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REVIEW ARTICLE

Intelligent Mango Canopies Yield Estimation Using Machine Vision

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Abstract

The use of technology in agriculture has grown imperative. To provide the expanding population's needs for food, agricultural productivity should rise. Computer vision technology has been used to solve the difficulties associated with manual yield estimation. This article present efficient mango fruit yield estimation system with color based pixel classification method with support to that a benchmark mango tree dataset is presented. Dataset is collected temporally under varying illumination conditions, distance and time for 5 months from its blossoming phase to the ripen phase of the fruit. The repository accounts for 21,000 images of mango trees. The proposed work initially preprocess the RGB image by converting into grayscale, HSV and YCbCr color models, each layers of color model are separately extracted and each layer is enhanced by applying techniques like Gaussian blur, histogram equalization to study the features and superiority of the mango images and best color layer which exhibits most dominant features are selected for next level processing. Further, proposed a two stage algorithm using color features to classify the pixels of mango fruit region. Finally, after fruit pixel classification the method is followed by mango fruit detection using Hough transform circle fitting technique. The proposed method could count up to 80% of mango fruits present in the image. This work offers specialized help for the visual recognizable proof and yield estimation of mango fruits and also for other fruits available in the environment.

Keywords Temporal dataset · Feature extraction · Fruit region detection · Segmentation · Color analysis

Introduction

The world is undergoing a profound digital transition, and computer vision is a key component of this fascinating technological advancement. Computer vision is central to many leading innovations, including self-driving cars, drones, face recognition and much more. The newest trend in agriculture is information and technology-based farming, and computer vision is key to bringing technology to farms. The primary goal of this effort is to create a dataset and construct an automated system for computing the production of mango fruits using computer vision. India is thought to produce half of all mangoes in the world, and it has the highest productivity rates of any nation. Furthermore, 23% of the area is used exclusively for the growth of mangoes, making up 39% of the land used for fruit crops. It should be mentioned that only in India are there over a thousand different varieties of mangoes grown. Flowering on the same tree can continue for a month due to differences in shoot maturity. Usually, it takes 5–6 months depending upon the cultivar to mature and ripen the fruits once after flowering. Due to the enormous growth of the population, there is a need for an unpredictable amount of agricultural production. Traditional methods of agricultural practices are affected by many factors. Particularly in the case of rural areas, due to urbanization and migration, it is witnessed that the farmland for production is being reduced every year. Further, the cost and time are considerably high. Climatic changes, water scarcity, and use of chemical fertilizers are some of the other factors that affect traditional practices. The issue raised in this work is caused by the demand for technology for automatic mango cultivation.

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Many crops have adopted early yield estimation in precision farming utilizing computer vision techniques. Farmers gradually embraced precision farming, which uses anything from basic technologies to cutting-edge technology [1]. Numerous studies on various fruit crop yield estimation methods have been published in the literature [2]. A computer vision technology was used to develop an algorithm for estimating apple fruit yield that could identify and categorize various fruit crops [3]. Utilizing deep convolution neural networks, yield estimation systems for 15 different fruit kinds have been developed. Citrus orchards with natural lighting make it easier to identify and detect green, immature citrus fruit with more accuracy and efficiency [4]. Created a reliable algorithm lighting situation it can be difficult to recognize and detect green, immature citrus fruit more precisely and effectively in groves with natural lighting and using a block chain technique to develop a reliable algorithm [5]. Proposed a method to guide harvesting robots by identifying citrus fruits and recovering from occlusion in environments with natural lighting, considering color data and outline fragments, to distinguish citrus fruits in changing lighting situations beneath the tree canopy [6]. Developed a technique to increase estimation of grape yield and sampling using prior yield data. They used agricultural data from the past and the present to forecast the yield [7]. Created an algorithm for the capture of photos of apple trees using 3D cameras for the purpose of locating and detecting red and bicolor apples [8]. Utilized 50 RGB photos of mango trees, a randomized Hough transform technique to identify the fruit's oval shape, and a back propagation neural network technique to identify fruits on the trees, achieving a 96.26% identification rate. Systems for quick and accurate fruit detection are built using the faster region-based CNN state of the art object detector [9, 10]. Two back propagation neural network models were built to forecast apple fruit production in the early and ripening phases, and picture segmentation was used to separate the pixels into fruit, foliage, and background [11]. Created an algorithm that investigates the presence or absence of apple trees depending on the quantity of image block-units, edges before identifying apple sections. To extract colors suitable for apple areas, the CIE $L^*a^*b^*$ color space is used [12]. To segment the pixels into fruit, foliage, and background, two back propagation neural network models were created to forecast apple fruit production in the early and ripening periods. [13] developed an entirely automated method for calculating grapevine yield that comprised accurate shoot detection and yield calculation using shoot counts derived from movies. [14] developed a trunk and branch segmentation technique based on deep learning-based semantic segmentation using the Kinect V2 sensor [15]. Wheat leaf rust and tomato mosaic disease were used as examples in this study. Throughout the next incubation period, the two crops' temperatures were regularly monitored using infrared thermal imaging technology. Galdames et al. [16] developed a method for identifying orange fruit in situ using a faster region-convolution neural network framework. [17] presents a brand-new mango yield estimation pipeline that makes use of unmanned ground vehicle line-scan HSI that is collected on the ground. [18] demonstrates the application of apples, mangoes, and almonds are among the orchard fruit that can be detected using the Fast R-CNN structure. In order to comprehend how the deployment of the detecting network truly functions, ablation studies are described. [19] created a region proposal network (RPN) that combines the recognition network and features from full-image convolution to offer almost free region proposals. However, there is no indication that a benchmark dataset, specifically for on tree mongo fruit crops, is available for thorough analysis which resulted in the creation of a dataset on mango fruit.

The overarching concept is to calculate fruit productivity. Images of mango trees are collected seasonally over the course of a year. From the fruit's flowering stage to its ripening stage, data is gathered. Images of the mango trees are captured with mobile phone cameras. The novelty of this study is as follows:

- A system using machine vision technique is proposed to count mangoes
- The proposed method is scale-invariant

The yield estimation of on-tree mango fruits is the primary goal of this work. The following describes the structure of this work: the data collection procedure is described in "Data Acquisition for Images" of the work's documentation. The proposed approach is described in "The Proposed Method", the results and analyses are shown in "Experimental Results and Discussion", and the conclusion is given in the subsequent section.

Data Acquisition for Images

The dataset contains images of mango trees that were captured during the day using a smartphone's primary camera at a resolution of 1920 by 1080 pixels. For the first 3 months of the data collection period, which lasted 5 months, data were gathered every 7 days. Based on fruit maturity, data collection frequency is then increased over the following 2 months. Each day, 800 shots are taken, including pictures of all the trees from the five different varieties. The photographs are taken during two periods, morning and afternoon, which are coordinated with the movement of the sun. Furthermore, the pictures of these trees have taken at 2 and 3 m away. The selected orchid trees range in age from 15 to 20 years old. The height of the trees above the ground varies between 7 and 8 feet. There are a total of 21,000 photos in the dataset. Over the course of a day, two sessions are needed to capture images of mango trees., with session 1 taking place between 9:30 and 10:00 am and session 2 between 2:30 and 3:00 pm, respectively (Figs. 1 and 2). As a result, the obtained images include a tree's outline. The acquisition does not include top or bottom views, though. Over the course of a 5-month season, the data were gathered. The mango fruit collection dataset can be shown as follows:

The Proposed Method

The initial stage in estimating the yield of mango fruits is to segment the tree, sky, soil, and other background areas in the image. A color based threshold-based classification method is applied to the background images of mango fruits and the classification of mango fruit regions. Hough transform circle detection is used to detect and count circular objects to estimate the yield. Figure 3 shows the flow of mango fruit yield estimation process.

Mango fruit yield estimation includes two stages. In the given image, the first step is to separate the fruit from the background, and the second is to separate the mango fruits. The algorithms were designed to differentiate mango fruits from the background, thereby removing the background region in the acquired photos; all pixels other than the foreground region were set to black. As a part of image pre-processing, Gaussian filters are applied to denoise the image (Fig. 4). Histogram equalization is applied to enhance the image's contrast.

The range of colors that can be formed using the three colorants red, green, and blue is known as the RGB color space. The RGB color model is used to analyze the color characteristics of mango trees. The R, G, and B color layers, which are used to represent images using histograms, can be used to see how the original image's foreground and background pixels are distributed. Once the background is removed, it is very challenging to identify the mango fruit

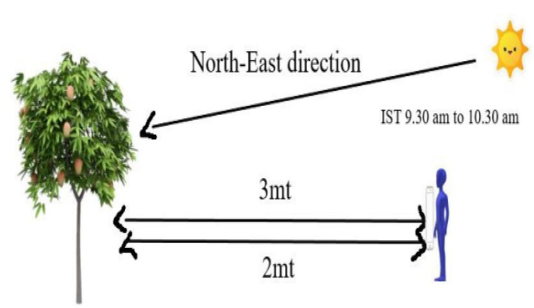


Fig. 1 Schematic of the visual system and image acquisition (session 1)

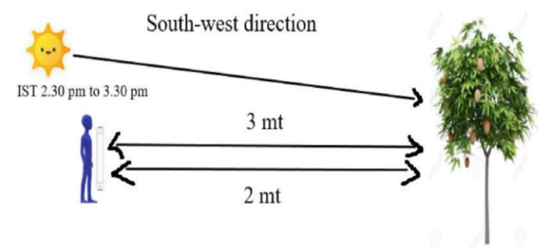


Fig. 2 Schematic of the visual system and image acquisition (session 2)

apart in RGB color space. Hence, background-removed RGB image is transformed to HSV color space, and each layer's histogram is shown (Fig. 5). Histograms are used to select threshold values for segmentation. For the purpose of segmenting the background and fruit region, The highest R, G, B, and S color space pixel values are used to determine the (R−G) and S values.

Given how similar the background is to the mango fruit region, it can be difficult to identify the fruit. The first stage in image processing is to separate the fruit from the background. The difference of R, G and B color values are used to classify mango fruit tree region from the background (Fig. 5).

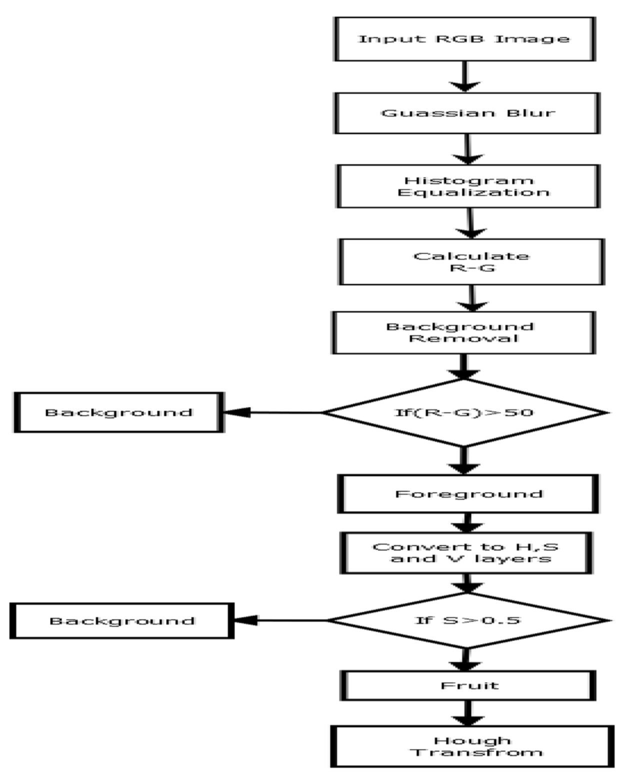


Fig. 3 Flowchart elucidating yield estimation of mango fruit

Fig. 4 Five different cultivars of mango fruit noise removed images

At a threshold color difference of R and B, the majority of the tree region possibly in an image distinguished from the background since these color layers displayed the largest amount of background. The difference found by taking into account the highest pixel value in the R and B histograms (Fig. 5b, d). R−B is 50 and the maximum pixel value in the B layer is 0, respectively. Based on histogram analysis, the threshold value to eliminate background is recognized at 50. This pixel's RGB color values are converted to zero, if (R−B) 50; else, the RGB color values of this pixel are retained. The segmented image with the histogram is depicted in Fig. 6. Background removal method is given below (MATLAB Code):

$$\text{Red} = \text{rgb}\ (:, :, 1);$$
$$\text{Green} = \text{rgb}\ (:, :, 2);$$
$$\text{Blue} = \text{rgb}\ (:, :, 3);$$
$$\text{Foreground region} = (\text{R} - \text{G}) > 50;$$

An image of a mango fruit tree that was taken under normal lighting conditions during the final phase of dataset collection, or the time when the fruit was ripening. Fruit area segmentation was done using the color spaces of blue, red, and green as well as saturation, hue, and value. The RGB image with the backdrop removed is changed to HSV color space (Fig. 5). A color will appear more "grey" and fade more quickly the lower its saturation appear, thus useful to identify the mango fruits in the image. The RGB to HSV conversion formula is as follows [20, 21], the RGB values are divided by 255 to change the range to 0–1.

$$\text{R}' = \text{R}/255$$
$$\text{G}' = \text{G}/255$$
$$\text{B}' = \text{B}/255$$
$$C_{\max} = \max\left(\text{R}',\ \text{G}',\ \text{B}'\right)$$
$$\text{C}_{\min} = \min\left(\text{R}',\ \text{G}',\ \text{B}'\right)$$
$$\Delta = C_{\max} - \text{C}_{\min}$$

$$\text{If}\{\text{R} - \text{B}\} > 50 \rightarrow \text{foreground region}$$
$$\text{If}\{\text{R} - \text{B}\} < 50 \rightarrow \text{background region}$$

An image of a mango fruit tree captured in normal illumination conditions during the last stage of dataset acquisition i.e., fruit ripening period. Blue, red and green and saturation, hue and value color spaces were used for fruit region segmentation. The background removed RGB image is converted into HSV color space (Fig. 5). The lower the saturation of a color, the more "greyness" is present and the more faded the color will appear, thus useful to identify the mango fruits in the image. The RGB to HSV conversion formula is as follows [21], the RGB values are normalized to 0–1.

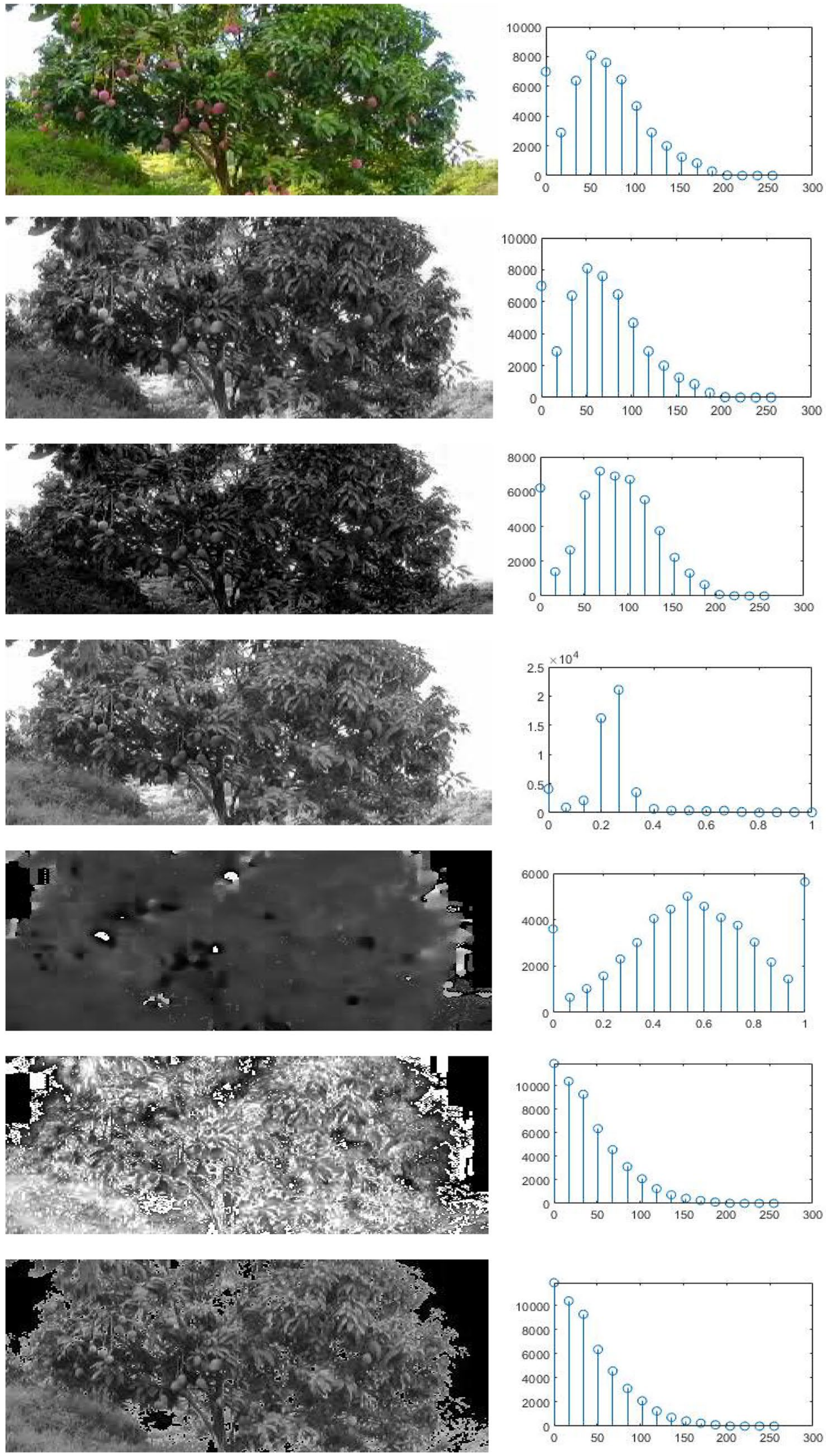


Fig. 5 Images and histogram with red, green, blue, saturation, and value color layers as the background

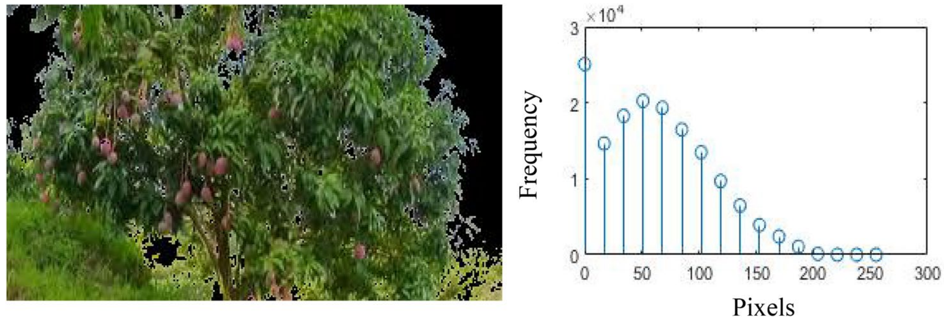


Fig. 6 Background removed image

$$\mathrm{R}' = \mathrm{R}/255$$
$$\mathrm{G}' = \mathrm{G}/255$$
$$\mathrm{B}' = \mathrm{B}/255$$
$$C_{\max} = \max\left(\mathrm{R}', \mathrm{G}', \mathrm{B}'\right)$$
$$\mathrm{C}_{\min} = \min\left(\mathrm{R}', \mathrm{G}', \mathrm{B}'\right)$$
$$\Delta = C_{\max} - \mathrm{C}_{\min}$$

Hue calculation:

$$H = \begin{cases} 60^\circ \times \left(\frac{G'-B'}{\Delta} \bmod 6\right), C_{\max} = R' \\ 60^\circ \times \left(\frac{B'-R'}{\Delta} \bmod 6\right), C_{\max} = G' \;\; B' \\ 60^\circ \times \left(\frac{R'-}{\Delta} G' \bmod 6\right), C_{\max} = B' \end{cases}$$

Saturation calculation:

$$S = \begin{cases} 0, & C_{\max} = 0 \\ \frac{\Delta}{C_{\max}}, & C_{\max} \neq 0 \end{cases}$$

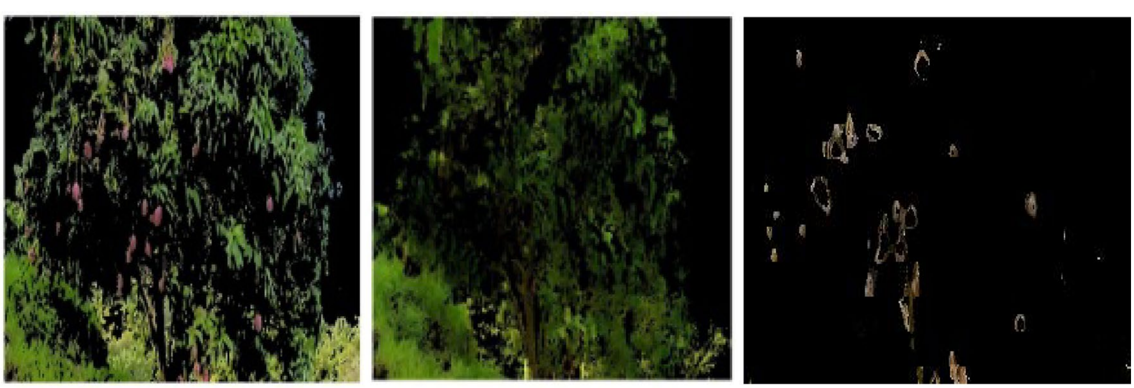
Value calculation: $V = C_{\max}$.

Before converting background removed image into HSV color space, to further pre-process the background removed image to remove the additional noise present in the image$(\mathrm{R}-\mathrm{G})/(\mathrm{G}-\mathrm{B}) > 1$ gives a filtered image which is further converted into the H, S and V components, differences were calculated for these pixels. The mango fruit region pixels in the image were segmented by saturation S color layer as follows:

If $S > 0.5 \rightarrow$ fruit region.

If $S < 0.5 \rightarrow$ background region.

Based on the experimentation with different thresholds with the hue, saturation and value layers, the main stream of the mango fruit pixels found greater than 0.5 saturation S, the background region pixels found below 0.5. If the color saturation S was 0.5, the background was set to black color. The results for the same threshold using hue and value is shown in Fig. 7. After mango fruit region segmentation some branches and leaves could be still observed, which forms noise by incorrectly recognizing the fruit region. Morphological operations like opening and closing with 2×2 circular structuring element were performed to remove noise present in the binary images (Fig. 8c). For the segmented image to detect the circular region Hough transform is applied by calculating the centroid of the segmented fruit region and by using maximum axis and minimum axis the range of radius is obtained.



(a) (b) (c)

Fig. 7 Results of fruit segmentation of **a** Hue, **b** Value and **c** saturation color layer

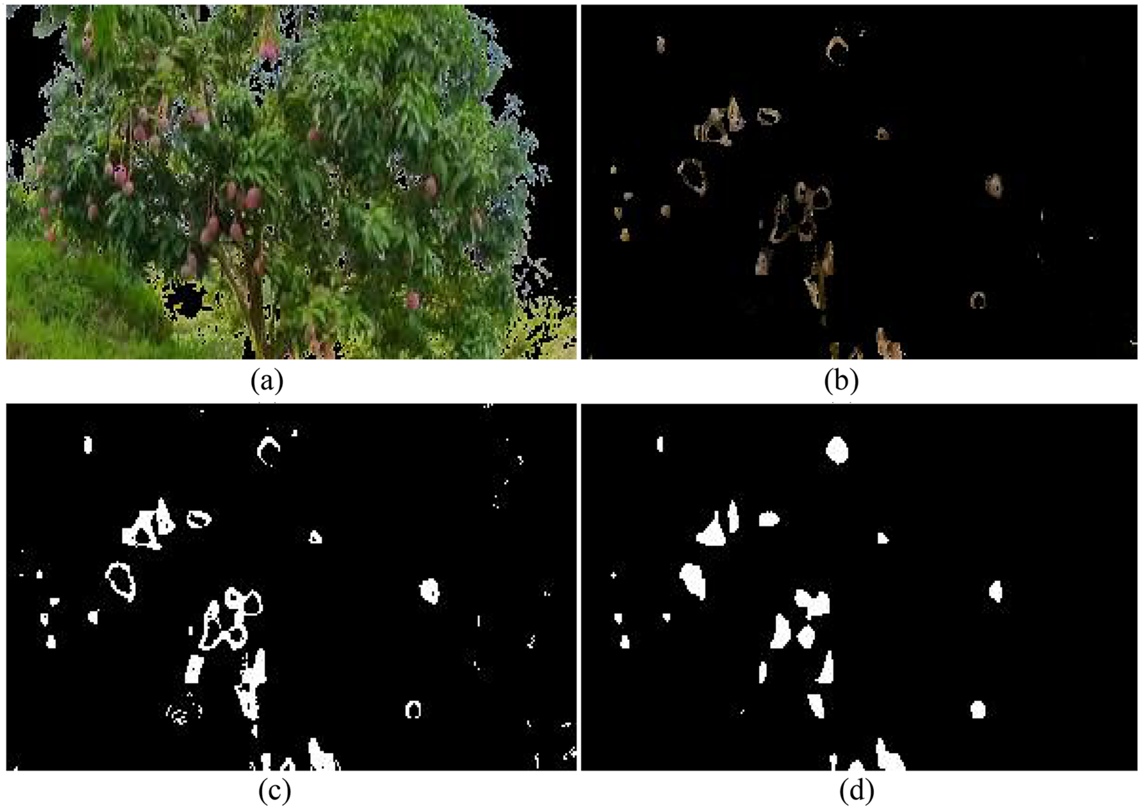


Fig. 8 Results of fruit segmentation **a** background removed image **b** fruit region segmented image **c** RGB image **d** image after morphology

Foreground region = (R−G)/(G−B) > 1.
Background region = (R−G)/(G−B) < 1.
%Convert from RGB to HSV color space.
Fruit region = (S) > 0.5
Background region = (S) < 0.5

Experimental Results and Discussion

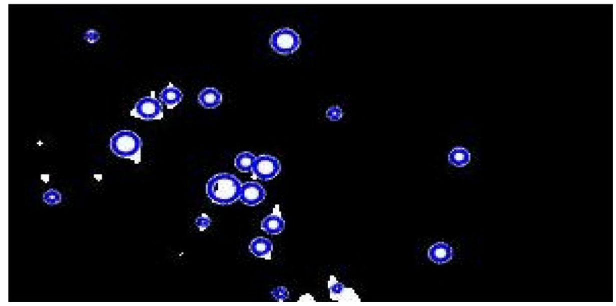
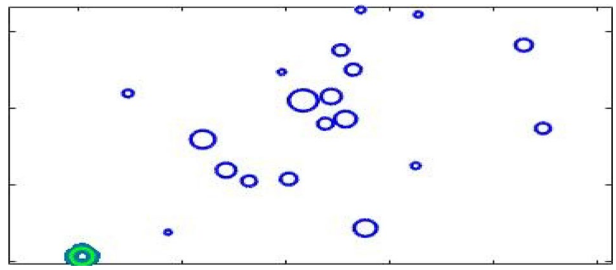
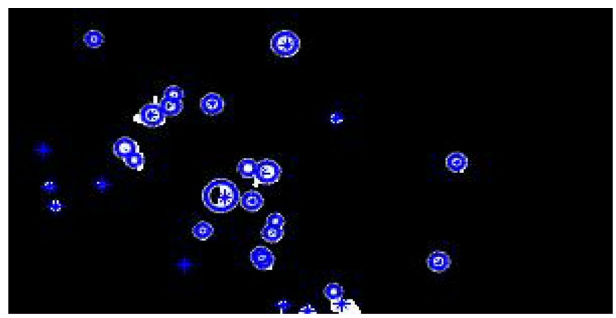
The initial step in developing the yield estimating system is to split the mango fruit from the other parts of the tree, which aids in the recognition and interpretation of the quantity of fruits present on the tree. To accurately identify the fruits in the image, the separation of mango through removing other parts of the tree is crucial. Based on color analysis, the HSV space exhibits the most distinct separation of the mango fruit region from the background, much like the human viewing model. As a result, the hue, saturation, and value color spaces were used in this study to specify the mango region. As an outcome, the backdrop zone is removed and only the fruit region is returned. The obtained dataset is subjected to color analysis, and the above part shows the classification of the mangoes from the backdrop zone. The designed algorithm could detect moderately obscured mango fruits.

The algorithm is implemented by considering only last day captured images of the dataset, fruits were at the matured stage. 400 images were selected for the experimentation, 300 images are used for training and 100 images are used for testing. The results of mango fruit segmentation and identification of mango fruits are given below (Fig. 8).

After mango fruit region segmentation to measure the continuous and discontinuous properties of the fruit region, such as an area, orientation, centroid, region props function is used and to define the range of radius to fit circles. Based on the experimentation with different circle fitting methods like RANSAC circle fitting, circle detection based on object geometry and Hough transform circle detection. Hough transform method gave better and accurate circle fitting results for the segmented image as shown in Table 1. RANSAC method gives good results but some fruits are missed, misclassification rate is high in detection based on object geometry. Compared to all three methods Hough transform performs well.

Hough transforms major axis and the minor axis is calculated using the measurement of the centroid of each region in the segmented image as depicted in Table 2. For each image range of the radius is calculated and circles are fit to the fruit region as a part of recognition (Fig. 9).

Table 1 Comparison of results of different circle fitting method results

SI No	Circle fitting method	Result
1	RANSAC Circle fitting method	
2	Circle detection based on object geometry	
3	Hough transform circle detection	

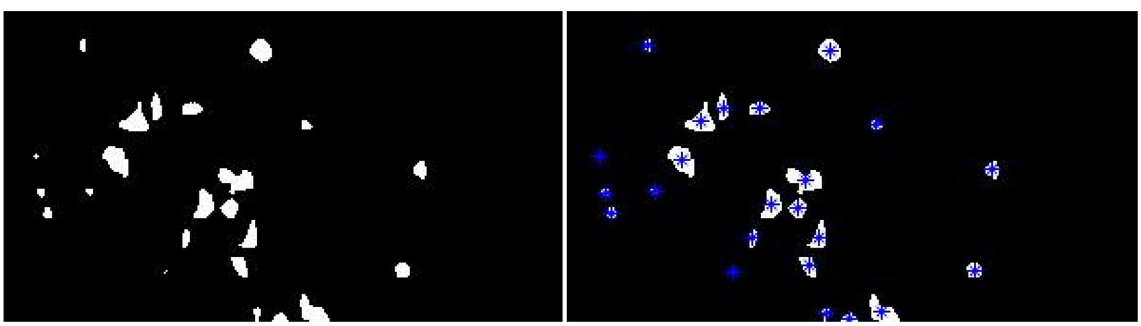
The same process is used for all 100 photos in the testing dataset, and Table 3 provides a summary of one tree's recognition findings. It ought to be noticed that only one direction of the tree is used to collect the categorized and identifiable fruits in this instance. The testing dataset contained 100 images of mango trees representing 5 different varieties. 80% of the mangoes were recognized, although 21% were missed and 25% had false positives inserted. The precision of identifying the fruit was 80%.

Figure 10 gives the comparisons of number of fruits identified by proposed algorithm and the ground truth. All five different cultivar mango tree image results are given; the proposed algorithm detects all the mango fruit present in the image with minimum false positive rate. This technique makes it feasible to calculate the yields of the mango fruit crop, which promotes the creation of early production forecasts for mango orchards using automated vision technology. These techniques might be used in agriculture such fully automated systems that operate independently or by tele-agronomists connected to the network. For the purpose of estimating fruit yield, this device would offer data via digital images and even live video that could be captured at various orientations and during any period of sunshine. This work is a step toward identifying potential faults in these algorithms, overcoming them, and creating thresholds.

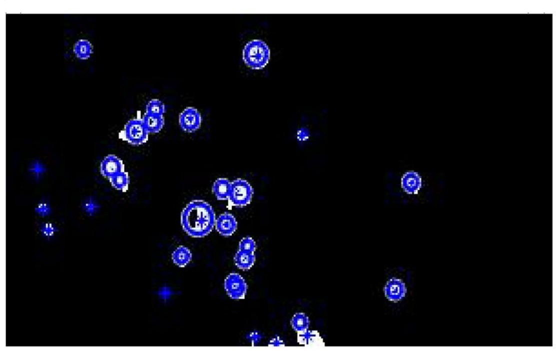
The proposed approach of mango fruit yield estimation varies from color-based mango fruit segmentation [22] in that it uses the RGB and YCbCr color spaces to divide up mango fruits into different segments. This approach was abandoned due to difficulties in locating leaves and fruits higher in the tree [23]. To extract green fruit features, it incorporates color model conversion, thresholding, histogram equalization, spatial filtering with Laplace and Sobel operators and Gaussian blur. They were able to identify numerous orange fruits with a tolerable inaccuracy. A method was developed to calculate the productivity of ripe citrus fruit, which is another fruit crop. This approach combined color classification and marker-controlled watershed algorithms to remove little, light-green citrus fruit [24]. A method of three dimensional view generation using a two—dimensional image can be utilized to build three dimensional views of captured photos for better yield estimation [25, 26].

Table 2 Major axis and minor axis of the segmented fruit region centroid is calculated using region props function

SI **No**	Centroid	Major axis	Minor axis
1	18	2.78088714861523	2.78088714861523
2	20.6250000000000	5.17257205130933	4.19507628544229
3	24.1666666666667	6.57405729721363	4.96695676867044
4	43.1052631578947	7.54402284605199	3.35578771269407
5	46.6666666666667	4.51422459329779	3.70579106701612
6	61.2715231788079	18.6349586010221	10.7598124951266
7	71.3484848484848	15.7999701022567	13.4424962717736
8	82.5645161290323	14.9390418503202	5.56369971999421
9	87.5000000000000	3.05505046330389	1.15470053837925
10	101.566666666667	11.4476478847208	6.87961740834660
11	98.3939393939394	10.4166970492646	4.15706863611439
12	108.356521739130	16.9123081855061	9.65652308098712
13	125.639751552795	20.8481611174053	11.7724859111454
14	122.042253521127	10.3459160431821	9.01839922784725
15	127.507462686567	13.1373098297518	6.83893319684070
16	133.162500000000	16.2147099142283	7.54237025503864
17	138.788990825688	12.6726097452789	11.1385858103512
18	136.590909090909	8.09944009212219	3.92170708334613
19	149.033333333333	8.31215372410821	5.15808862317931
20	166.244274809160	19.4290264812182	10.1309503569212
21	162.913043478261	6.43301003683897	4.90644664343971
22	214.629629629630	8.64294239075144	8.10657488908519
23	224.274509803922	9.62972475222973	7.11213829688391



(a) (b)



(c)

Fig. 9 Fruit region detection **a** fruit region segmented image **b** calculating centroids of the fruit region **c** Circle fitting using Hough Transform

Table 3 Fruit detection accuracy of the testing dataset

	Manual count	Accurately identifying	False Positive	Missed
Number of fruit	30	23	6	7
Percentage (%)	100	80	20	21

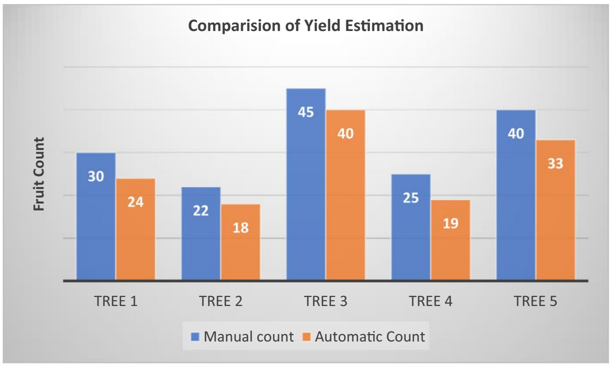


Fig. 10 Comparison of manual count and automatic count of mango fruit yield estimation

Conclusion

In this paper, a yield estimating system for mango fruit using machine vision techniques is proposed; a fruit recognition algorithm is created to distinguish fruit regions from the background. Based on color features, mature mango fruits were classified. A mobile phone camera was used to create a dataset of 21,000 photos of mango trees, which were taken in natural light from the flowering to ripening stages of the mango fruit trees. The two stages of color-based segmentation of fruit regions produce better results and lay the groundwork for estimating mango fruit production. Additionally, utilizing the segmentation findings, the Hough circular transform is applied to identify and account for the amount of mango fruits present in the image. Up to 80% of the fruits in the image may be counted using this technique. As the dataset was built in variable illumination condition and occlusion by leaves and branches the algorithm performance reduced to 80%. The system could recognize only the ripened fruits. As future work, using the built dataset there is a scope for building a successful mango fruit recognition system at the premature stage of mango fruit growth quite a few months before harvest.

Data availability The data that support the findings of this study are available from [M V Neethi] but restrictions apply to the availability of these data, which were captured personally for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of [M V Neethi].

Declarations

Conflict of Interest For the writers, there are no apparent conflicts of interest. Each co-author has examined and approved the manuscript's content, and none of the authors have any competing financial interests to mention.

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