

Introduction

The activity level of an animal (i.e., the distance it traveled) is an important proxy for its current health state. Sluggishness and lameness can be early indicators of illness [1].

Despite the common use of cameras on farms and ranches, limited time and resources prevent farmers from fully utilizing their monitoring capabilities. Additionally, the scale and variety of livestock footage make it impossible for traditional programs with pre-designed instructions to monitor sheep in real-time.

Deep learning allows us to autonomously glean insights from data that would otherwise go unused or require extensive human monitoring. However, there has not yet been an effective method to precisely track moving objects (i.e., livestock) over time without losing track, nor to accurately calculate the physical distance they have traveled in real time.

To address this gap, we developed an algorithm to accurately track sheep from frame to frame and compute the distance they traveled in real time, using YOLOv8 [2] as our foundational model for object detection in each individual frame.



Figure 1. A training example after data augmentation



Data Collection and Preparation

We collected footage from a local lowa farm. A random subset of frames was sampled from the video to create our dataset, and each sheep in every frame was labeled using bounding boxes.

The dataset was then split into training, validation, and test sets. Each example in the training set was augmented into seven examples by adjusting the brightness, exposure, and bounding box rotation (Fig. 1). Data augmentation helped the model better distinguish between the sheep and the background, improved its adaptability to different lighting conditions, and reduced the risk of overfitting.

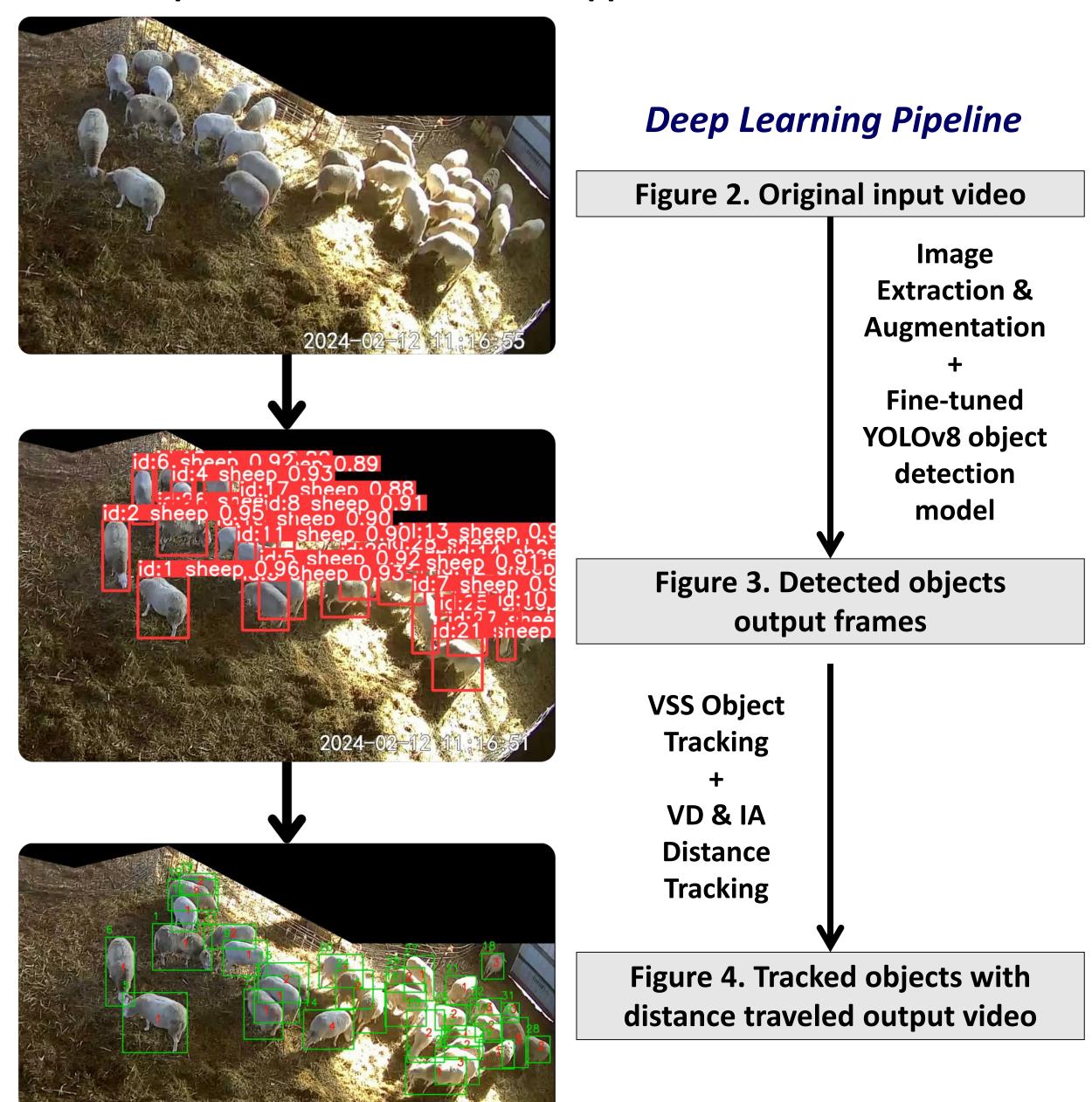
Monitoring Sheep Health with Deep Learning

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Method

- We fine-tuned an object detection model specialized in detecting sheep using YOLOv8.
- Using the number of sheep in the pen as an invariant, we developed an algorithm using vector similarity search to map the sheep from one frame to the next.
- We transformed 2D bounding box coordinates from detected images to 3D physical coordinates using vector decomposition and infinitesimal approximation.



Results

Class	Box	Box	Box	Box
	Precision	Recall	mAP50	mAP50-95
all	0.991	0.993	0.993	0.833

Box mAP50 indicated that 99% of predictions have over 50% Intersection over Union (IoU) with the ground truth.

Even under the stricter mAP50-95 benchmark, which measures the average performance across IoU thresholds from 0.5 to 0.95 in steps of 0.05, the model achieved a score of 0.833 out of 1.

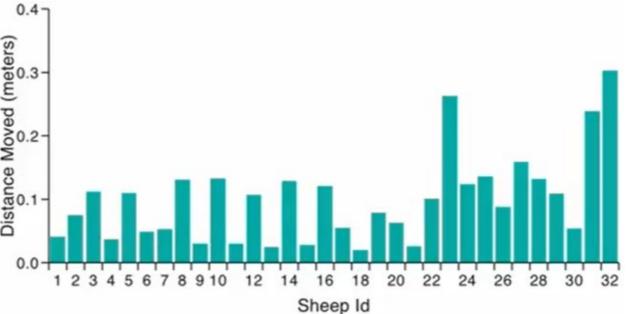


Figure 5. Bar graph of individual sheep movements at a specific time interval

Conclusion and Future Work

Our approach was able to accurately autonomously extract insights into sheep health through their movement, providing early warnings to farmers with minimal time and resource investment on their part.

Further improvements include refining the model's box mAP50-95 metric to calculate more precise distances. We will also test the model on a new dataset of sheep to assess its generalizability.

References

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