

GSJ: Volume 8, Issue 11, November 2020, Online: ISSN 2320-9186 www.globalscientificjournal.com

DEVELOPING A SELECTIVE TEA PLUCKING MECHANISM USING IMAGE PROCESSING FOR A DRONE-BASED TEA HARVESTING MACHINE

Abesinghe A.M.S.K.¹, Amaratunga K.S.P.^{*}, Ekanayake E.M.A.C²., Kavindi M.A.R.³, A.J. Mohotti⁴

¹Postgraduate Institute of Agriculture, University of Peradeniya, Sri Lanka.
*Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Sri Lanka, sanath.amaratunga@gmail.com
²Postgraduate Institute of Agriculture, University of Peradeniya, Sri Lanka.
³Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Sri Lanka.

⁴Department of Crop Science Faculty of Agriculture University of Peradeniya.

KeyWords

Haar-cascade classifier, Harvestable standard tea shoots, Image processing techniques, leaf detection.

ABSTRACT

A mechanism for detecting harvestable tea leaves in the field was developed based on an object detection framework, with the help of image processing techniques. The mechanism was developed for a drone based tea harvesting machine with a consideration of weight, method of plucking, the ability to reach the leaves (manoeuvrability), and suitable for using on a robotic arm mounted on the drone. Tea harvesting is mainly done manually in Sri Lanka. In addition to that, there are different types of machines introduced recently for harvesting tea shoots because of the existing labour shortage. The existing machine harvesting is non-selective and leads to poor quality of made tea [1]. Therefore, an autonomous, drone-based, selective tea harvesting system has been considered as an alternative solution to the problems associated with tea harvesting in Sri Lanka. A miniature camera (Raspberry pi 8 MP) mounted on an arm capturing the images of tea leaves were analysed using Haar-cascade classifier and image-processing techniques to detect harvestable standard tea shoots with two leaves and one bud, in real time. The detection process proposed was implemented through OpenCV Python. Haar-cascade classifier was trained with 1,000 images and tested with 165 real tea leaves. Training images were processed into required sizes and formats and performed the classifier training and finally tested for the selection performance. According to the results, the classifier could distinguish harvestable tea shoots from non-harvestable tea shoots and the objects in the tea field with an accuracy of 57.58%.

INTRODUCTION

Tea production is one of the major foreign exchange gathering paths in Sri Lanka. Nearly \$700 million annually coming to the country and 11% of total work force is governed by this sector [1]. However, there are several problems associate with the cost of production of tea due to higher labor cost, labor shortage, lack of skilled labor, low labor productivity, lack of specialists in the field and quality reduction etc. According to the Tea Research Institute Sri Lanka sources, it is obvious that the sector has higher labor shortage.

Harvesting is one of the most important operations in tea production. Tea harvesting is mainly done manually in Sri Lanka, but it consumes more labor. Therefore, different types of machines introduced for plucking tea leaves. According to the harvesting method, yield will vary. Most of the machine tea harvesters perform non-selective tea plucking. However, their productivity is high; quality is poor due to nonselectivity [1]. Literature says that usage of non-selective tea harvesting machines; in Sri Lankan tea plantations reduce the yield more than 50% compared to manual harvesting [1]. Therefore, an autonomous, drone-based, selective tea harvesting system has been considered as an alternative solution to the problems associated with tea plucking. Designing of drone-based tea harvesting mechanism requires several important areas to be addressed. Out of those, the weight of the mechanism and use of machine vision for selecting acceptable shoots to be plucked are considered as important in this study. Tea shoot detection using visual information is an important part in machine vision selective plucking of tea. Features such as size, shape, texture must be extracted from tea shoot images. For this kind of object detections, it was important to select a suitable object detection method in terms of speed and reliability because it is going to be used in an autonomous drone-based tea harvesting machine. Therefore, in this study Haarcascade object detection method was used for machine vision to detect the harvestable tea shoots. Haar-like feature extraction process is faster than "Histogram of Oriented Gradients" (HOG) features and it can be used even for low-resolution images [2].

Haar-cascade classifier based on Haar-like features generally combines with a boosted cascade classifier. While Haar-like features efficiently computed by integral images, AdaBoost choosing few the most significant highlights to represent the object. This technique effectively applying in numerous detecting processes, for example, face recognition [3], pedestrian detection [4], vehicle identification [5], and detecting of different commodities such as crop varieties [6], fruits [7] by machineries in modern agricultural world.

Requisite of this study was to develop a suitable object detection system that would be able to facilitate detection of harvestable tea leaves from tea fields, in real time. Ultimately, drone with a robotic arm system will be able to capture harvestable tea leaves accurately through a Raspberry pi camera module by applying morphological features on images. Therefore collecting of harvestable standard tea shoot images under natural field conditions and any other types of images from Google, processing them into required sizes and formats, performing of classifier training and finally testing and performance evaluation were the contributions of this study.

THEORETICAI BACKGROUND

Present-day world is full with novel approaches to automated farming practices with the aim of increasing quality and quantity of production, while reducing time and expenses. With that, motorization and mechanization have been started to engage with the tea industry as well. Automation has been accomplished with the help of artificial intelligent systems and it depends on machine vision. Because of these novel concepts, some of the technical words that are needed to understand this study have explained below.

Tea shoot standards

Study mainly focused on tea shoots consisted with two tender leaves and one dormant bud. It is very important to supply tender shoots except mature leaves to produce best quality tea. Depending on the required quality of made tea, harvesting method and the way of manufacturing may be different. However, the best quality tea is produced with standard tea shoots those have only 2-3 tender leaves and a bud. Dormant shoots with one leaf also acceptable for processing. However, acceptable tea shoots may be impacted by varying field conditions and other constraints [8].

Shoot growth have some differences based on cultivar, and the grown area. Tea clones such as TRI 2000, TRI 3000, and TRI 4000 series have introduced by Tea Research Institute (TRI) of Sri Lanka, and TRI 2023, TRI 2024, TRI 2025, TRI 2026 etc are the widely growing tea clones in Sri Lanka [1].

Haar-cascade classifier

Paul Viola and Michael Jones [9] initially suggested Haar-feature based cascade classifier for object detection. This was developed based on machine learning approaches, while focusing on a robust and rapid face detection method. The image based object detectors are sensitive for the training data; therefore, this algorithm had used a large number of sample images of faces and negative images for the training of the classifier [10].

Haar-cascade object detection framework was introduced under three main contributions. "Integral Image", a new image representation was the primus contribution of their work [9]. Secondly, a classifier was developed using "AdaBoost" with the lesser number of significant features [11]. As the final contribution, a method was developed for the integration of more complex classifiers in to a "cascade". It helps fast discarded of image background regions, and meanwhile more computational is doing on object-like regions [9].

Haar-like features

Simple feature values of images are the basic concept of classifying images in the Viola and Jones object detection algorithm (Haar-cascade classifier) [9]. Value of a feature is computed by the difference between sums of the pixel between adjacent rectangles [5]. This is called as Haar-like features (Figure 1) because of the similar computation to the coefficients of Haar-wavelet transformation [4]. Reasons for using Haar-features except direct pixel values are it requires number of features to achieve necessary knowledge and processing time of feature-based system is higher compared to a pixel-based system [9].



Integral image

Integral image (Figure 2) is a technique of calculating the value of Haar-like feature, while alternating the value of each pixel into a novel image representation [13]. Through this intermediate representation, it is possible to computate rectangle features instantly [9]. Integral image pixel values are the cumulative values of top and left pixel of the input image [6].



AdaBoost

Improving the performance of veriest learning algorithms called as "Boosting". Boosting helps to minimise the error of different "weak" learning algorithms as well [11]. Due to the large number of Haar feature generation, AdaBoosting exclude majority of available features, to ensure rapid classification. This allows focusing on smaller number of critical features. AdaBoost searching for higher degree of differences among every feature in training data set [4]. Outstanding boundary features between objects and non-objects consider as the best features [6].

Cascade classifier

Cascade classifier is a combination of complex classifiers to produce a multilevel structure that used to accelerates the detection process [15]. If an image comprising with desirable features or characteristics of a selected object, cascade classifier will lasting its activity until it completes all the steps. Image that travels along this complete classifier sequence is the desirable object image. Process termination in the middle of the process implies non-detection of the desirable object [6]. For the better understanding, Figure 3 simply illustrates the working pattern of a cascaded classifier sequence.



Figure 3: Cascade classifier

Methodology

Proposed tea leaf detector was developed under 4 steps.

Data collection

Training dataset comprised with both positive and negative data. Positive image dataset consisting with images of desirable object, while negative image dataset consisting with images that include any other type of objects except desirable object. In this study, images with standard type harvestable tea shoots were considered as positive images (Figure 4), and they were captured from tea fields in Hantana, Sri Lanka under natural daylight conditions (between 9 a.m. to 11 a.m. in each day). A DSLR camera (Nikon 7200 DSLR) was used to capture positive images. Meanwhile other types of images except tea shoots were considered as negative images (Figure 5), and they were collected from Google image search. Out of those total 1,000 training images, 600 were positive images and 400 were negative images.



Figure 4: Sample positive images for training the Haar-cascade classifier



Figure 5: Sample negative images for training the Haar-cascade classifier

Data manipulation

To improve the detection process, gray scale image processing technique was applied for both positive and negative images. At the beginning, all positive and negative images were RGB images. Importance of converting images from RGB to gray scale is that it facilitates easy processing of images, and gray scale images computationally less intensive due to the use of one channel (black-white).

Initially positive images had quite high resolution around 3300×2300. For the easy handling of images, it was scaled down into a convenient width and height dimensions such as 120×90. Meanwhile negative images also reduced into the same dimensions.

Classifier training

Proposed tea leaf detector was developed using Haar-cascade object detection framework. Simply this classifier training process

followed several steps.

- 1. Extracting Haar-like features
- 2. Tea shoot detection using AdaBoost
- 3. Merging training results

This tea shoot detector relied on Haar-like features. To extract Haar-features, sub-window sliding approach was applied, and then it was verified that the pixels under each location of sub-window were harvestable stage tea shoot. In this study, 25×25 pixel sub-window was used for the scanning of images.

While detections were happening, sub-windows were tested to identify whether it was a harvestable tea shoot or background. This was accomplished by AdaBoosting. A complete harvestable tea shoot could be detected (Figure 8) by merging different sub-window results.

Region of interest (ROI) selection at the beginning is important. In every situation, it speeded up the detection process as it allowed the code to consider only the important part of the image. It limited operations in to one sub-region. While ROI selection was done HighGUI (High Level Graphical User Interface) library in OpenCV, that allowed collaborative working in operating system, file system, and camera like hardware system. Therefore, windows had opened to display images, and it helped to handle mouse, and keyboard events.



This Haar-like feature object detection is popular in terms of face detection because of its efficiency of the face detection. Illumination will not affect due to the stable mutual ordinal relationship of various pixels in a particular region [2]. Equation 1 shows formula for valuation of a Haar-like feature, thus value calculated by taking the weighted sum of pixels under white regions and black regions.

$$X = \sum_{i=1}^{R} w_i \times \mu_i \tag{1}$$

R is the number of pixels consist in a Haar-like feature, w_i is the respective pixel weight of i th pixel, and μ_i is the grey value of i th pixel [7]. If a value was greater than the threshold, then it was considered as a feature of a harvestable standard tea shoot.

Integral image operation speeded up the Haar-feature calculation. This method facilitates pixel value calculation within any rectangular region by simple referencing of four corner points.

AdaBoost helping with the heavy number of Haar-features, for the efficient functioning of Haar-cascade classifier. Most of these features might not be useful for tea leaf detection; therefore, it was a challenge in terms of identifying most relevant features to detect harvestable tea leaves. Thus taking the advantage of AdaBoosting, number of "weak" classifiers were combined for constructing a "strong" classifier, and each weak classifier is searching for a specific type of features. While AdaBoosting, if a window failed at the particular set of features then the sub-window was considered as background. If a window succeed at a one stage then it forwarded to the next classifier likewise the process proceeded until detecting the tea leaves. Generally, number of features increasing with the stages.

Testing and performance evaluation

For the testing of trained cascade classifier, 165 real tea shoot samples were used. Testing was done under natural field conditions, in middle times of 9 a.m. and 11 a.m.

Performance evaluation of the tea shoot detector was done by means of accuracy. Test samples considered under 4 sub categories, such as True Positive (TP), True Negative (TN), False Positive (FP) and, False Negative (FN). Equation 2 define the formula for calculating accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
(2)

Results and Discussion

Proposed tea shoot detection algorithm was coded using OpenCV Python and trained using Windows 10 Intel Core i3-5005U CPU@ 2.00 GHz, 4 GB RAM. However, this work could be done with Matlab, this study was conducted in Python as it consumes less time, and be able to apply in OpenCV programs. Finally, performance evaluation was done to find the accurate detection rate of this tea leaf detector.

At the beginning, it was essential to identify best compatible hardware and software components for a drone-based tea harvester. Aim of this drone tea harvester is to detect harvestable standard tea shoots, and pluck suitable shoots by a robotic arm system. When developing drones it is essential to use lightweight hardware components to achieve efficient and effective flying. In the real time if it is going to identify harvestable shoots, it is necessary to have enough performance with the hardware components. Raspberry pi 8 MP camera (Quad-core 1.2 GHz processor) is light in weight; therefore, it was selected as the camera device to be used in this study. These cameras will facilitate lightweight, efficient detection system that suitable for drones. Test results in terms of accuracy shown in Table 1.

Table 1: Results of the selection of tea leaves using the developed tea leaf detector

	True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)
	55	36	40	34
Accuracy	57.58%			



Figure 7: Results of the trained Haar-cascade classifier

Test results exhibited that the classifier could distinguish harvestable standard tea shoots from any other types of non-harvestable tea shoots 57.58% accuracy rate. This is a mid-level accuracy rate. However, with further training it will be able to

achieve higher rate of accuracy than this. At the time of testing TP occurrence was high compared to FP. In addition to that, classifier could not detect all harvestable tea shoots successfully, thus FN occurred. In here FN rate was less compared to the other 3 types. To work well, less FN rate is necessary. Otherwise if the relevant object was classified as a negative one, then the step will terminate, and that error will not be corrected.

Due to the limited number of training data, classifier could not extract enough information from the tea shoots to be detect correctly. There were several FP occurred because of the limited number of training data, and other limitations occupied in the training dataset. To reduce this false alarm rate, definitely it will be effective if it could create Region of Interest (ROI) precisely. If so, most of the regions should occupy tea leaves except background regions. Most of the FP consisted with image backgrounds. Thereby can assume that bounding box demarcated ROIs possessed considerable amount of non-leafy areas, and that resulted FP. To avoid this FP occurrence, applying of a background filtering method also considered as a possible solution.

Due to some redundant behaviour of this training process, overtraining of the classifier or undertraining might can happen. Undertraining more likely to outputs more FP, thus considerable amount of FP will generate. It means while training the classifier, it might not have enough time (lesser number of stages) to carefully understand positives and negatives.

If overtrain, too many stages will train therefore; classifier will output empty test results. Accordingly, it will not be able to detect positive objects from images.

To obtain detection at different angles, it is better if could train separate Haar-cascade classifiers for different positional orientations of tea shoots such as 0, 45, 90 degrees. In addition, it is possible to create one training dataset to train single Haar-cascade classifier while collecting different angle tea shoots in to one dataset.

Ambient light intensity variation at the time of data collection and testing is extremely detrimental to the output of the detector, even the slightest ambient light intensity variation will affect to the image RGB values. However, in this study, training dataset contained only with grey scale images while those images had a narrow wavelength band. Therefore, light intensity coercion was not that much prominent. Grey scaling was the applied image processing technique, because it was easy to extract fore-ground from the background to get tea leaf boundaries.

Conclusion

Developing a harvestable tea shoot detector for an automated drone-based tea-harvesting machine was the ultimate goal of this study. For that, Haar-cascade object detection framework was used. While training, Haar-like features were extracted, consecutively AdaBoosting was done. Being a classifier, it was needed to merge number of weak classifiers to get the desirable outcome. To achieve successful detection, grey scale image processing technique was applied.

Experimental results revealed that the classifier has an ability to distinguish harvestable tea shoots up to some extent. However, 57.58% accuracy rate makes us to put over that it is necessary to improve this tea leaf detector further before apply in to the drone-based tea harvester.

As future works, it is necessary to increase dataset, and better if can apply more useful image processing techniques for positive images to make this tea leaf detector more accurate. Further image processing techniques such as blurring, and masking will facilitate accurate Region of Interest (ROI) selection. Also it will be more productive if can use tea shoot images in different angles for the training process.

References

- [1] N.V. Gunathilaka, E.D.R.T. Gunawardana, J.S.A.M. Rukshan, H.K.G. Punchihewa, R.K.P.S. Ranaweera, and L.N.S. Wijayasingha, "Development of an Improved Mechanism for Selective Harvesting of Tea," available at https://selectiveteaharvesting.wordpress.com/., April, 2015.
- [2] K.Y. Park, and S.Y. Hwang, "An Improved Haar-like Feature for Efficient Object Detection," Pattern Recognition Letters 42(1): 148-153, June 2014, doi: 10.1016/j.patrec.2014.02.015.
- [3] L. Cuimei, Q. Zhiliang, J. Nan, and W. Jianhua, "Human Face Detection Algorithm via Haar-cascade Classifier Combined with ThreeAdditional Classifiers," In Procedeeings of the 13th IEEE International Conference on Electronic Measurement and Instruments, IEEE, Yangzhou, China, 483-487, 2017, doi: 10.1109/ICEMI.2017.8265863.
- [4] G. Monteiro, P. Peixoto, and U. Nunes, "Vision-based Pedestrian using Haar-like Features, Robotica 24, 46-50, April 2006.
- [5] D.K. Ulfa, and D.H. Widyantoro, "Implementation of Haar-cascade Classifier for Motorcycle Detection," In Proceedings of the 2017 IEEE International Conference on Cybernetics and Computational Intelligence, IEEE, Phuket Thailand, 39-44, 2017, doi: 10.1109/CYBERNETICSCOM.2017.8311712.

- [6] C.S. Marzan, and N. Marcos, "Towards Tobacco Leaf Detection using Haar-cascade Classifier and Image Processing Technique", Proceedings of the 2nd International Conference on Graphics and Signal Processing, Association for Computing Machinery, Sydney, Australia, Oct. 2018, pp 63-68.
- [7] Y. Zhao, L. Gong, B. Zhou, Y. Huang, and C. Liu, "Detecting Tomatoes in Greenhouse Scences by Combining AdaBoost Classifier and Colour Analysis, Biosystems Engineering, Aug. 2016, vol. 148, 127-137, doi: V https://doi.org/10.1016/j.biosystemseng.2016.05.001.
- [8] M.A. Wijeratne, "Shoot Growth and Harvesting of Tea," 1st ed, Tea Reasearch Institute of Sri Lanka, Talawakelle, Sri Lanka, pp. 24, 2001.
- [9] P. Viola, and M. Jones, "Rapid Object detection using a Boosted Cascadebof Simple Features," In Proceedings of 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE, Kauai, Hi, USA, Feb. 2001, vol. 1, pp. 511-518.
- [10] "OpenCV", Open Source Computer Vision, https://docs.opencv.org/3.4/db/d28/tutorial_cascade_classifier.html.
- [11] Y. Freund, and R.E. Schapire, "A Decision-theoritical Generalization of On-line Learning and an Application to Boosting," In Computational Learning Theory: Eurocolt '95, Springer, Berlin, Heidelberg, vol. 904, 1995, pp 23-37.
- [12] R. Lienhart, and J. Maydt, "An Extended Set of Haar-like Features for Rapid Object Detection," In Proceedings of the International Conference Image Processing, IEEE, Rochester, NY, USA, 2002, 900-903.
- [13] S. Guennouni, A. Ahaitouf, and A. Mansouri, "A Comparative Study of Multiple Object Detection using Haar-like Feature Selection and Local Binary Patterns in Several Platforms," Modelling and Simulation in Engineering, 2015, 1-8.
- [14] O. H. Jensen, "Implementing the Viola-Jones Face Detection Algorithm", PhD thesis, Technical University of Denmark, DTU, DK-2800 Kgs. Lvngby, Denmark, 2008.
- [15] C. H. Setjo, B. Achmad, and Faridah, "Thermal Image Detection using Haar-cascade Classifier," 7th International Annual Engineering Seminar (InAES), Yogyakarta, 2017, pp.1-6.

