Traffic Flow Estimation Based on Deep Learning for Emergency Traffic Management using CCTV Images

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Emergency Traffic Management

- Emergency Traffic Management (ETM) is one of the main problems in smart urban cities
- The causes of traffic emergencies can be small-scale (e.g., vehicle crash) or large-scale (e.g., earthquake or tsunami)
- They can also be planned (e.g., scheduled maintenance, noticed evacuation before a disaster) or unplanned

Traffic Flow Estimation

- Identification of traffic flow is the first step in consolidated planning of managing traffic emergencies
- Typically performed by underground inductive-loops, pneumatic road tubes, and temporary manual counts
- These methods can not be used in large areas because of high cost, damages to road surface and difficulties of installation
- Today, CCTV systems are extremely common and mounted in many public areas to support real-time monitoring
- CCTV data can be used as the foundation for accurate traffic flow estimation

Traffic Flow Estimation Problem

The *traffic flow estimation* is identifying the number of vehicles during the t^{th} time interval at the i^{th} observation location in a transportation network which can be denoted as X_i^t

Research Questions

- What object detection algorithm is best suited to the CCTV image data set for vehicle detection?
- Can traffic flow be estimated by counting the number of vehicles in CCTV images using an object detection algorithm?

Methodology

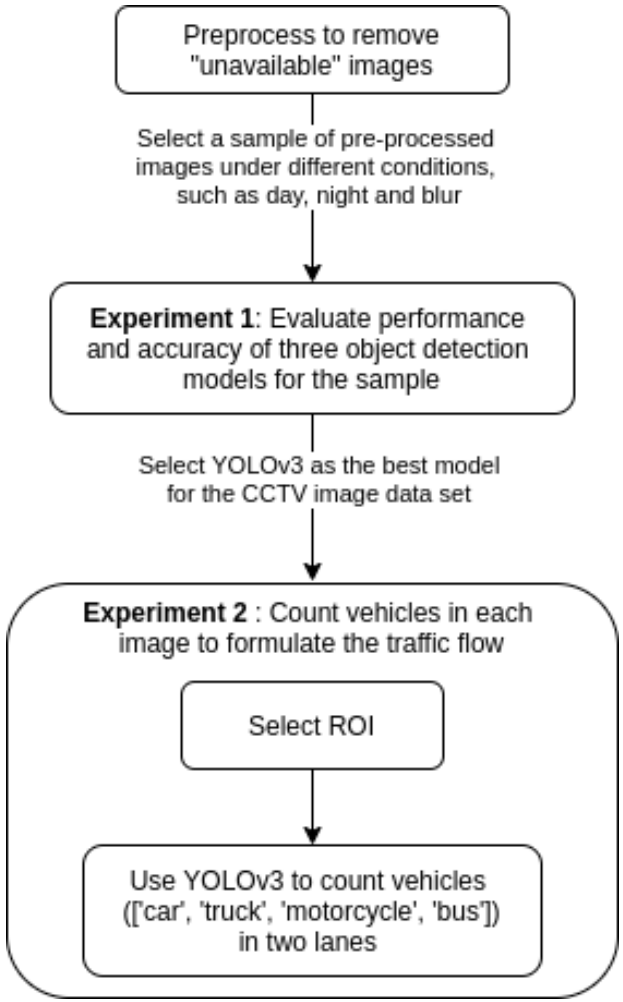
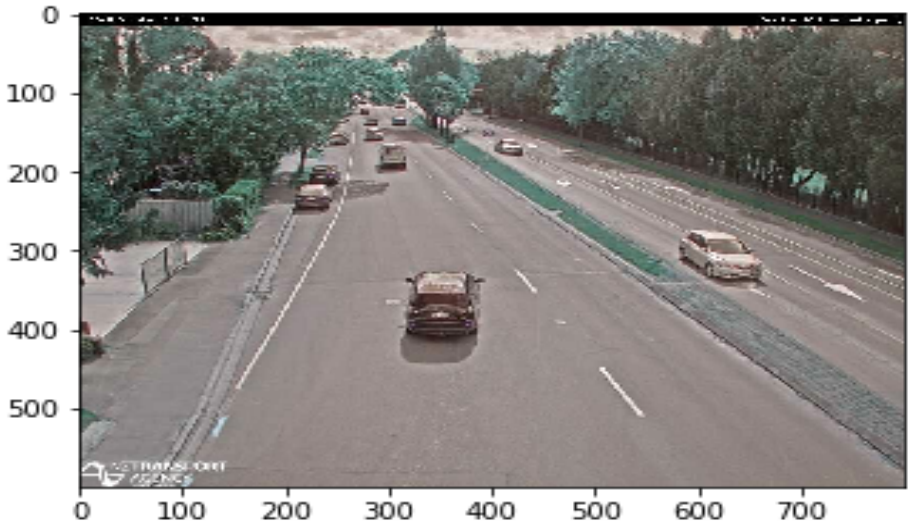
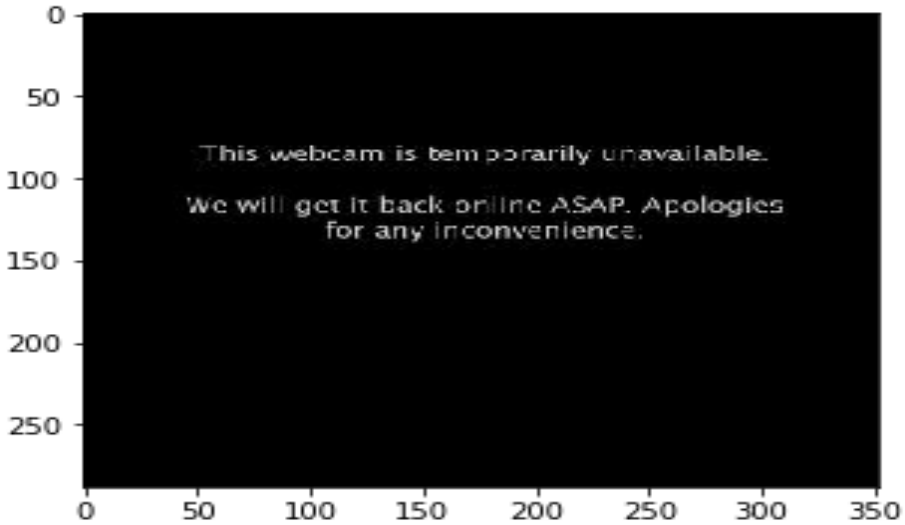


Figure: Methodology

Dataset

- CCTV image data set from NZTA traffic cameras API from 10th of October to 31st of October 2019 in Christchurch CBD
- Location : ”West along Yaldhurst Rd from Curletts Rd” (latitude -43.53074, longitude 172.56812)
- Size : 1.6 GB



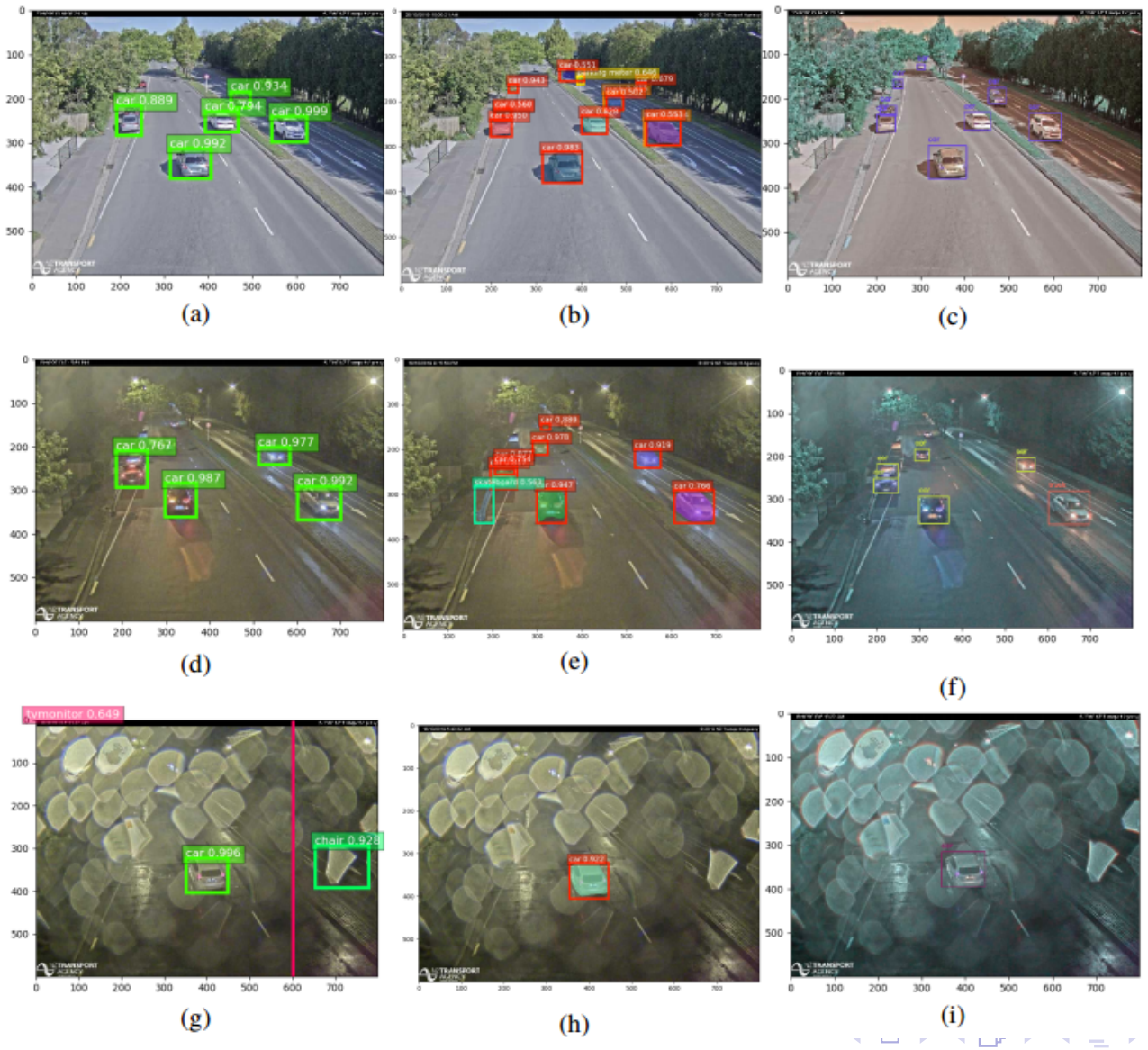


Dataset Cont.

Total number of images before pre-processing	24, 085
Total number of unavailable images	1, 519
Total number of images after pre-processing	22, 566

Table: Dataset before and after pre-processing

RQ1 - Experiment 1



Experimental Results - Experiment 1

Model	Performance/ mean time taken to detect vehicles (seconds)	Recall	Precision
YOLOv3	0.86	0.79	0.96
faster R-CNN	8.37	0.50	0.96
mask R-CNN	55.6	0.69	0.77

Table: Performance and accuracy of the three models for our CCTV data set

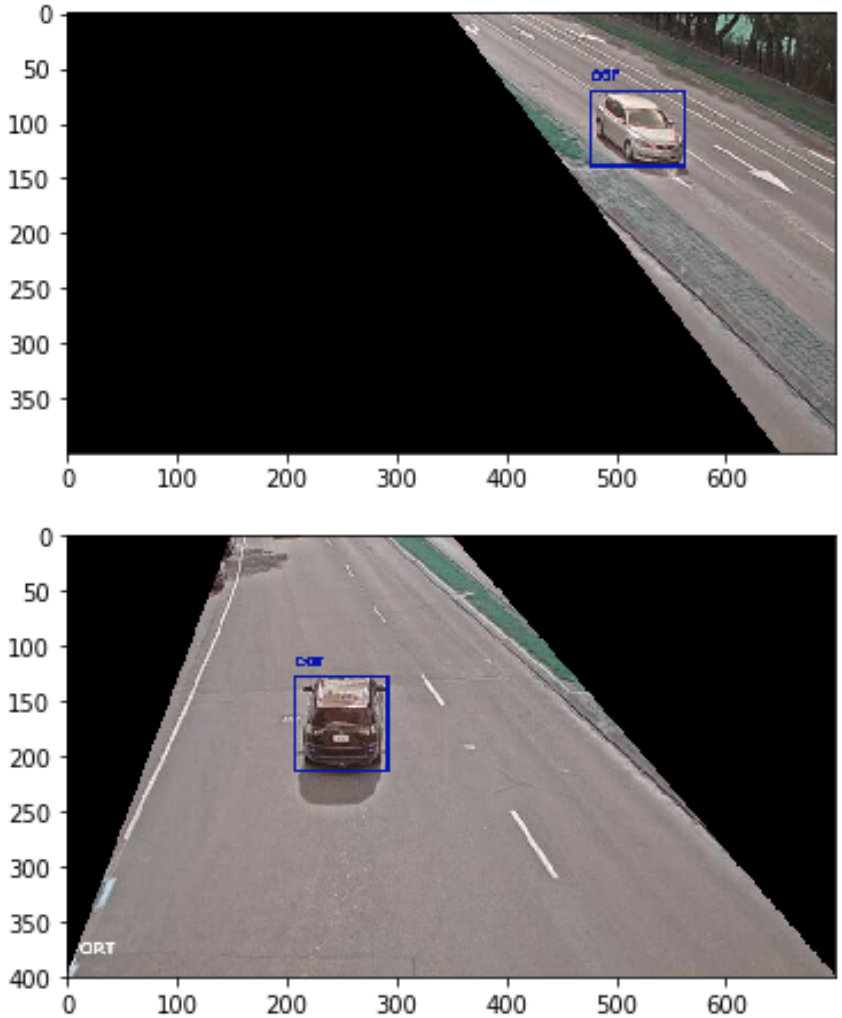
RQ2 - Experiment 2

Algorithm 1 ROI selection as a trapezium

1: **for** $i \in I$ **do**

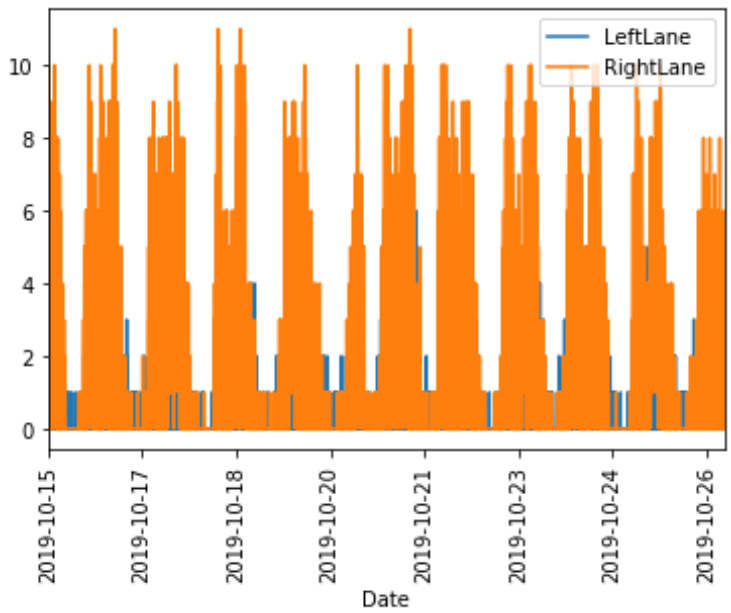
$y\_size, x\_size = i.shape[:2]$
$vert\_coef = 0.3333$
$hor\_coef = 0.312$
$v\_coef = vert\_coef$
$up\_left\_coef = hor\_coef$
$up\_right\_coef = 1 - up\_left\_coef$
$low\_left\_point = [0, y\_size]$
$low\_right\_point = [x\_size, y\_size]$
$up\_left\_point = [x\_size * up\_left\_coef, y\_size * v\_coef]$
$up\_right\_point = [x\_size * up\_right\_coef, y\_size * v\_coef]$

2: **end for**



Experimental Results- Experiment 2

Date	Time	LeftLane	RightLane
2019-10-15	14-44-00	1	0
2019-10-15	14-45-00	1	0
2019-10-15	14-46-00	0	4
2019-10-15	14-47-00	0	4
2019-10-15	14-48-00	0	4
2019-10-15	14-49-00	0	0
2019-10-15	14-50-00	0	0
2019-10-15	14-51-00	1	10
2019-10-15	14-52-00	1	10
2019-10-15	14-53-00	1	5



Conclusion

- We created a new, challenging data set by collecting CCTV images at each minute through the NZTA traffic cameras API, which includes a total of 24,085 images for the experiments discussed
- We evaluated the performance and accuracy of YOLOv3, faster R-CNN and mask R-CNN in detecting vehicles for the CCTV images
- We introduced a simple ROI algorithm to identify left-lane and right-lane in the CCTV images to identify the direction of vehicle movement. Then, we obtained the traffic flow counts for the selected road at Christchurch CBD

▸ Project extension

Thank You!