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Identification of olive cultivars using image processing techniques

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Abstract: As a country in an olive production zone, olive (*Olea europaea* L.) production is of great economic importance for Turkey. Turkey has 88 domestic and 28 foreign cultivars of olive, all of which are located in the Kemalpaşa Production and Research Garden (Olive Gene Bank) at the Olive Research Station in İzmir (38°25′34.7628″N, 27°25′22.9872″E). The aim of this study was the identification of olive cultivars using image processing techniques. For this aim, images of olives, taken at 2896 × 1944 pixel and 300 dpi resolution, were captured using a DSLR camera, and evaluations of pixels were used for considering the pixel distribution and dimension measurements. For this aim, MATLAB v2012 and Image j software were used. In the light of the obtained data, analysis of variance and Duncan's test were used to characterize the olive cultivars. As a result, all observed olive cultivars were identified at $P < 0.05$ significance level. *Sarı ulak*, *Gemlik*, *Edincik su*, *Memecik*, *Eşek zeytini*, *Ayvalık*, *Kilis yağlık*, *Uslu*, *Çilli*, and *Domat* olive cultivars were identified utilizing the validation process employing image processing and analysis techniques. Only the *Erkence* cultivar was not identified. Moreover, different classification techniques were applied to the olive stone color value data by the help of SPSS v22 and Clementine v12, which is a data mining software package from SPSS. In addition to the first results the *Erkence* cultivar was identified 69% with artificial neural networks.

Key words: Artificial vision, image analysis, olives, olive stone, varietal identification

1. Introduction

Olive is an important agricultural product worldwide, including Turkey. According to the FAO statistics of olive production income (2783 million US dollars), Turkey ranked 4th in the world. According to Turkish Statistical Institute data, Turkey has 168,997 olive trees (TSI, 2014a). Furthermore, Turkey has 1,768,000 t of olive production capacity with 2,301,323,969 ₺ income (TSI, 2014a, 2014b). As a country in the olive production zone, olive (*Olea europaea* L.) production is of great economic importance to Turkey. The geographical locations in Turkey with a predominantly Mediterranean climate (i.e. the Marmara, Southeast Anatolia, and Black Sea regions) have proved suitable for olive production. Differences can be observed in olive cultivars due to factors such as the wide spread area, condition climate differences of the regions, and foreigner pollination, and so it is important to determine the character of the image patterns of olive cultivars that are widespread in large areas of Turkey. In this respect, lots of research needs to be done to improve production. A common problem encountered in all of the studies is that the kinds of data obtained are insufficient for the determination of olive cultivars because the characteristics of olive cultivars depend on the ecological conditions. Phenotypic and genotypic origin molecular marker research cannot provide accurate olive cultivar determination data (Sakar Çakır, 2009) because the full genome sequences of all olive cultivars have not yet been determined. The cultivar determination process started with the determination of cultivars' pomological information.

Many people have studied the identification of olive cultivars around the world. For example, Diaz et al. (2000) developed four different algorithms for a machine vision system and used these algorithms for the identification of olives. In addition, they compared the performance of human-selected olive cultivars and machine vision algorithms. Bari et al. (2003) concentrated on identifying the characteristics of olives, and they stated that morphological characteristics are important factors for the identification of olives.

Diaz et al. (2004) worked on the classification of olives based on fruit surface defects in different quality categories.

Mendoza et al. (2006) examined sRGB, HSV, and L * a * b * color space and they stated that standard colors of fruits and vegetables as measured by a computerized

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imaging system can be used for the determination of product status.

Riquelme et al. (2008) studied color defects and morphological characteristics of olive cultivars.

Al Ibrahem et al. (2008) identified 19 different cultivars by using a direct measurement and image analysis method.

Moreda et al. (2012) worked on shape determination of horticultural produce using two-dimensional computer vision. They also stress that computer vision has become a proven, reliable tool for describing product shape.

Vanloot et al. (2014) stress that image analysis and metric evaluations of agricultural products like olive stones to determine the varietal origin require specialists who cannot always conclude with certainty because of a large number of cultivars identified.

True olive production is also important for lots of industrial applications since olive identification methods will affect the production characteristics of olives. The aim of this study was to identify the characteristics of some olive cultivars in Turkey's national collection using image processing and analysis techniques. In addition, the efficiency of image analysis was tested.

It is important that the correct cultivators are used in the correct climatic and soil conditions. In this way, both the quality of the aromatic structure of olive oils and their production rates will increase. The consumption of olives for both oil and the table are also important. At the same time, the energy needs can be met from biomass obtained from the olives. For example, Pattara et al. (2010) in their study evaluated the commodity, environmental, and economic aspects linked to different techniques for the pit recovery from olive pulp and olive pomace. These techniques have been demonstrated both at the level of production (increased income for olive extraction plants) and at the level of environmental sustainability (use of renewable fuels).

Mata-Sanchez et al. (2014) worked on the development of an olive stone quality system based on energetic biofuel parameters. They stress that in Andalusia (southern Spanish region), the olive industry presents a high potential for solid biofuel production because of residues generated from olive groves and the olive oil industry. In this region, 25% of residual biomass is produced by the olive sector, and olive stone residues are among the most important since production is at over 450,000 t/year.

The aim of this study was the identification of olive cultivars from their characteristics using image processing and analysis techniques. In this study, the International Olive Council (IOC) and European Union (EU) methods were used for olive cultivar determination, and so stone, fruit, and leaf data was used. Moreover, image processing and analysis techniques were used to achieve this goal.

2. Materials and methods

2.1. Fruit and leaf sample harvest

In this research, *Sarı ulak*, *Gemlik*, *Edincik su*, *Memecik*, *Eşek zeytini*, *Ayvalık*, *Kilis yağlık*, *Uslu*, *Çilli*, *Domat*, and *Erkence* olive cultivars were used (Figure 1). All cultivars were obtained from the Kemalpaşa Production and Research Garden (Olive Gene Bank) at the Olive Research Station in İzmir (38°25′34.7628″N, 27°25′22.9872″E).

Figure 1. Olive cultivars obtained from İzmir Kemalpaşa Olive Research Station.

Olive and leaf samples were harvested from 5 different trees randomly for each olive cultivar in October 2012. From each cultivar 220 olive fruit and 50 leaf samples were harvested. During the period of experimentation, olive cultivars were kept in cold storage (+4 °C, 80% humidity) at the Faculty of Agriculture, Department of Horticulture at Ankara University.

2.2. Color analysis measurement

To reveal the characteristics of olive cultivars' color, measurements were performed (Figure 2). A Minolta Cr200 model colorimeter was used for color measurements. Color values of 60 olive fruits for each olive cultivar were determined for color measurements. An average of 3 readings from different measurement points on the fruit surface were also used for color measurements. Twenty olive leaf samples were measured from the front and rear faces for color measurements of each cultivar. Moreover, an average of 3 different readings were used for color evaluations.

2.3. Imaging system

After the color measurement process, 100 samples were selected randomly from each olive cultivar, and they were photographed from 4 different views: from the front, handle hole, left, and tip sides (Figure 3). These imaging sides are also used as standard classification views at the Kemalpaşa Olive Research Station for identification of the national collection of Turkey's olive cultivars. In total, 4400 digital images were captured from 1100 olive fruits for the evaluations. A macro capture tripod was placed 40 cm away from the olives to obtain the digital images.

A Nikon D300s body with an 18–140-mm zoom lens was used for general purpose imaging, and a Nikon D800 with a 105-mm macro lens was used for macro captures. Captured images were stored as JPEG files. All images were captured in 2896 × 1944 pixel dimension and at 300 dpi resolution. Olive fruit and stone images were captured one by one, but leaf images were captured together in samples of 50. Blue color graph paper was used as a background

Figure 2. The leaf and fruit color measurement process as applied to olives.

a b c d

Figure 3. Front side (a), handle hole (b), left side (c), and tip side (d) of images of olive fruit.

for precision calibration. First, tests were performed for solving problems such as shaded areas and image focus clarity. With the aim of solving the problems, different lenses and flashes were tried. The problem of shaded areas was solved by using a ring flash. The image focus problem was also solved by using the 105-mm macro lens. After overcoming these problems related to digital imaging, olive cultivars were harvested from the national collection. After each olive fruit was photographed, it was placed into a numbered plastic bag (5 × 5 cm) for the next step to be ready for stone removal.

The same process was applied for each cultivar of olive leaf. Fifty leaf samples were used for each olive cultivar. Olive leaves were placed into two glass plates of 40 × 60 cm, with calibration graph paper set as the background (Figure 4). Then they were photographed from the front. For the 550 olive leaf measurements, 11 digital images were obtained. Each photographed olive leaf was placed into a numbered plastic bag (5 × 5 cm).

After the image capture process was completed, olive stones were removed from fruits with an extractor to determine the olive stone pattern structures. Afterward, the olive stones were cleaned using a knife and washed. Then the stones were maintained in plastic containers, containing a 10% bleach solution, for 15 h (Figure 5). For the last step, the olive stones were stored at –4 °C to prevent them from cracking because of physiological activity.

Removed olive stones were placed into numbered plastic bags (5 × 5 cm). All of the processing steps applied to the olive fruits can be seen in Figure 6.

2.4. Image processing and determination of sample dimensions

Photoshop (Adobe), Myriad v7 (IGC), Image J (Nih), and MATLAB v2012 (MathWorks Inc.) software were used for evaluations. To eliminate measurement errors during the image processing of the fruit and leaf, a segmentation process was applied to the images of the olives (Figure 7). Photoshop was used to remove the olive fruit and stone segmentations from the image backgrounds, and also for placing the calibration square. For this purpose, stone images were photographed with a calibration plate. Myriad v7 was used to determine olive fruit and leaf dimension measurements. MATLAB 2012 was used for developing dimension measurement software for length and width measurements of olive stones. Image J software was used for determination of pixel counts.

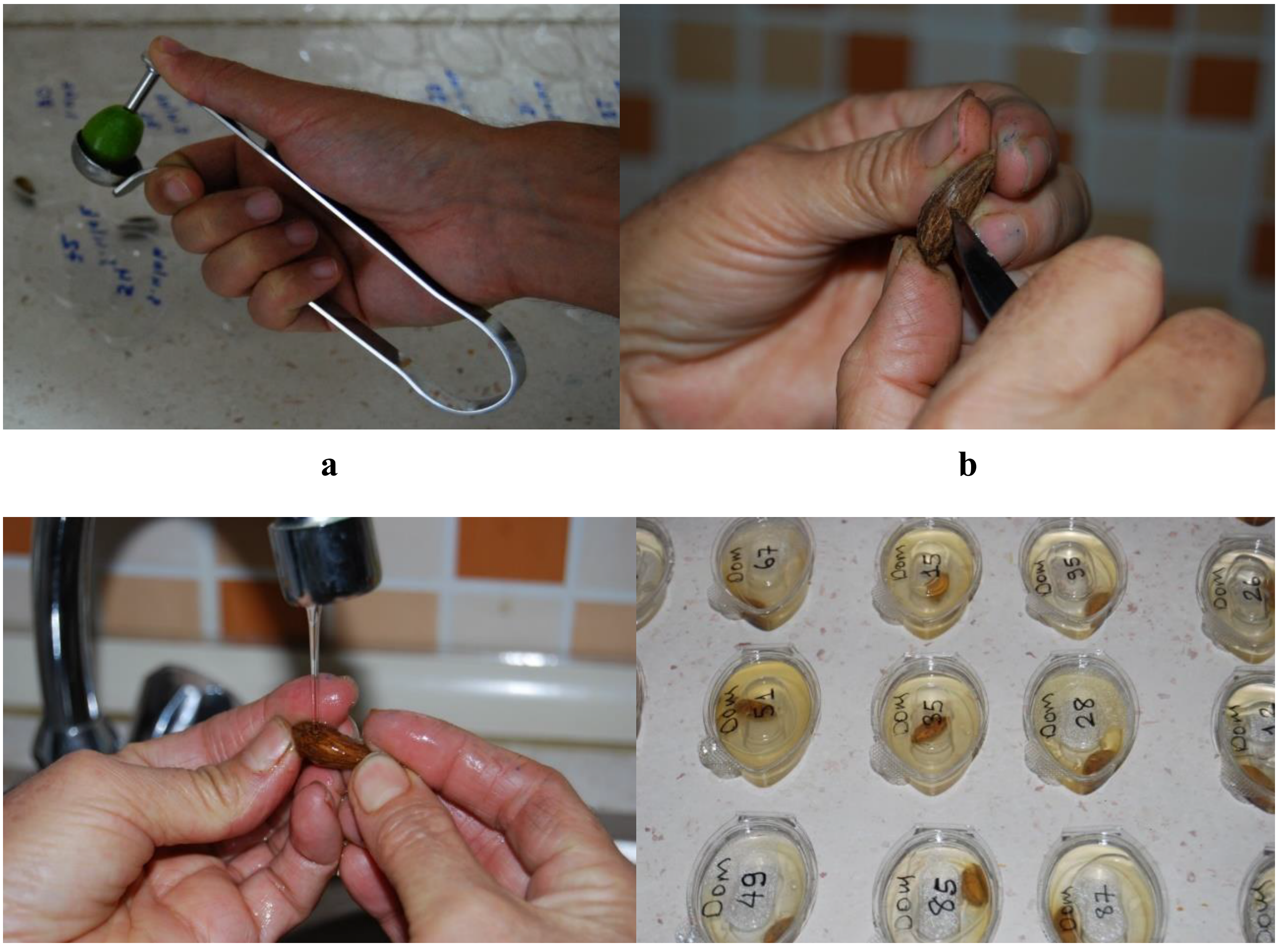
Each monochrome pixel value was counted from images. Then these counts were converted into '%' values for evaluation of the olive cultivars. The aim of '%' conversion is standardization of pixel counts for comparison of each image. The IOC and EU determination methods were used for the experiments. Özilbey (2011) explained these methods in his book, which outlines the properties of Turkey's olive cultivars. These methods are based on morphological and pomological measurements, i.e. olive tree measurements, leaf measurements, flower measurements, and fruit and olive stone measurements. At the same time, other studies in the literature were researched. Leaf characteristics were evaluated from the length and width of the leaves. The length and width of the fruits were also measured, and the front, handle hole, left, and tip side image data of olives were evaluated. For the stones' monochrome pixel distributions, the stones' length and width were investigated (Özilbey, 2011).

2.5. Stone getting process and measurements

After all the cleaning process of olives was completed, measurement software was developed using MATLAB v2012 (Figure 8). Length and width data were collected from the digital images of olive stones (Figure 9).

In addition, data histograms of stone images were evaluated. For this purpose, new images without calibration plates were obtained from the original images

Figure 4. Sample leaf images (Memecik cultivar).



a b

c d

Figure 5. The removal of an olive stone using a hand tool (a), cleaning of the removed olive stone using a knife (b), cleaning of the removed olive stones with water (c), stone samples cleaned with a solution (d).

Figure 6. All of the processes steps that result in a cleaned olive stone.

at the same resolution. After that, Image J software was used for determining the pixel frequency of color values between 0 and 255 (Figure 10). Then these frequencies were converted into '%' values for morphological evaluation of the olive cultivars. The purpose of this conversion was to make a healthy and equal comparison between all images. Thus, monochrome color values were used for the determination of the stone pattern for each olive cultivar.

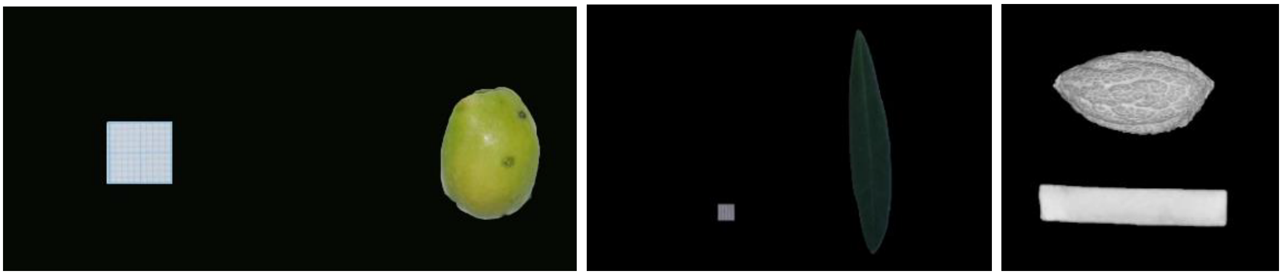


Figure 7. Background segmented images of olive fruit, a leaf, and stone, shown with a calibration plate.

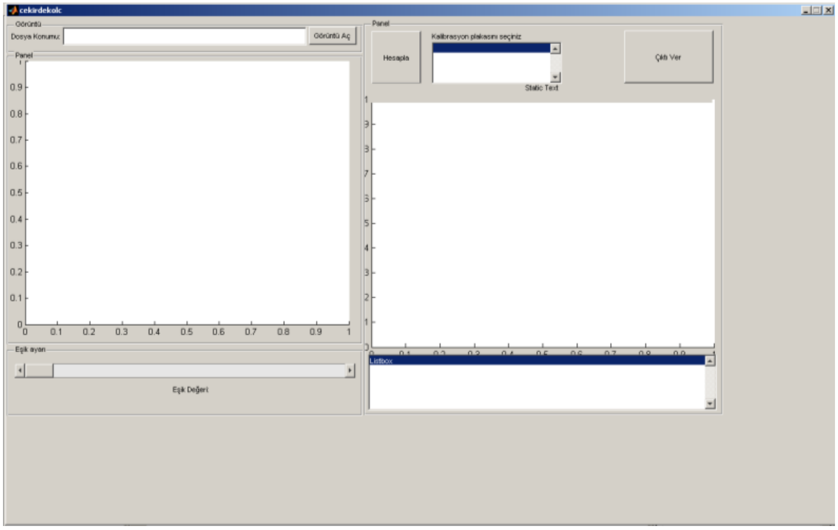


Figure 8. The olive cultivars determination software, which was designed using the MATLAB graphical user interface design tool.

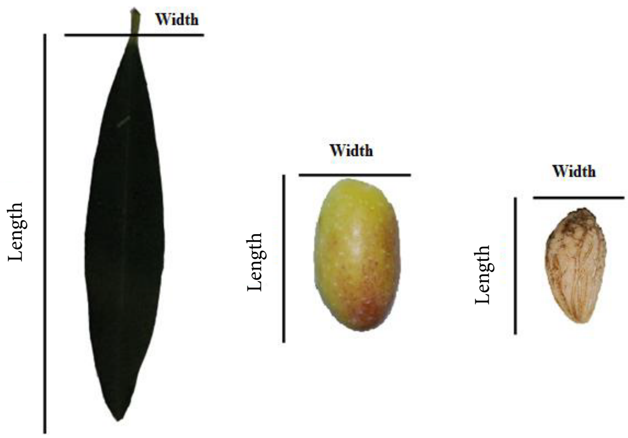


Figure 9. Collected data from the digital images of fruit, leaves, and olive stones.

2.6. Statistical analysis

Analysis of variance was conducted using Duncan's test to demonstrate the differences between the length, width, and color data results obtained from the fruits, leaves, and stones.

Our H_0 hypothesis was: There is no difference between the length, width, and color data of whole fruits, leaves, and stone populations according to variance analysis. The H_1 hypothesis was: At least one difference exists between the length, width, and color data from the

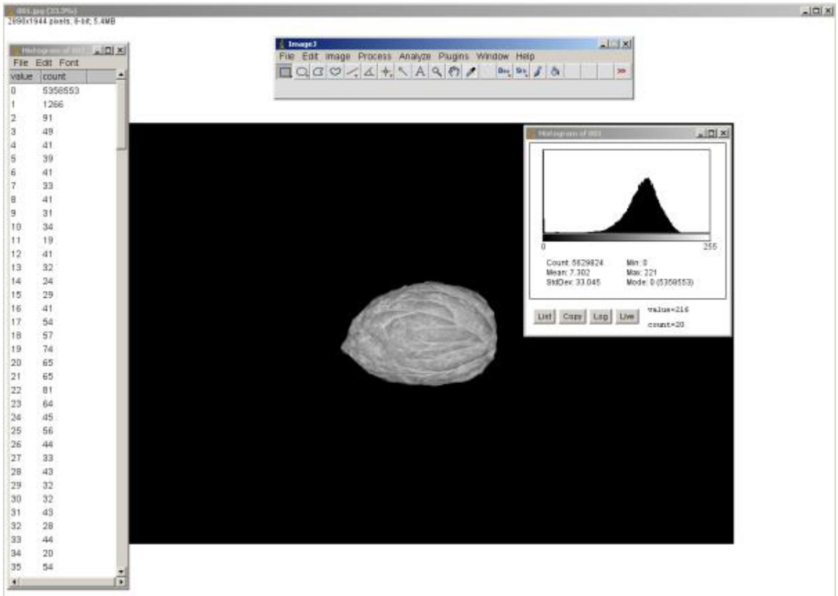


Figure 10. The determination of pixel frequency values of an olive stone, using Image J (Nih) software.

whole fruit, leaves, and stone populations according to variance analysis.

The literature shows that in such analyses the most appropriate statistical analysis is one-way ANOVA, and so we decided on that. One-way ANOVA analyzes differences between groups, according to the average of a dependent variable (Kalaycı, 2010). There are two basic rules for one-way ANOVA.

According to these basic rules, the variances of each group must show normal distribution and homogeneity. In line with this, Scheffe (1959) in his book stressed that characteristics must show normal distribution. According to this explanation, two basic rules were provided by each data group for the research requirements of one-way ANOVA.

To check the statistical results, 60 different stone samples were tested again. Firstly, pixel percentage and geometric dimensions of these samples were determined. Then cultivar types were recoded as renamed cultivars for the check. ANOVA and Duncan's test were applied to the renamed control cultivars with the previously analyzed cultivars. The new control cultivar that was detected in a similar SPSS v20 (IBM) Duncan result column with its previous cultivar is accepted as the true selected cultivar.

In addition, different classification techniques were applied to the olive stone color value data with the help of SPSS v22 and Clementine v12, which is a data mining software package from SPSS. *Sarı ulak*, *Gemlik*, *Edincik su*, *Memecik*, *Eşek zeytini*, *Ayvalık*, *Kilis yağlık*, *Uslu*, *Çilli*, *Domat*, *and Erkence* olives were coded as olive type 1 to 11, respectively, for the statistical analysis process. The results are described and detailed below.

1. Discriminant analysis: There are some assumptions to apply discriminant analysis to the data. The first assumption is the normal distribution for the variables. The second one is the equivalence of the covariance matrix. Moreover, there must not be a multicollinearity problem about independent variables. These data do not provide discriminant analysis assumptions; hence, discriminant analysis is not suitable for this data set.

2. Naïve Bayes: Two different methods for Bayes classification are provided in Clementine v12. The first one is the TAN model and the other is the Markov blanket model. Unfortunately, it does not include naïve Bayes classification. It is possible to apply naïve Bayes classification in SPSS v22 with the help of syntax; however, these syntax results do not contain the variable importance about the classification results. Hence naïve Bayes classification is not suitable for this data set.

3. Support vector machine: Support vector machine (SVM) is provided in Clementine v12. We apply this method when we compare the result with artificial neural networks; we do not prefer to classify this data with SVM, because training and testing results are not more efficient than neural networks.

4. K-nearest neighbors algorithm: K-nearest neighbors classification is not provided in Clementine 12; hence analysis is executed in SPSS v22. However, SPSS results do not include the importance values of the variables. Thus K-nearest neighbors classification is not suitable for this data set.

5. Artificial neural networks: There are six training methods in Clementine v12 for building neural network models. These methods are given as:

- Quick
- Dynamic
- Multiple
- Prune
- RBFN
- Exhaustive prune

We have used different types of training methods to predict olive classification from the independent variables (color codes). The implementation of artificial neural network with Clementine v12 is given below (Figure 11).

In order to prevent overtraining problems that can occur within neural networks, a randomly selected proportion of the training data is used to train the network. We select 90% of cases for training; then 10% of cases are used for testing. Six different neural network training methods in Clementine v12 are applied for the classification of olive types. Training and testing results according to different training methods, which are presented by Clementine v12, can be seen in the Results and discussion section.

The results of validation items are summarized in the Results and discussion section.

3. Results and discussion

Nowadays modern techniques and approaches eliminate these problems. The widely used image analysis techniques in agricultural areas are the solution to this problem. In this way, olive cultivar determination was done without the need for expensive processes or expert input. In this research, image processing and analysis techniques were used for the creation of an olive database. This database can also be used for biotechnological research since, as our research showed, the morphological data about olives we gathered (such as monochrome color sequences, or olive stone, fruit, and leaf width–length) give 90% accuracy, thus confirming the results.

Diaz et al. (2000) used four algorithms for comparing olive selection methods when examining human and machine vision. According to the results that they obtained from the first algorithm, the machine vision system failure was detected as 53%, and human failure was detected as 52.5%; for the second algorithm 63% and 42.5%; for the third algorithm 57% and 11.4%; and for the fourth algorithm 14% and 15%, respectively.

Bari et al. (2003) worked on olive characteristics, and they also stress that these features are 90% accurate in identifying olives.

Diaz et al. (2004) worked on olive classification, and they state that, according to the results, it is possible to classify olives at a rate of 90% based on artificial neural networks. In our research, the results showed that all observed olive cultivars were identified at a $P < 0.05$ significance level using first analysis of variance, and after that Duncan's test. *Sarı ulak*, *Gemlik*, *Edincik su*,

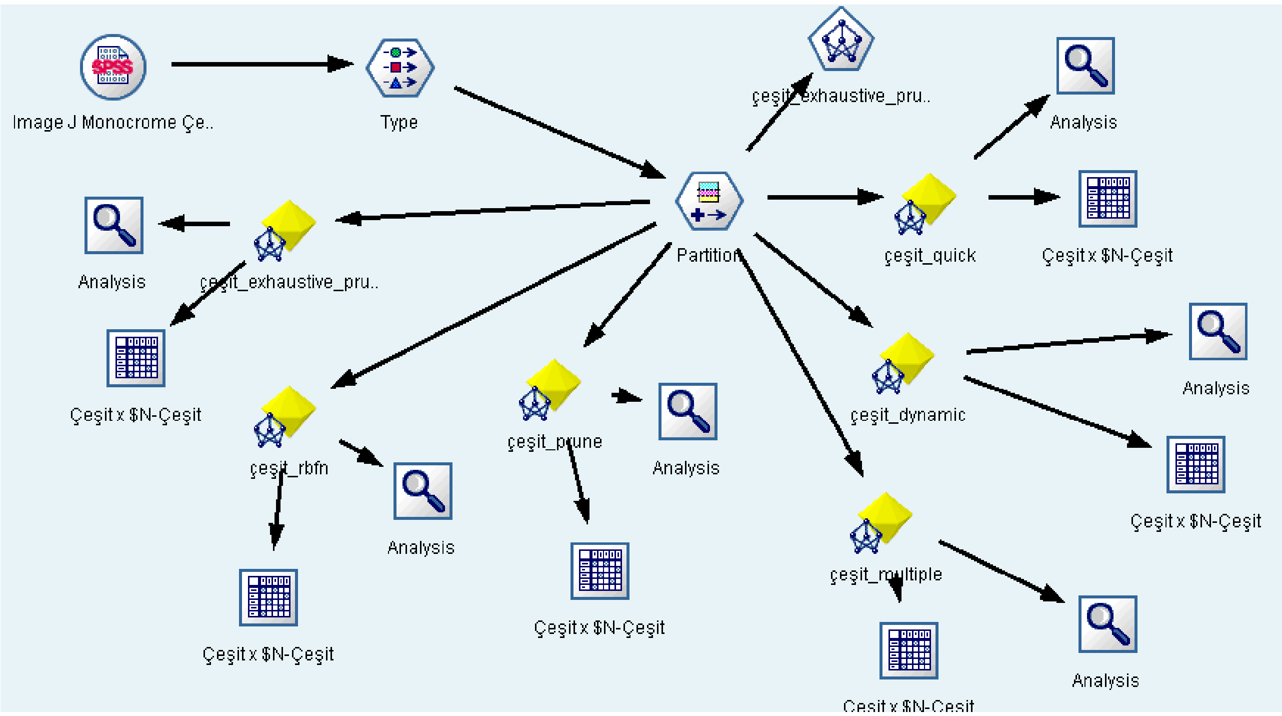


Figure 11. The implementation of artificial neural network with Clementine v12.

Memecik, *Eşek zeytini*, *Ayvalık*, *Kilis yağlık*, *Uslu*, *Çilli*, and *Domat* olives were identified utilizing the same validation process as that employed in the image processing and analysis techniques, as seen in Table 1. Only the *Erkence* cultivar was not identified, also shown in Table 2. The *Erkence* cultivar could not be identified because image patterns showed differences between stones. Perhaps these differences can be used as an evaluation tool to eliminate more stone samples.

Vanloot et al. (2014) worked on image analysis and metric evaluations of agricultural products such as olive stones, and they stress that the best model considers all the data obtained from front and profile pictures, and gives 100% correct classification. In our research, we also took images from four different sides of olives as seen in Figure 3, and you can see the results of the different sides of the olive images as used for olive identification in Table 3.

Al Ibrahem et al. (2008) stressed that the width–length ratio of olive stones can be used for identification of olive cultivars with a 60% success rate. We also give the identification results of the width–length measurements of the olives in Table 4.

Riquelme et al. (2008) stressed that according to the results of color defects and morphological characteristics, they achieved a 75%–97% success rate in their study.

Mendoza et al. (2006) worked on sRGB, HSV, and L * a * b * color space and they also stress that L * a * b * color space is the best color space for this kind of evaluation. We also used the same color space for our evaluations, and the results of the identified olives can be seen in Table 5.

According to Table 6, the most successful classification results are obtained when the exhaustive prune training

Table 1. The determination of olive cultivars from color codes between 1 and 255 ($P < 0.05$).

Cultivar	Color code
Sarı ulak	2, 6–15, 17, 18, 20, 21, 23–56, 58–76, 181, 182
Gemlik	1, 10–35, 37, 47–72, 169, 170, 187, 188, 234–239
Edincik su	2, 22, 186–188
Memecik	1, 3–5, 183, 184, 234
Eşek zeytini	8, 10–14, 30, 32–35
Ayvalık	1–4, 16, 145, 147–150, 186
Kilis yağlık	7, 8, 31, 39, 123–145, 147, 150, 186–189
Uslu	2–4, 15, 36, 38, 72, 95–123, 125, 128, 141, 143–147, 181–188, 239, 243
Çilli	1, 2, 4–11, 16, 20, 21, 39, 47, 123–159, 162–166, 179–222
Domat	5, 6, 31, 34, 101–145, 150–159, 162, 168–222
Erkence	33, 34, 78

Table 2. The determination of olive cultivars from color codes between 1 and 255 after validity test ($P < 0.05$).

Cultivar	Color code
Sarı ulak	2
Gemlik	169, 170, 234–239
Edincik su	2, 22
Memecik	3–5, 234
Eşek zeytini	8, 30, 32
Ayvalık	1–4, 16, 145, 147–150, 186
Kilis yağlık	31, 39, 123–132, 188, 189
Uslu	36, 38, 239, 243
Çilli	1, 16, 20, 21, 39, 47, 123–141, 179–189, 191, 204–222
Domat	5, 6, 30, 142–147, 169–186, 188–222
Erkence	-

Table 3. Identified cultivars according to the geometric parameters (P < 0.05).

Identification parameter		Cultivars								
Stone image of olive fruit	Length	*Sarı ulak*	*Gemlik*	*Memecik*	*Eşek zeytini*	*Kilis yağlık*	*Uslu*	*Çilli*	*Domat*	*Erkence*
	Width	*Sarı ulak*	*Ayvalık*	*Kilis yağlık*	*Çilli*	*Domat*				
Front side image of olive fruit	Length	*Sarı ulak*	*Eşek zeytini*	*Kilis yağlık*	*Çilli*					
	Width	*Sarı ulak*	*Edincik su*	*Eşek zeytini*	*Kilis yağlık*	*Çilli*	*Domat*	*Erkence*		
Handle hole image of olive fruit	Length	*Kilis yağlık*	*Erkence*							
	Width	*Eşek zeytini*	*Kilis yağlık*	*Çilli*	*Erkence*					
Left side image of olive fruit	Length	*Sarı ulak*	*Gemlik*	*Eşek zeytini*	*Kilis yağlık*	*Çilli*	*Domat*			
	Width	*Sarı ulak*	*Eşek zeytini*	*Çilli*						
Image of olive fruit tip	Length	*Eşek zeytini*	*Kilis yağlık*	*Çilli*	*Erkence*					
	Width	*Sarı ulak*	*Eşek zeytini*	*Kilis yağlık*	*Çilli*	*Erkence*				
Leaf image	Length	*Sarı ulak*	*Edincik su*	*Memecik*	*Eşek zeytini*	*Uslu*	*Çilli*			
	Width	*Eşek zeytini*	*Uslu*	*Domat*						

Table 4. Identified cultivars according to the geometric parameters after validity test (P < 0.05).

Identification parameter		Cultivars								
Olive stone	Width	*Sarı ulak*	*Gemlik*	*Memecik*	*Eşek zeytini*	*Kilis yağlık*	*Uslu*	*Çilli*	*Domat*	*Erkence*
	Length	*Sarı ulak*	*Ayvalık*	*Kilis yağlık*	*Çilli*	*Domat*				
Olive stone (validation test)	Width	*Sarı ulak*	*Gemlik*	*Kilis yağlık*	*Çilli*					
	Length	*Ayvalık*	*Kilis yağlık*	*Uslu*	*Domat*					

Table 5. Olive cultivar stones identified according to the color parameters (P < 0.05).

Identification parameter	Color parameter	Cultivars	
Fruit color	L*	*Uslu*	*Çilli*
	a*	-	-
	b*	*Erkence*	-
Leaf bottom color	L*	-	-
	a*	*Memecik*	*Erkence*
	b*	-	-
Leaf top color	L*	*Ayvalık*	*Domat*
	a*	-	-
	b*	*Domat*	-

method in artificial neural networks is applied. This result supports Diaz et al.'s (2004) study on olive classification. Furthermore, we obtained a higher accuracy classification percentage. We classify olives testing data at a rate of 91.74% by using the exhaustive prune training method in artificial neural networks.

Clementine v12 results also give the most important color codes according to different training methods. These color codes are summarized in Table 7.

According to Table 7, color code 1 has 3.35% effect to classify olive types with exhaustive prune training in artificial neural networks. The effects of other colors on olive classification can be interpreted in the same way.

In order to calculate the general classification accuracy, confusion matrixes were calculated for each training method (Tables 8–13).

According to the confusion matrix for the exhaustive prune method, olive type = 1 and olive type = 6 are classified

Table 6. Training and testing results.

Method	Training		Testing
Quick	Correct	839 (84.66%)	94 (86.24%)
	Wrong	152 (15.34%)	15 (13.76%)
Dynamic	Correct	742 (74.87%)	90 (82.57%)
	Wrong	249 (25.13%)	19 (17.43%)
Multiple	Correct	867 (87.49%)	96 (88.07%)
	Wrong	124 (12.51%)	13 (11.93%)
Prune	Correct	909 (91.73%)	96 (88.07%)
	Wrong	82 (8.27%)	13 (11.93%)
RBFN	Correct	616 (62.16%)	70 (64.22%)
	Wrong	375 (37.84%)	39 (35.78%)
Exhaustive prune	Correct	900 (90.82%)	100 (91.74%)
	Wrong	91 (9.18%)	9 (8.26%)

Table 7. Most important color codes and effects to olive classification according to different neural network training models.

Method	Color codes and effects (%) on olive classification
Quick	1 (3.49%), 3 (3.4%), 4 (1.82%), 2 (1.81%), 6 (1.72%), 5 (1.70%), 8 (1.49%), 7 (1.05%), 16 (1.02%), 10 (0.84%)
Dynamic	1 (2.26%), 6 (2.18%), 3 (1.83%), 16 (1.78%), 2 (1.76%), 8 (1.64%), 5 (1.55%), 4 (1.48%), 61 (1.19%), 154 (0.9%)
Multiple	1 (3.58%), 3 (2.90%), 5 (1.90%), 8 (1.73%), 4 (1.69%), 6 (1.65%), 2 (1.57%), 16 (1.39%), 7 (1.24%), 33 (0.78%)
Prune	1 (4.43%), 3 (3.11%), 43 (2.31%), 5 (1.99%), 12 (1.98%), 50 (1.97%), 20 (1.97%), 51 (1.93%), 183 (1.82%), 49 (1.81%)
RBFN	242 (0.59%), 3 (0.59%), 241 (0.58%), 238 (0.58%), 237 (0.58%), 236 (0.57%), 235 (0.57%), 239 (0.57%), 234 (0.57%), 240 (0.57%)
Exhaustive prune	1 (3.53%), 3 (2.28%), 5 (2.12%), 6 (2.04%), 8 (1.81%), 4 (1.58%), 2 (1.15%), 7 (1.13%), 12 (0.10%), 16 (0.94%)

Table 8. Confusion matrix for quick method (general classification accuracy = 84.81%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	100	0	0	0	0	0	0	0	0	0	0
10	0	97	0	0	0	0	1	0	1	1	0
11	1	4	52	2	10	9	2	0	16	3	1
2	0	0	0	98	0	1	0	0	0	1	0
3	0	1	12	0	71	4	1	0	3	8	0
4	0	1	6	0	2	60	16	0	4	11	0
5	0	1	0	0	0	9	87	0	1	2	0
6	0	1	0	0	0	0	0	99	0	0	0
7	0	1	5	1	5	1	0	0	87	0	0
8	0	0	0	0	8	2	4	0	3	83	0
9	1	0	0	0	0	0	0	0	0	0	99

Table 9. Confusion matrix for dynamic method (general classification accuracy = 75.63%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	98	0	0	0	0	0	0	0	0	0	2
10	0	91	2	0	0	0	0	1	6	0	0
11	0	3	1	0	41	25	0	1	29	0	0
2	0	5	2	79	2	2	1	1	6	2	0
3	0	0	1	1	82	9	0	0	7	0	0
4	0	0	1	0	7	74	11	0	3	4	0
5	0	1	0	6	1	11	78	1	0	2	0
6	0	0	0	0	0	0	0	100	0	0	0
7	0	4	1	0	22	4	0	2	67	0	0
8	0	0	0	0	26	6	5	0	0	63	0
9	1	0	0	0	0	0	0	0	0	0	99

Table 10. Confusion matrix for multiple method (general classification accuracy = 87.55%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	100	0	0	0	0	0	0	0	0	0	0
10	0	97	2	0	0	0	0	0	1	0	0
11	0	2	61	0	6	10	1	0	20	0	0
2	0	0	0	98	0	2	0	0	0	0	0
3	0	1	10	0	74	5	1	0	5	4	0
4	0	1	2	0	2	78	7	0	5	5	0
5	0	1	0	0	0	13	84	1	0	1	0
6	0	0	0	0	0	0	0	100	0	0	0
7	0	1	12	0	1	0	1	0	85	0	0
8	0	1	0	0	3	7	1	0	1	87	0
9	1	0	0	0	0	0	0	0	0	0	99

Table 11. Confusion matrix for prune method (general classification accuracy = 91.36%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	99	0	0	0	0	1	0	0	0	0	0
10	0	95	1	0	0	0	1	0	2	1	0
11	0	2	67	0	8	6	2	0	13	1	1
2	0	0	0	98	0	1	0	0	0	1	0
3	0	0	6	0	86	2	1	0	3	2	0
4	0	1	8	0	1	76	10	0	0	4	0
5	0	1	0	0	0	3	96	0	0	0	0
6	0	0	0	0	0	0	0	100	0	0	0
7	0	0	6	0	1	1	0	0	91	1	0
8	0	0	0	0	1	1	0	0	0	98	0
9	1	0	0	0	0	0	0	0	0	0	99

Table 12. Confusion matrix for RBFN method (general classification accuracy = 62.36%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	100	0	0	0	0	0	0	0	0	0	0
10	0	95	1	0	0	0	0	1	1	0	2
11	3	3	34	3	16	12	2	16	3	2	6
2	0	0	0	96	0	1	0	1	0	1	1
3	1	2	15	3	44	10	3	8	0	12	2
4	1	3	12	4	17	41	4	4	1	8	5
5	0	3	1	1	8	12	26	6	0	31	12
6	0	1	1	2	0	1	0	91	1	1	2
7	1	5	29	0	20	3	0	10	20	0	12
8	1	1	0	17	2	12	10	1	0	49	7
9	1	3	1	0	2	1	1	0	1	0	90

Table 13. Confusion matrix for exhaustive prune method (general classification accuracy = 90.91%).

	$N-Çeşit										
Çeşit	1	10	11	2	3	4	5	6	7	8	9
1	100	0	0	0	0	0	0	0	0	0	0
10	0	98	0	0	0	0	1	0	1	0	0
11	0	2	69	0	7	7	0	0	15	0	0
2	0	0	1	98	0	0	0	0	0	1	0
3	0	1	6	0	86	2	0	0	3	2	0
4	0	1	5	0	1	79	5	0	2	7	0
5	0	1	0	0	1	4	90	1	0	3	0
6	0	0	0	0	0	0	0	100	0	0	0
7	0	0	11	0	1	0	0	0	88	0	0
8	0	0	0	0	4	3	0	0	0	93	0
9	1	0	0	0	0	0	0	0	0	0	99

correctly at the level 100%, olive type = 9 is classified correctly at the level 99%; then correctly classified types are olive type = 10 and olive type = 2 (98%), olive type = 8 (93%), olive type = 5 (90%), olive type = 7 (88%), olive type = 3 (86%), olive type = 4 (79%), and olive type = 11 (69%).

As a result, our research combined with the extant literature shows that this identification method is cheap, fast, and reliable, with a high degree of accuracy, and is thus an alternative to genetic applications for the identification of olive cultivars.

4. Conclusion

At the end of this experimental research, we see that our expert method can be used for olive identification. Genetic identification methods provide more detailed information about olive cultivars, but this expert method is a fast, reliable, and cheap alternative to different identification methods and the identification by experts.

The regions of this research are limited to defined local olive cultivars of Turkey. Furthermore, primary identifications were evaluated from profile pictures of leaf, fruit, and stones. Some statistical analyses were performed that are mentioned in the literature for the local olive cultivar identification.

There are many different olive cultivars in the world. This expert method can be applied for these various cultivars, and then an olive cultivar database can be created. When we look at this aspect, this expert method offers a future vision of web-based databases of olive cultivars, while also starting off a web-based identification system. In addition, panoramic pictures of stones can give more information about olive cultivars because of the surface rise, while different statistical analysis may yield more useful outcomes for the identification of different olives around the world.

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