Automated Detection of Anomalies in the Nondestructive Evaluation of Materials：Algorithms, Findings, and Next Steps

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August 2015

Anomaly Detection in the Nondestructive Evaluation of Materials

Nondestructive evaluation (NDE) involves studying the properties of a material without causing damage to the material

- A basic example of NDE is a doctor using an x-ray to determine if a patient has a broken bone
- At NASA, NDE researchers are evaluating Computed Tomography (CT) scans in order to identify anomalies for improving and developing materials for stronger, lighter, and safer structures

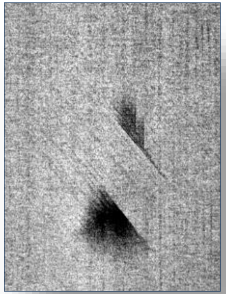
Current analysis of CT scans of materials:

- Is a time-consuming process
- Requires significant subject matter expertise
- Has only minimal automation

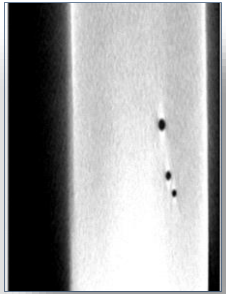
Automated Algorithms:

- Will help SMEs to design better material compositions and structures
- Will help SMEs with innovative composite additive manufacturing using ISAAC

CT Scan of Carbon Fiber



CT Scan of Stainless Steel



Outline

- Overview and Goals
- Statistical Algorithmic Techniques
  - Cross Hatch Regression
  - 2 Dimensional Regression
  - SME Validation Methodology
- Machine Learning Algorithmic Technique
  - Deep Learning – Convolutional Neural Networks

Nondestructive Evaluation (NDE)

- Inspect material for defects without causing changes (Doctor using x-ray)
- Techniques being used
  - Ultrasound
  - Thermography
  - **X-ray computed tomography (CT)**
    - **This anomaly detection work now focuses on CT data**

Objectives for "Big Data" in NDE

- Large volumes of data are collected (typically 2 GB and larger in a 4 hour time period)
- Currently procedure for reviewing data is displaying data on computer monitor and subject matter expert identities anomalies in data
- This can require examining as many as thousands of images or even regions of thousands of images to ensure all anomalies are detected
- It is desirable to develop methodologies to:
  - Reduce the amount of data that needs to be reviewed by a human
  - Identify subtle variations that are difficult for a human to detect due to low signal to noise ratios
  - Identify features more easily recognizable in three dimensions

Anomaly Detection in the Nondestructive Evaluation of Materials (NDE)

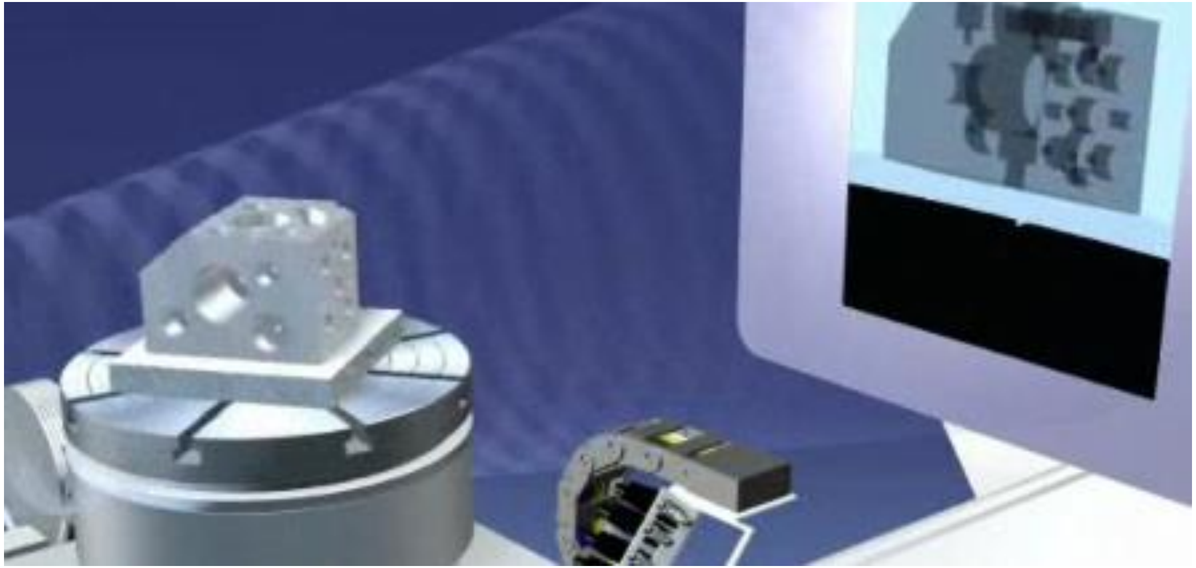
Develop Techniques and algorithms to automatically detect various kinds of delaminations in CT scans from nondestructive evaluations of materials.

Goals

1. Accurately identify and characterize anomalies in various materials and significantly reduce SME analysis time
2. Discover additional anomalies that were previously undetected by visual analysis of an image
3. Enable SMEs to design better material compositions and structures
4. Help SMEs with innovative composite additive manufacturing using ISAAC

X-ray Computed Tomography (CT)

Source of radiation

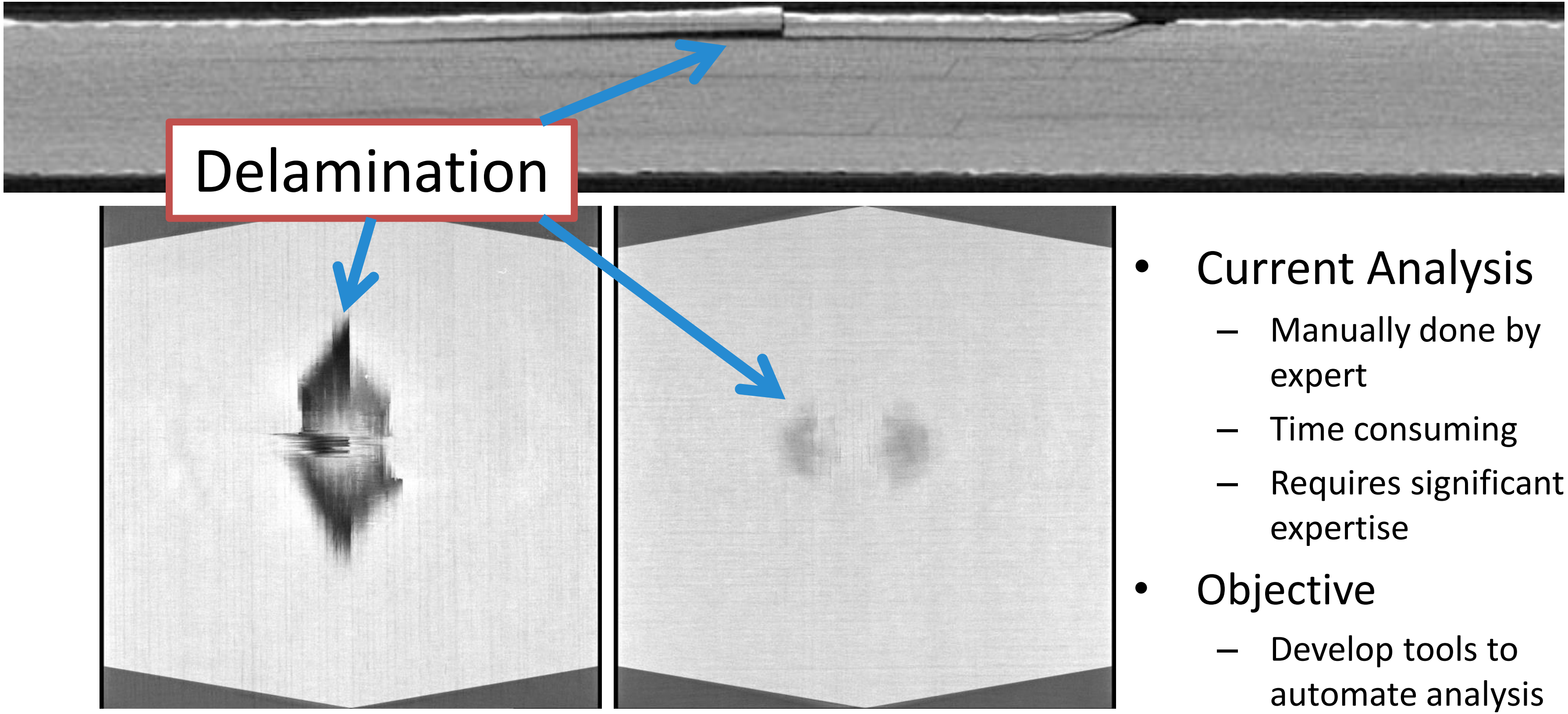


2-D shadowgraph

Turntable

- Specimen rotated on turntable
- 2-D "shadowgraphs" at multiple angles recorded
  - Intensity proportional to sum of densities along path through material
- 3-D structure reconstructed from 2-D shadowgraphs

Example of CT Data: Defects in Carbon Fiber

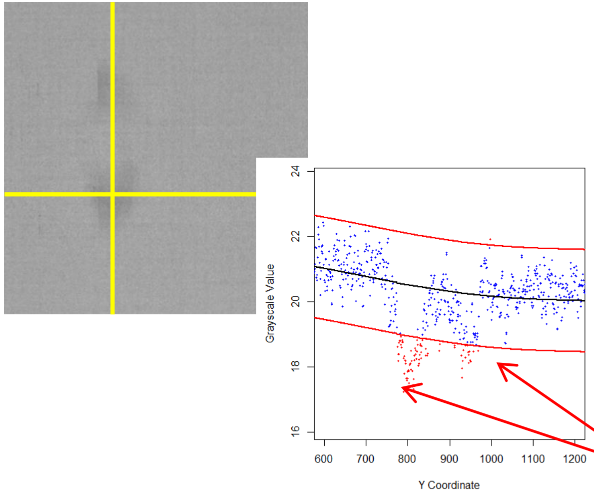


- Current Analysis
  - Manually done by expert
  - Time consuming
  - Requires significant expertise
- Objective
  - Develop tools to automate analysis

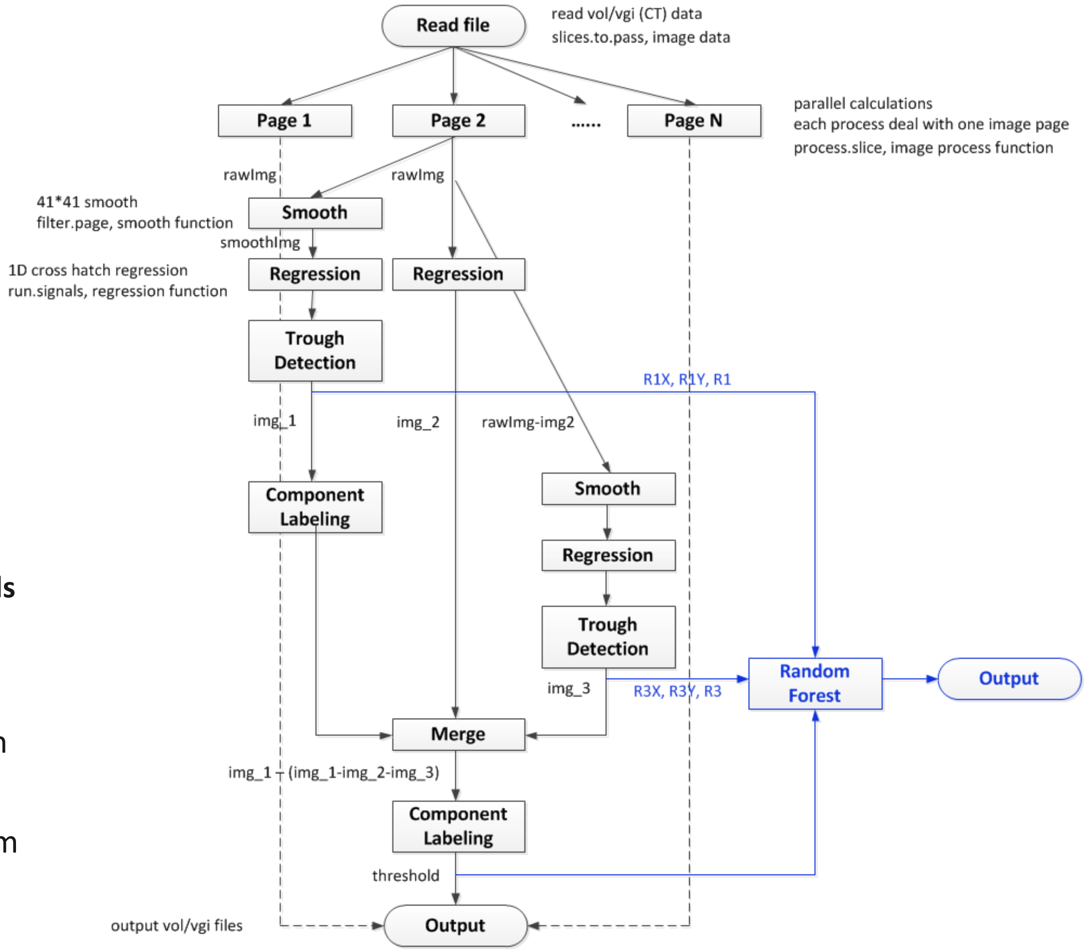
Algorithmic Techniques Being Developed

Technique	Data Analytics and Machine Intelligence Team Member
Crosshatch Regression (Statistical Algorithm)	Colin Lockard (CS Masters Student)
Two-Dimensional Regression (Statistical Algorithm)	Lin Chen (Software Developer)/Ray McCollum (Statistician)
Convolutional Neural Networks (Machine Learning)	Daniel Sammons (CS Masters Student)

Crosshatch Regression Technique



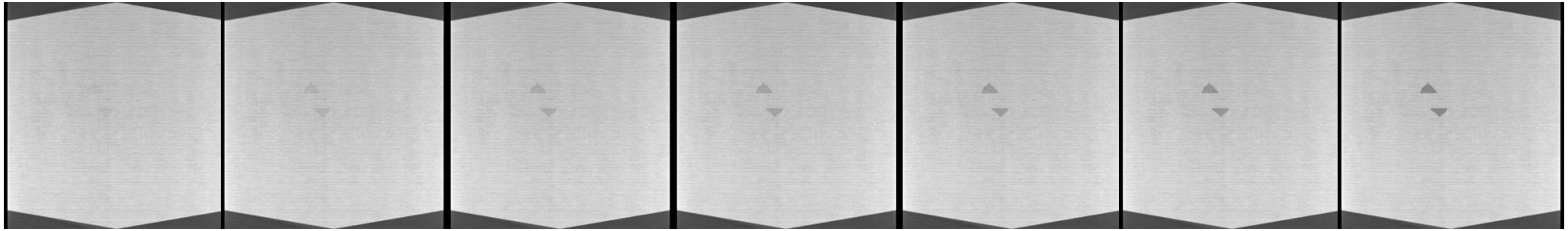
Anormaly Pixels



1. Divide image into series of x- and y-signals
2. Fit linear model to each signal with robust regression
3. Identify outliers against fitted model
4. Confirm delaminations using random forest algorithm

Results of Crosshatch Regression on Simulation Data

Simulated Data



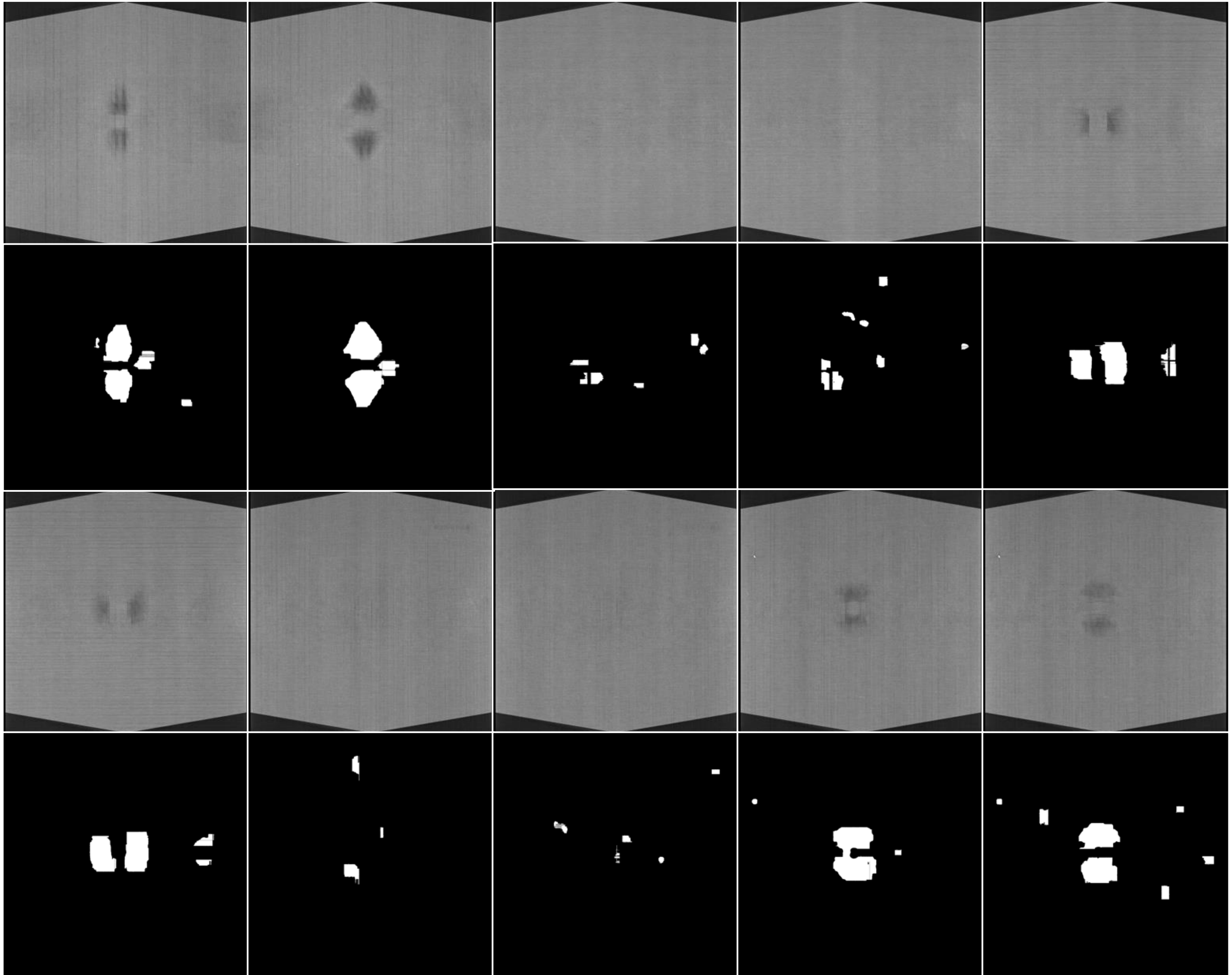
1 2 3 4 5 6 7

Precision		
Image #	Threshold	Random Forest
1	71.4%	61.3%
2	86.6%	56.7%
3	85.9%	55.9%
4	83.5%	56.6%
5	82.5%	57.7%
6	82.0%	59.0%
7	82.7%	62.1%
all	82.1%	58.5%

Recall		
Image #	Threshold	Random Forest
1	30.4%	75.6%
2	70.1%	97.2%
3	86.7%	99.2%
4	93.6%	99.7%
5	96.5%	99.8%
6	96.6%	99.9%
7	95.8%	100.0%
all	81.4%	95.9%

Crosshatch Regression Results on Experimental Data

- Good results overall
- Could be a few false positives
- SME validation will help



Key Findings and Next Steps for Crosshatch Regression

- Results are good on both simulated and experimental data

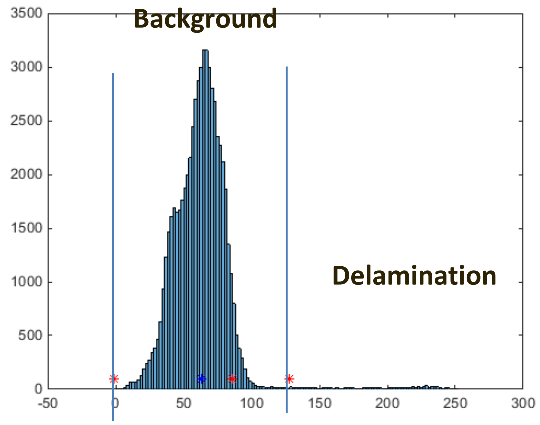
- Advantages
  - Accurately segment delaminations in carbon fiber CT
  - Ability to find anomalies in data

- Challenges
  - May have trouble generalizing to other defects/materials/modalities

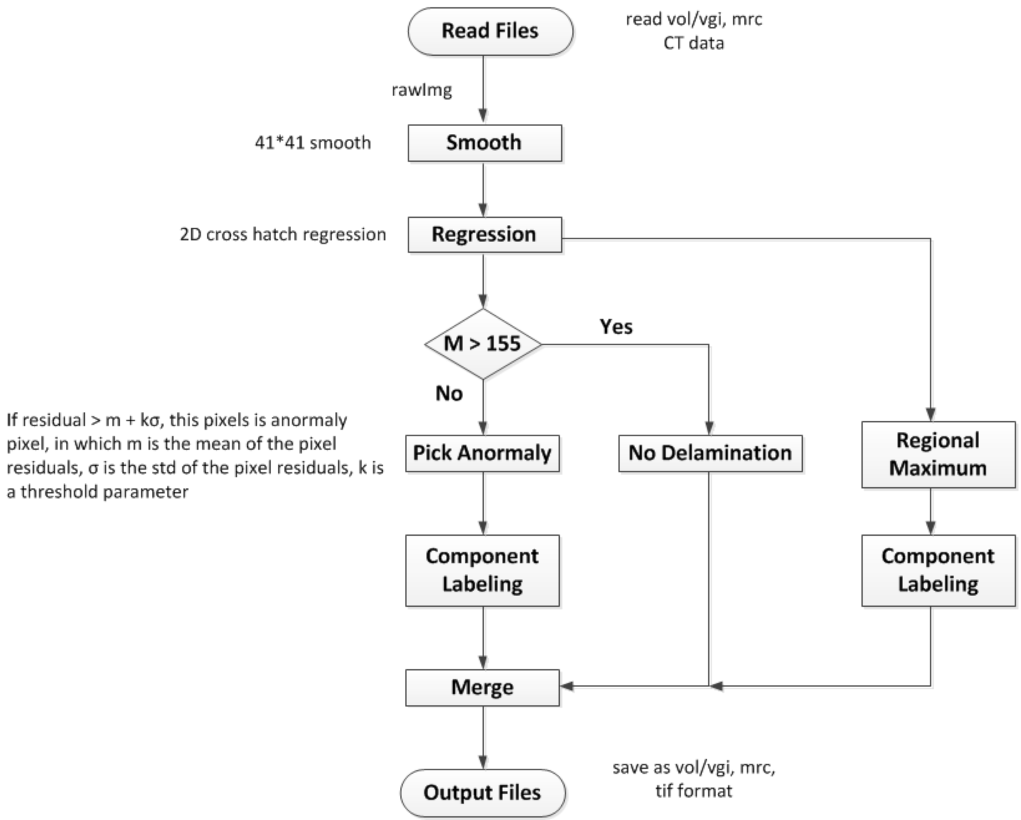
- Next Steps:
  - Validation by SMEs with more experimental data sets using GUI
  - Targeted use for structural analysis of materials in near future

Two-Dimensional Regression Algorithm

1. Smooth
2. Fit the pixels in a slice into a 2D regression function
3. Replace the pixel value by residual value, which is (regression value – pixel value)
4. Identify the anomaly pixels by histogram plot



If a residual value is out of family, the pixel is a delamination pixel

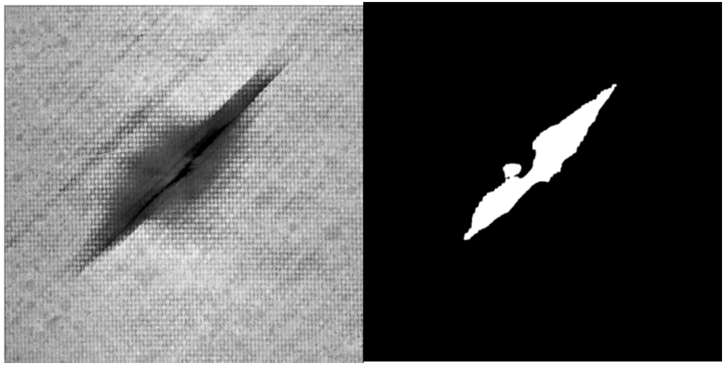


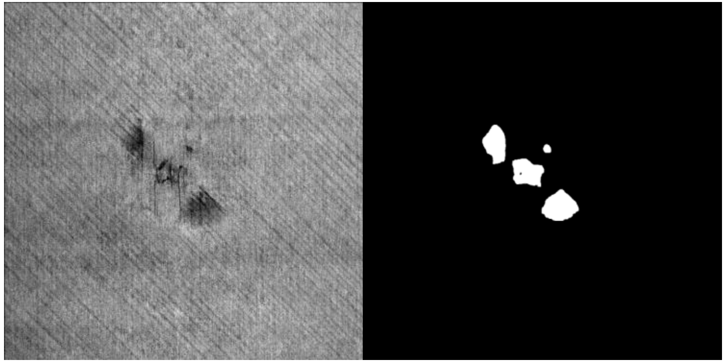
Results of Two-Dimensional Regression

Simulated Data

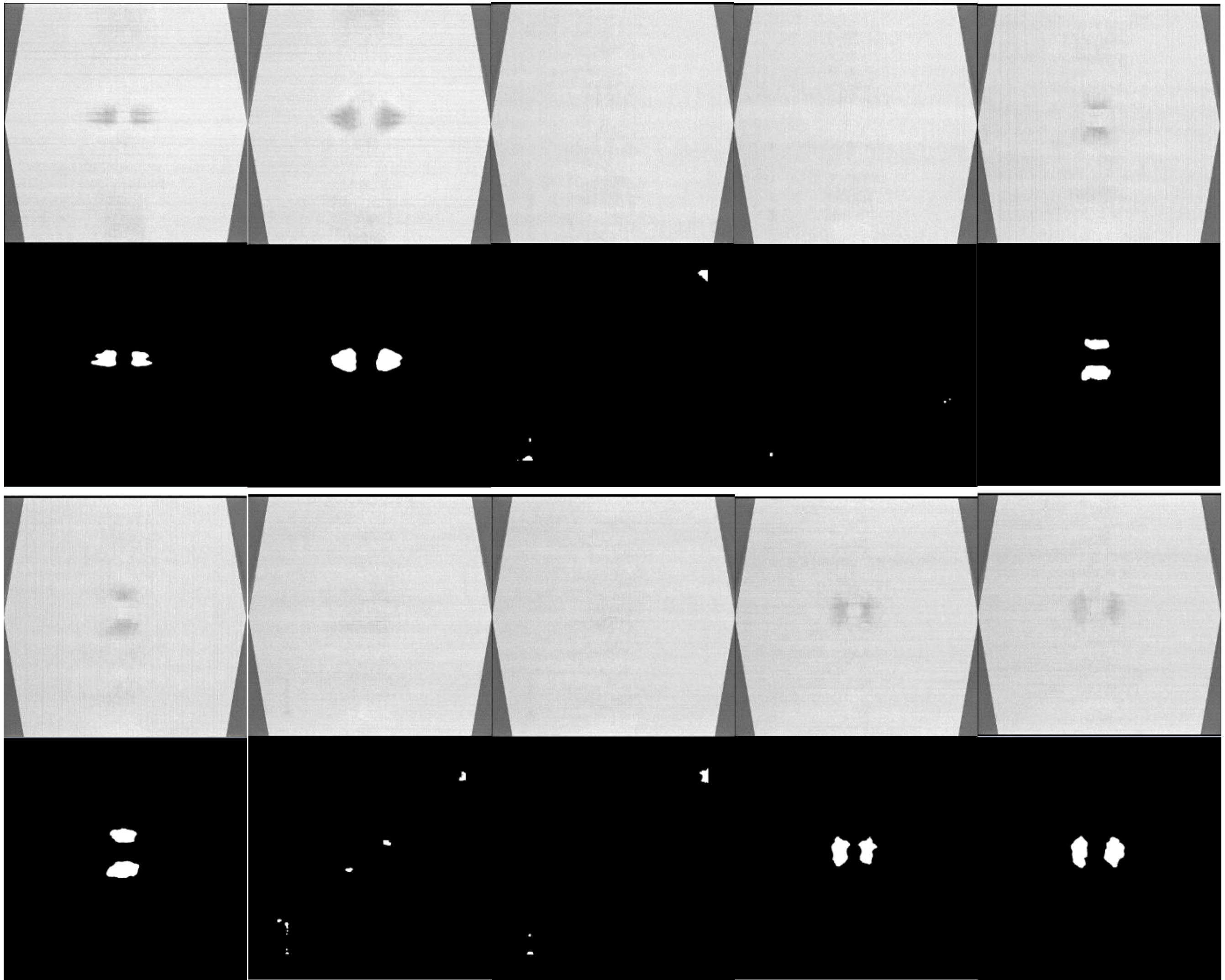
Metric	1	2	3	4	5	6	7
Precision	74.6%	92.6%	91.3%	89.3%	87.7%	86%	85.1%
Recall	11.6%	45.4%	64.8%	73%	77%	79.2%	81.6%
RMSD	261.4	99.6	60.9	45.4	26.6	18.1	17.2
Hausdorff	439.8	205.2	126	98.7	83.3	38.0	33.0

Real Data





Two-Dimensional Regression – Results
on experimental data
- Overall good results
- Could be a few false positives
- SME validation can help



Key Findings for Two-Dimensional Regression

- Results are good on both simulated and experimental data
- Advantages
  - Accurately segment delaminations in CT images
  - Very efficient algorithm
- Challenges
  - May have trouble generalizing to other defects/materials/modalities
- Next Steps:
  - Validation by SMEs with more real experimental data sets using GUI
  - Targeted use for structural analysis of materials in near future

SME Validation of the Two Statistical Algorithms

- So far…
  - Quantitatively validated using simulated data set
  - Passed the “look test” for real data
- Goal
  - Quantitatively validate with real experimental data sets

Validation Methodology

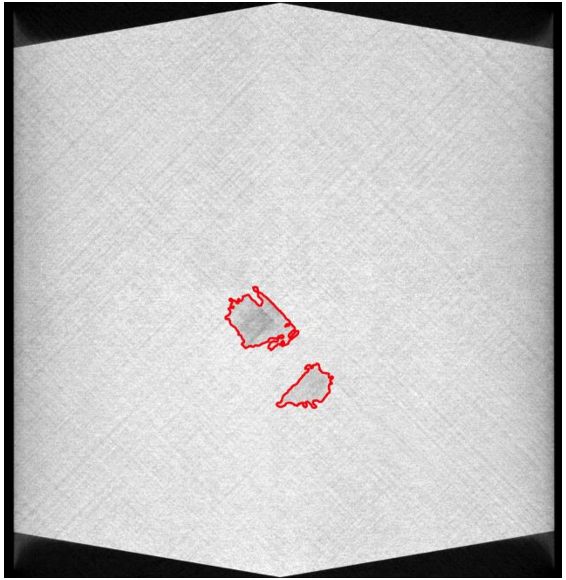
- Segment real data anomalies using pseudo-manual “Chan-Vese” segmentation algorithm
- Validate segmentations with SMEs
- Compare output of automated algorithms with validated segmentations and develop metrics for evaluation

Validation Methodology

Real Data

Segment with Chan-Vese[1]

Segmented Data



Validate with SME

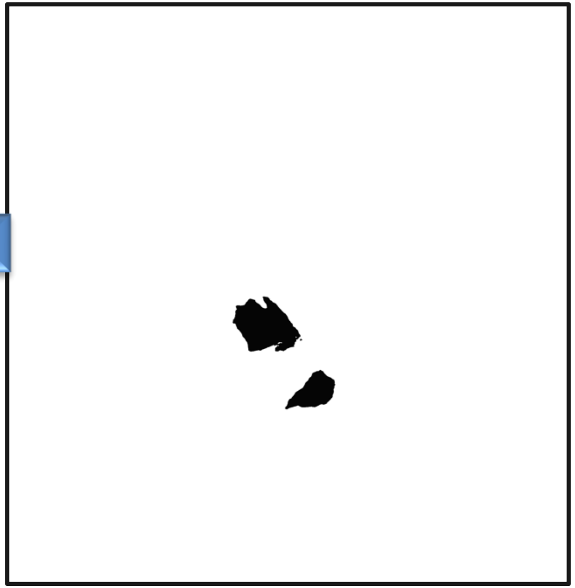
[1]Chan, Tony F., B. Yezrielev Sandberg, and Luminita A. Vese. "Active contours without edges for vector-valued images." *Journal of Visual Communication and Image Representation* 11.2 (2000): 130-141.

Validation Methodology Cont…

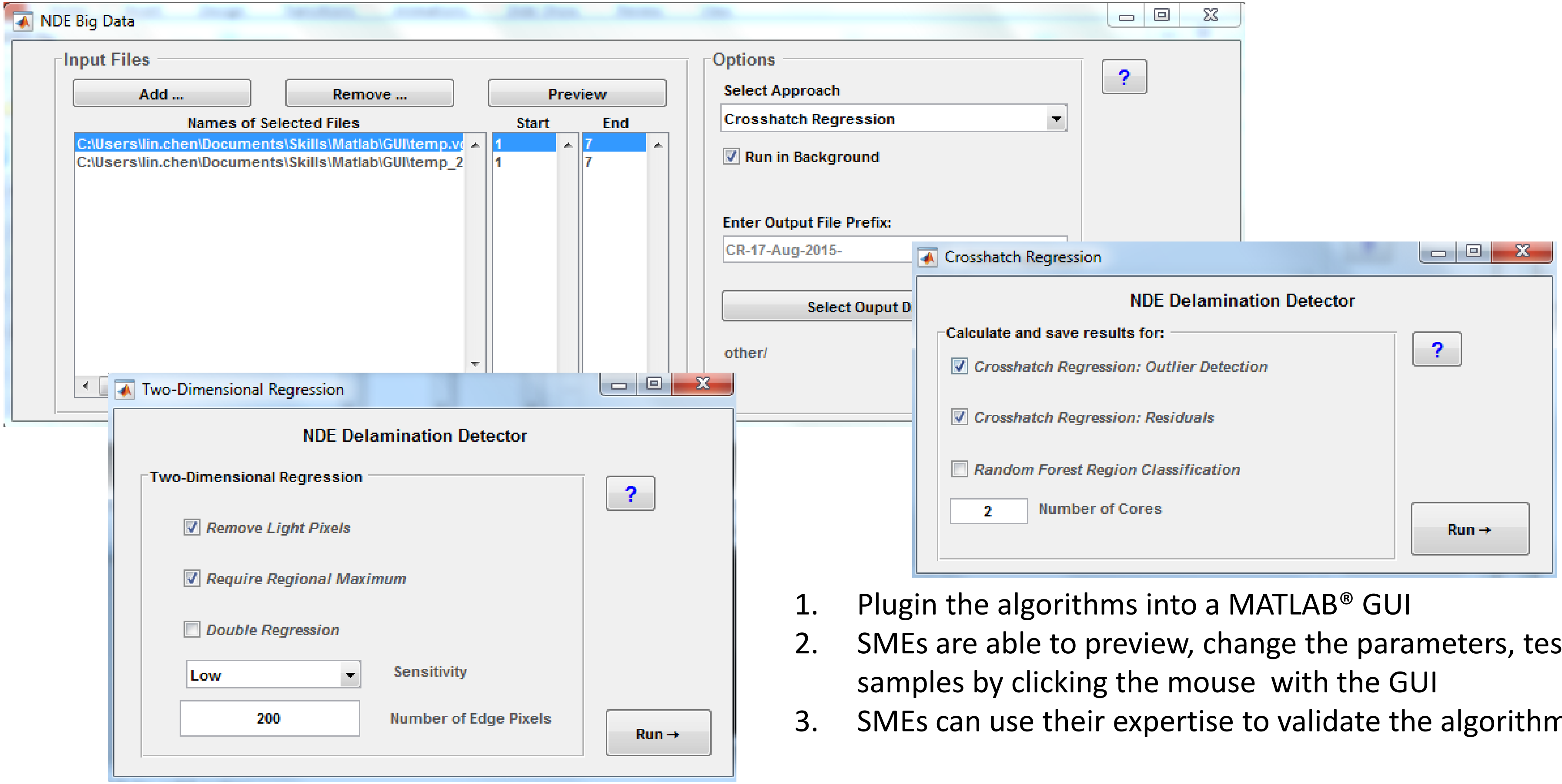
SME Validated
Segmented Data

Compute
Metrics
(Global TP/FP,
RMSD,
Hausdorff,
etc.)

Output from automated
segmentation



MATLAB® GUI for Validation



1. Plugin the algorithms into a MATLAB® GUI
2. SMEs are able to preview, change the parameters, test samples by clicking the mouse with the GUI
3. SMEs can use their expertise to validate the algorithms

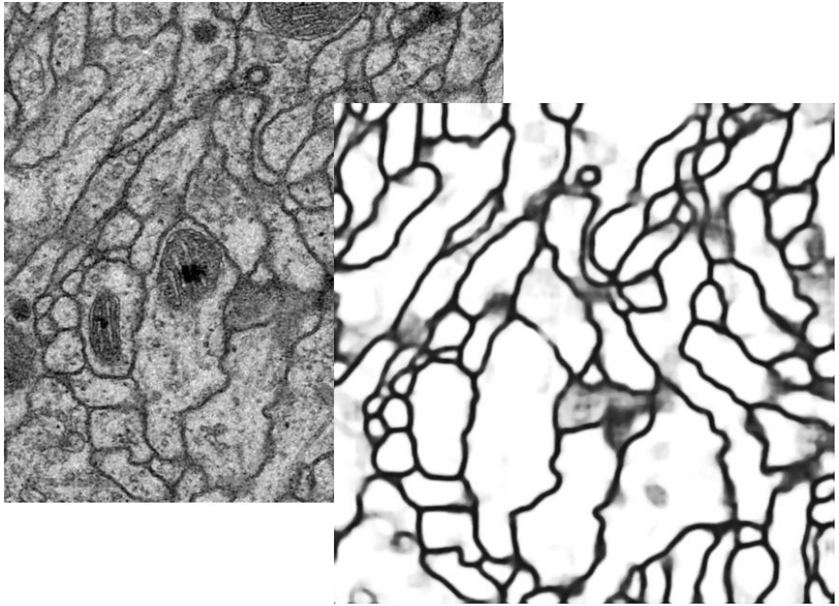
Convolutional Neural Networks (CNNs)

- CNNS are state of the art for image recognition task
- Based on Deep Learning techniques (advanced neural networks)
- Have a great potential for NDE challenge across materials and modalities

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

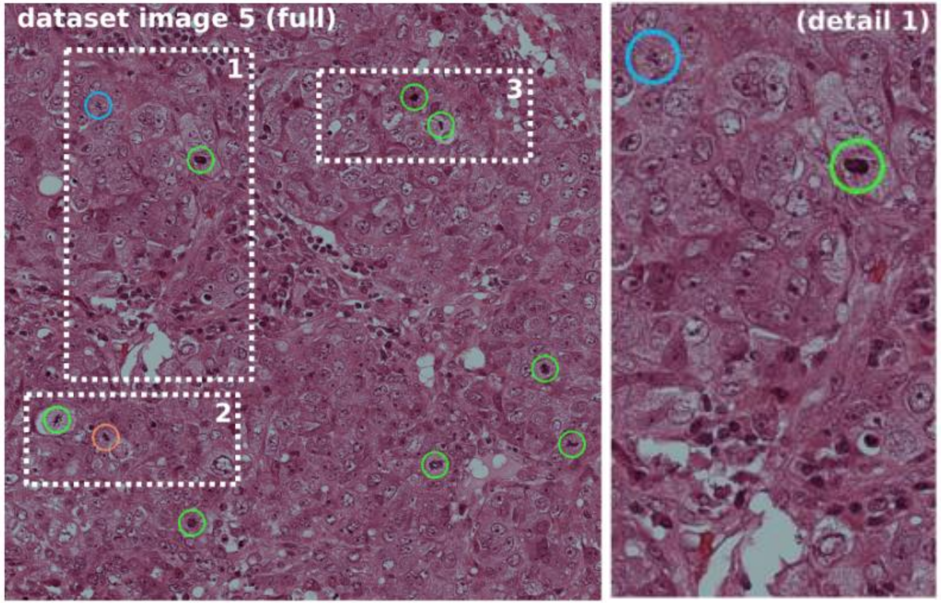
Successful Application of CNNs to Segment and Detect Objects in Medical Imagery

Neuronal Membrane Segmentation (IDSIA)



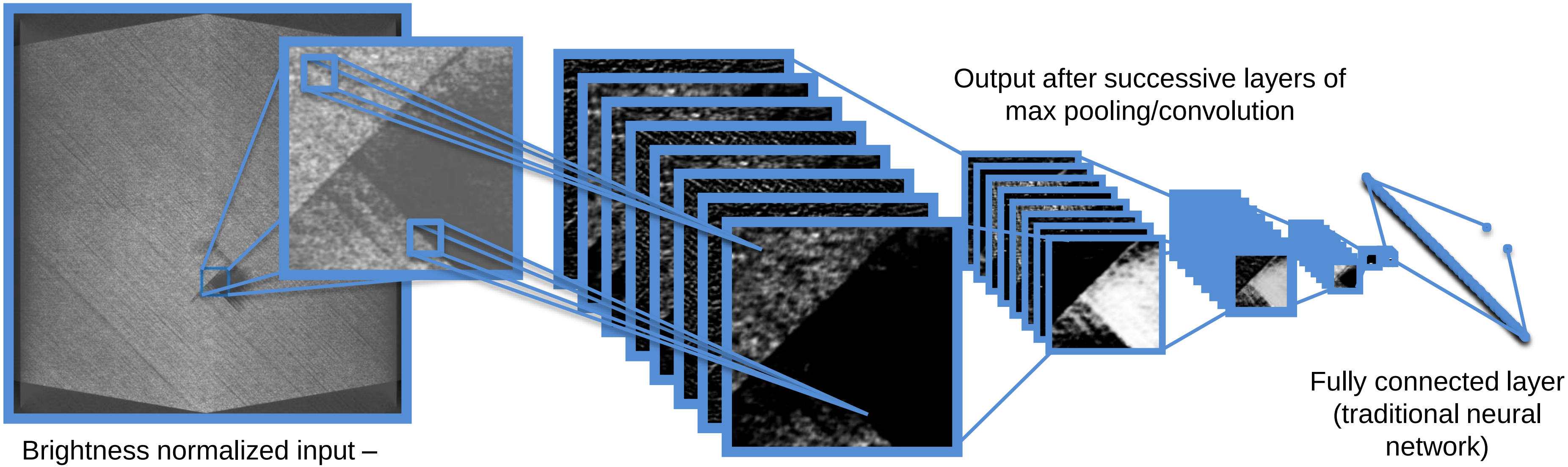
Ciresan, Dan, et al. "Deep neural networks segment neuronal membranes in electron microscopy images." Advances in neural information processing systems. 2012.

Mitosis Detection (IDSIA)



Cireşan, Dan C., et al. "Mitosis detection in breast cancer histology images with deep neural networks." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013.

Applying CNNs to NDE



Brightness normalized input – enlarged portion shows input window to the network

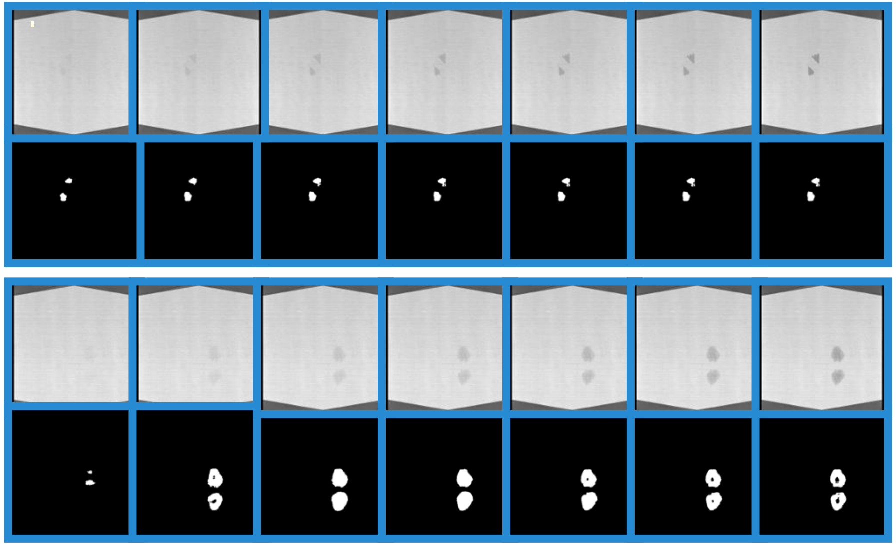
Output of first convolutional layer

- Highly non-linear model that **learns** features
- Alternating layers of **convolution** with learned kernel and **max pooling**
- Reduce input to 1-D vector (learned feature-vector) which is classified with a neural network
- Trained **patchwise** for segmentation

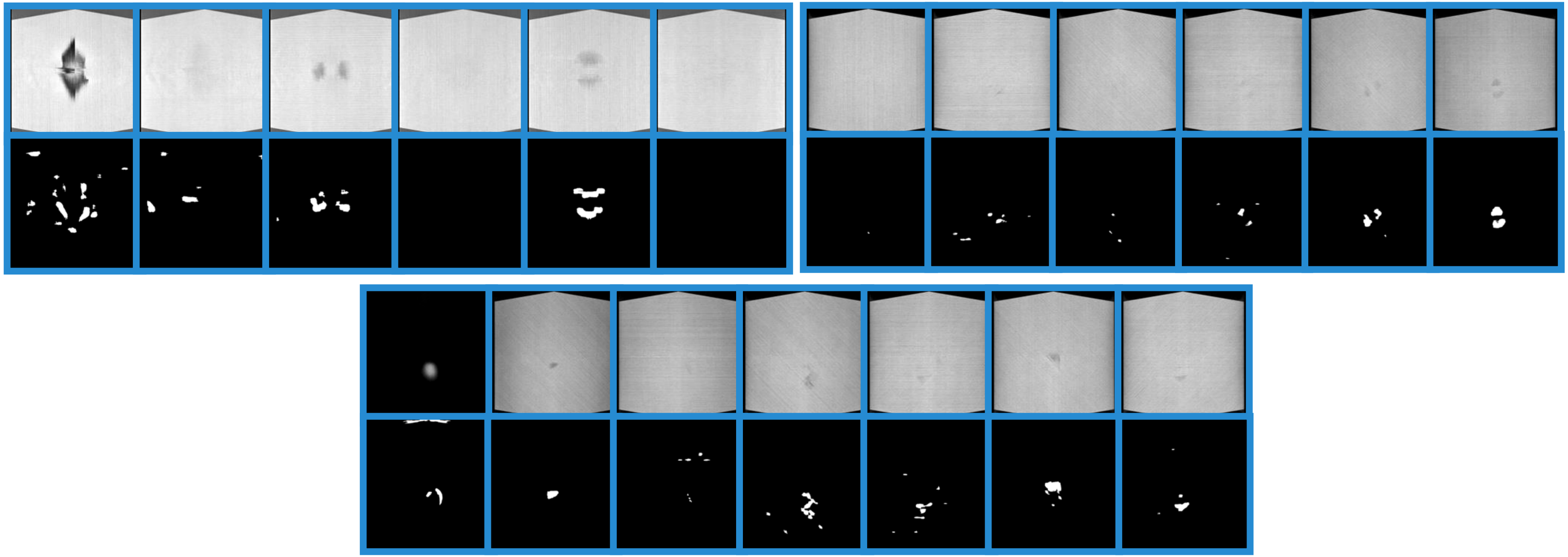
CNN Results on Simulated Test Set

Intensity	1	2	3	4	5	6	7	Total
Precision	74.82%	80.58%	72.01%	71.78%	73.15%	73.57%	73.58%	74.12%
Recall	22.80%	71.91%	81.98%	82.80%	81.60%	80.30%	78.41%	71.64%

	Count	Percent
Located ROIs	733	89.17%
Missed ROIs	89	10.83%
False Positive ROIs	127	13.19%



Results of CNN Analysis on Real Data



CNN Key Findings and Future Work

- Advantages
  - Identifies large number of defects with relatively few false positives
  - Ability to adapt to other defects/materials/modalities simply by changing training set
- Challenges
  - Struggles to correctly shape larger and smaller defects
  - Using more context to predict each pixel beneficial but using larger windows is computationally prohibitive
- Future Work
  - Multi-scale architectures would allow for more context without extra computational burden
  - Use CNN like an auto-encoder for anomaly detection
  - Consultation with ODU Professor with Deep Learning Expertise