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Determination of Pear Cultivars (*Pyrus communis L.)* Based on Colour Change Levels by Using Data Mining

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A B S T R A C T

Colour is an essential parameter at product quality control stages, and finally, it is necessary for the consumer marketing decision. It is possible to damage the products during the process from collection to storage. Also, it is a well-known condition, cold environmental conditions protect fruits from deformations negative effects, but most of the time, most of the consumers keep the fruits at room temperature in open packs during the consumption process. Also, this condition affects the product storage time. In this study, it is aimed that to determine the behaviours of the fruits in room temperature and humidity conditions. For this aim the colour change of the damaged pears were determined, in another term, colour change value from red to green and yellow to blue at the damaged pears were determined with lightness values by using image analysis technique and analysed with data mining methods. For this purpose, 100 "Akça" pear and 100 "Deveci" local pear cultivar used for experiments. Fruits were equally damaged by using a pendulum mechanism. The damaged fruits were kept at room temperature. Colour change areas on fruits were evaluated with X-rite Ci60 spectrophotometer, and the hardness of fruits was measured by using a fruit penetrometer. The colour (L, a, b) and ΔE values were analysed for the fruit cultivars. The relationship between fruit hardness and colour change were also demonstrated. The predictions were done supervised machine learning algorithms (Decision Tree and Neural Networks with Meta-Learning Techniques; Majority Voting and Random Forest) by using KNIME Analytics software. The classifier performance (accuracy, error, F-Measure, Cohen's Kappa, recall, precision, true positive (TP), false positive (FP), true negative (TN), false negative (FN) values were given at the conclusion section of the research. The best prediction were found at the Majority Voting method (MAVL) 98.458 % success given with 70% partitioning.

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Introduction

Adequate and high-quality agricultural production has become a necessity to meet the needs of the increasing world population. Trade of agricultural products can be produce as raw, semi-finished, or processed to meet the demands. Regardless of the other countries, our country is not able to offer some desired quality products to the market. As a result of this condition, the problem decreases to chance of competition for export. Many developed countries bring certain quality standards as a prerequisite for import products. The concept of product quality includes the characteristics of odour, taste, cleanliness, and exterior appearance. The transmission of products to the market especially must be undamaged and robust, and this condition is a factor increasing the chance of competition. Preventing product losses occurring at various stages within the chain extending from producer to consumer is necessary to protect the limited agricultural resources while increasing the foreign exchange revenues by introducing the surplus products to the foreign market. In this regard, the development of harvesting, transportation, cleaning, classification and storage conditions of agricultural products and packaging will play an important role in increasing our exports to the world markets. (Yurtlu, 2003; Beyaz, 2008).

A lot of studies were done in the literature to achieve this aim. For example, Beyaz et al. (2011) determined colour change on pears with colour parameters. Their experiment results showed that "L values" were more critical than a and b values. Wu et al. (2012) worked on the measurement of the colour distribution in the salmon fillet. They said that, used multiple linear regression (MLR) models with effective predictive wavelengths, which resulted in correlation coefficients reliable and rapid alternative to traditional colorimeter for measuring the colour of salmon fillet. Küçükönder et al. (2015) studied on the colour maturity of tomato with K-Star, Random Forest, and Decision Tree (C4.5) classification algorithms. According to their results, K-Star instance-based algorithm was found as a better classifier compared to the others. Taghadomi-Saberi et al. (2015) determined of cherry colour parameters with an artificial neural network. They stressed that evaluation of *L**, *a**, and *b** values showed the possibility of reliable use of this system compared with a chromameter. Demir (2018) worked on application of data mining and adaptive neuro-fuzzy structure to predict colour parameters of walnuts (Juglans regia L.) and he stressed that the equations which are obtained from their measurements can be used as a viable alternative instead of equations that vary depending on whether *a** and *b** are negative or positive. Additionally, Demir et al. (2018) studied on data mining approach for the prediction of fruit colour properties. They have applied laws algorithm to each cluster and 7 different prediction rules were obtained by them from *CI, h** and *C** parameters. They express that R^2 values of the rules were compared and the rules with the most accurate outcomes were identified.

In this research, it is aimed to predict colour changes at two different pear cultivars “Akça” and “Deveci”' pears as storage quality parameter. It is a well-known condition, cold environmental conditions protect fruits from deformations negative effects, but most of the time, most of the consumers keep the fruits at room temperature in open packs during the consumption process. Also, this condition affects the product storage time. In this study, it is aimed that to determine the behaviours of the fruits in room temperature and humidity conditions. The predictions were done supervised machine learning algorithms that are Decision Tree and Neural Networks with Meta-Learning Techniques; Majority Voting and Random Forest by using KNIME Analytics software. Also, the classifier performance (accuracy, error, F-Measure, Cohen's Kappa, recall, precision, true positive, false positive, true negative, false negative) values were given at the conclusion section of the research.

Material and Methods

Data Collection

The pears were obtained from a local market, because of this reason the measurement process was applied 1 week later after the harvest process. A total of 200 pears were taken from local market that are 100 Akça pears, and 100 Deveci pears, and they were damaged from different sides of their surfaces. Some biological material properties of the pears can be seen in Table 1. Fruits were numbered from the stem pits. Then, they were kept at room temperature, and measurements were done day by day until full decay (for five days). A database of 4000 data was obtained from the readings which were taken from damaged pear samples for five days (Figure 1). The database was composed of four numerical characteristics of *L*, *a*, *b* and ΔE colour values.

Spectrophotometer and Penetrometer Measurements

In this research, the X-rite Ci60 model portable spectrophotometer was used to obtain colour data from damaged fruits (Figure 2). Specifications of the X-rite Ci60 model portable spectrophotometer can be seen in Table 2.

Table 1. Some biological material properties of pears

Biological Material Properties	Akça Pear (Average)	Deveci Pear (Average)
Width	40 mm	78 mm
Height	60 mm	79 mm
Weight	44 gr	225 gr
Hardness	4 kg/cm^2	16 kg/cm^2

Table 2. Specifications of the X-rite Ci60 model portable spectrophotometer (Anonymous, 2020)

Short Term Repeatability - White	10 ΔE*ab on white ceramic
Measurement Geometry	d/8°
Inter-Instrument Agreement	0.40 ΔE*ab avg.
Illumination Spot Size	14 mm
Light Source	Gas-filled tungsten lamp
Measurement Spot	8 mm
Measurement Time	≈ 2 seconds
Photometric Resolution	0.01%
Spectral Analyser	Blue-enhanced silicon photodiodes
Spectral Interval	10 nm
Spectral Range	400 nm-700 nm
Spectral Reporting	10 nm
Colour Differences	[√/X], Δecmc, Δlab, ΔE00, Δreflectance, ΔE94, ΔXYZ, ΔL*a*b*, ΔYxy, , ΔL*C*h°, ΔL*u*v*, Verbal Difference
Colour Spaces	Lab, L*a*b*, Reflectance, L*C*h°, Munsell Notation, XYZ, Yxy, L*u*v*
Illuminates	A, C, D50, D65, F2, F7, F11 & F12
Standard Indices	[√/X], YI1925, WI Taube, ΔWI73, Reflectance, WI98, MI, Δreflectance, ΔWI Berger, WI73, MI6172, ΔYI98, ΔWI Hunter, GrayScale, WI Berger, Gloss, ΔYI73, ΔWI Stensby, YI98, WI Hunter, ΔYI1925, ΔWI Taube, YI73, WI Stensby, ΔWI98, Averaging, 555 Shade Sort
Sample/Measurement	4000
Calibration	White and Zero

Figure 1. Damaged Akça and Deveci pear samples

Figure 2. X-rite Ci60 model portable spectrophotometer used in the study (Anonymous, 2019)

Figure 3. Fruit hardness hand penetrometer

The spectrophotometer used to determine the colour values in the wavelength range of 400 - 700 nm. In this study, the measurements of the desired colour space (*L, a, b*) were done, also Euclidian distance between two samples in the Lab colour space (ΔE) were measured as the colour difference of the pears. The following formula calculates the ΔE value:

$$\Delta E=\left[\left(\Delta L^2\right)+\left(\Delta a^2\right)+(\Delta b^2)\right]^{1/2} \quad (1)$$

In this equation:
ΔE : Change in colour value,
ΔL : Brightness value
Δa : Colour change value from red to green,
Δb : Colour change value from yellow to blue (Beyaz et al. 2011).

Fruit hardness values were determined by using a hand penetrometer (Figure 3).

Decision Tree Algorithms

One of the standard algorithms is Decision Trees, which are used in data mining methods. Decision Trees aim to show object specifications, which predicts the value of a traced data by learning basic classification rules that are obtained from objects. Each node in a Decision Tree inserts a spec of an example that can be classified. Also, there are a lot of algorithms that are used to determine essential branches at collected data. Root, node, and branching criteria are the vital points of these algorithms (Silahtaroğlu, 2016, Köse, 2018).

Classification methods in decision trees are divided into two methods.
These are;

- Entropy-Based Algorithms (ID3 Algorithm, C4.5 Algorithm, etc.)
- Classification and Regression Trees (CART) (Towing Algorithm, Gini Algorithm, Random Forest Algorithm, etc.).

The C4.5 tree is an improved version of the ID3 tree. It is an algorithm based on entropy and information gain the same as the ID3 algorithm. Unlike the ID3 algorithm, pruning is performed in this algorithm (Köse, 2018). The following equation calculates entropy:

$$H(S)=\sum_{t=1}^{n} \rho i \times \log_2(\rho i) \quad (2)$$

H : Entropy,
S : Source,
p : Probability (Silahtaroğlu, 2016).

Gain information is obtained by calculating the differences between the weighted sums of the entropies of each sub-section (Silahtaroğlu, 2016). The following equation calculates the gain information:

$$D=H(D)-\sum_{t=1}^{n} P(D_i)\, H(D_i) \quad (3)$$

D : Gain information,
H : Entropy,
p : Probability (Silahtaroğlu, 2016).

In this study, the gain ratio was selected as a quality measure, and Minimum Description Length (MDL) was selected as the pruning method in Decision Tree.

Neural Network Algorithm

Neural networks are complex algorithms that work like a human brain. It works like a human's nervous system. The network system runs according to the complex data combination and transmission between nerve cell lines. Each combination has a critical weight value. The process has different steps between layers as the input layer, the hidden layers, and the output layer. The info is obtained from the input layer then transmit to the hidden layer for classification according to the critical weight value of the network finally, send to the output layer (Öztemel, 2012). In this study, KNIME data mining software artificial neural network structure and algorithm was used.

Majority Voting Techniques

Meta-learning is an advanced technique in data mining and meta-learning aims to learn from the predictions of the classifiers on a current validation data set. At the end of the classification, the meta-classifier works to train from the standard validation data set (Prodromidis et al., 2000). For this aim, Random Forest and Majority Voting Techniques were selected. This method is known as the form of voting by the majority according to the estimates obtained from the algorithms used. If there is equality in the algorithms used, the results of the algorithms are also examined. It is considered to be one of the simplest and most effective methods (Şeker and Erdogan, 2018). This method was only applied to machine learning algorithms.

Random Forest Algorithm

Leo Biean developed the Random Forest algorithm. The method runs according to complex answers of different trees finally gives a decision. Random Forest is an ensemble learning method in meta-learning. The Random Forest is the final version of the CART algorithm. It is one of the standard meta-learning methods that gives fast and straightforward. It decides randomly selected values and specifications then built different Decision Trees finally gives the average of results. (Mitchell, 2011). It is an algorithm that aims to increase the classification value by producing more than one decision tree during the classification process.

Data Analysis

The fruits kept at room temperature during the measurements done for 5 days. Because most of the time consumers keep the agricultural products at room temperature in open packs during the consumption process. Fruits are kept in the 25°C temperature and 40% humidity as the environmental conditions. Also, this condition affects the product storage time. Four digital reading was received as the fruit colour quality (*L*, *a* and *b* colour channels and ΔE values), a database that was created 4000 objects. In the database, the class assignments of the fruit qualities were determined. Using the KNIME Analytics Platform software, data were identified using descriptive statistical methods and then analysed by classification techniques used in data mining. In the classification the labelled values were tried to be estimated, the Majority Voting and Random Forest methods were used. 70% training – 30% test and 80% training - 20% test selected as partitioned methods. In the relevant part of the study, comparison performances and confusion matrix were given in the tables.

Results and Discussion

The study results showed that that the best prediction were done by the Majority Voting method (MAVL) with 98,458% success given by 70% partitioning. Following, the Random Forest algorithm showed 94% success. On the first day, the fruit colours were read with the help of a spectrometer without any damage. Therefore, Delta-E values for the first day were given as zero (0). The relationship between fruit hardness and colour change was demonstrated in Table 3. In Table 3, it is seen that first day two pear varieties have colour changes but as soft pear variety, Akça pear shows more colour changes in the other days. It was correlated with the average Delta-E (ΔE) values obtained from fruits. In addition to fruit hardness, Red colour change of the fruits also played a vital role, and orange shells showed less browning while yellow and green shells showed more browning. The confusion matrix and accuracy criteria of used algorithms were given in Table 4 and Table 5.

With a parallel understanding in the literature, Rajeswari and Arunesh (2016) analysed soil by using soil colour, texture, PH, EC, etc. parameters. For these purposes, they were used JRip, J48, and Naive Bayes algorithms. According to their study result, the success of JRip algorithms 98.18%, for J48 97.27% and Naïve Bayes 86.36%. Zareiforoush et al. (2016) classified milled rice grains using computer vision and artificial neural networks, support vector machines, decision trees, and Bayesian Networks. The experiment showed that the highest classification accuracy is 98.72%. Next, support vector machine with Universal Pearson VII kernel function (98.48%), decision tree with REP algorithm (97.50%), and Bayesian Network with Hill Climber search algorithm (96.89%) had the higher accuracy, respectively. Virgen-Navarro et al. (2016) monitored coffee bean colour using a neuro-fuzzy model based on digital images. The performance of the neuro-fuzzy model resulted better compared to conventional methods obtaining a coefficient of determination > 0.98.

Sabancı et al. (2017) classified wheat grains using an artificial neural network according to dimensions, colours, and textures parameters of 100 bread and 100 durum wheat grains. They said that the ANN model is trained with 180 grains and its accuracy tested with 20 grains for a total of 200 wheat grains. Tang et al. (2017) identified weed based on K-means and convolutional neural networks. The experimental results were found that K-means pre-training achieved 92.89% accuracy. Beyaz et al. (2017) identification some Spanish olive cultivars using length, width, and colour data of olives.

Table 3. The relationship between fruit hardness and colour change

Cultivars	Fruit Hardness	ΔE (1. Day)	ΔE (2. Day)	ΔE (3. Day)	ΔE (4. Day)	ΔE (5. Day)
Akça Pear	4 kg/cm^2	0	9.784816	3.86616	3.63344	3.39506
Deveci Pear	16 kg/cm^2	0	14.21650	2.58295	2.72176	2.51253

Table 4. Confusion matrix and accuracy criteria of used algorithms (70% training, 30% test)

Classifier	Confusion Matrix	Akça Pear	Deveci Pear	Accuracy (%)	Error (%)	F	Cohen's Kappa
DT	Akça Pear	133	20	89.333	10.667	0.893	0.787
	Deveci Pear	12	135			0.894	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.869	0.917	133	12	135	20
	Deveci Pear	0.918	0.871	135	20	133	12
ANN	Akça Pear	140	13	90.667	9.333	0.909	0.813
	Deveci Pear	15	132			0.904	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.915	0.903	140	15	132	13
	Deveci Pear	0.898	0.91	132	13	140	15
RF	Akça Pear	140	13	92.667	7.333	0.927	0.853
	Deveci Pear	9	138			0.926	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.915	0.94	140	9	138	13
	Deveci Pear	0.939	0.914	138	13	140	9
MAVL	Akça Pear	21876	599	98.458	1.542	0.984	0.969
	Deveci Pear	94	22381			0.985	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.973	0.996	21876	94	22381	599
	Deveci Pear	0.996	0.973	22381	599	21876	94

Table 5. Confusion matrix and accuracy criteria of used algorithms (80% training, 20% test)

Classifier	Confusion Matrix	Akça Pear	Deveci Pear	Accuracy (%)	Error (%)	F	Cohen's Kappa
DT	Akça Pear	71	21	84	16	0.816	0.675
	Deveci Pear	11	97			0.858	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.772	0.866	71	11	97	21
	Deveci Pear	0.898	0.822	97	21	71	11
ANN	Akça Pear	84	8	88	12	0.875	0.76
	Deveci Pear	16	92			0.885	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.913	0.84	84	16	92	8
	Deveci Pear	0.852	0.92	92	8	84	16
RF	Akça Pear	85	7	90.5	9.5	0.899	0.81
	Deveci Pear	12	96			0.91	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.924	0.876	85	12	96	7
	Deveci Pear	0.889	0.932	96	7	85	12
MAVL	Akça Pear	7890	310	98.34	1.66	0.979	0.966
	Deveci Pear	22	11778			0.986	
	Accuracy Criteria	Recall	Precision	TP	FP	TN	FN
	Akça Pear	0.962	0.997	7890	22	11778	310
	Deveci Pear	0.998	0.974	11778	310	7890	22

The cultivars were identified as 90% with Artificial Neural Networks. About this issue in literature Demir (2018) worked on application of data mining and adaptive neuro-fuzzy structure to predict colour parameters of walnuts (Juglans regia L.) and he stresses that root mean square error values of the adaptive neuro-fuzzy-based approach were respectively identified as 0.02 for Bilecik, 0.01 for Fernette, 0.02 for Fernor, 0.01 for Kaman-1, 0.01 for Maraş-12, 0.01 for Maraş-18, 0.01 for Sunland, 0.01 for Şen-2, 0.01 for Yalova-1, and 0.01 for Yalova-3 walnuts. Additionally, Demir et al. (2018) studied on data mining approach for the prediction of fruit colour properties. They have applied laws algorithm to each cluster and 7 different prediction rules were obtained by them from *CI*, *h**and *C** parameters. They express that R^2 values of the rules were change between 0.72-0.99%.

Conclusion

Determination of the oxidation areas due to the damage in pears is the feature to be considered in the design of harvesting, classification, packaging, transportation, and transmission machines. The image analysis technique is an indispensable method, especially in the design of machines that classify the fruits according to their quality. The data results provide us a chance to estimate the skin colour changes at bruised areas with data mining methods. This study shows that the image analysis techniques and data mining can be used to determine the colour values of pears or similar products. It is also thought to include results that can shed light on the studies in this area.

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