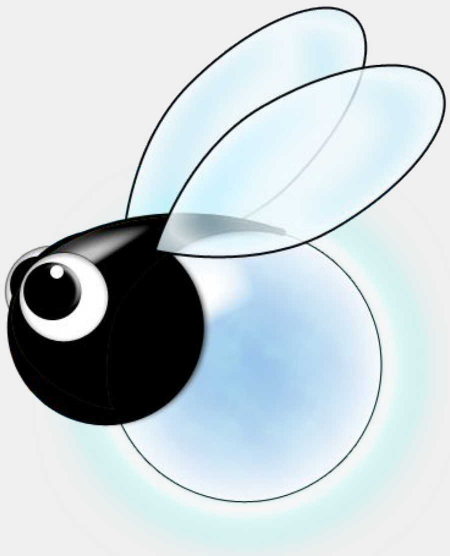
Firefly



Theme

Tech 4 Autonomous

Recognition of thin cross-section objects changing direction (e.g. a cyclist, pedestrian)

Outline

- The Problem
- Solution Proposal
- Implementation: Architecture
- Demonstration
- Future Scope

The Problem

Recognition of thin cross-section objects changing direction (e.g. a cyclist, pedestrian)

AUTOMOTIVE

Uber Self-Driving Car Fatality Reveals the Technology's Blind Spots

The ride-sharing company has halted its autonomous vehicle testing while it investigates the accident in Arizona

By Larry Greenemeier on March 21, 2018

READ THIS NEXT

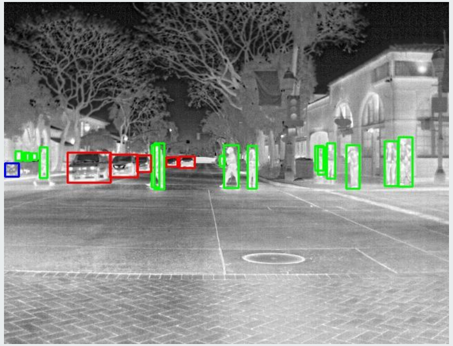
AUTOMOTIVE

A self-driving Uber sport utility vehicle struck and killed a pedestrian in Tempe, Ariz., on Sunday night. Elaine Herzberg, 49, had been pushing a bicycle across a busy road about 100 meters from the closest pedestrian crosswalk when she stepped in front of the vehicle, which was traveling 38 miles per hour in a 35 mile-per-hour zone, Tempe police chief Sylvia Moir told the *San Francisco Chronicle*. The fatal accident prompted Uber to temporarily halt testing of its driverless vehicles on public roads in Phoenix, Pittsburgh, San Francisco and Toronto.

Finding the best ways to do good.

In addition to worrying about how **safe** they are, how they'd handle tricky **moral trade-offs** on the road, and how they might make **traffic** worse, we also need to worry about how they could harm people of color.

If you're a person with dark skin, you may be more likely than your white friends to get hit by a self-driving car, according to **a new study** out of the Georgia Institute of Technology. That's because automated vehicles may be better at detecting pedestrians with lighter skin tones.



- Bicycles are generally considered “the most difficult detection” problem that autonomous vehicle systems face.
- Unmanned vehicles cannot rely on visible images while navigating in cloudy weather/ low sunlight or during the night.

How is it done today?

Camera(RGB) + LIDAR

We have already discussed, using only visible spectrum images would incur a lot of fatalities while working in dim/low light environment.

The data from LIDAR can be too coarse to detect objects at further distances and may lack the resolution to classify objects.

What to do?

When changing the world is difficult, we change ourselves.

If cars are going to drive the roads without human help, they need to be able to handle all of the challenges that come with it, regardless of whether they're connected to the world around them.

Implementation

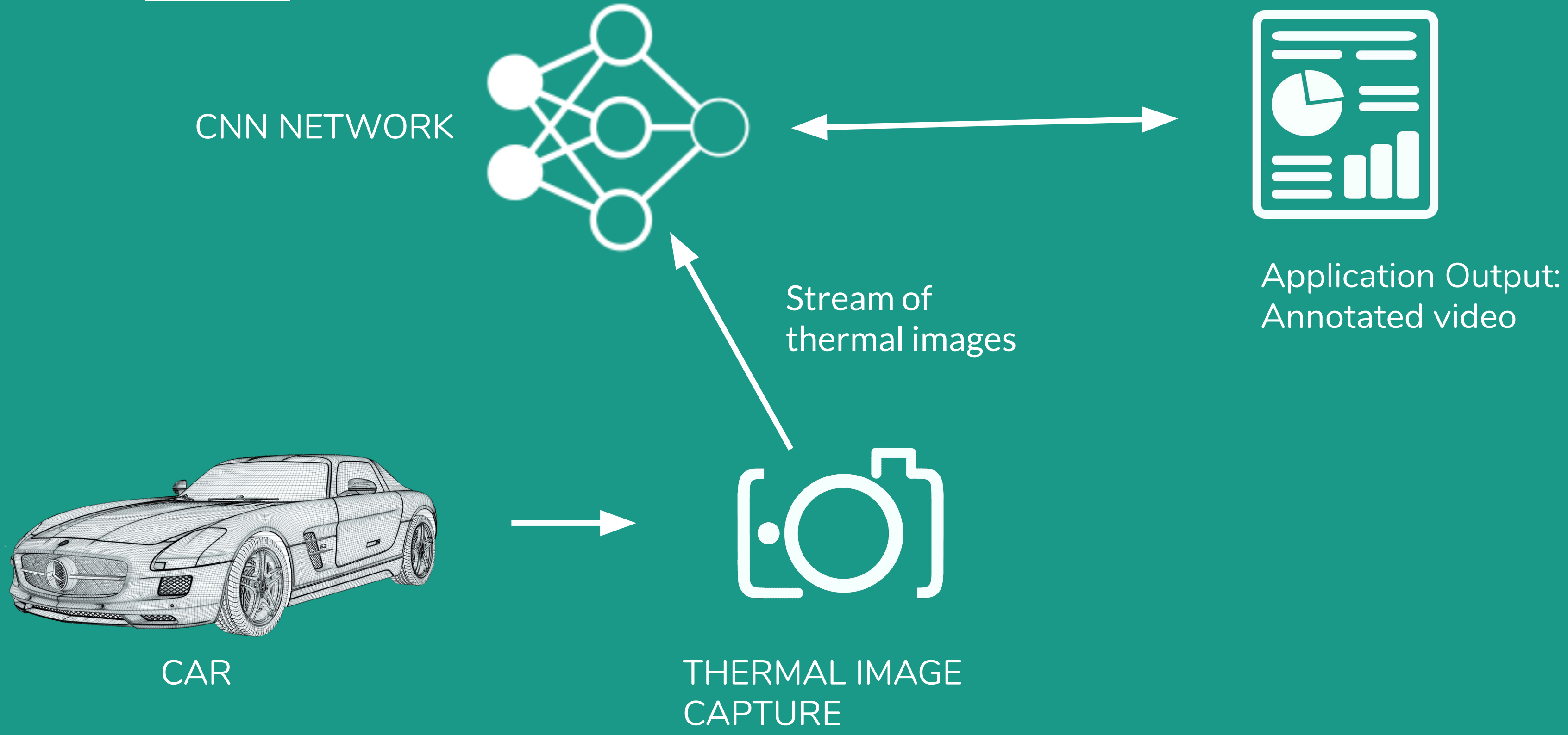
We use thermal Images!

- The FLIR dataset : helps detect and classify pedestrians, bicyclists, animals and vehicles in challenging conditions like total darkness, fog, smoke, inclement weather and glare.

- Provides a supplemental dataset beyond LiDAR, radar and visible cameras.

- Detection range: 4x farther than typical headlights.

SOLUTION ARCHITECTURE



How does the dataset(FLIR) look?

Why is it better than existing solutions?

Augmenting visible and thermal images with depth perception by LIDAR could help in precise detection and classification. With improved vision and perception the autonomous vehicles would be safer for the society.

A pedestrian is obscured by the fog in the RGB Image but is evident in the thermal image.

A pedestrian is obscured by smog in RGB while can be clearly seen in the Thermal image

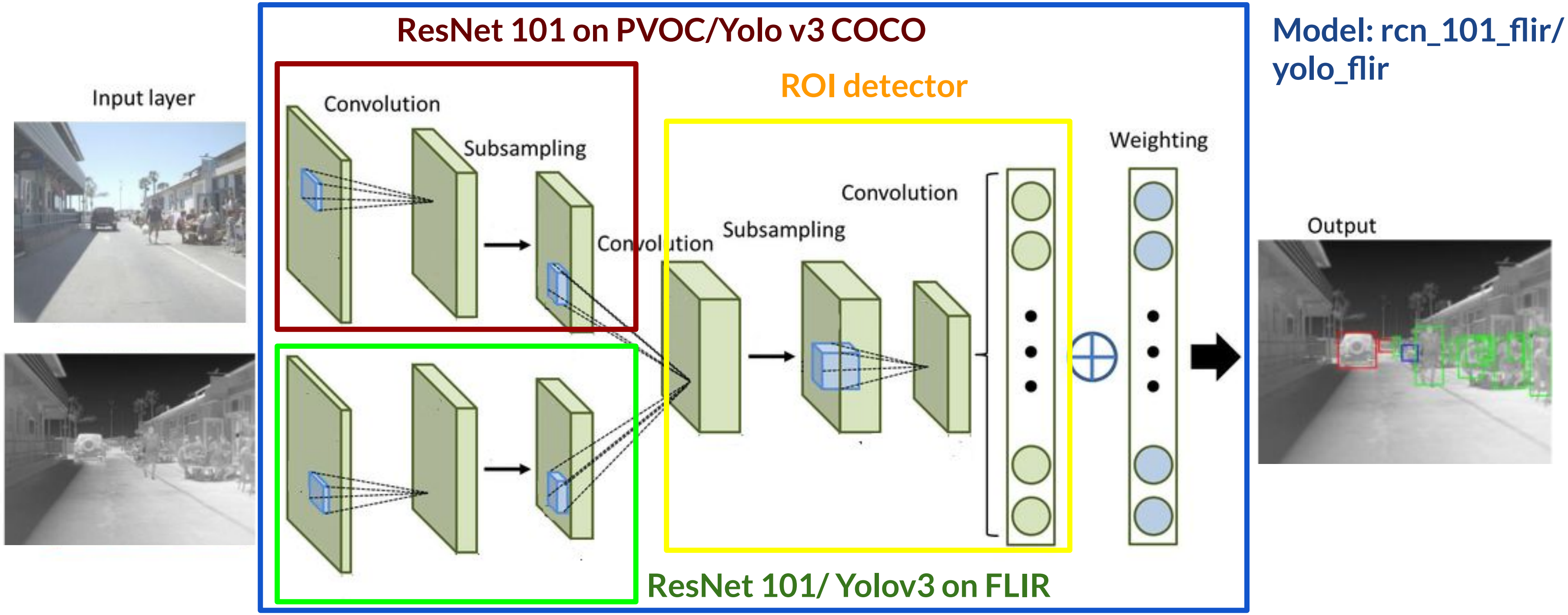
Approach

- **Preprocessing :** Enhance edges using a Butterworth high pass filter.

- **Pretrained RGB network on PVOC:** ResNet/ YoloV3 pre-trained detector initialized by **PASCAL-VOC**

- **Pretrained network on FLIR ADAS:** ResNet pre-trained detector initialized by **FLIR Dataset.**

- Training the combined architecture on thermal images to predict a Bounding box around ROI.



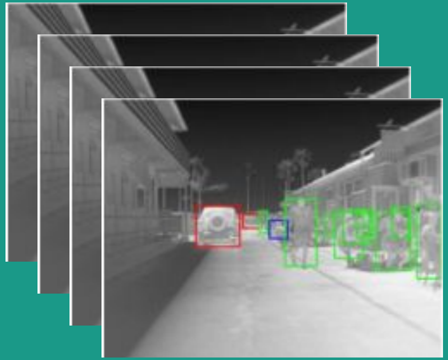
Deep learning architecture to Object Detection using Thermal Imaging. The network takes RGB and thermal images to predict a bounding box around ROI objects.

Why Resnet 101/Yolo v3?

Usage

Thermal Images or thermal image video stream

FLIR trained model:
rcn_101_flir yolov3_flir



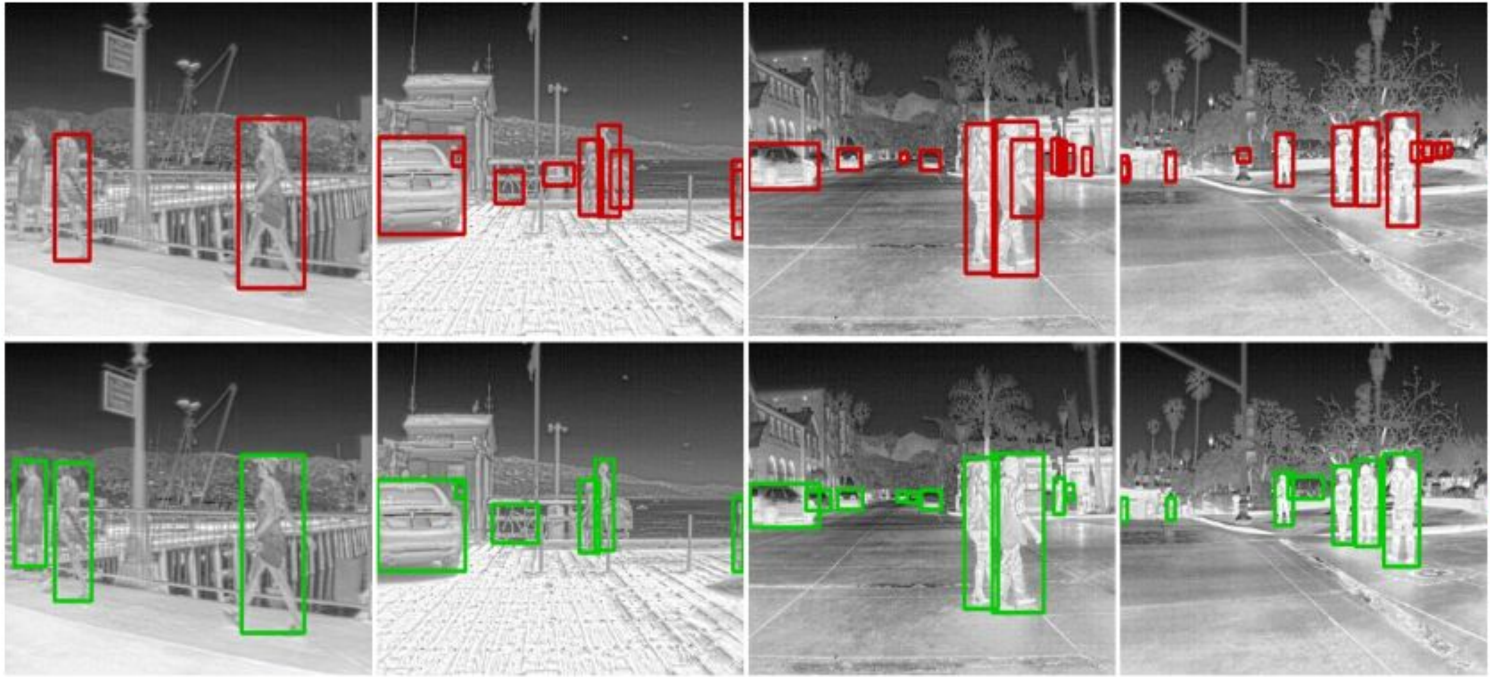
Input stream

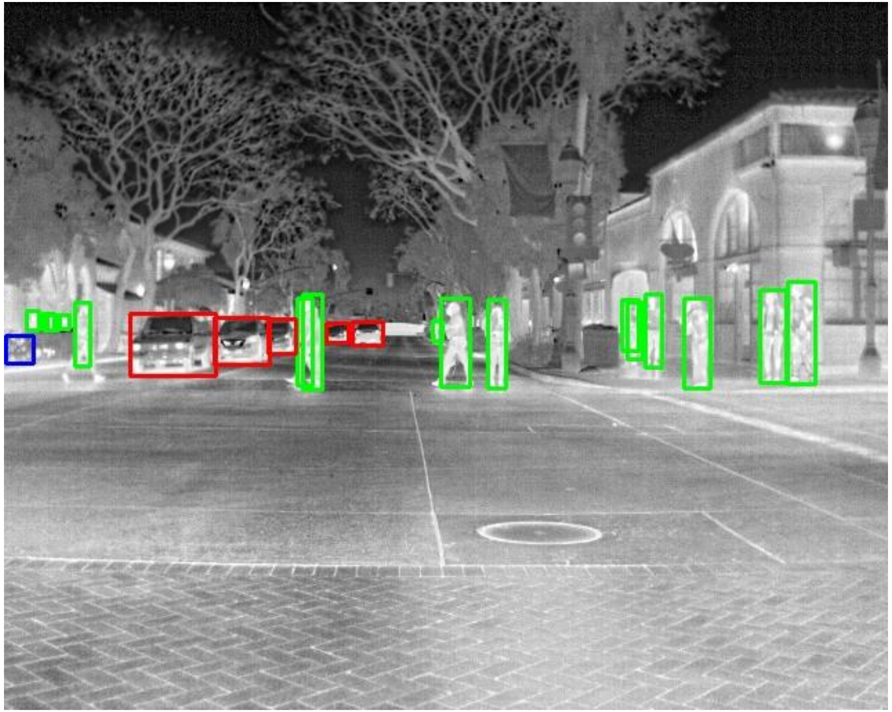
Output stream

Baseline (Green) vs Our results (Red)

Baseline[1]

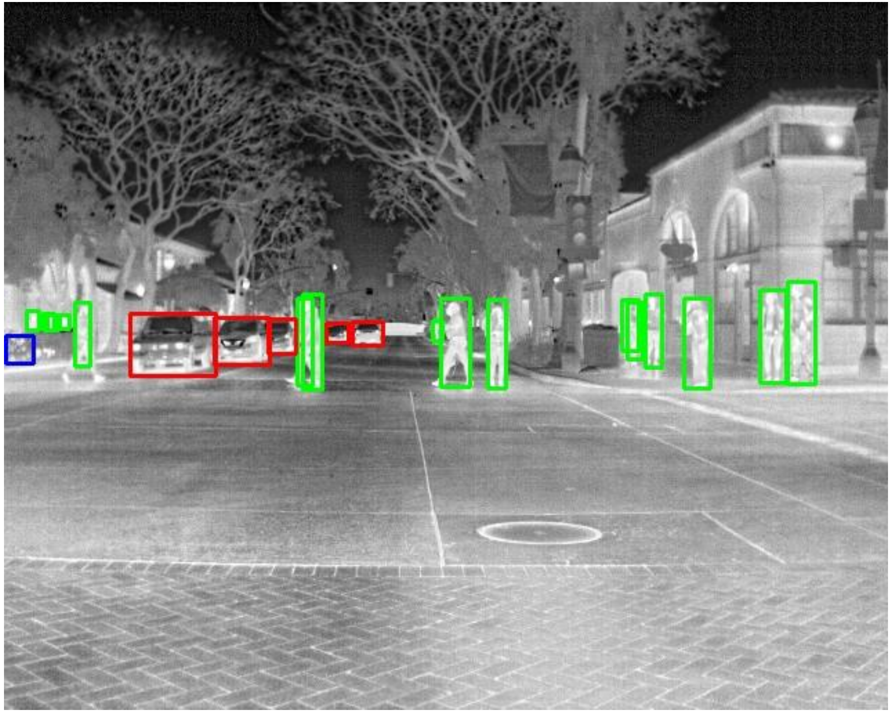
Our N/w

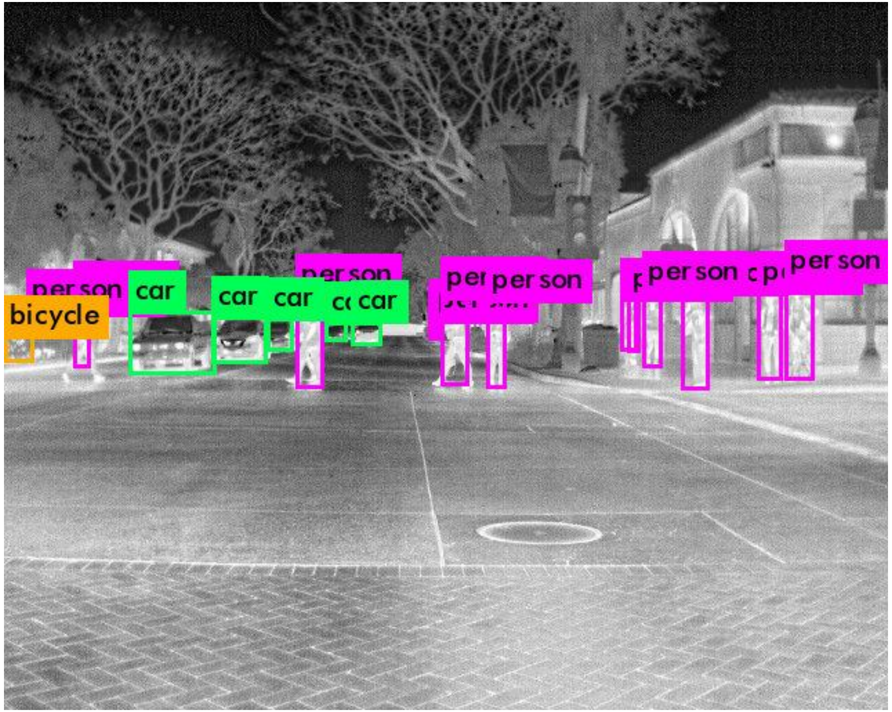




Ground Truth

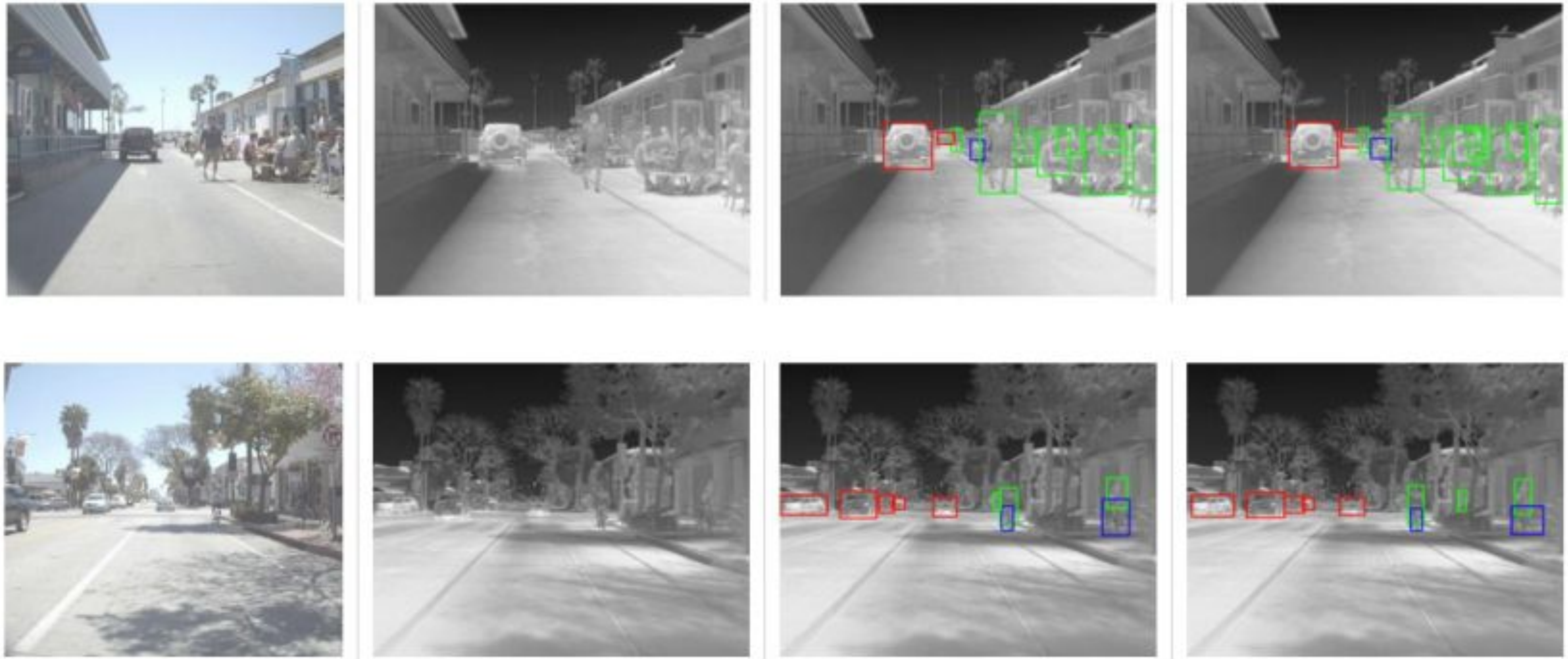
YoloV3 on RGB: Results





Ground Truth

YoloV3 on thermal results



Actual image | Thermal image | Baseline[1] results | Our results

RESULTS: Evaluation metric: Average precision

Mean average precision over all classes: **61.54 (59.91 on1/2 the data)**

This table shows the AP: Average precision over the three classes:

Model	**Bicycle**	**Person**	**Car**
Our model	49.43	64.47	70.72
Baseline: [1] Faster-RCNN	39.42	52.75	62.07

Difficulties

- Merging of foreground and background in thermal images especially during summers.
- Masking of heat signatures by warm clothes especially during extreme winters
- Missed detections when there is heavy occlusion.

Future Scope

1. Terrain detection to have a better control on the speed and have a smooth journey.

2. Add more categories for the thermal images dataset and analyse the network.

3. Combine optical flow information of hetrogenic agents(pedestrian, bus, car cycle etc.) to predict the motion trajectory using spatiotemporal information




Tech Stack

- Keras & TF: Deep learning framework API.
- OpenCV: Preprocessing of images
- Pandas & Numpy: Matrix computation and algebra.

Dataset: FLIR Thermal Dataset.

Team : HEURISTIC

Laisha Wadhwa
IIIT Sricity

Mehul Kumar Nirala
IIT Kharagpur

Source code

References

[1] S. Ren, K. He, R. B. Girshick, and J. Sun. Faster R-CNN:towards real-time object detection with region proposal networks.CoRR, abs/1506.01497, 2015.

[2] F. A. Group. Flir thermal dataset for algorithm training.https://www.flir.in/oem/adas/adas-dataset-form/, 2018.

Thank You

Questions?