

Team 9: Combat Wombats

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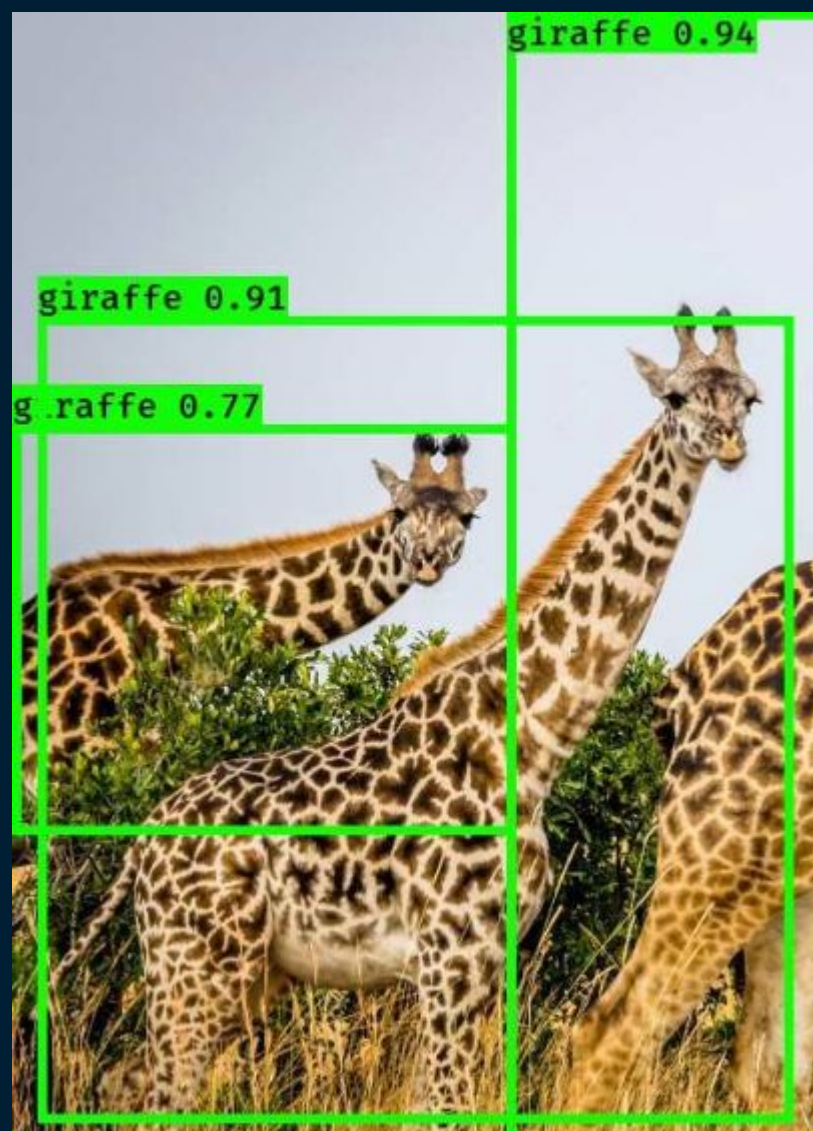
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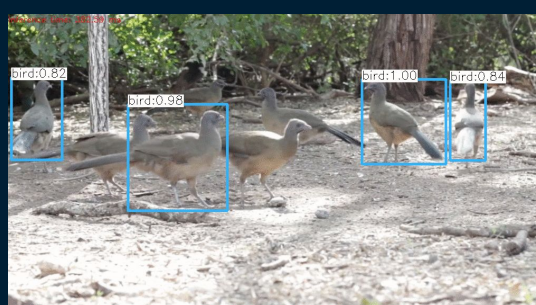
Introduction

Real-time object detection using machine learning has existed for several years, however historically the costs and computational requirements have been too high for many implementations.

Delivering a low-power, low cost solution presents an opportunity for industries and efforts that have yet to employ ML to solve difficult problems due to power or cost constraints.



Applications



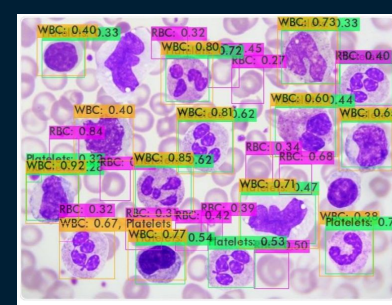
Wildlife

Wildlife monitoring and conservation efforts



Drones

Delivery and surveillance efforts



Medical

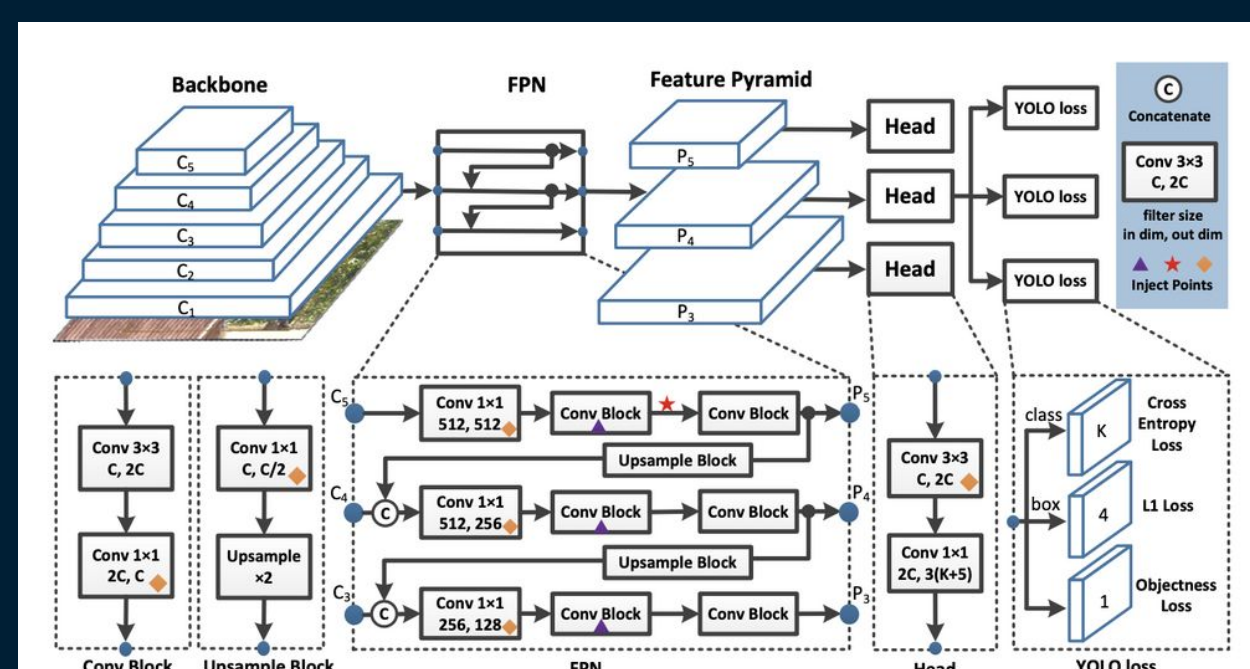
Medical diagnoses

The objective of this project was to train a deep learning neural network to perform object detection and deploy the model with optimization to the low-power, low-cost NVIDIA Jetson Nano.

Theory

The YOLOv7-tiny machine learning algorithm inputs video and outputs classified objects in real-time. Inference is run on the Jetson Nano GPU and the classified objects are displayed on a monitor.

- Webcam takes in video frames and passes them through an image pipeline to be analyzed by the YOLOv7-tiny model
- YOLOv7-tiny analyzes the input images and simultaneously creates bounding boxes around objects and classifies them



Target Performance Metrics

Frames Per Second	≥ 12
Power Dissipation	$< 10W$
Cost Constraint	\$300
mAP (Accuracy)	$\geq 30\%$

Balancing the tradeoffs between these metrics was essential to our project. Increasing FPS and mAP negatively impacts power dissipation, so tuning variables such as inference resolution, model size, and parameter precision was necessary to optimize the model enough to run on low-powered hardware.

Hardware Selection

Several hardware options exist, however few met the criteria of being able to run the latest object detection algorithms effectively while remaining low-cost.

The **NVIDIA Jetson Nano** was selected for the project due to its performance to cost ratio and developer support.



Preliminary Design

- Unoptimized YOLOv7 base model extracted from training on the COCO dataset in Google Colab and deployed to Jetson Nano
- Inference running on Jetson Nano using live webcam video

Optimization

- Baseline metrics were 7 FPS and 35% mAP
- The inference resolution was reduced to increase performance
- TensorRT optimization was implemented to reduce complexity of model

Results

Frames Per Second	~12
Power Dissipation	$< 10W$
Cost Total	\$272
mAP (Accuracy)	42% Avg

Target performance metrics were met. These are intermediate results that were recorded prior to completion of project.

Conclusion

Successfully deployed an optimized, real-time object detection model on the NVIDIA Jetson Nano and met all target performance metrics.

Low-power, low-cost solutions for object detection like this project present an opportunity for industries and efforts that have yet to take advantage of object detection to solve problems.