X-Net: A Deep Convolutional Neural Model for X-Ray Threat Detection

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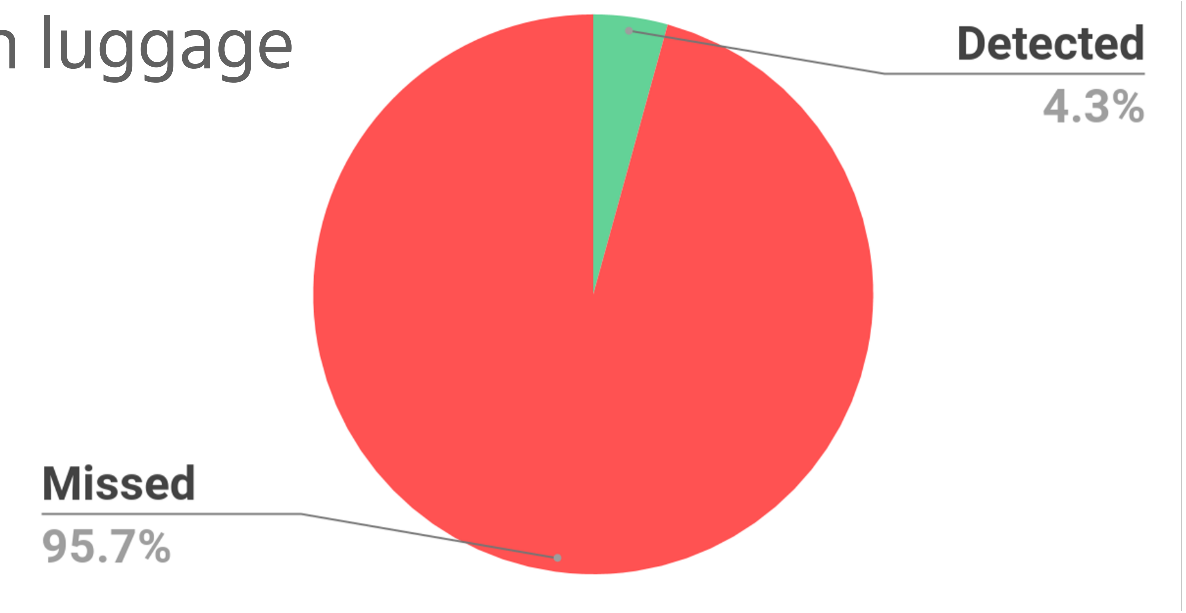
Introduction

Transportation Security Administration (TSA) is critical in ensuring airplane safety

Keeping passengers safe is crucial - failure to do so can lead to catastrophes like **9/11**

TSA: Detection of Luggage Threats

Problem: TSA fails to detect the vast majority of threats in luggage

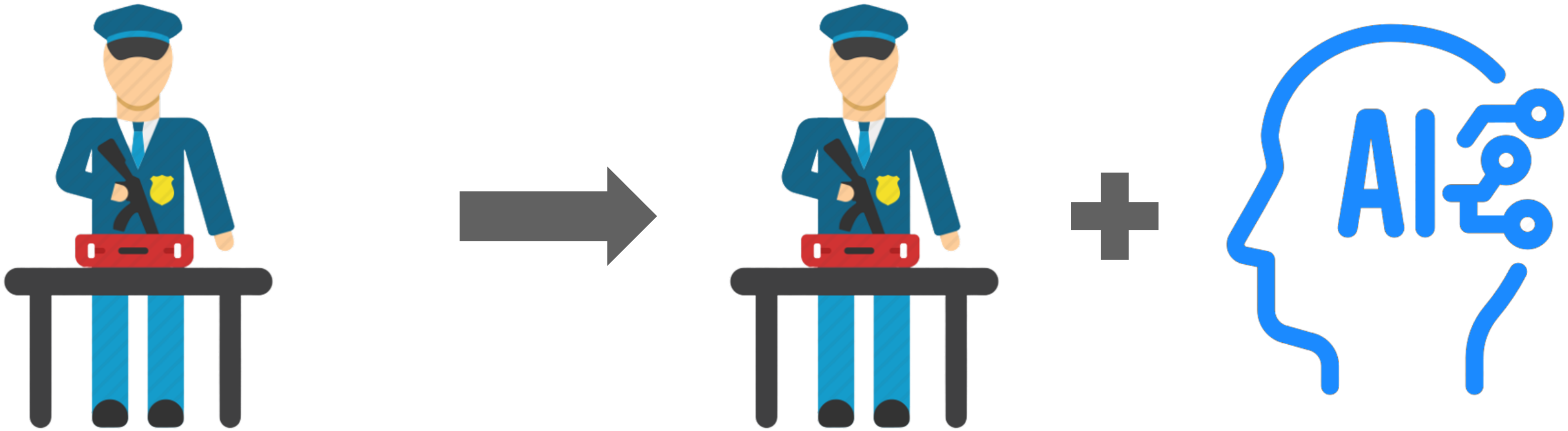


Sources: *Forbes, Newsweek, ABC News, The New York Times* (2015, 2017)

Proposal: AI Threat Detection

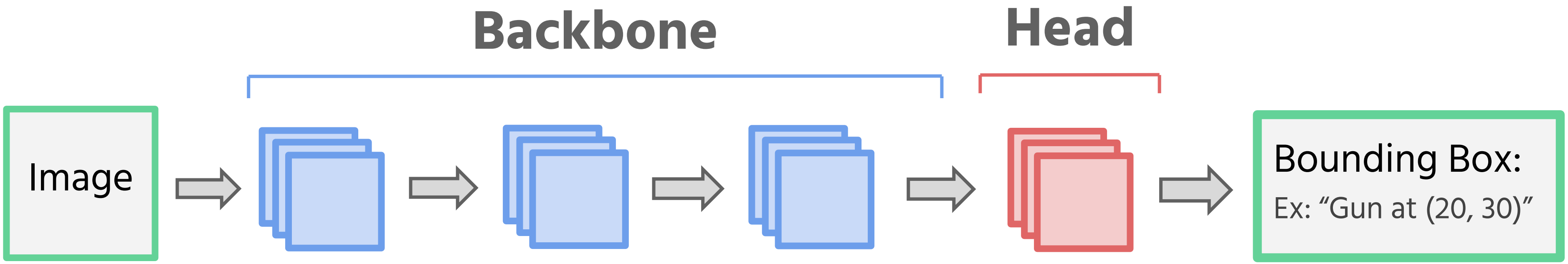
High error rate

Low error rate



Background: Convolutional Network

Convolutional neural networks: class of AI algorithms used for image analysis (ex: **YOLO**)



Innovation: X-Net

X-Net: baggage analysis convolutional model

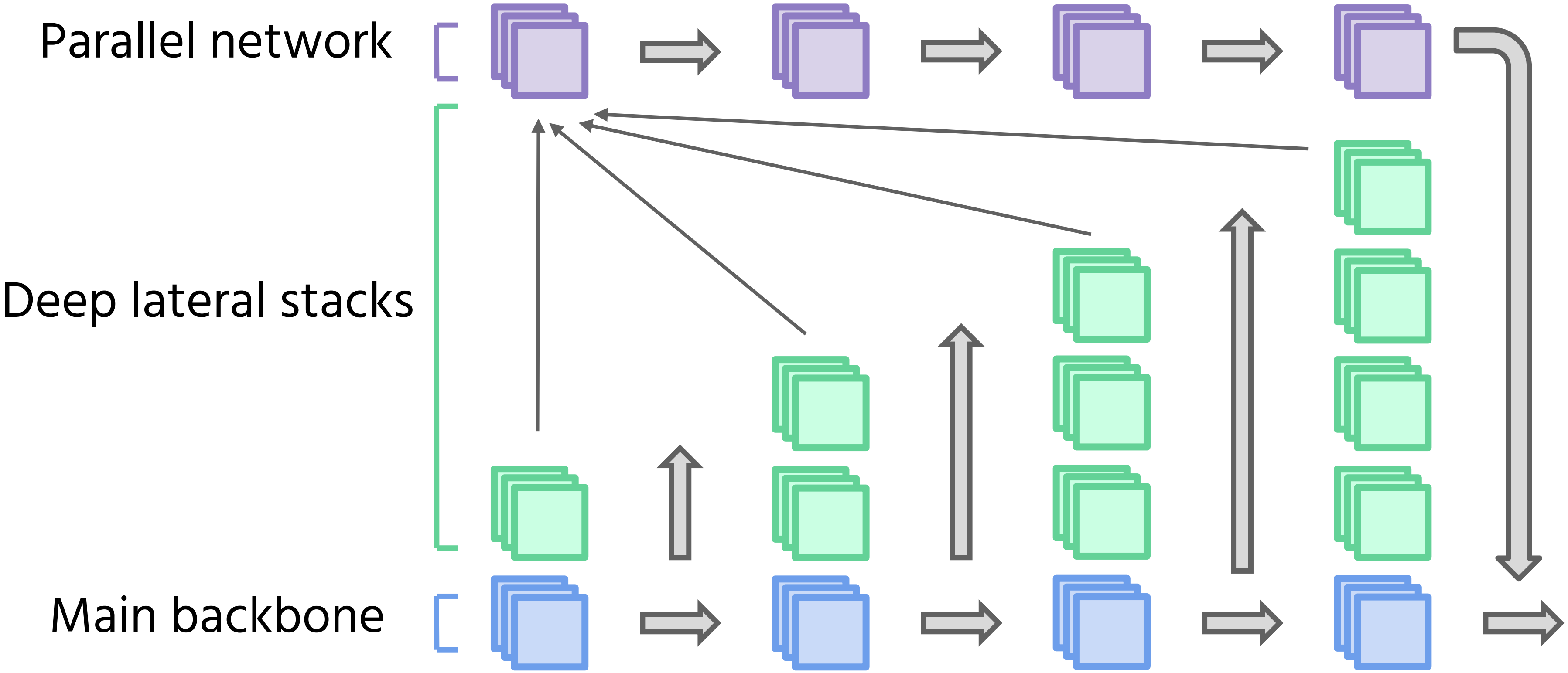
1. **Backbone**

   Deep lateral stacks and a **parallel networks**, which together help detect obscured threats

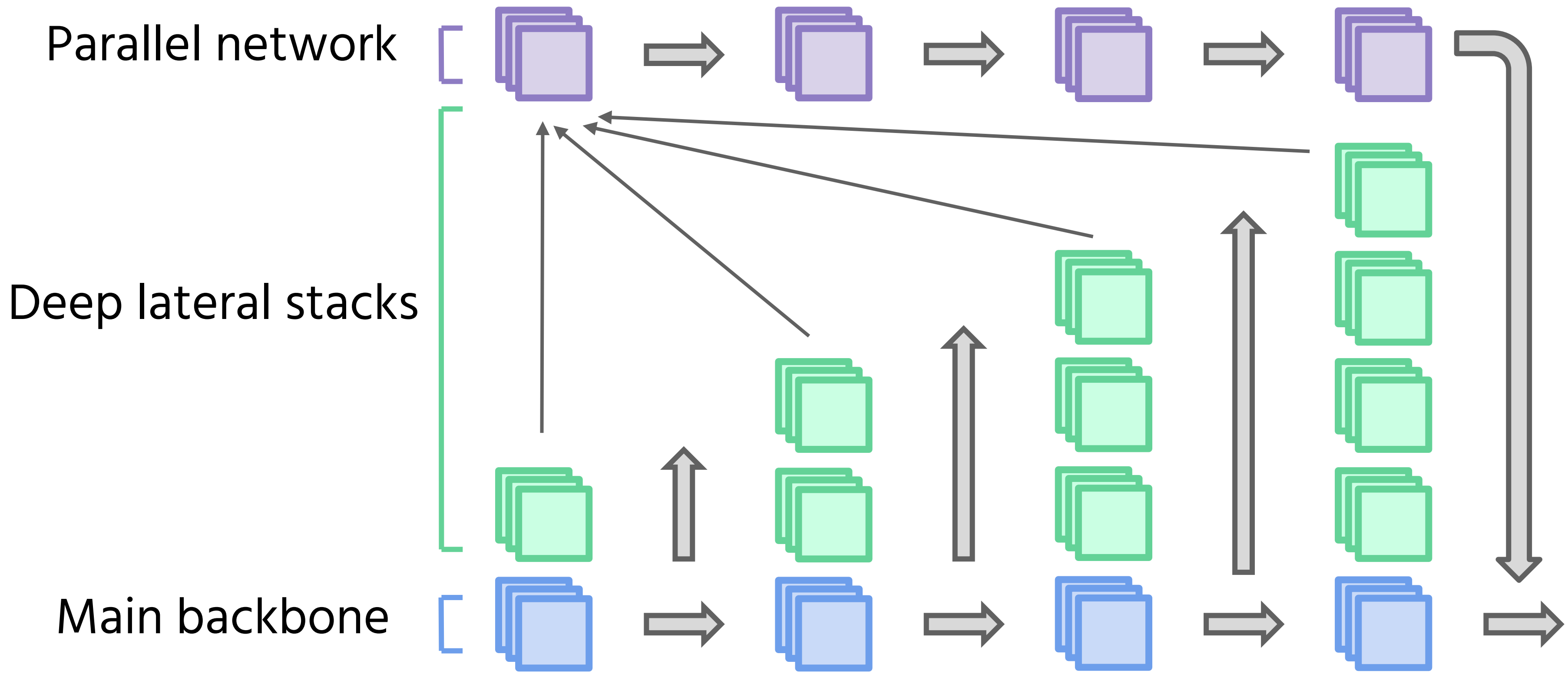
2. **Head**

   Outputs “bounding boxes”

X-Net: Backbone



X-Net: Backbone



X-Net: Gradient

1. **Gradient (∇)**

   Calculus tool that improves accuracy during training

2. **Gradient flow**

   The way gradients are employed during training

X-Net: Gradient Flow Optimization

Flow of gradients through **lateral stacks**:

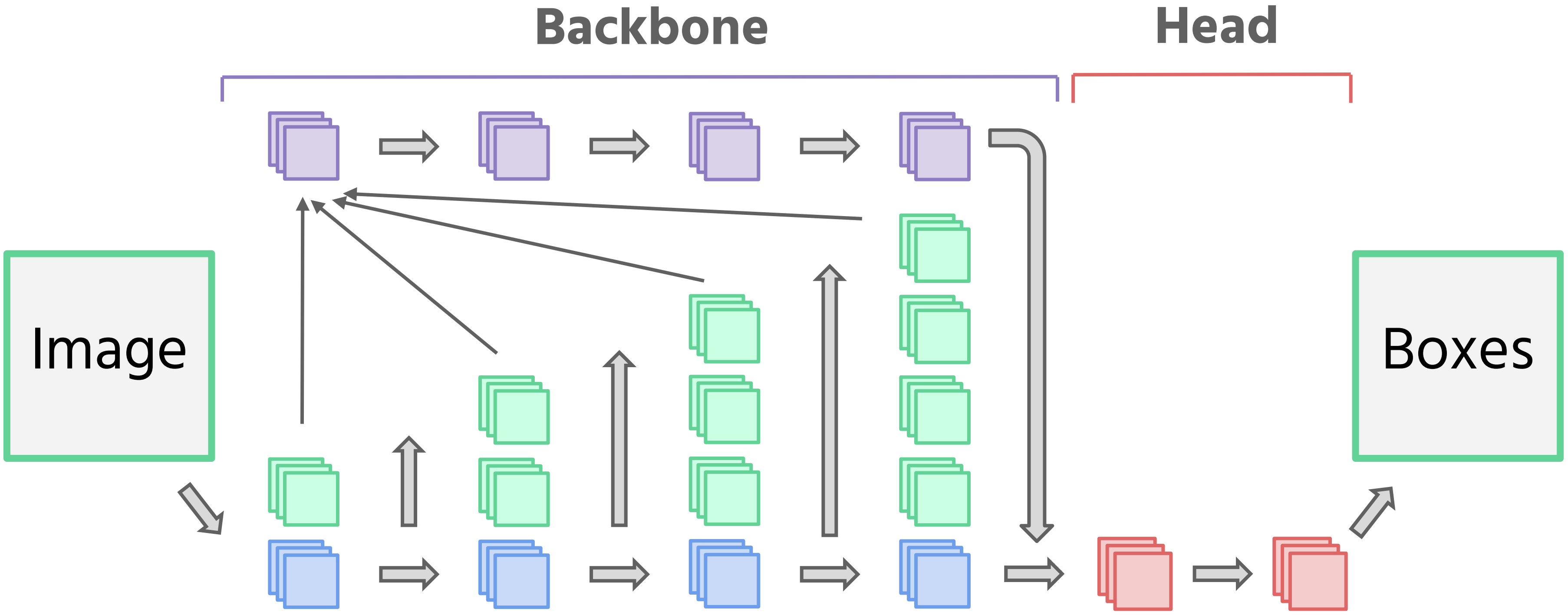
$$\forall \phi^{(i)},\ \nabla \phi^{(i)} = \frac{\partial L}{\partial C}\frac{\partial C}{\partial \phi^{(i)}} = \left(\nabla C_{n,m,k}\right)_{n \in \Re, m \in \Re,\ c(i-1) \leq k \leq ci}$$

*(**$\Phi^{(i)}$:** i-th lateral stack $\in \mathbb{R}^{a \times b \times c}$; **C:** parallel network input; **L:** loss function)*

Significance of above equation:

Each **lateral stack** develops independently of the others, allowing X-Net to be more diverse

X-Net: Full Structure



Methodology

Data: 11,000 training scans | 1,000 testing scans

Code: Python | Keras, TensorFlow

Hardware: NVIDIA GeForce RTX 2060

Training duration: 72 hours

Results: Accuracy Metrics

1. **Classification accuracy (mAP)**

   What threats are present in this baggage scan?

2. **Localization accuracy (mAP)**

   Where are the threats in this baggage scan?

1. Classification Accuracy

2. Localization Accuracy

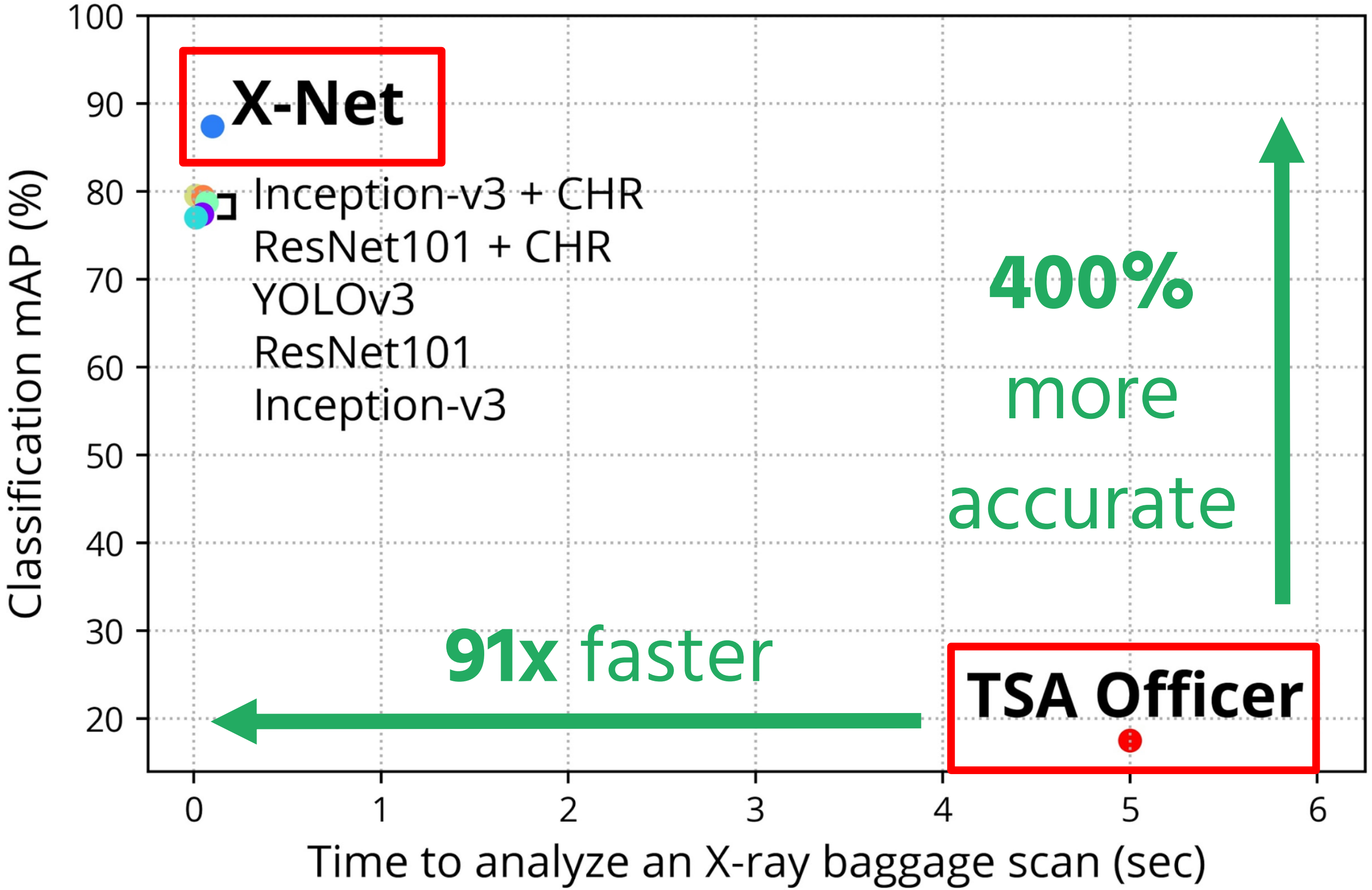


Figure 1. Classification mAP vs. Baggage Analysis Time

1. Classification Accuracy

2. Localization Accuracy

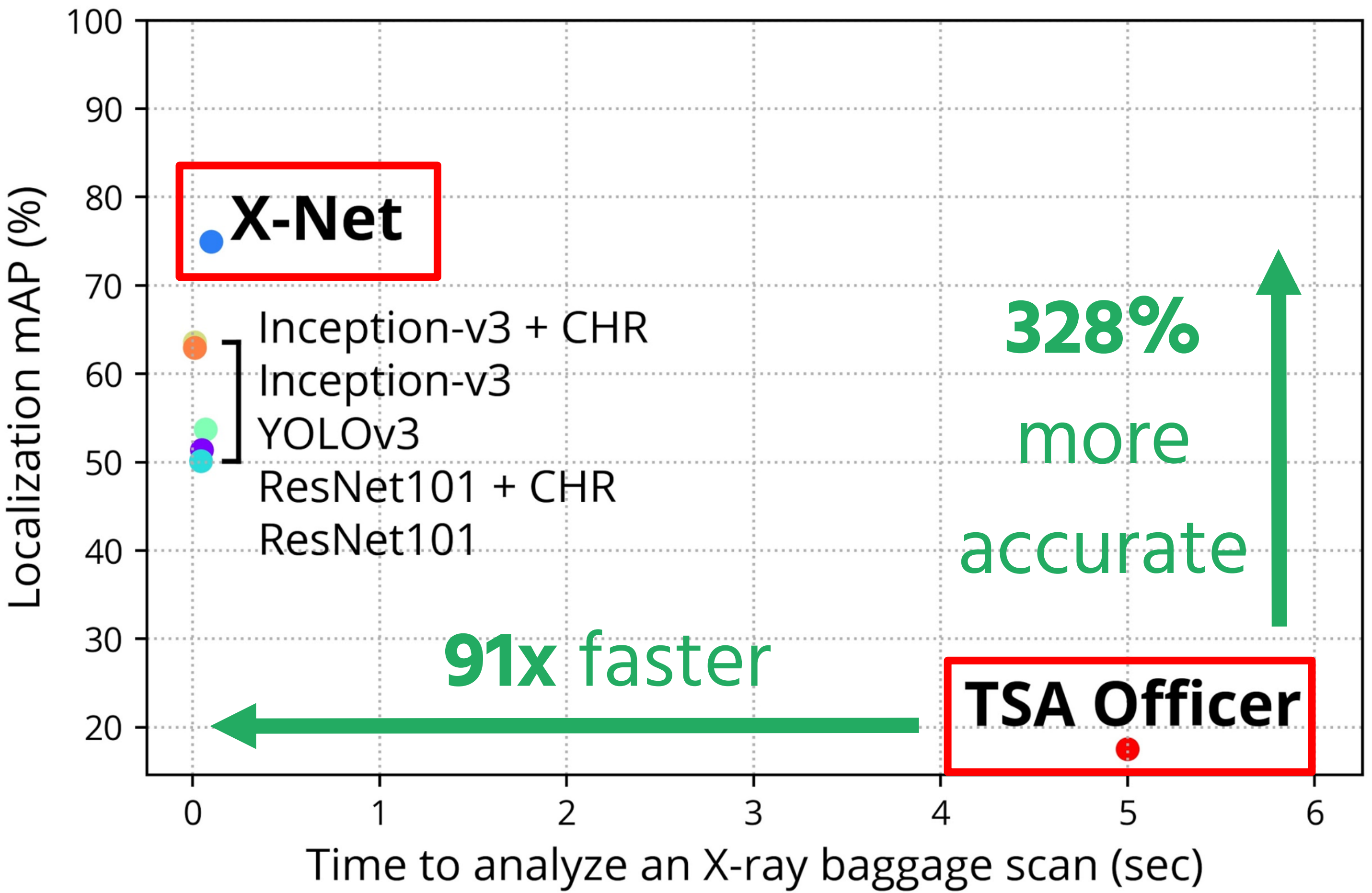
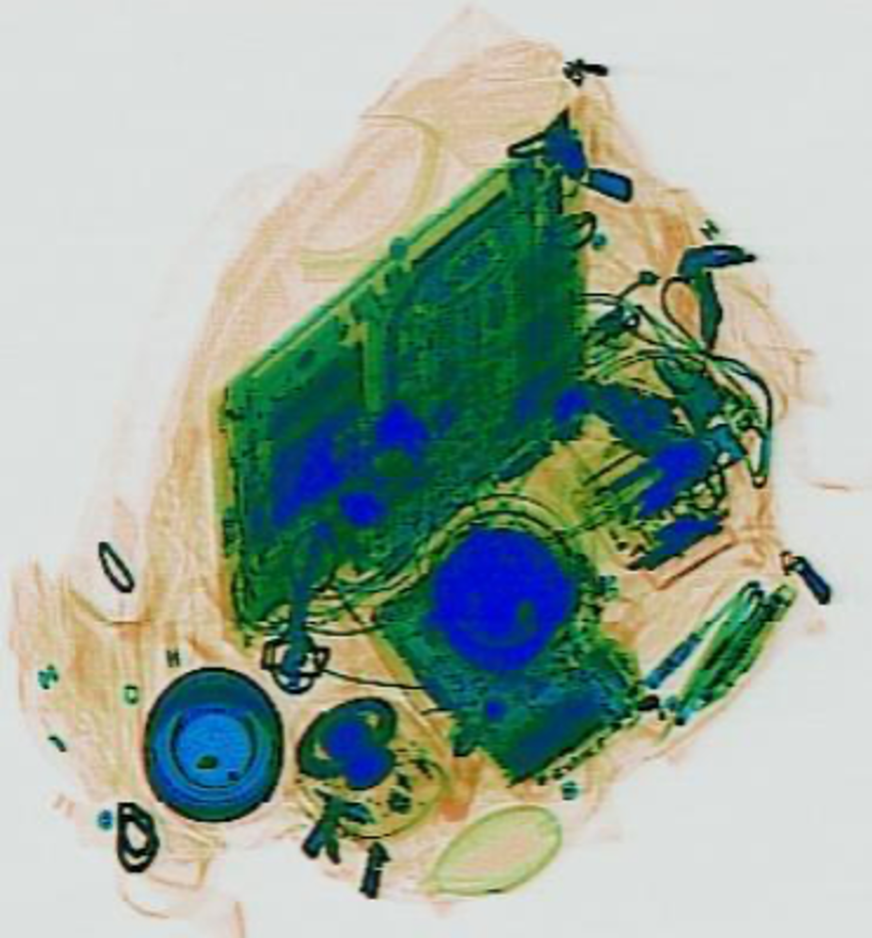
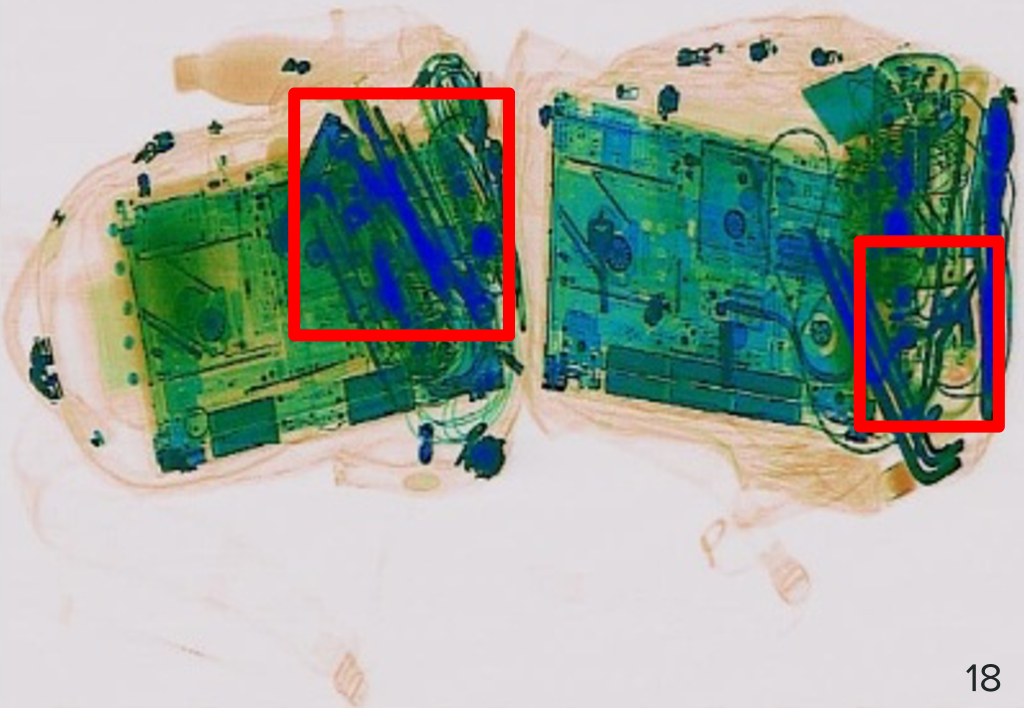


Figure 2. Localization mAP vs. Baggage Analysis Time

X-Ray Baggage Scan: Example





Source: SIXRay

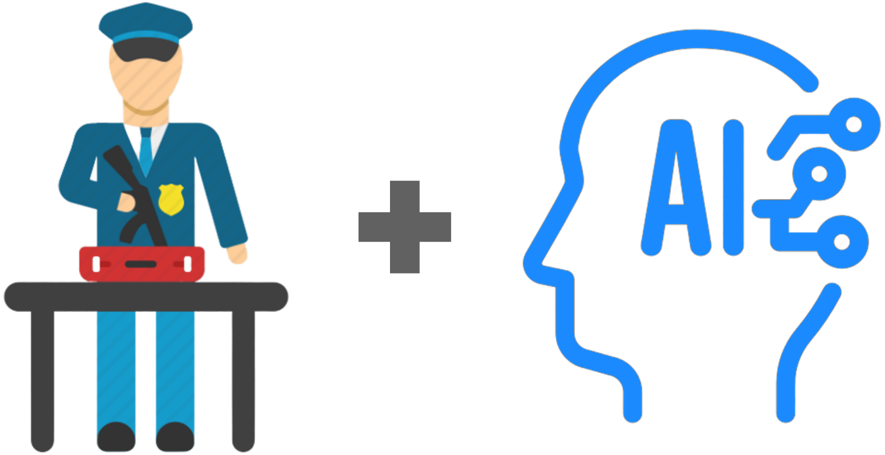
Discussion: Advantages of X-Net

	Fatigue level	Training
X-Net	**Never tires**	**Distributed / Cumulative**
TSA	30 min shifts	Individual

Sources: TSA, *Business Insider*

Discussion: Implementation of X-Net

A portable version of X-Net is only **$100** and therefore **economically feasible** to implement in airports



Discussion: Applications

Deep lateral stacks + parallel networks: empirically validated and applicable to other fields of AI

1. **Autonomous robotics:** self-driving cars
2. **Biometric security:** facial recognition
3. **Medical imaging:** cancer diagnosis

Thank you

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Appendix: Further Results Analysis

True Negative	False Negative	True Positive	False Positive
98.39%	2.02%	87.05%	10.36%

Appendix: Further Results Analysis

The limiting factor of X-Net's accuracy is not its design, but rather **lack of data**