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Automatic counting of grapes from vineyard images

Bashar Al-Saffar[1], Sami Arica[2,*] and Semih Tangolar[3]

[1]Computer Techniques Engineering Department, Al Salam University College, Baghdad, Iraq; [2]Electrical and Electronics Engineering Department, Cukurova University, Adana, Turkey; [3]Horticulture Department, Cukurova University, Adana, Turkey
*Corresponding author's e-mail: arica@cu.edu.tr

Harvesting, spraying, and yield estimation are difficult activities for farmers. They take time, many workers, and moreover, are not always accurate. Therefore, machines are required to ease and speed up harvesting, spraying, and yield estimation. In this study, automatic recognition of visible grape berries and bunches from Red, Green, and Blue (RGB) images acquired by a camera for harvesting, spraying machines, and yield estimation was investigated. The images of grapes of different sizes and colors were taken under divergent natural light conditions and contrasts. The freely available Iceland dataset containing white grapes and in addition, images of red white, and hybrid types of grape trees were picked and used in the study. Initially, the Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG) were extracted, individually and their combination were used as feature vectors. Next, the features obtained were categorized with Convolution Neural Network (CNN), Artificial Neural Network (ANN), and Support-Vector-Machine (SVM) separately. The samples of grape berry images in the Iceland dataset were employed to train the ANN and SVM classifiers. Finally, the grape bunches were detected by incorporating Density Based Spatial Clustering of Applications with Noise (DBSCAN) clustering method. The artificial neural network classifier with the combined features provided the best accuracy in single berry recognition. It is faster than SVM and CNN as well. The average accuracy, precision, and recall were 99.6%, 99.7%, and 99.5% respectively. The accuracies of grape berry and bunch detection from test images were obtained as 89.8% and 91.7% respectively. Results show that LPB+HOG as a feature with ANN as a classifier provide an efficient grape detection from images taken under variant natural illumination conditions.

Keywords: Image segmentation**,** vineyard images, precision agriculture, yield estimation.

INTRODUCTION

The recognition and counting of visual grapes in real sight are one of the main issues that should be solved in viticulture. Food and Agriculture Organization (FAO), reported that the highest productive fruit in Turkey is grape, the grape production increase in the world annually (FAO, 2017), may represent a problem in the future because of worker's costs and accuracy. The International Organization of Vine and Wine (IOV), reported that grape production is higher than 104 million tons in the world in 2016. The total production of grapes in Turkey in 2015 was 3.65 million tons, the exported amount was 1.75 million tons, representing 47.9% out of the total production. In 2016 the production of grapes in Turkey reached 4.2 million tons and the exported amount was 1.73 million tons, representing 43.3% out of the total production (IOV, 2015; IOV, 2016). Turkey is one of the countries that contribute about 5.3% out of the world in grape production. That shows the production of fresh grapes, dried grapes, and wine grapes represent the biggest economic activity in the world including Turkey. The world is facing many problems in grape production due to the lack of workers, costs, and the increment of costs of employment which affects grape quality, productivity, crop tracking, and harvesting time. On another hand, manual harvesting needs a number of laborers and is expensive, destructive, consuming time, and inaccurate (Quackenbush, 2017; Sajid *et al*., 2020). Because of these difficulties, the agricultural field needs to implement a new technology to help the farmers in the production and different aspects such as time, accuracy, quality, and productivity. The use of robotic systems for automatic grape detection and related processes in viticulture is one of the technologies that could help farmers to increase grape production, the accuracy of detection, and other tasks. This will include crop monitoring, management, and help in solving the existing difficulties of a worker shortage and increasing worker costs. Grape recognition is a very important topic of study that until now, has not been solved completely yet. In this study, we

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presented an algorithm that is able to detect visual grape berry and bunch in RGB images with no need for special illumination and color for any robotic machine.

Related Works**:** Most of the related research in viticulture is aimed to solve the difficulties in yield estimation color features in different color spaces (RGB, Hue, Saturation, Value (HSV), L*a*b*) have been used to detect white and red grapes. The visual grape detection based on the color descriptors typically show better results for red grape than white grape because of the similarity of white grape color with background and leaves. Liu *et al*. (2013) analyzed the relationship between several variables such as perimeter, pixel area, size, and grape number. There was a relation to the actual grape bunch weight, in order to determine the best estimation of the yield. Later the same authors proposed another method for detecting grape bunches of red color by employing segmentation in the HSV color space (Liu *et al*., 2015). A vector of features containing the information of bunch location, texture and bounding box pixel distribution was passed to a previously trained SVM classifier. A similar study (Luo *et al*., 2016) presented a grape cluster detection based on color and an AdaBoost framework for classification. They presented an adjoining cluster separator based on the calculation of the barycenter of the binary detection mask. A more sophisticated algorithm is proposed by (Chamelat *et al*., 2006) where HSV channel information along with Zernike moments were used to describe grape shapes and train a SVM classifier in order to identify grapes in images using a sliding window.

An illumination may cause reflections from berries which appear as small spots in an acquired image. This fact was utilized in studies by (Grossetete *et al*., 2012; Nuske, Gupta, *et al*., 2014). This technique may produce variant results because of the change in luminescence (Diago *et al*., 2015) or different light reflections caused by weather conditions such as rain over the fruit, spraying, generating multiple reflection points. To tackle problems caused by changes in natural illumination conditions, some methods employ artificial illumination by a specialized hardware to operate at night time (Nuske, Gupta, *et al*., 2014), which may imply higher operational costs.

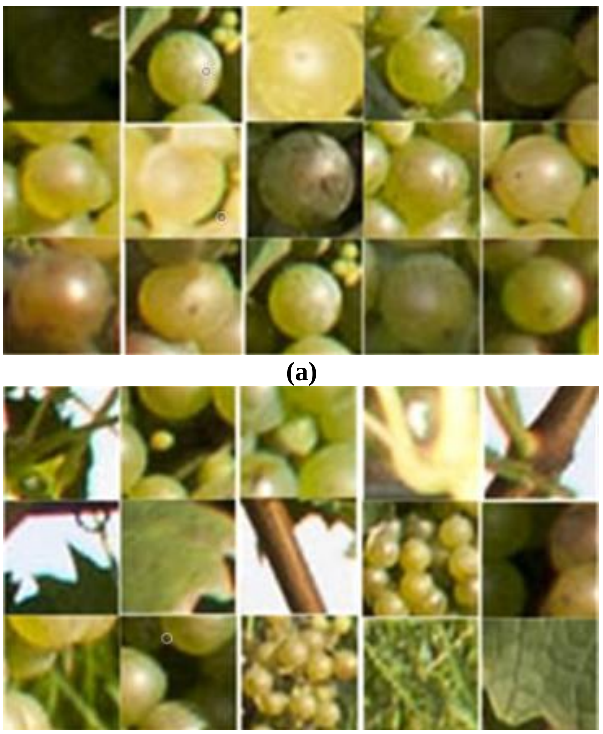
In (Škrabánek & Runarsson, 2015) designed a white grape detection method using a sliding window technique over the image. A SVM with radial basis function (rbf) has been used as a classifier. Results showed that the combination of HOG with LBP as a feature vector provided best results. A grape bunch was modeled by 3D reconstruction of the bunch by (Herrero-Huerta *et al*., 2015), and the volume, mass, and number of berries in each bunch were forecasted. The approach employed images from five different angles to reconstruct a grape bunch. A similar study was presented by (Liu *et al*., 2015), where the reconstruction of ten grape bunches were done by using one image taken under laboratory conditions. Here they used color segmentation to extract the grape berry from the background and applied circular Hough Transform to identify individual grapes and started creating the 3D model. In (Ivorra *et al*., 2015), a 3D surface was obtained using stereo cameras under ideal conditions in order to assess a bunch of grape parts related to the vineyard, mainly compactness (which affects the quality of the grapes that do not receive enough sunlight in the interior of the bunch). An approach presented by (Pérez-Zavala *et al*., 2018) was to extract the interest points by the Fast-Radial-Symmetry Transform (FRST) technique for detecting grape bunch and berry. Feature extraction was done by employing various techniques such as; Dense Scale Invariant Feature Transform (DSIFT), DAISY, HOG, LBP, and a combination of them and categorization was achieved by utilizing SVM, Support Vector Data Descriptor (SVDD). The combination of HOG and LBP features with SVM provided the best result. The author in (Śkrabánek, 2018) have been designed a Deep Convolutional Neural Network (DCNN) for classifying a single white grape berry from full color RGB low-resolution image.

MATERIALS AND METHODS

The steps of the proposed method is shown in (Fig. 2). Firstly, histogram equalization was applied to improve the grape berry detection. Next, the FRST was performed as a pre-detection task to find circular shapes in the image and at feature extraction stage the HOG and the LBP of the interest points specified by FRST were computed. Three classifiers; CNN, ANN and linear SVM were employed as classifiers individually to compare their time cost and categorization performance. As a separate process the CNN extracted features internally. The HOG, LBP, and their combination (HOG+LBP) were used independently to obtain their classification power. Therefore, seven tests were run: LBP with SVM, HOG with SVM, (HOG+LBP) with SVM, LBP with ANN, HOG with ANN, (HOG+LBP) with ANN and CNN. These steps involved identifying candidate berries. The best one in terms of categorization performance in seven approaches was chosen. The misclassified berries were removed and a finer segmentation was employed by utilizing the DBSCAN technique. The outcome of this phase may contain overlapping clusters; namely bunches. The overlapping bunches were separated in the final phase. The distance transformed of the mask image was computed and then number of the connected components was obtained to get number of bunches. And for this total bunch, the grape berries positions in the mask were clustered with k-means clustering algorithm. A more detailed description of the study is given in the following.

Data**:** In the proposed method, we have used two datasets. One is the Iceland data set, which was created by (Škrabánek & Runarsson, 2015) and was allowed freely. It has 3440 white grape berry images and 3440 non-berry images. The actual number of images is 25% of the total, and the other 75% was generated by rotating these images 90, 180, and 270 degrees. The images are the size of 40×40×3 in RGB color and have different illumination, sample variance in color, and berry size. They were employed to train a classifier. Some examples of these images are displayed in (Fig. 1). The data set contains also three images of grape trees too.

An alternative image collection was obtained by taking RGB photographs of grape trees from grape orchards in Adana (six images) and Tarsus (eight images) region in Turkey at day hours. The pictures were captured under natural illumination in order to meet the real and practical prerequisites. The grapes in this set were red, white, and hybrid type. These images and images of white grape trees from the Iceland data set were employed for validating the classifier.



(a)

(a)

Figure 1. Samples from Iceland dataset. (a) Positive (berry) images. (b) Negative (non-berry) images.

Platform**:** The Matlab™ (2018b) technical computing software accompanied with a neural network, computer vision, and digital image processing and convolution neural network toolboxes was employed to implement prepossessing, extract features and do classification. The custom made Matlab codes: FRST algorithm written by (Loy and Zelinsky, 2003), and DBSCAN algorithm implemented by (Mostapha, 2015) were also applied. A computer equipped with Intel Core-i7-7500U CPU@2.9 GHz processor and 12GB RAM was used to test and run the algorithm.

Method**:** The block diagram of the approach given in (Fig. 2) is described step by step in the following.

Pre-processing**:** Firstly, the colored berry images were converted to grayscale because the shape or geometric structure of the berry contains information. In order to improve the accuracy of single grape berry detection, some difficulties should be resolved such as different image sizes and resolutions, unequal illumination, and grape color. Therefore, it is necessary to process the images to make them appropriate for interest point detection. Consequently, their histogram was equalized to overcome contrast and illumination dissimilarity.

The image size of the berry images in the Iceland dataset were 40×40×3 and the attributes extracted from them were used for train the ANN and SVM classifiers after they were converted to grayscale and equalized. The CNN does not require feature extraction and it needs the image as its input. The input layer of the designed CNN demanded the image of 145×145×1 size and hence following the equalization step the gray berry images were resized to 145×145×1 to use with the CNN.

In the following the sequential steps are described.

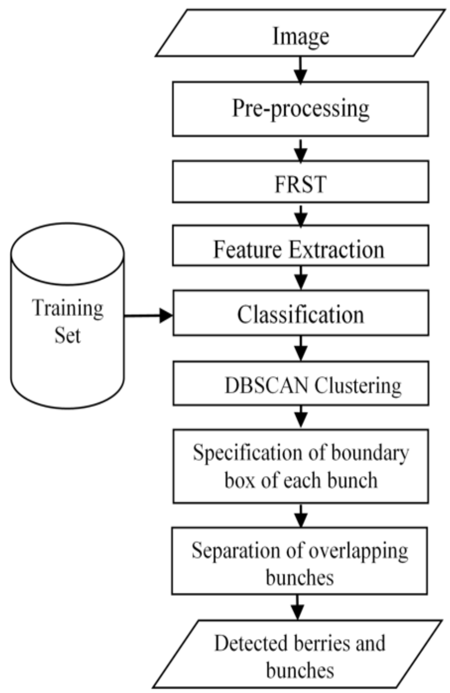
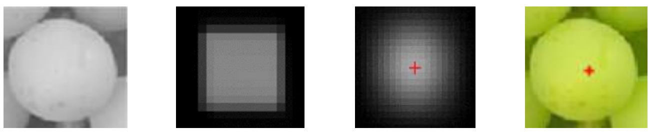


Figure 2. The flow chart of the proposed method.

Fast radial symmetry transform (FRST)**:** Berries have circular shape and center of this shape can be extracted by FRST. The possible berry centers are interest points or namely, salient points in the image. FRST was first introduced by (Loy and Zelinsky, 2003) and the authors in (Nuske, Wilshusen, *et al.*, 2014) utilized FRST for the detection of the salient points. FRST computes symmetry measure of a pixel for each radial distance $d_i \in D = (d_1, d_2, \cdots, d_n)$, and the total measure becomes a symmetry score for this pixel. Consequently, after pre-processing, the interest points were detected via FRST. The FRST was applied after down sampling the image to accelerate the processing time. The symmetry scores exceeding a certain threshold considered centers of circular shapes.

The output image of FRST is a gray image, has noise, and not smooth. Therefore an averaging filter of size 3×3 was used to smooth the image and next the spurious information from the image was removed by setting pixel values, which is lower than 10% of the maximum in the 3×3 window, to zero. The window slide over the image on pixel bases to suppress non-maximum pixels. (Fig. 3) illustrates this procedure.



(a) (b) (c) (d)

Figure 3. An example of salient point detection. (a) Input image. (b) The output of FRST. (c) Image after smoothing and suppressing non-maximum pixels. (d) Original color image and detected center.

Features which describe characteristics of a berry image were extracted. These features were then categorized by an ANN and SVM classifiers. Two attributes computed are described in the following.

Histogram of oriented gradients (HOG)**:** The HOG feature vector has been frequently used for object recognition. It depends on the shape characteristics of the image (Dalal and Triggs, 2005). It is based on the image gradient. The histogram for nine directions (0°, 20°, 40°,…, 160°) were computed from each 8×8 non overlapping cells of image of size 40×40 pixels. The normalization of histograms was obtained from overlapping blocks of size 2×2 cells. The block overlap was 1 cell in horizontal and vertical directions. A feature vector that consists of 576 attributes generated.

Local binary patterns (LBP)**:** An LBP feature is used to explore texture information in an image and is utilized commonly in the pattern recognition field (Ojala *et al*., 2002). An image pixel is compared with its neighbor pixels (8 pixels in a one-unit distance in vertical, horizontal and diagonal directions). If the neighbor pixel value is bigger than the pixel, it will set logic 1 to that pixel, else logic 0. Ordering of these eight logic values corresponds to a decimal value and presents an attribute of that pixel. The LBP was computed for detected salient points. The histogram of the LBP image of size 40×40 was computed and employed as feature. The histogram was computed for 10 equally spaced bins, and it was used as a feature vector.

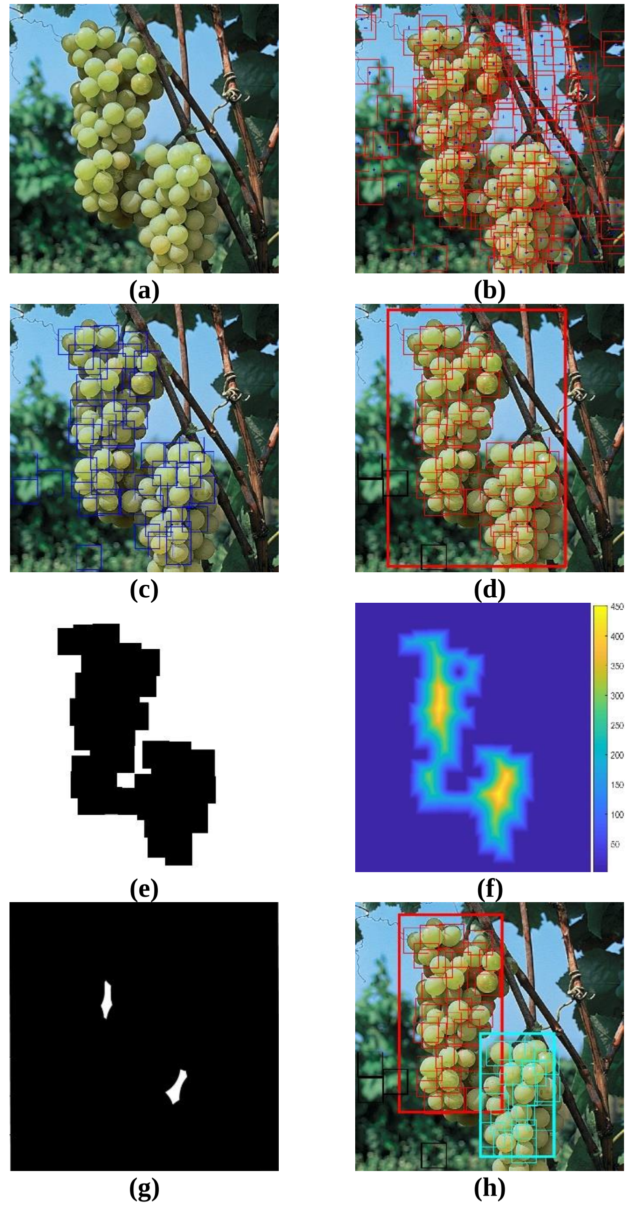


Figure 4. Neighbor grape bunch separation (Golden Muscat Grape, 2016). (a) Input image. (b)Interest point detection by FRST. (c) Result of the classification. (d) Bounding box after rejecting noise by DBSCAN (e) Binary image mask of detected area. (f) Distance transform. (g) Thresholded image. (h) The results of k-means clustering.

Classification**:** In this study, we have utilized three types of classifiers; ANN, CNN, and SVM to categorize image labels for single grape detection. These classifiers have been described below.

The ANN is a supervised machine learning classifier since it should be first trained (Basu *et al*., 2010). The ANN used in berry detection consisted of 10 hidden layers with sigmoid activations and tanh activation function in the output stage.

The SVM is also a supervised machine learning classifier (Djeffal, 2012). The separating boundary between two groups are decided by optimization; it reduces distance within groups while it increases the distance between two categories which is called margin. An SVM with linear separating boundary was employed for categorizing berries.

CNN has become very popular recently and is widely used in pattern recognition. What makes it attractive is that it does require feature extraction since features are obtained internally by CNN and its good performance in many applications (Chauhan *et al*., 2018). CNN usually contains more than one stage for filtering and the filter coefficients are learned in the training phase. For comparison purposes CNN was also utilized for grape berry recognition. The features are extracted based on linear filtering in two dimensions. The structure of CNN used in this study is as follows. The CNN was 15 layers deep. The input layer was of 145×145×1 size image and three of these fifteen layers were convolution (filtering). The convolution kernel size was 3×3 and adapted during the training stage. The kernel was shifted by one pixel in both vertical and horizontal directions; namely, the stride (step) is 1. The dimension of filter outputs was reduced by max-poling; that is the maximum value of 3×3 adjacent blocks of the output retains and others are removed. The Rectified Linear Unit (ReLU) was used as the activation function which means non-linearity at the output of a neuron; in other words, negative values were set to zero. At the final stage, Softmax classifier, which has the ability to determine the probability of the classes, generated the class name as a (grape berry or non-berry).

Density based spatial clustering (DBSCAN)**:** The outcomes of the classifier are identified berries. A grape bunch can be interpreted as a cluster of berries. The DBSCAN technique proposed by (Ester *et al*., 1996) aims to identify high density regions. This method of clustering was utilized for finding grape bunches. The grape berries that are close within epsilon were considered to be part of a grape bunch and ones that are distant more than epsilon and clusters with the number of berries lower than a threshold were treated as outliers and noise. The parameters epsilon and threshold were set according to grape berry size in images: the epsilon was set as the average berry diameter; threshold was chosen five which represent the minimum number of berries in each detectable cluster bunch.

This step reduced noise and generated clusters, each representing a grape bunch.

Neighbor bunch separation**:** Although density based specified grape bunches, there were some overlapping bunches detected as a single bunch. This phase separates overlapping bunches. For this purpose, the clustered image was converted to a binary mask. The distance transform of the binary image was computed and then the pixels which have distance measure over 75% of the maximum distance were designated. The total number of grape bunches were computed by counting connected components in the resultant image. The k-means clustering of pixel positions (Jain, 2010) was used to re-cluster the berry coordinates (position of interest points). This process was applied separately to each cluster of the output of the previous phase which was marked by its bounding box. (Fig. 4 and 5) displays this step and the flow chart respectively.

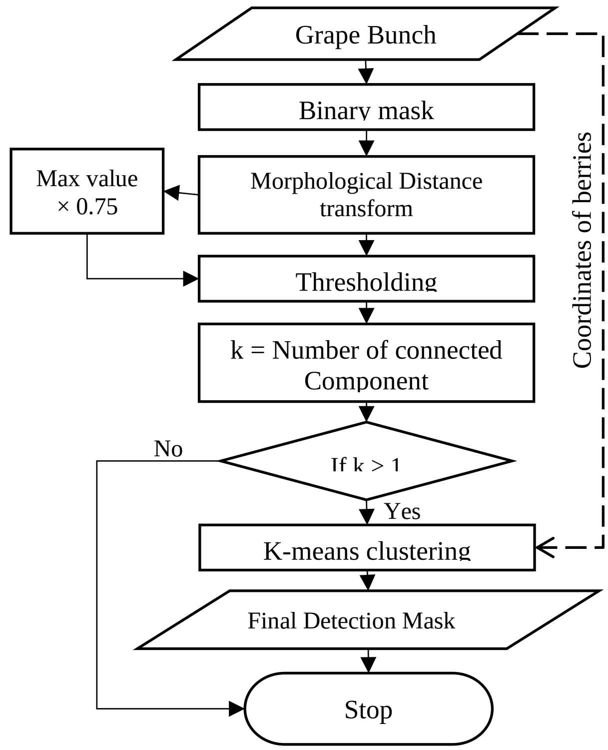


Figure 5. Algorithm for separating overlapping bunches.

RESULTS

Results of single grape berry detection utilizing the various features and classifiers are displayed in (Table 1). The results are an average of hundred runs and for each run, the training set and test set were selected randomly. 65% of data were used for training and the other 35% were employed for testing at each run. That is 4472 berry images out of 6880 images were used for training and the other 2408 images were employed for testing. The outcomes were obtained for various features, combinations of features and classifiers to examine the categorization performance of berry detection. In the case of CNN the features were extracted automatically. (Fig. 6) sketches the accuracy with respect to number of training images used to train the classifiers when the combination of HOG and LBP were handled. The accuracy of CNN was less

Table 1. The results of single grape berry recognition.

Classifier	Feature	Accuracy	Precision	FPR	Sensitivity	Average time (Sec.)
	HOG	98.80±0.190	98.80±0.28	1.19±0.280	98.80±0.296	0.0074
SVM	LBP	73.50±0.740	79.76±1.39	15.99±1.22	63.02±1.330	0.0071
	HOG+LBP	99.03±0.180	99.03±0.28	0.96±0.283	99.04±0.266	0.0079
	HOG	99.58±0.075	99.60±0.11	0.39±0.110	99.57±0.132	0.0058
ANN	LBP	85.68±0.490	89.49±0.85	9.50±0.880	80.88±0.751	0.0054
	HOG+LBP	99.64±0.073	99.7±0.094	0.293±0.04	99.59±0.117	0.0065
CNN		94.66±1.350	96.05±1.68	3.88±1.730	93.19±2.580	0.0095

than ANN and SVM classifier in spite of higher time consumption. The CNN requires more training images to reach its maximum performance. For the available number of training images the accuracy of ANN was larger than CNN by 4.98%, and SVM by 0.61%. The ANN had the lowest processing time as well. The ANN classifier with the combination of HOG and LBP attributes provided the highest precision, and sensitivity too. The accuracy, sensitivity and precision obtained were 99.64±0.073%, 99.59±0.117% and 99.70±0.094% respectively, and False Positive Rate (FPR) was 0.293±0.094%. The processing time was 0.0065 seconds per image. The results show that the ANN is faster than the other classifiers. The performance of grape berry detection has an influence on the success of grape bunch segmentation. (Fig. 6) displays the accuracies with respect to the number of training images from 70 to 4472 images for 2408 test images (35%).

The previous analysis was carried to decide the classifier and features to be used. The ANN with HOG and LBP features was chosen since it provides the highest classification accuracy and the lowest categorization time.

The algorithms shown in (Fig. 2 and 5) were applied for categorizing berries in grape tree images: three images from the Iceland dataset; nine images taken from Adana and Tarsus regions. The classifier was trained with complete 6880 berry images of Iceland dataset. The grape berry and bunch counting performances for these images are shown in (Table 2). The average accuracies of grape berry and bunch detection were obtained as 89.82±2.58% and 91.72±2.88% respectively.

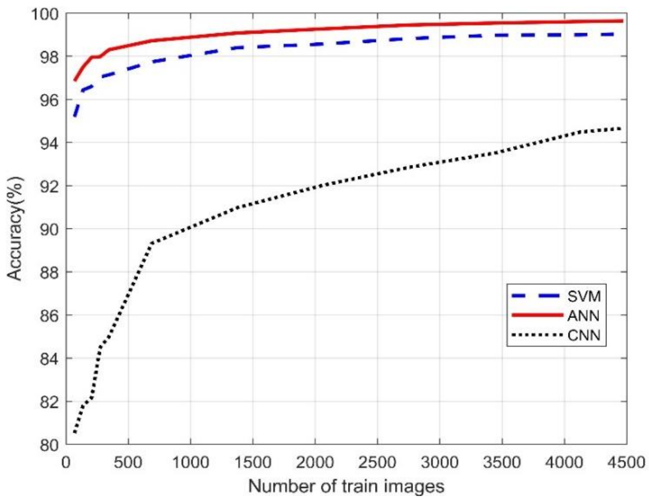


Figure 6. The accuracy with respect to the number of training images.

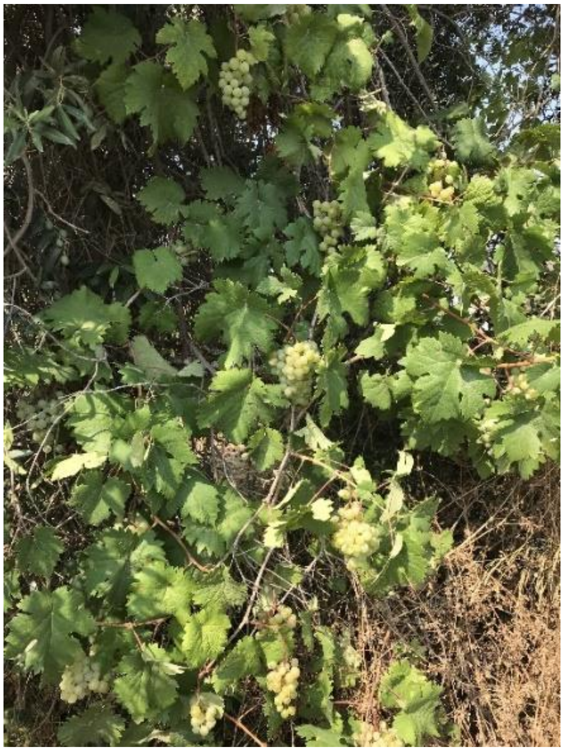
Grape berry pixel or area classification was also studied. The ground truth pixels were labeled manually. The average accuracy of grape pixel recognition was computed 96.97±0.95%. The average precision and sensitivity were 98.11±1.207% and 97.57±0.969% respectively. The sensitivity can be interpreted as the rate of correct detection

Table 2. The grape berry, bunch and area detection.

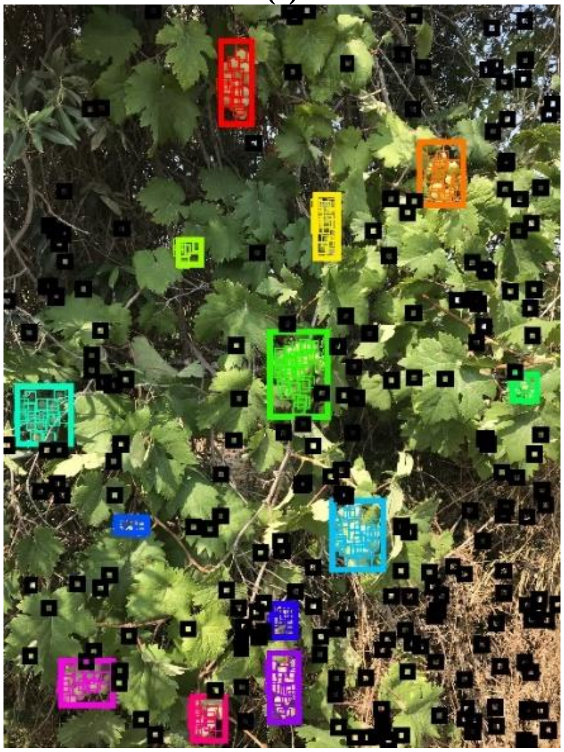
Dataset	Adana	Tarsus	Iceland	Average
No. of images	6	8	3	
Image size	1600×1200	3024×4032	3888×2592	
Illumination	Natural	Natural	Natural	
Distance	~1.2 m	~0.75 to ~1.5 m	~1.5m	
Accuracy (%) of grape bunches recognition	89.75±4.780	96.25±2.970	89.22±0.876	91.72±2.880
Accuracy (%) of berries recognition	89.72±1.870	93.06±1.360	86.65±4.500	89.82±2.580
Grape berry area detection by pixel classification				
Correct Rate (%)	93.15±1.541	98.19±1.008	99.59±0.300	96.97±0.950
Sensitivity (%)	94.67±2.036	98.56±0.660	99.50±0.212	97.57±0.969
Specificity (%)	78.75±5.374	96.56±3.610	92.55±2.530	89.28±3.830
Precision (%)	96.50±1.011	99.29±0.990	98.54±1.620	98.11±1.207
Classified Rate (%)	97.62±1.630	98.93±1.174	98.45±1.026	98.33±1.277

of grape pixels. It is observed that most false positive pixels resided in the close grape bunches. The grape detection results may be improved obtained by training the classifier with a large dataset of different vineyards and grape varieties. The Iceland data-set only involves white grapes under natural illumination with a fixed camera-plant distance, while the test data images include white, red, and mixed colors of grapes under natural illumination.

The proposed approach of grape berry and bunch recognition can be utilized for diverse aims in several vineyard management missions. Another application is background or leaf removal. The results obtained in the current study are better than the outcome reported in (Śkrabánek, 2018) the improvement in accuracy and precision has been 2.29%, and 3.2%, respectively in single grape berry recognition. Also, the accuracy, precision and sensitivity of grape berry detection are 4.27%, 0.7%, and 7.09% more than the work of (Pérez-Zavala *et al*., 2018) respectively. The grape bunch and berry detection were also improved by 1.21% and 11.38% accordingly. The enhancement was obtained by changing the bunch separation approach, classifier, and using the different features. The outcomes for some sample images are displayed in (Fig. 7 to 9).



(a)



(b)

Figure 7. A white grape image example from Tarsus dataset. (a) Original image. (b) Results of detection.

DISCUSSION

When the results are examined, it is observed that the ANN classifier with the combination of HOG and LBP attributes provided the highest precision and sensitivity. In addition, the ANN is also faster than the other classifiers.

The CNN classifier did not achieve the best result. The insufficient number of images may have caused that. Increasing the number of images might improve the success of the CNN model as demonstrated in (Fig. 6).

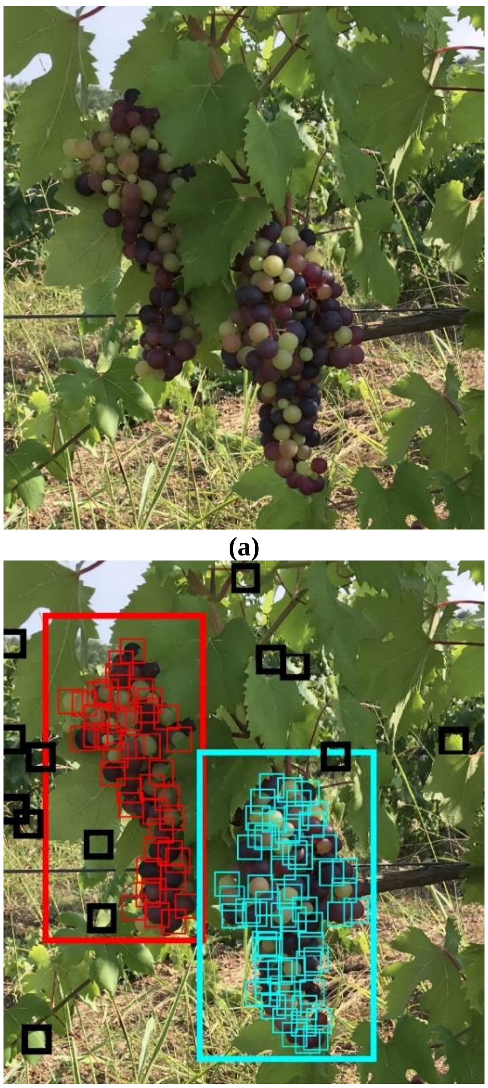
Since the grape bunch segmentation depended on grape berry detection, the performance of grape berry discovery was affected by the success of grape bunch segmentation.

The low image contrast, shadows, and occlusions directly affected the success of FRST and non-maximum separation steps. A failure in these stages led to false grape-berry and bunch detections. Moreover, when the DBSCAN algorithm did not cluster some berry centers, the ANN could not detect the berries owing to these centers, or found false berries. These issues are illustrated in (Fig.7 to 9).

Conclusions**:** The visual grape berry and bunch detection was investigated. It was shown that HOG and LBP attributes with ANN classifier which is integrated with DBSCAN clustering provides the best categorization in terms of processing time and accuracy. The proposed approach is capable of recognizing different grape types (white and red) captured under varying natural daylight conditions at particular camera distances and with divergent occlusion levels.

A post processing was required to separate overlapping grape bunches. The accuracy of grape berry and bunch was about 90% and slightly below 90% respectively Pixel or area classification was also investigated. The performance was over 90% for grape pixel and bunch categorization. Besides, CNN was also utilized. It has the ability to extract features adaptively. However, it requires a sufficient number (a quite large number of images compared to other classifiers) to maintain the optimum performance. The total number of images available was not enough and therefore the highest accuracy of the CNN was not reached.

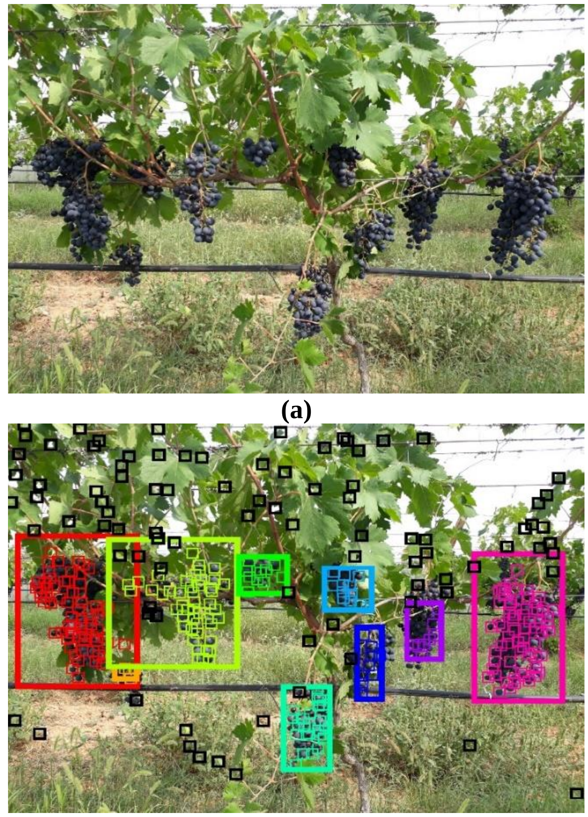
The proposed approach may be utilized for developing harvesting robot, removing leaf and separating grapes from grape tree image, selective spraying, and yield estimation as well.



(a)

(a)

Figure 8. A hybrid grape image from Tarsus dataset. (a) Original image. (b) Result of detection.



(a)

(b)

Figure 9. An image sample from Adana dataset. (a) Original image. (b) Result of detection.

***Authors' Contribution Statements*:** Bashar AL-SAFFAR: Data, Methodology, Software, Validation, Writing. Sami ARICA: Conceptualization, Methodology, Supervision, Writing. Semih TANGOLAR: Conceptualization, Data.

***Conflict of Interest*:** The authors declare no conflicts of interest.

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