Using Machine Learning to Automatically Detect Defects in CT

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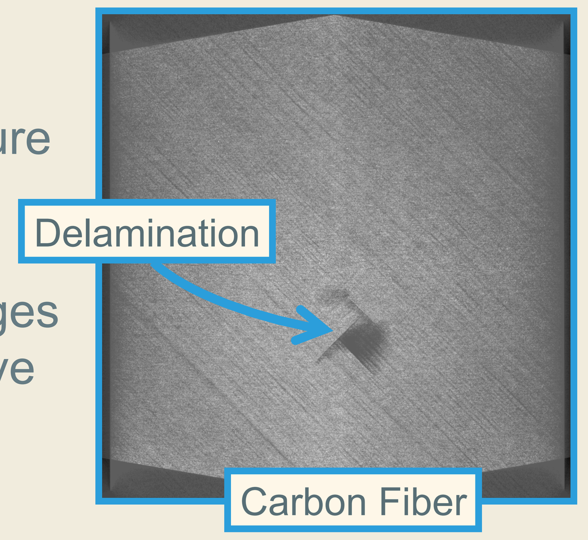
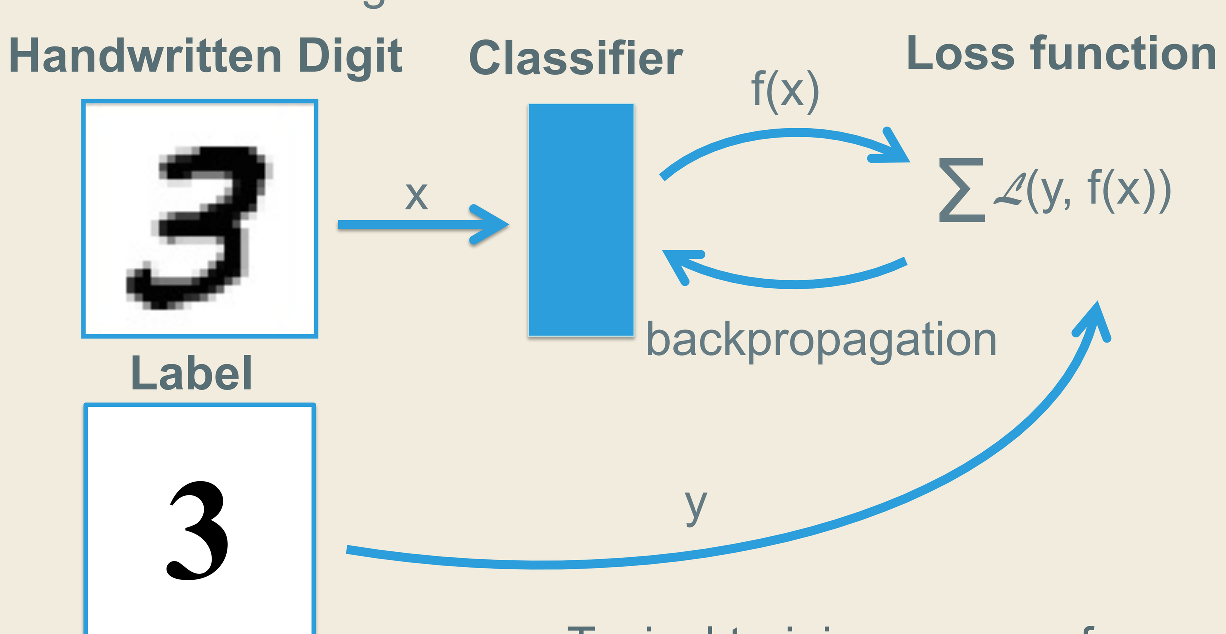
1. Introduction

- X-ray computed tomography (CT) can visualize internal structure of materials
- Currently, an expert manually analyzes images
- Extremely labor-intensive process



- Machine learning solves tasks by tuning parameters of a model based on labeled examples
- For example, a model can be trained to recognize handwritten digits on a bank check



Typical training process for machine learning

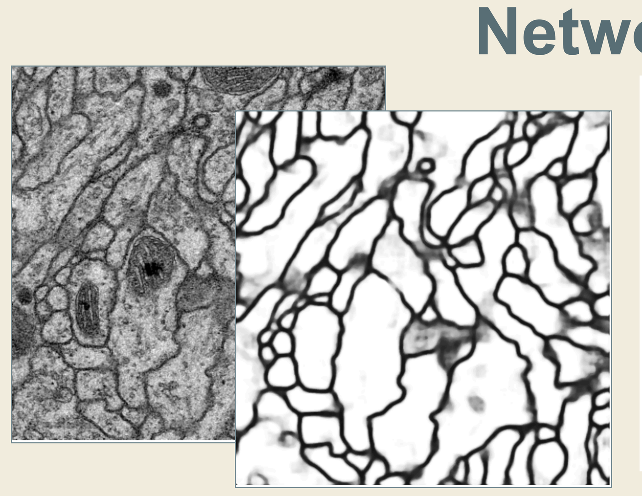
Objective

- Automate the analysis of CT data of composite materials using machine learning

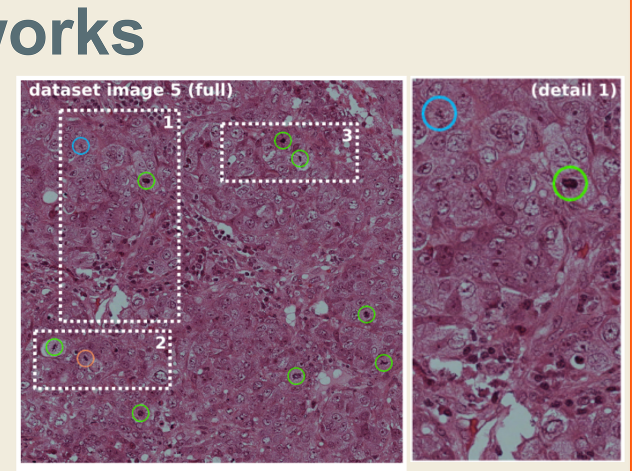
Why machine learning?

- Allows for relationships that cannot be defined by humans to be used to classify data
- Only requires labeled data and defined objective
- Adapting to new types of defects only requires changing training set
- State of the art for a number of similar tasks (see below)

Success of Convolutional Neural Networks



Neuronal Membrane Segmentation [1]

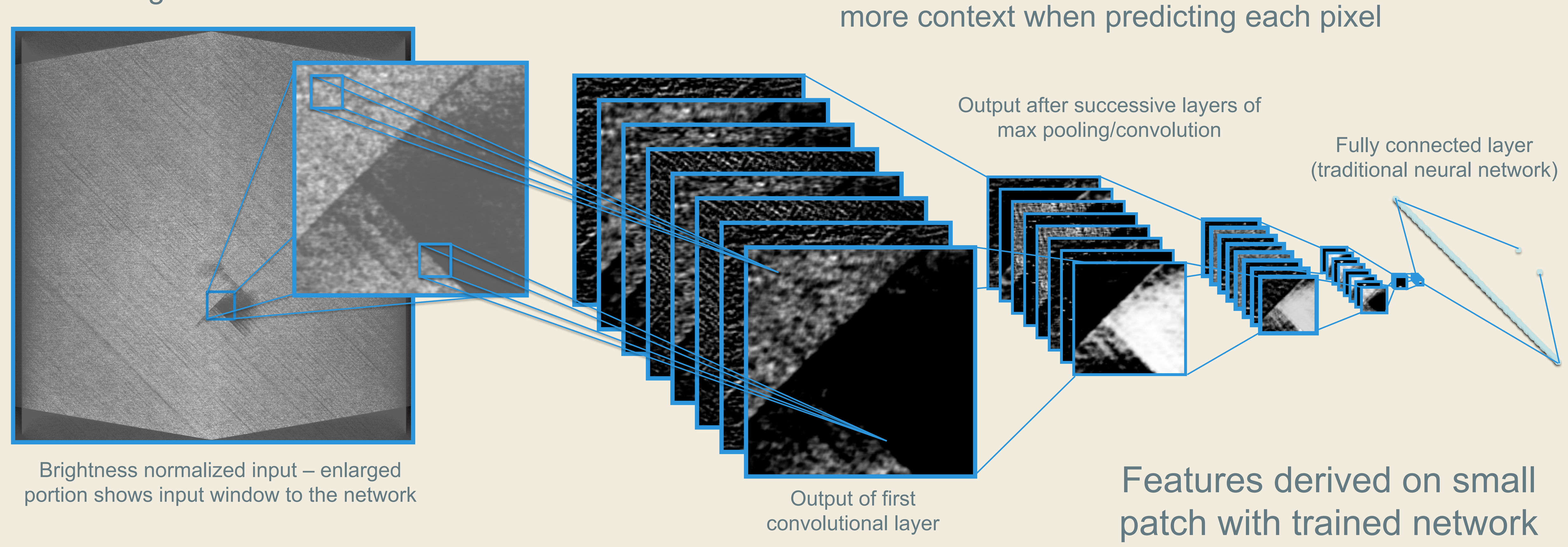


Mitosis Detection [2]

2. Approach

Convolutional Neural Network

- Consists of several alternating **layers** that learn a **hierarchy of features**
- **Convolutional layers** use trained kernel to emphasize different features
- **Max pooling** layers select most salient features from a small region
- 2-D input mapped to 1-D vector which is then **classified** using a traditional neural network
- Performs **dense prediction** by training to classify a small **window** around each pixel [1]
- Initially, 65 x 65 window used
- Currently using 201 x 201 window size to allow for more context when predicting each pixel



Features derived on small patch with trained network

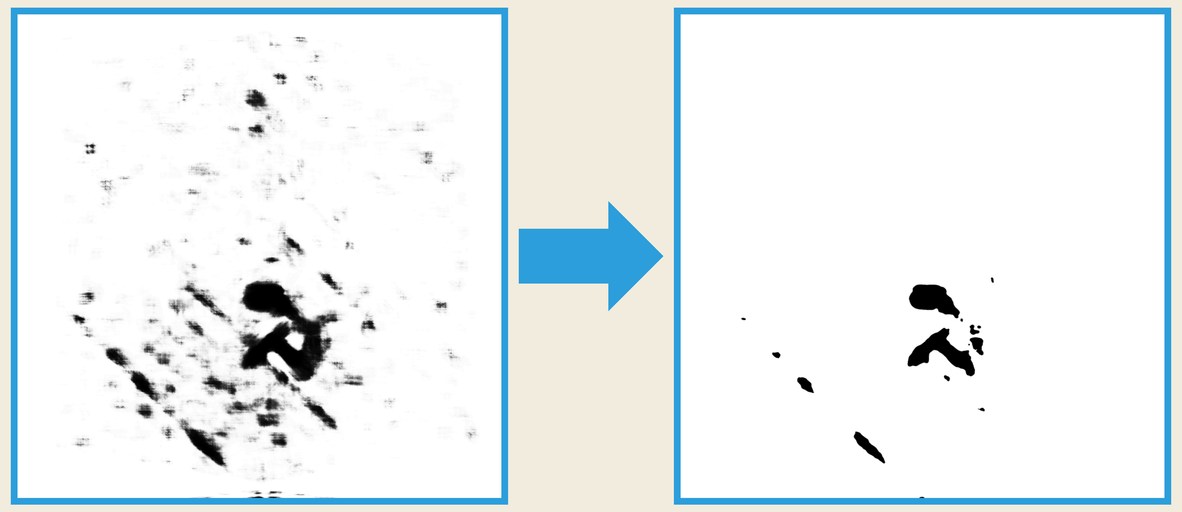
3. Details

Simulated Data

- Trained model on large simulated data set
- **Fine-tuned** with small, real data set to apply to real data

Post-processing

- Outputs **probability map** describing likelihood that a pixel is delamination
- Post-processing includes **thresholding** and smoothing with a **median filter**

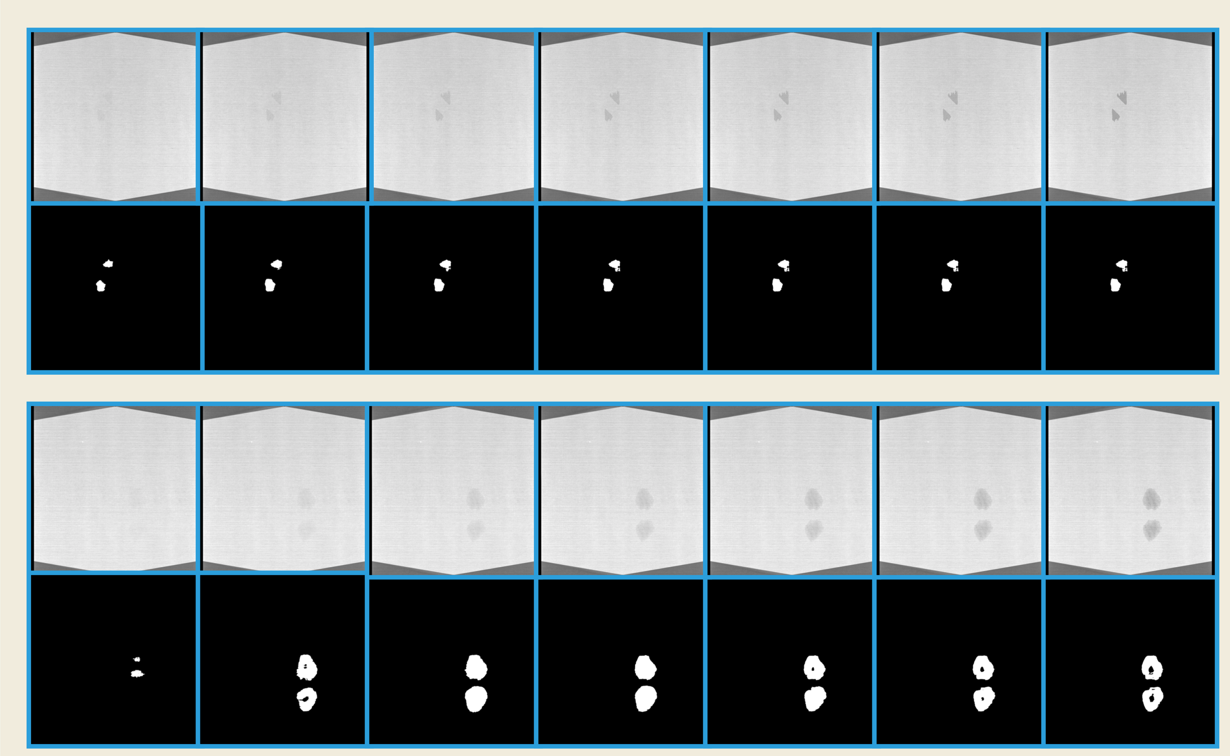


Raw output – intensity represents probability

After post-processing

4. Results

- Network tested on simulated data set

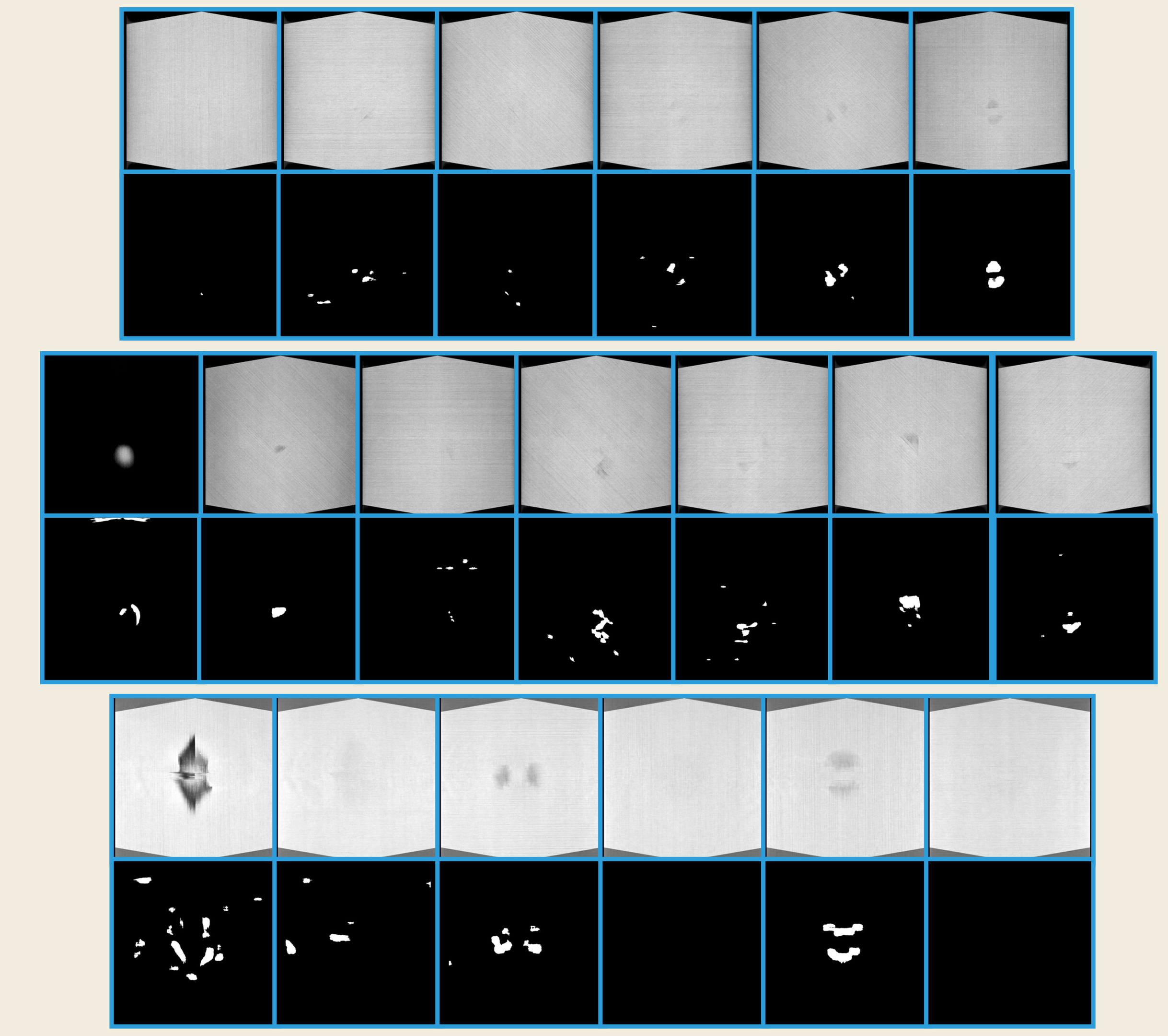


Top: Segmentation of synthetic data with delaminations of varying intensity; Bottom: Table describing ability to locate delaminations in larger data set

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

5. Results cont.

- Small real data set used to fine-tune network trained on simulated data
- Network used to classify unlabeled images



6. Conclusion

- Able to correctly identify large number of defects with relatively few false positives
- Could be used to increase confidence of expert analysis
- Struggles to correctly shape larger and smaller defects
- Using more context to predict each pixel beneficial but using larger windows is computationally prohibitive
- Multi-scale architectures would allow for more context without extra computational burden

7. References

1. Cireşan, Dan, Alessandro Giusti, Luca M. Gambardella, and Jürgen Schmidhuber. "Deep neural networks segment neuronal membranes in electron microscopy images." In Advances in neural information processing systems, pp. 2843-2851. 2012.
2. Cireşan, Dan C., Alessandro Giusti, Luca M. Gambardella, and Jürgen Schmidhuber. "Mitosis detection in breast cancer histology images with deep neural networks." In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013, pp. 411-418. Springer Berlin Heidelberg, 2013.

Acknowledgements

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