Reconocimiento de Patrones

Version 2023-2

Deep Learning - Introduction

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Ingenieria Electronica
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The Economist

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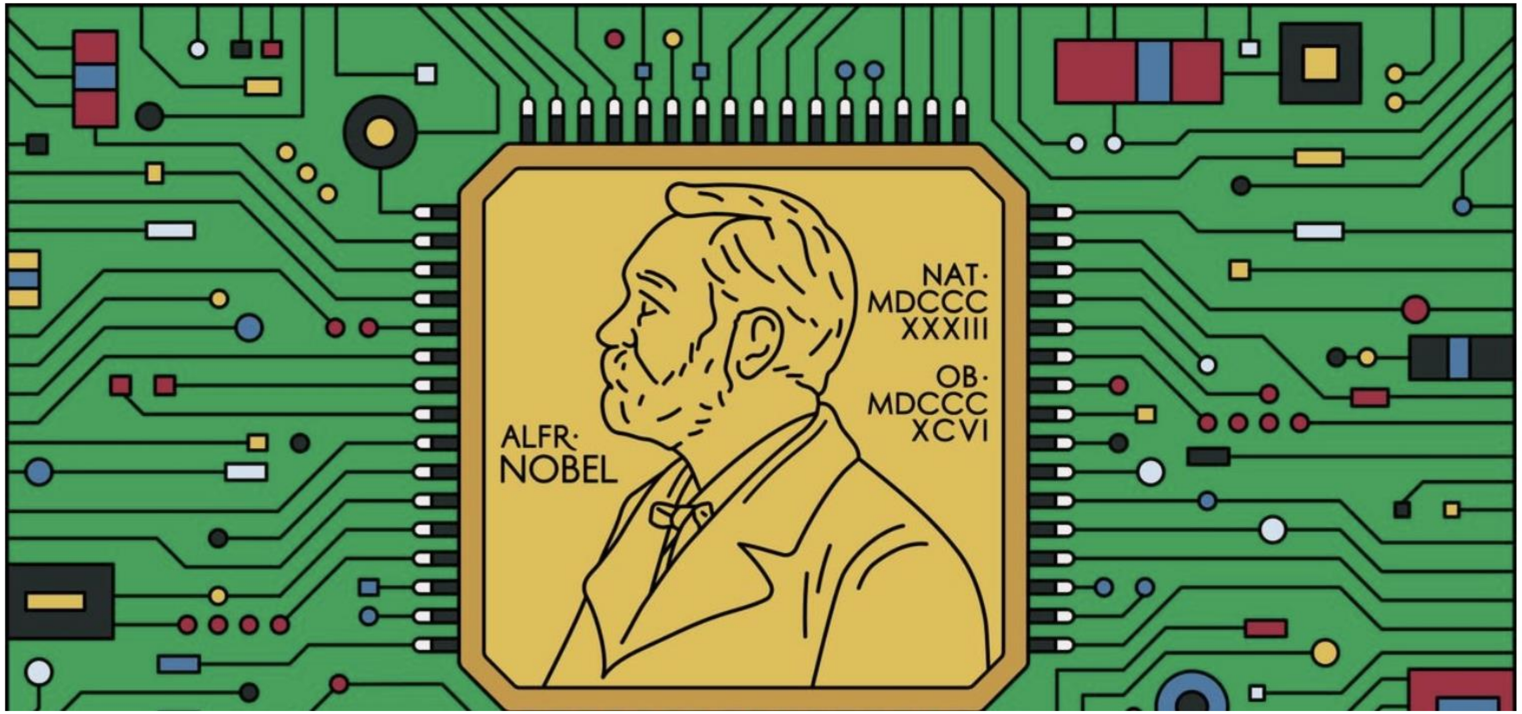
What If?

Jul 3rd 2021 edition ›

Rage against the machine: December 2036

What if an AI won the Nobel prize for medicine?

Controversy ensues when the greatest prize in medical research is awarded to a non-human. An imagined scenario from 2036



https://www.economist.com/what-if/2021/07/03/what-if-an-ai-wins-the-nobel-prize-for-medicine

npj | Digital Medicine

www.nature.com/npjdigitalmed

Corrected: Publisher Correction

ARTICLE OPEN

Development and validation of a deep learning algorithm for improving Gleason scoring of prostate cancer

Kunal Nagpal[1], Davis Foote[1], Yun Liu[1], Po-Hsuan Cameron Chen[1], Ellery Wulczyn[1], Fraser Tan[1], Niels Olson[2], Jenny L. Smith[2], Arash Mohtashamian[2], James H. Wren[3], Greg S. Corrado[1], Robert MacDonald[1], Lily H. Peng[1], Mahul B. Amin[4], Andrew J. Evans[5], Ankur R. Sangoi[6], Craig H. Mermel[1], Jason D. Hipp[1] and Martin C. Stumpe[1,7]

For prostate cancer patients, the Gleason score is one of the most important prognostic factors, potentially determining treatment independent of the stage. However, Gleason scoring is based on subjective microscopic examination of tumor morphology and suffers from poor reproducibility. Here we present a deep learning system (DLS) for Gleason scoring whole-slide images of prostatectomies. Our system was developed using 112 million pathologist-annotated image patches from 1226 slides, and evaluated on an independent validation dataset of 331 slides. Compared to a reference standard provided by genitourinary pathology experts, the mean accuracy among 29 general pathologists was 0.61 on the validation set. The DLS achieved a significantly higher diagnostic accuracy of 0.70 ($p = 0.002$) and trended towards better patient risk stratification in correlations to clinical follow-up data. Our approach could improve the accuracy of Gleason scoring and subsequent therapy decisions, particularly where specialist expertise is unavailable. The DLS also goes beyond the current Gleason system to more finely characterize and quantitate tumor morphology, providing opportunities for refinement of the Gleason system itself.

npj Digital Medicine (2019)2:48 ; https://doi.org/10.1038/s41746-019-0112-2

ORIGINAL RESEARCH article

Front. Neurosci., 28 February 2019 | https://doi.org/10.3389/fnins.2019.00097

Check for updates

A U-Net Deep Learning Framework for High Performance Vessel Segmentation in Patients With Cerebrovascular Disease

Michelle Livne[1,2*], Jana Rieger[1], Orhun Utku Aydin[1], Abdel Aziz Taha[3], Ela Marie Akay[1], Tabea Kossen[1,2], Jan Sobesky[2,4], John D. Kelleher[5], Kristian Hildebrand[6], Diet-mar Frey[1] and Vince I. Madai[1,2]

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Germany

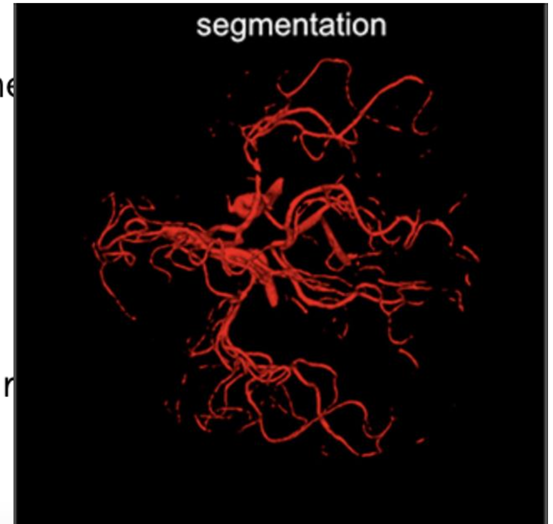
[2]Centre for Stroke Research Berlin, Charité - Universitätsmedizin Berlin, Berlin, Germany

[3]Research Studios Data Science, Research Studios Austria, Salzburg, Austria

[4]Department of Neurology, Johanna-Etienne Hospital Neuss, Neuss, Germany

[5]Information, Communication and Entertainment Institute (ICE), Dublin Institute of Technology, Dublin, Ir

[6]Department VI Computer Science and Media, Beuth University of Applied Sciences, Berlin, Germany



LETTER

doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1]*, Brett Kuprel[1]*, Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

Skin cancer, the most common human malignancy[1–3], is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Deep convolutional neural networks (CNNs)[4,5] show potential for general and highly variable tasks across many fine-grained object categories[6–11]. Here we demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. We train a CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets[12]—consisting of 2,032 different diseases. We

images (for example, smartphone images) exhibit variability in factors such as zoom, angle and lighting, making classification substantially more challenging[23,24]. We overcome this challenge by using a data-driven approach—1.41 million pre-training and training images make classification robust to photographic variability. Many previous techniques require extensive preprocessing, lesion segmentation and extraction of domain-specific visual features before classification. By contrast, our system requires no hand-crafted features; it is trained end-to-end directly from image labels and raw pixels, with a single network for both photographic and dermoscopic images. The existing body of work uses small datasets of typically less than a thousand images of skin lesions[16,18,19], which, as a result, do not generalize well to new images. We demonstrate generalizable classification with a new

LETTER

doi:10.1038/nature25988

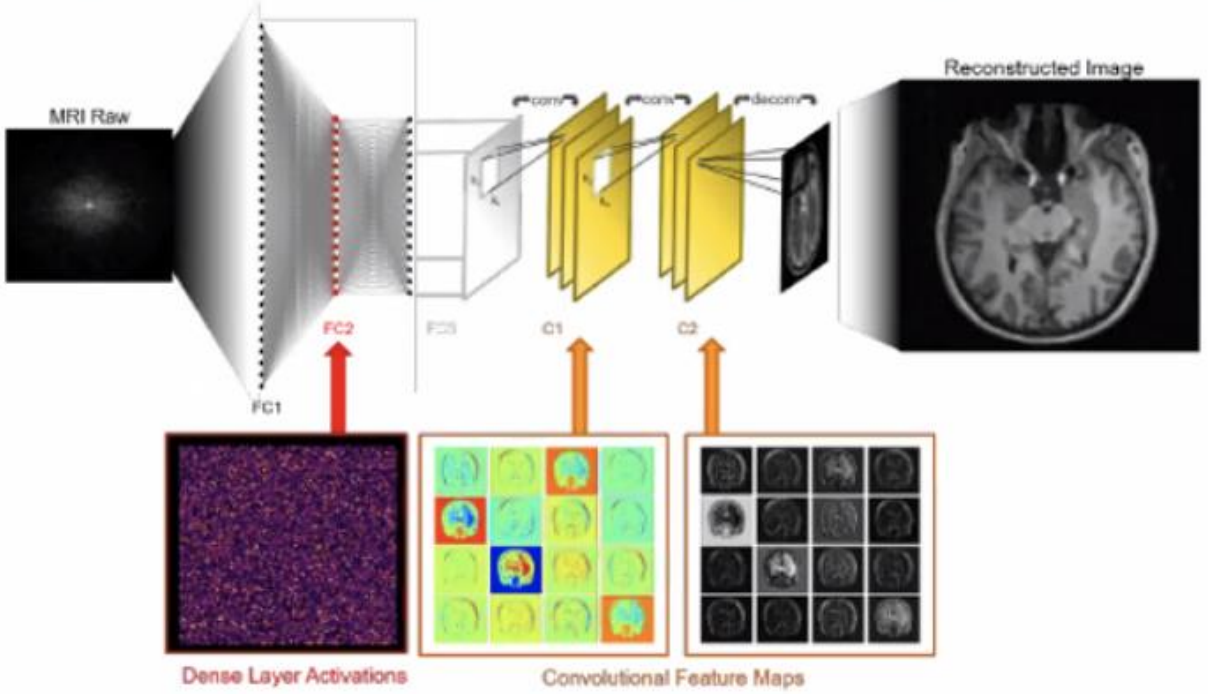
Image reconstruction by domain-transform manifold learning

Bo Zhu[1,2,3], Jeremiah Z. Liu[4], Stephen F. Cauley[1,2], Bruce R. Rosen[1,2] & Matthew S. Rosen[1,2,3]

Image reconstruction is essential for imaging applications across the physical and life sciences, including optical and radar systems, magnetic resonance imaging, X-ray computed tomography, positron emission tomography, ultrasound imaging and radio astronomy[1–3]. During image acquisition, the sensor encodes an intermediate representation of an object in the sensor domain, which is subsequently reconstructed into an image by an inversion of the encoding function. Image reconstruction is challenging

Inspired by the perceptual learning archetype, we describe here a data-driven unified image reconstruction approach, which we call AUTOMAP, that learns a reconstruction mapping between the sensor-domain data and image-domain output (Fig. 1a). As this mapping is trained, a low-dimensional joint manifold of the data in both domains is implicitly learned (Fig. 1b), capturing a highly expressive representation that is robust to noise and other input perturbations.

We implemented the AUTOMAP unified reconstruction framework



Neural Networks 131 (2020) 251–275

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

Review

Deep learning on image denoising: An overview

Chunwei Tian [a,b], Lunke Fei [c], Wenxian Zheng [d], Yong Xu [a,b,e,*], Wangmeng Zuo [f,e], Chia-Wen Lin [g]

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[b] *Shenzhen Key Laboratory of Visual Object Detection and Recognition, Shenzhen, 518055, Guangdong, China*
[c] *School of Computers, Guangdong University of Technology, Guangzhou, 510006, Guangdong, China*
[d] *Tsinghua Shenzhen International Graduate School, Shenzhen, 518055, Guangdong, China*
[e] *Peng Cheng Laboratory, Shenzhen, 518055, Guangdong, China*
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[g] *Department of Electrical Engineering and the Institute of Communications Engineering, National Tsing Hua University, Hsinchu, Taiwan*

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Real noisy images
Blind denoising
Hybrid noisy images

ABSTRACT

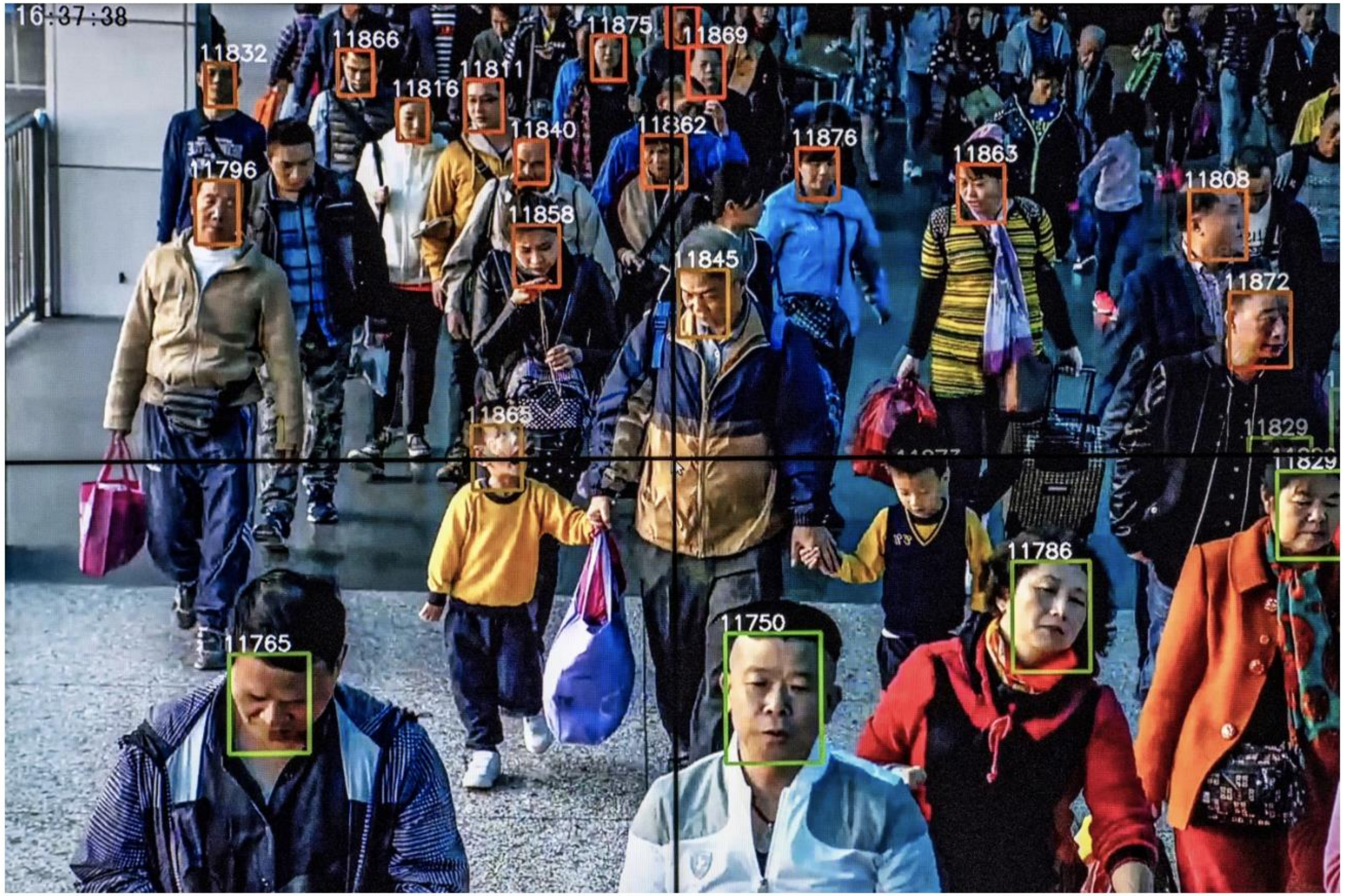
Deep learning techniques have received much attention in the area of image denoising. However, there are substantial differences in the various types of deep learning methods dealing with image denoising. Specifically, discriminative learning based on deep learning can ably address the issue of Gaussian noise. Optimization models based on deep learning are effective in estimating the real noise. However, there has thus far been little related research to summarize the different deep learning techniques for image denoising. In this paper, we offer a comparative study of deep techniques in image denoising. We first classify the deep convolutional neural networks (CNNs) for additive white noisy images; the deep CNNs for real noisy images; the deep CNNs for blind denoising and the deep CNNs for hybrid noisy images, which represents the combination of noisy, blurred and low-resolution images. Then, we analyze the motivations and principles of the different types of deep learning methods. Next, we compare the state-of-the-art methods on public denoising datasets in terms of quantitative and qualitative analyses. Finally, we point out some potential challenges and directions of future research.

MAGAZINE • CHINA

In China, Facial Recognition Tech Is Watching You

BY **EAMON BARRETT**

October 28, 2018 11:00 AM GMT-3



Where's Waldo? Monitors at the Beijing offices of A.I.-software startup Megvii play a video showing how its facial recognition software

How Tesla Is Using Artificial Intelligence to Create The Autonomous Cars Of The Future

Over 500,000 Teslas all over the world are feeding data back to Elon Musk's headquarters, to train their autonomous car algorithms. This data gives Tesla a huge advantage in the race to put more self-driving cars on the road.

App Store Preview

This app is available only on the App Store for iPhone and iPad.

iDetection 4+

Dream > Design > Deliver

Ultralytics LLC

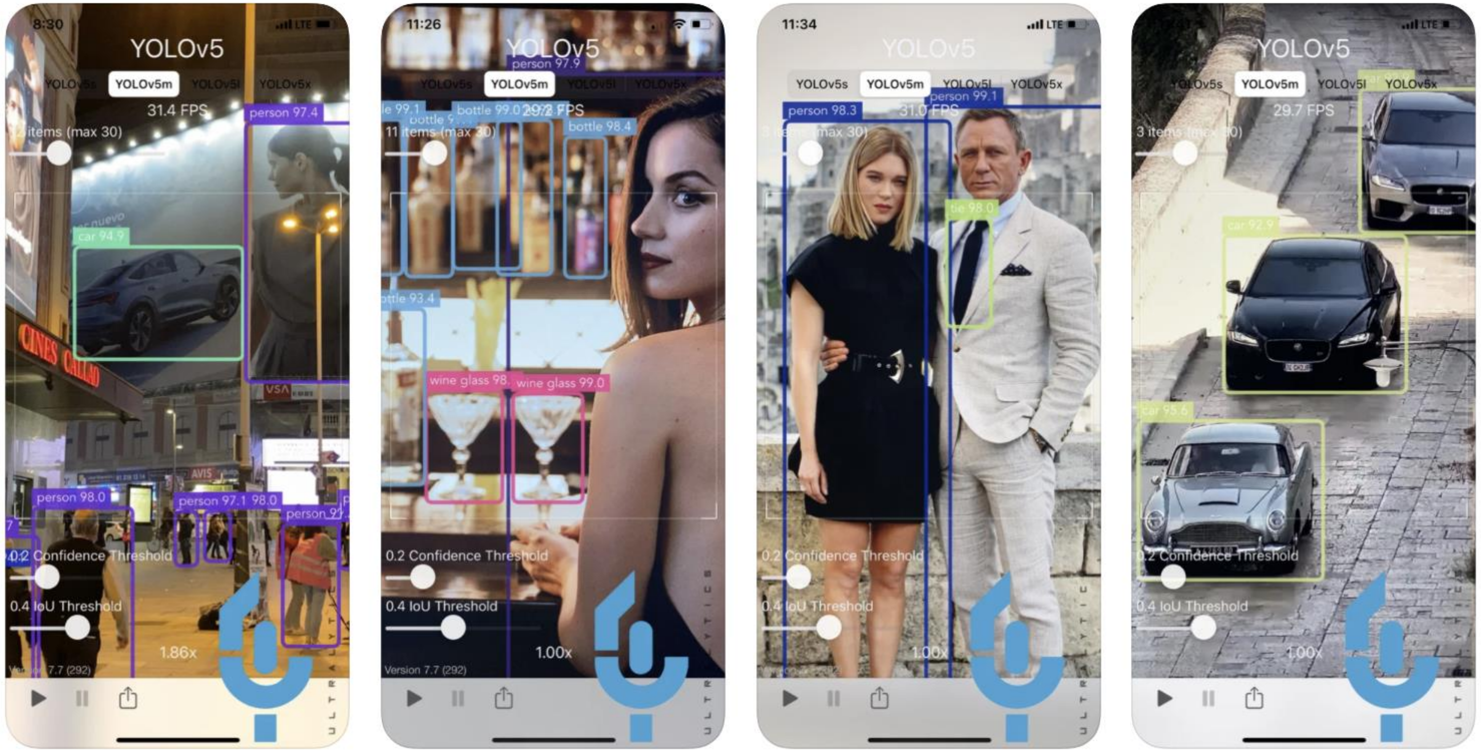
★★★★★ 4.5 • 39 Ratings

Free

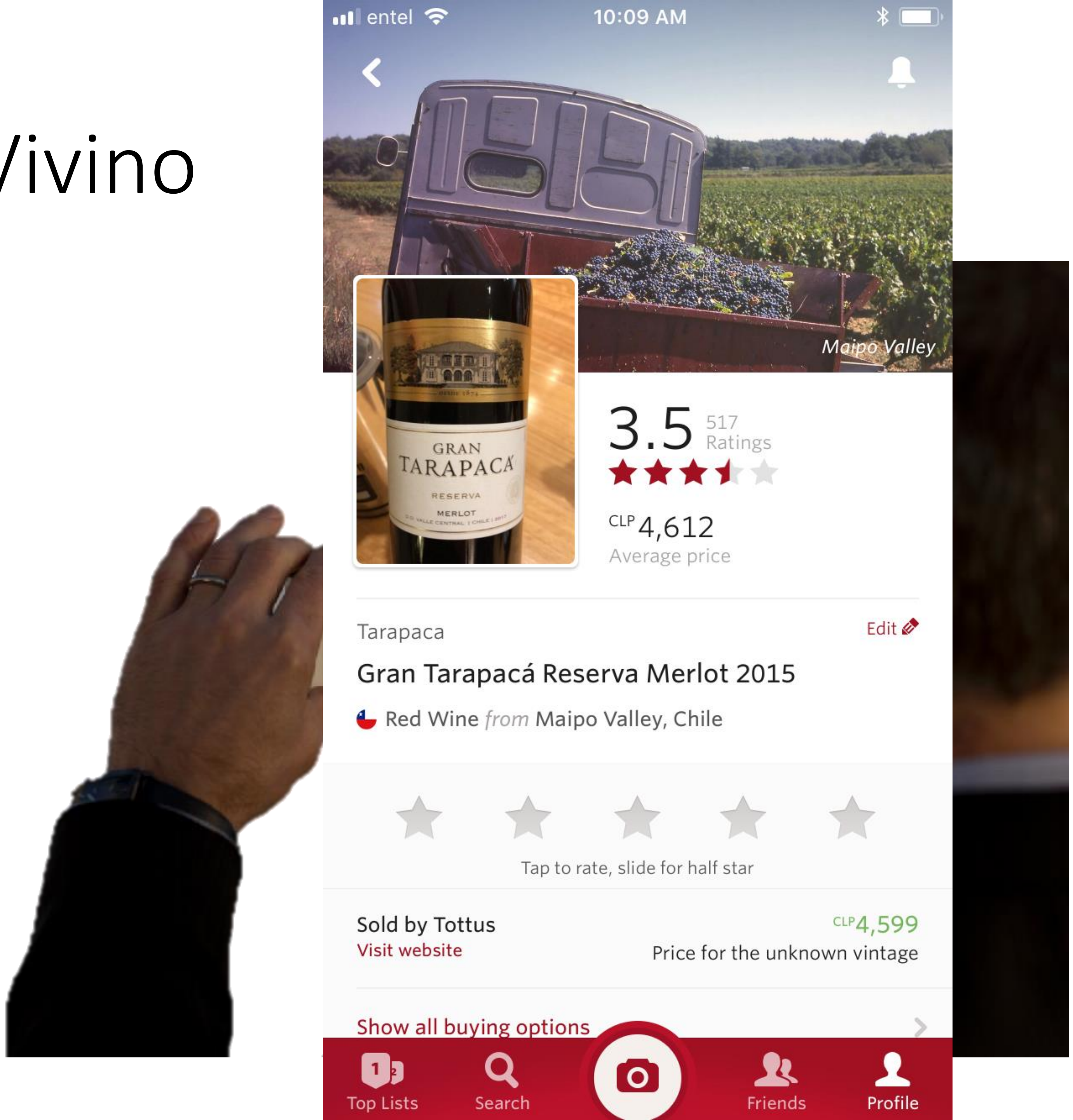
Object Detection

Screenshots

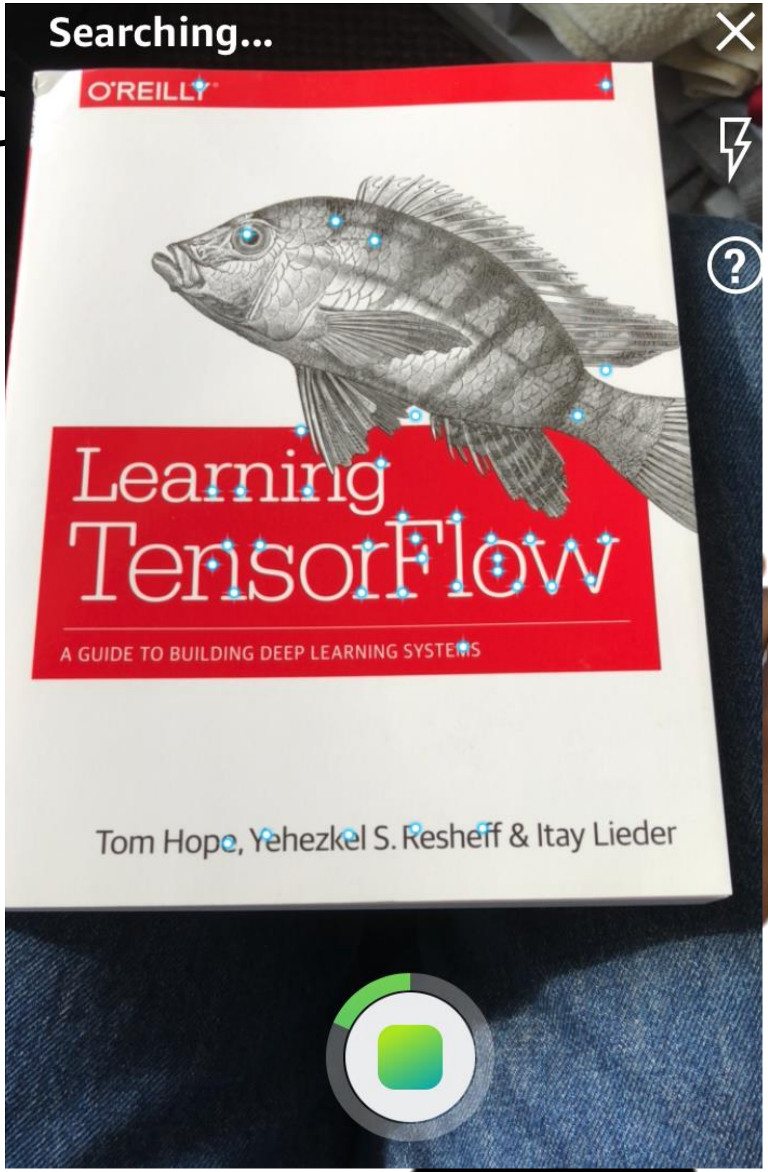
iPhone iPad

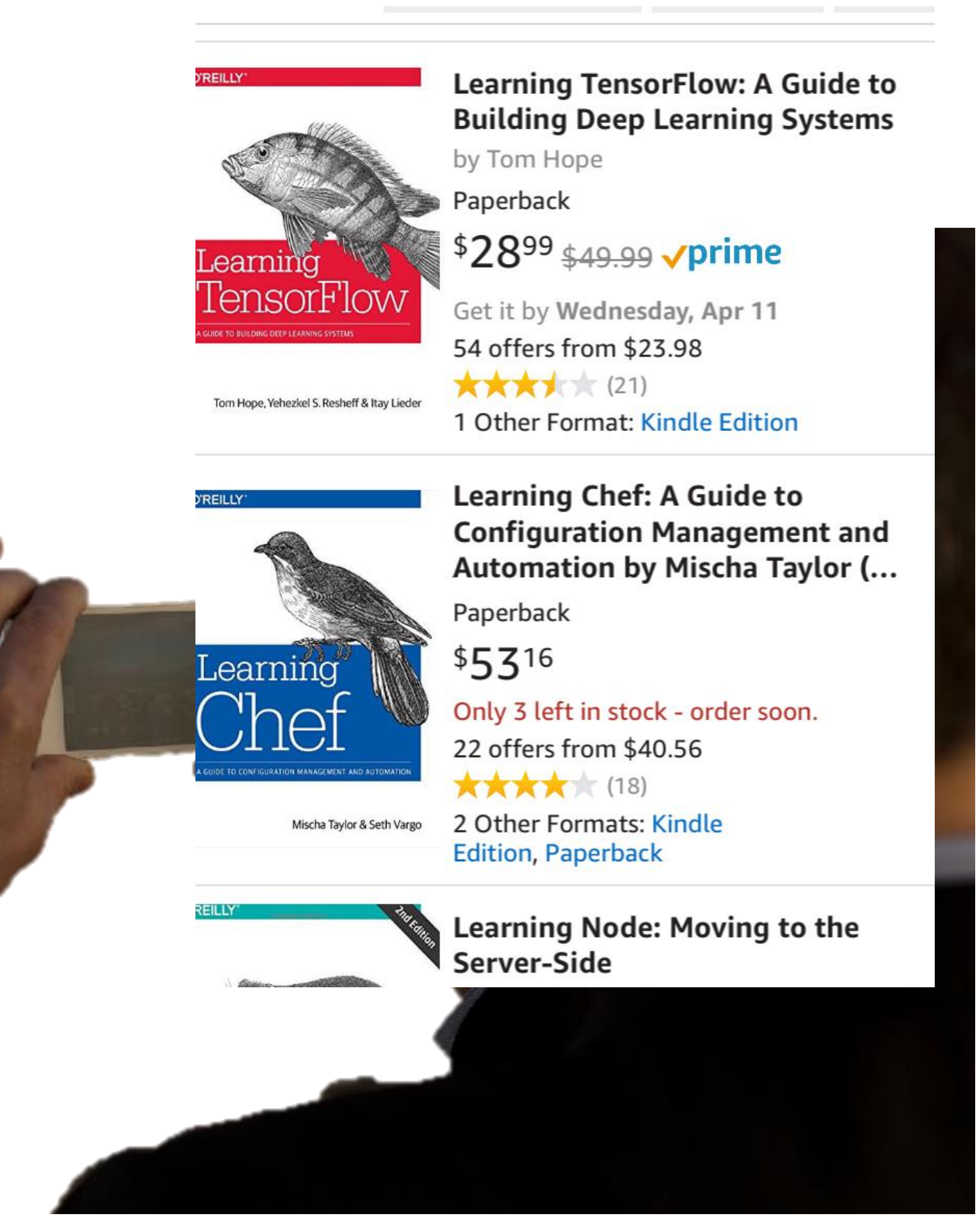


Applications: Vivino



Applic


Searching...
O'REILLY
Learning TensorFlow
A GUIDE TO BUILDING DEEP LEARNING SYSTEMS
Tom Hope, Yehezkel S. Resheff & Itay Lieder


Learning TensorFlow: A Guide to Building Deep Learning Systems
by Tom Hope
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106 STARTUPS TRANSFORMING HEALTHCARE WITH AI

… etcetera

Applications of Computer Vision

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Ingenieria Electronica
Universidad Popular del Cesar

> Five Applications of Computer Vision

Applications of Computer Vision

1) Image Classification
2) Image Processing
3) Object Detection
4) Anomaly Detection
5) Human + Computer Vision

- Problem
- Solution
- Examples

Applications

1) Image Classification
2) Image Processing
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Applications

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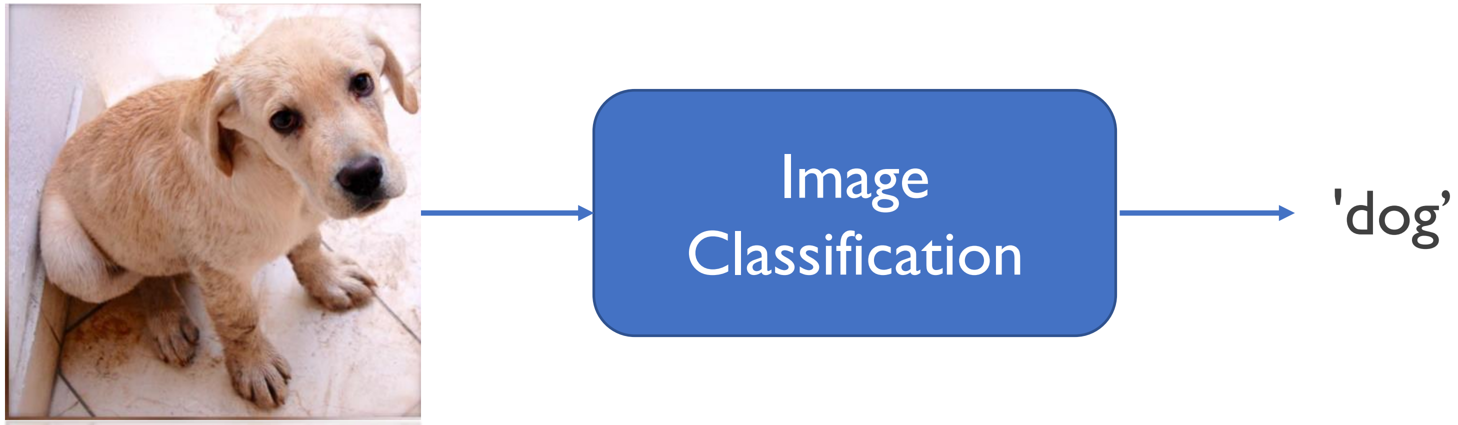
Image Classification – Problem

> Assign an image to a class or category



Input: image

Output: Class

Image Classification – Problem

> Assign an image to a class or category

Input: image

Image Classification

'cat’

Output: Class

Image Classification – Solution

Deep Learning Model: CNN

Convolutional Neural Network

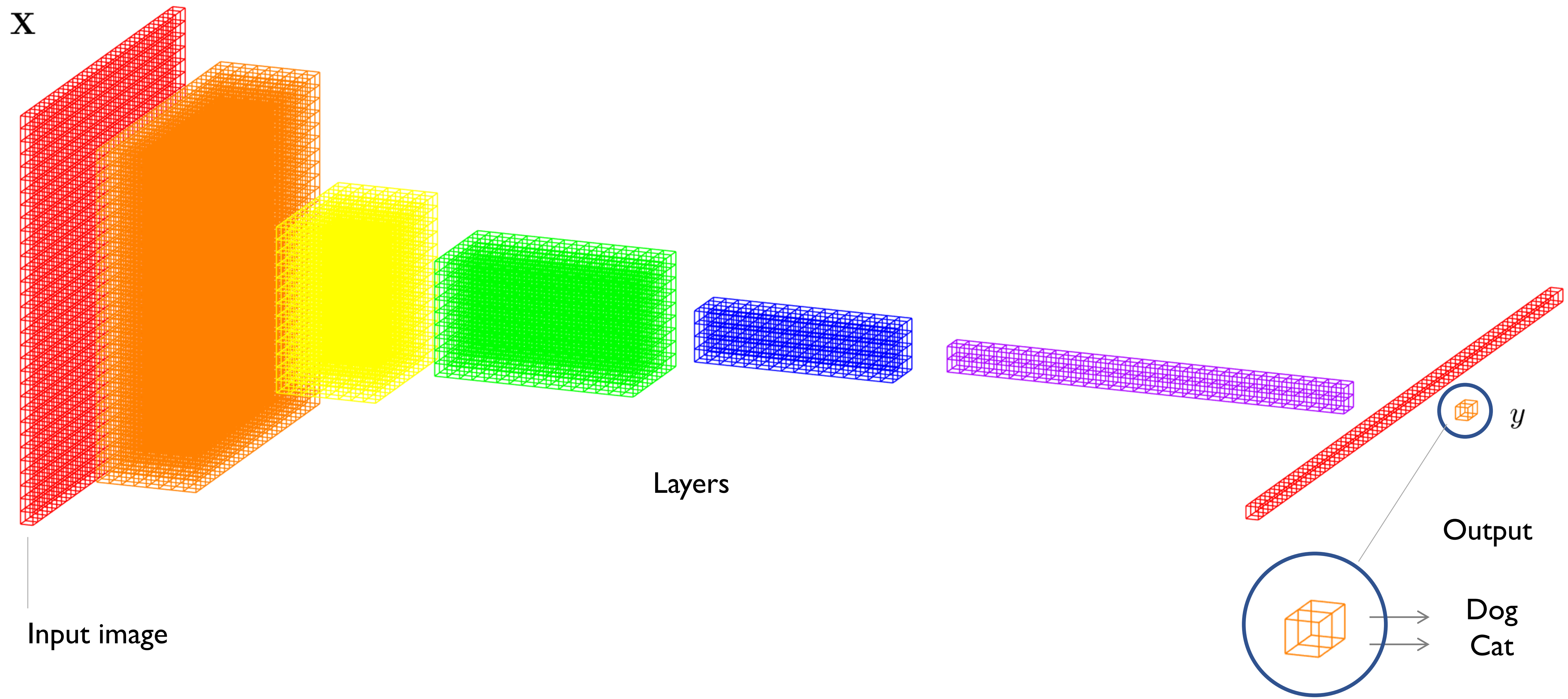


Image Classification – Solution

Deep Learning Model: CNN

Convolutional Neural Network

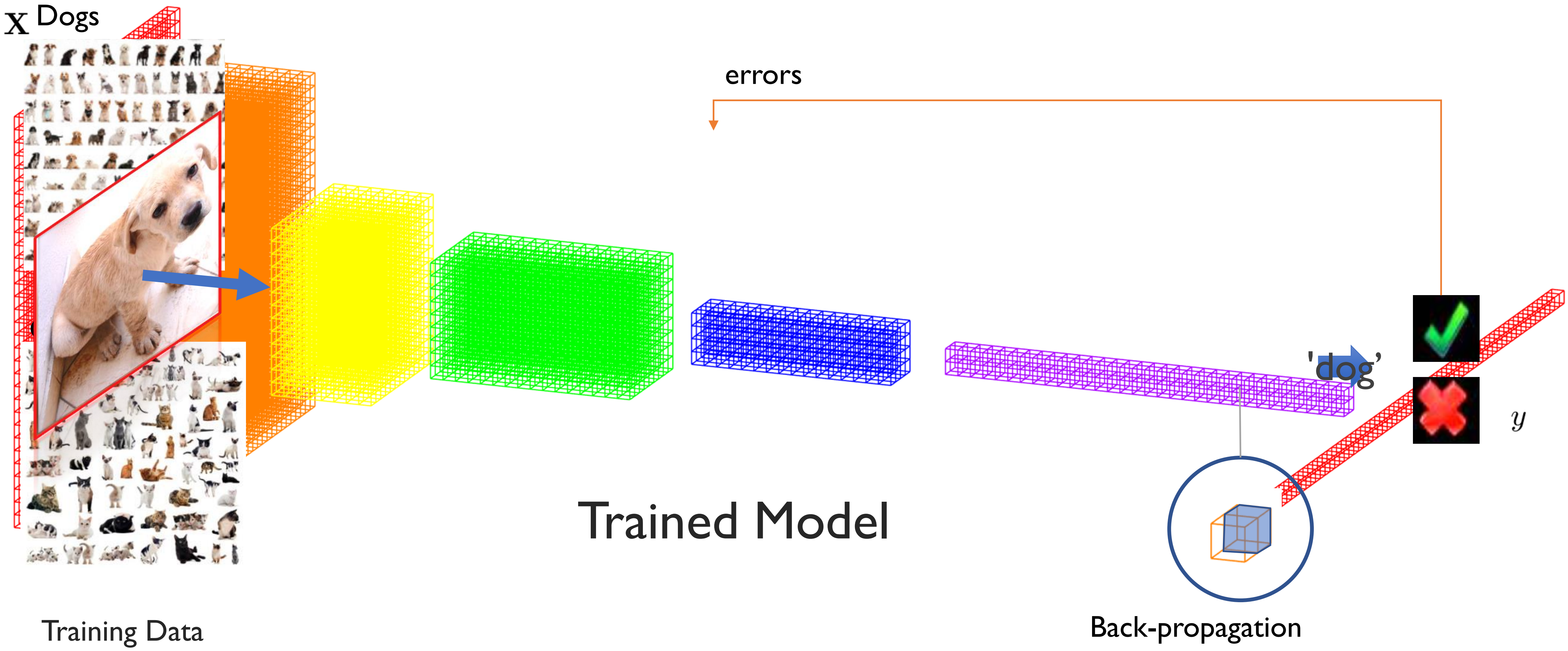


Image Classification – Example

COVID Detection with Rx

Classes → 0: NORMAL 1: NEUMONIA 2: COVID19

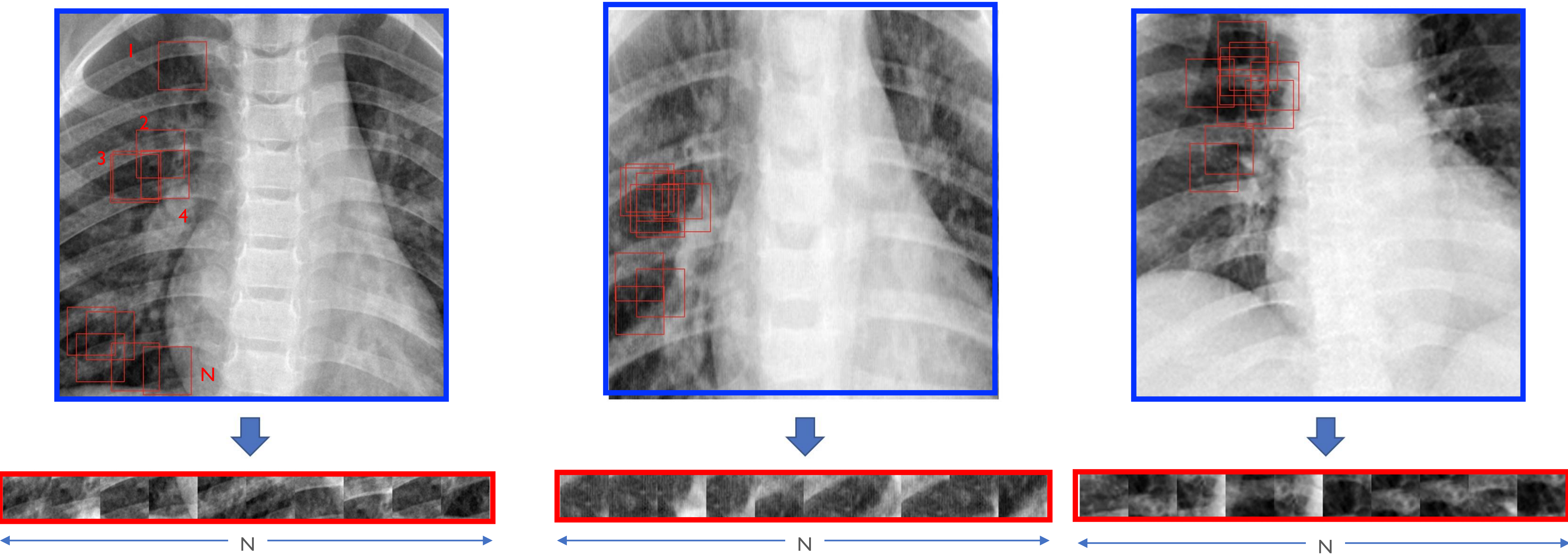
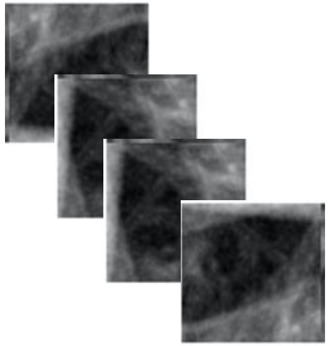


Image Classification – Example

COVID Detection with Rx

Training



15.840 patches

660 subjects*
(220 per class)

→ CNN

(80% training, 20% validation)
94.0% 91.7%

(*) 2 datasets: SIRM, UC

Trained model

Testing

3.640 patches

150 subjects*
(50 per class)

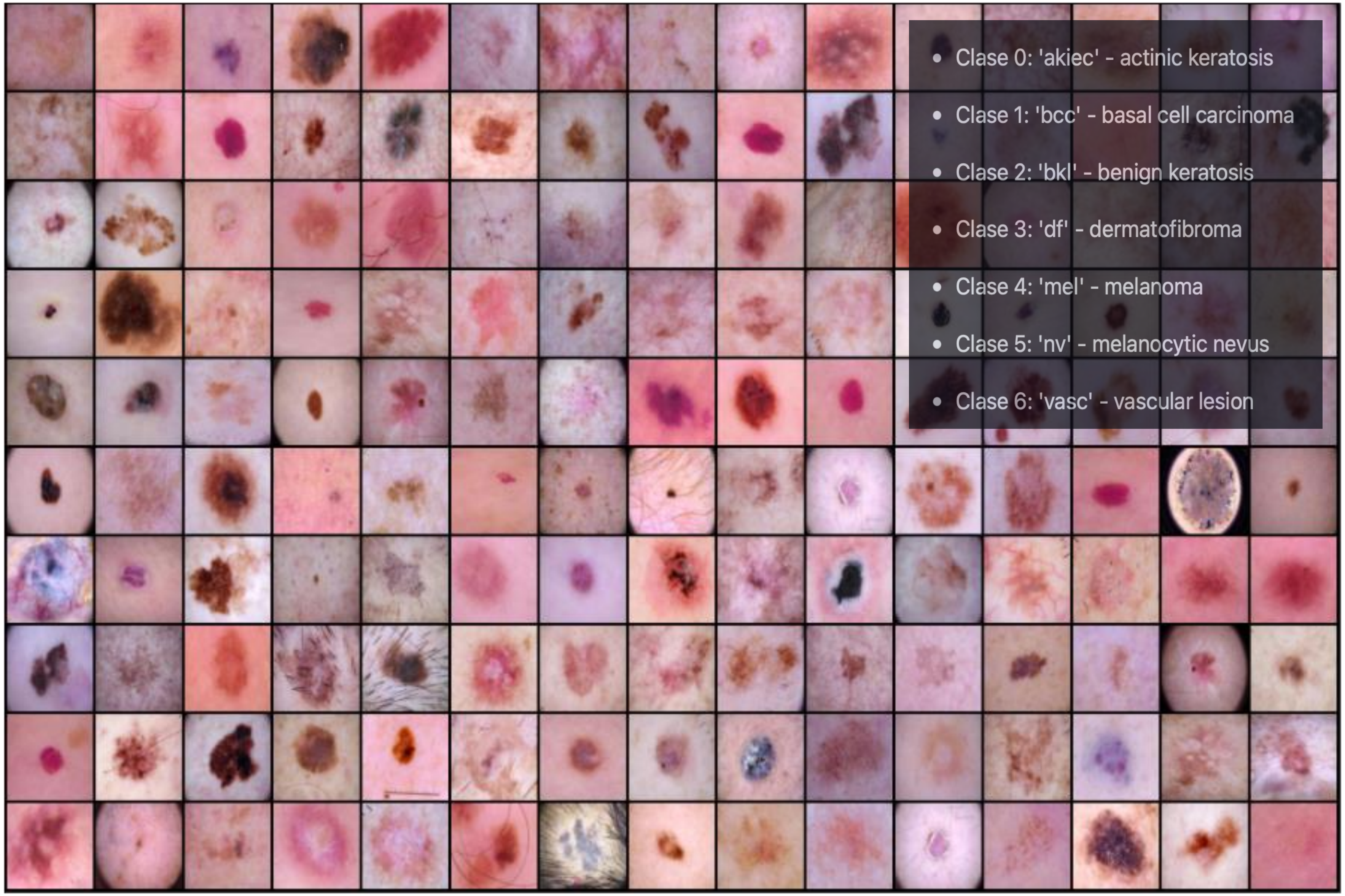
→ Image Classification → Majority Vote → output

88.9%

95.3%

Image Classification – Example

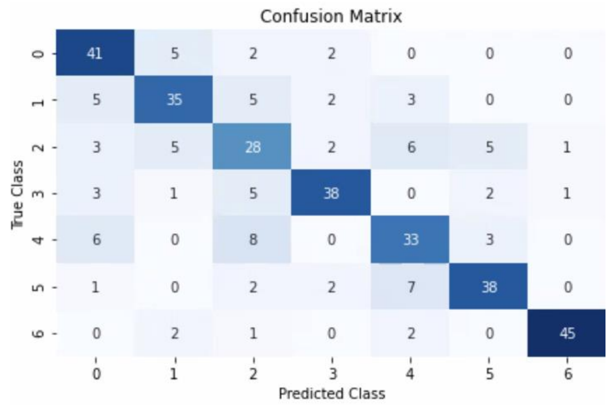
Skin Lesion Recognition



7 classes
5000 images*

CNN

73.71%



(*) ISIC dataset

Applications

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Applications

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Image Processing – Problem

> Get a target output image from an input image

Input: image

Output: Filtered image

Image Processing – Problem

> Get a target output image from an input image

Input: image

Output: Segmentation

Image Processing – Solution

Deep Learning Model: U-Net

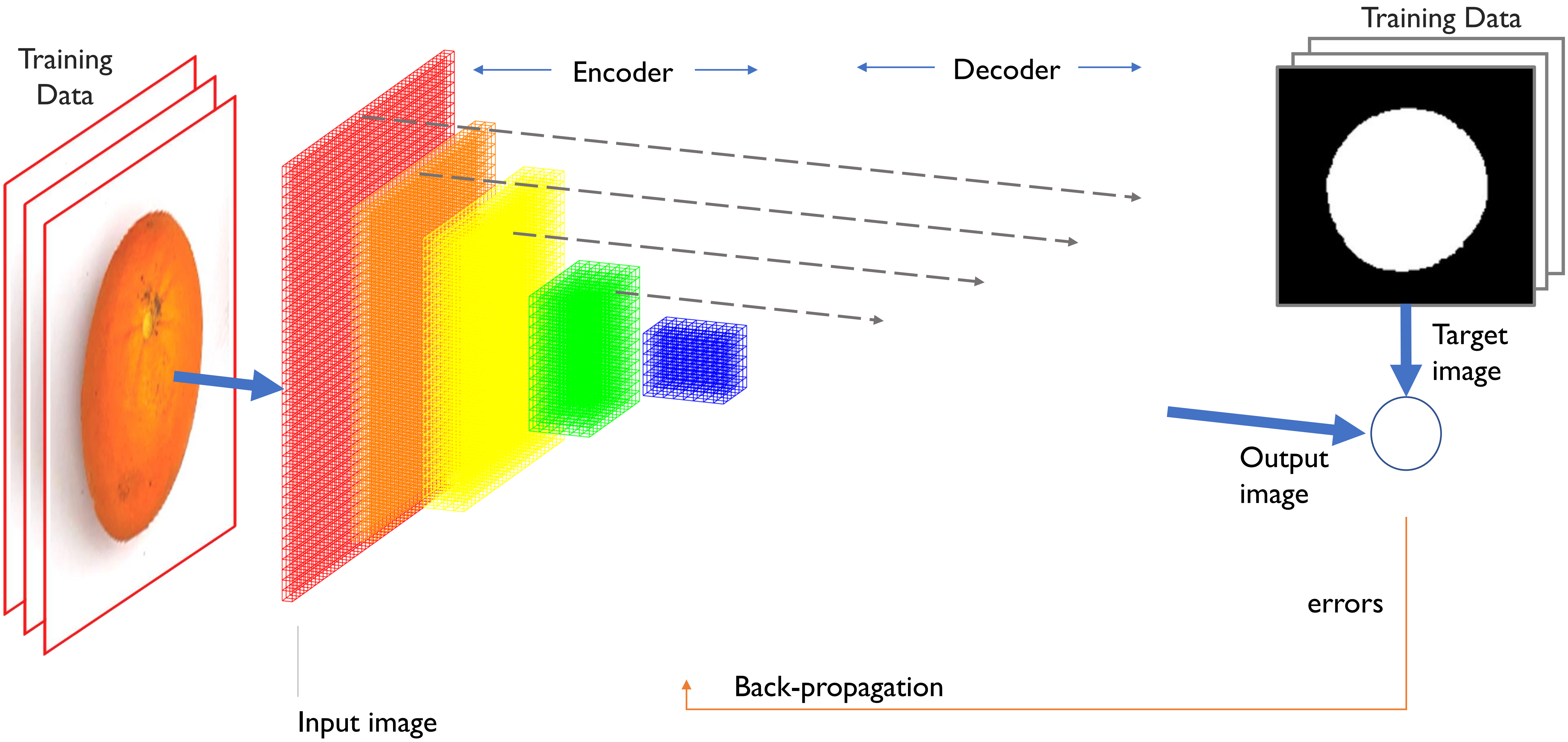


Image Segmentation
Example

Güiñas
Segmentation

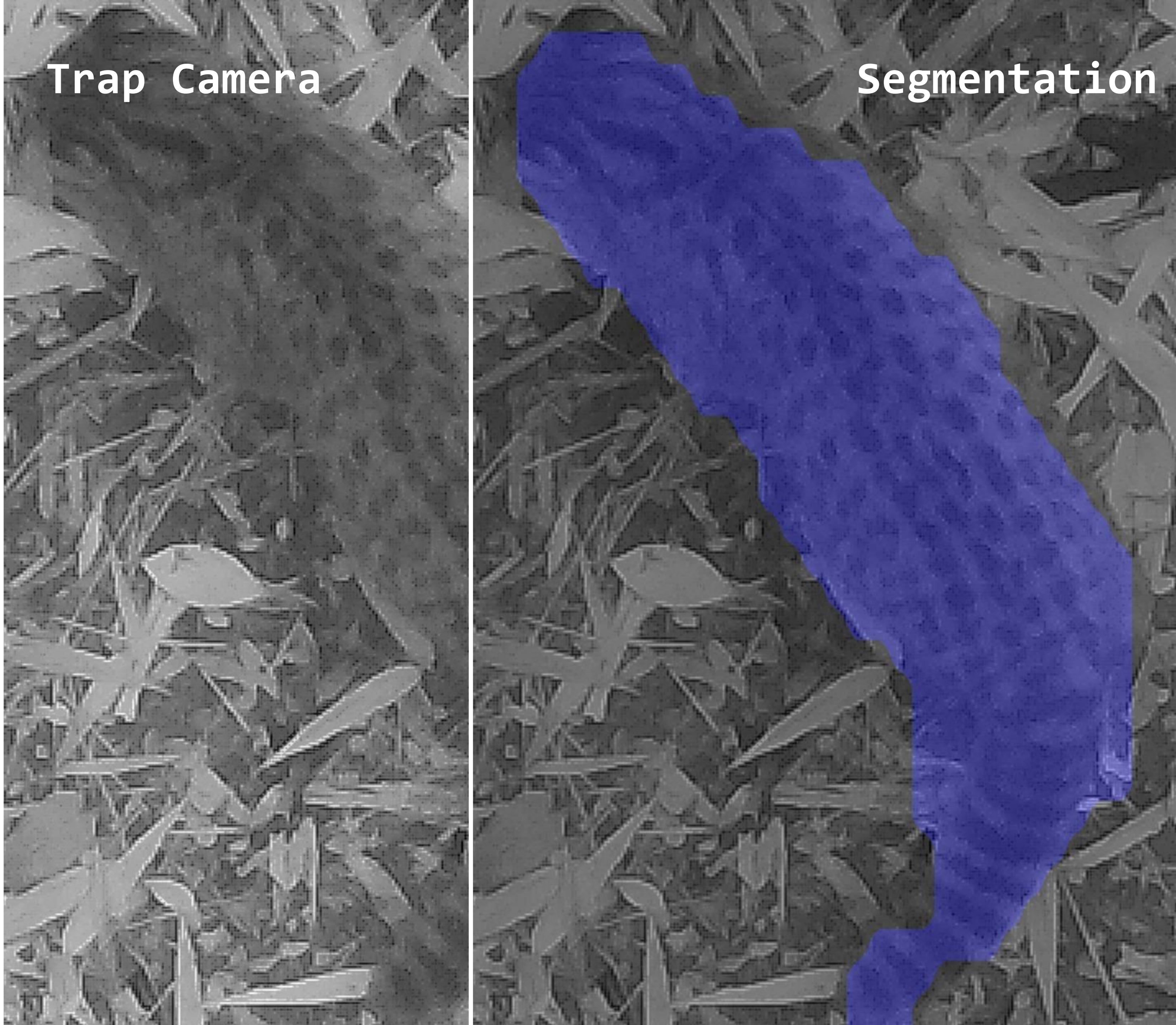


Image Segmentation Example

Skin Lesion Segmentation

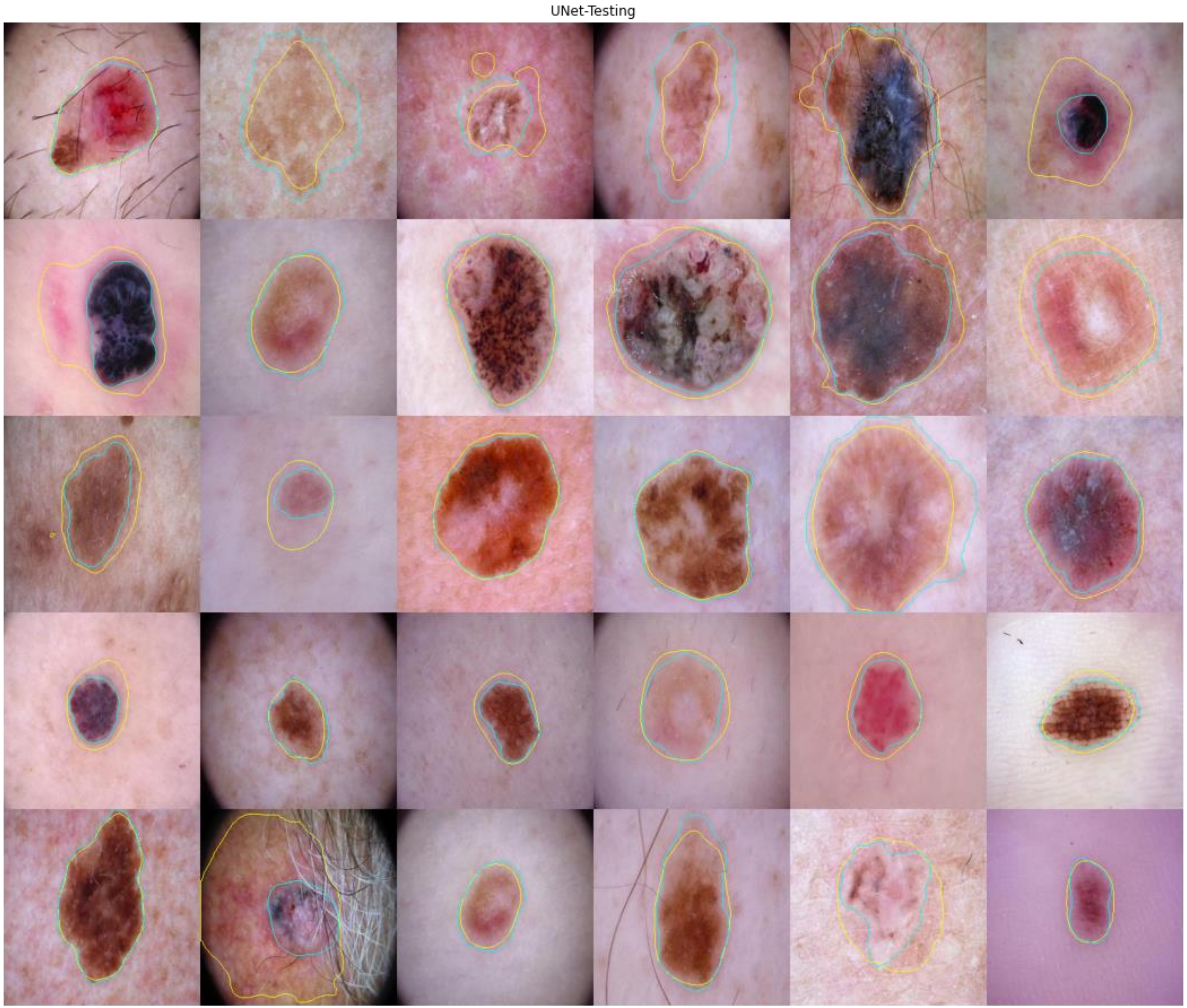
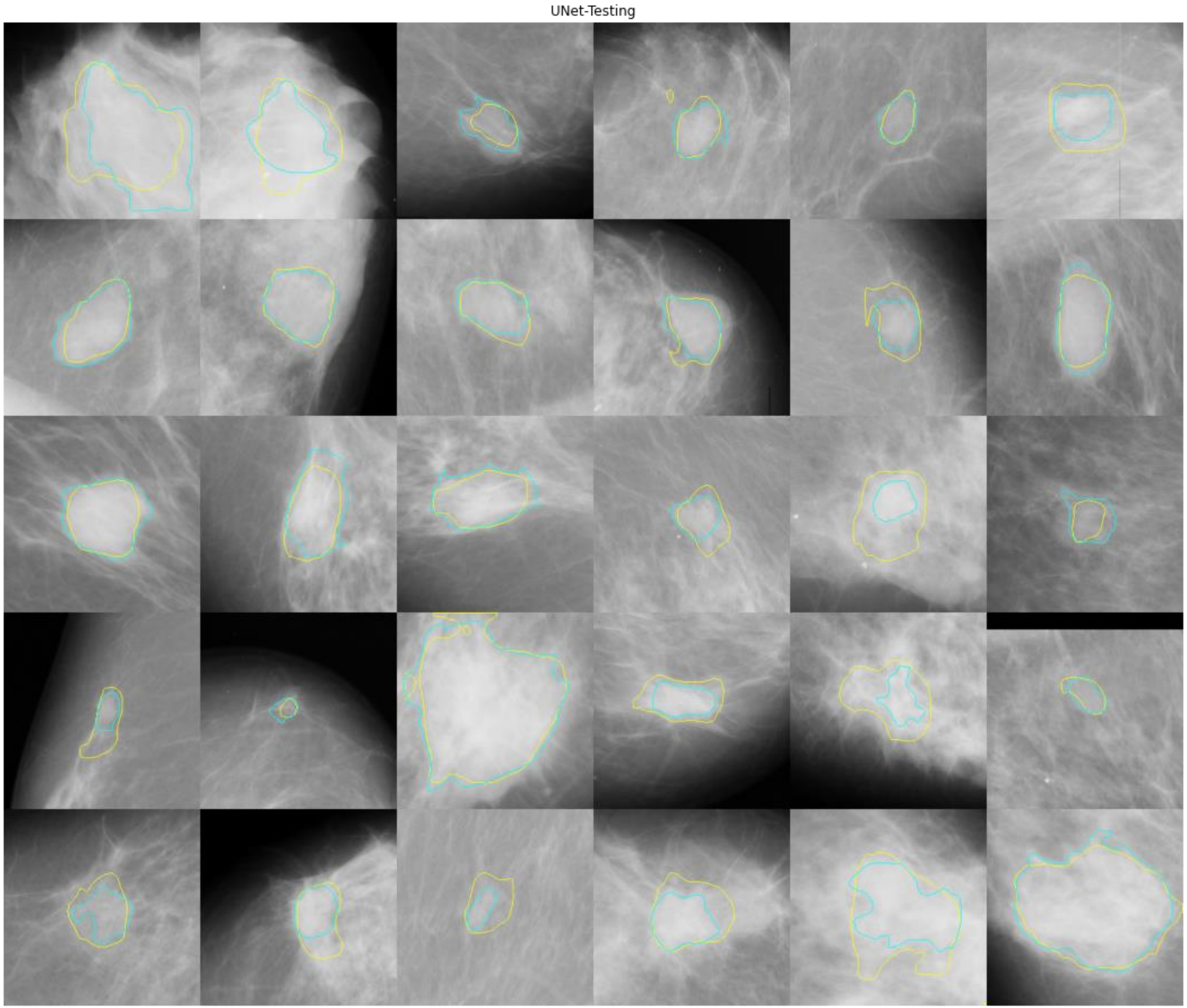


Image Segmentation
Example



Breast Tumor Segmentation

Applications

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2) Image Processing
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Applications

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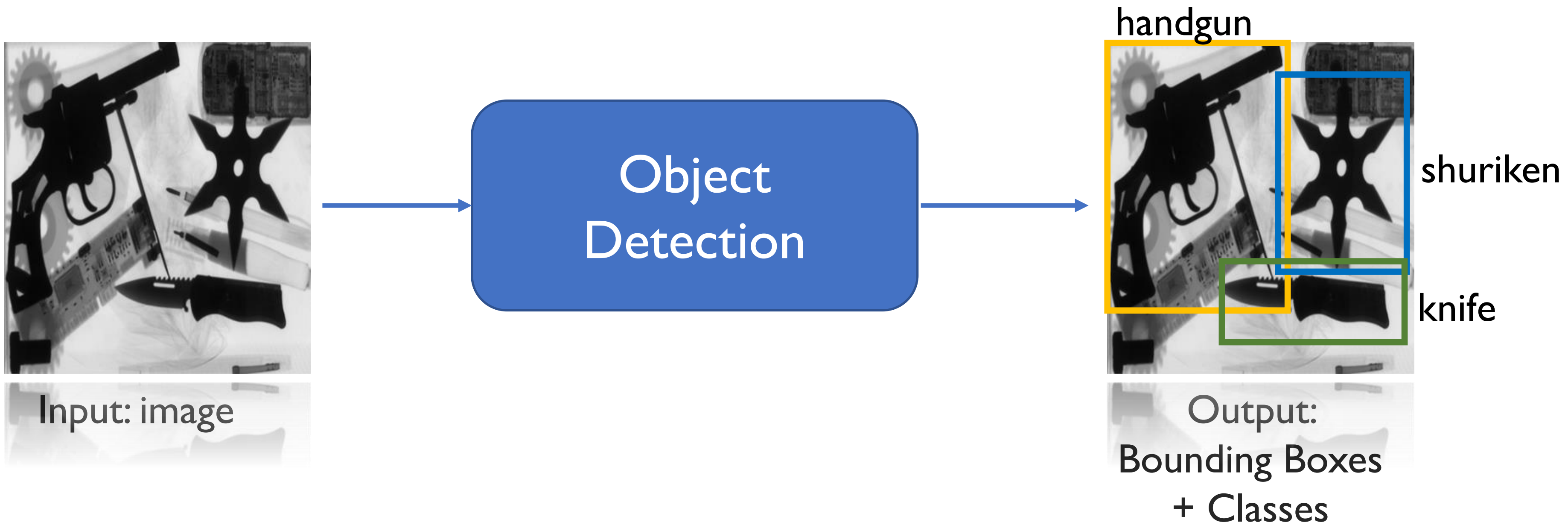
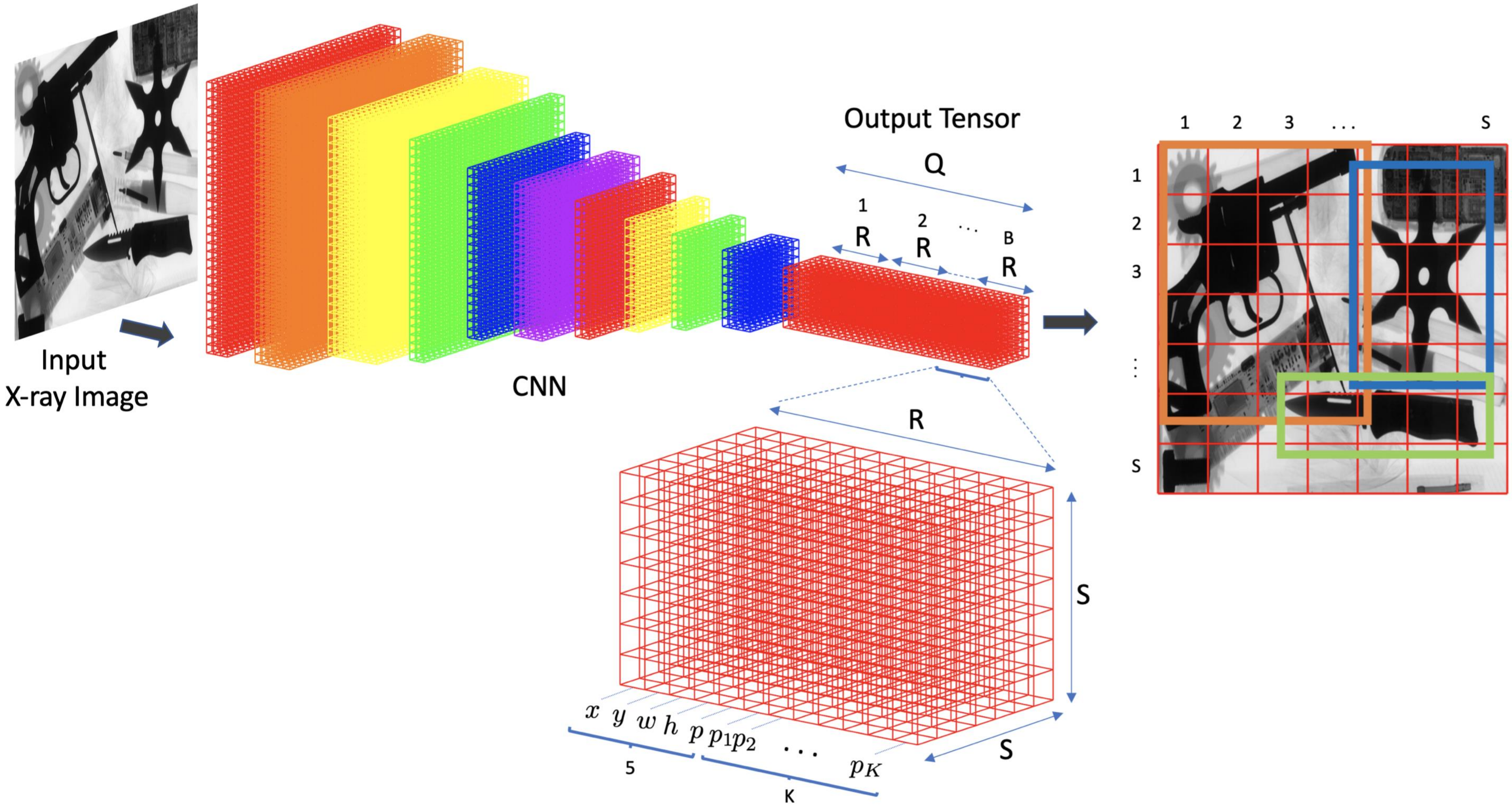
Object Detection – Problem

> Locate and classify objects



Object Detection – Solution

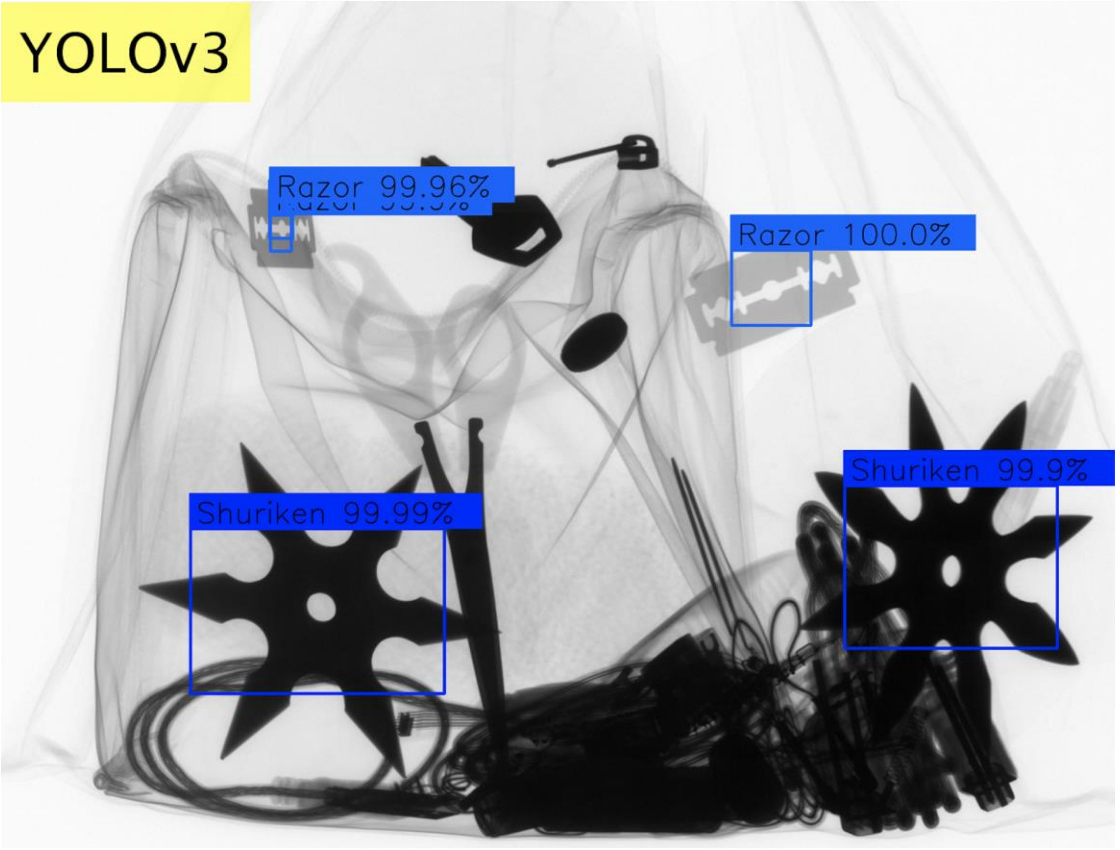
Deep Learning Model: YOLO

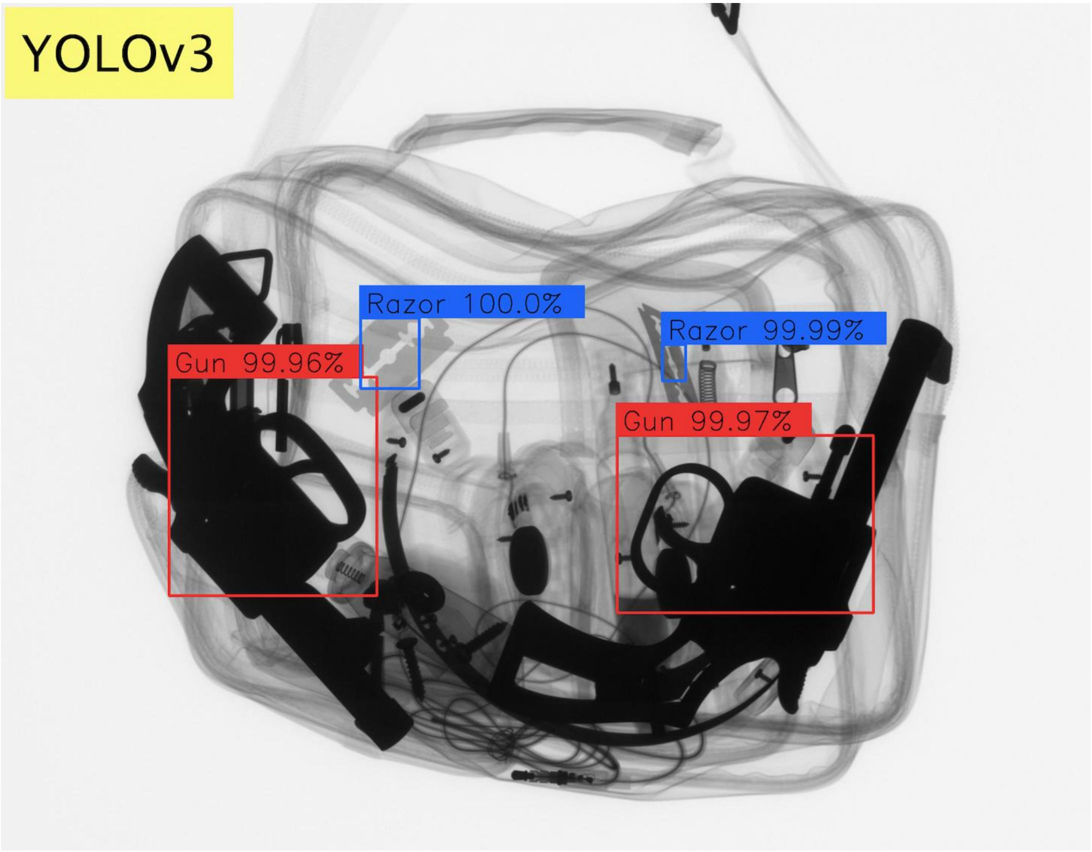


Object Detection – Example

Deep Learning Model: YOLO

Recognition of Threat Objects in Baggage Inspection

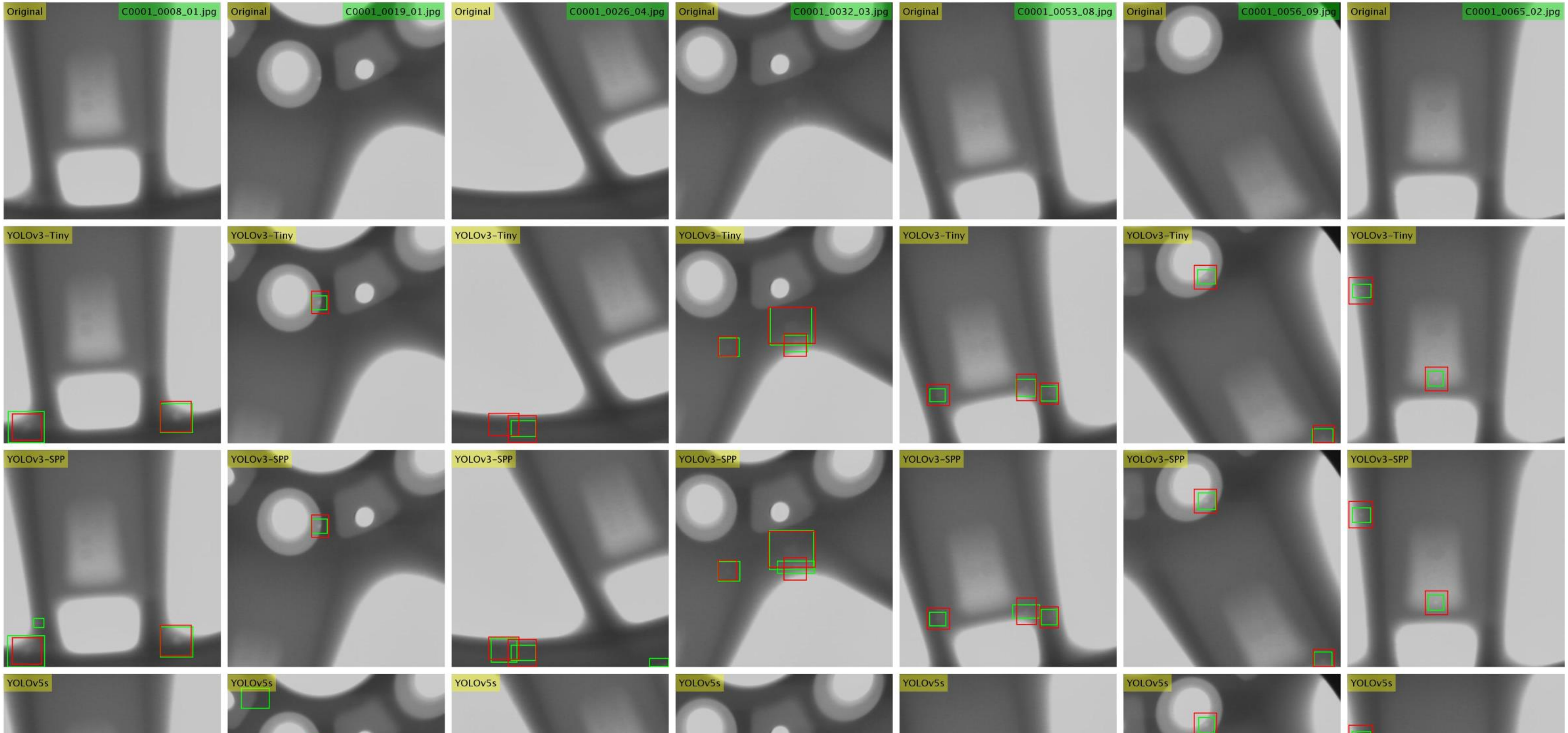




Object Detection – Example

Deep Learning Model: YOLO

Recognition of Small Defects in Aluminum Wheels

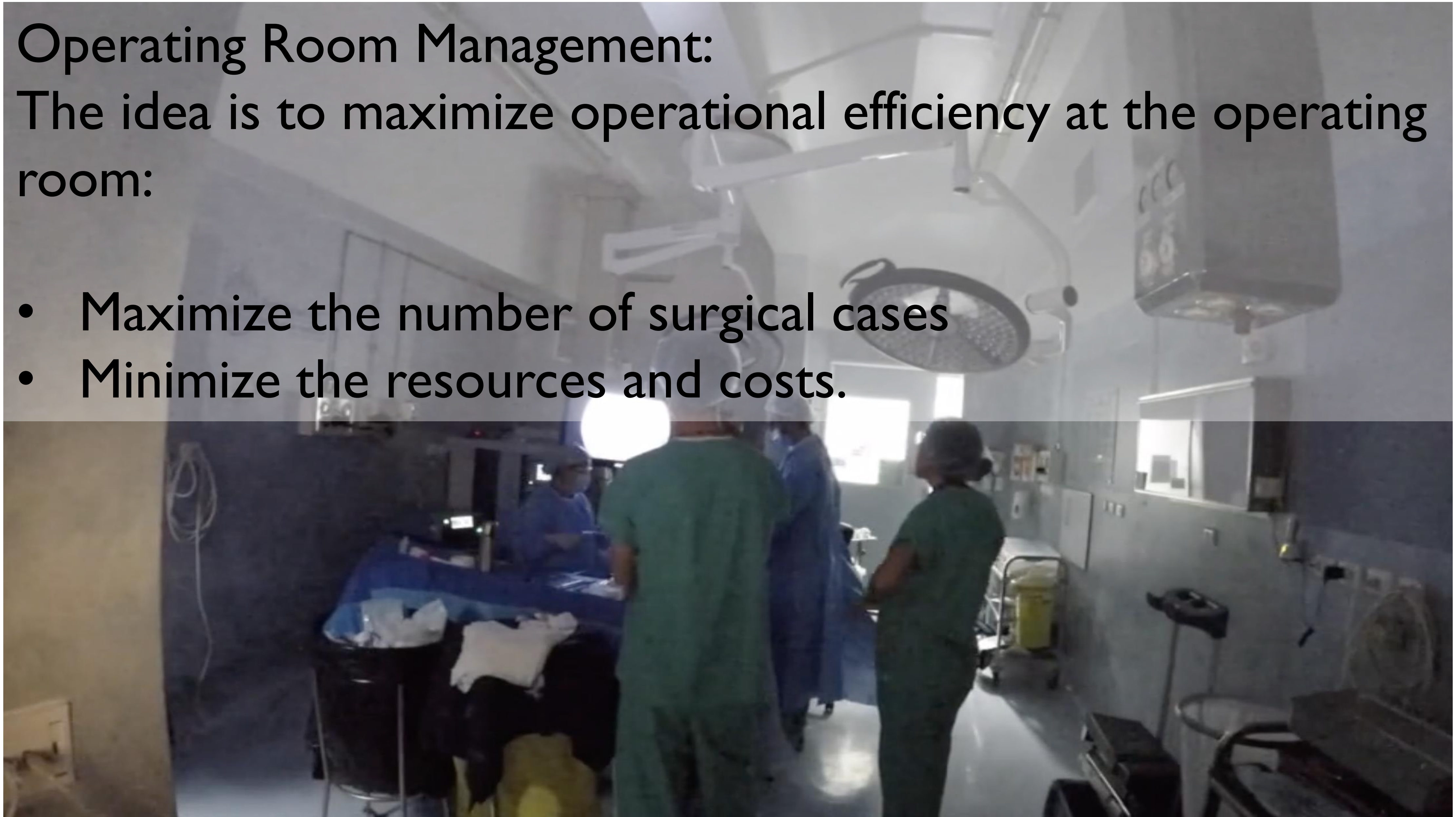


Object Detection – Example Monitoring of Operating Rooms

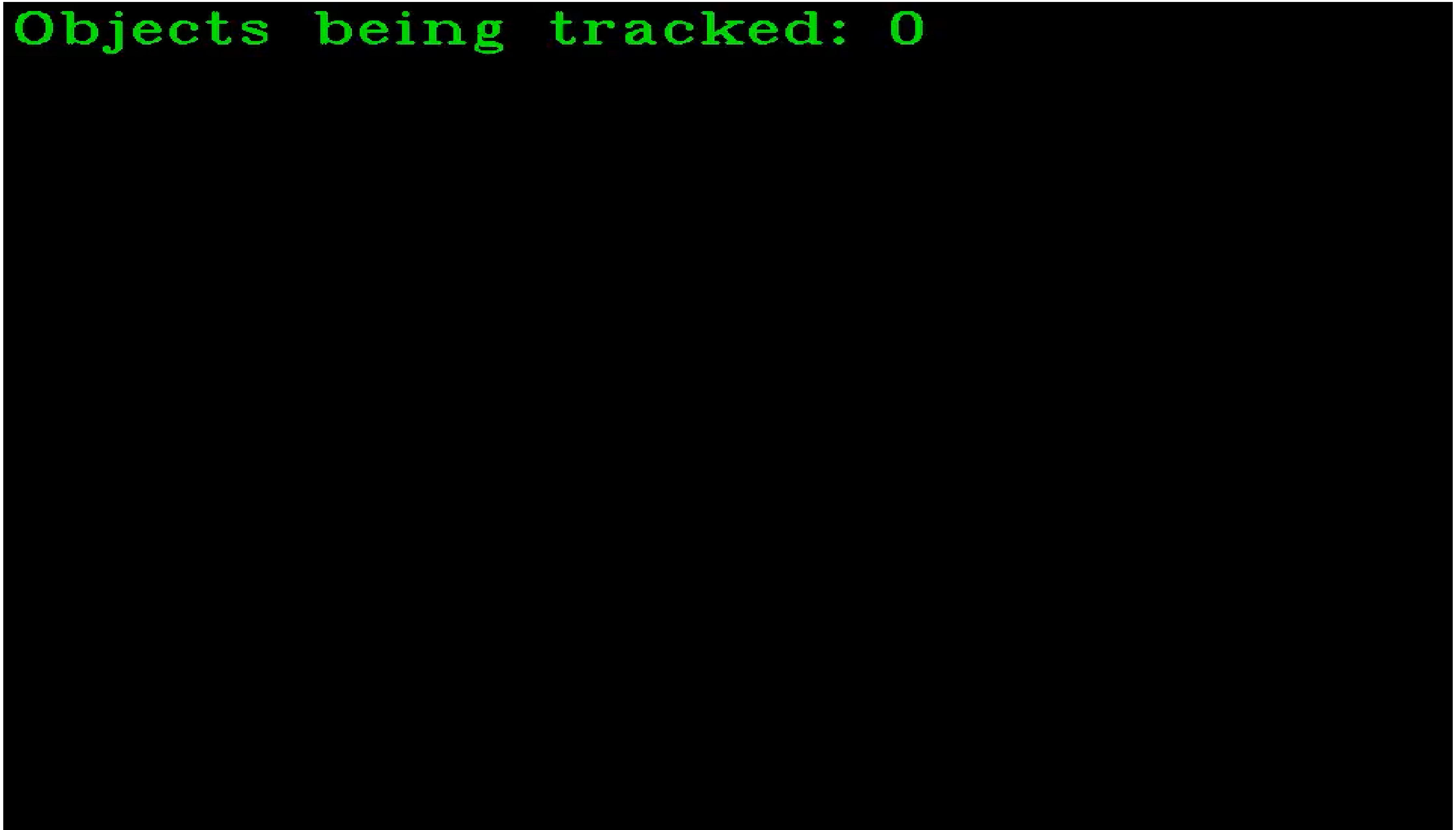
Operating Room Management:

The idea is to maximize operational efficiency at the operating room:

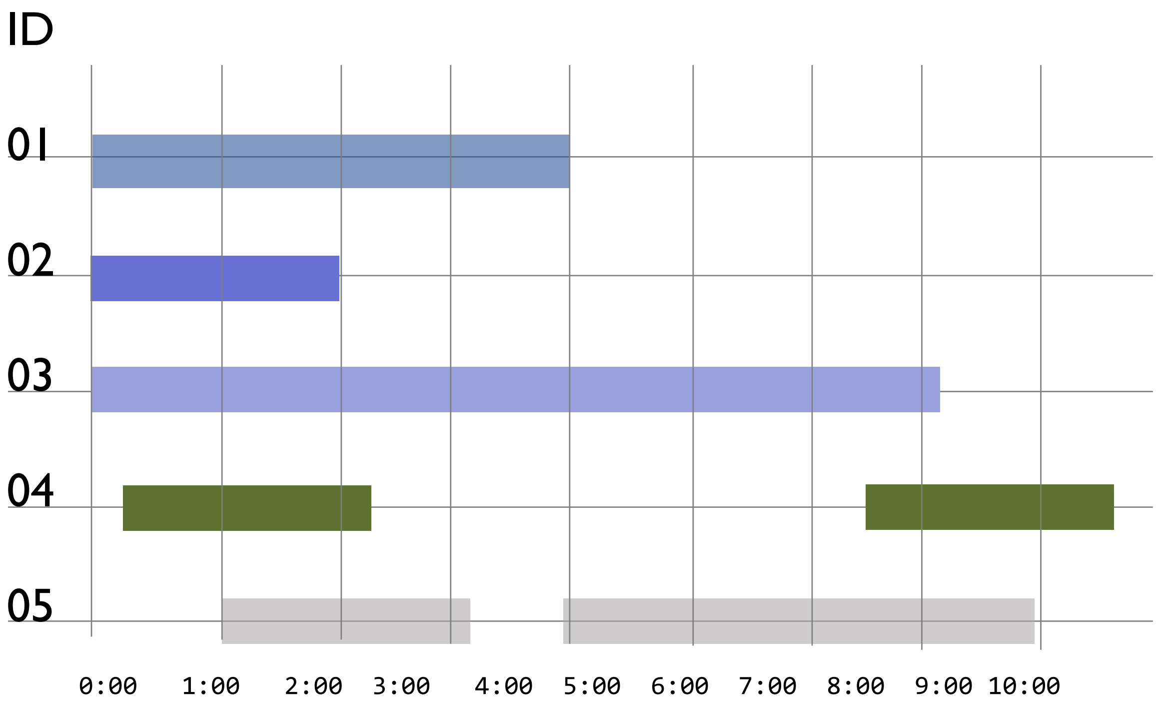
- Maximize the number of surgical cases
- Minimize the resources and costs.



Object Detection – Example Monitoring of Operating Rooms



Object Detection – Example Monitoring of Operating Rooms



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Applications

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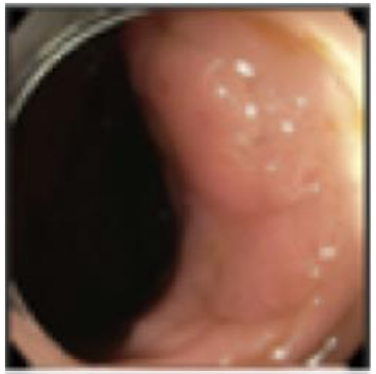
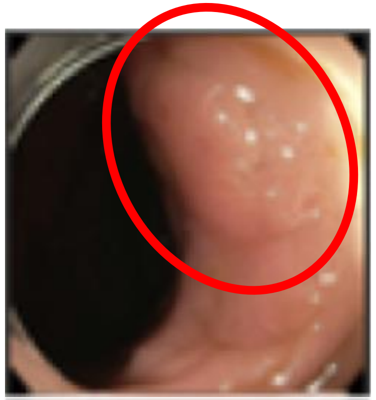
Anomaly Detection – Problem

> Detect an anomaly in an image



Input: image

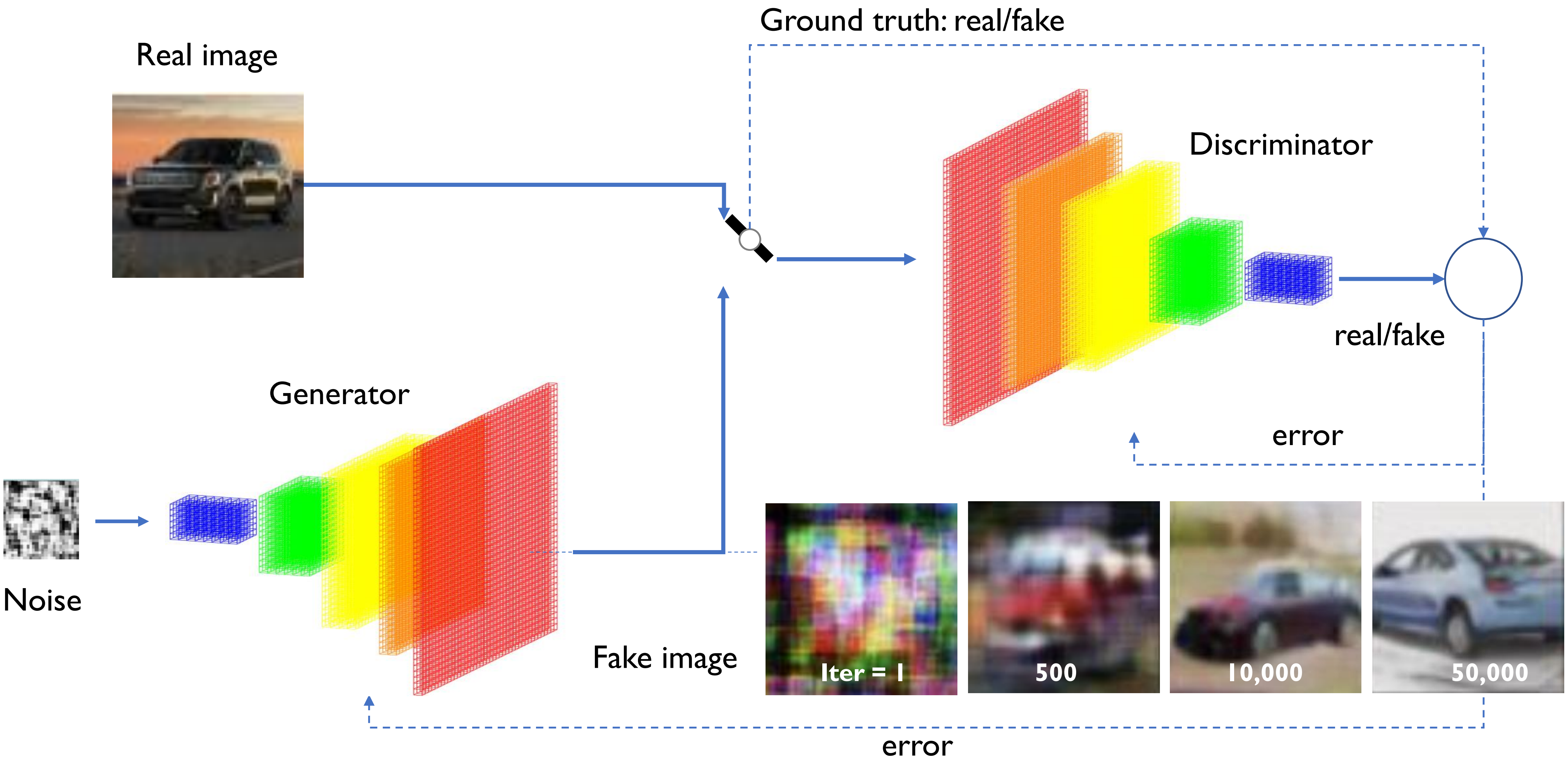
Anomaly Detection



Output: Detection

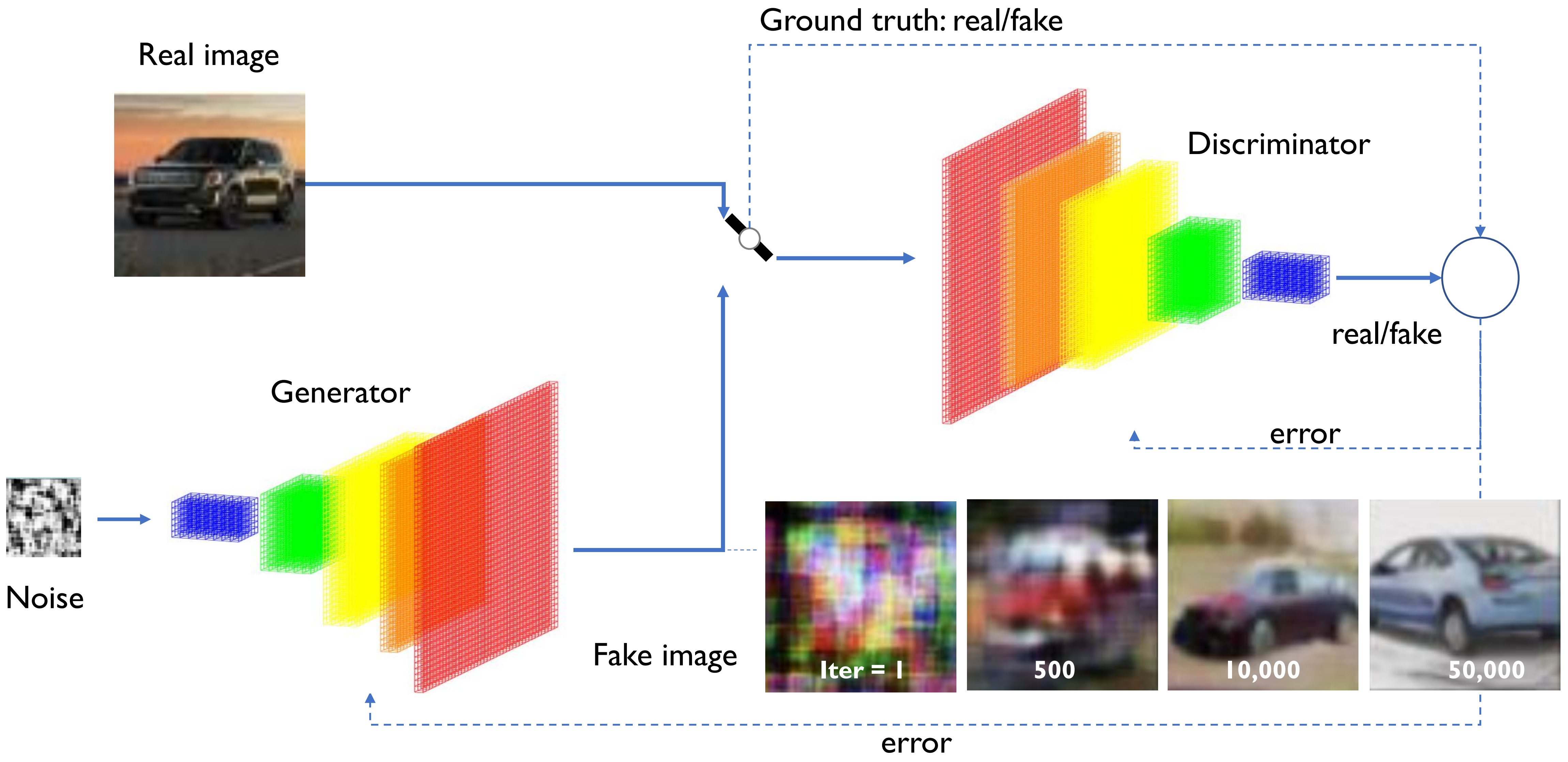
Anomaly Detection – Solution

Deep Learning Model: GAN
Generative Adversarial Network



Anomaly Detection – Solution

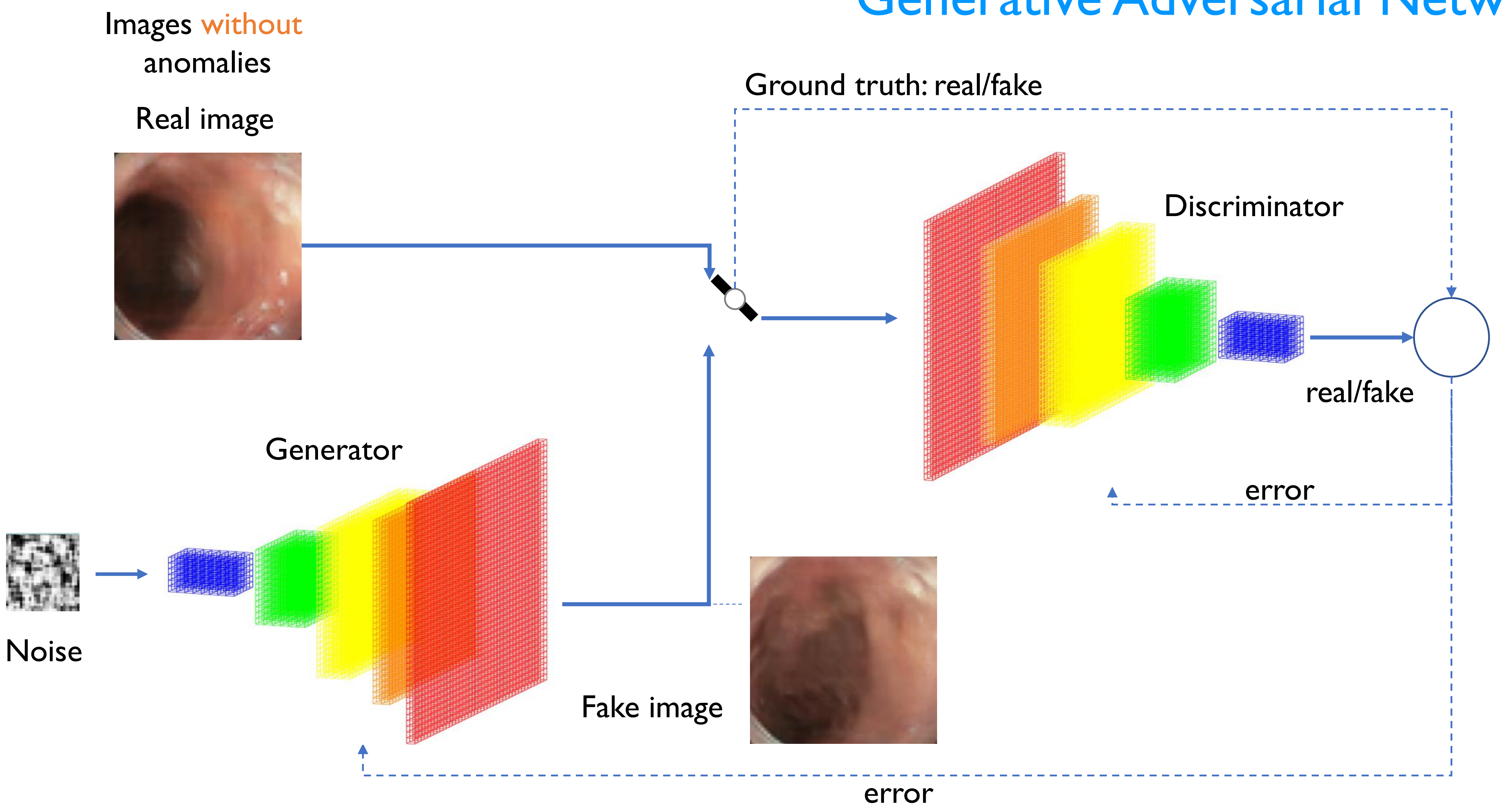
Deep Learning Model: GAN
Generative Adversarial Network



Anomaly Detection – Solution

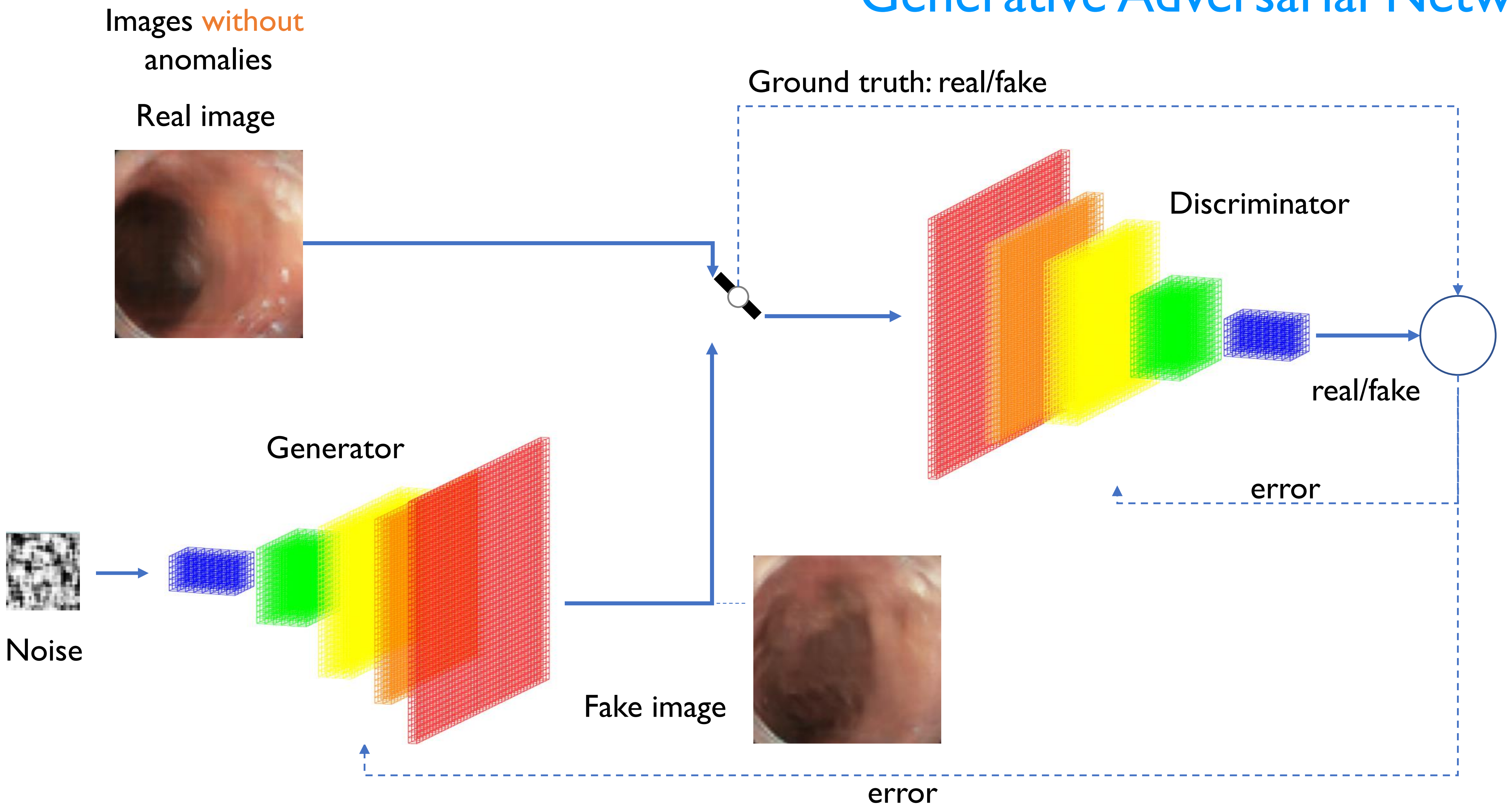
Deep Learning Model: GAN

Generative Adversarial Network



Anomaly Detection – Solution

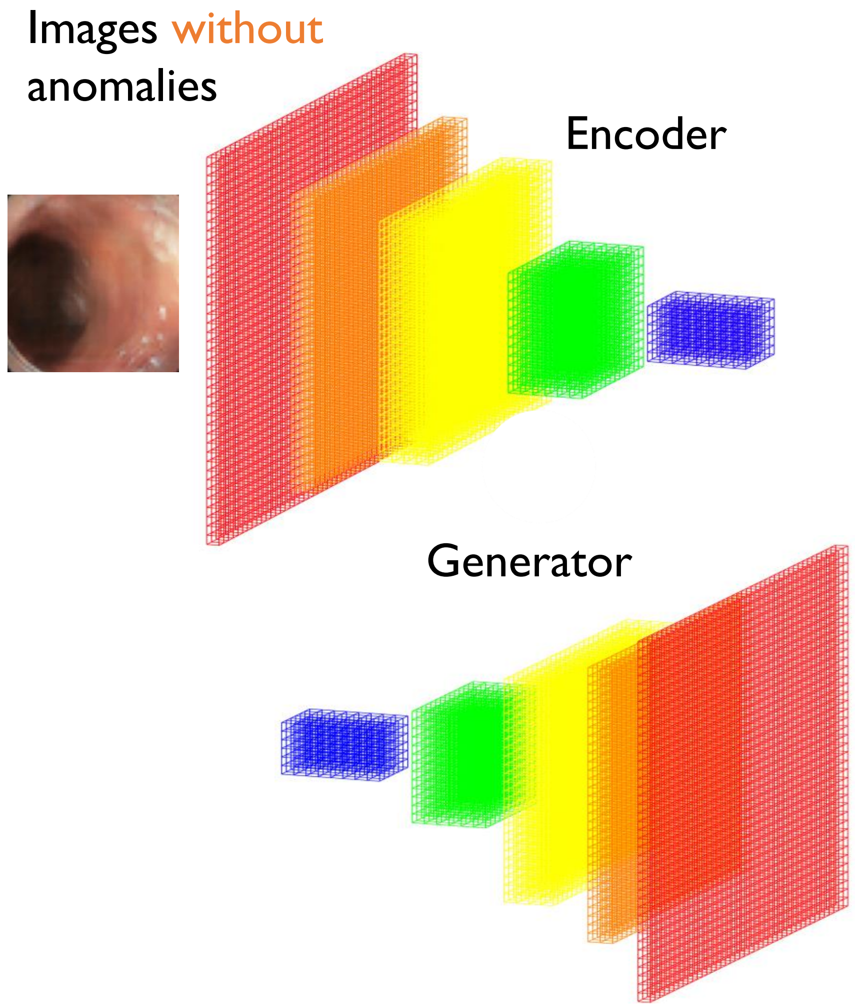
Deep Learning Model: GAN
Generative Adversarial Network



Anomaly Detection – Solution

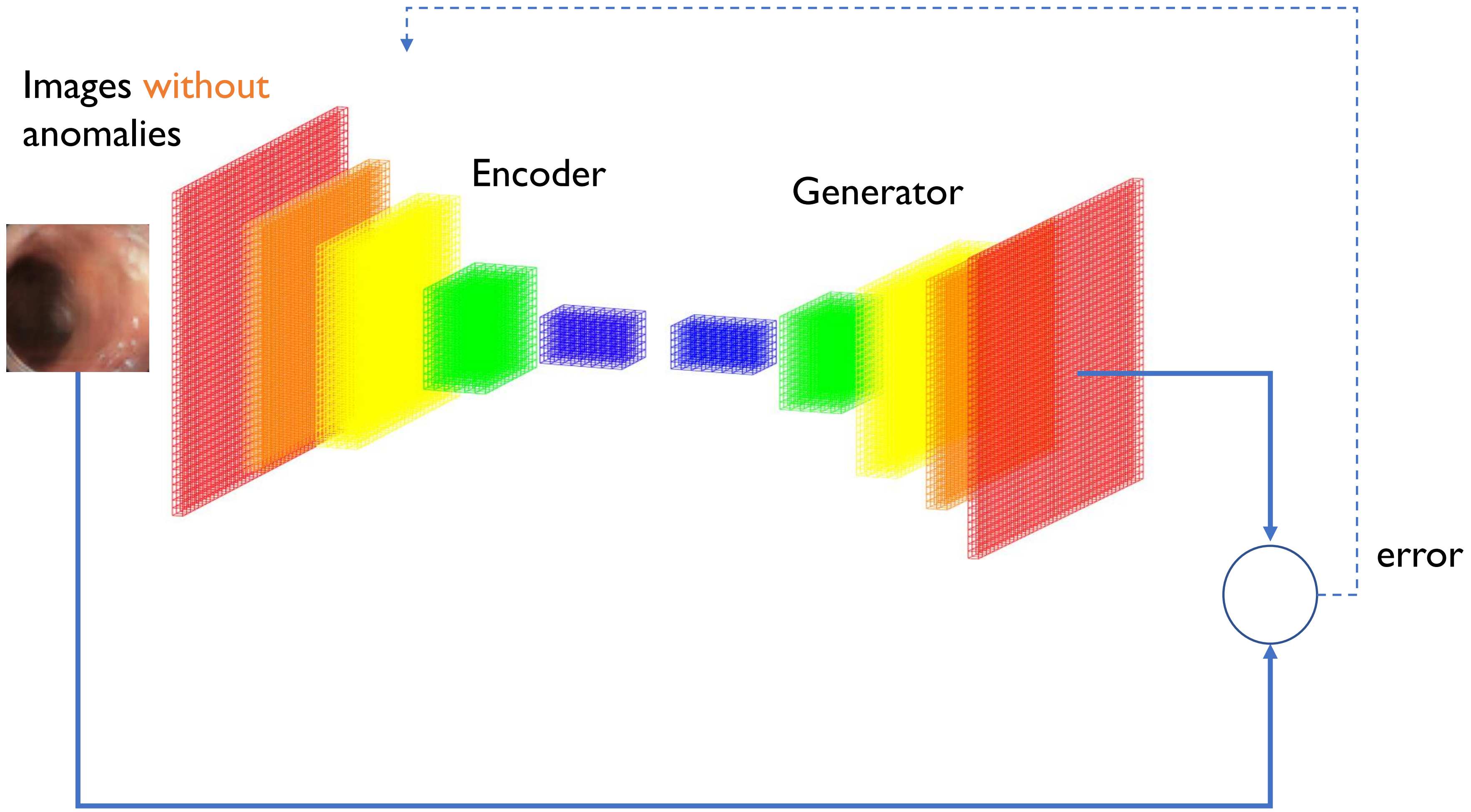
Deep Learning Model: GAN

Generative Adversarial Network



Anomaly Detection – Solution

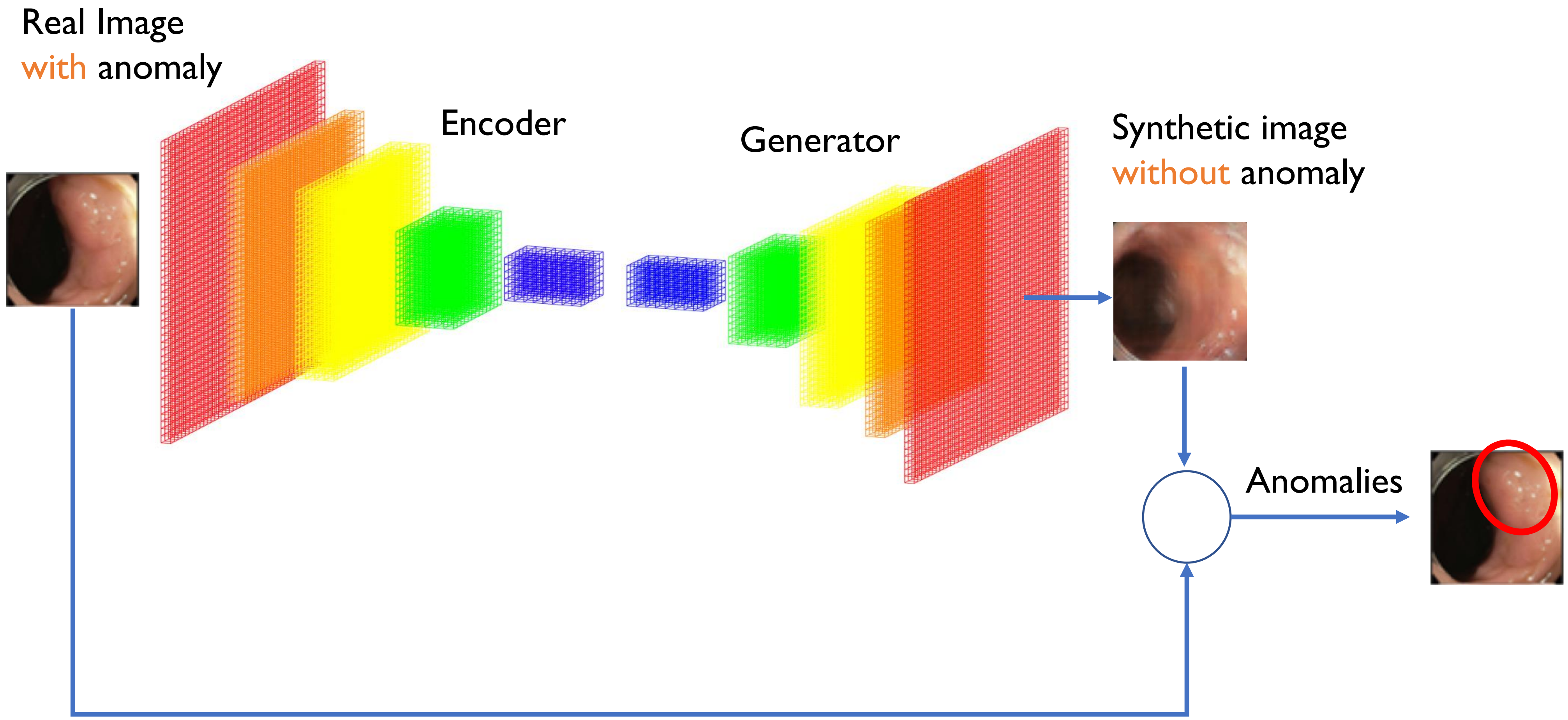
Deep Learning Model: GAN
Generative Adversarial Network



Anomaly Detection – Solution

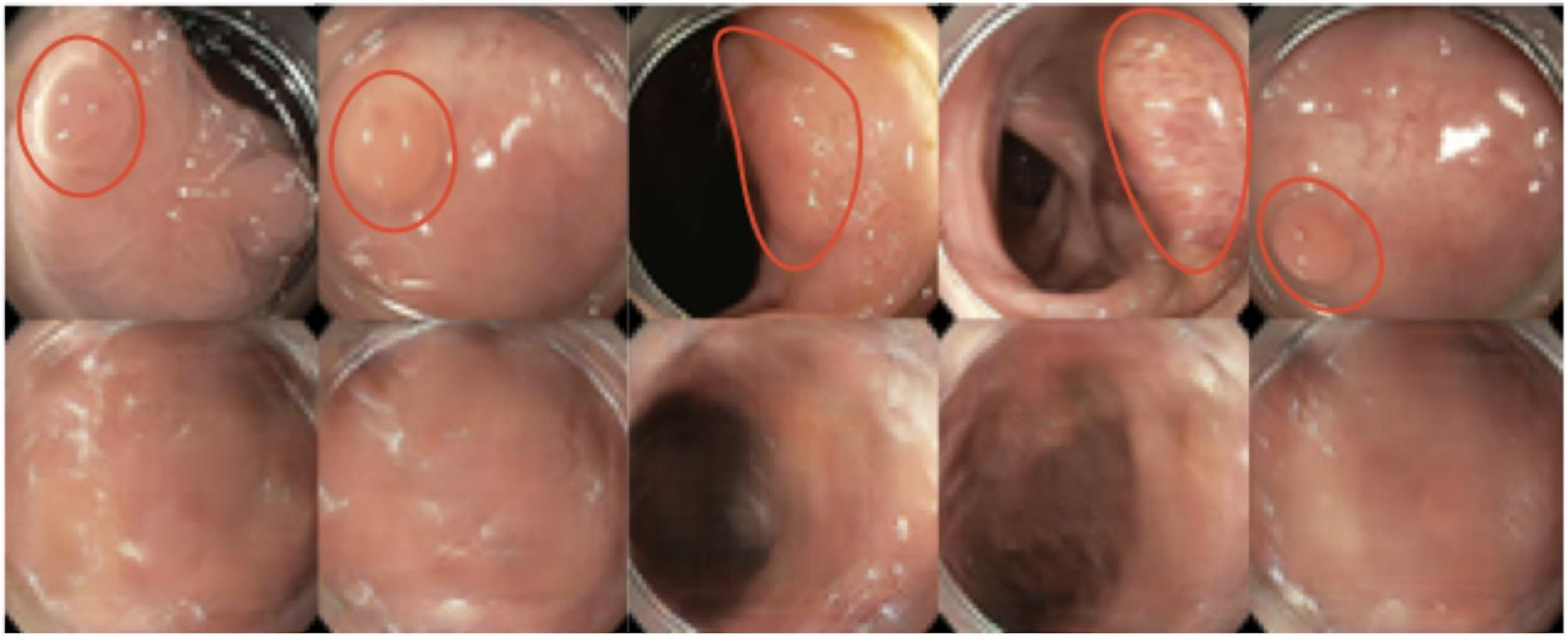
Deep Learning Model: GAN

Generative Adversarial Network



Anomaly Detection – Example

Colonoscopy video frames



Liu, Yuyuan, et al. "Photoshopping colonoscopy video frames." *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*. IEEE, 2020.

Applications

1) Image Classification
2) Image Processing
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Applications

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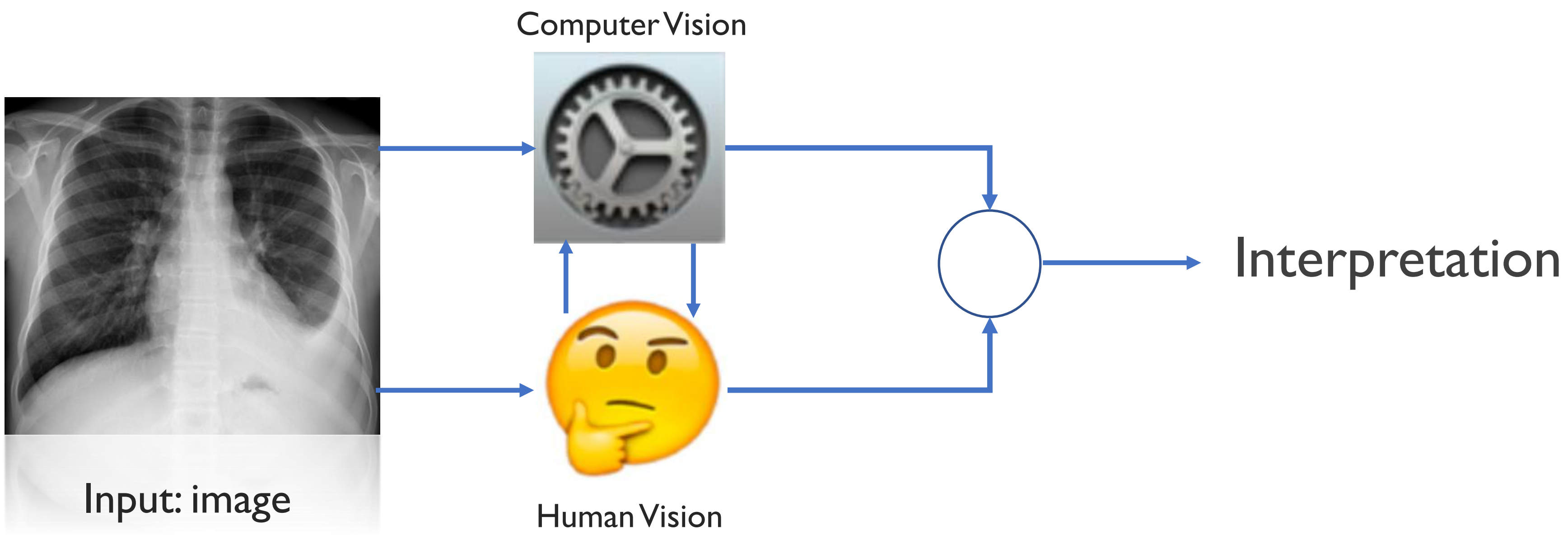
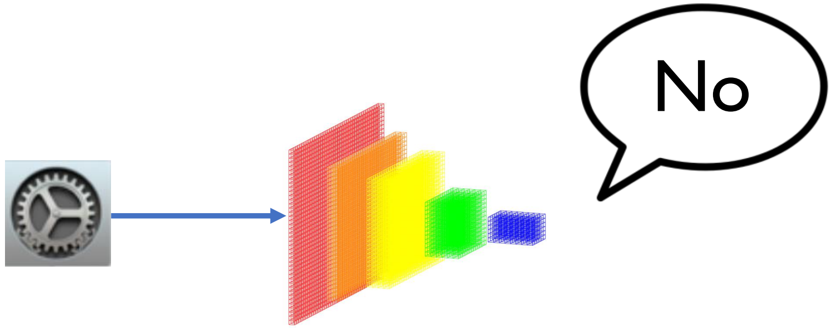
Human + Computer Vision – Problem

> How can Human Vision and Computer Vision work in collaboration?

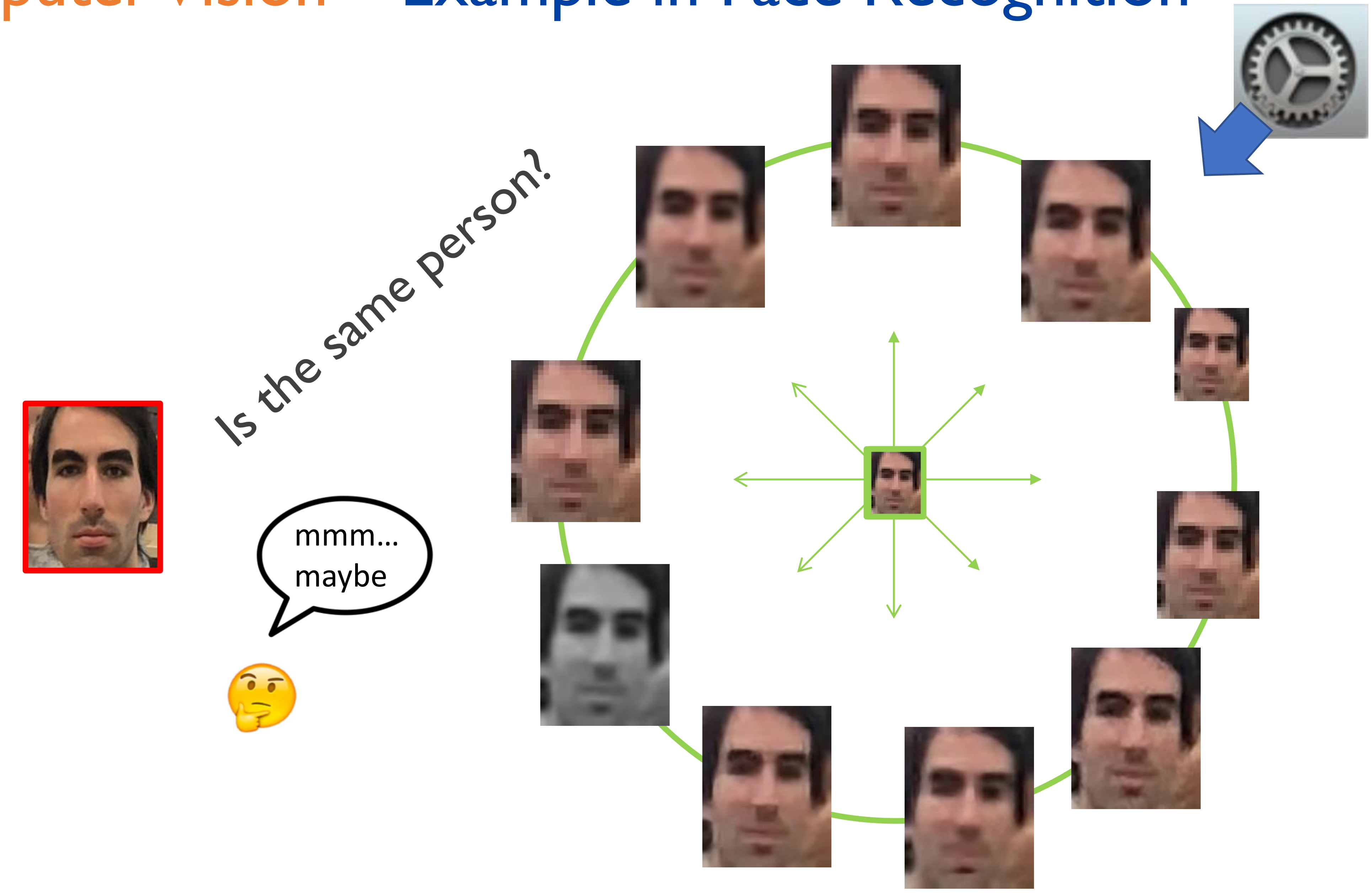


Human + Computer Vision – Example in Face Recognition

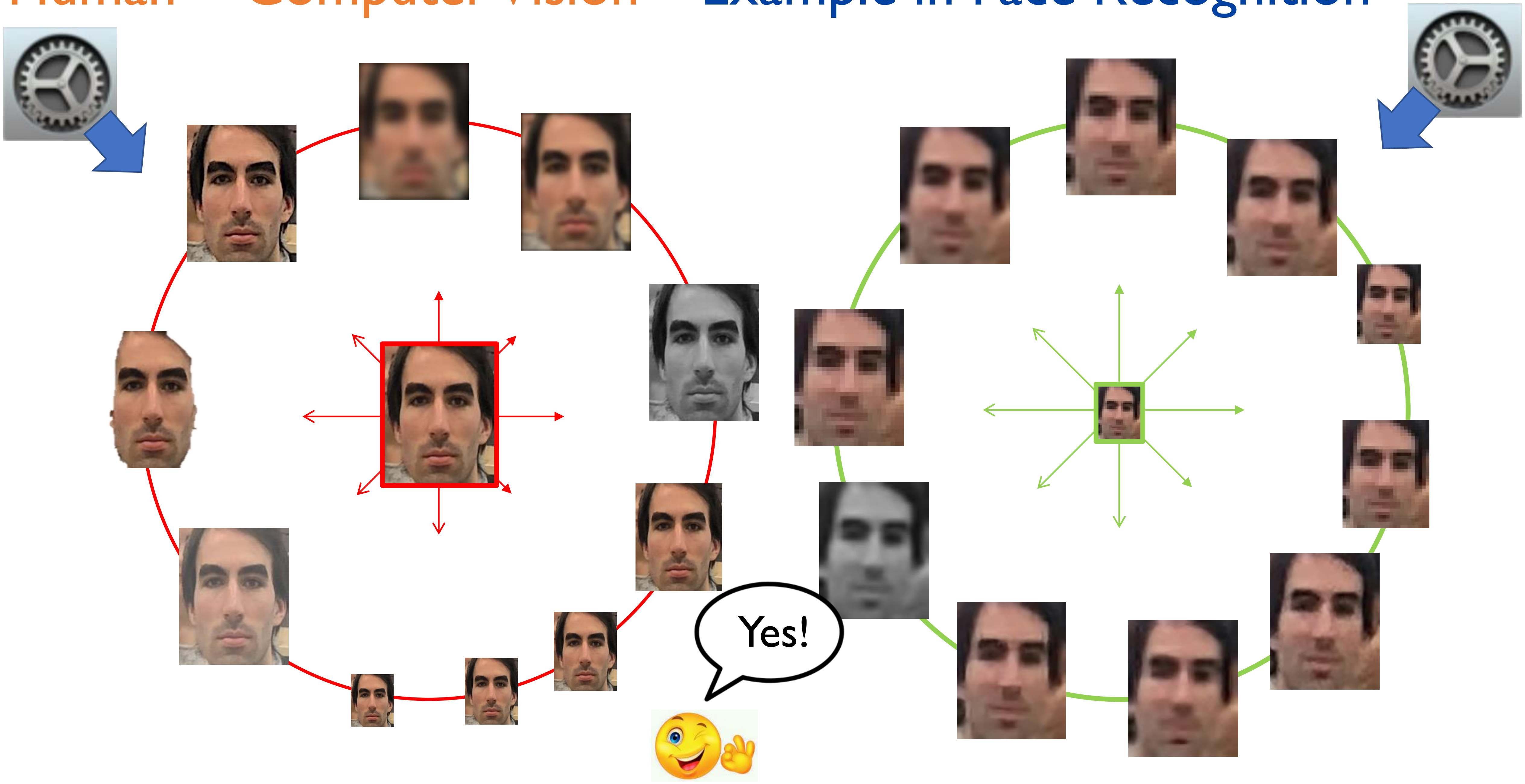
Is the same person?



Human + Computer Vision – Example in Face Recognition



Human + Computer Vision – Example in Face Recognition



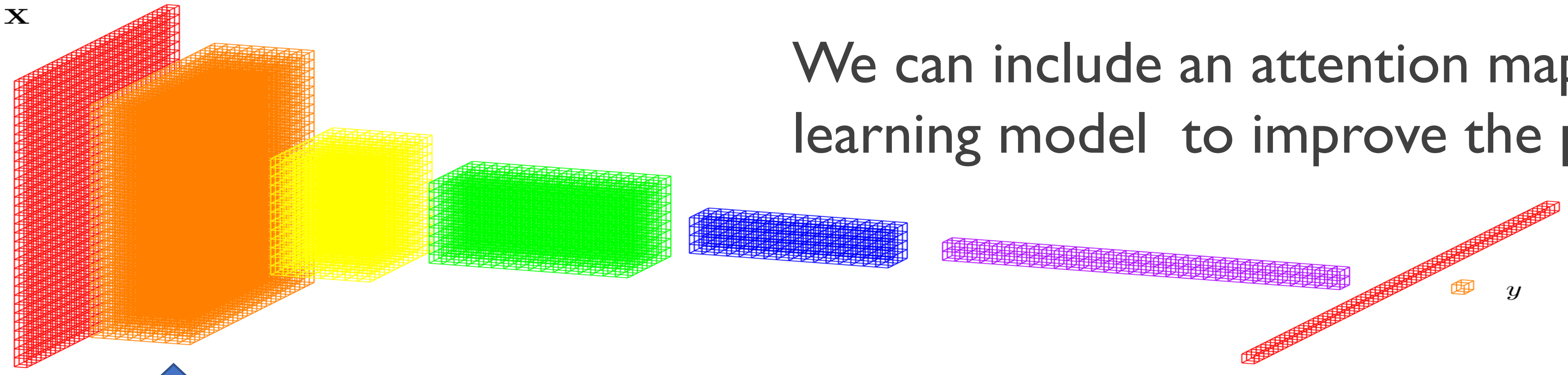
Human + Computer Vision – Example in Face Recognition

Is the same person?

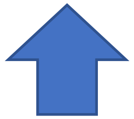
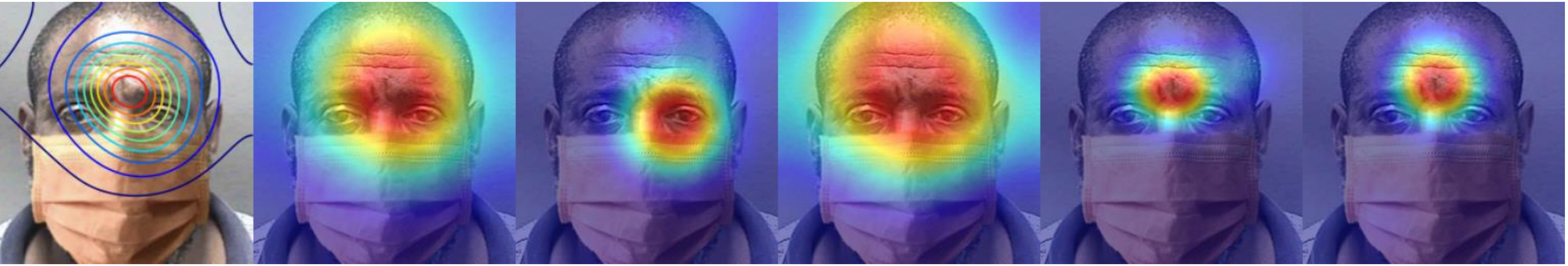
Where do you see when recognizing a face?

Which regions are more relevant for AI?

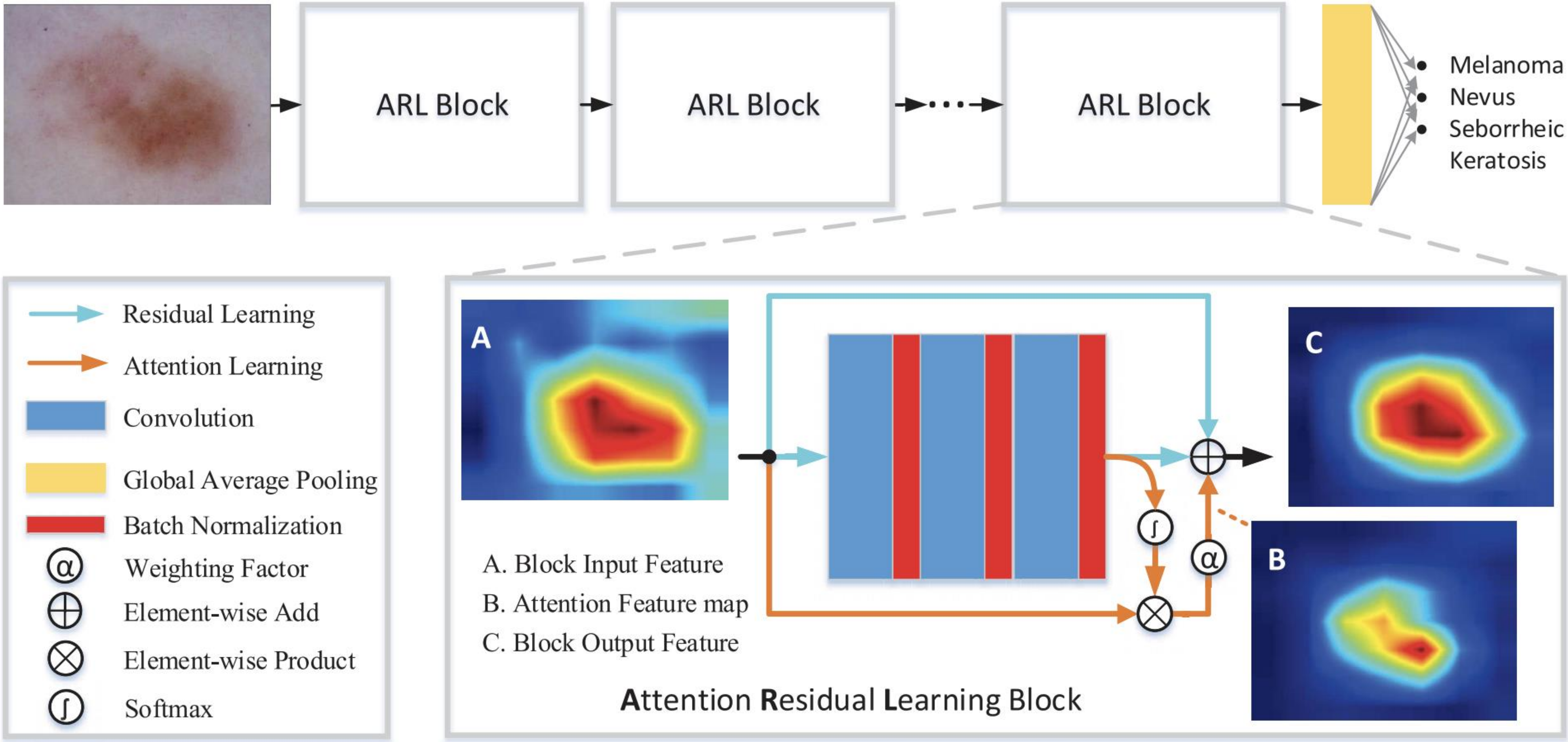
Human + Computer Vision – Example in Face Recognition



We can include an attention map in the deep learning model to improve the performance.

Example in Skin Lesion Classification



Zhang, Jianpeng, et al. "Attention residual learning for skin lesion classification." *IEEE transactions on medical imaging* 38.9 (2019): 2092-2103.

Applications

1) Image Classification
2) Image Processing
3) Object Detection
4) Anomaly Detection
5) Human + Computer Vision

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Algoritmos de Deep Learning del Curso

- Object Classification (CNN)
- Object Detection (YOLO)
- Tracking
- Segmentation (UNet)
- GAN
- Anomaly Detection
- Facial Analysis

- Face detection
- Face recognition
- Face restoration
- Age recognition
- Gender recognition
- Expression recognition
- Soft attributes
- Face clustering
- Pose estimation
- Explainability