Sheep and Grass Identification

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Background:

Kauricone is a New Zealand company that creates technology solutions for businesses including servers and software while reducing the number of resources used and waste created. Kauricone wants to integrate their Internet of Things (IOT) server to a solution that uses machine learning to detect sheep and read grass (dry matter) levels.

Rationale:

According to a Stats NZ Agricultural Production Survey, in 2019 there were ***26.8 million sheep in New Zealand*** ("Livestock numbers | Stats NZ", 2021). This R&D project of testing Kauricone's IOT servers in rural areas in New Zealand will assist in farming management and other agricultural endeavours.

The project will allow farmers to identify sheep through machine learning and assess dry matter levels within a paddock, all while reducing the usage of computing power. This project will improve automated systems for managing farms by reducing time and labour costs spent by farmers.

Project Approach:

This project is sectioned into 3 parts, The first part is developing a system that detects and counts the sheep. Second, is Identifying the sheep individually. And finally, detecting the level of dry matter in the grass. Consulting our mentor Parma, regarding the objectives of Kauricone he believed that we would not be able to achieve all 3 objectives and that we should drop part 2 as it is infeasible with the rest of the project scope and allocated time.

Objectives:

- To develop a vision system that detects and counts sheep within a paddock
- To use a vision system to identify sheep individually in a paddock
- To detect the level of dry matter within a paddock
- To have the first 3 goals run internally on Kauricone's ARM server
- To send the results of the first 3 goals to the farmer via text message or email.

Outcomes the client would like to see:

- 85% accuracy at sheep detection
- 90% accuracy at dry matter reading
- Server must run 24/7
- Notifications sent in regular intervals (At least once a day)

Project Product:

Using Kauricone's IoT Server, we need to write code that can automate the ETL processes of collecting images from a server, use machine learning algorithms to train models that detect sheep and assess dry matter levels in a paddock, and send an email to the client with a report of the algorithm's results.

For this project, we had to use the following tools, packages, libraries, and programming languages:

- Linux Shell Commands/Scripts (Server-based Operations)
- Linux Crontab (For Server Tasks Automation)
- Roboflow (For Annotation)
- JSON (Recording results in readable format)
- Python, Including the key packages of Detectron2, YOLOv5, PyTorch and OpenCV

PART 1: Sheep Detection

How it Works:

1. The camera takes a least 5 or more images throughout the day
2. The Detectron2 algorithm runs through all these photos
3. Detectron2 counts all the sheep in all the images
4. The median amount of the sheep detected in the paddock is calculated
5. An email is sent to the farmer with the time the images were taken, how many sheep could be seen from the images and the median number of sheep.

Main Artifacts Produced:

Sheep detection using Detectron 2

What did not work well:

- Occasionally sheep aren't in field of view so aren't' detected


Sheep Update for 09 October 2022 Inbox ×

teamsheepftw@gmail.com
to me

Hi Farm_Owner,

Results for 09/10/2022:
-Script Runtime: "2022-10-09 17:00:44.927943"
-Images Tested: 49
-Sheep Count Median: 1
-Sheep Count Maximum: 2

-Dry Matter Median: 92.62%
-Dry Matter Maximum: 98.28%
-Dry Matter Minimum: 0.66%

A sample of todays processed images are attached below.

--TeamSheep--

3 Attachments • Scanned by Gmail

The email the farmer will receive

Detectron2 Results

PART 3: Dry Matter Readings

How it Works:

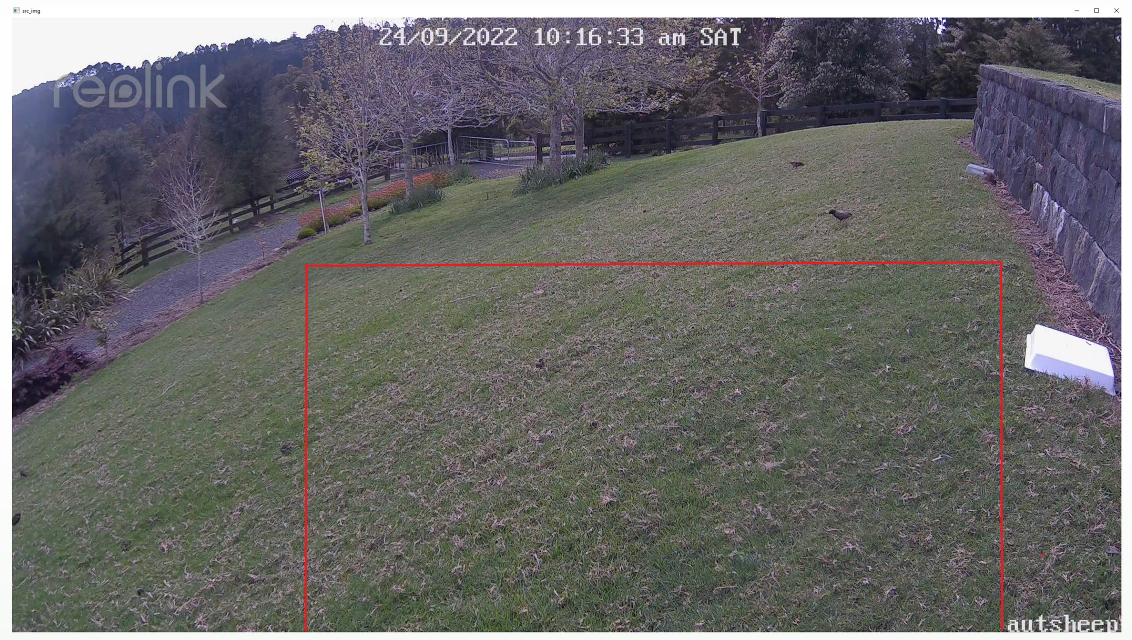
1. Crop a section of the image to only have grass
2. Get the average pixel color value of the cropped images
3. Get the RGB value of the average pixel color and run it through the model
4. Receive an output of either 1 or 0, 1 being more grass, 0 being less

Main Artifacts produced:

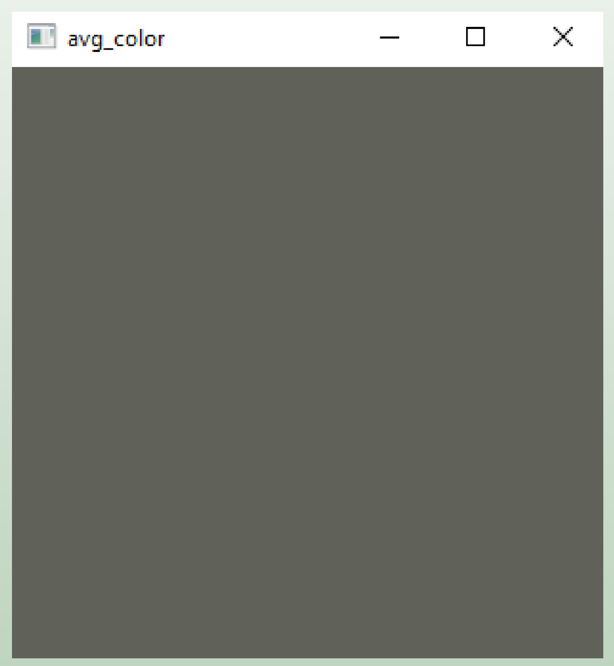
Dry Matter Identification using Neural Networks

What did not work well:

- Camera set up wasn't ideal
- Dry matter differences were too subtle
- Dataset used to train the model was too small
- Sheep interfere when cropping the images



What will be cropped from the original image



Average pixel color value

Challenges Faced:

- **YOLOv5 - > Detectron2**

Our client believed that using the You Only Look Once (YOLO) object detection system would be beneficial as it would be the most modern approach to detecting the sheep without having to build the model from scratch. We tried to use YOLO version 5 and produced a model with 71% accuracy. We were stuck on this accuracy, so we pivoted and used a different algorithm to train the model recommended by our moderator; the Detectron2 Framework.

- **Fuzzy Logic System -> Neural Network**

We began coding for dry matter reading by using a fuzzy logic system that took good grass and bad grass as input and produced rules for solution. The models were inaccurate because the fuzzy logic system couldn't produce rules that could accurately differentiate between good and bad grass.

Experiments and Results

By using Detectron2's pretrained models we managed to get an 84% accuracy on detecting sheep. We decided this was the best way to solve our problem as we lack enough images to train the model from a noise free dataset. The accuracy of the algorithm was consistent when the sheep were in the field of view of the camera and were inside the paddock. We believe we could achieve a better result if we could alter the position of the camera by moving the camera higher up and have it look down.

For part 3 we tried various methods to solve this problem mainly, fuzzy logic and neural networks (NN) to identify the dry matter within the grass. We settled on using NN as they were more adaptable to the task. We utilized a method which determines the average color pixel of the grass images and runs that output through a NN which, upon testing, gave a consistent 90% accuracy.

```
1/4 [======>.......................] - ETA: 0s - loss: 0.2042 - accuracy: 0.9062
4/4 [==============================] - 0s 997us/step - loss: 0.1915 - accuracy: 0.9286
[0.1914958655834198, 0.9285714030265808]
```

Dry Matter Algorithm Output

Kauricone IoT ARM server

Reference:

Livestock numbers | Stats NZ. Stats.govt.nz. (2021). Retrieved 3 October 2022, from https://www.stats.govt.nz/indicators/livestock-numbers.