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Tea Bud Leaf Identification by Using Machine Learning and Image Processing Techniques

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Abstract— This research paper concerns the machine learning approach for tea bud leaf identification. The tea bud identification is most important for the process of automated tea leaves grading machines. In the present situation, there are no methods to identify the tea bud leaf separately from the main tea leaf. Unfortunately developing of mechanism for identification process is impossible because the plucked tea leaves not in the same condition. Therefore, the identification is needs intelligent practice to detect the tea bud leaf. In this research, the machine learning object detection technique is developed and successfully used for identify tea bud leaf and the capability of this proposed technique is validated through experimental results obtained by performing experiments by using MATLAB software. According to results, the proposed methodology provides 55% of overall accuracy for identification.

Index Terms— Machine Learning, Cascade Classifier, Image Processing, HOG Features, Tea Leafs Grading, SVM, Object Detection, Tea Leaf Quality, Tea Bud Leaf Detection

1 Introduction

Tea harvesting policies include several aspects such as plucking process, plucking style, plucking intensity and plucking frequency. The tea planting industry that has successful harvesting policies in a tea estate has a direct impact on tea plantation production or rather viability. Typically, the presence of more than 75 to 80 per cent of good leaves (up to two leaves and a bud) as shown in Fig.1 ensures better product quality.

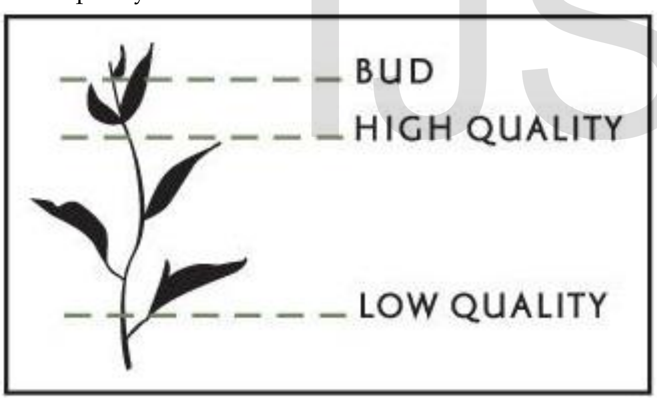

Fig. 1. Standerd quality levels of harvested tealeaf

Currently, most of the tea plantations in Sri Lanka do not consider fine plucked tea leave for the production due to the high tea demand of the market. Therefore, they plucked tea leaves with aged leaves including the bud and top two leaves (cores plucked tea) and directly feed into the production process. Due to that, the main grade tea market value decrease due to the low quality and low production.

Now they are looking for a new solution to separate uppermost two leaves and a bud from aged tea leaves (cores plucked tea) and process separately them to a final product. Therefore, in this research mainly focused on the design and development of a concept for identify bud from cores plucked tea leaves. By identifying the tea bud, it is possible to separate uppermost two leaves and a bud from aged tea leaves. In identifying process, it is not possible to use simple mechanisms to identify the tea bud because the plucked tea leaves not always in the same characteristics. Due to that reason the identifying system, need some intelligent behavior, therefore the identifying process achieved by using machine learning with image processing techniques. In the machine learning process, the operating system trained to identify tea bud and this trained model integrated with an industrial camera to identify tea bud. Machine learning techniques train digital systems to do and mimic the natural process: learn from experience and machine learning techniques are also popular for object recognition and offer different approaches to object recognition and object recognition is a broad term for the definition of a set of similar computer vision tasks involving object detection in digital images. Nowadays, most of the researchers use image-processing techniques for quality measuring and classification processes in agricultural products. According to the paper [1], they developed rice grain quality measuring process by using morphological image processing techniques. They extract morphological features of rice grains by using image processing. The paper [2] introduced a method for rice grain classification by using image processing techniques with Matlab software. In this background, this paper presents a new method for tea bud detection using machine vision and machine learning methods. It uses a cascade classifier-based method integrated with Histogram of Oriented Gradients (HOG) features and Support Vector Machines (SVM) classification for tea bud detection.

HOG evaluates the orientation and strengths of the gradient Tea bud image within an input image. Unlike the extraction process above, the HOG characteristics can be derive by transforming the area of the image into a particular area (cells). Every cell prepares a histogram of gradient directions for the pixels included in cells. The local histograms can be normalize in HOG process by calculating Intensity calculation over a wider region of the image (blocks) to increase accuracy. HOG approach commonly used for the identification of different artifacts. According to paper [3], the HOG classifier used to decide the direction of vehicle image for automated vehicles. Guzman et al. [4] the proposed technique for the identification of cars on roads by using HOG features and SVM classifier. The consequence of this identification decides whether the image frame contains a car or not. The paper [5] showed that the HOG approach used to detect humans and offer further inspection of pedestrian identification. Furthermore in the paper [6], The HOG features used for facial expression recognition, the basic facial expressions such as heartbreak, happiness, dislike, fear, temper and wonder. For the classifier, we used Support Vector Machines (SVM) for classifying tealeaf bud. SVM is a machine learning approach for the best make of decision boundary of classifying tea bud. Finally, we used multiple classifiers (cascade classifier) for acquire better performance.

2 Proposed Methodology

Following topics broadly explains the proposed methodology for tea bud identification.

2.1 Machie Learning Workflow

Machine Learning teach computers, how to mimics the natural or human processes by using experiences or data. Ma-chine learning calculations utilize computational strategies to “learn” data straightforwardly from information without depending on a predetermined equation as a model. The algorithms improve their performance adaptively, as the number of samples available for learning process [7]. The machine learning process done by two methods, which are supervised learning and unsupervised learning. The supervised learning method uses past inputs and outputs to train the systems so the trained model can forecast future values. The unsupervised learning method use only past input data sets to train the system, during the training process this learning algorithm identifies the pattern of input data. The goal of supervised machine learning is to construct a model in the presence of uncertainty, which makes predictions based on proof. A supervised learning algorithm uses a known set of inputs and outputs to train a model to calculate reasonable predictions for the response to new data. Supervised learning builds predictive methods with regression and classification techniques. In this research, classification method used to trains a model to generate reasonable predictions for the response to new image samples and this trained model called as Cascade Classifier. The cascade classifier needs positive and negative image samples for train the predictive model.

2.2 Cascade Classifire

The cascade classifier consists of a series of stages as seen in Fig.2, that each stage is a group of weak learners. The boosting technique used to train each stage. In the boosting process, the weighted average of decisions made by poor learners provided the ability to train a highly accurate classifier. During each stage, the classifier identifies the current location of the sliding frame generates either positive or negative value. The positive indicates the object is available and negative indicates object not available.

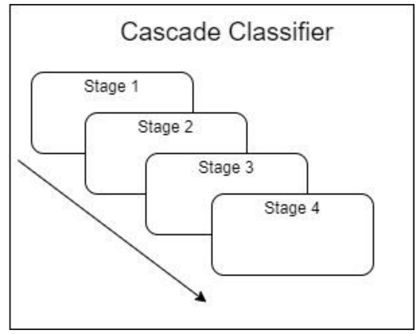

Fig. 2. Multy stage Cascade Classifire

If the label becomes negative, the detector frame moves to the next location after completing the classification of the current location. If the label indicates positive, that positive region pass to the next classifier stage. The trained object detector generates the location of the identified object when the last stage classified that region as positive. The cascade classifier developed by using these individual classifiers for image classification. A cascade classifier is a group of classifiers which each classifier connect on after one another and threshold value of each classifier calculated by the training algorithm (boosting algorithm) by using positive samples. In this research, we used 18-stage cascade classifier for tea bud detection. The stages designed to reject negative samples as fast as possible. The most of windows do not contain the object and the real positive windows are rare and take more time to confirm. In this research, Tea bud detection classifier uses HOG features for the detection process. Once the HOG features obtained then individual classifiers built based on the values of each HOG features. Then the last step was the classification process to detect tea bud of the tealeaf through the learning process of SVM classifier. The process of each stage in classification is shows in Fig. 3

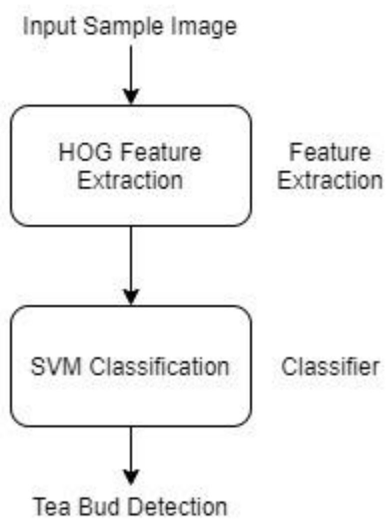

Fig. 3. Overview of the classification and identification process of stages in cascade classifier.

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2.3 HOG Feature Extraction

The development of HOG descriptor done by dividing the image into small cells. Every cell evaluates a gradient direction histogram for the pixel inside the cell. HOG process has four phases for object extraction [8]. In the first phase, the gradient values calculate by using a derivative mask in a horizontal and vertical direction as (1) and (2).

$$D_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \tag{1}$$

$$D_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \tag{2}$$

Then the convolution operation use to obtain x and y derivatives of object image I.

$$I_x = I_x \times D_x \text{ And } I_y = I_y \times y \tag{3}$$

The formula for estimating gradient magnitude is (4)

$$|G| = \sqrt{I_x^2 \times I_y^2} \tag{4}$$

The gradient orientation is given by,

$$\theta = \arctan \frac{I_x}{I_y} \tag{5}$$

The second step is the binning of spatial orientation. This phase has a purpose to give the polling process a result of a cell histogram. Every pixel of the tealeaf image within the cell separate according to the orientation. The pixels allocate the nearest bin in the range of 0 to 180 degrees. In the next phase, by using HOG descriptor the cell and histogram normalize to be a vector form. In the final phase, the normalization of the block achieved using the norm L2 as (6)

$$b = \frac{b}{\sqrt{\|b\|^2 + \varepsilon^2}} \tag{6}$$

Such four phases shows in Fig.4 for implementation of this HOG function in identifying the leaf bud.

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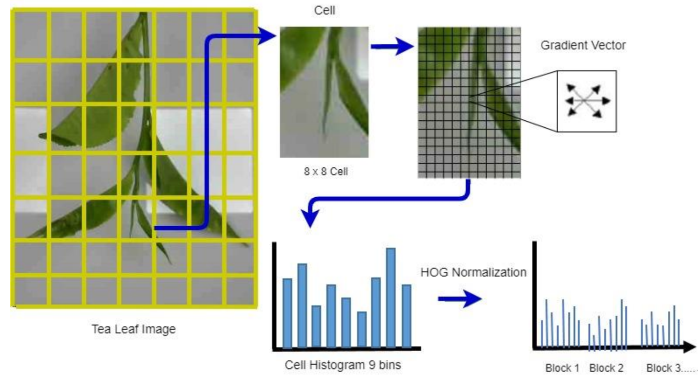

Fig. 4. Overview of HOG feature process to identification

After the HOG normalization, all the block descriptors converted into vector form. To identification process, the descriptor use detection window, which includes 52×32 pixel window. This detection window divided into 16×16 pixel blocks. Each block contains four cells each cell contains 8×8 pixel size with a 9-bin histogram and each block includes 36 values. Finally, all the vector results include the xml database for classification process; next step is classification by using SVM classifier.

2.4 SVM Classifire

In this research, the Support Vector Machine (SVM) learning algorithm used for the feature learning process in image classifier training. SVM can introduce as a supervised learning method strongly used to examine data for classification and regression processes [9]. SVM consists of searching at the appropriate boundary for the decision between the boundaries of the two groups. The decision boundary selected according to which the margin is maximum and the distance between margin and decision boundary should be short. Equation (7) used to separate samples according to two classes after the classifier was trained [10].

$$y(x) = \sum_{n=1}^{N} a_n t_n k(x_n, x_m) + b \tag{7}$$

The conditions for a_n:

$$(a_n) \geq 0 \tag{8}$$

$$a_n y(x_n) - 1 \geq 0 \tag{9}$$

$$a_n\left(t_n y(x_n) - 1\right) = 0 \tag{10}$$

In the identification process, according to the positive from the true image area and negative from the false image area, the SVM classifier classifies the area of tea bud from the main image. Before the testing phase, the SVM should trained by using obtained images from various tea leaves. These training images consists of positive images (tea bud images) and negative images (aged leaves, stem images). The positive samples consist only the object that needs to identify and the negative samples consist of objects that are not interested. In the next topic, we explained the SVM training process.

2.5 Cascade Classifire Training

The training process of classifier achieved by using a set of positive and negative samples. The provided positive image samples as shown in Fig.5 consists only regions of tea bud leaf and the negative samples as shown in Fig.6 consists unwanted parts of tealeaf. The Matlab Cascade Object Detector used to train the cascade classifier. In the training phase, the HOG features are extract from positive samples and stored in the xml database.

Fig. 5. Positive Sample (tea bud leaf)

Fig. 6. Negative Sample (aged tea leves and stem)

The proposed cascade object detector consists 18 stages for acquire better performance. For the training of cascade classifier, used 150 positive samples and 300 negative samples. The training process shows in Fig.7

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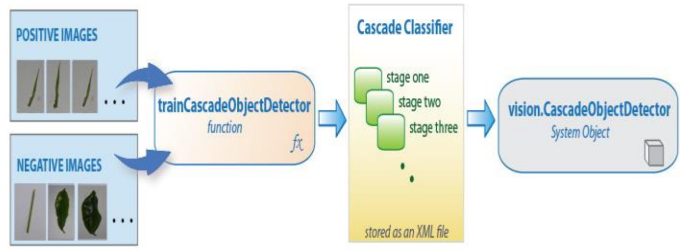

Fig. 7. Cascade classifire training process

3 Results and Discussion

The Fig.8 shows the developed classifier and evaluation process for achieving a classification result and the Matlab *trainCascadeObjectDetectro* function used to train the classifier model.

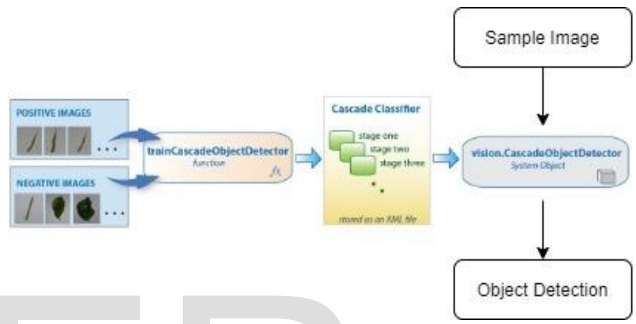

Fig. 8. Object detection process

The classifier trained by using 150 positive samples and 300 negative samples. In each training stage, the training process used above image samples and train the classifier. The training process consists of an algorithm, which generates decision boundary form of a support vector and the class of testing process determine by using this support vector. During the training process, these support vectors saved in xml database. According to training results, when increasing the training stages the processing time increased. The variation of the training time for each stage shown in Fig. 9.

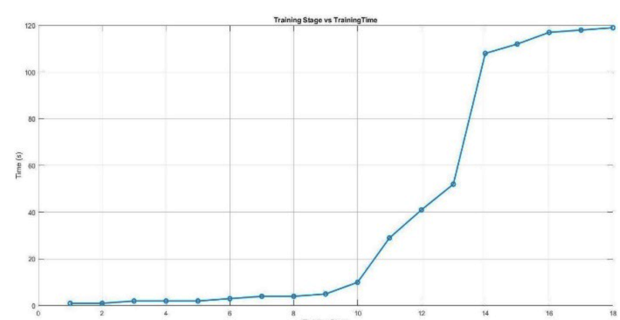

Fig. 9. Training Stages vs. processing time

The next step was a testing process using sample images. We used 40 tea leaves images for testing samples, which contains four length ranges of tea buds and selected 10 samples for each tea bud length ranges. By feeding each sample image in to the classifier, recode results according to classifier output, which was positive detection or negative detection. Table 1 shows that the test result for each tea leaves shows a different accuracy.

TABLE 1
THE TESTING RESULT OF THE SAMPLE IMAGES

Sample Set	Tea Bud Length (mm)	Result		Accuracy (%)
		Positive	*Negative*	
Set 1	0-10	3	7	30
Set 2	10-20	7	3	70
Set 3	20-30	8	2	80
Set 4	30-40	4	6	40

The lowest accuracy value occurs for minimum and maximum length ranges of tea bud. This caused by most of the positive training samples, not between these length ranges. During the testing process, the pixel area blocks will compare by cascade classifier. The maximum average accuracy value occurs for middle range (10mm-30mm) lengths because of most positive training samples with in the middle range lengths. According to the Table I, the proposed methodology has 55% of accuracy for all the testing tea leaves lengths. The negative results occur due to the deviation of the tea bud shape concerning the training samples. The Fig. 10 shows the positive sample image, which is successfully tea bud detected image by SVM classifier.

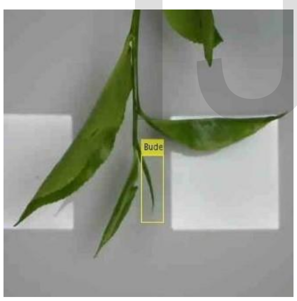

Fig. 10. Image of the positive sample

4 CONCLUSION

In this paper, a machine vision methodology was successfully developed and evaluated to identify tea leaf bud. According to the classification results the Histogram Oriented Gradient (HOG), feature descriptor give different results for tea bud identification. The results taken for four sets of tea leaves samples each set includes ten samples. The results show the overall accuracy from the identification is 55% for tea buds with a length of 0mm to 40mm. According to results, mid-range lengths between 10mm to 30mm give 75% of identification accuracy due to most training samples consists of this mid-range. According to the results, the training time depends on the number of sample images used, more images increase training time. The accuracy of the trained model depends on the number of image samples used to the training process. A large number of image samples increase the classifier accuracy. In this research, the SVM classifier was successfully developed and tested for the identification of tea bud. Therefore, this methodology can apply the development of tea leaves grading machines. For further developments, we hope to develop this methodology by using Deep Neural Networks and make a comparison between SVM classifier.

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