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An Effective Tea Leaf Classifier Using Faster R-CNN with Real-Time Object Detection

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Abstract-Tea is one of the most significant beverages preferred all across the world and is undoubtedly a huge cash crop in the world, grown in climatically restricted geographic areas. The best Tea is prepared from the best Tea leaves grown under optimum conditions. Since the quality and the condition of the tea leaves is so vital in the Tea Industry as a beverage, the classification of eligible tea leaves that should be plucked has become an active area of research as the Tea Cultivation industry itself is facing threats due to lack of labor. This paper is mainly focused on classifying the 21-days old tender tea shoots from the younger buds. Images of the Tea Leaves are fed to the classifier from a mobile camera. This proposed approach consists of three phases such as preprocessing, classification to process the fed image and predictions through real-time Object Detection. The captured images are preprocessed using the Grabcut-image segmentation technique in order to introduce masking to support the followed labeling process. The Faster R-CNN model is trained with the labeled images to classify the leaves into 2 - classes, ready to be plucked and not-ready to be plucked. The trained model is experimented with video footage to provide prediction through real-time Object Detection. The experimental results of the tested tea leaf images proved that the proposed method classifies the tea leaves with an IoU of 0.670.

Keywords : tender tea shoots, Tea - Leaf Classification ,Grabcut , Image-Segmentation ,Faster R-CNN Model ,Real-Time Object Detection

I. INTRODUCTION

Tea as a beverage is one of the most important cash crop in Sri Lanka [1], grown in climatically restricted geographic areas. According to the Central Bank statistics exporting the finest of Sri Lankan tea is one of the main sources of foreign income for Sri Lanka which accounts for 2% of the total GDP , contributing over the US $1.5 Billion to the economy as in 2018 [18].

Even though tea cultivation accounts for such significance within the Sri Lankan economy, according to the Labour Demand Surveys done by the Census Department the labor force needed for tea cultivation is on the drastic decline which encourages an automated solution to take over the crisis [19]. In the context of having an automated approach for tea plucking, tea - leaf classification is of the vital research areas.

Application of computer vision and pattern recognition towards the process of plant recognition has been carried out in the recent past[4]. Moreover, classification of leaves done based on the morphological features of leaves for the early diagnosis of plant diseases as well.

For the process of classification of tea leaves,the video footage of the tea leaves is converted to images and should be preprocessed for the removal of noise, edge or boundary enhancements and segmentation as well. Similarly, Interactive image segmentation which is a preprocessing technique uses the input images to iteratively refine the object segmentation mask. The masked images then should be labeled and fed into the CNN-model to be trained. The trained model could be used to predict the eligibility of the test data set whether to be plucked or not to be plucked.

The following sections would describe the related works involved regarding leaf recognition, the proposed methodology, and finally, the experimental results followed with the conclusion.

II. RELATED WORKS

Sugata and C. Yang et al., [4] proposed the VGG16 model CNN to carry out the process of leaf recognition. In order to predict location of leaves, pre-processing techniques such as Sharpening, Thresholding, Canny edge detection, Morphological operation, and image segmentation are adopted to extract regions in the image before doing classification. Since feed for the deep network should be large, they have enlarged the data set by doing several transformations: horizontal reflection, contrast enhancement, and rotations.

S. Ghosh, H. Kumar V and P. Kumar et al., [5] surveyed on different classification techniques for leaf classification.A comparison between techniques such as Principal Component Analysis (PCA) ,Decision Tree ,Naive–Bayes classifier (NBC),Bayesian Classification ,Probabilistic Neural Network , Support Vector Machine , Artificial Neural Networks,K-Nearest Neighbors , Genetic Algorithms and Learning Vector Quantization (LVQ) is done in this survey . The survey results reveal that Probabilistic Neural Networks ,when input is presented, it's first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input.The last layer which is the competitive layer in PNN structure produces a classification decision, where the class with maximum probabilities will be assigned by 1 and other classes will be assigned by 0 while on the other hand Support Vector Machine(SVM) is more capable to solve the multi-label class classification.

A. Periasamy et al.,[6] claims a selective tea leaf plucking robot belongs to agricultural automation field. This robot is designed considering selective tea leaf plucking and ergonomics aspects, which helps to operate robot without any fatigue. The robot was equipped with a leaf sensor, humidity sensor, temperature sensor, level sensor and color sensor. portable robot mechanism, multi-sensor, robot control unit, rail conveyer and distributing system with container arrangement.

This paper concentrates on building a tea plucking machine with intelligence sense to identify tea leaves.

Joffe, B., Ahlin, K., Hu, A. and McMurray, G. et al.,[11]proposed a leaf sampling system that uses a monocular camera and a 6-DOF robot arm to detect, track, and pick healthy and unhealthy leaves without prior knowledge about the plant.The Object detector is based on a Faster R-CNN architecture which can integrate a region proposal network with the classification and bounding box regression network along with Resnet101 as the feature extractor.Kept track on the identified leaves in several frames using a tracking method based on SURF(to speed up robust features).Automatic segmentation based on Grabcut algorithm is used to separate the pixels belonging to the leaf from the background within its bounding box and for data set labeling.For the leaf picking approach, has introduce new multi-leaf approach instead of single leaf approach, which can locate and grab multiple leaves in the frames. Have used filters in IBVS(Image-Based Visual Servoing), and Monocular Depth Estimation(MDA) and to control accumulated error.

Out of the related works discussed , the object detection approach proposed by Joffe, B., Ahlin, K., Hu, A. and McMurray, G. et al., [11] with Faster R-CNN architecture and image segmentation are the concepts used in this research.The proposed approach consists real-time object detection and tracking to classify the tea leaves.

III. METHODOLOGY

The proposed approach uses Faster R-CNN architecture. Faster R-CNN is just a modified version of Fast R-CNN which combines a RPN instead of the external region proposal network [13]. Though generally detection and classification are done as two different phases where Region Proposal Network(RPN) is used for detection and Region Convolutional Neural Network (RCNN) is used for classification. The RPN networks which include Selective search, greedy merges, provide the ROI (Regions of Interest). This region proposal step still consumes almost the same amount of time as the detection network. The two processes can be expensive on their own, but a cost-effective way is to share the convolutions between which is the use of Faster R-CNN. This can be an effective solution for better accuracy and detection time trade-offs [14].The approach tends to not solely decrease the detection time, however conjointly overcome the machine issues of the selective search algorithm.

This approach uses the Tensorflow Object Detection API to build the tea leaf detector to detect the tea leaves that need to be plucked where a real-time video footage is provided as input. The below mentioned basic steps are followed to build up the custom object detector . [9].

1. Organizing the work-space/training files
2. prepare/annotate image data-sets
3. generate tf records from such data-sets
4. configure a simple training pipeline
5. training a model and monitor progress

The tea leaf recognition method used in the proposed approach consists of two phases namely the image preprocessing and classification.

A. Image Pre-Processing

The input tea leaves images of 3024px x 3024px are captured from a 12MP camera.Then these collected images were cropped and were subjected to horizontal transformation to enhance the dataset.

Image sharpening

Along with image sharpening, the proposed approach uses edge detection methodologies to increase the features of the in-situ images.The Canny edge detection is used for the purpose. This algorithm is widely adopted because it can have good detection results. Figure 1 shows the sharpened in-situ leaves.

FIG. 1: In-situ image subjected to image sharpening

Instance-based Semantic Segmentation

To address the problem of efficient, interactive foreground/background segmentation in still images the proposed approach uses the segmentation tool, Grabcut which has a robust algorithm for "border matting" [16]. Figure 2 shows the semantically segmented in-situ leaves.

FIG. 2: Multiple Shoot with grab-cut

Labeling

'LabelImg' was used to label the images ready and not-ready. During labeling, the correct boundary of the tea shoot which is qualified to be plucked should be bounded as well as the tea shoots that are not ready to be plucked yet should be labeled. This task becomes relatively easy since the background is not filled with old tea leaves.

1. Identifying the leaves to be Plucked

Picking of young tea shoots having two to three leaves and soft dormant shoots is known as plucking .There are three types of plucking standards followed in the world namely [2],

- **Imperial pluck** - Bud is plucked only with one tender leaf from the top. From this way, the highest quality of the tea is obtained.
- **Fine pluck** - Bud is plucked with two tender leaves from the top. The quality of the tea made is slightly less than the imperial pluck.
- **Coarse pluck** - Bud is plucked with three or more leaves from the top. This produces the lowest quality out of the three methods of plucking.

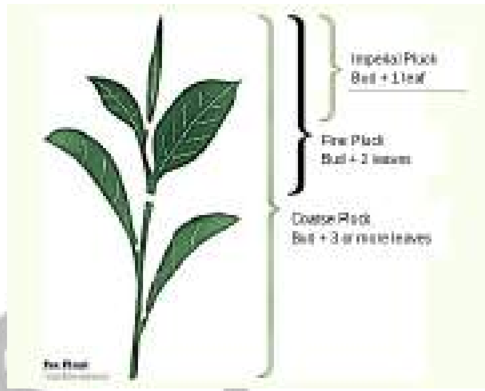

FIG. 3: The life cycle of a tea leaf from [3]

In the proposed approach, the Fine Pluck standard was followed since it is the widely used standard across Sri Lanka. Figure 3 shows the tea plucking practices followed.

An instance-based segmented typical ready - to be plucked singled tea leaf image is shown in the figure 4.

At the end of labeling, a .xml file is created for each image.

TensorFlow requires a label map, which namely maps each of the used labels to an integer values. This label map is used both by the training and detection processes. The label map for the data-set is as follows.

```
item {
    id: 1
    name: 'ready'
}
item {
    id: 2
    name: 'not-ready'
}
```

FIG. 4: Pre-processed 'ready' tea leaves

After labeling the images, TF record files should be fed into the object detector. For the purpose, all the .xml files need to be converted into .csv files then converted to .record files which would be the input files for the object detector.Figure 5 shows the labelling of in-situ leaves.

Tensorflow provides scripts to carry out these tasks.

FIG. 5: LabelImg interface during labeling

B. Classifier Model

The proposed approach uses the Resnet101 as the feature extractor[11] with Faster R-CNN. ResNets typically can go up to 101 layers whereas VGG networks can only go up to 19. Since deeper networks are usually better for image classification, ResNets are generally more accurate than VGG such as for ImageNet[**?**] and Coco[20][15].

The instance-based semantic segmentation model was trained with the Faster R-CNN network and used an implementation of the Tensorflow Object Detection API. The model was trained for 12k steps till it reached a loss of 0.42% with data augmentations such as random horizontal, vertical flip and 90-degree rotation.

IV. EXPERIMENTAL RESULTS

2160p video footages at 30fps, of the tea leaves were converted to images through python OpenCv and fed to the Faster R-CNN model for the predictions through the Tensorflow Object Detection API. The model achieved an IoU of 0.670 and this practical evaluation was done with footages of both ready and not-ready leaves being present.
The prediction metric readings of the bounding boxes created by the TensorFlow Object Detection API with Faster R-CNN Resnet101 model after being trained with the in-situ tea-leaf data set are discussed in the Analysis section.

Figures 6 & 7 are examples for real-time prediction results by the Faster R-CNN model for the video footage through bounding boxes.

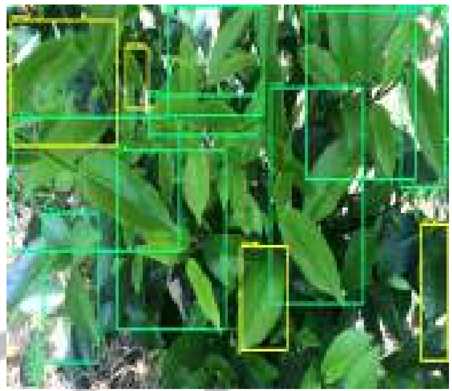

FIG. 6: Predictions - I

FIG. 7: Predictions - II

V. ANALYSIS

The Faster R-CNN architecture which works well with small objects ,the proposed approach recorded a mean IoU of 0.670 which suggests that the detection accuracy is 'good'.The bounding boxes showed no anomalies. The learning rate of the Faster R-CNN in the proposed approach was between 51ms-57ms.

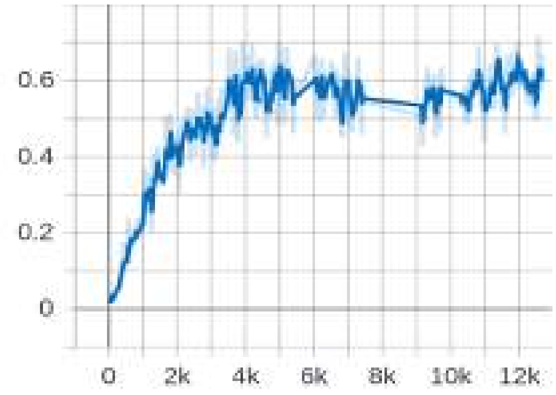

FIG. 8: Precision Graph - mAP@50IOU

The graph 8 illustrates IoU value at mean Average Precision 50 against the no. of steps trained for the Faster R-CNN Resnet101 model.(X-axis : mean Average Precision, Y-axis : no.of Steps)

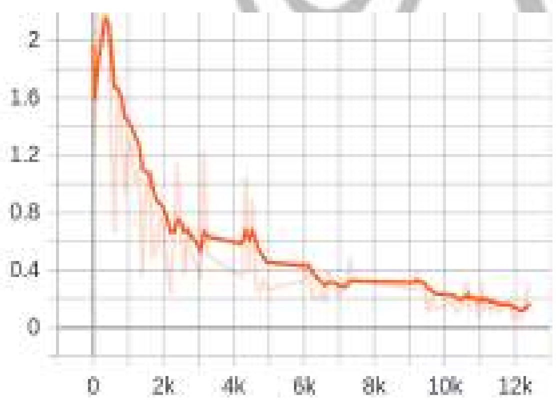

FIG. 9: Loss graph

The graph 9 illustrates the loss against the no. of steps trained for the Faster R-CNN Resnet101 model.(X-axis : mean loss, Y-axis : no.of Steps)

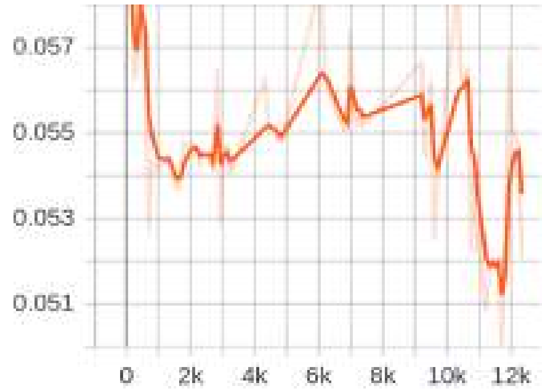

FIG. 10: Learning Rate

The graph 10 illustrates the learning rate against the time trained for the Faster R-CNN Resnet101 model.(X-axis : learning, Y-axis : time)

VI. CONCLUSION AND FUTURE SCOPES

This paper discussed an Effective Tea Classifying approach designed for with real-time object detection.

The approach consisted of three phases i.e, preprocessing , classification to process the fed image and predictions through real-time Object Detection.The images are preprocessed with image-sharpening, semantically segmented with Grabcut and Labelled with LabelImg. The feature extraction and classification is done by the Faster R-CNN model.The accuracy of the proposed approach is comparable to those reported in contemporary works.A salient feature of the current approach is the real-time object detection which would be extremely useful for quick and efficient classification of tea leaves in an automated tea plucking context.

Future would involve research along two directions: (1) calculating the depth and coordinates of the tea leaves and (2) determining the coordinates of the position on the tea shoot where the automated plucking should take place. Further the current approach of classifying the tea leaves using Faster R-CNN records an IoU of 0.670. In consideration of that fact, a different approach to obtain a higher IoU could be commenced as future work.

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