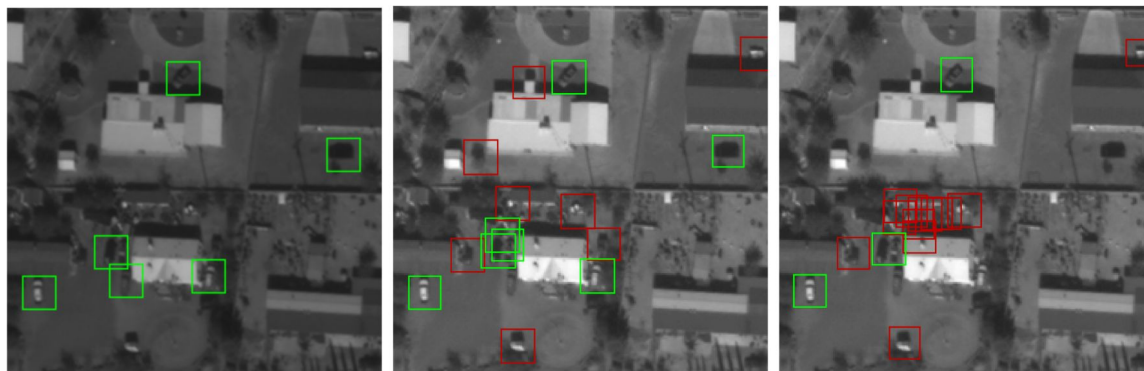


CiPSI and CiPSINet

A New Dataset and Network for Finding Cars in Panchromatic Satellite Images

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(a) Ground Truth

(b) Faster R-CNN CiPSINet

(c) Faster R-CNN ResNet-50

Overview

1. Dataset
2. Architecture
3. Classification
4. Detection
5. Future Work

Motivation

1. There are gaps in existing datasets for the classification and detection of cars in black and white satellite images.
2. Existing methods often use higher resolution images that are downsampled captured from drones or planes.

Problems with the drone/plane-based approach:

- No atmospheric distortions
- No wide field of view
- No cloud cover

CiPSI Dataset

The images are from the Worldview 3 and Worldview 4 satellites, and were provided by the European Space Agency. Locations include landlocked and coastal areas, and have a GSD of ~35cm.

Detection:

- Each scene was annotated by two people to ensure that all cars were found.

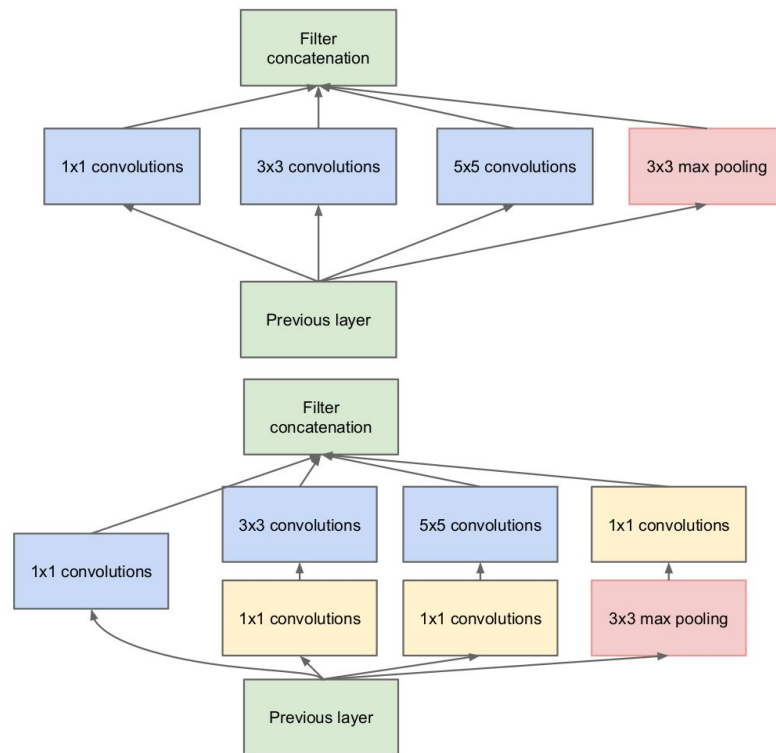
Classification:

- Each annotated car was clipped from the scene, including surrounding context (Mundhenk et al, 2016).
- Non-car regions were clipped from these scenes as well.

Existing Deep Learning Architectures

Inception

- Inception Blocks



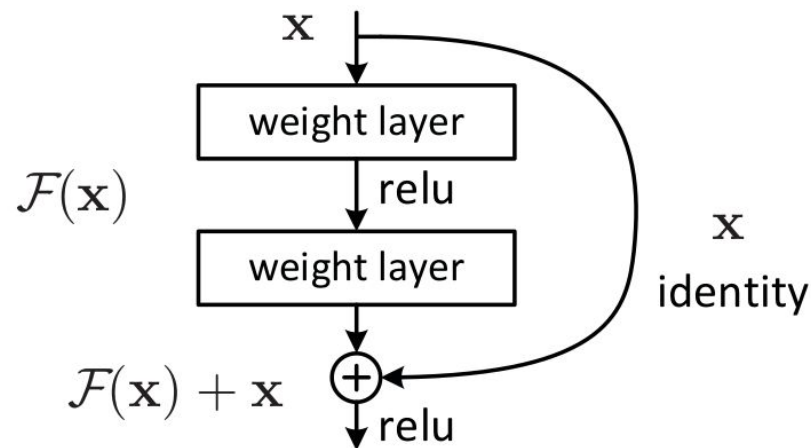
Existing Deep Learning Architectures

Inception

- Inception Blocks

ResNet and Wide ResNet

- Residuals
- Width vs Depth



Existing Deep Learning Architectures

Inception

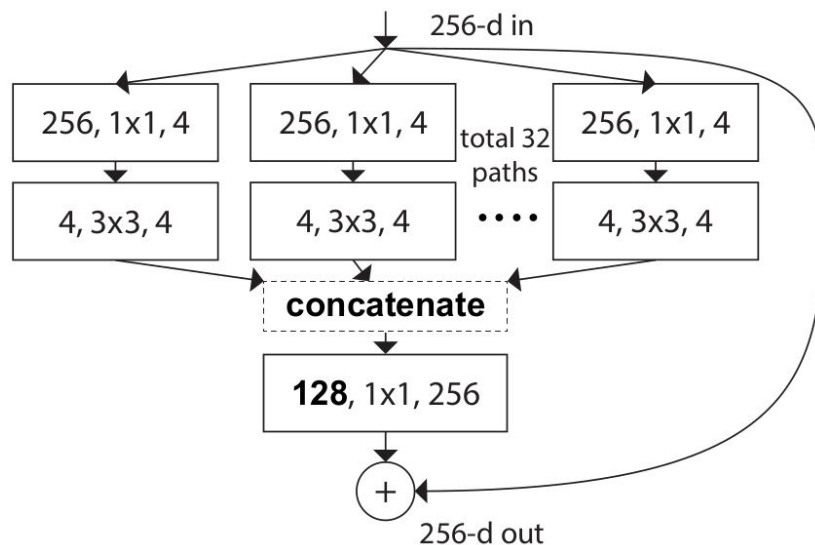
- Inception Blocks

ResNet and Wide ResNet

- Residuals
- Width vs Depth

ResNext

- Cardinality



The CiPSINet Architecture

The main techniques:

- Increase cardinality
- Limit width to keep costs low
- Limit filter size to keep costs low
- Limit depth to keep costs low - only 14 layers

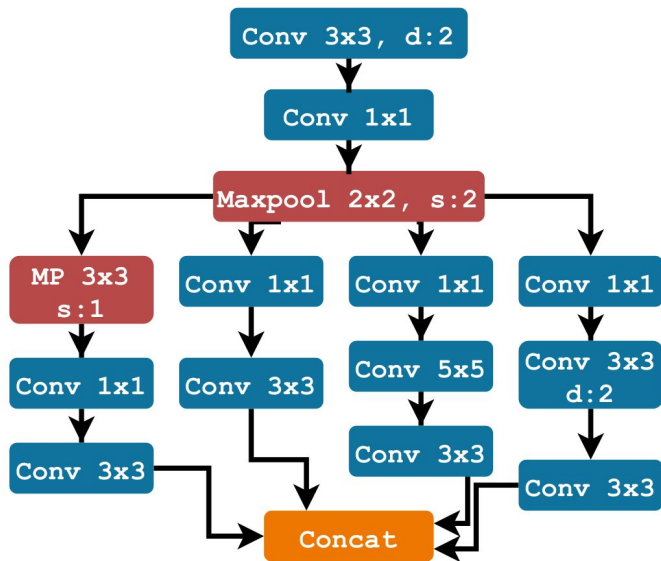
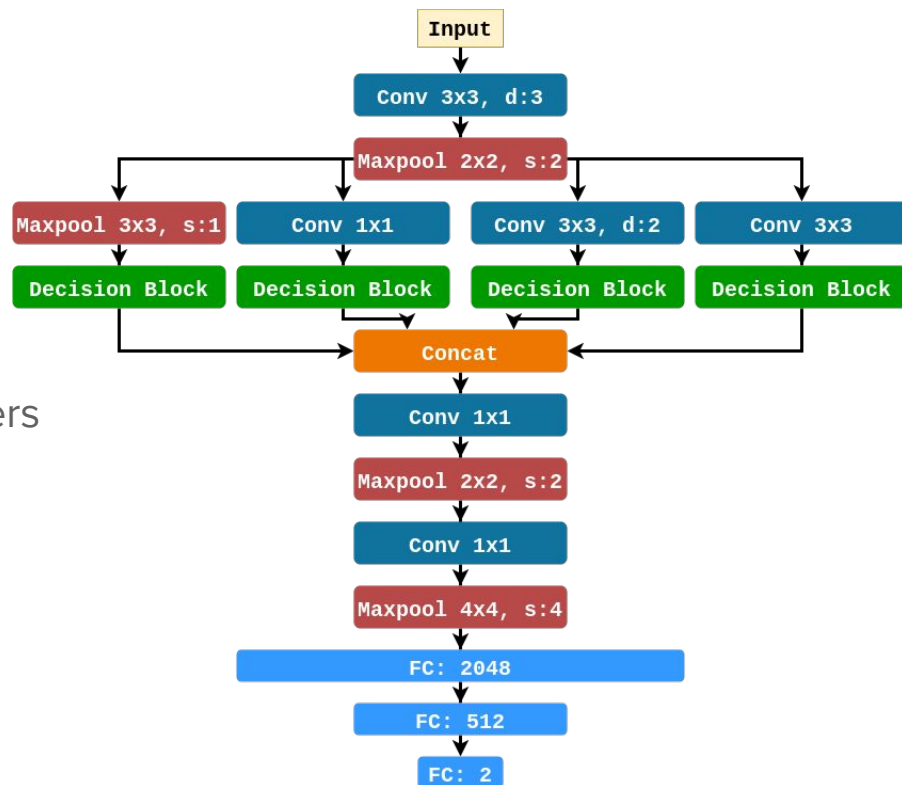


Fig. 1: The DecisionBlock architecture. s indicates stride, d indicates dilation. Both are 1 if not indicated. MP is MaxPool, Conv is convolutional, and Concat is Concatenate.

The CiPSINet Architecture

The main techniques:

- Increase cardinality
- Limit width to keep costs low
- Limit filter size to keep costs low
- Limit depth to keep costs low - only 14 layers



Classification Results

Results on test data after each epoch

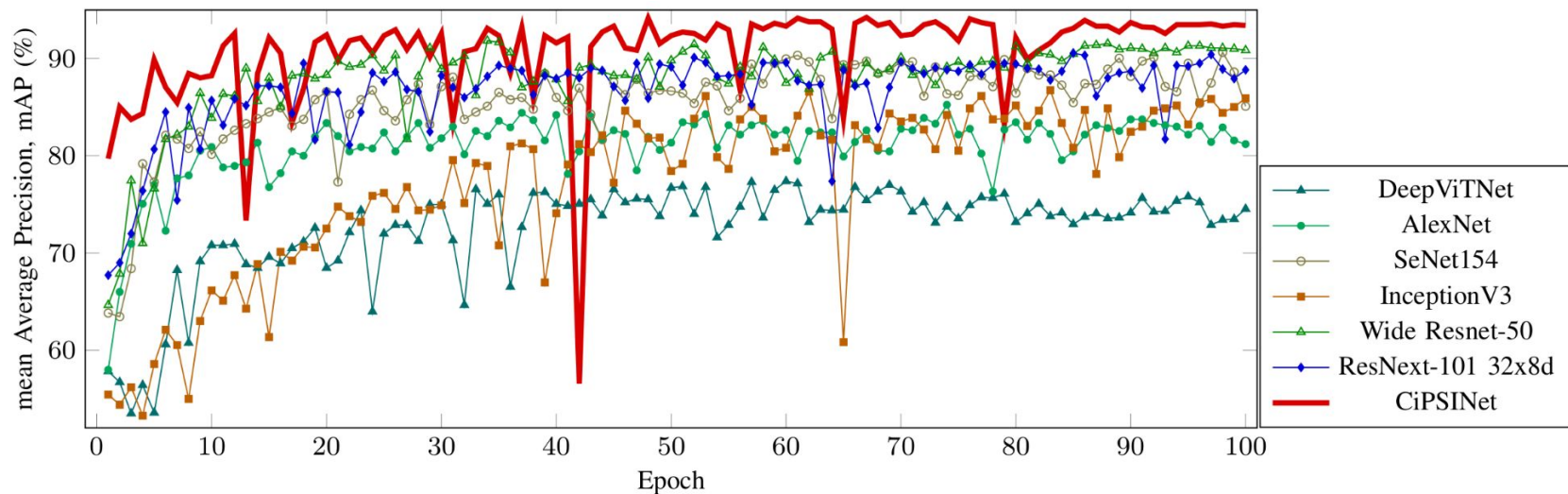


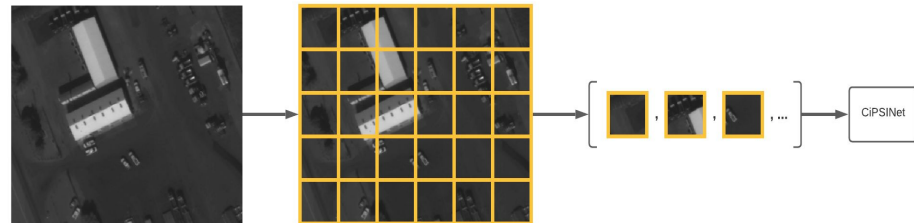
Fig. 2: The mAP of each network on the test data at the end of every epoch during training.

Detection Methods

Detection methods chosen for comparison:

1. Sliding Window

- Fixed-length window moves across the image
- CiPSINet classifies each cell as car or no car



2. Unsupervised-Segmentation-Generated Region Proposals

3. Faster R-CNN

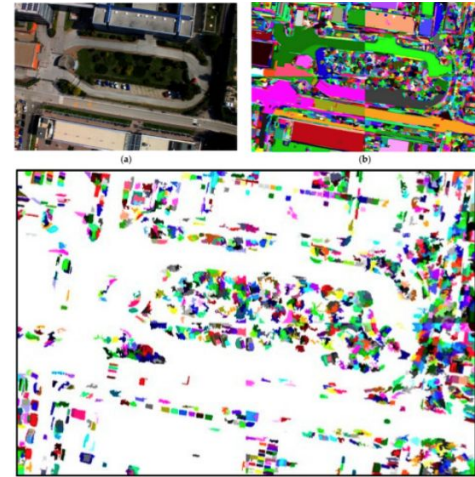
T. N. Mundhenk, G. Konjevod, W. A. Sakla, and K. Boakye, "A large contextual dataset for classification, detection and counting of cars with deep learning," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9907 LNCS, pp. 785–800, 2016.

S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," june 2015. [\[Online\]](#).

Detection Methods

Detection methods chosen for comparison:

1. Sliding Window
2. **Unsupervised-Segmentation-Generated Region Proposals**
 - Mean-shift segmentation
 - Classifying this using CiPSINet
3. Faster R-CNN

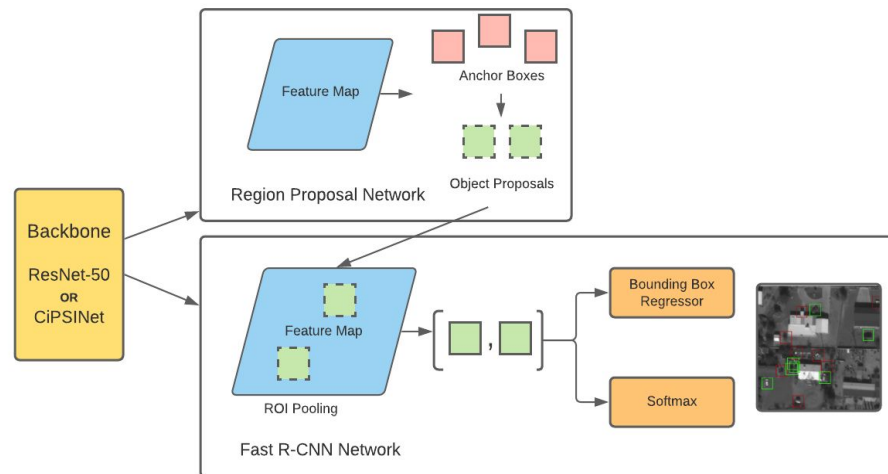


Regions obtained from mean-shift segmentation filtering

Detection Methods

Faster R-CNN with varying backbones:

- With Resnet-50 pre-trained on COCO
- With CiPSINet pre-trained on car classification



Faster R-CNN with ResNet-50 or CiPSINet backbone

Detection Results

Test Results				
Method	mAP @ 0.5	mAP @ [0.5, 0.95]	mAR @ [0.5, 0.95]	Time per Scene (ms)
F. R-CNN with CiPSINet	49.3	26.1	45.6	98.36
F. R-CNN with ResNet-50	36.2	21.4	42.5	34.49
Segmentation	3	1.2	34	2156.26
Sliding Window	< 0.1	< 0.1	1	12181.38

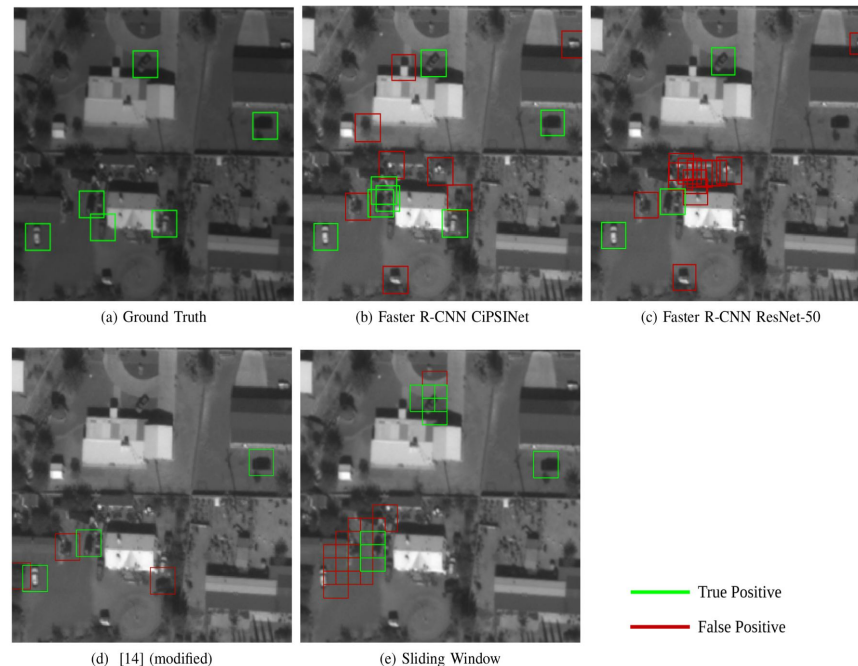


Fig. 3: Results of detection on a test scene. The ground truth is indicated in (a) by green boxes. In all other scenes the green boxes represent correctly identified cars, and the red boxes represent incorrectly identified cars.

Detection Results

- False positives identified by Faster R-CNN with CiPSINet and ResNet-50 as the backbone (Ref: images (a) and (b))
- Faster R-CNN with CiPSINet backbone identifies partially hidden cars as compared to Faster R-CNN with ResNet-50 (Ref: image (c) and (d))

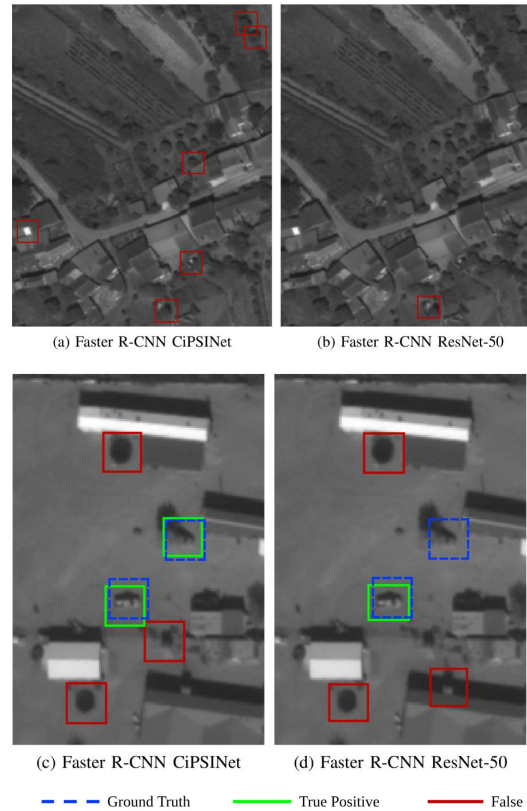


Fig. 4: Results of detection on two test scenes by Faster R-CNN with either CiPSINet or ResNet-50 as the backbone network.

Future Work

1. Dataset

- a. Continue to expand with further challenging examples (e.g. partially occluded cars)

2. Architecture

- a. Evaluate the performance on other benchmark datasets
- b. Ablation studies
- c. Continue to reduce the parameter count
 - i. Reducing fully connected layer size
 - ii. Using $n \times 1 \rightarrow 1 \times n$ convolutional filters ($n \times n > n + n$ for $n > 1$)

Questions

Thank you for your time!

Existing Deep Learning Architectures

Inception

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ResNet and Wide ResNet

- Residuals
- Width vs Depth

ResNext

- Cardinality

Dilated Residual Networks

- Dilation

