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Image Wavelet Scattering and Densenet Based Pistachio Identification

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Abstract

Today, computer-based systems are gaining importance in the agricultural sector in order to increase the economic value of products, industrial processing efficiency, and recognition of agricultural products. *Pistacia vera* (Kırmızı and Siirt pistachio) varieties grown in Turkey differ from each other in many ways such as price, nutritional value, shape and flavor. In this study, a classification model based on wavelet image scattering and DarkNet53 convolutional neural network (ESA) was developed to distinguish the Red and Siirt pistachio cultivars grown in our country. Within the scope of the study, the study was carried out with images of a total of 2148 pistachio varieties, 1232 of which are Kırmızı and 916 of which are Siirt. In order to classify these images, features of the images were obtained with wavelet image scattering and DarkNet53 convolutional neural network architecture, and then these features were classified with Support Vector Machines (SVM). By using wavelet image scattering and DarkNet53 ESA architecture, 97.98% accuracy was obtained as a result of the classification of the feature set of the images by SVM.

Keywords: Red variety , Siirt variety , Wavelet image scattering, DarkNet53, Support vector machines.

Dalgacık Görüntü Saçılımı ve DenseNet Temelli Fıstık Tanılaması

Öz

Günümüzde tarım sektöründe ürünlerin ekonomik değerlerinin ve endüstriyel süreçlerin verimliliğinin artırılması ve zirai ürünlerin birbirinden ayırt edilmesi için bilgisayar temelli sistemler önem kazanmaktadır. Ülkemizde yetiştirilen Kırmızı ve Siirt tipi fıstık çeşitleri fiyat, besin değeri, şekil, lezzet gibi birçok yönden birbirinden farklıdır. Bu çalışmada, ülkemizde yetişen Kırmızı ve Siirt fıstık çeşitlerini ayırt etmek için dalgacık görüntü saçılımı ve DarkNet53 evrişimsel sinir ağına (ESA) dayanan bir sınıflandırma modeli geliştirilmiştir. Çalışma kapsamında 1232 Kırmızı ve 916 Siirt çeşidi olmak üzere toplamda 2148 fıstık çeşitlerinin görüntüleriyle çalışma gerçekleşmiştir. Bu görüntüleri sınıflandırmak için dalgacık görüntü saçılımı ve DarkNet53 evrişimsel sinir ağı mimarisi ile görüntülere ait özellikler elde edilmiştir ve ardından bu özellikler Destek Vektör Makinaları (DVM) ile sınıflandırılmıştır. Dalgacık görüntü saçılımı ve DarkNet53 ESA mimarisi kullanılarak görüntülere ait oluşturulan özellik setinin DVM ile sınıflandırma sonucu %97.98 doğruluk elde edilmiştir.

Anahtar Kelimeler: Kırmızı fıstık, Siirt fıstığı, Dalgacık görüntü saçılımı, DarkNet53, Destek vektör makinaları.

1. Introduction

Pistachio harvest has an important place in Turkey as well as all over the world. Turkey ranks second in the World in terms of the annual production of pistachio (Şimşek, 2018). Pistachio is grown around Gaziantep, Şanlıurfa, Ceylanpınar and Adana cities of our country (Küden et al., 1994). Different types of pistachios are grown in Turkey (Mart et al., 1994). Multiple studies have been carried out on pistachios grown in our country due to the differences in their nutritional values, physical properties, shell thickness, size and width (Balta, 2002; Acar and Eti, 2009; Atli et al., 2005).

Pistachio is a branch of the cashew family and is of the species *Pistacia vera* L. (Onay et al., 2000). Pistachio is a very nutritious fruit and contains high carbohydrates, potassium and minerals (Everest, 2021). Quality controls such as production, marketing, storage and processing of pistachio, which is an agricultural product, are important. The important parameters of product quality are listed as size, shape, color and defect (Rashid, 2019). Thus, it is easier for the consumer to accept the products with a good appearance by removing the faulty products from the line. When Red pistachio is examined, some biological treatment in addition to daily foods through activities It helps protect against diseases. It is rich in vitamins and minerals (Çağlar et al., 2017). The Siirt variety is popular because it is a coarse-grained variety with high cracking rate and low periodicity, mostly grown in Siirt and Şanlıurfa (Akboğa and Pakyürek, 2020).

In traditional pistachio production, the selection of the quality product is done manually with human vision. Hand-selection of a large number of products causes intensive labor and resource wastage. Because the quality of the product is determined by human vision, the quality decreases as the sensitivity will decrease in repetitive and complex processes (Basaran and Ozcan, 2009). In order to increase the product quality, image processing techniques can be used by making use of computer science instead of manually controlling the product. Image processing can produce better results than human vision among intense images. Image processing works faster and more efficiently than humans by recognizing the product with the image of the product, processing the images and determining the quality of the fruit with appropriate tests (Simões et al., 2002).

Today, image processing has been used in many fields such as machine learning and deep learning, as well as in the agricultural sector. Increasing the quality of agricultural products is important in terms of marketing the product. In recent years, image processing techniques have been developed to increase the quality of agricultural products and many applications have been developed in this field. In the agricultural sector, image processing techniques have been used to detect diseases such as leaf spot, blight, downy mildew, and powdery mildew by using fruit and vegetable images (Khan et al., 2022; Shah et al., 2022; Leemans et al., 2002; Unay and Gosselin, 2005; Demir and Tümen, 2021).

An algorithm was developed by using the sound differences of open and closed shelled Pistachio s. The sound frequencies of the open and closed pistachio s placed on the steel plate have different coefficients. A feature vector was created from these sound differences and classification was made after applying image processing methods (Cetin et al., 2004). A virtual vision system is presented to classify open and closed pistachio s (Ataş and Doğan, n.d.). Classification was made using artificial neural networks (ANN) and SVM to distinguish peeled pistachios and similar undesirable products (Omid et al., 2017). A mechatronic system has been developed using SVM with images of Iranian pistachios that are structurally similar to pistachios (Nezhad and Ebrahımy, 2014). The SVM method was used to estimate the density of pistachio trees in arid or semi-arid regions (Fadaei et al., 2012). Deep learning algorithms have been used in various studies in many fields on image processing. A machine vision system with DNN is presented to distinguish open, rotten and unwanted Pistachio s using intermediate pistachio images (Farazi et al., 2017).

The other section of this study is organized as follows. In Section 2, materials, methods, used datasets and algorithms are mentioned. In Section 3, the proposed model for the classification of pistachio varieties is detailed. In Section 4, the findings of the experimental tests are mentioned. In Section 5, the results of the study are mentioned.

2. Material and Methods

2.1. Data Set

In this study, open access Kırmızı (Red) and Siirt pistachio varieties were used (Singh et al.,). In this data set, features such as morphological, shape and color were extracted. In this data set, a total of 2148 pistachio samples, 1232 of which are Red and 916 of which are Siirt pistachio species, were used. Pictures of these two pistachio species taken at different positions are shown in Figure 1 and Figure 2. Images of pistachio species have a width and height of 600x600. These images have 96 dbi resolution and 24 bit deep. As can be seen in the pistachio pictures, these species are distinguished from each other by multiple features such as shape, size, brightness and color.

Figure 1: Red Pistachio images.

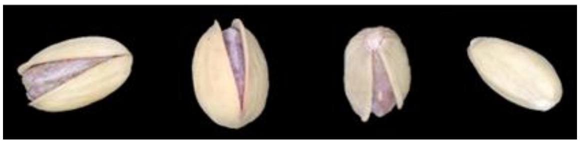

Figure 2: Siirt Pistachio images.

2.2. Darknet-53

Today, YOLO (You Only Look Once) and its derivatives are the leading algorithms used to detect objects from images accurately, quickly and with better performance through the image processing method (Wang et al., 2021). In this study, this CNN model was preferred because of its superior aspects. Darknet-53 is a derivative of the YOLO algorithm and it has been seen that better results are obtained from this algorithm (Redmon and Farhadi, 2018). The layered structure of Darknet-53 is given in Figure 3.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
2×	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2: Darknet-53 architecture (Redmon and Farhadi, 2018).

Darknet-53 divides the image into grids and if there are objects in the grid boxes, that is, if they are above a certain threshold, the object in the image is detected by detecting the middle point of the object. Otherwise, it indicates that there is no object in the specified box (Ren et al., 2015). Each box estimated using boxes at three different scales to find a multi-label classification that the box will contain (Lin et al., 2017). Similar to the pyramid concept, features are extracted between each layer by using the Convolution layer. The network uses 3x3 and 1x1 convolution layers for feature extraction and consists of 53 convolution layers in total.

2.3. Wavelet Image Scattering

For the classification of images, it is important to obtain the distinctive feature representations of the classes. The wavelet scattering method works by cascading the image through a series of wavelet transforms, nonlinearity, and averaging (Bruna and Mallat, 2013). A scattering operator computes an invariant image representation according to the motion of a group by applying a cascade of invariant and covariant operators computed with wavelet convolutions and modulus operators (Sifre and Mallat, 2013). Wavelet scattering transform based on wavelet transform is an improved time-frequency analysis method and consists of three steps. These steps are mathematically expressed in Equation 1-4 (Mei et al., 2021).

First, the complex wavelet transform of the x signal is recorded:

$$x * \psi_\lambda(t) + jx * \psi_\lambda^b(t) \tag{1}$$

Then the wavelet modulus coefficients are generated by a complex wavelet:

$$U[\lambda]x = |x(t) * \psi_\lambda| \tag{2}$$

The second step is to model the complex wavelet transform and obtain the nonzero wavelet coefficients:

$$|x(t) * \psi_\lambda| = \sqrt{\left|x * \psi_\lambda^a(t)\right|^2 + \left|x * \psi_\lambda^b(t)\right|^2} \tag{3}$$

The third step means calculating the mean convolutional scale.The wavelet scattering transform is calculated and represented as:

$$S[\lambda]x = |x(t) * \psi_\lambda| * \phi(u) \tag{4}$$

Here, $x(t)$ represents an original signal, $\psi_\lambda(t)$ represents the wavelet basis and $\phi(u)$ represents the scale function.

In this study, 600×600 pixel images were used as input. The number of wavelet filters per octave was determined as 2, and the criterion of invariance indicating the spatial support in rows and columns was determined as 60. 53 features of each image were obtained.

2.4. Support Vector Machines

Support Vector Machines developed by Vapnik are widely used in the literature for classification and regression problems (Vapnik, 1998). SVM machine learning method can effectively classify data in solving linearly separable or non-separable problems. SVM separates the data belonging to the separate category with as large a margin as possible by representing the data as a point in space, The model uses a hyperplane linear to classify new data. This linear line chooses a place far from the classes and maps the new data to the region to which it belongs (Toğaçar et al., 2020). In cases where the data set cannot be separated linearly, they can be linearly separated using kernel functions. In Figure 4, since the representative data on the hyperplane are not linearly separated, their separation in three-dimensional planar space is given as a representation.

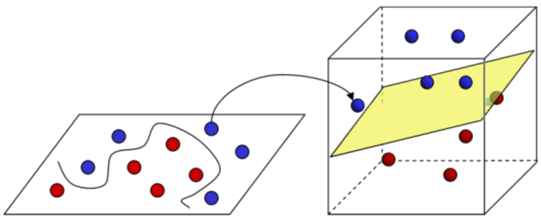

Figure 4. Separating the data set in three-dimensional planar space with the SVM kernel.

In this study, the features obtained from pistachio images were classified using the radial basis function kernel of support vector machines.

3. Proposed Model

In this study, wavelet image scattering, CNN and SVM methods were used to classify pistachio species with high performance and accuracy instead of “traditional manual discrimination”. An open access dataset was used to distinguish “Red” and “Siirt” pistachio images (Singh et al., 2022). In the proposed model, firstly, Wavelet Image Scattering algorithm and Avg1 layer of Darknet53 CNN model are used to extract features of pistachio species.

Then, the obtained features were tested with the SVM method. Finally, a new feature set was created by combining the features of both algorithms. This feature set is classified by SVM.

4. Results

In this study, confusion matrix was used to measure the performance of the model. There are actual values and predicted values in the confusion matrix. True positive (DP) and true negative (DN) represent correctly identified samples in the data set, while false positive (YP) and false negative (YN) represent incorrectly identified samples (Başaran et al., 2021). With the confusion matrix, the performance criteria in Equation 5-8 are calculated.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \tag{5}$$

$$\text{Sensitivty} = \frac{TP}{Tp+FN} \tag{6}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{7}$$

$$F-\text{Score} = 2 * \frac{Pre*Rec}{Pre+Rec} \tag{8}$$

In the first stage of the pistachio images experimental study, 53 features of each image were obtained by using the wavelet image scattering algorithm. Obtained features were classified by support vector machines. As a result of the experimental study, an accuracy rate of 85.27% was obtained. Performance results and complexity matrix obtained with wavelet image scattering features are given in Table 1 and Figure 5, respectively.

Table 1. Performance results of wavelet image scattering and classification of features of pistachio images by SVM.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Wavelet image scattering	85.27	91.62	76.73	87.71

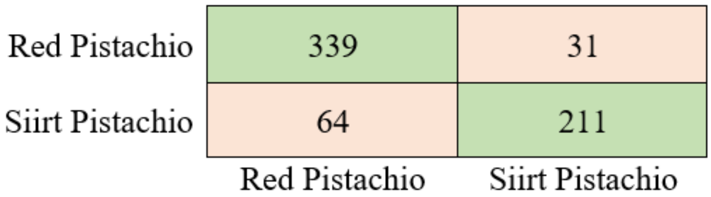

Figure 3. Confusion matrix obtained as a result of classification of features obtained by wavelet image scattering with SVM.

In the second stage of the experimental study, the data set was trained with the DarkNet53 CNN model. Deep features of images are extracted with Avg1 layer. After obtaining 1024 features of each image, these eatures are given as input to the SVM machine learning algorithm for classification. As a result of the study, pistachio images were classified with an accuracy rate of 95.34%. The obtained performance results are given in Table 2 and the complexity matrix in Figure 6.

Table 2. Performance results obtained by classifying the Avg1 layer features of the DarkNet53 model with SVM.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Darknet-Avg1	95.34	96.22	94.16	95.96

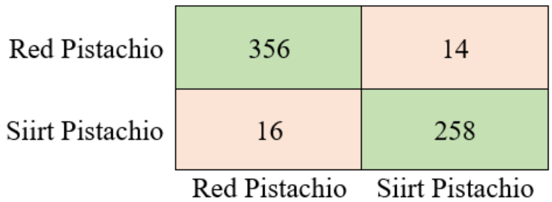

Figure 4. Confusion matrix obtained as a result of classification of DarkNet53 deep features with SVM.

At the last stage of the study, the features of wavelet image scattering and DarkNet53 CNN model images were combined to perform experimental studies with the proposed model. The new feature set obtained with 1051 features in total is given as an input to the SVM machine learning algorithm. As a result, an accuracy rate of 97.98% was obtained. In the proposed model, it has been observed that the performance results increase as a result of combining the DarkNet53 CNN model and wavelet image scattering features. The obtained performance results are given in Table 3 and the complexity matrix are given in Figure 7.

Table 3. Performance results obtained by SVM classification of the new feature set obtained with Wavelet image scattering and DarkNet53.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Darknet+wavelet image scattering	97.98	97.83	98.18	98.23

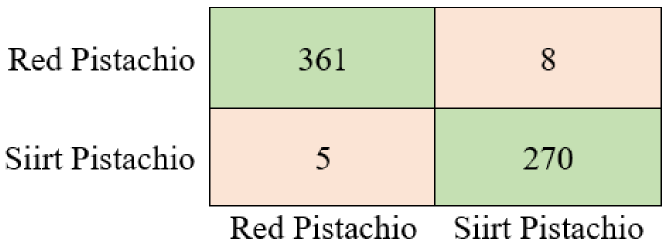

Figure 5. The confusion matrix obtained as a result of wavelet image scattering and classification with SVM of the new feature set obtained with DarkNet53.

5. Conclusion

In this study, using image processing techniques, the classification of Red and Siirt pistachio varieties with the highest performance and accuracy is made. In this study, wavelet image scattering and features of pistachio images were classified by SVM and an accuracy of 85.27% was obtained. The Avg1 layer features of the Darknet53 model were classified by SVM and 95.34% accuracy was obtained. In the classification of wavelet image scattering and the new feature set obtained with DarkNet53 with SVM, the best result was determined as 97.98%. As a result, it has been seen that better results are obtained when the features obtained from Darknet-53 and Wavelet Image Scattering algorithms are used together.

In future studies, it is planned to conduct deep learning-based studies with a larger data set and different peanut species.

6. Conflict of Interest

An interest in the author and the subject there is no conflict.

Declaration of Author Contribution

This article is 100% made by the author.

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