flaws and shape in the products to be offered to the market are important features in classification and grading. One of the most important quality features in fruits and vegetables is their appearance. The appearance not only affects the market value of the products, its preferences and the choice of the consumer, but it also affects the interior quality to a certain extent. Problems arising from processes such as classification, packaging and storage of fresh fruits and vegetables before they are placed on the market determine the market price formation and consequently affect the producer income (Pezikoğlu et al 2004). Manual quality control of the fruit takes time and labor intensive. Therefore, computerized vision systems are widely used for automation-based external quality control of food and agricultural products. Today, with advances in machine vision can produce accurate, fast, objective and efficient results in the non-destructive fruit classification due to the availability of low-cost hardware and software (Naik and Patel 2017).

According to the report of the Fresh Fruit and Vegetable Workshop published by the General Directorate of Agricultural Research and Policies in 2019, there was an increase of 24.03% in total fruit yield, 21.03% in the production area and 50.11% in the production amount. However, this increase causes approximately 30-40% of product to be wasted in total production due to wrong mechanization applications after harvest. Applications of post-harvest technologies can minimize the loss of fresh fruits and vegetables from harvest to consumption, reduce quantitative and qualitative losses, as well as maintain product quality, such as nutritional value, physical appearance and sensory properties. Some studies show that there are large differences between post-harvest losses of developing and developed countries, with estimated losses between 2% and 23% (Singh et al 2014). Studies on image processing have continued from past to present. For example; some of the researcher were used image processing techniques for edge detection, feature extraction and color detection of yellow, red and green apples in their study on yield mapping in peach fruit, using image processing techniques such as histogram thresholding and logarithm transformation, color, texture and shape of images taken under natural conditions. Feature extraction method has been used and algorithms have been developed. In the event that a fruit comes in front of the camera, the system processes the image taken from the camera and provides numerical and visual information about the size and color of the fruit examined on the screen (Tonguç 2007; Kim et al 2009; Kurtulmuş et al 2014). The researcher stated that some of the algorithms he developed have been successful in determining the fruit at the level of 85%. Sungur and Özkan (2015) made a quality control application using MATLAB software to detect pollution in chicken eggs and calculate egg volume. The researcher used the fuzzy logic algorithm to determine the degree of quality. According to the results obtained, the algorithm developed works with 98% accuracy. Örnek (2014) investigated the grading efficiency of the real-time image processing system developed with transverse and longitudinal roller-type mechanical carrot sorting machines. The classification of carrots on a belt, which can speed adjusted by a geared motor with classification machine is based on the analysis of these images. According to the results obtained, the ratio of carrots falling to the faulty section in a transverse roll, a longitudinal roll and real time classification machine was found to be between 0.65% - 99.33%, 18.39% - 88.90% and 5.42% - 9.03. Al-Shekaili et al (2016) classified the types of dates grown in various regions of Saudi Arabia according to their hardness. Instead of the traditional expensive and time-consuming methods used to determine the quality of dried fruits, they used artificial neural network and linear discrimination analysis methods by removing histogram and texture features from 1800 images, for example, in the computer vision system they developed. Researchers classified dried fruits into soft, semi-hard and hard. The results were successful for LDA and 84% for ANN and 77% for ANN. Jhawar (2016) classified taken from 160 orange photographs using the pattern recognition method. Designed classification system; data collection and processing, feature extraction and making decisions. Images were taken at a resolution of 640 × 480 pixels with a digital camera from a special box illuminated with 430 luxurious lights. According to the results of the study, 90% and 98% success was achieved in the classification of oranges. Ishikawa et al (2018), in their study, classified the strawberries by using the shape information taken from digital images. Using the SHAPE software, they used fruit length, width, projection area and fruit border lines data from 2969 photos for classification. They emphasized that the method of machine learning was successful in identifying strawberry fruits of nine different shapes. Li et al (2019) have developed an online optical and spectroscopic-based system for the rapid determination of internal and external quality in apples after harvest. A new image segmentation method has been developed in order to determine the image of apple containing all surface information in the online detection system consisting of the external quality detection mechanism and the internal quality detection mechanism. In the study, the fruit external quality assessment rate was 96.76%, the correlation coefficient in size measurement was 0.9763, and the root-mean-square error (RMS error) was 1.3243 mm.

In this study, apple, quince and orange fruit varieties were tried to be classified according to the color and size by developing an image processing algorithm.

Materials and Methods

Biological Materials

In this study, apple, orange and quince varieties were used as biological materials. In studies on the classification of fruits using image processing techniques, the number of sample sizes taken varies between 43 and 948 (Örnek 2014; Yabanova and Yumurtacı 2018). Besides these values, considering the statistical evaluation principles, the sample number for each variety was determined as 50 fruits.

Software and Measuring Devices

LabVIEW (Laboratory Virtual Instrument Engineering Workbench) package program was used to develop image process algorithm. And digital caliper was used to measure fruit diameter values. The digital caliper is capable of reading with a sensitivity of 1/100 mm. Xrite Ci60 model portable spectrophotometer was used to obtain color data from fruits. The spectrophotometer is able to determine the color values in the wavelength range of 400 - 700 nm in more than one color space and in this study, the desired L^* a^* b^* color space measurements was made. (Figure 1a).

Classification Unit

In the study, Logitech C930E model web cam was used to obtain images of fruits (Figure 1b). The dimensions of the camera are 29 × 94 × 24 mm and can take up to 1920 × 1080 pixels. The camera used is placed on a tripod so that the classification device can be seen from the top.

The belt conveyor, which is the most important component of the classification unit, was manufactured from stainless steel chrome sheet and aluminum material. The conveyor belt has a tape of 88 mm width, 2 mm thickness, 650 - 700 mm and is black and can eliminate the electrostatic effect. All of the fasteners of the belt conveyor are made of stainless material. The outer diameter of the drive roller is 32 mm, but there are holes of 25 mm depth and 8 mm diameter on both ends of the roller. One end of the drive roller is 14 mm, the other end is 17 mm in diameter and it is made of aluminum to prevent the bearings from rusting (Figure 1c).

The spindle conveyor drive roller of the DC motor operating the belt conveyor is coupled by direct engagement. The output speed of the DC motor reducer is 90 min^{-1} and the motor operates with a nominal 24V DC voltage. The speed of the band can be adjusted with a DC motor driver added to the system. The motor driver added to the system can control the motors in the range of 5 - 30 volts.

In the classification device, two pneumatic double-acting cylinders, which perform the main separation, are used. NPN type transistors were used to trigger the pistons. It is energized by means of 24 V with a capacity of 0,15 - 0,8 MPa as directional control valve. A pair of solenoid valves that control the pistons and a compressor with a maximum capacity of 6.8 bar producing the required compressed air has been added to the system.

(a) (b) (c)

Figure 1. Spectrometer and calibration plates (a), camera and tripod unit (b), Belt conveyor system(c)

Arduino development board was used to control the pneumatic pistons on the belt system. Arduino Uno is a development board that uses Microcontroller (ATmega328), which contains 14 digital input-output pins and 6 analog input pins that can be connected with various boards and other circuits.

Method

In the first stage of the measurements, the randomly selected apple, quince and orange varieties were numbered with labels affixed to the stem pit, and then the maximum distance between the flower pit and the stem pit of the fruits was measured and recorded. A total of 300 measurements were obtained. In the measurements carried out by the algorithm, the size readings were determined by first converting the RGB images taken from the fruits to the grayscale images and then determining the borders (edge detection). A platform placed under the fruits allows the widest parts to be measured by the camera. Under the camera, the fruit is placed so that the flower pit is below. The measurements were made according to the classification values specified in TSE standards. In Table 1, the minimum diameter values determined by TSI for apple, in Table 2. the length characteristics of the orange determined by TSE are also given. The algorithm developed for the apples is coarse and normal size, and for the oranges, the size number is between 0… 13, which is indicated on the front panel in the height indicators and classified by opening pistons on the belt.

Xrite Ci60 spectrophotometer color readings on the three surfaces determined from the vicinity of the stalk pit of fruits and the average of three-color channels (L, a, b) were obtained. The imported Lab color values are converted to RGB color space. Delta E is a measure of color difference and is determined using the Euclidean distance between two samples in the LAB space. Color image quality, the camera that captures images, etc. devices, compression on the image, restoration, rearrangement, image transmission depends on many factors such as (Ouni et al. 2008). For this reason, Delta E value is also given to indicate the color difference between the color values taken by spectrophotometry and image processing. Surfaces with color readings were then placed in a position where the camera could see, and the real-time measurement results of the developed image processing algorithm on the same surface were recorded in the Excel file. The color values are divided into classes only for apples within the standard set by TSE.

The size and color values read with caliper and spectrophotometer were entered into the developed image processing algorithm and the success of classifying the fruits correctly was determined.

Machine Learning Algorithms

In the readings performed by the algorithm, a database of three hundred objects with four numerical qualities (fruit diameter, R color channel, G color channel and B color channel) was created from the size and color values of apple, orange and quince. Class assignments (labels) of fruits whose qualities are determined in the database have been made. Using the KNIME Analytics Platform software, the data were introduced with descriptive statistical methods, and then analyzed with the classification techniques used in data mining. KNN, decision tree, Naive Bayes classification, Random Forest and MLP are used in the classification where tag values are tried to be predicted (Figure 2.). In the decision tree formation, gain information was taken as the basis of quality and minimum description length (MDL) was used as pruning method. Decision Tree algorithm evaluates how well each sample separates its attributes according to target classes by using information gain and entropy. The distinguishing feature with the least entropy is selected and used as a test at the root node of the tree. Entropy is a measure commonly used in information theory that characterizes the homogeneity of samples. The greater the difference of the data, namely the entropy measure, the more uncertain and unstable the results found with that data. If all objects are in the same class, entropy is zero (Silahtaroğlu 2016; Köse 2018). Entropy is calculated with the following equation:

$$\text{Entropy}(\text{Nj}) = \sum_{i=1}^{c} \frac{|\text{Ni}|}{|\text{Nj}|} \log_2 \frac{|\text{Ni}|}{|\text{Nj}|}$$

Here;

N_j: Total number of records of N attributes in the attribute set,

N_i: Refers to the number of records of the i'th option of the attribute N (Köse 2018).

The differences that occur according to this feature in order to make the correct classification at the stage of forming nodes and branches according to the distinguishing feature of the samples are called Gain

Information. Gain Information is obtained by calculating the differences between the weighted sums of the entropies of each subsection (Silahtaroğlu 2016). The Gain Information formula is given below:

$$D=H(D)- \sum_{t=1}^{n} P(D_i)\, H(D_i)$$

Here;
D: Gain,
H: Entropy,
P: Probability (Weight) (Silahtaroğlu 2016).

Using Bayes theory, it is used to calculate the probability values of the effects of each criterion on the result and to calculate which data is a member of which class (Çalış et al 2013). Naive Bayes classification technique analyzes the condition change situation. For example, in the case where B occurs, the probability of A occurrence is tried to be predicted. At the same time, it can be questioned as the possibility of B occurrence in the case where A occurs (Şeker and Erdoğan 2018).

The training and results processing of this method are very fast, but may be insufficient in solving complex classification problems. Bayes' theorem is calculated by the formula below.

$$\rho(A/B) = \left(\rho(B/A) \times \rho(A)\right)/\rho(B)$$

In the formula;
P (A): The predecessor probability of event A,
P (B): successive probability of event B,
P (B | A): Probability of B event when A event occurs,
P (A | B): When event B occurs, it is the probability of A event (Çalış et al 2013).

In addition, algorithms were run with 10- fold cross validation method in dividing training and test parts for classification. In this method, it is based on the principle of dividing the dataset into ten parts and using each piece as the test and the remaining nine pieces as the training set. The overall error and success rates of the system are calculated by taking the average of ten results.

Table 1. Smallest diameter measurements accepted by apples according to classes (Anonymous 2007a)

	Extra	Class I	Class II
Large size (L), mm	65	60	60
Normal size (N), mm	60	55	50

Table 2. Length characteristics of oranges (Anonymous 2007b)

Size No	0	1	2	3	4	5	6
Orange (mm)	92-110	87-100	84 - 96	81 - 92	77 - 88	73 - 84	70 - 80
Size No	7	8	9	10	11	12	13
Orange (mm)	67 - 76	64 - 73	62 - 70	60 - 68	58 -66	56 - 63	53 - 60

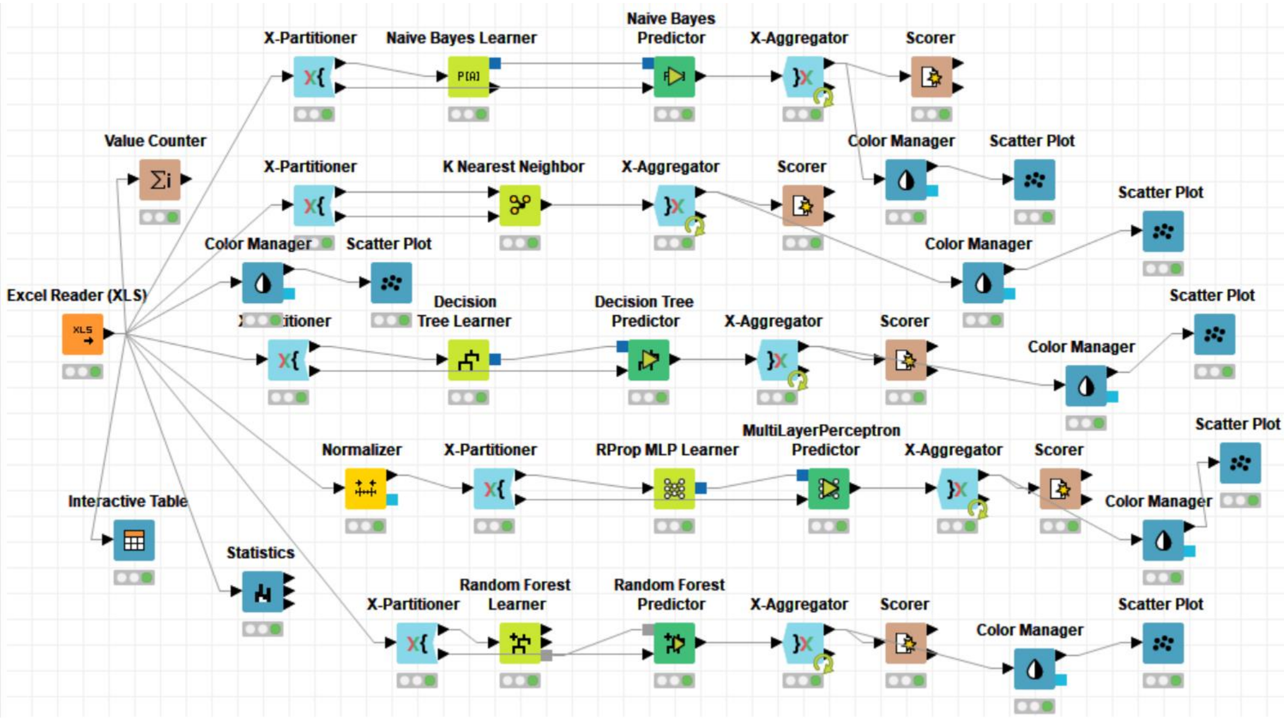

Figure 2. KNIME workflow

Results and Discussion

Screen of classification process of the algorithm developed are given in Figure 3. In the attempts made in the classification system for 50 Starkrimson Delicious varieties, 6 wrong classifications were made. In the classification made according to TS 100; for the extra class, the 1st piston was triggered and for the 2nd class apples, the 2nd piston was triggered. In apples that are in the first class, pistons were not triggered and passed directly over the belt. Its success in the classification in Starkrimson Delicious apple variety was 88%. In 50 Golden Delicious apple varieties, the classification success by dimensions was 100%. Er et al. (2013) studied real-time image processing for classification process of apple varieties using a the belt conveyor. Color, size parameters and fruit weights estimated from size and area values, and the system's success was 95.5% stated. Bul et al (2005) in their study on the classification of good and bad quality beans using image processing techniques, they achieved 87% success in real-time processing and classification of beans on the belt driven by two DC motors.

The orange classification process was carried out again according to the class numbers specified by TS 34. For 0-2 group, the first piston, for 3- 6 group, the 2nd piston was triggered, in 7-13 group, the pistons were not triggered and free passage was allowed. In orange varieties, there is the possibility of being in more than one group at the same time in terms of fruit diameter. According to TS 34;

Group 0....2: Oranges with a minimum diameter of 84 mm and a maximum diameter of 110 mm,

Group 3…6: Oranges with a minimum diameter of 70 mm and a maximum diameter of 92 mm,

Group 7...13: Refers to oranges with a minimum diameter of 53 mm and a maximum diameter of 76 mm. In the measurements of fruit sizes, if the product diameter was measured with the lower limits, it was evaluated as if it was in the following group. Because the diameter values measured by image processing are due to the tendency to give more values than the caliper (measured) diameter values. When analyzed, classification success by size for Washington Navel variety was 96% and 82% for Valencia Midknight variety. In the study of Jhawar (2016), 90% and 98% success were achieved in the classification of oranges by using the pattern identification method over the photos taken from 160 oranges.

Considering that there is no classification in terms of size and color in the quince classification process according to TS 1817. The classification process was made by determining the smallest and largest diameter values for both varieties and entering the lower and upper limit values of the diameter measurements that were read by the caliper in the algorithm. In both quince varieties, the 1st piston was triggered for correct classification, and the 2nd piston for incorrect classifications. With this method, system success was 95% with 5 incorrect readings in Ekmek quince variety and 86% with 7 incorrect readings in Eşme quince variety. When the upper and lower limit values obtained from the spectrophotometer were entered for each color channel, the success of apple varieties in terms of color was found to be 100%. However, orange and quince varieties were unsuccessful in the classification according to color because, there were no significant differences in colors. Delta E values ranged from 5.86 to 37.44 (Table 3.). In Figure 4, regression graphs of fruits are given.

Sabancı et al. (2016) Using image processing techniques to classify Golden Delicious, Granny Smith and Starking Delicious apple varieties, the values obtained by using Bayes Net, Naive Bayes, K Star, SMO, RBF Network, RBF Classifier, MLP Classifier, J48, Random Tree and Random Forest algorithms. they achieved a success rate of 95.56% with the J48 algorithm in their classification and 97.78% on the MLP Classifier algorithm in color classification. Küçükönder et al. (2015) KStar compared the success of the algorithms by classifying the color data from Random Forest and tomatoes using C4.5 algorithms. As a result of the comparison, they found the accuracy rates of Kstar, Decision Tree (C4.5), and Random Forest algorithms as 100%, 70.74%, and 98.30%, respectively. Al-Shekaili et al. (2016), in the study where they classified the varieties of dates grown in various regions of Saudi Arabia according to their hardness, extracting histogram and tissue properties from the monochrome images of 1800 samples, using artificial neural network (ANN) and linear discrimination analysis (LDA) methods, 84% for LDA and% for ANN. They have achieved 77 percent success. Dried fruits were classified as soft, semi-hard and hard in the study, 84% for LDA and 77% for YSA. Ataş (2016) used image processing to extract robust features in his study on Siirt pistachio, and classified the obtained mechanical data with NB, ANN and SVM, which are supervised machine learning algorithms. He stated that the highest classification success was ANN with an accuracy of 83.33%. Solak and Altınışık (2017) used image processing techniques and average-based classification and K-means clustering methods to identify and classify hazelnut fruits in their studies. While the hazelnut fruit detection was detected with 100% success by image processing, they achieved a classification success of 90% and 100%, respectively, with the other algorithms used. White et al. (2017) analyzed the length, width and color data determined by image processing from some olive varieties grown in Spain with ANN. The researchers reported that the diagnosis of fruit sizes with ANN can be made with 90% accuracy. Yabanova and Yumurtacı (2018) classified dynamically weighed eggs with support vector machines. In the application, they found 100% success in training and testing up to 11 input data. Koklu ve Ozkan (2020) studied on multi-class classification of dry beans. For this aim, taken images from dry beans and evaluated machine learning algorithms. MLP, SVM, KNN, DT algorithms scores were 92.36%, 100.00%, 95.03%, 94.36%, 94.92%, 94.67%, and 86.84% respectively. Confusion matrix and accuracy criteria for all algorithms are given in Table 4.

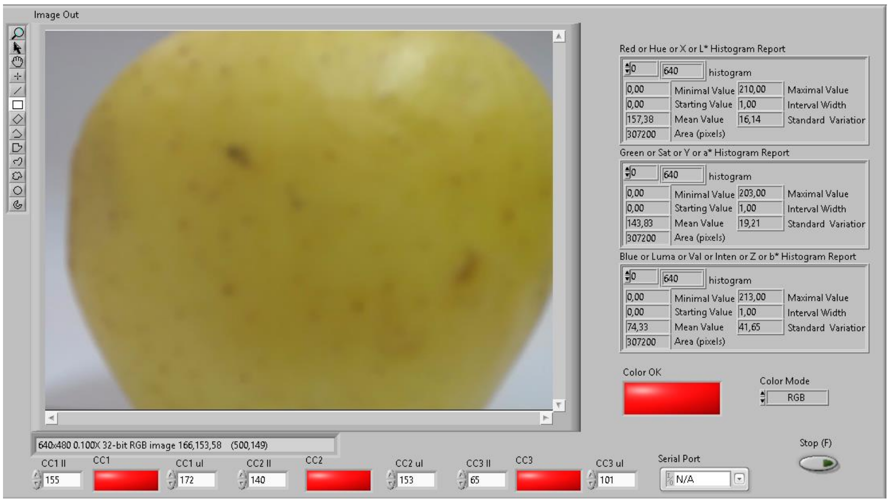

Figure 3. Screen of classification process

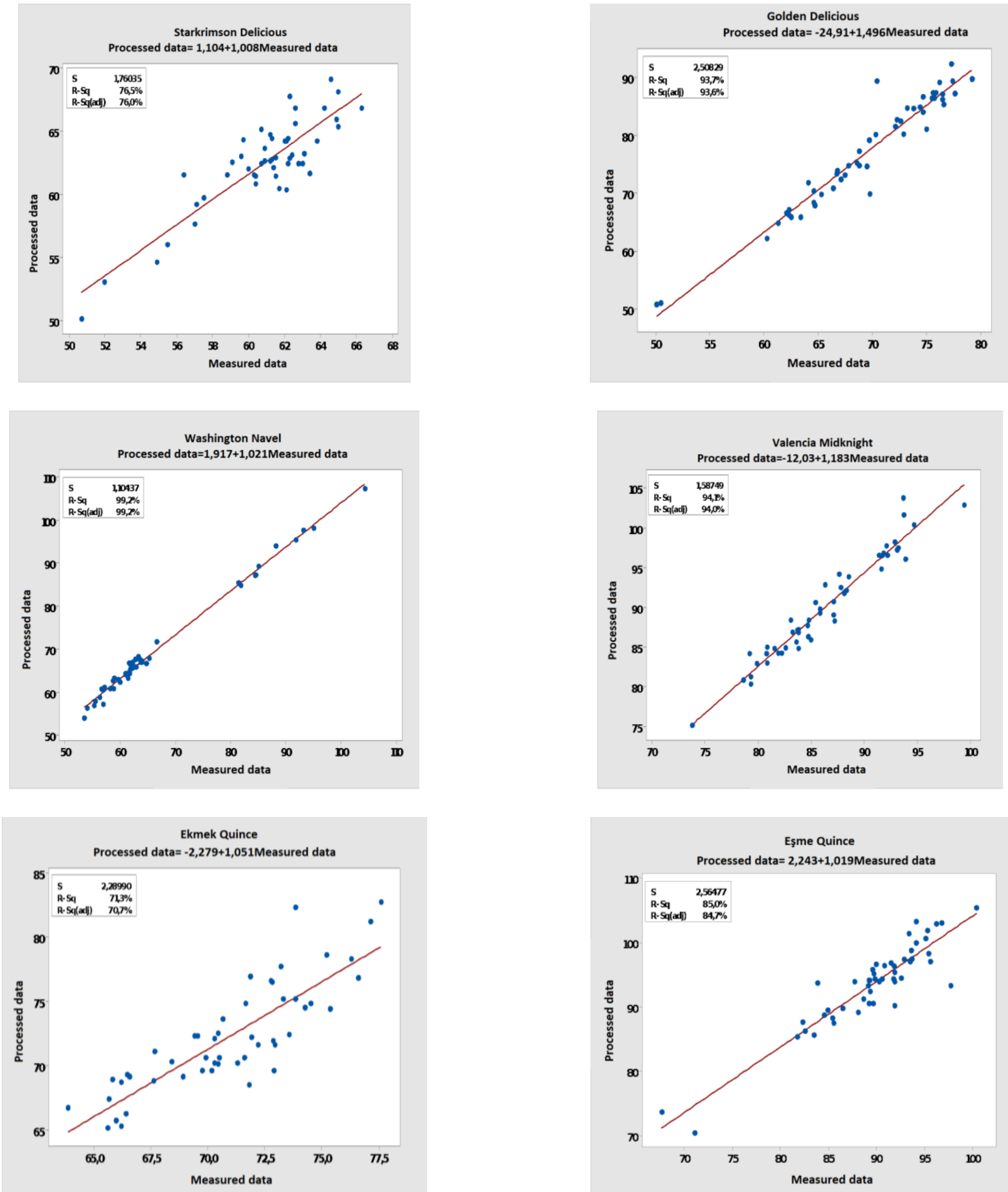

Figure 4. Regression graphs of fruits

Table 3. Delta E values of fruits

Sample no	Starkrimson Delicious	Golden Delicious	Washington Navel	Valencia Midknigh	Ekmek Quince	Eşme Quince
1	17.47	14.92	14.93	9.59	9.56	11.58
2	18.78	21,93	17.43	9.18	10.21	11.5
3	19.88	15.26	16.85	10.39	7.36	16.06
4	19.59	21.67	12.81	10.79	6.41	15.02
5	17.73	22.62	7.05	6.53	6.08	5.83
6	28.41	20.96	11.57	9.77	9.97	9.48
7	6.14	19.04	11.71	10.5	13.01	10.27
8	14.55	14.97	12.65	11.85	10.66	4.58
9	11.9	15.11	14.02	16.31	10.38	13.27
10	22.1	19.19	18.59	12.28	9.17	10.05
11	16.72	17.38	13.18	11.89	11.81	4.91
12	11.06	20.14	3.18	9.03	13.4	11.54
13	23.59	20.97	20.28	9.3	5.17	11.08
14	20.59	16.47	12.67	14.08	9.24	2.61
15	27.89	16.24	18.05	8.9	6.03	7.37
16	12.86	19.75	12.85	10.44	6.63	7.85
17	21.29	20.16	13.4	5.54	10.89	9.16
18	7.09	12.02	14.35	7.88	7.06	7.35
19	27.41	16.74	13.36	10.66	10.39	4.1
20	27.28	17.98	8.84	8.17	12	5.74
21	17.19	20.64	10.42	12.67	13.36	9.62
22	20.44	21.4	8.73	13.2	14.97	4.01
23	20.76	18.98	12.02	8.1	9.64	12.73
24	23.67	18.98	10.92	9.59	10.27	10.45
25	8.77	21.12	17.15	5.69	15.27	7
26	23.08	17.97	10.53	7.47	14.39	11.63
27	20.3	18.14	12.07	7.12	11.24	5.17
28	23.21	18.42	16.84	8.79	14.35	7.16
29	16.94	15.25	12.58	12.83	15.89	9.92
30	22.11	21.53	12.54	7.49	14.12	12.36
31	16.58	20.12	12.82	10.15	7.55	9.5
32	23.52	22.02	15.61	12.46	14.93	10.28
33	26.05	16.77	10.54	8.34	16.31	8.97
34	33.27	20.96	9.43	13.81	14.42	11.778
35	18.3	21.63	21.31	13.06	8.08	9.92
36	23.95	20.24	9.4	6.6	14.49	6.51
37	25.24	22	17.15	9.46	15.9	6.86
38	37.44	21.71	16.72	9.3	7.09	7.57
39	19.01	17.94	12.03	9.01	6.35	8.58
40	22.59	22	14.58	10.89	10.13	13.62
41	5.86	20.4	10.33	13.07	11.1	9.02
42	21.02	26.94	8.02	11.11	7.62	8.26
43	16.17	11.17	6.91	6.95	10.56	16.77
44	21.37	22.05	8.64	7.11	13.89	9.56
45	12.01	22.81	10.41	10.29	7.61	8.73
46	18.95	16.93	6.09	10.08	4.52	8.12
47	10.73	26.63	9.64	12.71	9.73	8.76
48	16.91	23.04	6.46	9.75	6.14	8.44
49	16.8	26.29	7.09	6.61	10.43	10.11
50	17.74	17.61	8.48	11.23	8.96	23.91

Table 4. Confusion matrix and accuracy criteria of algorithms

	Accuracy (%)	Error (%)	F-Measure	Recall	Precision	Sensitivity
KNN	93.667	6.333	0.826	0.905	0.905	0.76
DT	90.333	9.667	0.777	0.8	0.755	0.8
Naive Bayes	88.333	11.667	0.752	0.94	0.627	0.94
MLP	92.667	7.333	0.817	0.76	0.884	0.76
RF	94.333	5.667	0.848	0.84	0.857	0.84

Conclusion

In the study, an image processing algorithm was developed to classify fruits according to their size and color characteristics, and it was integrated into a classification unit and used in trials. On the other hand, the size and color values read on fruits by image processing software were evaluated with the estimator techniques used in data mining. Algorithms run with 10-fold cross validation method yielded highly accurate results. Both online and offline classification methods were successful for the fruits that were tested.

Information

This study is derived from the master's thesis entitled "Classification of Some Fruits with Image Processing Techniques" (Council of Higher Education: https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp) supervised by Prof. Dr. Mustafa Vatandas.

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