Deep Learning Applied to Weapon's Detection

smiths detection
bringing technology to life








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Conclusions and Key Takeaways

1. Automatic Threat Recognition (ATR) of non-explosive prohibited items is very challenging due to versatile & robust variations in orientation, magnification, threat size, shape, texture, and materials.
2. Deep Learning was implemented to perform ATR on weapons using a combination of supervised and unsupervised machine learning (semi-supervised) using regions with convolutional neural networks (faster-RCNN).
3. This implementation showed very good performance (P_d>95%, P_{fa}<5%) on a set of approximately 2800 scans of 40 guns. This suggests the promise of real time ATR for a broader range of prohibited items.
4. A challenge is the requirement for a lot of labelled (ground truth) training data. This effort used 2800 labelled threat scans and 100,000 non-threat scans for training, testing, and validation. Each scan yields images from 4 separate views.

Motivation and Opportunities

Seemingly endless list of prohibited items which pose risk to passengers

- Sharps
- Guns
- Blunt weapons
- Precursors

Impossible to characterize every prohibited item

- Versatile & robust to variations in size, shape, texture, materials

Need for real time results (< 1s)

- Users are intolerant of screening delays

Project Objectives

PROJECT GOAL: Collaborate with Dr. Larry Carin at Duke University to develop an Automated Threat Recognition capability for the AT-2 (HS 6040aTiX) checkpoint scanner that leverages deep learning approaches

Collaboration Details

- Smiths Detection
  - gathered training and validation datasets
  - implemented Duke's Deep Learning ATR
  - tested the implementation on the HS 6040 aTiX
- Duke University
  - developed and modified faster-RCNN for X-ray images
  - trained, tested, and validated for weapons ATR using provided data
  - supplied trained code to Smtihs Detection

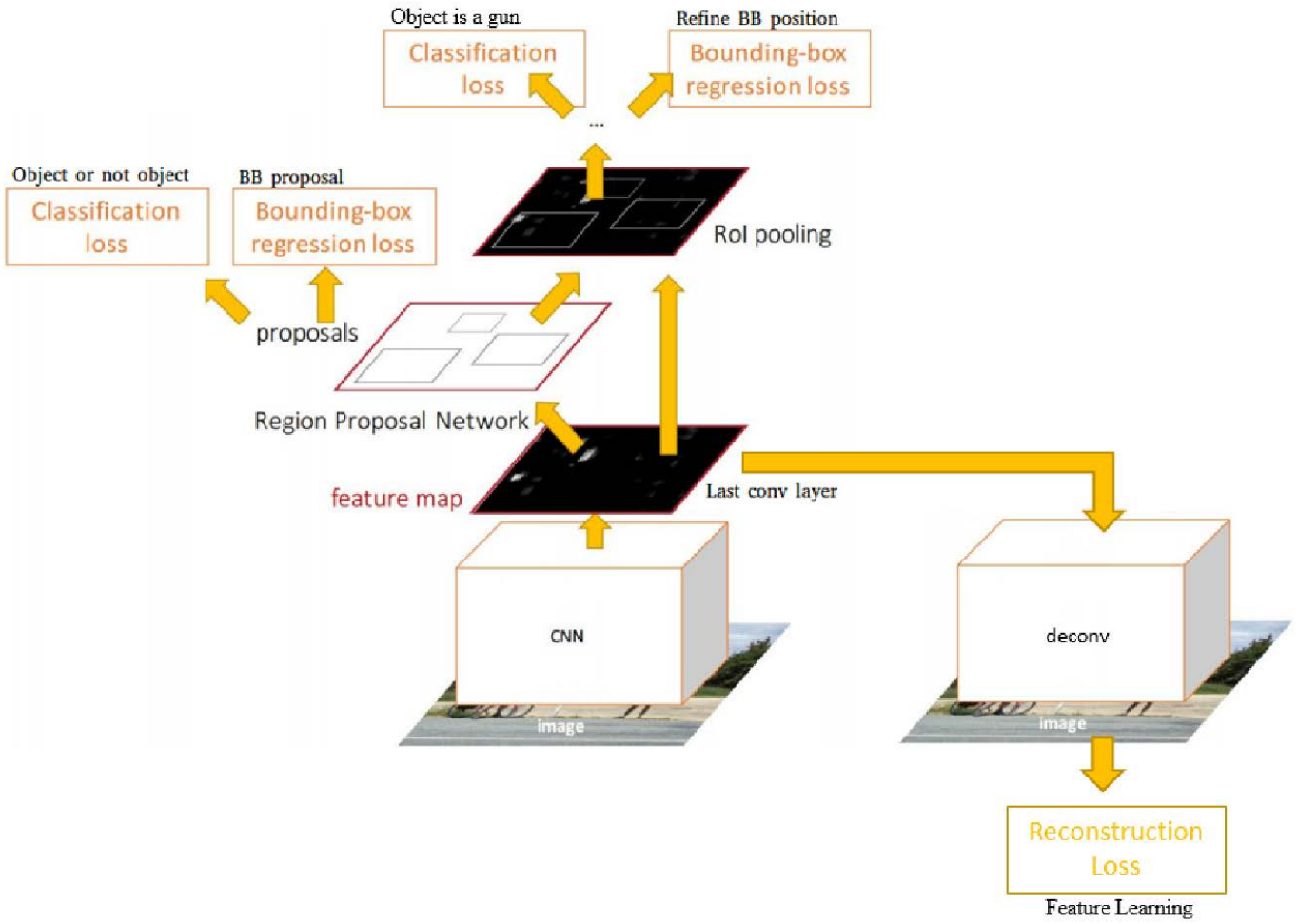
Key deliverables

- Detect and automatically annotate the presence of prohibited items in bags
- Determine the performance of these methods against collected datasets

Implement and test the DL methods

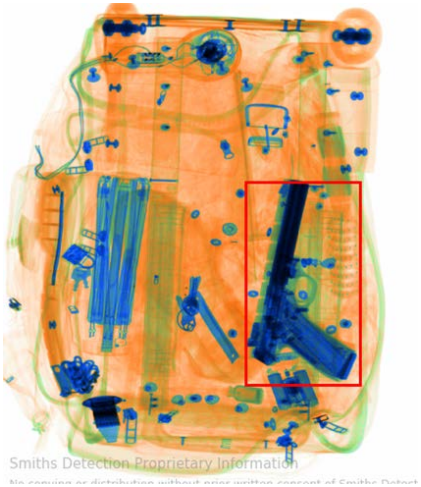
- off-line demonstrator
- on-line hosted by the Smiths Detection 6040 aTiX

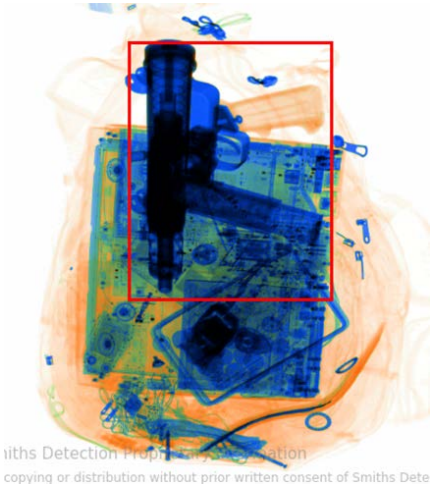
Method: ***Semi-Supervised Faster-RCNN***



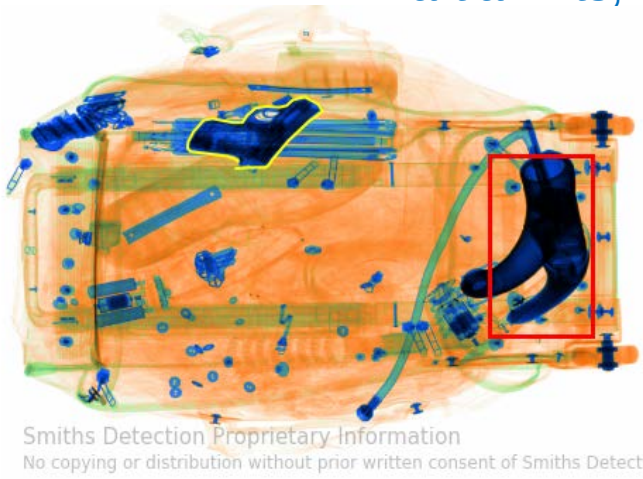
Sample ATR Results for Guns

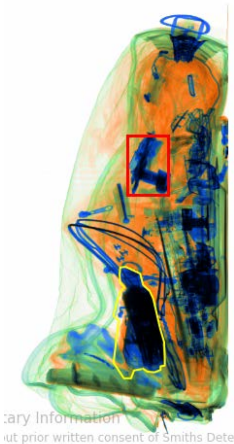
True Positives: Guns

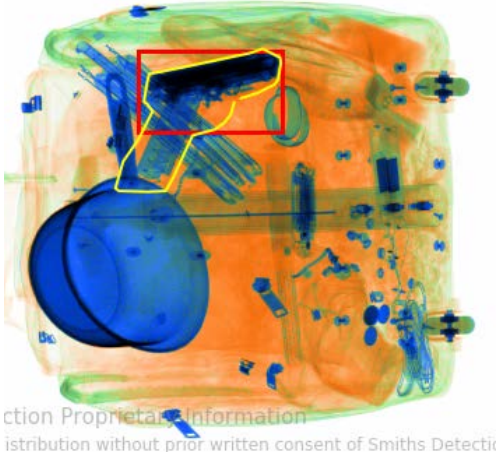




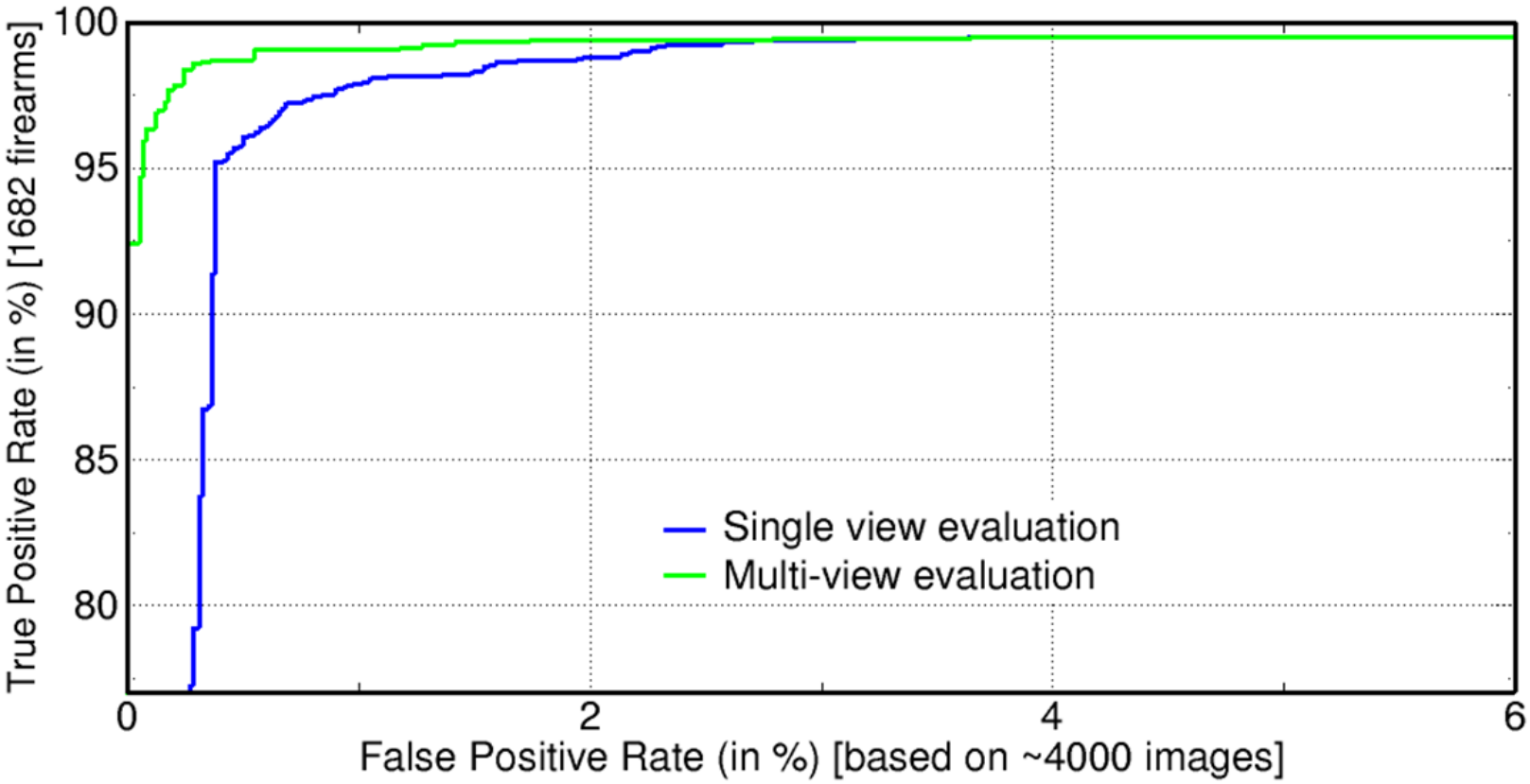
Partial Hits, Misses and False Positives: Guns







Deep Learning ATR Performance



Deep Learning Implementation Strengths

- X-rays are automatically copied to the evaluation laptop
- Evaluation time is approximately 500 ms on the laptop for a complete scan
- Reliable Detection even if the threat is occluded
- Works also in complex scenarios

Deep Learning Implementation Challenges

- Deep Learning methods need a lot of labelled data
- Deep Learning captures many different characteristics, including the shape of the prohibited item
  - Some prohibited items are easily reshaped or machined so as to be hidden in typical stream of commerce
  - Must de-sensitize the DL algorithm to shape for malleable/machineable threats
- Threat items evolve over time (shape, size, material)

Next Steps

The TSA contract has entered Phase II and will be completed next June. In the coming months Smiths and Duke will:

- Further develop the deep learning algorithm to include additional views and other preprocessed imagery.
- Extend to include a broader range of prohibited items:
  - Sharps
  - Gun Parts
  - Blunt Instruments
  - Precursors
- Test the deep learning algorithm for performance and robustness.
- Deliver to the TSIF.

dEMONSTRATION

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