U.S. ARMY COMBAT CAPABILITIES DEVELOPMENT COMMAND – ARMAMENTS CENTER

(U) Energetic Defects Characterization (EDC)

(U) An AI approach to automated defect recognition

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Project Overview

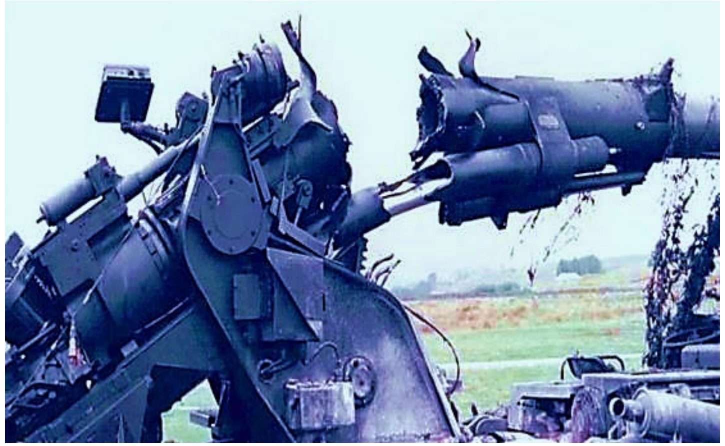
What is EDC?

Why does it matter?

ENERGETIC DEFECT CHARACTERIZATION

Problem:

- ***Defective*** artillery *have caused* catastrophic failures at gun launch, with ***consequences*** resulting in fatalities and damage to personnel and platforms.
- ***Current and future*** *energetic requirements* exceed prior gun/barrel designs and flight environments.



https://mothership.sg/2019/02/1997-waiouru-accident-history-nsf-die/

https://www.nbcnews.com/news/world/haunting-image-soldier-killed-blast-released-army-n754346

https://www.quora.com/How-does-an-exploded-shell-in-the-barrel-of-a-tank-look-like

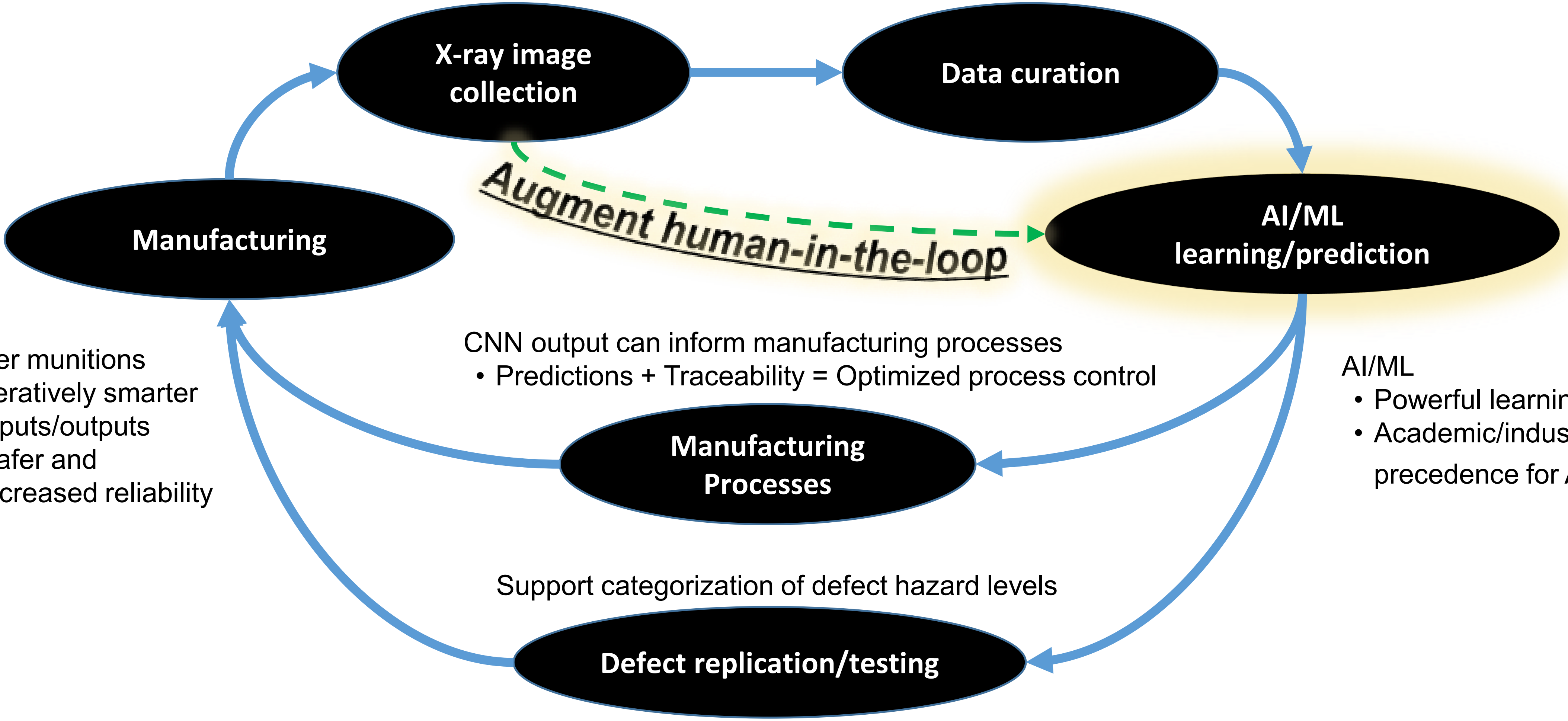
Solution:

- **Technical Approach**
  - Develop capabilities to enable experimental and computational evaluation & prediction of energetics with defects, AI/ML on images.
- **Deliverable**
  - Self-sufficient, stand-alone predictive capability

WHERE WE FIT INTO THE BIG PICTURE?

Imaging with defect detection in mind
- Instrumentation
- Calibration

Reporting with traceability and AI in mind
- Meta data
- Defect categorization



Better munitions
- Iteratively smarter inputs/outputs
- Safer and increased reliability

CNN output can inform manufacturing processes
- Predictions + Traceability = Optimized process control

AI/ML
- Powerful learning tools
- Academic/industry precedence for AI + X-ray

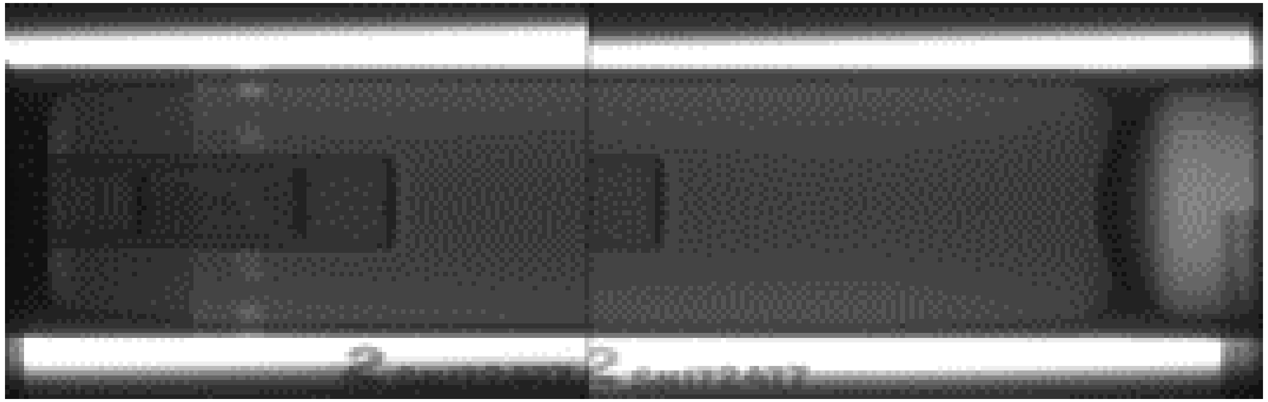
Support categorization of defect hazard levels

The Data

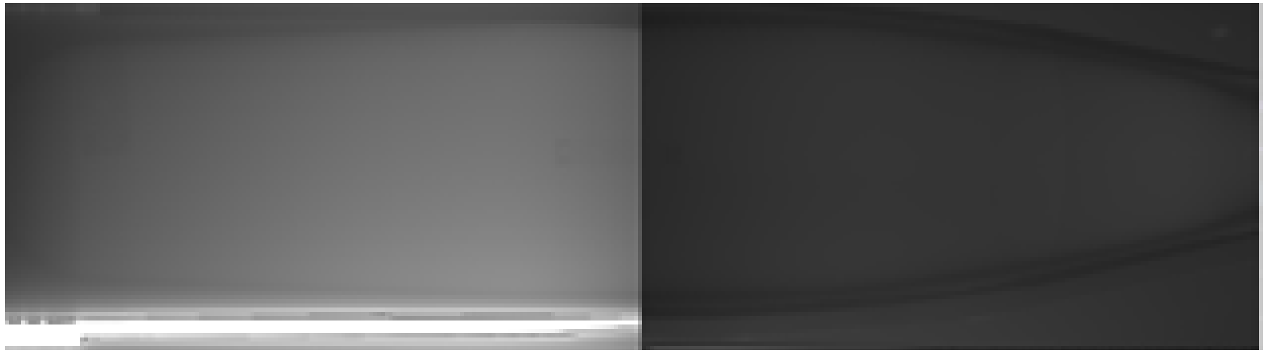
What format?

How much?

X-RAY DATA

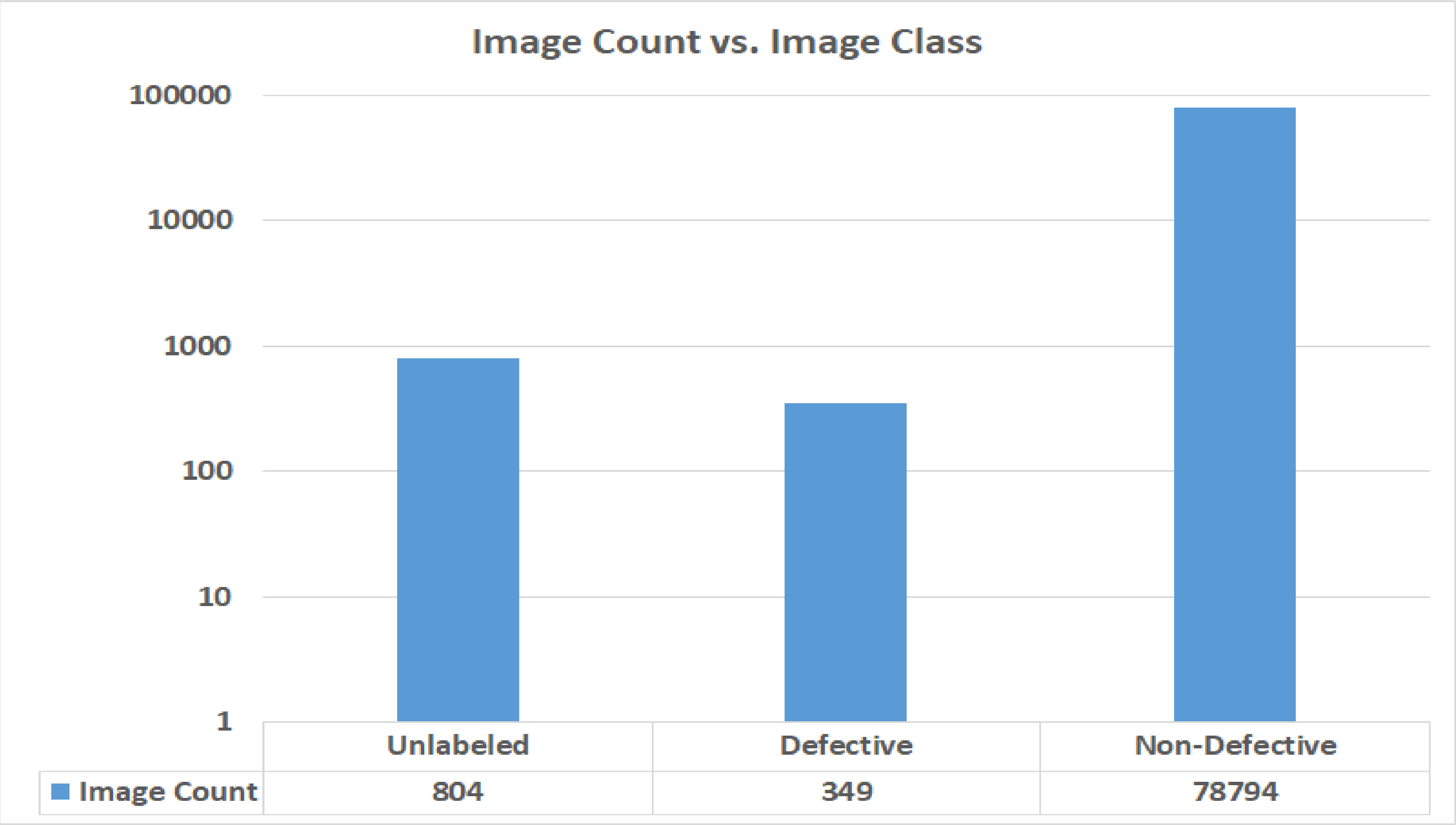


Type-1	2012—2015	Pressed	X-ray	4	600 GB
Munition	**Date**	**Explosive**	**Format**	**Aspects**	**Set Size**
Type-2	2020—2021	Melt Pour	X-ray	1	680 GB



TYPE-2 IMAGE SET CHARACTERISTICS

- Data suggests that only 1 in ~217 munitions is defective
- Will have to overcome data imbalance and any mislabeling

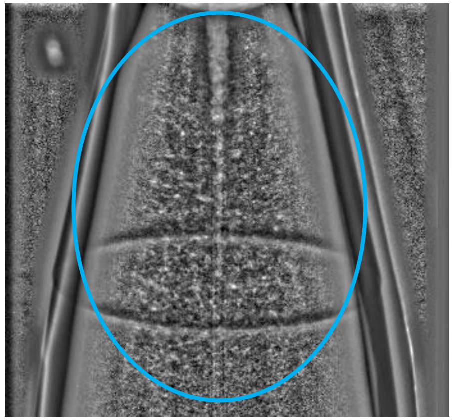


16 bit—grayscale—TIFF format

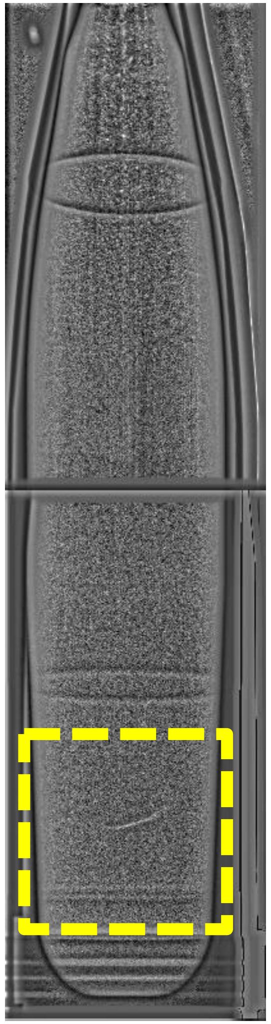
Considering Data Quality

Pedigree of labels?

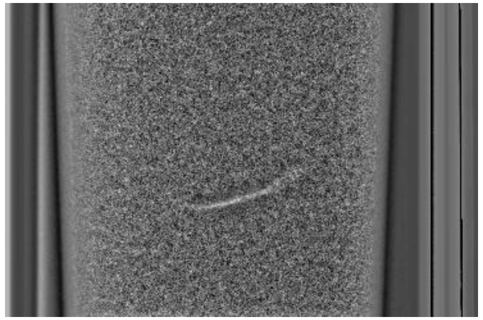
MANUAL IMAGE INSPECTION

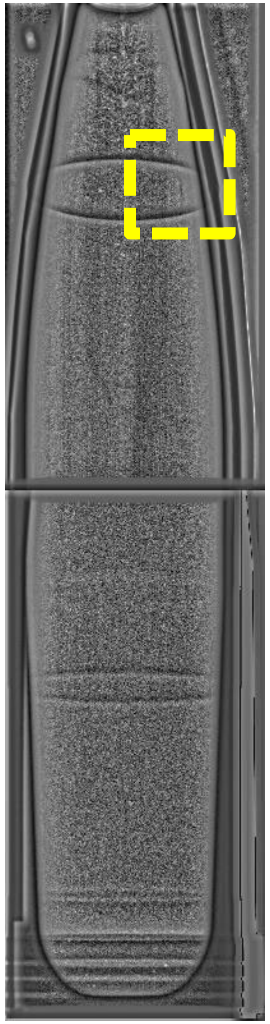


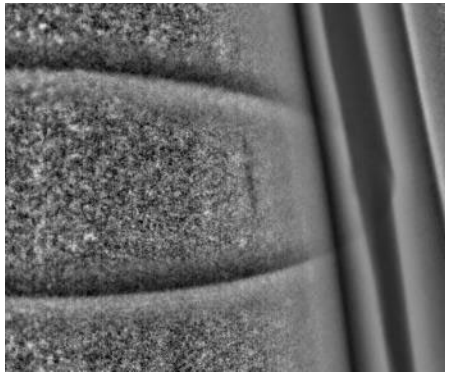
- **Labeled Defective**
- Shrink Porosity
- 37 Images



- **Labeled Defective**
- Cracks
- 58 Images

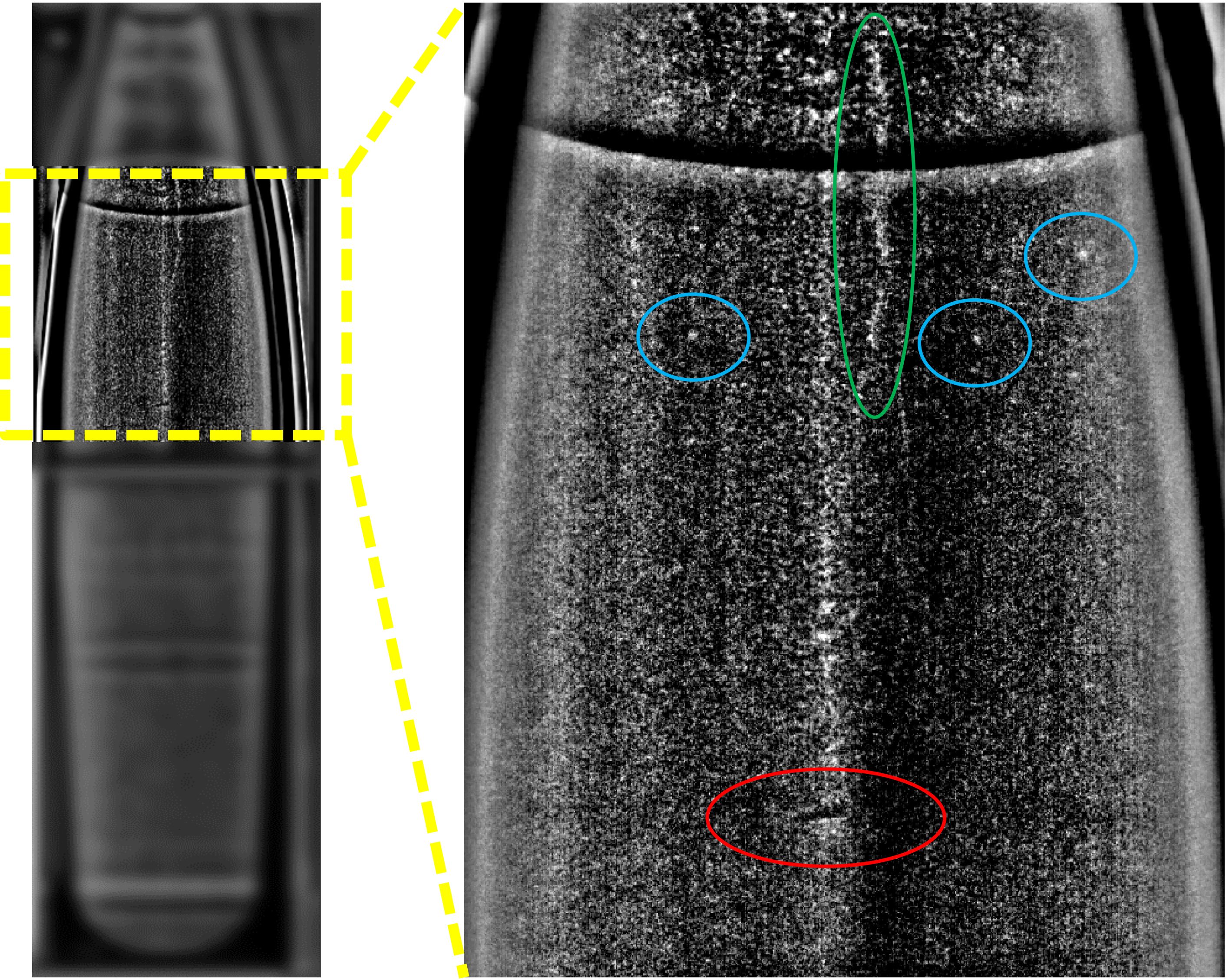






- **Labeled Defective**
- Foreign Material
- 8 Images

MANUAL IMAGE INSPECTION



Piping

Gas/shrink porosity

Crack

- **Is the data accurately curated for AI/ML?**
  - Image below **tagged as Non-defective**
  - **SME confirmed** presence of **anomalies**
    - **Possibly not sufficient to fail the Type-2 munition MILSPEC**

MANUAL IMAGE INSPECTION

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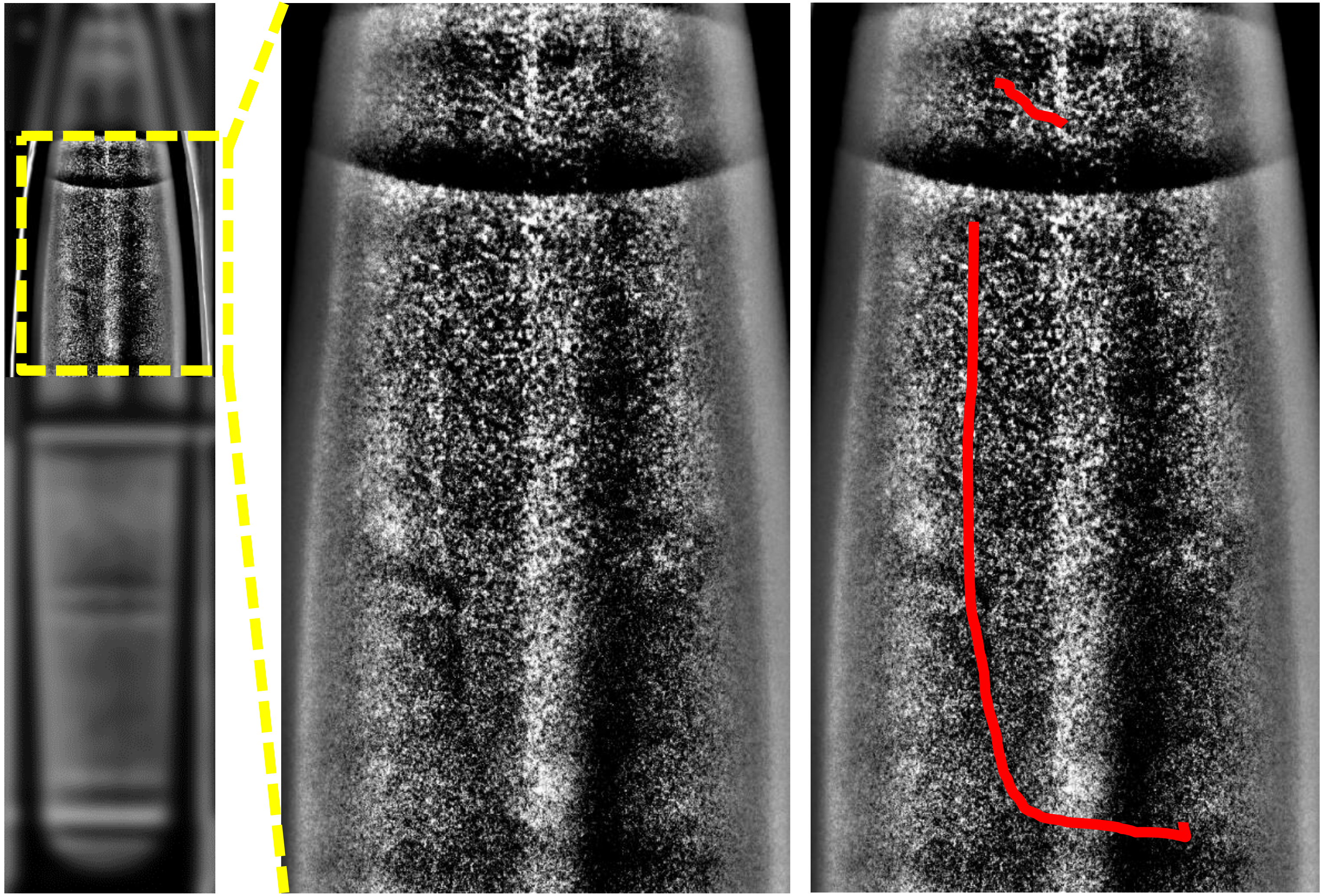


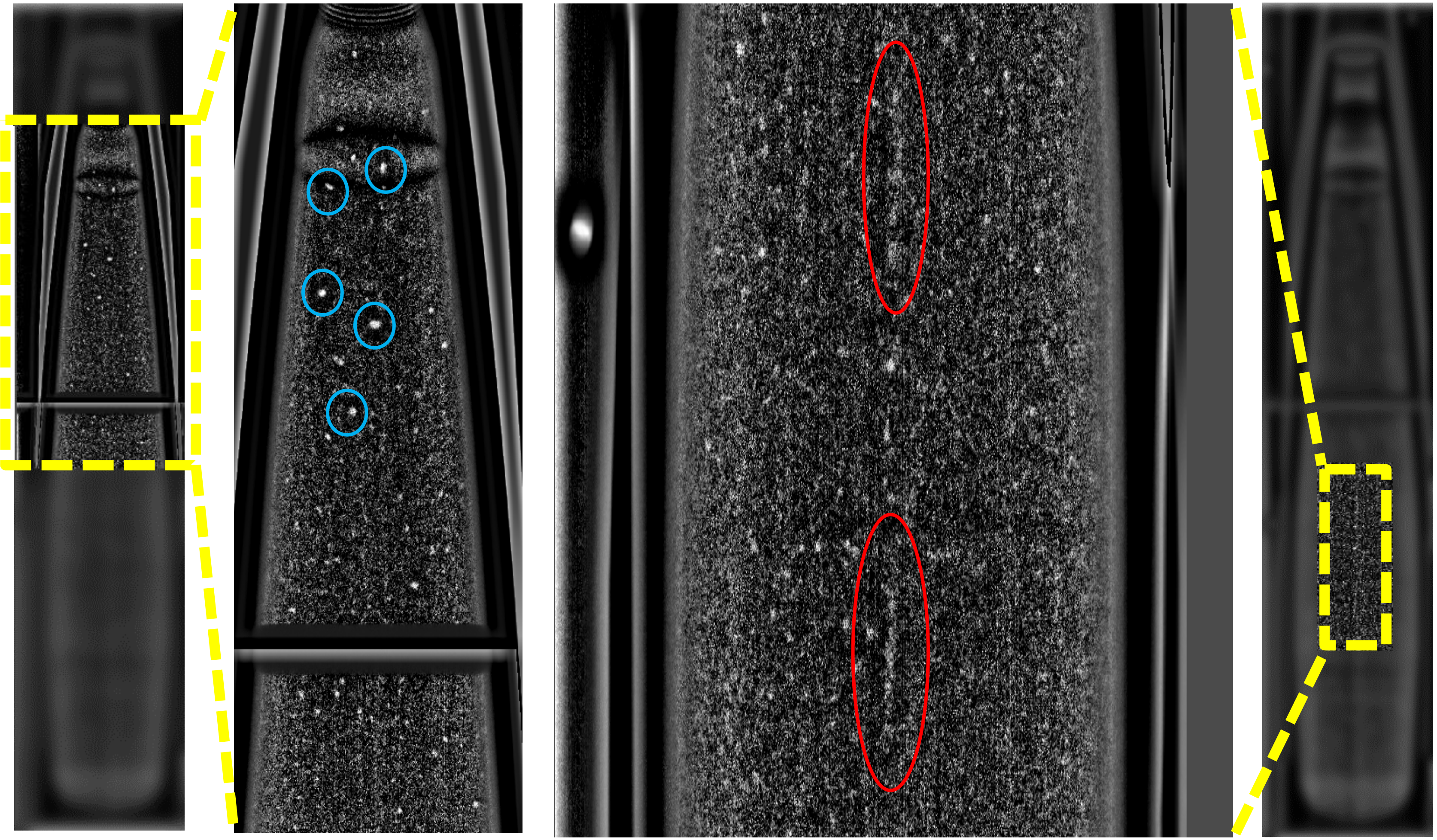
Piping

Gas/shrink porosity

Crack

- **Is the data accurately curated for AI/ML?**
  - Image below **tagged as "Non-defective"**
  - **SME confirmed** presence of **anomalies**
    - **Possibly not sufficient to fail the Type-2 munition MILSPEC**
    - Internal team assessed anomalies as a crack and the SME assessed as shrink porosity

MANUAL IMAGE INSPECTION



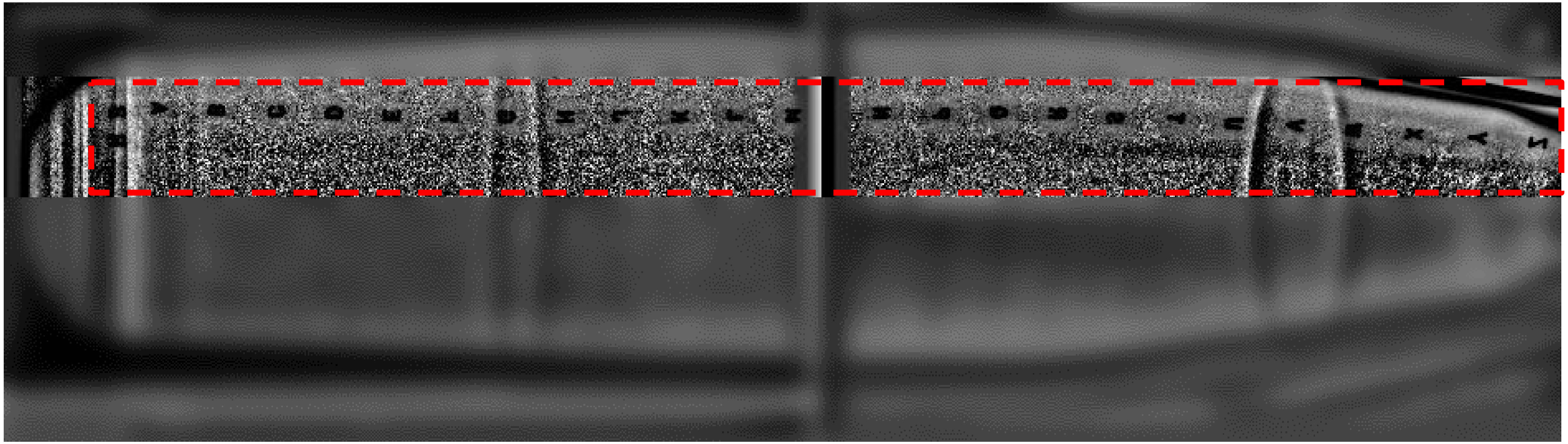
Piping
Gas/shrink porosity
Crack

- **Is the data accurately curated for AI/ML?**
  - Image not present in curation data but in the data set
  - **SME confirmed** presence of **anomalies**
    - **Possibly not sufficient to fail the Type-2 munition MILSPEC**

MANUAL IMAGE INSPECTION

- **Are the images consistent enough across class type?**
  – Image below has the alphabet running along the munition

- **Too easy to find inconsistencies by accident**
  – Traditional CNN classification labels are set without uncertainty
    - A cat is a cat, a dog is a dog
    - In contrast, the Type-1 munition images & labels are riddled with oddities



Can we use an anomaly detector to remove or reclassify outlier data?

High-level Methodology

Crawl, walk, run

PATH TO TRAINING ARMY DEFECT DETECTION MODEL

☆ **Current state**

Run

Deployment

- Standalone application
- Extendible to new defects

Walk

Implementation / Augmentation

- Leverage literature review architectures
- Iterative model adaption
  - 3rd goal : multi-class + anomaly detection
  - 2nd goal : multi-class { defect_1, …, defect_N, no defect }
  - ☆ **1st goal : binary classification { defect, no defect }**

Crawl

Academic/Industry Literature Review

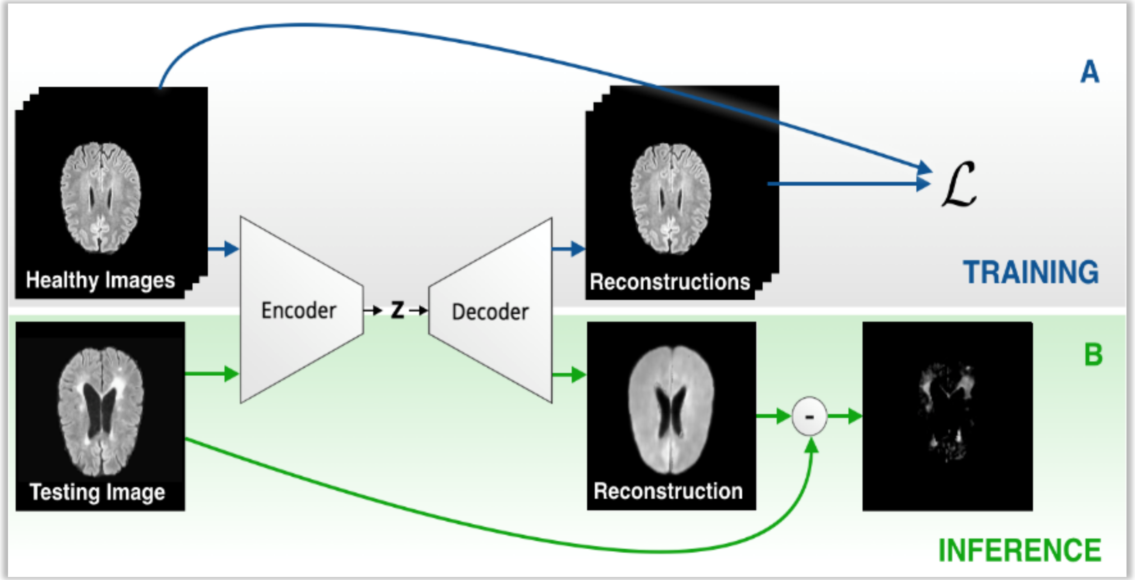
- Ready made CNN architectures for X-ray defect / anomaly detection
  - *https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6512995/*
  - *https://github.com/maxkferg/metal-defect-detection*
- Proven solutions are ripe for the picking, prevent reinventing the wheel, and are capable of transfer/extended learning

Binary Classification

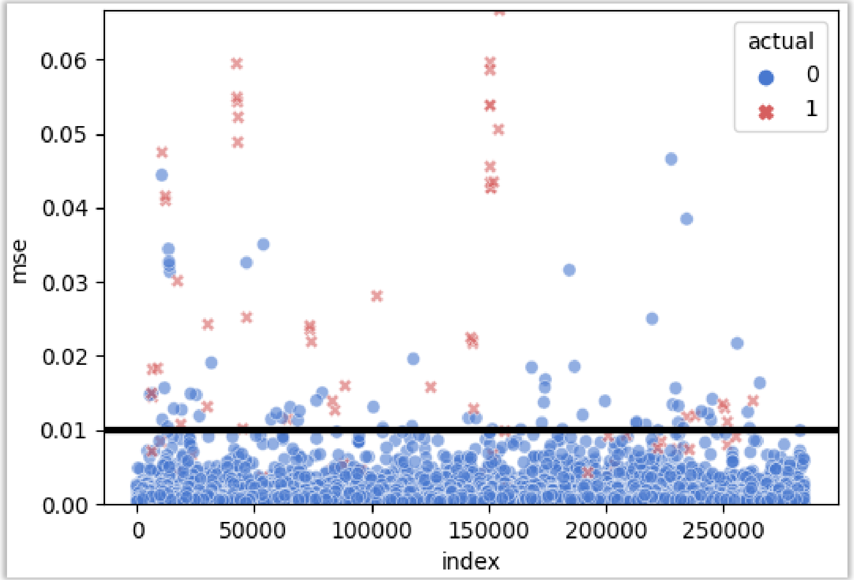
A layered defense approach

EDC AI PLANNED ARCHITECTURE

- **1st Layer : Autoencoder Anomaly Detector**
  - AI to characterize Non-defective munition images
    - Model learns a compression and decompression algorithm for Non-defective munition images
    - Trained model applied to Defective munition images will poorly compress and decompress resulting in a useful discriminator metric—reconstruction loss
    - Reconstruction loss analyzed via minimized cross-entropy to establish optimal threshold to flag outlier/anomalistic input images



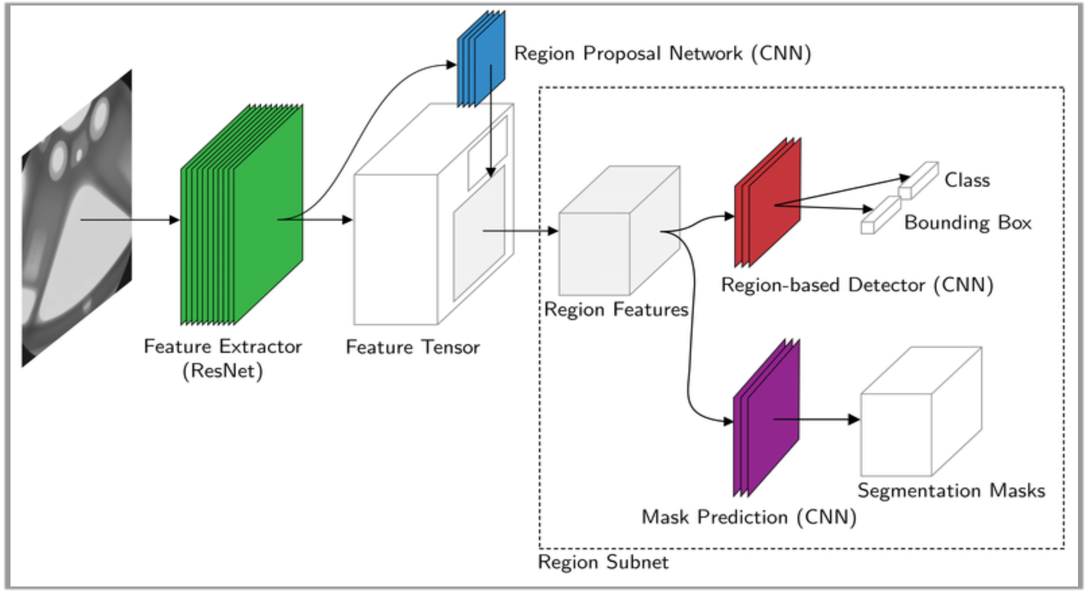
https://deepai.org/publication/autoencoders-for-unsupervised-anomaly-segmentation-in-brain-mr-images-a-comparative-study

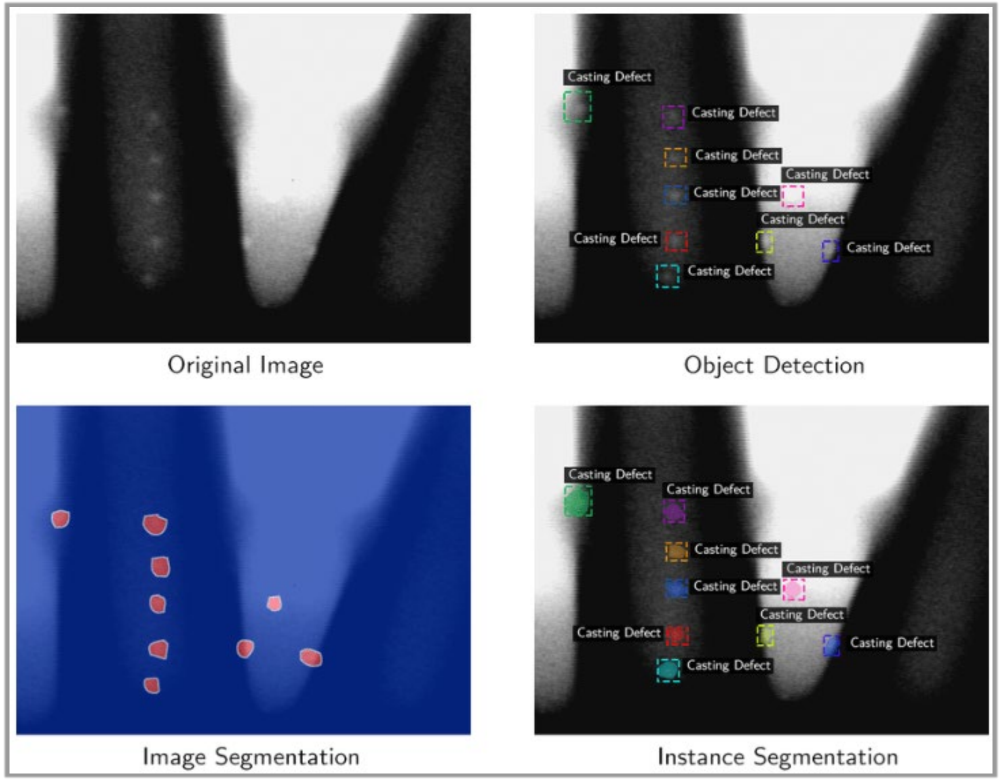


https://minimatech.org/wp-content/uploads/2021/02/threshold_line.png

EDC AI PLANNED ARCHITECTURE

- **2nd Layer : Feature Extractor + MILSPEC**
  - Line, edge, cluster detector
    - Length, width, density measurement
    - Assessments against MILSPEC thresholds
    - Flag and tag ROIs for expert analysis

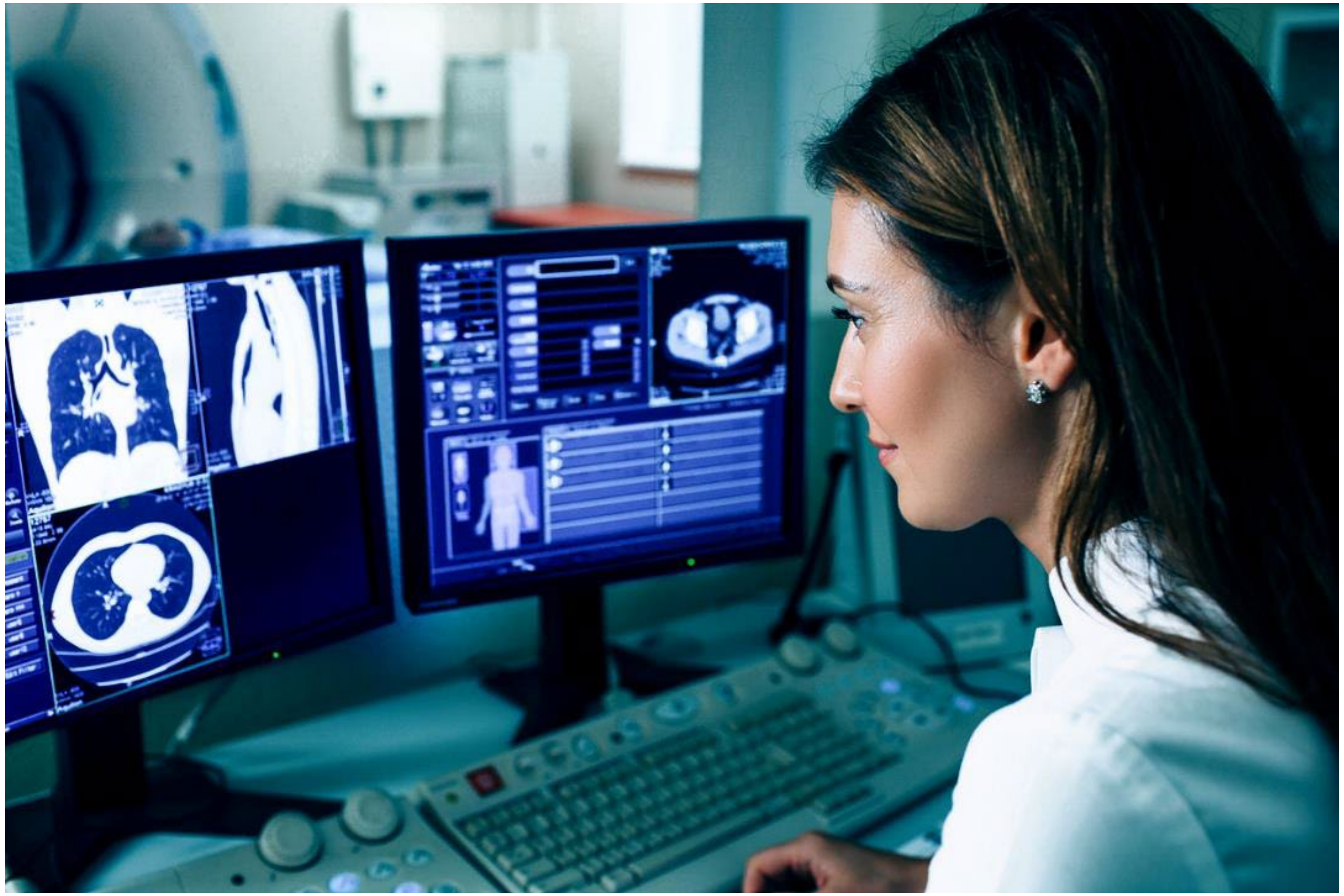




https://www.researchgate.net/figure/The-neural-network-architecture-of-the-proposed-defect-detection-system-The-system_fig5_327392506

EDC AI PLANNED ARCHITECTURE

- **3rd Layer : Human-in-the-loop**
  - Focused attention to flagged images failing 1st and 2nd layer AI filtering



https://windsorimaging.com/wp-content/uploads/2020/04/Windsor-Imaging-The-History-of-the-Digital-X-Ray.jpg

PLANNED ARCHITECTURE OVERVIEW

- **<u>1st Layer</u> : Autoencoder Anomaly Detector**
  - AI to characterize Non-defective munition images
    - Model learns a compression and decompression algorithm for Non-defective munition images
    - Trained model applied to Defective munition images will poorly compress and decompress resulting in a useful discriminator metric—reconstruction loss
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- **<u>2nd Layer</u>: Feature Extractor + MILSPEC**
  - Line, edge, cluster detector
    - Length, width, density measurement
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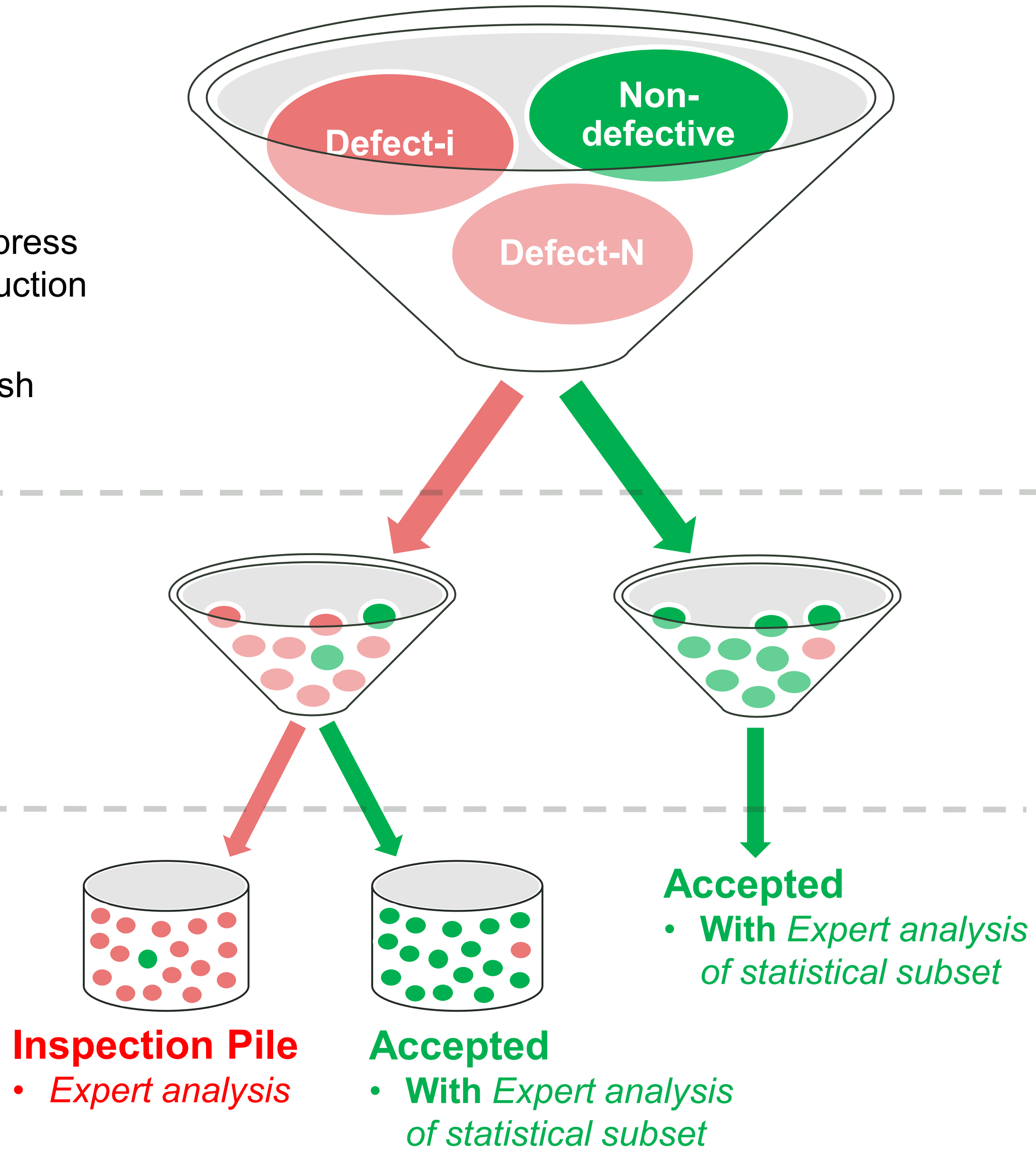
    - Flag and tag ROIs for expert analysis

- **<u>3rd Layer</u> : Human-in-the-loop**
  - Focused attention to flagged images failing 1st and 2nd order AI filtering



Computing Resources

What is HPCMP?

DOD HPCMP

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DOD High Performance Computing Modernization Program

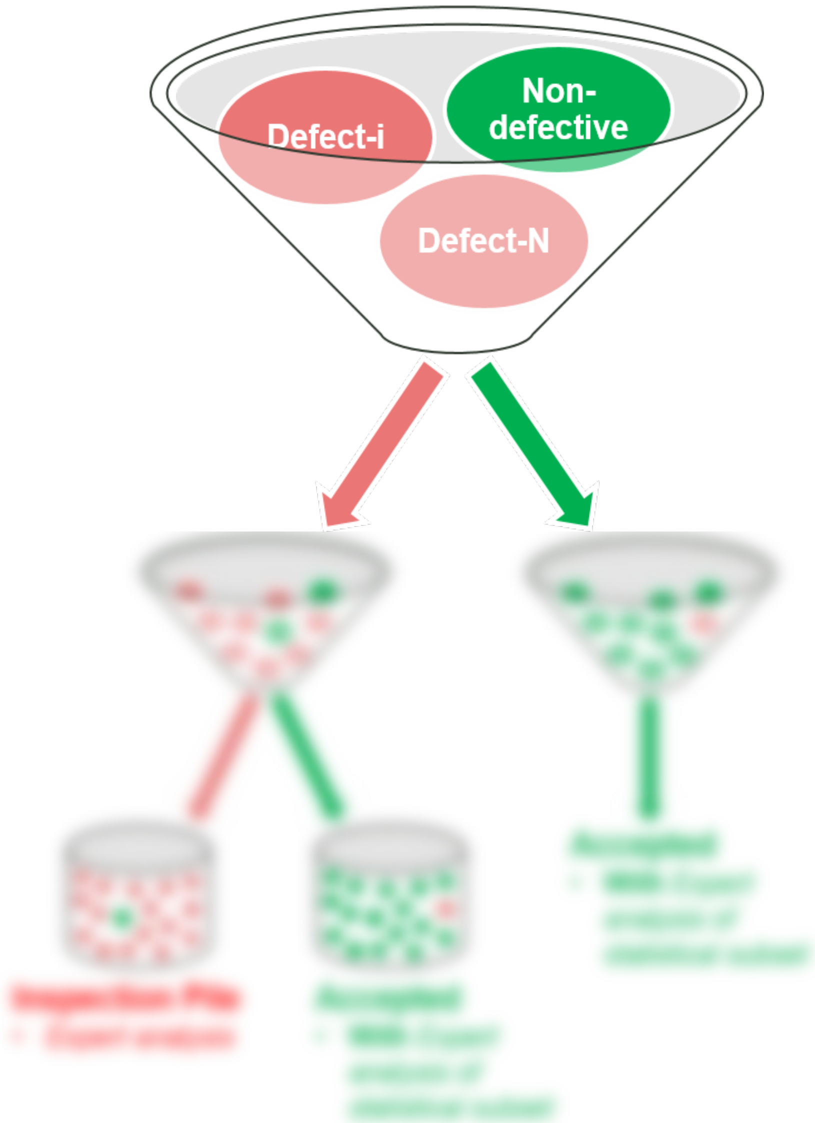
The U.S. Army Engineer Research and Development Center

ERDC ENGINEER RESEARCH & DEVELOPMENT CENTER — DISCOVER | DEVELOP | DELIVER

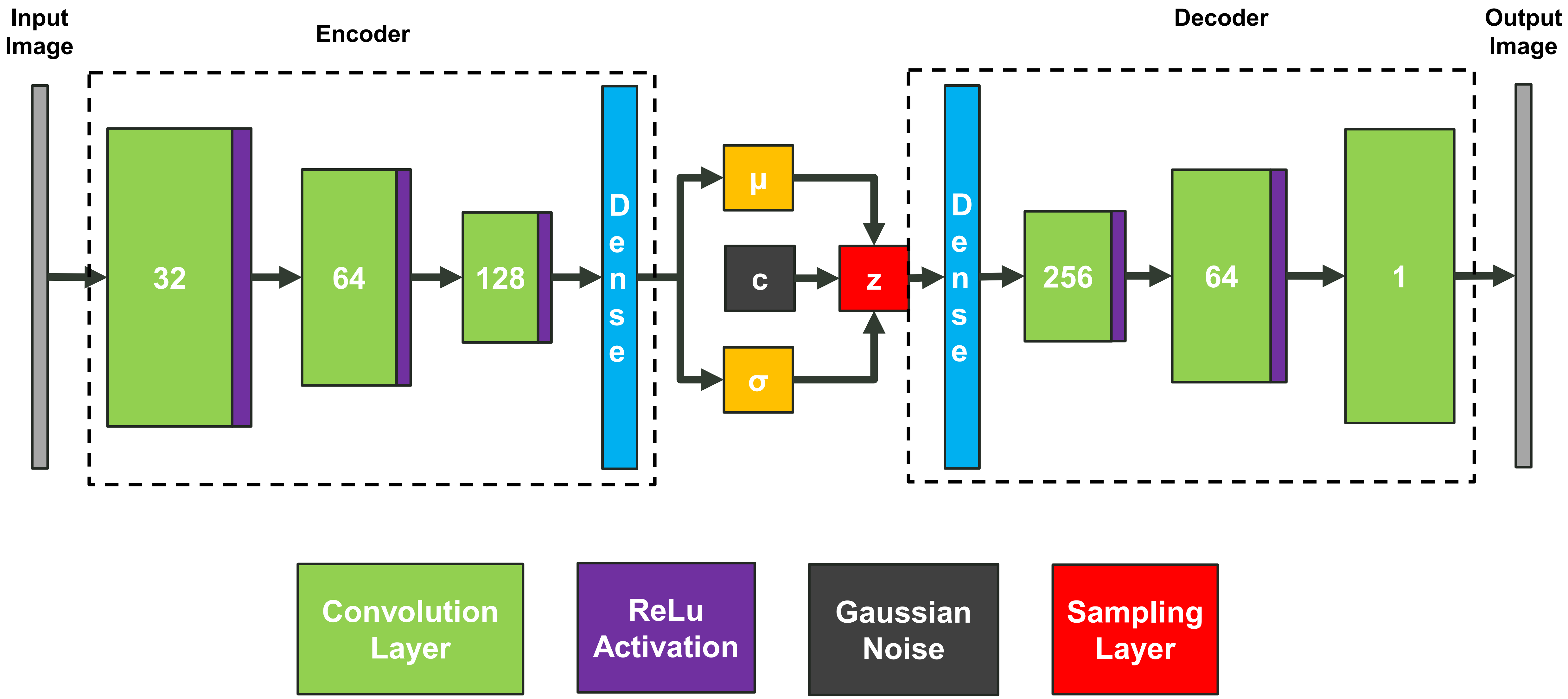
Onyx is a Cray XC40/50 system. It has 4,810 standard compute nodes, 4 large-memory compute nodes, 32 GPU compute nodes, 32 Knights Landing (Phi) compute nodes, and 64 Machine Learning Accelerator (MLA) multi-GPGPU nodes (a total of 4,942 compute nodes or 217,128 compute cores). It is rated at 6.06 peak PFLOPS.

1st Layer Architecture

The anomaly detector



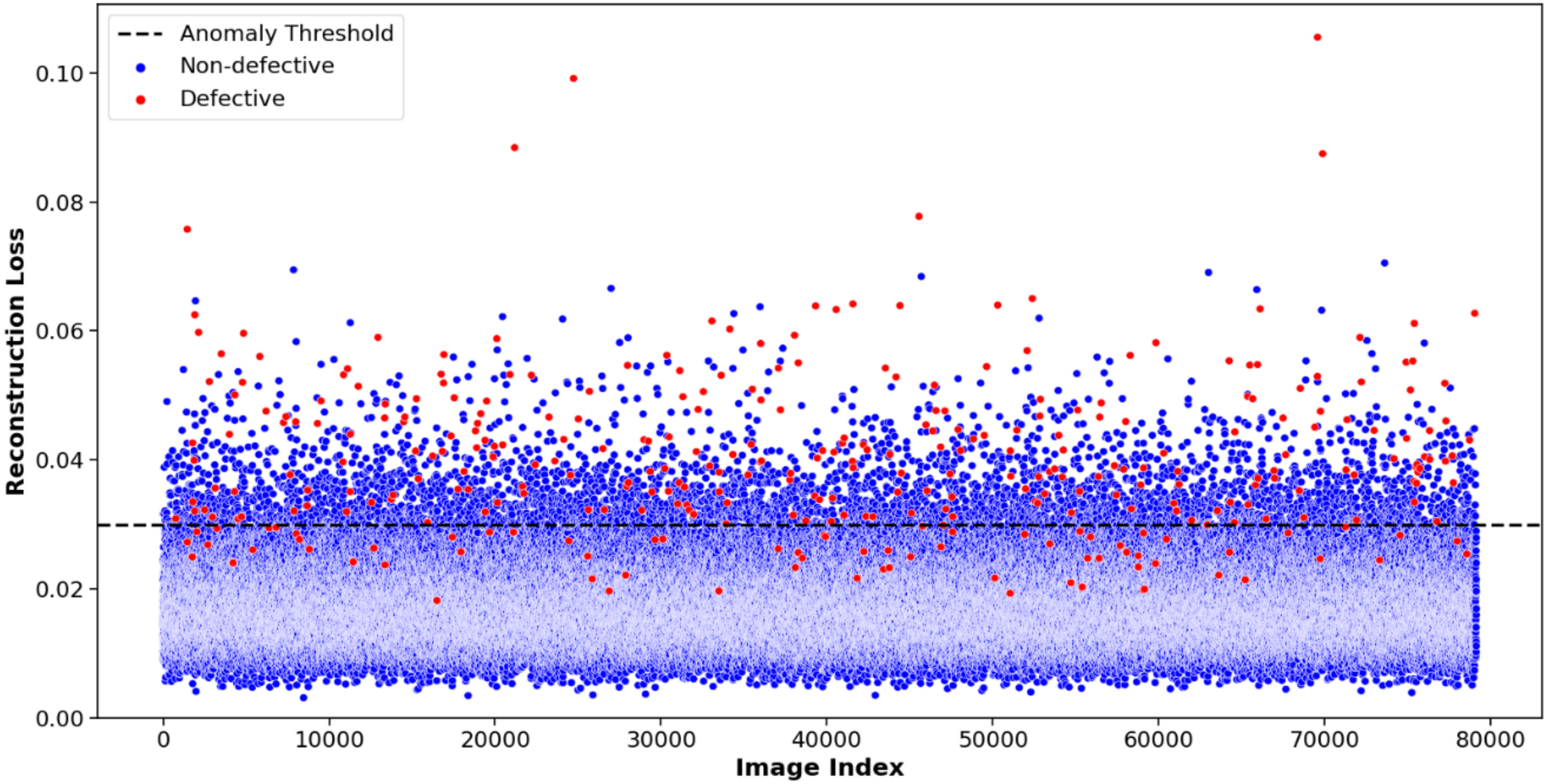
AUTOENCODER ARCHITECTURE



ANOMALY DETECTOR PREDICTIONS

Leverage 1st training to interrogate outliers from Non-defective image set

- Remove images with questionable class labels, e.g. images with alphabet soup
- Removals will tighten up learned distribution of normal image set
- Tighter normal image distribution makes setting anomaly threshold less subjective
- Effect will be decreased false positives



ANOMALY DETECTOR PATH FORWARD

1. **Mask image to isolate munition**
   - Noisy and distractive features occurring outside the munition ROI

2. **Reclassify or remove normal images having questionable labels**
   - Retrain the model

3. **Reevaluate Autoencoder threshold**
   - Minimized cross-entropy

		Predicted	
		Non-Defective	*Defective*
Actual	*Non-defective*	68847 (87.38%)	9947 (12.62%)
	Defective	74 (21.2%)	275 (78.8%)

Unacceptable performance given the stakes

Deployable Capability

Tooling and capability integration in parallel

DEPLOYABLE TOOLS

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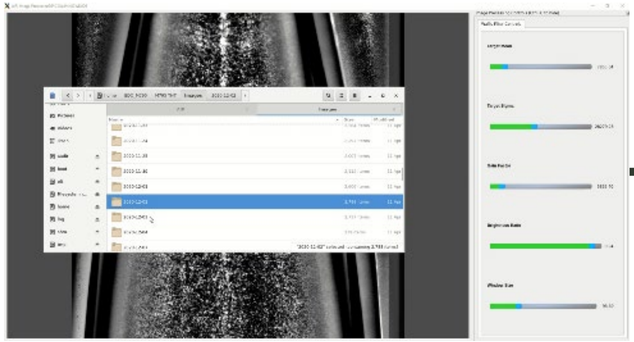
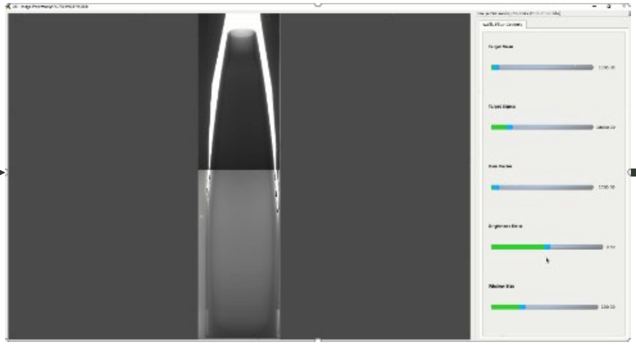
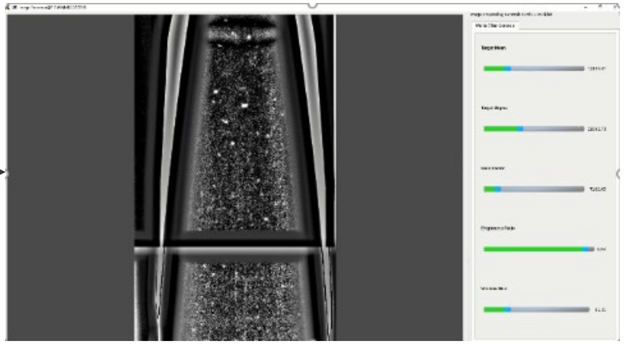
Wallis Filter



Browse & Drag-drop images

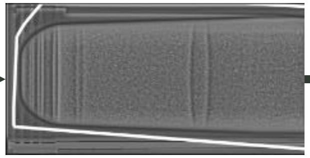


Apply filter settings & pan/zoom

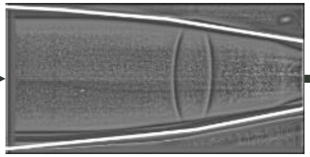


Edge Detection

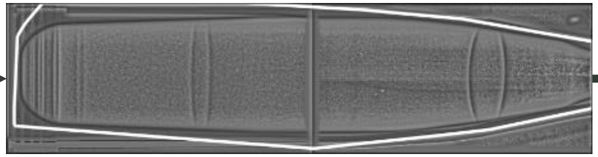
Wallis Filter



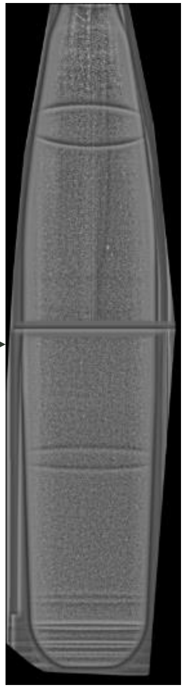
- Otsu Thresholding
- Contour Detection
- Dilation + Erosion
- Convex Hull



Combine Hulls



Background Subtraction



PATH FORWARD

Improving 1st Binary Classifier Layer
- Addressing data quality and outliers

Developing 2nd Binary Classifier Layer
- Feature Extractor + MILSPEC
- Collaborating with United States Military Academy

Striving to Reduce Catastrophic Events

https://www.nbcnews.com/news/world/haunting-image-soldier-killed-blast-released-army-n754346