Journal of Scientific & Industrial Research
Vol. 81, August 2022, pp. 866-872
10.56042/jsir.v81i08.57971

Computer Vision and Machine Learning Based Grape Fruit Cluster Detection and Yield Estimation Robot

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Received 06 December 2021; revised 07 July 2022; accepted 07 July 2022

Estimation and detection of fruits plays a crucial role in harvesting. Traditionally, fruit growers rely on manual methods but nowadays they are facing problems of rapidly increasing labor costs and labour shortage. Earlier various techniques were developed using hyper spectral cameras, 3D images, clour based segmentation where it was difficult to find and distinguish grape bunches. In this research computer vision based novel approach is implemented using Open Source Computer Vision Library (OpenCV) and Random Forest machine learning algorithm for counting, detecting and segmentation of blue grape bunches. Here, fruit object segmentation is based on a binary threshold and Otsu method. For training and testing, classification based on pixel intensities were taken by a single image related to grape and non-grape fruit. The validation of developed technique represented by random forest algorithm achieved a good result with an accuracy score of 97.5% and F1-Score of 90.7% as compared to Support Vector Machine (SVM). The presented research pipeline for grape fruit bunch detection with noise removal, training, segmentation and classification techniques exhibit improved accuracy.

Keywords: Image processing, OpenCV, Random forest, Scatter plot

Introduction

Now, smart systems with artificial intelligence and data analysis in the agriculture field emerge as a large agro-technology. Robotics, GPS controlled system, remote sensing etc. technologies are changing the present agriculture working system. The advances in computational power in electronics engineering with machine learning techniques enhance the growth in agricultural production. The availability of resources and good monitoring analytic is optimizing crop quality.[1] Fruits are important among common cultivation crops around the world because of its significance of good nutrition and health benefits.

In India, it is 31.2% of commercial cultivation with an area of 6.5 million hectares producing 97.3 million tons yield.[2] In recent years, researchers around the world are working deeply in the area of fruit farming. The interesting part of this research is to increase the frequency of monitoring and quality of the fruits which maintain the demand of food and supply. Development of intelligent vision system to distinguish and find the grape bunch in the vineyard is little difficult, but new technologies with artificial intelligence and machine learning algorithms has somehow ease the task of localizing the grapes.[3] In agro-technology, the intelligent system carries out detection and classification tasks. Many authors have provided solutions for fruit detection and localizing under various natural conditions in an uncontrolled lighting environment.[4]

A need for precision in agriculture and how ground robots combined with a camera strengthen the robotic vision applications for automated agriculture field control with proper localization and detection is already reported.[5] Authors also gave importance to investigate more methods for different fruit detection, and yield prediction which reduces the time and human efforts.[6] For this, researchers emphasize the various image processing techniques to solve the hardship of labor in agriculture. Many algorithms for detecting, localizing, segmentation, counting of fruits aroused to improve the work and precision. New understanding and techniques are filling the gap in improving the working conditions in agriculture. Robotic vision vehicles efficiently becoming faster in the detection and segmentation of the fruits that allows continuous supervision in the field.[7] The robotic vision algorithms have provided the platform in which the working mechanism of harvesting robots handles detection, localization and segmentation of fruits under different environment conditions,. Furthermore, the occlusion problem often comes into a picture with similar color as a fruit's leaves (green

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on green). In an unstructured environment, researchers are focusing on these problems to make more advance robotic vision systems.[8]

The automation in agriculture could help farmers to reduce their effort and working time which could be more effective and efficient as compared to traditional methods of farming. In this research, image processing concept through the python OpenCV platform is used for fruit identification through vision detection. Fruit identification means recognizing a particular feature through unique structure like pattern, texture, color and type of fruit. It is focused on reducing labor cost, daily working hours, environmental impact, safety issues and most important is framer's effort.

Related Work

Various techniques developed by researchers on visual technologies for detection and classification of an object through images taken by robots in the agriculture field. These are broadly described in this section.

Researchers implemented such system to detect grape bunches.[9] The database consists of 190 and 35 images of white and red grapes respectively. Morphological dilation and color mapping methods are used on an output image which represents black areas. The author tested the proposed system with an image resolution of 1.3 mega pixels. The achieved accuracy rate is 97% and 91% for white and red grapes respectively. A new approach was reported to detect grapes in outdoor conditions consisting of 18 images.[10] The images were sub-divided into blocks having a size from 6 to 10 pixels by using Zernike moments. These moments estimate invariance with respect to features like scale and rotation. The Red-Green-Blue (RGB) image is converted into the Hue Saturatuion Value (HSV) image, moments are computed on a gray level pixel having m and n moment order. The order of 10^{th} and 11^{th} is computed by the Zernike moments which represent 72 descriptors. SVM classifier used the image database with a learning step of block size 16×16 pixels having a performance of less than 0.5% for the recognition of grapes. A method to detect apple fruit from thermal images was presented by Stajnko *et al.*[11] There is small difference between apple color and other parts of plant in an image, so author used morphological operations to separate apple and other parts in an image. Another development is an intelligent control wheeled robot for a real-time path tracking system.[12] The Wheeled Mobile Robots (WMR) was inter-linked with visual sensor and charge controlled device using fuzzy controllers for the tracking system. The RGB images converted to HSI image, then target edges extracted after removing noises. The angle and distance inputs were given to the Cerebellar Model Articulation Controller (CMAC) for robot movements.

Strawberry detection through visibility characteristics with size, shape and color was specified by Liming & Yanchao.[13] The dataset consists of 224 strawberries for testing and validation analysis. Shape feature is extracted with a line drawn on the boundary. Classification k-means clustering method is used and colour feature obtained from the colour model L*a*b*. Where L is the lightness and a* and b* are two color channel components, in which a* channel used for strawberry fruit feature extraction and diameter measurement. The result is quite good with a success rate from 90% to 100% in the automated strawberry grading system. More features for feature extraction with L*a*b* colour space were added by Syal *et al.*[14] A total of 25 apple images were taken for each training and testing phase. Image pre-processing was done by using 7×7 Gaussian filter to reduce the different lighting conditions and blur. Polygon mapping is use for sample selection to categorize into fruits, leaves, branches and background areas. Mean of a* and b* component is taken for segmentation in the test images based on Euclidean distance measurement comparison. After segmentation, circle function was fitted for individual apple counting.

A color-based method to find the red pomegranate on the tree with 100 images taken in outdoor lighting conditions was presented by Akin *et al.*[15] Researchers take the difference of R, G and B values with the help of index values to differentiate background and pomegranate classes in 2D chromaticity spaces on scatter plots. After differentiating fruit, the segmentation is done through the threshold method and it is located in the position of geometric centers in binary image. This approach shows the improvement of illumination and occlusion problems. The accuracy rates nearly about 90% for fruit detection.

Researchers proposed method to characterize citrus fruit quality.[16] The author applied a threshold-based histogram technique to segment whether the object is defective or not. Defective fruits then segmented using HSV color space and are clustered. Datasets of

150 images of oranges and mozambis was created. The proposed method extracted the texture feature and segments using a 3D color co-occurrence matrix. The method achieved 93% accuracy for both oranges and mozambis.

Another study proposed a hybrid segmentation approach to classify grape seeds on their maturity level.[17] The technique was an amalgam of supervised and unsupervised segmentation which classifies two classes of grape seed one was mature and other was immature. A multi-layer perception was used for supervised segmentation. Many descriptors were computed and used for feature extraction i.e. intensity, haralick, Gabor, Local Binary Patterns (LBP) and crossing line. The dataset consists of 120 seed images taken for training and testing. The classification result showed 100% effectiveness in training and for the test set 100% and 93% for immature and mature class, respectively.

Based on the previous research among fruits, grape is most challenging for the research area because of its compactness, small size and time-consuming process in harvesting. In this research, vision system based mobile robot is developed for blue grapes bunch detection and counting. The prototype uses less expensive electronics like raspberry pi, pi camera, dc motors and others which aid to farmers in their productivity.

Methodology

This section describes the construction of a robot prototype for detecting blue grapes. The system is semi-automated where movement of robot can be controlled by operator.

The block diagram of the proposed system is shown in Fig. 1. In this system the robot clicks the fruit image to further analyze and pre-process using raspberry pi based on the image size and pixels. Developed prototype is categorized into three sections.

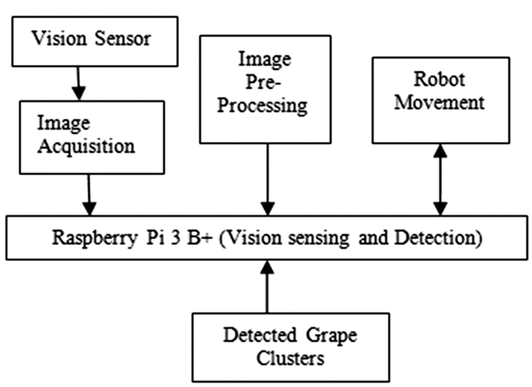

Fig. 1 — Proposed system block diagram

Robot Prototype Hardware

The prototype consists of raspberry pi 3 b+ as a single board computer, pi camera, dc gear motors, battery and motor driver controller. The grape detection and bunch counting are done in raspberry pi 3 b+ with installed OpenCV tool and random forest algorithm. OpenCV is an open computer vision library and firmware is designed in python. Developed hardware prototype of robot is shown in Fig. 2. The motor driver controller controls the acceleration and direction of the motors.[18]

Here L298N based Motor Controller acts as intermediary between robot's microcontroller, batteries and motors. A motor controller is necessary because a microcontroller can only provide roughly 0.1 Amps of current whereas most actuators (DC motors, DC gear motors, servo motors etc.) require several Amps. The L298N is a dual H-Bridge motor driver which allows speed and direction control of two DC motors at the same time. The module can drive DC motors that have voltages between 5 and 35 V, with a peak current up to 2 A.

A power bank of 5 V, 2 Amps is used to power the raspberry pi and direction control is done with a laptop via Wi-Fi protocol. Many researchers are using Machine Learning algorithms to classify different objects in image. The algorithms examine the accuracy, sensitivity, specificity rate that tells the truthfulness of finding the object.

Acquisition of Images

Image collection is done by a 5 MP pi camera mounted on the robot. The camera captures the still images of the blue grape bunches in the field. The operator controls the movement of robot when it sees a real time view by pi camera in the field. Prototype

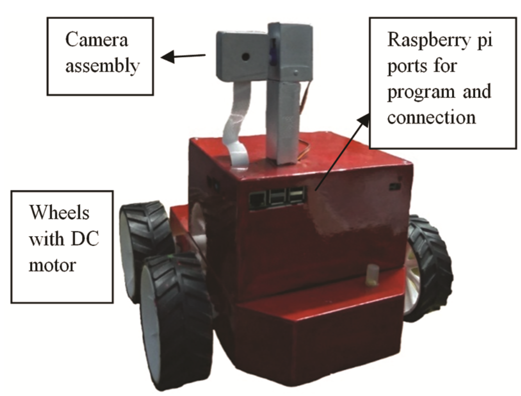

Fig. 2 — Developed Robot Prototype

robot with a camera mounted on its top is shown in Fig. 2. The Pi camera clicks grape fruit images for computations and analysis. The captured images as per the prototype testing are shown in Fig. 3. Further, images are sent to the raspberry pi 3b+ for pre-processing and analysis.

Pre-processing and Detection

The captured images are pre-processed for removing noise. OpenCV library is used for image analysis and optimization with image filtering, blurring, morphological operations and threshold tools. The library is imported in raspberry for image analysis.[19]

There are various approaches to detect an object in an image. It is mainly based on color, size, texture and shape. The OpenCV read images in Blue-Green-Red (BGR) format which is further converted to (Red-Green-Blue) RGB format. All the pre-processing steps are shown in Fig. 4.

The pre-processing of images done with OpenCV library in the raspberry pi and various feature extraction processes are shown in Fig. 5.

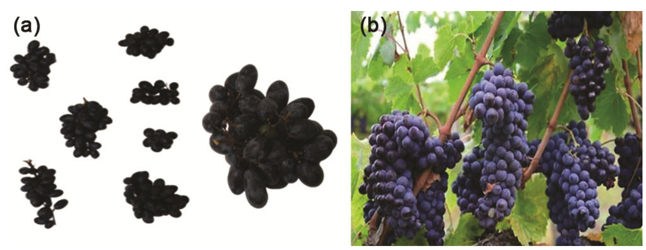

Fig. 3 — Grapes Images (a) Captured by pi camera (b) Test image

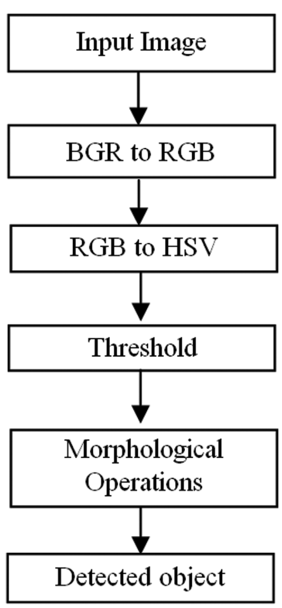

Fig. 4 — Flow Chart of System

The input images are converted to HSV images. The H, S, and V components of HSV color space are Hue, Saturation, and Value. From these, the H component is used for binary threshold with the Otsu method. To separate grapes pixel intensities, scatter plot is planned to differentiate between grape and non-grape pixels. For this, 1000 random pixels are choosen from the images to see the perfect separation. The image of scatter plot is shown in Fig. 6.

However, some pixel values in images have similar values related to grapes pixel values. These values are considered as noise in the image and these noises are removed with morphological operations like erosion and dilation. The white portion in the binary image is considered to be grape bunches. After getting the

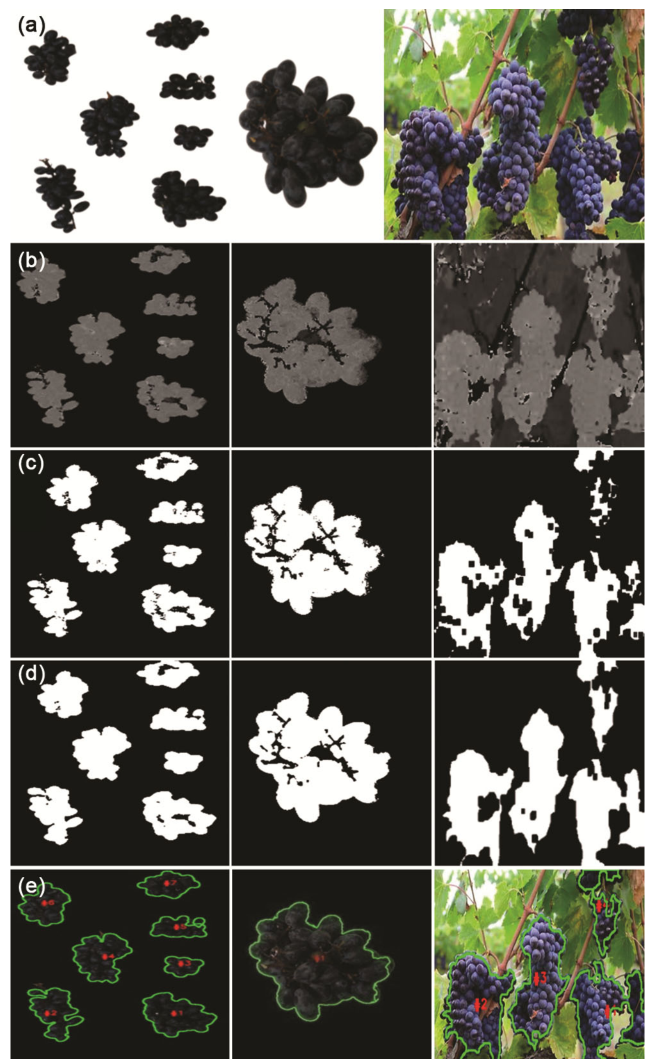

Fig. 5 — Pre-processing image processes (a) input images (b) H image from HSV (c) Binary image with noise (d) Binary image without noise (e) Grapes detected images with number of bunches.

grape bunches the object is targeted with enclosed contour and number of bunches are counted.

The dataframe pixel values of red, green, blue color channels and hue component pixel values are considered as features. The binary value pixels, which mainly belong to grape and not grape in an image is shown in Fig. 7.

Image pixel classification also tested with the Random Forest algorithm in which the training and testing of the pixels of the H component images evaluated to grape and non-grape. For this, an intensity value array of R, G, B, and H images is created. The pixel data from the data frame is divided into training and testing data. To control the randomness and sampling of the features, estimator value is taken as 10 and random state value is considered as 42 in Random Forest algorithm. After training and testing of data, a confusion matrix is generated for calculating the model accuracy and F1-Score. The confusion matrix is shown below:

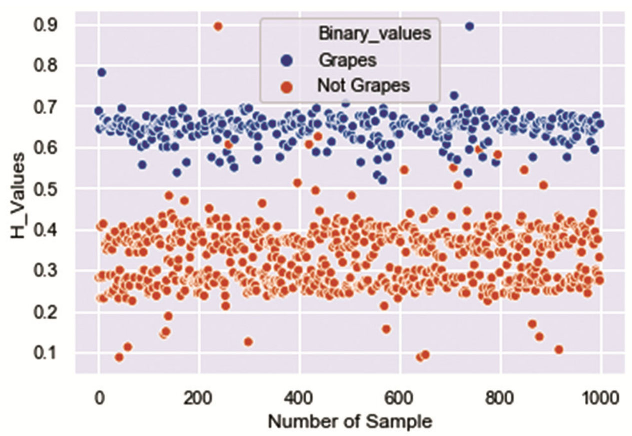

Fig. 6 — Scatter plot of random 1000 pixels

Index	R_Values	G_Values	B_Values	H_Values	Binary_values
11721	0.142077	0.19403	0.291262	0.64375	Grapes
16728	0.0491803	0.0696517	0.11165	0.63125	Grapes
34511	0.31694	0.348259	0.529126	0.68125	Grapes
4305	0.355191	0.383085	0.509709	0.66875	Grapes
18882	0.131148	0.179104	0.252427	0.64375	Grapes
18958	0.540984	0.572139	0.65534	0.6375	Grapes
35111	0.278689	0.338308	0.504854	0.66875	Grapes
963	0.15847	0.208955	0.247573	0.6	Grapes
6340	0.15847	0.208955	0.330097	0.65625	Grapes
4549	0.398907	0.457711	0.587379	0.64375	Grapes
15467	0.84153	0.870647	0.825243	0.48125	Not Grapes
13351	0.300546	0.353234	0.407767	0.6125	Grapes
20882	0.0819672	0.0895522	0.101942	0.5875	Not Grapes
17519	0.322404	0.19403	0.325243	0.85625	Grapes
12740	0.125683	0.159204	0.262136	0.66875	Grapes
24122	0.333333	0.39801	0.543689	0.65625	Grapes
21897	0.224044	0.253731	0.412621	0.68125	Grapes
8672	0.0382514	0.0597015	0.092233	0.625	Grapes
12734	0.0382514	0.039801	0.0631068	0.6375	Grapes
15942	0.15847	0.243781	0.38835	0.65	Grapes

Fig. 7 — Dataframe set of pixel values

Confusion Matrix of RF: [[439 85] [52 4936]]

The accuracy and F1-Score of the model based on the number of pixels training and testing in an image is 97.5% and 90.7% respectively.

Results and Discussion

For experimentation, input images are captured with a pi camera and some images are tested from Google images. The prototype is capable of detecting and counting blue grape bunches for validation. The RF and SVM algorithms performance is examined with its parameters as shown in Table 1 and Table 2, respectively.

The various performance parameters in Table 1 and 2 show the true positives, false negatives, true negatives, false positives, accuracy, sensitivity, specificity and F1-score. The bar chart to compare the performance of the models depending on different parameters is shown in Fig. 8. These are calculated as below:

Accuracy = (TP + TN)/(TP + TN + FP + FN)
Sensitivity = TN/(FP + TN)
Specificity = TP/(FN + TP)

Table 1 — Performance parameters of RF algorithm

Parameters	Performance outcome Values %		
True Positives (TP)	4936	Accuracy (ACC)	97.5
False Negatives (FN)	52	Sensitivity (TPR)	98.9
True Negatives (TN)	439	Specificity (TNR)	83.7
False Positives (FP)	85	F1-score	90.7

Table 2 — Performance Parameters of SVM algorithm

Parameters		Performance outcome	
Values %True Positives (TP)	4955	Accuracy (ACC)	96.7
False Negatives (FN)	33	Sensitivity (TPR)	99.3
True Negatives (TN)	378	Specificity (TNR)	73.1
False Positives (FP)	146	F1-score	83.5

Table 3 — Comparison of Performance Parameters

Study	Algorithm Used	Result
Ref. 18	OpenCV, K-means	Fruit Size and Color Maturity, 8 seconds for image analysis
Ref. 19	OpenCv, Knearest, Gabor Filters	5 sec for image analysis
Ref. 9	OpenCV, Morphological Operations	Red grape, 6–7 seconds for image analysis, Accuracy is 91%
This work	OpenCV, RF, Morphological Operations	Pixels dataframe, 12 seconds for image analysis, RF accuracy is 97.5%

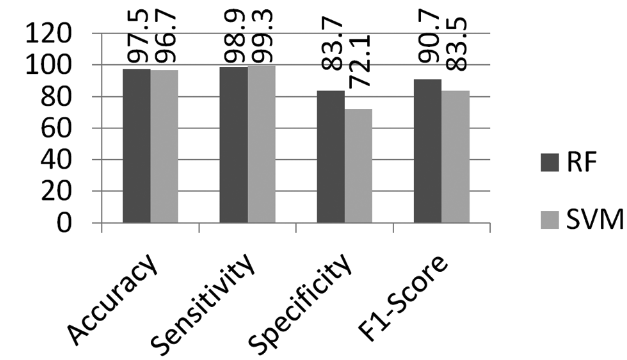

Fig. 8 — Performance outcome comparison

```
Total number of bunches: 7
area of 0st is 10145.5
area of 1st is 6482.5
area of 2st is 2516.0
area of 3st is 8985.0
area of 4st is 3566.0
area of 5st is 6373.0
area of 6st is 3801.5
[10145.5, 6482.5, 2516.0, 8985.0, 3566.0, 6373.0, 3801.5]
10145.5
```

Fig. 9 — Showing Number of bunches with pixel areas

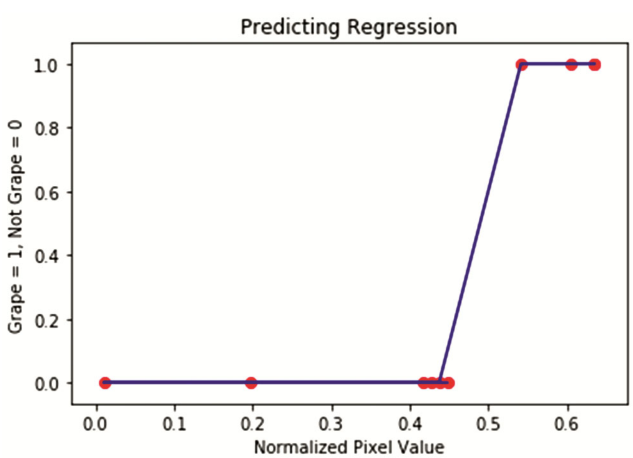

Fig. 10 — Regression prediction on sample pixels

The counted number of grape bunches in an image appeared in Fig. 9. The area of bunches in an image is also mentioned.

On comparison the random forest algorithm performance is better than support vector machine algorithm. The accuracy is better in random forest.

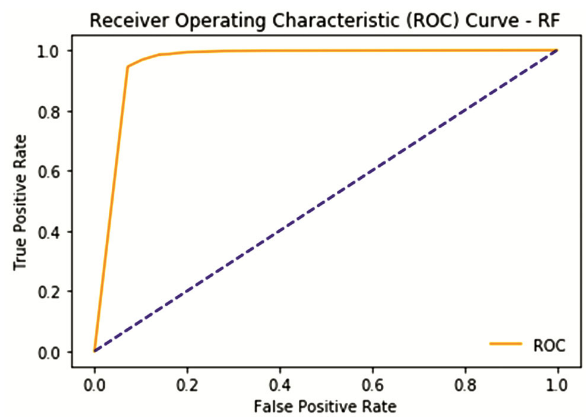

Fig. 11—ROC Curve of Random Forest algorithm

The parameters true positive and true negatives are also good in random forest.

Total time taken for result is approx. 4 to 5 seconds on computer and 10–12 seconds on raspberry pi 3 b+. The predicted line accuracy of some samples of pixels with respect to the grape pixels is shown in Fig. 10. Here, value 0 represent the non-grape pixel and value 1 represent the grape pixel. The x-axis shows the normalized value of pixels ranging 0–255 becomes 0 to 1. The value 0 represents the area outside the grape region which is not considered in the contour area.

The ROC curve between true positive and false positive values is shown in Fig. 11. Each point on the ROC curve represents a sensitivity/specificity pair. The ROC value obtained is 96%. It means that the model is capable to distinguish the positive and negative classes like 0s as 0s and 1s as 1s.

With OpenCV and the machine learning algorithms random forest and support vector machine achieved a good performance. The OpenCV identified blue grapes calculating pixel area of the grape bunches where the random forest achieved a good result with an accuracy score of 97.5% and F1-Score of 90.7% as compared to SVM.

From the above comparison in Table 3, the researchers used OpenCV, morphological operations with Raspberry Pi. It is predicted that the time taken in computation for image analysis in this work is little more with an addition of modelling of machine learning algorithm but accuracy is also improved.

Conclusions

In this research adapted methodology and image analysis methods represent the ability of robotic vision implementation in the real world where random forest and support vector machine learning algorithms achieved a good performance with an accuracy score of 97.5% and F1-Score of 90.7%. Further, computation time can also be reduced if number of epochs can be minimized in machine learning model, but this affect the accuracy of the system. To increase the computation time JetsonNano platforms can be used as they are more compatible with artificial intelligence framework. Quality of images captured for the detection of fruit also matters in performance.

For this investigation, some constraints were considered:

1. The study is limited to only one fruit i.e. grapes; and cannot be applied to multi-class fruits detection and sorting.
2. The experimental work well on images taken during day time but does not support images taken at night time for grapes detection.

In future, scope of this work will be focused on implementing fully automated autonomous robot using RoS operating systems, LIDAR, GPS, Mangnetometer and RF communication. More precise, development of faster algorithm for large datasets, 3D location mapping can also be explored.

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