Onepanel

Statement of Work ("SOW")

Object Detector(s) for Quantification of Coconut Rhinoceros Beetle Damage in Roadside Video Surveys

For Dr. Aubrey Moore, Ph.D. Entomologist, University of Guam

v1.1

Onepanel
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Revision History

Revision date	Revised by	Approved by	Description of change
Jun-04-2020	D.S.	D.S.	Initial version

Effective Date

This Statement of Work will be effective on the date the initial deposit is made and will be entered into between the University of Guam ("Client") and Onepanel, Inc ("Contractor" or "Company") and incorporates the provisions of the agreement.

Background

The client intends to identify qualified entities with skills in computer vision and machine learning which may be interested in collaborating on the development of an automated system that uses image analysis of roadside video surveys to detect and quantify coconut rhinoceros beetle damage in images collected during roadside video surveys.

Coconut palms on several Pacific Islands are being damaged and killed by outbreaks of coconut rhinoceros beetle (CRB). Damage is done when adult beetle bore into the crown to feed on sap. Fronds developing within the crown are damaged when the beetle bores through them. This damage becomes evident as distinctive v-shaped cuts when these fronds emerge and unfurl. If the borehole passes through the meristem (the growing tip), the palm may be mortally wounded, losing the ability to generate additional fronds. Mortally wounded palms eventually die when existing fronds senesce and fall off, leaving a dead, standing trunk.

There is a need to monitor CRB damage for two reasons:

- To measure changes in time and space, especially changes in response to control activities, on islands infested with CRB
- Early detection of CRB damage on newly invaded islands

In the past, CRB damage surveys have been performed by direct observation by skilled individuals. We propose that this work can be automated by digital analysis of roadside videos collected by dash cams.

Objectives

Object Detection Model Development:

One or more object detectors will be designed and trained to count the number of healthy coconut palms, CRB-damaged coconut palms (indicated by v-shaped cuts), and dead coconut palms (dead, standing trunks) in each video frame. For training purposes, roadside videos will initially be uploaded from microSD cards to an internet repository.

When object detectors are operational, they will probably be run on a local machine eliminating the necessity of uploading large files to an internet server.

Output Data:

Output data will include camera location, time stamp, and the number of coconut palms visible in each frame classified into three damage levels (healthy, damaged, dead).

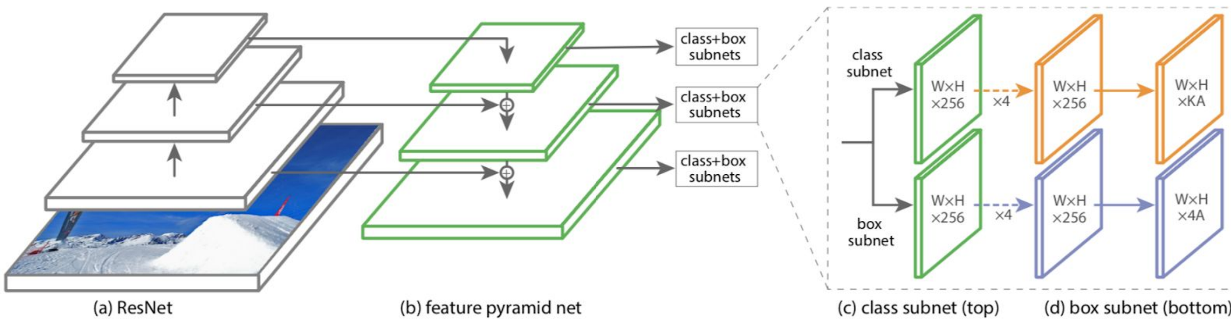
Reports containing maps will be developed to visualize these data.

Sample Model and System Architecture:

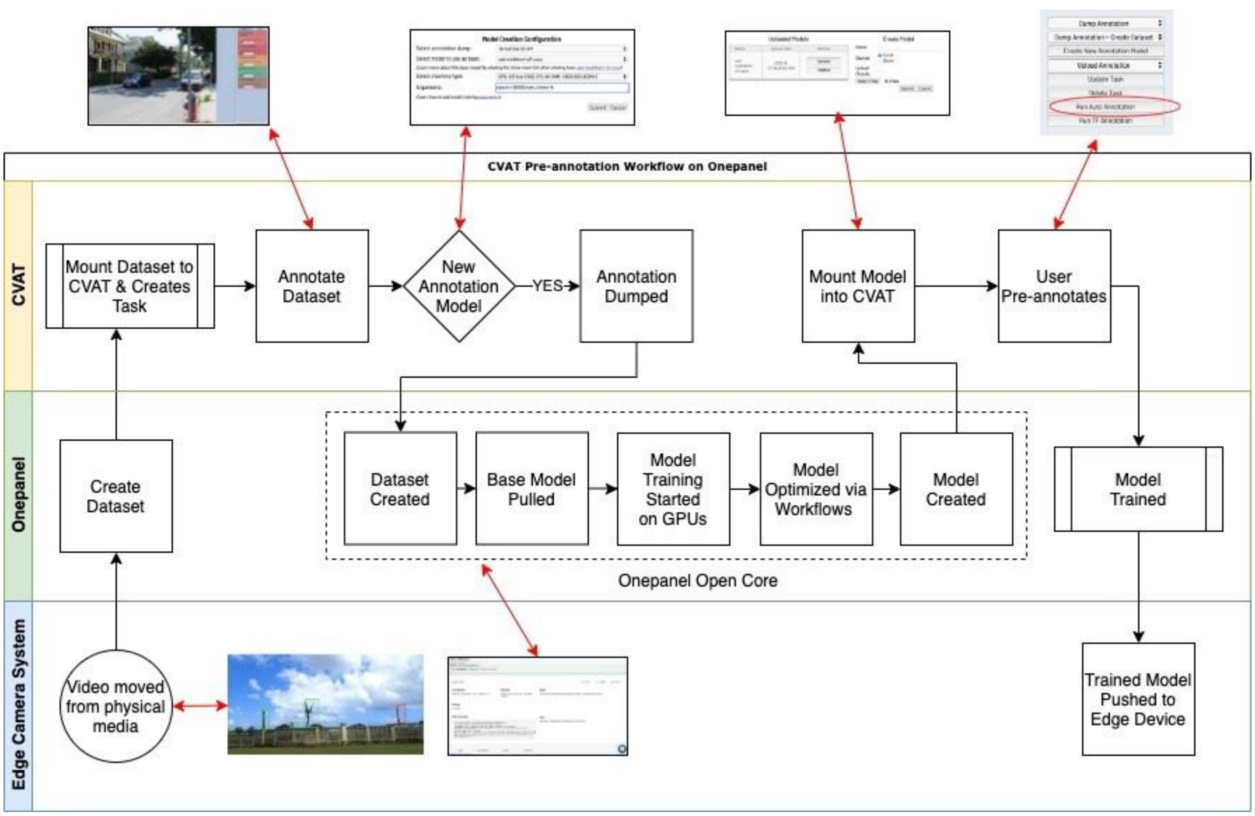
We will try multiple state-of-the-art deep convolutional neural networks on the provided dataset. There are two types of models for Object Detection: single-shot (i.e Yolo) and multiple-shots (i.e faster-rcnn). The single-shot models are considered faster than the latter one but the latter one is usually more accurate.

We will train both types of models and perform a study to find out which one works the best. These models are very sophisticated in terms of computational complexity and require a lot of time to train. One of the modes that we are aiming to train is called Faster-RCNN which is considered very accurate in general even in the case of small objects.

Below is a sample model architecture:



Sample Computer Vision Pipeline Architecture:



Scope

The scope of the engagement will include the following deliverables:

Deliverable	Description
Deep learning models	Fully trained and tested object detector(s) capable of detecting all coconut palms classified into three mutually exclusive groups ● Healthy coconut palm (no CRB damage) ● CRB-damaged coconut palm (indicated by v-shaped cuts) ● Dead coconut palm (dead standing trunk)
Comprehensive reports around model operation and training parameters	● Complete documentation including a validation report for the object detector(s) and all source code ● Suggested parameters for operational video survey recording (optimal frame size, minimum frame rate, etc.)
Computer Vision Pipeline as Code	● Completed YAML software code for the entire computer vision pipeline that can be ported to Onepanel Core open source environments
Pipeline architecture workflow documentation	● Documentation outlining pipeline and procedures:: ○ Infrastructure deployment ○ Dataset ingestion ○ Dataset pre-processing ○ Data annotation workflow ○ Model training ○ Pre-annotation ○ Model deployment

Requirements

The system must be built using free open-source software (FOSS). Preferred components include Linux, OpenCV, Python, Jupyter, and CVAT.

The system should be designed so that it can be operated locally in early detection mode on remote Pacific Islands which do not have access to modern telecommunications networks.

The distribution of turnkey systems on Raspberry Pis would be ideal.

Key Assumptions

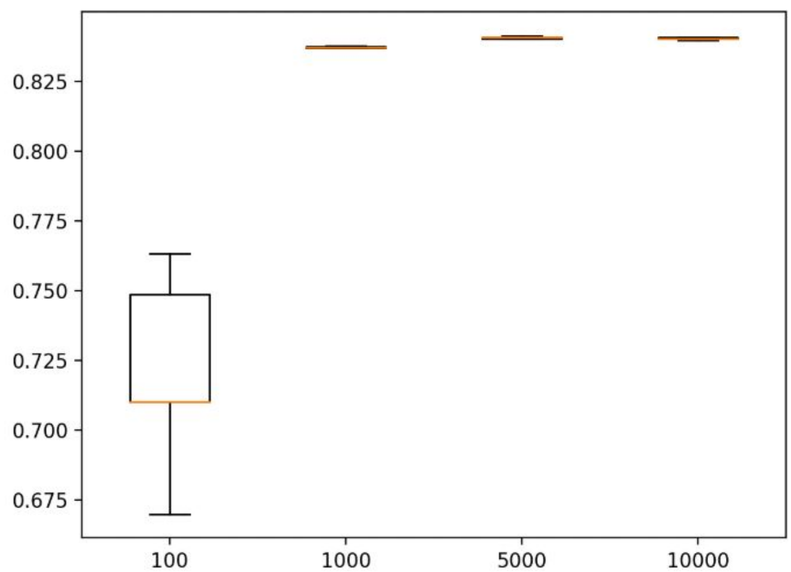
To ensure successful completion of this engagement Onepanel will expect the client to:

- Provide sufficient training, test, and validation data that represents the various lighting conditions, camera angles, resolutions, and target objects for each model class
    - It is highly recommended that we train models on a large dataset as the size of the dataset significantly impacts the accuracy of the model. There is no standard size for the dataset but we recommend at least a few thousand frames with unique scenes containing all three classes.

      Please note that all frames in a given video cannot be considered unique since most consecutive frames look similar and do not provide new information to our model.

      The training dataset should be diverse and should contain all the scenarios (i.e lighting/weather conditions) that you might expect at test time. This will ensure that the model performs well in different lighting and weather conditions.
    - It is generally considered that the more training data increases the accuracy of the model. This is a very general observation and it depends largely on the complexity of the dataset and model.

      Below is a Box and Whisker plot for a similar study that characterizes the relationship between the dataset size and accuracy. An increase in the dataset size will subsequently improve accuracy.



[Box and Whisker plot of Train Size vs Accuracy]

- ○ We will divide the dataset into two sets: train and test set. The train set will be used to train the model, and the test set will be used to evaluate the trained model. The ratio for this train/test split will be 80:20. That is, we will use 80% of the dataset for training and 20% for testing. Depending on the size, we may reduce the test size. We expect around 4000 images with varying scenes to produce good results. Depending upon the quality of the images (i.e diversity of lighting) we may need more or fewer images.

- ○ It is recommended that there are at least a few thousand (i.e 2k) objects of each class. Please note that the number of images could be less than the total number of objects since one image might have multiple objects. Also, note that the class-imbalance could lead to deterioration of the model's accuracy. It is highly recommended that the train set has equal representation for each class. A minor class-imbalance can be solved through data-augmentation and other techniques.

- GPS synched frame data will need to be evaluated before this task can be completed. This will depend on the type of metadata synced to each frame/image. The Client shall prepare requirements for mapping data products with respect to specifics around mapping tools, layout, data types, etc.

- Provide subject matter expertise to clearly define annotation requirements and sufficient samples of annotated data.
- Perform a sufficient review of annotated data to ensure that offshore annotation teams can continue to perform bulk annotation work efficiently.
- Coordinate activities across Client team members assigned and Onepanel resources. This includes facilitating working sessions, communicating tasks and delivery dates, and monitoring progress.
- Provide necessary documentation or access to resources needed to understand sources and integration requirements.
- Set priorities and manage work assignments for the project team which may include internal and external resources. In the event that Client alters work plan and/or deliverables, Onepanel may not be able to complete deliverables listed in this Statement of Work.

Place of Performance

Onepanel will deliver the engagement using a mix of on-site (CONUS) and off-shore resources for the duration of the agreement.

Period of Performance

This project will be completed on July 31st, 2020***

***Delays with resource availability, decision making or other factors will affect our ability to complete this work within the proposed schedule.

Estimated Pricing

Estimates of the project prices are listed below and are based on the scope and assumptions included in this Statement of Work. The final invoice with any applicable discounts will be sent separately.

Roles	Description	Blended Rate	Hours	Cost Estimate
DevOps Architect	Design and validate system architecture	$125	80	$10,000
DevOps Engineer	Build and implement Onepanel Core and Kubernetes backbone for computer vision pipeline	$125	40	$ 5,000
Deep Learning Engineer	Design, build and test deep learning models	$125	160	$20,000
Project Manager	Provide project management support throughout the life of the project	$125	40	$5,000
Annotators	Provide annotation and quality control review of computer vision video frames	NA	4,500 frames per day 38 days $540 per day	$20,520

***Rates do not include T&E which Onepanel will bill to the client for the actual costs when incurred. The client would be responsible for authorizing these expenditures in advance.

Payment Terms

A deposit of 30% is due upon invoice. 70% will be due upon the successful completion of the project dated July 31st, 2020. The final payment is due upon project completion. Unless otherwise specifically provided herein, all amounts payable by Company hereunder will be paid by check or wire transfer to the mailing address provided below:

Wire Instructions and Corporation Information:

Mailing Address & Contact:	**Onepanel, Inc Wire Instructions:**
Donald Scott Onepanel, Inc. 660 4th St. Unit #652 San Francisco, CA 94107 **Corporate Address:** Onepanel, Inc. 2035 Sunset Lake Rd., Suite B-2 Newark, DE 19702 DUNS: 081270468 EIN: 82-3208671 Delaware C-Corp. Start date: 10/30/2017	Phone number: +1-415-350-4344 Account number: 259669056 Routing number: 322271627 SWIFT Code: CHASUS33 Onepanel, Inc. 2035 Sunset Lake Rd., Suite B-2 Newark, DE 19702 **Chase Bank Branch:** 401 California St, San Francisco, CA 94104

Acceptance

The client named below verifies that the terms of this Statement of Work are acceptable. The parties hereto are each acting with proper authority by their respective companies.

Onepanel, Inc. ______________________________ Company Name	______________________________ Client Company Name
Donald Scott ______________________________ Full Name	______________________________ Full Name
Chief Revenue Officer ______________________________ Title	______________________________ Title
______________________________ Signature	______________________________ Signature
June 5th, 2020 ______________________________ Date	______________________________ Date