Technische Universität Kaiserslautern

Real-time Object Detection for Disaster Management from Aerial Imagery

Accelerated deep learning for immediate disaster response

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Group Members:

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FINAL
DEFENSE
PRESENTATION

FYP CHECKLIST

- FYP report reviewed by the Advisor ☑
- FYP report uploaded on PMS ☑
- FYP demo reviewed by the Advisor ☑
- FYP demo uploaded on PMS ☑
- Course Feedback ☑

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Introduction

- Quick identification of extent of disaster helps minimize losses and alleviate impacts of disaster.
- Unmanned Aerial Vehicles (UAVs) facilitate enhanced situational awareness for many emergency response applications due to operation in remote and difficult-to-access areas

Problem Statement

Lack of appropriate and rapid assistance to disaster victims due to ineffective identification and assessment of disaster-stricken area.

1

DETECTION

Tardy identification of disasters causes widespread fatalities as well as economic damage

2

INTERNET CONNECTIVITY

Communications breakdown and disconnections due to disasters

3

LOCALIZATION

Its time consuming for rescue teams to locate and aid victims

Fatalities and economic losses worldwide

Austrialian Bush fires nearly 186 hectares burnt

Floods, fires and earthquakes can cause massive loss of life , if not timely managed

Proposition

A deep-learning approach to effective and immediate disaster response and management

Objectives

Following are the objectives of this project:

1

Disaster Area Estimation

Spatial estimation of area impacted by disaster

2

Victim Localization

Identification and localization of humans and vehicles from live feed

3

Accelerated Real-time inference

Memory and power-efficient models accelerated to produce results in real-time

System Overview

UAV Surveillance

Disaster / Catastrophe →

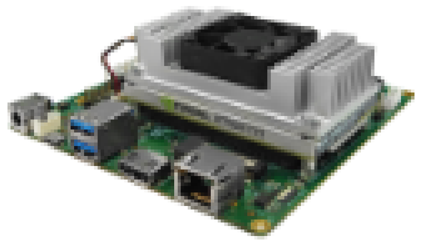
Image
Location
Height data →

Transmitted to

RTDM MODULE

Onboard analysis

Results on User Interface

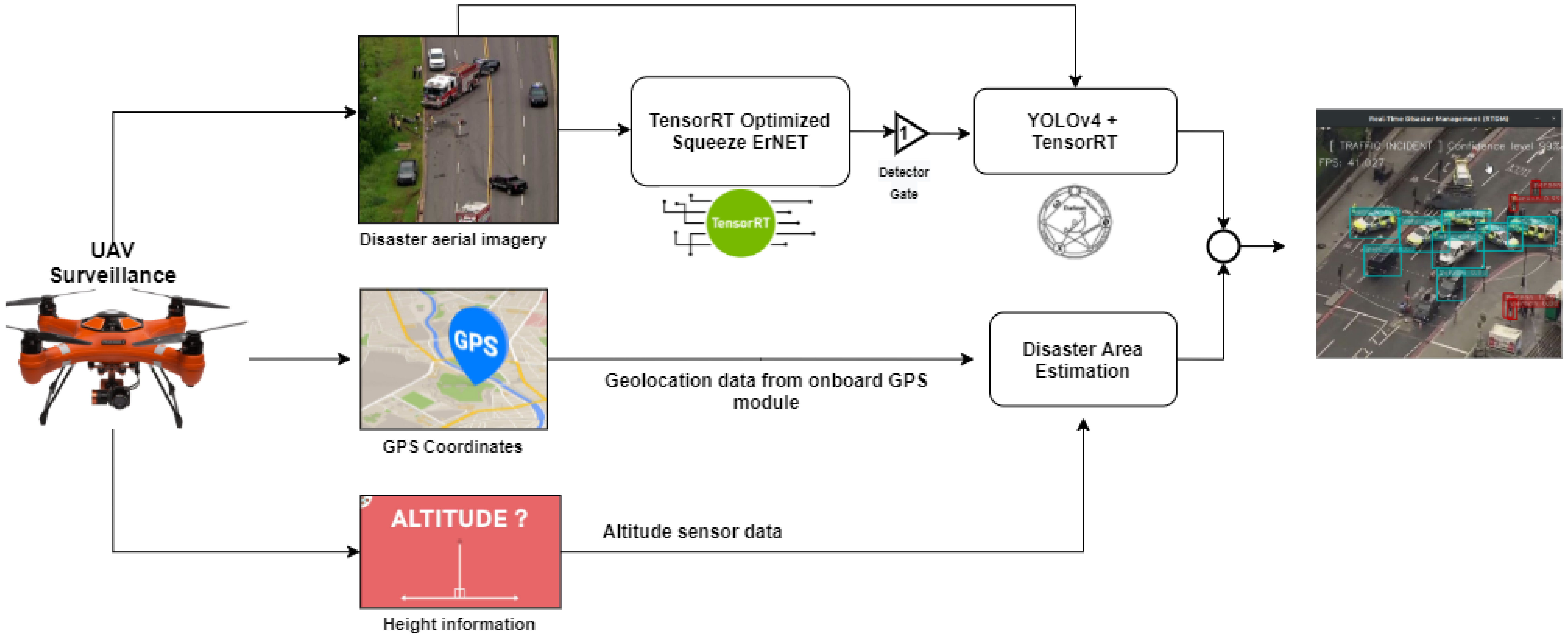


NVIDIA JETSON TX2

LiPo Battery +Peripherals

RTDM: **R**eal **T**ime **D**isaster **M**anagement

Real-Time Disaster Management (RTDM) Module



Methodology

A three step approach

1

Real-Time Classification

Accelerated deep neural network with minimum memory footprint for on board processing

2

Real-Time Object Detection

Detection of humans and vehicles with substantial mAR and mAP score on aerial imagery

3

Hardware Deployment

Integration and deployment of proposed models on embedded platforms

Novel Contributions

A state-of-the-art deep-learning approach to effective disaster management and response

1

Architecture

A compressed deep neural network to classify a disaster struck area in real-time

2

Dataset

Introduction of an object-detection dataset for emergency response in VOC format

3

Object-detection

An accurate object-detection model to quickly localize humans and vehicles in a disaster scene from a UAV

4

Hardware Accelerator

Development of a hardware accelerator for the proposed models

Datasets

AIDER

A dedicated dataset for disaster classification is referred as AIDER (Aerial Image Dataset for Emergency Response Applications. It contains 5 disaster classes and 6433 images.

ODDER

Object Detection dataset for Emergency Response- named as ODDER. It contains 2 classes - person and vehicle and about 1428 images.

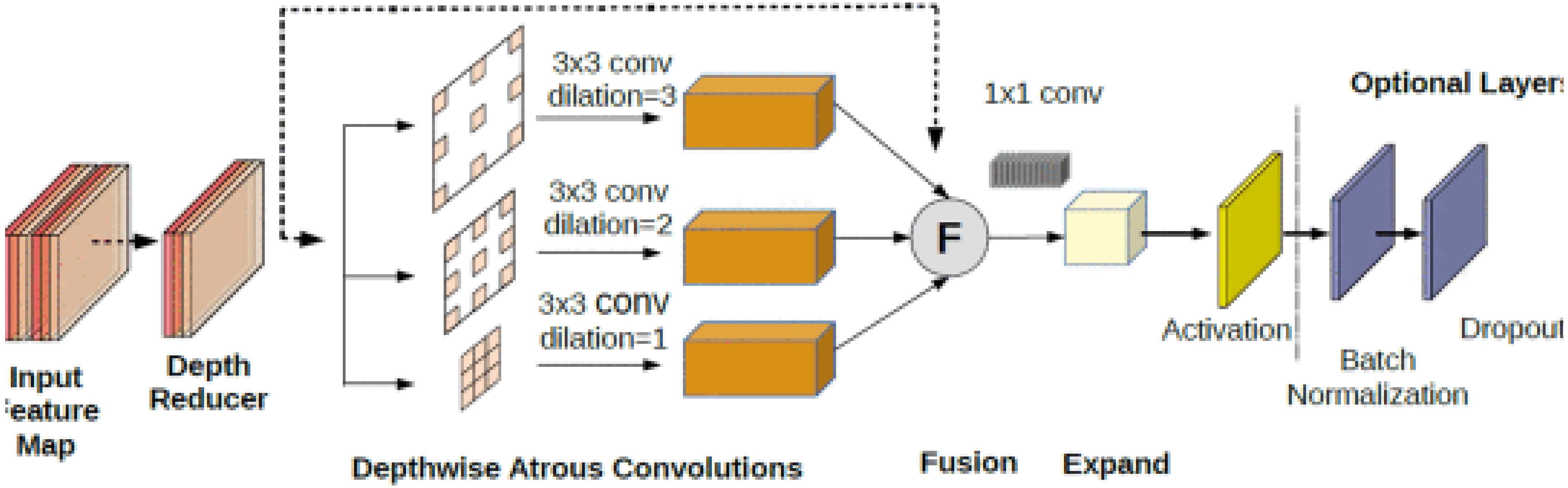
Disaster Detection Timeline

- DATA AUGMENTATION
- MODEL IMPLEMENTATION
- TUNING & OPTIMIZATION
- TENSORRT ACCELERATOR

- Augmented the AIDER Dataset with Gaussian Blur, RandomCrop, Flip and rotate transformations
- Implemented 3 lightweight DNN architectures for efficient classification
- Utilized multiple model optimization tools to achieve maximum performance
- Developed NVIDIA TensorRT-accelerated classification model and deployed on NVIDIA Jetson TX2

Disaster Detection

CNN architectures based on a custom module have been developed in PyTorch for disaster detection on aerial imagery. Atrous convolution block is basic building block of our proposed architectures which accounts for variable resolution aerial imagery using dilated convolutions and feature fusion.



Proposed Architectures

We have proposed two custom novel architectures for disaster image classification having ACFF as their fundamental building block.

1

Squeeze ErNET

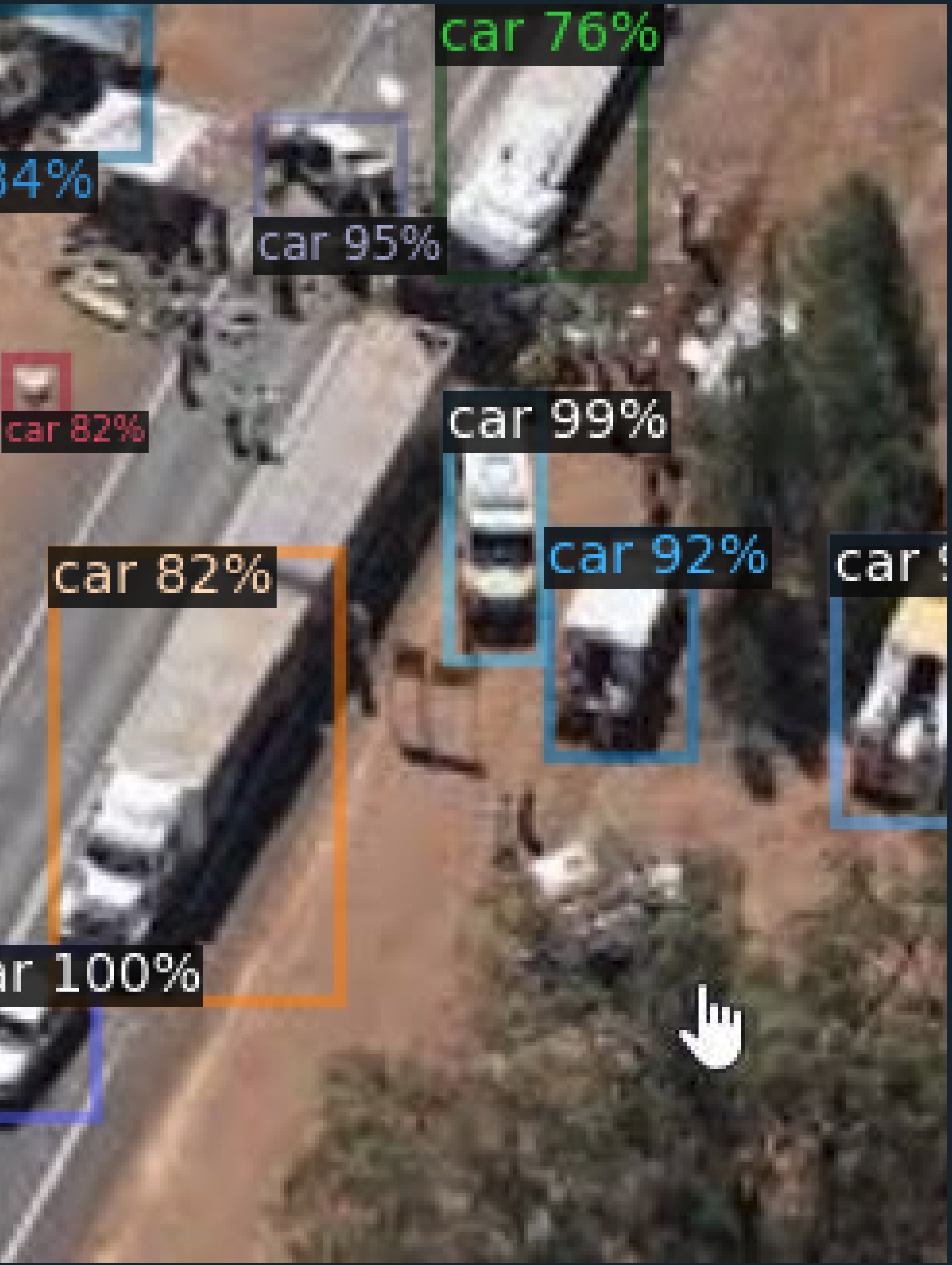
2

Squeeze ErNET RedConv (Reduced Convolutions)

- DATA LABELLING
- SOTA MODELS TEST
- CUSTOM MODEL IMPLEMENTATION
- TUNING & OPTIMIZATION
- TENSORRT YOLO ACCELERATION

Victim Localization Timeline

- Labelling of Aerial Imagery Datatset for Emergency Response (AIDER) for object detection in Pascal VOC format
- Comparison and analysis of trained models with Faster-RCNN and YOLO v5,v4 and v5
- ACFF Backbone YOLO implementation
- Transfer learning
- Hyper parameter optimization
- TensorRT Acceleration for real-time performance



Object Detection

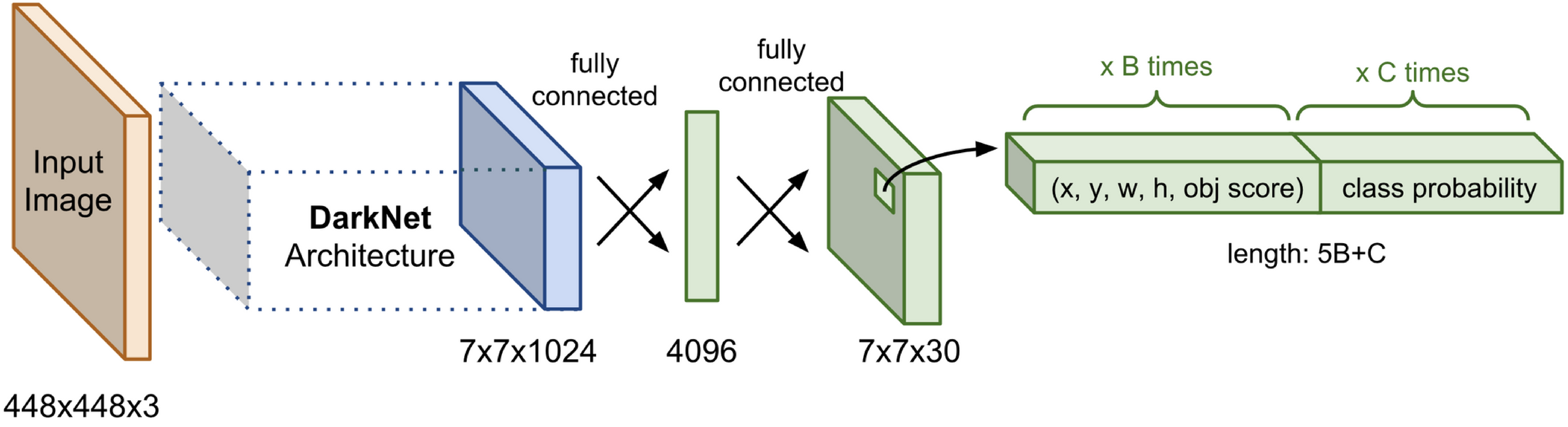
Detecting humans and vehicles in a disaster classified image is used to estimate the number of victims stuck in disaster-affected area

We have used YOLOv4 - an end-to-end approach for detecting objects in aerial imagery and optimized the model for AIDER-Detect to attain maximum performance and efficiency.

*results of facebook AI's detectron2 on AIDER-DETECT

YOLOv4

YOLO is a state-of-the-art technique for object detection. YOLOv4 consists of Yolo layers and a deep CNN backbone which captures all the spatial information.



Training Methodology

MODEL

- Two custom CNN classifier architectures were trained in **PyTorch** on the AIDER dataset
- The state-of-the-art YOLOv4-Tiny object detector was trained on the AIDER-Detect dataset

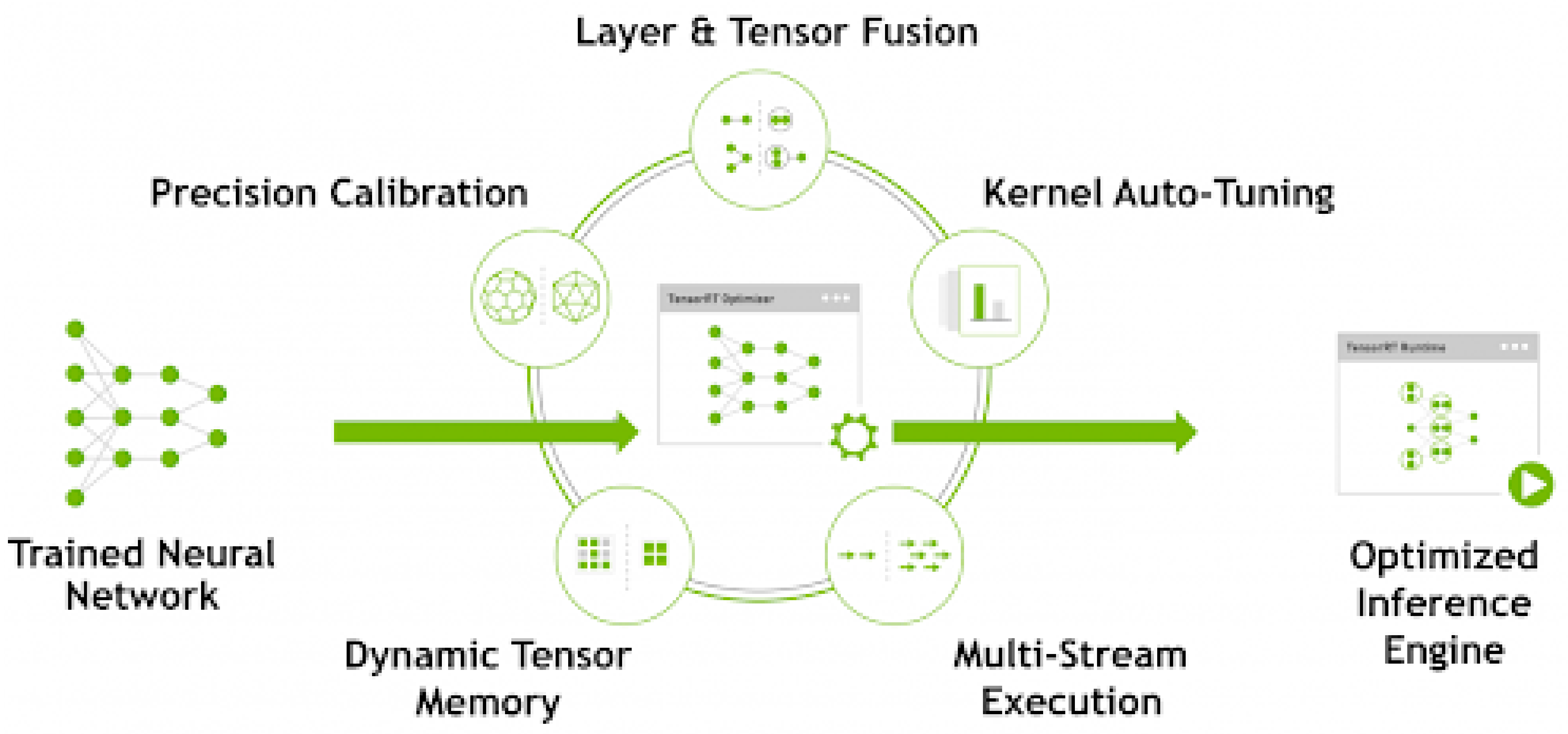
OPTIMISATION

- Used multiple hyperparamter tuning frameworks for optimal parameter search for classification
- Utilized best-performing training parameters for YOLOv4 for detection training
- **Transfer learning** with darknet53

CUSTOM LOSS

- Implemented Focal Loss to reduce class imbalance in detection training

TensorRT Optimizations



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Reduced Precision

TensorRT performs precision calibrations of weights and activations of a neural networks for accelerated performance.

02

Layer Fusion

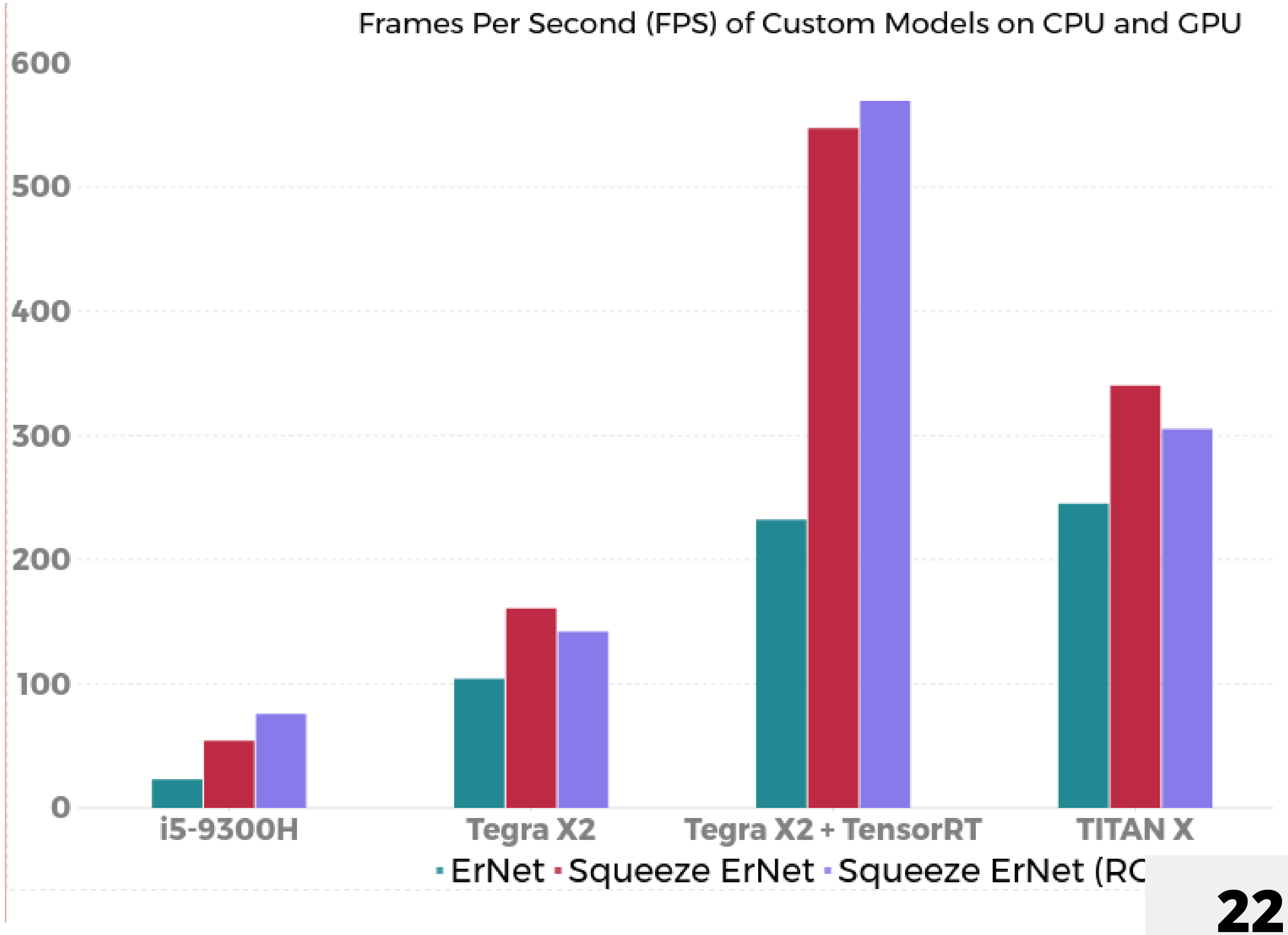
TensorRT performs layer fusions to compress the dynamic computation graph of a neural network

Classification Results

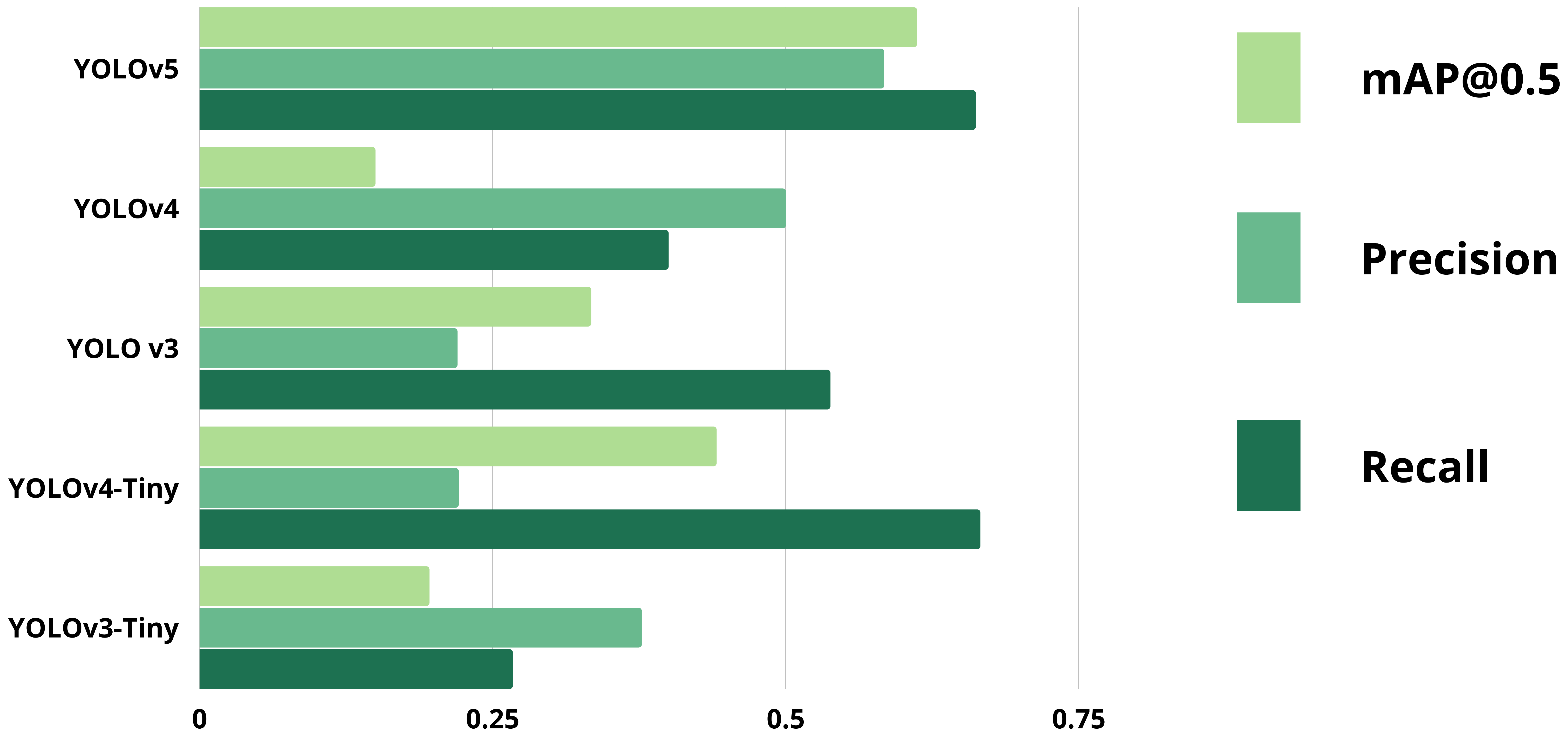
Model Architecture	Average Accuracy	F1 Score
Emergency Net (From Paper)	90.1	95.6
ErNET	94.2	96
Squeeze_ErNET	92.5	95.5
Squeeze_ErNET (RC)	93	96
Inception W1A1	71.3	67
Inception W2A2	91.4	82

Inference Results

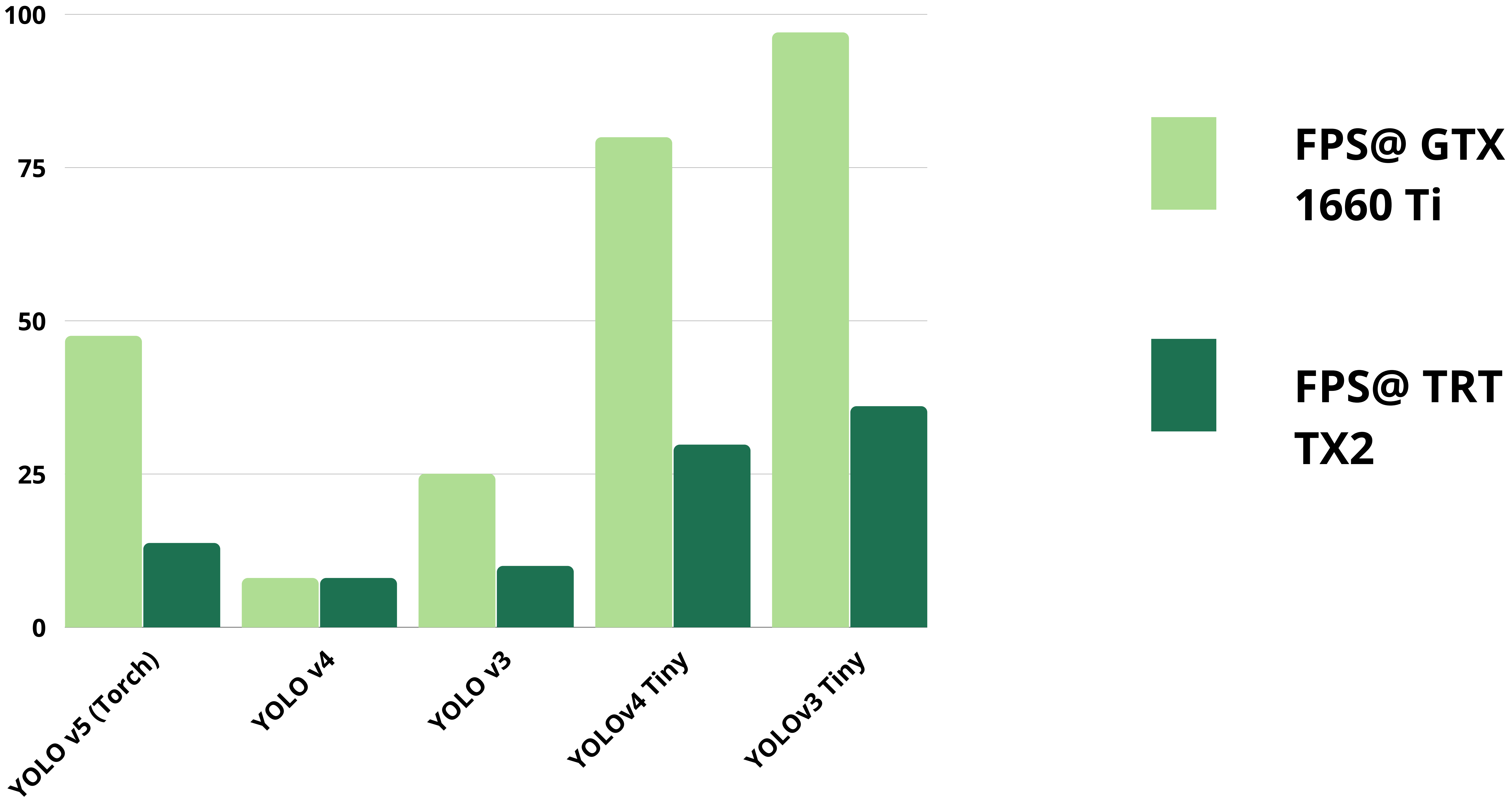
As depicted in the bar chart, NVIDIA TensorRT accelerated models perform exceptionally faster than the vanilla CUDA-accelerated models. Specifically, the Squeeze ErNet model runs at 140 FPS on the NVIDIA Jetson TX2 Module (powered by Tegra X2) while the same model accelerated by NVIDIA TensorRT hits 416+ FPS (2.97X)



Object Detection Results



Object Detection Inference



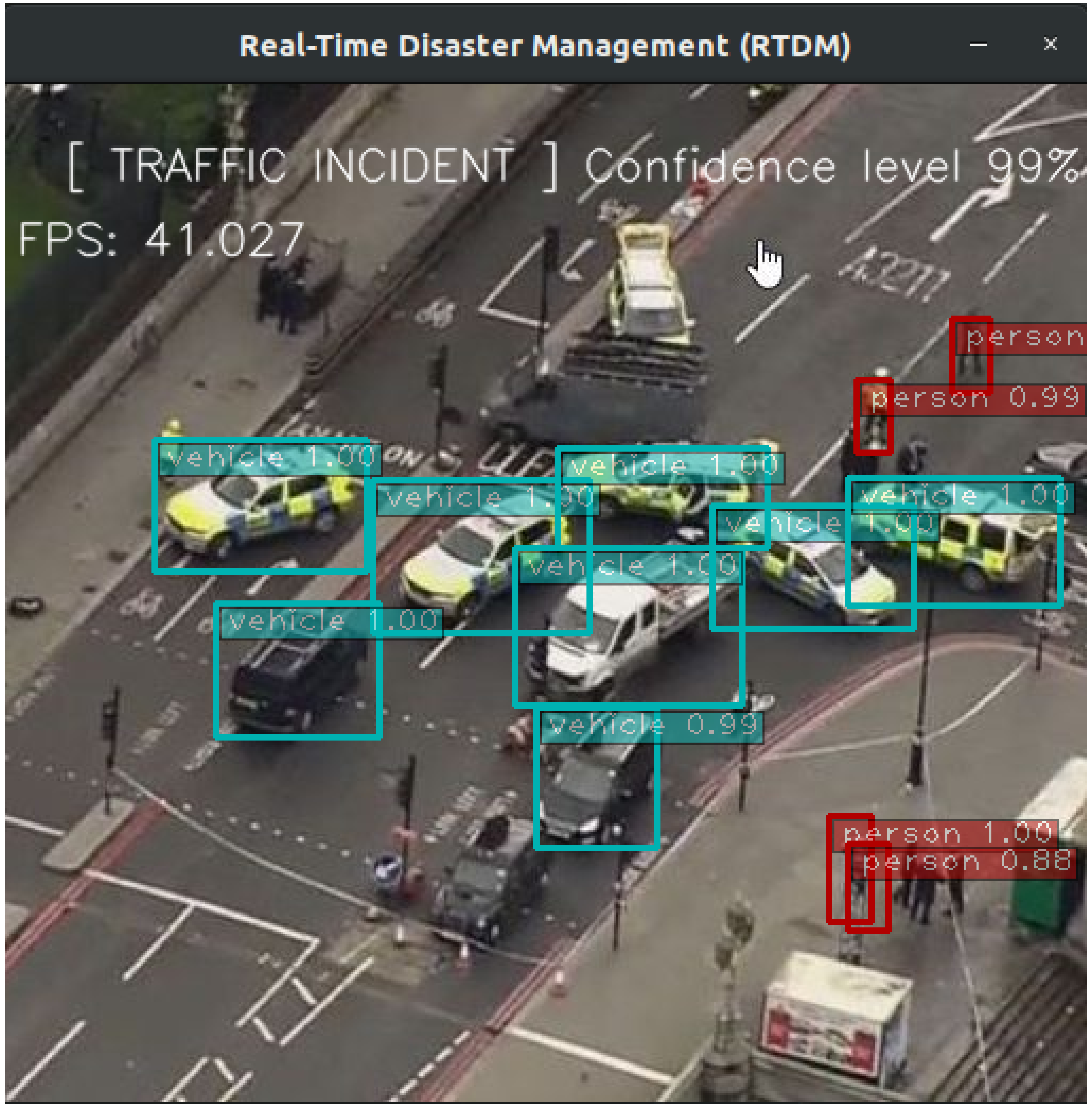
- **Drone Height (H)**
- **Field of View (θ)**
- **Aspect Ratio (r)**

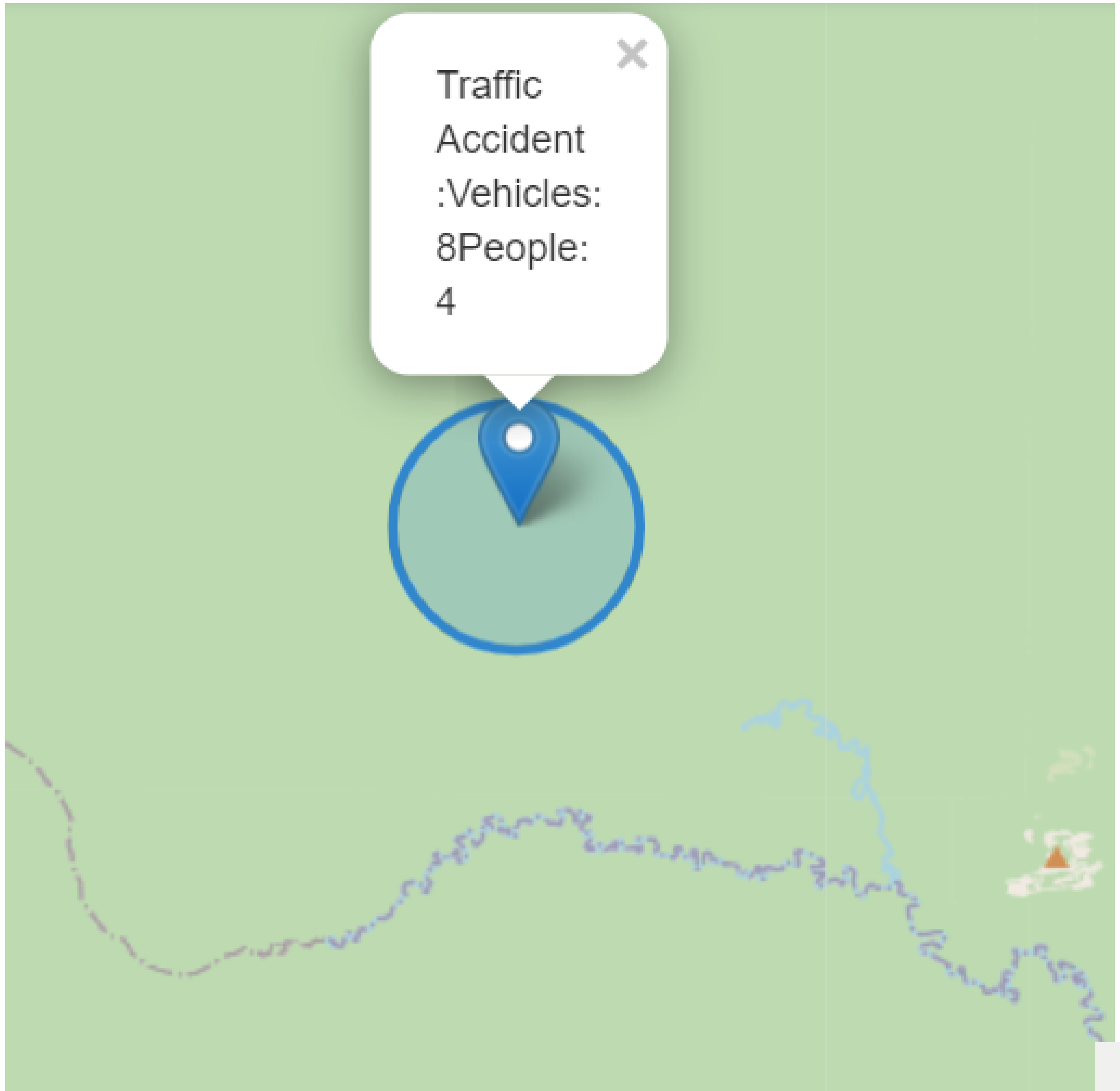
Disaster Area Estimation

Area estimation of image footprint is used for disaster mapping. We approximate the area represented by the image captured by the drone at a *height (**h**), field of view (**θ**) and with image aspect ratio (**r**)* as:

$$A = \frac{r\left(2h\tan\frac{\theta}{2}\right)^2}{1+r^2}$$

Results at a glance





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Future Work

Some natural extensions to this work that would help expand and strengthen the results:

- Custom object detection models for disaster response
- Extending the detection dataset
- Aggresive quantization for improved performance
- Testing other object detection approaches i.e CornerNET for ODDER

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Work Division

Its difficult to actually divide tasks as this work has been a continuous process of exploring, testing related work and brainstorming

Maryam Sana

- Classification architectures
- Hyperparameter tuning
- Object detection SOTA testing
- Literature review
- Data labelling

Siraj Qazi

- Classification architectures
- TensorRT acceleration
- Literature review
- Data augmentation
- Object detection SOTA training

Resources

THANK YOU

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