Automatic Detection and Classification of Diseases in Medical Image Analysis

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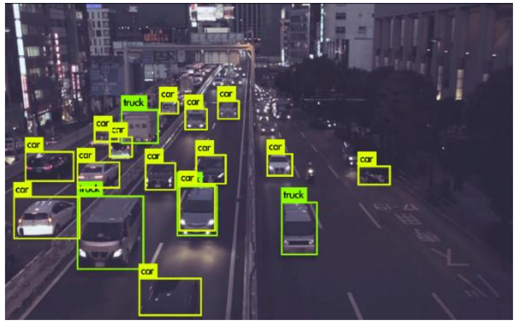
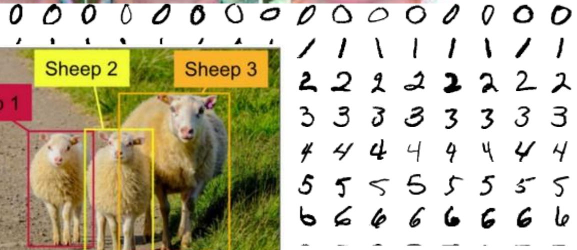
- **Computer Vision** is to have machines see and understand images and videos.
- In this discipline, we are developing algorithms which automate task that humans can do

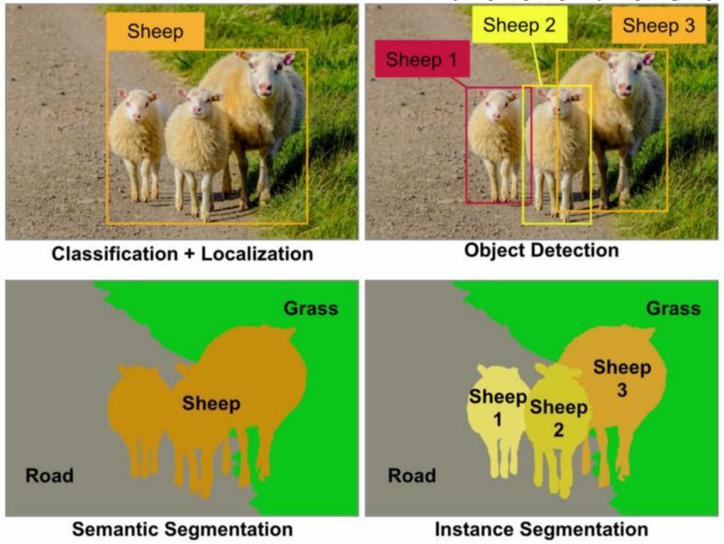
Candemir, S., Borovikov, E., Santosh, K.C., Antani, S., Thoma,G. (2015). Rsilc: rotation-and scale-invariant, line-based color-aware descriptor. *Image and Vision Computing*, *42*, 1-12.

Target Tracking (human, cars..)



https://www.move-lab.com/





Ravindra Parmar
https://towardsdatascience.com/detection-and-segmentation-through-convnets

Stereo Correspondence

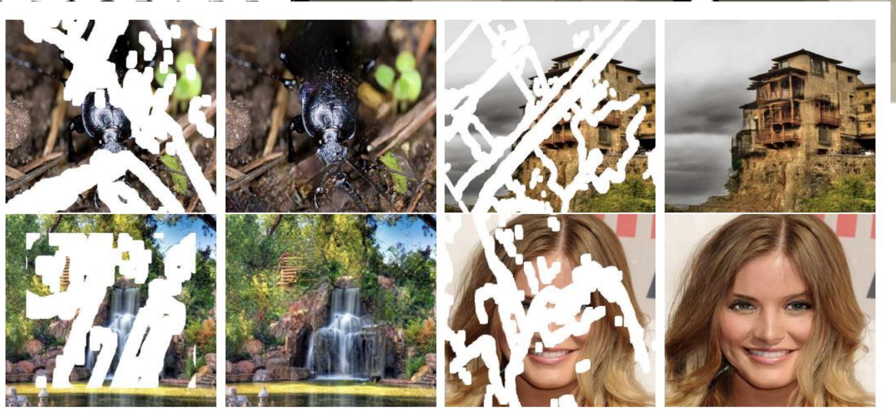


Image Reconstruction “Image Inpainting for Irregular Holes Using Partial Convolutions”

Medical Image Analysis

- Automate **tasks that doctors can do**
- understanding radiology scans (assigning a label as normal/abnormal)
- Grading level of severity

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

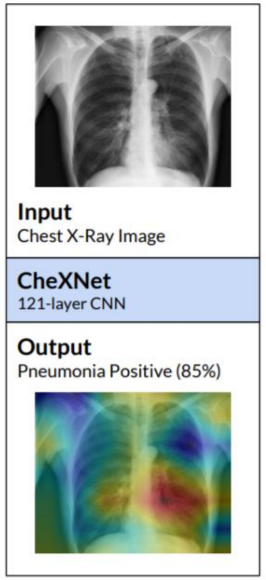
- Dataset: 28175 retinal images
- Graded by a panel of 54 US licensed ophthalmologists
- The algorithm computes diabetic retinopathy severity from the intensities of the pixels in a fundus image.

CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pranav Rajpurkar*[1] Jeremy Irvin*[1] Kaylie Zhu[1] Brandon Yang[1] Hershel Mehta[1] Tony Duan[1] Daisy Ding[1] Aarti Bagul[1] Robyn L. Ball[2] Curtis Langlotz[3] Katie Shpanskaya[3] Matthew P. Lungren[3] Andrew Y. Ng[1]

Abstract

We develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. Four practicing academic radiologists annotate a test set, on which we compare the performance of CheXNet to that of radiologists. We find that CheXNet exceeds average radiologist performance on the F1 metric. We



applied sciences
MDPI

Article

Visualization and Interpretation of Convolutional Neural Network Predictions in Detecting Pneumonia in Pediatric Chest Radiographs

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check for updates

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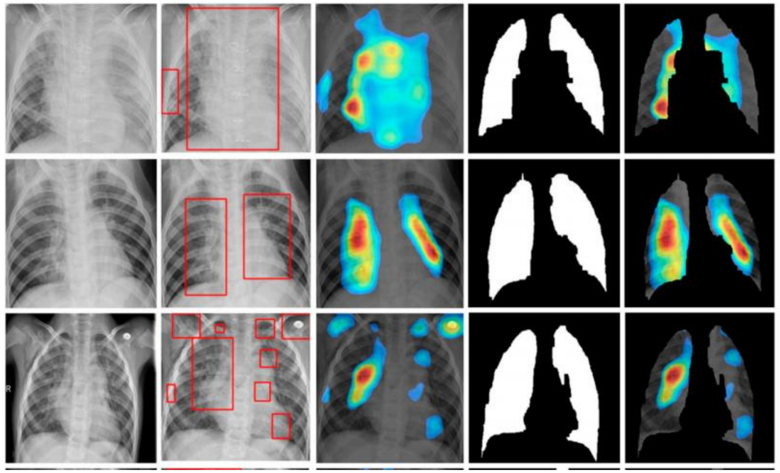
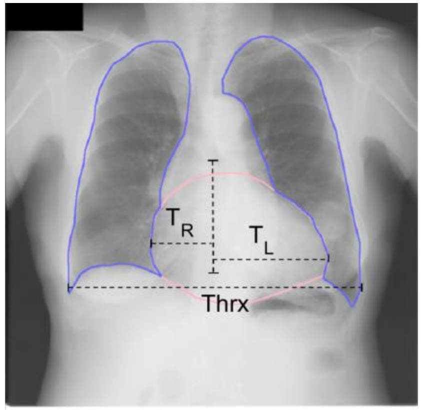
Abstract: Pneumonia affects 7% of the global population, resulting in 2 million pediatric deaths every year. Chest X-ray (CXR) analysis is routinely performed to diagnose the disease. Computer-aided

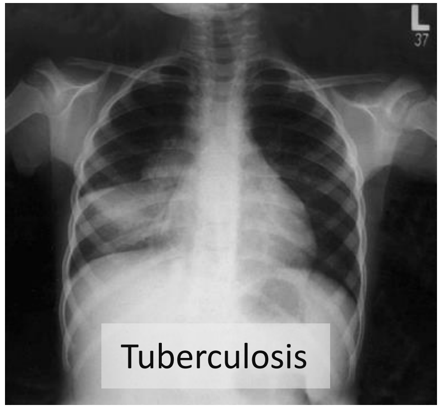


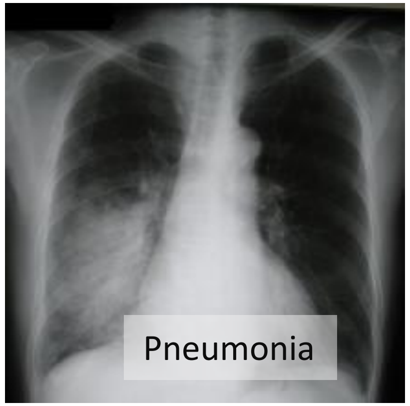
How machines make a decision? (Conventional Way)

- Collect data
- Obtain annotations
- Read image/image sequences
- Feature engineering
  - descriptors (e.g., SIFT, SURF, Haar)
  - models the visual information
- Train a machine learning algorithm
  - e.g. support vector machines
- Define the metrics
- Measure the model performance on validation data
- Deploy



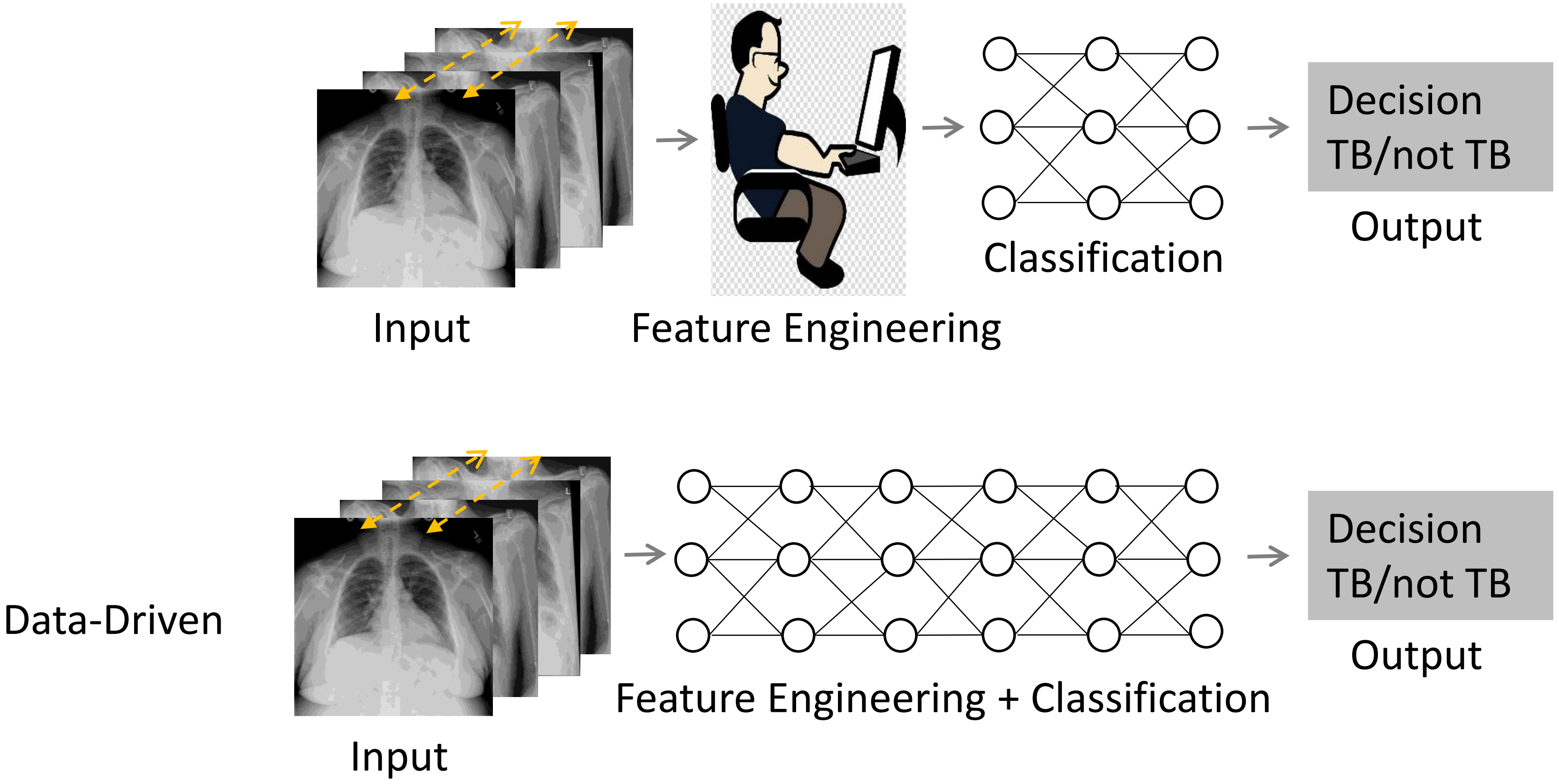
CTR: The ratio between the **maximum transverse cardiac diameter** and the **maximum thoracic diameter** measured between the inner margins of ribs.





Conventional Approaches vs. Deep Learning

- massive amount of data
- advances in GPU technology which able to process this massive amount data
- **computer vision systems designed with deep neural networks produce more accurate results than conventional approaches.**



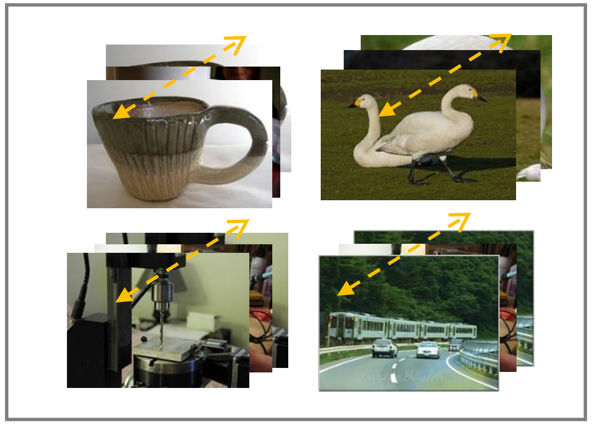
Is life much easier now?

- Training a deep neural network architecture requires a large amount of training data.
- **In biomedical imaging domain, annotated data is limited** due to the expertise necessity for annotation.
- Types of houses… Flickr (image/video hosting service)… Crowdsourcing options (e.g., Amazon mechanical Turk)
- Developing a system to detect stenosis on Coronary Computed Tomography Angiography?
  - Who is going to annotate the image sequences?   (you need an expert in cardiovascular radiology)
    - *Stenosis is narrowing in the coronary artery lumen occurs when atherosclerotic plaque accumulates in the wall of the coronary artery tree.*
    - *Coronary Computed Tomography Angiography is a non-invasive imaging modality for evaluating patients with chest pain*.
  - Is there a tool to collect these annotations? (annotation is time-consuming, you want to use doctors time as efficient as possible)
    - Literature have some general annotation tools, are they clinician friendly?
    - Optimizing the transfer human knowledge to a machine learning model…
- What kind of neural network architecture would be suitable for your problem?
- Hyper-parameter optimization! (hyper-parameters : variables that needs to be set before the training process starts)
- Large number of learnable parameters to estimate, Overfitting!
- Computationally expensive,
  - requires graphical processing units (GPUs) for training.

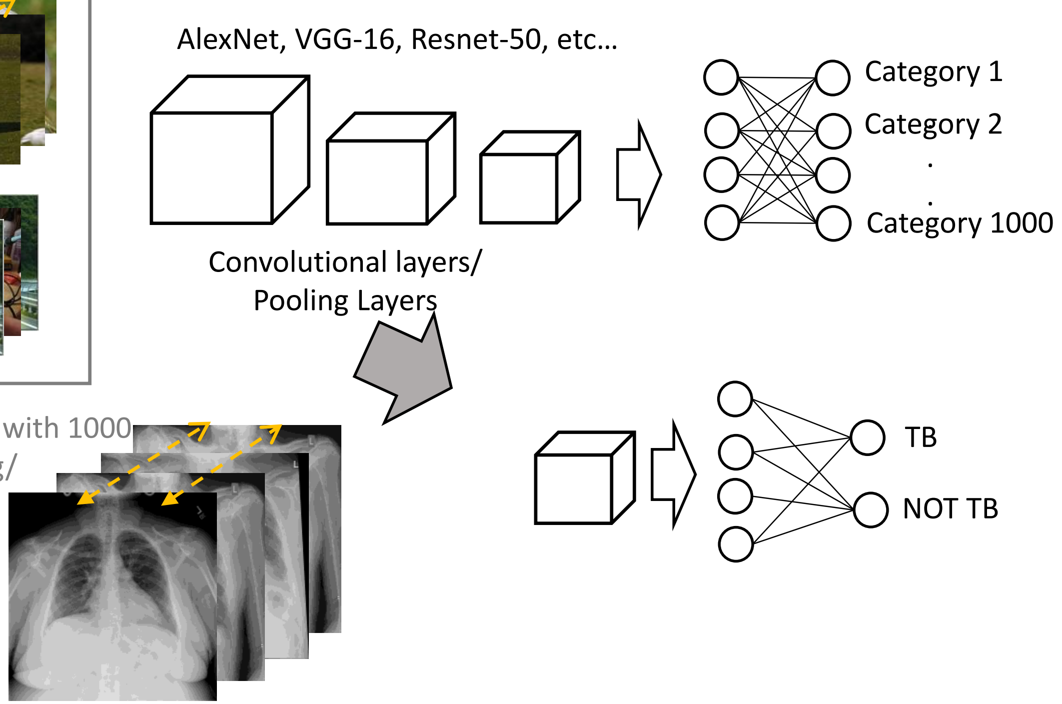
Transfer Learning

There are some solutions, when your data is limited. One solution is using **pre-trained models**.

Transfer learning employ weights from pre-trained architecture and apply fine tuning.



ImageNet: 1.2. Million general images with 1000 categories. http://www.image-net.org/



Overfitting

-- Augmentation

-- Regularization (weight decay, drop out)

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R&D

AI^2: A Team Effort

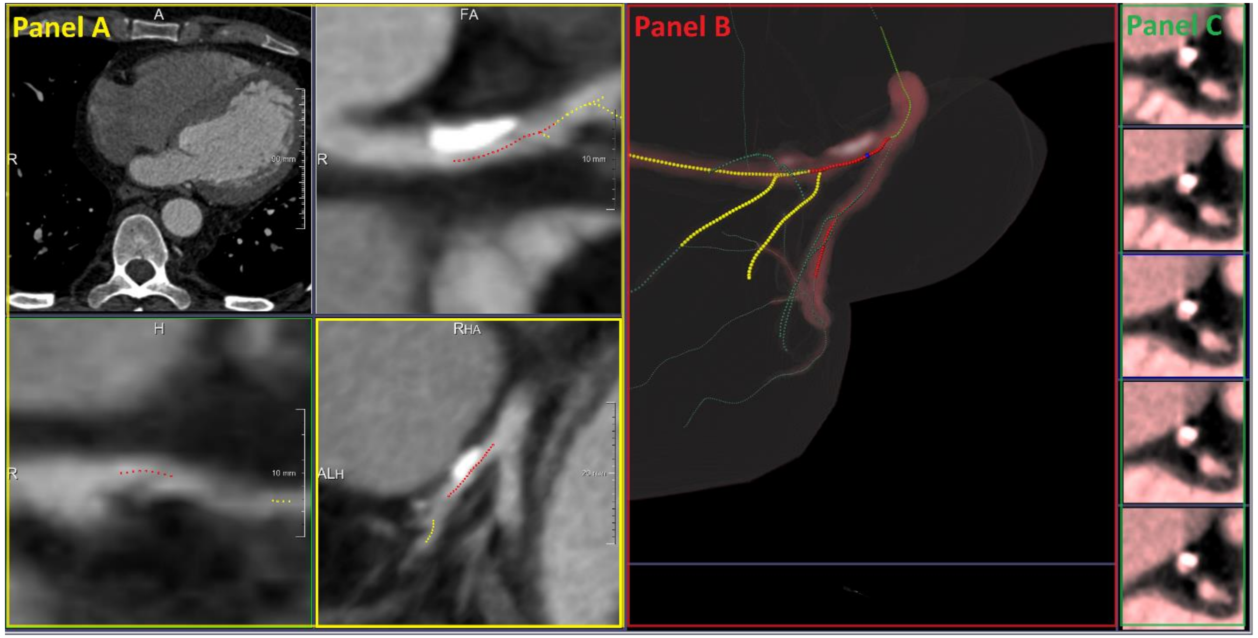
Projects

- Coronary Artery Screening
- Early Alzheimer Detection with multimodal analysis
- Brain Metastasis Detection
- Intracranial Hemorrhage Detection
- Bone Fracture Detection

http://aii.osu.edu/
http://aii.osu.edu/category/projects/

Coronary Artery Screening for Abnormality detection (Stenosis detection)

Coronary Artery Screening for Abnormality detection (Stenosis detection)



Credits:

Clinician friendly GUI development: Dr. Mutlu Demirer

Clinical Annotation: Prof. Dr. Richard White (Principle Investigator)

Architecture

- 3- Dimensional Convolutional Neural Networks
- Supervised algorithm
- Trained with vessel volumes extracted from Coronary Computed Tomography Angiography examinations of patients with and without atherosclerosis.

Annotation

- 493 CCTA scans examination,
- 247 contained coronary artery stenosis,
- 246 of them were free of coronary artery atherosclerosis.
- 641 coronary arteries with atherosclerosis selected among the major coronary arteries.
- Our investigator-expert with 33-year experience in cardiac imaging annotated the vessel branches.

Augmentation

- To mitigate the overfitting, we accumulate the training data by randomly rotating the MPR volumes between 0 and 360 around the vessel centerlines.

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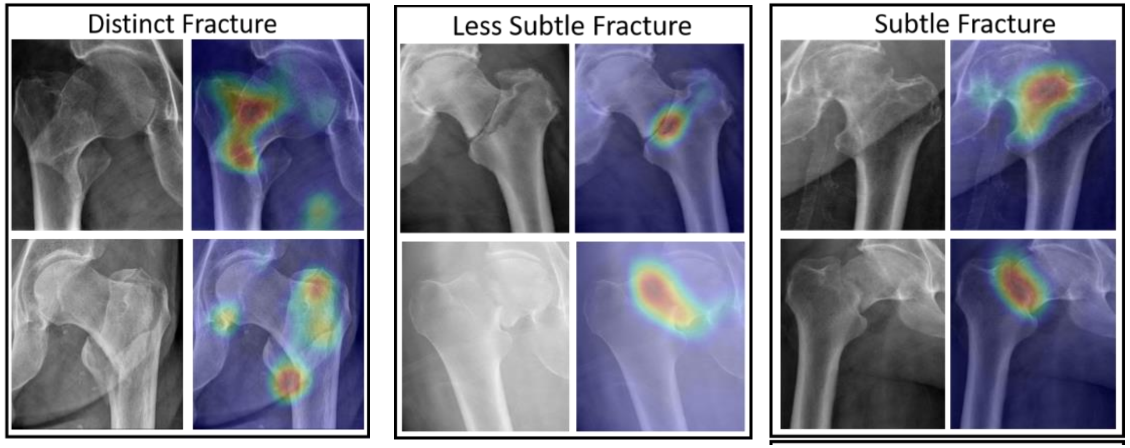
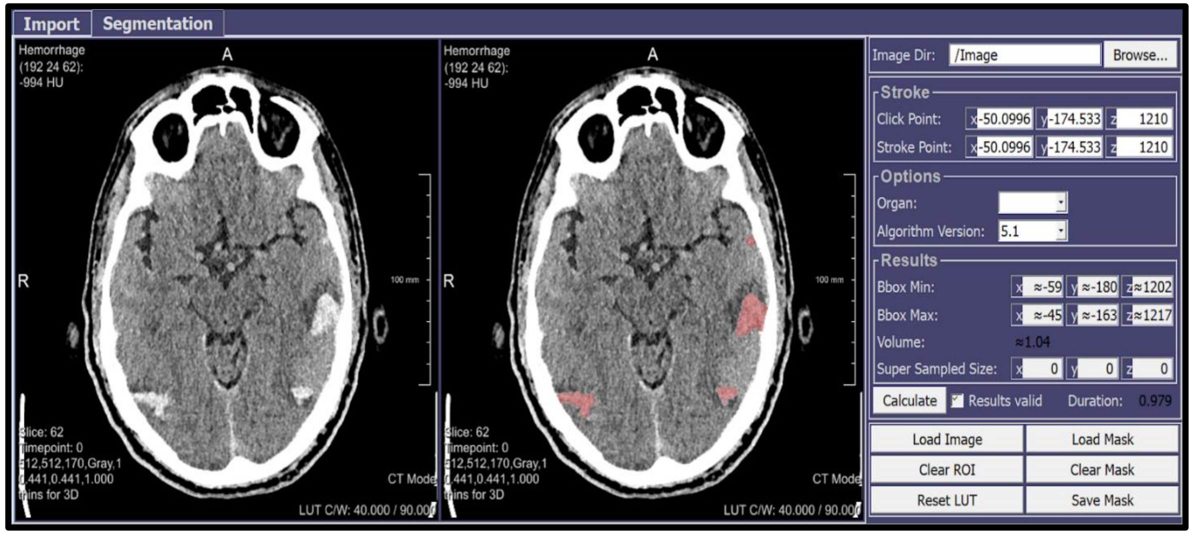
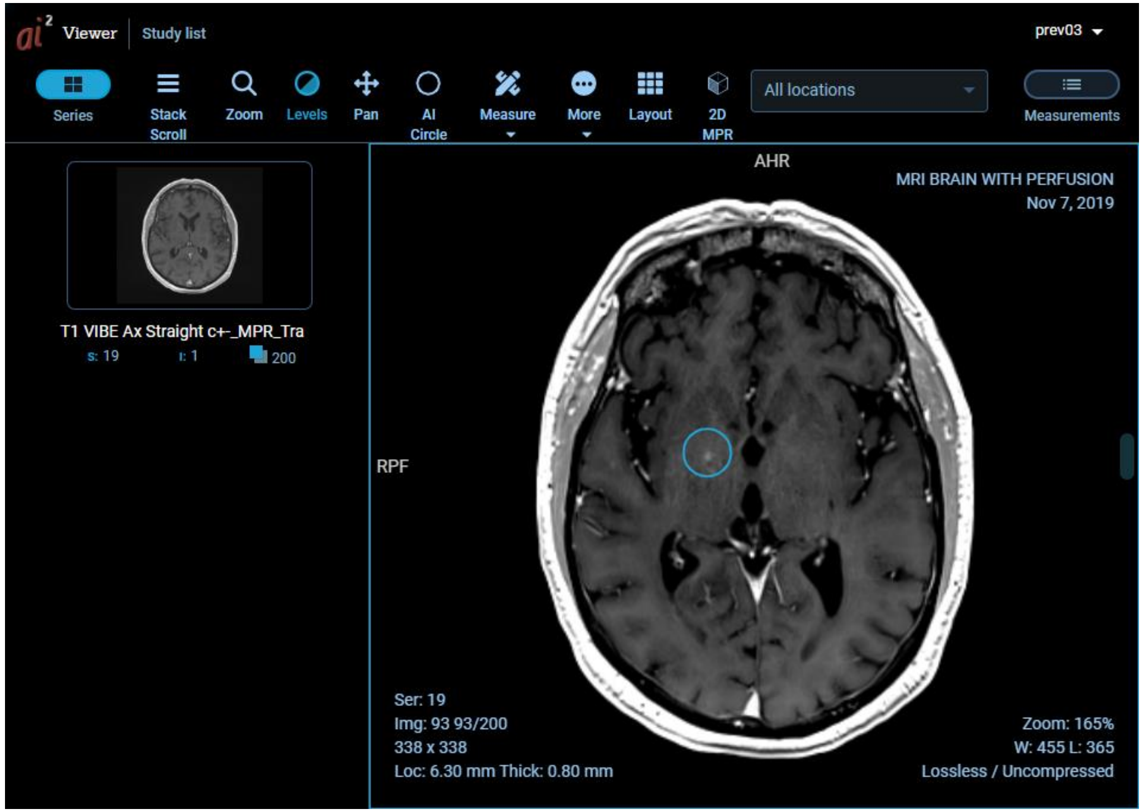
Bone Fracture Detection



CT Intracranial Hemorrhage



Brain Metastasis



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