Design of an Automatic Image Detection Algorithm for On-tree Green Citrus Fruit

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***Abstract*: An automatic on-tree green fruit detection algorithm developed using Machine learning. It is difficult to differentiate green citrus from its background due to the correlation in the color of leaves and fruit. The detection is done using histograms of oriented gradients (HOG), Local binary patterns (LBP), Haar & Support Vector Machine on the training of 2100 on-tree green fruit images. The results show that the proposed approach is capable of automatically detecting the green citrus fruit with a high degree of accuracy. The results can optimize by proper selection of several stages and false-positive rates in the training process. The results are compared with ground truth data. The proposed algorithm is suitable for yield measurement/ monitoring analysis of crops for agriculture applications.**

***Keywords:* LBP, HOG, Haar, Viola-Jones Algorithm, Cascade Classifier, Green Citrus**

1. INTRODUCTION

Image processing and computer vision contribute very much to fruit recognition, localization, and classification. The key applications of computer vision in agriculture are effective identification, estimation and classification of fruit from its background in its natural environment. Automated computer vision technologies now offer great opportunities for better management of crops. The system is developed for the identification of green citrus fruit from its identical background. Identifying green citrus fruit is one of the major challenges because the color of the fruit and the leaves is similar. The challenging situations for a computer vision algorithm are (1) work under natural outdoor conditions, (2) non-uniform illumination conditions and (3) Partial fruit occlusion by the plants, stems or other fruits[1].

2. BACKGROUND

Detection and counting of immature citrus fruits in natural canopies were suggested using a machine vision algorithm for on-tree color images. A novel 'Eigen fruit' approach was used to classify green citrus, color, circular Gabor texture analysis. Blob analyses were carried out to combine multiple detections for the same fruit. In the study, 75.3 percent of the real fruits were detected successfully using the proposed algorithm[2].

Technologies for machine vision have been developed for fast and accurate crop yield predictions in the field. One method was implemented using dense segmentation based on texture and the use of shape-based fruit detection for automatic fruit counting in images of mango trees, and comparison was made with existing techniques[3].

The machine-learning algorithm was developed to accurately detect individual intact tomato fruits and The results of fruit identification were 0.80 recall, while the accuracy was 0.88. The recall rate for mature, immature and young fruits were 1.00, 0.80 and 0.78 respectively [4].

Recognition of ripe litchi and estimation of pick points are often difficult issues for a robot to pick in a natural environment. The experiments show that the accuracy of recognition of nocturnal litchi was 93.75 percent and the average recognition time was 0.516 s. The highest accuracy for calculating the picking point is 97.5 percent at different depth distances, while the lowest is 87.5 percent. Its work offers technical support for litchi-picking robots with visual localization technology [5].

A public camera image dataset was used to investigate and evaluate three commonly used approaches to object detection, Histogram of Oriented Gradients (HOG), Haar-like features and Local Binary Pattern (LBP). The findings show that LBP features perform better than the other two forms of ' HOG ' and ' Haar ' features with a higher detection rate. A novel and robust detection algorithm was suggested, using a combination of various feature descriptors and AdaBoost cascade classification[6].

The block-matching approach and SATD were used to identify potential pixels of fruit that were closer to the template. Using a feature selection method and using a kernel SVM classifier, five texture features were selected to remove false positives. The final decision was made regarding false-positive elimination and the number of fruits in each picture was counted[7].

The color segmentation system detects exactly the fruit regions in the image. It surpasses edge-based segmentation results. So the method of edge detection was not as effective as the color segmentation; The color algorithm was able to detect mangoes with an accuracy of 85-90 percent [8].

Basic process flow of fruit classification and grading. Characteristic extraction methods for color, size, shape, and texture are explained by the features of SURF, HOG, and LBP. Finally, some approaches to machine learning such as KNN, SVM, ANN, and CNN are explored in brief [9].

The author also presents the quality evaluation of tomato-based on a computer. They defined the statistical color characteristic, the color texture features the tests, the accuracy rate for defective / non-defective and ripe/unripe tomato picture was 100% and 96.47% [10].

Authors have worked to efficiently locate the fruit on the plant, which is one of the most critical criteria for the fruit harvest process. Color and shape analysis was used to segment the images of various fruits under various illumination conditions. the pre-processing of the input image was performed first, segmentation of a fruit image, labeling of the binary noise-removed image to isolate the fruits, fitting the circle to the edge points. The results indicate that the proposed method can precisely segment the occluded fruits with 98 percent output[11].

The approach used for background subtraction was the Watershed Image. Comparisons had been made between a neural network, Naive Bayes and algorithms for the decision tree. The decision tree has the highest accuracy rate using CA as the metric with a value of 93.13 percent. The Naive Bayes and a neural network provided a 91.94 percent accuracy score, 92.84 percent individually for the classification of orange image conditions such as mature, unripe and scaled. Precision and sensitivity are also used to test the method for all three classifiers using an efficiency metric. The decision tree classifier with Precision and Sensitive metric has the highest precision rate of 93.45 percent and 93.24 percent compared to the classifier Naive Bayes [12].

The learned classifier is applied to identify the image that is used to measure image accuracy. For example, Recall, Precision, F-measure, False Positive was used for the experiment to test the results. Two separate image sets, one for a single-scale case containing 170 images of a car, the second for a multi-scale case with 108 images of a car of different size and rotation. With the analysis, they express that recall-precision curves are more fitting than ROC curves to calculate the effectiveness of object detection techniques [13].

A case study was performed using 15 different types of fruits and vegetables. This data set also has different effects on the pose, variability, crop yield, and partial occlusion. Different descriptor was used to extract the image feature based on color, texture, and shape. The MSVM is used for the classification and training They have finally provided 93.84 accuracy levels [14].

The fruits and vegetables were classified using CNN. The results show that the VGG model has achieved a 95.6 percent accuracy rate [15].

3. MATERIALS AND METHODOLOGY

On-tree citrus fruit images were captured from the farm in the varying lighting conditions and camera angles with different distances between camera and tree. The fruit scenes on both the sunshine side and the shadow side of the tree were picked at random from the citrus canopy. A total of 2100 images of citrus fruits were collected.

3.1Block Diagram of the Proposed Algorithm

3.1.1Positive and Negative Instances

This section describes the training of algorithms with green citrus fruits as positive samples and Negative samples like Leaf stems and other backgrounds.

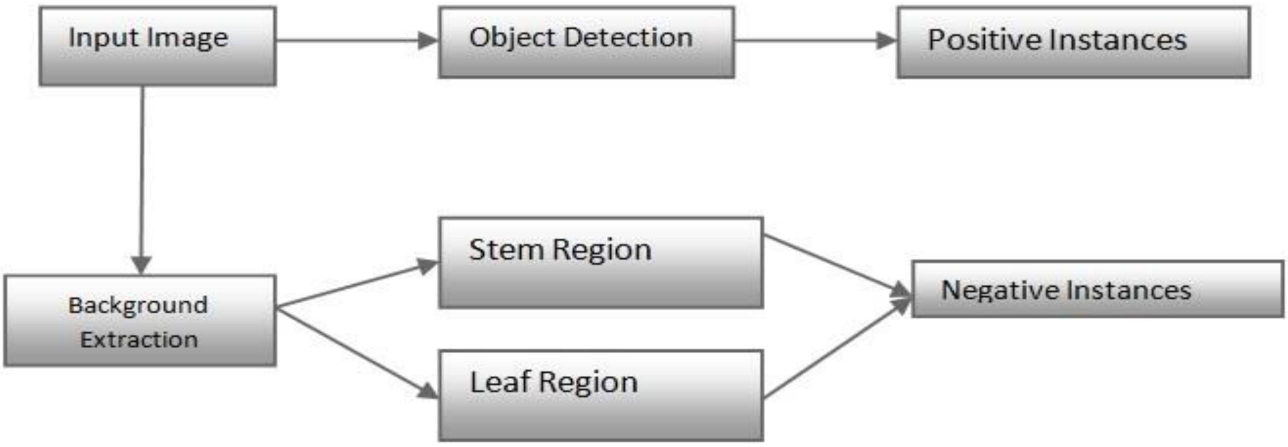

Fig. 1 Data set for Positive and Negative Instances

1.2Green Fruit Detection block diagram

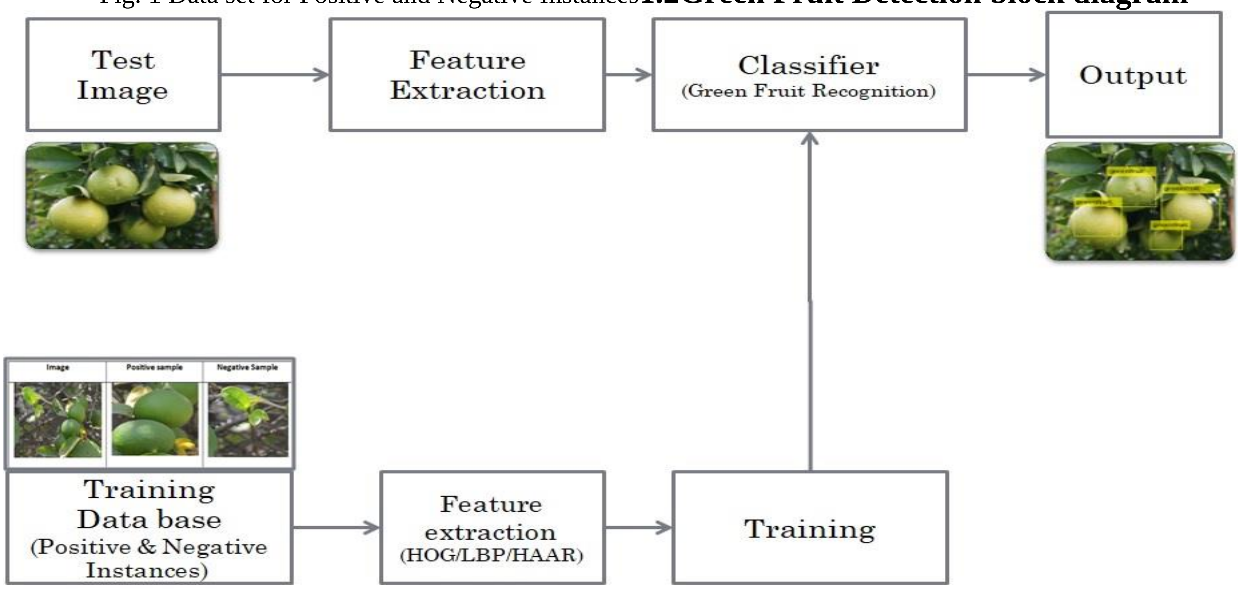

Fig. 2 Block Diagram of Green Fruit Detection

Initially, different images containing single fruit and multiple fruits along with leaf, stem, and background were taken. In this green citrus fruit was taken as the Region of Interest (ROI) as positive instances while leaf, stem, and background were considered as negative instances. From these labeled data ground truth for the training of algorithm created.

Cascade training is done with a set of positive objects (Green Citrus windows) and a set of negative images (Leaf, stem, and background). To obtain reasonable accuracy it is necessary to specify the number of cascade layers, the feature type (Haar, LBP or HOG) and the function parameters.

To get better results, the size of the training object should be as close to the size of the object being measured as possible. An algorithm was trained for different values of false positive (false alarm rate). In this implementation, authors have used “Haar”, “LBP” and “HOG” as the feature type for training. A comparison was done based on training time and detection results for different features.

4. EXPERIMENTAL EVALUATION

This section describes the formation of datasets and results obtained during various phases of training and testing of the algorithm. On-tree citrus fruit images were captured from the farm in the varying lighting conditions and camera angles with different distances between camera and tree. The fruit scenes were picked at random from the citrus canopy on both the sunshine side and the shadow side of trees.

A total of 2100 images of citrus fruits were collected. The images were captured using a digital camera with full resolution (NIKON D3200): 6,016 × 4,000 From the citrus trees when the fruit was immature green. To develop Green fruit detection algorithm MATLAB Version 9 was used on 64 bit Intel®Core (TM) i5-9300H 2.40 GHz CPU with 8 GB RAM, 4GB NVIDIA GeForce GTX1050, and a 64-bit Operating System Computer.

4.1. Training Methodology

The training of the algorithm uses a total of 1600 images which contains 1000 fruit images and 600 non-fruit images (leaf and stem). Each of the 1000 fruit images contains one or several fruits**.** Training of algorithm was done with a selection of different features like ‘LBP’,’ HOG’ and ‘Haar’.

Fig.3 shows the image captured from the on-tree Citrus tree, its positive sample which is a citrus fruit and negative samples like leaf and stems.

Fig. 3 Image, positive and negative samples

4.2. Experimental Result of Green Fruit Detection Algorithm

Around 500 number of on-tree images for testing purposes. Here we implemented the histogram of the Oriented Gradient Approach and SVM classifier approach.

Fig. 4 Results of different lighting condition and Background

4.3. Results and discussion

In the testing of the on-tree Green Fruit detection and Classification algorithm total, 500 images were used. The result of the algorithm is compared with the ground truth data. The positive difference between the values of algorithm and Ground Truth fruit count indicates that the algorithm detects more fruits than actual fruits due to the similarity of color and size of the leaf. A negative difference indicates that the algorithm detects fewer fruits than actual fruits because of the hidden, overlapping of fruit by leaf or stems. The below graphs shows the comparison of Fruit count by the algorithm and Ground truth data.

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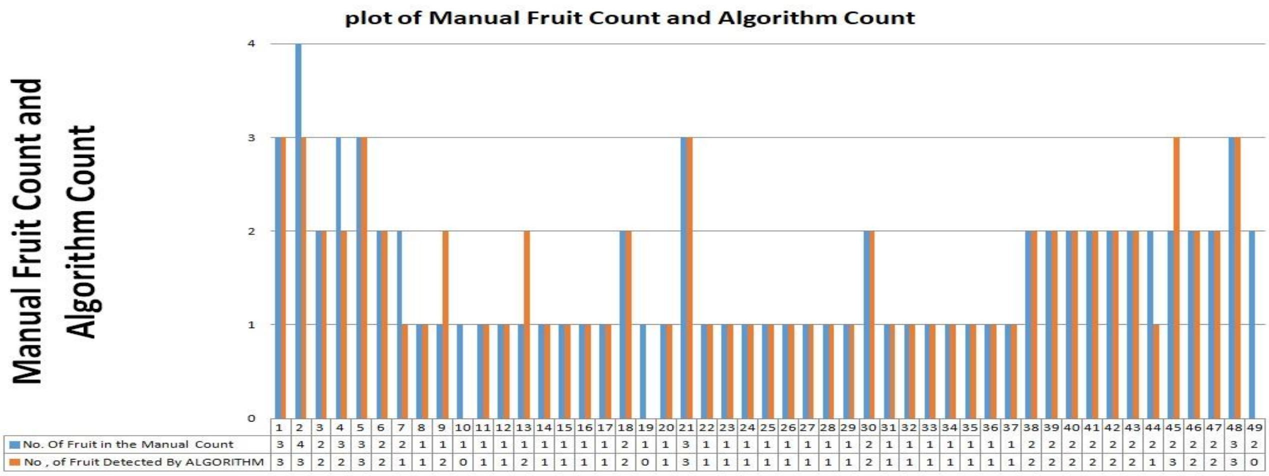

Fig. 5 Plot of Manual fruit Count and Algorithm Count

The above plot shows the comparison of the results of No, of Fruit Detected by Algorithm and manual Fruit Count for 100 images. From the plot, it can be seen that in most of the case Manual Fruit count and Algorithm fruit count are the same but in some cases where there is an overlapping of fruits, fruit occlude by leaf or stems, then algorithm can’t detect fruit. While in some cases due to similarity in color and shape of the leaf, it misclassified leaf as a fruit.

Figure 6 shows the confusion matrix for 3 different types of features which are ‘LBP’, ‘HAAR’ and ‘HOG’

LBP		Predicted Class	
		Fruit	Non Fruit
Actual Class	Fruit	890	110
	Non Fruit	145	455

HAAR		Predicted Class	
		Fruit	Non Fruit
Actual Class	Fruit	925	75
	Non Fruit	94	506

HOG		Predicted Class	
		Fruit	Non Fruit
Actual Class	Fruit	930	70
	Non Fruit	80	520

Fig. 6 Confusion matrix

Table 1 Shows the Performance parameters for On-tree Citrus Fruit Detection using three features ‘HOG’, ‘LBP’ and ‘Haar’. The most widely used basic measures of classifier performance are Accuracy (ACC), Precision (PREC), Recall (REC) and F1-Score.

a) ACC = (TP + TN) / (TP + TN + FN + FP)
b) PREC= TP / (TP + FP)
c) REC= TP / (TP + TN)
d) F1 SCORE=2 * PREC * REC / (PREC + REC)

Note: TP: true positives; TN: true negatives; FP: false positives; FN: false negatives[16]

Table 1 Comparison of Performance parameter for three types of Features

Features	HOG	LBP		HAAR
Precision	92.08%	85.99 %		90.78%
Recall	93.00 %	89.00 %		92.50 %
Accuracy	90.63 %	84.06 %		89.44 %
F1 Score	92.54 %	87.47 %		91.63 %
Training Time	835 sec	245 sec		7459 Sec

From the above table, it can be seen that the Precision of ‘HOG’ and ‘Haar’ Feature was 92.08% & 90.78 % which was better than ‘LBP’ feature of 85.99 %. The training time of ‘Haar’ Feature was 7459 sec which is more as compared to ‘LBP’ which was 245 sec and ‘HOG’ which was 835 sec. Accuracy of ‘Haar’ and ‘HOG’ was 91.63% and 92.54 % respectively but the result of ‘HOG’ was better in terms of Training Time and Precision.

5. CONCLUSIONS

In this paper, an algorithm was designed to detect green citrus from its identical background. The performance of the algorithm was tested using precision, recall and accuracy, which was found as 92 %, 93% & 90 % respectively for HOG Feature , 86 %, 89% & 84 % respectively for LBP Feature , 91 %, 93% & 89 % respectively for Haar Feature. The proposed algorithm is suitable for yield measurement/ monitoring analysis of crops for agriculture applications.

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