An Integrated Machine Learning Camera for Wildlife Detection

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Abstract

Expanding urbanization in California results in increasing isolation and segmentation of wildlife habitats. To understand the problem, biologists want to be able to count the appearance of animals in habitats. A new wildlife camera trap system is being developed, using edge computing to optimize the collection and classification of wildlife images in real time. A waterproofed prototype that will constantly record videos in the wild and process data in real time using trained AI is described along with a process for validation of the new system in direct comparison with typical current methods. In addition, wildlife counts acquired as control data are analyzed and showed that after doing the comparison of six weeks data between the data collected from island and the corridor, the island has the most deer appearance. Knowing the deer's habitat, this project can now test the AI around that area and decrease intrudes.

1.0 Introduction

Large areas of land are being urbanized every year, resulting in a decrease of land area as habitat for wildlife. Because of increasing population, about 60% of wildlife land around the world has been wiped out. Urbanization isolates different sections of wildlife habitats and resident animal populations, which can decrease genetic diversity (Furlan, 2012) of the resident animal populations because of restricted gene flow. Wildlife corridors provide a solution to these issues, as they allow animals, and their genetic material, to traverse between the different habitats. To gather data about wildlife, conservation scientists use wildlife cameras deployed in remote areas to measure the number of animals that pass through the area in order to understand animals more and know how much of an effect increasing population has had on their lives. This project proposes an alternative camera that can minimize these limitations by sorting data while the camera is running, to allow less loss of data.

1.1 Background

1.1.1 Wildlife Corridors

Wildlife or green corridors allow connections between isolated areas or habitats. The difference between the island and the corridor can be shown in Figure 1.

Conservationists are concerned with understanding and protecting the green corridors because if animals are unable to move between isolated habitats, the gene pool will become less diverse, which ultimately results in a decline in species diversity (Furlan, 2012). A green corridor is an area of wildlife separated by human habitat. An island is an area that contains wildlife populations and natural habitats. The predicted comparison between the corridor and the island is that the corridor has more wildlife action than the island as corridors connect different habitats of wildlife, while islands are isolated by urbanization such as roads and houses. This is the conjecture of the project.

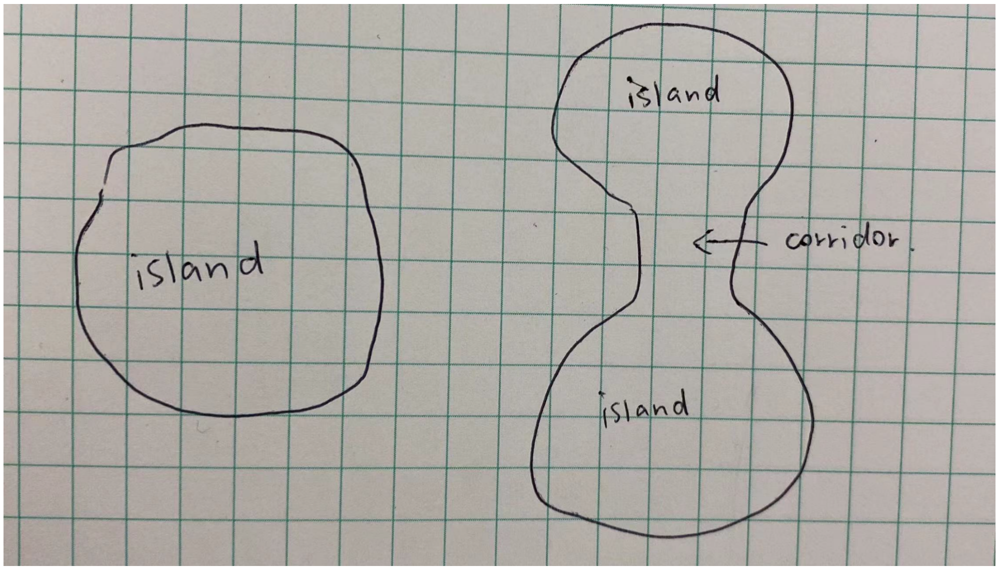

Figure 1: Difference between island and corridor

1.1.3 Machine Learning

Artificial Intelligence (AI) focuses on learning through data by imitating human intelligence and their neural network, allowing machines to predict outcomes and perform tasks through data analysis rather than programming (Oracle). Machine learning is a branch of artificial intelligence that focuses on building methods that "learn" and improving performance on certain tasks.

1.1.3.1 Image Recognition

Image recognition is a subcategory in machine learning and AI which analyzes patterns and regularities in data sets. Image recognition uses deep learning, a family of machine learning methods that commonly make use of convolutional neural networks (CNN) to learn the similar features from a large data set. The convolutional neural network is a network structure for deep learning that allows the AI to learn directly from data, eliminating the need to manually extract the different features and similarities. As training of AI through data progresses, the AI will be able to learn more sophisticated features in the images, until the model can accurately differentiate between objects. AI training is comparable to the learning of a toddler and it is given information, or data, to help it distinguish what name is matched up to what object (Decher, 2021). After each training, the AI will then be tested on new data, and if the model is unable to decipher between the different classes, the model will go through training again till it is able to differentiate the test data.

1.1.3.2 Edge Computing

Image recognition machine learning software typically runs on large computing clusters, dividing data among several computers. This allows each computer to focus on sorting one specific category of data. Alternatively, edge computing refers to the data analysis that is as close to the originating source as possible. For wildlife detection there are multiple benefits of using edge computing. Edge computing allows there to be real time processing of data which allows information to need minimal time to analyze. It also allows the data processing to be as close to the origin as possible, which allows for little data loss from transferring the data. Despite it being close to the origin, it still has access to clusters. Limitations include having less computing power than clusters, and requiring a lot of power to run it

1.1.3.3 Motion detection

Three methods of motion detection can be used in wildlife cameras, active motion sensors, passive motion sensors, and constant video recording. Action motion detectors, also known as radar-based motion detectors, emit a radio wave or microwave signal. The detector senses the shift to the frequency of the reflected wave when it bounces off objects in the area. The passive method senses infrared signals produced from the heat (WatElectornics, 2022). Most popular camera traps use the passive method as it can detect the body heat of animals passing by. Constant video recording is the third method. In this method, a camera will constantly record video. An AI with image recognition (section 1.1.3.1) will analyze each frame from the camera and store only the frames containing animals.

1.1.3.4 Night Vision

The traditional camera trap, such as the SpyPoint uses infrared sensors that allow the camera traps to capture images of animal activity at night. Currently, after analyzing the data collected from the motion detecting camera, the project found that around 60%, from previous data collection, of animal activity is captured at night, however, the current camera is not equipped with infrared sensors for night vision. The ability to count animal activity is important for scientific study and to fully understand the impact of urbanization in animals.

1.2 Literature Review

Related Study #1 - Panda Facial Region Detection Based on Topology Modelling. The University of Electronic Science and Technology of China developed an experiment to apply topology models as a method for enhancing image recognition of giant pandas. By turning the images of the pandas into just black and white images, this experiment used the Haralick Region Glowing in order to spread out the connected regions. The part that will be shown on the image will be parts that are black on pandas, using that skill can help them identify each individual black area on the panda more easily. This experiment also used Double Triangular Topology

Modelling to identify different pandas, by creating a triangle that connects a panda's eyes and nose, they can tell the difference between each pandas by the difference between each of triangles. By using Face Centroid Detection, they could find the central point of a panda's face and differentiate them by identifying different center points. The methods used here demonstrate that individual animal identification is possible, which is a long term goal for this project.

Related Study #2 - What can we learn from wildlife sightings during the COVID-19 global shutdown? A group of conservationists from Occidental College developed an experiment to investigate if the global shutdown caused by the pandemic can affect wildlife. One of the conservationists, Zellmer, designed this experiment in 2020 to prove the statement summarized: the global shutdown can affect wildlife while affecting the urban environment in different ways. Their experiment used community science to get the Biodiversity databases to make comparisons between wildlife data before the shutting down and after to see the change happening during the pandemic. It is also using data comparison, but between locations instead of time frames. Because Long-term urban ecological research can make comparisons between new wildlife sightings using standardized practices, their experiment uses this to display more data with less time. Our experiment also used automated detection to collect animal data through spypoint camera traps, same as the spypoint camera to the wildlife animal detection project, also used for comparison and data analysis. The methods used here are a lot like the methods used in this project. Data comparison through spypoint camera traps and enlarged databases could help this project with detection more animals and analyzing more data in less time.

After interviewing with Dr. Zellmer, there are currently remote wildlife cameras set up by the AFC, which is Arroyos Foothill Conservationists' Wildlife Research Camera Team in five wildlife habitats. The Occidental College group monitors animal movement using wildlife cameras in Cottonwood Canyon, Millard Canyon, Rosemont Canyon, San Rafael Hills and Verdugo Mountains. These camera traps use commercial cameras that are connected to a motion sensor. Whenever a movement is detected from the sensor, it triggers the camera to take an image.

Megadetector is the method the conservationists use to collect wildlife data, it creates a frame that locates the animal and returns a coordinate of the animal's location on the picture with the confidence level it has toward the data it provided. However, the Megadetector is currently only available on clusters.

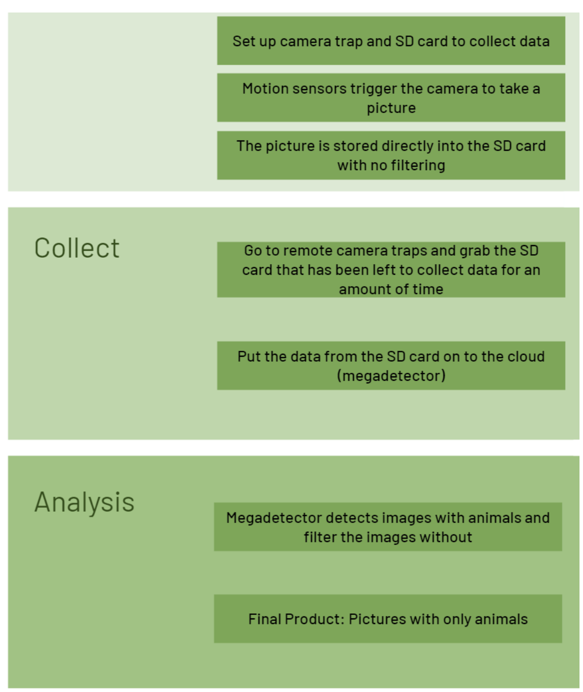

Figure 2: Current method used by Zelmer, 2020 including megadetector.

Illustrated in figure 2 is the current process that is being used by Occidental College group based upon using the megadetector for image analysis. There are a few steps in the process where data loss can occur, such as transport of data and uploading data to the megadetector because the SD card might get destroyed during the process, and human labor can also cause data loss because humans make mistakes. Based on previous data provided by the Occidental group, they found a 70% false positive rate.

1.3 Problem Statement

Wildlife conservationists who are tracking animal populations in urban areas need a way to optimize their data collection process. While the current method of utilizing wildlife camera traps can yield useful data, the manual collection and processing of image data is the limitation of the current method since it is a prototype. A new wildlife camera trap system is proposed, using edge computing to optimize detection and classification of wildlife images collected in real time.

2.0 Methods

A process has been developed that will constantly record video outside in the wild and process data in real time. The python scripted model will return the object detected inside the pictures framed selected from the video formatted data using only AI and no human labor involved to increase the accuracy and decrease data sorting time.

When the megadetector needs six steps to do all the work, the edge computing method this project is using only requires at most three steps. This project combined the middle four steps in megadetector, which is the most time consuming and mistake-happening part, into one step using edge computing so that data sorting time will be decrease and mistakes won't happen.

Megadetector	Edge Computing
Set up camera trap	Set up camera
Motion sensor triggers camera, which takes a picture	Constantly records video, detect animals real time and counts
Upload data [images] onto the cloud	
Megadetector detects images with animals and filters images without	
Volunteers checks eachimage and counts	
Returns total number of animals of each kind	Returns total number of animals of each kind

Figure 3: Process consolidation with Edge Computing

The proposed system will be constantly recording video, and collecting frames that include change using machine learning. This system is the solution to the lack of motion detection our camera traps will have.

The proposed solution of the camera will not have night vision, which will decrease the amount of data that is available. With the current data set, around 60% of it is night time, which

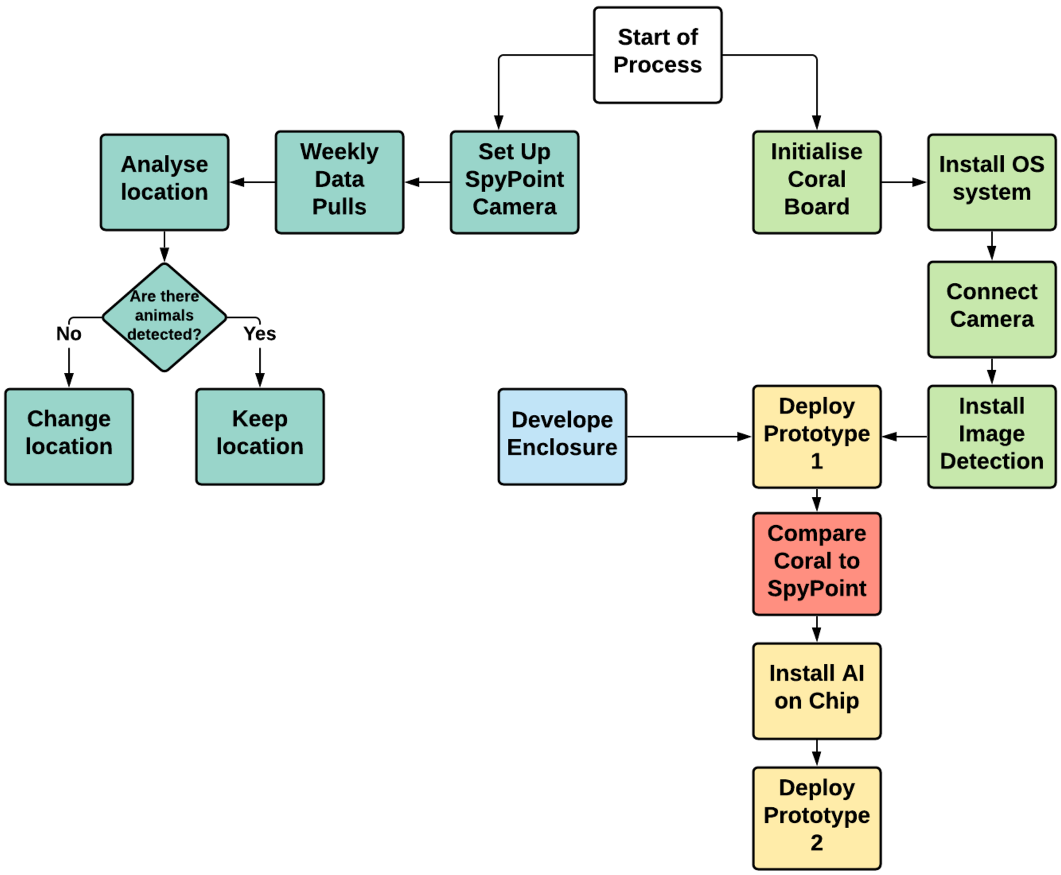

Figure 4: Proposed Edge computing process

is quite a large percentage. However, the current technology is not accessible in the forms that are available. Instead, the camera will be focused on optimizing all other aspects of collecting data. The current camera trap uses the passive infrared sensors, which detects the natural radiation emitted from animals or humans. A Coral Dev Board Mini will be utilized as the edge computing device that can run tensor flow lite and accept images selected from the video data from a camera.

2.1 Wildlife Camera Trap - Control Data

When the edge computing system is developed, a deployment site will be needed where the new system can be compared directly to legacy systems for validation. In preparation and in an effort to understand local wildlife patterns nearby, two Spypoint cameras are installed on campus at Flintridge Sacred Heart Academy. The campus is bordered on one side by a Wildlife Island and on the other by a Wildlife Corridor that connects to the San Gabriel mountains (see Figure 5).

Figure 5: Campus location

One camera was deployed in each area. One facing the island and one facing the corridor. According to Figure 5, Chloe Cam was the spypoint camera facing the corridor, so it can gather data of animals all the way from San Gabriel Mountains. Jojo Cam was the spypoint camera facing the island, it collects data of wildlife around human habitats. Six weeks of data has been collected, was manually sorted and has been shown as graphs for better comparison.

2.2 Edge Computing Development - Platform and Process

The edge computing platform selected is the Coral Mini Dev Board. This platform runs Tensor flow, which the megadetector (section 1.2) is currently using. The Coral Board was chosen for easier access to TensorFlow lite, which is the edge computing model of TensorFlow clusters. The board is able to run the camera and AI models most efficiently using a Linux terminal accessed from another laptop.

2.3 Proof of Concept of Coral Board

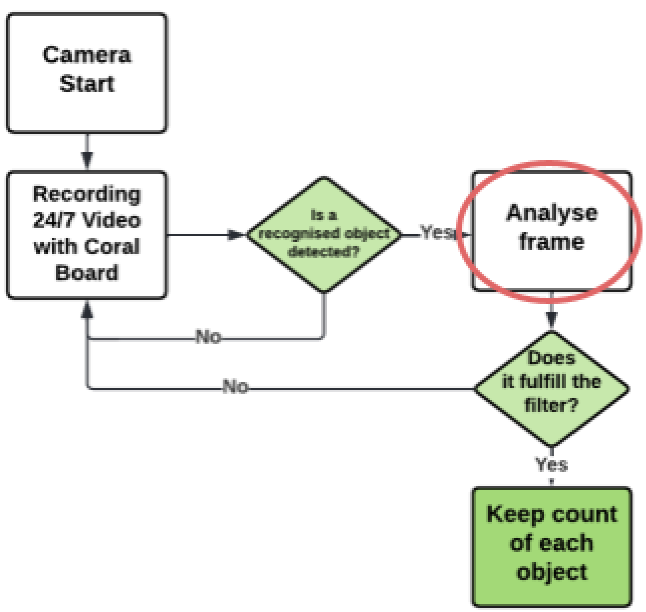

Figure 6: Device Flowchart

The project is focused on the filtering and analyzing the data from a camera video stream. The initial model used for a proof of concept demonstration is the pretrained demo model that uses an image as the input, and detects whether the image contained a specific object. The model would output a boolean of whether or not the image contained the object. The current model takes in video outputted by the camera, and runs object identification. The pre-training on this model allows for the detection of common objects, with a large list of 1000+ objects in the training set. The goal of this proof of concept is to be able to filter out the output so that only certain tags that are important are tagged. The model outputs the name of the object and the confidence score from 0-1 of how confident it is of the detected object, which is used for filtering.

To validate the filter for the most optimized data, data was collected from experimentations of showing a recognized object in front of the model facing a blank wall. The result consisted of total times the object was detected, false-positives, which refers to when the model counts an object when it is not in the frame, and false-negatives, which refers to when the object doesn't count when it is in the frame.

2.4 Edge Platform Enclosure

An enclosure is needed to house all the elements of the Edge Platform Camera, including the Coral Dev Board, the Camera and a power supply. It must be suitable for an outdoor deployment (e.g. waterproof, windproof, animal proof, etc.)

Figure 7: Spypoint Camera vs. Enclosure

The enclosure is formed with two halves of box, one fits into the other partially. The size of the interior box, which contains the camera and the coral board, is 13 cm x 10.2 cm x 5 cm. There is a window for the camera on the left top side of the box. It is covered with see-through plastic to prevent water from leaking in. There are platforms designed for both the camera and the coral board to be drilled in with spacers in between to protect the hardware. On the outside of the interior box, there is a layer of rubber band attached to the outside around the box, 3 mm next to the opening. It is a waterproof feature of the enclosure.

Figure 8: Interior box connected to the power supply

2.5 Battery life

The power needed for the coral is 2 watts. The total energy that the power supply can provide maximally is 36 watt-hours. After calculation, the battery was calculated to last for 18 hours when connected to a full running coral board and the camera, 36 / 2 = 18. The common battery usually has the energy of 1323 watt-hours, it is way more power than the power supply being used. But the reason why this project chose the power bank battery is because this is a prototype decision.

2.6 Validation Plan

To validate the project, the camera will be deployed parallel to the spypoint that has been collecting datas for months because both will be aiming at the area where wildlife are active the most, the island. The custom camera will be able to constantly record during the day and count animals later in the frame selected from the video formatted data using trained AI. In that case, this project will have more optimized data. The project will also be comparing the data collected using custom hardware between the corridor and the island. So that the trait of the land animal movement will be discovered therefore their habitat will be protected. In order to reach success in this project, the coral will have to count the number of animals similar to the spypoint camera with at most 2 units with high confidence. For example, if the coral counts 10 deers with low confidence and the spypoint counts 6, that will count as failure. But if the coral counts 10 deers with high confidence and the spypoints counts 9, that will count as success. By then, the custom machine learning camera will be as good as the spypoint.

3.0 Results

3.1 Coral Board Model Filter Data Analysis

The data collected from a camera was set up facing a blank wall. A recognised object was shown to the camera 25 times with a filter of a confidence score of >0, >0.5, and >0.7. The data shows no false-positives once there was a >0.5 (out of 1) confidence score filter in place. However, with a confidence score filter, the false positive rate becomes 28%. The results are shown below.

Total Images	Confidence Score	Number of Detected	False-Positives	False-Negatives
1,374	>0	23	2	2
1,082	>0.5	19	0	6
936	>0.7	17	0	8

Figure 9: Camera Filter Detection of Cellphones

3.2 SpyPoint Data analysis

The prediction for the data analysis result is that the corridor will have more animal appearances than the island. After further analysis, the island has more animal appearance than the corridor, which is the opposite of the prediction at the beginning of the data collection. For Corridor camera, there are 12.18% positive data out of all datas, for spy point #2, there are 7.65% positive data out of all datas. The manual sorting and tagging of image data is extremely time intensive, averaging about 1 minute per image (48 hours / 3000 images). Results of the data from the 6 week period Nov. 12th - Dec. 22nd are shown. Deer counts (by day and by week) are shown comparing the camera set up in the corridor vs the island.

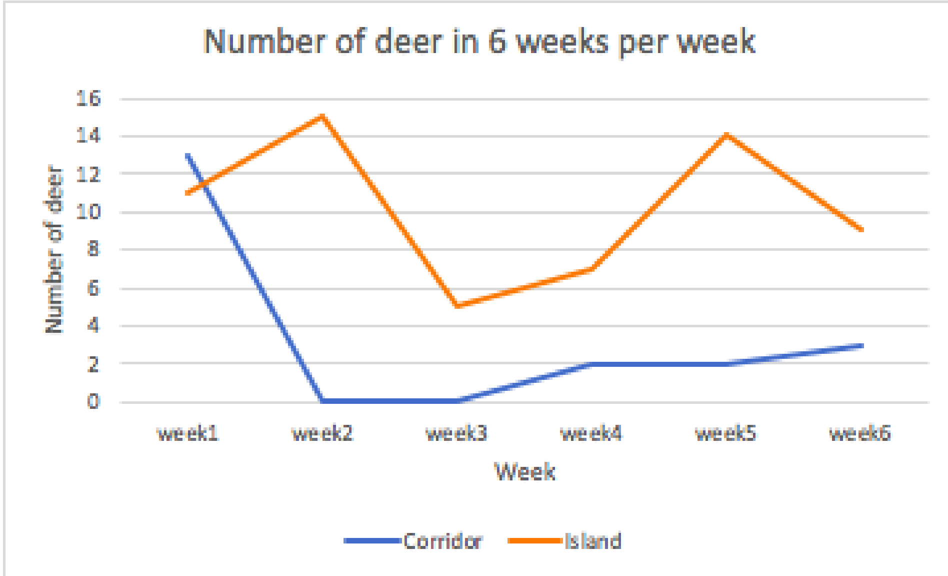

Figure 10: Graph of total deer per week in 6 weeks (Corridor vs. Island)

4.0 Discussions

After analyzing six weeks of data, it showed that the island has the most deer appearance compared to the corridor in six weeks. It is interesting because according to the overall data, the corridor has more percentage of positive data than the island, but when the data is focused on the land animal such as the deer, the island has more positive data than the corridor. It could be because when analyzing the overall data, it counted the data as the amount of pictures that contain animals, but when doing the six weeks data, it counted the animal appearance. For example, six pictures that contain the same animal would count as one appearance. The corridor spypoint is deployed to a lower tree branch facing the animal trait, the island spypoint is deployed to a higher tree branch facing directly to the deer trait. Another possible cause for the result could be that the corridor spypoint was so low that sometimes the camera would slip and hang on the branch without pointing at the trait.

When collecting the data using the spypoint cameras, the batteries of the spypoint camera will need to be repaired after two to three weeks depending on the trigger amount. The power used for the custom machine learning camera will have less time than two to three weeks because instead of triggering the camera, it constantly records video format data so it will use more power than the spypoint. However, it will reduce the amount of negative data. The power will be able to run 24/7 on the device because the power supply will be refilled artificially.

The coral board data from the results of the experiments showed no low false-positives with confidence score filter, which was favorable results. This optimizes the data in comparison to the SpyPoint data, which has a 91% false-positive rate. However, there is a 28% false-negative rate, which is high because of the filter. Without the filter the false-negative becomes 8%, however there were 2 false positives detected. The most optimal filter is a confidence level of 0.5

and above, as it has no false-positives with the least amount of false-negatives. This allows the most amount of images captured while minimizing any false positives. The most optimal data sorting would include no human labor.

5.0 Conclusions

Increasing urbanization in California is resulting in increasing isolation and segmentation of wildlife habitats. This project created a machine learning camera for wildlife detection and is able to count the appearance of animals in habitats. A waterproofed prototype that will constantly record videos in the wild is described along with a process for validation of the new system in direct comparison with typical current methods. After doing the comparison of six weeks of data between habitat on the island and the corridor, the island has the most deer appearance and is more wildlife-active. With that information, this project can now protect wildlife animals by decreasing the intrusion toward known habitats, the island.

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7.0 Appendices

Figure 11: First prototype

Figure 12: Second Prototype

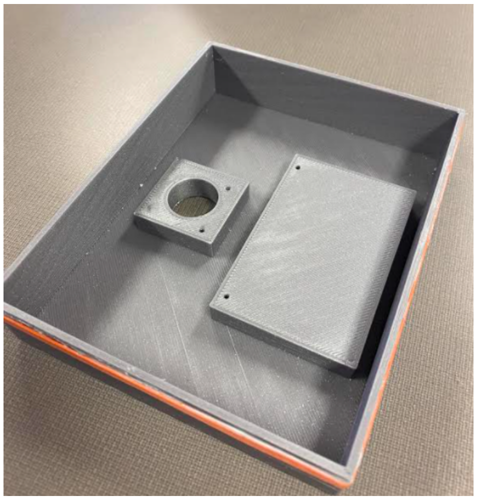

Figure 13: Third Prototype

Figure 14: Fourth Prototype

Figure 15: Camera Chloe location

Figure 16: Camera Jojo Location

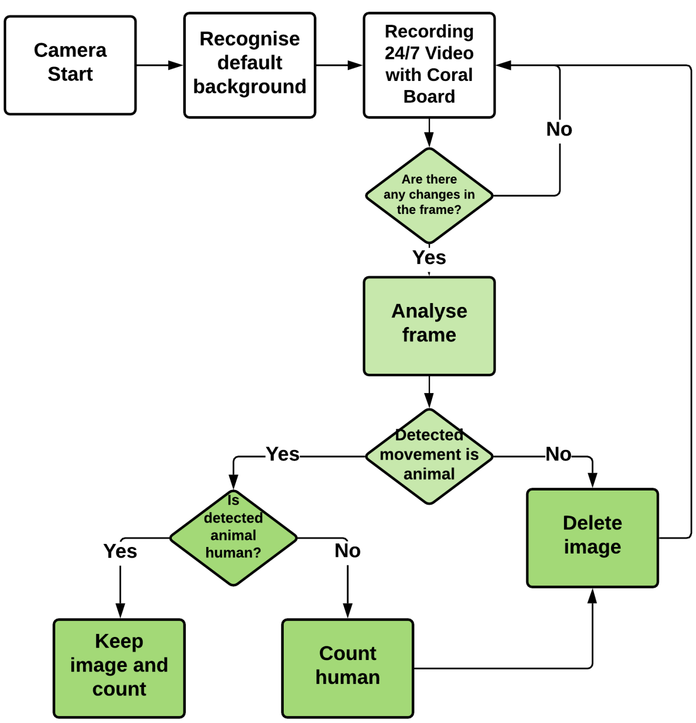

Figure 17: Flow chart of working device.