Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 4793293, 13 pages
https://doi.org/10.1155/2021/4793293

Research Article

Classification of Date Fruits into Genetic Varieties Using Image Analysis

Murat Koklu,[1] **Ramazan Kursun**,[2] **Yavuz Selim Taspinar**,[3] **and Ilkay Cinar**[1]

[1]*Department of Computer Engineering, Selcuk University, Konya, Turkey*
[2]*Guneysinir Vocational School, Selcuk University, Konya, Turkey*
[3]*Doganhisar Vocational School, Selcuk University, Konya, Turkey*

Correspondence should be addressed to Murat Koklu; mkoklu@selcuk.edu.tr

Received 9 September 2021; Revised 18 October 2021; Accepted 22 October 2021; Published 10 November 2021

Academic Editor: Javier Martinez Torres

A great number of fruits are grown around the world, each of which has various types. The factors that determine the type of fruit are the external appearance features such as color, length, diameter, and shape. The external appearance of the fruits is a major determinant of the fruit type. Determining the variety of fruits by looking at their external appearance may necessitate expertise, which is time-consuming and requires great effort. The aim of this study is to classify the types of date fruit, that are, Barhee, Deglet Nour, Sukkary, Rotab Mozafati, Ruthana, Safawi, and Sagai by using three different machine learning methods. In accordance with this purpose, 898 images of seven different date fruit types were obtained via the computer vision system (CVS). Through image processing techniques, a total of 34 features, including morphological features, shape, and color, were extracted from these images. First, models were developed by using the logistic regression (LR) and artificial neural network (ANN) methods, which are among the machine learning methods. Performance results achieved with these methods are 91.0% and 92.2%, respectively. Then, with the stacking model created by combining these models, the performance result was increased to 92.8%. It has been concluded that machine learning methods can be applied successfully for the classification of date fruit types.

1. Introduction

Date fruit (*Phoenix dactylifera*), which has about 200 types and more than 2500 species worldwide, is an edible and a nutritive fruit [1–3]. Date fruit can be classified by evaluating with image analysis and pattern recognition techniques. The differences in view, distance, and lighting exposure are the obstacles encountered in terms of performing a reliable classification. In order to make a successful classification, interclass similarities and differences should be handled cautiously. Therefore, the studies on fruit recognition and classification have been carried out based on the visual features extracted from images.

In short, easily determining the changes in the surface area and color values of the agricultural products with image analysis techniques facilitates the classification studies [4]. In the literature, there are numerous automatic classification and sorting systems based on image processing for various fruits, such as citrus, apple, date fruit, strawberry, mango, lemon, tomato, and pulses [5–10]. Morphological features are frequently used in the classification of fruits and vegetables [11, 12]. In another study carried out with seven different date fruit types, the k-nearest neighbor (cityblock), k-nearest neighbor (Euclidean), discriminant analysis, and neural networks classification methods have been tested by properly preparing 15 different visual features on the image data. The highest accuracy rates achieved as a result range between 89% and 99% [13]. In addition to the local binary pattern (LBP) and Weber local descriptor (WLD) methods used in order to extract the details of a date fruit's tissue pattern, the feature extraction method based on the Fisher discriminant ratio (FDR) was also applied to select more important features than these two methods. The data obtained through these methods were classified using the multiclass support vector machine (SVM) [14]. The data obtained as a result of the segmentation of the images obtained for the determination of the date fruits' ripening stages with the Otsu method was classified with the support vector machines (SVM) method, and an accuracy of 92.5% was achieved on 160 images [15]. In another study, in which 6 features extracted from date fruit images are used, it is stated that the SVM classifier, ANN, random forest (RF), and decision trees (DT) give better results than the classification approaches. As a result of the classification of features obtained from date fruit images, with two different neural network models, which are back propagation and radial basis function (RBF) networks, and the method of multilayer perceptron (MLP), 87.5% and 91.1% success performances were achieved, respectively [16].

In a study using barley grains, features were extracted using the Spatial Pyramid Partition Ensemble computer vision method, and machine learning methods were classified. They achieved 75% success with the kNN model and 100% success with the J48 model [17].

Date fruit, which has many varieties throughout the world, is used in the production of food, medical, and cosmetic products [18]. Expert opinion is needed to distinguish date fruit varieties due to different nutritional value, different consumption times, different prices, and quality differences [13]. Computer vision systems are used without the need for an expert in order to quickly distinguish the quality, size, and type of date varieties [19, 20]. In this way, the process from the production stage to the consumption stage can be shortened [21]. With this type of agricultural technologies, it is possible to increase the productivity in the agricultural industry [22].

When the literature is examined, it is seen that various machine learning methods have been tried for the classification of the date fruit. There are not many studies in which hybrid methods such as the stacking model is used. Within the scope of this study, as well as the models based on the LR and ANN, the stacking model that combine works according to the results of these two models have been tried. By using these models, date fruits were classified with a total of 34 features such as morphological, shape, and color characteristics obtained from date fruits. While determining these features, other studies on the field were also considered, and it was investigated whether the classification success is impacted by the number of features extracted.

In the second chapter, information on the methods of image acquisition, image processing, feature extraction, and success performance analysis will be given. In the third chapter, the LR, ANN, and stacking methods will be explained. In the fourth chapter, the results of the study will be presented. Last, in the fifth chapter, suggestions will be made together with the evaluation of the study.

2. Materials and Methods

In this section, acquisition of date fruit images, features extraction, and also the logistic regression (LR), artificial neural network (ANN), and stacking methods used for the classification process will be explained. Besides, the performance metrics of the classification results will be given. Figure 1 shows the general process steps of the study.

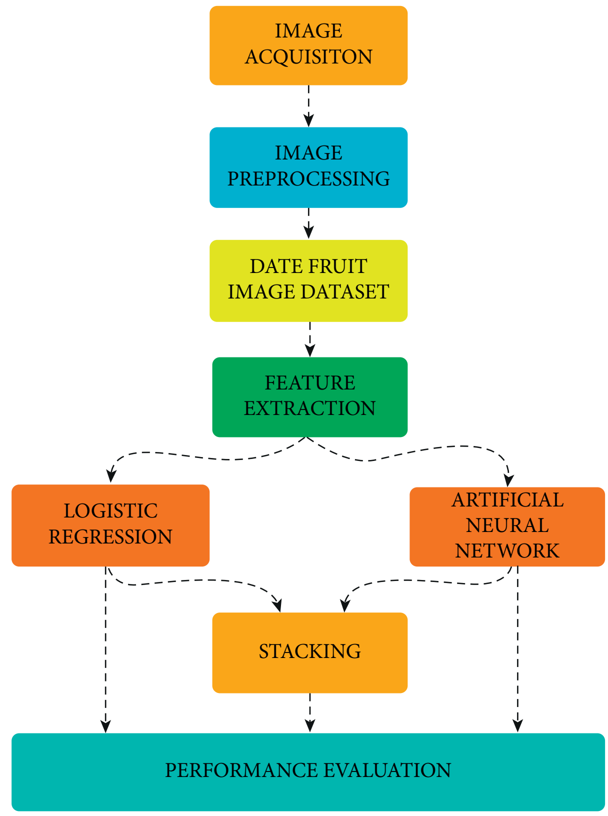


Figure 1: Process steps for classification of date fruit.

Accordingly, the steps performed are image acquisition, images processing, and feature extraction. Afterwards, the performance analyzes were evaluated by completing classification processes carried out according to LR, ANN, and stacking methods.

2.1. Image Acquisition. In this study, the classification process was performed for 7 different date fruit types, that are, Barhee, Deglet Nour, Sukkary, Rotab Mozafati, Ruthana, Safawi, and Sagai. Barhee 65, Deglet Nour 98, Sukkary 204, Rotab Mozafati 72, Ruthana 166, Safawi 199, and Sagai 94 samples were used from palm varieties, respectively. Date fruit is a fruit grown in countries neighboring Turkey. Therefore, access to varieties is very easy. There is a market where many types of dates are sold. In the study, ready-to-eat date fruits obtained from these markets were used. A CVS was set up such as the system given in Figure 2, for the image acquisition and captured images of the date fruits were transferred to the computer environment. The camera used in the setup is placed on a closed box with an LED light system. The future robot S100 series smart camera used to capture images has a resolution of 1280×1024. This camera, which has a CMOS-type 1.3 MP sensor, captures 90 FPS images in order to quickly take images in the installed conveyor system.

The images of date fruits were obtained via a mechanism that does not receive external light, so that preprocesses can be completed quickly. During image processing, the background and shadows should be cleaned according to the

Figure 2: Example of the system established to obtain images.

band speed and ambient light conditions [23]. Via automatically cleaning the shadows and background color that emerged during the illumination, clear date fruit images were obtained. Green color is used in the background in order to easily distinguish the palm image from the background. RGB values of green color were determined as $R = 106$, $G = 210$, and $B = 175$. Using these color values, the image was color filtered, and the date fruit image was obtained without a background [24]. This process is shown in Figure 3. In the study, classification processes were performed with features extracted from 898 images of 7 different date fruit types.

2.2. Image Processing and Extraction of Morphological Features. The obtained images were converted into grayscale and binary images for feature extraction. Basically, the operations were performed on methodologies of threshold and pixel information. At the end of the image processing, each date fruit was examined separately, and a set of features were extracted from them. The Otsu method, one of the commonly used image thresholding techniques, was used within the scope of the study [25]. This method specifies a variable that can distinguish between two or more groups found in nature. Generally working on gray level images, the method only checks how many times each color is present on the image. Therefore, the color distributions of the images are first calculated, and then, all processes are performed on this distribution sequence.

The progress of the method can be briefly summarized as follows:

(1) The distribution and probabilities of each density level are calculated

(2) Initial setting $\omega_i(0)$ and $\mu_i(0)$

(3) Step by step $t = 1$ maximum density for all possible thresholds

  (a) Update for ω_i and μ_i
  (b) Calculation for $\sigma_b^2(t)$

(4) The desired threshold corresponds to the maximum value $\sigma_b^2(t)$

A total of 34 features, including also 12 morphological [26], 4 shape [27], and 18 color [28] features, were extracted [29]. The features used in the study are given in Table 1.

2.3. Date Fruit Features Dataset. The date fruit types selected to be examined in the study are Barhee from the Palestinian region, Deglet Nour from the Algeria region, Sukkary, Safawi, Sagai, and Ruthana from the Saudi Arabia Riyadh and Medina region, and Rotab Mozafati from the Iran region. These selected date fruits are the most common and frequently grown types in their region of belonging. Table 2 provides the general characteristics of the date fruit types used in the study, while Table 3 provides places to statistical averages of the features obtained from the date fruits.

2.4. Performance Analysis. In numerous fields of science, classification techniques have been applied for many problems. There are several ways to evaluate the classification algorithms. To evaluate the classification algorithms, the correct metric analysis must be interpreted correctly [30, 31]. The confusion matrix summarizes the correct and incorrect classifications, in the form of a table [32].

True positive (TP) refers to correctly classified positive samples, true negative (TN) refers to correctly classified negative samples, false positive (FP) refers to incorrectly classified positive samples, and false negative (FN) refers to incorrectly classified negative samples. A seven-class confusion matrix was used since a seven-class classification problem was worked on in the research. The multiclass confusion matrix used is given in Table 4.

To make the detailed performance analysis of the models, there are different metrics besides the classification success [33]. F-score, precision, recall, and specificity metrics are the other metrics utilized to measure models' performance. Calculation of performance metrics with a seven-class confusion matrix is given in Table 5.

AUC (area under the curve)–ROC (receiver operating characteristic curve), which is another method to be used when it is necessary to control or visualize the performance of multiclass classification problems, is one of the most important evaluation criteria to check the performance of any classification model [34]. It is a performance measurement for classification problem at various threshold settings. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a certain decision threshold. A test with perfect separation has a ROC curve that passes through the upper left corner (100% sensitivity and 100% specificity). Therefore, the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test [35].

3. Classification Models

In order to evaluate the proposed classification methods, a dataset was created with the features extracted from date fruits. LR and ANN models and the stacking model created by combining these two models were used in classification processes.

3.1. Logistic Regression Analysis. The logistic regression method is often used to analyze the probability of the outcome emergence using the relationship between two or

(a) (b) (c)

Figure 3: Processing the obtained images of the palm fruit stages. (a) Initial status. (b) Cleaned status. (c) Final status.

Table 1: Features depending on the external appearance used in the study.

Main features	Subfeatures		
Morphological features	Area Perimeter Major axis Minor axis Eccentricity Roundness	Equivalent diameter Solidity Convex_area Extent Aspect ratio Compactness	
Shape features	Shapefactor_1 Shapefactor_2	Shapefactor_3 Shapefactor_4	
Color features	Mean RR Std. dev RR Skew RR Kurtosis RR Entropy RR All Daub4 RR	Mean RG Std. dev RG Skew RG Kurtosis RG Entropy RG All Daub4 RG	Mean RR Std. dev RR Skew RR Kurtosis RR Entropy RR All Daub4 RR

Table 2: Date fruits used in the study and their features.

Date fruit type	Images	Color and size	Origins
Barhee		It is amber in color at harvest and then turns a golden-brown color. It is small to medium in size with a hard shell	Basra, Iraq
Deglet Nour		It is a medium- to large-sized date fruits variety that matures from amber to dark brown after harvest	Not specific
Sukkary		It is golden in color and is a medium-sized date fruits variety	Al Qassim region, Saudi Arabia
Rotab Mozafati		It has a full, dark brown appearance. It is a medium-sized and fleshy date variety	Kerman, Iran

Table 2: Continued.

Date fruit type	Images	Color and size	Origins
Ruthana		It has brown and gold colors. It is a medium-sized date fruit variety	Madinah, Saudi Arabia
Safawi		It has a dark black cherry color and the tips are brown. It is a medium-sized date fruit variety	Madina, Saudi Arabia
Sagai		The tips are dry, golden in color, and the undersides are brown and soft. It is a medium-sized date variety	Arabian Peninsula, especially Saudi Arabia

Table 3: Statistical averages of the features extracted from date fruits.

Feature	Barhee	Deglet Nour	Sukkary	Rotab Mozafati	Ruthana	Safawi	Sagai
Area	405213.4000	233743.3571	145147.4000	433983.6000	387115.9000	334367.8000	286873.0000
Perimeter	2321.5050	1831.4420	1436.3210	2411.0460	2376.3100	2329.1860	2051.2770
Major axis	815.3703	680.2224	537.8438	836.1045	832.4755	881.3856	755.9785
Minor axis	634.6560	440.2732	342.9496	664.3262	599.8809	488.4889	492.6769
Eccentricity	0.6214	0.7566	0.7633	0.5950	0.6869	0.8264	0.7519
Equivalent diameter	716.9042	543.4765	427.5469	742.7018	701.0097	650.1046	602.3296
Solidity	0.9940	0.9843	0.9872	0.9931	0.9803	0.9734	0.9712
Convex_area	407666.2000	237428.9082	147027.0000	436990.5000	394846.1000	343399.9000	295203.7000
Extent	0.7665	0.7608	0.7551	0.7639	0.7367	0.6869	0.7314
Aspect ratio	1.2885	1.5500	1.5659	1.2618	1.3920	4.4836	1.5369
Roundness	0.9413	0.8707	0.8766	0.9369	0.8600	0.7762	0.8535
Compactness	0.8797	0.8004	0.7980	0.8898	0.8430	0.7405	0.7987
Shapefactor_1	0.0020	0.0030	0.0038	0.0019	0.0022	0.0057	0.0027
Shapefactor_2	0.0016	0.0019	0.0024	0.0015	0.0016	0.0015	0.0017
Shapefactor_3	0.7746	0.6420	0.6378	0.7929	0.7116	0.5521	0.6392
Shapefactor_4	0.9942	0.9882	0.9927	0.9945	0.9853	0.9897	0.9760

Table 4: Seven-class confusion matrix.

		Predicted						
		Barhee	Deglet Nour	Sukkary	Rotab Mozafati	Ruthana	Safawi	Sagai
Actual	Barhee	$\mathbf{T_1}$	F_{12}	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}
	Deglet Nour	F_{21}	$\mathbf{T_2}$	F_{23}	F_{24}	F_{25}	F_{26}	F_{27}
	Sukkary	F_{31}	F_{32}	$\mathbf{T_3}$	F_{34}	F_{35}	F_{36}	F_{37}
	Rotab Mozafati	F_{41}	F_{42}	F_{43}	$\mathbf{T_4}$	F_{45}	F_{46}	F_{47}
	Ruthana	F_{51}	F_{52}	F_{53}	F_{54}	$\mathbf{T_5}$	F_{56}	F_{57}
	Safawi	F_{61}	F_{62}	F_{63}	F_{64}	F_{65}	$\mathbf{T_6}$	F_{67}
	Sagai	F_{71}	F_{72}	F_{73}	F_{74}	F_{75}	F_{76}	$\mathbf{T_7}$

Table 5: Performance metrics equation for seven-class.

Metrics	Equation
Average accuracy	$\mathrm{TP}_i + \mathrm{TN}_i/\mathrm{TP}_i + \mathrm{TN}_i + \mathrm{FP}_i + \mathrm{FN}_i$
Average precision (P)	$\mathrm{TP}_i/\mathrm{TP}_i + \mathrm{FP}_i$
Average recall (R)	$\mathrm{TP}_i/\mathrm{TP}_i + \mathrm{FN}_i$
Average F-score	$2 * P_i + R_i/P_i + R_i$
Average specificity	$\mathrm{TN}_i/\mathrm{TN}_i + \mathrm{FP}_i$

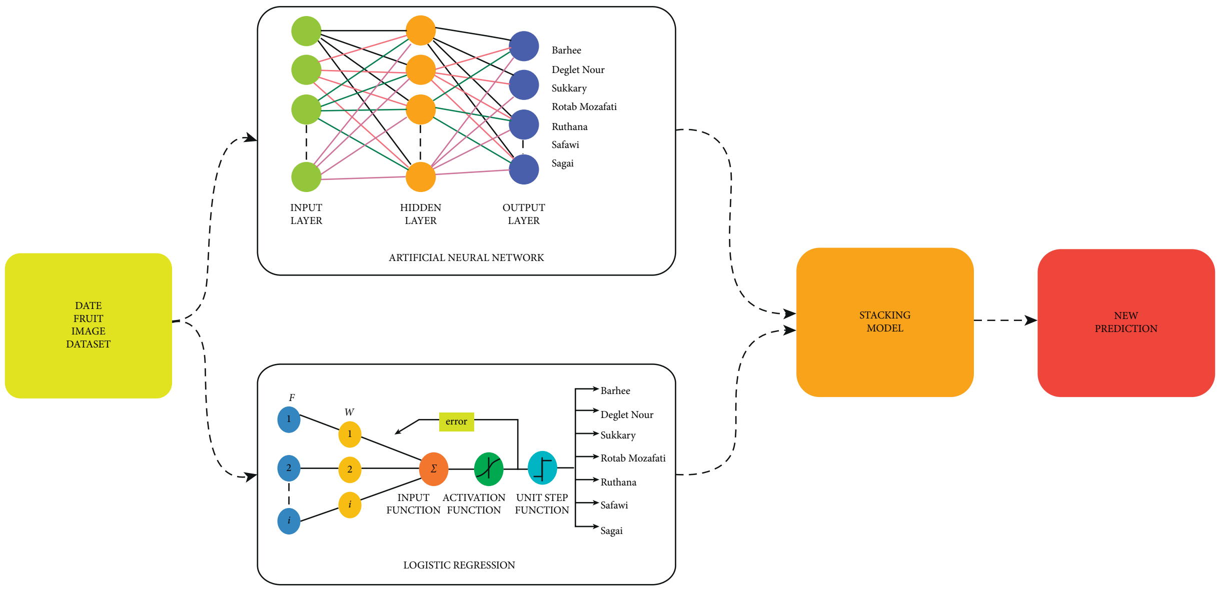


Figure 4: The created stacking model.

more variables. The result is obtained by fitting the achieved logarithmic ratios and explanatory variables to a linear model [36]. Logistic regression analysis is calculated as

$$\log\left(\frac{P(Y=1\mid X)}{1-P(Y=1\mid X)}\right)=\beta_0+\beta_1X_1+\cdots+\beta_nX_n, \tag{1}$$

where $Y=(0,1)$ is the binary variable, $X=(X1,\ldots,Xn)$ are the "n" explanatory variables, and $\beta=(\beta 0,\ldots,\beta n)$ are the regression coefficients to be estimated based on the data. The logistic regression model is an analysis method that is frequently used in many fields from physical sciences to social sciences, such as engineering [37], biomedicine [38], social sciences [39], and agriculture [40]. Consequently, logistic regression analysis is used to analyze a dataset with one or more independent variables that determine a result [41, 42].

3.2. Artificial Neural Network. An artificial neural network (ANN) is a set of algorithms trying to recognize the main associations in a dataset that mimics the way of human brain works [43, 44]. In computer science, on the other hand, the neural network (ANN) model is a simple basic mathematical model that describes a function of $F\colon X\longrightarrow Y$ in which nonlinear relationships between input variables on the X side and output variables on the Y side can be determined [45]. It is used in many basic fields such as engineering [46], medicine [47], agriculture [48], and social sciences [49]. The "neuron" in a neural network is a mathematical function that collects and classifies the information according to a particular architecture. The network has a strong resemblance to statistical methods such as curve fitting and regression analysis [50].

3.3. Stacking. Stacking is a machine learning algorithm in which two or more models are trained to solve the same problem and combined to achieve better results. Mainly, it aims at obtaining more accurate and/or robust models when the weak models are combined correctly and can be obtained. For this reason, it has been observed that the classification performance is improved by combining the estimations of multiple different classifiers under a single robust estimation [51, 52]. By combining the ANN and LR methods and with the results obtained with these models, the stacking model was created. The created model is shown in Figure 4.

4. Experimental Results

In order to classify the date fruits used in the study, the features of 898 preprocessed date fruits were extracted. In total, 34 features were extracted for each date fruit based on 3 main features, which are morphological, shape, and color features. A dataset was created with these extracted features. For the classification process, ANN and LR models were created and performance metrics were obtained. In addition, the performance metrics of the stacking model created by combining these two models were compared with both models. The cross-validation method, a method for splitting the dataset into parts, was used to evaluate the classification models and to train the model [53]. With this method, the dataset is split into a certain number of subsets as training and testing. In the study shown in Figure 5, the number of sample repetitions (k) was determined as 10.

The performance results were evaluated with the ROC curve and confusion matrix. Table 6 provides the AUC value, accuracy, F1 score, precision value, recall value, and specificity value, which are the performance metrics of classification measurements, respectively. According to the table, ANN and LR methods have achieved success over 90%. By obtaining the highest accuracy of 92.8% with the stacking model, a combination of these two models, high success was obtained from both models applied separately. The confusion matrix values are given in Table 7 for all models.

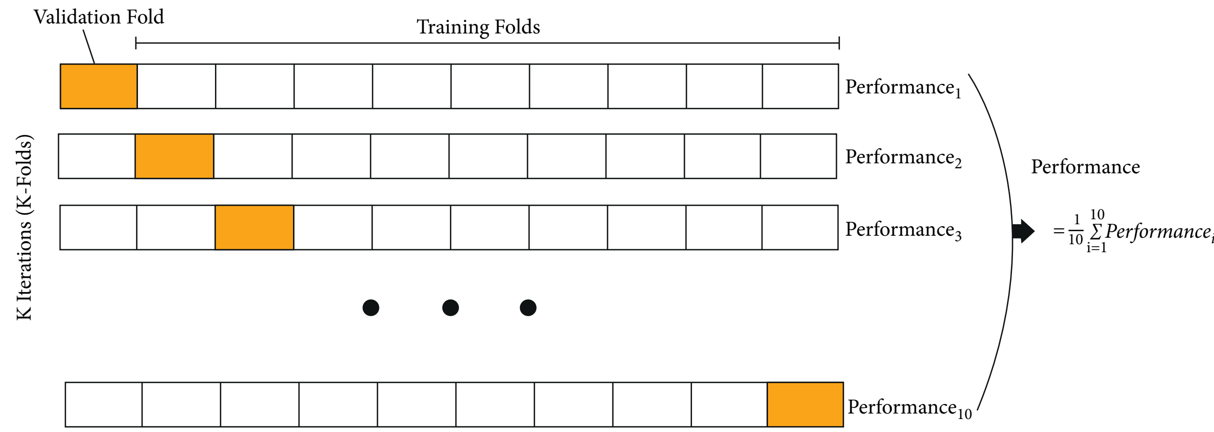


Figure 5: Cross-validation example preferred for the study.

Table 6: Performance results of classification performances.

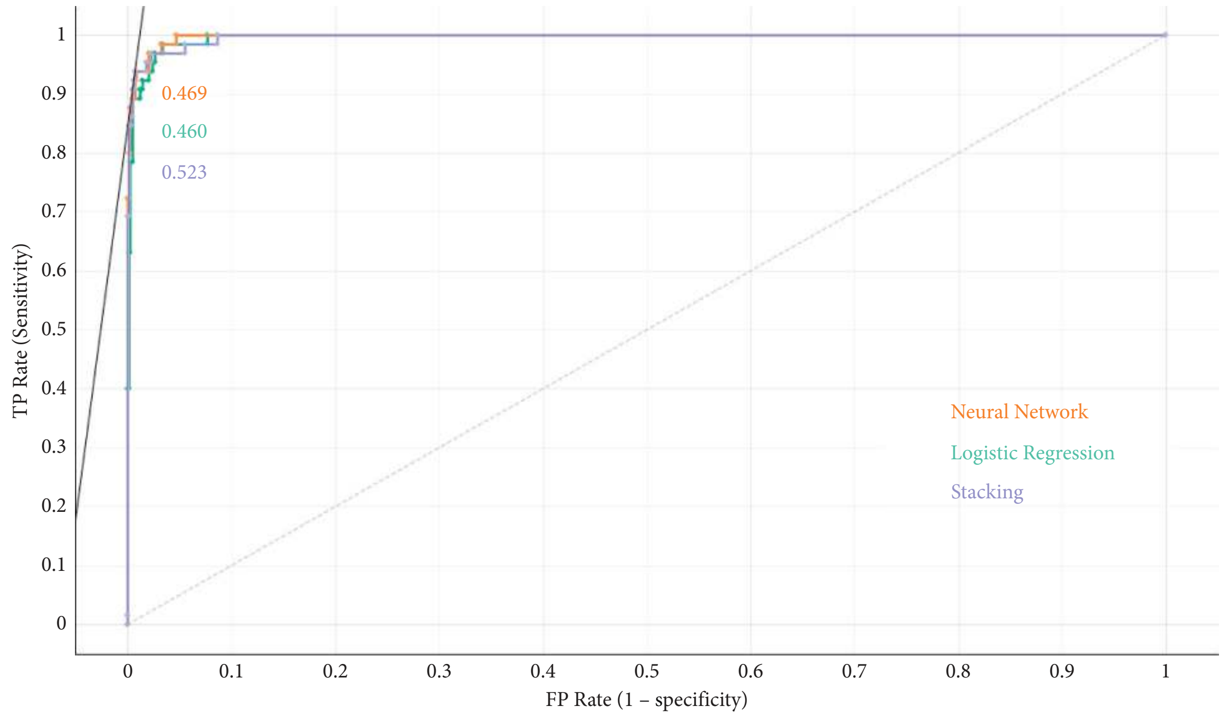
Model	AUC	Ca	F1	Precision	Recall	Specificity
Stacking	0.991	0.928	0.927	0.927	0.928	0.988
Neural network	0.993	0.922	0.922	0.921	0.922	0.987
Logistic regression	0.991	0.910	0.907	0.908	0.910	0.984

Table 7: Confusion matrix of all models.

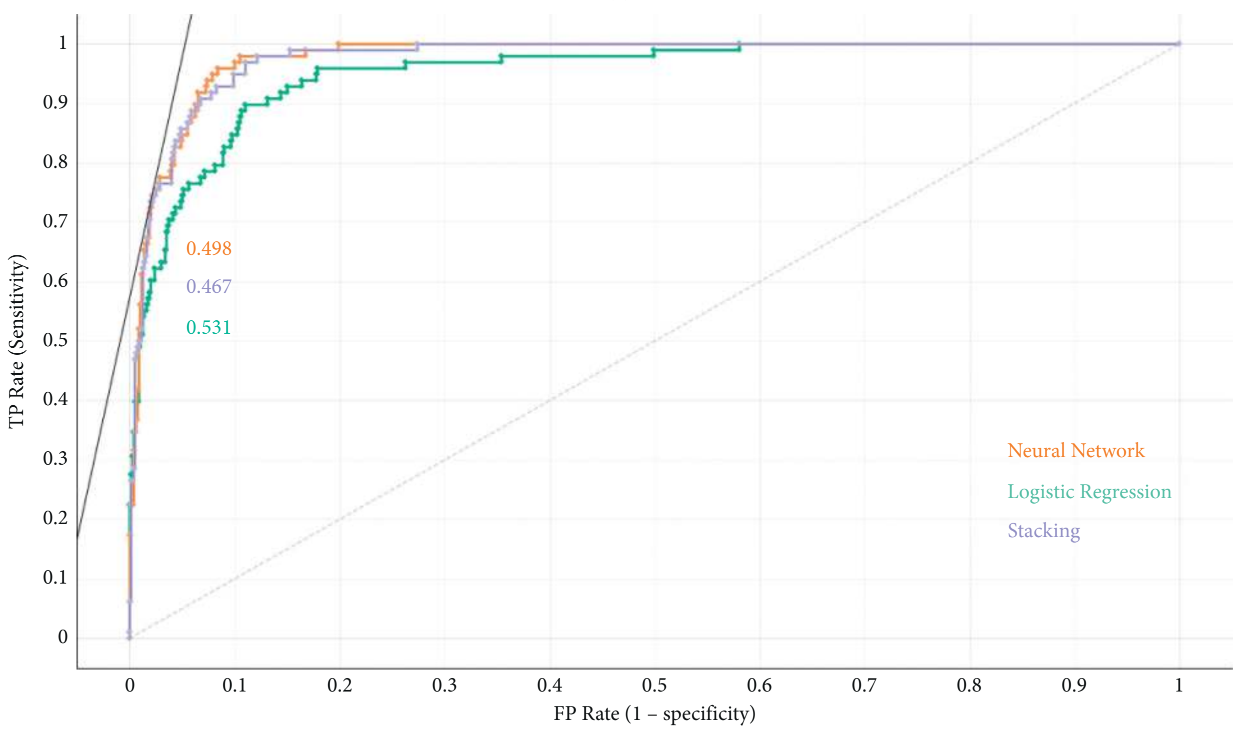
Methods LR, ANN, stacking		Predicted							
		Barhee	Deglet Nour	Sukkary	Rotab Mozafati	Ruthana	Safawi	Sagai	∑
		54	0	0	6	3	0	2	
	Barhee	58	0	0	5	1	0	1	65
		58	0	0	5	1	0	1	
		0	63	19	0	3	1	12	
	Deglet Nour	0	74	12	0	0	1	11	98
		0	73	13	0	0	1	11	
		0	4	199	0	0	0	1	
	Sukkary	0	7	196	0	0	0	1	204
		0	6	197	0	0	0	1	
		2	0	0	67	2	0	1	
	Rotab Mozafati	3	0	0	67	2	0	0	72
Actual		3	0	0	67	2	0	0	
		0	1	0	0	161	0	4	
	Ruthana	1	3	0	0	161	0	1	166
		1	2	0	0	161	0	2	
		0	0	1	0	0	196	2	
	Safawi	0	0	1	1	0	196	1	199
		0	0	1	0	0	197	1	
		0	11	0	0	3	3	77	
	Sagai	1	12	0	0	3	2	76	94
		1	9	0	0	2	2	80	
	∑	56	79	219	73	172	200	99	898

According to the confusion matrix, Safawi is the date fruit with the highest classification success for all models, while Barhee is the model with the lowest classification success.

In machine learning, AUC-ROC curve is also utilized for evaluating the performance of a classification problem. In the AUC-ROC curves (Figure 6) obtained for each date fruit in the study, the x-axis shows the FP ratio and the y-axis shows the TP ratio. When the AUC-ROC curves are examined, it is seen that the success performance is high in Safawi date fruit. The closer the upper left corner of the curve is to 1, the better the success performance.

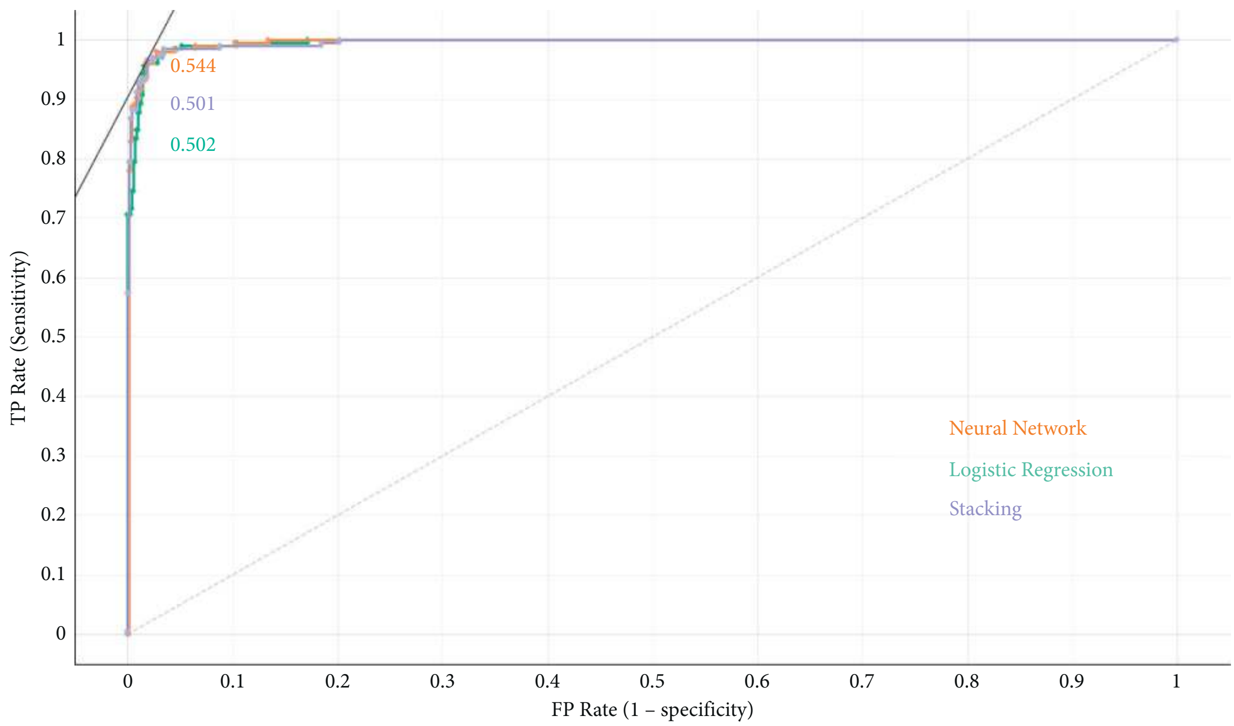


(a)

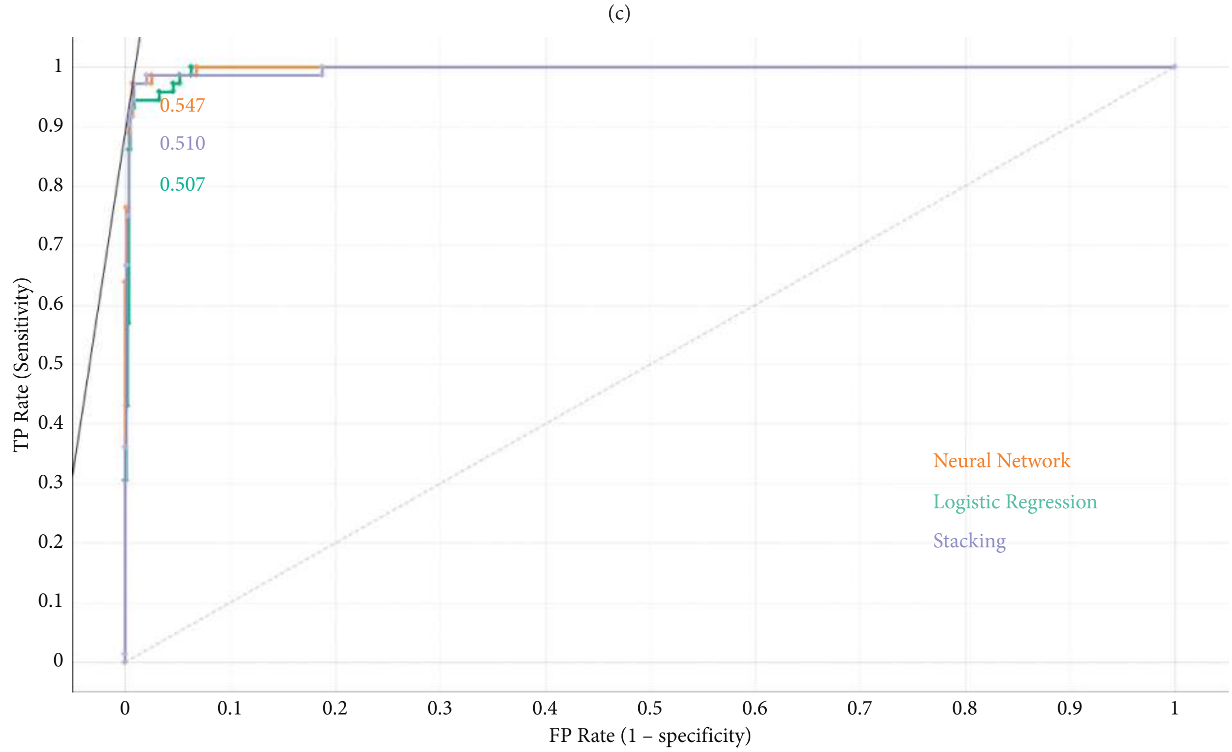


(b)

Figure 6: Continued.

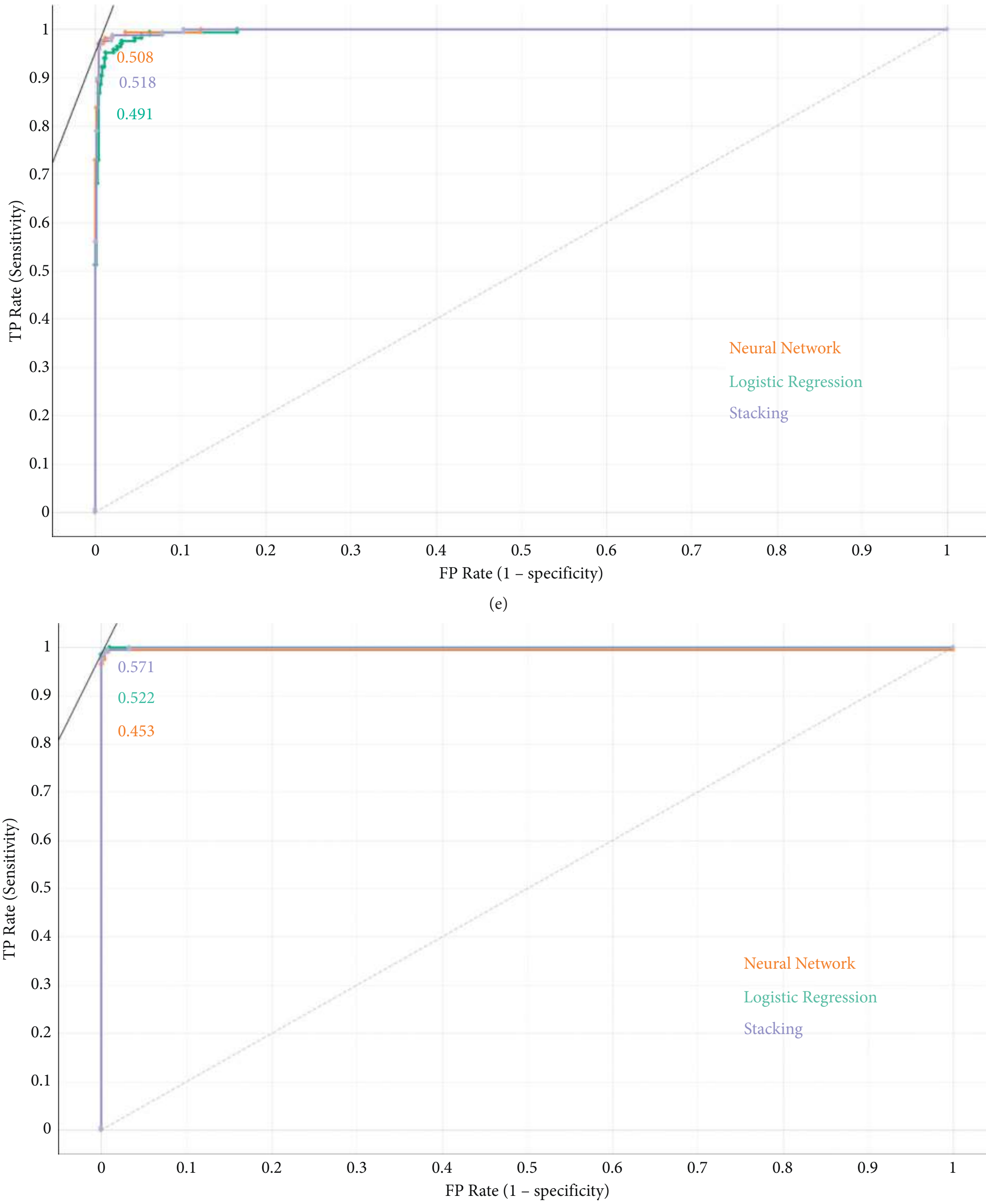


(c)



(d)

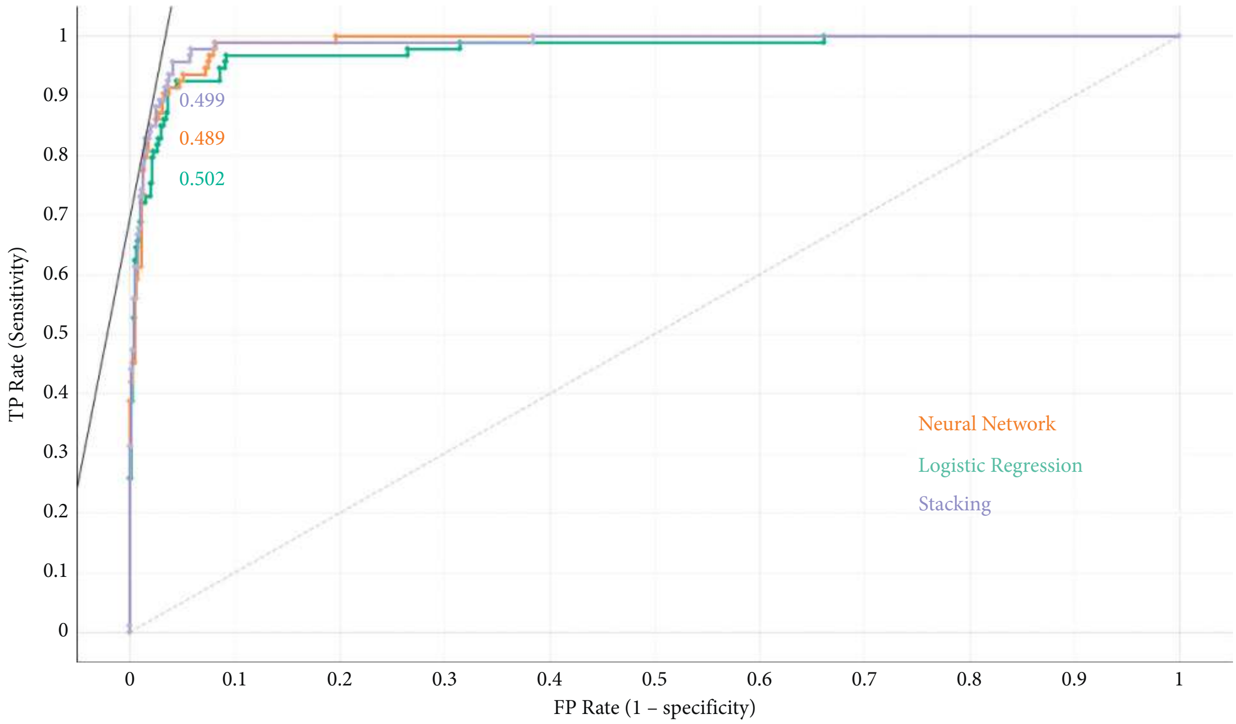
Figure 6: Continued.



(e)

(f)

Figure 6: Continued.



(g)

Figure 6: AUC-ROC curves of the methods used for each date fruit in the study. (a) Barhee date fruit. (b) Deglet Nour date fruit. (c) Sukkary date fruit. (d) Rotab Mozafati date fruit. (e) Ruthana date fruit. (f) Safawi date fruit. (g) Sagai date fruit.

5. Conclusions

In this study, a system has been put forth, with the aim of classifying the date fruits automatically without needing time-consuming and complex physical measurements. When previous studies are examined, it is seen that LR and ANN basic machine learning methods have been tried in classification with extracting more features from a date fruit. Furthermore, better results were obtained through the stacking method created by combining these two methods. In classification studies, high performance results in classification can be achieved not only with common machine learning methods but also with new stacking methods to be created by combining two or more of these methods. More successful results can be obtained by developing end-to-end classification models using the images of date fruit with deep learning models. Inspired by this study, it can be presented to the service of the users with the date fruit classification program with the help of a software on mobile phones. With the developed smartphone application, it is thought that consumers can have information about the type by classifying any date fruit sold over the counter. By extracting more features in classification studies, it is thought that success rates can be increased in the classification of not only date fruits but also other vegetables, fruits, legumes, or any object.

Data Availability

The dataset used in the study can be accessed from the link https://muratkoklu.com/Date_Fruit_Datasets.xlsx.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This project was supported by the Scientific Research Coordinator of Selcuk University.

References

[1] S. Khalid, N. Khalid, R. S. Khan, H. Ahmed, and A. Ahmad, "A review on chemistry and pharmacology of ajwa date fruit and pit," *Trends in Food Science & Technology*, vol. 63, pp. 60–69, 2017.

[2] M. Siddiq, S. M. Aleid, and A. A. Kader, *Dates: Postharvest Science, Processing Technology and Health Benefits*, John Wiley & Sons, Hoboken, NJ, USA, 2013.

[3] L. N. Eoin, "Systematics: blind dating," *Nature plants*, vol. 2, no. 5, p. 16069, 2016.

[4] A. Beyaz, R. Ozturk, and U. Turker, "Assessment of mechanical damage on apples with image analysis," *Journal of Food Agriculture and Environment*, vol. 8, no. 3&4, pp. 476–480, 2010.

[5] A. M. Vyas, B. Talati, and S. Naik, "Colour feature extraction techniques of fruits: a survey," *International Journal of Computer Applications*, vol. 83, no. 15, 2013.

[6] S. Naik, B. Patel, and R. Pandey, "Shape, size and maturity features extraction with fuzzy classifier for non-destructive mango (Mangifera Indica L., cv. Kesar) grading," in *Proceedings of the 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR)*, July 2015.

[7] R. Pandey, S. Naik, and R. Marfatia, "Image processing and machine learning for automated fruit grading system: a technical review," *International Journal of Computer Applications*, vol. 81, no. 16, pp. 29–39, 2013.
[8] I. Cinar and M. Koklu, "Classification of rice varieties using artificial intelligence methods," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 7, no. 3, pp. 188–194, 2019.
[9] S. Jana and R. Parekh, "Shape-based fruit recognition and classification," in *Proceedings of the International Conference on Computational Intelligence, Communications, and Business Analytics*, September 2017.
[10] E. Kaya and İ. Saritas, "Towards a real-time sorting system: identification of vitreous durum wheat kernels using ANN based on their morphological, colour, wavelet and gaborlet features," *Computers and Electronics in Agriculture*, vol. 166, Article ID 105016, 2019.
[11] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: a review," *Journal of King Saud University-Computer and Information Sciences*, vol. 33, no. 3, 2018.
[12] A. Beyaz, D. M. Martínez Gila, J. Gómez Ortega, and J. Gámez García, "Olive fly sting detection based on computer vision," *Postharvest Biology and Technology*, vol. 150, pp. 129–136, 2019.
[13] A. Haidar, H. Dong, and N. Mavridis, "Image-based date fruit classification," in *Proceedings of the 2012 IV International Congress on Ultra Modern Telecommunications and Control Systems*, October 2012.
[14] G. Muhammad, "Date fruits classification using texture descriptors and shape-size features," *Engineering Applications of Artificial Intelligence*, vol. 37, pp. 361–367, 2015.
[15] A. Septiarini, H. Hamdani, L. Za, and A. A. Kasim, "Image-based processing for ripeness classification of oil palm fruit," in *Proceedings of the 2019 5th International Conference on Science in Information Technology (ICSITech)*, October 2019.
[16] K. M. Alrajeh and T. A. Alzohairy, "Date fruits classification using MLP and RBF neural networks," *International Journal of Computer Applications*, vol. 41, no. 10, 2012.
[17] J. F. Lopes, L. Ludwig, D. F. Barbin, M. V. E. Grossmann, and S. Barbon, "Computer vision classification of barley flour based on spatial pyramid partition ensemble," *Sensors*, vol. 19, no. 13, p. 2953, 2019.
[18] C. J. Miller, E. V. Dunn, and I. B. Hashim, "The glycaemic index of dates and date/yoghurt mixed meals. are dates "the candy that grows on trees"?" *European Journal of Clinical Nutrition*, vol. 57, no. 3, pp. 427–430, 2003.
[19] K. Vijayakumar and C. Arun, "Automated risk identification using NLP in cloud based development environments," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–13, 2017.
[20] A. Voulodimos, N. Doulamis, and A. Doulamis, "Deep learning for computer vision: a brief review," *Computational Intelligence and Neuroscience*, vol. 2018, Article ID 7068349, 13 pages, 2018.
[21] S. K. Behera, A. Rath, A. Mahapatra, and P. K. Sethy, "Identification, classification & grading of fruits using machine learning & computer intelligence: a review," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–11, 2020.
[22] K. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: a review," *Sensors*, vol. 18, no. 8, p. 2674, 2018.
[23] T. Korohou, C. Okinda, H. Li et al., "Wheat grain yield estimation based on image morphological properties and wheat biomass," *Journal of Sensors*, vol. 2020, Article ID 1571936, 11 pages, 2020.
[24] L. Maddalena and A. Petrosino, "Exploiting color and depth for background subtraction," in *Proceedings of the International Conference on Image Analysis and Processing,* Springer, Cham, Germany, 2017.
[25] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.
[26] N. S. Visen, N. S. Shashidhar, J. Paliwal, and D. S. Jayas, "AE—automation and emerging technologies: identification and segmentation of occluding groups of grain kernels in a grain sample image," *Journal of Agricultural Engineering Research*, vol. 79, no. 2, pp. 159–166, 2001.
[27] A. Pazoki, F. Farokhi, and Z. Pazoki, "Classification of rice grain varieties using two artificial neural networks (MLP and neuro-fuzzy)," *The Journal of Animal & Plant Sciences*, vol. 24, no. 1, pp. 336–343, 2014.
[28] A. Arefi, A. M. Motlagh, and R. F. Teimourlou, "Wheat class identification using computer vision system and artificial neural networks," *International Agrophysics*, vol. 25, no. 4, 2011.
[29] M. M. Oliveira, B. V. Cerqueira, S. Barbon, and D. F. Barbin, "Classification of fermented cocoa beans (cut test) using computer vision," *Journal of Food Composition and Analysis*, vol. 97, Article ID 103771, 2021.
[30] A. Tharwat, "Classification assessment methods," *Applied Computing and Informatics*, vol. 17, no. 1, 2020.
[31] G. Çinarer, B. G. Emiroğlu, and A. H. Yurttakal, "Prediction of glioma grades using deep learning with wavelet radiomic features," *Applied Sciences*, vol. 10, no. 18, p. 6296, 2020.
[32] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Computers in Biology and Medicine*, vol. 111, Article ID 103345, 2019.
[33] M. A. U. H. Tahir, S. Asghar, A. Manzoor, and M. A. Noor, "A classification model for class imbalance dataset using genetic programming," *IEEE Access*, vol. 7, pp. 71013–71037, 2019.
[34] M. Bicakci, O. Ayyildiz, Z. Aydin, A. Basturk, S. Karacavus, and B. Yilmaz, "Metabolic imaging based sub-classification of lung cancer," *IEEE Access*, vol. 8, pp. 218470–218476, 2020.
[35] M. H. Zweig and G. Campbell, "Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine," *Clinical Chemistry*, vol. 39, no. 4, pp. 561–577, 1993.
[36] G. James, *An Introduction to Statistical Learning*, Springer, Berlin, Germany, 2013.
[37] H. Hemasinghe, R. S. S. Rangali, N. L. Deshapriya, and L. Samarakoon, "Landslide susceptibility mapping using logistic regression model (a case study in Badulla district, Sri Lanka)," *Procedia Engineering*, vol. 212, pp. 1046–1053, 2018.
[38] M. Kim, Y. Song, S. Wang, Y. Xia, and X. Jiang, "Secure logistic regression based on homomorphic encryption: design and evaluation," *JMIR Medical Informatics*, vol. 6, no. 2, p. e19, 2018.
[39] J. Kuha and C. Mills, "On group comparisons with logistic regression models," *Sociological Methods & Research*, vol. 49, no. 2, pp. 498–525, 2020.
[40] İ. Çinar, M. Koklu, and Ş. Taşdemir, "Classification of raisin grains using machine vision and artificial intelligence methods," *Gazi Journal of Engineering Sciences*, vol. 6, no. 3, pp. 200–209, 2020.

[41] Z. Bursac, C. H. Gauss, D. K. Williams, and D. W. Hosmer, "Purposeful selection of variables in logistic regression," *Source Code for Biology and Medicine*, vol. 3, no. 1, pp. 17-18, 2008.

[42] S. Dreiseitl and L. Ohno-Machado, "Logistic regression and artificial neural network classification models: a methodology review," *Journal of Biomedical Informatics*, vol. 35, no. 5, pp. 352–359, 2002.

[43] I. A. Ozkan, "A novel basketball result prediction model using a \concurrent neuro-fuzzy system," *Applied Artificial Intelligence*, vol. 34, no. 13, pp. 1038–1054, 2020.

[44] K. G. Sheela and S. N. Deepa, "Review on methods to fix number of hidden neurons in neural networks," *Mathematical Problems in Engineering*, vol. 2013, Article ID 425740, 11 pages, 2013.

[45] D. Z. Antanasijević, V. V. Pocajt, D. S. Povrenović, M. Đ Ristić, and A. A. Perić-Grujić, "PM10 emission forecasting using artificial neural networks and genetic algorithm input variable optimization," *The Science of the Total Environment*, vol. 443, pp. 511–519, 2013.

[46] A. Yasar, I. Saritas, M. A. Sahman, and A. O. Dundar, "Classification of leaf type using artificial neural networks," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 3, no. 4, pp. 136–139, 2015.

[47] S. Koçer and A. E. Tümer, "Classifying neuromuscular diseases using artificial neural networks with applied autoregressive and cepstral analysis," *Neural Computing and Applications*, vol. 28, no. 1, pp. 945–952, 2017.

[48] K. Sabanci, "Detection of sunn pest-damaged wheat grains using artificial bee colony optimization-based artificial intelligence techniques," *Journal of the Science of Food and Agriculture*, vol. 100, no. 2, pp. 817–824, 2020.

[49] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. Mohamed, and H. Arshad, "State-of-the-art in artificial neural network applications: a survey," *Heliyon*, vol. 4, no. 11, Article ID e00938, 2018.

[50] K. Suzuki, *Artificial Neural Networks: Methodological Advances and Biomedical Applications*, BoD–Books on Demand, Norderstedt, Germany, 2011.

[51] E. K. Tang, P. N. Suganthan, and X. Yao, "An analysis of diversity measures," *Machine Learning*, vol. 65, no. 1, pp. 247–271, 2006.

[52] F. Divina, A. Gilson, F. Goméz-Vela, M. García Torres, and J. Torres, "Stacking ensemble learning for short-term electricity consumption forecasting," *Energies*, vol. 11, no. 4, p. 949, 2018.

[53] M. Koklu and I. A. Ozkan, "Multiclass classification of dry beans using computer vision and machine learning techniques," *Computers and Electronics in Agriculture*, vol. 174, Article ID 105507, 2020.